Chair of Energy Network Technology

Doctoral Thesis

Synthetic Load and Generation Profiles in Industry

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AFFIDAVIT

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ABSTRACT

The introduction of new technologies and processes, particularly the adoption of renewable energy sources, brings increased volatility into the dynamic relationship between manufacturing industries and their counterparts in the energy markets. To address this challenge, industrial energy research is dedicated to bringing forth dynamic, holistic and more straightforward solutions. One of these solutions involves the development of load and generation profiles, which allows for a detailed examination of how individual industries consume and generate energy over time. These valuable insights enhance the collaboration among key stakeholders, including grid operators, energy suppliers, and industrial players. As a result, it significantly improves decision-making processes, fostering advancements in the industrial sector.

Throughout an extensive literature research, it can be concluded that a holistic solution on synthetic load and generation profiles in industry has not been developed yet. State-of-the-art works either rely on vast amounts of data or focus solely on selected applications such as generating electricity load profiles for specific industrial subsectors. Recognizing this research gap, this thesis presents novel developments for generating load (and generation) profiles (LPs) and waste heat profiles (WHPs) of the entire industrial sector encapsulated in an all-in-one software solution named “Ganymed”.

Overall, the industrial sector is divided into energy-intensive and non-energy-intensive subsectors. As the energy-intensive subsectors exhibit a limited product and process variety, a bottom-up methodology starting with data on the process level is applied. Throughout the enhancement of the simulation method of discrete event simulation, these processes can be accumulated to whole production routes, which offers the basis for generating LPs and WHPs for energy-intensive subsectors. It can be stated that processes must contain data on energy-relevant and time-resolved properties to achieve LP and WHP generation. Here, the most energy-intensive processes influence the resulting LPs and WHPs of individual industries to the greatest extent. Especially batch-operated processes make up for main shares in peak loads. Non-energy-intensive subsectors exhibit more complex production routes, deeming a top-down approach to be the more suitable methodology for depicting them. Various industrial databases form the basis for novel findings within these energy system analyses, which are further deployed to generate LPs and WHPs for these subsectors. For example, this thesis uncovers subsector-specific “economy of scale” effects for industrial energy systems, correlations of shift models and deployed employees at the plant, calculations for maximum outlet temperatures of industrial waste heat etc.

Both methodological approaches are embedded into the software environment “Ganymed”, being the first-of-its-kind of software for generating synthetic LPs and WHPs of the industry.

KURZFASSUNG

Neue Technologien und Entwicklungen wie der Ausbau von erneuerbaren Energiequellen erhöhen die Volatilität im Energieverbund aus produzierender Industrie und anderen Energiemarktteilnehmern. Im Lichte dieses Spannungsfelds ist es die industrielle Energieforschung, die sich im höheren Maß auf die Entwicklung von dynamischen und ganzheitlichen Lösungen fokussieren muss. Ein Teilbereich dieser Lösungsansätze sind zeitbezogene Last- und Generationsprofile. Mit Hilfe dieser Methoden können die zeitbezogenen Energieverbräuche und -umwandlungen von industriellen Standorten generiert und untersucht werden. Diese Entwicklungen unterstützen unterschiedliche Zielgruppen wie Netzbetreiber, Energieversorger oder Industrieunternehmen, indem sie das Zusammenspiel am Energiemarkt maßgeblich fördern und somit den strategischen Entscheidungsprozess langfristig verbessern.

Um Zuge einer umfassenden Literaturrecherche zeigte sich, dass ganzheitliche Lösungsansätze für zeitbezogene, synthetische Last- und Generationsprofile im industriellen Kontext noch nicht entwickelt wurden. Derzeitige Forschungsbemühungen benötigen entweder große Datenmengen oder behandeln nur ausgewählte Fragestellungen wie die Entwicklung von reinen Stromlastprofilen für spezielle Industriestandorte. Im Kontext dieser Forschungslücke zeigt diese Arbeit neueste Fortschritte für die Generierung von synthetischen Last- und Erzeugungsprofilen (LPs) sowie Abwärmeprofilen (WHPs) für den gesamten industriellen Sektor gebündelt in einer einzelnen Softwarelösung genannt „Ganymed“.

Im Allgemeinen kann der industrielle Sektor in energieintensive und nicht-energieintensive Subsektoren eingeteilt werden. Da die energieintensiven Subsektoren eine geringere Produkt- und Prozessvielfalt aufweisen, wurde zunächst ein Bottom-Up Ansatz entwickelt, der an der Prozessebene der einzelnen Industrien ansetzt. Durch diskrete Ereignissimulation können Prozesse zu Produktionslinie verbunden werden. Dies ist die Basis für die Generierung von energiebezogenen Profilen. Hierbei müssen die hinterlegten Prozesseigenschaften sowohl Bezug zu Energie- als auch zu Zeitabläufen aufweisen. Des Weiteren zeigte sich, dass nur ein kleiner Teil an Prozessen für den Hauptteil des Energieverbrauches verantwortlich ist. Nicht-energieintensive Subsektoren weisen eine erhöhte Komplexität auf. Durch den Einsatz unterschiedlicher Datenbanken werden im Rahmen dieser Arbeit neue Erkenntnisse für den Bereich der Energiesystemforschung generiert. Hierbei wurden zum Beispiel die Tragweite wirtschaftlicher Skaleneffekte für industrielle Energieverbräuche, Korrelationen zwischen Schichtmodellen und Mitarbeiteranzahlen, neue Kalkulationsarten für die Ermittlung von maximalen Rauchgastemperaturen etc. erfolgreich untersucht und aufgedeckt.

FOREWORD

After finishing my master's studies by the end of 2019, my initial thought was actually not to pursue the scientific pathway any further. The last months were filled with hour-long studying and writing my thesis. Metaphorically, my battery was empty. Just as this level of stress slowly declined again after weeks, my underlying curiosity, interest and love for discovering new things and actively applying my creativity came back to me.

This is where I approached my later supervisor and head of the Chair for Energy Network Technology Thomas Kienberger, who is the first person, I want to say thank you to. A topic for my PhD thesis was quickly found and thus I started my professional career shortly before Covid-19 arrived. In times of major and shifting uncertainties, Thomas was able to create a stable working ground for his young researchers. Over the last three years, I managed to navigate through unknown waters under his guidance. Nearly most of the time, we worked on a level of consistent straightforwardness and distinct dedication, stripping away unnecessary complexity and revealing the true nature within my work in energy research.

Throughout this course, I consider myself lucky enough to work side by side with my forward-thinking colleagues at the Chair for Energy Network Technology. First and foremost, I’d like to thank Chris and Peter, with whom I closely worked together in an extensive project called “NEFI – New Energy for Industry”. Our cooperation was distinguished by easy and direct communication, always ready for active sparring and joint development of new thoughts on an absolutely high level of dedication and timely progress. I’m thankful for this time and grateful that a close friendship on a personal level evolved from our endeavours in the last three years.

When continuing to look at the personal side of my life, I also want to say thank you to my family and, firstly, to my parents Elfi and Jörg. They supported me throughout my PhD even with the slightest nuances of care there can be. Starting with my father, who never waives from showing his pride in my chosen course in any situation, or my mother, who always lends me an open ear when times have gotten busy. Through the last three years, I'm also grateful to see my little brother David grow up into an outstanding individual. He also discovered his interest in the technical field as he now pursues environmental studies at the HTL Leoben (and additionally – unlike his bigger brother at his age – is a much more dedicated sportsman).

At last, my biggest thanks are dedicated to my fiancée and soon-to-be wife Lisa. As it lies in the nature of life, not only professional but also personal challenges and downsides can occur from time to time. Throughout the part of my life, I spent together with Lisa, she wasn't frightened by any instances that arose and brought light and joy even into the darkest times. To put it scientifically: When extrapolating my life with her into the future, I cannot be more curious and confident, that our together path will be the brightest of all things in my life.

Thank you!

CONTENTS

NOMENCLATURE

LP	Load (and generation) profile
WHP	Waste heat profile
GHG	Greenhouse-gas
DSM	Demand side management
EEX	European Energy Exchange
CHP	Combined heat and power
PV	Photovoltaic
EAF	Electric arc furnace
ORC	Organic Rankine cycle
IEA	International Energy Agency
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne
P1-4	Papers 1 to 4
C1-2	Conference proceedings 1 to 2
EOS	Economy of scale
EMAS	Eco-Management and Audit Scheme
ETS	Emission Trading System
IAC	Industrial Assessment Centre
LF	Load factor
WHF	Waste heat fraction
DES	Discrete event simulation
GUI	Graphic user interface
RES	Renewable energy sources
DFT	Discrete Fourier transformation

HEX	Heat exchanger
WH	Waste heat

LIST OF FIGURES

List of Tables

1 INTRODUCTION

Technological advancements are the key solution against the rising challenges of the climate crisis [1]. Digitalisation forms the basis for future developments of energy efficiency measures, new processes, renewable energies, advancing energy infrastructure etc. along the path to climate neutrality [2]. These developments afflict all parts of the global economic landscape, although their respective state of implementation varies extensively.

Especially the manufacturing industry plays a crucial role throughout this transformational process [3], when investigating its considerable shares of 21% of greenhouse gas (GHG) emissions [4] and 20% of the total energy consumption in Europe in 2022 [5]. Company internally, the transformation process calls for new processes, new business models and managerial change. Externally, policy regulations and customer demand change in a fast-moving pace creating a constantly alternating channel for the industry to navigate through. This interplay unfolds new areas for energy research to bring forth advancements and assist the industrial landscape in securing its economic value.

Digital energy system models support the industry for those present and future challenges. These models range in their application as they can be deployed for depicting the current status of the industry, assessing other technologies and trends and evaluating their impact on the physical energy system [6]. An integral part of energy system models is the subject of depicting the time-resolved energy generation or consumption behaviour of a respective consumer or consumer groups within dedicated profiles [7]. Such profiles bear significant advantages as they can quickly identify specific issues in the energy systems of manufacturing industries as well as energy grids and help to derive strategies for adapting measures such as demand side management (DSM) or enhancing grid capacities [8]. These time-resolved methods are developed for various applications and systems, however, often tend to be progressively complex in their development and deployment when their respective scope enlarges [9]. Thus, state-of-the-art concepts are mostly either bound to extensive data availability or limit themselves to smaller fields of application.

As the industry has to nevertheless take part in the energy transition, this thesis suggests a new uniform solution for generating synthetic load and generation profiles, by approaching the industrial sector in a standardised manner and investigating similarities and distinctions in its functionalities. Different methods for these examined specific manifestations are then combined into an all-in-one software as the combined interface for the end user.

2 CONTEXT AND RESEARCH NEED

The following chapter describes the context in which this study is embedded as it firstly establishes a sound and standardised definition of underlying research work, secondly processes the latest state-of-the-art regarding the subject of industrial load and generation profiles and thirdly defines the scope and application of developed research studies, which answer still open research questions and hereby create a holistic contribution to the field of digital energy systems.

2.1 Load and Generation Profiles in Theory

2.1.1 Energy Systems in a Time-Resolved Context

Overall, consumers and suppliers regarding holistic energy systems are interlinked via dedicated structures [10], as Figure 1 shows.

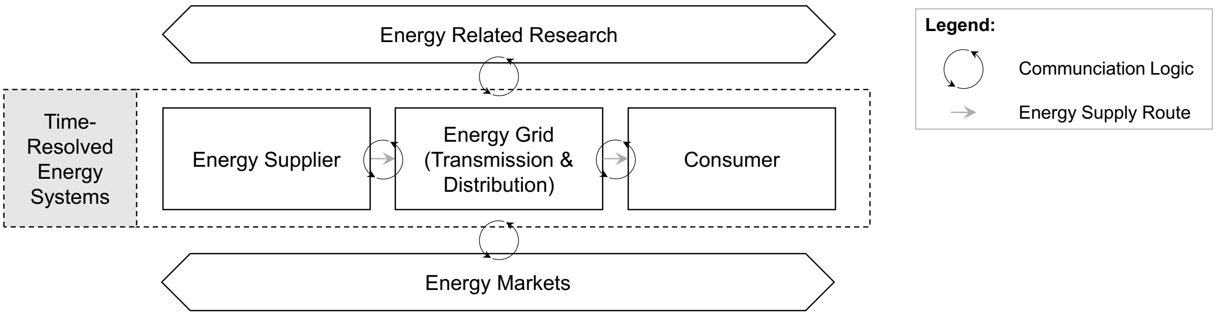

Figure 1: Involvements and stakeholder groups within the time-resolved energy-related environment.

The most elementary depiction of the energy supply route contains energy suppliers, energy transmission and distribution and consumers. All participants generate, transmit and consume energy in an alternating, time-resolved manner. The energy supplier generates or obtains energy, like electricity or natural gas. Then, the energy transmission system, maintained by e.g. grid operators, transports this energy across long distances through power lines or pipelines. Finally, consumers, like households and industries, rely on this energy supply to meet their daily needs. The cooperation among these participants is crucial for a dependable and sustainable energy supply and, in e.g. Europe, is mainly handled through the liberalized energy markets. [11]

Energy (system) related research acts as a cross-functional role to observe, analyse and develop new measures, which improve the interplay between the other actors.

2.1.2 Definition of Load and Generation Profiles

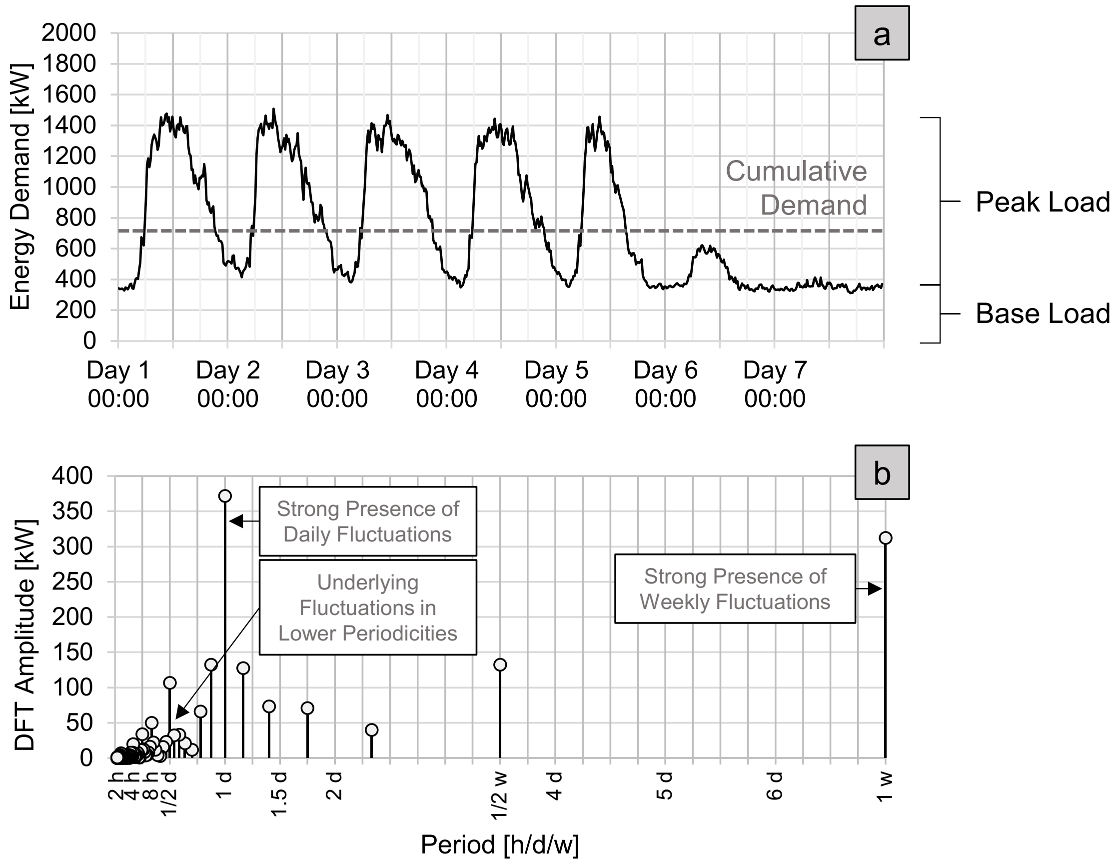

Figure 2: Definition of loads and generation profiles: (a) a weekly LP of an industrial company and (b) the results of the DFT analysis of this LP

Overall, load (and generation) profiles (LPs) depict the fluctuating energy demand (or generation respectively) of single consumers or consumer groups within a defined period of time, as shown in Figure 2 (a) [12]. Within the context of this work, LPs refer to the time-resolved energy demand of single consumers (e.g. single production processes like an electric arc furnace) or consumer groups (e.g. whole production routes). Furthermore, industrial waste heat profiles (WHPs) are a subgroup of LPs and resemble time-resolved (generated or consumed) waste heat.

Energy consumption is regarded as energy supplied and used (e.g. converted from final energy to useful energy categories like mechanical drive) over a certain period of time, stated in watthours e.g. [kWh], and demand as the time-resolved load at every single point in time, in watt e.g. [kW]. The integral of an LP (the area under a profile), standardly defined as energy demand [kW] over a period of time [h], expresses the energy consumed [kWh]. Both energy consumption and demand are mathematically declared as positive if a process is supplied with energy, or negative if a process supplies energy (e.g. generation of waste heat). These definitions correspond to the definitions in common literature [13]. Moreover, the resulting profiles can be divided into a constant and variable section, shown as peak and base load within Figure 2 (a). Base load represents the minimum level of energy demand in the load profile persisting throughout the depicted time. This is often associated with the consumption of essential services and processes that run continuously, such as lighting, ventilation or appliances on standby. Peak loads are elevated from the base loads and include the peak demand, which is the highest point in the LP.

A discrete Fourier transformation (DFT) analysis of individual LPs offers the advantage of investigating periodically occurring fluctuations in profiles [14]. This analysis decomposes the input signal (e.g. LP) into a sum of periodic sine and cosine components and therefore depicts the amplitudes of all variant fluctuations in the profile. This analysis oftentimes finds its use in estimating short-, mid- and long-term energy storage for individual energy systems. Figure 2 (b) shows the DFT amplitudes of the decomposed LP over a weekly period range exemplarily. A strong dominance of daily (1 d) and weekly (1 w) fluctuations can be observed. This can be confirmed by investigating Figure 2 (a) and concluding that daily fluctuations occur regularly in the first five days and the overall LP spans over one week. The DFT analysis also gives insights into the magnitude of short-term fluctuations located at smaller periodicities. For example, if an LP appears smoother (meaning variations in the LP are reduced) the corresponding amplitudes in the DFT are decreased. [14]

The share of base and peak loads in an LP depends on the underlying, depicted consumer and consumer groups. The simultaneity factor is an insightful value in designing (energy) supply systems as it describes the share of simultaneously occurring loads of individual consumers in a consumer group [15]. The simultaneity factor is 1 if just one consumer is supplied with energy and decreases with the rising number of individual consumers in a group. If load peaks of individual consumers are accumulated, the resulting LP will exhibit the superimposition of these single loads. Naturally, if more consumers are depicted in the group, their individual peak demands, occurring at different times, will be balanced out in the resulting LP. As the cumulative peak load of the consumer group shrinks, the resulting LP will appear more even and the simultaneity factor decreases. Thus, the decomposed LP within a DFT analysis will exhibit reduced amplitudes, especially in areas of smaller periodicities.

In the context of generating LPs, corresponding profiles are obtained through different methodologies. Overall and alongside scientific literature, this work divides these profiles into standard load (and generation) profiles, synthetic load (and generation) profiles and profiles from the time-resolved modelling of individual consumers [16]. Figure 3 outlines the results from these methodologies and their implications on their properties.

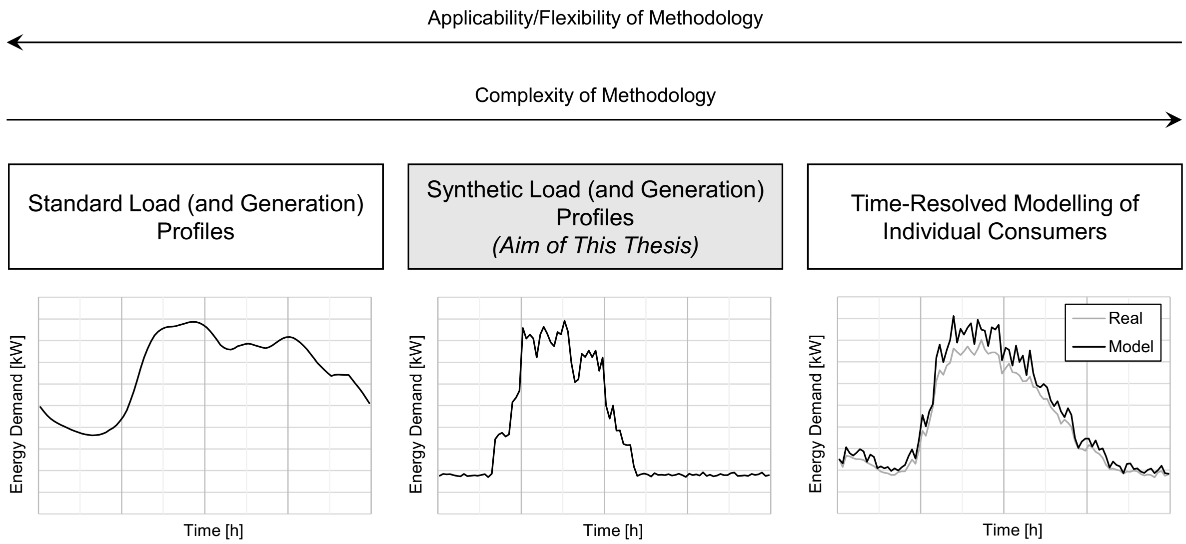

Figure 3: Comparison between standard LPs, synthetic LPs and time-resolved modelling of consumers. From left to right, the complexity of the applied methodology increases, demanding a more extensive amount of reliable data. However, the flexibility of the methodology decreases, limiting the possibility of easily shifting and applying this methodology to other energy consumers.

2.1.2.1 Standard Load (and Generation) Profiles

A standard LP refers to a representative profile that is used as a benchmark or reference for a selected group or category of consumers [17]. These high aggregated profiles are quick to obtain as they result from mathematical functions from data analysis of measured consumer groups and can be allocated to targeted consumers via equivalence factors from these normalized profiles. They oftentimes find their application in grid and energy market management to grasp possible energy demands of consumer groups beforehand and to initiate measures for the to-be-foreseen implications on the energy system. Standard LPs are, for example, well-fitted for the sector of buildings to depict loads of multiple households. However, they are not applicable anymore for smaller consumer groups or even individual consumers as they are not able to depict LPs with higher simultaneity factors and DFT amplitudes with smaller periodicities. [18]

2.1.2.2 Synthetic Load (and Generation) Profiles

Synthetic LPs can depict individual consumers and small consumer groups [19]. While standard LPs are created through cluster analysis and extrapolation of measured data, synthetic LPs are typically generated through deterministic and stochastic algorithms. Synthetic LPs rely more on a sound understanding of the depicted energy system rather than on measured profiles and target a successful depiction of the main load characteristics of a consumer or consumer groups including increased short-term periodicities. A downside of this approach is that the underlying methodology for synthetic LPs is generally more complex than for standard LPs. To reduce complexity, residual loads or uncertainties regarding the to-be-depicted energy system are bridged with stochastics (e.g. loads with small periodicities depicted by Gaussian distribution). This thesis aims for the depiction of synthetic profiles (LPs and WHPs) for the entire industrial sector.

2.1.2.3 Time-resolved Modelling of Individual Consumers

The optimization of individual energy systems grants an efficient interplay of individual consumers, integrates new processes resourcefully and aims to cut down energy costs [20]. Especially for larger and more complex energy consumers like industrial locations, energy optimization measures bear fruitful solutions for optimal energy use. Time-resolved modelling of individual energy consumers (e.g. industrial processes) can act as a precursor for the development of these optimization algorithms. The developed model is based on real-life data and is therefore limited to the application of the individual, local energy system only. It aims to resemble the time-resolved loads and generation including all occurring periodicities and fluctuations of the processes as accurately as possible through mathematical simulation [20]. The generated LPs act as a base for the investigations of further optimization measures and new process integration. These tailor-made models are, however, unfit to be flexibly applied to other consumers or consumer groups and require a soundproof data pool in the beginning.

2.1.3 Fields of Application of Load and Generation Profiles

By depicting the load and generation time-resolved, valuable insights into the behaviour of the energy system of consumers and suppliers can be derived. As energy systems are typically investigated statically, time-resolved energy analyses bear more detailed information as they reveal at which points in time deviations from the statically cumulative demand (e.g. load peaks) occur [21]. The depiction of this volatile behaviour is an important factor in the overall energy system. Overall, LPs impact the following partaking roles in a holistic energy system. As the research aim of this work especially targets the manufacturing industry, the following fields of application particularly emphasize the consideration of this economic sector:

2.1.3.1 Implications for Energy Suppliers

In recent years, the role of energy suppliers, besides conservative power plants, was increasingly attributed to other participants in the overall energy systems as well. Technological advancements and renewable energy sources brought more and more energy suppliers to the table. This circumstance ranges from e.g. big wind and solar farms, to individual households and industrial sites [22]. The latter can provide the public energy system not only with electricity but also excess heat from thermal energy-related production processes [23]. The development of energy generation profiles for these categories can reveal further potentials to be tapped and investigate their impact on the overall energy system, especially in the context of dedicated measures like redispatch (see subsection 2.1.3.3 below).

2.1.3.2 Implications on Energy Markets

As the rising implementation of renewable energies in recent years further afflicts the energy system with demanding volatility, energy market operations face increasing movement within day-ahead and intraday trading [24]. However, especially for industrial consumers, dedicated time-resolved energy system analyses are only scarcely developed. Oftentimes, the highly aggregated, standard LPs are the first and only option for these applications, which are not sufficiently designed for short-term trading, especially for smaller consumer groups or even individual consumers, as described above [25]. Thus, continuously further developed and industry-specific synthetic LPs fulfil the need for cost and energy-efficient trading as they provide more detail.

2.1.3.3 Implications on Energy Grids and System Operators

Within the context of energy volatility, physical energy transmission is limited to the grid's capacity [26]. With increasing renewable generation capacities these limits are reached sooner than later, demanding either to upgrade existing grid infrastructure or to intermittently and locally latching-in existing, often inefficient and with fossil energy-powered plants [27]. The latter option is additionally not only responsible for increasing CO_2 emissions but also cost-intensive [28]. For example, the costs of these so-called "redispatch" measures in Austria amounted up to 100 Mio. € in 2021 [29]. Thus, the spatial introduction of synthetic LPs within the overall energy systems provides a more precise identification of infrastructural hot spots for local expansion of the energy transmission system efficiently. Industrial sites play a vital role in this consideration following their energy-intensive production.

2.1.3.4 Implications for Energy Consumers

The role of all economic sectors of building, transport and manufacturing industry in reaching the climate goals is accompanied by medium and long-term investment projects. New and existing technologies and business cases are to be implemented in their respective energy systems to provide efficient energy and CO_2 emission reduction. As this work especially aims at the manufacturing industry, the generation of synthetic LPs of these industries can help to investigate the impacts of all planned measures. For example, the implementation of microgrids is a key technology for optimizing the energy loads and reducing grid fees of individual industrial plants [30]. To assess the impact of this technology before its installation, the generation of location-specific, synthetic LPs forms an easier-to-obtain base of information compared to the installation of a real-life metering concept on site.

2.2 State-of-the-art for Load and Generation Profiles

State-of-the-art methodologies are investigated in the next step. This bridges the gap to still open research areas, which were identified and closed within this study.

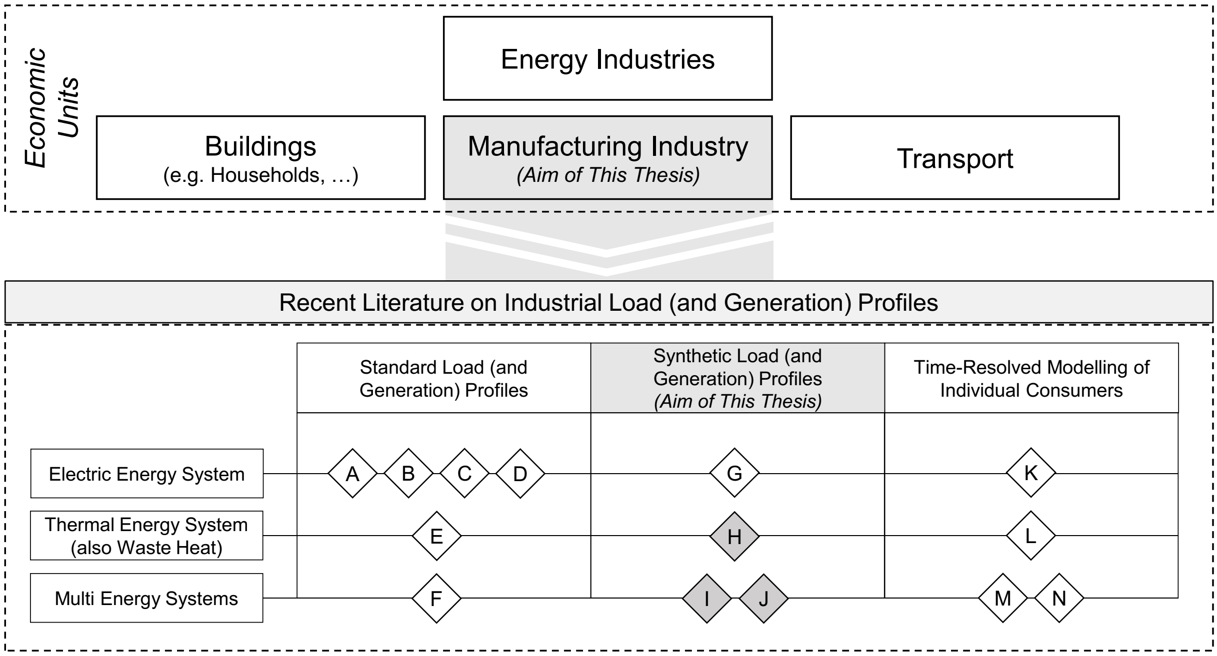

Figure 4: Classification of selected, state-of-the-art methodologies from the recent years in the context of LP and WHP generation in industry: A: Hernández et al. [31], B: Valdes et al. [32], C: Dedic et al. [33], D: Richard et al. [34], E: Jesper et al. [35], F: Starke et al. [36], G: Sandhaas et al. [19], H: Binderbauer et al. [37], I: Binderbauer et al. [38], J: Binderbauer et al. [39], K: Dietmair et al. [40], L: Lecompte et al. [41], M: Dock et al. [20], N: Thiede et al. [42]

The European Commission states a concise classification of economic units as “buildings”, “energy industries”, “transport” and “manufacturing industry” [43], which is shown in Figure 4. For all units, respective methods for investigating time-resolved energy systems (and their load and generation patterns) were developed in the past. In the next chapters, firstly, the advancements within other economic units are outlined, secondly, recent methodologies for industrial consumers with the highest impact in scientific literature are described (as also shown in Figure 4) and thirdly these studies are put into context with this work.

The taxonomy table in the Appendix compares the selected studies for industrial application from Figure 4 in more detail along their objectives, LP types, aggregation levels, systemic approach, solving methods, constraints and potentials.

2.2.1 Buildings

The classification of buildings contains residential households and tertiary services. To assess the impact of the load and generation of these energy consumers, standardised LPs are the first point of application. As described above, they are easy to obtain for different consumer groups, however, are not able to depict smaller consumer groups or individual consumers due to their high aggregated character [16]. Generally, standard electricity LPs are calculated for groups of more than 400 single households under 100 MWh [44]. Esslinger and Witzmann [18] state that the application of standard electricity LPs for consumer groups under 150 households does not provide representative results anymore. In light of increasing decentralised energy generation, the authors propose a method to depict LPs of smaller consumer groups. These calculations are mainly based on probabilistic methods for standard LPs and result in valid approximations to real-life selected single consumers.

Especially for depicting natural gas consumption, the seasonal influence strongly alters the resulting LPs due to heating appliances. Winter seasons result in both higher base and peak loads than compared to summer [45]. This effect is particularly present in the sector of households and tertiary services. In these cases, standard LPs are further advanced to ambient temperature-dependent profiles based on the “SigLinDe” function. Here, the ambient temperature $\mathrm{T_{amb}}$ acts as a scaling factor for an underlying LP correction to calculate the corresponding hourly demand $\mathrm{E_{SLD}}$ as formula I shows below. For a $\mathrm{T_{amb}}$ = 8 °C, $\mathrm{h(T_{amb})}$ equates to 1. $\mathrm{h(T_{amb})}$ is larger than 1 for ambient temperatures under 8 °C and smaller than 1 for temperatures above 8 °C. The mathematical regression of this correlation is developed through a mixed linear and Sigmoid function. [46]

$$\mathrm{E_{SLD}} = \mathrm{E} \cdot \mathrm{h(T_{amb})} \cdot \mathrm{F_{WT}} \qquad \mathrm{I}$$

Formula I further includes E as average, not corrected natural gas consumption [kWh] per hour and a scaling factor $\mathrm{F_{WT}}$ incorporates the respective influence of weekends and weekdays on the energy consumption.

Overall short-term variabilities (amplitudes at smaller periodicities following DFT analysis) within the respected natural gas LPs are less distinct than for electricity. This is because natural gas consumption for heating purposes within buildings expresses itself rather steadily (e.g. water heating or room conditioning) [47]. However, because “SigLinDe” is not bound to end-use appliances (e.g. a water boiler) but external ambient temperatures, certain inaccuracies cannot be excluded to a full extent. LPs from ambient temperature correcting formulas like “SigLinDe” can be allocated to the group of synthetic LPs as they do not aggregate existing data like for standard LPs but trace back to properties (in this case, the time-resolved ambient temperature gradient) for individual consumers.

Pflugradt et al. [48] created a holistic approach to generate synthetic LPs of households for electricity, natural gas and other energy carriers. Unlike the others mentioned above, this methodology focuses on the lowest level of aggregation, thus, the load pattern of energy-consuming appliances within residential homes. Moreover, this method is interlinked with further information like the time-dependent behaviour of the residents. The corresponding calculations combine the individual consumers to depict the entire energy system via a bottom-up approach. This offers more advanced LPs in terms of accuracy and detail. However, the methodology's comprehensiveness limits the accessibility for easy and swift evaluations. This trade-off is common throughout all examined fields of time-resolved energy system analysis.

2.2.2 Transport

Analyses of the load and generation within the mobility sector mainly refer to the interaction of E-mobility and the local electricity distribution grid. The aim of generating electricity LPs is to assess the impact of electric vehicle charging on the local grid and the development of further advancements for its respective integration e.g. vehicle-to-grid [26]. Vopava et al. [26] evaluate various approaches of methods for simulating the time-resolved charging of E-vehicles for examining grid reinforcement needs. The authors found that LP methods are typically developed within two categories:

The first group synthesizes the charging loads based on probabilistic correlations, e.g. the driver's behaviour: For example, within the spatial model of Fischer et al. [49] an extensive data analysis shows that parameters like household type and economic status influence the number of vehicles per household and occupation of the driver impacts the time-resolved utilisation of mobility infrastructure (e.g. parking time, charging time, …). A developed, probabilistic Markovian model then outputs the electricity LPs based upon these correlations above and evaluates the impact on the local distribution grids.

The second category validates data directly measured at vehicle charging stations and derives models from revealed correlations. For example, Neaimeh et al. [50] applied real-life electricity LPs from charging processes to model their spatial and time-resolved impact on generic distribution grids. The authors' findings suggest the implementation of new measures, e.g. DSM, to support the grid stability in the next step.

2.2.3 Energy Industries

Energy industries refer to economic units, which are principally set at the beginning of the energy conversion chain. They are responsible for the production and distribution of grid-bound (e.g. electricity, natural gas, …) or grid-unbound (e.g. coal, fuel oil, …) energy carriers based on primary energy and resources [43]. Production factors influence the temporal availability of generated energy carriers. On this matter, especially electricity generation is driven by various factors ranging from internal (e.g. maintenance, …) to external (e.g. daytime, season, …). These uncertainties within time-resolved energy production heavily impact the economic units downstream and their determination is therefore of major importance.

Throughout investigations of real-life plants (e.g. nuclear power, wind farms, hydroelectric, PV, …) derived capacity factors subject to the temporal availability of produced electricity [51]. For individual points in time capacity factors state the ratio of generated electricity to the theoretical maximum output, which is defined to be reached at continuous and full operation:

$$\mathrm{CF_t} = \frac{\mathrm{E_{gen,t}}}{\mathrm{C} \cdot \Delta\mathrm{t}} \tag{II}$$

Formula II states the mathematical formulation of the time-resolved capacity factor $\mathrm{CF_t}$ [-] based upon the generated electricity $\mathrm{E_{gen,t}}$ [kWh], overall maximum capacity C [kW] within a defined period of time Δt [h].

Like standard LPs for the sector of buildings, capacity factors tend to be afflicted by uncertainties attributed to their cumulative, high-aggregated calculation. Especially for depicting highly volatile, renewable energy generation like PV or wind other approaches bear clearer advantages. Exemplarily, the following resources can be named:

"Renewables.ninja" [52] is a web-based tool which provides energy generation profiles from PV and wind generation for timely resolutions of hours and above. The profiles are synthesized based on location information, weather data, forecasts and characteristic generation curves.

The "Global Wind Atlas" [53] is also a web solution which generates time-resolved generation data from wind sources based on spatial and historical weather data. The depiction of a heat map outlines the top potential areas for increased power yield. However, this tool only provides daily profiles from these data sources.

The "PVGIS tool" [54], developed by the European Commission, provides hourly generation data from PV, also based on georeferenced and characteristic generation curves. Moreover, the selection of individual PV technologies provides more evaluation options for generated profiles.

A series of other studies investigate the simulation of energy generation profiles from renewable sources, however, this cannot be covered to this extent in this thesis. The mentioned tools outline the importance of evolving research methodologies into concrete software applications providing usability and scalability of the developed approaches.

2.2.4 Manufacturing Industry

The industrial sector lies within the aim of energy-related research of this study. As this sector's properties and classification are described more thoroughly in the methodology section below, this study emphasizes that the applied industrial energy system surpasses the other sector's systems in regard to its comprehensiveness: For example, besides electricity, the significant share of high-temperature end-use applications/processes (e.g. smelting ovens) within this sector makes process heat related, time-resolved analyses an essential instrument for gathering insightful information [38]. Moreover, process heat, which can potentially be converted from various energy carriers, can also be recovered within or outside the plant (e.g. as waste heat) for further utilisation [23]. Supplied fuels can also be utilised as feedstock in production processes [55], which contributed further to the complexity of the sector when conducting energy system analyses.

Figure 4 shows selected works from literature in recent years, which target the examination of the time-resolved behaviour of energy systems of industrial subsectors and plants and, by that, generated respective impacts in the context of energy-related research. Here, the distinction between methodologies for developing standard LPs, synthetic LPs and time-resolved models of individual sites is outlined. Especially for the latter, various studies have been developed in recent literature, but this thesis only describes four selected works as they specifically outline the importance of LP generation in their respective research.

Through the depicted classification it can be observed that recent studies already heavily investigated the development of standard LPs for industries. In the studies by e.g., Valdes et al. [32] or Jesper et al. [35] “k-means” cluster analyses of electricity and heat profiles respectively reveal prominent, reoccurring features in the LPs. This leads to the derivation of mathematically formulated equations, which make a standardised approximation to real-life energy demand of industrial consumer groups possible.

Similar to the development of standard LPs in other economic units, studies for industrial applications also tend to develop their methodologies in a top-down manner. This means that data is generally gathered and analysed on a high aggregated level of e.g. an entire industrial subsector, to then depict smaller consumer groups downstream [31]. Since standard LPs do not apply to individual consumers (as described in the sections above), the application of these methodologies is limited to a certain extent. However, the focus of recent literature increasingly lies on revealing LP variations between e.g. industrial subsectors or working and weekend days [31]. These efforts for more detailed system analyses could potentially provide better applicability of industrial, standard LPs in the future. The comparison of further depicted literature studies for standard LPs in Figure 4 is outlined in the taxonomy table in the Appendix.

Time-resolved modelling of individual consumers like industrial plants requires a tailor-made methodology and a profound knowledge and database of the to-be-depicted energy system. As described in section 2.1.2.3, the development of LPs is here oftentimes regarded as the first step and necessary tool to investigate the application and impact of systemic measures (like DSM) or new technologies and processes in the existing industrial site. For example, Thiede et al. [42] developed a model based on generic energy flow-oriented manufacturing simulation. The aim is to assess real-life facilities and the impact of energy reduction measures. The overall methodology is conducted via multiple steps and requires extensive data from the respective, to-be-investigated plant. Analyses regarding factory internal or external waste heat recovery are not explicitly stated within the work. Dock et al. [20] further exploited multi energy system analyses for a selected steel mill applying the electric arc furnace (EAF) route to generate LPs and WHPs based upon plant-specific measurements and application of Markov models. This multi energy analysis does not differentiate between plant internal or external waste heat usage but offers insights on still untapped potentials regarding energy flow and waste heat utilisation for the respective facility. Lecompte et al. [41] deployed a model which solely generates WHPs of a real-life steel mill for investigating the implementation of waste heat recovering organic Rankine cycle (ORC).

All the above literature works of time-resolved models investigate individual plants in a bottom-up manner. This approach is initiated at the lowest aggregation level (e.g. single industrial processes) and assembles the facility and underlying production by investigating the systemic combination at these levels. This, however, results in a higher degree of complexity for the situated method and the need for specific data from the lowest aggregation level.

In conclusion, it can be stated that, while standard LPs (deployed by top-down calculations) offer wider flexibility in their reproducible application but lack the depiction of individual consumers and their features, time-resolved models (deployed by bottom-up calculations) specifically aim for detailed industrial sites, however, require extensive data and tailor-made models to be initiated. This leads to the question, of whether the nature of both categories can be combined sufficiently by developing a methodology for generating synthetic LPs, which offer representative results of individual consumers and still manage the flexibility to be applicable for a broader range of industrial subsectors at the same time.

Merely Sandhaas et al. [19] were found in recent literature to step into this question by depicting synthetic electricity LPs. The authors combined top-down standard LPs with bottom-up models, distinguishing shares of useful energy categories in their LPs (e.g. process heating and cooling, lighting, mechanical drive, …). The bottom-up models solely depict periodical fluctuations in the energy consumption of continuous and batch/discontinuous mechanical drives. The authors apply their methodology for three IEA subsectors.

2.3 Research Need and Scope of This Work

Time-resolved energy system analyses to generate LPs are already well developed within the economic sectors of buildings, transport and energy industries, as outlined above. Within the scope of these methodologies, the main aim is to provide a better understanding and improved integration within electricity grids and infrastructure. Manufacturing industries exhibit more complex energy systems and single consumers like individual plants are responsible for high shares of energy consumption. Thus and in the context of intrinsic boundaries set by traditional economic (e.g. cost, quality or time) and environmentally driven objects (e.g. reduction of energy and CO_2 emissions) and extrinsic impacts from regulations and society, industry is increasingly obliged to deploy and gather more knowledge on the most detailed subareas of their production system [56].

The literature review shows that methodologies to generate industrial LPs have been developed in recent literature studies for different use cases. Here, especially the focus lies on the generation of standard LPs or concrete time-resolved modelling of individual manufacturing sites, as described above.

The findings from the literature review can be condensed to the following aspects, which present still unanswered research gaps:

- <u>Lack of synthetic LPs of the entire industrial sector</u>: Developed standard LPs of the manufacturing industry offer valid approximations to whole consumer groups. However, they do not sufficiently depict individual or more complex energy consumers. Throughout the development of concrete time-resolved modelling methodologies, this aim can be reached. However, these require tailor-made approaches, an extensive (real-life) data basis and longer development times. A gap between these two variants can be filled by synthetic LPs, which firstly offer better flexibilities for applying different use cases and secondly are able to depict major characteristics of individual or complex energy consumers as well. In overall, holistic methodologies for generating these synthetic LPs in industry have not been thoroughly developed in recent literature yet.

- Lack of thoroughly investigated impacts on LPs: There is no holistic study, which investigates and reasons the multitude of factors influencing the time-resolved energy demand and generation behaviour of industrial plants. For example, top-down studies (e.g. for standard LPs) solely examine the common characteristics of LPs but do not further document the underlying origins of these patterns. Bottom-up studies (e.g. in the context of time-resolved models of individual plants) largely reason these impacts only on process level.
- Lack of multi energy system approach: As Figure 4 shows, the main share of literature studies investigates the development of LPs for electricity. While this is a valid consideration for other economic units like buildings or transport, the industry is afflicted by significant shares of high-temperature applications and process heat, as described above [57]. The depiction of heat and fuels for thermal useful energy can be deemed as a still neglected field within this context.
- Lack of depicting energy generation and conversion in LPs (especially waste heat): Standard LPs purely cover the load behaviour of the industry. Time-resolved models also manage the investigation of energy conversion and generation within the selected manufacturing plant, especially for the subject of waste heat generation and utilisation. However, no study in the latest research advances to generate specifically WHPs of different industrial plants on a more holistic level.

In conclusion, a holistic approach for generating synthetic, industrial LPs for different energy carriers should be embedded into a standalone software as a definitive solution for the industrial sector. This can assure a user-friendly methodology as the complexity is stripped away by the nature of the software environment, but still put time-resolved multiple energy system analysis into practice by combining top-down and bottom-up methods. To realise this goal, this work is put together by interlinked research studies and conference proceedings. Through this, the identified research gap left open within the mentioned bullet points above can be closed by bundling these findings and developments and concentrating them under the following research questions:

- R1: Is the depiction of synthetic load and generation profiles for individual industrial sites of different subsectors of the entire industrial sector possible?

- R2: What underlying factors and conditions like subsector characteristics, process properties, methodological approaches (e.g. bottom-up and top-down calculations) and data availability influence synthetic load and generation profiles?
- R3: Can the developed methodologies for generating synthetic load and generation profiles be adapted to also depict industrial waste heat profiles?

To sufficiently answer these research questions, the next chapters discuss and present the developed methodology in this work interlinked with corresponding publications.

3 METHODOLOGY

This chapter unveils the underlying, common basis which was put into practice for the individual investigations and developments for answering the overarching research questions from above. These individually developed methods are then further outlined in the published works. This chapter also describes their respective connections and contributions to this overall study.

3.1 Classification of Manufacturing Industry

Within the development of a holistic approach for generating synthetic LPs and WHPs of industrial consumers, the concise classification of the industrial sector is key. Due to the great heterogeneity of the industry in terms of processes, products and further characteristics, the sector is to be investigated by introducing standardised parameters and descriptions.

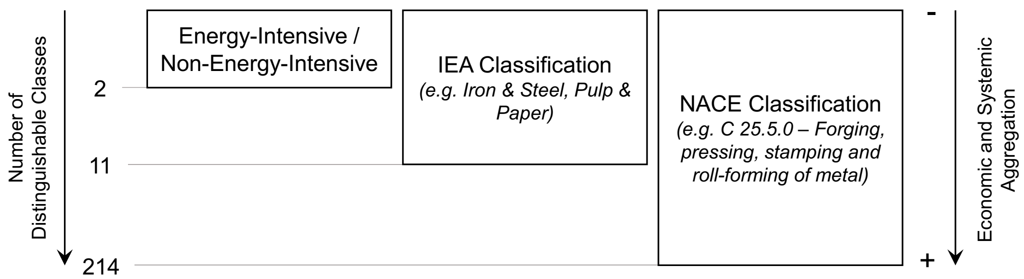

Figure 5: Level of detail and aggregation in the context of industrial classification schemes

The basis for investigating the structure of the industrial sector is represented through a set of three interlinking classifications (Figure 5):

1. Energy-intensive / non-energy-intensive subsectors: This definition states two groups regarding the subsectors' respective energy consumption. The allocation of subsectors to these two groups varies depending on legislators, institutions and countries. The European Commission discloses energy-intensive subsectors based on the application of selected production processes. These processes can for example be electrolysers, metallurgic processes, chemical reduction processes, processes for glass fabrication etc. [58].
2. IEA (International Energy Agency) classification [59]: The IEA constitutes individual industrial subsectors based on their produced goods e.g. iron & steel, pulp & paper, machinery etc. These subsectors can be allocated to energy-intensive and non-energy-intensive groups from above.

3. NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) classification [60]: Regarding the economic classification, the European Commission further utilises NACE codes within a graduated system. The first level describes the economic units themselves. Here, the class “C - Manufacturing” equals the industrial sector in its entirety. NACE codes including two digits are aligned with the aggregation level of the IEA classification, e.g. “C 24 – Manufacture of basic metals” and iron & steel. Two additional lower aggregation levels state more detailed classifications, e.g. NACE-3 class “C 24.4 – Manufacture of basic precious and other non-ferrous metals” and NACE-4 class “C 24.4.2 – Aluminium production”.

All three classification schemes can be interlinked with each other and describe the structure of the industrial sector via different aggregation levels.

3.2 Systematic Approach for Methodologies

Due to the high heterogeneity of the industrial sector, the classifications above are to be applied to support the development of holistic methodologies.

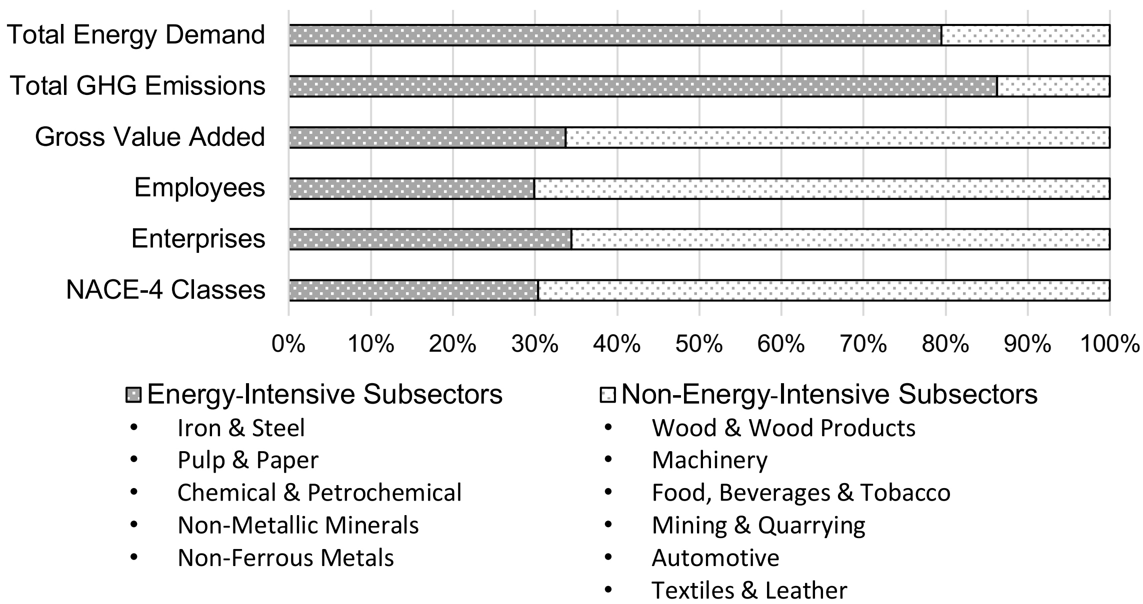

Figure 6: Comparison of energy-intensive and non-energy-intensive subsectors in regard to total energy demand, total greenhouse gas (GHG) emissions, gross value added, number of employees, number of enterprises and number of NACE-4 classes in Europe.

The need for a holistic and definitive solution for the outlined research aim calls for standardised approaches in accordance with the specific subsectors’ properties. The most prominent definition of energy-intensive and non-energy-intensive subsectors (according to IEA) offers a good basis to put the development of overall methodological approaches into practice in the first place. Figure 6 shows the comparison of both subsector groups and the allocation of IEA subsectors respectively. All compared parameters originate from the European Commission (Eurostat) [4] sources. It can be observed that the energy-intensive subsectors exceed non-energy-intensive industries regarding total energy consumption and GHG emissions. However, this is not the case when considering gross value added, number of employees, enterprises and number of NACE-4 classes. These results reason for a separate development of methodological approaches for depicting energy-intensive and non-energy-intensive subsectors respectively.

Overall, the limited number of varying products and production processes of energy-intensive subsectors, which can be indicated through the low number of NACE-4 classes, benefits the development of bottom-up methods. The advantage of this approach, as already mentioned, lies in its highly detailed calculations as they are executed at the lowest aggregation level (e.g. process level). Especially for energy-intensive production routes, data and information on single processes are widely available in literature or originate from dedicated research projects (e.g. time-resolved modelling of individual industrial plants). This fact further supports the application of bottom-up methods.

For non-energy-intensive industrial subsectors, where process-specific data is rather sparse, top-down methods might be more advantageous. Here, high-aggregated data from industrial surveys and databases can be utilised to examine selected correlations, where conclusions for individual industrial plants can be derived. Based on these conclusions, LPs and WHPs can be generated stochastically.

The methodology for generating synthetic LPs and WHPs varies in accordance with the depicted systemic aggregation level. Standardised aggregation levels in industry are process, manufacturing, plant and subsector levels, as Figure 7 shows [42]. Between these levels, energy can be generated/converted/consumed as a function of the selected systemic level. Figure 7 additionally states the implication of bottom-up and top-down methods within this system.

The prominent touch point of the two selected approaches lies at plant level as the main aim of this work is to generate dedicated profiles for this level. This satisfies the needs of the identified stakeholders like grid operators, energy-related research and energy suppliers (see Figure 1). To further broaden the field of application for the developed methodology, the bottom-up methods also allow the generation of LPs and WHPs at manufacturing level. Dynamic profiles of single processes based on physical or thermodynamic calculations or standardised subsector profiles are not within the scope of this work.

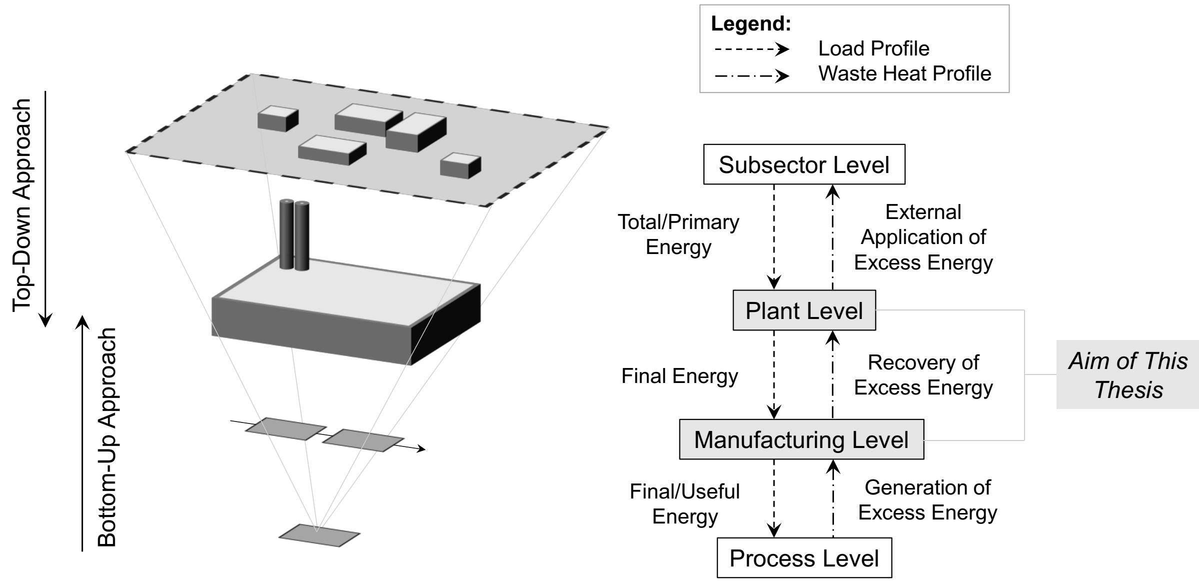

Figure 7: Systemic aggregation levels of the industrial sector including applied methodological approaches and aim of this thesis. Internal recovery cycles (e.g. from waste heat or excess energy like steam) are not depicted.

3.3 Development of Methodologies

The structure of this thesis can be divided into four partaking methodologies, illustrated in Figure 8. Appendices B and C give more information on the individual studies.

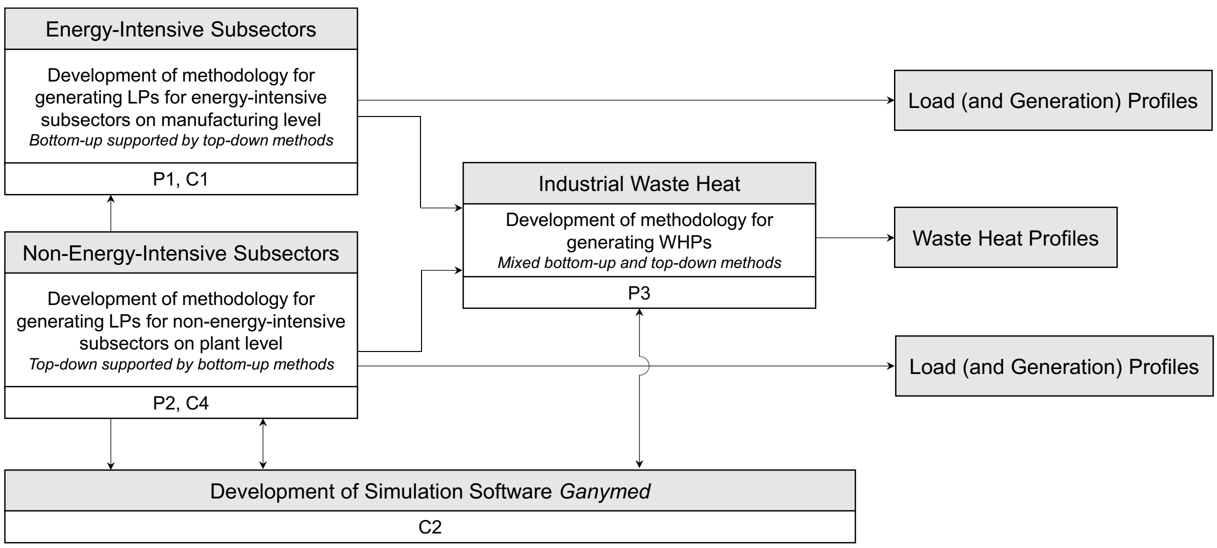

Figure 8: Methodologies of this work and their respective connections as well as contributing scientific papers and conference proceedings.

For depicting synthetic LPs of energy-intensive industries, a bottom-up approach supported by stochastic top-down methods was developed. Paper 1 (P1) [38] as well as conference proceeding 1 (C1) [61] contributed to this development. In this context and as declared above, the bottom-up approach aims to generate synthetic LPs of individual production routes or whole industrial plants (manufacturing and plant level in Figure 7), starting from process level. The individual processes are combined following subsector and plant-specific production logics. The underlying data is gathered at process level and on default contains information on e.g. process specific runtimes, specific energy consumption, unit and batch sizes, etc. (see section 4.1.2). The time-resolved interaction between these processes is the backbone for generating the respective LP and is managed by discrete event simulation. To bridge the gap of uncertainties (e.g. unknown production times, buffer times, …) individual assumptions are formed and supported by stochastic methods such as Gaussian distributions and Markov chains.

The LP generation of non-energy-intensive subsectors is achieved through a top-down approach supported by a process-specific bottom-up method. The top-down approach is initiated at subsector or plant level (Figure 7) and employs different industrial databases. These databases contain datasets like yearly energy consumption and demands, production capacities, number of employees, etc. of individual plants from Europe and the U.S. Correlation analyses of these datasets are utilised to develop individual regression models. These models are interlinked to generate LPs similar to standard LPs. To further enhance the LPs, a developed bottom-up method incorporates data on the most energy-intensive processes into the LPs via Markov chains. Paper 2 (P2) [39] describes this and paper 4 (P4) [62] covers a partaking novel finding in regard to “economy of scale” of industrial energy systems from this approach.

WHPs are a subgroup of LPs, as declared in the sections above. Because the conducted literature review revealed a clear lack of WHPs, the already executed methodologies of both subsector groups (energy-intensive and non-energy-intensive) were developed further to depict synthetic WHPs. For energy-intensive subsectors, the process-specific data was extended to cover properties relevant to waste heat-specific calculations (e.g. operating temperatures, outlet temperatures, waste heat energy carriers, …). This in combination with heat exchangers within the methodology provides the successful generation of synthetic WHPs from LPs via the same bottom-up approach. For non-energy-intensive industries, literature research on waste heat fractions from individual production plants and subsectors was conducted. These waste heat fractions are then superimposed on the already generated synthetic LPs. Paper 3 (P3) [37] outlines these enhanced methodologies.

All developed methodologies are embedded into a software environment called “Ganymed” as their underlying connection. “Ganymed” was developed based on the programming language “Python” and is publicly available. Conference proceeding 2 (C2) [63] describes the applied architecture of “Ganymed” and the solution for combining all methodologies via the development of this standalone application.

4 RESULTS

This section presents the joint results of the mentioned publications and studies from above as well as answering the research questions, which were initially stated. The main anchor point for this discussion is formed around Figure 9. Firstly, the impact factors, which are found to influence the development and manifestations of synthetic LPs in industry, are presented. Additionally, these impact factors are allocated to the different systemic aggregation levels, shown in Figure 7, outlining where these factors are occurring. Lastly, the implications of these impact factors are combined through the developed methodologies for generating the targeted profiles for the plant and manufacturing level.

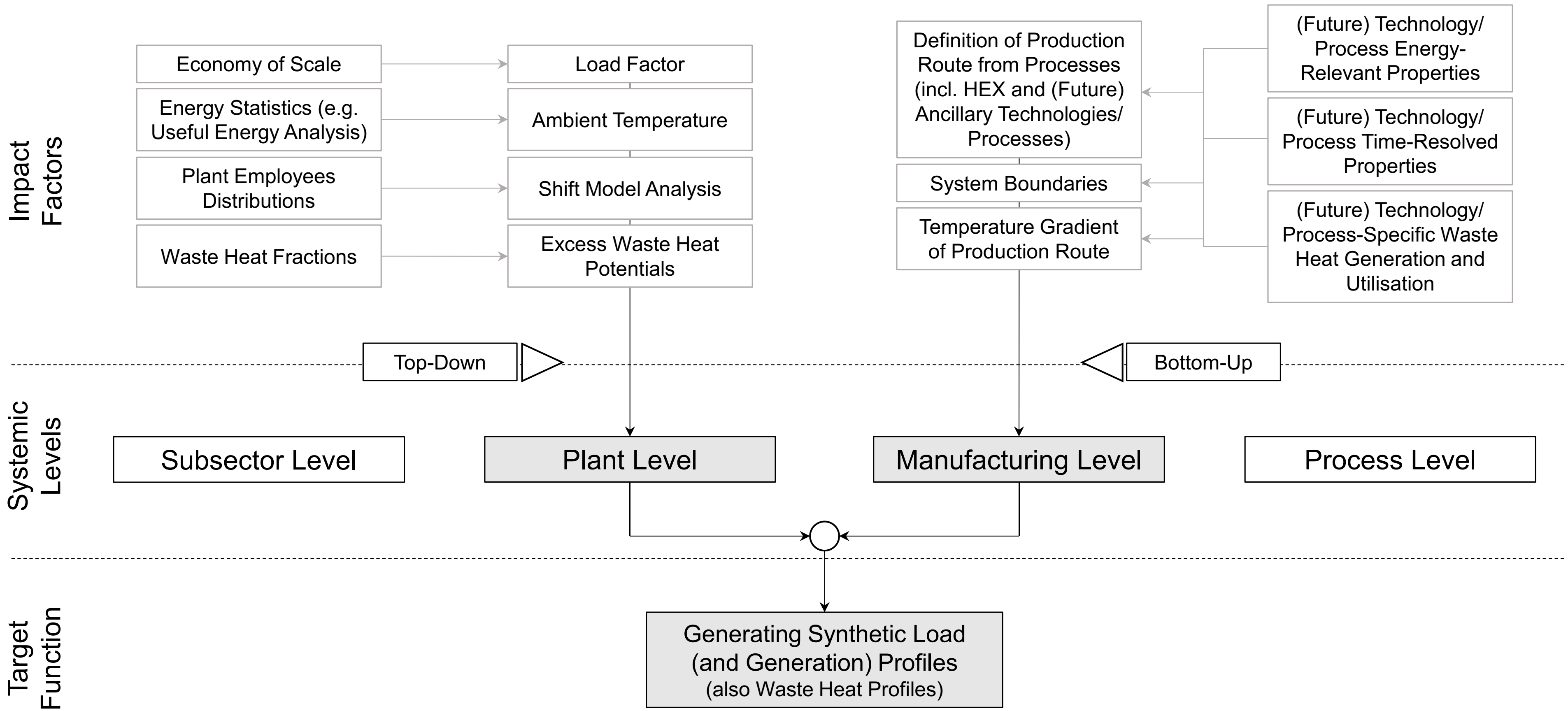

Figure 9: Systemic approach for generating LPs in industry: Individual impact factors are combined either top-down or bottom-up to generate representative synthetic LPs on plant or manufacturing level.

4.1 Impact Factors for Generating Load and Generation Profiles in Industry

4.1.1 Impact Factors for Top-Down Methodologies from Subsector to Plant Level

Data on subsector level is oftentimes regarded as the first basis for holistic energy system analyses [38]. This aggregation level also sometimes plays a role in the development of standard LPs, where alternative or more detailed information on lower levels is scarce (e.g. in the economic sector of buildings) [64].

The industrial subsectors vary highly regarding their deployed processes and production routines. However, within the individual studies of this thesis, certain effects from these varieties were successfully investigated on subsector level. These impact variables were found to have a distinct influence on the generation of LPs in individual industrial energy systems. This data – generated (stochastically or deterministically) on subsector level – is further combined and facilitated top-down to develop a more comprehensive understanding of generating synthetic LPs and WHPs on plant level. This improves the level of detail for individualising the properties of generated profiles for the to be depicted industrial plant accordingly.

4.1.1.1 Economy of Scale and Load Factor

“Economy of scale” (EOS) is an effect, which typically finds its application in microeconomics to express specific cost reduction in correlation to a higher production output/capacity [65]. Through this paradigm, areas of cost-optimised production and reasons for declining cost efficiency in operation can be assessed.

Within the studies in P2 and P4, industrial databases of the programme “Industrial Assessment Centre” (IAC) [66], funded by “U.S. Department of Energy”, the “European Eco-management and Audit Scheme” (EMAS) and the “European Emission Trading System” (ETS) were analysed. These databases contain surveys of plant and NACE subsectors specific data on number of employees, energy demand and consumption, production hours, capacity etc. amounting to around 25 000 data points. Throughout correlation analyses, it was found that the energy consumption of individual industrial plants is characterised by the EOS effect, outlined in Figure 10. However, this effect (namely “energy of scale”) differs from subsector to subsector, again, emphasizing the heterogeneity in industrial energy systems.

A very small amount of studies practically identify this "energy of scale" effect and only for the economic sectors of energy industries and buildings [67]. Especially for the manufacturing

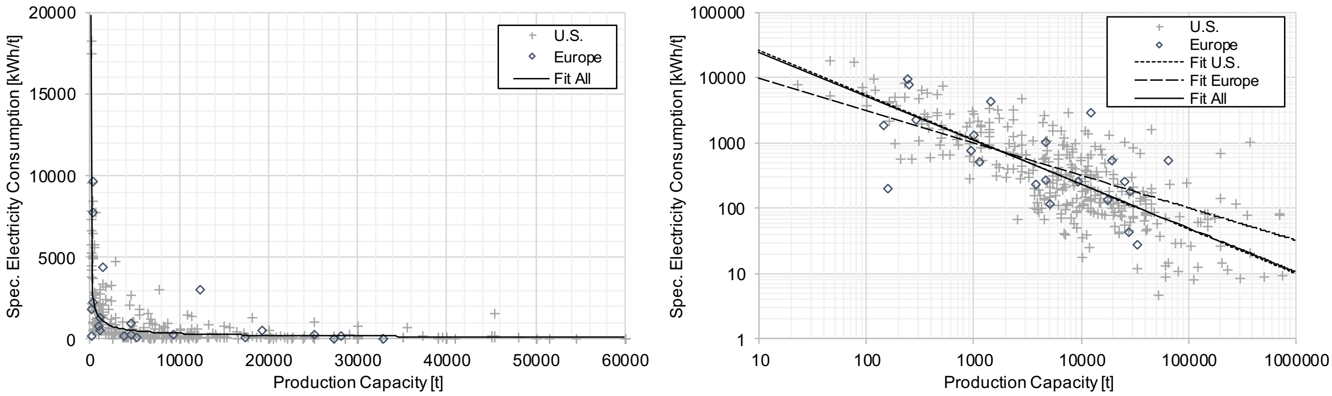

Figure 10: Energy-related EOS effect within the sector NACE 25 for electricity based upon industrial data points from U.S. and Europe; Left: normal plot, Right: logarithmic plot

industry, no literature sources were found. Through the development of NACE-specific fit functions, the corresponding electricity and natural gas consumption of individual industrial plants can be assessed top-down.

For the generation of industrial LPs, the average energy consumption of a single industrial plant (see Figure 2) without process-specific information is thus acquired as a first step through data from real-life plants. This provides insights regarding the before mentioned, distinct energy variances of facilities of the same subsector. These novel consumption-related findings are to be facilitated further top-down to generate plant-specific and major LP influencing load factors (LFs) [68] to describe the plant's energy demand:

LF sets in a range from 0 to 1 and is typically calculated for electricity systems [68], however, can be applied in the context of natural gas too (see P2).

$$\mathrm{LF} = \frac{\mathrm{E}}{\mathrm{P} \cdot \mathrm{t}} \qquad \text{III}$$

In general, the LF is calculated (see formula III) from the ratio of energy consumption E [kWh] to peak demand P [kW] within a time interval t [h] of a respective energy consumer. Thus, the LF represents the shape of individual LPs as the load of consumers with lower LFs is generally characterised by higher shares of peak loads (or in comparison by minorly expressed base loads) than consumers with higher LFs. DFT analysis shows stronger amplitudes at high periodicities in these cases. This can be observed in Figure 11, which shows a comparison of two generated industrial electricity LPs from the mentioned studies.

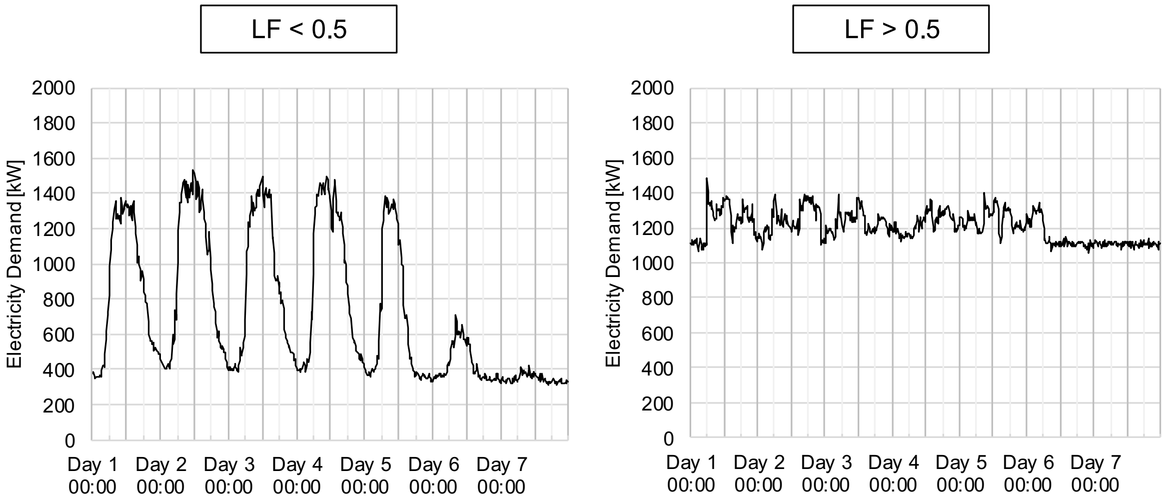

Figure 11: Comparison of LFs of two generated electricity LPs of industrial plants with similar load peaks

Regarding LP generation, the energy consumption and peak demand of a single industrial site can be retrieved stochastically from the previously mentioned EOS fit functions. The corresponding LF is then deployed as a major impact factor on the properties of the generated LPs and is utilised to improve existing synthetic LPs in accordance with "energy of scale". About LFs for natural gas consumption, the ambient temperature dependency of the respective plant has to be considered (see next section).

4.1.1.2 Energy Statistics and Ambient Temperature Dependency

Jesper et al. [35] state that the ambient temperature dependency of the heat demand in industry is a driving factor for respective LPs and WHPs. P2 describes that – unlike in residential buildings – the heat demand in industry is divided into two segments: The first segment is ambient temperature independent as the heat demand is provided to supply the facility with process heat. The second segment is ambient temperature-dependent to supply the facility with space heating, as this demand is naturally higher during winter months than during summer [69]. This influences the generation of LPs of (heat generating) energy carriers and WHPs extensively as the share of the two segments varies subsector specifically, evidentially proven in P2 and P3. Publicly available data of energy statistics like the "Useful energy statistic" by "Statistics Austria" [70] bears information on applied quantities of final energy carriers to supply useful energy categories (e.g. process heat, room conditioning and water heating, etc.) subsector resolved. The share of ambient temperature-dependent and independent demand can therefore be acquired. It can be stated that the ambient temperature dependency in energy systems of subsectors which are energy-intensive and deploy high-temperature applications (e.g. iron & steel industry, non-metallic minerals industry, …) is less distinct than for non-energy-intensive industries (e.g. machinery industry, textiles & leather industry, …).

To depict the influence of ambient temperature on the LP of (heat generating) energy carriers at plant level, the calculated shares between process and ambient temperature-dependent heat demand are further processed. Figure 12 shows these shares additionally. While process heat is regarded to remain constant throughout the year on average, the ambient temperature dependency of room conditioning calls for an adjustment to meet seasonal influences [35]. In P2, the "SigLinDe" function is deployed, which utilises a mixed linear and Sigmoid regression function to compute an adjusting factor for the heat demand, as stated in the sections above [46]. Figure 12 shows the average, adjusted demand when implementing a monthly temperature variance. This can be further disaggregated into weeks or days, according to the data availability of the temperature gradient (see P2). Through this adjustment in combination with the beforehand calculated LFs, the overall ambient temperature dependency in LPs can be assessed.

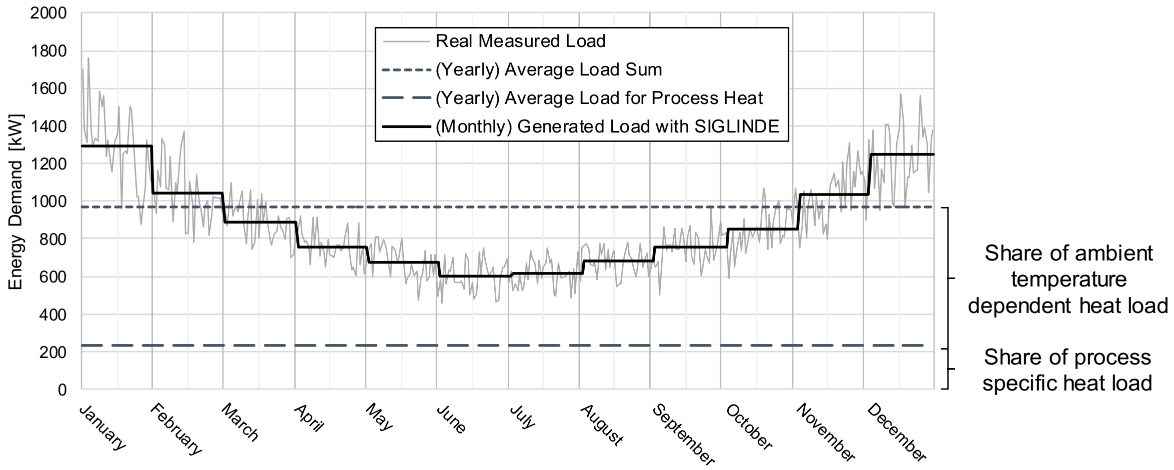

Figure 12: Yearly dependency within yearly LP of heat generating energy carriers in the machinery subsector including share of ambient temperature dependent and process specific heat lead from "Useful energy statistic" and adjusted load sum with "SigLinDe"

4.1.1.3 Plant Employees Distributions and Shift Model Analysis

Besides data from energy-related databases, another impact factor of generating synthetic LPs can be located in the discrete number of employees at the to-be-depicted plant. According to the outcomes of the analyses in P2, this is because the number of employees correlates to the deployed shift model at the plant and therefore to the energy consumption pattern itself (e.g. peak loads at weekday production, base loads at weekends non-production etc.). As stated in P2, the development of subsector-specific distributions to stochastically assess the number of employees of individual facilities, for which the information on employees is not publicly available, deploys further knowledge regarding the generation of LPs and WHPs. Figure 13 shows the developed probability density function for the distribution of number of employees of the subsector NACE 25.6.1 from P2 respectively. The data originates from the "Austrian Herold business database" [71]. Through the resulting data fit (exponential function) in Figure 13, the number of employees for the selected subsector can be derived stochastically.

Figure 13: Exemplary probability density function from P2 for the subsector NACE 25.6.1

The type of shift model, likely to be applied at a respective industrial plant, is the next major impact factor for the corresponding LPs which utilises the subsector-specific stochastic functions from above [72]. The shift model dependency of LPs and WHPs can for example be observed in Figure 11 on the left. During production times, the peak loads are generally higher than during times off-shift (in Figure 11 on weekends). In conclusion, under the circumstance of a known shift model type (e.g. 80 h/week as of two shifts), the occurrence of production and non-production times and therefore the shape of the generated LPs and WHPs can be estimated [72].

It was found that the number of employees at the plant correlates to different types of applied shift models: P2 describes that the IAC database is used to retrieve basic information on production hours and number of employees of single industrial plants for all NACE subsectors. Figure 14 top describes the process of the generation of derived probability densities as functions of production hours and employees of different shift model types. After generating these probability density functions, they are applied to determine the shift model with the highest probability for the input parameter of a selected number of employees and NACE subsector (Figure 14Figure 14 bottom).

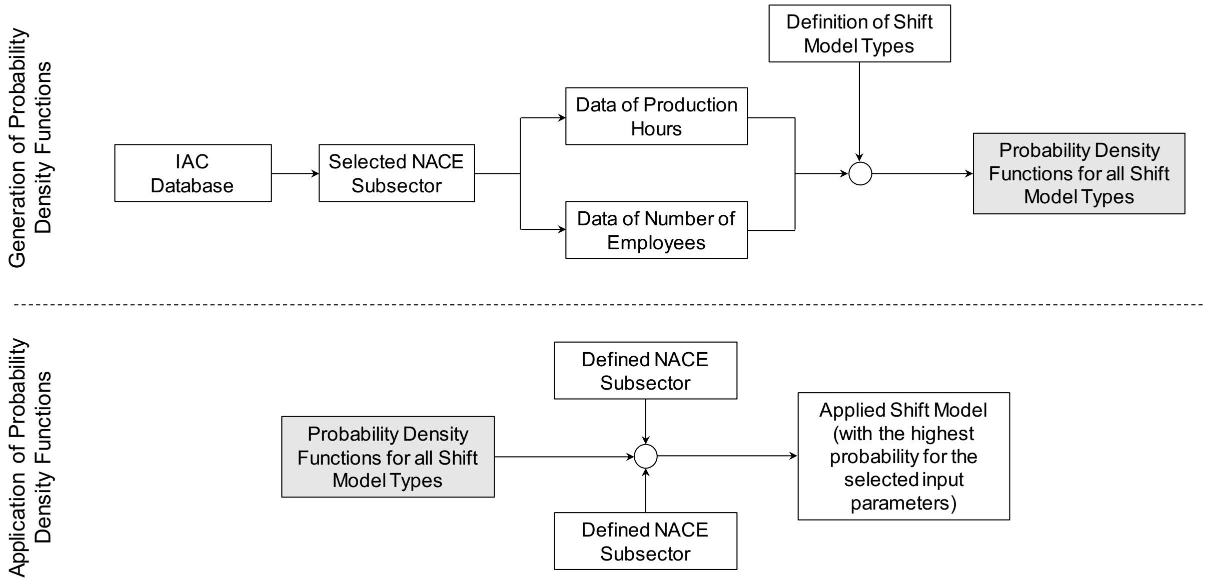

Figure 14: Generation and application of probability density functions for assessing industrial shift models.

Figure 15 shows the result of generated probability density functions of the NACE subsector "C 16.1.0 – Sawmilling and planing of wood". In P2, five groups of weekly production hours, for which specific shift models can be allocated, were defined [73]. For example, 80 h/week indicate a two-shift model with 16 productive daily hours over five working days. 120 h/week can indicate either three shifts with 24 h over five working days or two shifts with 20 h over six working days. It can be observed that for up to 200 employees in this sector, the stochastic evaluation of data shows that a single-shift model has the highest probability of being applied, followed by the two-shift model. Limitations to this approach can be seen at high numbers of employees (in Figure 15 >600) as a clear derivation between the probability densities can no longer be assessed since data for such big plants is rare. For these special cases, the methodology in P2 outlines that a systemic disaggregation of the individual plant into production divisions might be advisable.

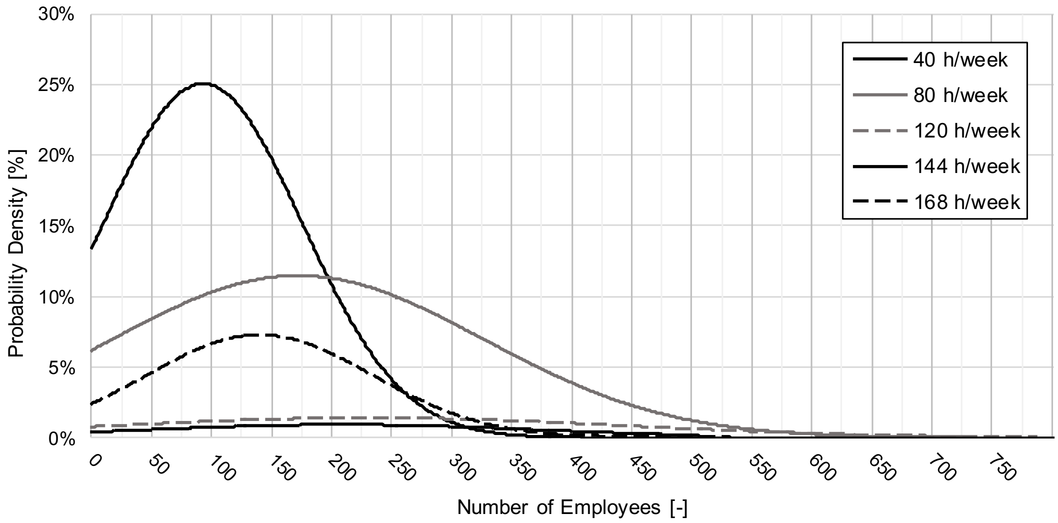

Figure 15: Generated probability density functions of different production hours of the NACE subsector "C 16.1.0 – Sawmilling and planing of wood"

4.1.1.4 Waste Heat Fractions and Excess Waste Heat Potentials

The methodology for the generation of WHPs on plant level top-down does not include process-specific information. Here, the aim is to solely generate WHPs of waste heat rejected from the plant, either for supplying a nearby district heating grid or for depicting the remaining unused heat at a specific (elevated) maximum temperature for subsequent internal use. In combination with LPs for heat-generating energy carriers, it was found that waste heat fractions (WHFs) offer an interesting option when process-specific waste heat data is sparse. WHFs from literature sources are developed based on plant-specific measurements or retrieved from CO_2 emission data. They are generally stated on subsector level and for a chosen reference temperature (as stated in P3) [74]. Regarding the energy density of derived WHPs, formula IV describes the calculation of waste heat flows for each time step based on the respective LP for heat-generating energy carriers:

$$\dot{Q}_{WHP,t} = f_{WH} \cdot \dot{Q}_{LP,t} \qquad \text{IV}$$

With $\dot{Q}_{WHP,t}$ as waste heat from the plant at time step t, f_{WH} the subsector specific WHF and $\dot{Q}_{LP,t}$ the heat load at time step t.

In combination with the observations of ambient temperature dependencies from section 4.1.1.2, it can be stated that the energy density $\dot{Q}_{WHP,t}$ is only slightly influenced by seasonal changes due to the minor waste heat potential of energy for room conditioning application.

Following the calculation of waste heat flows, the assessment of heat transfers to e.g. district heating grids demands information on the specific maximum temperature of the generated heat in WHPs [23]. In P3 it is stated that the information of WHFs including reference temperature from literature can be applied to calculate the maximum temperature based upon the assumption that the generated heat originates from natural gas combustion. Figure 16 shows this method. Following the assumption of adiabatic combustion of natural gas, an overall function in dependency on the rated thermal input can be depicted. The rated thermal input can be divided into useful energy (plant internal use), WHF (plant external potential) and losses. Subsector-specific reference temperatures (T_{min}) from literature and their respective WHFs can therefore be located in this graph to assess the maximum/outlet temperature T_{max}. In combination with EOS and shift model analysis, the plant-specific generation of waste heat at a specific T_{max} can be facilitated. P3 describes this approach methodologically.

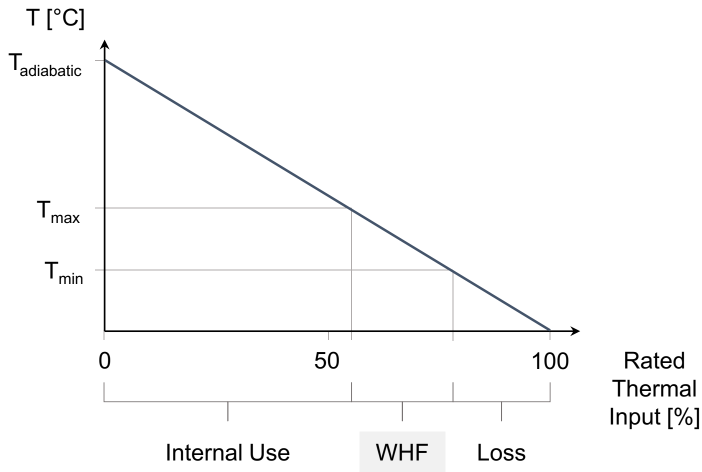

Figure 16: Allocation of WHFs and reference temperatures from literature (T_{min}) to calculate maximum outlet temperatures (T_{max}) of the waste heat.

4.1.2 Impact Factors for Bottom-Up Methodologies from Process to Manufacturing Level

P1 situates that the level of detail and granularity in generating synthetic LPs and WHPs via bottom-up approaches is solely influenced by the scope and quality of underlying data of the lowest systemic level. Furthermore, P1 and P3 describe that process-specific information is available to a greater extent, especially for well-documented production routes of energy-intensive subsectors. On the one hand, this enables the opportunity to investigate the time-resolved behaviour of industrial plants in higher detail from the process level to the manufacturing level, however, on the other hand, demands more complex methodologies handling these extensive datasets.

Within this thesis the lowest aggregation level of the developed bottom-up approach is located at individual processes (see Figure 7) e.g. electric arc furnace (EAF) of the iron & steel industry or pulp cookers/digesters of the pulp & paper industry [55]. By accumulating these processes to overall production routes on manufacturing level, the desired LPs and WHPs can be generated in a bottom-up way.

4.1.2.1 Processes and Production Routes for Generating LPs

P1 states the finding that a concise standardisation of production processes in regard to their properties is of major importance when firstly conducting literature research and secondly developing suitable methodologies. Concerning the generation of LPs, the process properties are divided into time-resolved and energy-relevant properties, as Figure 9 shows. The first contributes to the timely offset/variance of loads in the LP, while the last is responsible for the magnitude of the process-specific energy demand itself. Exemplarily, time-resolved properties cover batch or continuous operations. Both can be further detailed, as batch involves not only operating times, but also loading, halting and discharging periods, and continuous as the main contribution to base loads without specific discontinuities. Regarding energy-relevant properties, the methodology uses the application of either process-specific energy consumption or single load profiles – both in [kWh/t] – as an easy and efficient solution. The information on both time-resolved and energy-relevant properties relies on the underlying data from literature. This dynamic approach also makes the implementation of new technologies possible, which inflict more energy-efficient use e.g. biological pre-treatment in mechanical pulp digesters [75]. Moreover, the flexible use of this methodology enables first steps in concrete time-resolved modelling of individual industrial plants if the underlying real-life data of the facility is provided to a sufficient extent. This means that, following the classification of LPs from Figure 3, this bottom-up approach not only allows to it generate synthetic LPs, but also comparable synthetic LPs of real-life plants.

The design of individual production routes from the implemented processes heavily influences the generated LPs. For example, industrial processes can be aligned in series or parallel [76]. The methodology applies the paradigm of discrete event simulation (DES) to generate LPs of the selected production route within this bottom-up approach. P1 and C1 cover this methodology in detail. It was found that DES is a suitable approach for handling and depicting the timely interactions between the produced products and production processes to depict their most prominent load characteristics in synthetic LPs [77]. Through the application of DES, it is possible to calculate individual production routes as long as a logical connection (flow of products) between the processes is given. Figure 17 shows the developed advancement of the DES paradigm for industrial production logic, which was undertaken in this thesis. Here, the production route is defined between a discrete start and end point. In between these two objects, processes can be aligned individually. When the simulation is initiated, discrete products (e.g. tonnes of steel) are moved in the indicated direction of the material flow, generating single LPs along the way, when interacting with production processes. It is to be stated that this steady-state approach is only applicable to generate synthetic LPs. DES in this thesis does not include modelling of dynamic process operations (e.g. load peaks of process ramp-ups or operational states of the process overall).

A precise definition of system boundaries supports the characterisation of the LP generation [78]. When setting the system boundaries according to Figure 17 (a), an individual load pattern in correspondence to the time-resolved and energy-relevant properties of process 1 is generated. Figure 17 (b) shows the contributions of individual processes in an LP for the case of a broader system boundary. Depending on the processes' individual time-resolved and energy-relevant properties, single process-specific shares make up the overall LP.

The combination of this rather deterministic simulation approach with stochastic methods is an advisable option to further alter and diversify the resulting LPs. Besides the nominal process parameters from the literature, fluctuations in their time-resolved and energy-relevant properties can be included stochastically. The mean energy consumption or process can be altered by stochastic distribution of the respective properties, resulting in small periodical fluctuations. This is shown in Figure 17 (c). The shaping parameters (μ and σ^2) of the stochastic distribution were retrieved from deviations in the properties of the processes in different literature studies if stated. It was assumed that these deviations are distributed along Gaussian distribution.

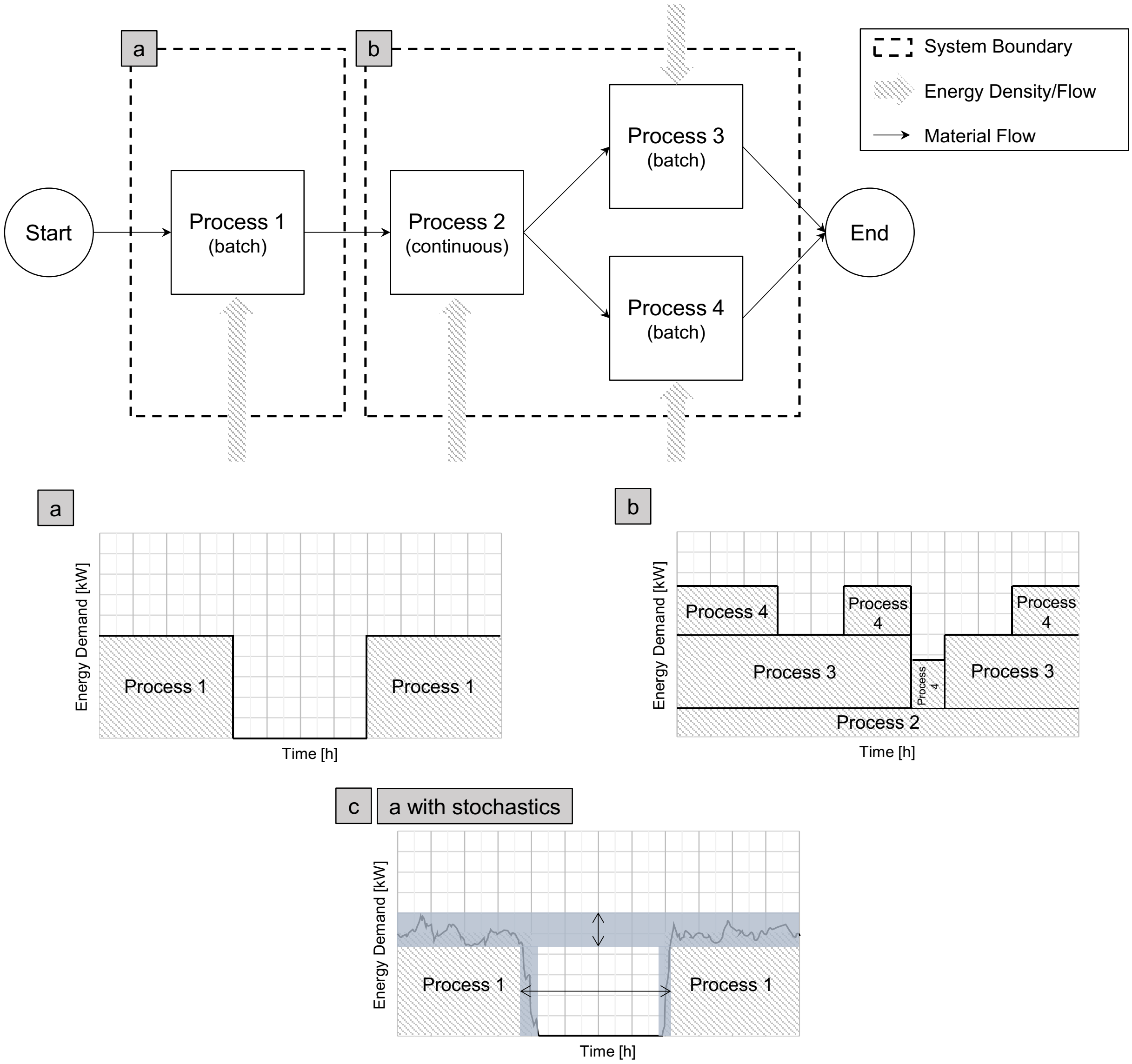

Figure 17: Individual production route including simple LP generation form separate system boundaries for (a) single process, (b) accumulated processes and (c) single process with stochastic fluctuations.

4.1.2.2 Waste Heat Production and Allocation for Generating WHPs

When generating WHPs, the underlying impact variables are – besides the already mentioned definition of system boundaries on manufacturing level and the energy-relevant and time-resolved process properties on process level – the quantity and source of generated waste heat as well as its thermodynamic (plant internal or external) allocation [79].

The generated waste heat density and outlet temperature of processes can be assessed throughout literature research, which is described in P3. Although the methodology for generating synthetic WHPs for energy-intensive subsectors solely depicts the manufacturing level, the major advantage of the bottom-up approach is that waste heat originating from production processes can be reintegrated into the energy demand of other processes, following the logic of DES. In “Ganymed”, this is realised via the implementation of heat exchanging units (HEXs) to generate WHPs. Figure 18 shows this method. The generated waste heat $\dot{Q}_{WH,Process,y}$ can be allocated to processes within the depicted production route according to their thermo-technical properties of operating temperature and process-specific heat demand. The latter is already defined throughout the generation of synthetic LPs (see section above), while the information on operating temperatures inflicts the need for an overall temperature curve of the depicted production route.

In the case of Figure 18, the thermo-technical properties of process *x* allow the supply of $\dot{Q}_{HEX}$ via a dedicated HEX to reduce its overall (heat-generating) energy demand. The heat transfer can be depicted in a corresponding $\dot{Q}/T$ diagram (see Figure 18 right). In this case, the entire heat demand of process *x* can be substituted by $\dot{Q}_{WH,Process,y}$. A fraction of $\dot{Q}_{WH,Process,y}$ is discharged as $\dot{Q}_{excessWH}$ at T_{HEX}, which could potentially be further applied within or outside the plant in e.g. district heating grids. By setting the system boundary according to Figure 18, the WHP of $\dot{Q}_{excessWH}$ is to be generated from the given process-specific information.

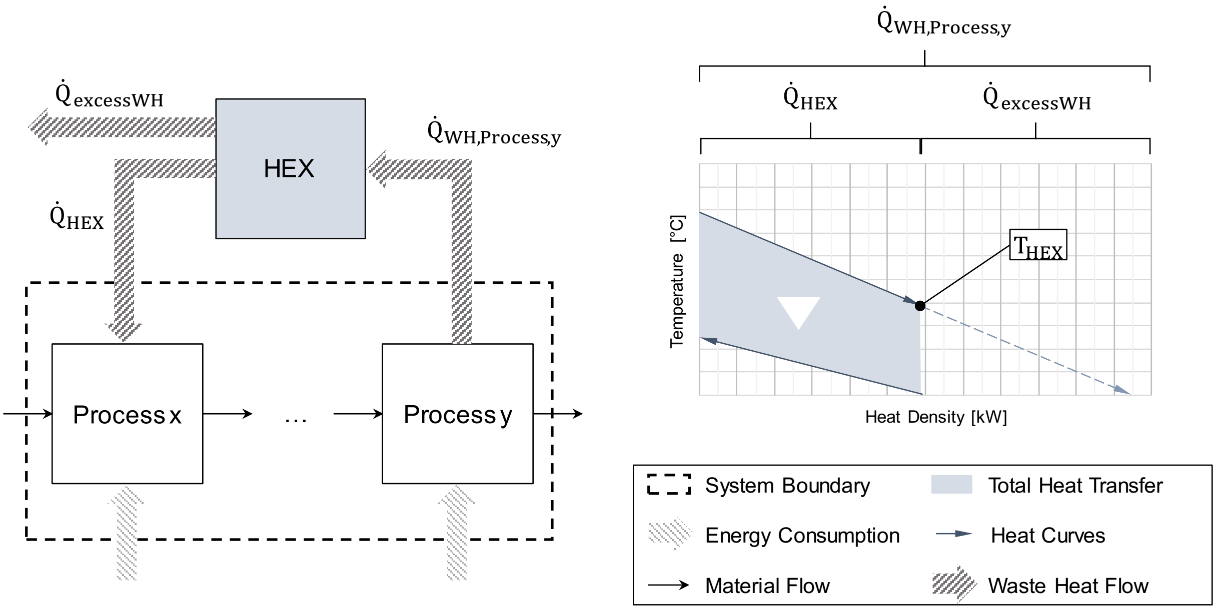

Figure 18: HEX configuration for heat transfer between process y and process x

4.2 Development of “Ganymed” and Implementation of Methodologies

The developed top-down and bottom-up methodologies present themselves with a range of input parameters and varying encapsulated methods. The software environment "Ganymed" was developed throughout this thesis as the underlying basis for the developed methods. This allows to gather all literature data in dedicated databases, embedding the developed methodologies into the software and improving its usability via the deployed graphic user interface (GUI) as described in C2.

Figure 19 shows the implementation and workflow of the developed methodologies within the software environment of “Ganymed” which is described in the following. White boxes are encapsulated in the software and are not accessible to the user. Grey boxes allow user interaction through the GUI.

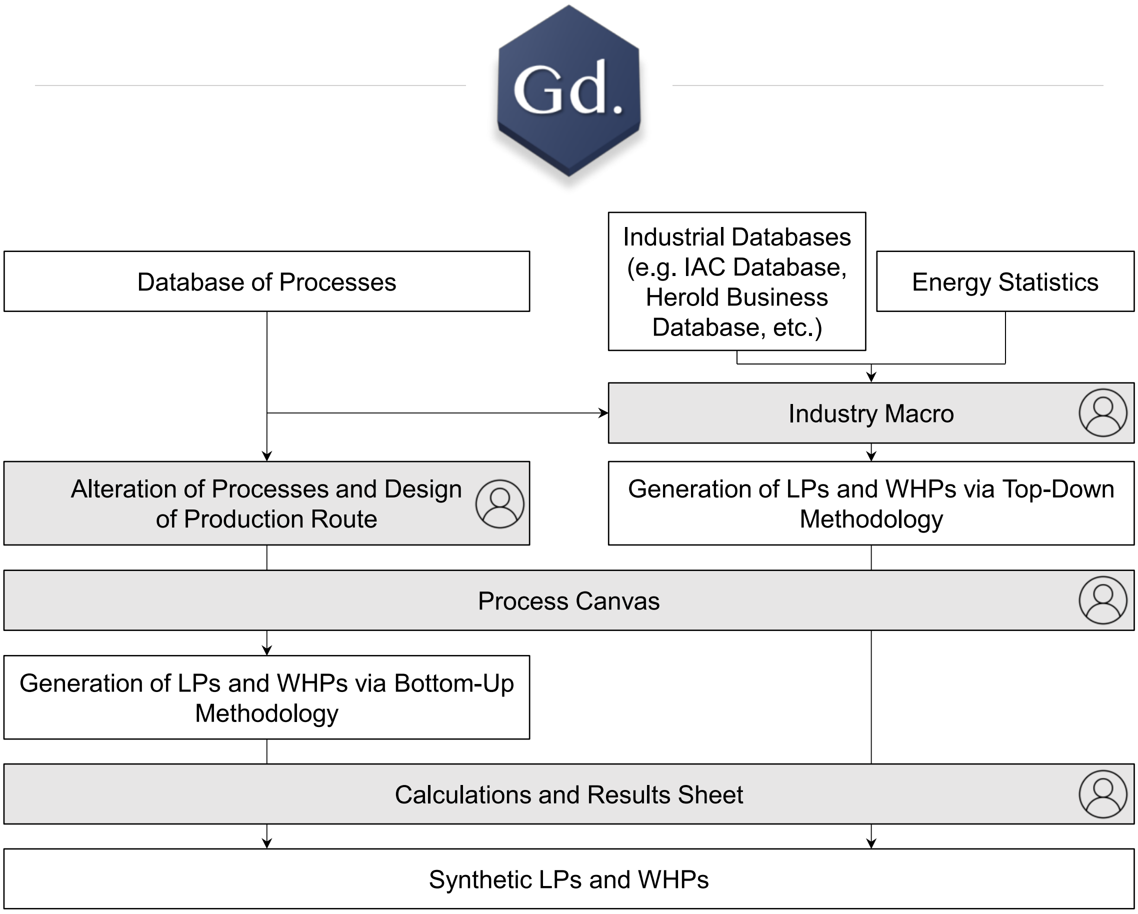

Figure 19: Inner workflow of “Ganymed”; Grey boxes indicate where the user can actively interact with the software.

All process-relevant data from prior literature research is incorporated into the database of “Ganymed”. The user can load these processes into the GUI on the process canvas, where they can be altered and aligned to an overall production route as shown in Figure 20. System boundaries and busbars for energy carriers can be additionally inserted. In the case of Figure 20, a predefined template of the blast furnace route was loaded into “Ganymed” by the user. After the user finishes the alteration of the production route and underlying processes, the simulation can be initiated and the resulting synthetic LPs and/or WHPs can be obtained from the calculations and results sheet (see Figure 21). The according profiles can be exported as a “.csv” file.

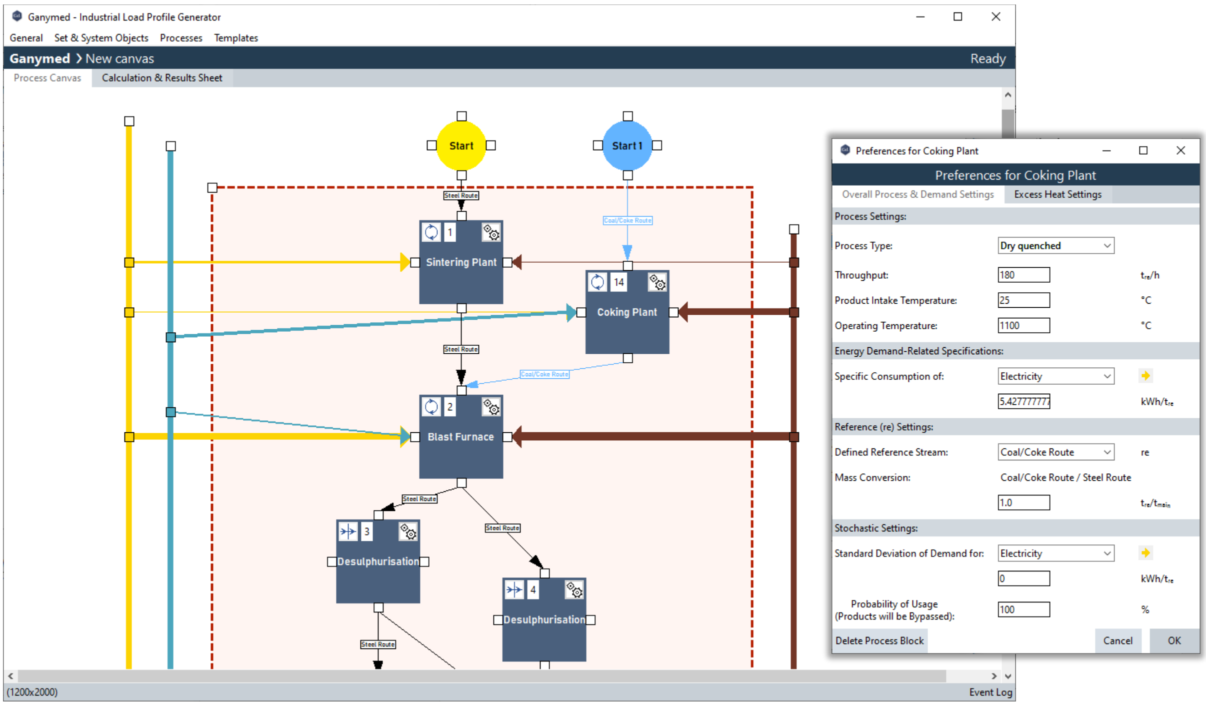

Figure 20: Process canvas including blast furnace production route and process properties menu for coking plant.

Figure 21: Generated synthetic LPs in the calculations and results sheet.

An industry macro contains the top-down methodology for generating synthetic LPs and WHPs of non-energy-intensive industries and is realised as a plugin (see Figure 22). The macro itself is handled like a standard process object on the process canvas but deploys the top-down methodology within its specific properties. Hence this methodology is more complex in terms of heterogeneity of databases and impact variables, the generation of LPs and WHPs is executed in a traceable step-by-step manner. Within this sequenced approach the synthetic LPs and/or WHPs of the selected industry are generated and thereafter act like single profiles of this specific macro. After the user runs through this macro, the route on the process canvas can be simulated following the DES paradigm and the profiles are shown in the calculations and results sheet again. This enables that the industry macro can be combined with other macros (e.g. when depicting individual divisions of large production facilities) or interlinked with up- or downstream additional production processes from the mentioned bottom-up methodology for energy-intensive industries on the same process canvas.

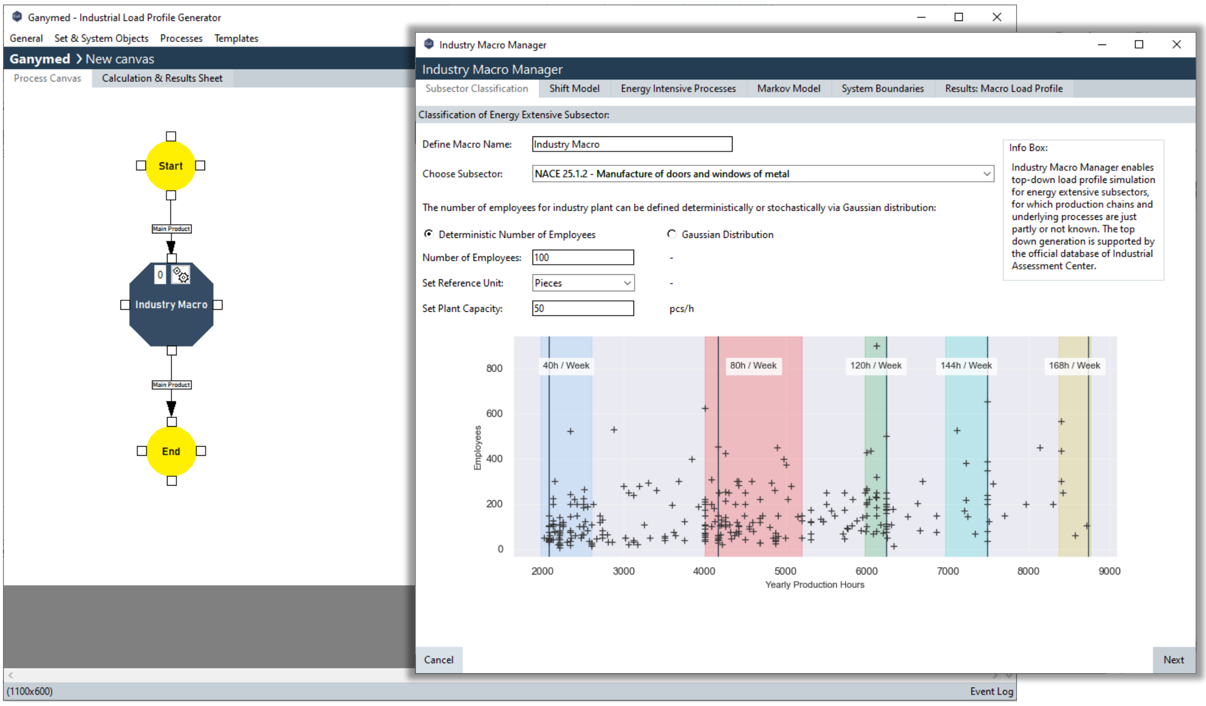

Figure 22: Appearance of the industry macro and implementation in the GUI

"Ganymed" is an .EXE software realised with the programming language Python, executable for Windows-based systems with >8GB RAM and Intel i5 core or equivalent. Software licenses or the utilisation of programming languages are not mandatory. "Ganymed" is accessible via "www.evt-unileoben.at".

5 CONCLUSIONS

5.1 Discussion

The industry progresses to cleaner technologies and transitions its production to GHG-neutral and more energy-efficient variants. As a result, energy suppliers and energy grids are obliged to comply with this movement, accelerating volatile renewable energy production and distribution [13]. To investigate these impacts and support this energy transition, novel solutions from energy research cannot only be developed statically but rather examine the behaviour and interaction of respective energy systems at different points in time, represented through load (and generation) profiles (LPs). This provides better insights for the application of volatile energy sources, demand on future energy grids and current as well as future consumption processes. [13]

Overall, LPs of the industry can assume three manifestations: Standard LPs, LPs from time-resolved modelling of consumers and synthetic LPs. While easy-to-handle standard LPs are only applicable to whole groups of consumers, time-resolved modelling approaches aim for a distinct representation of an individual energy system through mathematical simulation. Synthetic LPs take up the space in between these two groups, depicting the main load characteristics of individual consumers, while offering a holistic application for different consumers. [19]

Throughout this thesis, the topic of synthetic LPs for the entire industry was studied and developed. Within this chapter, the results from above are concluded and key take-away messages in the context of the initial research questions from section 2.3 are formulated:

The presented literature analysis showed that methodologies for developing LPs are widely developed within economic sectors apart from the industry (section 2.2). Recently developed methodologies for industrial consumers are described in section 2.2.4 in more detail. It is outlined that methodologies for industrial application have mostly been created in the context of standard LPs and individual time-resolved models in recent literature. This however limits the scope of application and thus does not sufficiently support holistic energy system analyses of an already intricate sector. In conclusion, the development of synthetic LPs, which are capable of grasping the industrial sector in its entirety, has been identified as a still unanswered, but necessary field for energy system research.

The high heterogeneity of the industrial energy system is to be met with standardised classifications first. Here, the classification system of energy-intensive and non-energy-intensive subsectors and definitions of IEA and NACE to these two groups were applied (section 3.1). Throughout literature research and analyses of energy and economic statistics, it can be formulated that energy-intensive subsectors are part of the basic material industry producing only a limited amount of varying products by underlying production processes. Non-energy-intensive industries are responsible for a broader process and product variety. This fact is to be respected in developing LP methodologies.

Throughout the literature research for this thesis within other economic units of transport, energy industries and buildings it was also found that the focus of LP methodologies lies on depicting the electricity demand of consumers. The main aim here is to provide robust time-resolved forecasts for energy consumers within day-ahead and intraday trading and therefore assess cost-saving measures [10]. Investigations on electricity LPs were also developed for the manufacturing industry, but again only for selected industrial locations (in case of time-resolved modelling), as declared above, or only on high aggregation levels (in case of standard LPs). Besides the requirement for generating (synthetic) electricity LPs on a more detailed but holistic level, another subject still left unanswered can be identified: Industrial consumers employ high-temperature applications to a greater extent than in other economic sectors. This inflicts the need for generating multi energy LPs and corresponding waste heat profiles (WHPs). LP methodologies should therefore not be limited to electricity LPs only as potentials for future research endeavours in industry heavily lies in multi energy analyses.

In alignment with both key take-away messages above, this thesis describes the developed bottom-up methodology for energy-intensive industries and a top-down methodology for non-energy-intensive industries respectively (section 3.2). Alongside these approaches, this thesis concludes that the development of standardised system boundaries for allocating the generated synthetic LPs and WHPs is of high importance. Section 3.2 depicts the characteristics of system boundaries as standardised aggregation levels. It can be stated that the definition of system boundaries has to be regarded as the basis for the calculation of LPs and WHPs because not only energy but also time-resolved properties of the generated profiles are altered accordingly. This is also reasoned in section 4.1.2.1 specifically for waste heat calculations in this context. To fulfil the respective aim, the joint methodologies generate profiles for the manufacturing and plant levels.

The developed top-down methodology handles the generation of synthetic LPs and WHPs based on impact variables developed from subsector to plant level by the systemic aggregation levels (section 4.1.1). Within this thesis, impact variables which exhibit pronounced effects on the generation of LPs and WHPs were identified. The most prominent findings are described followingly:

Throughout the investigation of industrial databases, it was found that the cost-reducing effect of "economy of scale" (EOS) also applies to electricity and fuel consumption in industry. It was furthermore proved that this effect varies depending on the subsector which is represented by the subsector-specific fit functions. Through this analysis, the overall energy consumption of single industrial plants can easily be derived and thus can be declared as an underlying effect influencing the generation of LPs and WHPs. The same fit functions can be utilised for describing industrial facilities in the U.S. and in Europe [62]. This could potentially mean, that the EOS effect is independent of economic locations with similar technological progress. To prove this hypothesis, the analysis needs to be extended to other geographical regions like Asia or Australia.

LPs and WHPs from heat-generating energy carriers are not only driven by process-specific heat consumption. The heat and fuel consumption in industry is also partially afflicted by ambient temperature, as state-of-the-art studies already proved [35]. To cope with this, energy statistics were applied to investigate the share of useful energy categories for ambient temperature-dependent applications (e.g. room conditioning) and ambient temperature-independent process heat. Therefore, ambient temperature-dependent applications are responsible for a yearly alteration in LPs and WHPs on top of supplied process heat, which is rather constant throughout the year. As high aggregated energy statistics were utilised to prove this point top-down, future research activities may develop a more plant-specific analysis. This could potentially reveal industries with the highest potential for technologies like seasonal heat storage.

Working shift models contain key information on production and non-production times in industrial plants and influence the shape of LPs and WHPs accordingly. However, industries apply shift models varyingly. By disaggregating data on employees and on yearly production hours to standardised shift models it was found that shift models can be linked to the number of employees at the respective industrial plant. Through this finding, the temporal allocation of production times and therefore higher peak demands within a week can be assessed. In terms of advancing synthetic LP and WHP generation, more extensive analyses of shift models can potentially lead to higher levels of detail within the profiles. [39]

Waste heat fractions (WHF) offer condensed insights on industrial waste heat potentials. WHFs of industrial subsectors and different literature sources were combined with thermodynamic analyses to calculate the average outlet temperature of all subsectors [37]. The WHFs and the corresponding outlet temperature can be applied to generate synthetic WHPs from already existing LPs. In this approach, internal heat storage is neglected. However, throughout this finding, it can be stated that peaks of waste heat can be assessed through occurring peak times of heat-generating energy carriers such as fuels. When additionally including thermal inertia effects, this could theoretically support analyses on external waste heat utilisation (e.g. district heating) at last.

The bottom-up methodology for generating synthetic LPs and/or WHPs for energy-intensive industries relies on process-specific data. By interconnecting processes to production routes, an underlying steady-state simulation logic generates material flows and therefore LPs and WHPs.

As the process level is the lowest level of aggregation in these studies, standardisation of industrial processes is a mandatory topic. Two groups of process-specific properties have a distinct impact on the generated LPs: Energy-relevant properties (e.g. spec. energy consumption, …) are responsible for the magnitude of the loads, while time-resolved properties (e.g. process times, …) exhibit the temporal occurrences of loads in the profiles [38]. Analysing these two properties separately (e.g. by summing up process-specific energy consumption) delivers erroneous results of the energy system. For generating synthetic LPs and WHPs, energy-relevant and time-resolved properties have to be combined to generate accurate results.

Especially regarding time-resolved properties, it was found that the classification of batch and continuous working processes is helpful. While continuous processes make up for base loads, batch-operated processes have a lasting impact on peak loads. This is especially essential in the case that selected batch processes are energy-intensive in the respective facility such as smelting ovens. Concerning energy-relevant properties, it can be stated that only a small amount of production processes are responsible for the main share of energy peak demands. As this finding is of major importance to synthetic LP and WHP generation, energy-intensive processes were also included through bottom-up calculations in the mainly top-down methodology for non-energy-intensive subsectors.

Concerning waste heat calculations for generating WHPs, both waste heat sources and (internal as well as external) sinks are to be defined accordingly. Especially internal waste heat sinks/utilisation require information on process-specific temperature gradients [37]. This means that – besides the thermodynamic definition of waste heat sources –the temperature curve of the entire production route has to be regarded as the basis for the allocation of waste heat and therefore generating WHPs.

Overall, the developed methodologies are adjusted to energy-intensive and non-energy-intensive industries. To conclude, bottom-up approaches require more detailed and specific data, top-down approaches may easier slide off into inaccurate results due to their higher aggregation levels (see Figure 23). Considering these facts, the methodologies in this thesis were arranged in a way to also benefit from single opposing methods in both variants: In the bottom-up methodology, stochastic top-down calculations to generate individual fluctuations were included in the generated LPs and WHPs. The top-down methodology for non-energy-intensive industries includes bottom-up Markov chains for integrating the most energy-intensive processes into the calculations, as mentioned above. Through this alteration, top-down approaches generate better applicable results and bottom-up approaches require less detailed amount of underlying data.

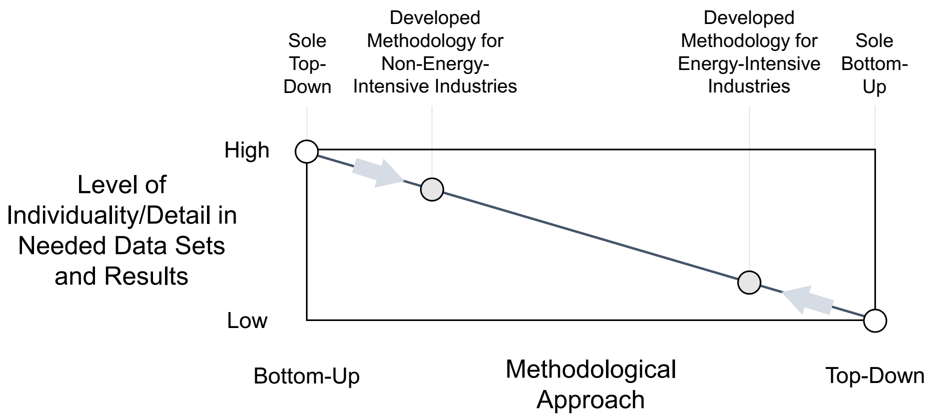

Figure 23: Combination of bottom-up and top-down approaches in this thesis to improve flexibility of methodologies and accuracy of results.

As both approaches still vary from each other in terms of structure in calculations and required databases, the design of user interaction is a key feature when developing a holistic solution. Therefore, the software "Ganymed" was developed to incorporate the created methodologies and enhance user interaction. In conclusion, it can be stated that <u>the application of standalone software environments including GUIs has to be considered as a go-to solution for complex energy system analyses.</u>

5.2 Uncertainties and Limits of Methodologies

The generation of all variants of LPs and WHPs is a trade-off between accuracy in results, applicability of the methodology and its complexity. Especially regarding the aim of this thesis, the generation of synthetic LPs and WHPs for the entire industrial sector demands a maximum degree of applicability by depicting the majority of industrial consumers to a sufficient level and minimizing the degree of the methodology's complexity. However, this is inevitably accompanied by uncertainties which limit aspects of the methodology and which originate from purposely made decisions while developing this research task.

The methodology for non-energy-intensive subsectors generates synthetic LPs and WHPs for a representative week. Although the application and definition of different shift models allow variances in the LPs, individual days (e.g. in case of public holidays or vacation days) cannot be altered and are not incorporated in the methodology yet. Furthermore, cases of part-time work (e.g. part-time production on Saturdays) were also neglected in this methodology. Alongside this statement, the application of shift models from data originating from sole U.S. databases has to be questioned critically. As production routines will certainly be handled differently between the U.S. and Europe, more data from European plants can only be beneficial to further enhance the generated profiles. However, industrial data from Europe is scarcely available, which should be taken into consideration.

To provide a more flexible methodology for non-energy-intensive subsectors, production processes are incorporated via Markov chains in a bottom-up approach. Like energy-intensive subsectors, the properties of these processes were surveyed and identified from literature. These processes are responsible for the main share of energy (as already concluded in the section above). The residual of the LP is scaled to a representative level based on the effect of "economy of scale". Oftentimes, energy-intensive processes could not be assessed thoroughly enough as underlying data from literature was missing. This problem was coped with by assuming similar production processes from related subsectors. For example, the subsectors of "Manufacture of electric motors, generators and transformers" and "Manufacture of batteries and accumulators" were assumed to have similar production processes.

The underlying simulation paradigm of the methodology for energy-intensive subsectors is discrete event simulation (DES). This method was deemed suitable for generating synthetic LPs as it is initiated on the detailed enough process level but does not require complex alterations to apply to different subsectors at once. Additionally, this approach allows to make certain simplifications and standardization, e.g. when only specific energy consumption of individual processes was available from literature. This methodology is a steady-state approach, meaning that dynamic or transient patterns of the processes (e.g. load peaks from process ramp-ups) were neglected to cope with the trade-off of covering all energy-intensive subsectors with a single methodology. More detailed investigations would require additional extensive amounts of data and would shift the generated LPs from synthetic to the group of time-resolved modelling, which was not in the scope of this study.

Extensive literature research was conducted to provide the necessary process-specific data for the methodology and for DES. Oftentimes, documents of best available technologies (BAT) were found to contain the needed data. BAT documents typically feature state-of-the-art processes. However, the industry applies also more dated production processes, which would express changes in energy intensity and production patterns compared to their more advanced counterparts.

Individual processes form production routes through logical interconnection. The information on production routes mainly focuses on the most prominent designs from literature studies. Major uncertainties were naturally identified in the alterations of the literature production route compared to real-life production. To cope with this problem, “Ganymed” allows the user to alter production processes individually. Additionally, DES limits the application of auxiliary processes or other production logics. Non-production times (e.g. at weekends or outside of production shifts like in the methodology for non-energy-intensive subsectors) can yet only be roughly depicted through buffering points as DES executes the production logic until all batches/products are processed. As a result, the methodology for energy-intensive subsectors is still more centred around the manufacturing level itself than around the overall plant level.

Both methodologies (for energy-intensive and non-energy-intensive subsectors) were further enhanced to generate synthetic WHPs. In alignment with the statement above, waste heat calculations from DES do not cover heat storage and dynamic/transient heat transfer processes. This means that all generated excess heat is either utilized again or emitted in the same time period within the simulation without any time-resolved shifts of the energy.

For non-energy-intensive subsectors, WHFs were applied to generate WHPs from synthetic LPs. The high-aggregated character of the surveyed WHFs from literature should be deemed worth further investigation. The current status only depicts and gathers subsector-specific/averaged WHFs from international studies due to the lack of more detailed waste heat analyses on lower aggregation levels. Waste heat recovery technologies are certainly matured differently within the studies of surveyed countries. Their comparability is therefore to be questioned. Furthermore and like above, the assumption was made that waste heat is emitted in that moment, when the plant is supplied with energy for thermal application as depicted in the LPs.

All methodologies are incorporated in “Ganymed” to provide a single solution of this thesis. The industry macro of non-energy-intensive industries acts like an individual process on the GUI of “Ganymed”. Through this, the user can handle and generate all synthetic LPs and WHPs of all industrial subsectors by interacting just on the process canvas. However, the methodology for energy-intensive subsectors is closer located on manufacturing level and the methodology for non-energy-intensive subsectors is solely on plant level. This means that individual production processes on the process canvas have to be designed in a way that they comply with the weekly generated interval of the industry macro. This variance is to be considered when merging individual processes with the industry macro via the DES logic.

6 OUTLOOK

“Ganymed” is a concrete advancement into a holistic solution, generating synthetic, multi energy LPs and WHPs for the entire industrial sector. By pinpointing areas where “Ganymed” is to be improved and by identifying future applications, LP and WHP generation of the industry can be further propelled. Future developments are discussed in this section along the industrial, systemic aggregation levels of this work (see Figure 7):

- From process to manufacturing level: The current methodology for energy-intensive subsectors generates synthetic LPs and WHPs on a steady-state basis via stepwise calculation of time-resolved loads from individual process-specific properties. Because of the holistic aim of this study, these properties were simplified and standardised to a certain extent to cope with the level of detail from literature studies (e.g. specific energy consumption). Future developments should focus on enhancing the view of how processes in "Ganymed" are handled. If also the transient and dynamic character of a production process (e.g. process ramp-up peak loads, transient waste heat exchange, …) can be depicted in a more standardised manner in “Ganymed”, also their interconnection can be studied more thoroughly. This means that additional auxiliary technologies and measures like energy storage and demand side management could be successfully incorporated and their LPs analysed. This is also of special importance in the light of novel production processes and routines, which might arise in the future and are to be implemented in "Ganymed". Therefore, the methodology moves away from its steady-state character, also the application of DES in its current state should be questioned and further enhanced. These developments would transition the methodology into time-resolved modelling. However, the trade-off to rising complexity in the approach should be considered carefully.
- From manufacturing to plant level: An improved interaction of the energy-intensive and non-energy-intensive methodologies should be of increased interest for future developments. The merging of the most positive aspects of both methodologies into one holistic approach between manufacturing and plant levels should be considered as a valid option. The corresponding LPs and WHPs of energy-intensive subsectors could be lifted to plant level in a reproducible manner by developing more extrapolative methods similar to the scaling effects of the non-energy-intensive subsectors which cope with not depicted auxiliary processes with lower energy intensities or even base loads. The view on non-energy-intensive subsectors would certainly benefit from analyses of real-life profiles of their manufacturing level. Hereby, the impact of the production on non-energy-intensive plants can be

investigated more deeply. Regarding this, it should be contemplated that some subsectors are stronger driven by underlying (energy-intensive) processes (e.g. EAF) than others. Figure 23 in the conclusion section states the convergence of both methodologies. When fully merging the two methodologies, individual subsectors could be allocated on a range stating the extent of the application of process-specific (or manufacturing) methods and extrapolative methods. Figure 24 shows this merged range for three NACE subsectors exemplary as a progression to Figure 23. The shares of process bound/specific methods and extrapolative methods would differ from subsector to subsector, making room for incorporating subsectors with more energy-intensive processes as well as bridging uncertainties of – process wise – rather unknown subsectors by extrapolative methods in a flexible way.

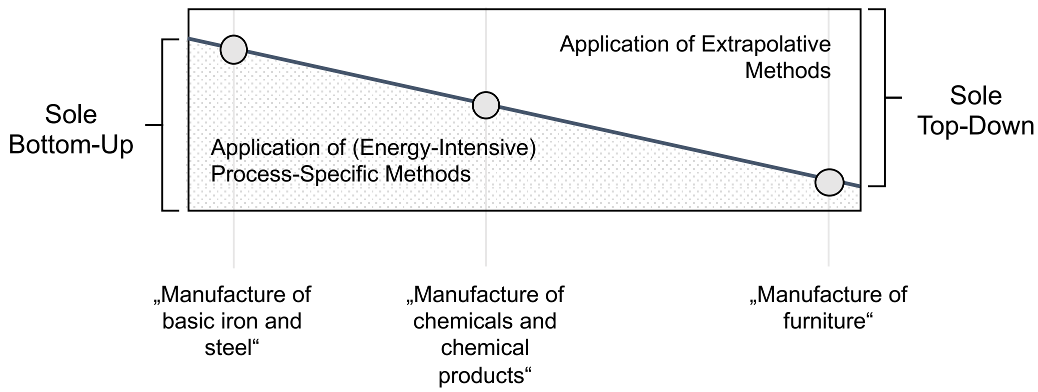

Figure 24: Range of applying process-specific and extrapolative methods for three suggested NACE subsectors. The allocation of the three subsectors in this range is based on assumptions.

- From plant to subsector level: Following the argumentation above, it can be stated that industrial energy system analyses on subsector level offer important insights when information on lower aggregation levels like real-life LPs, process data etc. is scarcely available. Especially for these subsectors, high aggregated data is the first entry point for further analyses and development of extrapolative methods like stated above. This work has shown that various correlations on subsector and plant level of the industrial energy system (e.g. EOS, WHFs, shift model correlations) have not been examined thoroughly enough in literature yet. Future research endeavours should focus on further strengthening these methods. Especially in the context of industrial waste heat, WHFs should be refined more and combined with waste heat potentials from real-life data. This provides better approximations when assessing waste heat potentials of different subsectors. Overall, global energy system research should be screened regularly to profit from the most recent databases and thereby continuously advancing the generation of synthetic, industrial LPs and WHPs in "Ganymed".

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APPENDIX A: TAXONOMY TABLE

Table 1: Taxonomy table and comparison of selected literature sources in the context of LP and WHP generation in industry

	Source	Objective	Variety Energy Flows	LP Type	Approach	Aggregation Level	Solving Method	Constraints	Potentials
A	Hernández et al. [31]	Data processing and validation for generating clustered LPs of industrial parks	Single	Standard	Top-Down	Subsector Level	- k-means clustering of measured data from individual plants of different subsectors and application of self-organizing mapping - Generation of standard LPs and validation via real measured LPs	- The definition of industrial parks does not allow further disaggregation to individual plants - Thermal LPs not in scope	- Verification of the influence of all weekdays and holidays on LP generation
B	Valdes et al. [32]	Clustering of measured yearly LPs and derivation of standardised loads	Single	Standard	Top-Down	Plant to Subsector Level	- Identifying data clusters from measured yearly LPs of the food and paper industry - Derivation of standard LPs based on clustered data	- Only limited access to the methodology of this study - Only limited scope in terms of industrial subsectors and multi energy flows	- Examination of yearly profiles advantageous for future energy system research
C	Dedic et al. [33]	Data clustering and generation of representative, standard LPs	Single	Standard	Top-Down	Plant to Subsector Level	- Fuzzy c-means data clustering of measured LPs of selected industrial subsectors - Generation of representative electricity LPs	- Clustered data inflicts strong resemblance to standard LPs - Only limited scope in terms of industrial subsectors and multi energy flows	- High potential due to a two-year-long observation period
D	Richard et al. [34]	Identifying DSM measures for medium-sized enterprises	Single	Standard	Top-Down	Plant Level	- Clustering of measured data from individual plants of different subsectors - Specific customer-oriented derivation of flexibility potentials	- Methodology not exploitable for further LP generation on top of the specific application	- Verification of the influence of working and weekend days on LPs
E	Jesper et al. [35]	Developing new methods for analysing heat demand of industrial and commercial facilities	Single	Standard	Top-Down	Plant to Subsector Level	- Data analysis of k-means clustering and regression of real measured thermal LPs - Derivation of reproducible shape factors for thermal LPs for every investigated LPs	- Sole top-down approaches could potentially disregard underlying process-specific effects - Only nine industrial subsectors included	- Examination of seasonal fluctuations in industrial sectors noticeable
F	Starke et al. [36]	Deriving and comparing flexibility potentials of all industrial subsectors	Multiple	Standard	Bottom-Up/Top-Down	Plant to Subsector Level	- Iteration of standard LP to meet subsector-specific load factor - Integration of single LPs of most energy-intensive processes - Derivation of flexibility potentials and DSM measures	- Partial integration of thermal consumers and respective thermal LP generation - Time resolution at one hour	- Load factor iteration as an efficient and simple solution for LP generation, where data is scarce

Appendix A: Taxonomy Table

	Source	Objective	Variety Energy Flows	LP Type	Approach	Aggregation Level	Solving Method	Constraints	Potentials
G	Sandhaas et al. [19]	Generation of synthetic electricity LPs for three industrial subsectors	Single	Synthetic	Bottom-Up/Top-Down	Process to Subsector Level	- Dividing synthetic electricity LPs into useful energy categories - Top-down method applies standard LPs for useful energy categories apart from mechanical drive The bottom-up method applies to model continuous and discontinuous mechanical drive	- Assumption that only mechanical drive is subdued to short-term fluctuations - Thermal LPs not in scope - No ambient temperature dependency on useful energy categories of heating	- Good reproducibility - Main load characteristics depicted with easy-to-apply methodology
H	Binderbauer et al. [37]	Generation of synthetic WHPs for the industrial sector	Single	Synthetic	Bottom-Up/Top-Down	Process to Subsector Level	- Process-specific waste heat data in combination with discrete event simulation paradigm generates profiles for energy-intensive subsectors - Literature survey of waste heat fractions of non-energy-intensive subsectors	See sections 4 and 5	See sections 4 and 5
I	Binderbauer et al. [38]	Establishing synthetic LP generation for single sites of energy-intensive industries	Multiple	Synthetic	Bottom-Up	Process to Plant Level	- Establishment of a database regarding industrial processes - Adaption of discrete event simulation for industrial application and bottom-up LP generation - Development of a standalone application	See sections 4 and 5	See sections 4 and 5
J	Binderbauer et al. [39]	Establishing synthetic LP generation for single sites of non-energy-intensive industries	Multiple	Synthetic	Bottom-Up/Top-Down	Plant Level	- Investigations on industrial databases and examination of correlations - Development of stochastic algorithms based on findings - Integration of most energy-intensive single processes - Generation of overall stochastic methodology	See sections 4 and 5	See sections 4 and 5
K	Dietmair et al. [40]	Developing a model for optimisation of energy efficiency measures in the manufacturing industry	Single	Time-resolved Models	Bottom-Up	Process to Manufacturing Level	- Describing the states of individual processes with statistical discrete event formulation - Comparison of generated electricity profiles with real-life machine profiles - Derivation of use scenarios for the processes and depicting energy saving potentials	- Only applicable for specific production processes with that configuration of production states	- Moderate use of highly detailed data in combination with stochastic methods improves reproducibility
L	Lecompte et al. [41]	Examination of thermal waste heat potentials for physical implementation of ORC process	Multiple	Time-resolved Models	Bottom-Up	Plant Level	- Measurements of processes on site and development of a model for evaluation of thermal waste heat flows on site - Scenario development for integration of ORC process	- Complexity of methodology could be disadvantageous if the case study is to be reproduced - Application for other plants is only partly possible	- Novel and detailed insights into ORC waste heat recovery process and modelling for future simulation works

	Source	Objective	Variety Energy Flows	LP Type	Approach	Aggregation Level	Solving Method	Constraints	Potentials
M	Dock et al. [20]	Modelling of real-life EAF steel mill for optimised time-resolved operation	Multiple	Time-resolved Models	Bottom-Up	Process to Plant Level	- Conducting measurements at the real-life steel mill to be modelled - Examining correlations and developing time-resolved models based on Markov chains - Derivation and validation of LPs for electric and thermal loads and flexibility options	- Bottom-up modelling requires extensive real-life data - Developed energy system model only applicable at the respective plant	- Novel and detailed insights into EAF steel mill processes and modelling for future simulation works
N	Thiede et al. [42]	Developing an energy flow-oriented manufacturing simulation including economic investigations e.g. DSM and energy efficiency measures	Multiple	Time-resolved Models	Bottom-Up	Process to Plant Level	- Analysis and measuring of process-specific energy flows - Modelling of the respective plant - Validation of generated LPs - Derivation of DSM potentials	- Bottom-up modelling requires extensive real-life data - Complexity of methodology could be disadvantageous if case study is to be reproduced	- Detailed methodology for bottom-up calculations in all industrial subsectors

APPENDIX B: PEER-REVIEWED SCIENTIFIC ARTICLES

Article P1

P. J. Binderbauer, T. Staubmann, T. Kienberger, Synthetic load profile generation for production chains in energy intensive industrial subsectors via a bottom-up approach, Journal for Cleaner Production (2022) 130024, https://doi.org/10.1016/j.jclepro.2021.130024

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Table 2: Author contribution statement for article P1.

Activity	Contributing authors
Conceptualization	Binderbauer, P.J., Kienberger, T.
Methodology	Binderbauer, P.J., Staubmann, T., Kienberger T.
Data curation	Binderbauer, P.J., Staubmann, T.
Software development and validation	Binderbauer, P.J., Staubmann, T.
Modelling	Binderbauer, P.J., Staubmann, T.,
Investigation and analysis	Binderbauer, P.J., Staubmann, T.,
Visualization	Binderbauer, P.J.
Writing (original draft)	Binderbauer, P.J.;
Writing (review and editing)	Binderbauer, P.J., Kienberger, T.

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Synthetic load profile generation for production chains in energy intensive industrial subsectors via a bottom-up approach

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ABSTRACT

Iron & Steel, Pulp & Paper, Non-Metallic Minerals and Chemical & Petrochemical are the most energy intensive subsectors, even though they utilise only a limited range of production processes compared to other sectors like Machinery or Food & Beverages. To support future efforts for decarbonising the European industry, this study aims to develop a methodology to correctly and dynamically depict all relevant production processes of the mentioned subsectors and to generate synthetic load profiles (LP)[1] based upon their consumption and generation behaviour. In a first step, the energy intensive subsectors and their main production processes are identified. A standardised research approach is used to correctly depict their characteristics e.g. runtime, energy consumption and generation, unit sizes etc. Next, a methodology for modelling the timely behaviour of these production processes and for generating synthetic LPs is developed. This method is based upon the bottom-up approach of discrete-event simulation combined with stochastics. The developed methodology is then implemented into the simulation software *Ganymed*. Finally, the results of this methodology are validated via a case study, modelling the primary steel production route of an Austrian steel mill. In overall, the synthetic electricity LP shows good approximations to the measured one with a mean absolute percentage error of 6.08% for the simulated five days in total. However, a stronger deviation of the generated LP compared to the measured counterpart can be noted at the last two days. This deviation results from a reduction of the capacity during the real life production. This, however, can be taken into account in the synthetic generation given a more extensive data basis. Consequently, *Ganymed* can be deemed as a suitable software for generating energy consumption and generation behaviour of processes and production chains of energy intensive industries.

1. Introduction

The European industry accounts for 21% of greenhouse gas (GHG) emissions (energy and process related) (European Commission, Statistical Office of the European Commission, 2021) and 20% of the gross inland energy consumption in 2020 (European Environment Agency, 2021). Thus, this sector undoubtedly has to take part in the energy transition. In addition, efforts to decarbonise the industry are even higher when compared to other sectors: This is due to its process diversity, technological complexity, varying GHG emission sources (e.g. process specific emissions) and use of energy carriers from different feedstock (Fleiter et al., 2018).

The development of comprehensive energy system models may help to overcome these challenges and align the industrial sector with the European net-zero GHG emission goals (European Commission, 2019). The dynamic character of simulation models allows to get hold of fast changing trends and technologies, evaluate their impacts on the physical energy system efficiently and, therefore, support the strategic decision-making for the energy transition.

To integrate this sector into such models, technological and systemic characteristics of the industry have to be taken into account. This can be achieved by structuring the industrial sector throughout a standardised approach and applying suitable calculation methodologies. Due to increasing volatility of the energy system, models further examine future grid capacities and demands for energy suppliers (Böckl, 2020). Here, the calculation of timely resolved behaviour of energy consumption and generation of industrial consumers in terms of load profiles (LP) play a

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[1] LP … Load Profile.

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List of acronyms

LP	Load Profile
GHG	Greenhouse Gas Emissions
PV	Photovoltaic
kWh	Kilo Watt Hours
MWh	Mega Watt Hours
TWh	Tera Watt Hours
e.g.	Exempli Gratia
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne
IEA	International Energy Agency
PVC	Polyvinyl Chloride
P	Power
t	Tonnes
min	Minutes
h	Hour
EAF	Electric Arc Furnace
GUI	Graphical User Interface
CHP	Combined Heat & Power
SIP	Sintering Plant
COP	Coke Oven Plant
BF	Blast Furnace
DS	Desulphurisation Unit
BOF	Basic Oxygen Furnace
LF	Ladle Furnace
VOD/VD	Vacuum (Oxygen) Degasser
HR	Hot Rolling
MAPE	Mean Absolute Percentage Error
TV	Total Variability

key factor. The generation of such LPs will be discussed in detail in this paper.

1.1. State of research

In recent years, numerous studies and models on analysing the industrial energy system have been developed. Mostly, the main aim of these are to investigate long-term emission reduction, higher energy efficiencies and implementation of renewables or future technologies (Fais et al., 2016). The results of these studies are then integrated into model-based decarbonisation strategies for either the whole industrial sector (Fais et al., 2016), individual subsectors (Bajpai, 2016) or breakthrough technologies (e.g. by investigating the impact of these technologies like PV plants or electrolyser) (Rootzén, 2015). In most of them, the development of an emission or energy reduction pathway is statically calculated and determined.

In regard to timely resolved energy consumption, a range of studies and models on the dynamic characteristics of consumer structures of the energy system can be found in literature. Especially for the mobility and private sector, various models were developed:

In the mobility sector, models for simulating the energy consumption of electric vehicles at charging stations were developed to determine the effects on the power grid. These approaches are established either based on measured data or accurate modelling of the driver's behaviour (Iversen et al., 2014). The mentioned data origins from measurements at charging stations (Neaimeh et al., 2015) or from statistical data (Leou et al., 2014). Vopava et al. (2020) examined these approaches in detail.

In the residential and private sector, standard load profiles for electricity are calculated for groups of more than 400 single consumers under 100 MWh (e-Control AT). However, the accuracy of the standard load profiles strongly decreases with a decreasing number of single consumers due to the stronger variation of the cumulative loads. Pflugradt and Muntwyler (2017) developed a holistic model for simulating synthetic profiles of single residential consumers in low-voltage grids without utilising standard load profiles. The bottom-up calculations within this method include various parameters, e.g. behaviour of the residents, consumptions of household appliances etc. A similar methodology was developed by Müller et al. (2020). Esslinger and Witzmann (2012) created an energy demand model for generating LPs of smaller consumer groups, entirely based on probabilistic calculations. Both bottom-up approaches exhibit valid approximations to the behaviour of the selected consumer categories and groups.

However, only a small number of studies on generating load profiles of consumers in the industrial sector can be found in literature. Starke et al. (2013) examined synthetic LPs of various industrial subsectors via probabilistic, mixed bottom-up and top-down approaches. The study identifies energy intensive manufacturing processes and typical production hours of various industrial subsectors to calculate a range of load factors adjusted to the individual sector. Via genetic algorithms a standardised LP is created. Based on the identified load factors, the standard LP is adapted according to the selected subsector in terms of fluctuating energy demand and overall consumption. The results of this approach are hourly-resolved electricity LPs, for which analysis of demand response possibilities for the chosen subsector are conducted.

Other studies simulate LPs for selected production plants (Dock and Kienberger, 2019) or industrial parks (Hernández et al., 2012) by e.g. analysing and clustering of measured data and identifying consumption patterns. Measures for optimising production processes or implementing new technologies at the plant site can be derived from these analyses. However, these approaches require a large scaled data basis.

Throughout this literature research it was found that a holistic framework for generating detailed, synthetic LPs for various energy carriers of all industrial subsectors has not been developed yet. However, for investigating the future energy system and requirements for grid operators and suppliers such models are crucial. Based on this knowledge, the comprehensive simulation software *Ganymed* (Binderbauer, 2021) was developed. The aim of this paper is to present the methodology and results of this tool.

1.2. Open research questions and structure of this paper

In context of the industrial sector, only a small amount of methodologies for the generation of synthetic LPs was found in literature, as concluded above. This leaves unanswered research questions and space for developing novel LP generation methods, which will be covered throughout this paper:

- Which approach shall be applied to develop a simulation methodology covering energy intensive, industrial subsectors? In what way shall industrial processes be standardised for integrating into the investigated methodology? Which simplifications have to be used? Which limitations and assumptions (e.g. system boundaries) have to be respected?
- How can individual process properties and conditions (e.g. batch/continuous operations, various material streams, parallel/serial process alignment, …) be depicted accurately? How can deterministic and stochastic simulation methods be combined?

Within this paper, the development of the proposed and underlying methodology of the software *Ganymed* is presented, answering the questions above. After outlining the main results of an extensive literature research in Section 1.1, a comprehensive methodology description follows in Section 2. Therefore, the European industrial landscape is divided into subsectors by IEA (International Energy Agency, 2021) and classified into groups regarding their energy consumption. (Section 2.1). The characteristics, typical production chains and processes of these subsectors were researched and are structured in Section 2.2. As a next step, a methodology based upon discrete-event simulation was developed and enhanced (Section 2.3). To prove the functionality of the developed methodology, Section 3 presents and discusses a selected case study of an existing production plant of the Iron & Steel sector in Austria.

2. Methods

2.1. Methodological research, approach and classification of the industrial landscape in Austria

To develop a comprehensive solution for generating LPs of various production chains of different industrial subsectors, an overall methodology approach was developed. This approach includes the following steps:

1. Division and classification of the industrial landscape
2. Research on characteristics of subsectors and processes
3. Development of a suitable methodology for generating synthetic LPs of researched industries
4. Integration of the developed methodology into the simulation software *Ganymed*

Industrial subsectors are defined by the International Energy Agency (IEA) (International Energy Agency, 2021) as depicted in Fig. 1. These sectors exhibit a good basis for further investigations. Additionally, other product specific classifications like NACE (Statistics Austria, 2008) were assessed. However, they were deemed as non-suitable for overall simulation approaches due to their higher level of complexity and sectioning.

Sejkora et al. (2020) assessed the primary energy consumption for all IEA subsectors in Austria with 139 TWh, as their shares are shown in Fig. 1. This study aims to depict the most energy intensive subsectors Iron & Steel, Pulp & Paper, Chemical & Petrochemical and Building Materials/Non-Metallic Minerals. Based on extensive literature research on these subsectors and their processes following key characteristics can be defined:

- Energy intensive subsectors are part of the primary production or industry and either extract and process raw or produce basic materials (European Economic, 2009).
- These subsectors exhibit a limited range of varying production processes and principles. Therefore, product variety is smaller than in other manufacturing subsectors, e.g. Machinery (Lechtenböhmer et al., 2016). The production processes can be described as homogenous.
- Only a few of the production processes account for the main share of energy consumption within a subsector (Johansson et al., 2012).

Due to these characteristics, production chains and their underlying processes can be depicted throughout a bottom-up approach. The generation of LPs of energy intensive subsectors are the main subject of this study.

2.2. Research on characteristics of industrial subsectors and processes

Fig. 2 depicts the method for researching various production chains and processes of the selected energy intensive subsectors.

Throughout an extensive literature research regarding the mentioned industries, typical production chains and their characteristics were identified. These characteristics were then studied and the most energy intensive and commonly operated processes within these production chains were further investigated. An overview of these selected production chains can be seen in Table 1. Certain product specific processes are operated in every subsector at the end of production in order to guarantee characteristics of the product to be produced (e.g. coating of high-quality paper).

In a next step, the scope of investigated production chains for further analyses was defined. Extraction, mining and transportation activities were excluded from the analyses as they are often located outside of the production/manufacturing plant border. Individual product refinement steps like coating of paper or special surface treatments of finished steel billets were not considered further as they exhibit lower energy demands compared to the main processes and are difficult to depict via a bottom-up analysis due to their variety and complexity. However, *Ganymed* enables user-defined process individualisation and system boundaries, which make an implementation of said processes possible, provided a sound data basis is given.

The identified processes were examined in more detail in a next step. Parallel and serial subproduction chains are implemented to meet the individual needs in different industrial plants. For example, regarding the Pulp & Paper sector, discontinuously working pulp digesters are operated in parallel and alternating to ensure a steady flow of pulp for the continuous follow-up processes (Paul Binderbauer, 2021). In the

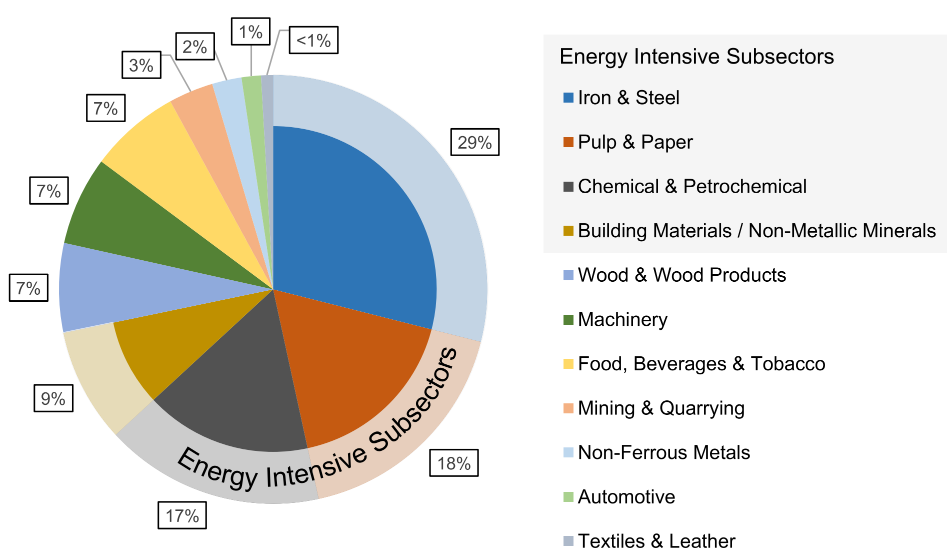

Fig. 1. Share of primary energy consumption of industrial subsectors by IEA in Austria.

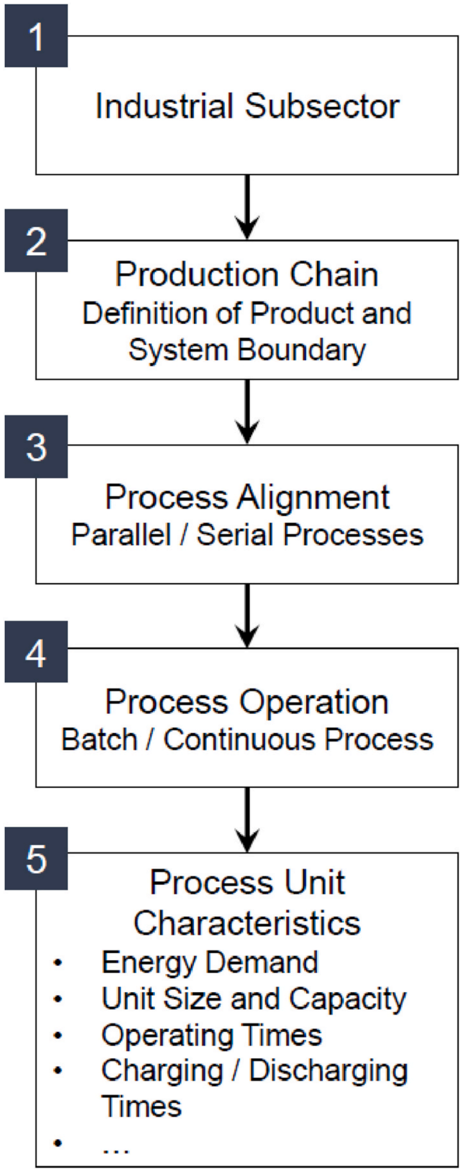

Fig. 2. Standardised approach for researching characteristics of industrial subsectors and processes.

Iron & Steel sector large process units like the electric arc furnace (EAF) are mostly implemented as a single process (Heinen, 1997). The follow-up processes are then operated in parallel and alternating to cope with the according batch sizes efficiently (Degner, 2009).

For generating synthetic, industrial LPs, detailed information on batch and continuous processes are essential. Fig. 3 shows the standardised approach, which defines the researched process characteristics. Continuous working equipment (e.g. paper calendar) is characterised by a steady throughput (e.g. material flow in t/h). Batch processes (e.g. EAF) are loaded with a certain quantity of material (e.g. in tonnes) and operate for individual durations (e.g. in hours, minutes, …). Typical ranges of energy consumption or generation can be determined for both process operations. These energy related characteristics are assessed for the energy carriers Electricity and Direct Fuel as well as for the useful energy categories Steam and Thermal Heating (see Section 2.3).

Table 1
Main production chains of energy intensive subsectors, which were researched and analysed throughout this study.

Iron & Steel	Pulp & Paper	Non-Metallic Minerals	Chemical
• Blast Furnace Route (Corradini et al., 1999; Degner, 2009; Ecker, 2013; European Steel Association, 2007; Remus et al., 2013) • Electric Arc Furnace Route (Aichinger, 2015; Heinen, 1997; Messer Group) • (Product Specific Processes (e.g. Alloying, Design of Final Product e.g. Rails, …) (Corradini et al., 1999; Degner, 2009))	• Pulp Production via Kraft, Sulphite, Thermomechanical or Mechanical Processes (Bajpai, 2016; Chan and Kantamaneni, 2015; Jacobs Greenville and Institute of Paper Science and Technology, 2006; Rahnama Mobarakeh et al., 2021; Suhr et al., 2015) • Paper Production (Bajpai, 2016; Chan and Kantamaneni, 2015; Jacobs Greenville and Institute of Paper Science and Technology, 2006; Rahnama Mobarakeh et al., 2021; Suhr et al., 2015) • (Product Specific Processes (e.g. Coating, Sizing, …) (Bajpai, 2016))	• Cement Production (Fleiter et al., 2013; Gruber) • Lime Production (Schimmel, 2019; Szednyj and Brandhuber, 2017) • Glass Production (Fleiter et al., 2013; Moser et al., 2017) • Brick and other Ceramic Production Routes (Fallmann and Weiß, 2018; Moser et al., 2017)	• Oxygen Production (Brown et al. Messer Group; Shen and Wolsky, 1980) • Ammonia Production (Brown et al.; European Commission, 2007) • Chlorine Production (Brown et al.; Resource Dynamics Corporation, 2002) • Ethylene Production (Brown et al. Gaines and Shen) • Polyethylene Production (Brown et al.) • Polypropylene Production (Meyers) • (Further Processing Routes (e.g. Fertiliser, Urea, PVC, …) (Fleiter et al., 2013))

The results of this methodology heavily depend on the quality of the presented data in literature. It was found that mostly consumption and generation is issued in average, specific energy consumption. For example, a batch working pulp digester consumes electricity in a range from 44 to 170 kWh/$t_{Air\_Dried\_Pulp}$ (Bajpai, 2016) and steam from 700 to 1370 kWh/$t_{Air\_Dried\_Pulp}$ (Jacobs GreenvilleInstitute of Paper Science and Technology, 2006). To calculate process specific LPs based on specific energy consumption, as described above, these values are multiplied by the process throughput for continuous and by capacity per operating time for batch processes. The resulting LPs can be described as an average load profile for this process (Fig. 3 (a)/(c)). However, in some cases, singular, process specific LPs were found in literature (see Section 3). These LPs are then implemented into the simulation framework (Fig. 3 (b)/(d)). Additionally, the user can modify the process' properties freely within *Ganymed*.

2.3. Methodology for the generation of synthetic load profiles

2.3.1. General methodology

Table 2 shows the target categories Electricity, Direct Fuel, Steam and Thermal Heating for which LPs can be generated. Direct Fuel refers to energy carriers, which transfer heat directly onto the product during energy conversion (e.g. oil, gas, coal, biomass, etc.). The distinction

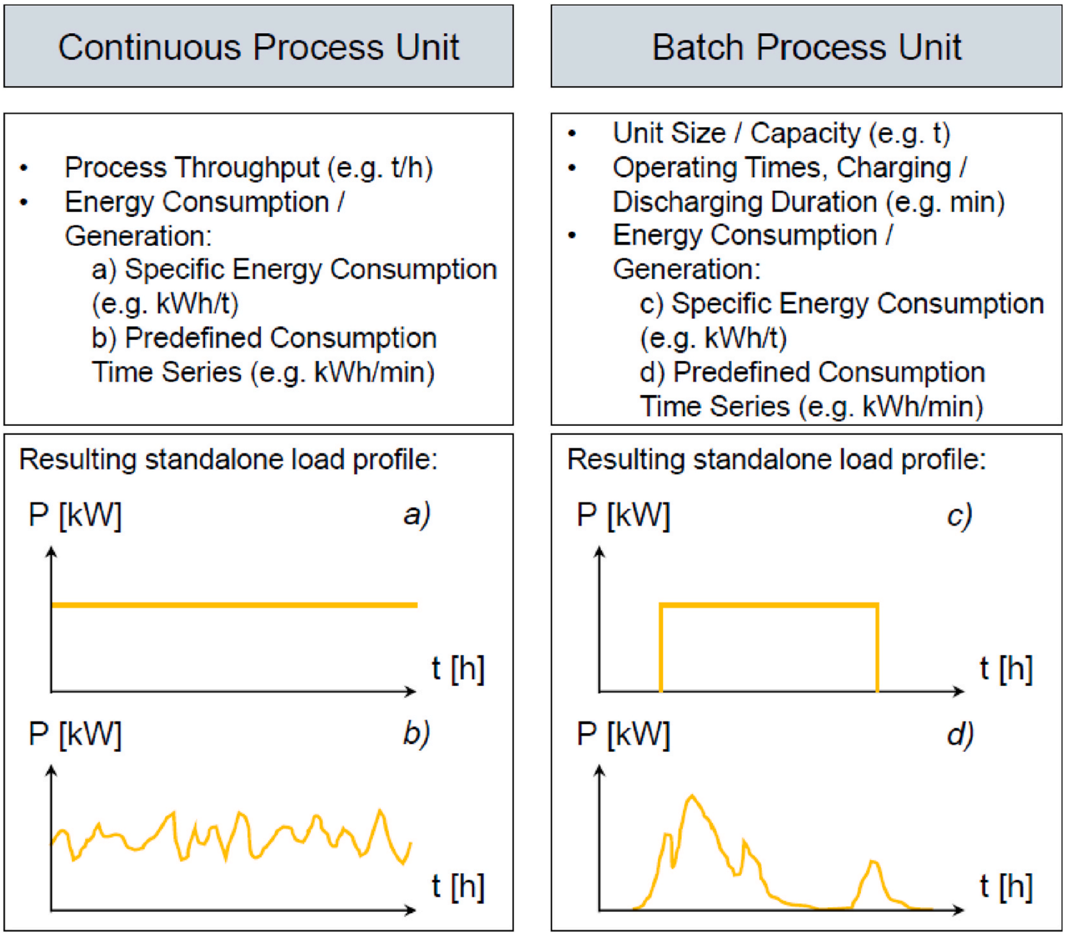

Fig. 3. Description of Continuous and Batch Processes: (a) Resulting LP based upon specific energy consumption of continuous processes; (b) Predefined singular LP of continuous processes from literature or measurements; (c) Resulting box-like LP based upon specific energy consumption of batch processes; (d) Predefined singular LP of batch processes from literature or measurements.

Table 2
Target categories of the LP generation in reference to useful energy categories and application temperature ranges.

Energy Carriers/Useful Energy Categories (European Commission, Statistical Office of the European Commission, 2021)	Application & Temperature Range in *Ganymed*
Electricity	–
Direct Fuel	High-Temperature Range
Steam	Medium-Temperature Range
Thermal Heating	Low-Temperature Range

between Direct Fuel, Steam and Thermal Heating was made due to applied temperature ranges.

As mentioned above, energy intensive subsectors utilise a limited amount of processes, which can be depicted effectively throughout a bottom-up approach. For generating the desired LPs discrete-event simulation was found to be the most promising bottom-up methodology. This method was implemented via object-oriented programming in Python and further improved to adequately depict industrial processes, as described in the following sections.

Discrete-event simulation depicts a sequence of interactions of i active components (e.g. tonnes of steel) with m resources (e.g. industrial processes like blast furnace, etc.) via time-proceeding events as described by Banks (2003). This simulation principle was then embedded into the standalone application *Ganymed*.

Fig. 4 describes the adapted discrete-event environment in terms of generating LPs for industrial processes.

As depicted in Fig. 4, the environment needs to be set up (c) before initiating the simulation (d) through *Ganymed*'s graphical user interface (GUI) (b). The user controls both actively by defining a production chain from an amount of individual processes as well as a number i of active components at first, which shall then be processed during the simulation.

During setup, the simulation environment (a) receives all needed information from outside its boundaries (e). This information contains a blueprint for a generic process class including default literature data (e.g. the process' name, its operating type (batch/continuous), unit size, capacity, throughput, energy consumption and generation, information on energy fluctuations, …). Based on this blueprint n specific process resources (e.g. pulp digester containing default values) are created (f).

Based on the user's input, a certain amount m of processes of the same resource n involved in the production chain are created in the software interface (e.g. two blast furnaces operating in parallel). The derived m objects (g) inherit the default information of the corresponding class resource. However, their characteristics can be adapted via the software interface before initiating the simulation (h). This enables a dynamic process individualisation by the user on top of the included default data from literature.

The user then establishes the order in which the created processes are aligned by defining a coordination matrix (see Section 2.3.2.2). Furthermore, processes can run in serial or parallel. These simulation specific features are explained in the following sections. Through the system preferences, the user can specify a number i of active components as a main product, e.g. i = 100 tonnes of steel per total runtime. This

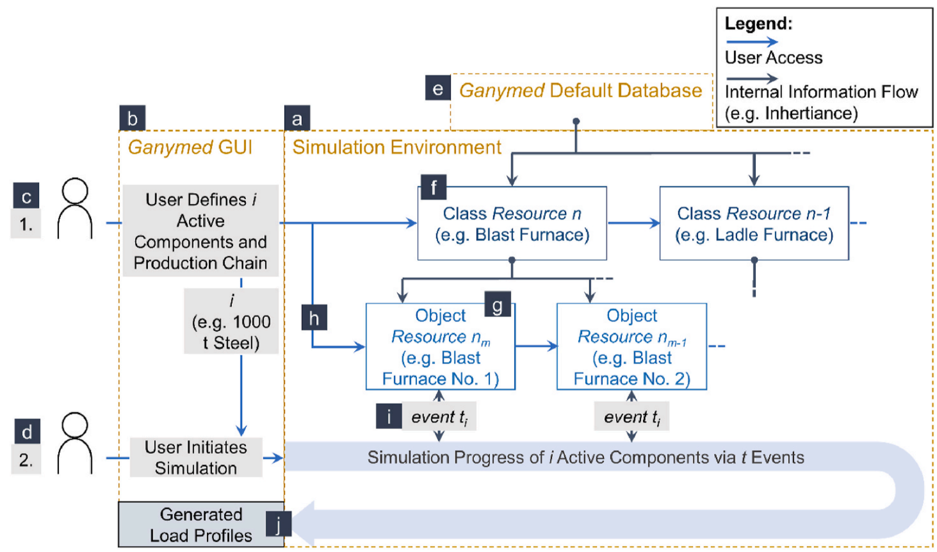

Fig. 4. Adaption of discrete-event simulation in *Ganymed*.

amount will then be passed through the user-defined process order sequentially.

Throughout the process order, resources are occupied by a number of active components sequentially according to their capacity. The corresponding events (i), which occur at different times over the simulation, halt the resource/process for the defined operating time, while active components not involved in the processing are aligned in a queue in front of this resource. During these process durations, singular LPs for the individual process steps are calculated. After the simulation has finished, the LPs of the object resources are summed up to represent the total LP of the defined production chain (j).

Fig. 5 shows a simplified generation of the overall LP based on summation of two individual process consumptions. In this example, two serial processes operate two active components (one tonne per component each) during the simulation ($i = 1, 2$). Both resources vary in regard to their runtime and consumption. The coloured rectangles in the depicted overall LP present the singular, average profiles of the corresponding processes. As the first tonne ($i = 1$) is processed in resource 1 over an operating time of 2.7 min, the associated singular LP is added into the chart. The second tonne ($i = 2$) waits in the queue of resource 1. After the processing is finished, the first tonne is passed onto the second resource, which creates the first blue share of the total LP at t = 2.7 min to 4.7 min. At the same time, the second active component ($i = 2$) is processed in resource 1. This component then occupies the second resource after the finished operation in process 1. Thus, a total LP (yellow line) of the electricity demand of this production chain can be depicted.

2.3.2. Application for industrial processes

Due to the large amount of variations of industrial processes and their operation, the basic discrete-event simulation approach needs to be enhanced extensively. Certain features and topics, which ensure a valid approximation to real production chains, are included in the simulation software *Ganymed*. The underlying methodology is explained in the following sections.

2.3.2.1. Behaviour of batch and continuous processes. To realise batch and continuous operating types, the smallest functional unit of one tonne of the finished product is specified as active component, as described above. Therefore, the capacity attribute of continuous processes is set to 1. The operating time of these occupied processes for one tonne of the finished product is defined by the reciprocal of the throughput (t/h). Continuous processes don't contain idle times like charging or discharging activities. A constant flow of active components and/or long enough queues for every continuous working resource is required. Short timely offsets of arriving active components in long production chains in the simulation (resulting in idle times and fluctuating energy demand) are bridged. Thus, a continuous LP is calculated as described in Section 2.2.

The capacity of batch operating processes is defined by literature data or the user, e.g. 65 tonnes of steel. The resource is loaded with the active components over a certain period of time until the capacity is met.

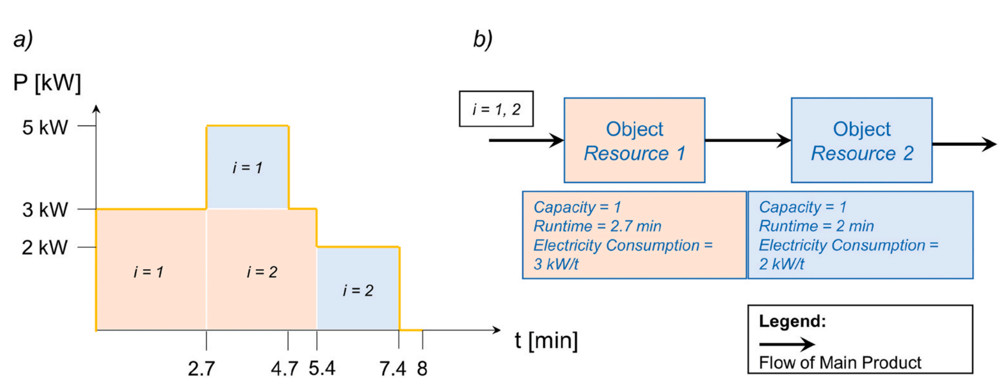

Fig. 5. (a) Resulting LP of a simplified production route (resource 1 and resource 2); (b) Process flow diagram for resource 1 and resource 2 as well as their properties.

This duration, as part of the overall process' runtime, is defined as the charging phase and results in a null line in the corresponding LP (Fig. 3 (d)). The processing with its specific energy consumption starts as the event of the batch resource is halted for the defined operating time. After this time has elapsed, the active components are forwarded to the next process in the order of arrival for a defined discharging time. For the period of the operating time, a singular LP is calculated.

2.3.2.2. Alignment of processes. As described above, processes of production chains can be aligned freely by the user through the GUI of *Ganymed*. This also includes serial and parallel operating subchains. However, this requires boundaries, which define the start and end point for the flow of active components, as well as attributes, which depict the direction of the flow in between the processes.

For this purpose, a coordination matrix is applied, which contains all directional vectors including the individual addresses of the created resource objects. The overall production chain operates between a start and end object, defined by the user. Fig. 6 (b) shows a coordination matrix for the directional vectors of the depicted process chain (a). The first column in the coordination matrix contains the address of the object, where the active components are transferred from. The address in the second column describes the target object. At the beginning of the simulation, the algorithm searches the first column for the defined start object. On that basis, the following processes can be aligned and triggered sequentially according to the items in the coordination matrix.

As shown in Fig. 6 (a), processes can also be aligned in parallel by the user. In this case, the first column of the coordination matrix contains the address of the object, where the active components departure, multiple times (see (b) line 3 and 4). Therefore, the allocation of the components to the following processes has to be managed in a way, which depicts real operations sufficiently. Table 3 gives an overview of possible allocations for parallel processes, resulting from literature research (Máté Hegyháti and Ferenc Friedler, 2010). For example, the user can select individual objects, which are scheduled primarily (Object Preferences). Batch processes can be loaded consecutively considering the chosen degree or depending on their operating time.

2.3.2.3. Auxiliary material consumption and production. As the production of the main product progresses, various auxiliary materials are consumed and produced, e.g. production of black liquor in a pulp production plant (Rahnama Mobarakeh et al., 2021). These additional materials can affect the energy consumption and generation of the overall production plant.

As described in sections above, the main production route processes the main product. A total LP is generated through specific energy consumption assigned to tonnes of the main product, e.g. 100 kWh/t_{Pulp}. Fig. 7 shows this main production line indicated by black, directional arrows.

The resulting coordination matrix for the main product is presented in Fig. 7 (b). Additionally, auxiliary material (green arrows) is processed in resource 3 and then added into resource 1. For this material stream, Fig. 7 (c) shows the associated extension to the coordination matrix. In this case, the process characteristics of resource 3, for example capacity,

Table 3
Implemented types for decision process of allocating product flows to follow-up parallel process subchains.

Allocation for All Process Types	Allocation for Batch Process Types Only
• Random Allocation • Consistent Allocation • Object Preferences	• Allocation based upon the degree of loading • Allocation based upon the operating time

energy consumption/generation, etc. are referenced to the actual auxiliary material, e.g. 200 kWh/$t_{WoodChips}$. To prevent inconsistencies in the overall material flow, mass conversion values are introduced to convert the auxiliary material to the main product. For example, the mass conversion ratio for wood chips to pulp in a Kraft production chain is about 2 (Rahnama Mobarakeh et al., 2021). For processes, which operate auxiliary material streams, the mass conversion is multiplied with the process' characteristics to reference to the main product:

$$200\ \frac{kWh}{t_{WoodChips}} * \frac{2}{1}\frac{t_{WoodChips}}{t_{Pulp}} = 400\ \frac{kWh}{t_{Pulp}} \tag{I}$$

At resource 1, the previously explained ratio can be taken into account. The methodology coordinates the chronological order in accordance to the implemented mixing and mass conversion ratios. Auxiliary material can also be produced as a by-product, e.g. black liquor (Fig. 7 (a) light-blue directional arrows). The resulting extension to the coordination matrix is shown in Fig. 7 (d). There, mixing and mass conversion ratios are also taken into account.

2.3.2.4. Implementation of stochastic methods. Singular LPs of standalone consumers can alternate over a vast range (Esslinger and Witzmann, 2012). Furthermore, the implemented data for selected processes, e.g. specific energy values like 100 kWh/t_{Pulp} (see Fig. 3 (a)), depict only their average consumption and generation behaviour. To bypass certain insecurities and gaps in the data pool and in order to avoid box-like, unrealistic LPs, the bottom-up methodology is supported by stochastic methods, as suggested by Gao et al. (2018).

The first approach of implementing stochastic methods into the methodology is based on Gaussian distribution. This is already discussed in literature regarding LP generation for private households (Probst et al., 2011). Other references describe the application of Markov chains, e.g. for the simulation of big consumers like the EAF (Dock and Janz, 2020) or evaluation of lighting demand patterns in households (Widén et al.).

Fig. 8 (a) shows the application of Gaussian distribution. For a given standard deviation σ, a distribution for fluctuating the energy consumption or generation from μ can be calculated for every time step t of the load profile.

Both μ, and the standard deviation σ for selected process units are defined by literature data or the user. Based on this information, a cumulative distribution function *F(P)* is calculated at *t*, as shown in Fig. 8 (a):

$$F(P) = \frac{1}{2}\left(1 + \text{erf}\left(\frac{P-\mu}{\sqrt{2\sigma^2}}\right)\right) \tag{II}$$

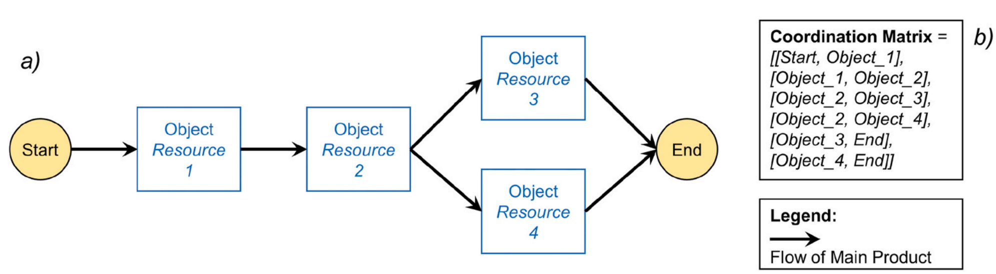

Fig. 6. Alignment of processes in serial and parallel manner; (a) Showing a possible production chain along with its coordination matrix in (b).

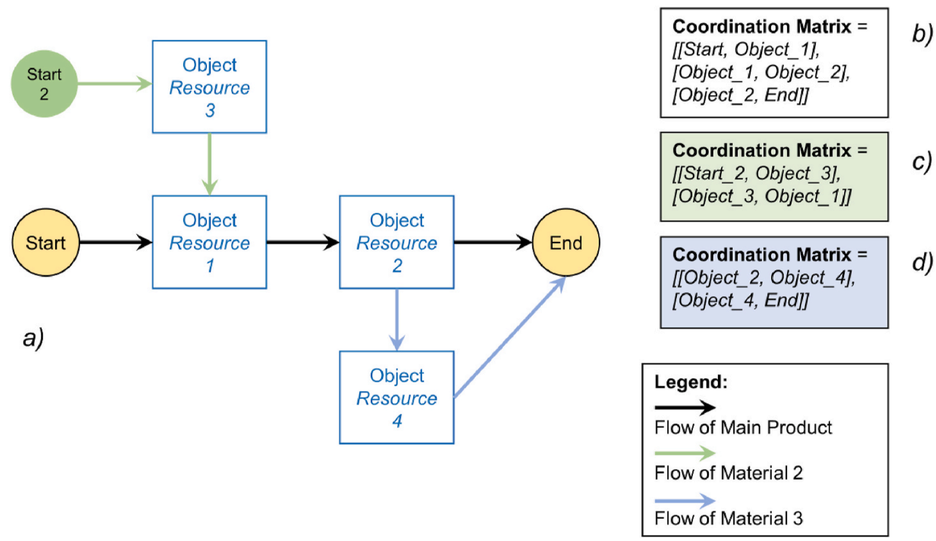

Fig. 7. Production chain with auxiliary material routes; (a) Depicted production chain along with its coordination matrix (b) and its extensions in (c) and (d).

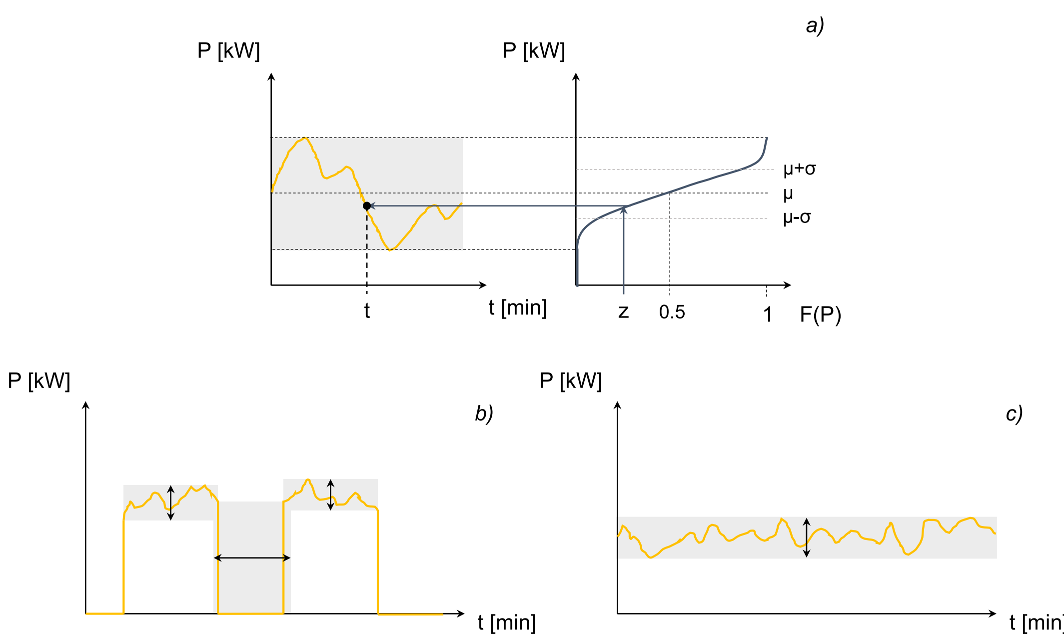

Fig. 8. Application of Gaussian distribution in LP generation of *Ganymed*: (a) Cumulative distribution function generating the deviation from μ at t; (b) Resulting fluctuation of energy demand and charging/discharging phases of batch processes; (c) Resulting fluctuation of energy demand of continuous processes.

For the time step *t*, a random distribution factor *z* between 0 and 1 is drawn. This factor acts as a result of the cumulative distribution function *F(P)*. The associated power level *P* is calculated through cubic interpolation. The resulting fluctuations of energy consumption and generation is shown in Fig. 8 (b), for batch working processes, and Fig. 8 (c), for continuous processes, respectively.

Additionally, Gaussian distribution is also applied for alternating charging/discharging durations of batch processes (see Fig. 8 (b)).

2.3.2.5. Implementation of system boundaries. Calculations of energy flow balances can be performed for various system dimensions. For this, user-defined system boundaries were introduced into the methodology, which represent an essential calculation basis for LP generation of the defined production chain.

As energy flows intersect system boundaries, their timely behaviour can be assessed to generate LPs. To achieve this, these energy flows, representing the target categories in Table 2, were introduced into the methodology, as depicted in Fig. 9 with bold arrows.

Object resources/processes can take part in the production itself and, therefore, consume final energy (e.g. electricity for wood debarker) or transform energy carriers within or outside the industrial plant (e.g. CHP-plant, blast furnaces, etc.), which are defined as “autoproducers” by the United Nations (United Nations, 2017).

As Fig. 9 shows, the integrated custom boundaries for generating LPs can be defined for system dimensions starting from single processes ((b) and (c)) to the overall plant (a). The resulting LPs are attributable to these different system levels. Fig. 9 (b) shows the defined boundary for a single production process, which consumes electricity only. The generated LP will only depict the consumption behaviour of this process. This also applies for the autoproducer in Fig. 9 (c). However, here, the resulting LPs of the produced categories steam and electricity will be negative. Because discrete-event simulation needs to handle specified mass flows, the mass flow of natural gas (depicted in light green directional arrows) has to be taken into account, while the energy input and

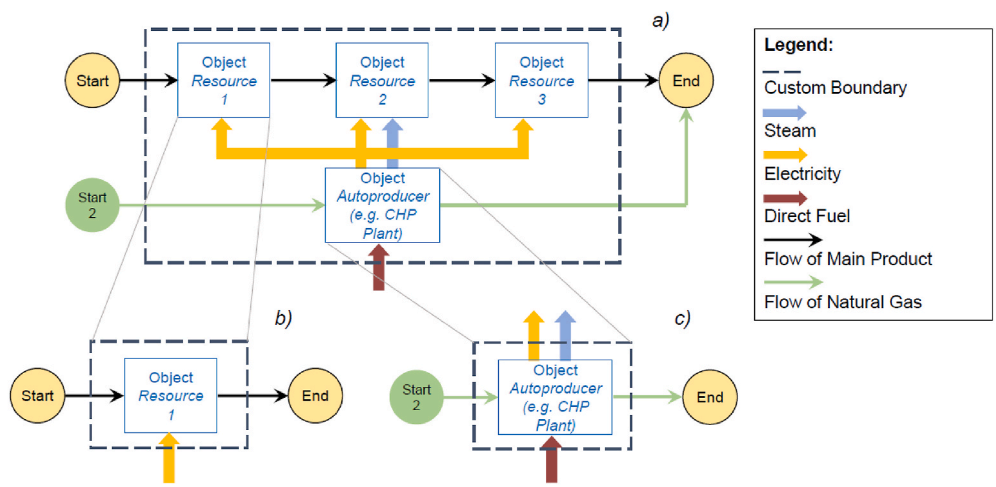

Fig. 9. Application of system boundaries in *Ganymed*; (a) Overall production plant boundary including (b) single production processes and (c) transformation processes.

output of this transformation process has to be defined accordingly via bold arrows. Fig. 9 (a) will only generate a LP for direct fuel as all other energy carriers are handled inside the boundary.

This range of user-defined system boundaries enables the generation of LPs for various system dimensions and included processes. For example, all final energy consuming processes can be depicted effectively. Through minor adaptions autoproducers within the plant border can be included in the calculation to generate LPs of the overall facility. Through this, not only the plant's consumption but also the generation of excess heat or electricity supply to the public energy system can be calculated respectively.

These key adaptions of discrete-event simulation represent the overall methodology of *Ganymed*.

3. Load profile validation case study

3.1. Overview

In the following section a selected case study is presented to validate the functionality of the developed simulation software *Ganymed* (Case study and software available at ganymed.ga) and its presented methodology. Therefore, the Blast Furnace route of Voestalpine GmbH in Donawitz in Austria is investigated. Vital information of the production chain design (Degner, 2009) and the processes' capacities (Ecker, 2013) originate from literature and open accessible platforms (e.g. Voestalpine Website). Consumption and generation behaviour of all unit operations are either based on measured singular LPs or averaged consumption characteristics. Ecker (2013) presents a measured electricity LP for the plant in Donawitz for a self-defined system boundary. The generated

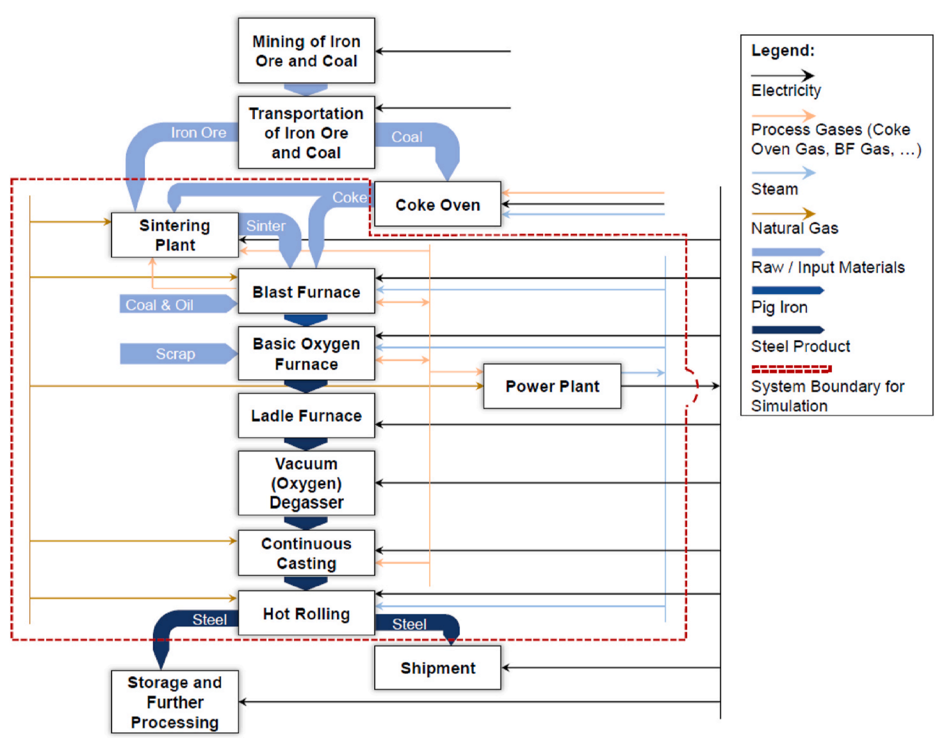

Fig. 10. Overall production chain of selected case study.

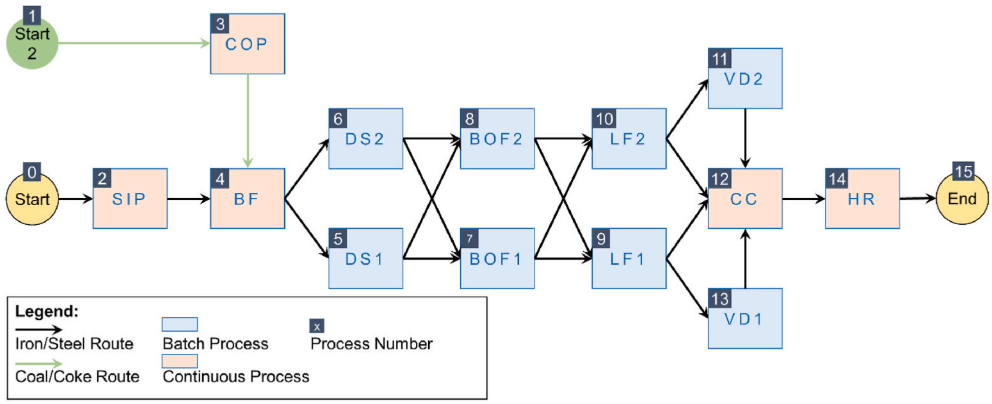

Fig. 11. Implementation scheme of production chain in *Ganymed*.

synthetic LP will be compared to this measured profile in Section 3.3.

Fig. 10 shows the overall production chain for producing steel billets in Donawitz from cradle to gate. Processes outside the shown system boundary defined by Ecker (2013) are not included in the LP generation. It is noted, that Fig. 10 doesn't present the quantity of process units involved, which are shown in Fig. 11. Since the presented LP only depicts electricity, the system boundary is set accordingly to intersect with the electricity consumption flows in Fig. 10. Process gases (e.g. Coke oven gas, blast furnace gas, converter gas, …), natural gas and steam flows will not be respected within the simulation. The coke oven is excluded from the system boundary since coke is directly transported to the site in Donawitz. It is included in the overall production process nevertheless to depict a coherent Blast Furnace route. Additionally, the installed power plant in Donawitz is excluded from the calculation. However, *Ganymed* would be able to determine LPs for all energy categories as depicted in Fig. 10.

3.2. Model description

Based on the information above, a block flow chart (Fig. 11) for the implementation in *Ganymed* has been developed. The pig iron production in Donawitz is performed with one blast furnace (BF), which receives input materials (sintered iron ore and coke) from a sintering plant (SIP) and an external coke oven plant (COP, excluded from calculation). From literature data an average production output of raw steel of 180 t/h was determined. It is assumed, that the BF is operated continuously. The product batches for DS, BOF, LF and VD of 65 t result from the tapping process. This quantity is aligned with the continuous output of 180 t/h. It was found, that this ensures a steady flow of products within the defined production chain. The primary steel production includes two desulphurisation units (DS) and two basic oxygen furnaces (BOF) with a capacity of 65 t, which represents the size of one batch originated from the BF. This capacity is also assumed for the installed lade furnaces (LD) and the vacuum (oxygen) degasser/decarboniser units (VD). The following operating units, continuous casting (CC) and hot rolling (HR), are operated continuously and are aligned with the production output of the BF.

Fig. 11 shows that the main batch processes are aligned in parallel. To ensure a steady flow of active components even through alternating processing times, the following processes can receive products from either two of the preceding units. This is realised through overlapping directional arrows in the coordination matrix. The two vacuum degasser units are installed to meet the required steel product specifications (Schröcker, 2014). Because these specifications can vary, both VD units are assumed to operate with a probability of 50%.

The main product route (black directional arrows) utilises "tonnes of steel" as active components. All corresponding processes characteristics are referred to these components. The system also includes the auxiliary material coal/coke, which is simulated as active component for the COP. The characteristics of COP are also referred to tonnes of steel. According to literature, the mass conversion factor is set to 1 (Degner, 2009).

Energy related consumption and generation of the processes involved were extracted from literature sources. All continuous processes are specified with averaged consumption values. The behaviour of batch operated processes, except the VD units, are characterised by predefined time series as of literature data (Fruehan, 1998). With regard

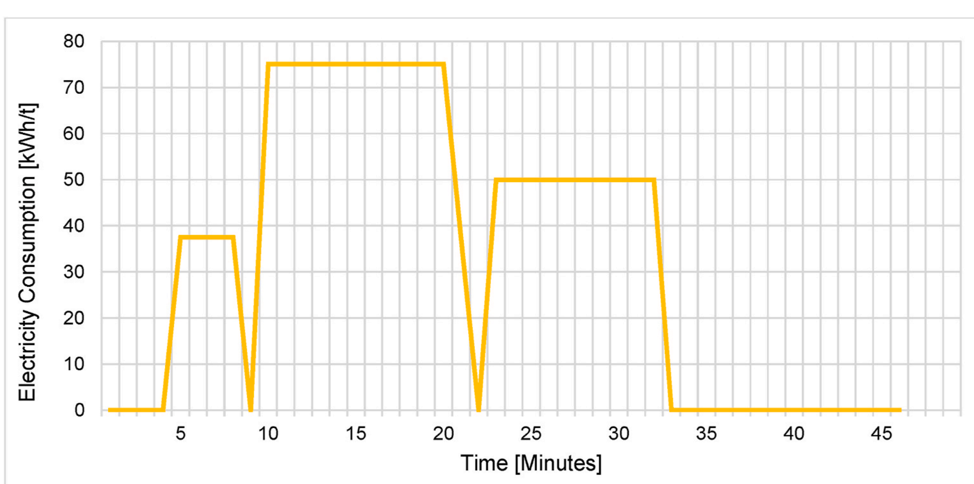

Fig. 12. Singular LP of the ladle furnaces from literature.

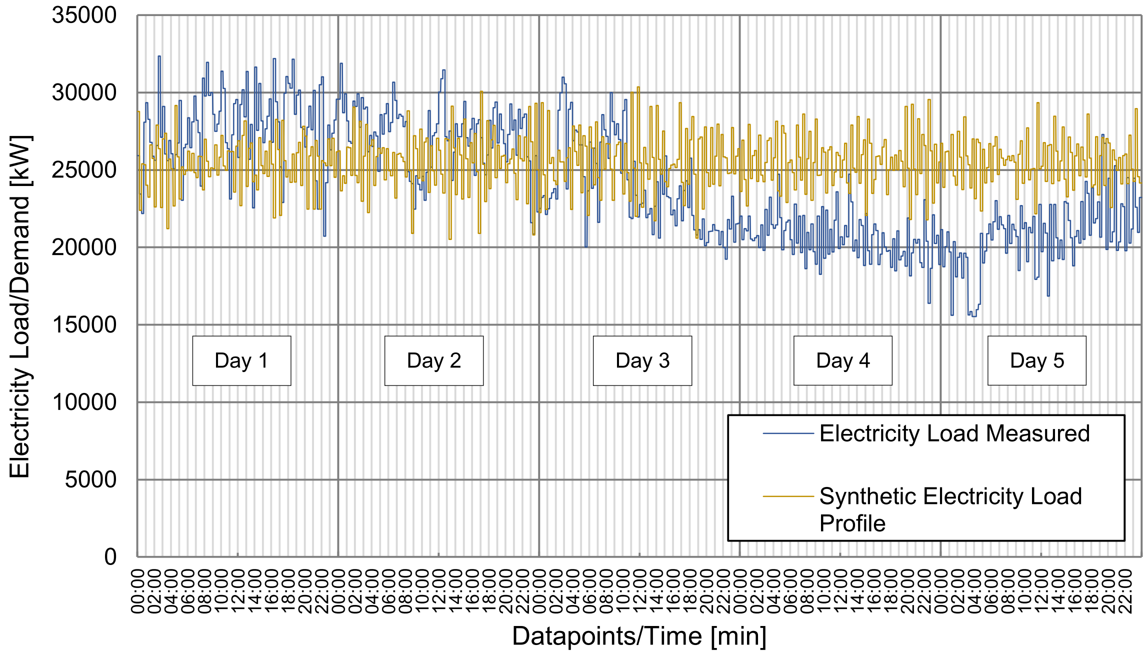

Fig. 13. Results of selected case study, comparing measured LP (Blue) to generated synthetic LP (Brown) for 5 working days. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

to this, Fig. 12 shows the singular LP for electricity of a lade furnace unit as an example. The consumption behaviour results from different heating phases of the furnace for one ladle (65 t).

3.3. Results and discussion

The electricity LP of Ecker (2013) was measured within five working days (Monday – Friday). A synthetic LP for the production chain mentioned above with a depicted time of total 7200 min was generated respectively.

Fig. 13 presents the generated synthetic electricity LP in comparison to the measured profile by Ecker (2013) of the existing production site.

For the analysis and comparison of the synthetic LP to the measured profile, the average electricity consumption, total variability and the mean absolute percentage error (MAPE), following the depicted equation, were assessed:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_m - P_s}{P_m}\right| * 100\% \qquad \text{(III)}$$

As $n = 7200$ represents the total number of data points/minutes, P_m constitutes the measured and P_s the electricity demand of the synthetic LP at the time t.

Table 4 presents the overall results and the deviation of the measured and synthetic LP. As the mean average percentage error of around 6.08% shows, the synthetic profile exhibits good approximations to the measured data in terms of average electricity consumption. The total variability per day (TV) presents the difference of maximum and minimum electricity demand for one day:

$$TV = Maximum\ Electricity\ Demand - Minimum\ Electricity\ Demand \qquad \text{(IV)}$$

For the second day, the maximum variability of the measured LP is slightly higher than the synthetic profile, resulting in a mean average percentage error of 13.17%.

Fig. 14 shows the percentage error (PE) of all compared data points following the equation:

$$PE = \left|\frac{P_m - P_s}{P_m}\right| * 100\% \qquad \text{(V)}$$

A strong deviation can be examined within the last two days. This is due to a noticeable fluctuation in the measured LP, resulting in a decreased electricity demand. Ecker (2013) reasoned this varied consumption in his work with an unexpected reduction of the production capacity and a partly shutdown of selected processes in Donawitz at that time. A polynomial fit (4th degree) shows the resulting fluctuation of the percentage error in Fig. 14. In this case, the fitted deviation rises to 30%. It is noted, that, under known circumstances regarding the alternating production capacity, a reduction of the percentage error within the last two days is possible.

Regarding the performance of *Ganymed*, the generation of the presented LP was completed in a runtime of 12.5 seconds. An examination of maximum queue lengths of active components for every process during this calculation shows lengths of 75 tonnes steel on average. This is in accordance to the chosen batch sizes (65 t) of batch operated processes (e.g. DS, BOF, LF, VD). The synthetic production chain exhibits no major idle times for the active components. Thus, the performance of *Ganymed* can be described as satisfactory. The performance will decrease when implementing further processes to the overall chain or by increasing the number of active components and runtime.

The mentioned altering production capacity or more detailed singular LPs of all involved process can heavily reduce the remaining percentage error. This requires a sound basis of information and data. However, the dynamic and adaptable characteristics of *Ganymed* allows the simulation of synthetic industrial LPs based on the user's data on top of the underlying default data. Missing or undetailed information could

Table 4
Analysis and comparison of generated LP, covering the MAPE of mean electricity consumption and the TV of a representative day.

Mean Electricity Consumption	
Measured Load Profile:	24061.58 kW
Synthetic Load Profile:	25525.66 kW
MAPE:	6.08%
Total Variability (TV) of Day 2	
Measured Load Profile:	11023.21 kW
Synthetic Load Profile:	9571.21 kW
MAPE:	13.17%

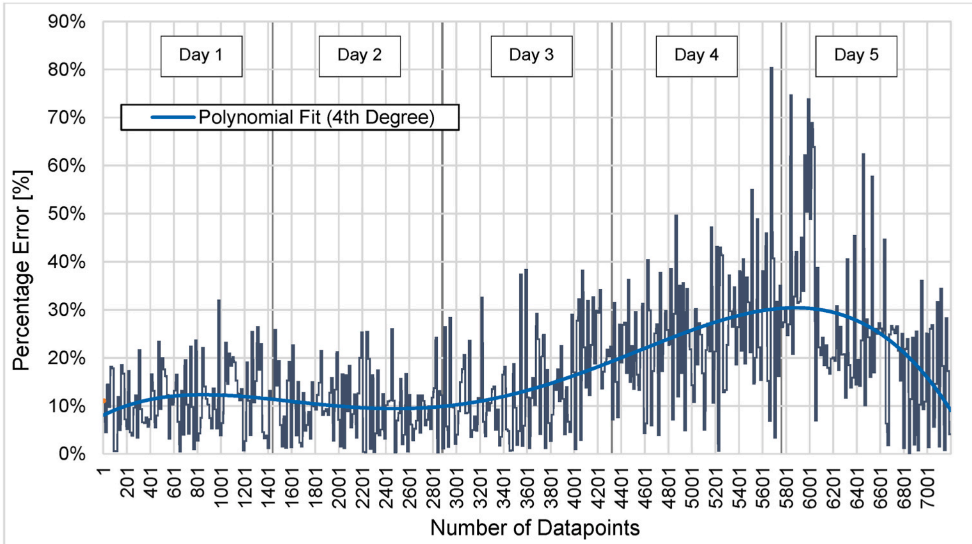

Fig. 14. Percentage error and polynomial fit of all compared data points between measured and generated LP.

be improved by reinforced implementation of stochastic methods.

4. Conclusions & outlook

Throughout this paper, a comprehensive methodology for generating synthetic load profiles (LP) for the industrial landscape is presented. This approach involves energy intensive subsectors, which are characterised by homogenous process chains. It was found, that because of the limited amount of process and product variety of these raw material processing subsectors, the bottom-up methodology of discrete-event simulation is a suitable method for generating LPs for various energy carriers. This method was combined with basic stochastic models and improved to meet the depiction of industrial processes. A following case study modelling an existing Iron & Steel production chain proved the functionality of the established software.

In conclusion, the results of the presented methodology exhibit satisfactory approximations in depicting existing production chains and their timely resolved consumption. Thus, *Ganymed*, as discrete-event simulation is applied, adjusted to industrial processes and principles, can be deemed as a suitable software for generating synthetic load profiles of production chains of the selected subsectors. This approach requires a sound basis of information, which was created throughout this study and will be extended continuously. Furthermore, the methodology shall be improved further throughout future research. The presented case study shows the need for implementing variable production capacities. This can be achieved, for example, by introducing shift models or daytime-depending capacities into *Ganymed*. Shift models can, for example, incorporate non-producing times like weekends into the generated LPs. If this detailed information is not available, stochastic methods can be improved further by e.g. fluctuating the operating times or batch sizes of involved processes. For example, in the Iron & Steel industry batches are often subject to alternating sizes. These alternating factors can be addressed via stochastics.

As described in Section 2.2, further processing steps like rail rolling mills or coating processes were not taken into account yet. This is due to the vast variety of possible processes involved, which is a disadvantageous factor for developing bottom-up simulation approaches. However, the development of a top-down simulation of other industrial subsectors can take these further processing steps into account. The implementation of this simulation approach will be the main topic of a follow-up study.

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CRediT authorship contribution statement

Paul Josef Binderbauer: Conceptualization, Methodology, Software, Validation, Writing – original draft, Visualization. **Thomas Kienberger:** Conceptualization, Writing – review & editing, Supervision. **Thomas Staubmann:** Methodology, Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.130024.

Appendix

The GUI of *Ganymed* was developed via the Python library “Tkinter”. A screenshot of the software interface is shown in Fig. 15. The process canvas enables the creation of various process objects and their user-defined arrangement via drag and drop. This ensures the specification of dynamic and flexible production chains during user setup. The alignment of processes is consistent with the mentioned methodology explained above.

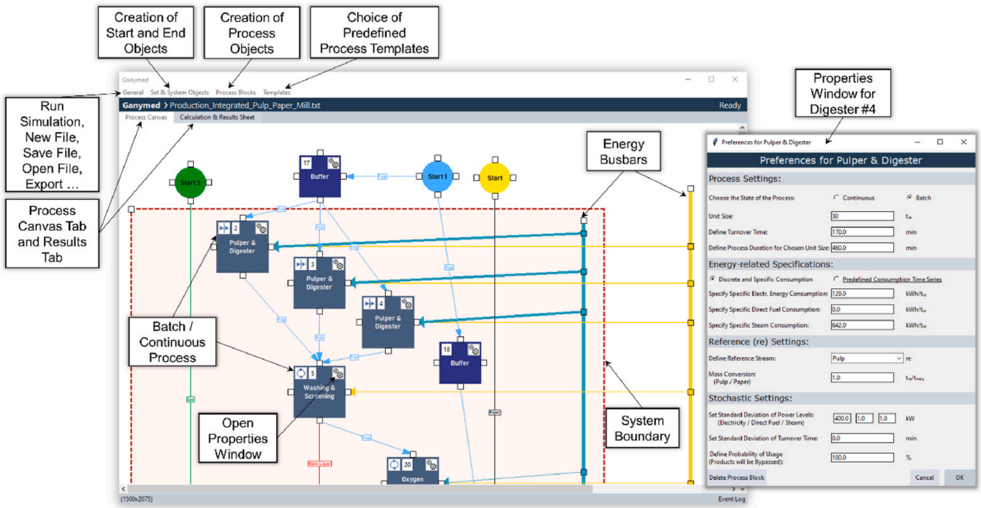

Fig. 15. *Ganymed* GUI Process Canvas and Preference Window of selected process.

The visual representation of a process object contains its consecutive number, a type symbol (batch/continuous), a process properties button, which opens the preference window (see Fig. 15), and four anchor points. The anchor points are the basis for incoming and outgoing material and energy flow arrows. The preference window displays the properties of the selected process object. These properties are the key information for the simulation framework and can be adapted by the user.

As mentioned above, the production chain operates within the defined start and end objects. After the user finished the arrangement of the overall production line, including start and end objects, the simulation can be initiated. A loading bar indicates the simulation's progress.

After completion of the simulation, the user can switch to the calculation and results sheet as shown in Fig. 16. Here, the overall simulated load profile is displayed. This load profile includes the user defined simulation time as well as start-up and shutdown operations of the entire production chain. Via "Data Handling" the user can manipulate the simulated load profile, e.g. copy and paste representative parts of the load profile or cut statistical outliers or faulty boundary effects. Based on this, the user can generate and export a defined weekly load profile for the specific target values and energy carriers.

Fig. 16. *Ganymed* GUI Calculation & Results Sheet.

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Article P2

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Table 3: Author contribution statement for article P2.

Activity	Contributing authors
Conceptualization	Binderbauer, P.J., Kienberger, T.
Methodology	Binderbauer, P.J., Keuschnig, A., Kienberger T.
Data curation	Binderbauer, P.J., Keuschnig, A.
Software development and validation	Binderbauer, P.J.
Modelling	Binderbauer, P.J.
Investigation and analysis	Binderbauer, P.J., Keuschnig, A.
Visualization	Binderbauer, P.J.
Writing (original draft)	Binderbauer, P.J.;
Writing (review and editing)	Binderbauer, P.J., Kienberger, T.

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Synthetic load profiles of non-energy intensive industrial sites: A combined bottom-up and top-down approach

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ABSTRACT

The heterogeneous nature of the industrial sector in terms of process and product variety often hinders assessments of its energy consumption. The generation of synthetic load profiles (LPs) however offers a key instrument to support energy suppliers, grid operators and industries themselves by quickly evaluating the impacts of energy efficiency measures, fuel switch, new technologies etc. Currently, such LP generators are only developed for single real-life industry plants or require comprehensive beforehand data. Within this study, we propose a new model for generating synthetic LPs of industrial process chains without the need for extensive, plant-specific data. This solution includes a series of bottom-up and top-down approaches. We analyse different data sources and develop algorithms based on underlying data science methods and technical and economical modelling paradigms like Markov chains or Economy of Scale. Here, we describe novel findings e.g., a method that proves the prediction of industrial shift models from a top-down perspective or effects on the energy demand of industrial plants for rising production capacities. Furthermore, we prove that only some production processes in industrial facilities are responsible for the main share of their energy demand, as the residues can be modelled by numerical analyses. We validate the developed approach by generating synthetic electricity LPs of different real-life industrial plants and comparing the results to measured LPs. This study contains five case studies, of which we found valid approximations of our synthetic LPs to the measured, real-life plants. However, our model's results differ from measured LPs, especially when depicting lower energy demands (< 200 kW). Furthermore, long-term periodicities e.g., part-time working hours on Saturdays have not been incorporated into our model yet, which leads to certain inaccuracies. We quantified these effects within this study. This, nevertheless, leaves open areas for future research work.

1. Introduction

The modern energy system is confronted with significant challenges. The climate crisis presents itself as one of the most fundamental humanitarian crises. However, the fast-increasing rate of the implementation of renewable energies heavily influences the volatility of supplied energies and therefore the stability of the overall energy system [1].

In the age of digitalisation, we can deem ourselves lucky enough to hold the needed means to develop fruit-bearing solutions for solving these challenges. Energy system models play a vital role in this context, especially for energy suppliers and grid operators. These instruments support the strategic decision-making for the energy transition by incorporating topical trends and technologies and swiftly evaluating their impact on the physical energy and grid system [2].

As the European industry is accountable for around 20% of the gross inland energy consumption [3], it has to take a major part in the energy transition. Whereas the development of energy models in the mobility and residential sectors is well underway, industrial models are lagging behind in terms of their dynamic and comprehensive character [4]. To accelerate this process, our motivation lies in proposing novel approaches to depict the dynamic demand and generation behaviour of single industrial sites in terms of timely high-resolved load profiles (LPs) as we therefore can introduce new aspects and improvements to global energy system models. As we already demonstrated a model for energy intensive industries in our preceding study [5], we now want to address the depiction of the more complex, non-energy intensive industries like Machinery, Food & Beverages etc. The generation of LPs for the mentioned industries will therefore be the main topic of this study.

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List of Acronyms

LP	Load Profile
DSM	Demand Side Management
IAC	Industrial Assessment Center
kWh	Kilo Watt Hours
MWh	Mega Watt Hours
TWh	Terra Watt Hours
e.g.	Exempli Gratia
NACE	Nomenclature statistique des activités économiques dans la Communauté européenne
IEA	International Energy Agency
PVC	Polyvinyl Chloride
P	Power/Energy Demand
E	Energy Consumption
t	Tonnes
min	Minutes
h	Hour
SEC	Specific Energy Consumption
EOS	Economy Of Scale
LF	Load Factor
MAPE	Mean Average Percentage Error
DFT	Discrete Fourier Transformation
GUI	Graphic User Interface

1.1. State of research

In our preceding study [5], we discussed recent developments in modelling methodologies, which allow the depiction of dynamic consumption patterns and therefore generation of LPs of consumers and consumer groups in the mobility [4] and residential sectors. In the latter, for example, a comprehensive model by Pflugradt and Muntwyler [6] was developed, generating LPs of single households based on residential behaviour and consumption of household appliances. This bottom-up methodology can be applied to design local energy systems, for which simple standardised LPs are deemed too inaccurate [7].

Our findings show that several models for the industrial sector have been developed to statically determine their energy consumption [5]. This allows the investigation of e.g. long-term emission reduction or the utilisation of renewable energies [8]. However, timely high-resolved synthetic LP generation represents a key solution for evaluating future grid demands, scheduling energy supply, or implementing demand-side management (DSM) measures.

Based on the literature research in our preceding study, we further investigated existing modelling approaches for generating LPs of industrial sites. We found only a few, which we classified in Fig. 1 depending on their systemic application (thermal LP, electric LP, multi-energy LP) and methodology (bottom-up, top-down). We also assessed how many industrial subsectors can be depicted by the proposed approach without relying on additional, external data (user-wise) or real-life measurements.

Sandhaas et al. (A) [9] developed a top-down methodology, to model electricity LPs based on normalised daily LPs of five industrial subsectors. These normalised LPs were divided into eight end-use applications (useful energy categories) such as mechanical drive, lighting, heating etc. The fraction of allocation of the useful energy categories to the resulting electricity LP was defined by investigating industrial databases. LP fluctuations were introduced via the application of stochastics. The generation of thermal LPs was not covered within this work, which certainly is another major field of application due to the high rate of industrial, thermal consumers [16].

Jesper et al. (B) [10] created a methodology for generating thermal LPs by analysing real measured data from more than 6 industrial subsectors via k-Means clustering and regression analysis. They found strong evidence that – unlike electricity loads – industrial, thermal LPs are partly following ambient temperatures. This effect can also be observed for residential homes in the private sector. Similar analysis methods like Jesper et al. were conducted by Richard et al. (C) [11] to identify DSM measures and by Dedić et al. (E) [13] for small and medium-sized enterprises. The latter study also includes examinations on working days (distinction of different working days and holidays) and their implications on LPs. Valdes and Camargo (D) [12] also investigated real measured LPs, however, they did not utilise k-Means clustering.

Dock et al. (F) [14] developed a bottom-up method for generating electrical and thermal LPs of production lines of the Iron & Steel subsector. Their model is based upon real-life measurements of major process units like the electric arc furnace or the ladle furnaces. The corresponding LPs are generated by using Markov chains.

Thiede et al. (G) [15] offer a generic energy flow-oriented manufacturing simulation. Through this bottom-up approach, DSM and energy efficiency measures on factory level can be derived. This model can be applied to different industrial sites and incorporates detailed process control schemes and economic assessments. However, the applied methodology relies on comprehensive measurements and production chain knowledge on-site beforehand.

Within our preceding study (H) [5] we developed a methodology for depicting LPs of energy intensive subsectors. We found that energy intensive industries "exhibit a limited range of varying production processes and principles" [5]. Based on this finding, we developed a bottom-up approach supported by top-down algorithms incorporating the simulation of production lines via discrete event simulation. Throughout this study, we covered the main production lines of the subsectors Iron & Steel, Paper & Pulp, Chemical and Non-Metallic Minerals, defined by the International Energy Agency (IEA) [17].

A summary table compares the investigations of this study to the mentioned past research works in more detail, see Appendix.

1.2. Research hypotheses and structure of this paper

Based on the literature review above, we conclude that the first important groundwork for generating LPs of selected industrial subsectors has been laid out successfully. However, we found major open research areas, especially regarding the methodology's comprehensiveness and scope for covering the entire industrial sector and more than one energy carrier. The goal of this study is to extend our existing approach by developing a methodology for covering the more complex, non-energy intensive subsectors like Machinery or Food & Beverages as well. To reach this goal we situate the following hypotheses:

- Non-energy intensive industries apply a wider range of production paradigms and processes compared to energy intensive industries. Sole bottom-up models will fail to reach the mentioned goal because of the great scope of vital data while the results of sole top-down models are too undetailed. The conducted literature review, as the main results are stated above and in Fig. 1, supports this hypothesis

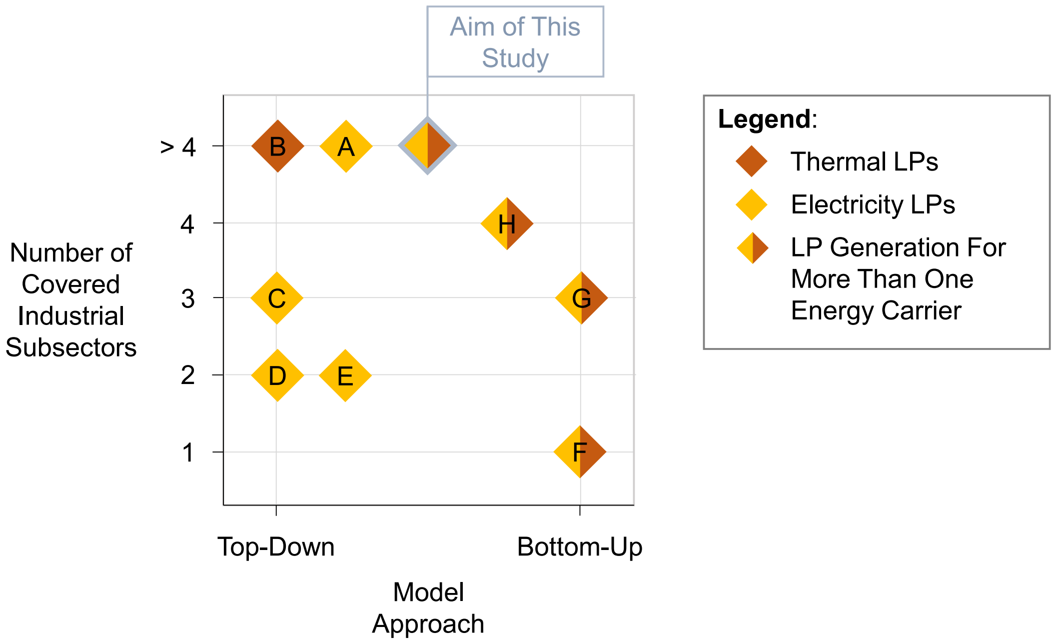

Fig. 1. Assessment of developed models for generating industrial LPs: (A) Sandhaas et al. 2022 [9], (B) Jesper et al. 2021 [10], (C) Richard et al. 2017 [11], (D) Valdes and Camargo 2021 [12], (E) Dedić et al. 2022 [13], (F) Dock et al. 2021 [14], (G) Thiede et al. 2022 [15], (H) Binderbauer et al. 2022 [5] ; See summary table in Appendix for more details of these literature studies.

by demonstrating that either single energy carriers are included in the shown top-down methodologies or multi-energy carrier methodologies are developed by incorporating extensive databases for a bottom-up approach. A combined bottom-up and top-down approach will adequately depict these industrial subsectors without relying on extensive process-specific data but covering multi-energy systems, nevertheless.

- The applied shift models at real industrial sites influence the energy demand and generation pattern of industrial sites strongly. Hernández et al. [18] investigate the impact of working days and weekends or holidays on electrical LPs, however, did not examine the fluctuating behaviour during working days (production and non-production times) for other energy carriers as well.
- The energy consumption behaviour of industries during peak times can be traced back to a limited amount of energy intensive process units. We assume that this behaviour already determined the energy demand in energy intensive industries [5], which can also be seen in the non-energy intensive sectors as well.
- The microeconomics paradigm of Economy of Scale can be applied to assess the energy consumption of industrial plants.

We will prove these hypotheses throughout this study as we thoroughly assess the non-energy intensive subsectors in Section 2. Therefore, an overview of the developed methodology will be presented first and explained in a detailed manner in the following subsections. Of these, Section 2.1 includes the handling of input variables for the model, followed by the explanation of our shift model calculator (Section 2.2). Regarding the bottom-up approach within this study, we developed a dynamic Markov-chain model for integrating the energy-consuming behaviour of energy intensive production processes (Section 2.3). In Section 2.4, our approach for assessing weekly consumption and demand of industrial plants based upon Economy of Scale is described. These models are complemented by a load factor analysis and a comprehensive iterative algorithm in Section 2.5. To evaluate the functionality of our approach, Section 3 contains five conducted case studies, which are described and analysed extensively. Finally, Section 4 concludes this study, by reflecting on the hypotheses stated above.

2. Methodology

The distinction between energy intensive and non-energy intensive industrial subsectors varies slightly depending on legislators and their systemic interpretation. The European Commission denotes subsectors as energy intensive if certain processes are included within the production line. Such processes are for example electrolyser units, chemical reduction processes, processes for metal production or glass fabrication etc. [19]. In our preceding study, we pointed out the characteristics of these subsectors. However, this developed approach finds its limitations when it comes to non-energy intensive subsectors:

Fig. 2 shows that non-energy intensive subsectors account for around 28% of the total energy consumption in Austria of 135 TWh [16]. Even though this share is rather small compared to energy intensive industries, further analysis in terms of employment and gross value-added shows that non-energy intensive subsectors take a bigger role within the overall industrial landscape, as illustrated in Fig. 2. Additionally, we can conclude that the product and process variety of these subsectors is much more comprehensive than in energy intensive industries. This can easily be derived when examining the European NACE classification, which categorises the IEA-defined subsectors in more detail by introducing a graduated system [21] : For example "C 16.2.1 – Manufacture of veneer sheets and wood-based-panels" is a part of "C 16 – Manufacture of wood and of products of wood and cork", which can be assigned to the IEA subsector "Wood & Wood Products". While non-energy intensive industries make up 149 of the product-specific 4-digit NACE classes, energy intensive subsectors only account for 65 [20]. It can be reasoned that these products' extensive subsectors can be covered either by deploying new simulation methodologies or providing a comprehensive database, even larger than for energy intensive industries. Our

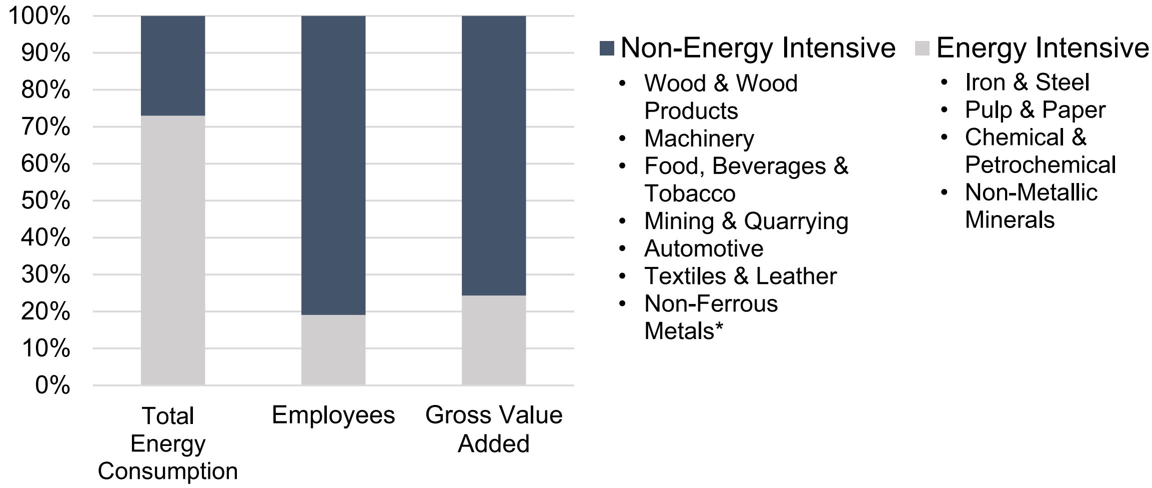

Fig. 2. Comparison of energy intensive and non-energy intensive industrial subsectors regarding total energy consumption [16], the total number of employees and gross value added for 2019 [20] ; *Non-Ferrous Metals is part of the energy intensive industry, however, due to the small share of primary non-ferrous metal production in comparison to secondary in Austria, we classified this sector as non-energy intensive.

motivation however lies in the depiction of LPs for industrial sites via an efficient and user-friendly methodology without the need for individualised, beforehand data (e.g., measurements on site).

Prominent industrial databases along these classifications utilised in this study are for example ETS (Emission trading system) database, EMAS (Eco Management and Audit Scheme) database, EuroStat and IAC database.

Our literature review shows that top-down methodologies mainly cover the generation of LPs for single energy carriers (see Fig. 1). Bottom-up methods depict more than one energy carrier, however, require a more extensive, site-specific database. We conclude that top-down models rely on the site's sole electricity or natural gas metering for energy suppliers but manage to cover more industrial subsectors, while bottom-up models build up on underlying processes and consumption of various and internally produced energy carriers like steam. Thus, our developed methodology incorporates both top-down approaches to maximise the number of targeted subsectors and bottom-up approaches to increase the LP depiction of selected energy carriers.

Fig. 3 depicts the developed methodology for generating representative synthetic LPs of fictitious and non-fictitious industrial sites of selected non-energy intensive subsectors. The methodology can be divided into five partaking algorithms which we will discuss in the following chapters in detail.

The following databases are incorporated into the methodology:

- Herold Business Database [22] : This database contains information on site and NACE subsector-specific employment of companies in Austria including over 400 000 data points.
- Industrial Assessment Center (IAC) Database [23] : This database involves surveys of site and NACE subsector-specific information on employment, energy demand, production hours and capacity in the U.S. containing around 20 000 data points. The programme IAC is funded by the US Department of Energy (DOE).
- Useful Energy Analysis by Statistics Austria [24] : This classification lists the final energy demand on the IEA subsector level in Austria.

For generating synthetic LPs for fictitious or non-fictitious sites of non-energy intensive industries, the number of employees, selection of a specific NACE subsector and the production capacity act as primary input parameters by the user (a). By determining the employment information and NACE classification the most probable deployed shift model is identified (b). To generate the production activity during the defined shift model, we developed a dynamic Markov model (c). The result is an unscaled LP reflecting the most energy intensive processes from the Markov model. This LP is then scaled within an iterative algorithm to meet the statistically determined plant characteristics from an Economy of Scale model (d).

We incorporated this methodology in an open access, free-to-use software called *Ganymed*, where we already implemented the generation of LPs of energy intensive industries from our preceding study [5].

2.1. Methodology input factors

The first part of the proposed methodology, as shown in Fig. 3 (a), covers the initial input information for setting up an industrial site. This information contains the selected NACE industrial subsector, to which the site can be assigned, the production capacity (e.g., t/h) and the number of production employees of the site. The number of employees can be either defined by the user deterministically or via stochastic distribution of analysed, single companies from Herold Business Database [22]. For the latter option, we developed a dedicated fit algorithm, which approximates the subsector-specific data by a power function. The probability densities of all considered data points from Herold Business Database act as regression points for the fit as depicted in Fig. 5 (b).

When the user chooses the stochastic option for determining the number of employees in the selected NACE subsector, the algorithm draws a random number z as a result of the cumulative distribution function. This random number z is outputted by a pseudo-random number generator, which is developed based on the logic of Mersenne-Twister. Through determining z, a possible number of employees for the manufacturing plant can be calculated stochastically as the yellow arrow indicates.

Fig. 4 shows an exemplary application of this stochastic assessment for the subsector "NACE 25 – Manufacture of fabricated metal products". The Herold Business Database presents 1314 individual Austrian industrial plants with their respective number of employees for this sector. We calculated an average employment number of 21 employees per plant. The Structural Business Statistics by Statistic Austria [20] also states the average number

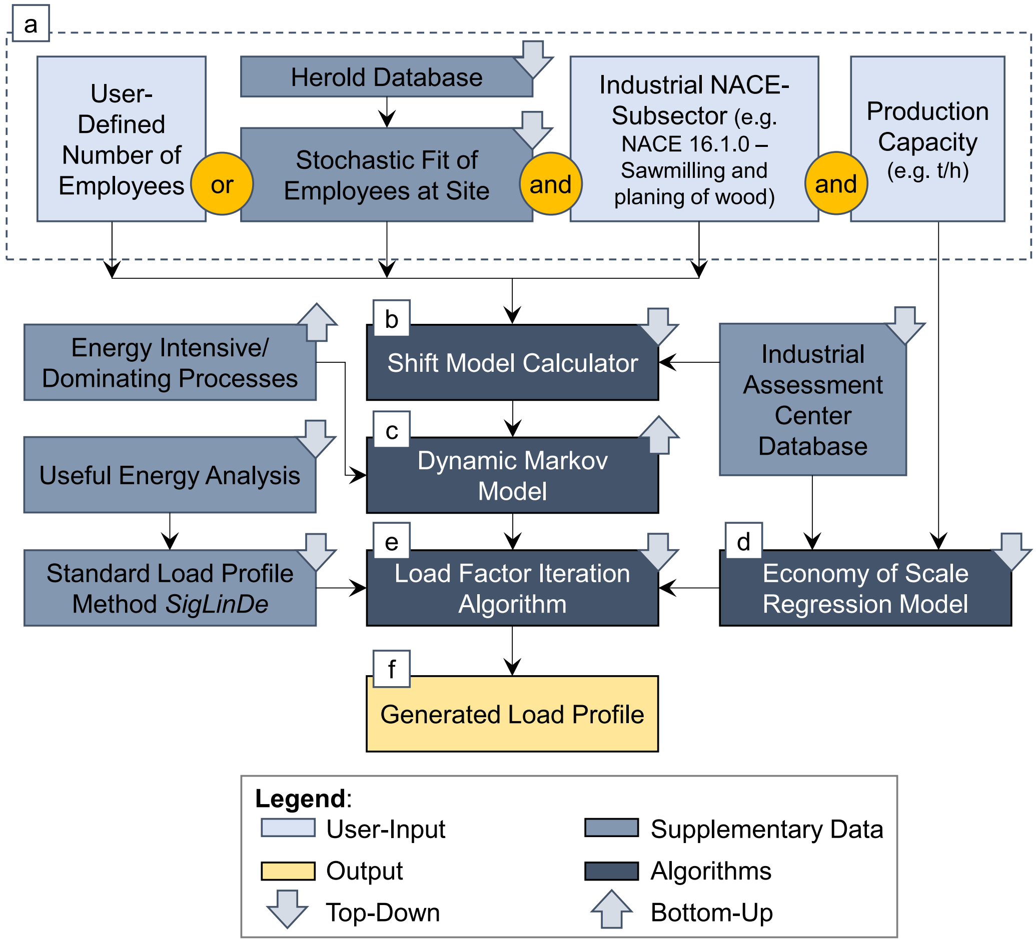

Fig. 3. Overall LP generation methodology: (a) Input variables, (b) Algorithm to calculate the applied shift model with the highest probability, (c) Bottom-up model of dynamic Markov chains incorporating most energy intensive processes, (d) Regression model based upon Economy of Scale, (e) Iteration algorithm for scaling generated LPs, (f) Generated LPs.

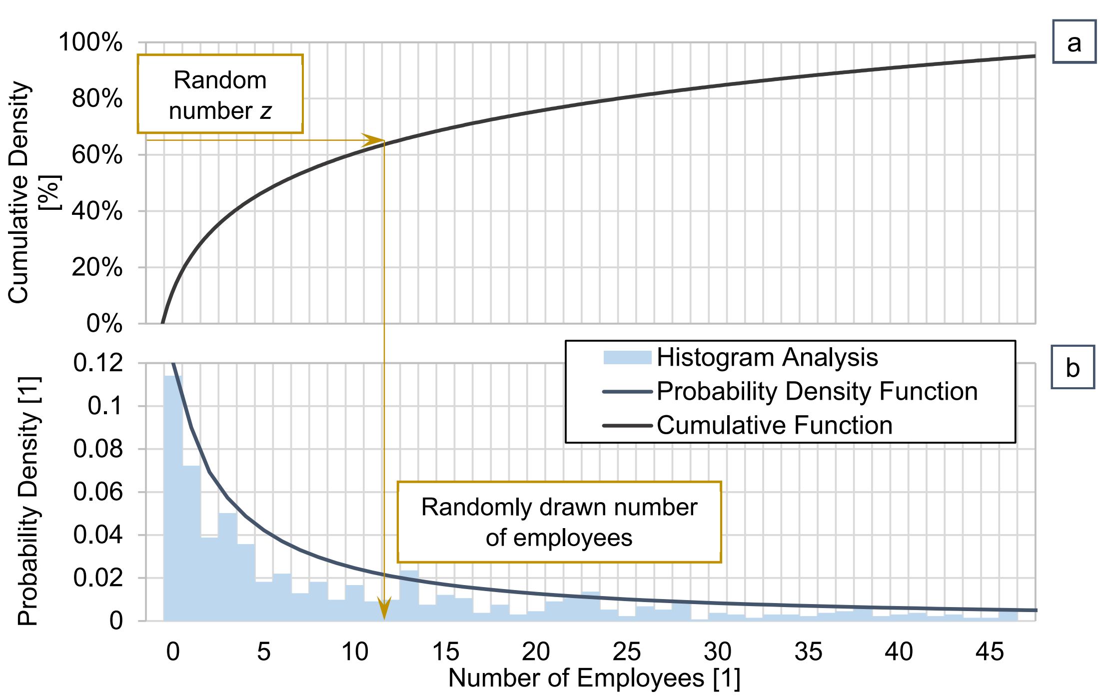

Fig. 4. (a) Cumulative density and (b) Probability density functions NACE subsectors: NACE 25.6.1 - Treatment and coating of metals.

of employees for all subsectors. Thus, the calculated average can be justified by the report by Statistic Austria, which reveals 20 employees for the mentioned subsector. This can be deemed as the first satisfactory correspondence of our investigations. The histogram analysis in Fig. 4 (b) presents the probability densities of the collected 1314 data points. We limited the x-axis of the figure to 48 employees. The corresponding fit function for the cumulative density function from Fig. 4 (a) is given by the following formula:

$$x = e^{\left(\frac{f(x)-0.0227}{0.2385}\right)} \tag{1}$$

In this formula, *f(x)* equals the randomly drawn number z between 0 and 1 (0% and 100%) as the input parameter to calculate the number of employees x based upon the regression function.

To prove an adequate regression fit of assumed normally distributed data points, we conducted a statistical t-test [25]. Here, we transferred the probability densities from (b) into a logarithmic plot. The corresponding fit can now be investigated on a linear relationship, for which we set a significance level α of $\alpha = 0.05$. The test shows a P-value of $P = 0.02$, which is lower than the significance level α. The hypothesis of normally distributed data points around the linear fit function in the logarithmic plot and, thus, correlation in Fig. 4 (b) can be accepted. We note that we investigated every NACE subsector on statistical significance.

2.2. Shift model algorithm

Based on real-life measurements and the analysis of industrial LPs, Dehning et al. [26] found a dependency of plant-specific LPs on the implemented shift models at the site. The authors classified phases, where the main production during the daily shift takes place, as "production times" and phases outside of shift times as "non-production times". We reason that during the phase of production, energy consumption is higher than during non-production. In conclusion, the knowledge of the shift model being used is vital for generating LPs of the corresponding industrial site.

In the first step, we assumed that the applied real-life shift model depends on the specific NACE subsector and company size. Sen [27] examined this on yearly production hours from the IAC Database [23] via a histogram analysis. The author found elevated peaks of yearly production hours directly corresponding to the mean value of weekly working hours of major shift model groups. Furthermore, the study defined upper and lower working hour limits for these proposed shift model groups. We identified these shift model groups to be also sufficient for depicting European shift models. However, we altered some of the proposed working hour limits to meet European standards e.g. according to statutory vacation days or maximum amount of working hours per week [28]. The defined shift model groups are listed in Table 1.

Next, Sen [27] concluded and proved that industrial subsectors apply these shift models varyingly. Based on these findings we examined each NACE subsector by the proposed working hours and related shift models from Table 1. Fig. 5 (b) shows a scatter plot of the number of employees and applied production hours of real-life industrial plants of the subsector NACE 16.1.0 in the IAC Database. We marked the working hour ranges of identified shift model groups with different colours accordingly and analysed the data points within these ranges via probabilistic analyses. The results of these analyses are probability density functions as shown in Fig. 5 (a). These subsector-specific density functions enable the determination of the most probable applied shift model for a certain company size or selected number of employees. For example, in the subsector NACE 16.1.0 the probabilistic analysis, as depicted in Fig. 5, show that a company with 100 production employees will apply shift model A of 40 h/week followed by shift model B of 80 h/week. For higher numbers of employees, the application of shift model B becomes more likely. For over, in this case, 600 employees, a stochastic determination is not possible anymore due to the small number of representative data points at these values. For these special cases, the to-be-depicted industrial site should be divided into production areas (e.g., assembling, coating, etc.), which are then treated as single sites. As the information of the number of employees is generated out of the approach, we have discussed in Fig. 3 (a), typical production and non-production times based upon shift models for generating the according LP can be assessed.

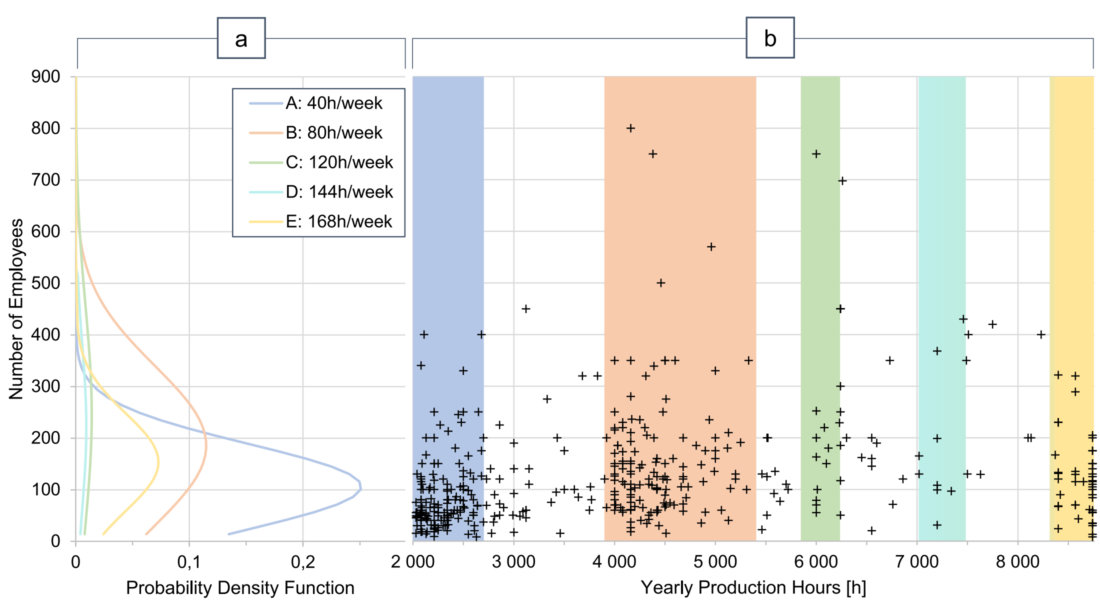

Fig. 5. Examination of "NACE 16.1.0 – Sawmilling and planing of wood": (a) Probability density functions of all shift model groups, (b) Scatter plot showing employment and applied production hours of industrial plants along with defined working hour ranges of defined shift model groups. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Classification of shift models via shift model groups including their applied working hours and limits.

Shift Model Groups	Shift Model	Upper Limit	Lower Limit
Group A: 40 h/week	8 h / 5 days – Single Shift	52 h/week (assuming a maximum of 12 h/shift)	37.5 h/week (assuming 7.5 h/shift)
Group B: 80 h/week	16 h / 5 days – Two Shifts	104 h/week (assuming a maximum of 12 h/shift)	75 h/week (assuming 7.5 h/shift)
Group C: 120 h/week	24 h / 5 days – Three Shifts	120 h/week	112.5 h/week (assuming 7.5 h/shift)
	20 h / 6 days – Two Shifts		
Group D: 144 h/week	24 h / 6 days – Three Shifts	144 h/week	135 h/week (assuming 7.5 h/shift)
	20 h / 7 days – Two Shifts		
Group E: 168 h/week	24 h / 7 days – continuous	168 h/week or 8760 h/year	160 h/week

2.3. Dynamic Markov model

Our previously presented algorithms are the sole top-down approaches. These algorithms allow the generation of generic information in a disaggregated way. However, they do not support the depiction of typical energy demand fluctuations in the LPs in any form. Furthermore, to thoroughly integrate possibilities to individualise and probabilistically diversify the depicted sites we developed a bottom-up algorithm complementing the other approaches.

Similar to our preceding study, typical characteristics of production processes like energy consumption per unit, production times etc. were assessed. Due to the mentioned process diversity of the non-energy intensive industries our research is only limited to the most energy intensive and (production-wise) dominating processes. Typically, we included three to four processes per NACE subsector in this algorithm.

Markov chains describe sequences of discrete states over time for single processes [29]. A Markovian transition matrix contains probabilities for the process to pass from a current state to the next one. Dock et al. [14] applied Markov chains for modelling an electric arc furnace for 40 different states resulting in a 40 by 40 transition matrix. The demand of all states was based on real-life load measurements.

Because our approach relies on process information from literature, we established 7 standardised states which we describe within dedicated Markovian transition matrices: Off, Ramp-up, Processing, Shutdown, Service, Failure and Stand-by. Swiderski et al. [30] similarly classify process states to evaluate machinery readiness and reliability and to identify optimisation measures. Our assessed processes can operate within these states by a predefined 7 by 7 transition matrix. However, the entries of this transition matrix are subject to change because the likelihood of a process to pass from state 1 (Off) to state 2 (Ramp-Up) varies depending on the current phase (e.g. non-production or production), which we described in Section 2.2. Therefore, the Markov model is not determined statically, but dynamically as a function of time as also described by Sandholtz et al. [31] for another field of application.

Fig. 6 explains the overall applied, dynamic Markov model and corresponding states for a selected process and for the most basic shift model (40 h/week). We added a transition phase (Fig. 6 (b) and (c) in yellow) to the existing production and non-production phases. This is because not all production processes are usually turned on or off at the same time. Fig. 6 (b) shows that the production capacity during the production phase is at 100%, while during the non-production phase at 0%. To correctly model this behaviour, the states of all corresponding processes must be managed via four different transition matrices α, β, γ and δ Fig. 6 (a). Each of these matrices contains different transition probabilities for the processes, applied at different phases. For example, the probabilistic transition from Off to Ramp-Up in matrix α during non-production times is always 0%. However, in matrix β this probability is near 100%, because of a production start (other states during production start can be Failure and Service). Additionally, the model avoids forbidden state transitions like from Off to Shut down. It is noted that we applied this paradigm for production processes which are operated by personnel and therefore correlated to the given shift models. We found that processes like kilns, operated to dry woodchips or veneer wood over a longer period (NACE 16.1.0), operate mainly without personnel during non-production times [32]. These processes do not correlate to the given shift model, are continuously running and are therefore modelled with a single transition matrix which is equivalent to matrix γ. In both cases, shift-model independent and dependent, the matrix γ defines the production dynamic of the processes. The underlying data is based upon the overall operating time of each process in relation to the length of the production phase as well as Failure and Service probabilities from literature [30]. Regarding the transition between processes, we applied the simulation paradigm of discrete event simulation [33]. Here, a logical sequence of the production stream can be simulated. For example, in the subsector NACE 16.1.0, a typical energy intensive process sequence would be starting from wood logging, wood sawing and finishing of wood planks.

Fig. 6 (c) shows an example of the specific energy consumption (SEC) of a shift model correlated process over time. All other transitions in α are at 0% except for Off to Off, Off to Failure or Off to Service. In each of these cases, the SEC of this process is 0 kWh/t. In the first transition phase (yellow), the matrix β is applied which is for turning on the process. We assumed that the timely length of the transition phase is 30 min which, however, can be adapted freely by the user. During the production phase, the matrix γ is applied, while the second transition phase involves mainly Shutdown or Service states.

In conclusion, this applied Markov model contains four 7 by 7 transition matrices. For other, more complex shift models this number increases. Furthermore, when including shift breaks as

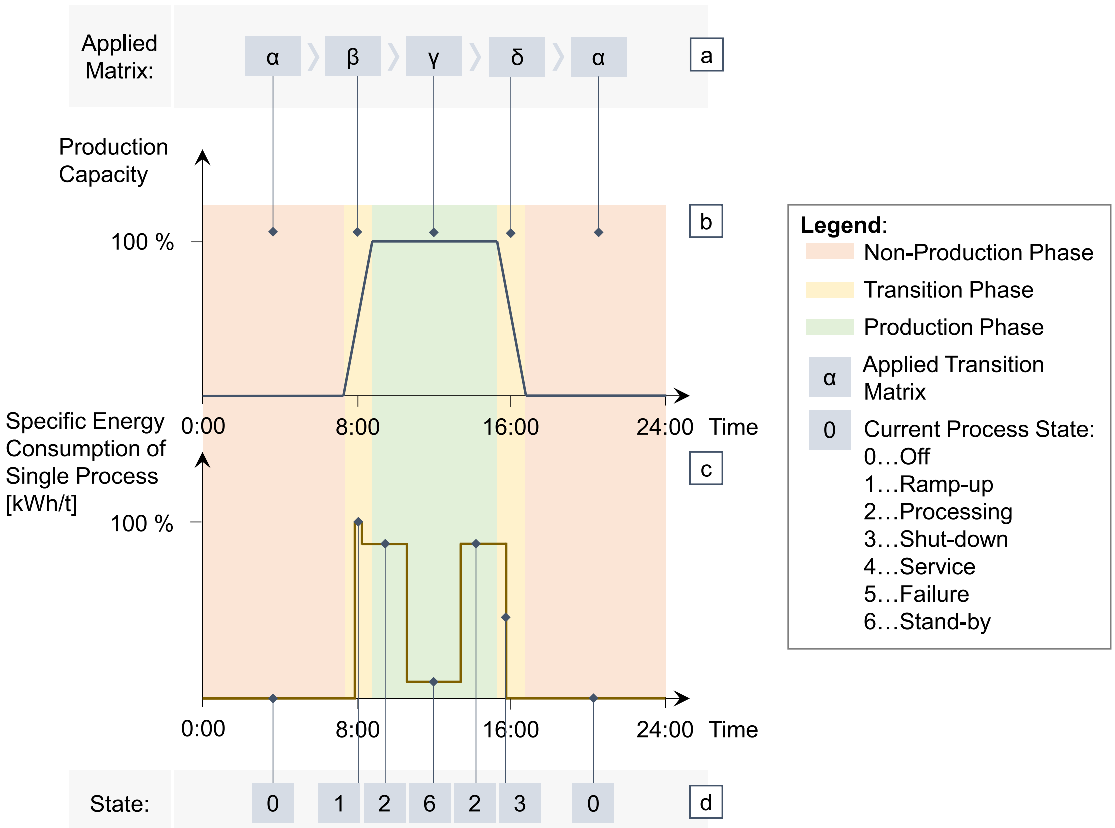

Fig. 6. (a) Transformation of the applied transition matrix according to the current production phase; (b) Plant production capacity as a function of time and current production phase; (c) Specific energy consumption of a selected process during different production phases. Here the process takes up various states (d) in accordance with the current transition matrix from (a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

transition or non-production phases, more transition matrices must be added. This functionality is included in the software *Ganymed*.

2.4. Economy of scale - Regression model

The dynamic Markov model is applied to depict energy demand fluctuations of industrial processes. However, this does not finally constitute the finished LP. It is necessary to expand the resulting fluctuations' profile by the average energy consumption, which is typical for industrial sites in the chosen NACE subsector and with this size.

The IAC database provides information on electricity and direct fuel (e.g., natural gas, coal, oil etc. for thermal application) consumption of the investigated single sites. These energy carriers are termed final energy carriers at the plant border. Additionally, the IAC database contains the electricity peak demand for one selected month of the given fiscal year respectively. Both average consumption and peak demand are vital information to further refine the generated process-specific profile from Section 2.3 to a synthetic, site-specific LP as described in Section 2.5.

To correctly assess the average energy consumption of the generated site, the dependent variable must be linked to given, explanatory variables. As also production capacity of the single sites is given by the IAC database, we utilise the effect of Economy of Scales (EOS) to reason a correlation between the specific energy consumption (SEC) and the production capacity. EOS describes the dependency of applied production input factors on the produced output [34]. It mainly finds its use as an instrument in microeconomics to express cost reduction effects when increasing production. Only a very small amount of studies practically apply this effect for assessing SEC: For example, Ironmonger et al. [35] show that EOS is applicable for residential households, where the SEC depends on the number of residents.

Fig. 7 shows the evaluated data for the subsector NACE 16.1.0 for production-specific electricity (a) and direct fuel (c) consumption. The observed data resembles the single industrial sites in the IAC database. The corresponding fit lines indicate the EOS effect [36]: A higher specific energy consumption can be observed at small production volumes. When the capacity increases, production becomes more efficient in terms of input consumption, which is energy in our case. This result is especially interesting as it can be observed for the different industrial sites of the specific subsectors in general. We further evaluated the fit functions by generating a corresponding double logarithmic plot of Fig. 7 (a) and (c) in (b) and (d). The observed linearity is a common proof to identify EOS in microeconomics [37]. The linear dependency of both logarithmically scaled variables can be expressed via the following function:

$$Log\,(c) = a - b\,Log(Q) \tag{2}$$

c represents the input factor per unit of capacity (e.g. cost [€/m^3] or energy in our case [kWh/m^3]) and Q the production capacity [m^3] [37]. The production capacity can also be referred to as tonnes [t] or other units.

To thoroughly prove the statistical correlation of these EOS parameters in Fig. 7, we investigated the depicted relationship further by examining statistical indicators underlying the hypothesis of correlation between specific energy consumption and

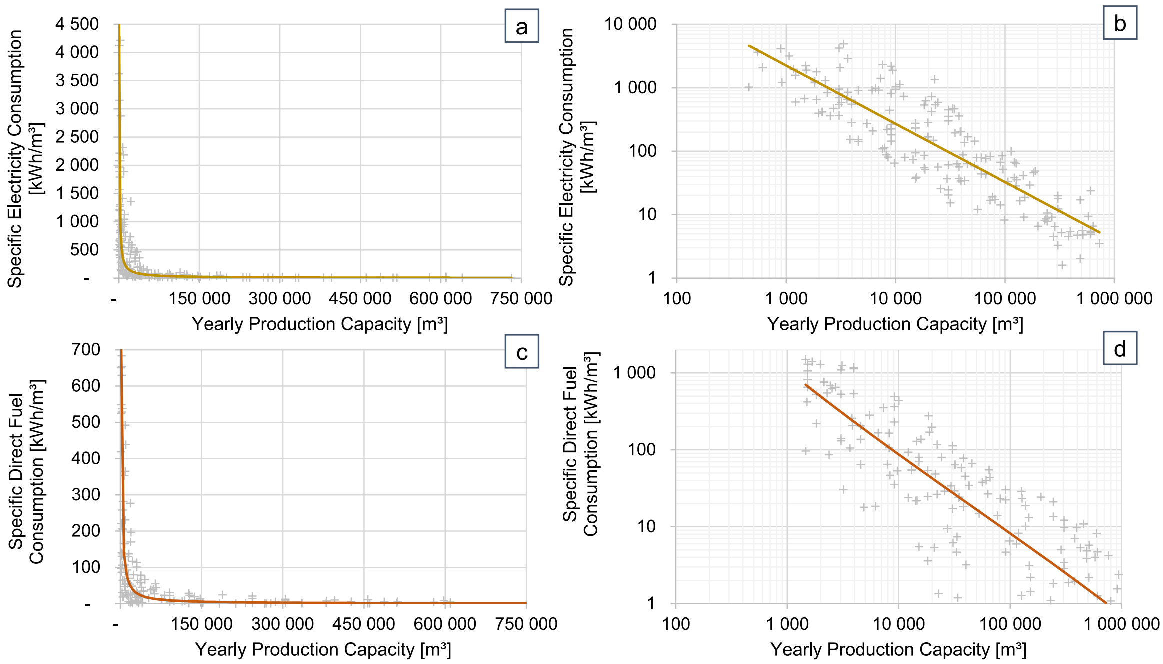

Fig. 7. EOS effect of the subsector "NACE 16.1.0 – Sawmilling and planing of wood" for (a) specific electricity consumption, (b) double logarithmic plot of electricity consumption, (c) specific direct fuel consumption, (d) double logarithmic plot of direct fuel consumption.

production capacity [38]: Fig. 8 shows these evaluations for the depicted EOS correlations from Fig. 7 for electricity and direct fuel respectively. As the linearity of logarithmic data can clearly be observed in Fig. 7, the independence of residuals is investigated in Fig. 8(a) and (c) to prove that no relationship between the predicted values from the linear regression and its errors is existent. The hypothesis is met when the correlation factor r and the average of included residuals $\bar{x}$ is approximately 0 [25]. For residuals of electricity data points these indicators equal $r = 0.000218$ and $\bar{x} = 0.000055$, for residuals of direct fuel data points $r = -0.081$ and $\bar{x} = -0.360$ respectively. It can be observed that these indicators of direct fuel data points deviate stronger from 0 than electricity data points. Besides the independency of errors, the normality of these residuals is further proof of a statistical linear relationship: Here, a normal probability plot includes the residuals of all data points in comparison to the z-value, which equals the multiplication factor of the standard deviation from the mean average of all residuals. The assumption of linearity is met, when the distribution of residuals is approximately normal, indicated by a linear relationship in these plots (as shown in Fig. 8 (b) and (d)). For both sets of data points (electricity and direct fuel), the last method indicates normal distribution successfully. At last, we investigated our hypothesis of normality by conducting a t-test, investigating the significance of the shown data for a significance level α of $\alpha = 0.05$. The test shows a P-value of $P = 5.608 * 10^{-48}$ for electricity consumption and $P = 3.712{*}10^{-31}$ for direct fuel consumption, which are both significantly lower than the significance level α. In conclusion, the assumption of the linear relationship between specific energy consumption and production capacity in a logarithmic context is proven, hence all relevant statistical indicators demonstrate satisfactory results.

Via these fit curves for each NACE subsector from Fig. 7, a typical specific electricity and direct fuel consumption for every industrial site with a specified size and sector can be assessed. The user-defined production capacity of the site (see Fig. 3 (a)) for which a synthetic LP should be generated, acts as an input parameter for the fit curves to calculate the corresponding SEC.

2.5. Load factor iteration algorithm & generation of final load profiles

In this last step of our proposed LP method, we combine the time-resolved energy demands reached from the dynamic Markov model and the determined real-life plant-specific energy consumptions and demands from the EOS model, as Fig. 9 shows. The main goal is to calibrate the baseload of the energy demand profiles from the Markov model (Fig. 9 (a)), mainly covering the energy intensive process demands during production phases. We managed this by utilising the stochastically determined industry and site-specific energy consumptions and demands from the EOS regression model (Fig. 9 (b)), as described in Section 2.4.

The backbone of this calibration step is the calculation of an underlying load factor (LF) for the site, which origins from the EOS regression model. The LF ranges from 0 to 1 and is typically calculated for electricity, but can be applied for direct fuel too [39]. It, therefore, offers important insights into the assumed shape of LPs as the energy demand of consumers with lower load factors fluctuates stronger than that of consumers with higher ones. The load factor is calculated through:

$$LF = \frac{E}{P \cdot t} \tag{3}$$

As the ratio is calculated of E as energy consumption [kWh] to P as peak demand [kW] in the time frame t [h].

The peak demand for both electricity and direct fuel is to be determined in the next step. However, the calculation of both parameters varies. While monthly industrial electricity consumption is rather constant throughout the year, monthly direct fuel consumption presents itself as a function of ambient temperature [10]. However, the demand for both electricity and direct fuel fluctuates, as already explained in Section 2.3, due to changing process states.

2.5.1. Determination of the scaled electricity peak

In terms of electricity, the IAC database contains information on the peak demand for a selected month in the given fiscal year of all surveyed sites. Because consumption is measured

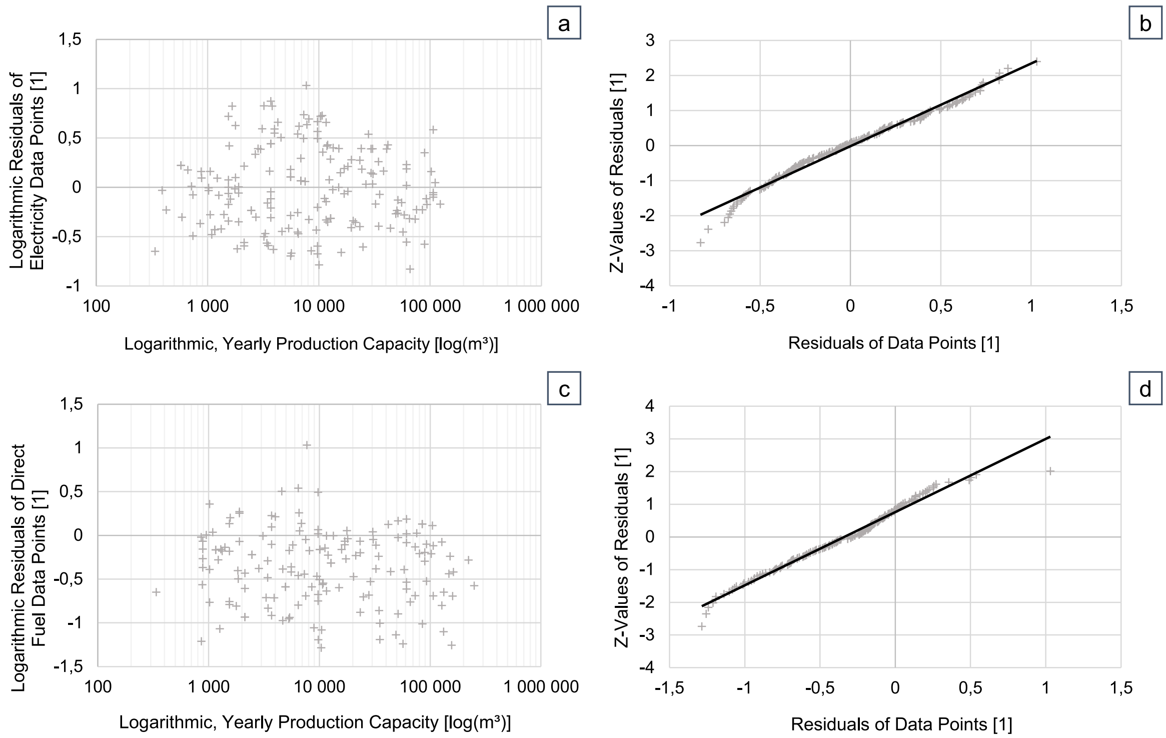

Fig. 8. Statistical proof of assumptions of EOS correlation of the subsector "NACE 16.1.0 – Sawmilling and planing of wood": (a) Residual plot of electricity consumption, (b) Normal probability plot of electricity consumption data points, (c) Residual plot of direct fuel consumption, (d) Normal probability plot of direct fuel consumption data points.

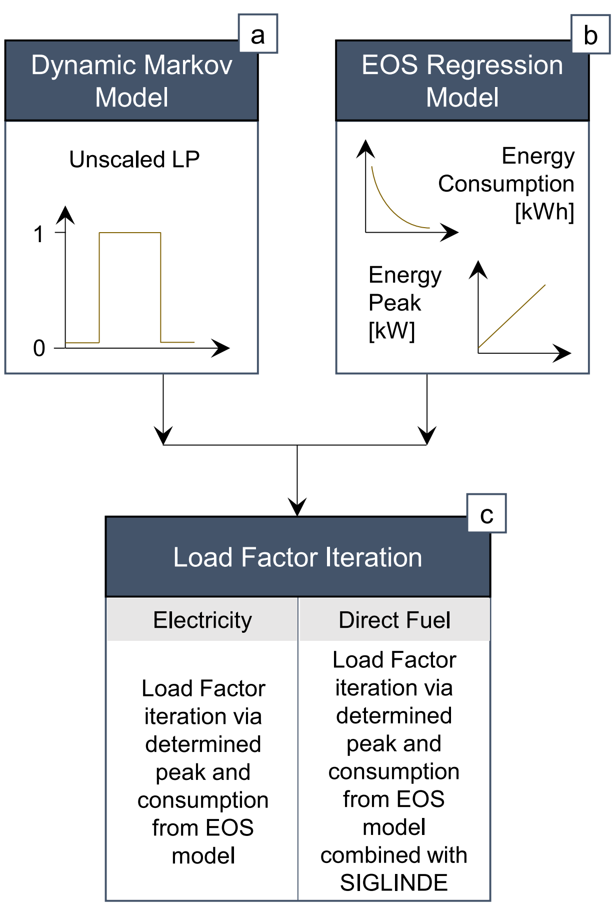

Fig. 9. Workflow of the combination of dynamic Markov model (a) and EOS regression model (b) within load factor iteration (c).

in kWh and peak demand in kW, a linear relationship of both parameters is given. *Ganymed* generates linear fit functions for all observed data points of the corresponding NACE subsectors. By determining the electricity consumption from the EOS model in the first step, the peak demand can be assessed next, by applying the following linear equation:

$$E = m \cdot P + b \tag{4}$$

With E as energy consumption [kWh], m as slope [h], P as peak demand [kW] and b as intercept [kWh].

For determining the electricity peak, we neglect ambient temperature variations, unlike direct fuel peaks (see the section below).

2.5.2. Determination of the scaled direct fuel peak

Direct fuel demand is not constant over a year. Unlike the electricity demand, a share of the direct fuel demand of industrial sites is influenced by ambient temperature. Jesper et al. [10] proved this through an extensive industrial LP analysis. This ambient temperature-dependent share mainly originates from space heating or air conditioning appliances and is more distinctive during winter months, as Fig. 10 (a) and (b) show. The other part of direct fuel demand is attributable to thermal energy for process heat and is therefore rather constant throughout the year [40]. Statistic's Austria [24] states these shares of non-ambient temperature-dependent and ambient temperature-dependent thermal energy for each industrial subsector. Throughout this information, the assessed direct fuel consumption from the EOS model can be separated accordingly.

The non-ambient temperature-dependent demand is calculated similarly to the assessment of the electricity peak, see 2.5.1. Regarding the share of direct fuel demand, which is ambient temperature dependent, we utilised the *SigLinDe* function for the calculation [41]. Here, the ambient temperature $T_{Amb.}$ acts as an input for *SigLinDe* to calculate a multiplication factor h for the

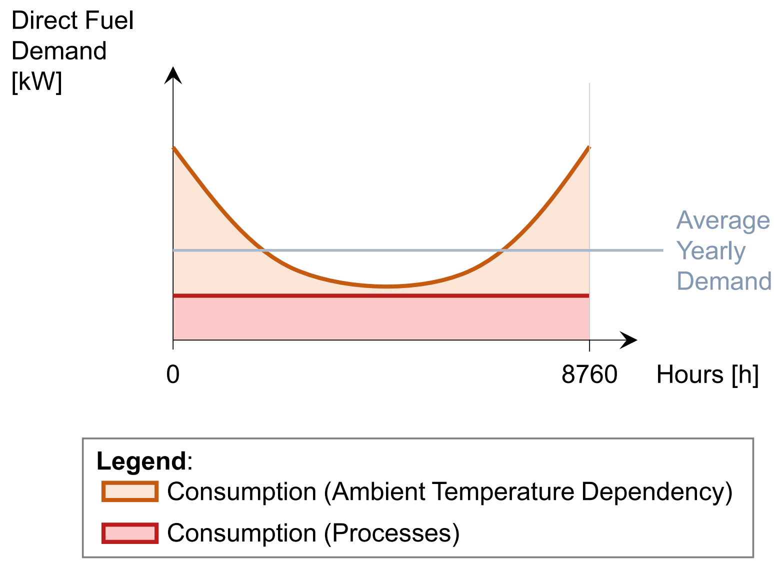

Fig. 10. Yearly direct fuel demand, divided into ambient temperature-dependent consumption and process-specific consumption.

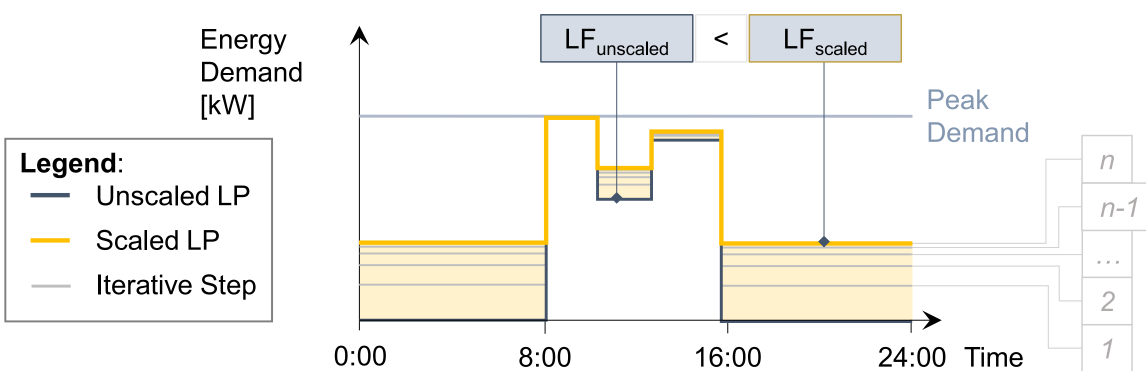

Fig. 11. Iteration of unscaled LP from the Markov model to generate the finished (scaled) LP.

corrected direct fuel consumption. For an ambient temperature of 8 °C the multiplication factor is set to 1 on default. The factor is larger than 1 for temperatures under 8 °C and smaller than 1 for temperatures above 8 °C. The underlying regression function of *SigLinDe* is a mixed linear and Sigmoid function [41] . We implemented an hourly-resolved temperature profile of Austria for one year. However, *Ganymed* also allows the implementation of other temperature profiles as well as the selection of the month, for which the LP shall be generated. The adapted direct fuel consumption E_{SLD} per hour can then be calculated via

$$E_{SLD} = E \cdot h\left(T_{Amb.}\right) \cdot F_{WT} \tag{5}$$

with E as average natural gas consumption [kWh] per hour, which is the share subtracted as explained above, and F_{WT} as a factor of the associated day of the week in correlation with the shift model. The overall direct fuel peak demand is calculated via the sum of both hourly peaks (ambient temperature dependent and non-ambient temperature dependent). With this information, the direct fuel LF from equation (3) can be assessed.

2.5.3. Load factor iteration

Based on the given information, *Ganymed* calculates the load factor for electricity and direct fuel to scale the given LPs from the Markov model. These LPs mainly contain information on the main contributions to the energy demand, originating from selected processes. However, these still show a certain grade of deviation compared to the finished LP. This is because smaller units and general base loads (e.g., ventilation, lighting, base loads from smaller appliances and processes, …) are neglected in the Markov model. By iterating the LPs from the Markov model to meet the assessed load factors (see Sections 2.5.1 and 2.5.2) this lack of information can be bypassed. As we mentioned in Section 1.1, a similar method is applied by Starke and Alkadi [42] for electricity demands. In this study, however, the unscaled load profile is based on standardised LPs.

Fig. 11 shows a simplified, iterative scaling of an LP with n iterative steps. The target LF can either be smaller or higher than the LF from the Markov model. Our algorithm fixates the established peak (determined according to Sections 2.5.1 and 2.5.2) and lowers or raises the residual demands to be in accordance with previously determined LF (and therefore overall energy consumption) in the considered time period. To do so, after each iterative step, an integral is calculated to assess the new area under the LP, which is equivalent to the energy consumption. If the current consumption corresponds to the assessed consumption (in other words, when $LF_{unscaled} == LF_{scaled}$) from the EOS model, the iteration is ended. Furthermore, the user can specify a different load factor instead of the one from the EOS model through the *Ganymed* GUI at any time.

Throughout this chain of algorithms, an LP for electricity and/or direct fuel can be generated. The *Ganymed* GUI offers a simple step-by-step menu to synthesise a fictitious or existing industrial plant quickly and efficiently.

Table 2
Information on the selected five case studies. This input data is applied in the developed algorithm in Ganymed.

Case number	NACE subsector	Number of employees	Production capacity
Case 1	10.8.5 – Manufacture of prepared meals and dishes	36	0.9 t/h
Case 2	22.2.2 – Manufacture of plastic packing goods	49	1.8 t/h
Case 3	27.1.1 – Manufacture of electric motors, generators and transformers	7	0.05 t/h
Case 4	31.0.1 – Manufacture of office and shop furniture	4	0.08 t/h
Case 5	25.5.0 – Forging, pressing, stamping and roll-forming of metal; powder metallurgy	21	0.5 t/h

Table 3
Underlying energy intensive processes and literature sources in each case study.

Case number	Energy intensive production process	Literature sources
Case 1	• Grading unit • Grinding unit • Cooking tunnel	[44–46]
Case 2	• Raw material shredder • Forming unit • Extruder	[47–49]
Case 3	• Wiring process • Forming unit • Assembling process	[50]
Case 4	• Vacuum unit • Side spindle • Assembling process	[51,52]
Case 5	• Heating unit • Forging process • Deburring process	[53,54]

3. Validation of developed method

3.1. Case descriptions

We validated the developed methodology by conducting various case studies, of which five will be presented in this study. The presented data for this study's validation process is published by Braeuer [43]. Each case represents a real-life manufacturing plant from Germany and contains information on its industrial subsector, company size and production capacity as well as real-life measured, 15-min resolved yearly electricity LPs. The validation of direct fuel LPs is not part of this publication, because of data protection regulations of partaking companies.

Through personal correspondence, further information on the industrial plants was assessed as shown in Table 2. This data acts as input for the developed method. The LPs generated with *Ganymed* are validated by comparison with the real measured LPs of each corresponding NACE subsector. We selected these five cases to represent the broadest possible application for all non-energy intensive industries.

The information on energy intensive production processes as input for the dynamic Markov model, specific for all selected cases, was based upon different literature sources as Table 3 shows.

Overall, Fig. 12 gives an overview of the data flow for the conducted five case studies starting from input parameters in Tables 2 and 3 to the outputted LPs and follow-up evaluation and analysis. The utilised databases are not shown in this figure. Overall, the selected industrial subsector and the defined number of employees from Table 2 act as input parameters for the shift model calculator. Data of energy intensive production processes from Table 3 in combination with the identified shift model initiate the generation of the unscaled LPs. The Economy of Scale regression model calculates representative load factors based on the information on production capacity from Table 2. These load factors then scale the already generated LP to bridge the gap of unknown additional processes in each case.

3.2. Results and discussion

We modelled each case in *Ganymed* along the outlined data flow described in Fig. 12: Because the number of employees for each case is given deterministically in Table 2, the stochastic calculation via power function fit from Section 2.1 was not executed. The algorithm determined the most applicable shift model as described in Section 2.2 for cases 1 to 5 as follows: A 8 h/day (40 h/week) shift for cases 1, 3 and 4, a 24 h/6 days (144 h/week) shift for case 2 and a 16 h/5 days (80 h/week) shift for case 5. We generated electricity LPs for all five case studies based on the identified shift models and the information on energy intensive processes to feed the dynamic Markov model.

As mentioned in Section 2.5 the yearly electricity demand for an industrial plant can be described as mostly independent of ambient temperature. Thus, we overlaid 52 weekly LPs (52 weeks/year) from each of the measured plants for validating the synthetic LP. Fig. 13 shows these 52 weekly LPs in blue as well as their average LP in red for the selected case 1. The generated, synthetic LP is shown in black. The demand is depicted in 675 single 15-min values per LP. Furthermore, we deemed this interval as suitable due to the correlation with the energy market, as intraday trading is conducted at a minimum of quarter-hour intervals [55].

We validated the deviation of the synthetic LP from the measured ones by generating boxplots and calculating the mean-average-percentage-error (MAPE) for each case. We used each boxplot diagram in Fig. 14, corresponding to each case study, to evaluate the deviation of the synthetic LP (shown as single line indicators) to the measured data in the boxes. Through this, the magnitude of the deviation can be analysed. In overall, the middle line of the single boxes indicates the median of all values. The bottom and top edges of the boxes show the lower and upper quartiles of all data points. Thus, 50% of all data points lie within the box. Both whiskers of every box indicate the last data point, which is not declared as an outlier anymore (<1.5 times the interquartile range/box length starting from the boxes' edge).

The grey boxes exhibit the overall average demands for each of the 52 measured LPs. We compare this with the average demand of the synthetic LP, shown as single line indicators to the right of the grey boxes. The following boxes (light yellow, green, blue, red) in each boxplot contain the 52 data points during a selected time. We agreed upon selecting four chronological 15-min time stamps: the 10th hour in the week, the 37.5th hour in the week, the 75th hour in the week and the 105th hour in the week. In the examination of the results, we focus on the most prominent time of production, which is the weekdays from Monday to Friday. For this, we evenly distributed the marked time stamps as described above within the weekdays and neglected the distinct evaluation during weekends. Each of the coloured boxes is then compared to the corresponding point-in-time in the synthetic LP, again shown as single line indicators. Additionally, Fig. 13 shows these time stamps.

Regarding the mean-average-percentage-error (MAPE) based analysis, we applied the following equation:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_m - P_s}{P_m}\right| * 100\% \qquad (6)$$

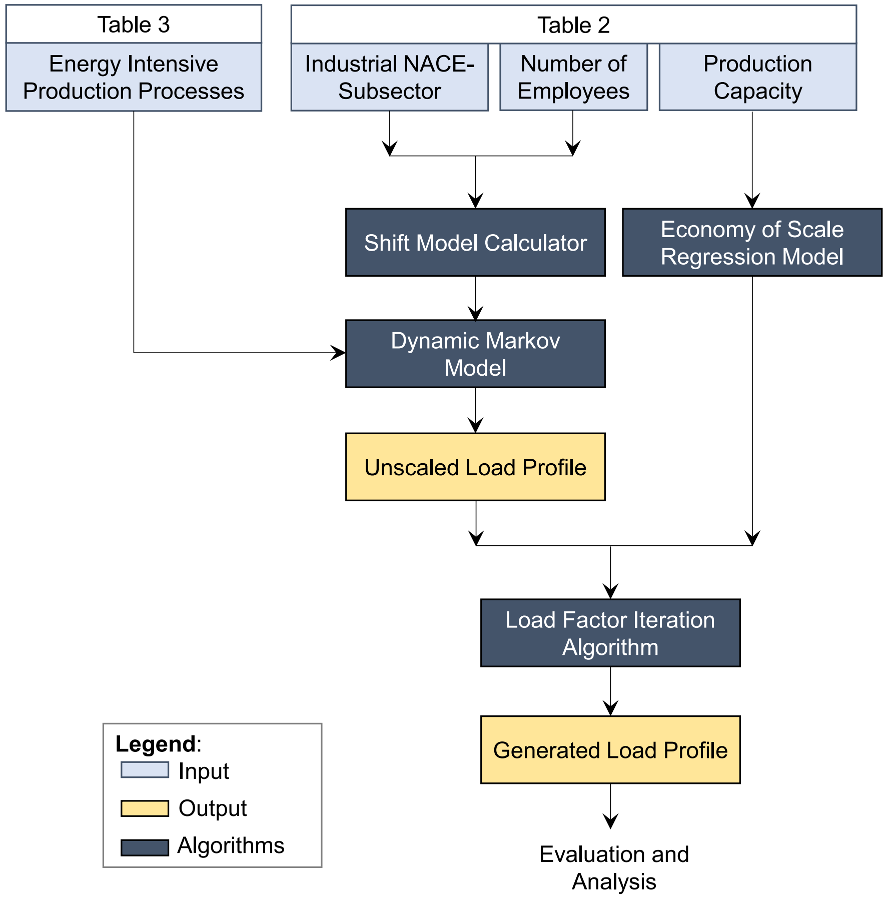

Fig. 12. Data flow from input parameters to outputted LPs for all case studies.

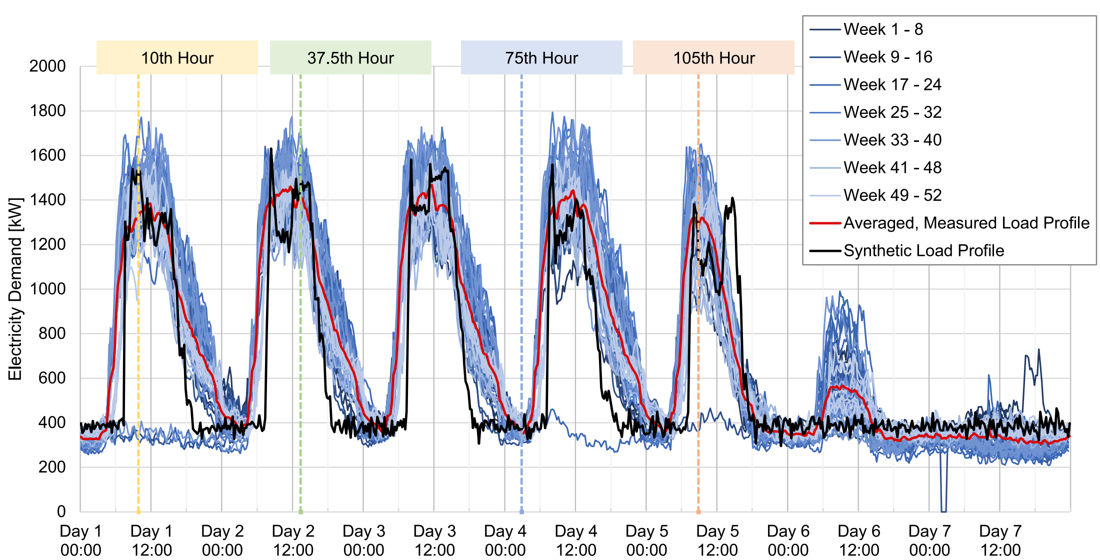

Fig. 13. Comparison of weekly measured electricity LPs of one year (blue) and averaged measured LP (red) with synthetic, generated LP (black). The marked time stamps (light yellow, green, blue, red) correspond to the boxplot in Fig. 14. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As $n = 675$ represents the total number of data points per LP, P_m constitutes the measured and P_s the electricity demand of the synthetic LP at each time stamp (hour of the week) t.

The resulting MAPEs are included in Table 4. Additionally, we evaluated the deviation of the maximum peak and minimum demand between the average (measured) and the synthetic LP similarly to formula (5).

The synthetic LPs in cases 1 and 2 show on average a good approximation to the measured LPs, especially regarding the deviation of minimum demand. The peak demand varies slightly

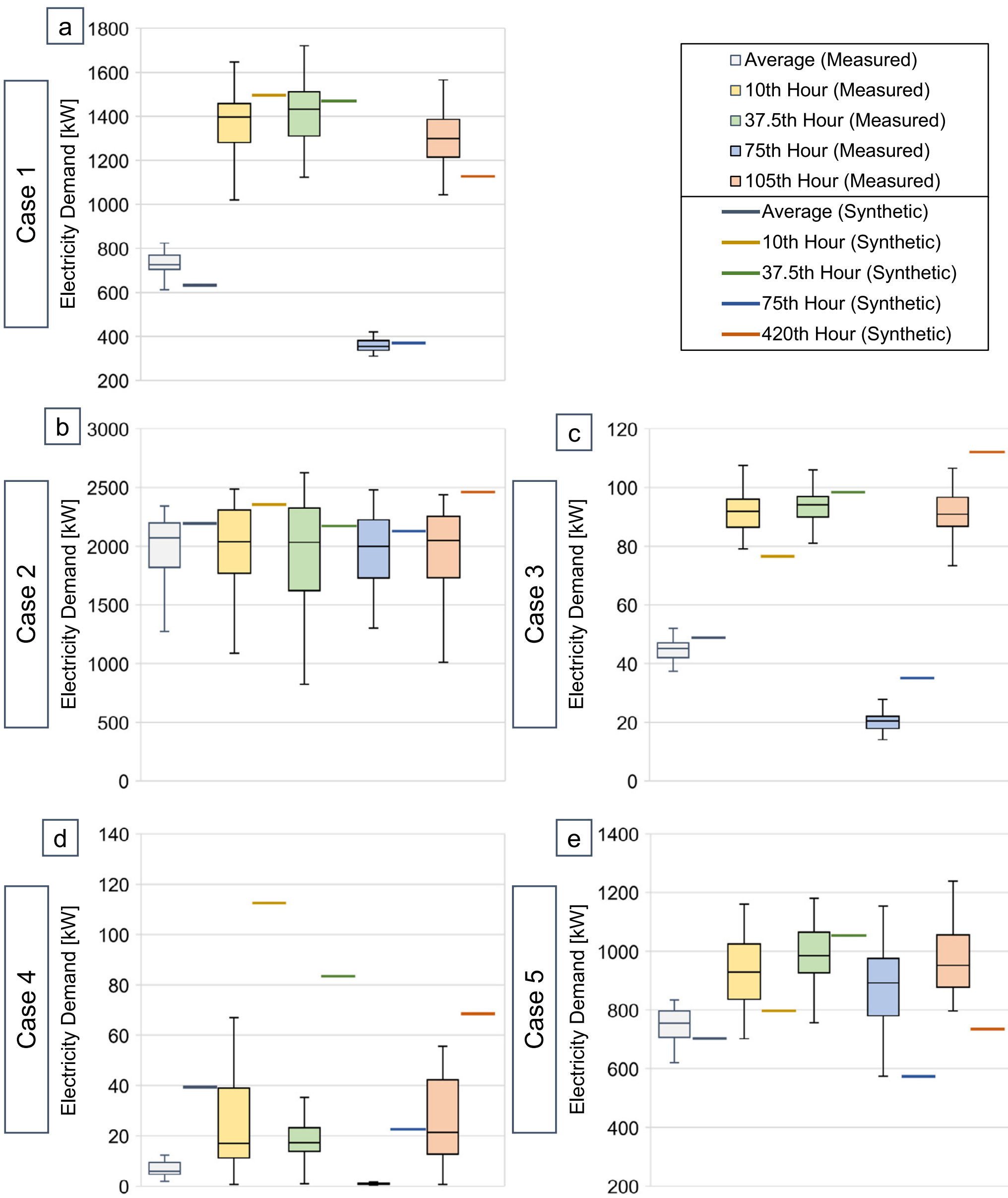

Fig. 14. Boxplot diagrams for evaluating the deviation of the synthetic LPs (single line indicators) compared to the measured data (boxes). All boxes include 52 data points (as of 52 weeks per year) for different times in the LP. For all five boxplots case 1 is shown in (a), case 2 in (b), case 3 in (c), case 4 in (d) and case 5 in (e).

Table 4
Resulting MAPEs, deviation of maximum peak and minimum demand between average (measured) and synthetic LP for all five cases.

Case number	MAPE	Deviation peak demand	Deviation minimum demand
Case 1	19%	11%	2%
Case 2	11%	30%	4%
Case 3	35%	17%	7%
Case 4	644%	345%	57%
Case 5	29%	26%	49%

more, possibly because the average (measured) LPs fluctuate less due to the arithmetical calculation, which can also be observed for case 1 from the red curve in Fig. 13. Case 1 exhibits a sufficient approximation with low deviation at different time stamps too, which is shown in Fig. 14 (a). The overall data point variance is higher in case 2. Nevertheless, all synthetic time stamps align with the boxes satisfactorily (Fig. 14 (b)).

Case 3 shows a higher MAPE, however, slightly less deviation regarding maximum and minimum peak, possibly due to higher fluctuations of the synthetic LP. This can also be observed in Fig. 14 (c) as the demand during each of the four single time stamps lies outside the boxes of the boxplot. This variance probably results from generating the LP at very low power levels. We will explain this effect in the following paragraph for case 4.

The modelled and measured results of case 4 vary dramatically with an overall MAPE of 644%. During the execution of our case studies, we experienced major deviations between measured and synthetic LPs at low energy peak demands under 200 kW. We found that the linear relationship between peak demand and consumption (as we indicated in Section 2.5.1) exhibits large error rates in some NACE subsectors at these low demands. Often, the linearity remains inconclusive in these areas. This leads to the fact that the algorithm estimates higher peak demands. This results in major deviations between the measured and synthetic LPs. We originally found this incidence in cases 3 and 4. We modified the algorithm to process a non-linear fit, when the variation of

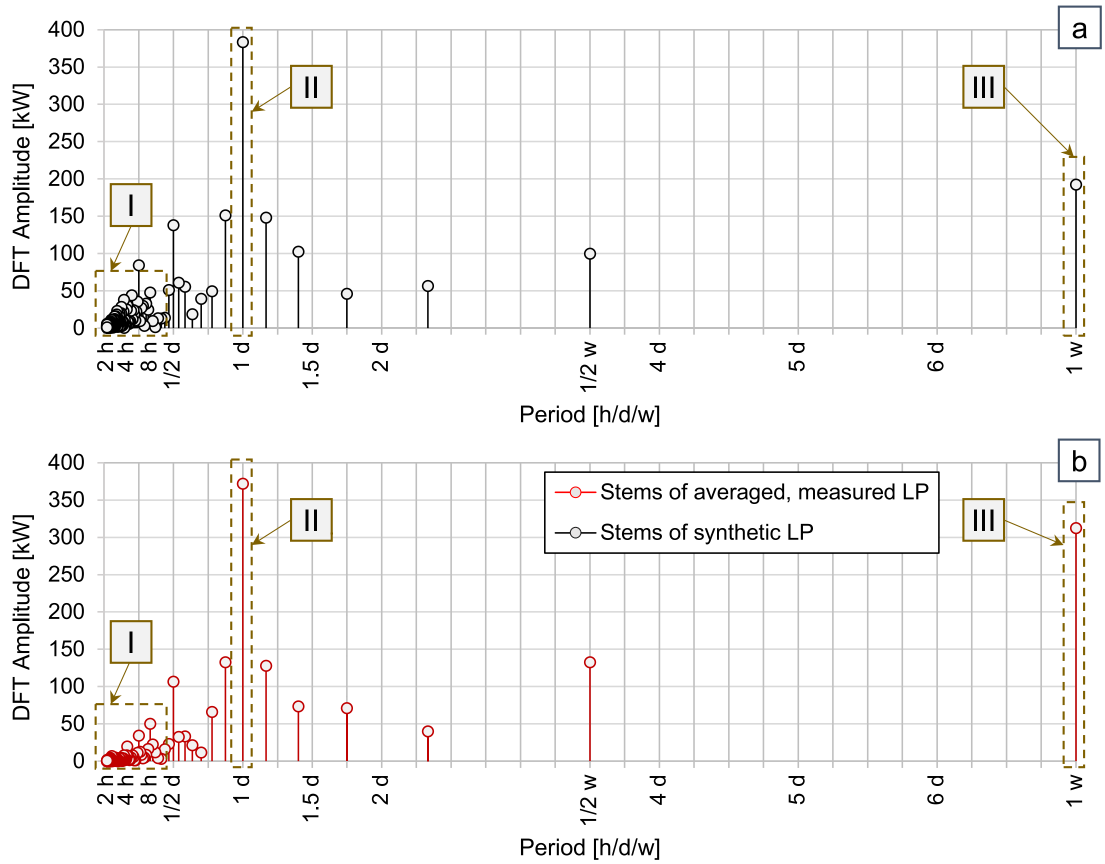

Fig. 15. DFT stem plots and corresponding amplitudes for (a) synthetic LP and (b) average (measured) LP of case 1. The following segments are highlighted in (a) and (b): (I) – Higher fluctuations of the synthetic LP in a short-term manner, (II) – Strong dominance of the signal with 24 h periodicity, (III) – Higher amplitude for a weekly fluctuation in measured LP. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the linearity increases at low demand levels. Based on this non-linear fitting function the adjusted peak demand is forwarded to LP generation. This modification exhibits valid results in case 3. However, case 4, which is located in another NACE subsector, is not afflicted by these changes. Case 4 shows the limitations of our model. For these cases, the execution of a sole bottom-up approach, which we developed in our previous work [5], may be more advisable.

Case 5, again, exhibits acceptable results. The minimal demands of the synthetic LP are slightly lower than in the measured LPs, which can also be observed in Fig. 14 (e).

In cases 1, 3, 4 and 5, where the applied shift model indicates a significantly lower or no production during weekends, the measured LPs nevertheless show a slight increase in the electricity demand during Saturdays. We could not assume the reason for this.

In the next step, we performed a Discrete Fourier Transformation (DFT) analysis of the average (measured) and the synthetic LPs of all cases to evaluate these mentioned and further periodical features. The DFT decomposes any given input signal into a sum of periodic sine and cosine components, for which frequency, amplitude and phase can be assessed. Groiß [56], for example, examined yearly electricity residual loads by conducting a DFT with the means of analysing their periodical potential for i.e. long-, mid- or short-term storage.

Fig. 15 shows the DFT analysis for case 1 of (a) the synthetic LP and (b) the average (measured) LP. We highlighted three comparable segments. The first segment (I), representing short-time fluctuations, exhibits higher DFT amplitudes of the synthetic LPs indicating stronger fluctuations with those periodicities. As we already mentioned, due to the arithmetic calculation, the average (measured) LP tends to show less rapidly alternating fluctuations. This can also be seen in Fig. 13 by comparing the red and black coloured LPs, especially during non-production phases. Overall, the definition of 15-min intervals tends to inflict less strong fluctuations within the overall LP than for smaller intervals (e.g. 1- or 10-min) [57]. This is due to the calculated average within these intervals. A strong dominance of a daily periodicity can be observed in both plots in the second segment (II). The observed amplitudes reach very similar values. This also exemplifies the applied 8 h/day (40 h/week) shift model as a high changing rate of the LP during working days is present. The most distinctive difference between measured and modelled LPs can be noted in the third segment (III). Here, the amplitude of the measured LP at weekly periodicity is significantly higher than in our synthetic model. This underlines the presence of weekend loads (especially Saturday), which we can currently not depict within our model. As we also evaluated the results from DFT for cases 3, 4 and 5, we found the same weekly, long-term dominance in the DFT amplitude being more thoroughly developed in the measured LPs.

4. Conclusions & outlook

As we established a well-functioning, bottom-up model for generating load profiles (LPs) for energy intensive industries in our preceding study [5] , we now present a combined top-down and bottom-up algorithm to cover the remaining non-energy intensive subsectors. Through this, we are closing the gap by incorporating the whole industrial sector to create, to our knowledge, the first comprehensive software for generating timely high-resolved, synthetic energy demand and generation profiles, called *Ganymed*.

To conclude our study, we reflect on our hypotheses stated in Section 1.2:

- The non-energy intensive industrial subsectors outnumber the energy intensive industries regarding employment, gross value added and produced products as we showed in Section 2. These more comprehensive subsectors demand a wider range of implemented methods for generating LPs rather than a sole bottom-up approach. Also, existing methodologies lack the assessment of multi-energy carriers without the need for extensive databases. In our first hypothesis in Section 1.2, we situated that a combined bottom-up and top-down approach will adequately depict the non-energy intensive industries on a multi-energy level without extensive process-specific data. We, therefore, developed a mixed methodology with top-down methods incorporating real-life plant data and a bottom-up algorithm for implementing the timely resolution of process energy demands into the overall methodology.
- To prove our second hypothesis, we built on the expertise of Hernández et al. [18], who outlined the dependency between working days, weekends and holidays in industry and electrical LPs. We showed that production and non-production times during working days need to be interlinked for the generation of multi-energy LPs in form of concrete, well-defined shift models. Moreover, thermal LPs are not only influenced by the hour of the day but also by the ambient temperature, which needs to be considered in LP generation. We showed this dependency in Section 2.5.2.
- The consideration of the most energy intensive processes within a non-energy intensive plant will suffice for generating industrial LPs. As we already stated this finding in our preceding study [5], we now apply this fact in our developed methodology. A representative LP can be generated by calibrating the remaining peak demand and the base load via existing real-life plant data. This also changes the need to gather extensive process-specific data for depicting multi-energy carriers within bottom-up approaches.
- From a top-down point of view, the dependency between the specific energy consumption of industrial plants and production capacity can clearly not be described linearly. It constitutes itself via a logarithmic function. Thus, this effect indicates that the microeconomics' paradigm of Economy of Scale practically affects the energy system as well. Therefore, we described the specific energy consumption of industrial plants of different subsectors as logarithmic fit functions in relationship to the production capacity.

At last, the results of the presented methodology exhibit satisfactory approximations in depicting real-life production facilities with an overall mean percentage error of around 20% for plants with weekly peak demand higher than 200 kW. However, we found that the demand of smaller consumers ($<$ 200 kW) often differs from the results in our approach, even after corrections in our algorithm have been made. We assume that this deviation results from a higher heterogeneity of the daily work and included processes in small facilities. As we described in our preceding study, a sole bottom-up approach might be more advisable here. When analysing the periodicities of the synthetic LPs, we found more fluctuations with higher frequencies and a weaker dominance of weekly periodicities when compared to measured LPs. The first feature is probably due to the comparison with an average, measured LP. The second one reveals the necessity of including load behaviour on weekends in the algorithm, which could not have been approached until now due to limited access to information on industrial shift models.

As we strive for developing our model further, we will optimise certain features and algorithms in the future. Firstly, we will enlarge our existing, incorporated databases. Secondly, we will enhance our EOS model and the iterative load factor algorithm to assess peak demands more thoroughly. In this regard, energy economic paradigms like time-of-use can potentially further improve the generation of LPs in this methodology.

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CRediT authorship contribution statement

Paul Josef Binderbauer: Conceptualization, Methodology, Software, Validation, Writing – original draft, Visualization. **Aaron Keuschnig:** Methodology, Validation, Data curation. **Thomas Kienberger:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 5
Summary table comparing current study with past research.

	Objective	Subsectors (IEA)	Energy carrier	Approach	Solving method	Constraints
[9]	Generating synthetic industrial LPs	5 (Food, Beverages & Tobacco; Machinery; Iron & Steel; Non-Ferrous Metals; Non-Metallic Minerals)	Electricity	Top-Down	• Based upon normalised LPs from literature • Divided into energy end uses • Applying fluctuation to generated LPs	• Solely based upon normalised profiles • No process-specific data available
[10]	Investigating the dependency between heat profiles and ambient temperature	6 (Food, Beverages & Tobacco; Chemical & Petrochemical; Iron & Steel; Machinery; Automotive; Non-Metallic Minerals)	Natural gas/Heat load	Top-Down	• Normalising the data • k-means clustering of measured LPs • Regression analysis	• Extensive data necessary • High aggregation level

(*continued on next page*)

Table 5 (*continued*).

	Objective	Subsectors (IEA)	Energy carrier	Approach	Solving method	Constraints
[11]	DSM measures for medium-sized industries	3 (Iron & Steel; Chemical & Petrochemical; Food, Beverages & Tobacco)	Electricity	Top-Down	• k-means clustering of compartments of measured LPs • Investigating similarities • Derivation of operating and scheduling modes	• Extensive data necessary • High aggregation level
[12]	Investigating DSM potential of paper and food industries	2 (Pulp & Paper; Food, Beverages & Tobacco)	Electricity	Top-Down	• Normalising the data • k-means clustering of measured LPs	• Extensive data necessary • High aggregation level • Limited subsectoral investigation
[13]	Generating synthetic industrial LPs for market-oriented operation of power systems	2 (Machinery; Food, Beverages & Tobacco)	Electricity	Top-Down	• Statistical analysis and derivation of load shape factors of measured LPs • Fuzzy c-means clustering of monthly generated LPs • Combining the clustering results in general LPs	• Utilisation of data from only 18 different industrial plants
[14]	Modelling of synthetic LPs of real life production plant	1 (Iron & Steel)	Electricity, Natural gas/Heat load	Bottom-Up	• Measurement at site • Modelling of measured LP via Markov chains	• Only applicable at the specific site • Measurements necessary
[15]	Optimisation of manufacturing scheduling and DSM potential	3 (Pulp & Paper; Machinery; Chemical & Petrochemical)	Electricity, Natural gas/Heat load	Bottom-Up	• Energy system assessment at site • Modelling of singular processes • Generating LPs on various systemic levels • Integration in further economic investigations	• Extensive data necessary • Complex methodology including various parameters
[5]	Generating synthetic industrial LPs of energy intensive subsectors	5 (Iron & Steel; Pulp & Paper; Chemical & Petrochemical; Non-Metallic Minerals; Non-Ferrous Metals)	Electricity, Natural gas/Heat load	Bottom-Up	• Collection of process-specific literature data • Integration in discrete event simulation	• Only applicable for production route itself
This Study	Generating synthetic industrial LPs of non-energy intensive subsectors	7 (Wood & Wood Products; Machinery; Food, Beverages & Tobacco; Mining & Quarrying; Automotive; Textiles & Leather; Non-Ferrous Metals)	Electricity, Natural gas/Heat load	Top-Down and Bottom-Up	• Stochastic analyses of industrial databases • Fits for employee number, energy demand and production shifts • Energy intensive processes depicted by Markov model • Combination of top-down and bottom-up approaches	• Limited to databases • Outliers of daily shifts possible

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Article P3

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Table 4: Author contribution statement for article P3.

Activity	Contributing authors
Conceptualization	Binderbauer, P.J., Hammer, A., Lachner, E., Kienberger T.
Methodology	Binderbauer, P.J., Hammer, A., Kienberger T.
Data curation	Binderbauer, P.J., Klingenstein N.
Software development and validation	Binderbauer, P.J.
Modelling	Binderbauer, P.J., Hammer, A.
Investigation and analysis	Binderbauer, P.J., Hammer, A., Lachner, E.,
Visualization	Binderbauer, P.J.
Writing (original draft)	Binderbauer, P.J.;
Writing (review and editing)	Binderbauer, P.J., Kienberger, T.

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Research Paper

Regarding the generation of time resolved industrial waste heat profiles

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A B S T R A C T

The timely transient energy supply or insufficient temperature levels of industrial waste heat (IWH) hinders the full exploitation of its energy and CO_2 emission reduction potentials. This outlines the necessity for investigating IWH in a time resolved manner, which, however, is still widely disregarded, especially in generalized industrial energy system analyses and research. Within this study, we present our developed first-of-its-kind approach, which addresses this topic from a holistic system perspective and enables the generation of time resolved IWH profiles for all industrial subsectors. The backbone of our approach is the distinction of energy-intensive subsectors (e.g. Non-Metallic Minerals) and non-energy-intensive subsectors (e.g. Food & Beverage Production), as both vary in regard to their underlying process designs, production routines and data accessibility. Concerning the first group we found that time resolved IWH profiles can be generated by combining process specific data in a bottom-up manner with temperature gradients of the whole production route throughout the paradigm of discrete event simulation. We investigated further that IWH profiles of non-energy-intensive subsectors are depicted by examining existing subsector resolved waste heat fractions and combining this information with plant-specific load profiles in a top-down manner. We practically prove our findings for both groups within (1) a case study of generating IWH profiles of a real-life cement production mill as part of energy-intensive subsectors and (2) outline the analysis of waste heat fractions for the non-energy-intensive subsector of food production exemplarily. Both cases reflect the above findings successfully and with satisfactory results, which can therefore be regarded as basis for future research work concerning time resolved IWH.

1. Introduction

The exploitation of industrial waste heat (IWH) is regarded as a go-to solution for reducing the energy consumption and CO_2 emissions of industrial plants [1]. From a systemic point of view, IWH is utilized internally for site-specific heating and/or externally within district heating grids for further usage off-site (e.g., in residential buildings). The International Energy Agency (IEA) foresees the exploitation of the maximum economic potential of IWH to be achieved by 2030 [2]. The current deployment status is still far off this maximum. For example, energy system analyses of the European industrial sector estimate current unused technical potentials to still amount to up to 817 TWh/a [3]. From a technical point of view, besides temperature issues, a major limiting factor concerning the utilization of these untapped potentials is caused by the fluctuating, timely instability of generated waste heat [4]. This hinders a constant supply of thermal energy for consumers and therefore requires additional efforts to be considered by e.g., energy system development, deployment of demand side management (DSM) and storage measures.

A solution for bridging the challenges of unstable IWH on a holistic energy system level lies in the generation of time resolved IWH profiles. As a result, future analyses of industrial energy systems can easily assess the potential of IWH for internal or external utilization for different industries, production sizes and time frames. Following this context, our goal within this study is to present an approach, which covers the generation of IWH profiles for manufacturing sites and for the entirety of the industrial sector.

1.1. State of research

Within the context of our research aim of time resolved IWH analysis and generation, we conducted an extensive literature review of current studies also dedicated in adjacent research fields of industrial energy systems. In general, we found that existing studies mainly cover two

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areas:

1. Studies, which quantify waste heat spatially as a source for e.g., external use in district heating grids on a high aggregated level. This research mainly applies low aggregation time frames like months or years for their respective assessments.
2. Studies on individual process and technology level, which examine novel technological advancements into e.g., existing industrial designs for more efficient site own use. This research generally applies detailed data on a high timely resolution in e.g., seconds or minutes to assure the technology's system integration.

To provide a better overview of both fields, we allocated these categories to industrial aggregation levels in Fig. 1. Followingly, we provide a more detailed description of both categories and outline the resulting research gap, which we address in this study.

For the first category, as an example, McKenna et al. [5] present an energetic and exergetic analysis-based model for assessing waste heat loads and their technical recovery potentials for the entire industrial sector in the UK. Therefore, the authors calculate the respective heat load of various sites of several industrial subsectors based on emission trading system (ETS) reports. The IWH recovery potentials are then assessed via heat recovery fractions from measured manufacturing plants from other sources. These analyses bear important information on the cross-sectoral industry-to-heating-grid IWH potentials, however, do not consider detailed time resolved behaviour as they solely incorporate yearly data. Persson et al. [3] and Brueckner et al. [6] conduct similar analyses for Europe and Germany respectively for different years.

The second category of research studies involves heat recovery technologies and site-specific recovery opportunities on individual process and technology level. Here, the focus lies on the industrial implementation of novel technologies and assessing their economic and technical feasibility for recovering IWH for e.g., internal usage. To thoroughly proof a successful system integration of the respective technology, the time resolved generation of IWH on-site is significant. Within this context, Lecompte et al. [7], for instance, conduct a case study for incorporating an organic Rankine cycle (ORC) for recovering IWH within an electric arc furnace (EAF) mill. Because the EAF is operated batch-wise, IWH is only generated time varyingly. The authors state the challenges in implementing IWH recovery technologies for timely unstable production behaviour and point out the necessity of examining the time resolved generation of IWH in terms of IWH profiles.

In another example, Dock et al. [8] present a model for investigating energy and CO_2 emission reduction in an EAF mill. Here, the time resolved energy consumption in terms of load profiles (LPs) forms the basis of the study. Dock et al. further generate IWH profiles to investigate the time resolved IWH generation, internal recovery and process integration on-site to reach their desired aim.

In general, the consensus within state-of-the-art studies seizes the challenges caused by the characterizing influence of the time-dependent production and process behaviour on IWH generation in industry [4]. The usage of waste heat potentials – internally as well as externally – must be subordinated to the production design. Thus, the time resolved supply from IWH does in general not resemble the time resolved heat demand – internally and externally. This is especially true when investigating batch processes that are not operated continuously and therefore strongly influence the fluctuation of IWH supply. Literature studies above state that it is necessary to thoroughly examine the fluctuation of IWH to fully exploit its energy consumption and CO_2 emission reduction potential.

As a result from our literature research, we conclude that subsector specific, high aggregated analyses and concrete technological studies on low aggregation levels are already well developed. However, we investigated that – to our knowledge – no studies connected both groups and transferred their generated knowledge onto plant level in a time resolved context. Within this study, we, therefore, investigate time resolved IWH generation and utilization on plant level for the entire industrial sector by the generation of IWH profiles. This will bridge the gap between both already addressed categories and brings potentials to more detailed holistic energy system analyses e.g., developing decarbonization scenarios, or for embedding individual technological advancements into more comprehensive energy systems (e.g., heating grids). This interconnection is shown in Fig. 1 and forms the research gap, we address with our work.

1.2. Research hypotheses and structure of this paper

Information on cross-sectoral spatial IWH utilization and process specific waste heat data is already put in place by various studies, as shown above. We found that the time resolved behaviour of IWH generation and utilization on plant level is not examined thoroughly yet. However, to fully exploit the whole potential industry internal and external IWH utilization might bear, this issue is a mandatory research area to be handled. As the generation of IWH profiles shall be examined

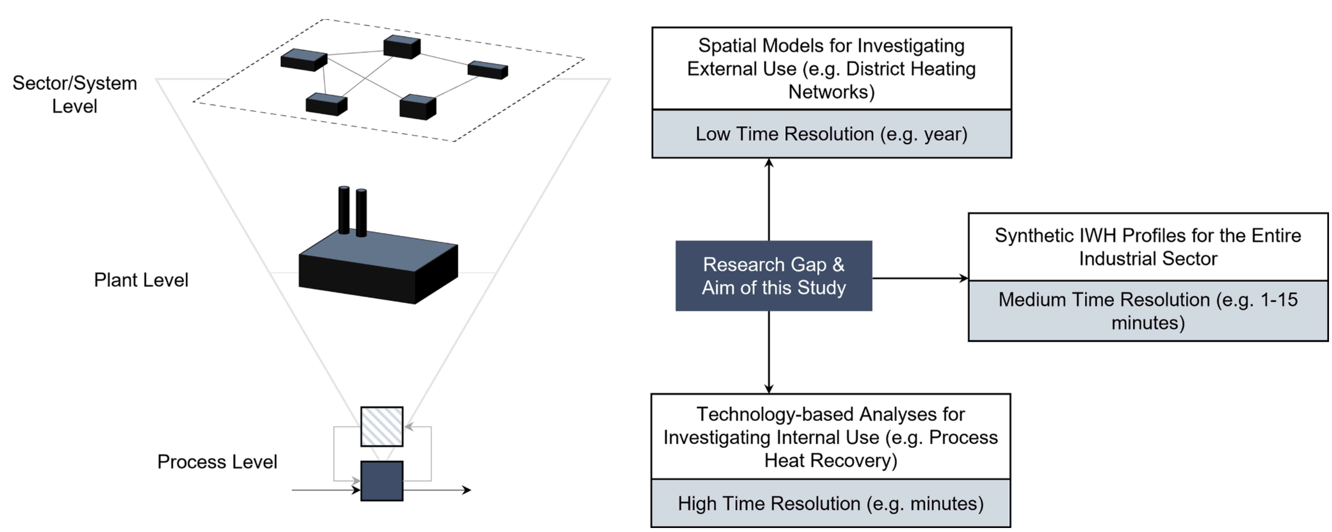

Fig. 1. Comparison of current research areas regarding IWH utilization in industry and aim of this study: Spatial models, which investigate external use within district heating grids on a high aggregated level and low time resolution or technology-based analyses for internal, on-site use with high level of detail in time resolution. Research gap for time resolved IWH generation and utilization on plant level is still unaddressed.

for the entire industrial sector, the following situated hypotheses are to be validated within this study:

- H1: System boundaries are crucial when investigating IWH utilization. The adaption of system boundaries will alter the corresponding IWH profiles in terms of both time and temperature-resolved patterns.
- H2: The generation of IWH profiles demands data regarding operating temperatures and time resolved properties of all process steps within the to-be-investigated single processes or overall production routes.
- H3: IWH is subject to specific time resolved fluctuations. Therefore, industrial energy systems require a timely assessment and optimization to thoroughly exploit the full IWH recovery potential.

We will prove these hypotheses throughout this study. To initiate our investigations, a precise definition of IWH (section 2.1) and applicable industrial system boundaries (section 2.2) is crucial within our developed study. After classifying the industrial sector as energy-intensive and non-energy-intensive, the respective IWH assessment methodologies are described in sections 2.3 and 2.4. We furthermore conduct a case study generating synthetic IWH profiles and validating the selected results in section 3. Finally, section 4 concludes this study by reflecting on the hypotheses stated above.

2. Methodology

To kick-off our methodology, we split the industrial sector into energy-intensive and non-energy-intensive subsectors, defined by the IEA [9]. Within our prior study [10] we found that the first group exhibits higher energy consumption but relies on a smaller number of production processes, while non-energy-intensive subsectors produce more complex products via a large number of varying production principles. For both groups, their respective shares of primary energy consumption in Austria are outlined in Fig. 2 exemplarily. We show that, although energy-intensive subsectors exhibit higher shares of energy consumption, non-energy-intensive subsectors exceed regarding their number [11]. Due to their different characteristics and underlying heterogeneity concerning products, processes and production routines, both groups are to be approached via different methodologies.

Within our prior studies [10], we developed a methodology for generating load profiles (LPs) for energy-intensive and non-energy intensive subsectors. Regarding the first, the methodology for generating IWH profiles is tightly interlinked with the existing bottom-up approach of the sequencing and process execution logic of discrete event simulation for generating synthetic LPs. We extended the classification of all involved processes within these subsectors by waste heat data such as intake, operating and outlet temperature, thermal energy flow rate, the waste heat energy carrier, etc. We retrieved these data from literature studies, which examine IWH on process level and technical recovery potentials on the low aggregated level outlined in Fig. 1. These process specific parameters present in combination the technical

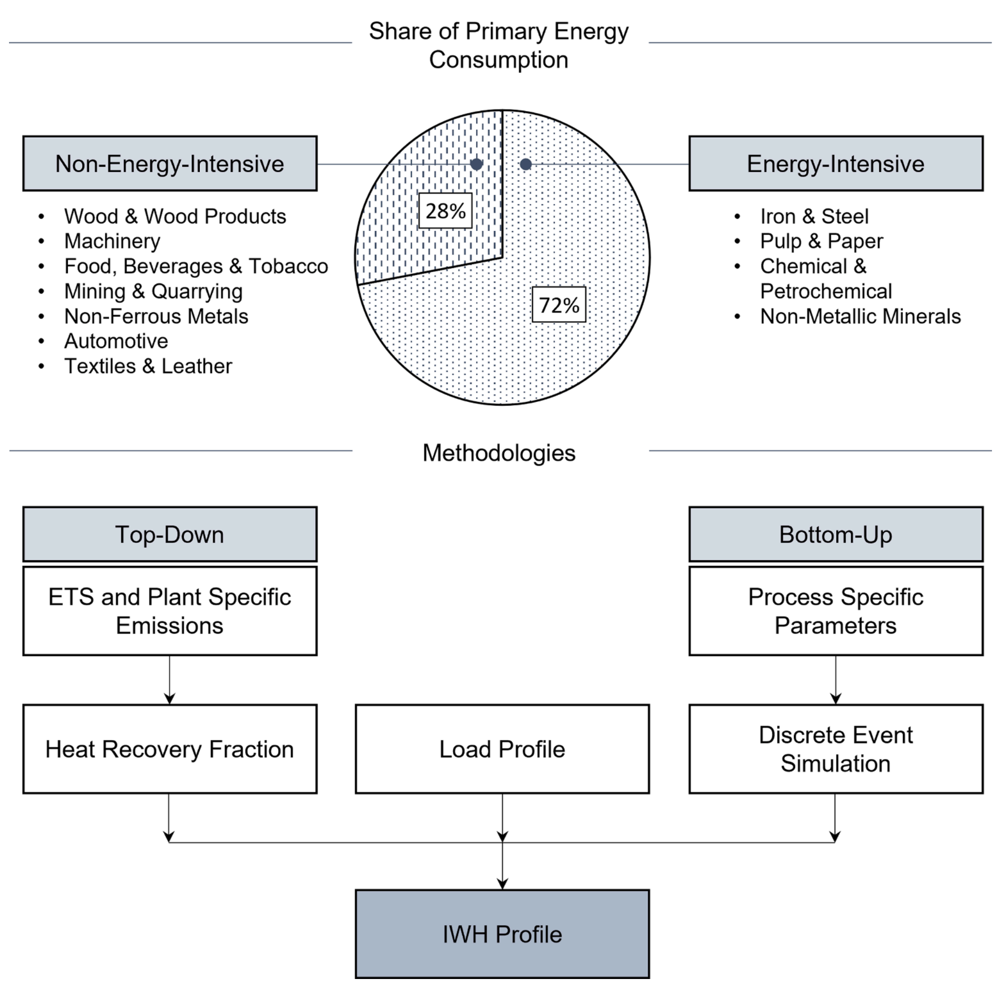

Fig. 2. Share of primary energy consumption of non-energy-intensive and energy-intensive industrial subsectors in Austria; Developed methodologies for both groups.

recovery potentials of the process. The utilization of this IWH is realized within our methodology via sensible or latent heat transfer within dedicated HEXs. The time resolved operation of the processes is then interlinked with waste heat generation, internal waste heat recovery/ consumption, and external waste heat utilization. In combination with the also generated LPs, IWH profiles are generated.

The methodology for non-energy-intensive subsectors does not incorporate process specific information hence the subsectors' complexity of processes and production routines. Here, we conducted extensive literature research on subsector-specific data regarding output IWH recovery fractions, determined based on measurements and plant-specific emissions on high-aggregated level as also outlined in Fig. 1. The combination of these recovery fractions with existing LPs allows for the calculation of synthetic IWH profiles.

2.1. Definition and classification of generated IWH

For the development of a comprehensive methodology, which enables the generation of synthetic time resolved IWH profiles for different systemic boundaries and industrial subsectors, a concise definition of IWH is a crucial factor. Within our study, we define IWH as energy that is rejected by industrial processing units, which operate at temperatures above ambient temperature [12]. The excess energy is carried by a waste heat energy carrier, whose thermal energy flow rate $\dot{Q}_{IWH}$ [W] is driven by either sensible or latent heat transfer. Sensible heat transfer thermodynamically applies, when a system remains in one phase and the heat from or to the system is depicted via a temperature difference as formula (1) explains:

$$\dot{Q}_{IWH} = \dot{m}_{Carrier} \times c_{p,Carrier} \times \Delta T \quad \text{with } \Delta T = T_{outlet} - T_{ambient} \tag{1}$$

with $\dot{m}_{Carrier}$ [kg/s] as the mass flow of the waste heat energy carrier, $c_{p,Carrier}$ [J/(kg K)] specific heat capacity of the waste heat energy carrier and ΔT the temperature difference [K] between process outlet temperature T_{outlet} (hot-end at heat transfer) and reference / minimum use temperature T_{min} or $T_{ambient}$ (cold-end at heat transfer), which we refer to the ambient temperature in this study [13]. Per the principle of energy conservation, the process outlet temperature has to be equal to or lower than the operating temperature of the process itself.

Latent heat transfer applies for systems within phase transition (e.g., steam generation). The heat absorbed or emitted is directly involved in this transitional process, which is driven under constant temperature. The corresponding waste heat is calculated through formula (2):

$$\dot{Q}_{IWH} = \dot{m}_{Carrier} \times h_{Carrier} \tag{2}$$

with $\dot{m}_{Carrier}$ [kg/s] as the mass flow and $h_{Carrier}$ [J/kg] as specific latent heat of the of the waste heat energy carrier.

Fig. 3 shows these definitions together with a respective $\dot{Q}/T$ diagram of the rejected energy flow of process P1 as sensible or latent heat transportation.

Depending on the energy flow rate and technical feasibility, a fraction of this rejected energy can be recovered for useful purposes either internally within the industrial plant itself and/or externally as input for district heating grids [14]. The method for generating the utilization of these IWH potentials is also conducted via sensible or latent heat transfer.

This recovery process, in general, is deployed by incorporating a closed or open heat exchanging network with a respective carrier medium e.g., thermal oil, hot water, etc. Different technologies can be applied for this recovery. Brueckner et al. [6] divide these technologies in direct and indirect categories according to their planned usage. Direct systems recover IWH and utilize it as the same form of energy, while indirect technologies convert the heat into other energy forms. Thus, heat pumps, heat exchangers, boilers, thermal heat storages and refrigeration cycles are direct heat recovery technologies, whilst thermoelectric generators, ORC, Kalina cycles, etc. transform the collected waste heat into electric or mechanical power [15]. Throughout both categories, input energy consumption, which would require a conservative energy supply, can be reduced. We outline novel technological developments in both groups: Within direct technologies, especially high temperature heat pumps are in focus in recent research endeavours as e.g., Jiang et al. [16] present the low global warming potentials of centrifugal heat pumps supplied with IWH for temperature ranges above 100 °C with new refrigerant components. In another example, Jouhara et al. [17] show the application of heat pipe heat exchangers in energy-intensive industries via a theoretical model and practical implementation. The authors outline the importance of novel recovery technologies in high-temperature industries like energy-intensive subsectors and present a scalable guideline for implementing heat pipes in other locations. For indirect recovery technologies, Miao et al. [18] examined recently the impact of unstable IWH generation on thermoelectric generators and concluded that certain patterns of IWH instability can also lead to improvement in thermoelectric power generation. Piri et al. [19] combine compressed-air energy storages with a multiple-step Kalina recovery cycle and outline the future potential of its system integration.

To thoroughly assess the accumulated IWH for both single processes and overall production routes in industry, we introduced an exergetic classification of the rejected and recovered energy. Table 1 shows the classification of exergetic levels of the IWH, separated into different

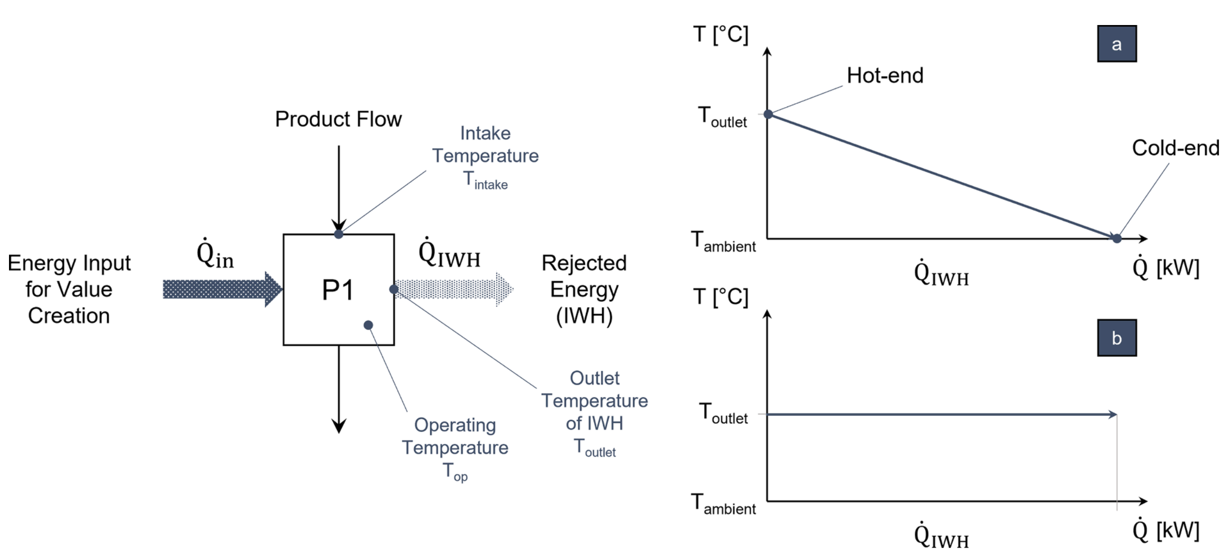

Fig. 3. Process P1 specific waste heat; Definitions of temperatures and energy flows as well as $\dot{Q}/T$ diagrams for (a) sensible or (b) latent heat generation.

Table 1
Exergetic levels of IWH for different temperature ranges.

Exergetic Level	Temperature Range/Level
Low-grade IWH	$T_{ambient} - 50\ ^\circ C$
Medium-grade IWH	$50\ ^\circ C - 100\ ^\circ C$
High-grade IWH	$100\ ^\circ C - 400\ ^\circ C$
Very High-grade IWH	$>400\ ^\circ C$

temperature ranges. The recovery potential rises with increasing IWH grading [15].

The rejected energy is carried by waste heat energy carriers. These vary regarding their properties like composition, material, state, etc. We agreed upon classifying four waste heat energy carriers: "Flue Gas", "Exhaust/Cooling Air", "Waste/Cooling Water" and "Steam and Air with Condensable Water", as shown in Table 2. We disregarded changes in the material composition and overall system pressure. We furthermore assumed that steam is saturated and utilized at 12 bars within industrial energy systems. Superheated steam is not included in our calculations. For "Flue Gas", "Exhaust/Cooling Air" and "Waste/Cooling Water" we apply sensible heat transfer in line with formula (1). "Steam and Air with Condensable Water" refers to phase transitional processes like described above and applies latent heat transfer within our IWH calculations.

All waste heat analyses conducted in this study are regarded as theoretical technical potentials as defined by Panayiotou et al. [20]. As part of the technical potential, the theoretical technical potential is calculated by applying theoretical or generic process specific analyses. The deployed calculations deliver time resolved IWH potentials, which can be recovered by extracting the heat from the waste heat energy carrier and utilizing it again.

Within our study, we restrict our methodology to depict the potentials of time resolved IWH and its utilization via latent and sensible heat transfer within the direct technology of general heat exchangers (e.g., heat pipes). We do not depict other recovery technologies like thermal energy storage, ORC, etc. yet.

Furthermore, we conduct no optimization measures within time resolved IWH generation (e.g. pinch point analysis, loss limitation, …) as our research goal is to generate synthetic IWH profiles for holistic energy system analyses. Via the application of synthetic IWH profiles, impacts of industrial plants on the overall energy system via e.g. district heating can be assessed more thoroughly and with an improved timely resolution.

2.2. System boundaries of industrial plants

Due to the diverse utilization of generated IWH within or outside industrial plants, we introduced system boundaries for adequate allocated calculations in our methodology. These system boundaries act as a holistic template and can be superimposed for every manufacturing plant for each industrial subsector.

Fig. 4 shows the defined system boundaries for an industrial plant in general. The system consists of units for energy conversion and consumption. Furthermore, we introduced two systemic levels into this scheme. The plant level acts as the plant's border. The public grid is located outside this boundary and all units outside this perimeter are not owned by the manufacturing plant [21]. The conservative energy supply route corresponds to the energy flow into and within the plant, which does not include IWH recovered flows. The energy distribution unit receives energy from outside the plant from the grid e.g., electricity or gas. This unit is responsible for supplying all other units within the plant-level border. However, the energy distribution unit can also receive energy from within the border, e.g., in case of on-site energy generation via PV or CHP plants or in case of recovered thermal energy. The latter can then be submitted to the public grid, e.g., within district heating networks. The manufacturing level lies within the plant border and contains all processes which are directly involved in value-creating production. Production auxiliary units like ventilation, lighting, etc. are located outside the manufacturing level. Within this border final energy, e.g., electricity or gas, is converted to useful energy, e.g., heat or mechanical drive. IWH can be generated within the plant at different units and recovered by deployed direct recovery technologies of heat exchangers as described in section 2.1. Within our definitions, IWH is generated within energy converting units like the on-site energy generation, final energy transformation or process own useful energy consumption. The energy recovery system applies heat exchangers to recover IWH internally (via the loop back into the manufacturing level) or utilize IWH externally within local district heating grids.

In general, the developed system boundaries can be allocated either to the manufacturing level, which results in IWH profiles of all production processes, or the plant level, which contains IWH profiles for waste heat leaving the facility, which meets our initial research aim.

Table 2
Classification of waste heat energy carriers and their descriptions.

Waste Heat Energy Carrier	Description
Flue Gas	Carrier of sensible heat which originates from combustion processes
Exhaust/Cooling Air	Waste heat potentials from hot or warm products from production (e.g., product puffer), plant indoor exhaust air or machine cooling
Waste/Cooling Water	Water based waste heat potentials which leave production processes and originates from cleaning or cooling purposes
Steam and Air with Condensable Water	Steam as energy carrier or condensation of water within flue gas from/for evaporation or drying purposes

2.3. Methodology for energy-intensive subsectors

As mentioned above, due to homogeneous production schemes of energy-intensive subsectors, we extended the already developed bottom-up approach for generating synthetic LPs to include IWH calculations.

We present a standardized process through which the time resolved IWH potentials of any user- or pre-defined production route can be allocated for recovery within or outside the facility. Its chronological order is shown in Fig. 5. At first, the potentials of generated IWH for the user- or pre-defined production processes are assessed via literature surveys. In the second step, the IWH recovery can be depicted via sensible or latent heat transfer. The excess, time resolved IWH, which is not recovered within the facility, is then calculated for external or additional internal utilization in terms of exploiting its technical potential. All results offer time resolved IWH profiles at the end of this depicted methodology. Analyses of economic feasibility are not included within the calculations but can be done in an additional post-processing step.

2.3.1. Assessment of technical IWH potentials

The backbone of IWH profile generation for energy-intensive subsectors is discrete event simulation. This simulation paradigm depicts the timely interaction of discrete products (e.g. tonnes of steel) with individual production processes [22]. The sequence of interactions is defined by designed production routes containing these processes. When an interaction with a process takes place, a corresponding process specific energy consumption profile is generated. As a result, a cumulative LP of the respective energy carrier is created. We developed this approach in our preceding study to generate synthetic LPs of energy-intensive industries [10].

This time resolved energy demand analysis acts as the basis for further IWH generation and consumption calculations, because these time resolved profiles are tightly interlinked with the production behaviour and energy input of each process [4]. This means, that a process cannot generate waste heat if it's currently not in a producing state, e.g., turned off. As our aim is to generate time resolved IWH

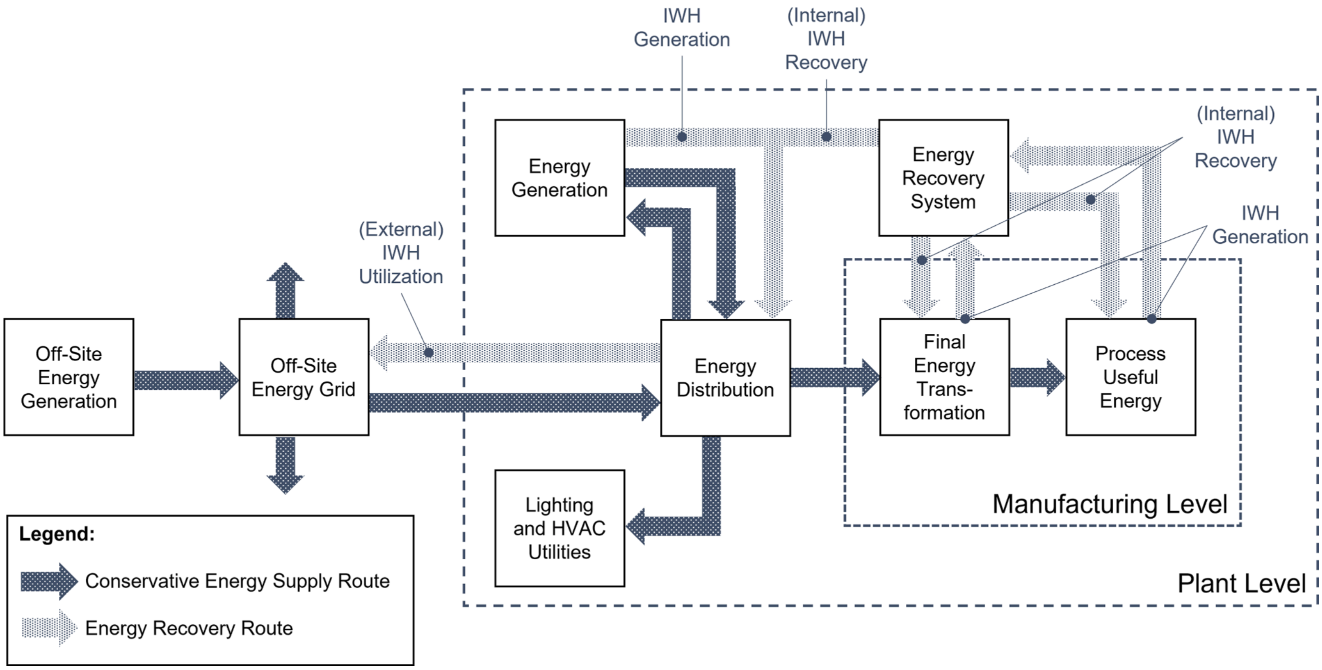

Fig. 4. Overall industrial system boundary for allocation of IWH flows within and outside a fictitious industry plant.

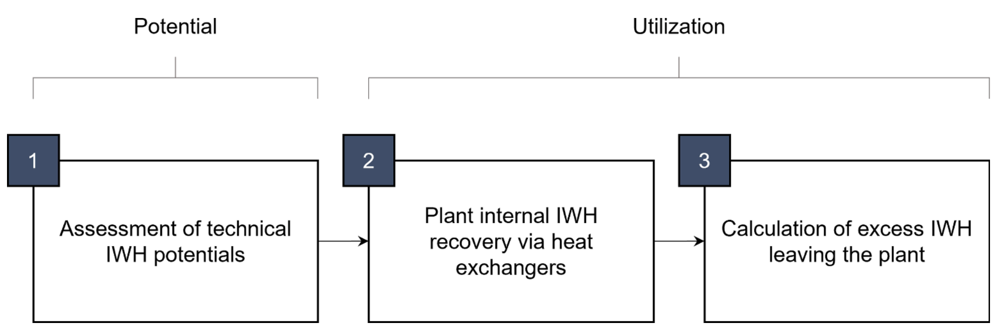

Fig. 5. Process of assessing time resolved IWH for the selected production routes in our methodology.

profiles on higher aggregated plant level, any thermal inertia effects are already included in the averaged IWH potentials from individual processes or in the process state of ramp-down. In conclusion, the time resolved behaviour of energy demand and generating waste heat for each process has to follow the same pattern of process states e.g., off, ramp-up, producing, etc.

Within our methodology, we defined a process classifying system (see Table 3). All properties are pre-defined with process specific values from literature research and can be adapted freely by the user.

Regarding the collection of IWH properties of processes, we conducted an extensive literature review for standardised production routes, which we originally defined in our prior study [10]. This approach is practically outlined in our developed case study in section 3. In general, process and subsector specific studies present data on operating temperatures. For example, Feng et al. [23] investigate the conservative iron and steel production route via blast furnaces and outline the operating temperature of the sintering plant to be around 1300 °C. Besides this, we retrieved the data on technical IWH potentials (outlet temperatures, thermal energy flows, waste heat energy carriers) either through own calculations or literature survey again: Regarding the latter, we investigated recent (heat exchanger) direct recovery technologies for the respective production routes in literature. For example, Caputo et al. [24] present data for the technical IWH potential of radiant heat exchangers for rotary kilns in cement production routes. The authors conclude that a maximum of 34.7 % of the total fuel input can be technically recovered from housed-in heat exchangers. This data is applicable to thermal energy flow of exhaust air within our methodology. For processes which bear technical IWH recovery potentials but

Table 3
Process classification in our methodology, divided into existing process properties for generating synthetic LPs and adapted IWH properties.

	Batch Operated Process	Continuous Operated Process
Standard Process Properties	• Unit Size [t] • Turnover Time [min] • Operating Time [min] • Specific Energy Consumption [kWh/t] • Energy Consumption Time Series [kWh/t per min] • Material Stream Reference Stochastic Settings	• Throughput/Capacity [t/h] • Specific Energy Consumption [kWh/t] • Material Stream Reference • Stochastic Settings
IWH Properties	• Intake Temperature [°C] • Operating Temperature [°C] • Outlet Temperature of IWH [°C] • Thermal Energy Flow [kWh/t] or Mass Flow [kg/s] and Specific Thermal Capacity [kJ/ (kg K)] of Waste Heat Energy Carrier • Waste Heat Energy Carrier	

lack underlying data in literature, we applied thermodynamic calculations on heat transfer from fuel input for retrieving their theoretic potentials. In a next step, we estimated efficiency factors for depicting their technical potential.

Fig. 6 explains the overall methodology for IWH-generating processes for energy-intensive industry sectors and the generation of simplified, time resolved profiles. Here, a production route with two processes (P1, P2) – aligned sequentially – is supplied with specific energy flows. P1 is operated as a batch process and P2 is continuously working. These operational behaviours inflict the pattern of generated LPs. The respective singular LPs of both processes are then summed up to represent the overall LP of the depicted production route. The literature data categorized in Table 3 is used for the calculation of the accumulated IWH profiles. As previously mentioned, the time resolved pattern of the generated IWH is interlinked with the time resolved energy demand. Thus, the processes' behaviour – originating from the paradigm of discrete event simulation – can be adapted accordingly. The cumulative IWH profile is then again, the sum of all singular, process specific IWH profiles. We note that, within this example, thermal inertia effects are already included on average in the IWH profile of P1 energy-wise. Due to lack of underlying data their time resolved impact on the generated IWH profile cannot be depicted yet. Additionally, we like to outline that thermal inertia effects do not impact the generated IWH profiles on a holistic energy system level to that extent, which we aim for in this study (see section 2.1). Therefore, we like to outline again that the generation of IWH profiles via our methodology does not model individual processes explicitly but depicts their average energy consumption and generation time resolved and this may limit the application of our methodology.

2.3.2. Plant internal IWH recovery via heat exchangers

We showed in the previous section that waste heat potentials of all involved processes of a specific production route can be defined via the quantitative, time resolved parameters of the temperature difference and energy flow rate [25].

Following the definition of selected production routes and its maximum technical IWH potentials (Step 1 in Fig. 5), we investigate its technical recovery within heat exchangers next. In case of cumulating more than one IWH flow from different processes, resulting parameters from Table 3 are to be generated: The corresponding quantitative parameters for cumulative, mixed IWH flows from i out of m processes are calculated via formulas (3), for sensible heat transfer (4) and latent heat transfer (5):

$$\dot{Q}_{IWH,m} = \sum_{i=0}^{m} \dot{Q}_{IWH,i} \tag{3}$$

$$T_{IWH,m} = \frac{\sum_{i=0}^{m} \left(\left(\frac{1}{k_{IWH,i}} \right) \times T_{outlet,i} \right)}{\sum_{i=0}^{m} \left(\frac{1}{k_{IWH,i}} \right)} \quad \text{with } k_{IWH,i} = \frac{1}{\dot{m}_{Carrier,i} \times c_{p,Carrier,i}} \tag{4}$$

$$T_{IWH,m} = \frac{\sum_{i=0}^{m} \left(T_{outlet,i} \right)}{m} \tag{5}$$

The corresponding HEX for recovering the technical IWH potentials time resolved is either set as operating in counter-current or co-current flow. Furthermore, a minimal temperature difference due to technical functionality and structural limits is defined within our methodology. We disregarded the options to specify HEX efficiency losses and cross-

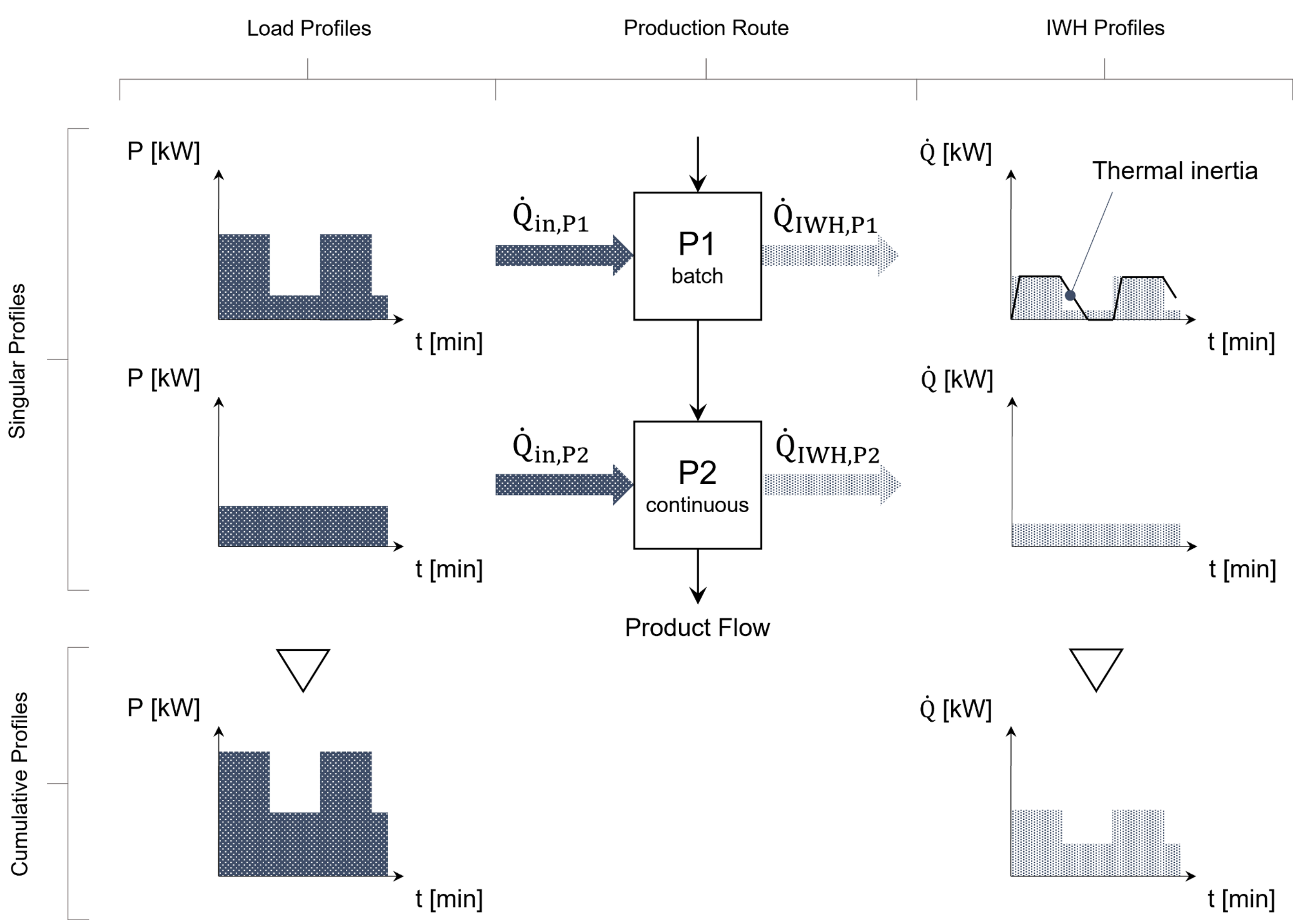

Fig. 6. Order of simplified IWH profile calculation. Thermal inertia effects, as indicated, are averaged in the following summation of IWH profiles. The timely resolution of thermal inertia effects is neglected.

current flow.

Furthermore, we note that the generation of IWH profiles through our methodology does not include optimization analyses for the most efficient waste heat utilization. Therefore, we disregarded pinch point analyses and the construction of composite curves hence these calculations require time resolved optimization. Along this, we also like to note, that the possibility of including thermal energy storage is not part of the methodology yet. As energy storage is not specifically bound to the timely production behaviour of the production route (unlike currently involved production processes), a besides developed methodology for solely depicting time resolved charging and discharging profiles should be developed in the future. To incorporate this in the presented methodology, firstly, a classification of currently developed thermal storage solutions is to be made, secondly, a method for generating IWH profiles of energy storages on the basis of discrete event simulation is to be developed and thirdly, this method is to be incorporated in the existing solutions along different use case scenarios (e.g. application of thermal peak shifting, etc.).

Fig. 7 shows the allocation of IWH from process P2 to P1 within a counter-current operated HEX for either sensible (a) or latent heat transfer for e.g., steam supply (b). The externally supplied energy demand $\dot{Q}_{in,P1}$ of P1 is to be reduced by the recovery process. $\dot{Q}_{IWH}$ is the overall waste heat potential of P2, $\dot{Q}_{HEX}$ is defined as the maximum heat flow to be recovered and utilized in P1. To successfully transfer heat, the operational state of P1 requires a temperature difference, which is given through the difference of intake (cold-end) $T_{intake,P1}$ and operating temperature (hot-end) $T_{op,P1}$. This is well-defined by the second law of thermodynamics as heat only flows from a hot to a cold state as the entropy of an isolated system always increases [26]. A corresponding $\dot{Q}$/T diagram (Fig. 7) enables the graphical evaluation of heat transfer from P2 to P1 within the HEX. Within the $\dot{Q}$/T diagram, the top line (hot curve) indicates the heat discharged from P2, and the bottom line (cold curve) the required heating demand. The marked area shows the transferred heat from P1 to P2 in total. Within this example, the mean conservative energy demand $\dot{Q}_{in,P1}$ can be substituted through the IWH recovery as the entire heating demand line in the $\dot{Q}$/T diagram can be covered by the hot curve without violating the minimal temperature difference T_{PP} (pinch point), which is given through the technical feasibility of heat conduction. Furthermore, the remaining heat flow $\dot{Q}_{excessIWH}$ of the hot curve (grey line) is to be discharged outside the manufacturing level at a temperature of T_{HEX}.

Fig. 8 shows an example of special cases of IWH $\dot{Q}$/T diagrams which can be depicted throughout our developed methodology. For all special cases, the minimal temperature difference is set to T_{PP}. We note that these examples outline analyses from a general, geometrical point of view for intersecting cold and hot curves in the context of assessing T_{HEX} or $\dot{Q}_{HEX}$. These analyses apply for sensible and latent heat transfer curves. For the latter, the slope of the curves is zero as shown in Fig. 3 (c) and (f).

Fig. 8 (a) resembles a counter-current flow HEX in which the operating temperature (hot-end) of the cold curve exceeds the outlet temperature (also hot-end) of the hot curve. In this case, only a fraction of the IWH can be internally recovered in P1. The remaining energy demand which lies between the temperatures $T_{op,P1}$ and $T_{outlet,P2}$ cannot be substituted entirely. Waste heat for external use remains.

Fig. 8 (b) shows a counter-current flow with a cold-end temperature of the hot curve above ambient temperature. Furthermore, the energy demand of the cold curve exhibits a smaller slope due to higher mass flows or a higher specific heat capacity compared to the hot-curve flow. Throughout this configuration, the generated IWH of P2 can be internally utilized for substituting a fraction of the energy demand of P1. No IWH for external use remains.

Fig. 8 (c) shows a counter-current flow- for latent heat transfer to the cold curve. Here, only a part of the required latent heat can be provided through the heat transfer.

Fig. 8 (d) resembles a co-current flow. Here, the cold curve intersects

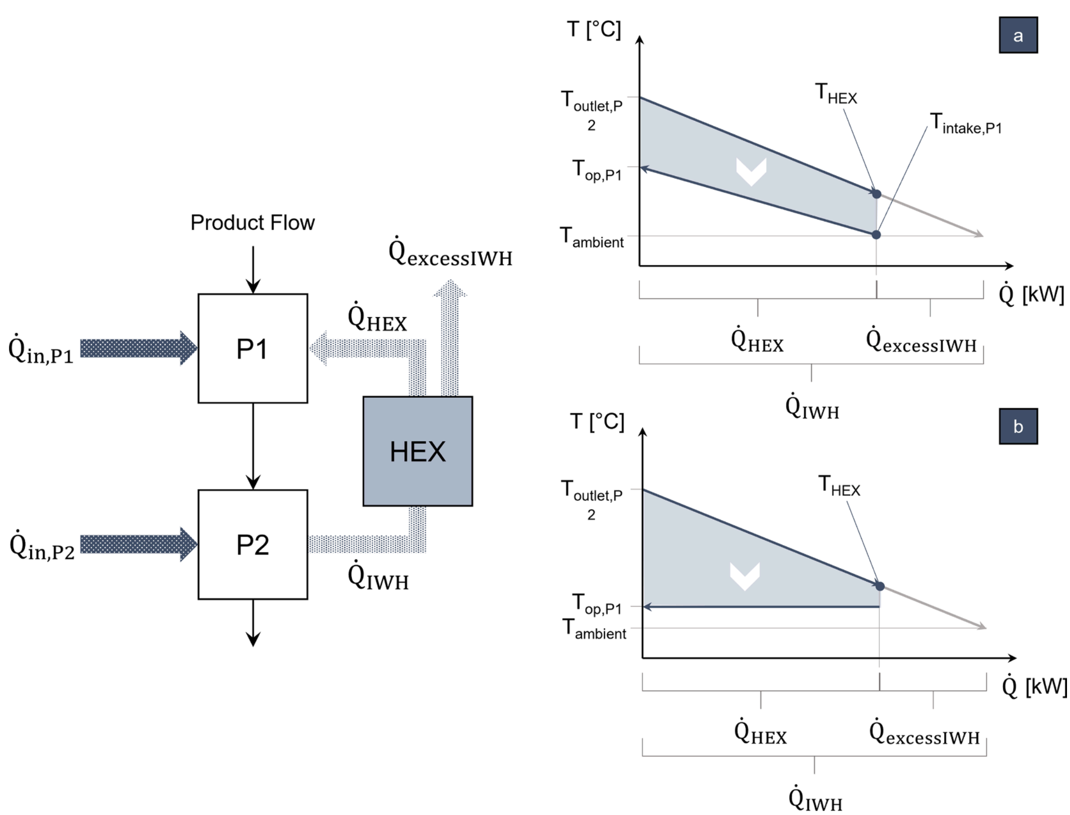

Fig. 7. Waste heat recovery between processes P1 and P2 via counter-current flow for (a) sensible or (b) latent heat transfer.

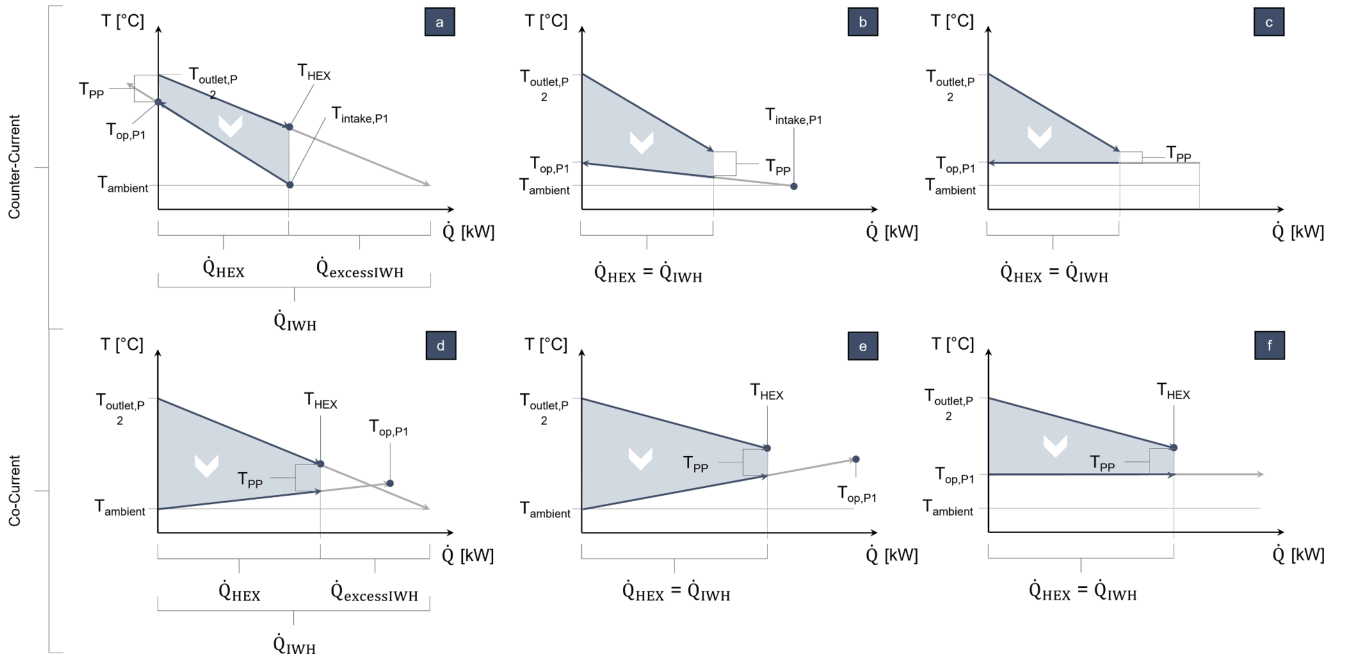

Fig. 8. IWH recovery special cases: (a) Counter-current flow with a hot-end temperature of the cold curve above the hot-end temperature of the hot curve (sensible heat transfer)), (b) Counter-current flow with a smaller slope and smaller cold-end temperature of the cold curve (sensible heat transfer), (c) Counter-current flow with no slope and smaller temperature level of the cold curve (latent heat transfer), (d) Co-current flow with the intersection between hot and cold curve (sensible heat transfer), (e) Co-current flow with the hot-end temperature of the cold curve above the cold-end temperature of the hot curve (sensible heat transfer), (f) Co-current flow with the smaller temperature level of cold curve (latent heat transfer).

the hot curve. As a result, only a fraction of the generated IWH can be internally recovered. Furthermore, the substitution of the energy demand of P1 can only be executed partially. Waste heat for external use remains.

Fig. 8 (e) is a co-current operated HEX of which the desired operating temperature of P1 lies above the cold-end temperature of the IWH generating P2 and the ambient temperature. This case allows the internal recovery of the entire generated IWH. However, because of the temperature configuration of the cold curve, only a fraction of the total energy demand of P1 can be substituted. No IWH for external use remains.

Fig. 8 (f) shows a co-current flow for latent heat transfer to the cold curve. Here, only a part of the required latent heat can be provided through the heat transfer.

To allocate recovered IWH internally, all involved processes (serial or parallel) are to be connected logically as retrieved from literature review and from our prior publication [10]. Excess heat can only be transferred if the intake temperature of an individual process equates (minus T_{PP}) the operating temperature (the outlet temperature) of the corresponding preceding process. Fig. 9 shows this approach for a simplified serial production route in general.

Within our developed methodology, buffer units to depict process route integrated storage and stock items are implemented. For example, in the Iron & Steel industry, hot coils are often placed in storage [27] before being further processed. In the meantime, these products cool down and emit heat. As this energy is recoverable under our described theoretical technical potential [28], the buffer units can be declared as IWH potentials. The data of this technical potential is again retrieved in the same manner as already mentioned in section 2.3.1. Because of the lack of underlying data from literature for this special case, we apply a theoretical calculation first. Here, the overall heat content of the buffered items (e.g., 1 tonne of steel coils) is calculated through the temperature of the items (above ambient), the specific heat capacity of steel and mass (or mass flow) of the coils. An estimated loss term adjusts this theoretical potential to represent the technical potential. This energy is then emitted through thermal convection as the waste heat carrier of exhaust/cooling air. Furthermore, all buffer units operate at ambient temperature by default. Thus, these units can be placed within the production route to disrupt the temperature gradient if necessary.

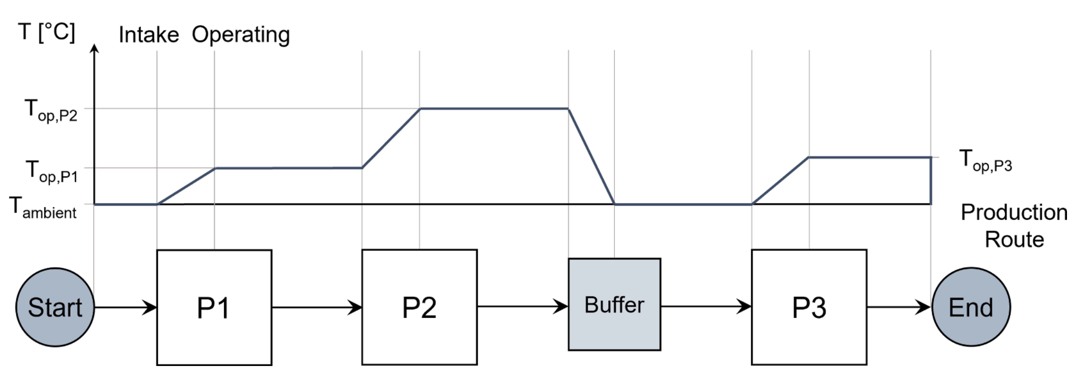

Fig. 9. Temperature gradient of an exemplary production chain.

2.3.3. Calculation of excess IWH leaving the plant

The calculation of IWH which is currently not utilized internally within the plant can be specified as excess IWH potentials. These potentials can be either used by an enhanced plant's own IWH utilization or discharged from the plant for external use. The latter indicates the possibility for district heating application if the required conditions like timely behaviour, temperature range, etc. [4] are met.

The calculation of excess IWH potentials ($\dot{Q}_{excessIWH}$) depends on the definition of implemented system boundaries, as we introduced in section 2.2. Fig. 10 (a) and (b) depict the developed approach for calculating time resolved profiles through the application of different system boundaries. This simplified example contains a counter-current flow HEX configuration with intersecting hot and cold curves within the respective $\dot{Q}/T$ diagram (sensible heat transfer). The minimal temperature difference T_{PP} is set accordingly. The intersection of energy flows with the specific system boundary defines the time resolved profile to be calculated. In this case, Fig. 10 (a) shows the result LP, when the system boundary is set to cover the energy demand $\dot{Q}_{in,P1}$ of P1. By defining the specific configuration of the implemented HEX, the fraction of the energy demand of P1 is substituted by $\dot{Q}_{HEX}$ resulting in an adapted LP with reduced demands (see Fig. 10 (a)).

To calculate the respective excess IWH $\dot{Q}_{excessIWH}$, the system boundary is to be implemented as shown in Fig. 10 (b). As the boundary intersects both $\dot{Q}_{IWH}$ and $\dot{Q}_{HEX}$, their mathematical difference resembles $\dot{Q}_{excessIWH}$ resulting in a – based upon the continuous behaviour of P2 – static profile.

With more than one HEXs implemented in a production route, the corresponding excess IWH profile is calculated by the sum of all $\dot{Q}_{excessIWH}$ profiles.

2.4. Methodology for IWH profile calculation for non-energy-intensive subsectors

The increased process and product variety in non-energy-intensive subsectors hinders bottom-up energy system analyses as applied in energy-intensive industries [10]. In our preceding study [10] we developed a new top-down approach to generate synthetic LPs (electricity and direct fuel) for non-energy-intensive subsectors. We now combine IWH calculations with the beforehand generated LPs to generate IWH profiles. Due to the nature of top-down calculations, all LPs and IWH profiles are simulated again in reference to the plant-level system boundary, as also described by our research aim (see Fig. 4).

Here, we apply waste heat fractions (WHF) to generate IWH profiles in combination with the existing synthetic LPs. The WHF f_{IWH} [-] is defined by formula (6):

$$f_{IWH} = \frac{\dot{Q}_{excessIWH}}{\dot{Q}_{in}} \quad (6)$$

As $\dot{Q}_{excessIWH}$ [W] is the rejected heat left unused within the plant border and $\dot{Q}_{in}$ [W] the cumulative energy flow into the plant, which is responsible for generating IWH which is assumed to be e.g., natural gas.

2.4.1. Data collection

We conducted extensive literature research to identify WHFs for all industrial subsectors. We found that, because of their higher potential of IWH, a significant share of WHFs refers to energy-intensive subsectors. Although we apply the WHFs to determine the IWH profiles for non-energy-intensive subsectors mainly, we included the WHFs of energy-intensive industries in our investigation to complement and validate the WHFs of non-energy-intensive subsectors at the same time.

All included studies address excess IWH potentials, which are under current circumstances not recovered on site and therefore correspond to our definition of WHFs (see formula (6)). The studies vary regarding

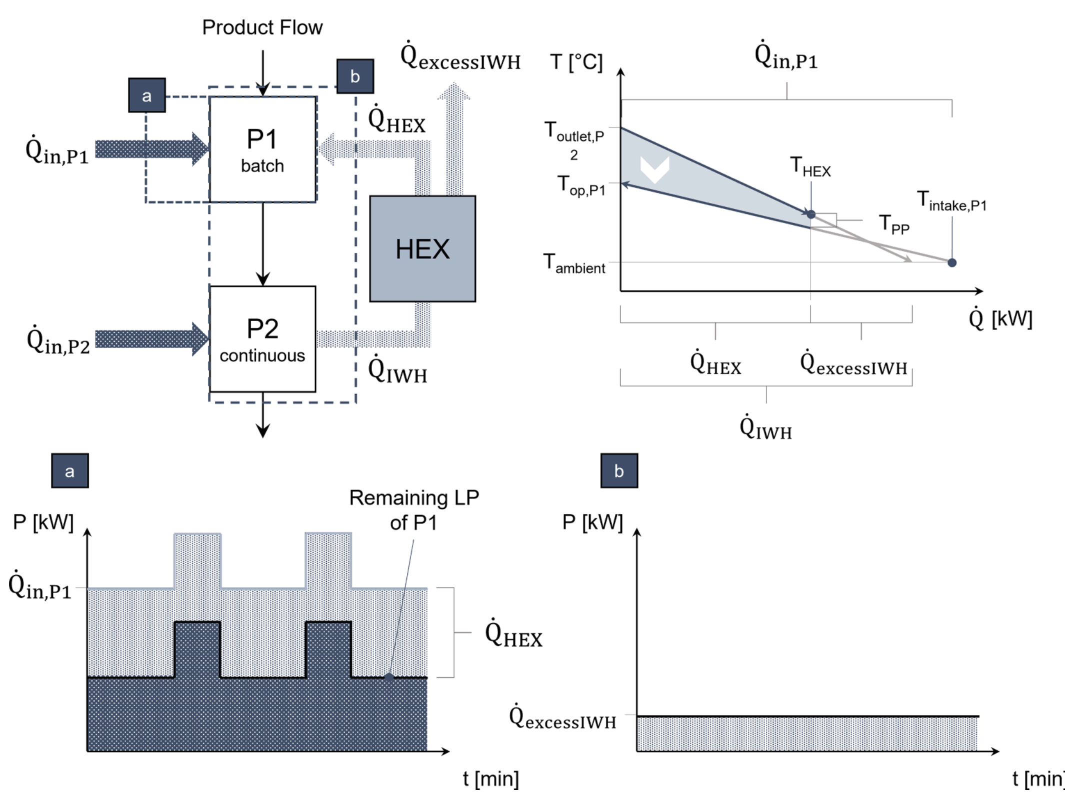

Fig. 10. Application of system boundaries for a simplified production route, (a) expressing the results for energy demand after IWH recovery and (b) remaining excess IWH potentials.

their implemented data sources (e.g., via measurements at real-life industrial plants, via combustion equations from data from the EU Emission Trading System (ETS), via conducting cross-sectoral surveys, etc.), systemic applications (e.g., country, industrial subsector, etc.) and calculation approaches (e.g. reference temperature, etc.). In overall, the reference or minimum use temperature of the excess IWH is defined as the lower limit as part of the temperature difference, which accounts for the recoverable excess heat flow. We apply this information to examine cross-sectoral IWH potentials.

Helgerud et al. [29] conducted a study for assessing the IWH potentials of Norwegian industries. Within this study, the authors examine 72 physical manufacturing plants, which make up 63 % of the overall energy demand of the industrial sector in Norway. The plant's IWH potentials, which are not further used internally, are investigated and classified by temperature levels. The reference temperature of the respective IWH potentials is 0 °C.

McKenna et al. [5] published a study investigating IWH and their technical recovery potentials via a spatial model for the UK. One of the aims of the study is to quantify IWH and its utilization. The authors, therefore, gathered WHFs from literature themselves. These sources are not included in our research. The corresponding reference temperature of all WHFs is set to 0 °C.

Hammer et al. [30] assessed the IWH potentials of industrial plants by applying bottom-up calculations for energy-intensive industries and top-down approaches for non-energy-intensive subsectors. For the first approach, the process configuration and respective waste heat properties of real-life manufacturing plants are examined. Subsequent calculations yield the estimation of WHFs. We utilized some of the process specific waste heat data within our methodology for energy-intensive subsectors, see section 2.3. Regarding non-energy-intensive subsectors, the heat demand of all industrial subsectors can be identified based on the ETS reports. The authors then apply combustion equations for known energy carriers of these subsectors to calculate the expected IWH potentials. The reference temperature for these calculations is set to 0 °C.

Pellegrino et al. [31] conducted a study on the overall industrial sector in the US. The centrepiece of their study is the evaluation of energy usage and loss patterns of single industrial sites from different industrial subsectors. Energy-related industry surveys form the basis for the calculations. The collected energy losses, which are not further utilized within the plant, are classified as excess heat leaving the plant and referenced to the ambient temperature of 25 °C.

Papapetrou et al. [32] based their work on a study, which originally assessed WHFs for the UK in 2003 [33]. The authors further adjusted these fractions to apply to the European industry of 2015. They did this by incorporating the evolution of energy efficiency, technological advancements and conditions of the European industry in these twelve years. All waste heat calculations are referred to the ambient temperature of 25 °C.

Persson et al. [3] assessed the IWH availabilities in Europe on plant level and allocated these potentials to regional and national heat consumptions of the building sector to investigate the required capacities of a future European heating grid. The basic WHFs needed for these examinations originate from 410 European real-life manufacturing plants, grouped and averaged by their industrial subsector classification and are referred to the ambient temperature of 25 °C.

Brueckner et al. [6] investigated the IWH potentials of the entire industrial sector in Germany. The calculations are based on emission data surveys of all states in Germany. The waste heat potentials are then calculated via combustion equations and are checked for plausibility by conducting selected surveys and measurements on-site. Only waste heat within flue gas is considered within this study and the reference temperature is set to 35 °C. The author reasons the definition of this reference temperature due to the limited economic feasibility of IWH recovery and its overall low potential below 35 °C.

Pehnt et al. [34] calculated the remaining waste heat potentials of the German industry for temperatures above 140 °C. To meet their goal, the authors also incorporated the WHFs from Helgerud et al. [29] for the subsectors of Iron & Steel, Chemical and Non-Metallic Minerals, but expanded the calculation of WHFs on other subsectors via top-down calculations of national energy balances.

To complement this literature survey, we included our own WHF calculations. We utilized the database *Industrial Sites: Industrial Database for EU28 + Norway* by Manz et al. [35] stating the referred subsector (NACE classification), the energy consumption and the IWH of >1000 single industrial sites in Europe. The data originates from different sources like the ETS, the European Pollutant Release and Transfer Register (E-PRTR), etc. as the retrieved information on site-specific emissions is used to adjust the mentioned parameters above. Only IWH above 100 °C is included in this database. We found 160 data points for the subsector Iron & Steel (NACE C24.1), 295 for Cement (NACE C23.5), 195 for Glass (NACE C23.1) and 410 for Pulp & Paper production (NACE C17) to be suitable for our calculations. By applying formula (6) we calculated the respective WHFs for these subsectors.

All surveyed WHFs are shown in Table 6 in the Appendix section.

2.4.2. *Data analysis and calculation of maximum use temperature*

We calculate the IWH profiles for non-energy-intensive industries by multiplying the corresponding WHFs (according to Table 6) with the LPs of the depicted manufacturing plant, generated according to the methodology described in [10]. To also successfully examine the exergetic potential (as described in section 2.1), the temperature level of the generated IWH flow is to be determined as well. The goal of our further investigations regarding the surveyed WHFs, depicted in Table 6, is therefore to compute IWH profiles together with the subsectors' averaged maximum excess temperature (hot-end) of the rejected IWH together with the defined reference / minimum use temperature (cold-end), which originates from stated literature sources from section 2.4.1.

The maximum excess temperature of IWH (T_{max}) rejected from the industrial plant is generally not given in literature. Therefore, we apply further theoretical calculations including the given WHFs and reference / minimum use temperatures (T_{min}) from the investigated literature studies to compute T_{max} for every NACE subsector. We again conduct these evaluations within a respective $\dot{Q}/T$ diagram, see Fig. 11, as T_{max} can be determined from linear regression of the literature studies' T_{min} values and corresponding assumptions of utilized thermal energy content within the plant.

In Fig. 11, the x-axis shows the relative rated thermal input based on the lower calorific value of the employed fuel. The y-axis shows the temperature in °C. For supplying useful energy to industrial end-use applications, the share of employed natural gas in comparison to all applied fuels in e.g. Austria accounts for around 54 % [36]. Here,

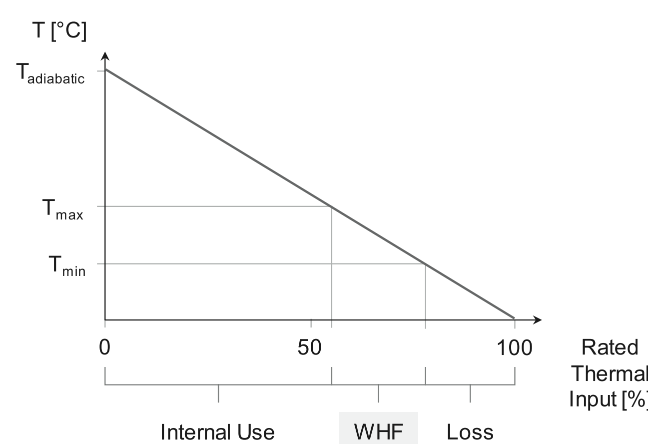

Fig. 11. Rated thermal input in contrast to adiabatic flame temperature and location of respective WHFs.

biogenic gases are excluded, but approximately make up for the same heat content as natural gas. Subsequently, we assume that natural gas, as the main employed fuel in industrial use, is to be incinerated at a stoichiometric air-to-fuel ratio of 1, whereas the condensation of involved water is disregarded (no involvement of latent heat transfers). Under these considerations, the respective adiabatic flame temperature is 1950 °C for natural gas [37]. This maximum value would be achieved within a theoretical system of no losses [38] or no heat transferred to other systems. Through this assumption, an additional datapoint next to the mentioned temperature values above (T_{max} and literature values of T_{min}) is included, additionally reinforcing the linear function in the $\dot{Q}/T$ diagram. As Fig. 11 indicates, the total rated thermal input can be divided into the following three compartments:

1) The fraction of site-own internal heat use between temperatures of $T_{adiabatic}$ and T_{max} in Fig. 11
2) The fraction of heat rejected but technical recoverable (WHF) between temperatures of T_{max} and T_{min} in Fig. 11
3) The fraction of heat "lost" or no longer considered as a result of the definition of reference / minimum use temperature T_{min}

As mentioned above, for each NACE subsector listed in Table 6, the corresponding WHFs from literature are referred to different reference / minimum use temperatures T_{min}: 0 °C, 25 °C, 35 °C, 100 °C, 140 °C, if available. The WHF externally utilized (e.g., in district heating) is a function of the reference temperature T_{min} as e.g., higher T_{min} equates to smaller shares of heat flows for properties of natural gas, while T_{max} is fixed by the cumulative IWH generation of industrial processes. In this case, T_{min} can also be referred to as the supply temperature of the given district heating system.

By incorporating the data point T_{min} and the corresponding WHF into the linear $\dot{Q}/T$ function/plot shown in Fig. 11, we can calculate the respective T_{max}. Hence our literature survey states different T_{min} values with varying WHFs based on individual methods, we averaged the resulting T_{max}. Fig. 12 shows the exemplary case of this calculation for the subsector "NACE C10 – Manufacture of food products": The literature survey (see Table 6) states WHFs for the three reference temperatures 0 °C, 25 °C and 35 °C. These data points are incorporated in the linear function disclosed by the rated thermal input [%] and $T_{adiabatic}$ of 1950 °C for natural gas, as described above. All three data points yield individual T_{max} values, of which we calculated the average to be 215 °C. As the WHFs of literature sources originate from different methodologies and databases, an underlying deviation within the calculation of T_{max} cannot be excluded definitively.

Naturally, more data regarding the WHFs of a corresponding subsector causes a more robust calculation of T_{max}. Thus, our top-down approach finds in limitations in the depiction of T_{max} for data sets with only one or two data points (e.g., "NACE C13 – Manufacture of textiles"). Additionally, there are also difficulties when examining IWH parameters of whole subsectors which are extremely heterogeneous in

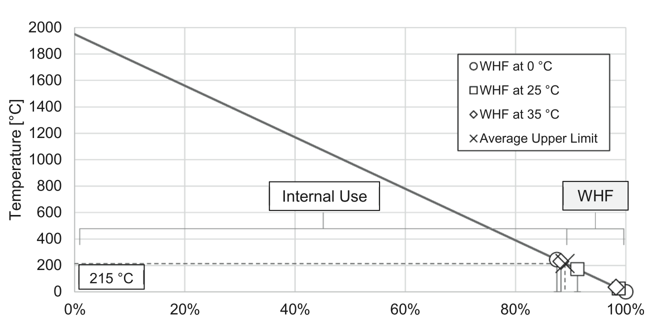

Fig. 12. Exemplary Q/T diagram and included WHFs of 0 °C, 25 °C and 35 °C of the subsector "NACE C10 – Manufacture of food products".

terms of the product and process variety. We, therefore, made plausibility checks for these calculated T_{max} values. For example, the calculation of T_{max} of "NACE C13 – Manufacture of textiles" based upon just one value, results in a staggering 600.5 °C. Panayiotou et al. [20] state that, even though the subsector employs mainly low to medium-temperature processes, manufacturing plants also might deploy dirt removal and oxidation units, which operate at high temperature ranges up to 1200 °C. This underlines that our calculations of T_{max} are subsector averaged examinations, heavily depending on the quality of the literature-based WHF.

3. Validation of developed bottom-up methodology

3.1. Overview

The functionality of the developed methodology is incorporated in a case study describing a simplified energy system of a real-life cement production plant in Austria, which directly corresponds to the explained methodology for energy-intensive industries of section 2.3. The goal of this case study is to depict the production route of the physical plant as accurately as possible via a bottom-up approach and generate synthetic LPs for electricity and fuel demands and internal and external IWH profiles of the site. Here, the focus especially lies on the generation of IWH profiles of cumulative IWH potentials, which leave the facility at plant level as excess IWH potentials. This practically employs the developed default scheme for industrial system boundaries from Fig. 4. All generated profiles are then compared to yearly energy demands and technical IWH potentials for validation since measured IWH profiles are not accessible. The yearly energy demands and technical IWH potentials of the site are a result of prior investigations conducted by Hammer et al. [30], which are not publicly available, but are to be described in the following section.

Fig. 13 depicts the overall process of IWH profile generation for this case study in line with our methodology described above. As declared, steps 1 and 2 are partly conducted by Hammer et al. [30] combined with additional data from literature and will be described in the following section. Step 3 contains the set-up of the to-be-depicted production line according to the logic of Fig. 5 from section 2.3.

Through publicly available company sources, the overall clinker production of the cement mill can be estimated at 78 t/h at full operation hours of 8000 h per year [30]. The reference temperature is set to 25 °C.

3.2. Calculation of yearly technical IWH potentials

Prior investigations on the real-life cement mill included the calculations of its yearly IWH potentials. These potentials are investigated as excess heat potentials, which could be further tapped from a technical point of view but are currently disregarded and rejected from the plant level. Regarding investigating these potentials, Hammer et al. [30] applied corresponding calculations to production units with the highest IWH potential as of cyclone preheater, rotary kiln and clinker cooler, shown in Fig. 14.

To accumulate a better understanding of heat flows within this usually closed system, we inserted sectional boundaries for those units into the overall production route, providing the opportunity to examine all processes as differentiated production steps.

Initial raw material mills grind the input materials (limestone, clay, …) to meet the required particle size. Within these mills, the raw input material is preheated from waste heat $\dot{Q}_{IWH,Cyc}$ originating from the cyclone preheater. Here, the raw material is further heated until reaching the desired material temperature of around 900 °C [39]. The following calcinatory endothermically decomposes the limestone ($CaCO_3$) into carbon dioxide (CO_2) and lime (CaO) as basis material for cement clinker production at this temperature level [40]. The energy

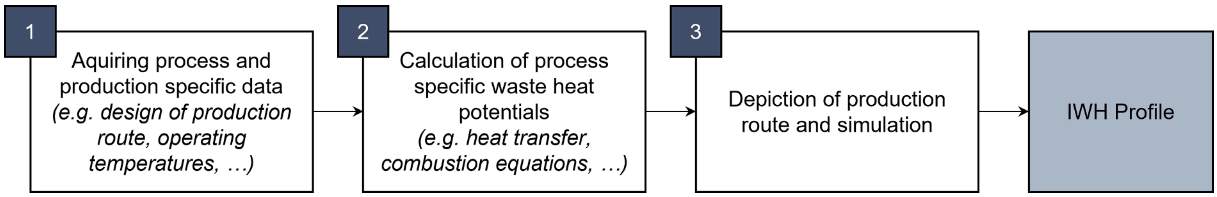

Fig. 13. Process of conducting the selected case study.

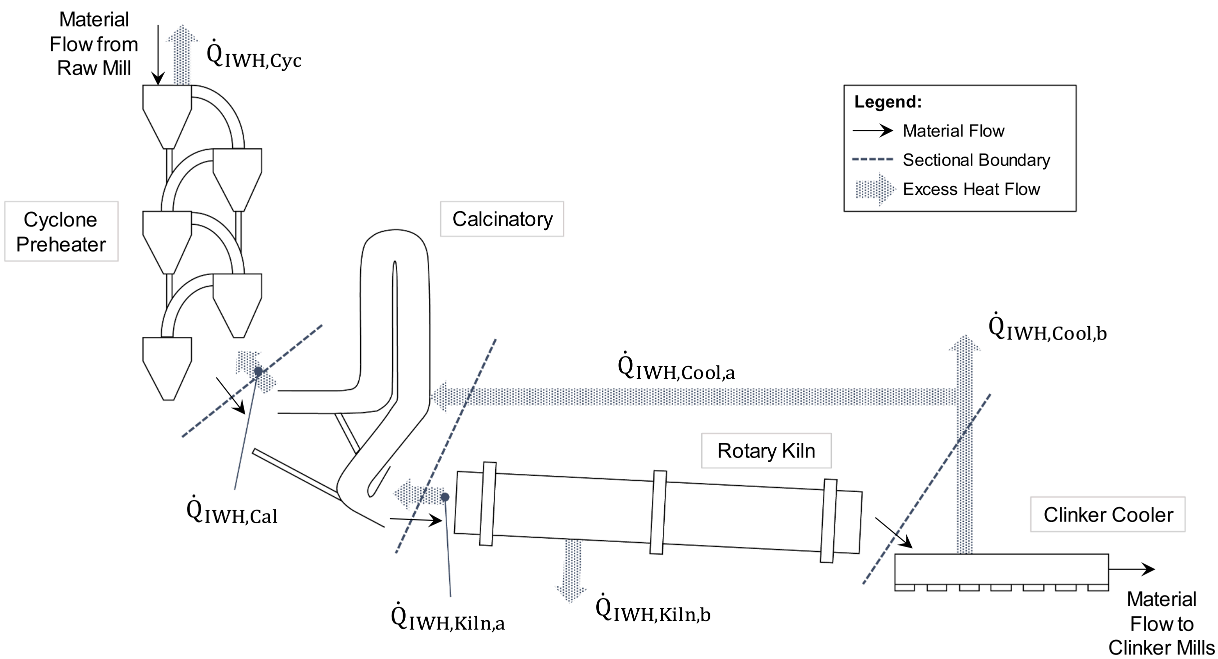

Fig. 14. Production units included in IWH potential calculations (Energy demands e.g., based on main and auxiliary firing not depicted).

demand of the calcinatory is covered by waste heat from downstream cooling units $\dot{Q}_{IWH,Cool,a}$, hot flue gas $\dot{Q}_{IWH,Kiln,a}$ at around 1050 °C from the rotary kiln and auxiliary firing of fuels (e.g. alternative fuels) [41]. The rotary kiln sinters the incoming material to compact clinker granules at elevated temperatures of 1500–2000 °C [42]. The main burners inflicting the required heating demand are located at the far end of the rotary kiln. Thus, not only hot flue gas is generated ($\dot{Q}_{IWH,Kiln,a}$) but also thermal radiation heat of the kiln itself ($\dot{Q}_{IWH,Kiln,b}$). The hot clinker leaves the kiln at 1450 °C and is cooled to temperatures of around 120 °C in a subsequent clinker cooler [43]. This cooling process is carried out by the utilization of intake cooling air. 70 % of the hot cooling air leaving the clinker cooler is recovered for covering the heating demand in the calcinatory ($\dot{Q}_{IWH,Cool,a}$) while the residue ($\dot{Q}_{IWH,Cool,b}$) is discharged to an electrostatic precipitator [44].

As we already mentioned, Hammer et al. examined the technical IWH potentials of this plant statically. We utilize their process and mass specific IWH content values for our IWH profile generation. As this production line generally applies IWH in counter-current flow HEXs, we flowingly describe the calculations by Hammer et al. backward, starting at the process of clinker cooling:

Based on the temperature difference of the cooled-down clinker (1450 °C to 120 °C) and its mass flow of 78 t/h, the overall cooling demand ($\dot{Q}_{IWH,Cool,a} + \dot{Q}_{IWH,Cool,b}$) is calculated as 8.56 MW or 109.56 kWh/t by Hammer et al. The respective cooling air/residue flue gas leaves the clinker cooler at 275–300 °C [45]. As mentioned above and by Hammer et al., 70 % of this hot gas together with the flue gas from the rotary kiln $\dot{Q}_{IWH,Kiln,a}$ preheats the calcinatory. $\dot{Q}_{IWH,Kiln,a}$ is calculated based on combustion equations for firing alternative fuels. $\dot{Q}_{IWH,Kiln,b}$ describes the thermal radiation of the kiln. Through correspondence with personnel from the cement plant, Hammer et al. estimated the heat content of the thermal radiation at around 29.25 kWh/t at 300 °C. The cyclone preheater and the calcinatory are considered as one process to calculate the generated heat flow $\dot{Q}_{IWH,Cyc}$, which consists of three fractions stated by Hammer et al.:

1) The heat content of the hot CO_2 share within the flue gas mass flow, resulting from the decomposition of limestone
2) Hot flue gas share, resulting from firing direct fuels as auxiliary burners within the calcinatory
3) The heat content of 70 % recovered cooling air from the clinker cooler

The sum of the heat content of all three fractions is around 134.01 kWh/t. The thermal radiation of both units is disregarded due to their small energy content. The temperature of this mixed gaseous flow is calculated by applying formula (6) again and can be estimated at 300 °C, which is confirmed by literature (250–300 °C) [46].

3.3. Model description and simulation

Based on the calculations by Hammer et al. above, the IWH profiles of the production route are simulated, which is to be described followingly. The full production route of this case is shown in Fig. 15.

Due the complexity of the examined production route and its underlying energy system, certain assumptions and simplifications had to be made: The residual heat content of the cooled-down clinker at 120 °C is generally removed in a follow-up post-cooling process step. This re-

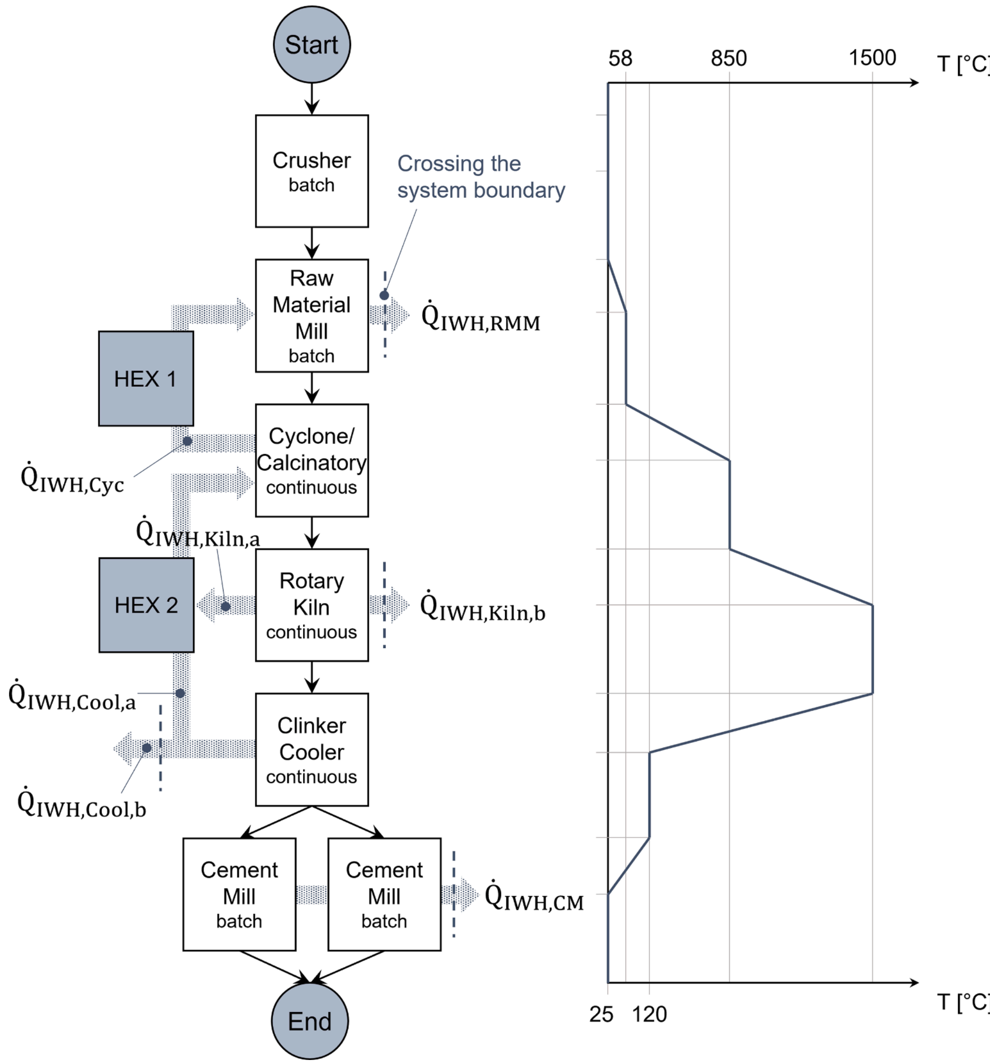

Fig. 15. Design of the selected production route for simulation. Left: Production route with associated IWH flows, allocated HEXs and system boundaries, Right: Temperature chart as of intake and operating temperature of each process.

duces the thermal stress of the material before further processing in clinker/cement mills [47]. We investigated 14.19 kWh/t to be cooled off within the post-cooling units but disregarded the implementation of this unit hence its general low energy consumption within the overall energy system. Alternatively, we attributed the IWH content to the follow-up cement mills as $\dot{Q}_{IWH,CM}$. Through personal correspondence, we found out that two cement mills are deployed at the real-life production facility. We, thus, divided the production flow of 78 t/h equally to both parallel processes, see Fig. 15.

The clinker cooler, rotary kiln and calcinatory are operated continuously. We placed the HEX 2 (Fig. 15) in counter flow operation recovering $\dot{Q}_{IWH,Cool,a}$ and $\dot{Q}_{IWH,Kiln,a}$.

Hammer et al. [30] did not further investigate the exhaust air leaving the cyclone preheater because of its general low IWH potential. In the real-life plant and within literature reviews, the exhaust air from the cyclone preheater is led into the raw material mills to early initiate the water removal process and to also precipitate gaseous SO_2 in the exhaust air [48]. We, therefore, included this IWH recovery within HEX 1 (Fig. 15), which reduces the excess technical IWH potential.

Overall, the IWH flows $\dot{Q}_{IWH,RMM}$, $\dot{Q}_{IWH,Kiln,b}$, $\dot{Q}_{IWH,Cool,b}$ and $\dot{Q}_{IWH,CM}$ contribute to the total amount of technical excess IWH potentials, which will be time resolved within the simulation. The heat flows crossing the process specific system boundaries in Fig. 15 are calculated accordingly. The corresponding operating temperatures of each process are taken from literature research [48]. The overall temperature chart of this production route is also depicted in Fig. 15. We note, that – as declared in section 2.3.2 – the intake temperatures for process specific allocation of waste heat flows originate from the operating temperatures of the preceding processes.

All incorporated IWH flows are summarised in Table 4. For example, $\dot{Q}_{IWH,RMM}$ is neither known from literature nor calculated by Hammer et al. [30]. Therefore, this energy flow is not stated but can be investigated within our simulation: $\dot{Q}_{IWH,RMM}$ is to be constituted by

Table 4
Implemented IWH flows including their respective waste heat energy carrier, upper temperature limit (hot-end) and prior calculated energy content.

IWH Flow	Waste Heat Energy Carrier	Upper Temperature (Hot-End) [°C]	Energy Content [kWh/$t_{Clinker}$]
$\dot{Q}_{IWH,RMM}$	Exhaust Air	>58 °C	To be calculated
$\dot{Q}_{IWH,Cyc}$	Exhaust Air	250–300 °C	134.01 kWh/t
$\dot{Q}_{IWH,Kiln,a}$	Flue Gas	1050 °C	210.50 kWh/t
$\dot{Q}_{IWH,Kiln,b}$	Exhaust Air	251 °C	29.25 kWh/t
$\dot{Q}_{IWH,Cool,a}$	Flue Gas	275–300 °C	76.70 kWh/t
$\dot{Q}_{IWH,Cool,b}$	Exhaust Air	275–300 °C	32.86 kWh/t
$\dot{Q}_{IWH,CM}$	Exhaust Air	120 °C	14.19 kWh/t

Table 5
Finale comparison of IWH potentials and energy consumption, including the results from this case study and the calculations of Hammer et al.

	Our Calculations [GWh]	Hammer et al. [30] [GWh]	Deviation [%]
IWH potential 25–50 °C	17.13 GWh	18.37 GWh	7 %
IWH potential 50–100 °C	34.27 GWh	35.77 GWh	4 %
IWH potential 100–400 °C	98.75 GWh	106.80 GWh	7 %
Sum IWH potential	150.15 GWh	160.94 GWh	7 %
Electricity consumption	66.67 GWh	78.13 GWh	15 %
Direct fuel consumption	624.30 GWh	610.76 GWh	2 %
Sum energy consumption	690.97 GWh	688.89 GWh	1 %
Share of IWH potential to energy consumption	21.7 %	23.3 %	7 %

determining certain degrees of freedom:

1) $\dot{Q}_{IWH,RMM}$ is a fraction of the recovered $\dot{Q}_{IWH,Cyc}$.
2) The overall specific thermal capacity of raw material $c_{p,RawMaterial}$ for a temperature range of 25–58 °C is given.
3) The upper temperature limit of the exhaust air shall exceed 58 °C as the raw material is fully heated throughout this IWH recovery.

The minimum temperature difference T_{PP} at both HEXs is set to a minimum of 10 °C. All further process specific properties are based upon our prior examinations regarding load profile generation [10].

3.4. Case study results and discussion

By designing all dedicated IWH flows in Table 4, HEX 1 (between cyclone/calcinatory and raw material mill) and HEX 2 (between clinker cooler, rotary kiln and cyclone/calcinatory) can be defined accordingly. Based on the three points of configuration the transferred heat flow in HEX 1 can be depicted by a corresponding $\dot{Q}$/T diagram, shown in Fig. 16: $\dot{Q}_{IWH,Cyc}$ represents the overall heat flow of the hot curve, the heating demand of the raw material mill the cold curve. The marked area is the overall energy recovered through HEX 1. As it can be observed in Fig. 16, the entire heating demand of the raw material mill can be covered by recovery of $\dot{Q}_{IWH,Cyc}$.

The marked square indicates the outlet temperature of HEX 1 $T_{HEX\ 1}$. The share of the hot curve which is not recovered in HEX 1 equals the unused IWH potential, which we associate to $\dot{Q}_{IWH,RMM}$ in this case. Therefore, the average heat flow of $\dot{Q}_{IWH,RMM}$ can be estimated at around 105 kWh/t at 221 °C.

HEX 2 is defined in an according manner, however, is not explicitly explained in this study.

All not recovered heat flows like the internally unused potential of the plant shown in Fig. 16 are calculated time resolved, based upon the paradigm of discrete event simulation as described in section 2.3.

Fig. 17 shows the results of the IWH calculations of this case study for a time frame of 24 h. The black curve indicates the overall IWH profile as a sum of the dedicated exergetic levels according to Table 1, which we obtained through the calculations.

There is no IWH share of the higher exegetic level >400 °C, which can also easily be derived from the information of upper temperatures of heat flows crossing the system boundary of the depicted production route, which are all set at <400 °C (see Table 4). The main share of the IWH potential can be found at the high-grade exergy level of 100–400 °C, which corresponds to the processes' upper temperatures in Table 4. In comparison, medium- and low-grade exergy IWH flows are lower affiliating to smaller temperature differences in these levels (25 °C and 50 °C) leading to smaller absolute heat flow values.

In regard to the time resolved pattern, it can be observed, that the overall IWH profile exhibits high fluctuations. As can be investigated in Fig. 15, three out of five processes generating unused IWH potentials are operated batch-wise. This operating condition includes standstill and loading times causing a timely fluctuating behaviour, which, thus, explains the dominance of the generated fluctuations.

The area under the profiles represents the accumulated energy-wise IWH potential within the time frame of 24 h. We calculate the area under the curves and scale the time frame further up to meet the full operation hours of 8000 h per year. This enables the comparison to the calculated static and technical IWH potentials by Hammer et al. [30]. As the data regarding specific IWH flows is based on their prior calculations, the deviation of our IWH profiles is expected to be minor. We furthermore generated electricity and direct fuel LPs throughout our prior developed methodology and compare the corresponding energy consumption to the static calculations by Hammer et al.

Table 5 shows the results of these evaluations. It can be observed that the overall deviation of yearly IWH potentials is – as expected – in an acceptable deviation range of 7 %, resulting from 150.15 GWh from our simulation and 160.94 GWh from Hammer et al. [30]. This deviation also corresponds well to the results within the three exergetic levels and is in general lower than the results from Hammer et al. [30]. This can be reasoned as we further implemented a HEX 1, which recovers IWH for the raw material mill, reducing the overall potential by 29 kWh/t or 18 GWh on average.

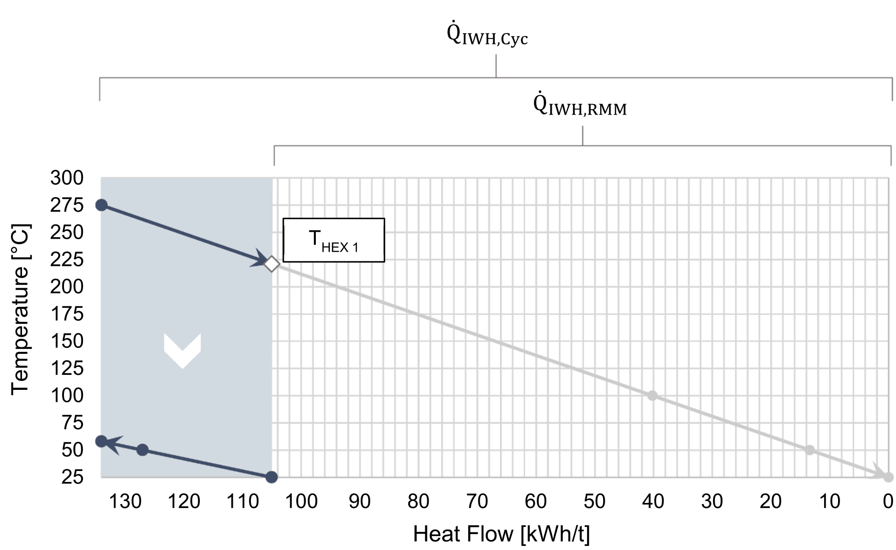

Fig. 16. Q/T diagram of HEX 1.

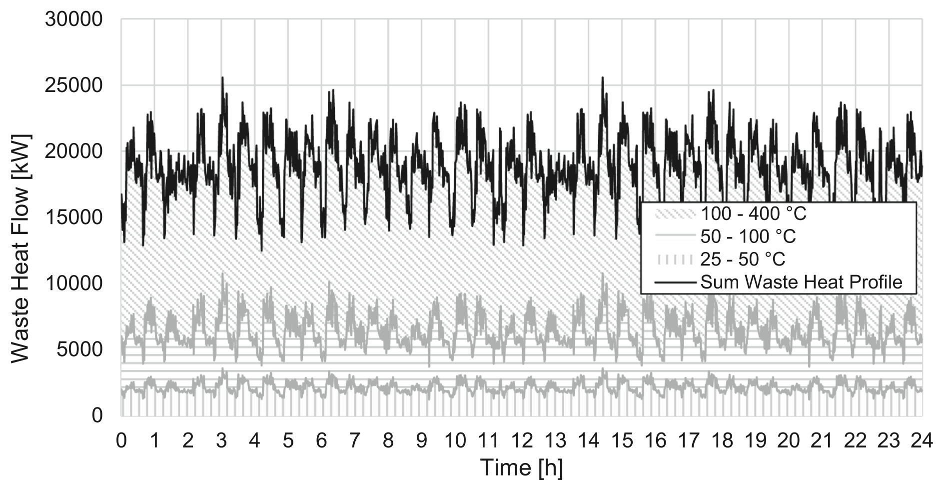

Fig. 17. Time resolved IWH profiles including exergetic classification of defined temperature levels.

As we utilized process specific data from literature further on top of the calculations by Hammer et al. these deviations could additionally be reasoned.

In regard to the generation of LPs for the calculation of electricity and direct fuel consumption, we employed our already existing methodology. This bottom-up methodology uses process specific energy consumption data from literature sources. Hammer et al. [30] utilize top-down approaches for calculating the energy consumption of the plant by investigating ETS databases. We like to note the small deviation between the two different calculation approaches. The maximum deviancy of 15 % can be observed within electricity consumption.

In this study, the share of technical IWH potential compared to the calculated energy consumption equals 21.7 %. This means that within our case study, we investigated almost a quarter of the yearly energy demand of the plant to be left unused as recoverable IWH potential. There are still various possibilities for utilizing this fraction: For example, this potential can be employed further within the plant for preheating purposes (as we demonstrated within HEX 1). The excess heat could also be potentially stored in seasonal heat storages for residential buildings or employed as steam in site-specific power generation [49]. Because the IWH potentials are still generated at high-temperature levels, current studies and investigations propose a direct thermal linkage with other industrial plants in the vicinity of the IWH producer to reduce the energy consumption of the targeted plant [50]. Furthermore, applicable incorporation within district heating systems might be advisable as well as long as its limitations (e.g. flow temperature range) are not violated [14].

In conclusion, the investigated case study exhibits acceptable results in terms of deviation from the preceding examinations of Hammer et al. [30].

4. Conclusion

Industrial waste heat (IWH) forms a central point of contact for future decarbonization measures in industry. In the context of time resolved IWH, we found that current studies either investigate single technology and process implementation for recovering IWH on a highly detailed level minute-wise or spatial on subsector level on a monthly or yearly basis. We concluded that no solution has been developed yet, which enables the generation of time resolved IWH on plant level for the entire industrial sector. As this establishes our research aim, we have developed two methodological approaches for energy-intensive and non-energy-intensive industrial subsectors which cover this research gap: Energy-intensive subsectors are well documented in literature and deploy only a limited amount of different production processes and principles [10]. We therefore developed a bottom-up approach, which connects individual processes to production routes and simulates the generated IWH based upon discrete event simulation. Non-energy-intensive subsectors deploy a vast range of different production processes and are thus to be investigated top-down. Here, we surveyed waste heat fractions from different literature sources and analysed them along thermodynamical calculations. The resulting fractions can then be employed with already generated load profiles to calculate time resolved IWH of individual industrial plants. For both approaches, we presented practical examples to constitute their functionality. In line with both methodological approaches, we now reflect on the hypotheses raised in section 1.2:

- H1: The implementation of system boundaries can be regarded as the basis of calculations for generating time resolved IWH profiles. Depending on the defined system boundaries, energy flow calculations vary regarding their results. This was practically proven by applying the standardized system boundaries of section 2.2 in the shown case study of section 3. The outlined example demonstrates the practical implementation of boundaries and their implications. As a result, it can be stated that system boundaries inflict the generated IWH profiles in terms of both time and temperature-resolved patterns.
- H2: In both proposed methodological approaches (for energy-intensive subsectors – see section 2.3 – for non-energy-intensive subsectors – see section 2.4) we found that the combination of energy flows and operating or waste heat temperatures is needed to correctly depict the timely resolution of generated IWH. This is in line with our theoretical definition of waste heat in section 2.1 and our practical investigations within the case study in section 3 proving this hypothesis.
- H3: While investigations in our shown $\dot{Q}/T$ diagrams handle mathematically averaged loads, the simulated IWH flows of time resolved profiles within internal heat exchangers or outside the plant can be subject to significant fluctuations. This, however, poses a major challenge for holistic energy system analyses. Especially, batch operated production processes inflict unstable IWH generation patterns to the overall time resolved profiles. This means that time resolved IWH assessments are required for exploiting the full potential of IWH, especially for timely unstable production processes.

The investigation of time resolved IWH offers novel insights for exploiting the whole potential this measure might bear. As a first step, our study examines this field of research successfully uncovering the complexity of this topic. This compels us to point out the necessity of examining this field of research even further. As the optimization of production routes is not a topic of this current study, it might be an important factor in future research. For example, alternative IWH recovery technologies like ORC, thermoelectric generators etc. (as explained in section 2.1) shall be incorporated in the methodology. Furthermore, e.g., pinch point analyses in also time resolved $\dot{Q}/T$ diagrams within optimization frameworks could potentially unravel these problem areas and give opportunities to utilize IWH potentials further. Also, our investigations can feed into holistic system analyses by e.g., combining spatial resolutions with IWH profiles to develop national decarbonization scenarios. Furthermore, our future work can also benefit from more detailed technological analysis, also incorporating e.g., thermal inertia effects or thermal energy storage applications into the methodology if the required data is available to a sufficient extent. Regarding thermal energy storage, next research steps can be taken by analysing the literature on current storage solutions and incorporating them along selected use case/scenarios (e.g. thermal peak shaving) in the existing methodology on the basis of discrete event simulation. Concerning the methodology for non-energy-intensive subsectors, more data on waste heat fractions can impact the overall approach in a beneficial way. This also provides room for further investigations like incorporating other energy carriers or water condensation within flue gas into the presented fit function. Regarding this, our study can be employed as the basis for the following, more complex investigations.

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CRediT authorship contribution statement

Paul Josef Binderbauer: Conceptualization, Methodology, Software, Writing – original draft. **Andreas Hammer:** . **Elisabeth Lachner:** . **Nikolaus Klingenstein:** Conceptualization, Methodology. **Thomas Kienberger:** .

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 6

Summary of literature research regarding WHFs [–] of NACE classified industrial subsectors; Maximum Use Temperature from our calculations.

NACE-2	NACE-3	Description	Helgerud et al. [29]	McKenna et al. [5]	Hammer et al. [30]	Pellegrino et al. [31]	Papapetrou et al. [32]	Persson et al. [3]	Brueckner et al. [6]	Pehnt et al. [34]	Own IWH Calculations	Calculated Max. Use Temperature T_{max} [°C]
10		Manufacture of food products	0.15	0.1			0.05	0.1	0.1			215 °C
11		Manufacture of beverages	0.15	0.1			0.05	0.1	0.14			241 °C
12		Manufacture of tobacco products					0.05		0.12			195,75 °C
13		Manufacture of textiles							0.29			600,5 °C
14		Manufacture of wearing apparel							0.06			152 °C
15		Manufacture of leather and related products				0.27			0.2			488,25 °C
16		Manufacture of wood and of products of wood and cork							0.1			230 °C
17		Manufacture of pulp and paper products			0.18	0.2	0.19	0.25	0.09		0.09	319,5 °C
18		Printing and reproduction of recorded media					0.06		0.03			117,75 °C
19		Manufacture of coke and refined petroleum products				0.28						571 °C
	19.2	Manufacture of refined petroleum products				0.28		0.25				541,75 °C
20		Manufacture of chemicals and chemical products		0.1		0.1	0.04	0.25	0.09	0.08		245 °C
21		Manufacture of basic pharmaceutical products and pharmaceutical preparations							0.08	0.03		194,75 °C

(*continued on next page*)

Table 6 (*continued*)

NACE-2	NACE-3	Description	Helgerud et al. [29]	McKenna et al. [5]	Hammer et al. [30]	Pellegrino et al. [31]	Papapetrou et al. [32]	Persson et al. [3]	Brueckner et al. [6]	Pehnt et al. [34]	Own IWH Calc-ulations	Calculated Max. Use Temperature T_{max} [°C]
22		Manufacture of rubber and plastic products							0.17	0.03		282,5 °C
23		Manufacture of other non-metallic mineral products	0.4	0.1		0.25	0.24	0.25	0.15			440,3 °C
	23.1	Manufacture of glass and glass products	0.4	0.2	0.57	0.25			0.15	0.03	0.19	471,45 °C
	23.2	Manufacture of refractory products	0.4		0.32	0.25			0.15			514 °C
	23.3	Manufacture of clay building materials	0.4		0.36	0.25			0.15			527 °C
	23.5	Manufacture of cement, lime and plaster	0.4	0.15	0.21	0.25			0.15		0.15	421,87 °C
24		Manufacture of basic metals	0.3						0.19			495,25 °C
	24.1	Manufacture of basic iron and steel and of ferro-alloys	0.3		0.19		0.33	0.25	0.19	0.3	0.33	563,75 °C
	24.2	Manufacture of tubes, pipes, hollow profiles and related fittings, of steel	0.3		0.18				0.19			436,75 °C
	24.4	Manufacture of basic precious and other non-ferrous metals	0.12	0.1			0.06	0.25	0.19	0.03		271 °C
25		Manufacture of fabricated metal products							0.19	0.03		302 °C
26		Manufacture of computer, electronic and optical products							0.18			386 °C
27		Manufacture of electrical equipment							0.31			639,5 °C
28		Manufacture of machinery and equipment							0.16	0.03		272,75 °C
29		Manufacture of motor vehicles, trailers and semi-trailers							0.12	0.03		233,75 °C
30		Manufacture of other transport equipment							0.38			776 °C
31		Manufacture of furniture							0.12			269 °C
32		Other manufacturing							0.08			191 °C
Reference / Minimum Use Temperature T_{min} from literature [°C]			0 °C	0 °C	0 °C	25 °C	25 °C	25 °C	35 °C	140 °C	100 °C	

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Article P4

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Activity	Contributing authors
Conceptualization	Binderbauer, P.J., Kienberger T.
Methodology	Binderbauer, P.J., Kienberger T.
Data curation	Binderbauer, P.J.
Software development and validation	Binderbauer, P.J.
Modelling	Binderbauer, P.J.
Investigation and analysis	Binderbauer, P.J., Woegerbauer, M., Nagovnak, P.,
Visualization	Binderbauer, P.J.
Writing (original draft)	Binderbauer, P.J., Woegerbauer, M., Nagovnak, P.,
Writing (review and editing)	Binderbauer, P.J., Kienberger, T.

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The effect of "energy of scale" on the energy consumption in different industrial sectors

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ABSTRACT

This study investigates the concept of "energy of scale" in industrial energy systems, focusing on the reduction of specific energy consumption as production capacity increases. Using data from more than 25 000 industrial plants in Europe and the United States (U.S.), we develop fit functions for different industrial subsectors to validate the "energy of scale" effect. Our findings confirm that "energy of scale" exists in industrial energy systems and varies across subsectors. The effect is consistent between Europe and the U.S. We identify that energy-consuming units involved in value creation within production chains have the most significant influence on the scaling effect. This discovery has important implications for policy makers, facility managers, and energy researchers, providing new avenues for promoting energy efficiency and supporting the transition to cleaner energy sources.

1. Introduction

The field of energy system analyses is thriving within the realm of energy-related research, decision-making policies, and business consulting. Particularly in light of current events, these methods offer a valuable tool to swiftly evaluate energy systems and grasp the rapid changes in trends and technologies (Kebede et al., 2022). By conducting spatial and time-resolved analyses, novel solutions can be derived to address unanswered challenges in achieving climate neutrality, benefiting stakeholders across various levels (Fleiter et al., 2018).

Although energy system analyses have made significant progress in the residential and mobility sectors, their application to industrial analyses is still in its early stages (Vopava et al., 2020). The industrial sector presents unique challenges due to its diverse processes, technologies, and products (Binderbauer et al., 2022). Furthermore, this sector is a major contributor to energy consumption and greenhouse gas emissions (GHG) (European Environment Agency, 2021). Consequently, energy research is increasingly compelled to develop new approaches for assessing the industrial sector from both economic and technical perspectives. Furthermore, the establishment of cross-sectoral instruments is crucial to enable comprehensive energy system analyses (Nagovnak et al., 2022).

Within this context, it is beneficial to incorporate economy-based concepts into the analysis of industrial energy systems to drive progress towards climate neutrality. When economic factors are considered alongside technical aspects, a more comprehensive understanding of the energy landscape of the industrial sector can be obtained. This integration allows for the identification of cost-effective strategies and incentives that promote sustainable practices and investments in cleaner technologies. Economic considerations help align climate goals with financial viability, making it more attractive for industries to adopt greener alternatives. Therefore, within this study we want to shed light on the connection between economic scaling effects and energy consumption of industrial plants and underline our investigations with practical, real-life data.

1.1. Economy of Scale

As we investigate the impact of the microeconomic concept of "economy of scale" (EcOS) on industrial energy systems, we first describe EcOS and its economic magnitude.

EcOS is a fundamental microeconomic concept that plays a crucial role in economic analysis and business strategy. It explains the relationship between the average unit costs of producing a specific good or service and the scale of production. As production output increases, there is a correlation of decreasing average unit costs. However, if the average unit costs increase with higher production output, the indication of "diseconomy of scale" is present, as depicted in Fig. 1 (Besanko

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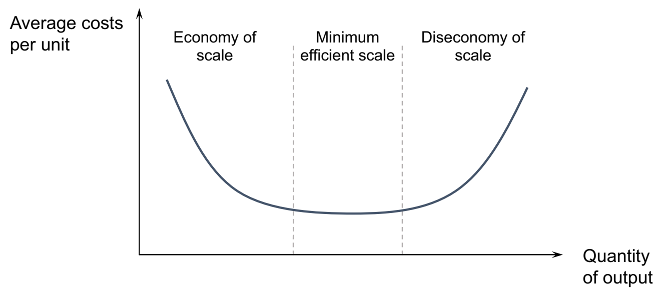

Fig. 1. The EcOS effect areas in a U-shaped pattern.

et al., 2013).

A closely related concept is "economy of scope", which examines the impact of producing a variety of goods or services together rather than separately. When a company expands its range of products, there is a decrease in average unit costs, indicating economy of scope (Panzar and Willig, 1975).

In economic-related investigations, two types of average cost curves are commonly used to illustrate the effects of EcOS. The first type exhibits a U-shaped curve, suggesting that as production output increases, manufacturing plants initially experience EcOS. This leads to a decline in average unit costs. However, there is a plateau at the minimum efficient scale, where average unit costs remain constant. Beyond this point, "diseconomy of scale" emerges, which causes average unit costs to increase in large quantities of production (see Fig. 1). The curve depicts this initial cost reduction, followed by a flattening and subsequent increase in average costs due to impacts such as limited resource duplication, land or managerial skills, and increasing coordinational complexity (Silvestre, 2018).

The second type of average cost curve is L-shaped, assuming a decrease in average costs to a minimum efficient scale followed by a plateau of constant average unit costs. It does not exhibit "diseconomy of scale" at higher output levels (Besanko et al., 2013). Existing studies for various industrial subsectors (Johnston, 1956) indicate that real-life manufacturing plants typically show L-shaped unit cost regression rather than U-shaped. The strategic significance lies in determining the minimum efficient plant size (MEPS), which represents the point of minimum production capacity for optimal cost efficiency (see Fig. 2). MEPS depends on the capital intensity of the industrial location (Panzar and Willig, 1975) and serves as an indicator of market size and the market share held by the plant owner. A high MEPS-to-market size ratio implies increased market power (Pratten, 1972).

EcOS originates from two main factors of spreading of fixed costs and the physical properties of production. Fixed costs, resulting from indivisibilities in the production process, can be spread over a larger volume of output as production increases, leading to a decrease in average unit costs. The physical properties of production, such as the cube-square rule, also contribute to EcOS by allowing production capacity to increase at a faster rate than costs. Other factors, such as inventory management, density economics and division of labor, also contribute to EcOS. The experience curve, on the other hand, relates to cost reduction through accumulated knowledge and experience over time. Although closely related, the experience curve and EcOS are distinct concepts (Yelle, 1979).

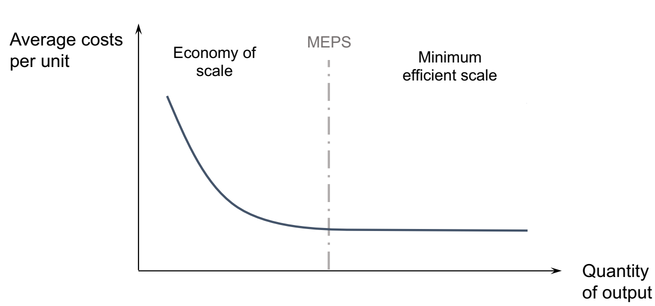

Fig. 2. The EcOS effect areas in an L-shaped pattern including the point of minimum efficient plant size (MEPS).

1.2. Energy-related Investigations in Literature

The connection between EcOS and its impact on industrial energy systems has not been thoroughly investigated in the existing literature. However, studies have explored the concept of "economy of scale" in the context of residential buildings and electricity generation:

Ironmonger et al. (Ironmonger et al., 1995) examined energy use in residential households with a focus on EcOS per capita. They analyze real data from the Australian Bureau of Statistics, considering household sizes ranging from one to five residents. Through a comprehensive demographic study, the authors observed a consistent decrease in Australian household sizes over the past 80 years. As a result, they predict that the energy consumption of residential housing per capita will increase exponentially if the trend of decreasing household size continues in the future.

Browning et al. (Browning et al., 2010) employ the concept of EcOS to model residential households' energy consumption. Their study evaluates expenditure patterns for various household scenarios, such as individuals living alone or married couples with income disparities.

Nowakoski et al. (Nowakoski and Loomis, 2023) investigate the impact of EcOS on the wind industry in the United States since 1980. The authors analyze the trend towards larger wind turbines and wind farms, examining the economic performance and future potential of onshore and offshore wind turbine industries. The study demonstrates how the wind industry has successfully utilised EcOS to reduce electricity production costs significantly, making wind energy competitive with conventional fossil-fuel power generation alternatives.

Although these studies shed light on the application of EcOS to energy consumption in buildings and to energy generation of wind farms, there is still a need for research exploring the direct link between EcOS and industrial energy systems. Further research is needed to understand the potential implications and benefits of EcOS in the industrial sector. Within our work in industry- and energy-related research, we discovered that industrial energy systems strongly correspond to the economic paradigm of EcOS. To our knowledge, this is the first study that practically proves the correlation between industrial energy consumption and production capacity by examining extensive amounts of data originating from European and American manufacturing locations. We namely denote this effect as "energy of scale" (EnOS).

1.3. Research Hypotheses and Structure of this Paper

By investigating >25,000 individual georeferenced manufacturing plants from Europe and the U.S., our goal is to find new correlations of the application of scaling production capacities regarding energy consumption for industrial energy systems. To envelop our examinations, we formulate the following scientific research question:

- Q1: Can a scaling effect for energy consumption in the industry be practically identified based on the existing paradigm of EcOS?
- Q2: What methods and classifications must be deployed to investigate the effect of EnOS? Which limitations and scope of application arise from these examinations? What underlying effects impact the formation of EnOS? Are there interlinks to the existing paradigm of EcOS?
- Q3: What potential fields of applications does the discovered effect of EnOS have? Which stakeholder groups can benefit from these investigations?

Throughout this study, we answer the research questions proposed above. In Section 2, we describe the overall methodology of this study. Firstly, we classify the industrial subsector by already developed classification schemes by the European Commission (Section 2.1). In Section 2.2, we introduce a universal definition of industrial energy systems, to which we refer our following investigations of plant-specific energy consumption and origins of EnOS. Section 2.3 describes the overall data handling methods when generating fit functions of EnOS and verifying their statistical significance via dedicated tests. These methods are practically outlined in Section 3 as we demonstrate the EnOS paradigm and its statistical testing (Section 3.2) for a selected industrial subsector. We discuss these results and describe possible fields of application of EnOS in Section 4. We conclude our study with finishing statements in Section 5. At last, the appendix furthermore includes the fitted parameters for electricity and natural gas consumption of all investigated industrial subsectors as well as the graphic representation of EnOS of an additional subsector.

2. Methodology

In this section, we describe the applied standardised methodology of approaching the paradigm of EnOS. As a basis for our investigations, we first classify the industrial sector and the industrial energy system. Subsequently, we illustrate the data handling methods we utilised in our work.

2.1. Industry Classification

Within this study, we approach the industrial energy system from a top-down point of view. A top-down methodology generally examines highly aggregated data that is combined and analysed to gather correlations and insights on functionalities of more detailed aggregation levels (Widén et al., 2009). Compared to bottom-up calculations, this approach offers the advantage of deriving cross-sectoral conclusions and strategies with a limited amount of data available. As we encounter the industrial sector in terms of energy consumption and economic behavior such as production capacities, etc., a concise classification of the corresponding energy system is a mandatory field of action.

We divided the industry into energy intensive and non-energy intensive subsectors (International Energy Agency, 2022). Fig. 3 shows the respective comparison of these two groups (Rieseberg and Wörlen, 2012). Energy intensive industries exceed in terms of overall energy consumption and greenhouse gas (GHG) emissions (European Commission, Statistical Office of the European Union, 2021). Therefore, they are often the central topic in energy-related research areas. However, when examining both groups more thoroughly, it can be derived that non-energy intensive industries are, in fact, of high relevance in terms of their involvement in the overall economic landscape. This can be explained by the higher shares of gross value added, number of employees and enterprises (European Commission, Statistical Office of the European Union, 2021). Thus, we conclude that energy system analyses and their impact on strategic decision-making processes should not be exclusive to energy intensive industries, but also include non-energy intensive subsectors to derive holistic solutions for inducing climate neutrality in industry and sustaining the economic landscape.

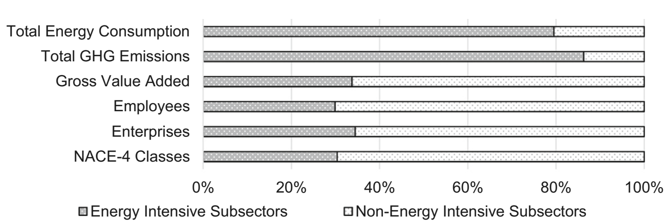

Fig. 3. Comparison of energy intensive and non-energy intensive industries by total energy consumption, total GHG emissions, gross value added, number of employees, enterprises in Europe and subsectoral classification.

Besides the definition of energy intensive and non-energy intensive subsectors, other classification schemes have been developed, which classify the industry on different aggregation levels in further detail. The most prominent classifications are based upon the work of the International Energy Agency (IEA) (International Energy Agency, 2022) and the European "Nomenclature statistique des activités économiques dans la Communauté européenne" (NACE). The corresponding association between all groups is shown in Table 1. The NACE classification itself categorises all manufacturing activities further by introducing a graduated digit-based system. For example, "C24 – Manufacture of basic metals" (NACE-2) can be further disaggregated to "C24.4 – Manufacture of basic precious and other non-ferrous metals" (NACE-3) and "C24.4.2 – Aluminum production" (NACE-4). Within this study, we apply only the overall sector and NACE classification.

2.2. Industrial Plant Boundaries

Fig. 4 shows the definition of the systemic boundaries and included energy conversion units for industrial plants in general (Binderbauer et al., 2022). The plant boundary marks the inclusion of plant-owned on-site units (for both energy transformation and final energy utilisation) and the exclusion of off-site energy generation and grid systems. The public grid can supply the plant with energy, as the latter can also supply the grid (e.g. in case of waste heat or excess electricity production).

Table 1
Comparison of industrial classification schemes.

Overall sector classification	IEA classification	NACE-2 classification
Energy intensive	Iron & Steel (& Non-Ferrous Metals)	C24 – Manufacture of basic metals C25 – Manufacture of fabricated metal products, except machinery and equipment
	Pulp & Paper	C17 – Manufacture of paper and paper products C18 – Printing and reproduction of recorded media
	Chemical & Petrochemical	C19 – Manufacture of coke and refined petroleum products C20 – Manufacture of chemicals and chemical products C22 – Manufacture of rubber and plastic products
	Non-Metallic Minerals	C23 – Manufacture of other non-metallic mineral products
Non-energy intensive	Wood & Wood Products	C16 – Manufacture of wood and of products of wood and cork
	Machinery	C26 – Manufacture of computer, electronic and boards C27 – Manufacture of electrical equipment C28 – Manufacture of machinery and equipment
	Food, Beverages & Tobacco	C10 – Manufacture of food products C11 – Manufacture of beverages C12 – Manufacture of tobacco products
	Mining & Quarrying	B – Mining and quarrying
	Automotive	C29 – Manufacture of motor vehicles, trailers and semi-trailers C30 – Manufacture of other transport equipment
	Textiles & Leather	C13 – Manufacture of textiles C14 – Manufacture of wearing apparel C15 – Manufacture of leather and related products
	Other	C21 – Manufacture of basic pharmaceutical products and preparations C31 – Manufacture of furniture C32 – Other manufacturing

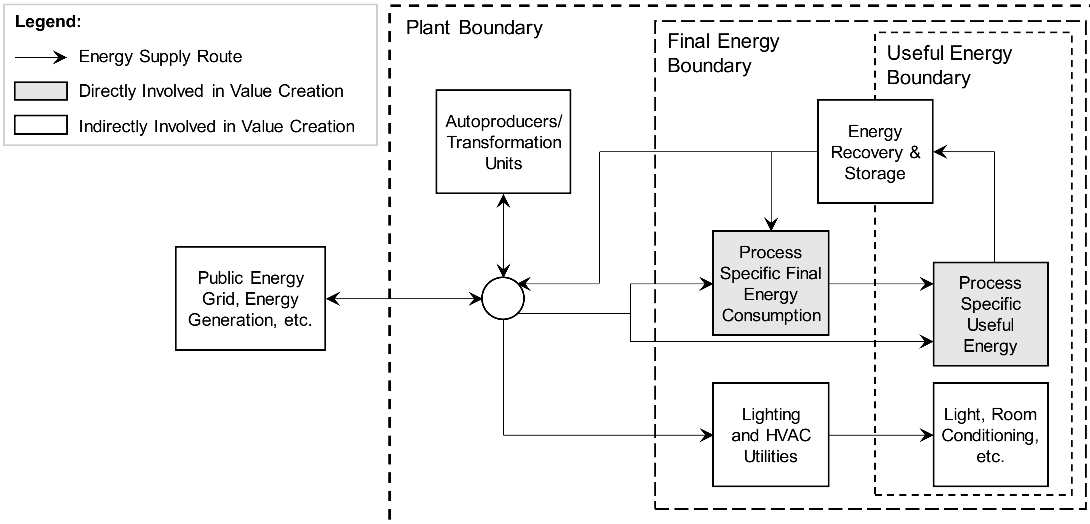

Fig. 4. A standardised definition of the energy system of industrial plants.

Within the plant boundary, the energy from the grid is distributed to different energy-converting/consuming units, which can either be directly or indirectly involved in the value creation process.

Autoproducers or transformation units (e.g. CHP plants, blast furnaces, power plants, …) convert energy from outside the plant or within (e.g. from other auto producers) and output the respective transformed energy for final energy application (e.g. electricity from power plants) or to the public grid (e.g. waste heat from blast furnaces). Within the final energy boundary, final energy is consumed (e.g. electricity or fuel demand of processes or lighting and room conditioning utilities) and converted to applicable useful energy (e.g. process heat, lighting, room conditioning and heating, …). Along this way, energy can be recovered or stored and applied for internal (e.g. waste heat recovery) or external (e.g. district heating) applications.

Units directly involved in value creation are processes which are mainly responsible for creating a product, e.g. the production route itself, and therefore directly correspond with the production output. Accompanying units, which are indirectly involved in value creation, support the production process, for example, by providing light or storing excess energy (Thiede, 2012).

Our following examinations of EnOS correspond to the plant boundary and therefore involve all on-site energy conversion units.

2.3. Methods for Exploring EnOS

As our goal within this study is to prove the significance of the discovered EnOS effect, we extensively enhance our databases and methodology by incorporating data curation and statistical tests. This

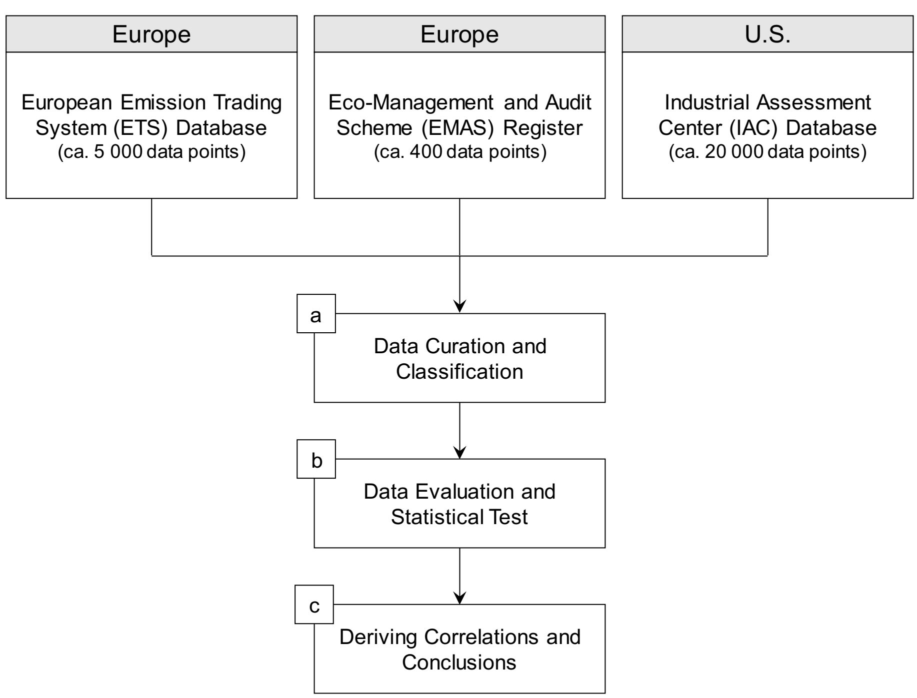

Fig. 5. The overall methodology for investigating the effect of EnOS on the European and American industrial landscape; Three georeferenced databases are included in our analysis as we (a) align and curate the data to meet corresponding comparability, (b) develop and evaluate fit functions, as well as statistically test our hypotheses, and (c) derive correlations from our mathematical findings.

enables the investigation of EnOS and its specific impact on every industrial subsector as well as the derivation of conclusions for finding the correlation to economic effects and its cause.

Fig. 5 explains the overall methodology to investigate EnOS in the industry. The basis of our study forms three dedicated databases and sources, which state plant-specific information from Europe and the U. S.:

- European Emission Trading System (ETS) database (European Commission, 2023a): The ETS database is a crucial tool for monitoring and managing carbon emissions in the European Union (EU). It acts as a central hub to keep track of emissions allowances, verified emissions reports, and the companies involved. The database enables companies to trade emissions permits, which encourages them to reduce their greenhouse gas emissions. This market-based approach promotes the adoption of cleaner technologies and helps the EU meet its climate goals. The ETS database ensures transparency and accountability through regular monitoring and reporting, making emissions trading an effective tool for promoting environmental sustainability in Europe. Pezzutto et al. extracted around 5000 individual data points from this database and included auxiliary data from other sources like E-PRTR (European Pollutant Release and Transfer Register), VDeH Steel database, RISI Pulp and Paper etc. We incorporate this data set into our method. The dataset is accessible through: https://gitlab.com/hotmaps/industrial_sites/industrial_sites_Industrial_Database.
- Eco-Management and Audit Scheme (EMAS) register (European Commission, 2023b): The EMAS register database is a valuable resource for monitoring and recording environmental performance within the EU. It serves as a central repository for companies and organizations that have voluntarily implemented EMAS, providing information on their environmental management systems, achievements, and audits. The database promotes transparency and accountability by offering public access to environmental data, allowing stakeholders to assess the ecological impact of registered entities. EMAS register database encourages continuous improvement and sustainable practices by recognizing and rewarding organizations that demonstrate commitment to environmental stewardship, ultimately contributing to a greener and more sustainable Europe. We extracted data from around 400 individual reports covering information from single manufacturing facilities like in the ETS database above. The dataset is accessible through: https://webgate.ec.europa.eu/emas2/public/registration/list
- Industrial Assessment Center (IAC) database (Industrial Assessment Center, 2022): The IAC is a programme formed around 31 technical universities in the U.S. and is funded by the U.S. Department of Energy (DOE). The objective of the programme is to support industrial companies in reducing energy use and cost, as well as implement new technological advances such as waste heat recovery, electrification, etc. The IAC conducts energy audits and assessments in participating sites and proposes plant-specific improvements for the energy system. All evaluations and recommendations of anonymous sites are accumulated within the IAC database. Here, plant-specific data like sectoral allocation, production capacity, energy consumption, etc. is listed within over 20,000 data points. The dataset is accessible through: https://iac.university/#database

The main contributions from all mentioned databases are data points from individual real-life manufacturing plants containing their respective subsector allocation, electricity consumption, natural gas consumption, production capacity and fiscal year. To achieve valid comparability of this data from the three databases, corresponding alignment measures must be taken into account (Fig. 5 (a)): Regarding the IAC database, all subsectoral data is referred to SIC (Standard Industrial Classification) codes (Fertuck, 1975). These are manufacturing classification codes utilised in the U.S. and are to be converted to NACE codes in the first step. Concerning the production capacity, the corresponding unit is varyingly disclosed as tonne, kilograms, pieces, square or cubic metres etc. for different industrial subsectors. As the unit of pieces is deceptive, we agreed to convert this unit into tonnes by surveying the average weight of manufactured products within the selected NACE subsector. For example, in "C28.3.0 – Manufacture of agricultural and forestry machinery" the weight of a respective product can be estimated to be around 20 t (Horn et al., 2004). Overall, the unit of production capacity targeted for our studies is tonnes. This data classification process is interlinked with a follow-up data curation, which sorts out raw data outliers above 95 % or below 5 % of production capacity and energy consumption for each subsector.

In the next step, the curated and subsector-resolved data is evaluated and fit functions for EnOS are derived (Fig. 5 (b)). The development of these functions to the raised energy data for individual NACE subsectors in correspondence to EcOS is the main part of our analysis within this work. In the next step, we prove the statistical significance of the EnOS functions developed by conducting statistical *t*-tests and linearity tests (Verma and Abdel-Salam, 2019). Thus, we can reason the mathematical significance of EnOS. We note that data availability varies depending on the NACE subsector. Our first approach is to generate fit functions for the NACE-2 codes. If the number of data points is high enough to derive these correlations at a lower aggregation level, the NACE-3 or NACE-4 subsectors are additionally examined. We set a threshold of 75 data points per subsector. In this case, if the subsector exhibits <75 data points at a respective NACE level, we moved up to a higher NACE level to include other subsectors in this class as well. We present the development of fit functions and the conduction of statistical tests for a representative subsector in Section 3.

Table 2 shows the design of the joint dataset out of the individual three databases above. The output parameters after our analysis are shown in Table 5 in the appendix.

Finally, we discuss the paradigm discovered by EnOS and its possible impact and potential in the future analysis of the energy system (Fig. 5 (b)). Additionally, we derive possible origins of EnOS by establishing comparisons with EcOS in Section 4.

3. Results of EnOS

3.1. Data Evaluation for Selected NACE Subsector

When investigating the parameters of electricity consumption, natural gas consumption and production capacity of single real-life manufacturing plants within all databases, a correlation of the pronounced EnOS effect can be clearly assessed between the specific energy consumption (SEC) e [kWh/t] and the production capacity C [t].

Fig. 6 to Fig. 9 show exemplary results of this data extraction and evaluation for the sector "C25 – Manufacture of fabricated metal products, except machinery and equipment". We conducted data evaluation for electricity and natural gas consumption respectively. Although Figs. 6 and 7 indicate EnOS within a linear plot similar to Fig. 1, we also included double-logarithmic versions for both energy carriers to enable a more transparent evaluation.

All drawn scatter points resemble the data of single manufacturing facilities from the U.S. and Europe, consistent with the before mentioned databases. Due to the smaller data sets of European databases, the number of individual data points is reduced. In the case of the selected subsector, 351 data points are overall included in the corresponding plots after data curation, of which 24 originate from Europe.

We conducted data fits via power functions (see the linear plots in Figs. 6 and 7) following the formula (1):

$$e = b \cdot C^{m} \tag{1}$$

Such power functions appear as linear relationships in the double-logarithmic plots of Figs. 8 and 9. From a mathematical point of view, the observed linearity resembles the effect of EcOS (Berthouex, 1972),

Table 2
Design of joint database and included parameters.

NACE subsector	Number of locations / datapoints	Yearly electricity consumption [kWh]	Yearly natural gas consumption [kWh]	Yearly production capacity [t]	Slope electricity m [kWh/t^2]	Intercept electricity b [log (kWh/t)]	Slope natural gas m [kWh/t^2]	Intercept natural gas b [log(kWh/t)]
	Input parameters				Output parameters			
…	…	…	…	…	…	…	…	…

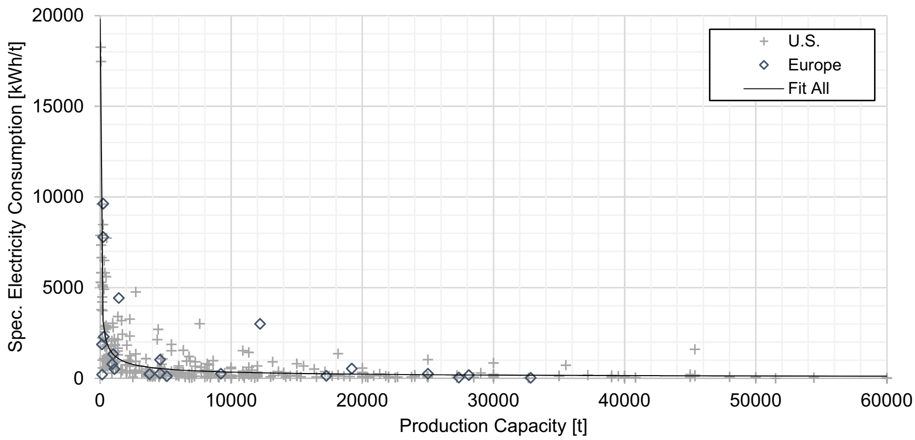

Fig. 6. NACE 25 - EnOS effect of electricity (linear plot).

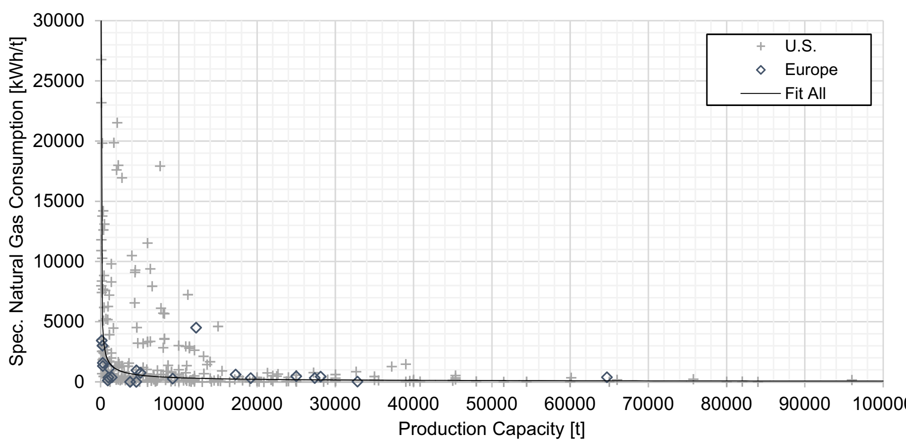

Fig. 7. NACE 25 - EnOS effect of natural gas (linear plot).

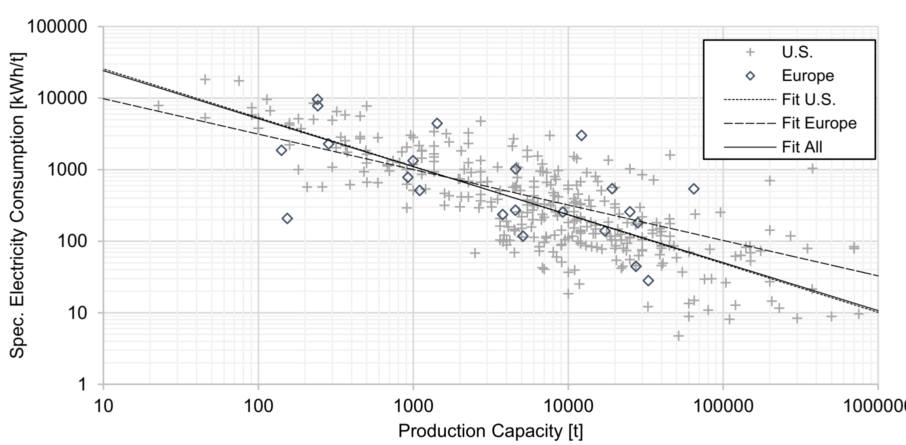

Fig. 8. NACE 25 - EnOS effect of electricity (double-logarithmic plot).

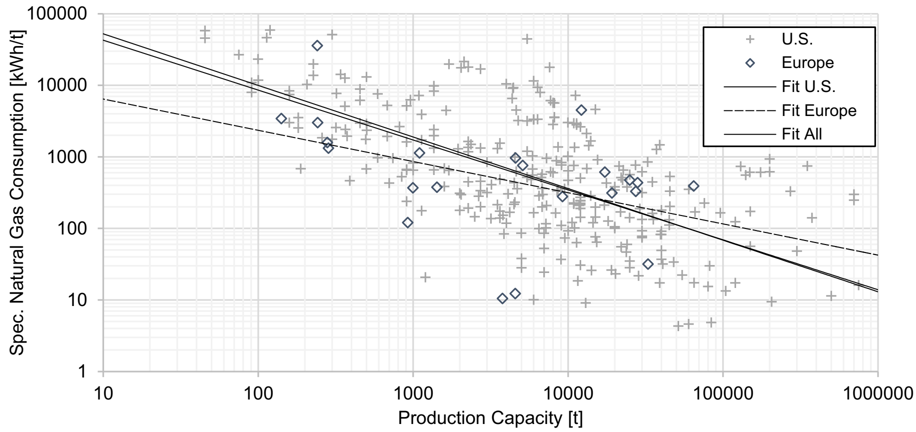

Fig. 9. NACE 25 - EnOS effect of natural gas (double-logarithmic plot).

which can be deemed as the first concrete point of proof for EnOS (see Section 1.1). The linear correlation of both logarithmic variables (in the case of EnOS: the dependent variable of SEC and the explanatory variable of production capacity) can be expressed by applying formula (2):

$$log(e) = b - m \cdot log(C) \quad (2)$$

In formulas (1) and (2), e represents SEC [kWh/t] and C represents the production capacity [t] in our case. The values b and m equal the intercept and slope of the linear fit accordingly. By applying the double-logarithmic approach, the accumulation of data points in areas of high density (the near of the origin in the linear plots) can be evaluated in more detail.

Figs. 8 and 9 furthermore include fits of the U.S. and European data points and the overall fit of the entire data. The parameters of these exemplary fitted plots are shown in Table 3.

The major observations can be declared as follows:

1. All data points follow a linear regression within the double-logarithmic plots. This corresponds to the mathematical formulation of EcOS. Within the linear plots, the scaling effect is shown as power functions. The specific energy reduction effect gets increasingly weaker at higher production capacities (around >20,000 t for electricity and > 3000 t for natural gas), indicating the existence of a possible optimum point for subsector-specific facility system size and production output.
2. Natural gas consumption data appears to be subject to higher fluctuations compared to electricity. This can be seen by examining the residuals of the data points in Fig. 9 compared to the shown fit curve. We experienced this result in all investigated NACE subsectors.
3. It can be observed that the fits of the American data correspond well to the European data. In all evaluations, the fitted European slope is reduced minimally.

We discuss and reason these observations in the interpretation and discussion part of this study (Section 4) accordingly. Furthermore, the fitted parameters of all investigated industrial subsectors as well as additional double-logarithmic plots of the EnOS effect for the sector "C23 – Manufacture of non-metallic mineral products" are included in the appendix part of this study. The observations described above (except for capacity specifications) apply to all other investigated subsectors.

Table 3
Fitted parameters of subsector "C25 – Manufacture of fabricated metal products, except machinery and equipment".

Energy carrier	Slope m [kWh/t^2]	Intercept b [log(kWh/t)]
Electricity	0.68	5.12
Natural gas	0.70	5.33

3.2. Statistical Testing

By conducting tests, we verify the statistical significance of the observations made above. We mainly validate the corresponding application of linear fits within the double-logarithmic plots of specific electricity and natural gas consumption to confirm the correlation between SEC and production capacity (Montgomery et al., 2021). We check our assumptions and observations by investigating the correlation within EnOS via four evaluations for cumulative fits (see Figs. 10 and 11) (Verma and Abdel-Salam, 2019):

1. Check on linearity and calculation of Pearson correlation factor r
2. Independence of residuals and calculation of the respective correlation
3. Normality of residuals
4. Conducting *t*-tests on linear slopes

We already observed a linear relationship between SEC e and production capacity C through the corresponding figures and, as also stated above. The Pearson correlation factor r indicates the strength of the correlation as absolute values >0.7 generally describe a strong relationship between dependent and explanatory variables (Verma and Abdel-Salam, 2019):

$$r = \frac{\sum (C_i - \overline{C})(e_i - \overline{e})}{\sqrt{\sum (C_i - \overline{C})^2 (e_i - \overline{e})^2}} \quad (3)$$

Within formula (3), C_i and e_i represent the single samples of production capacity and SEC, $\overline{C}$ and $\overline{e}$ the mean of the samples respectively over the sum of all included data points.

Table 4 shows the results of the calculation of r for the respective graphs in Section 3.1. As we already declared in the above observations,

Table 4
Results of the calculation of Pearson correlation factor for all data sets of subsector "C25 – Manufacture of fabricated metal products, except machinery and equipment".

Energy carrier	Employed data set	|r|
Electricity	Data Europe	0.72
	Data U.S.	0.81
	Data All	0.80
Natural gas	Data Europe	0.53
	Data U.S.	0.70
	Data All	0.69

the overall correlation for natural gas tends to be weaker compared to that for electricity. In general, all correlation factors exhibit a satisfactory result, except for the relationship within the European data points for natural gas. We reason this deviation due to the small amount of representative data points in this sector-specific data set. However, because of the overall reduced correlation within the analysed natural gas data sets, it can be assumed that a stronger underlying effect influences the specific consumption, which we cannot identify at this stage.

Overall, both data sets from Europe and U.S. exhibit a moderate to strong correlation to the overall fits. We can therefore prove the mentioned observation that the effect of EnOS is actually independent of the economic location, namely Europe and the U.S. This could potentially show the presence of a global effect of EnOS. However, more georeferenced data, e.g. from Asia, is needed to confirm this hypothesis.

To further validate the data fits to be non-biased within their correlation of variables, we present correspondent plots of residuals for electricity and natural gas for the selected NACE subsector in Figs. 10 and 11.

All residuals are defined as the mathematical difference between the fitted data points and the corresponding fits. The correlation factor for both residual data sets should be approximately 0 to verify the independence of the data points from other underlying and biasing effects (Verma and Abdel-Salam, 2019).

In the case of the selected NACE subsector, the correlation factors are $7.054 \cdot 10^{-5}$ for electricity and -0.589 for natural gas respectively. Both factors can be deemed satisfactory, although again the natural gas data exhibits a weaker correlation. As we have already stated, this data set seems to be influenced by another underlying effect.

Within the third evaluation, the distribution of residuals is tested as statistically significant linear fitting demands a normal distribution of errors around the fit lines (Verma and Abdel-Salam, 2019). Therefore, we plotted the normal probability values Z on the y-axis and the logarithmic residuals of the data sets on the x-axis of Figs. 12 and 13. The Z-values of the probability correspond to the standard normal probability distribution calculated with the respective residuals by applying the following formula:

$$Z = \frac{X - \mu}{\sigma} \tag{4}$$

Mean μ and standard deviation σ are derived from the set of residuals and X represents the individual residuals. Both mean μ lie at -0.003 for electricity and 0.014 for natural gas. Furthermore, we plotted the individual function of formula (4) as a black line to indicate the deviation of all data points in more detail.

It can be seen that the data points are largely distributed normally. For both plots, the tails of data points at higher residuals deviate farther from the black-coloured linear fit. This result could potentially indicate the existence of more outliers below the 95 % deviation limit we removed within data curation. However, we did not observe this deviation in all examined NACE subsectors.

We support these graphical evaluations by conducting a *t*-test on the slopes of the linear regression fits, which is a common evaluation tool for linear regressions. We stated a null hypothesis in which SEC and production capacity do not correspond, since the true slope m equals 0 (Verma and Abdel-Salam, 2019). The respective alternative hypothesis indicates a relationship between both parameters:

$$H_0 : m = 0 \text{ versus } H_A : m \neq 0 \text{ at } \alpha = 0.05 \tag{5}$$

The *t*-test is a two-sided variable test applying a confidence level of $\alpha = 0.05$ as indicated in formula (5). The resulting *P*-value for electricity was calculated to be $7.193 \cdot 10^{-41}$ and for natural gas $2.200 \cdot 10^{-29}$. Both values are significantly lower than α. This implies that the null hypothesis is to be rejected and the relationship can be proven as statistically significant.

4. Discussion

4.1. Discussion of Results

As visualised above, all fit functions indicate the scaling effect of EnOS, practically demonstrated for energy consumption (electricity and natural gas) of industrial plants. Moreover, data fit functions for Europe and the U.S. are largely coherent. Despite the differing cost structures of electricity and natural gas on both continents, the mechanism of energy scaling in the industry appears to be quite conformable. The weight of this observation increases in light of recent developments in global energy markets.

We have indicated in the previous section that stronger, plant-specific alterations in natural gas consumption per output can be observed as slightly stronger than for electricity. We state two possible reasons for this observation: For one, natural gas is largely involved in heat generation for end-use applications. While electricity demand is rather constant throughout the year, heating demand increases during cold weather seasons (Jesper et al., 2021). Moreover, real-life industrial plants within the databases may not require consistent heating demand.

As, furthermore, a wider range of alternative sources for substituting natural gas (e.g. biogas, etc.) is available, and deviations of yearly natural gas consumption in independent industry samples will occur naturally (Pucker et al., 2012). Furthermore, the deviation of natural gas may indicate oversized or undersized heat-producing equipment in single industrial plants. For example, Bukurov et al. (Bukurov et al., 2016) state that gas boiler sizing for heating applications is often designed incorrectly resulting in inefficient energy consumption. On the contrary, electricity-consuming units can be adjusted more accurately with regard to energy end-use.

The observed L-shape of our EnOS results mathematically displays the close correlation of the observed paradigm with the already deeply

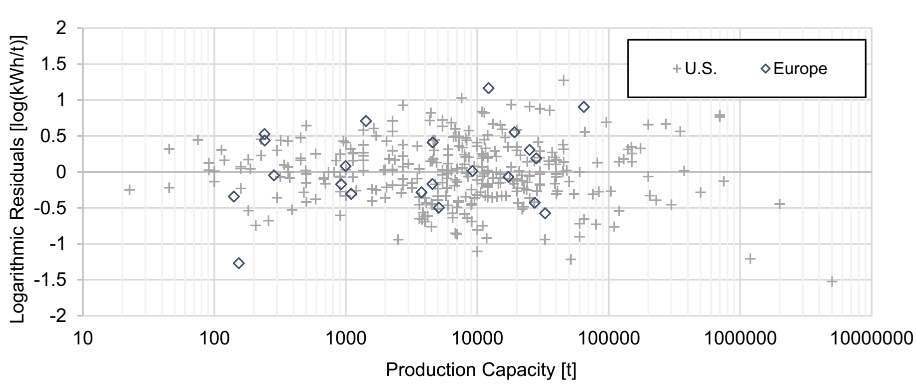

Fig. 10. NACE 25 - residual fit for electricity data set.

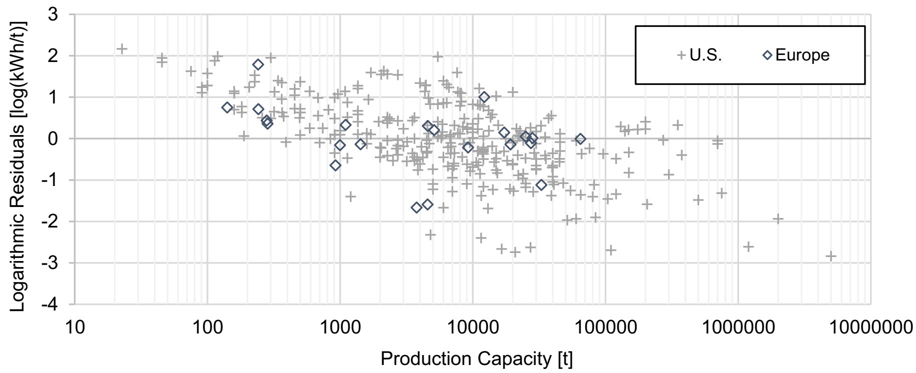

Fig. 11. NACE 25 - residual fit for natural gas data set.

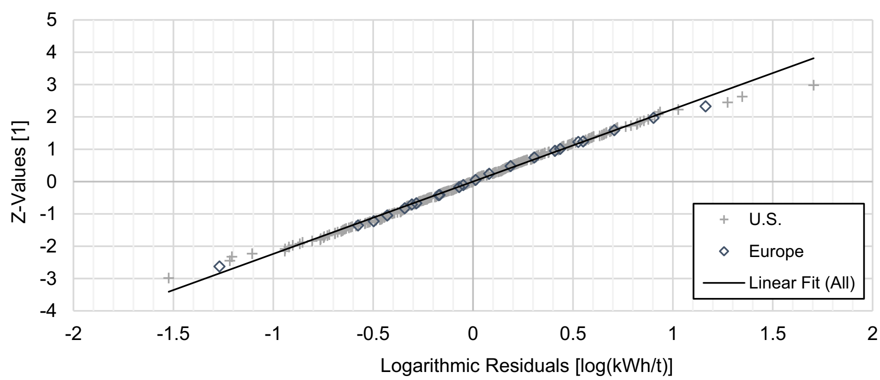

Fig. 12. NACE 25 - normal probability plot for selected electricity data set.

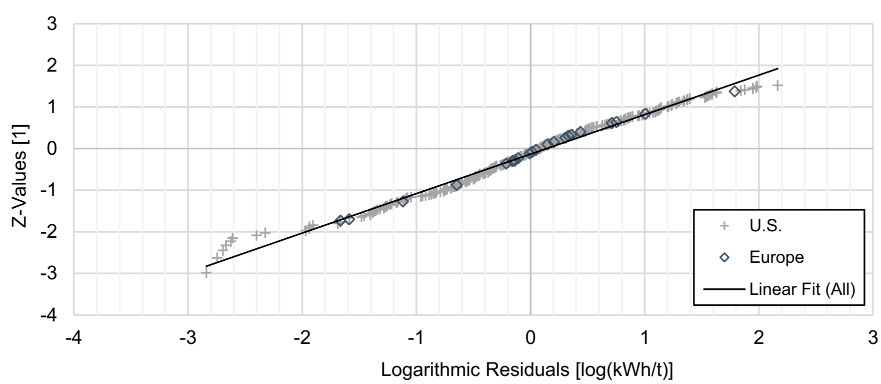

Fig. 13. NACE 25 - normal probability plot for selected natural gas data set.

investigated EcOS in the literature. As already described above, EcOS also includes areas where unit-specific costs at growing production rates increase once more. An equivalent of this "diseconomy of scale" effect cannot be observed within our data sets of EnOS. We reason the non-existence of this effect in EnOS because of our chosen approach of using a large sample size of individual real-life industrial plants: The corresponding facility managers are encouraged to operate the plant to increase revenue. While single production processes may have to run at alternating efficiencies from time to time, managers of industrial locations will build up total capacity only to the point where production is still economically beneficial. This is also proven by studies by John Johnston (Johnston, 1956) for EcOS as we described in Section 1.1.

The strong correlation of specific energy consumption and production capacity of EnOS can best be compared to the EcOS driving factors considering the production with regard to decreased overhead/fixed costs per produced output. Although variable costs directly apply to single products, increased overhead costs are evenly distributed on the production capacity, resulting in decreased unit-specific costs. In parallel, this means that energy systems are also to be divided into "overhead and variable energy consumers". We already outlined this hypothesis in Fig. 4 as energy-consuming units, which are directly involved in value creation (e.g. production processes), are responsible for variable shares, and units indirectly involved in value creation (e.g. lighting, HVAC, etc.) are responsible for overhead shares of consumed energy. Moreover, overhead/fixed costs are affected by step-fixed increases with rising production output as we described in Section 1.1. Similarly, in value creation indirectly involved units are related to the size of the plant and thus their energy consumption can also be considered as step-fixed.

Another resemblance in EnOS driving factors in comparison to EcOS origins is the physical properties of the involved processes (see Section 1.1). While EcOS employs the square-cube rule to assess unit-specific cost reduction for increased machine sizes, unit-specific energy reduction as a function of increased production capacity could potentially be traced back to the theory of similarity (Moschoudis et al., 2014-1014). Assuming that the size of production units increases with increasing production capacity, the theory of similarity expresses the growth of electrical efficiency η and reduction of electrical losses P_V by formula (6) and (7):

$$\eta \sim 1 - \frac{l_0}{l_1} \tag{6}$$

$$P_V \sim \left(\frac{l_1}{l_0}\right)^3 \tag{7}$$

As l_0 indicates the original unit length, and l_1 the increased unit length (Grabner, 2007). Similar investigations can be conducted for thermal efficiency losses.

As an additional driving factor, the application of learning curves might also support the effect of EnOS as described above in Section 1.1. Learning curves are described as unit cost-reducing effects derived from qualitative performance gains as a function of production capacity (Yelle, 1979). This can in parallel be deployed for energy-related subjects as well. Additionally, the skill set of employees is increased by e.g. employee training courses concerning energy-saving measures at the plant.

Another analogy to EcOS can potentially be found regarding the point of minimum efficient plant size (MEPS), see Section 1.1. While MEPS, derived from EcOS, indicates the most cost-efficient production capacity, our developed fit curves can express subsector-resolved benchmarks on optimum points of production capacity and energy efficiency respectively.

4.2. Fields of Application

The discovery of EnOS can potentially serve different fields of application for different stakeholders, as illustrated in Fig. 14. Here, we disaggregated potential applications from cross-country/global level to single facility levels in correspondence to energy-related research, industrial stakeholder groups, and policy makers.

At the national or global level, policy makers can take advantage of the insights into plant sizes and specific energy consumption provided by EnOS to design effective industrial financing programmes focused on energy efficiency for manufacturing plants. This allows governments to develop tailored decarbonisation pathways for industries with higher production rates, optimising energy consumption per gross value added and accommodating the unique needs of industrial subsectors.

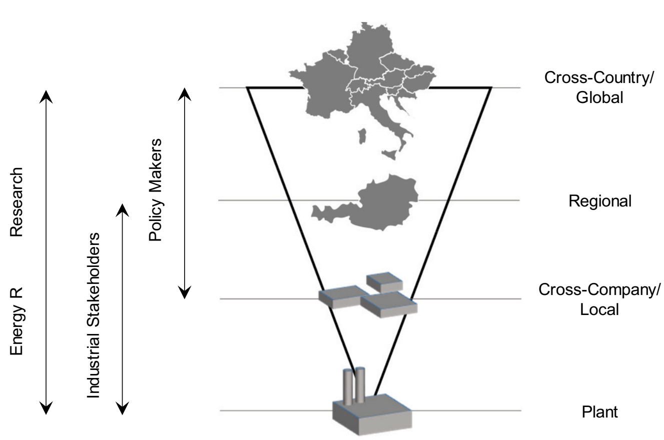

Fig. 14. Fields of application for EnOS in correspondence to selected stakeholder groups and aggregation levels.

Additionally, the impact of emerging technologies such as high-temperature heat pumps, hydrogen, and industry-specific technologies (e.g. electric arc furnace in the steelmaking process) can be thoroughly investigated within the context of overall industrial energy systems. These findings inform the modeling of energy scenarios and facilitate more fitting decision-making by policy makers.

Inclusion of industry-specific characteristics also fosters collaboration and incentivises regional stakeholders, both politically and economically, to cluster production locations within industrial parks based on EnOS-derived benchmarks. However, the decision-making process should consider the potential additional value gained through specialised workforce and equipment at different sites. Georeferencing industrial parks by connecting subsector-specific EnOS data with geographic information further enhances regional policies and planning.

At the company or plant level, EnOS findings help identify benchmark values for plant and company managers, both within and across subsectors. By comparing specific energy consumption with the identified optimum for the respective subsector, plant managers can evaluate their company's energy performance. The large sample size used to establish the EnOS paradigm enables the identification of general trends in plant-specific production, reducing the risk that managers are relying on misleading assumptions.

Furthermore, the research community, at both national and supranational levels, can benefit from EnOS findings. The extensive sample size allows for the assessment of general trends and the identification of specific areas of interest within subsectors. This knowledge proves invaluable in efforts to improve energy efficiency and achieve climate neutrality in the industrial sector. By comparing general plant parameters with subsector-specific energy consumption per production output at the onset of research projects, researchers can save time and resources by focusing on the most critical areas for improvement.

Overall, the “energy of scale” effect offers significant implications and potentials across different system levels and for various stakeholders. It provides valuable insights for policy makers, encourages cooperation and incentives among regional stakeholders, helps plant and company managers assess energy performance, and supports research efforts to advance energy efficiency and climate neutrality in the industrial sector.

5. Conclusions

Scientific literature on scaling effects in manufacturing industries has been limited to the economic side of production. Several mechanisms of “economy of scale” (EcOS) have been investigated that provide important information on cost-saving potentials. However, scaling effects for energy systems have been widely neglected in the literature up to now. As we have thoroughly proven the existence of “energy of scale” (EnOS) for industrial energy systems, we now conclude this study by reflecting on the research questions from Section 1.2:

Q1: By investigating 25,000 georeferenced industrial locations from Europe and U.S., an EnOS effect correlating production-specific energy consumption (for electricity and natural gas) and production capacity has been shown successfully. By dividing the industrial sector into aggregated subsectors, we furthermore demonstrate that the scaling effect alternates depending on the subsector by deriving subsector-specific fit functions from the involved databases (see Appendix). Moreover, we state that the investigated subsector-specific correlations from Europe and U.S. are coherent, seemingly outlining a potential global effect.

Q2: To thoroughly investigate the industrial energy system, we apply subsectoral classification schemes of IEA and NACE. On this basis, we evaluate the data originating from three different databases (two from Europe and one from the U.S.) to demonstrate EnOS. We furthermore then retrieve fit functions from our analysis. Conducted *t*-tests underline the stochastic significance of the findings. We reason the existence of EnOS by comparing its origins to EcOS. The most prominent hypothesis for EnOS is that industrial energy systems must be divided into energy-consuming units, which are directly and indirectly involved in value creation such as production processes and lighting and HVAC units. When decreasing the production capacity, the energy consumption of units indirectly involved in value creation is more strongly influenced by the output-specific energy consumption, practically following power functions.

Q3: The EnOS effect provides a broad tool for better understanding system inefficiencies, both on a regional or national level, as well as on plant level. Although the investigation of EnOS is only at its beginning, several areas for potential application can be identified on a multitude of stakeholder levels. Most importantly, the application of EnOS findings per subsector can facilitate the identification of important areas of action regarding the energy consumption of production facilities due to the applied robust sample size. Such indications can be of interest to both decision-makers on a wider geographic level (e.g. policy makers or system researchers) and company managers on plant level. All of these stakeholder groups profit from an independent and solid benchmarking basis in their work of moving their industrial focus group towards sustainable growth.

To leverage the potential of EnOS, expanding research on the identified paradigm is necessary. Most importantly, additional data points, both from Europe and the U.S. as well as other continents and entities can increase the weight of the proposed paradigm and improve the accuracy and applicability of subsectoral results. On the basis of the already available and investigated databases, existing economic systems, both on a plant level and regional or national level, should be investigated for correlation. This step will be crucial to the further benefit of the identified concept with respect to efforts to achieve climate neutrality and resource efficiency.

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CRediT Authorship Contribution Statement

Conceptualisation, designed the research, and developed the method Paul Binderbauer (P.B.), Matthias Woegerbauer (M.W.) and Peter Nagovnak (P.N.); methodology, P.B. and P.N.; literature research M.W.; writing—original draft preparation, P.B., P.N. and M.W.; review and editing, Thomas Kienberger (T.K.). All authors have read and agreed to the published version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 5
Interpolation data for all investigated industrial subsectors by formula (2); statistical tests were conducted for these subsectors along the described significance testing in Section 3.2.

NACE code	Slope electricity m [kWh/t^2]	Intercept electricity b [log(kWh/t)]	Slope natural gas m [kWh/t^2]	Intercept natural gas b [log(kWh/t)]	Number of locations / datapoints
C10	0.5929	11.3993	0.6210	12.2615	321
C10.11	0.3044	8.9571	0.4834	11.2831	80
C10.13	0.5869	11.5851	0.5425	11.3628	78
C10.3	0.5705	11.3404	0.5491	12.1134	76
C10.51	0.6529	11.9753	0.6956	13.1133	80
C10.6	0.7874	13.5443	0.8719	14.2599	124
C10.71	0.6672	12.0794	0.6507	12.7649	132
C10.85	0.4447	9.7555	0.4693	10.7484	93
C10.9	0.7289	11.9573	0.7053	12.4465	101
C11	0.5766	9.2152	0.6038	10.3886	320
C11.05	0.5957	10.3652	0.5674	11.0345	79
C11.07	0.5576	8.0652	0.6402	9.7426	82
C12	0.5766	9.2152	0.6038	10.3886	166
C13	0.4889	10.9233	0.6075	10.4074	275
C13.1	0.0810	8.3518	0.2080	5.0871	72
C13.2	0.5530	12.4848	0.8553	15.3264	79
C13.9	0.8328	11.9333	0.7593	10.8086	135
C14	0.6873	9.7597	0.8104	11.4839	121
C15	0.6873	9.7597	0.8104	11.4839	95
C16	0.8473	13.4725	0.8616	14.2580	412
C16.1	0.8343	13.3855	0.8487	14.0943	86
C16.21	0.8965	14.6745	0.8541	15.6349	76
C16.23	0.8112	12.3575	0.8820	13.0449	123
C17	0.9852	6.5232	0.9912	6.2441	91
C18	0.9852	6.5232	0.9912	6.2441	77
C19	0.9812	6.4339	1.0121	6.4143	111
C20	0.9910	6.4982	1.0222	6.4784	99
C21	1.0407	15.5050	0.9393	15.7362	176
C21.1	1.0407	15.5050	0.9393	15.7362	75
C22	0.6339	12.4199	0.8302	13.4126	378
C22.1	0.6775	12.7546	0.7482	13.4256	101
C22.21	0.5142	11.4198	0.7886	12.3529	81
C22.22	0.7100	13.0852	0.9539	14.4593	86
C23	0.7211	5.39189	0.6270	5.45799	171
C24	1.0678	7.0335	1.0121	6.5098	102
C25	0.6812	5.1245	0.7035	5.3323	351

(continued on next page)

Table 5 (*continued*)

NACE code	Slope electricity m [kWh/t^2]	Intercept electricity b [log(kWh/t)]	Slope natural gas m [kWh/t^2]	Intercept natural gas b [log(kWh/t)]	Number of locations / datapoints
C25.11	0.6886	11.5488	0.7887	12.3043	106
C25.12	0.9568	13.9456	0.9466	14.2112	92
C25.5	0.6801	12.3737	0.7488	13.6044	96
C25.61	0.7927	12.8888	0.7177	13.6255	75
C26	0.9673	14.5831	0.9971	13.9151	303
C26.11	1.0149	15.4412	1.0243	14.5664	77
C26.12	0.9596	14.5338	1.0596	14.3907	103
C26.51	0.9276	13.7743	0.9075	12.7882	94
C27	0.8739	13.1759	0.9849	14.2369	102

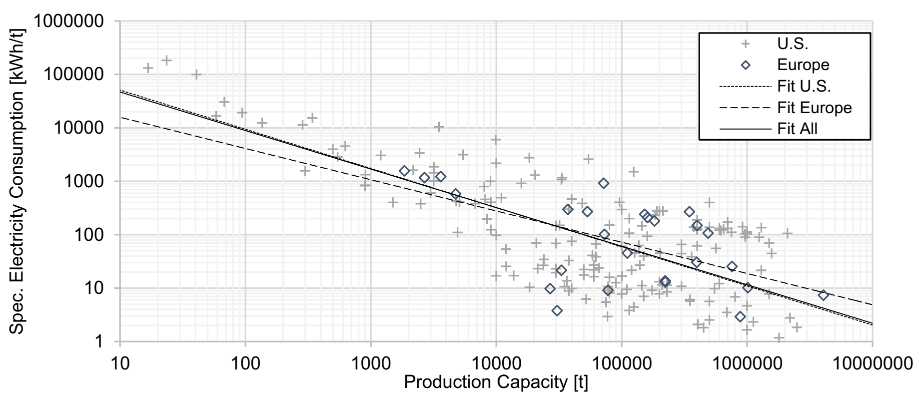

Fig. 15. NACE 23 – EnOS effect of electricity (double-logarithmic plot).

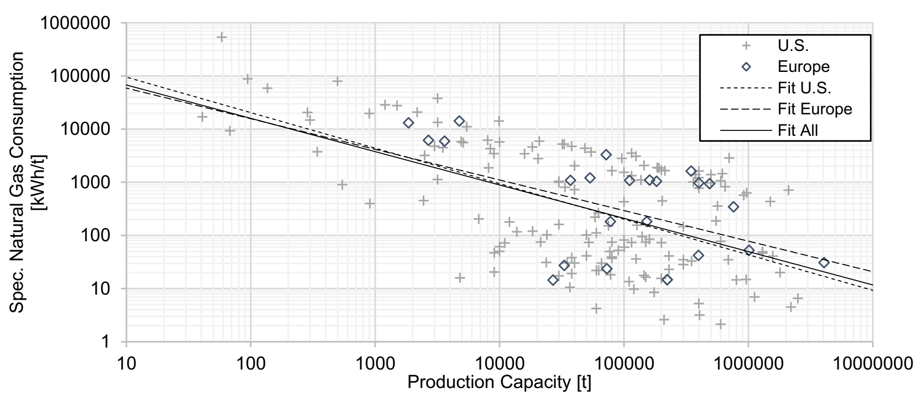

Fig. 16. NACE 23 – EnOS effect of natural gas (double-logarithmic plot).

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APPENDIX C: FURTHER SCIENTIFIC DISSEMINATION

Conference Proceeding C1

P. J. Binderbauer, M. Hofstätter, T. Kienberger, Synthetic Load Profile Generation for Production Chains in Energy Intensive Industrial Subsectors, in: 17. Symposium Energieinnovation, Graz, Austria, 2022.

Conference Proceeding C2

P. J. Binderbauer, T. Kienberger, Ganymed – The development of an industrial load profile generation software, in: Proceedings of the 2nd NEFI Conference 2022, Linz, Austria, 2022.

Synthetic Load Profile Generation for Production Chains in Energy Intensive Industrial Subsectors

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Kurzfassung/Abstract: The generation of synthetic load profiles offers the possibility to easily and efficiently depict the dynamic energy consumption and generation of single consumers. Therefore, it is vital for evaluating future challenges for the physical energy system, support the forecast models of grid operators and energy suppliers and improve deriving demand side management measures for consumers. In this paper, we present *Ganymed* as a suitable software for assessing energy consumption and generation behaviour of production chains in energy intensive industrial subsectors. A dynamic user interface allows a swift and easy application and adaption of processes and production routes. The underlying methodology is based upon discrete-event simulation as a case study is applied to prove the functionality of *Ganymed*. Within this case study, we modelled a part of a production chain of an existing cement plant and compared the generated load profiles to measured ones. The results show good approximations to the measured load profile with an average deviation of 4.1%.

Keywords: Industry, Load Profile, Software, Energy Model

1 Introduction

The industrial sector is accountable for 37% of the overall primary energy demand in Austria [1]. Therefore, the industry undoubtedly has to take part in the energy transition [2]. The development of comprehensive energy system models may help therewith and align the industrial sector with the European net zero greenhouse gas (GHG) emission goals. Energy system simulations allow to get hold of fast changing trends and technologies, evaluate their impacts on the physical energy system and support the strategic decision making for the energy transition. Due to increasing volatility within the energy system, various models incorporate analysis of future grid demands and for energy suppliers [3]. Hence, the calculation of timely resolved behaviour of energy consumption and generation of industrial consumers in terms of load profiles (LP) play a key factor.

1.1 State of Research and Scope of the Work

The goal of most energy system models is to efficiently depict long-term GHG emission pathways, the impact of increased energy efficiencies or the implementation of future technologies and renewable energy sources [4]. A number of these models investigate the mentioned factors in a coarsely time-resolved way. The impact of these factors on the finely resolved energy consumption patterns (e.g. hourly resolved values) of consumers is often disregarded because of the extensive and detailed scope of this task. However, the development of such models is crucial for grid operators and energy suppliers to adequately improve their forecast models or for industrial sites themselves to support their demand side management.

Throughout an extensive literature research, we found that such models were developed for the mobility and residential sector. Vopava et al. [5] examined approaches in the mobility sector simulating the energy consumption of electric vehicles at charging stations. These models are either based on modelling of the driver's behaviour [6] or measured data [7]. In the private sector, behavioural characteristics of residents were also investigated by Pflugradt and Muntwyler [8] to synthesize corresponding load profiles (LP) of the single households.

Models for LP generation for the industrial sector were not developed in a such far reaching scope yet [9]. We reasoned this because the industrial sector holds a more heterogeneous nature in terms of energy consuming or generating factors than compared to mobility and residential. Some studies like Starke et al. [10] or Thiede et al. [11] investigate the industrial sector nevertheless. However, their models require a deep base of data before being applied.

Therefore, our overall goal is to develop a methodology for generating synthetic LPs for various energy carriers like electricity, direct fuel or steam of production chains of all industrial subsectors and provide an extensive database within the user-friendly software environment *Ganymed* [12]. The default data can be applied to instantly depict the consumption and generation behaviour of real or fictitious industrial sites and can be extended with new data anytime. The software can be downloaded via *ganymed.ga*.

2 Methodology of *Ganymed*

We divided this chapter into two parts covering the overall model and simulation paradigm first. Afterwards we describe the application of the base model for industrial processes which was developed throughout our studies.

In a first step, we applied the classification of the International Energy Agency (IEA) to divide the industrial sector into energy intensive and non-energy intensive subsectors [13]. We integrated the energy intensive subsectors Iron & Steel, Pulp & Paper, Chemical and Non-Metallic Minerals into *Ganymed* first, since we concluded that these sectors only exhibit a limited range of different and energy demanding production processes and principles. The product variety is smaller compared to other non-energy intensive subsectors [9]. Therefore, a bottom-up approach can be applied to depict those subsectors.

Throughout a standardised research approach, we investigated all four subsectors and their underlying processes and production chains extensively. We characterised the processes in regard to their runtime, operating type (e.g. continuous or discontinuous), specific energy demand or time series etc. The other non-energy intensive subsectors will also be introduced into the system.

2.1 Overall Model Paradigm

After building up a sound database of the included industrial subsectors, we developed a calculation approach based upon discrete-event simulation. Via this paradigm, a sequence of interactions of i active components (e.g. tonnes of steel) with m resources (e.g. industrial processes like blast furnace etc.) can be depicted [14]. Therefore, a logical production route can be designed and its timely resolved energy demand evaluated. We enhanced the simulation paradigm extensively to meet the necessary requirements for depicting industrial process routes of the mentioned energy intensive industrial subsectors.

Figure 1 shows the overall functionality and the adaption of discrete-event simulation in *Ganymed*. We defined the backend of *Ganymed* as the simulation environment (a), while its graphical user interface (GUI) (b) takes the role of the frontend. The user defines or sets the desired production chain with its containing processes and the amount of components, which shall be processed, within the GUI (c). The classes of all included processes (f) in the default database (e) create *m* specific object resources (e.g. three pulp digesters in one production route). Via drag and drop the user can then dynamically design the desired route and interlink all processes with each other (h).

When this setup is finished, the user initiates the simulation (d). All included processes operate within the defined production route and sequence via timely events (i). The energy consuming (or generating) behaviour of the processes is added up to depict a general LP (j).

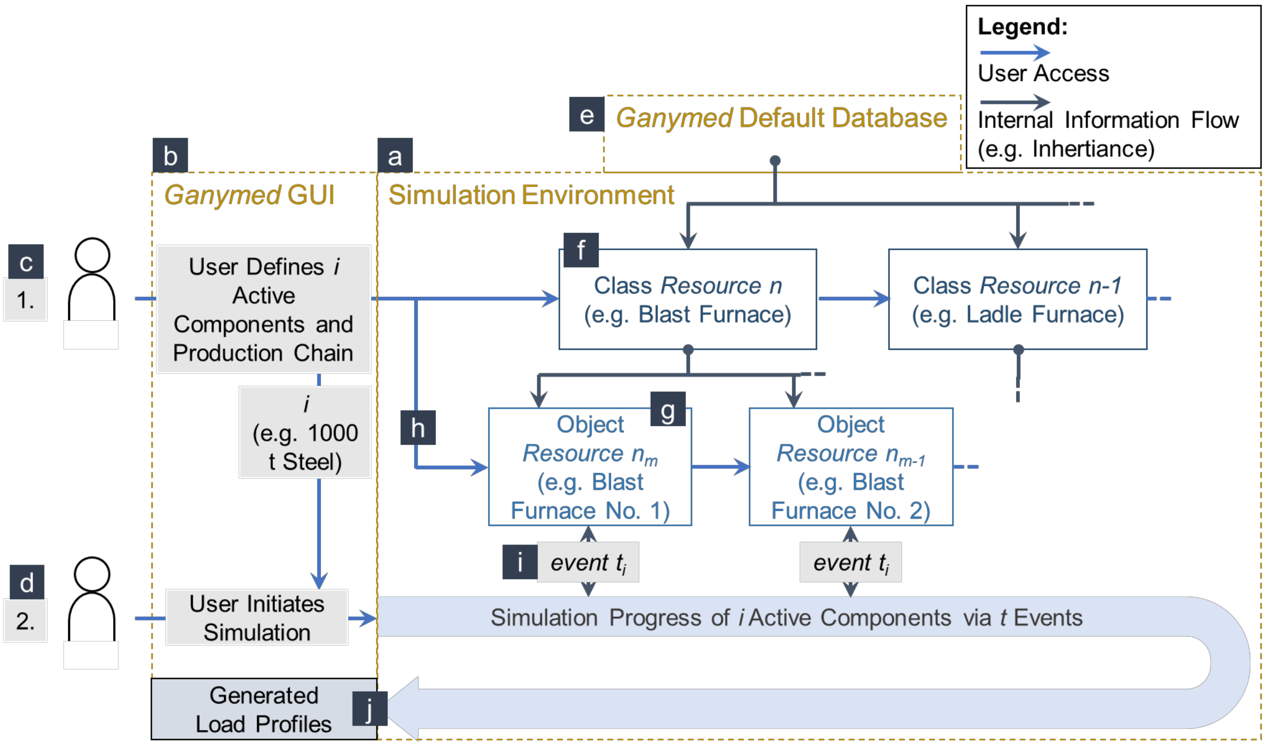

Figure 1: Functionality and simulation operation of Ganymed

2.2 *Ganymed*'s Application on Industrial Processes and Production Routes

As we described above, the paradigm of discrete-event simulation is applied to adequately depict industrial processes and their operational behaviour.

For one, all depicted processes are divided into discontinuous (batch) and continuous processes. Continuous processes are characterised by throughput (e.g. in t/h), batch-wise ones by unit size (e.g. in t) and operating times including charging and discharging durations.

The alignment of these processes to a production route can be performed freely and dynamically by the user as mentioned above. To successful communicate this structure from the GUI to the simulation environment, a coordination matrix is applied. Figure 2 (a) shows a possible production route in *Ganymed*, whose start and end point is defined accordingly. The coordination matrix (b) of the main product route (indicated by black directional arrows) contains the address of each dispatching and receiving process. Furthermore, subproduction chains can be aligned in serial or parallel.

Figure 2 also shows the application of different materials streams besides the main product in *Ganymed*. For example, the main product can be defined as pulp (in Figure 2 (a) indicated by black arrows). A possible auxiliary material could be recycled paper as indicated by green arrows. A by-product of chemical pulp production is black liquor [15] (see blue arrows in Figure 2 (a)), which can also be depicted in *Ganymed*. The coordination matrix for recycled paper and black liquor model implementation is extended accordingly (Figure 2 (c) and (d)).

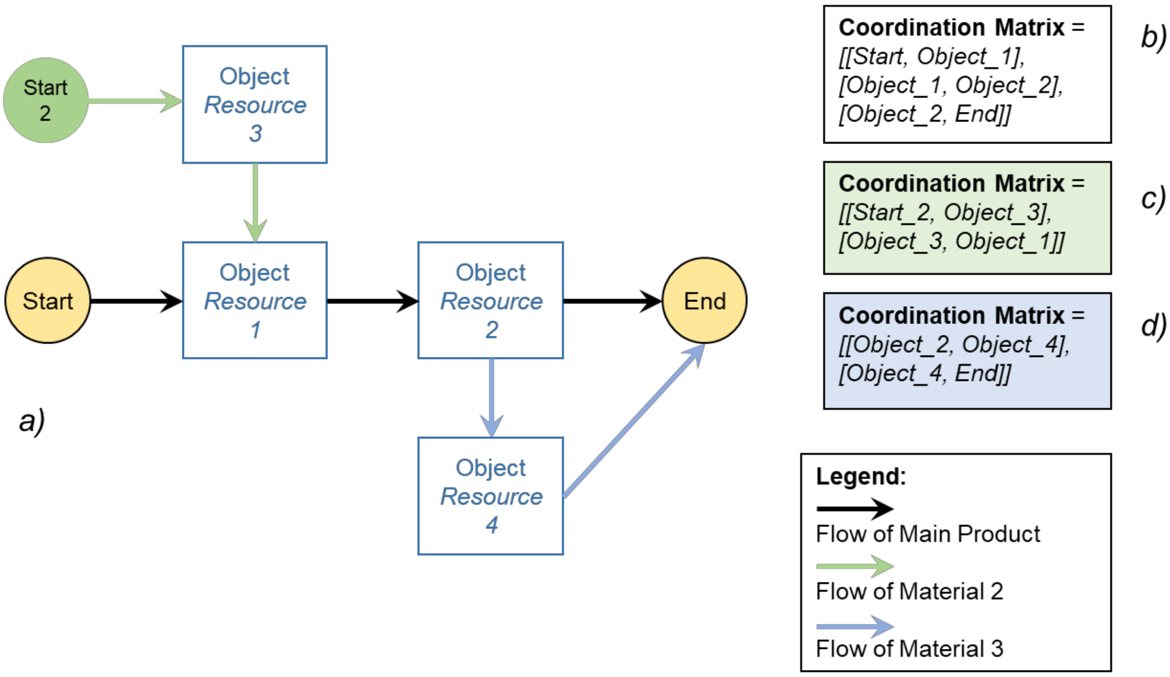

Figure 2: (a) Possible production route in Ganymed with a according coordination matrix for the main product in (b) and the auxiliary material streams in (c) and (d)

All calculations of energy flow balances can be performed for various system dimensions. Therefore, we introduced user-defined, variable system boundaries into *Ganymed*.

A production route typically contains several production related processes as shown in Figure 3 (a). These processes either take part in the production itself and consume final energy (e.g. electricity for pulp digester) or transform energy carriers within or outside the industrial site (e.g. CHP plants, electrolysers, blast furnaces…). The latter are defined as “autoproducers” by the UN Energy Statistics regime [16].

The bold arrows in Figure 3 indicate the energy streams/carriers. When defining the balance border as shown in (a), *Ganymed* will only generate synthetic direct fuel LPs due to the intersection of this energy carrier with the system boundary. Electricity and steam is generated and consumed within the border. However, the user can adapt the boundary to just depict the electricity LP of e.g. object resource 1 (b). Additionally, the energy consumption and generation behaviour of the included autoproducer can be assessed, when the boundary is defined accordingly in (c). The dynamic system boundaries are therefore capable of depicting the energy consumption and generation of single processes, parts of the manufacturing route or the overall industrial site.

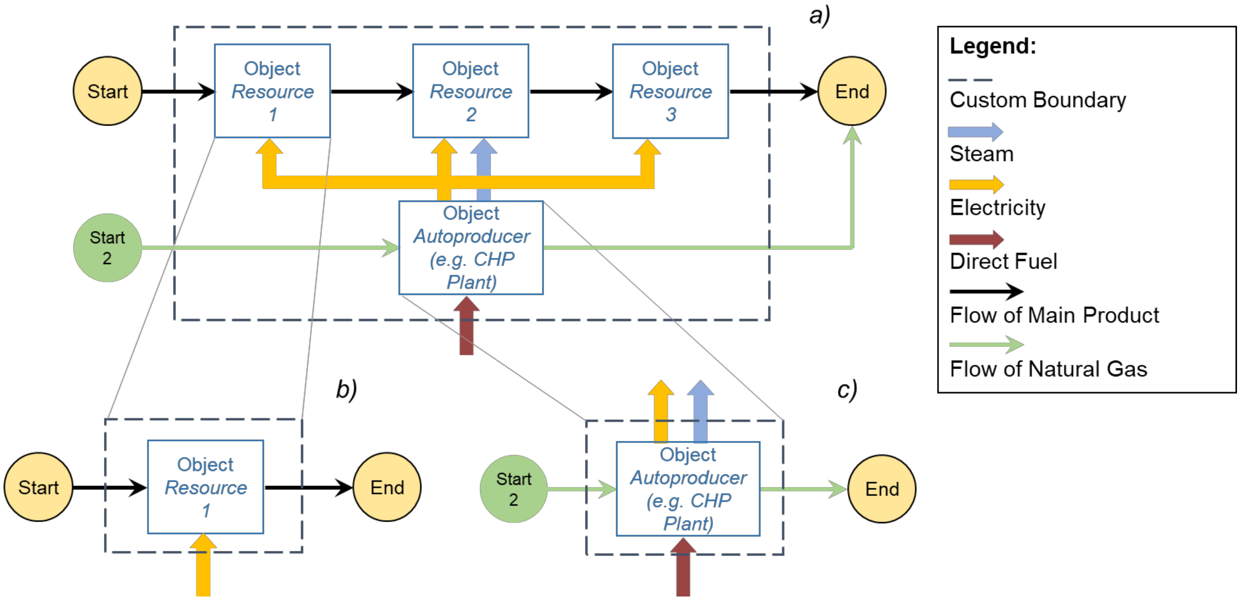

Figure 3: System boundaries in Ganymed: (a) Overall production plant boundary including (b) single production processes and (c) autoproducers

3 Case Study

We evaluated the functionality of *Ganymed* via various case studies modelling the consumption behaviour of real industrial sites. In a preceding study [9] we investigated an iron & steel mill in Austria and found good approximations of our results to the measured data.

For this paper, we'd like to present a case study modelling the electricity demand of an existing cement plant based upon the work and measurements of Lidbetter et al. [17]. In this study the most energy intensive part of the cement production route is described and its underlying real electricity demand is published. Lidbetter et al. derived DSM measures from their analysis and improved the energy efficiency at the real production site.

We implemented the given process layout of this study shown in Figure 4 in *Ganymed*. The main part of the process chain consists of two parallel sub-production routes, which are designed similarly. However, the starting crusher unit as implemented in all cement mills is not included in the route. Two roller mills process the raw meal to meet the specific grain size for the finished product and are operated batch-wise. After this step two raw meal silos act as a buffer for the incoming raw meal and its further processing. We calculated the mean time of storage based upon the mentioned study as 5 minutes per tonne main product. Two follow up rotary kilns burn the raw meal continuously. These units are excluded from the energy balance because they are responsible for just a small share of the overall electricity consumption. However, they are nevertheless part of the sequential simulation to depict the real production flow as accurate as possible. The following clinker silo stores excess material and therefore buffers any fluctuations of material flow. The two remaining ball mills (cement mills) refine the clinker to the finished product.

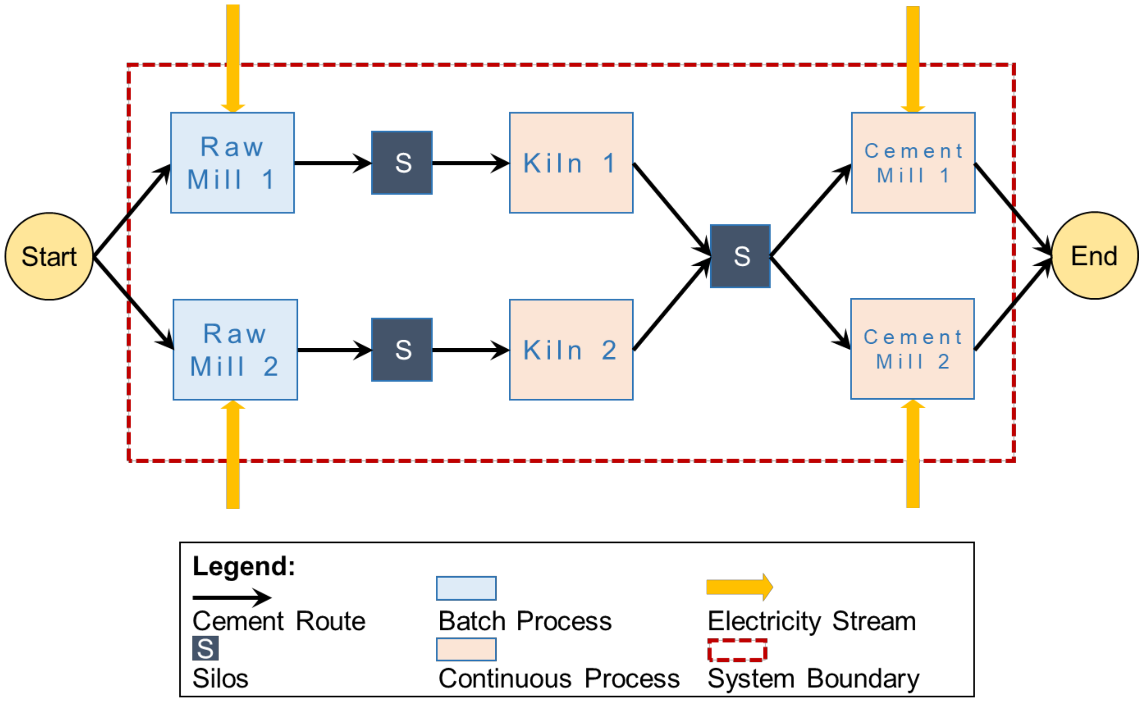

Figure 4: Process layout of Lidbetter et al. [17] as implemented in Ganymed

The electricity consuming behaviour of raw mill 1, raw mill 2, cement mill 1 and cement mill 2 will be assessed throughout this case study. Further information on the included process units are shown in Table 1 as they are classified as either batch (blue) or continuous (orange) processes in accordance to Figure 4. We implemented the corresponding throughput, unit sizes and durations from Lidbetter et al. in our model, while the corresponding electricity consumption origins from the *Ganymed* database. Furthermore, we altered the mean consumption slightly because the underlying literature data from our database lists these demands in ranges.

Table 1: Characterisation of processes in this case study

Name	Throughput [t/h]	Unit Size [t]	Duration [min]	Charging and Discharging Time [min]	Specific Electricity Consumption [kWh/t]
Raw Mill 1	-	240	60	10	15
Raw Mill 2	-	150	45	15	17
Kiln 1	120	-	-	-	-
Kiln 2	80	-	-	-	-
Cement Mill 1	130	-	-	-	29
Cement Mill 2	180	-	-	-	25

The simulation was conducted in 6.2 seconds with a production of around 200 tonnes cement per hour over a course of 5 days.

Figure 5 shows the comparison of the generated synthetic LP of the shown system in Figure 4 and the measured LP from Lidbetter et al. It is noted that we excluded downtimes due to repair, which mainly occurred at raw mill 1 during time of measurement and result in null lines in the measured LP, because these influences could not have been predicted. Additionally, due to the summation of just four process units these sudden downtimes of one unit would have caused an unrealistic impact on the overall LP.

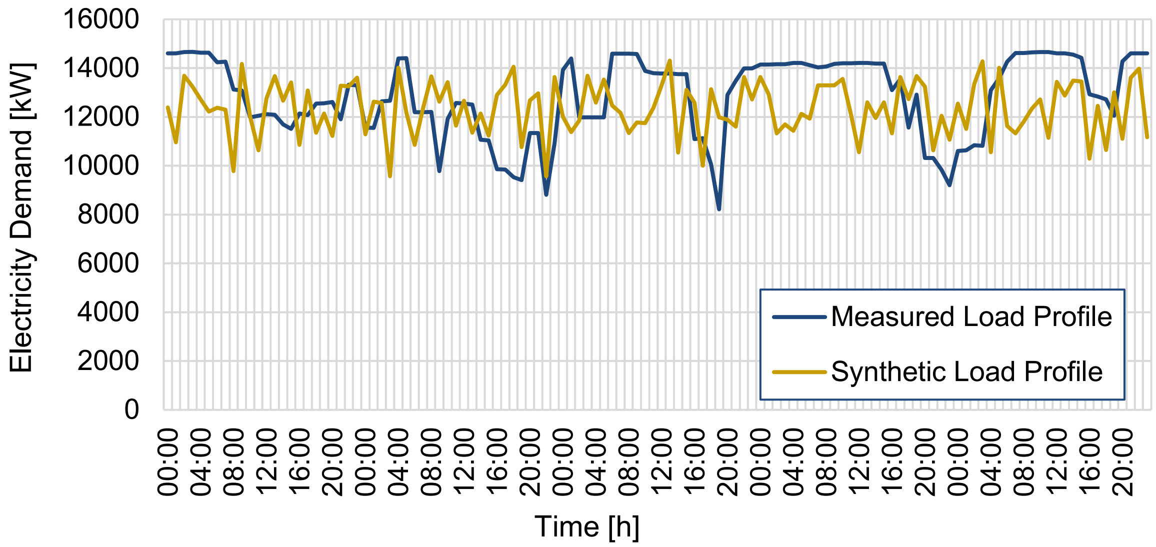

Figure 5: Comparison of synthetic LP in Ganymed to real measured LP

It can be observed that *Ganymed* provides a good approximation to the measured LP. The mean electricity demand of the synthetic LP lies at 12341.03 kW, of the measured LP at 12867.52 kW, which results in a deviation of around 4.1%. The overall fluctuation of the synthetic LP is more present because the range of the data points varies slightly as the histogram analysis in Figure 6 indicates. It can be observed that the electricity demand of the synthetic LP is influenced by normal distribution to a greater extent than the measured counterpart, which is more biased in the direction of higher demand values.

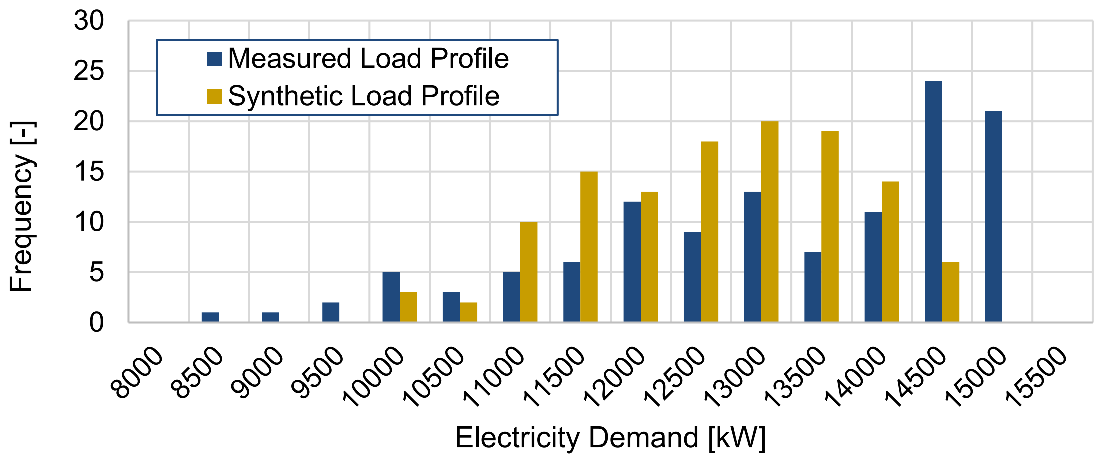

Figure 6: Histogram analysis of data points from both LPs

4 Discussion & Outlook

Energy system models with higher times resolutions (e.g. 15 min/1 h) provide the necessary means to evaluate future challenges of the physical energy system. This includes all partaking bodies from energy suppliers and grid operators to consumers. Generation of synthetic load profiles (LP) support this process by swiftly calculating demands on the energy grid and reveal areas where counteractions have to be taken.

In our study, we apply *Ganymed* as a user-friendly and highly adaptive solution for designing new or existing industrial production chains and evaluate their energy consumption and generation behaviour. The derived LPs can be generated for various energy carriers and system boundaries.

Within the applied case study, modelling an existing cement production plant we found good approximations to the overall electricity consumption and fluctuation range. The data density of the synthetic LP varies slightly compared to the measured LP. However, given the existing data from literature, we deem this case study as sufficient enough to prove the functionality of *Ganymed*.

Future work will introduce a more extensive application of data analysis to also depict other energy extensive industrial subsectors. Furthermore, shift models and economic sciences will be taken into account to enlarge the provided algorithms and database in *Ganymed*.

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IV. Presentations: Industrial Process Optimisation

GANYMED – THE DEVELOPMENT OF AN INDUSTRIAL LOAD PROFILE GENERATION SOFTWARE

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Abstract: The rising volatility of industrial energy systems bears new challenges for all energy related research endeavours. The transition of physical energy systems into the digital world can bring forth new solutions by swiftly evaluating trends and changes and their implications. One of these solutions lies in the generation of synthetic industrial load profiles, which majorly support the strategic decision making for energy suppliers, grid operators and industrial plants itself when implementing new technologies or renewable energies at industrial sites. However, due to the heterogeneity of the industrial landscape in terms of processes and production route structures, there are still solutions missing for depicting all industries in a standardised and user-friendly way. We therefore developed the simulation software *Ganymed* and implemented methodologies and data bases for generating the LPs of user-defined production routes as well as for synthetic industrial sites. These methodologies consist of the time based simulation paradigm of discrete event simulation for evaluating the energy intensive industrial subsectors and of stochastic algorithms handling open accessibly databases for analysing non-energy intensive subsectors. These approaches are encapsulated within the software framework and are controllable via a graphic user interface.

Keywords: Industry; Load Profile; Simulation; Energy System; Generation; Software; Interface; Ganymed

1 INTRODUCTION

Rapidly changing environmental and socio-economic influences confront the modern energy system with significant challenges. However, the rising digitalisation offers novel solutions for solving these problems. Energy system models play a vital role within this topic, especially in terms of assessing external impacts and developing optimisation measures.

The industry acts as a major part of the global energy system. In Europe, the industrial landscape is accountable for around 20% of the gross domestic energy consumption [1]. However, compared to other energy consuming sectors like residential and mobility, assessments and models for the industrial sector exhibit to be more challenging in their development due to the industry's heterogeneous nature in process and product variety [2]. Therefore, there are still vast open research areas to cover in energy research activities. One of these areas is the development of approaches to depict the dynamic demand and generation behaviour of industrial sites [3]. Because of major technological advancements in the recent and upcoming years and the increasing implementation of renewable energies, knowledge of the dynamic energy demand of consumers offers important insights for grid operators, energy suppliers and industries themselves [4]. We therefore present *Ganymed*, a developed software for generating synthetic load profiles (LPs) of industrial sites. This software is, to our knowledge, the first of its kind for the industrial sector.

2 DEVELOPING *GANYMED*

2.1 Overall Industry Classification

To develop an approach covering the entire industry, the sector needs to be classified in a standardised way. We conducted this classification via researching certain characteristics of the industrial energy system e.g. energy consumption, gross value added, number of employees, applied processes, products etc. According to the EU commission, the industrial sectors can be structured in energy intensive and non-energy intensive, of which the first one – as part of the primary industry – "exhibits a limited range of varying production processes and principles" [2]. Figure 1 shows the share of primary energy consumption and distribution

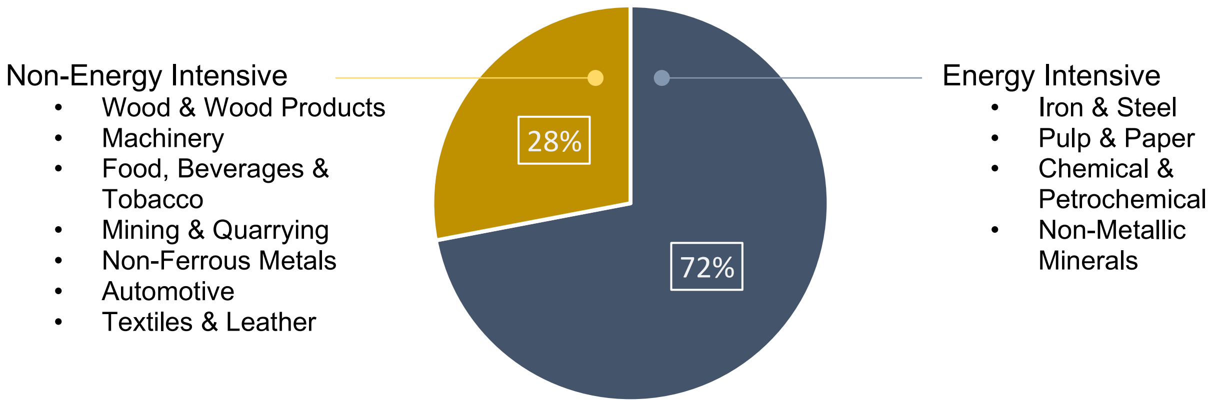

Figure 1: Shares of primary energy consumption 2019 of industrial subsectors in Austria

by subsectors of these two groups [5]. For the latter we apply the classification according to IEA [6] which is the basis for our further investigations.

2.2 Establishing Methodologies

As our main research goal is to generate LPs for single industrial plants, we developed and applied different methodologies based on the subsector classification above. We utilised the programming language Python to create a software environment combined with a graphical user interface (GUI). By developing *Ganymed* we embedded these simulation methodologies into this environment. Here, we want to give a short overview over the approaches for generating LPs for the energy intensive and non-energy intensive subsectors.

2.2.1 Load-profiles for Energy Intensive Subsectors

As we declared above, because of the limited process and product variety of energy intensive subsectors, information and data on process level can be gathered through literature research and measurements in a straightforward way. We applied a bottom-up approach for handling this data and generating LPs from process to plant level. The approach is based upon the paradigms of object oriented programming (OOP) and discrete event simulation (DES) [7].

Figure 2 shows the developed methodology for energy intensive subsector. We published a detailed description of this work in Binderbauer et al. [2].

When the user creates a new process step as e.g. a pulp digester, etc. on the GUI, Ganymed searches through its database for the according process information (1). The

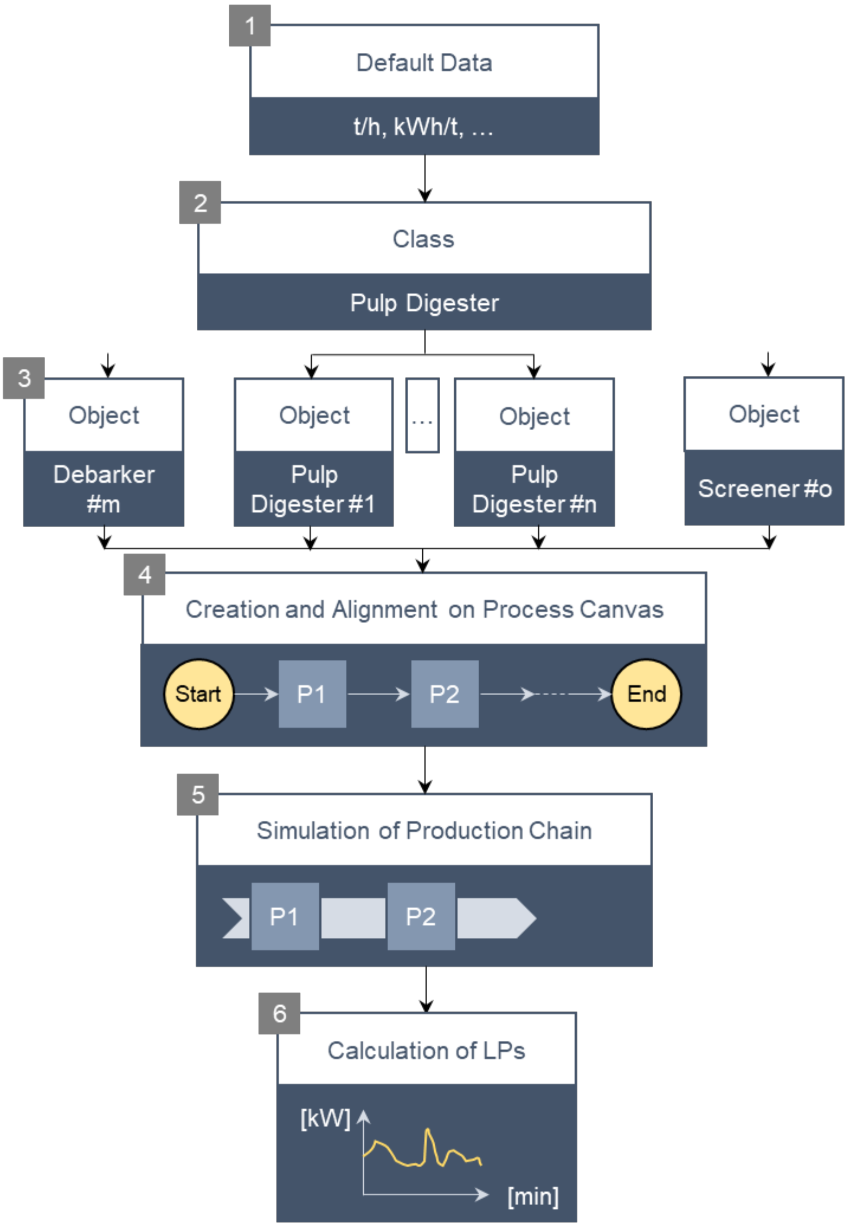

Figure 2: Methodology for generating industrial LPs for energy intensive industries

resulting dataset contains information on the process' capacity, operating times, single energy consumption times series or specific energy consumption operating type etc. An overall process class (2) contains functions, which determine how the process is handled in the GUI and during simulation. With this standard process, various industrial processes with similar functionalities can be depicted in an efficient manner. By receiving data from the overall database, process objects are created (3). The processes' properties contain the default data and can be overwritten independently by the user. In a next step, the user aligns all considered processes in the GUI to meet the desired overall production chain via drag and drop (4). The user then connects the processes from a defined start and end object by connecting all involved objects via product material streams. Alternatively, the user can "load in" predefined production chain templates e.g. integrated pulp & paper production via Kraft process etc., which already contain a predesigned production route. After conducting the desired adaptions, the user then initiates the simulation (5). Here, we utilised the approach of DES, which we adapted to meet industrial characteristics. Via DES, a predefined amount of discrete batches (e.g. tonnes of pulp or steel) is created at the start object. These batches are then send through the aligned production route in a sequential order. When a batch is operated in a process, the sequence before the simulation is halted until the process finished the operation of the current batch. During this stop-and-go processing, single process energy demand pattern at certain times during simulation. After all batches are finished, these single energy demand profiles are summed up to generate the resulting production route LP (6).

2.2.2 Load profiles for Non-Energy Intensive Subsectors

Even though, the non-energy intensive subsectors make up for less than a third of primary energy consumption in industry (Figure 1), they exceed the energy intensive subsectors in regard to number of employees, added value and varying products [8]. Thus, these subsectors are to be involved in energy system and LP analyses as well. However, because of the high number of different processes and production routes a sole bottom-up approach for generating LPs like in section 2.2.1 will reach its limits [9]. This is because the required database will be far greater compared to the energy intensive subsectors, regardless

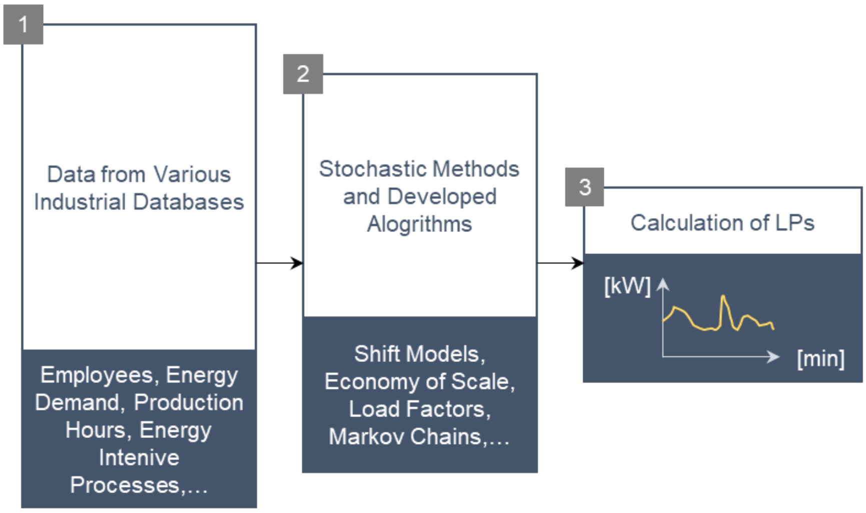

Figure 3: Methodology for generating LPs for non-energy intensive subsectors

if the information can be acquired in a satisfactory way. We therefore developed a more top-down methodology for depicting these subsectors, which is shown in Figure 3.

We utilized various databases for revealing correlations between number of employees, annual and product specific energy demand, production hours etc. of single plants and their corresponding LPs (1). The databases are the Industrial Assessment Center database [10], Herold Business database [11] and Useful Energy Analysis by Statistics Austria [12]. Based on the data from (1) we investigated various correlations e.g. between shift models and LPs. [13]. In (2) we developed algorithms to predict necessary target values based upon these correlations e.g. stochastically determining possible shift models for defined number of employees or assessing the specific energy consumption based upon production capacity and the microeconomic effect of economy of scale. Information of known most energy intensive processes in these subsectors are handled within dynamic Markov chains and make up for the peak demand in the LPs. These LPs are then further scaled by utilizing load factors based upon the data from the databases (3). We described the developed approach more in detail in our recent publication [14].

2.3 Combination of all Industrial Subsectors within *Ganymed*

We created the software environment *Ganymed* as a framework for implementing all developed approaches for generating industrial LPs. From a programming point of view, the architecture of *Ganymed* is divided into several scripts, which are handled by the core script "Main Code", see Figure 4. The "Main Code" also contains a master class, which operates the

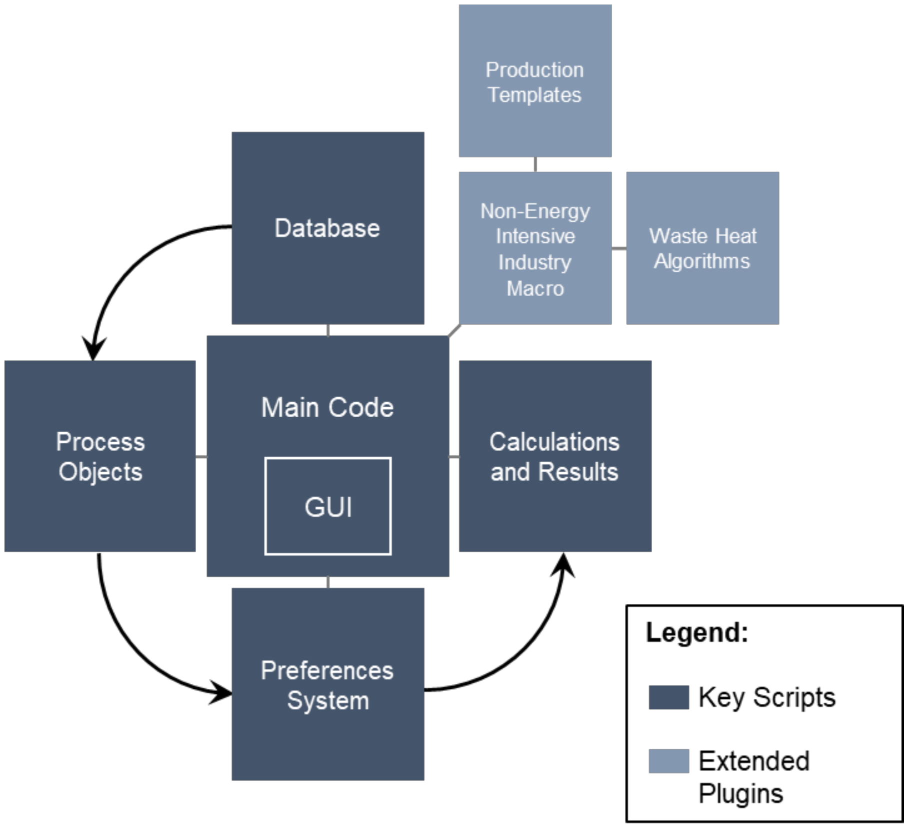

Figure 4: Ganymed's architecture and implementation of key scripts and extended plugins

GUI and the remaining software environment.

All other classes in *Ganymed* inherit from this master class and are encapsulated from direct access of the user. Because the software is built around the depiction of energy intensive subsectors, the corresponding scripts are the main pillars of *Ganymed'*s architecture (key scripts in Figure 4). Within the process canvas in the GUI, processes are created, aligned and adapted by the user. The black arrows in Figure 4 indicate the chain of effects which is also depicted in Figure 2.

The implementation of non-energy intensive subsectors was achieved by developing a so-called "Industry Macro". We designed this macro to act as a process, however including the full range of approaches for depicting non-energy intensive processes as outlined above. Through this, the macro can still be part in the process canvas and be included in the simulation without the need of introducing major changes into the programme's architecture. Here, the Industry Macro is an external script, which is loaded into *Ganymed* on user's requirement. A similarly handled script is the data on production route designs ("Production Templates").

In an upcoming study, the generating of waste heat profiles for both energy intensive and non-energy intensive sectors will be made possible within *Ganymed*. This will also act as an external script.

2.4 Single Process depiction on the Process Canvas

The creation and configuration of processes on process canvas takes an important role within *Ganymed*. Figure 5 shows a visual representation of an exemplary process on the canvas as well all process dependent preferences, to be freely adjusted by the user. The square which depicts 1 of *n* process objects can be moved freely by the user via drag and drop. The material in- and outflows are indicated by thin arrows, which are to be aligned by the user or predefined in the production route templates. These material routes pass the created batches from DES from on process to another.

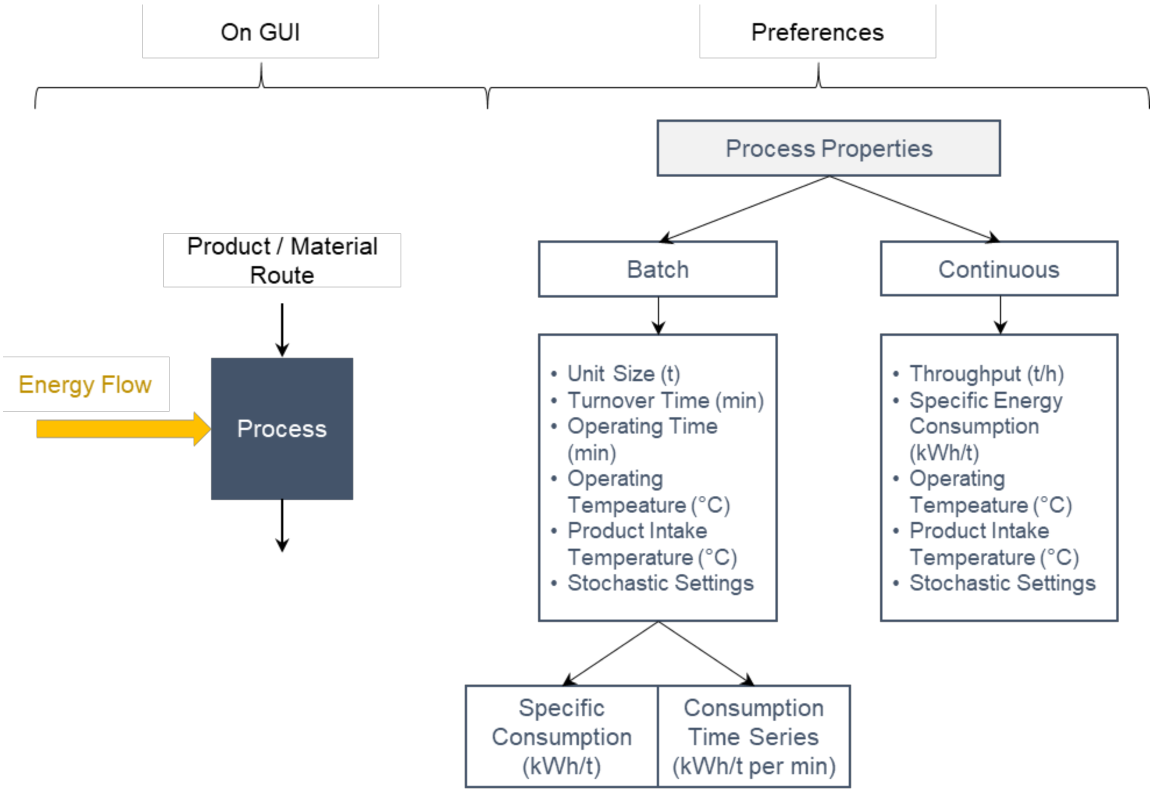

Figure 5: Process representation on GUI and accompanying properties

Also the visual representation of energy flows of different implemented energy carriers in and out of the process are to be established in the same way. Additionally, the user can create movable system boundaries on canvas. With these, the LPs of singular parts of the overall production chain can be depicted without the need of changing the whole route. For energy system research these boundaries can be applied for evaluating LPs on different systemic levels, e.g. plant border, final energy, useful energy, etc. The eligible energy flows have to intersect the system boundary accordingly.

Within the script "Process Objects" (see Figure 4), a template of the shown process properties is created and filled with the respective default process data from the database. These datasets are stored in arrays. *Ganymed* classifies processes in regard to their operating characteristics in batch and continuous working processes. The specific properties are defined according to this classification. Furthermore, batch working processes can either apply specific energy consumption or energy consumption time series (e.g. singular processes' LPs). The latter can be imported via .CSV-sheets (see Figure 5).

The process properties of throughput, unit size, turnover time, operating times and energy consumption directly correspond to DES and the generation of LPs. Operating temperature and product intake temperature are datasets for generating waste heat profiles and are handled by waste heat algorithms in *Ganymed*.

2.5 Production route depiction on the Process Canvas and *Ganymed*'s GUI

The interface between the user and the main code is established through a GUI. The script is based upon the Python library Tkinter [15]. The GUI is separated in three compartments: Menu, process canvas and calculation & results sheet.

Figure 6 shows the process canvas in *Ganymed*. In the "General" section the user can initiate the simulation, save, open current files or create a new process canvas. Also, the global settings like overall stochastic fluctuations, labelling of flows, overall production capacity, etc. can be adapted throughout this menu.

The menu for "Set & System Objects" enables the creation of all start and end points for the production route. Furthermore, through this menu new energy carriers and material flows can be established. Also, system boundaries and the non-energy intensive industry macro can be created on canvas.

All single processes can be accessed through the "Process menu". Here, the processes are divided into mechanical, thermal, chemical and special (e.g. CHP, buffer points, etc.) processes.

The "Templates menu" allows the user to insert the already mentioned predefined production routes for Pulp & Paper, Iron & Steel, Chemical or Non-metallic Minerals industries.

When a mentioned process or production route is chosen, the corresponding visual representation of the objects are created on the process canvas. Each process consists of the process' name, continuous/batch symbol, consecutive object number, preferences' button and four anchor points, see Figure 7. Through clicking on the anchor points, material and energy flows to other processes and busbars can be established. By clicking on the process square itself, the process can be moved freely on the canvas via drag and drop.

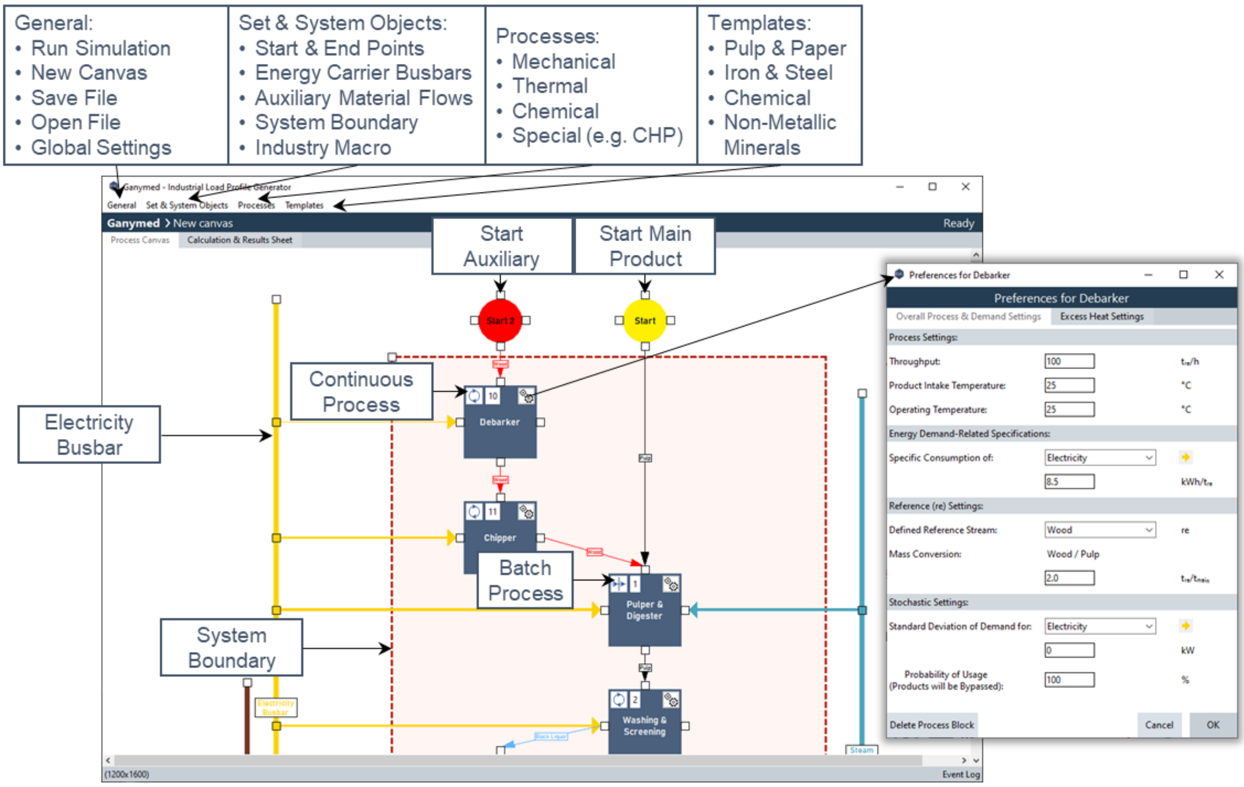

Figure 6: Ganymed's GUI: Process canvas and preferences of process

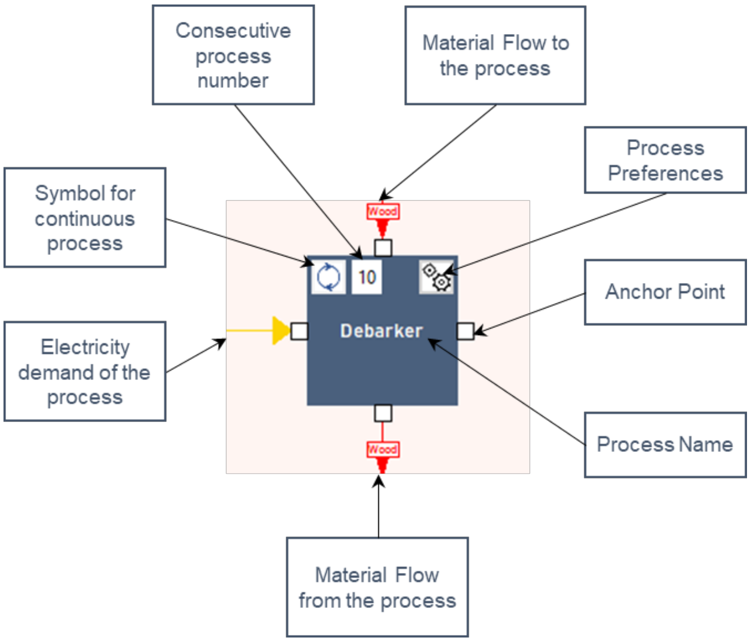

Figure 7: Visual representation of a process on process canvas

After the simulation is finished, the user can switch to the calculation & results sheet to view the generated LPs and export them, see Figure 8. On this frame, the user can also select and cut out representative parts of the LP to generate a weekly LP. The export is done via .CSV-format. On this sheet, the user also can view the evaluations on waste heat profiles and longest queue lengths of batches for single processes.

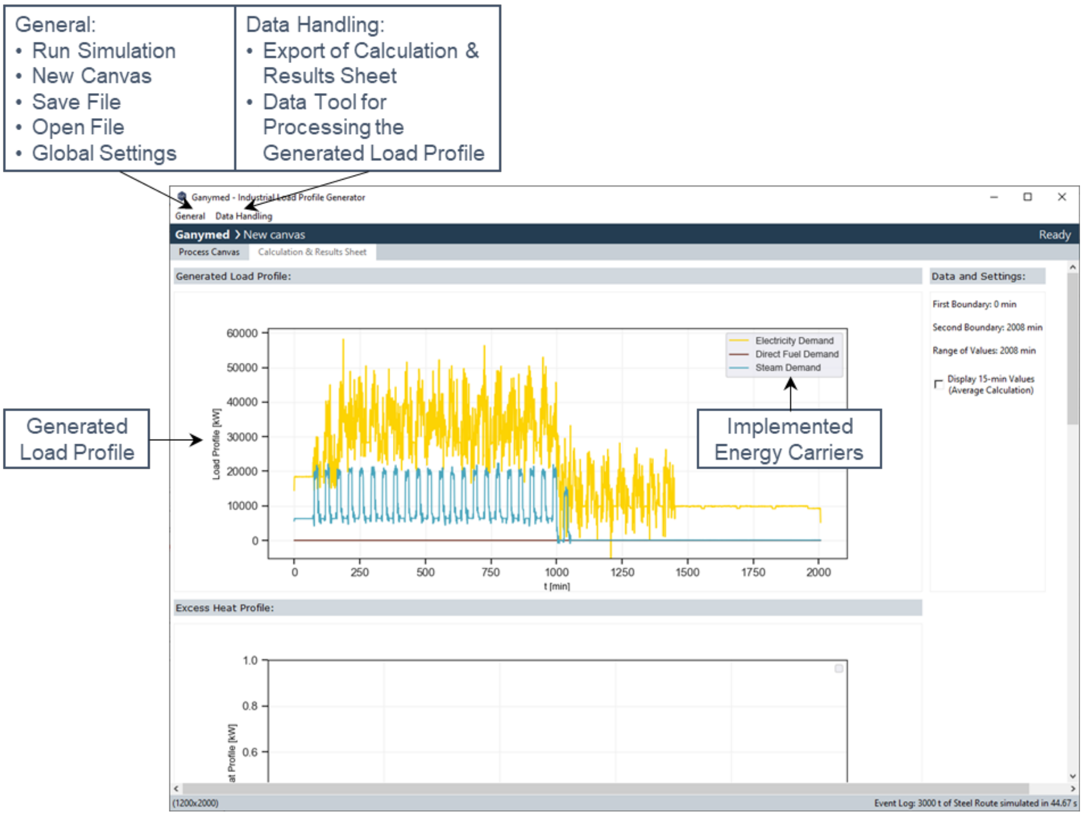

Figure 8: Ganymed's GUI: Calculation & results sheet

3 CONCLUSION

By utilising the idea of object oriented programming e.g. encapsulation, inheritance, classes and objects, industrial processes can be handled systemically adequate and accurate. In combination with simulation paradigms like discrete event simulation and with data bases for stochastically analysing non-energy intensive industries, load profiles for the overall industrial sector can be depicted thoroughly. To wrap these methodologies in a user-friendly way, we embedded the approaches in a standalone application framework to create the software *Ganymed*. This software is executed as an .EXE file and is based upon the Python library Tkinter. All processes within *Ganymed*'s GUI can be aligned via drag and drop. They consist of default information e.g. spec. energy consumption, capacity, etc. from literature review, which can be adapted freely by the user. *Ganymed* consists of five key scripts, one of which acts as the main component for connecting all methods in the software framework. Three additionally scripts e.g. methodology for non-energy intensive industries are built in as plugins and are called on user command. The software is free to use and downloadable via *ganymed.ga* [16].

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5 FURTHER INFORMATION

Ganymed is an .EXE software, executable for Windows® based systems with > 8GB RAM and Intel i5 core or equivalent. Extra licenses or the utilisation of programming languages is not mandatory. *Ganymed* is accessable via *www.ganymed.ga*.

APPENDIX D: INDIVIDUAL CONTRIBUTION OF THE AUTHOR

Table 6: Contribution of the author of this thesis to the appended publications and papers in percent

Publication / Paper	Concept-ualization	Methodology and Software Development	Investigation and analysis	Manuscript writing
P1	80	90	90	80
P2	80	100	100	80
P3	80	95	100	80
P4	90	100	90	80
C1	80	90	90	80
C2	80	100	100	80