On the design of on-site energy conversion systems for manufacturing companies with special consideration of hierarchical planning aspects

Cumulative Doctoral Dissertation

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List of scientific contributions

Within this doctoral dissertation, the following (submitted) scientific contributions (C1-C4) are presented. The articles are arranged according to their order of appearance in this dissertation. The referred rankings relate to the VHB-JOURQUAL3, a journal rating which has been published by the German Academic Association for Business Research (VHB).

Contribution 1

Ganschinietz, C. (Under review/revision). Design of on-site energy conversion systems for manufacturing companies – A concept-centric research framework. Journal of Cleaner Production, rated B.

Contribution 2

Ganschinietz, C.; Gahm, C.; Hartmann, J.; Tuma, A. (Working paper). Design of on-site energy conversion systems for manufacturing companies – A review and literature analysis. Will be submitted to Journal of Cleaner Production, rated B.

Contribution 3

Gahm, C.; Ganschinietz, C.; Denz, F.; Tuma, A. (Under review). A flexible approach for the dimensioning of on-site energy conversion systems for manufacturing. Computers & Industrial Engineering, rated B.

Contribution 4

Gahm, C.; Uzunoglu, A.; Wahl, S.; Ganschinietz, C.; Tuma, A. (Working paper). Approximate anticipation of base-level reactions by machine learning techniques used to substitute the solving of complex nesting problems. Will be submitted to European Journal of Operational Research, rated A.

Note: Appendixes and References are added subsequent to the corresponding contribution.

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I

Introduction

I.A Motivation

There is a supposed conflict between economic objectives and the striving for a sustainable production of goods. Interestingly for certain strategic planning decisions, both objectives may even support each other to a certain degree. One of these planning problems is the design of an energy conversion system (ECS) which supplies a manufacturing company with the necessary energy for its production processes. The complementary support of economic and ecological objectives and the motivation to install an ECS can be explained by several observations.

The first observation is that due to the global industrial development and strong worldwide population growth (Bazmi and Zahedi, 2011) the demand of energy has risen steadily in recent years (Al Moussawi et al., 2016). This leads to a growing scarcity of fossil fuels, which are used to meet the majority of energy demands (Erdinc and Uzunoglu, 2012; Bhattacharyya et al., 2017), and therefore, rising energy prices (Rager et al., 2015; Al Moussawi et al., 2016). This strong reliance on exhaustible non-renewable reserves, restrictions and failures of the established infrastructure, the global competitive situation, and geopolitical insecurities put increasing pressure on energy supply infrastructures (Bazmi and Zahedi, 2011).

Second, the industrial sector is one of the main consumers of energy within the European Union (EU), and can be held accountable for almost 25% of the EU's total energy consumption (Eurostat, 2019). Furthermore, a German study shows that in 2017 a total of 90% of industrial energy consumption was used for production processes. Thereof 68% are used for process heat and process cold, 22% for mechanical processes, and only 10% for other purposes such as room heating, lighting, or communication (Ziesing, 2018). Thus, this study identifies the production processes of manufacturing companies as the focal point for energy savings in industry.

Third, due to their high energy consumption, social and political pressure on industries to operate more sustainably is growing. This pressure intensifies even further, as societal concern on the issue of increasing emissions of potentially climate-damaging greenhouse gases caused by combustion of fossil fuels (Ahmadi et al., 2015) progressively rises nowadays. But in contrast to society demanding change towards more sustainable industries, in most affluent societies the consumption and use of goods and products cannot easily be dispensed with. Therefore, the abandonment of production is no solution in order to comply with the demands of society to save energy.

Summarizing these observations, manufacturing companies have an immense incentive to save energy during production processes for a sustainable production from an ecological, social, and political perspective and to spare costs from an economical perspective. The difficulty in saving energy during production processes is that energy is a non-substitutable and indispensable production factor (Gahm et al., C3; Rager, 2008; Gahm et al., 2016). Consequently, besides the energetic optimization of production processes, the required amount of energy must be used as efficiently as possible. In addition, the industrial sector has the motivation for a strategically independent and efficient energy supply (Ghadimi et al., 2014).

One auspiciously measure to secure energy supply and to increase the energy efficiency simultaneously, is the installation of on-site ECSs (cf., Campana et al., 2019; for other measures see Ganschinietz et al., C2). This measure saves the most energy, and thus is especially cost efficient, when the overall energy conversion efficiency is as high as technically possible (less dissipation of useful energy). Consequently, if the ECS is designed and integrated adequately to the specific application case, it may decrease total costs and increase energy efficiency at the same time (Behzadi et al., 2019). Besides an ecological, social, and political striving for high energy efficiency, an ECS' "[…] appropriate sizing is one of the most important issues that results in having a cost-effective energy system" (Khiareddine et al., 2018). Concluding, an adequate design of ECS for manufacturing companies with a high energy efficiency is aspired by many parties and is therefore the subject of this doctoral dissertation.

The adequate design of onsite ECS is a complex, planning problem specific, and strategic decision topic for every application case. However, especially for manufacturing companies this planning complexity increases even more due to the hierarchical interdependency between the energy supplying ECS and the energy demanding production system (PS). Because of this interdependency, the PS`s varying energy demand during production processes can immensely influence an ECS's overall energy efficiency. Consequently, for an adequate design with high energy efficiency, this interdependency has to be considered during ECS design although it increases the problem complexity. This complexity has resulted in numerous publications on different specific planning problems within an unstructured research field. For these reasons and to identify and address unresolved topics of this research field, this doctoral dissertation comprises four contributions (C1-C4) which focus on the answer and clarification of the following research questions:

- RQ1: How can the research area of ECS design for manufacturing companies be structured and which planning factors are crucial for an adequate ECS design?
- RQ2: Which individual planning problems of ECS design have been addressed thus far or reveal a deficiency in research?
- RQ3: How can different complex and individual planning problems of ECS design be addressed to increase energy efficiency?
- RQ4: How do the most important planning factors influence ECS design and ECS energy efficiency for manufacturing company?
- RQ5: How can the concept of hierarchical planning be incorporated during ECS design?

This doctoral dissertation is structured as follows: First an introductory section provides the theoretical foundation by outlining characteristics and hierarchical interdependencies of ECS design for manufacturing companies. Next, the raised research questions RQ1 to RQ5, are subsequently addressed by a total of four scientific publications in section II. Closing, a summarizing discussion of the contributions` added value, and an outlook on opportunities for future research is given in section III.

I.B Organizational and technical background of energy conversion system planning

This section explains the application of energy in manufacturing companies, the relationship between the energy demanding PS and the energy providing ECS, as well as the concept of hierarchical planning in general and in the context of ECS design.

I.B.1 Energy provision and application in manufacturing companies

Energy is a non-substitutable production factor and plays a special role in manufacturing companies because it is essential for almost every production process. In general, production processes are executed by the production units (PUs) of a PS (manual processing by workers is excluded in this context). To that, the PUs are used to fulfill the tasks defined by working plans of the production orders representing the product(s) to be produced. Hereby, a small amount of the energy demand of a manufacturing company's PS is caused by peripheral equipment used to put PUs in a condition to perform the actual production process. However, production processes themselves demand the largest share of the overall energy demand of a PS.

Due to the importance of energy in manufacturing companies, Figure I.B-1 depicts the energy supply and energy application in manufacturing companies and is based on the findings of Denz (2015) and Gahm et al. (2016).

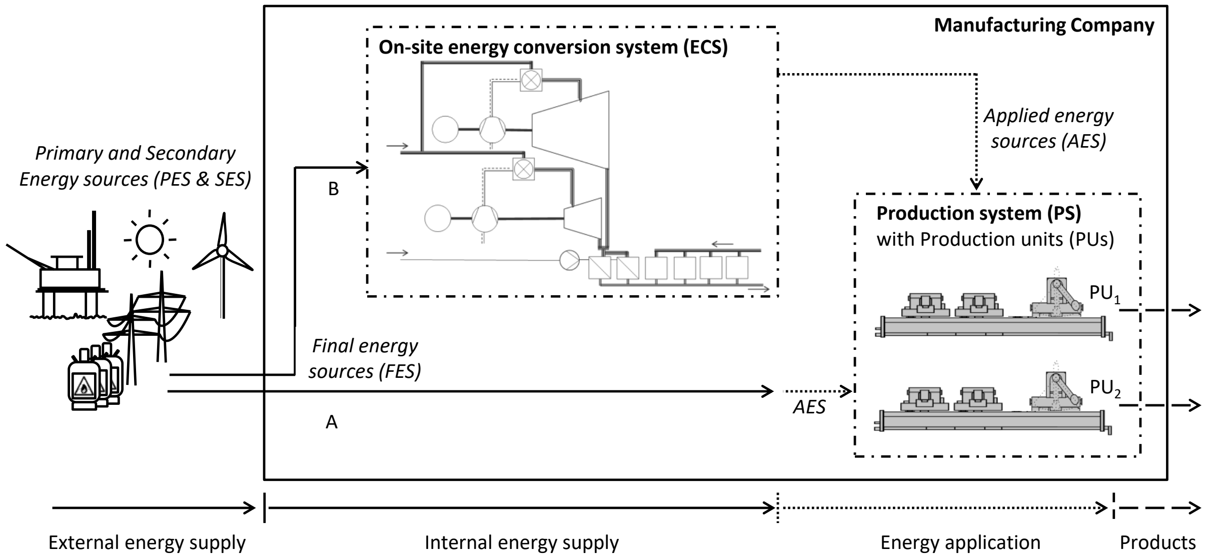

Figure I.B-1: Energy supply and application in manufacturing companies

In Figure I.B-1 the arrows depict the transport of energy by energy sources (also called energy carriers). The external energy supply can be based on primary energy sources (PES) like solar energy, or secondary energy sources (SES) like electric power. As soon as the ownership of energy sources is transferred to a manufacturing company, they are referred to as final energy sources (FES). These FES can either be used directly by the production units of the production system, as in case A, or they have to be transformed to fitting applicable energy sources first, as in case B. In case B the FES are transformed by an on-site energy conversion system into the desired applied energy sources (AES), which in turn can be used by the PUs. In the latter setting, a strong relation between the ECS and the PS exists, since the PS demands the AES that the ECS has to provide.

The specific amount and type of AES (e.g., heat or electrical power) required by the PUs primarily depends on the actual production processes. The production process in turn is essentially determined by the desired product and its production volume. This means that the AES demand for most production processes can be determined in advance. In consequence, the information on AES demands is already available before production is carried out and therefore, the information can be used to increase energy efficiency in manufacturing companies by different measures (e.g., by energy-efficient scheduling or ECS planning). A more detailed analysis of energy application in manufacturing companies can be found in Dietmair and Verl (2009), Avram and Xirouchakis (2011), Duflou et al. (2012), and Li et al. (2014).

Based on this very general discussion of energy application in manufacturing companies, a more detailed analysis of the relationship between AES demand of the PS and AES supply offered by the ECS is carried out in the following.

I.B.2 On the relationship between production system and energy conversion system

In manufacturing companies, a PS consists of one or more PUs, which are available for production process execution (assuming that the production system is already determined). As soon as a task of a production process is scheduled on a PU, the actual AES demand per time unit can be determined. Furthermore, if several PUs require the same type of AES, a cumulated AES demand can be determined. This relationship is illustrated in Figure I.B-2 (cf., Rager et al. 2015):

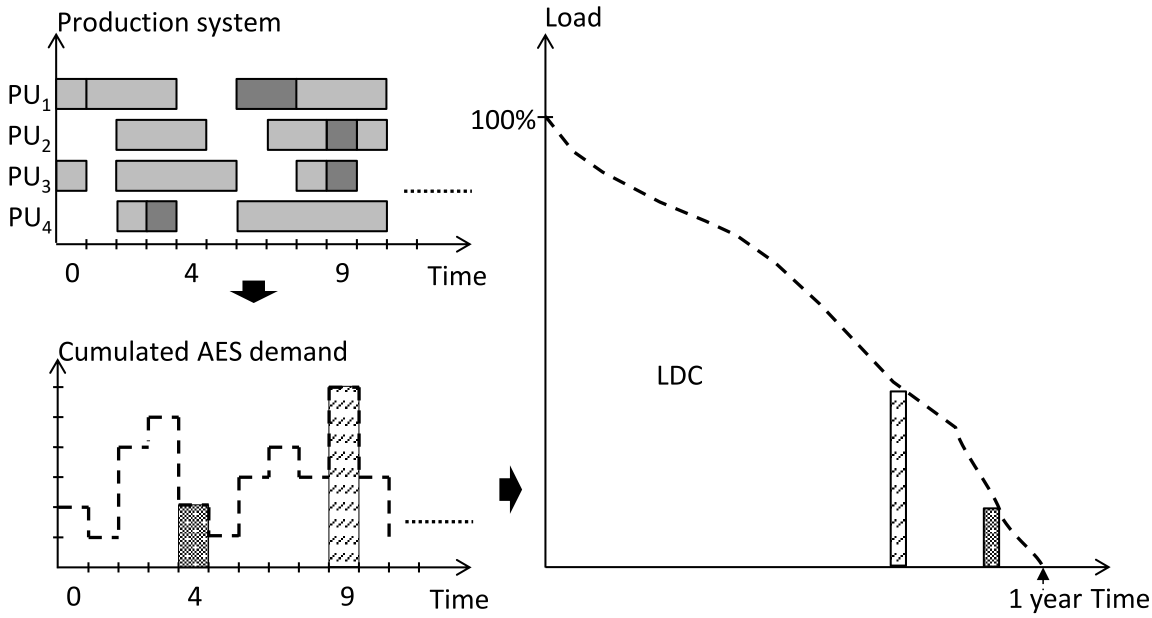

Figure I.B-2: Relationship between PS and cumulated AES demand to be supplied by the ECS

An exemplary production schedule (Gantt-chart on the upper left) shows task executions on four PUs. Tasks with a light gray background indicate an AES demand of one unit, and tasks with a dark gray background indicate AES demands of two units. This production schedule leads to the cumulated AES demands depicted on the lower left of Figure I.B-2 and shows that the executed production scheduling for a PS determines and influences the resulting cumulated AES demands per time unit. For analysis, cumulated AES demands can be visualized by load duration curves (LDCs). Here, the cumulated AES demands are arranged in a descending order either in an absolute or relative load scale. It is common to visualize data of one year. An exemplary LDC is depicted on the right side of Figure I.B-2 (the marked bars visualize the relationship between cumulated AES demands and LDC). Summarizing, since the ECS has to provide the demanded AES, the PS planning and production scheduling has an immense influence on the ECS design. More information on the relationship between PSs and ECSs can be found for instance in Mignon and Hermia (1996), Herrmann and Thiede (2009), Agha et al. (2010), Zhang et al. (2013), Merkert et al. (2014), Moon and Park (2014), Denz (2015), or Gahm et al. (2016).

Given the structural issues defined by case B (see Figure I.B-1), the basic purpose of an on-site ECS is to convert PES and/or SES to provide a specific type of AES requested by the PUs of the PS. Usually, a manufacturing company operates one ECS[1] to efficiently fulfill the cumulated AES demands of a specific type. For a most efficient AES supply, the ECS needs to operate at its nominal load (i.e., the load at which the ECS operates with maximum efficiency) for as long as possible. This is, because an operation at partial loads (i.e., any load different from the nominal load) leads to efficiency losses (cf., Aguilar et al. 2007, Kaikko and Backman 2007, Théry et al. 2012, Gibson et al. 2013, Pruitt et al. 2013, Denz 2015, Sun and Liu 2015, or Darrow et al. 2017). Consequently, assuming a manufacturing company's AES demand would be constant over time, for the most efficient AES supply the ECS's nominal load would be fitted to this constant demand. In reality, however, the AES demands of manufacturing companies are (usually) not constant over time, in fact they even vary strongly for each time unit, depending on the executed production schedule. This forces the ECS operation for most of the time to deviate from the nominal load for an accurate AES demand fulfillment, which leads to conversion inefficiencies. Consequently, the PS`s varying AES demands during production processes immensely influence an ECS's overall energy efficiency negatively. Thus, the efficiency of the on-site ECS strongly depends on an adequate design with respect to the PS.

I.B.3 Hierarchical planning of energy conversion systems for manufacturing companies

For an optimal design of an ECS for manufacturing companies, the ECS design and its operation and the design of the PS and its operation (with a corresponding production scheduling), need to be determined simultaneously. Since these individual planning decisions influence each other, the resulting optimization problem is quite complex.

For exactly those cases, where a simultaneous solving of all occurring planning problems within a total model is hardly practicable and a pure successive planning is not sufficient, the concept of hierarchical planning has been developed and can be traced back to Hax and Meal (1973), Bitran et al. (1981), Bitran and Tirupati (1993) and Schneeweiß (1995) amongst others. In hierarchical planning, the planning problem is split into individual, interlinked subtasks on the basis of factual criteria in order to reduce complexity. Hereby the interdependencies between the interlinked subtasks must be considered during problem splitting and the subsequent solving of the subtasks (Gahm, 2010). This process is called decomposition and hierarchical structuring. The concept of hierarchical planning in general is illustrated in Figure I.B-3 (cf., Schneeweiß, 1995).

[1] Note that also the operation of several ECS or the operation of an ECS consisting of several conversion units (CUs) is possible, but for a better understanding the following explanation assumes the operation of one ECS.

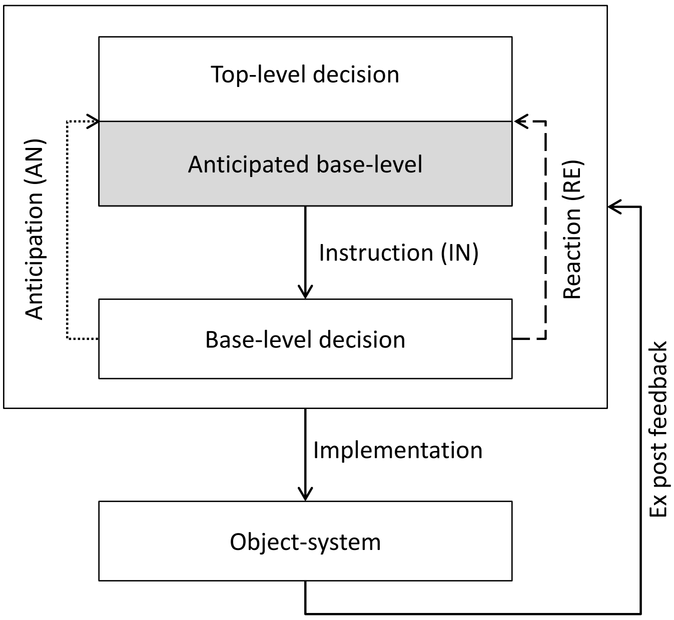

Figure I.B-3: Concept of hierarchical planning

Figure I.B-3 consists of two exemplary hierarchical planning levels, namely the top-level and its subordinate base-level. Hereby, the top-level represents long-term decisions and determines the frame within which the decisions of the subordinate base-level have to be reached (Stadtler et al., 2015). Consequently, the base-level represents short-term decisions which can be determined in dependency of the top-level decisions. A planning problem can be decomposed into an arbitrary number of decision levels (but at least two decisions levels, cf., Stadtler et al., 2015). This can be realized by the previous base-level becoming the top-level to a new subordinate decision level.

During hierarchical planning, the hierarchical coordination between the decision levels is realized by vertical top-down and bottom-up influences (Schneeweiß, 1995). In Figure I.B-3 the hierarchical influences between individual planning sub-tasks are represented by arrows. Solid arrows depict actual top-down influences called instruction (IN), dotted arrows represent anticipated bottom-up feedforward influences called anticipation (AN), and dashed arrows stand for bottom-up feedback influences called reaction (RE).

The procedure to find a feasible solution with the concept of hierarchical planning is as follows: The base-level provides its most relevant aspects or an aggregated version of itself to the top-level (AN). This information is used by the top-level to anticipate the base-level reaction for a proposed solution and thus, to make more appropriate suggestions. The proposed top-level solution (providing the frame in which decisions of the base-level have to be determined) is given to the base-level (IN) for an admissibility check and evaluation. Results from the base-level are afterwards returned to the top-level via a bottom-up feedback (RE). In case the proposed solution is not feasible or suitable, the base-level requests a recalculation of top-level decisions. Ultimately, if the negotiations between top-level and base-level determine a feasible solution, the results are implemented into the object-system to appraise the solution. The object-system returns the evaluated final solution and can influence the top-level and base-level via an ex-post feedback.

Regarding the anticipation of base-level reactions, different methods are possible. For instance, a simplified model of the base-level can be incorporated by simple rules, aggregation, assumptions, simulations, and/or simplified constraints. However, all these alternatives require the top-model to solve an additional aggregated version of the base-model during planning. For this reason, it is always a tradeoff between the degree of detail considered in the aggregated base-level or the reduction of complexity and the saving of computation time. Instead of considering a simplified version of the base-level, other methods, which approximate the reaction of the base-level, offer the potential for a very high quality base-level anticipation with a relatively short computation time. This approximation can be particularly promising if the necessary information for anticipating base-level reactions has not been sufficiently explored thus far. To create these approximations of the base-level reactions, different methods, for instance machine learning techniques such as decision trees, support vector machines, and artificial neural networks, are possible.

As stated above, with its high complexity, the design of an ECS for manufacturing companies is a suitable candidate for hierarchical planning. However, due to the strong relation between the PS and ECS, a direct application of hierarchical planning which “only” considers vertical influences is not sufficient. The vertical influences depict the relation between the ECS design and the ECS operation or the relation between the PS planning and the corresponding production scheduling. But for the relation between production scheduling and ECS operation the concept needs to be extended by horizontal influences. Figure I.B-4 illustrates these vertical and horizontal influences during the design of ECS based on the fundamentals of hierarchical planning.

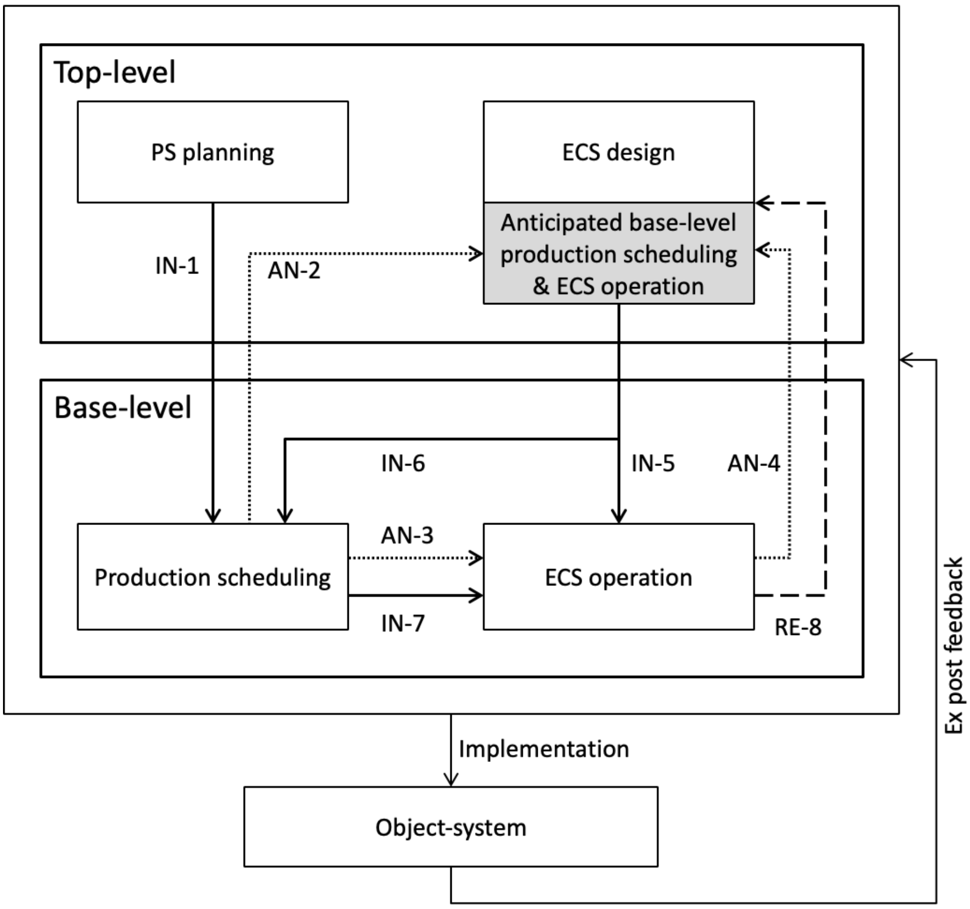

Figure I.B-4 Hierarchical ECS design concept

Here, the top-level decisions are the PS planning and the ECS design, whereas the base-level decisions are the production scheduling and the ECS operation. In addition to conventional hierarchical planning, the base-level decisions influence each other, and production scheduling depends on two superior top-level decisions.

Assuming that all strategic, long-term decisions about the PS (e.g., production processes and equipment, production unit arrangement) are already made, the energetic characteristics of the PS and the corresponding operational, short-term production scheduling problems are defined in instruction 1 (IN-1). According to the planned PS, the production schedules can be calculated. As already stated above, these production schedules define the cumulated AES demands[2] and thus, can influence the ECS design and ECS operation (cf., section I.B.2). Consequently, these resulting AES demands from production scheduling must be anticipated during ECS design (AN-2) and to estimate the corresponding ECS operation (AN-3). The ECS operation in turn is used as anticipated information (AN-4) during the top-level ECS design. Having the data of the anticipated production scheduling and ECS operation, the top-level proposes an ECS design to the base-level (IN-5 and IN-6). The proposed ECS design and its parameters (IN-6) are then integrated into production scheduling with energy-

[2] The data basis for AES demands can be historical data from manufacturing execution or production scheduling, but also be a result of so called "simulative scheduling" that will be discussed in more detail in Gahm et al. (C3).

efficient scheduling approaches. These actual scheduling decisions (IN-7) together with the proposed ECS design parameters (IN-5) determine the operational behavior of the ECS. The actual ECS operation provides its reaction (RE-8) about the suitability and energy efficiency of the proposed ECS design and if necessary, requests a recalculation of the top-level decisions.

After giving a short introduction on the application of energy, the interrelation of the PS and the ECS in manufacturing companies, as well as the hierarchical problem structure the research concept is introduced in the following.

I.C Research concept and contributions

This section places the contributions compiled within this dissertation into the context of the research concept. In addition a short summary of each contribution and their answered research questions is provided.

Figure I.C-1 illustrates the research concept and shows the contextual interrelations and mutual influences of the contributions by grey arrows. Furthermore, Figure I.C-1 assigns the addressed research questions (RQ1-RQ5) to each contribution (C1-C4).

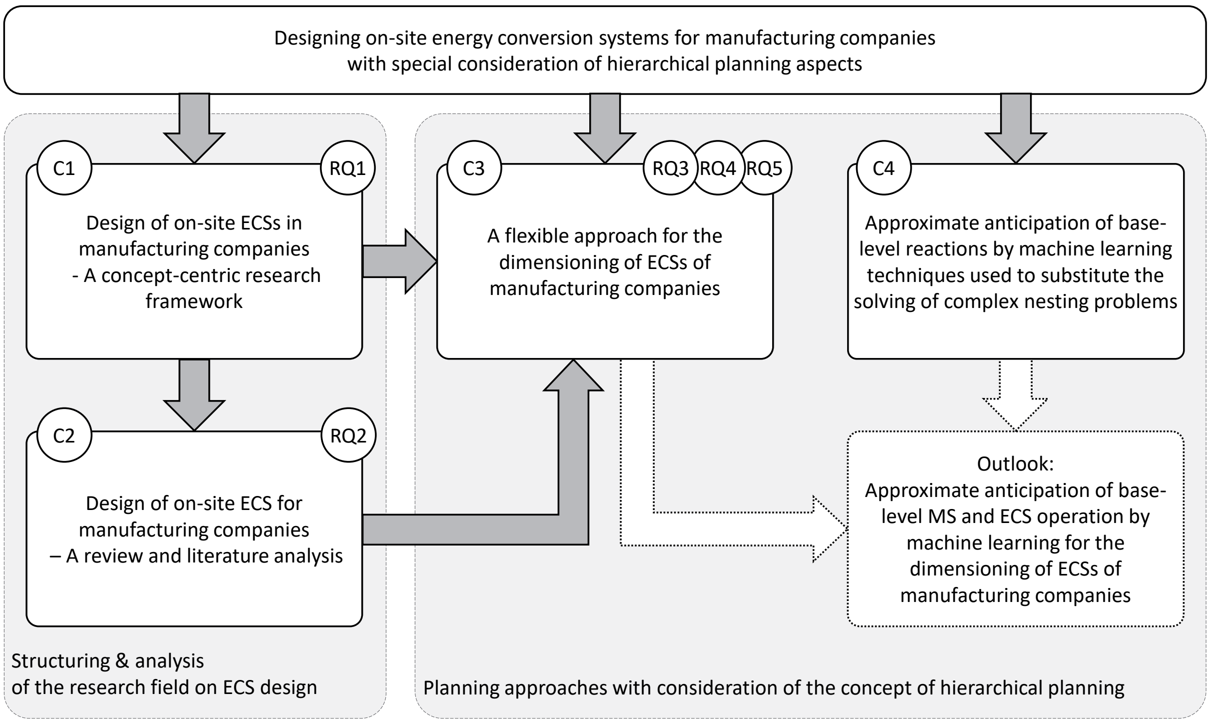

Figure I.C-1: Research concept and thematical classification of contributions

To answer RQ1-RQ5 this doctoral dissertation comprises four contributions, including three (C1-C3) which focus directly on the design of ECS for manufacturing companies, whereas the fourth contribution (C4) addresses a new method for an approximative anticipation function in hierarchical planning. This anticipation function, exemplary for nesting problems in manufacturing companies with machine learning, can be adapted and applied to the anticipation of base-level production scheduling and ECS operation during ECS design. To fully disclose not only the conducted research but also the opportunities for future research, the dotted arrows depict how the elaborated findings are applicable in the next research step (outlook).

Regarding ECS design in manufacturing companies, it needs to be considered that their production processes cause (strongly) varying energy demands, which can have a major negative influence on the efficiency of an ECS. To design an ECS adequately, each design approach needs to be carefully fitted to the planning problem at hand. This, combined with the various design possibilities, and the high complexity of ECS design in general, leads to countless publications addressing specific ECS design problems. To identify and categorize these numerous publications Ganschinietz (C1) presents a concept-centric ECS design framework (ECSDF), which structures existing and upcoming publications about the design of on-site ECSs for manufacturing companies. The development of the framework follows recommendations of Webster and Watson (2002), Seuring and Müller (2008), Vom Brocke et al. (2009), and Gahm et al. (2016) to define the ECSDF in an iterative manner. The resulting ECSDF consists of eight main categories, 27 sub-categories, and 126 attributes, which represent aspects essential for a high quality ECS design for manufacturing companies. The developed ECSDF answers RQ1[3] by unifying and structuring the understanding of the planning factors crucial for ECS design. Furthermore, it enables a corresponding analysis of existing literature in this field.

Consequently, in Ganschinietz et al. (C2) a structured literature review according to the ECSDF is conducted. For that purpose a search string-based literature search in the database Web of Science with a consecutive forward and backward search is performed. After reviewing over 600 publications, a total of 120 ECS design approaches are classified according to the ECSDF. These classified approaches form the base for an empirical analysis to gain insights about the existing state of the art as well as opportunities for further research topics. This analysis utilizes the results of RQ1 and answers question RQ2[4] as it displays which planning problems have been addressed and solved by the research community so far. As a result, the analysis identifies several opportunities for future research, for instance, the realistic modelling of partial load efficiencies, the consideration of ramp up constraints during ECS operation, and the development of a flexible design approach regarding the ECS type, FES

[3] RQ1: How can the research area of ECS design for manufacturing companies be structured and which planning factors are crucial for an adequate ECS design?
[4] RQ2: Which individual planning problems of ECS design have been addressed thus far or reveal a deficiency in research?

supply, and AES types. By doing so, Ganschinietz et al. (C2) disclose the motivation behind research questions RQ3[5] and RQ4[6]

On the basis of Ganschinietz (C1), Ganschinietz et al. (C2), and the elaborated importance of increasing the energy efficiency of ECS (cf., section I.A), Gahm et al. (C3) propose a flexible and robust ECS design approach with the objective to increase energy efficiency. They propose an ECS comprising of two complementary conversion units with different characteristics to provide AES for the energy demanding PS as efficiently as possible. To incorporate hierarchical interdependencies of the PS (and production scheduling) with the ECS design (and ECS operation), simulative scheduling is used to anticipate prospective AES demands during the top-level decision on the ECS design. For a more realistic anticipation of the prospective ECS operation, a non-linear modelling of the efficiency characteristics of CUs is utilized. To solve the planning problem, a highly efficient heuristic and a mixed-integer non-linear program is proposed. This flexible approach is independent of specific AES and FES types and not specified on a specific ECS type. One more aspect, which differentiates this flexible approach from existing literature, is the experimental analysis of energy efficiency influencing factors. This experimental analysis investigates different types of companies, scheduling objectives, CU parameters, and different part-load efficiency modelling approaches (piecewise-linear vs. non-linear) and their influence on the energy efficiency. Thus, besides research question RQ3, this contribution answers RQ4 by investigating the influence of different scheduling objectives, technical CU parameters, and part-load efficiency modelling approaches on the ECS design. Moreover, it addresses RQ5[7] by incorporating the concepts of hierarchical planning by the anticipation of different production scheduling objectives and aspects of the ECS operation during the decisions of the top-level ECS design.

One further aspect for future research identified by Ganschinietz et al. (C2) is the insufficient technical analysis of operational characteristics of CUs. Especially characteristics resembling CU state transitions, load transitions, and the related conversion efficiencies are not yet sufficiently researched[8]. Consequently, these characteristics are difficult to consider during top-level decisions, since they are either too complex to be modelled mathematically or cannot be modelled due to the lack of information. Only Shamsi et al. (2019) and Gahm et al. (C3) consider ramping constraints[9] at all, however in an aggregated and simplified way. Thus, to be able to consider the negative influences of these transitions on the additionally needed amount of final energy sources, they need to be either defined (e.g., by physical experiments or observations) or approximated. The advantage of the approximation is that the exact behavior does not have to be calculated, which can reduce necessary

[5] RQ3: How can different complex and individual planning problems of ECS design be addressed to increase energy efficiency?
[6] RQ4: How do the most important planning factors influence ECS design and ECS energy efficiency for manufacturing company?
[7] RQ5: How can the concept of hierarchical planning be incorporated during ECS design?
[8] For a detailed definition of these operational characteristics cf., Ganschinietz (C1).
[9] Ramping constraints are one of the possibilites to modell the compliance to restricted load transitions.

computation time and the dependency on the exact definition of physical behavior. One possible approach to approximate these influences is the application of machine learning techniques (for instance decision trees, support vector machines, and artificial neural networks). This approximation of base-level reactions can not only be applicable in ECS design, but also in other hierarchical planning problems. For this reason, Gahm et al. (C4) investigate the suitability of machine learning techniques for the approximation of base-level reactions on an interlaced production planning and production scheduling problem. More precisely, the approximation technique is defined and applied on a serial-batch scheduling problem with a subordinate complex nesting problem. Hereby, the top-level scheduling decision comprises batching of jobs (i.e., the grouping of small items to be cut out of a large object), allocation of these batches to machines, and sequencing. To verify the feasibility of a batch (subordinate base-level decision), the solving of the corresponding complex nesting problem (i.e., the spatial arrangement of all items without overlapping within the large object) becomes necessary. This can be very time consuming. To enhance this planning process, Gahm et al. (C4) propose the approximative anticipation of base-level nesting reactions by the application of machine learning techniques. Instead of solving the complex nesting problem, the feasibility of a batch is approximated. This approximation offers a very high quality of base-level anticipation with a relatively short computation time. With this contribution Gahm et al. (C4) lay the foundation for machine learning techniques as anticipation function for other hierarchical planning problems, exemplary for the use in ECS design.

In the next four sections, contributions C1 to C4 are presented as submitted.

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II

Contributions

II.A Contribution 1:
Design of on-site energy conversion systems for manufacturing companies – A concept-centric research framework

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Abstract: The conscientious use of energy progressively gains importance in society and the pressure on manufacturing companies to use energy more efficiently increases from an economical, ecological, and social perspective. Since on-site energy conversion has been identified as a measure to increase energy efficiency, manufacturing companies often operate on-site energy conversion systems (ECS) to provide the energy required by their production processes. These production processes cause (strongly) varying energy demands, which can have a huge negative influence on the efficiency of an insufficiently designed ECS. This reason combined with the various design possibilities and the high complexity of ECS design in general, lead to numerous publications addressing specific ECS design problems. These numerous publications make it laborious to identify adequate design approaches for individual application cases, especially due to the lack of an established research framework for this area. Therefore, we present a concept-centric ECS design framework (ECSDF) to classify existing and upcoming publications about the design of on-site ECSs for manufacturing companies. The introduced ECSDF enables the identification of relevant design approaches from an industrial perspective, the identification of opportunities for future research from the scientific perspective, and unifies the understanding of the crucial ECS design aspects in general.

Keywords: Energy conversion system, on-site, classification, research framework, manufacturing

1 Introduction

The conflict between globally rising energy demands (Upadhyay and Sharma, 2014) with the inherently scarce resources for demand fulfillment (Gahm et al., 2016) and continuously increasing fuel costs (Al Moussawi et al., 2016) calls for action. With the industrial sector being one of the main users of energy in the European Union (Eurostat, 2019), manufacturing companies have an immense impact on the global energy usage. This results in a great responsibility for manufacturing companies to use energy conscientiously. With energy as a non-substitutable and indispensable production factor (Gahm et al., 2016), it is vital to use energy as efficiently as possible to preserve resources from an ecological perspective and to save costs from an economical perspective.

Regarding energy provisioning in general, decentralized on-site energy conversion (for example by cogeneration and trigeneration systems) has been identified as one of the main measures to improve energy efficiency (cf., e.g., Liu et al., 2014 or Keshavarzzadeh et al., 2020). Other measures are for instance, general energy saving measures (Abdelaziz et al., 2011), the usage of renewable energy sources (Bukar and Tan, 2019), or efficiency increases for installed ECSs (Rashid et al., 2019). To fully benefit from the efficiency potentials of on-site energy conversion, energy conversion systems (ECSs) have to be accurately designed under consideration of the most relevant design parameters (e.g., size, system type, energy sources, operational range, …) as these parameters have an immense influence on an ECSs overall efficiency (Ghadimi et al. 2014). This influence on the overall efficiency increases even drastically, when the applied energy sources demand is varying over time (Yokoyama et al., 2002). Thus, regarding the ECS`s efficiency, an accurate design is especially important for on-site ECS in manufacturing companies as their energy demands vary strongly depending on the operation of their production system.

To accurately design a highly efficient and individualized on-site ECS for a manufacturing company, the state-of-the-art of this research field should be taken into account. But in the current literature, the considered parameters have become more and more diversified (Yokoyama et al., 2015) and the increasing number of proposed ECS design approaches focus on various different aspects. Therefore, the identification of the most related ECS design approaches for a specific design problem is a great challenge. To essentially support researchers and decision makers in this, we propose a new concept-centric research framework to classify existing and upcoming ECS design approaches.

The values added by our proposed ECS design framework (ECSDF) are manifold: The ECSDF

- builds a knowledge base for decision makers to identify relevant design approaches
- facilitates the search within existing design approaches
- comprises the most relevant aspects to be considered by ECS design approaches (for manufacturing companies) and helps to analyze and structure individual planning problems

- forms the base for empirical analyses of the research field
- can disclose research gaps and provide insights for future research

As this paper focuses on the development of the ECSDF, it is not going to provide a review or classification of the existing ECS design literature.

The paper is organized as follows. Section 2 contains an analysis of literature reviews and related work conducted in the research field. Afterwards, section 3 describes in detail the methodology applied for the development of the new concept-centric ECSDF. Then, section 4 defines and elaborates the categories and attributes of the framework. Section 5 concludes the article.

2 Related work

In literature, the dimensioning of on-site ECS for manufacturing companies is continuously discussed. Besides complex solutions for individual planning problems, authors review existing literature to analyze and structure design approaches and to simplify the finding of adequate literature (Cho and Lee, 2014). During the performed structured literature search, we identified 32 reviews and frameworks on the design and operation of on-site ECSs.These reviews/frameworks mainly focus on specific aspects. Therefore, they can be distinguished in reviews/frameworks on design- and/or operation-based ECS approaches, on ECS configuration possibilities, on specific types of ECS with different energy sources as input (e.g., cogeneration, or trigeneration systems with renewable or hybrid renewable energy sources), and on applied methodologies (e.g., solution methods) for different ECS types with different energy sources. In the following we summarize and differentiate existing reviews and frameworks about on-site ECS design and carve out the necessity of our concept-centric framework.

Some reviews distinguish between design-based, operation-based, and design-and-operation-based ECS approaches. Note, that for the design of an ECS mainly the design-based and design-and-operation-based ECS approaches are relevant, but for the sake of completeness, the determined operation-based reviews will also be briefly discussed here. O'Brien and Bansal (2000) focus on a design-based approach and additionally classify the existing literature according to the three basic types. A pure design-based review is provided by Biezma and Cristóbal (2006). It focuses on the economical view of ECS design and presents objectives used to optimize the selection of cogeneration systems. This review is exclusively about economic objectives and neglects other design aspects. In contrast, other reviews focus strictly on the operation-based approaches. Padhy (2004) published a survey on the unit commitment problem in the power industry and gives an overview of the operational characteristics of ECSs. Another review on the operation of ECSs was published by Xia and Elaiw (2010), in which they focus on the difference between two operational strategies. Additionally, both Xia and Elaiw (2010) as well as Padhy (2004) analyze applied solution methods. Furthermore, Cho et al. (2014) published an operation-based review on performance improvements and optimization of ECSs in form of combined cooling, heating, and power systems. Herein, they name publications on adequate ECS design and focus on the enhancement of already existing ECSs.

Regardless of whether approaches are design-based or design-and-operation-based, some reviews differentiate approaches according to their components (e.g., types of conversion units) and configuration possibilities. For example in order to adequately design an ECS, Cho and Lee (2014) classify energy conversion systems according to their components. Similar to that, but with a defined focus on trigeneration plants, Al-Sulaiman et al. (2011) and Jradi and Riffat (2014) conduct a review related to their installed prime movers and corresponding selection criteria. Hereby, Jradi and Riffat (2014) further investigate system configurations and the latest operational strategies.

A third group of reviews focuses on specific types of ECSs (e.g., cogeneration or trigeneration systems). For instance, Liu et al. (2014) provide a literature survey addressing cogeneration and trigeneration systems. The survey comprises ECS types, CU types, operational strategies, and optimization methods for the sizing of cogeneration systems. Liu et al. (2014) depict the identified CU types and give a textual summarization of the identified solution methods. Al Moussawi et al. (2016) published a concept-centric review about trigeneration technologies. Within this framework, the authors focus on trigeneration systems and use the classification categories prime movers, CU types, energy storage systems, and heat recovery systems. They provide information about all possible combinations of the elements of these categories. Furthermore, the authors give an overview of solution methods used for trigeneration system design. Al Moussawi et al. (2017) published a continuing review, which emphasizes the importance of the distinction between cogeneration and trigeneration systems during the design process as well as the differences between cogeneration and trigeneration CUs. Additionally, Al Moussawi et al. (2017) provide a selection table to choose adequate CUs depending on specific, application case related parameters.

Not only cogeneration and trigeneration systems are discussed in reviews, but also energy systems with renewable or hybrid renewable energy sources as input, called renewable or hybrid renewable energy system (RES / HRES). For example, Upadhyay and Sharma (2014) published a review on the configurations, operation, and design methodologies of hybrid systems. They classify according to four aspects that need to be considered during the design and implementation of hybrid energy systems: configuration, evaluation criterions, sizing methodologies, and operational strategies. Similar to Upadhyay and Sharma (2014), Al-falahi et al. (2017) provide a review on optimization methodologies for the sizing of HRES. They consider three aspects which comprise the configuration, the assessment parameters (comparable with goals and objectives) and sizing methodologies found in literature. For each aspect they provide an extensive concept-centric overview.

Next to the different system types, a widely analyzed topic in reviews are the applied solution methods for solving the ECS design (decision) problem. Regarding energy systems in general, Bazmi and Zahedi (2011) published an author-centric literature review about the role of optimization modeling techniques in power generation. They summarize the content of each considered author´s publication in the energy and power sector as well as for decentralized energy generation systems. Zeng et al. (2011) conducted a textual author-centric review about the optimization of energy system planning and greenhouse gas emission mitigation under uncertainty through the application of inexact optimization modeling methods and model-based decision support tools. Bargos et al. (2018) examined computational tools and operations research methods for the design and optimization of industrial cogeneration systems. Frangopoulos (2018) analyzed the current state, recent trends, and challenges in sizing and operation methods of energy systems in general.

Next to solution methods for ECS in general, also solution methods related to RES and HRES are subjects of reviews. Baños et al. (2011) provide a literature review on applied solution methods in the context of RES. To that, they structure their review according to the types of renewable primary energy sources (PES; e.g., wind power or solar energy) and provide a text-based and author-centric listing for each type of PES. Similar to that, but in a concept-centric manner, Iqbal et al. (2014) examine RES with respect to different types of renewable PES, and additionally investigate different modes of operations and types of objective functions. In contrast to an overview of diverse PES as input Yilmaz and Selim (2013) published a review on methods of HRES design that are specialized on ECS that especially include biomass as energy source. Regarding solution methods on optimum design of HRESs, Erdinc and Uzunoglu (2012), Luna-Rubio et al. (2012), and Chauhan and Saini (2014) published reviews on sizing methods applied on HRESs in general, whereas the reviews of Zhou et al. (2010), Sinha and Chandel (2015), Khare et al. (2016), and Bukar and Tan (2019) are specialized on the current state and recent trends of optimum sizing methods specifically applied for wind and photovoltaic based HRESs. Additionally to the sizing methodologies, Sinha and Chandel (2015) and Khare et al. (2016) provide an overview of operation optimization techniques, whereas Bukar and Tan (2019) added a fuel cell to their stand-alone photovoltaic-wind energy systems and investigated the latest developments in operational strategies. Furthermore, Khare et al. (2016) included reliability aspects into their review. Also concerning solution methods for specific renewable systems, Scott et al. (2012) focus on multi-criteria decision making for bioenergy systems, Lin et al. (2014) study wind power ECSs and reliability based system planning, and Khatib et al. (2016) concentrate on technical, economic, and social objectives for photovoltaic systems with batteries. In comparison to the reviews just mentioned, Bahramara et al. (2016) reversed the review process and investigate publications which apply one specific optimization method (the software HOMER) for the design of any HRES.

Other reviews do not focus on applied solution methods but on specific ECS types and their representation in literature. Eriksson and Gray (2017) for instance critically review current approaches on design and optimization of HRES with a hydrogen fuel cell and propose criteria addressing economical and socio-political design objectives.

In Table II.A-1, all previously discussed reviews and frameworks on ECS design are depicted with regard to their addressed aspects. In the last row, the uniqueness and the completeness of our developed ECS design framework is emphasized. Note that the ECSDF concentrates on the ECS related aspects but not on solution methods or objectives because these aspects are not necessarily ECS related. Of course, when conducting a literature review, these aspects should also be considered.

Table II.A-1: Investigated aspects of existing reviews and frameworks

Reviews & frameworks \ Considered aspects	Design of ECS	Operation of ECS	ECS configuration	Cogeneration systems	Trigeneration systems	HRES	RES	Restricted by specific ECS/PES	Solution methods	Objectives of design	Reliability aspects	Interdependencies with Production system
Al-falahi et al. (2017)	x		x			x			x	x		
Al-Sulaiman et al. (2011)	x		x		x							
Al Moussawi et al. (2016)	x		x		x				x			
Al Moussawi et al. (2017)	x		x	x	x							
Bahramara et al. (2016)	x					x			x			
Baños et al. (2011)	x						x		x			
Bargos et al. (2018)	x	x		x					x			
Bazmi and Zahedi (2011)	x								x			
Biezma and Cristóbal (2006)	x									x		
Bukar and Tan (2019)	x	x				x		x	x			
Chauhan and Saini (2014)	x					x			x			
Cho and Lee (2014)	x	x	x									
Cho et al. (2014)		x			x					x		
Erdinc and Uzunoglu (2012)	x					x			x			
Eriksson and Gray (2017)	x	x				x		x		x		
Frangopoulos (2018)	x	x							x	x		
Iqbal et al. (2014)	x	x					x		x			
Jradi and Riffat (2014)	x	x	x		x							
Khare et al. (2016)	x	x				x		x	x		x	
Khatib et al. (2016)	x		x					x		x		
Lin et al. (2014)	x							x	x		x	
Liu et al. (2014)	x	x	x	x	x				x			
Luna-Rubio et al. (2012)	x					x			x			
O'Brien and Bansal (2000)	x	x										
Padhy (2004)		x							x			
Scott et al. (2012)	x	x						x	x	x		
Sinha and Chandel (2015)	x	x				x		x	x			
Upadhyay and Sharma (2014)	x	x	x			x			x	x		
Xia and Elaiw (2010)		x							x			
Yilmaz and Selim (2013)	x					x		x	x			
Zeng et al. (2011)	x								x			
Zhou et al. (2010)	x					x		x	x			
ECSDF	x	x	x	x	x	x	x				x	x

Summarizing, most of the discussed publications are reviews with a very specific focus (e.g., certain aspects or types of ECSs) and lack a general applicability and a comprehensive consideration of all relevant aspects crucial for ECS design. In addition, the specific requirements of manufacturing companies are hardly considered. This means, to the best of our knowledge, there is no all-encompassing concept-centric framework supporting an accurate ECS design for manufacturing companies. This confirms the need for a new ECS design framework in order to facilitate the search for adequate literature and to analyze and structure design approaches and problems. Of course, concepts, aspects, categories, etc. that are used by the previously described reviews are analyzed and incorporated into our framework whenever appropriate. The complete methodology for the development of our ECSDF is described in the following section.

3 Methodology and literature scope

The methodology to develop the ECSDF follows a combination of recommendations on literature reviews and the development of research frameworks from Salipante et al. (1982) and Gahm et al. (2016) (which itself is based on the processes proposed by Webster and Watson (2002), Seuring and Müller (2008), and Vom Brocke et al. (2009)). According to these authors, literature should be categorized concept-centric instead of author-centric, because an author-centric categorization fails to analyze the literature systematically, whereas a concept-centric categorization structures literature in a research area in logical groups (Webster and Watson, 2002). For this reason, we develop a concept-centric research framework.

For the development of the ECSDF for manufacturing companies, the current state of science has to be considered by a comprehensive literature sample (because we cannot guarantee that all high-quality articles are considered, it is always a sample). To determine a comprehensive literature sample, we follow the iterative research procedure of Gahm et al. (2016), (cf., Figure II.A-1).

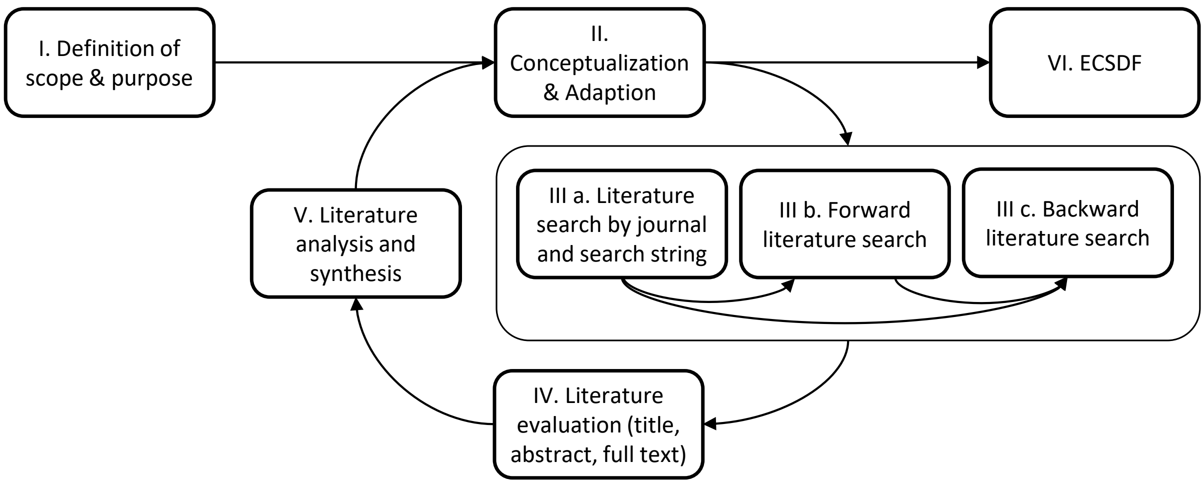

Figure II.A-1: ECSDF development based on a structured literature search

Note, that the steps II., III., and VI. of the research process are slightly adapted compared to Gahm et al. (2016): phase II. and VI. were renamed and in phase III., the identified publications from the forward search are additionally considered within the backward search process.

3.1 Definition of scope and purpose

First, the thematical scope of the research field and thus, of the literature sample for the development of the ECSDF must be defined. To that, a clear definition of the research field covered by the literature sample and the framework is set up. Based on this definition, a guideline for the relevance assessment of journals and articles is defined (further referred to as *scope and purpose criteria*).

3.1.1 Definition of the research field

To define the research field of the ECSDF, we start with an analysis of the possibilities of energy procurement for manufacturing companies. Regarding energy procurement in general, Rager et al. (2015) and Gahm et al. (2016) describe three main procurement cases (A, B, and C) together with the relevant systems and entities, which are depicted in Figure II.A-2 and described in the following.

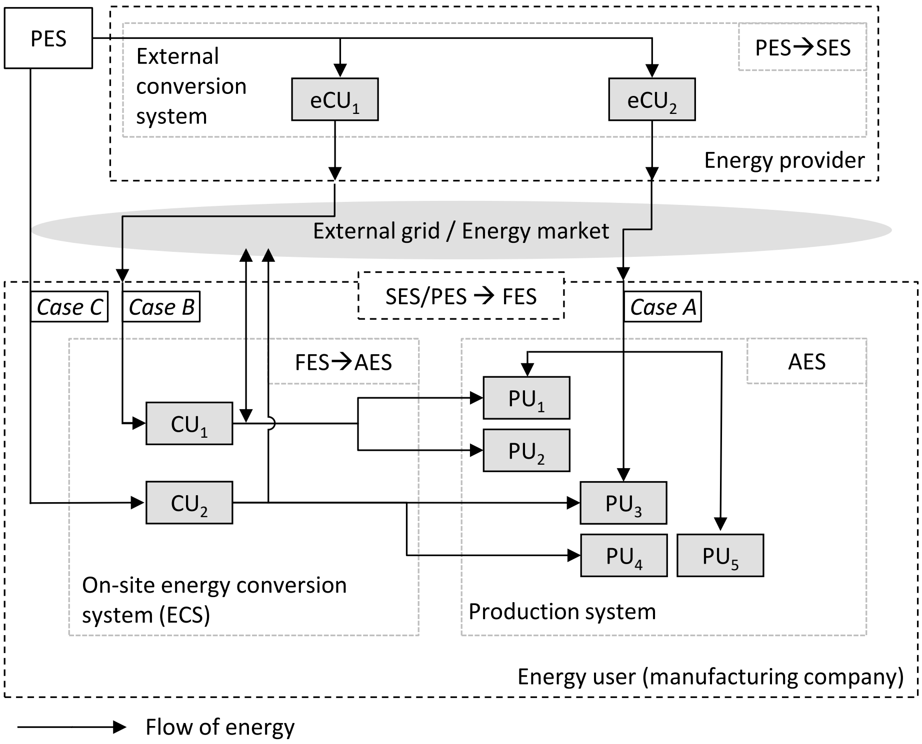

Figure II.A-2: Procurement of energy sources in manufacturing companies - relevant systems and entities

Energy is transported or stored by energy sources (also called energy carriers). Energy providers transform primary energy sources (PES) (e.g., solar or wind energy) with external conversion units (eCU) into secondary energy sources (SES) (e.g., power). At the moment the ownership of SES is transferred to the energy user (the manufacturing company), they are referred to as final energy sources (FES).

These FES can either be directly used as applied energy sources (AES) by the production units (PUs) of a manufacturing companies' production system (cf., Case A: flow of energy from eCU_2 to PU_1, PU_3, or PU_5 in Figure II.A-2) or need to be converted before being applied. In the latter case, the FES is the input for an on-site energy conversion system`s conversion unit (CU). Hereby, an ECS can comprise an individual number of CUs. The CUs convert the FES into the desired AES before it can be used by production units (cf., Case B: flow of energy from eCU_1 over CU_1 to PU_1 and PU_2 in Figure II.A-2). Additionally, the flow via an external conversion system can be avoided by using the PES directly as input for an on-site CU. In this case the PES serves as FES and is directly converted into the AES (cf., Case C: flow of energy from CU_2 to PU_3 and PU_4 in Figure II.A-2). In addition, the ECS can interact with the external grid and/or energy market. Our ECSDF classifies and structures approaches, which design ECS for manufacturing companies as in cases B and C.

3.1.2 Scope and purpose criteria

Based on the definition of the research field, the *scope and purpose criteria* for the journal and article selection is defined in this section.

The focus of the ECSDF is on the design of ECS and therefore, only publications dealing either with the design or with the design and operation of ECSs are relevant. Consequently, articles dealing exclusively with the operation of ECSs (e.g., the energy flow, inlet pressure, or operational temperature of CUs) are excluded. Furthermore, to focus on the ECS design for manufacturing companies, an article is considered as relevant when it designs on-site ECSs in a manufacturing context (for a definition of the corresponding industrial sector see section C in United Nations, Department of Economic and Social Affairs, 2008). Consequently, commercial energy production at energy providers; the design and operation of the central grid, its layout, or extensions; and publications on on-site ECSs of city districts and public or private buildings (e.g., administrative offices, hospitals, or households) are excluded. Note, that the ECSDF can be suitable for non-industrial ECS design contexts with similar constraints as in the case of manufacturing companies (e.g. varying energy demands). Furthermore, the mere installation of an energy storage system is not part of the literature sample. Also, publications which have an ECS as a production system (which coincidentally can be an ECS; e.g., a hydrogen production system), are excluded.

3.2 Conceptualization

The iterative part of the research process starts with step II. (Conceptualization & Adaption). During the first iteration of the conceptualization phase the topic of interest is investigated in general. Hereby, a deduction of the first categories and attributes of the ECSDF while analyzing existing reviews and literature of previous publications is undertaken (like proposed by Salipante et al., 1982, Webster and Watson, 2002, and Seuring and Müller, 2008). This results in a first version of the ECSDF.

Further results of the first conceptualization phase are the definition of the scope of journals to investigate and the definition of the keywords (in order for the search procedure to be reproducible).

The definition of the scope of journals is based on the "SCIMAGO Journal & Country Rank", which provides the SJR-Index. The SJR-index is a number-based score for journals measuring the impact or prestige of its articles (Guerrero-Bote and Moya-Anegón, 2012). The journal selection is based on a journal ranking, because journal rankings identify high-quality journals and, according to Webster and Watson (2002), the most important publications are found in the most renowned journals. In addition to a journal ranking, the SJR provides sub-areas and sub-categories classifying journals with similar topics.

Table II.A-2: Considered sub-areas and sub-categories for journal selection

Sub area	Sub category
Energy	Energy Engineering and Power Technology (En. Eng. & Pow. Tech.)
	Energy (miscellaneous) (En.)
	Renewable Energy, Sustainability and the Environment (Ren. En. Sust. & Environ.)
Engineering	Electrical and Electronic Engineering (Electri. & Electro. Eng.)
	Engineering (miscellaneous) (Eng.)
	Industrial and Manufacturing Engineering (Ind. & Manu. Eng.)
	Mechanical Engineering (M. Eng.)

Within the sub-areas and sub-categories selected for this review (cf., Table II.A-2), we assume that the most quality research is published in scientific journals and thus, exclude books, theses, conference proceedings and trade journals (as done by Rubio et al., 2008 and Gahm et al., 2016). All investigated journals are published in the English language, peer reviewed, and rated with an SJR-index greater than 1 to assure an adequate quality (further revered to as *journal criteria*). Subsequently, journals are excluded if they do not fit the topic according to the scope and purpose criteria (cf., section 3.1) considering their title, contents, and main focus. Finally, 47 appropriate journals have been identified for the aspired literature search. The journals identified in this process phase are listed in Table II.A-3. Next to the journal selection, also the keywords were determined. The complete combinations of journals and keywords define the so called "search string" depicted in the appendix A-1.

3.3 Iterative framework development

The iterative framework development process comprises the steps III. a. – III. c. and the succeeding steps IV., V., and II. in an iterative manner (cf., Figure II.A-1). In the first iteration (starting with step III. a.), a literature search by journal and keywords is conducted in the Web of Science database. This database is used as it hosts all 47 relevant journals. The search string`s application (in the advanced search tool in all databases and all years) reveals the “initial hits”: a set of 416 articles. This kind of search does not claim to be complete, but it is extensive, structured, and reproducible.

Within the initial hits, the literature evaluation (IV.) preselects the relevant approaches by reviewing title, abstract, and keywords. Then, all preselected approaches are checked for their relevance by a full text review. In both steps, the articles are identified as relevant (or irrelevant) according to the criteria defined in section 3.1. Regarding the initial hits, 8 relevant articles have been identified.

These 8 articles are analyzed and synthesized (V.) in order to be classified by the incumbent version of the ECSDF. In case approaches address terms or aspects which are not yet represented in the incumbent ECSDF, we adapt the ECSDF (II.).

In the second iteration, the forward search (III. b.) with all subsequent steps is conducted. The forward search is based on the 8 identified publications and is carried out to find literature that cites these publications. Regarding the forward search, only approaches which fulfill the *journal criteria* and *scope and purpose criteria* (cf., sections 3.2 and 3.1) are added to the literature sample. This iteration identifies 14 additional ECS design approaches as relevant.

To get a more comprehensive literature sample, in the last iteration (starting with step III. c.), a structured backward search is performed based on the 22 previously identified approaches. This final iteration leads to 22 additionally identified approaches.

This iterative procedure leads to 44 ECS design approaches to be analyzed. Note that the 44 identified articles are the result of the thorough analysis of titles, abstracts, and full texts of over 600 potentially relevant articles.

Table II.A-3 summarizes the reviewed journals and the number of relevant articles (depicted according to their publishing journals after each search iteration) from the iterative framework development. Note, that the 47 journals from the structured literature search are marked with an asterisk (*). Furthermore, Table II.A-3 shows in which quartile (Q1-Q4) each journal is ranked by the SJR. It stands out, that journals with an SJR >1 are most of the time considered to be in the top 25% of journals within each sub-category. The number of 51 journals in total (only 4 more than in the search string) indicates that the research field is analyzed in a sufficient manner, as not many further journals were identified through the forward and backward search of the search process.

Table II.A-3: Reviewed journals and identified relevant articles (state: May 2020)

Journal name (initial hits search string search)	SJR index and quartile of sub-categories								Articles identified by			
	SJR-Index	En. Eng. & Pow. Tech.	En.	Ren. En. Sust. & Environ.	Electri. & Electro. Eng.	Eng.	Ind. & Manu. Eng.	M. Eng.	Keyword search	Forward search	Backward search	Total
Applied Energy* (47)	3,61	Q1	Q1					Q1			2	2
Applied Thermal Engineering* (18)	1,78	Q1					Q1				4	4
Chemical Engineering Science	1,00						Q1				2	2
Computers and Chemical Engineering	1,00									3	5	9
Desalination	1,81							Q1			2	2
Energy* (58)	2,17		Q1		Q1		Q1	Q1	2		3	6
Energy Conversion and Management* (44)	2,92	Q1		Q1					3	2	1	6
IEEE Transactions on Industry Applications* (10)	1,50				Q1		Q1		1			1
International Journal of Hydrogen Energy* (33)	1,14	Q1		Q2					1	3	2	6
Journal of Cleaner Production* (18)	1,89			Q1			Q1			1		1
Renewable & Sustainable Energy Reviews* (7)	3,63			Q1						1		1
Renewable Energy* (32)	2,05			Q1					1	2	1	4
Solar Energy* (9)	1,54			Q1						2		2
Computers & Industrial Engineering* (2), Electric Power Systems Research* (4), Energy & Environmental Science* (5), Energy Economics* (3), Energy for Sustainable Development* (0), Energy Journal* (0), Environmental Research Letters* (2), Experimental Thermal and Fluid Science* (0), IEEE Journal of Emerging and Selected Topics in Power Electronics* (1), IEEE Journal of Photovoltaics* (0), IEEE Power & Energy Magazine* (0), IEEE Transactions on Energy Conversion* (9), IEEE Transactions on Industrial Electronics* (14), IEEE Transactions on Power Delivery* (5), IEEE Transactions on Power Electronics* (8), IEEE Transactions on Power Systems* (21), IEEE Transactions on Sustainable Energy* (14), IET Generation, Transmission & Distribution* (8), IET Power Electronics* (2), IISE Transactions* (1), International Journal of Electrical Power & Energy Systems* (17), International Journal of Engineering Science* (1), International Journal of Heat and Mass Transfer* (7), International Journal of Production Economics* (1), International Journal of Production Research* (4), International Journal of Thermal Sciences* (2), Journal of Modern Power Systems and Clean Energy* (0), Journal of Operations Management* (0), Nano Energy* (4), Nonlinear Analysis: Real World Applications* (0), Production and Operations Management* (0), Production Planning & Control* (0), Progress in Energy and Combustion Science* (0), Progress in Photovoltaics* (0), Solar Energy Materials and Solar Cells* (3), Sustainable Energy Technologies and Assessments* (3), Journal of the Energy Institute* (0)												
Total									8	14	22	44

Of course suitable articles from the initial conceptualization phase and the related work section are included in the ECSDF development. Finally, over 76 articles (design approaches, reviews, frameworks etc.) form the literature sample to develop the ECSDF.

The described methodology results in the ECSDF which is described in the following section.

4 The concept-centric ECS design framework

The developed concept-centric *ECS design framework* consists of eight main categories with several sub-categories and attributes by which any ECS design approach for manufacturing companies can be classified. The main categories of the concept-centric framework are the *Basic design approach*, *ECS type*, *ECS operation*, *Energy sources*, *CU types*, *CU operation*, *AES demand/FES supply*, and *Relations to other systems* (cf., Figure II.A-3).

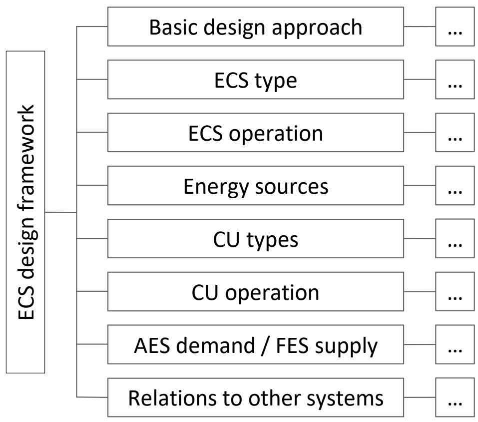

Figure II.A-3: Main categories of the ECS design framework

Each of these main categories can consist of multiple sub-categories (groups of attributes) and attributes that are explained in detail in the following sections. To that, each section contains one or more figures, which illustrate the category to be explained (highlighted in a light grey) with its sub-categories and corresponding attributes. Whenever the category or its attributes are related to one of the previous frameworks or reviews, these are acknowledged and cited within the descriptions.

Note that a complete classification of the analyzed ECS design approaches is provided within the digital supplementary material. Therefore, to keep the text clear, we omit a complete list of references for each attribute but provide most informative references wherever it is appropriate.

4.1 Basic design approach

The first main category *Basic design approach* categorizes publications according to their treated decisions. To that, the category is subdivided into *Scope* and the *Decision field* (cf., Figure II.A-4).

4.1.1 Scope

During the design of an ECS for manufacturing companies, the relation between the ECS and the production system (PS) is an integral part as this relation strongly influences the ECS design. As a result, the sub-category *Scope* differentiates between the attributes *AES demand fulfillment*, *AES demand fulfillment & limited FES/PES*, and *AES output maximization* (cf., Figure II.A-4).

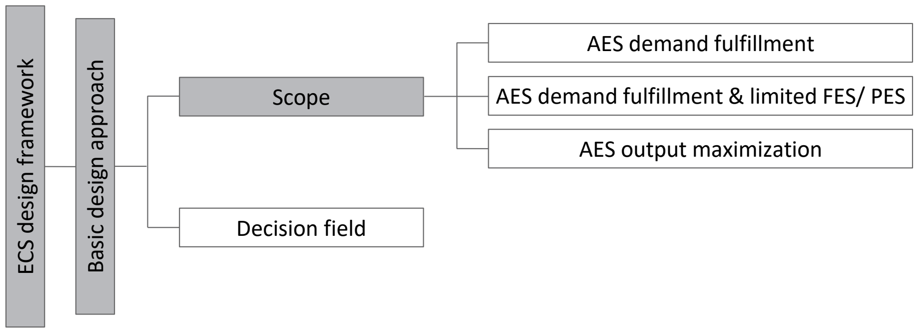

Figure II.A-4: Sub-category Scope

The category *AES demand fulfillment* classifies approaches which design the ECS with the main goal to fulfill the AES demand of the PS (e.g., Leif Hanrahan et al., 2014 or Rad et al., 2016). The attribute *AES demand fulfillment & limited FES/PES* is similar, but classifies approaches which additionally consider a limited availability of FES/PES (e.g., when the FES/PES is a renewable energy source like solar or wind energy) (e.g., Amusat et al., 2016 or Campana et al., 2019). For both attributes, the AES demand can be static or varying. The third attribute *AES output maximization* classifies approaches which design ECS not with the goal to fulfill a given AES demand, but with the goal to maximize the ECS`s possible AES output. In this setting, the PS's output relies on the amount of AES the ECS provides (e.g., Ahmadi et al., 2015; Bhattacharyya et al., 2017; Keshavarzzadeh et al., 2020). An example is the hydrogen production with renewable energy sources as FES. Here, the optimized design of an ECS defines the AES output und therefore, the hydrogen production volume.

4.1.2 Decision field

The category *Decision field* describes the details of what (e.g., size of CUs) and how (e.g., a selection from a predefined set) major decisions regarding the ECS design are made. For that purpose, the category is divided into the two sub-categories *Decision topic*, i.e., what is decided, and the *Decision type*, i.e., the how is it decided (cf., Figure II.A-5).

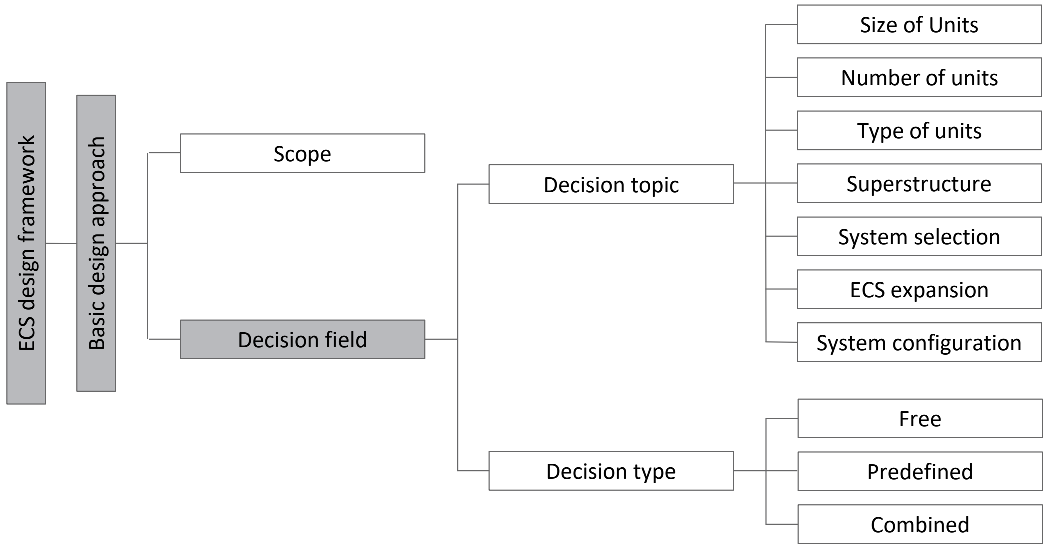

Figure II.A-5: Sub-category Decision field

One way to differentiate ECSs is by the parameters number, size, and type of installed CUs (cf., Cho and Lee, 2014). Within the category *Decision topic,* we accordingly differentiate approaches by the *Size of units*, *Number of units*, *Type of units*, *Superstructure*, *System selection*, *ECS expansion,* and *System configuration*.

The attribute *Size of units* refers to the maximum capacity of CUs (e.g., Chitgar and Moghimi, 2020), *Number of units* refers to the quantity of installed CUs (e.g., Keshavarzzadeh et al., 2020), and *Type of units* refers to the selection of different technologies (e.g., a selection between gas-fired or coal-fired boilers; e.g., Aguilar et al., 2008; Sun and Liu, 2015; Alirahmi et al., 2020a). The attribute *Superstructure* means that selectable units (e.g., with distinct sizes and/or types) are considered as candidates for an ECS. The real structure of the ECS is created by selecting some units from the suggested superstructure candidates (e.g., Voll et al., 2013; Andiappan et al., 2015; Yokoyama et al., 2015). The attribute *System selection* classifies approaches in which complete ECSs (not individual CUs) are compared to one another. There is no decision on the number, size, and type of any CU but just the decision between complete, discrete systems (e.g., Pendergrass, 1983; Yokoyama et al., 2014; Campana et al., 2019; Abbasi and Pourrahmani, 2020). The attribute *ECS expansion* classifies approaches which extend already existing ECSs (e.g., Roy, 2001; Voll et al., 2012; Shamsi et al., 2019). The attribute *System configuration* classifies approaches which, in addition to design aspects, optimize "operational" design variables. Examples for these operational design variables are the turbine inlet pressure, the operation temperature, or the orientation angle of the photovoltaic system. Approaches can only be classified by the attribute *System configuration* when they also optimize at least one of the other decision topics (e.g., Najafi et al., 2014; Khanmohammadi et al., 2017; Alirahmi et al., 2020b). Nonetheless, we found this additional decision topic worth adding to the framework as it provides additional information about the planning approach. Note that these attributes are non-exclusive.

Because the decision on the previously described decision topics can have different degrees of freedom, the category *Decision type* depicts whether the decisions are *Free*, restricted by a *Predefined* set*,* or a combination of both (*Combined*).

If an approach determines all considered *Decision topics* not from a limited amount of discrete options, but optimizes the considered decision topics during the design process, it is categorized as *Free* (e.g., Emadi and Mahmoudimehr, 2019; Chitgar and Moghimi, 2020). In contrast, if an approach determines all considered decision topics by choosing between discrete options, it is categorized as *Predefined* (e.g., Marechal and Kalitventzeff, 1998; Won et al., 2017; Ghorbani et al., 2019). When more than one decision topic is determined, the degree of freedom can vary between and within each decision topic. Therefore, the attribute *Combined* is necessary in the case that within one approach some decision topics are determined *Free* and some others are *Predefined* (e.g., Papoulias and Grossmann, 1983; Luo et al., 2014; Kazi et al., 2015; Campana et al., 2019). Note that these attributes are exclusive.

4.2 ECS type

The main category *ECS type* classifies ECSs according to their basic type by classifying them by the number of provided AES (cf., Andiappan et al., 2014). To this, we differentiate between the attributes *Singlegeneration system*, *Cogeneration system*, *Trigeneration system*, *Polygeneration system* and *Flexible* (cf., Figure II.A-6). Some attributes of this category have also been used by Liu et al. (2014) and Al Moussawi et al. (2016; 2017).

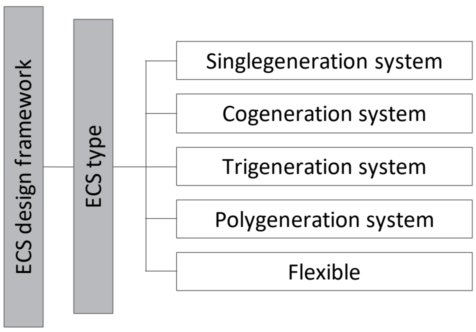

Figure II.A-6: Category ECS type

In order to create an unambiguous definition of the ECS types, the attribute S*inglegeneration system* classifies an ECS which converts FES into a single AES. A *Cogeneration system* (*Trigeneration system*) is an ECS which converts FES into two (three) AES. A *Cogeneration system* is most commonly a combined heating and power (CHP) system, whereas a *Trigeneration system* is usually a combined cooling, heating, and power (CCHP) system (cf., Andiappan et al., 2014; Al Moussawi et al., 2017). When an ECS converts FES into more than three energy sources, it is categorized as a *Polygeneration system* (e.g., Papoulias and Grossmann, 1983; Carvalho et al., 2014). In case, approaches can design multiple kinds of ECS types (e.g., CHP and CCHP), they are classified as *Flexible* (cf., Azit and Nor, 2009).

The strict categorization and clear definition into the different *ECS types* proves necessary, as so far, some authors use the definitions in different contexts. For instance, occasionally authors talk about cogeneration systems although they provide more than two AES (e.g., Azit and Nor, 2009). Other approaches group heat and cold into one thermal energy source. Afterwards, they generate cold and/or heat by further processing the thermal energy sources provided by CUs (e.g., Yokoyama and Ito, 2002; Benam et al., 2015). In this case also no unified definition is used for the corresponding ECS types. Thus here, an ECS is categorized depending on whether it processes the thermal energy sources into just heat or cold (cogeneration system), or both (trigeneration system). Note, that the attributes of the category *ECS types* are usually mutually exclusive but in case of a comparison between different *ECS types*, they can be non-exclusive.

4.3 ECS operation

The literature analysis carved out that, during the design of an ECS, the operation of the prospective ECS is considered in different ways. Thus, the main category *ECS operation* categorizes approaches according to the way the prospective operation is considered during the design phase. Therefore it classifies approaches according to the sub-categories *Hierarchical integration* and *Operation strategies* with their attributes and the attribute *Operation Optimization* (cf., Figure II.A-7).

4.3.1 Hierarchical integration

The sub-category *Hierarchical integration* consists of attributes explaining the interdependencies of design decisions and operational decisions, as it is important to take their hierarchical relationship during design into account (Ghadimi et al., 2014). A detailed description of the concept of hierarchical planning in general can be found in Schneeweiss (2003) and of hierarchical interdependencies during ECS planning in Yokoyama et al. (2014). In literature, some authors (implicitly) differentiate between a separate (Aguilar et al., 2007), iterative (Aguilar et al., 2007), anticipating (Aguilar et al., 2008), or a simultaneous (Aguilar et al., 2008) optimization of the design and the operation of an ECS. Accordingly, the category *Hierarchical integration* classifies the different integration types of an ECS's operation by the mutually exclusive attributes *Top-down*, *Top-down with feedback*, *Anticipation*, and *Simultaneous* (cf., Figure II.A-7).

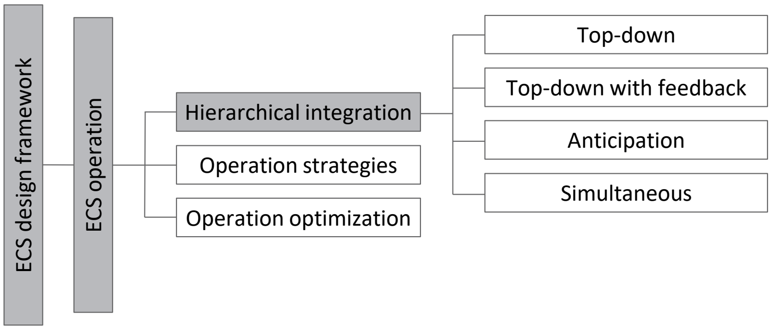

Figure II.A-7: Sub-category Hierarchical integration

The integration type *Top-down* means a strict top-down relationship between ECS design and ECS operation, i.e., the ECS operation is only used for evaluating the preceding, independent design decision (cf., e.g., Varbanov et al., 2005; Ghadimi et al., 2014; Alirahmi et al., 2020a). However, no design decisions are changed due to the evaluation, but one ECS design can be compared to another ECS design and the best design can be chosen. Hereby, exemplary evaluation criteria can be operational costs, investment costs, or energy consumptions.

In contrast, approaches to be classified by the integration type *Top-down with feedback* use feedback information resulting from ECS operation related to a specific ECS design to adjust the incumbent ECS design in an iterative manner (cf., e.g., Roy, 2001; Amusat et al., 2017). Hereby, a definition of the feedback information and the procedure on how to integrate this feedback is mandatory.

The third integration type *Anticipation* directly integrates some aspects of the ECS or CU operation into the ECS design. In doing so, some aspects and/or simplified (relaxed) aspects of the subordinate ECS or CU operation are integrated and others are not (otherwise, the ECS design might be getting to complex). The concrete ECS and CU operation aspects can be considered in individual detail and combinations during the ECS design. An Example for a CU operation aspect is the compliance with minimum time intervals between which a CU can be switched on and off (cf., e.g., Aguilar et al., 2008; and section 4.6). An Example for the anticipation of ECS operation is the usage of an operation strategy (e.g., Smaoui et al., 2015; Morais et al., 2020). By using such an operation strategy, an ECS's operational behavior is integrated without optimizing it.

Last attribute of hierarchical integration is called *Simultaneous* and classifies design approaches, which determine the design and operation of an ECS at the same time. Note that hereby the complete relevant subordinate ECS operation problem must be considered.

4.3.2 Operation strategies

To take the interdependencies between the design and operation during the design stage into account, operation strategies simulate the prospective behavior of the ECS in a simplified way, i.e., by following strategy-specific rules. The difficulty hereby is that not every strategy does necessarily exploit all benefits of every ECS and thus, has to be selected carefully (Kavvadias and Maroulis, 2010).

The sub-category *Operation strategies* comprises typical representatives as sub-categories and attributes. We propose to distinguish strategies according to the sub-category *AES demand following* and the attributes *FES supply following*, *Individual strategy*, and *Continuous operation*.

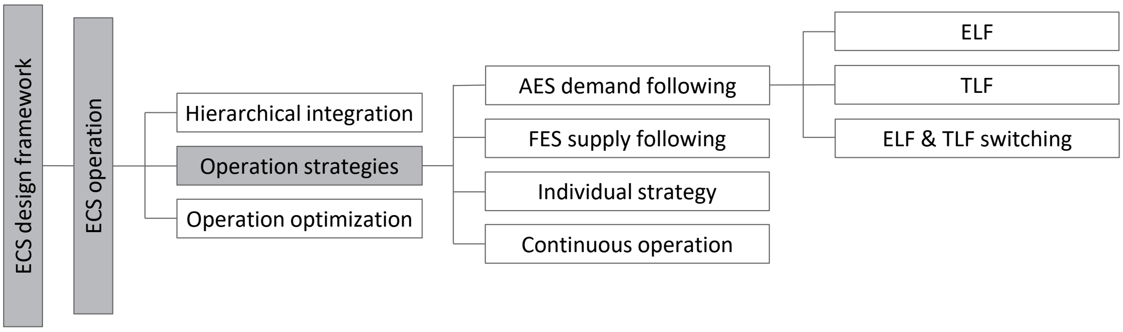

Figure II.A-8: Sub-category Operation strategies

The sub-category *AES demand following* comprises approaches where the ECS operation is directly coupled to the AES demand and consists of the attributes electrical load following *(ELF)*, thermal load following *(TLF)*, and the attribute *ELF & TLF switching* (cf., Figure II.A-8). When following the *ELF* strategy, the priority of the ECS operation is to provide the electrical load demand as exactly as possible, independent of whether a deviation from this demand following would be beneficial (cf., e.g., Ghadimi et al., 2014; Al Moussawi et al., 2017; Morais et al., 2020). The strategy TLF is similar to ELF, but with the priority to follow the thermal load demands as exactly as possible (cf., e.g., Ghadimi et al., 2014; Al Moussawi et al., 2017; Shamsi et al., 2019). In both strategies additional recovered heat during ELF or generated electricity during TLF can occur, but is treated as a byproduct (Ghadimi et al., 2014). The attribute *ELF & TLF switching* classifies approaches in which ECS operation interchanges between the ELF and TLF strategy depending on AES demands (Andiappan and Ng, 2016).

The attribute *FES supply following* classifies approaches in which the conversion process completely depends on the FES supply. This means, the amount of available PES/FES (e.g., mostly in the form of uncontrollable occurrence of wind or solar energy) determines whether or not the ECS is operating and the corresponding amount of AES provided (cf., Bernal-Agustín and Dufo-López, 2010; Behzadi et al., 2019; Waseem et al., 2020). The provided AES are either directly used by the PS or transferred to an energy storage unit. In this case, the PS's production rate is directly influenced by the PES/FES availability and no active decision on the ECS operation is made.

The attribute *Individual Strategy* represents individual tailor-made or modified operation strategies sporadically used by a single or only a few approaches. Examples of such strategies are peak shaving (cf., e.g., Kavvadias and Maroulis, 2010), separate heat/ power generation (cf., e.g., Ghadimi et al., 2014), rule based operation (cf., e.g., Mavromatis and Kokossis, 1998; Amusat et al., 2017), and electrical/ thermal equivalent demand following (cf., e.g., Kavvadias and Maroulis, 2010). Note that a more detailed discussion on energy management strategies in the context of stand-alone renewable ECSs can be found in Bukar and Tan (2019).

Approaches are classified by the attribute *Continuous operation* whenever the ECS operation is at a constant operation level and is not determined by the availability of PES/FES nor by a given AES demand. This is for instance the case when hydrogen (e.g., Chitgar and Moghimi, 2020) and/or fresh water is produced (e.g., Keshavarzzadeh et al., 2020).

4.3.3 Operation optimization

During ECS design, the operation of the ECS can also be part of the optimization. Sometimes this approach is actually called optimization, in other cases, it is called an optimal dispatching strategy (cf., e.g., Ghadimi et al., 2014; Liu et al., 2014). For an approach being classified by the attribute *Operation optimization*, the approach needs to consider design and operational decision variables (e.g., Hui and Natori, 1996; Abbasi and Pourrahmani, 2020). Be aware that optimization not necessarily means that a mathematical optimum is reached, but also suboptimal solutions calculated by heuristics are appropriate. In case the design and operation are optimized at the same time, the approach is also classified as *Simultaneous* (e.g., Shang and Kokossis, 2005; Carvalho et al., 2014; Amusat et al., 2016).

Note, that the attributes within the sub-category hierarchical integration are exclusive. Whereas the attributes of the sub-category *Operation strategies* and the attribute *Operation optimization* are non-exclusive, as for instance, an approach can compare an operation strategy to an optimization procedure or the most suitable operation strategy is selected.

4.4 Energy sources

The main category *Energy sources* classifies approaches according to their *FES type* (input energy sources) and their *AES type* (output energy sources) (cf., Figure II.A-2, Figure II.A-9, and Figure II.A-10).

Note that in this section, the term energy sources is used because the final attribute of each sub-category are energy sources (e.g., steam or hot water), even though intermediary sub-categories are common properties of energy sources (e.g., heat) but not energy sources by definition.

4.4.1 FES types

The sub-category *FES types* differentiates FES by the sub-categories *Renewable*, *Non-renewable, Re-used* and *Flexible* (cf., Figure II.A-9) because ECS design approaches have to take corresponding aspects (e.g., concerning supply availability) into account.

Renewable energy sources occur in forms of, e.g., *Wind, Solar, Hydro, Marine, Geothermal energy* or *Bioenergy* (cf., Shiun et al., 2012 or Ellabban et al., 2014). Non-renewable energy sources are, e.g., *Coal, Natural gas, Oil based fuels,* and *Nuclear energy* (cf., Shafiei and Salim, 2014). Electric power, has a double position as it can be renewable, non-renewable, or a combination of both, depending on its characteristics. Note, that if an approach does not define if the electric power is renewable or non-renewable, we classify it according to both *power* attributes because the electric power from the grid consists of an energy mix. Furthermore, *Re-used* energy sources are the waste of other systems and are re-used by the ECS, e.g., *Exhaust gas* or *Exhaust heat* (with the energy sources hot water, air, or steam) (cf., e.g., Roy, 2001). The attribute *Flexible* classifies approaches, which can be applied to different types of FES (e.g., Iyer and Grossmann, 1998; Voll et al., 2013).

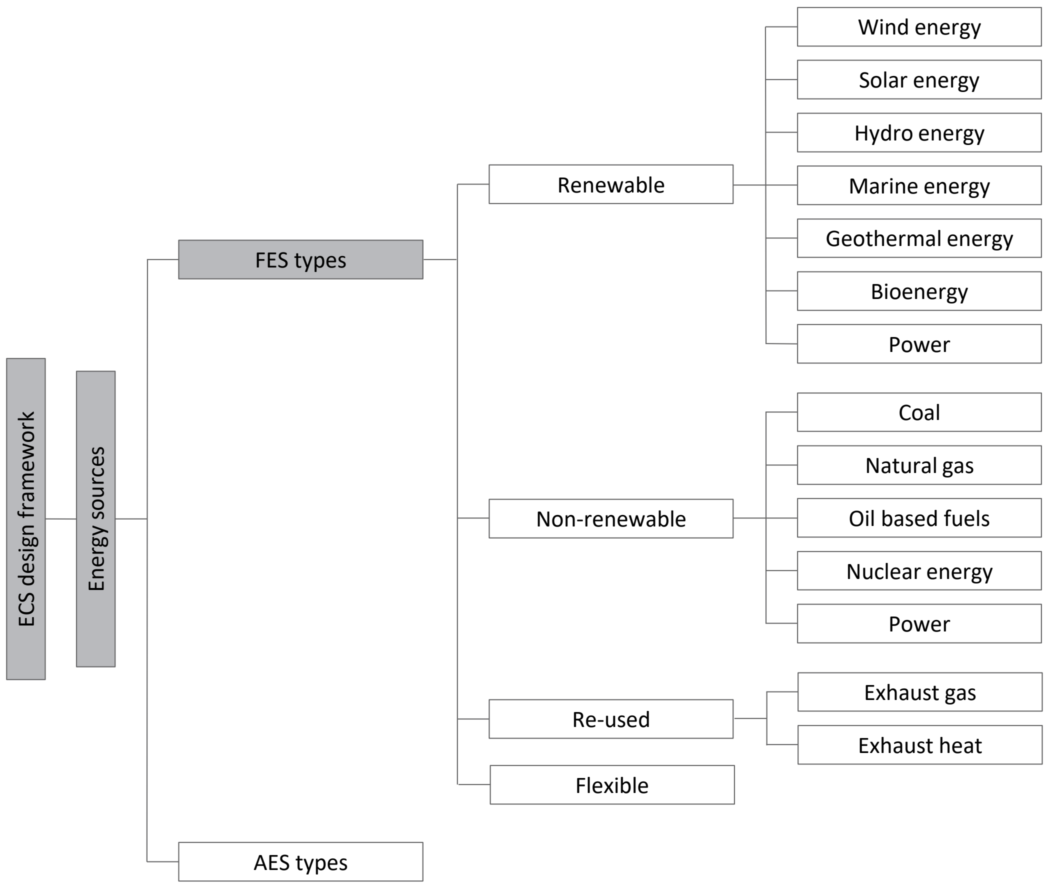

Figure II.A-9: Sub-category FES types

The attributes of the category *FES types* are non-exclusive. For instance, more than one attribute of *FES types* can be considered when an ECS consists of more than one CU which use different FES as input.

4.4.2 AES type

The AES is directly applied by the production units of a manufacturing company's production equipment (machines etc., cf., Figure II.A-2). The category *AES types* differentiates between the two sub-categories *Primary AES* and *Secondary AES* as well as the attribute *Flexible* (cf., Figure II.A-10). This differentiation is introduced to highlight the AES the ECS is primarily designed for and the AES that result from a combined (secondary) production (e.g. from cogeneration or trigeneration systems).

The attribute *Flexible* classifies approaches, which can be applied to different types of AES (e.g., Iyer and Grossmann, 1998; Voll et al., 2012).

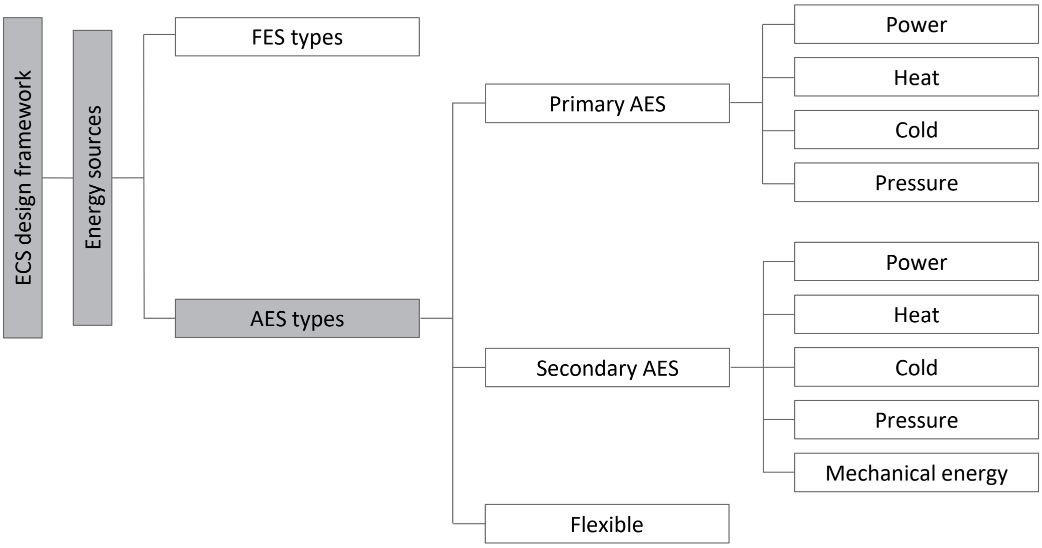

Figure II.A-10: Sub-category AES types

4.4.2.1 Primary AES

The *Primary AES,* specifies the deliberately controlled output of the ECS (e.g., by an operational strategy, see section 4.3). It is called "primary" AES since the whole ECS's design and operation is optimized to fulfill the demand of this AES as efficient as possible. The most common types of primary AESs are classified by the attribute electric *Power* and the sub-categories *Heat* (with the AES attributes hot water, air, or steam), *Cold* (with cold water, or air), and *Pressure* (with steam, air, or oil) (e.g., Aguilar et al., 2008; Tichi et al., 2010; Abbasi and Pourrahmani, 2020; Morais et al., 2020; Figure II.A-10). If an ECS design approach considers more than one AES (e.g., steam and power) but does not explicitly define which of the AES is the primary one, all AES are considered as primary AES.

4.4.2.2 Secondary AES

The category *Secondary AES* classifies approaches which consider "byproducts" of the conversion process (e.g., within CHP or CCHP systems) and thus, a second (or third) AES. Be aware, that the provided amount of *Secondary AES* depends on the amount of the *Primary AES*. For instance, if an approach optimizes the fulfillment of the primary AES demand (e.g., steam) through an CHP which can additionally provide electric power as a byproduct, then electric power is the *Secondary AES*.

The aggregated sub-categories for the *Secondary AES* are similar to the *Primary AES*: *Power*, *Heat* (with the AES: hot water, - air, and -steam), *Cold* (with cold water, and - air), *Pressure* (with steam, air, or oil), and additionally *Mechanical energy* (cf., e.g., Andiappan and Ng, 2016; Emadi and Mahmoudimehr, 2019; Keshavarzzadeh et al., 2020; Figure 11).

Note, that the attributes of the category *AES types* are non-exclusive, because if an approach uses or compares several operational strategies (e.g., TLF and ELF cf., Ghadimi et al., 2014), more than one AES can be categorized as a *Primary AES* as well as a *Secondary AES*.

4.5 CU types

There exist several possibilities to classify CUs within an ECS design framework. As every CU converts one form of energy (e.g., chemical energy) into another form of energy (e.g., thermal energy) (cf., Shiun et al., 2012) and/or one energy sources (e.g., gas) to another energy sources (e.g., steam) (cf., Rager et al., 2015), these aspects could be the basis for the categorization. The first aspect of energy form conversion is not directly reflected by the ECSDF, because some CU integrate several conversion steps (e.g., internal combustion engines) and it is hardly possible nor helpful to dismantle CUs for identifying all energy form conversions. The second aspect of energy source conversion is also not unique for every CU as for example boilers can convert gas to steam or power to steam, depending on whether they are an electrical or a gas-fired boiler. Therefore, we follow the recommendations of several authors and use concrete manifestations of CUs as attributes for the category *CU types* (cf., Cho and Lee, 2014; Liu et al., 2014 and Sun and Liu, 2015; Al Moussawi et al., 2016).

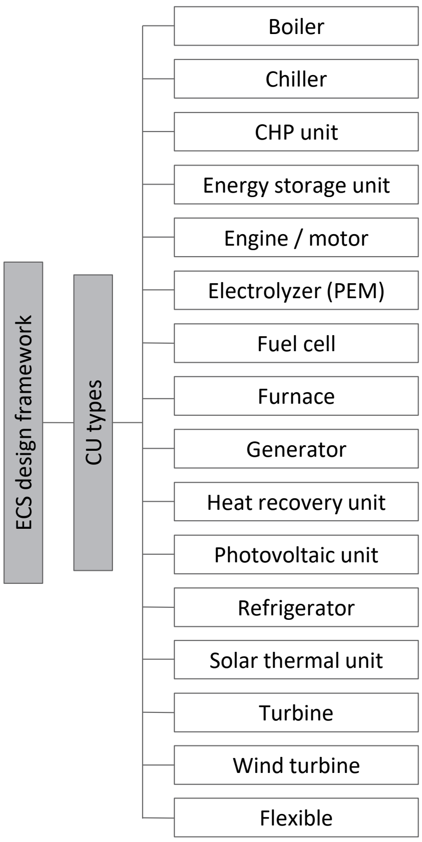

Figure II.A-11: Category CU types

The attributes are depicted in Figure II.A-11. Most of them are self-explanatory and not explained in more detail, but note that most of them aggregate concrete unit specifications. The attribute *Boiler* for instance unifies gas-fired and electrical boilers as well as all boilers which provide any pressure of steam or heat of water. The attribute *Chiller* unifies for instance absorption and compression chillers. The attribute *CHP unit*, describes an arrangement of CUs to a combined heat and power (CHP) unit that is not specified in more detail. *Energy storage units* unifies for instance batteries, compressed air storages or hydrogen storages. *Fuel cells* unifies for instance solid oxide (SOFC) or proton-exchange membrane fuel cells (PEMFC). Heat recovery units unifies for instance heat exchanger or heat recovery boiler. The attribute *Refrigerator* unifies absorption, electric, and compression refrigerators. The attribute *Solar thermal unit*, which defines units (e.g., power tower, solar panel, etc.,) collecting solar energy and converting it into heat (in contrast to photovoltaic units which provide power). The attribute *Turbine* unifies for instance gas, steam, and micro turbines.

The additional attribute *Flexible* classifies approaches which are not specialized on any specific CU type, but can address different CU types.

All these attributes are non-exclusive because an ECS can consist of more than one CU. Note, that approaches are only classified by the attribute *Electrolyzer* when the electrolyzer does not serve as a production unit for commercial hydrogen production but to supply AES as part of the ECS and/or to convert surplus AES for energy storage.

During the literature analysis we observed that, in addition to these typical CUs, extra units like control units, pumps, AC/DC converter, DC/DC converter, inverter, compressors, or rectifier are installed. As these units are essential for ECSs but not a distinguishing feature they are not included into the ECSDF.

4.6 CU operation

Approaches considering the design and operation of an ECS may consider different operational characteristics of the individual CUs during the ECS design. These operational characteristics are represented in the category *CU operation* comprising of the sub-categories *CU states*, *CU loads*, and *CU efficiency* (cf., Figure II.A-12).

4.6.1 CU states

The sub-category *CU states* is about the different operational states a CU can operate at (e.g., *Off* and *On (idle)*) and the transition between these states. Thus, the *CU states* comprise the sub-categories *State types*, i.e., the operational states, and the *State transitions,* which represent the conditions of switching between two states (cf., Figure II.A-12).

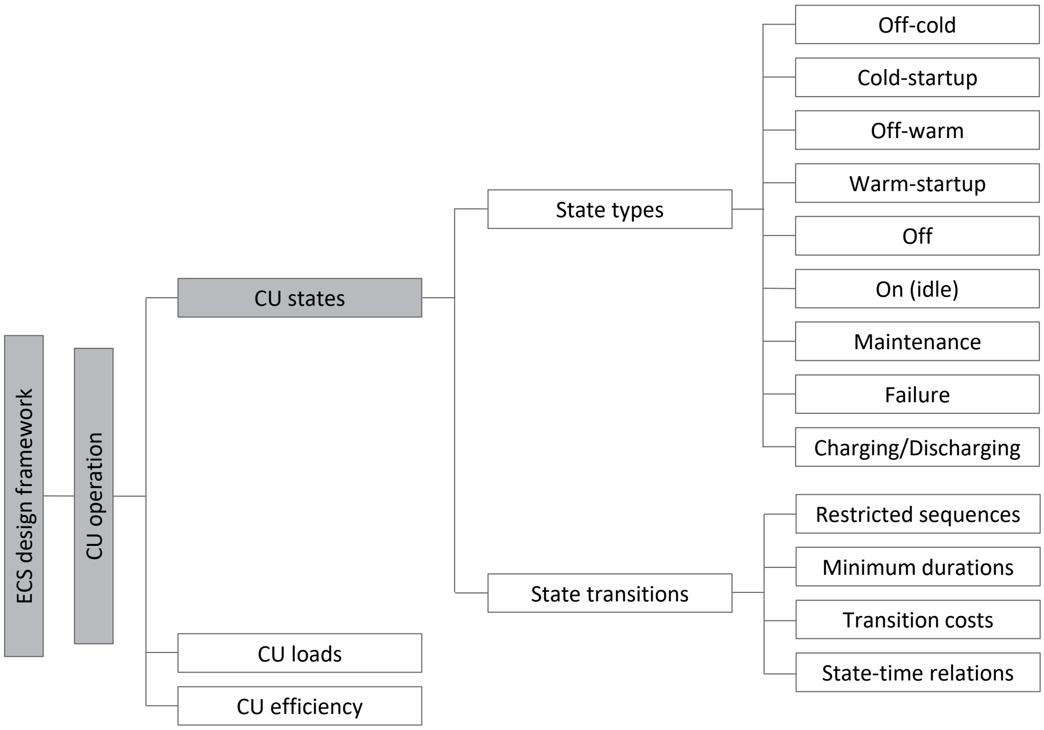

Figure II.A-12: Category CU operation

4.6.1.1 State types

The *State type* considered by any approach that considers *CU states* at all is the operating state, i.e., the state in which a CU is converting FES into AES. As this state is represented in every approach, it is not included into the ECSDF as it does not provide any helpful information. Beside the operating state, further states are considered in literature (cf., e.g., Aguilar et al., 2008; Sun and Liu, 2015; Amusat et al., 2017): The state *Off-cold*, i.e., in which the CU is not converting and has spent a minimum amount of time off, making a specific (cold) startup process necessary to reach the operating state. The state *Cold-startup*, i.e., the explicit state in which the CU switches from *Off-cold* to operating. These startup states can take several hours and during startups FES is consumed but no AES is provided. The state *Off-warm*, i.e., the state in which the CU is not converting and has not yet spent a maximum amount of time *Off*, making a specific (warm) startup process necessary to reach operating state. The state *Warm-startup*, i.e., the explicit state in which the CU switches from *Off-warm* to operating. The state *Off*, i.e., in which the CU is turned off and is not converting and not consuming any FES. Here, a transition between the states *Operating* and *Off* is possible without a transition state in between. The state *On (idle)* (also called hot standby), i.e., the state in which the CU is not converting but consumes FES to preserve its state to reach its operating state immediately (without an explicit startup process). The state *Failure*, i.e., in which the CU has an error and cannot convert anymore, making a maintenance procedure or repairs necessary to operate again. The attribute *Failure* represents (stochastic) CU breakdowns and thus, the consideration of the state *Failure* should imply the consideration of the ECS`s reliability. The state *Maintenance*, i.e., the explicit state in which the CU is not available as it receives repairs or maintenance. Furthermore, if a CU is an energy storage system, the state *Charging/Discharging* can be considered (because approaches always consider both states when considering the charging or discharging process, a differentiation is unnecessary).

4.6.1.2 State transitions

A state transition is the switching from one *State type* to another. Generally, state transitions are subject to certain physical rules, e.g., a CU cannot change from *Off-cold* to *Operating* state directly without a *Cold-startup* process in between or a CU cannot change its state from *Operating* to *Cold-startup* as it is not possible. To consider these physical rules during ECS design (and operation), an appropriate representation of state transition restrictions is necessary. This can be accomplished in several ways, e.g., by *Restricted sequences* specifying the order in which the CU state types can be run through (e.g., Sun and Liu, 2015), by *Minimum durations* specifying how long a CU must remain in a specific CU state at least before it can switch to another CU state (e.g., Aguilar et al., 2008), by *State-time relations* specifying the time needed to switch between two distinct CU states (transition times can vary depending on between which states the transition takes place), or by *Transition costs* (e.g., in form of additional FES requirements, losses of useful energy, or monetary values (e.g., Sun and Liu, 2015).

Note, that all attributes of the sub-category *CU states* are non-exclusive.

4.6.2 CU loads

In the operating state, a CU provides a specific amount of AES, named (operational) load. The sub-category *CU loads* specifies the different loads a CU can provide and the transition between these loads. Thus, the category *CU loads* comprises the two sub-categories *Load types*, i.e., the different operational loads, and *Load transitions,* which represent the conditions of switching between different loads (cf., Figure II.A-13).

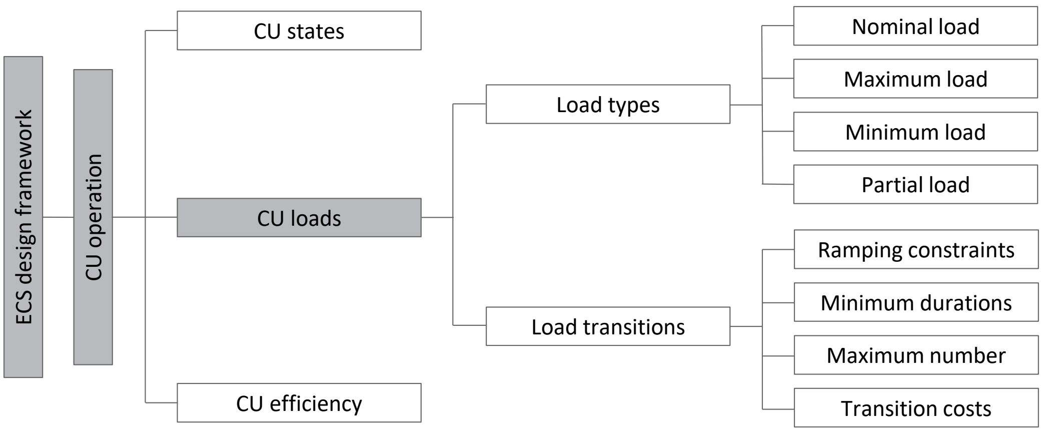

Figure II.A-13: Sub-category CU loads

4.6.2.1 Load types

The attributes of the sub-category *Load types* reflect the way the different amounts of AES provided by the ECS are considered by a design approach (cf., Figure II.A-13). The first three attributes address discrete load points. The first attribute, the *Nominal load,* classifies approaches which explicitly consider the nominal load (also called design point), i.e., the load at which the CU operates with maximum conversion efficiency. The second attribute is the *Maximum load*, i.e., the highest possible load and thus, a CU's maximum AES capacity. The third attribute is the *Minimum load*, i.e., the lowest possible load a CU can provide before it must be shut down due to technical reasons. Together the *Maximum load* and the *Minimum load* determine the operational range of a CU. The last attribute is called *Partial load*. In contrary to the first three attributes, this attribute does not only classify approaches considering discrete load points, but approaches considering any loads within a CU's operational range. Regarding partial loads, approaches can consider continuous partial loads (i.e., the CU can provide any partial load within its operational range (cf., Azit and Nor, 2009 or Morais et al., 2020) or a limited number of discrete partial loads (cf., Roy, 2001 or Gibson et al., 2013).

We would like to emphasize that even though every CU underlies physical restrictions in the maximum and minimum providable loads, it does not mean that every approach is classified into the corresponding attributes. The attributes *Maximum*, *Minimum*, *Nominal* and *Partial loads* are only classified for an approach, that explicitly defines or considers them. For instance Abdelkader et al. (2018) explicitly consider maximum and minimum operational loads in the constraints 19 to 22, and Yokoyama and Ito (2006) consider *Maximum loads*, *Minimum loads*, and continuous *Partial loads*. Strongly related to partial loads is the category CU efficiency discussed in section 4.6.3.

4.6.2.2 Load transitions

Load transitions (similar to *State transitions*) refer to the switching between different loads. Load transitions are subject to certain physical rules, e.g., a CU cannot change from the minimum load to the maximum load within an arbitrarily short time. To classify approaches according to the respected physical rules during ECS design and operation, the category *Load transitions* provides the following attributes: *Ramping constraints* (i.e., an approach considers the maximum height of a load change a CU can manage within a certain amount of time cf., Shamsi et al. (2019)), *Minimum durations* (i.e., an approach considers the minimum amount of time a CU must remain at one load at least, before it can switch to another load), *Maximum number (*i.e., consideration of a maximum amount of times a CU can perform load transitions within a specific time interval), and *Transition costs* (i.e., an approach considers additional energy requirements, loses of useful energy, efficiency losses, or monetary values for a load transition).

All attributes of the sub-category *CU loads* are non-exclusive.

4.6.3 CU efficiency

Each CU has its individual conversion efficiencies, which are generally listed in the CU's specifications (Azit and Nor, 2009). Most approaches consider load-dependent conversion efficiency characteristics, as the efficiency strongly depends on the CU's operational load (Ghadimi et al., 2014), or age- and size-dependent efficiency characteristics. The ECSDF considers these aspects in the category *CU efficiency* and differentiates between the attributes *Constant, Discrete*, *Linear*, *Piecewise-linear*, *Non-linear*, *Performance degradation*, and *Scale-effect* (cf., Figure II.A-14).

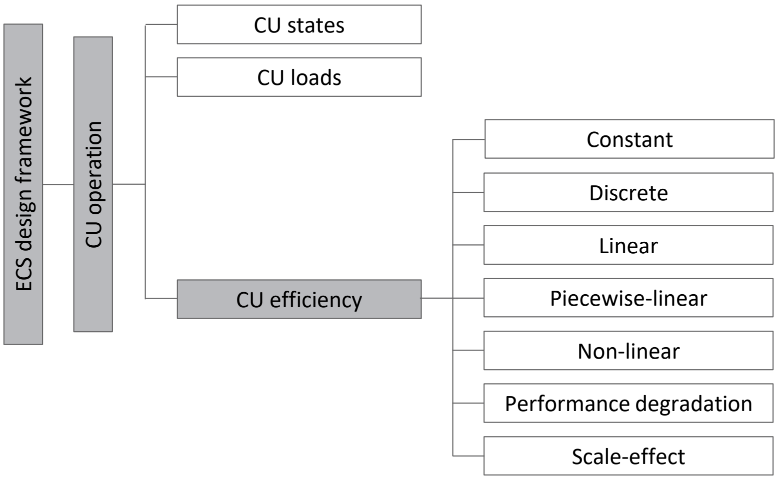

Figure II.A-14: Sub-category CU efficiency

The attribute *Constant* classifies approaches considering one single conversion efficiency value for the CU's entire operational range (cf., Behzadi et al., 2019), or in rare cases for a CU with a single nominal load (cf., Cho and Lee, 2014). The attribute *Discrete* classifies approaches considering a few discrete efficiencies with corresponding discrete loads (e.g., for the minimum-, maximum-, nominal, or a discrete partial load, cf., Roy, 2001). When approaches consider different continuous efficiencies, they determine the efficiencies via a function based on the load. Thus, the attributes *Linear*, *Piecewise-linear*, and *Non-linear* classify approaches according to their considered efficiency functions (cf., e.g., Tichi et al., 2010; Voll et al., 2013). The attribute *Performance degradation* classifies approaches which consider a degradation of efficiency over the CU lifetime, for instance due to CU ageing (cf., e.g., Guinot et al., 2015). The attribute *Scale-effect* classifies approaches which consider CU efficiencies depending on the CU size. Hereby, the *Scale-effect* determines the proportionality between the increase in size and the thereof resulting increase of the (nominal) efficiency of a CU (cf., Gibson et al., 2013).

Note, that these attributes are non-exclusive. This is for example the case, if an ECS design approach considers more than one CU and assumes different efficiency characteristics for each CU (cf., Tichi et al., 2010).

4.7 AES demand / FES supply

Because the (strongly) varying AES demands of the production system severely impact the efficiency of the ECS (cf., Yokoyama and Ito, 2002; Ashok and Banerjee, 2003; Ghadimi et al., 2013, 2014), the consideration of historical and/or future (estimated) AES demands is mandatory to design an appropriate on-site ECS for manufacturing companies. But not only the characteristics of the AES demand influence the ECS design but also an accurate consideration of the prospective FES supply is needed for designing appropriate ECSs (Khatib et al., 2016).

As the characteristics of AES demand and FES supply are (almost) identical, they are both represented by the main category *AES demand/FES supply* which classifies design approaches accordingly. To indicate which case is characterized by the attributes of this main category, we use the "auxiliary" attributes *FES & AES related* and *Only FES related* and define the following conventions: If only AES demands are characterized, no auxiliary attribute is selected (cf., Maia and Qassim, 1997; Spyrou and Anagnostopoulos, 2010; Emadi and Mahmoudimehr, 2019); If the AES demand and FES supply are characterized, the auxiliary attribute *FES & AES related* is selected (cf., Won et al., 2017; Abbasi and Pourrahmani, 2020); And if only the FES supply is characterized, the attribute *Only FES related* is selected (cf., Kamel, 1995; Khalilnejad and Riahy, 2014; Tebibel and Labed, 2014; Waseem et al., 2020).

The actual classification is then based on the attributes *Stochastic* (cf., O'Brien and Bansal, 2000; Yokoyama et al., 2014) and the sub-categories *Time dependency, Aggregation level*, *Aggregation method*, and *Data basis* (cf., Figure II.A-15).

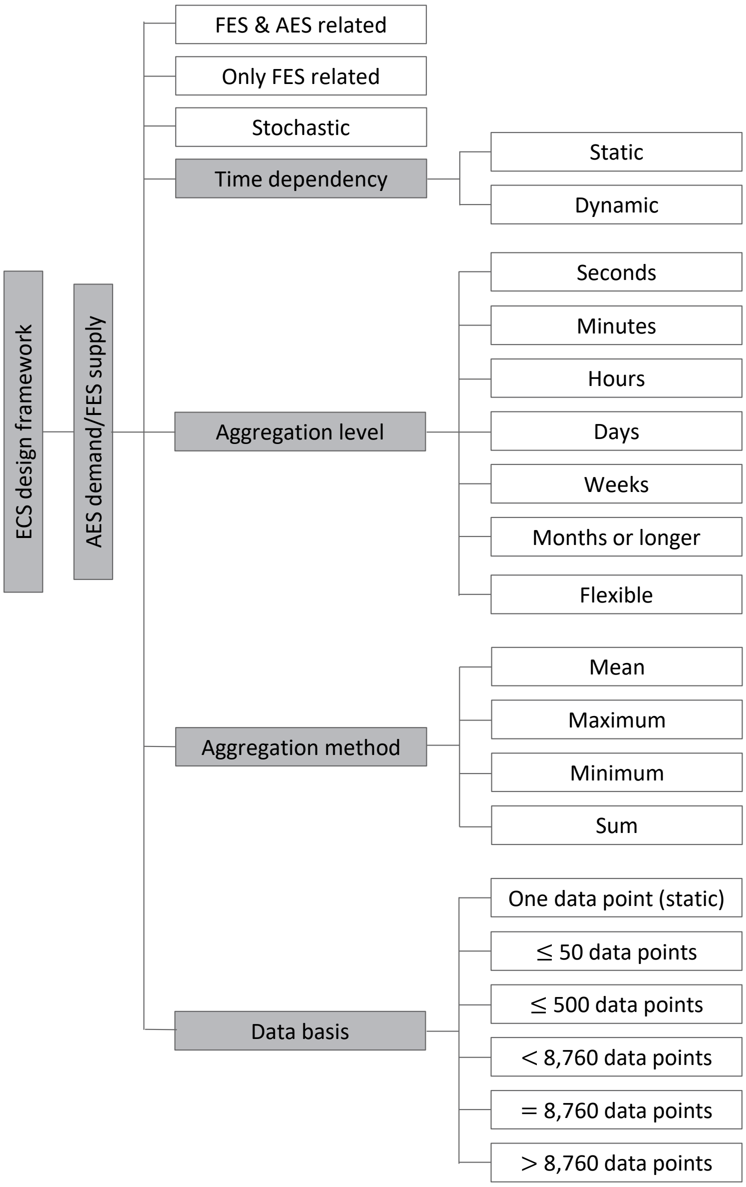

Figure II.A-15: Category AES demand/FES supply

The attribute *Stochastic*, classifies design approaches which consider uncertain AES demand/FES supply to determine robust ECS designs (Yokoyama et al., 2014). Hereby, a scenario or sensitivity analysis or the modelling of AES demand/FES supply variations by probabilistic distributions imply a classification by the attribute *Stochastic* (e.g., Andiappan et al., 2015; Amusat et al., 2017).

4.7.1.1 Time dependency

Depending on the behavior over time, the sub-category *Time dependency* classifies AES demand/FES supply by the attributes S*tatic* and *Dynamic* (cf., O'Brien and Bansal, 2000). Hereby, the attribute *Static* classifies design approaches which consider only a single *Static* AES demand/FES supply (e.g., Marechal and Kalitventzeff, 1998; Keshavarzzadeh et al., 2020), whereas *Dynamic* classifies design approaches considering dynamic AES demand/FES supply which vary over time (e.g., Campana et al., 2019; Shamsi et al., 2019).

4.7.1.2 Aggregation level and aggregation method

Regarding the AES demand/FES supply at all, the considered amount of data and the way the AES demand/FES supply is modelled has a large influence on the accuracy of the design. For instance, Kavvadias and Maroulis (2010) recommend to take at least one year of historical data (e.g., in form of load duration curves) into consideration for designing a trigeneration plant and Azit and Nor (2009) state that the modelling must be as detailed as possible but also as aggregated as necessary. To these aspects, the sub-categories *Aggregation level* and *Aggregation method* are introduced (cf., Figure II.A-15). These terms are used because AES demand/FES supply are always modelled in an aggregated manner and the sub-categories classify the characteristics of the aggregation, which provides the appropriate level of detail.

The sub-category *Aggregation level* classifies approaches according to the smallest time interval for which the AES demand/FES supply is considered. To that, it differentiates between the attributes *Seconds* (which considers intervals within the range of one second up to 59 seconds; cf., e.g., Saha and Kastha, 2010 or Jallouli and Krichen, 2012), *Minutes* (i.e., one minute up to 59 minutes; e.g., Ghadimi et al., 2014), *Hours* (i.e., one hour up to 23 hours; e.g., Amusat et al., 2017), *Days* (i.e., one day up to 6 days), *Weeks* (i.e., one week up to 4 weeks)*, months or longer* (e.g., Sun and Liu, 2015)*,* and *Flexible. Flexible* classifies approaches which give instructions on how to adapt their approach to any appropriate aggregation level.

For every aggregation level, the AES demand/FES supply has to be determined. The sub-category *Aggregation method* classifies approaches depending on the applied technique to determine the AES demand/FES supply for each aggregation level. To that, the sub-category differentiates the attributes *Mean, Maximum*, *Minimum,* and *Sum*. The aggregation method *Mean* (*Maximum/Minimum/Sum*), calculates the mean (maximum/ minimum/ sum) of all available AES demand/FES supply values within the time interval specified by the aggregation level (e.g., Tebibel and Labed, 2014; Bhattacharyya et al., 2017; Alirahmi et al., 2020b).

Note, that the attributes within each sub-category are mutually exclusive, unless a comparison between different considerations of AES demand/FES supply is made.

4.7.1.3 Data basis

Furthermore, we found a broad difference in the considered data basis within the analyzed approaches. The considered data basis vary from one considered data point to more than 8,760 data points (e.g., representing 365 days with 24 hours). The considered data basis has a huge influence on the reliability of the prospective ECS and the computational efforts of the solution methods applied to solve the ECS design problem. For this reason, and to make approaches comparable, the sub-category *data basis* with its attributes *One data point (static)*, *≤ 50 data points*, *≤ 500 data points*, *< 8,670 data* *points*, $=$ *8,670 data points*, and $>$ *8,670 data points* is introduced (cf., Figure II.A-15). Each attribute describes an upper limit on the considered data points of an approach and classifies them accordingly. Hereby, a data point can represent any time unit which is defined by the *Aggregation level* (e.g., minutes or hours).

4.8 Relations to other systems

ECS design approaches may consider the relationship between the ECS and other systems (cf., Figure II.A-2). Thus, the main category *Relations to other systems* classifies ECSs according to their interaction and relationship with other systems and differentiates between the sub-categories *External grid* and *Energy market*, representing some of these systems and their attributes (cf., Figure II.A-16).

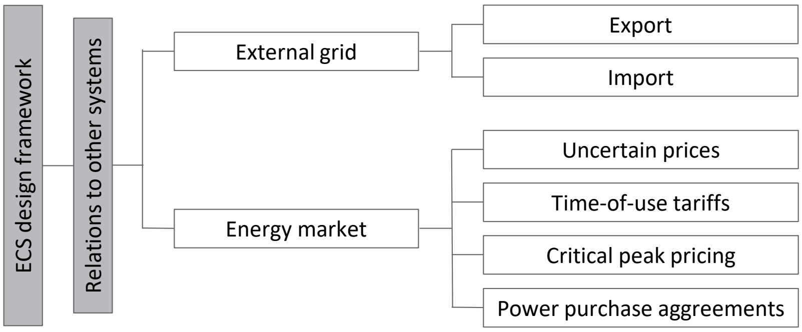

Figure II.A-16: Category Relations to other systems

In general, connections to an *External grid* allow the import of AES from and/or the export to the grid. Since on-site ECSs are expected to be self-sufficient, they should be able to fulfill the base AES demand without exchanges with the external grid (Aguilar et al., 2008). Therefore, many approaches do not permit any AES exchange with the external grid during the design. In contrast, other design approaches explicitly allow the exchange of AES with the external grid in order to maximize the overall benefit (cf., e.g., Azit and Nor, 2009) or to minimize the overall costs (cf., e.g., Gamou et al., 2002). These aspects are considered in the ECSDF by the two attributes *Export*, i.e., the allowance to sell converted AES to the grid; and *Import*, i.e., the allowance to buy "missing" AES from the grid (note, that not the import of FES is reflected by this attribute). These attributes are non-exclusive, as an *Import* as wells as an *Export* can be considered by an approach.

Furthermore, an interaction with the *Energy market* could be considered. This sub-category differentiates between attributes to classify approaches that design an ECS with regard to external energy market influences like *Uncertain prices* or demand side management (demand response) mechanisms like *Time-of-use tariffs*, *Critical peak pricing*, or *Power purchase agreements* (cf., e.g., Kavvadias and Maroulis, 2010; Gibson et al., 2013; Cho and Lee, 2014). These attributes also are non-exclusive.

5 Conclusion

Rising energy demands, scarce resources, and continuously increasing resource costs require a more efficient use of energy in the industrial sector — from an ecological and an economical perspective. To use and acquire energy as efficiently as possible, on-site ECSs have been identified as one of the main solutions. To fully benefit from the efficiency potentials of on-site ECSs, the ECSs have to be designed accurately under the consideration of the relevant design aspects. This accurate design is especially relevant when designing an ECS for manufacturing companies, as their varying energy demands strongly decrease an inaccurately designed ECS`s efficiency. Hereby, the many aspects that are crucial for an adequate ECS's design and the design's high complexity force researchers to focus on different design aspects for individual planning problems. This has led to a huge number of problem-specific approaches. Although this increasing number of approaches is very appreciated, it complicates the search for most related ECS design approaches for a specific design problem and the structuring and analysis of the research area. In Consequence, an all-encompassing framework with unambiguous and unified definitions is desperately needed.

Therefore, we developed the ECSDF. It is developed from an initial scope of more than 44 carefully selected publications and 32 preceding reviews and is composed of eight main categories, 27 sub-categories and 126 attributes representing aspects which are essential for a high quality ECS design for manufacturing companies. Of course, the current state of the framework is not final but future literature analysis will lead to continuous adaptations like performed in the iterative development process.

Next step to fully exploit the benefits of the developed ECSDF is the analysis of the classified articles by an extensive literature review (the classification of ECS design approaches used for the ECSDF development can be found in the digital supplementary material). Unfortunately, there is no space in this paper to perform such an analysis adequately.

In summary the ECS design framework`s main contributions are to provide a knowledge base for decision makers for identifying relevant design approaches, to facilitate the search within the existing literature, to unify the understanding of the crucial design aspects, to support the analysis and structuring of individual planning problems, and to provide the base for an empirical literature analyses to disclose research gaps and provide insights for future research.

6 Appendix

A-1: Search string

The abbreviations of the search string mean the following:

TI = title

TS = title, abstract, and key words

SO = journal name

TI = (conversion OR planning OR generation)

AND TI = (model* OR optim* OR dimensioning OR design*)

AND TS = (combined heat and power OR chp OR cogeneration OR cchp OR combined cool* heat* power OR trigeneration OR photovoltaic* OR pv OR Solar* OR turbine OR hydro power OR fuel cell* OR biogas* OR biomass OR boiler* OR combustion engin* OR heat pump* OR stand alone OR energy system* OR power system* OR wind power)

AND TS = (size* OR scale* OR dimensioning* OR design*)

AND TS = (plant* OR industr* OR produc* OR compan* OR firm* OR enterprise* OR corporation* OR concern* OR manufactur*)

NOT TS = (hospital OR building OR grid OR household OR store* OR schedule* OR commercial energy OR region* OR area* OR district* OR market)

AND SO = (Applied Energy OR Applied Thermal Engineering OR "Computers & Industrial Engineering"OR Electric Power Systems Research OR Energy OR Energy & Environmental Science OR "Energy Conversion and Management" OR Energy Economics OR Energy for Sustainable Development OR Energy Journal OR Environmental Research Letters OR "Experimental Thermal and Fluid Science" OR "IEEE Journal of Emerging and Selected Topics in Power Electronics" OR IEEE Journal of Photovoltaics OR IEEE Power & Energy Magazine OR IEEE Transactions on Energy Conversion OR IEEE Transactions on Industrial Electronics OR IEEE Transactions on Industry Applications OR IEEE Transactions on Power Delivery OR IEEE Transactions on Power Electronics OR IEEE Transactions on Power Systems OR IEEE Transactions on Sustainable Energy OR IET Generation Transmission & Distribution OR IET Power Electronics OR IISE Transactions OR International Journal of Electrical Power & Energy Systems OR International Journal of Engineering Science OR "International Journal of Heat and Mass Transfer" OR

International Journal of Hydrogen Energy OR International Journal of Production Economics OR International Journal of Production Research OR International Journal of Thermal Sciences OR JOM OR Journal of Cleaner Production OR "Journal of Modern Power Systems and Clean Energy" OR Journal of Operations Management OR Nano Energy OR Nonlinear Analysis: Real World Applications OR "Production and Operations Management" OR Production Planning & Control OR "Progress in Energy and Combustion Science" OR Progress in Photovoltaics OR Renewable & Sustainable Energy Reviews OR Renewable Energy OR Solar Energy OR "Solar Energy Materials and Solar Cells" OR "Sustainable Energy Technologies and Assessments" OR Journal of the Energy Institute)

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II.B Contribution 2: Design of on-site energy conversion systems for manufacturing companies – A review and literature analysis

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Abstract: The conservation and efficient use of resources is an omnipresent topic in today´s society and industry. In this context, to cover production process energy demands more efficiently, manufacturing companies started to install energy conversion (utility) systems (ECSs) on-site. To fully exploit the benefits of on-site ECSs, versatile factors, such as the characteristics of demand, conversion units, or energy sources, must be considered during ECS design. Particularly the interdependencies of the ECS and the production system (PS), which are mainly reflected in the PS's strongly varying energy demands the ECS has to cover, must be considered by ECS designs for manufacturing companies. The manifold properties and the degrees of freedom for instance regarding the conversion technology or conversion unit size make the planning task challenging and the scientific literature diverse.

To assist scientists and real-world decision makers, Ganschinietz (2020) developed a concept-centric ECS design framework to structure existing and forthcoming ECS design approaches. In this contribution, the ECS design framework is used to classify existing ECS design approaches identified by a structured literature search. The classified approaches form the base for several empirical analyses performed to gain insights about the existing approaches as well as starting points for further research topics.

Keywords: energy conversion system, on-site, manufacturing, review, classification

1 Introduction

The constantly growing demand for products and their consumption has put pressure on industrial production and its supply chains to decrease negative impacts on the environment and society (Rajeev et al., 2017). These negative impacts become especially obvious when considering the fact that industry accounts for approximately 25% of the total energy consumption in the European Union (Eurostat, 2019). This pressure and the current energy supply situation, combined with the fact that energy is a non-substitutable production factor, motivates (manufacturing) companies to reorient themselves towards a strategically expedient management and optimized utilization strategy of the (scarce) resource energy (Ghadimi et al., 2014). This reorientation can be achieved in different ways, for instance by energy-oriented production scheduling (Liu et al., 2020), energy saving measures (Abdelaziz et al., 2011), sustainable and renewable energy sources usage (Bukar and Tan, 2019), efficiency increases for installed ECSs (Rashid et al., 2019), or by installing on-site ECSs at manufacturing companies (Keshavarzzadeh et al., 2020).

Particularly the installation of on-site ECSs is an attractive possibility for manufacturing companies to meet energy demands independently, increase energy supply reliability, save costs, and, with an accurately designed ECS, improve energy efficiency and act more sustainably. Thereby, an accurate ECS design strongly depends on the planning environment and its implications for the ECS design. Regarding manufacturing companies, particularly the strongly varying energy demands resulting from the production system must be considered during ECS design, because the demand variations can lead to long running times in partial load operation, which negatively influence the ECS's overall conversion efficiency. This is due to the technical property that conversion efficiencies are lower at partial loads, i.e., the more the load deviates from the nominal load (design point), the lower the conversion efficiency (cf., Aguilar et al., 2007, Voll et al., 2013, or Li et al., 2016). Beside this major aspect for an appropriate ECS design for manufacturing companies, several other aspects must be considered. Because of the numerous aspects and because of numerous possible ECS topologies (comprising the number and type of conversion units und technologies, type of input energy sources, etc.), identifying related ECS design approaches in literature is challenging. To support this process, Ganschinietz (C1) recently proposed a new, concept-centric research framework for the classification of ECS design approaches (ECSDF).

The contribution of this paper is the application (and extension) of this ECSDF by a comprehensive literature review and classification according to the ECSDF, combined with a consecutive empirical analysis of the literature about design approaches for on-site ECSs at manufacturing companies. Compared to the original ECSDF, we extended the scope of the literature sample to expand the focused research field in order to generate more general conclusions. Furthermore, we added three main categories (objective system, solution method, and application case) to enrich the information created with the review and analysis.

The paper is structured as follows: Section 2 provides a short overview on the ECSDF. In section 3 , the methodology for the literature review and the adaptation of the ECSDF is described and section 4 gives a detailed description on the categories added to the ECSDF. Successively, section 5 presents an excerpt of the literature classification which forms the base for the empirical analysis in section 6 . Major findings are presented in section 7 . Section 8 concludes the paper.

2 Related work

To structure the current state of science for the design of on-site ECSs for manufacturing companies, Ganschinietz (C1) proposes the concept-centric ECS design framework ECSDF to classify existing and upcoming ECS design approaches. The benefits of this framework are manifold: First, the ECSDF unifies the understanding and definition of the most relevant aspects to be considered for an adequate ECS design (for manufacturing companies) and thus, enables scientists to analyze and structure their planning problems accordingly. Second, the ECSDF facilitates the search within existing design approaches and provides an excellent knowledge base to enable decision makers to identify relevant design approaches. Third, the ECSDF can be used to analyze research progress and directions, to disclose research gaps, and to provide insights for future research by classifying ECS design approaches according to the ECSDF (Ganschinietz, C1).

The ECSDF classifies ECS design approaches by eight main categories comprising, 27 subcategories, and 126 attributes. The eight main categories are illustrated in Figure II.B-1 (in Figure II.B-1, AES stands for applied energy sources, FES stands for final energy sources, and CU for conversion unit; for more details on the terms cf., Ganschinietz, C1).

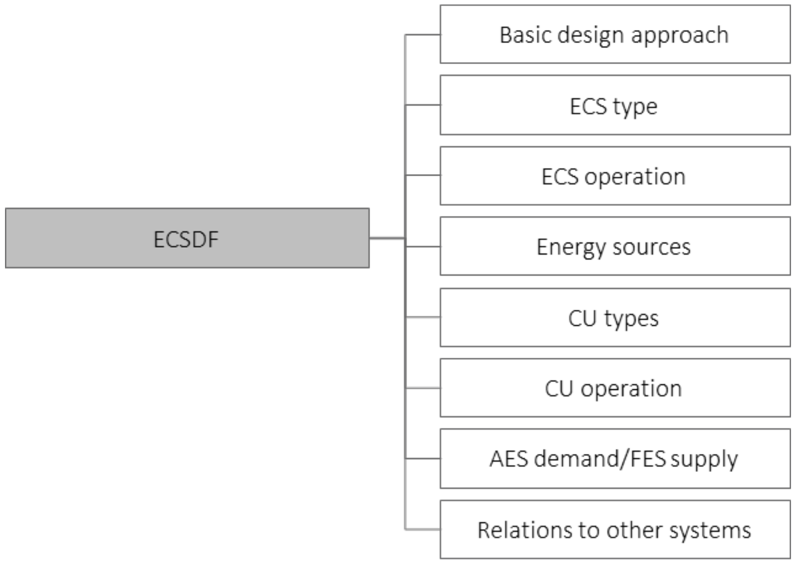


Figure II.B-1: Main categories of the ECS design framework by Ganschinietz (C1)

Because related reviews, frameworks, and other meta-analyses are exhaustively discussed by Ganschinietz (C1), we omit the repetition here but like to emphasize that this is the first article that uses the ECSDF to perform a structured literature review and analysis.

3 Methodology and Scope

The methodology used for the review and analysis is basically the same as used in Ganschinietz (C1). We use the same iterative research process but with an extended scope and continuous framework adaptations (cf., Figure 1 in Ganschinietz, C1; process adjustments are marked bold).

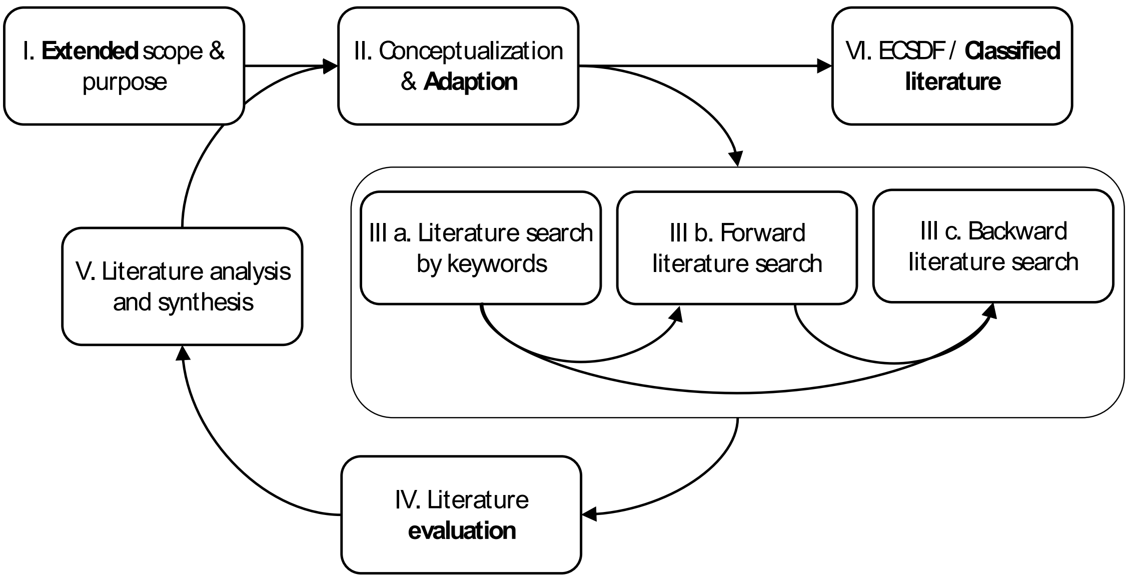


Figure II.B-2: Iterative literature search, analysis, and synthesis process

To classify, review, and analyze all ECS design approaches that are applicable at manufacturing companies, we do not limit the relevant literature to articles that directly address production systems or industry, but consider all articles that address design problems considering strongly varying AES demands. Accordingly, we adapted the subcategory *Scope* in the ECSDF (in Figure II.B-3 the two new attributes are marked light grey, and PES stands for primary energy sources; for more details on the term cf., Ganschinietz, C1).

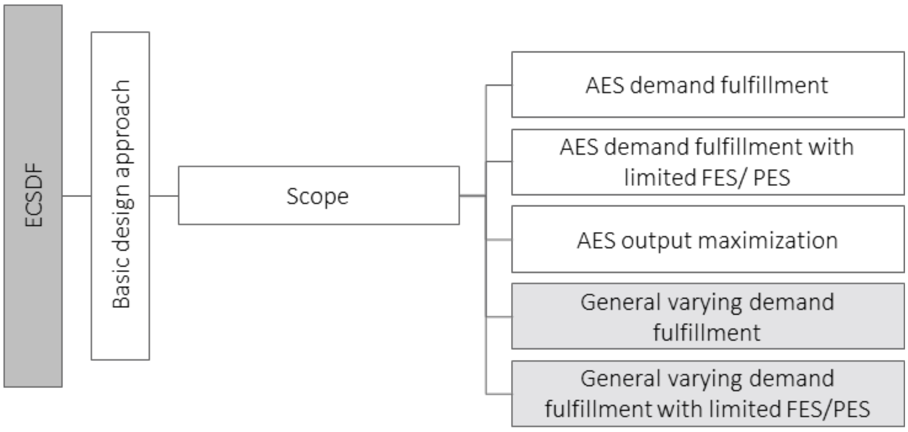


Figure II.B-3: ECSDF adaptations

The other scope and purpose criteria for the article selection are the same as in (Ganschinietz, C1): only articles either dealing with the design or with the design and operation of ECSs are considered and articles exclusively dealing with the operation of ECSs are excluded. Furthermore, articles addressing the topics commercial energy production (for markets), design and operation of the central grid, its layout, or extensions, and publications on on-site ECSs of city districts and public or private buildings (e.g., administrative offices, hospitals, or households) are excluded (if not explicitly considering varying AES demands). Also articles only addressing the mere installation of energy storage systems are excluded.

To reflect the new literature scope, we slightly adapted the keyword search (see the Appendix A-1) and considered the new scope and purpose criteria in the literature evaluation step (IV.). With the iterative search procedure (keyword search, forward search, and backward search), we identified 120 relevant articles that fulfill the scope and purpose criteria and are published in a journal having an SJR-Index greater than 1. Because most important publications of a research field can be found in renowned journals (Webster and Watson, 2002), we use the SJR-Index (provided by the "SCIMAGO Journal & Country Rank") for journal selection. The SJR-Index is number-based score measuring the impact or prestige of a journals articles (Guerrero-Bote and Moya-Anegón, 2012).

The complete literature sample used for the review and analysis in this paper is depicted in Table II.B-1:

Table II.B-1: Reviewed journals and identified relevant articles (state: May 2020)

	SJR index and quartile (Q) of sub-categories								Num. relevant articles			
Journal name (initial hits by search string)	SJR-Indicator	En. Eng. & Pow. Tech.	En.	Ren. En. Sust. & Environ.	Electri. & Electro. Eng.	Eng.	Ind. & Manu. Eng.	M. Eng.	Search string	Forward search	Backwards search	Total
Applied Energy* (47)	3,61	Q1	Q1					Q1			10	10
Applied Thermal Engineering* (18)	1,78	Q1					Q1				6	6
Chemical Engineering Science	1,00						Q1				2	2
Computers and Chemical Engineering	1,00									3	6	9
Computers in Industry	1,01					Q1					1	1
Desalination	1,81							Q1			2	2
Energy* (58)	2,17		Q1		Q1		Q1	Q1	2	2	13	17
Energy and Buildings	2,06				Q1			Q1		1	1	2
Energy Conversion and Management* (44)	2,92	Q1		Q1					3	4	9	16
Energy Policy	2,17		Q1								4	4
IEEE Transactions on Energy Conversion* (9)	1,78	Q1			Q1				1		2	3
IEEE Transactions on Industry Applications* (10)	1,50				Q1		Q1		1			1
IEEE Transactions on Power Delivery* (5)	2,13	Q1			Q1						1	1
IEEE Transactions on Power Systems* (21)	3,43	Q1			Q1				1			1
International Journal of Elec. Power & En. Systems* (18)	1,20	Q1			Q1				1		1	2
International Journal of Hydrogen Energy* (33)	1,14	Q1		Q2					2	4	6	12
Journal of Cleaner Production* (18)	1,89			Q1			Q1			1		1
Journal of the Energy Institute * (0)	1,26	Q1		Q1	Q1						1	1
Renewable & Sustainable Energy Reviews* (7)	3,63			Q1						1	1	2
Renewable Energy* (32)	2,05			Q1					1	3	9	13
Solar Energy* (9)	1,54			Q1					1	3	9	13
Swarm and Evolutionary Computation	1,65										1	1

Electric Power Systems Research* (4), Energy & Environmental Science* (5), Energy Economics* (3), Energy for Sustainable Development* (0), Energy Journal* (0), Environmental Research Letters* (2), Experimental Thermal and Fluid Science* (0), IEEE Journal of Emerging and Selected Topics in Power Electronics* (1), IEEE Journal of Photovoltaics* (0), IEEE Power & Energy Magazine* (0), IEEE Transactions on Industrial Electronics* (14), IEEE Transactions on Power Electronics* (8), IEEE Transactions on Sustainable Energy* (14), IET Generation, Transmission & Distribution* (8), IISE Transactions* (1), International Journal of Engineering Science* (1), International Journal of Heat and Mass Transfer* (7), International Journal of Production Economics* (1), International Journal of Production Research* (4), International Journal of Thermal Sciences* (2), Journal of Modern Power Systems and Clean Energy* (0), Journal of Operations Management* (0), Nano Energy* (4), Nonlinear Analysis: Real World Applications* (0), Production and Operations Management* (0), Production Planning & Control* (0), Progress in Energy and Combustion Science* (0), Progress in Photovoltaics* (0), Solar Energy Materials and Solar Cells* (3), Sustainable Energy Technologies and Assessments* (3)

	Search string	Forward search	Backwards search	Total
Total	13	22	85	120

Altogether, more than 620 articles have been evaluated during the iterative search process. Hereby, the search string resulted in 13 relevant ECS design approaches (from 416 initial hits), the forward search added 22 and the backward search 85 relevant articles. Overall this leads to a literature scope of 120 ECS design approaches to be classified by the ECSDF.

4 Framework extensions for analysis

The eight main categories of the ECSDF constitute the core of the following literature review, classification, and analysis. Beside these main categories and their attributes explicitly related to ECSs, we additionally analyze the ECS design approaches with regard to the more common aspects *Objective system*, *Solution method*, and *Application case*. As the structuring of information and knowledge in form of categories has shown to be useful, we also organize these three aspects in categories (with sub-categories and attributes). The complete structure of the ECSDF including the extensions is provided within Figure II.B-25 to Figure II.B-27 in the Appendix A-2 and the digital supplementary material. Note that in the following figures, not all attributes for any sub-categories are depicted to keep the figures clear. To provide a better overview, attributes are marked grey, while categories are marked white.

4.1 Objective system

The category *Objective system* consists of the sub-categories *Objective criteria*, multi-criteria decision making (*MCDM*), and *Evaluation horizon* (cf., Figure II.B-4). Note, that for the sub-category *Objective criteria* only sub-categories are illustrated in Figure II.B-4 (due to the high number of attributes; the complete set of attributes can be found in the complete classification provided within the digital supplementary material). The three sub-categories of *Objective criteria* characterize the objective criterion or the objective criteria used to evaluate and/or optimize an ECS design. If multiple criteria are used, an approach is also classified by methods from the research field of multi-criteria decision making (*MCDM*) (or a related field). Here, we focus on the most often used ones (more details can be found in the literature classification): *Satisficing constraint* indicates approaches where at least one objective is transferred to a constraint with a lower (or upper) bound, *Pareto* indicates approaches depicting Pareto fronts and related concepts, and *Analytical* indicates approaches where a single objective criterion is used for optimization and other criteria are "only" used to evaluate the results. The attribute *Other* classifies approaches not using one of the MCDM methods above. The sub-category *Evaluation horizon* depicts the ECS lifetime considered by most of the objective criteria (e.g., "total annual costs").

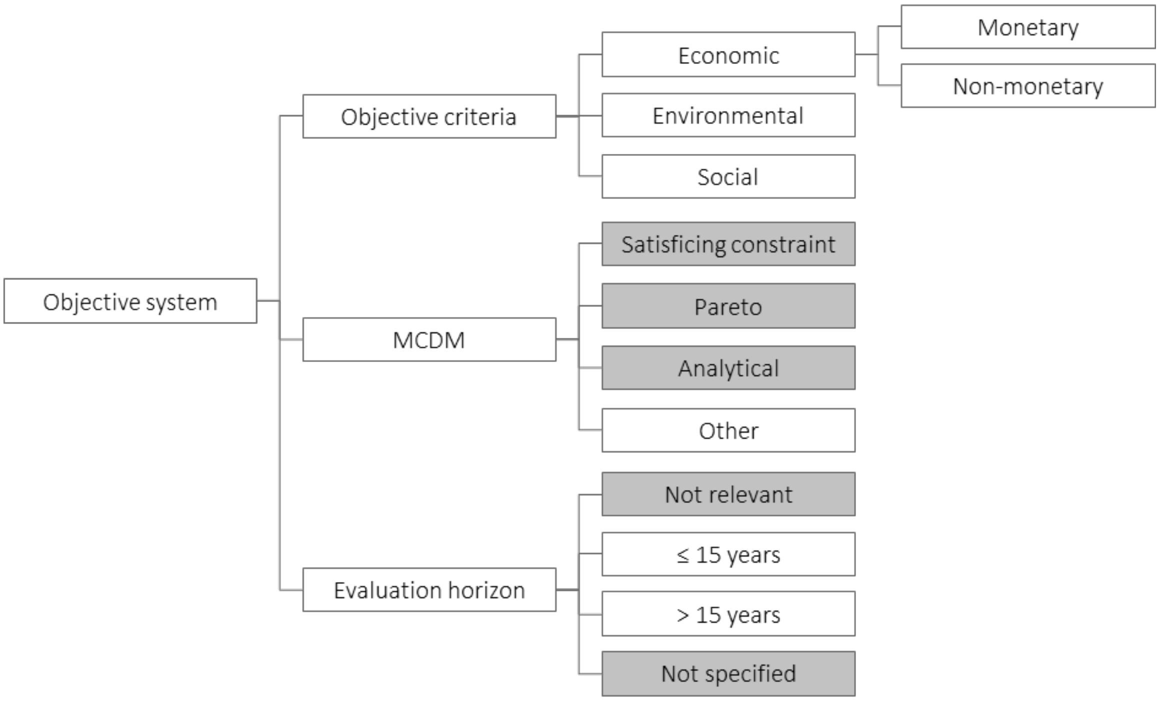


Figure II.B-4: Sub-categories and attributes to characterize the objective system

Remark that the attribute *Not relevant* has a very different meaning compared to *Not specified*: the first one means that this information is not required because of the objective criteria, whereas the latter one means that the information is not given in the article.

4.2 Solution method

The category Solution method comprises the sub-category Model type which reflects the type of the optimization model (Linear program, Mixed-integer linear program – MILP, Quadratic program – QP, nonlinear program – NLP, or Mixed-integer non-linear program – MINLP) or if “only” a mathematical formulation of the decision problem is presented. Beside the model type, further self-explanatory sub-categories and attributes are depicted in Figure II.B-5 (further details can be found in Table II.B-7 and in the complete classification provided within the digital supplementary material).

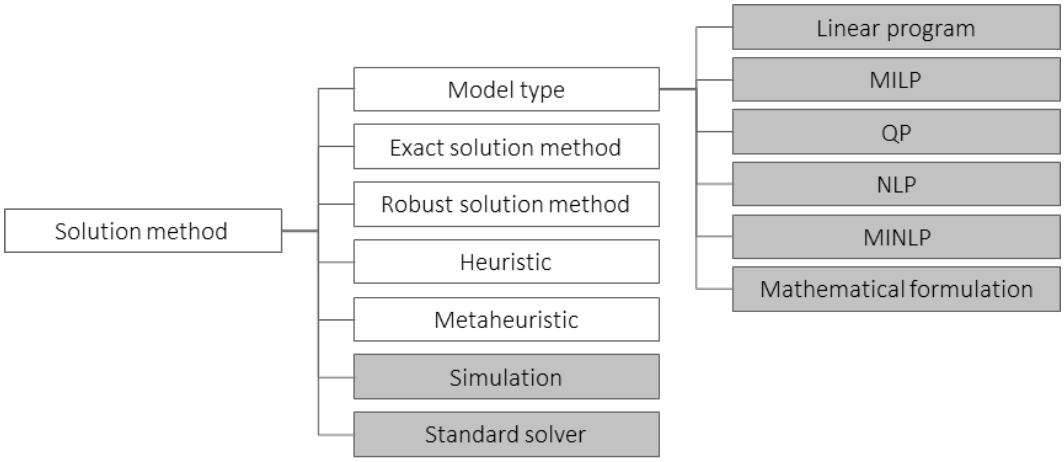


Figure II.B-5: Sub-categories and attributes to characterize the solution method

Note that even if an optimization model is specified, not necessarily a standard solver (like CPLEX or Gurobi) must be used to solve the planning problem.

4.3 Application case

Within the third additional category *Application case*, we use the attribute *Real world evaluation* to mark an ECS design evaluation based on data from a real-world application case. The sub-category *Non-industrial* marks contributions related to districts or buildings (e.g., hospitals). All industry related publications are classified according to the industrial sector (as defined and numbered by the "International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 4" - United Nations, Department of Economic and Social Affairs, 2008).

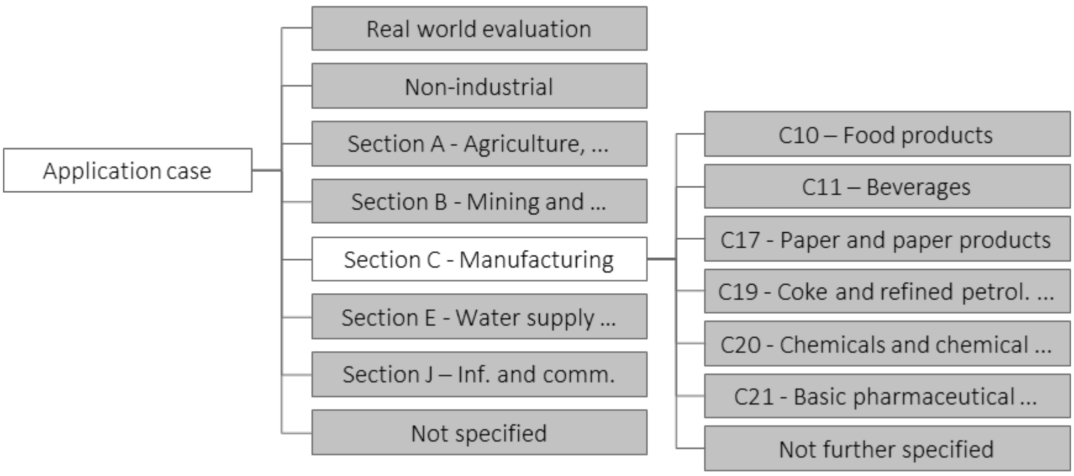


Figure II.B-6: Sub-categories and attributes to characterize the area of application

Note, that even when an industrial sector can be derived from a manuscript, not necessarily a real-world evaluation has been performed.

5 Literature classification

Because of the large number of 120 identified relevant articles, we cannot present the complete classification of all relevant papers within the paper. Instead, to put the ECSDF into perspective, we present an exemplarily classification of a subset of articles: Table II.B-3 to Table II.B-7 show the classification of 22 excerpted articles (one per letter of the alphabet and name of the first author). The complete classification with a maximum level of detail regarding categories, sub-categories, and attributes is provided as supplementary material.

Although it’s impossible to depict the complete classification here, we show in Table II.B-2 the extent and results of the classification for the 120 approaches for the first 5 attributes of sub-category *Scope*:

Table II.B-2: Sub-category Scope of the 120 classified ECS design approaches

Scope (Number of classified articles)	Classified approaches
AES demand fulfillment (26)	Papoulias and Grossmann, (1983), Pendergrass, (1983), Kamel, (1995), Hui and Natori, (1996), Maia and Qassim, (1997), Iyer and Grossmann, (1998), Marechal and Kalitventzeff, (1998), Roy, (2001), Shang and Kokossis, (2005)), Varbanov et al. (2005), Aguilar et al. (2008), Azit and Nor (2009), Tichi et al. (2010), Voll et al. (2012), Gibson et al. (2013), Voll et al. (2013), Carvalho et al. (2014), Ghadimi et al. (2014), Leif Hanrahan et al. (2014), Luo et al. (2014), Kazi et al. (2015), Smaoui et al. (2015), Sun and Liu (2015), Rad et al. (2016), Shamsi et al. (2019), Morais et al. (2020)
AES demand fulfillment with limited FES/PES (5)	Andiappan et al. (2015), Amusat et al. (2016), Andiappan and Ng (2016), Amusat et al. (2017), Campana et al. (2019)
AES output maximization (19)	Mavromatis and Kokossis (1998), Bernal-Agustín and Dufo-López (2010), Spyrou and Anagnostopoulos (2010), Khalilnejad and Riahy (2014), Najafi et al. (2014), Tebibel and Labed (2014), Ahmadi et al. (2015), Bhattacharyya et al. (2017), Khanmohammadi et al. (2017), Won et al. (2017), Behzadi et al. (2019), Emadi and Mahmoudimehr (2019), Ghorbani et al. (2019), Abbasi and Pourrahmani (2020), Alirahmi et al. (2020b), Alirahmi et al. (2020a), Chitgar and Moghimi (2020), Keshavarzzadeh et al. (2020), Waseem et al. (2020)
General varying demand fulfillment (36)	Muselli et al. (1999), Gamou et al. (2002), Khodr et al. (2002), Yokoyama et al. (2002), Yokoyama and Ito (2002), Frangopoulos (2004), Beihong and Weiding (2006), Koutroulis et al. (2006), Chicco and Mancarella (2007), Sanaye et al. (2008), Kavvadias et al. (2010), Kavvadias and Maroulis (2010), Saha and Kastha (2010), Wang et al. (2010), Carpaneto et al. (2011a, 2011b), Carvalho et al. (2011), Carapellucci and Giordano (2012), Kumar et al. (2013), Cho and Lee (2014), Kaabeche and Ibtiouen (2014), Yokoyama et al. (2014), Arcuri et al. (2015), Benam et al. (2015), Guinot et al. (2015), Wu et al. (2015), Yokoyama et al. (2015), Li et al. (2016), Zeng et al. (2016), Kaabeche et al. (2017), Zhu et al. (2017), Abdelkader et al. (2018), Du Guangqian et al. (2018), Forough and Roshandel (2018), Khiareddine et al. (2018), Kaabeche and Bakelli (2019)
General varying demand fulfillment with limited FES/PES (34)	Dufo-López and Bernal-Agustín (2005), Bernal-Agustín et al. (2006), Diaf et al. (2007), Dufo-López and Bernal-Agustín (2008), Yang et al. (2008), Kashefi Kaviani et al. (2009), Li et al. (2009), Ekren and Ekren (2010), Roy et al. (2010), Belfkira et al. (2011), Dufo-López et al. (2011), Kaabeche et al. (2011a, 2011b), Erdinc and Uzunoglu (2012), Jallouli and Krichen (2012), Askarzadeh (2013), Castañeda et al. (2013), Zhou et al. (2013), Belmili et al. (2014), Cano et al. (2014), Feroldi and Zumoffen (2014), Maleki and Askarzadeh (2014), Sharafi and ELMekkawy (2014), Maleki et al. (2015), Maleki and Pourfayaz (2015), Malheiro et al. (2015), Ahmadi and Abdi (2016), Destro et al. (2016), Dufo-López et al. (2016), Heydari and Askarzadeh (2016), Maleki et al. (2016), Soheyli et al. (2016), Acuña et al. (2018), Anoune et al. (2018)

Note, that in following classification tables, the second column depicts the total number of all relevant ECS design approaches classified by the corresponding attribute.

Table II.B-3: Exemplary literature classification (22/120) - Part I/V

ECS design framework	.../120	Abbasi and Pourrahmani (2020)	Behzadi et al. (2019)	Campana et al. (2019)	Destro et al. (2016)	Ekren and Ekren (2010)	Feroldi and Zumoffen (2014)	Gamou et al. (2002)	Heydari and Askarzadeh (2016)	Iyer and Grossmann (1998)	Jallouli and Krichen (2012)	Kaabeche and Bakelli (2019)	Leif Hanrahan et al. (2014)	Maia and Qassim (1997)	Najafi et al. (2014)	Papoulias and Grossmann (1983)	Rad et al. (2016)	Saha and Kastha (2010)	Tebibel and Labed (2014)	Varbanov et al. (2005)	Wang et al. (2010)	Yang et al. (2008)	Zeng et al. (2016)
Basic design approach	-																						
Scope	-																						
AES demand fulfillment	26									x			x	x		x	x			x			
AES dem. fulf. & lim. FES/PES	5			x																			
AES output maximization	19	x	x												x				x				
Gen. var. dem. fulfillment	36							x				x						x			x		x
Gen. var. dem. fulf. & lim. FES/PES	34				x	x	x		x		x											x	
Decision field	-																						
Decision topics	-																						
Size of units	83	x		x	x	x		x	x	x	x	x	x			x		x	x		x		x
Number of units	52						x					x									x	x	
Type of units	18																						
Superstructure	26									x				x		x	x			x			
System selection	15	x	x	x																			
Expansion of ECS	6																						
System configuration	13	x													x							x	
Decision type	-																						
Free	64				x	x	x	x	x		x	x			x			x	x		x	x	x
Predefined	30	x	x										x	x			x						
Combined	26			x						x						x				x			
ECS type	-																						
Singlegeneration system	59		x	x		x	x		x		x	x						x	x			x	
Cogeneration system	30	x											x		x		x						
Trigeneration system	22				x			x						x						x	x		x
Polygeneration system	4															x							
Flexible	6																						
ECS operation	-																						
Hierarchical integration	-																						
Top-down	13									x										x			
Top-down with feedback	16												x										
Anticipation	79	x	x	x	x	x		x	x		x	x		x	x		x	x	x		x	x	x
Simultaneous	12						x									x							
Operation strategies	92		x	x		x	x		x		x	x	x	x	x	x	x	x	x	x	x	x	
AES demand following	37											x		x						x			
Electrical load follow. (ELF)	33											x											
Thermal load follow. (TLF)	13																			x			
ELF and TLF switching	1																						
FES supply following	24		x	x		x					x								x				
Individual strategies	26						x		x		x		x					x			x		
Continuous operation	18														x		x					x	
Operation optimization	41	x			x			x		x						x					x		x

Table II.B-4: Exemplary literature classification (22/120) - Part II/V

ECS design framework	.../120	Abbasi and Pourrahmani (2020)	Behzadi et al. (2019)	Campana et al. (2019)	Destro et al. (2016)	Ekren and Ekren (2010)	Feroldi and Zumoffen (2014)	Gamou et al. (2002)	Heydari and Askarzadeh (2016)	Iyer and Grossmann (1998)	Jallouli and Krichen (2012)	Kaabeche and Bakelli (2019)	Leif Hanrahan et al. (2014)	Maia and Qassim (1997)	Najafi et al. (2014)	Papoulias and Grossmann (1983)	Rad et al. (2016)	Saha and Kastha (2010)	Tebibel and Labed (2014)	Varbanov et al. (2005)	Wang et al. (2010)	Yang et al. (2008)	Zeng et al. (2016)
Energy sources																							
FES types																							
Renewable	79	x	x	x	x	x	x		x		x	x	x					x	x	x		x	x
Wind energy	47			x		x	x					x	x					x				x	
Solar energy	65		x	x	x	x	x		x		x	x							x			x	
Geothermal energy	7	x																					x
Power	3																						
Bioenergy	8						x		x											x			
Non-renewable	71			x	x			x		x			x	x	x	x	x	x		x	x		x
Coal	3																						
Natural gas	36							x		x			x	x	x		x				x		x
Oil based fuel	41			x	x									x		x	x	x		x			
Power	6									x													
Re-used	9																						
Flexible	5									x													
AES types																							
Primary AES																							
Power	110	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x			x	x
Heat	52				x			x		x				x		x	x			x	x		x
Cold	24				x			x						x		x				x	x		x
Pressure	1																						
Secondary AES	31	x													x		x			x			
Power	20																x			x			
Heat	18	x													x								
Cold	12																						
Flexible	4									x													
CU types																							
Boiler	42				x			x		x				x		x	x			x	x		x
Chiller	17																				x		
Combined heat and power (CHP) unit	8												x								x		x
Electrolyzer	21	x									x								x				
Energy storage unit	58			x	x	x	x				x											x	x
Engine / motor	18				x													x					
Fuel cell	20						x	x			x				x								
Generator	32	x	x	x														x					
Heat recovery unit	35		x											x	x	x				x	x		x
Photovoltaic unit	57		x	x	x	x	x		x		x	x							x			x	
Refrigerator	9							x															
Solar thermal unit	11		x																				
Turbine	50	x								x				x	x	x	x			x			
Wind turbine	46			x		x	x					x	x					x				x	
Flexible	6																						

Table II.B-5: Exemplary literature classification (22/120) - Part III/V

ECS design framework	.../120	Abbasi and Pourrahmani (2020)	Behzadi et al. (2019)	Campana et al. (2019)	Destro et al. (2016)	Ekren and Ekren (2010)	Feroldi and Zumoffen (2014)	Gamou et al. (2002)	Heydari and Askarzadeh (2016)	Iyer and Grossmann (1998)	Jallouli and Krichen (2012)	Kaabeche and Bakelli (2019)	Leif Hanrahan et al. (2014)	Maia and Qassim (1997)	Najafi et al. (2014)	Papoulias and Grossmann (1983)	Rad et al. (2016)	Saha and Kastha (2010)	Tebibel and Labed (2014)	Varbanov et al. (2005)	Wang et al. (2010)	Yang et al. (2008)	Zeng et al. (2016)
CU operation	-																						
CU states	-																						
State types	-																						
Off-cold	1																						
Cold-startup	3																						
Off-warm	0																						
Warm-startup	0																						
Off	55				x		x	x	x	x	x							x					x
On (idle)	7																						
Failure	9																x						
Maintenance	4																						
Charging/Discharging	45			x	x		x				x											x	
State transitions	-																						
Restricted sequences	2																						
Minimum durations	3																						
Transition costs	2																						
State-time relations	1																						
CU loads	-																						
Load types	-																						
Nominal load	27			x														x	x				
Maximum load	60			x			x	x		x	x	x	x					x				x	
Minimum load	71			x	x	x	x	x		x	x	x	x					x					
Partial load	100	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x
Load transitions	-																						
Ramping constraints	1																						
Minimum durations	0																						
Maximum number	0																						
Transition costs	0																						
CU efficiency	-																						
Constant	66		x	x				x		x	x	x			x	x			x		x	x	
Discrete	2					x																	
Linear	13								x								x						
Piecewise-linear	12				x		x													x			x
Non-linear	22	x																x					
Performance degradation	2																						
Scale effect	3																						
Relations to other systems	-																						
External grid	-																						
Export	40	x		x									x		x		x			x			
Import	47			x				x		x			x				x			x	x		x
Energy market	-																						
Uncertain prices	4																						
Time of use tariffs	7												x							x			
Critical peak pricing	5																x						
Power purchase agreements	1																						

Table II.B-6: Exemplary literature classification (22/120) - Part IV/V

ECS design framework	.../120	Abbasi and Pourrahmani (2020)	Behzadi et al. (2019)	Campana et al. (2019)	Destro et al. (2016)	Ekren and Ekren (2010)	Feroldi and Zumoffen (2014)	Gamou et al. (2002)	Heydari and Askarzadeh (2016)	Iyer and Grossmann (1998)	Jallouli and Krichen (2012)	Kaabeche and Bakelli (2019)	Leif Hanrahan et al. (2014)	Maia and Qassim (1997)	Najafi et al. (2014)	Papoulias and Grossmann (1983)	Rad et al. (2016)	Saha and Kastha (2010)	Tebibel and Labed (2014)	Varbanov et al. (2005)	Wang et al. (2010)	Yang et al. (2008)	Zeng et al. (2016)
AES demand/FES supply	-																						
FES related	11																		x				
FES & AES related	36	x		x	x	x							x					x				x	
Stochastic	17							x										x					
Time dependency	-																						
Static	24	x	x											x	x	x	x			x			
Dynamic	97			x	x	x	x	x	x	x	x	x	x					x	x		x	x	x
Aggregation level	-																						
Seconds	2										x							x					
Minutes	4												x										
Hours	77			x	x	x	x		x			x							x		x	x	x
Days	1																						
Months or longer	9									x													
Flexible	2																						
Aggregation method	-																						
Mean	28			x				x											x				
Maximum	2																						
Minimum	1																						
Sum	3					x																	
Data basis	-																						
One data point (static)	21	x	x											x	x	x	x			x			
≤ 50 data points	15									x													
≤ 500 data points	19							x			x							x					
< 8,760 data points	3																						
= 8,760 data points	57			x	x		x		x			x							x		x	x	x
> 8,760 data points	5					x							x										
Objective system	-																						
Objective criteria	-																						
Economic	118	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Monetary	114	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Non-monetary	52	x	x	x			x		x			x			x		x	x				x	
Environmental	26			x											x					x	x		x
Social	1																						
Multi-criteria decision making	64	x	x	x			x		x			x			x		x	x		x	x	x	x
Satisficing constraints	20						x		x			x						x				x	
Pareto	23		x	x											x		x						x
Other	10	x					x								x						x		
Analytical	13																			x			
Evaluation horizon	-																						
Not relevant	32		x		x					x	x		x	x		x			x				
≤ 15 year	9														x								
> 15 years	51	x		x		x	x		x			x						x				x	
Not specified	28							x									x			x	x		x

Table II.B-7: Exemplary literature classification (22/120) - Part V/V

ECS design framework	.../120	Abbasi and Pourrahmani (2020)	Behzadi et al. (2019)	Campana et al. (2019)	Destro et al. (2016)	Ekren and Ekren (2010)	Feroldi and Zumoffen (2014)	Gamou et al. (2002)	Heydari and Askarzadeh (2016)	Iyer and Grossmann (1998)	Jallouli and Krichen (2012)	Kaabeche and Bakelli (2019)	Leif Hanrahan et al. (2014)	Maia and Qassim (1997)	Najafi et al. (2014)	Papoulias and Grossmann (1983)	Rad et al. (2016)	Saha and Kastha (2010)	Tebibel and Labed (2014)	Varbanov et al. (2005)	Wang et al. (2010)	Yang et al. (2008)	Zeng et al. (2016)
Solution method	-																						
Model type	-																						
Linear program	1																						
Mixed-integer linear program	23							x								x			x	x			
Quadratic program	1																						
Nonlinear program	4							x										x					
Mixed-integer nonlinear prog.	11																						
Mathematical formulation	83	x	x	x	x	x	x		x	x	x	x	x		x		x				x	x	x
Exact solution methods	9									x													
Total enumeration	2																						
Branch-and-bound	4																						
Branch-and-cut	1																						
Dynamic programming (DP)	1																						
Robust solution method	17							x									x	x					
Stochastic DP	1																						
Minimax regret	3																						
Markov model	3																x						
Multi-level programming	3																						
Monte Carlo Simulation	5																						
Chance-constrained prog.	2																						
Scenario / sensitivity analysis	8							x										x					
Heuristics	11																						
Metaheuristics	51	x	x	x	x	x	x		x			x		x	x		x				x	x	x
Simulation	19			x							x		x							x			
Standard solver	21															x							
Application case	-																						
Real world evaluation	85				x	x		x	x	x	x	x	x	x	x	x			x	x		x	
Non-industrial	57				x		x	x			x	x									x		x
Section A - Agriculture, …	4			x					x														
Section B - Mining and …	5																						
Section C - Manufacturing	46	x	x							x			x	x		x	x		x	x			
C10 - Food products	3																						
C11 - Beverages	1																						
C17 - Paper and paper products	2																						
C19 - Coke and refined petrol.	4													x		x	x						
C20 - Chemicals and chemical …	21	x	x																x	x			
C21 – Basic pharmaceutical …	2																						
Not further specified	13									x			x										
Section E - Water supply, …	8	x													x								
Section J – Inf. and comm.	2					x																x	
Not specified	6																	x					

6 Empirical analysis

Due to the fact that only a partial extract of the 120 classified approaches can be shown inside this paper, not all analytical results described in the following are directly traceable by the data within the manuscript but by the complete literature classification provided in the supplementary material.

The temporal development of articles describing ECS design approaches that are suitable for the on-site AES supply at manufacturing companies is illustrated in Figure II.B-7. Generally, a continuously increasing trend with a peak in 2014 and the following years is observed.

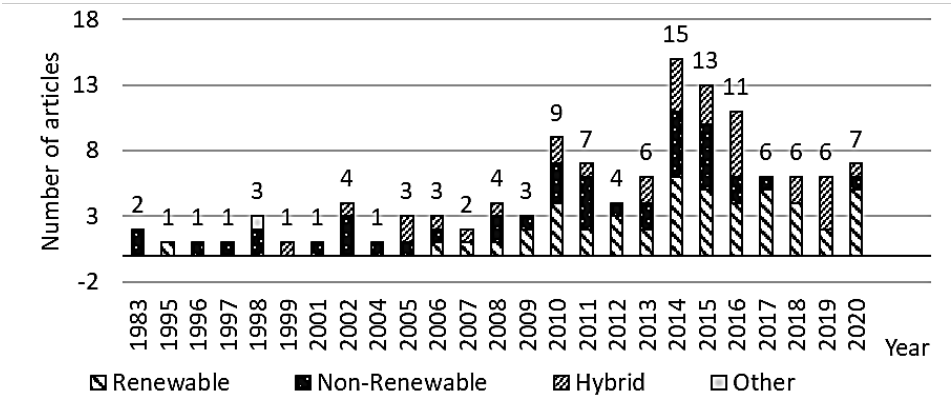


Figure II.B-7: Temporal development (state: Mai 2020)

Further on, the focus on renewable and hybrid ECSs increased from 2006 to 2020.

Note that, if not stated otherwise, all numbers in the following figures and legends depict the absolute numbers of articles that are classified by the corresponding attribute or sub-category.

6.1 Scope and decision topics

The scope distribution of the analyzed ECS design approaches is depicted in Figure II.B-8 (along with the related decision topics).

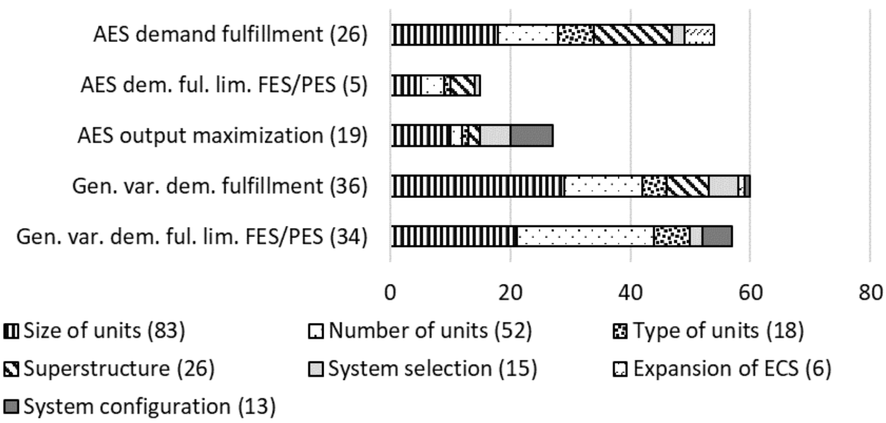


Figure II.B-8. Relationship between *Scope* and *Decision topic*

Most of the analyzed ECS design approaches are designed to fulfill (varying) energy demands (101), of which only 31 are directly related to production systems. Despite the fact that AES demands from production system are strongly varying in most cases, 13 of the 31 production related ECS design approaches only consider static demands and five do not consider partial loads (which can be seen as mandatory for ECS design for manufacturing companies). On the one hand, we can state that most of the articles targeting *AES output maximization* are related to the application case of hydrogen production by using renewable (or hybrid) ECSs. On the other hand, articles targeting *General varying demand fulfillment with* and *without limited FES supply* (70) are mostly related to the energy supply of districts (30), hospitals (6), or buildings (22). As Figure II.B-8 illustrates, there is a high diversity regarding decision topics but in most articles, the *Size* (maximum capacity) and/or the *number* of CUs is determined. The use of a *Superstructure* is also common. We would like to mention here, that it was very difficult to determine the decision topic for several articles and that the decision topic should be clearly stated in the abstract of an article.

6.2 ECS types

Regarding the considered ECS types (cf., Figure II.B-9), it is worth to mention that almost any approach designing a singlegeneration system (55/59) uses renewable energy sources as FES to provide power as AES (58). This can be traced back to the fact that most of these approaches design ECS to fulfill general varying AES demands at remote locations.

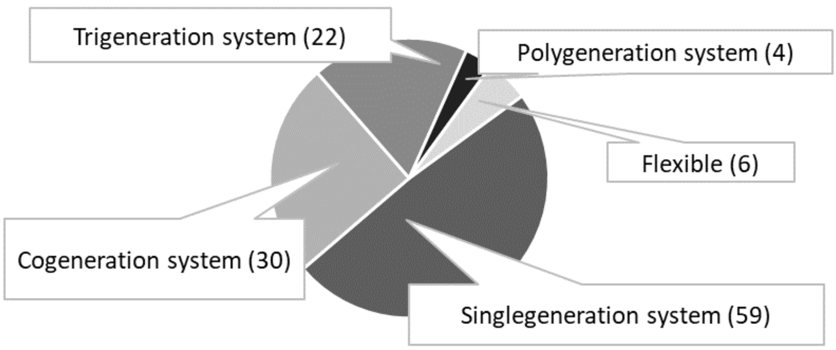


Figure II.B-9: ***ECS type*** **analysis**

6.3 ECS operation

As Figure II.B-10 illustrates, there is an apparent majority of ECS design approaches that anticipate operational behavior and integrate the most important aspects of ECS operation into the design decision. However, a few approaches even do a simultaneous optimization.

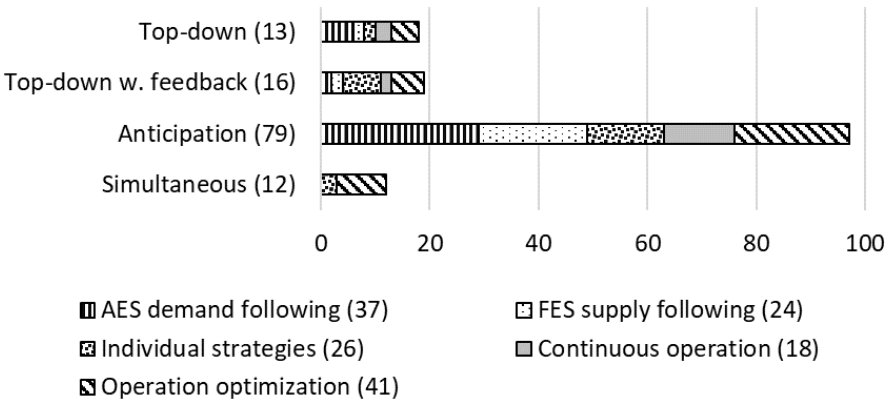


Figure II.B-10: Relationship between *Hierarchical integration* and *ECS operation*

Concerning the modelling of ECS operation decisions, most approaches perform an optimization and the second most integrate AES demand following strategies (e.g., electrical load following or thermal load following).

6.4 Energy sources

The great diversity of ECS approaches regarding energy sources is best illustrated by Figure II.B-11 and Figure II.B-12: twelve different FES types (cf., Figure II.B-11) are used to provide more than nine different AES types (comprised by the six attributes in Figure II.B-12; e.g., power or heat). Note, that the attributes depicted in both figures are not exclusive.

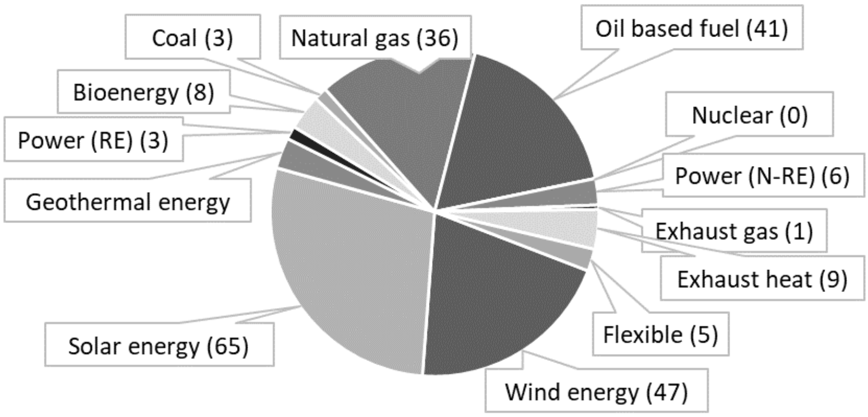


Figure II.B-11: Diversity of *FES types*

The figures also show that the number of flexible ECS design approaches is very small: i.e., approaches that are flexible regarding FES type (5), regarding AES type (4), or regarding FES and AES type (4).

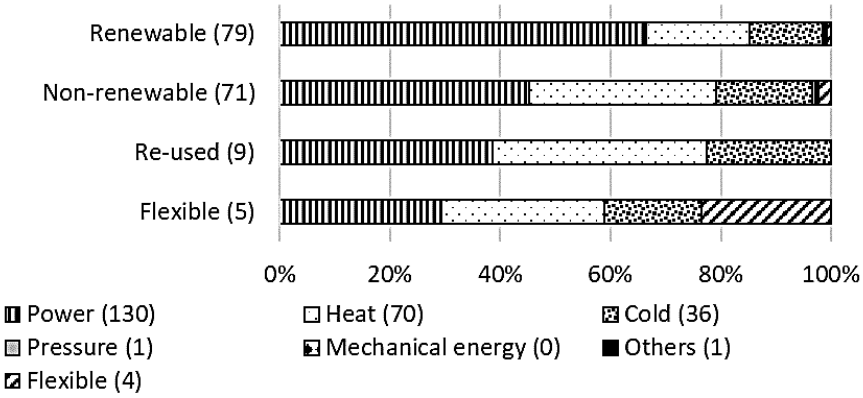


Figure II.B-12: Relationship between *FES types* and *AES types* (primary and secondary)

6.5 CU types

Figure II.B-13 perfectly illustrates the enormously large decision field of ECS design (particularly when considering that the shown attributes are generic terms for many different unit manifestations).

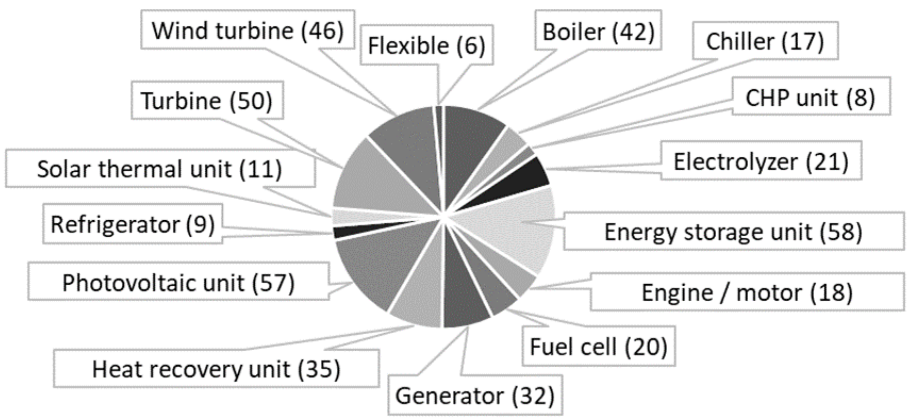


Figure II.B-13: Diversity of considered *CU types*

The figure also shows that only a few ECS design approaches are flexible regarding CU types.

6.6 CU operation

The small number of articles that consider *CU states* is generally surprising (cf., Figure II.B-14), especially when taking into account that most considered states are related to the "simple" *off* state and to battery *Charging/ discharging*. Depending on the *CU type*, the consideration of states, especially the state *on (idle)*, should receive more attention. Generally, the aspect of different *CU state types* and *State transitions* should at least be discussed when designing an ECS.

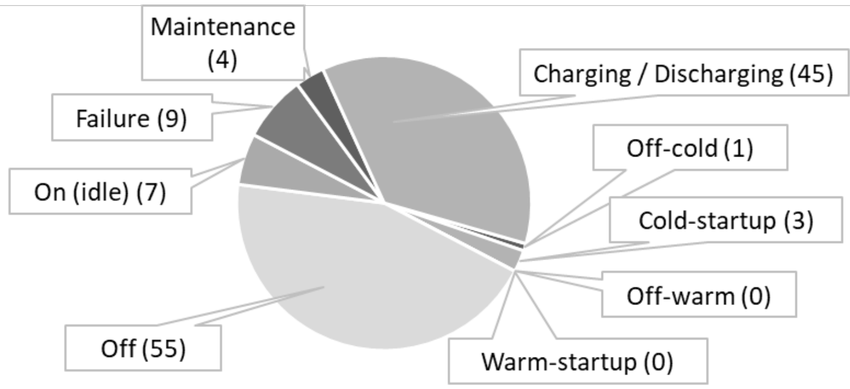


Figure II.B-14: CU state types analysis

Regarding *CU loads* (cf., Figure II.B-15), we observed that only a few authors differentiate between the *Nominal load* (i.e., the load at which the CU operates with maximum conversion efficiency; also called design point) and the *Maximum load*. Of course, for some *CU types* this might be correct, but for others this is a model simplification which should at least be discussed.

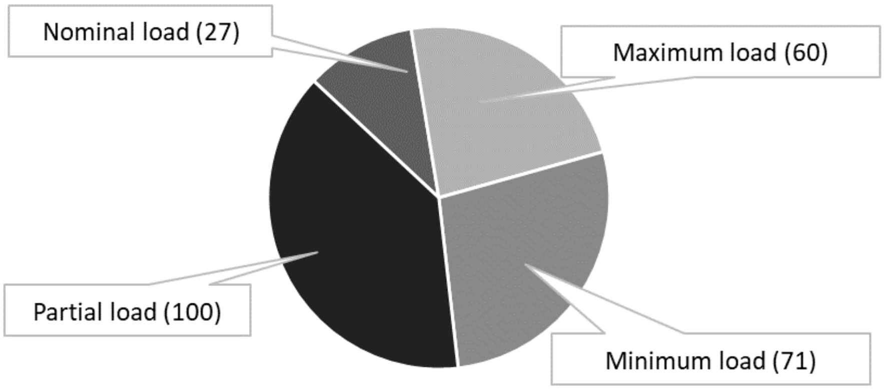


Figure II.B-15: CU loads analysis

In this context, we also would like to emphasize that 51 of the 100 ECS design approaches considering *Partial loads* use a *Constant* conversion efficiency, i.e., conversion efficiencies that are independent of the actual load. However, the reasonability of this simplification or whether more complex modelling approaches (e.g., *Linear*, *Piecewise-linear*, or *Non-linear*) should be used, is seldomly discussed. Altogether the other 49 approaches considering partial loads consider the following *CU efficiency* characteristics: 2 discrete loads and efficiencies, 13 articles apply a *Linear*, 12 a *Piecewise-linear*, and 22 a *Non-linear* load-efficiency relationship. Concerning *Load transitions*, we must report that only one article addresses this topic by a ramping constraint: Shamsi et al. (2019).

6.7 AES demand / FES supply

As Figure II.B-16 shows, 21 ECS design approaches base on a single AES demand point (*One data point (static)*) and the majority, 62 design approaches, consider *8,760 data points* or more for the design of an ECS (note that only approaches related to AES demands are considered here). Here, the *8,760 data points* represent the hours of one year (365 days with 24 hours).

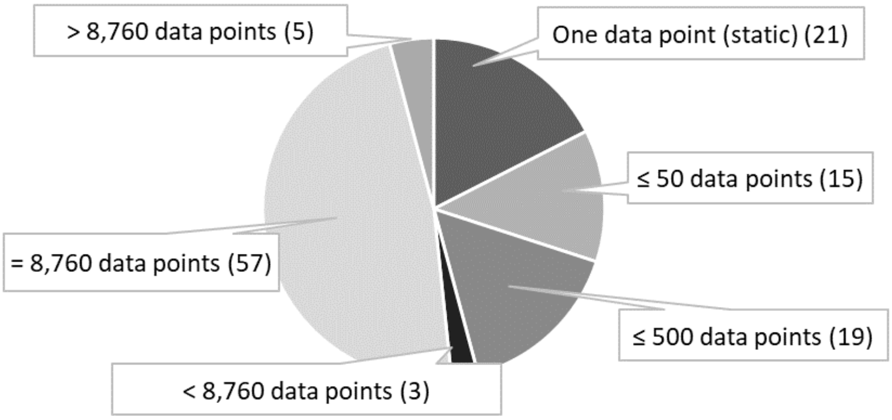


Figure II.B-16: Data basis of AES demand related approaches (number of data points in one optimization scenario)

The *Aggregation level* (time resolution) for most articles (77) is *Hour*.

Regarding these observations, it seems that most of the analyzed approaches do not consider the special characteristic of strongly varying demands in manufacturing companies in an appropriate manner. In this context, it is also worth mentioning that only 17 articles address *Stochastic* AES demands.

Analyzing the remaining main category *Relations to other systems*, it is worth to highlight that 64 ECSs are designed to fulfill AES demands as autonomous system without any connections to a grid and that only 17 articles consider special market relations like *Uncertain prices* or *TOU tariffs*.

6.8 Objective system

The first additional category to be analyzed, is the *Objective system*. As to be expected, the majority of articles optimizes economic objectives, *Monetary* as well as *Non-monetary* ones (cf., Figure II.B-17). At least, 26 articles address *Environmental objectives* but only one approach considers *Social objectives* (Dufo-López et al., 2016).

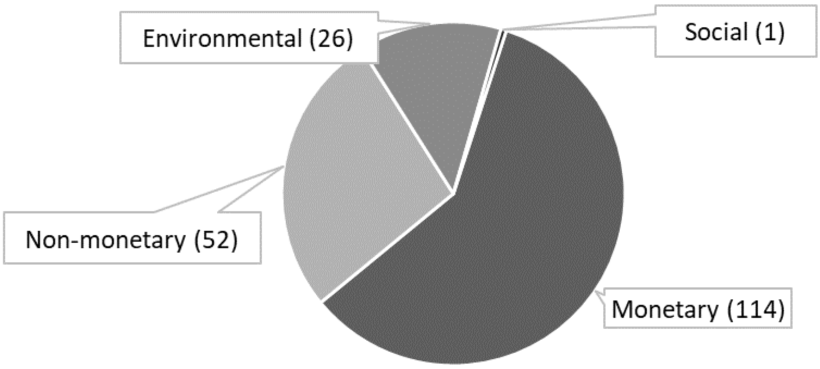


Figure II.B-17: Number of articles per type of objective criteria

Analyzing the applied *Monetary* criteria (cf., Figure II.B-18), *Non-monetary* criteria (Figure II.B-19), and *Environmental* criteria (cf., Figure II.B-20), we observed a great diversity which makes a comparison between approaches very difficult. Even if the same *Monetary* criteria (e.g., total annual costs) is used, the components that are included in the costs (e.g., investment costs, operational costs, maintenance costs, replacement costs, salvage costs, …) are very heterogenous.

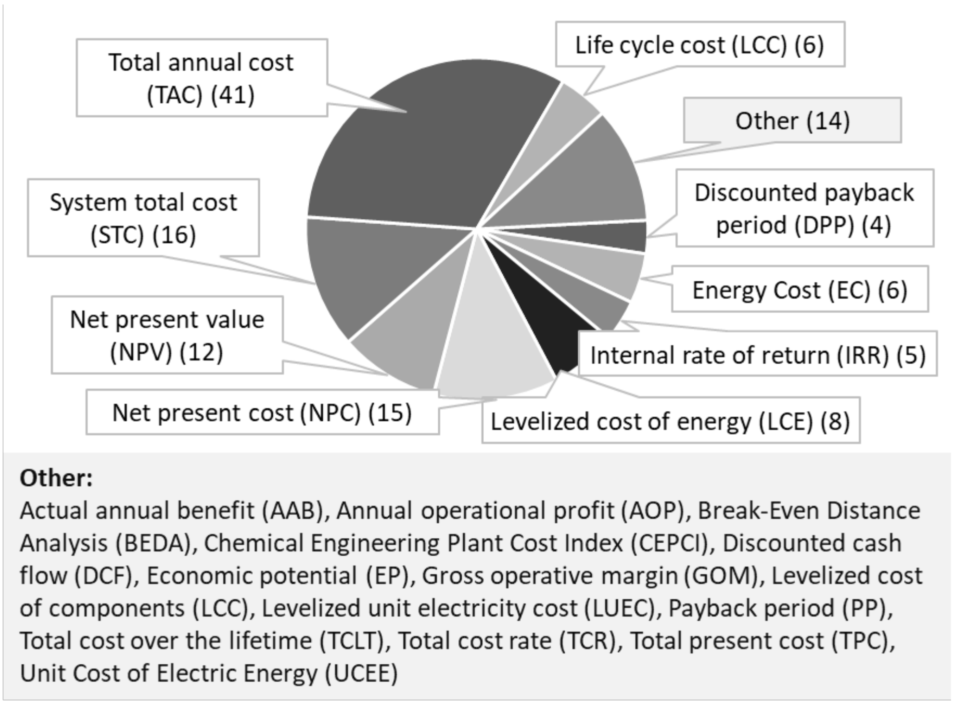
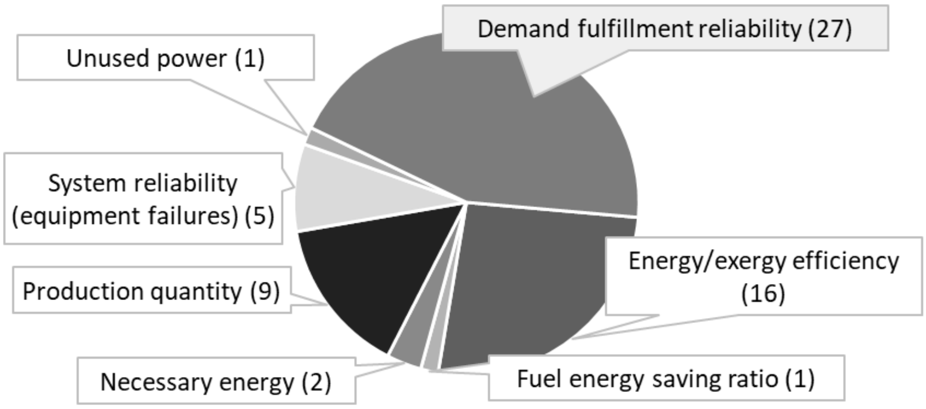
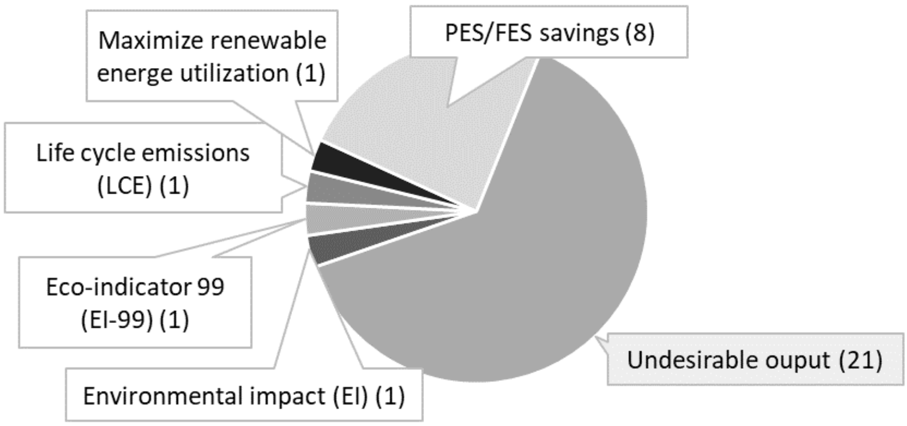


Figure II.B-18: Diversity of considered *Monetary* criteria



Demand fulfillment reliability (27):
Deficiency of Power Supply Probability (3), Energy index of reliability (2), Expected energy not supplied (6), Loss of power supply probability (12), Loss of load propability (4), Relative Excess Power Generated (2), Load Dissatisfaction Rate (1), Loss of heat supply probability (1), Maximum Daily Power Failure Time (1), Maximum expected energy not supplied (1), Minimum reliability level (1), Relative energy not supplied (1), Total energy deficit (1), Unmet load (1)

Figure II.B-19: Diversity of the considered *Non-monetary* criteria



Undesirable output:
Dumped energy (1), Gas emissions (19): air pollution (1), carbon dioxide (16), NOx (4), SOx (3), other (1)

Figure II.B-20: Diversity of the considered *Environmental* criteria

The only article addressing social objectives, namely "Maximization of human development index (HDI)" and "Maximization of job creation" is from Dufo-López et al. (2016).

Altogether 64 ECS design approaches consider more than one objective criterion, whereas 20 use a *Satisficing constraint* (mostly on demand fulfillment reliability), 23 use *Pareto*-frontier related concepts, 13 use *Analytical* approaches, and 10 use *Other* concepts like lexicographical optimization (1), weighted sum (4), goal programming (1), TOPSIS (4), or LINMAP (1).

The analysis of the used *Evaluation horizon* underlines the great heterogeneity of the applied objective systems: 51 articles use horizons greater than 15 years, 9 not more than 15 years, and 32 articles use objective criteria without considering system lifetimes (cf., Figure II.B-21).

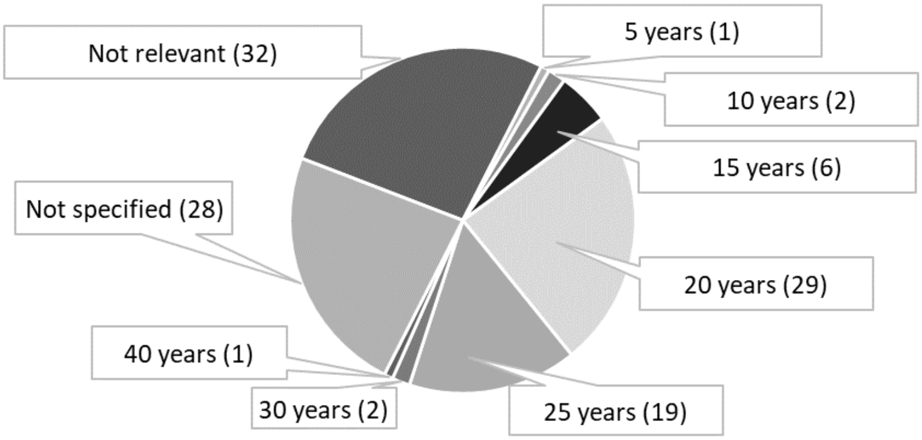


Figure II.B-21: Diversity of the considered *Evaluation horizons*

At this point we would like to criticize that it was not possible to extract all planning horizons from the articles even if they are used within the objective criteria.

6.9 Solution methods and model types

As Figure II.B-22 shows, the majority of articles (83) provides mathematical formulations to describe the interdependencies of the ECS and uses non-exact solution methods for solving the decision problem (remember that the model types and solution methods are non-exclusive, i.e., one article can use more than one model type or solution method). Nevertheless, several authors propose optimization models und use standard solvers (mostly CPLEX and Lingo).

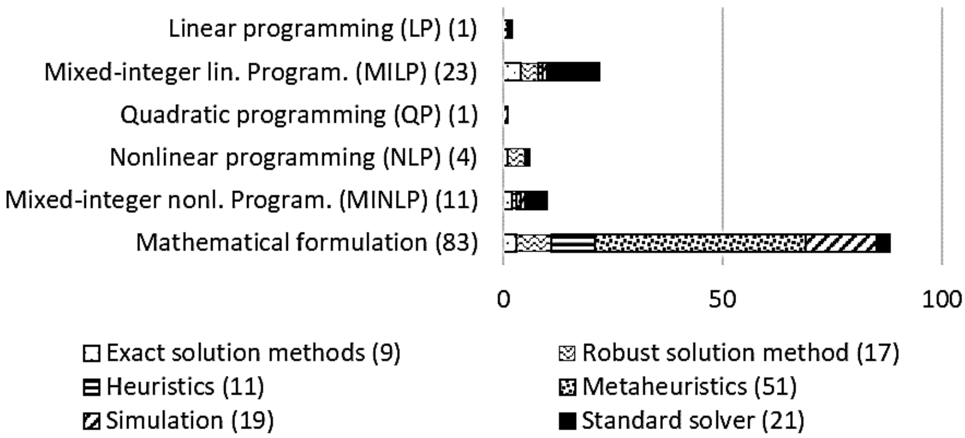
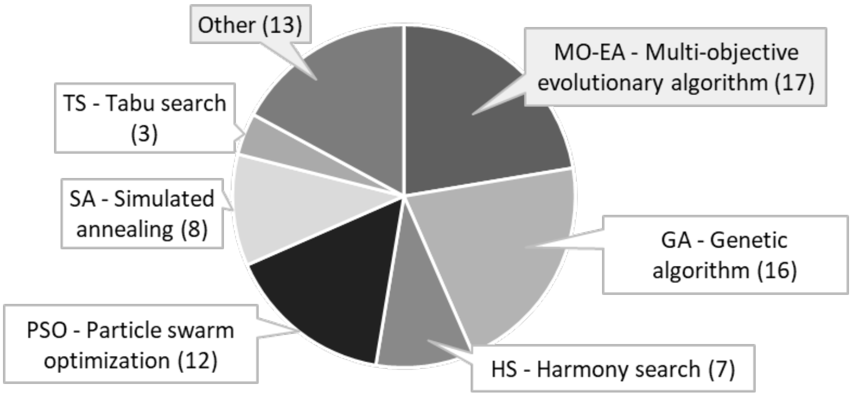


Figure II.B-22: *Model types* and *Solution methods*

Most often applied solution methods are metaheuristics. This is explained by two reasons: First, metaheuristics can tackle almost any kind of optimization problem and provide a sufficient solution quality in a reasonable time (in most cases). Second, there exists a great variety of evolutionary algorithm capable to solve multi-objective optimization problems (mostly based on the Pareto frontier concept). The diversity of applied metaheuristics is illustrated by Figure II.B-23.



Multi-objective evolutionary algorithm (MO-EA)
NSGA-II (8), NSGA-III (1), MOEA (6), MOGA (5), AMGA (1), SPEA 2 (1)
Other:
Ant lion optimizer algorithm (ALO), Bat algorithm (BA), Biogeography-based optimization (BBO), Big Bang - Big Crunch algorithm (BB-BC), Bee swarm optimization (BSO), Comprehensive learning PSO (CLPSO), Dividing rectangles algorithm (DIRECT), Firefly algorihm (FA), Grey wolf optimizer (GWO), Imperialistic Competitive Algorithm (ICA), Jaya algorithm (JA), Krill Herd Algorithm (KH)

Figure II.B-23: Diversity of applied metaheuristics

6.10 Application case

Figure II.B-24 illustrates the great diversity of the 65 industrial application cases considered by the articles.

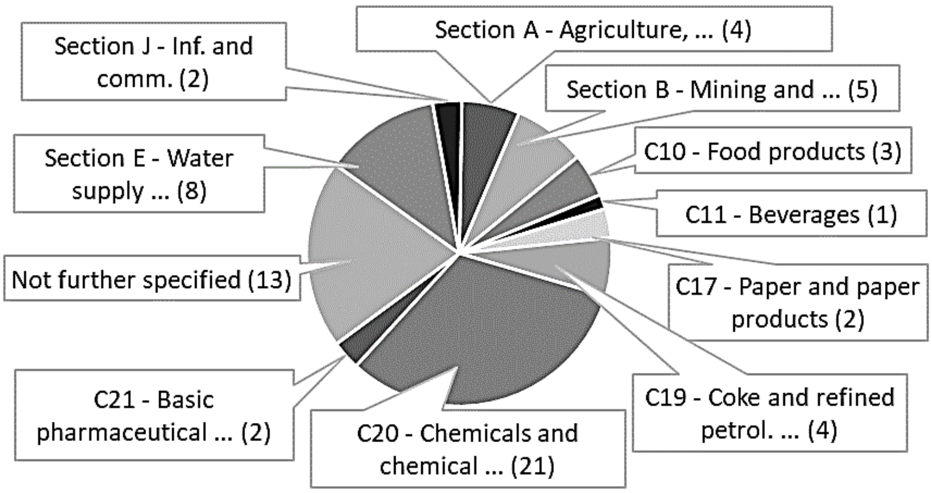


Figure II.B-24: Areas of application (only industry-related articles)

Most often considered application cases are from *Section E* and *Section C20*: Articles classified by *Section E* (“Water supply; sewerage, waste management and remediation activities”) are related to fresh water production (7) and articles classified by *Section C20* (Section C - Division 20 - Class 2011: "Manufacture of basic chemicals") are related to hydrogen production (15).

Altogether 57 articles address non-industrial application cases (32 districts or remote sites, 22 buildings and 7 hospitals) and six articles do not specify any specific application case (but all of them consider varying AES demands).

From the total of 120 articles, the majority (85) articles use real-world data for the evaluation.

Note that the total number of articles is greater than 120 because some articles consider several application cases or address several industrial sectors simultaneously (e.g., hydrogen and freshwater production; Abbasi and Pourrahmani, 2020).

7 Major findings

Based on the previous analysis, we would like to emphasize several major findings and derive further research topics for improving the design of ECSs for manufacturing companies:

- Most of the design approaches are very specific regarding the ECS type (cf., Figure II.B-9), FES supply (cf., Figure II.B-11) and AES types (cf., Figure II.B-12). The other way around, only a few design approaches are flexible regarding these aspects. The development of flexible ECS design approaches would certainly be helpful for a broad application of on-site ECSs.
- The heterogeneity of the research field results in several challenges. For instance, there exist no benchmark data sets (e.g., providing the AES demand of a company) to enable a reasonable comparison of different planning approaches and solution methods. Such comparisons are only made within single contributions and therefore are somehow limited. Also, the broad variety of used evaluation criteria (cf., Figure II.B-18, Figure II.B-19, and Figure II.B-20) combined with different evaluation horizons (cf., Figure II.B-21) make comparisons between articles almost impossible.
- Batteries and hydrogen storage systems, or a combination of both, are used to compensate supply uncertainty of renewable energy sources. Sometimes an additional generator using non-renewable energy sources is integrated to reduce storage cost and increase fulfillment reliability. However, most of these ECSs are designed for non-industrial application cases. Therefore, the design of such ECSs for manufacturing companies should be considered in further research.
- The operational characteristics CU states, CU state transitions, partial load behavior, load transitions, and related conversion efficiencies are hardly considered by the analyzed ECS design approaches. For instance, only Shamsi et al. (2019) consider ramping constraints. Accordingly,

we propose the analysis of their influences on the ECS design and the development of concepts and modelling approaches for their consideration.

- Although many articles design an ECS that will be in operation for many years, performance degradation over time is only considered by two approaches. The same holds true for scale-effects on the performance related to the size of CUs. To model these aspects appropriately for ECS design, a detailed (technical) analysis of both aspects would be appreciated.
- The generation and/or preparation of the data that is used for evaluation purposes is often not properly described. Information about aggregation methods, the aggregation level, or the number of data points is sometimes hard to extract. But since this is an important aspect for the application of the proposed ECS design approaches, a more thorough explanation of the data used for optimization is recommended.
- Because production processes and units are very sensitive on energy shortages, system and AES demand fulfillment reliability are of highest importance for manufacturing companies. If the AES provisioning fails only for seconds, the impact on the production can be drastic. Therefore, the CU state *Failure* should receive more attention (only nine articles are classified by this attribute) and either fallback strategies like grid connections (e.g., for the AES power) or other reliability measures (e.g., for the AES steam) should be considered. At least, a sufficient number of AES demand points should be considered to achieve a reliable ECS design. In this context, we would also like to emphasize that the aggregation level of hours (used by 82 authors) is very “high” and that a more detailed aggregation level (e.g. of minutes) would be more appropriate to model the highly varying AES demands of production systems.

8 Conclusion

Because energy is a non-substitutable production factor and environmental concerns have drastically increased in recent years, measures to provide energy for production processes in a more sustainable way (e.g., with a higher energy efficiency) have become an increasingly important topic. One such measure to increase the energy efficiency are on-site ECSs. To support the installation of on-site ECSs at manufacturing companies, numerous ECS design approaches have been published in the recent years. However, the research field addressing this topic is very heterogenous (which can be seen by the diversity of journals in Table II.B-1) and the lack of a comprehensive research framework to structure the field was only recently resolved by the concept-centric ECS design framework proposed by Ganschinietz (2020).

The four contributions of this paper are provided within the sections 4 to 7 : First, we extended the scope to ECS design approaches that are either related to production systems or consider varying AES demands, because these approaches can be transferable on ECS design for manufacturing companies. Furthermore, for an in-depth analysis, we extended the ECSDF by three main categories: *Objective system*, *Solution method*, and *Application case*. Second, we identified 120 approaches to be relevant (by evaluating over 620 papers found by the structured literature search process) and reviewed and classified them according to the ECSDF. Third, an empirical analysis based on the classified articles has been performed. Finally, major findings were elaborated. These major findings also provide opportunities and topics for further research that are particularly, but not only, important for the design of ECSs for manufacturing companies.

Beside the possibility to analyze the research area of ECS design in a structured manner, the ECSDF can also be used to identify major aspects that must be considered when designing an application case specific ECS and to determine minor aspects that can be ignored or modelled in a simplified way. Therefore, we would like to recommend authors to use the ECSDF to analyze and classify their planning problems and design approaches and to discuss major and minor aspects accordingly. To support this process, we provide the complete classification of the 120 relevant ECS design approaches and an overview of the ECSDF in the digital supplementary material.

9 Appendix

A-1: Adapted keyword search

Abbreviations of the search string mean the following:

TI = title

TS = title, abstract, and key words

SO = journal name

TI = (conversion OR planning OR generation)

AND TI = (model* OR optim* OR dimensioning OR design*)

AND TS = (combined heat and power OR chp OR cogeneration OR cchp OR combined cool* heat* power OR trigeneration OR photovoltaic* OR pv OR Solar* OR turbine OR hydro power OR fuel cell* OR biogas* OR biomass OR boiler* OR combustion engin* OR heat pump* OR stand alone OR energy system* OR power system* OR wind power)

AND TS = (size* OR scale* OR dimensioning* OR design*)

AND TS = (plant* OR industr* OR produc* OR compan* OR firm* OR enterprise* OR corporation* OR concern* OR manufactur*)

NOT TS = (grid OR store* OR schedule* OR commercial energy OR region* OR area* OR market)

AND SO = (Applied Energy OR Applied Thermal Engineering OR "Computers & Industrial Engineering"OR Electric Power Systems Research OR Energy OR Energy & Environmental Science OR "Energy Conversion and Management" OR Energy Economics OR Energy for Sustainable Development OR Energy Journal OR Environmental Research Letters OR "Experimental Thermal and Fluid Science" OR "IEEE Journal of Emerging and Selected Topics in Power Electronics" OR IEEE Journal of Photovoltaics OR IEEE Power & Energy Magazine OR IEEE Transactions on Energy Conversion OR IEEE Transactions on Industrial Electronics OR IEEE Transactions on Industry Applications OR IEEE Transactions on Power Delivery OR IEEE Transactions on Power Electronics OR IEEE Transactions on Power Systems OR IEEE Transactions on Sustainable Energy OR IET Generation Transmission & Distribution OR IET Power Electronics OR IISE Transactions OR International Journal of Electrical Power & Energy Systems OR International Journal of Engineering Science OR "International Journal of Heat and Mass Transfer" OR International Journal of Hydrogen Energy OR International Journal of Production Economics OR International Journal of

Production Research OR International Journal of Thermal Sciences OR JOM OR Journal of Cleaner Production OR "Journal of Modern Power Systems and Clean Energy" OR Journal of Operations Management OR Nano Energy OR Nonlinear Analysis: Real World Applications OR "Production and Operations Management" OR Production Planning & Control OR "Progress in Energy and Combustion Science" OR Progress in Photovoltaics OR Renewable & Sustainable Energy Reviews OR Renewable Energy OR Solar Energy OR "Solar Energy Materials and Solar Cells" OR "Sustainable Energy Technologies and Assessments" OR Journal of the Energy Institute)

A-2: Complete structure of the ECSDF including the extensions

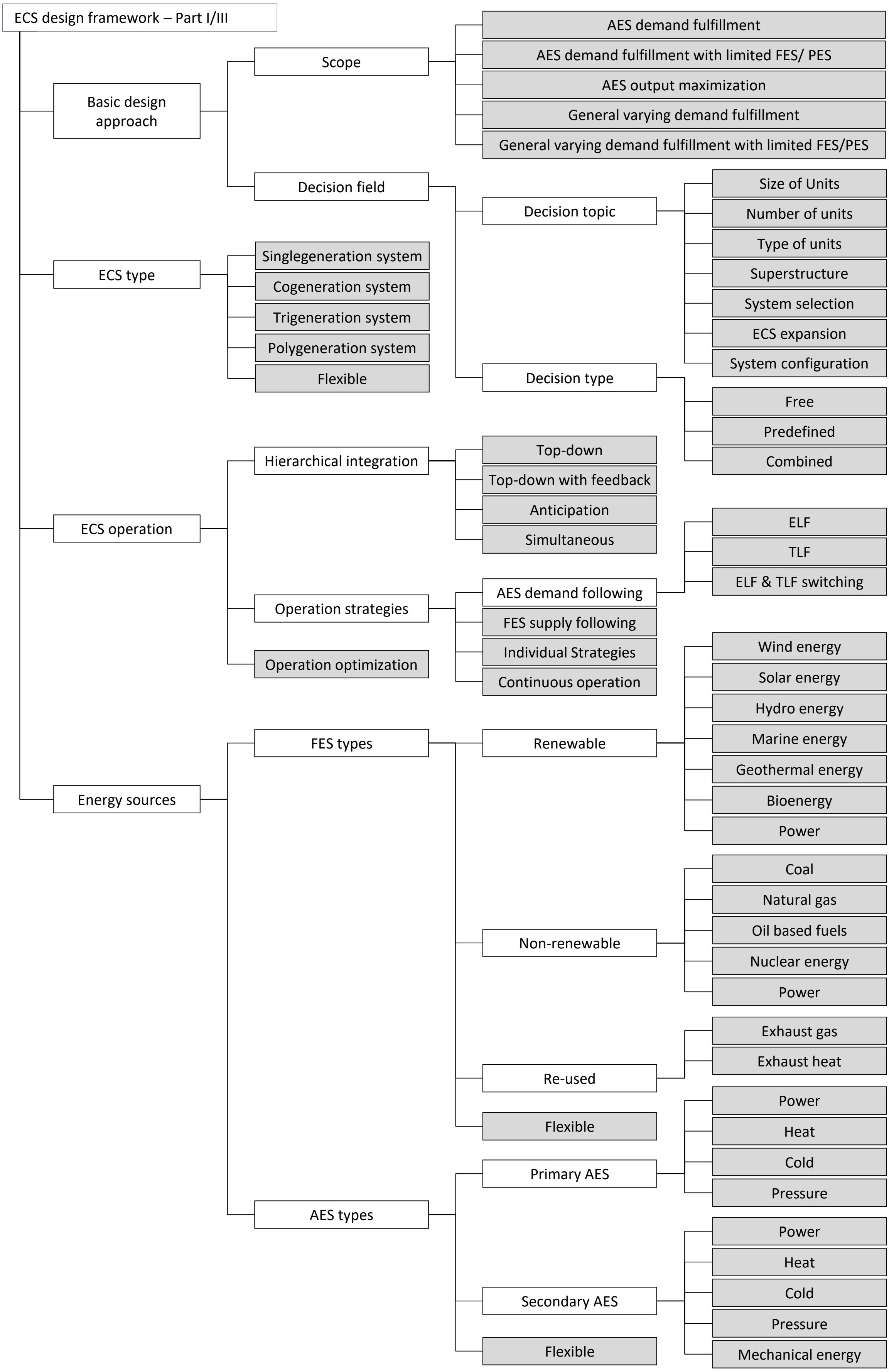


Figure II.B-25: ECSDF part I/III

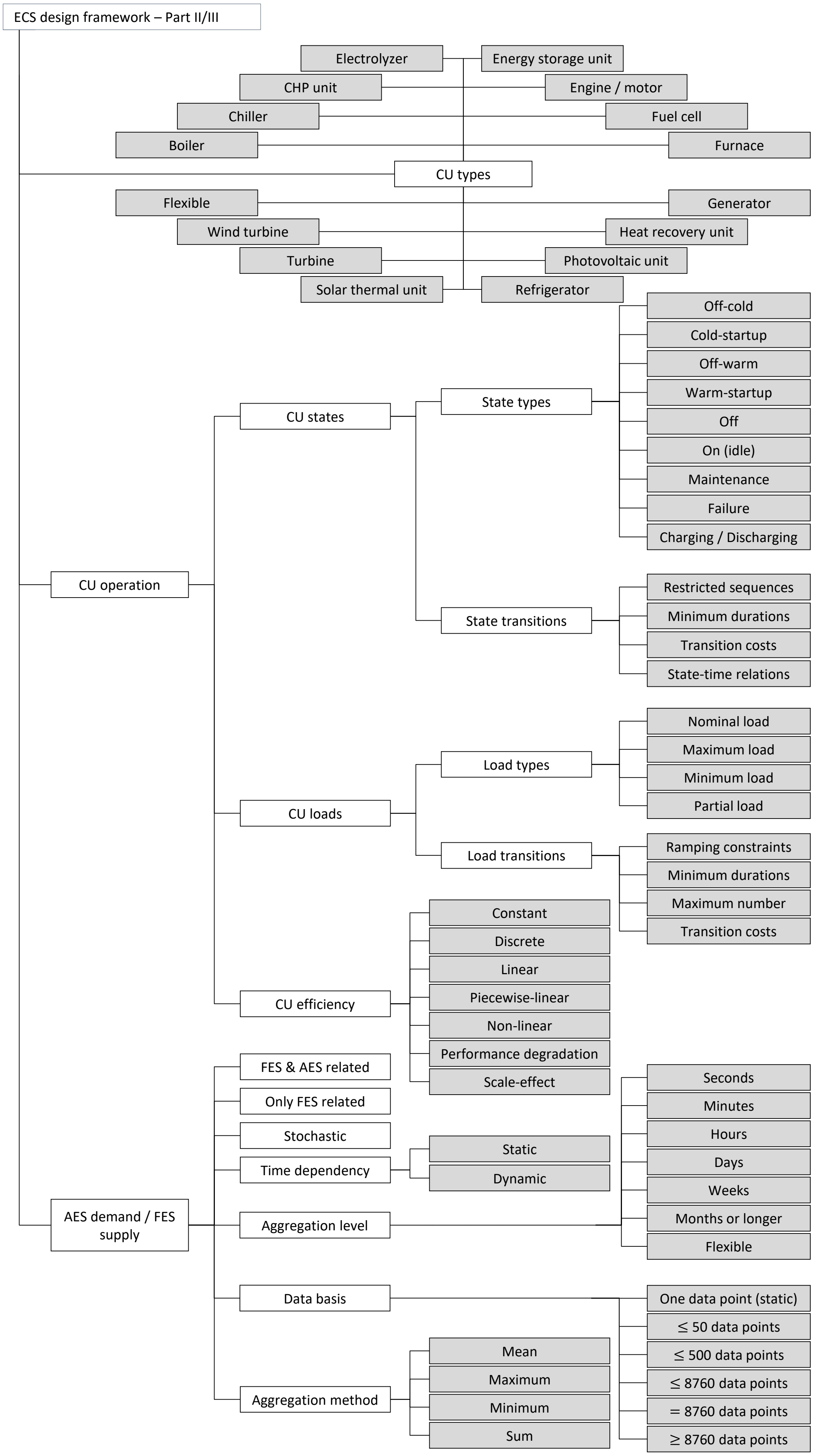


Figure II.B-26: ECSDF part II/III

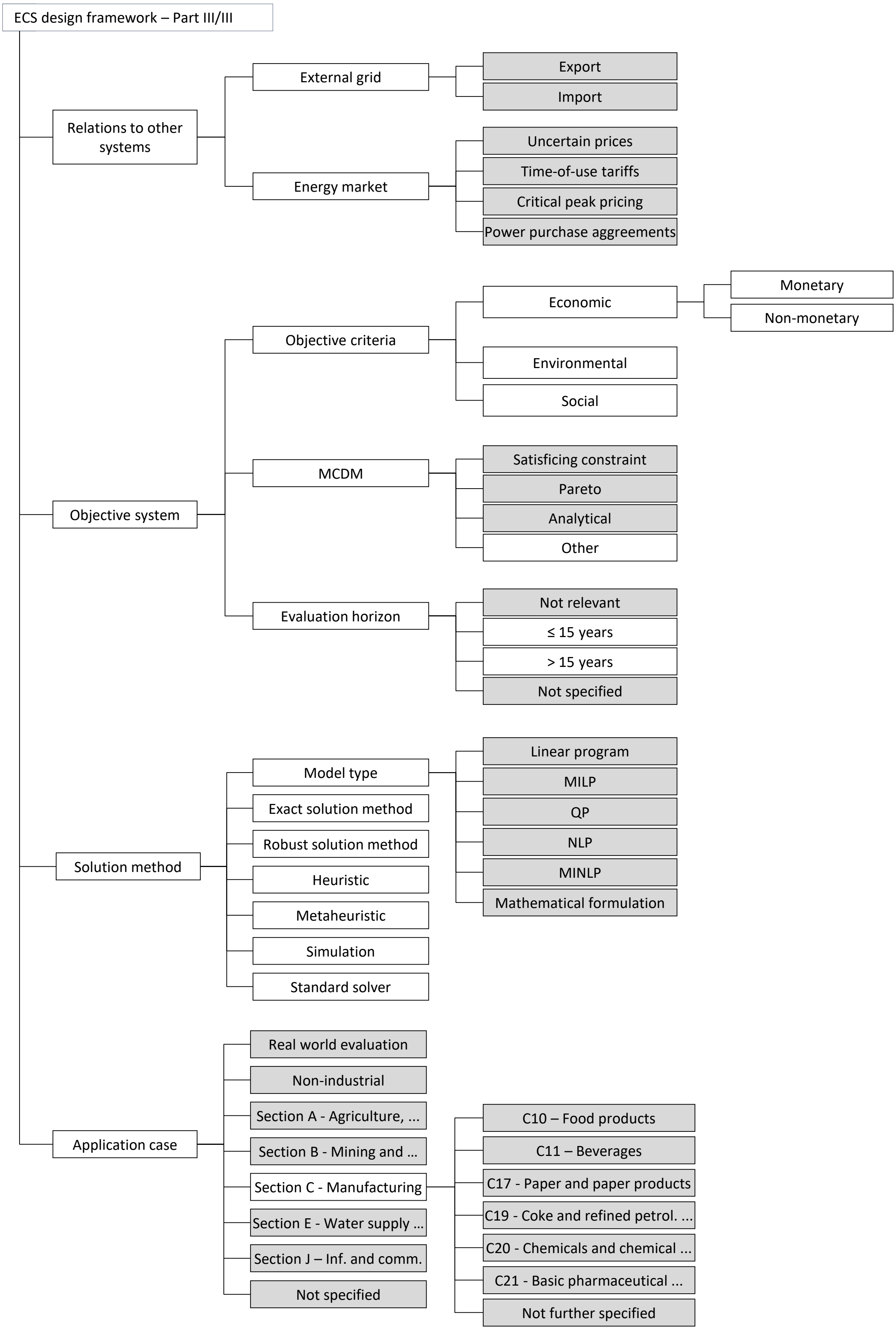


Figure II.B-27: ECSDF part III/III

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II.C Contribution 3:
A flexible approach for the dimensioning of energy conversion systems of manufacturing companies

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Abstract: Besides electricity, many industrial production processes require other applied energy sources (AES) such as steam or pressure. To transform primary or secondary energy sources into the required AES, manufacturing companies often operate their own on-site energy conversion system (ECS) comprising of several conversion units (CUs). Most important parameters determining a CU's overall degree of efficiency are its dimension (maximum load) and the design point (nominal load) at which the CU operates with maximum efficiency. Thus, we present a new ECS planning approach maximizing the energy efficiency by specifically optimizing these two parameters. Regarding manufacturing companies, particularly the varying AES demand from production processes and the resulting part-load operation of CUs have to be considered during ECS design. Furthermore, as many types of CUs have a nonlinear relationship between partial loads and the corresponding conversion efficiency, this relationship must be considered appropriately. In our experimental analysis, the influence of a nonlinear and a linear modelling approach of this relationship on the ECS design is evaluated. Furthermore, because our planning approach is based on AES demand time series resulting from production scheduling, we investigate the influence of different scheduling objectives on the AES demand and in turn, on the ECS design. To solve the planning problem, we propose a highly efficient heuristic and a mixed-integer nonlinear program that reflects the nonlinear efficiency characteristics of CUs. The experimental analysis investigates different types of company types, scheduling objectives, CU parameters, and part-load efficiency modelling approaches and shows that all these factors can have remarkable influences on the design and the energy efficiency of an ECS.

Keywords: conversion (utility) systems, energy efficiency, manufacturing, nonlinear programming

1 Introduction

The sustainable development of a society is strongly related to the sustainable development of its manufacturing companies (Jovane et al., 2008 and Haapala et al., 2013) and their overall energy demand (in 2017, industry accounted for approximately 24.6% of the total energy consumption in the European Union; Eurostat, 2019). However, the execution of manufacturing processes is inevitably paired with the application of energy and there is no option to abandon manufacturing for the sake of lowering energy demands. Instead, improving energy efficiency, i.e., the ratio between energy input and the desired output of a production process (for a more specific definition of energy efficiency, see e.g. Fysikopoulos et al., 2014), is an effective measure to guarantee a desired production output at a minimum energy demand.

In manufacturing companies, applied energy sources (AES) are used to run production processes that are executed by production units (e.g., machines or chemical reactors) of the production system (PS). For a detailed analysis of energy application in production see for instance Dietmair and Verl (2009), Herrmann and Thiede (2009), Avram and Xirouchakis (2011), Duflou et al. (2012), Li et al. (2014) or Gahm et al. (2016). According to Gahm et al. (2016), a production system's AES demand is either supplied directly by an external energy provider or it has to be converted by an internally operated conversion (utility) system. Also, a combination of both is common. In the latter cases, on-site (energy) conversion system (ECS) consisting of one or more conversion units (CUs) supply the production system with a specific AES (e.g., steam or pressure) by converting primary energy sources (e.g., oil or coal) or secondary energy sources (e.g., electricity or fuel) into the required type of AES (e.g., steam/heat or compressed air). As soon as the ownership of these energy sources is transferred to the manufacturing company (the final energy user), the energy sources are referred to as final energy sources (Gahm et al., 2016). Analyzing this structure, it becomes obvious that improving the energy efficiency in manufacturing companies can be achieved by various measures on different decision levels: e.g., in the short-term, by energy-efficient scheduling (cf., Gahm et al., 2016 or Biel and Glock, 2016) or in the long-term, by an appropriate design of energy conversion systems (cf., e.g., Sun and Liu, 2015 or Yokoyama et al., 2015).

In this paper, our goal is to improve the energy efficiency of manufacturing companies by optimizing the design of internally operated ECSs. To that we propose a new flexible planning approach for energy conversion system dimensioning (ECSD), i.e., for determining the size (maximum capacity) and related parameters (like the nominal load; i.e., the load at which the CU operates with maximum efficiency; also called design point) of its CUs. This long-term (strategic) measure is used because an appropriate dimensioning can remarkably reduce conversion inefficiencies (i.e., the dissipation of useful energy). Next to the basic design, the extent of these inefficiencies depends on the technical conversion process and its characteristics as well as the operational behavior and control of the ECS and its CUs. Therefore, we present an analysis of conversion processes and CU characteristics and carve out several starting points for avoiding inefficiencies. These technical characteristics of ECSs are particularly analyzed with regard to manufacturing companies where two special aspects must be considered: First, the AES demand arising from the production system is highly dynamic and can strongly vary from period to period (e.g., minute to minute). Second, we have the opportunity to directly influence the course of the AES demand by controlling the production process execution (in contrast to other settings where "only" measures like demand side management are possible; cf., Gahm et al., 2016). Consequently, our paper makes the following contribution to literature:

- Our approach is flexible because it is suitable for almost any type of AES and CUs and is not limited to specific ones. We achieve this flexibility by considering common (type unspecific) characteristics of CUs.
- Regarding CU characteristics, we explicitly consider a CU's part-load behavior combined with nonlinear part-load efficiencies, which is rarely done in literature but very important in the context of manufacturing companies (due to the highly dynamic AES demands).
- In addition, we consider the relationship between the production system (scheduling) and the ECS during the ECSD by a hierarchical integration of the interdependencies between PS, ECS operation, and ECS design. In doing so, we particularly analyze the influence of production scheduling objectives on the ECS design.
- Finally, to get a robust ECS design with regard to uncertain future AES demands, within each AES demand time series that is used during ECS dimensioning, we incorporate a complete production year with 240 production scenarios.

From the perspective of a manufacturing company's decision-maker, the results of our ECSD approach (suitable CU dimensions and several basic parameters) can be used to pre-select the most suitable AES type-specific CUs based on CU-producer data. Then, the pre-selected CUs can be used as input for AES-specific planning approaches (e.g., based on superstructures) from the literature. From the perspective of a CU-producer, the ECSD results can be used by CU-engineers to develop more appropriate CUs for specific production processes and/or manufacturing companies. To that, we elaborate insights into the most important CU parameters and further planning factors influencing the ECS design for manufacturing companies.

To solve the ECSD problem at hand, we present a highly efficient tailor-made heuristic and a mixed-integer nonlinear program (MINLP).

The structure of this article is as follows: The analysis of the organizational and technical background of ECS design and the most relevant literature is depicted in section 2 . The new ECSD approach is described in Section 3 and the developed solution methods are presented in section 4 . In Section 5 , we specify the experimental design before we analyze the influences of several planning parameters (e.g., CU characteristics or scheduling objectives) on the energy efficiency of an ECS in section 6 . Conclusions are drawn in section 7 .

2 Background and literature

To provide a general understanding of the organizational and technical backgrounds, this section examines two main aspects that must be considered during ECSD. First, the interdependencies between the AES-demanding PS and the ECS are explained and second, the most important technical characteristics of CUs are analyzed.

2.1 On the interdependencies between PS and ECS

Most ECS design approaches in literature solely take the interdependencies between the long-term design and the short-term operation of conversion systems into account but neglect the interdependencies to the production system. Such approaches are sufficient for ECS design tasks related to district heating, building supply, or power generation for grids, but should be adapted in the case of ECS design for manufacturing companies. In contrast to ECS planning environments in which the AES demand can only be influenced to a limited extent (e.g., by demand-side management or demand response programs; for a brief overview on these topics cf., Merkert et al., 2014), manufacturing companies can directly influence the temporal course of AES demands by aligning production process execution (cf., Figure II.C-1; a similar illustration can be found in Rager et al. 2015).

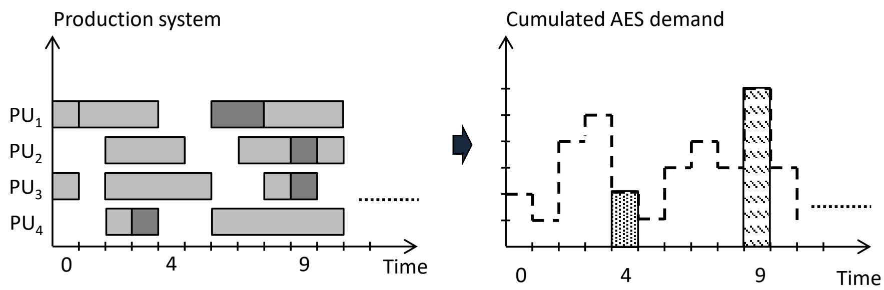


Figure II.C-1: Interdependencies between PS and the cumulated AES demand to be supplied by the ECS

In manufacturing companies, one or more production units (PUs) are available for production process execution. These PUs require specific AES to fulfil the process steps (tasks) defined by the working plans. As soon as tasks are scheduled on the PUs, the AES demand per time unit can be determined for most production processes. If several PUs require the same type of AES, a cumulated AES demand arises. In Figure II.C-1, a production schedule (Gantt-chart on the left) shows task executions on four

PUs (tasks with a light grey background indicate an AES demand of one unit, whereas tasks with a dark grey background indicate an AES demand of two units). This schedule leads to the cumulated AES demands depicted on the right of Figure II.C-1.

In spite of the direct interdependency between PS and ECS and the associated influence on the ECS operation and in turn on the design of a ECS, this interdependency has currently almost only been considered by energy-efficient scheduling approaches (e.g., by Moon and Park, 2014, Rager et al., 2015, Schulz et al., 2019 or Liu et al., 2020; for more approaches, see Gahm et al., 2016) and operational ECS planning approaches (e.g., by Mignon and Hermia, 1996, Agha et al., 2010, Zhang et al., 2013, or Zulkafli and Kopanos, 2017). To the best of our knowledge, only Denz (2015) considers this relationship in terms of ECS design.

Of course, the relationship between the long-term design and the short-term operation of ECS (cf., e.g., Gamou et al., 2002, Ghadimi et al., 2014a, Wakui and Yokoyama, 2014 or Yokoyama et al., 2015) is also a main aspect for ECS design because the long-term ECS design sets the constraints on the attainable efficiency in the short-term. Regarding this relationship, the design approaches in literature can be differentiated according to the way they consider ECS operation. Some approaches consider the top-down relationship by first fixing the ECS design and then evaluating its operational performance with and without operation optimization (e.g., Azit and Nor, 2009, Forough and Roshandel, 2018, or Alirahmi et al., 2020). In contrast to the top-down approaches, an integrated, iterative top-down approach explicitly uses feedback from ECS operations to influence the subsequent design decisions (e.g., Kavvadias and Maroulis, 2010, Benam et al., 2015, or Amusat et al., 2017). Most design approaches consider ECS operation by integrating some operational characteristics and thus, anticipate an ECS's operational behavior (e.g., Khiareddine et al., 2018, Emadi and Mahmoudimehr, 2019, or Keshavarzzadeh et al., 2020). In doing so, the ECS operation can be part of the design decision (e.g., Wang et al., 2010, Ghadimi et al., 2014b, or Sun and Liu, 2015) or not (e.g., Gibson et al., 2013, Benam et al., 2015 or Kazi et al., 2015). Our design approach anticipates the relation between long-term design and ECS operation by integrating some operational aspects directly (e.g., partial loads and part-load efficiencies) into the design decisions and others (e.g., minimum load level durations) indirectly by an approximate anticipation.

2.2 Technical characteristics of conversion units

An energy conversion process is always associated with losses of useful energy and the magnitude of these losses depends on the technical process and its characteristics, i.e., on the technical characteristics of the conversion units. One of the most important technical CU characteristics is the energy conversion efficiency which. This energy conversion efficiency of a CU is strongly related to its part-load utilization (also called off-design loads, i.e., any load different from the nominal load), because the efficiency of most CU's suffers in partial load (cf., e.g., O'Brien and Bansal, 2000a, O'Brien and Bansal, 2000b, Aguilar et al., 2007, Kaikko and Backman, 2007, Théry et al., 2012, Gibson et al., 2013, Pruitt et al., 2013, Denz, 2015, Sun and Liu, 2015, or Darrow et al., 2017).

In principle, literature agrees (for most types of CUs) that conversion efficiencies are lower at partial loads and that the more the load deviates from the nominal load, the lower the conversion efficiency (cf., e.g., Frangopoulos, 2004, Varbanov et al., 2004, Aguilar et al., 2007, Sanaye et al., 2008, Azit and Nor, 2009, Kavvadias and Maroulis, 2010, Tichi et al., 2010, Dufo-López et al., 2011, Voll et al., 2012, Castañeda et al., 2013, Voll et al., 2013, Ghadimi et al., 2014a, Arcuri et al., 2015, Destro et al., 2016, Li et al., 2016). This effect of efficiency loss is particularly relevant for ECSs at manufacturing sites because of to the varying AES demands, these ECSs will operate at CU`s partial loads for most of the time (e.g., Varbanov et al., 2004). Figure II.C-2 illustrates a nonlinear dependency between (part) load and conversion efficiency for two representative CUs (A and B) and introduces the corresponding CU parameters $MinL$, $NomL$, $MaxL$, η_{MinL}, η_{MaxL}, and η_{NomL}.

For the minimum load ($MinL$) at which a CU can operate, the nominal load ($NomL$) at which the CU operates with maximum efficiency, and the maximum load ($MaxL$) at which a CU can operate (i.e., its dimension or maximum capacity), the corresponding efficiencies η_{MinL}, η_{MaxL}, and η_{NomL} can be obtained easily in most cases (e.g., with technical documentations or literature; cf., e.g., Pruitt et al., 2013). Figure II.C-2 shows two CUs: CU A represents a CU having a small operational range (*MaxL-MinL*) and a high nominal load efficiency at the expense of high part-load efficiency losses, while CU B represents a CU having a broad operational range and small part-load efficiency losses at the expense of basically lower efficiencies. Note that the higher minimum load of CU A could cause the provisioning of unnecessary AES if the required AES is lower than $MinL^A$, and thus the overall efficiency of CU A could decrease. The influence of operational ranges and related efficiencies on the ECS design is analyzed in this contribution (cf., section 6.2).

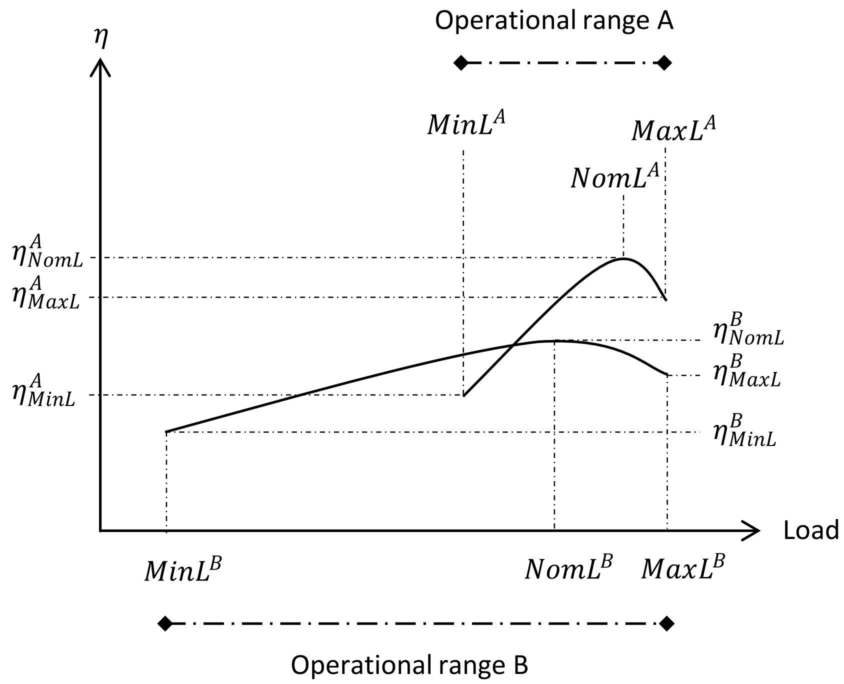


Figure II.C-2: Load-efficiency curves illustrating the relationship between (partial) load and conversion efficiency

Although in principle the literature agrees on efficiency losses in part-load operation (for most CUs) and on the importance of an appropriate modelling of the part load behavior (cf., Azit and Nor, 2009; Arcuri et al., 2015), the efficiency modelling is not unified. Several authors like Frangopoulos (2004), Sanaye et al. (2008), Dufo-López et al. (2011), Castañeda et al. (2013), Arcuri et al. (2015), and Li et al. (2016), use a nonlinear modelling approach to achieve a most accurate part-load behavior representation. This most accurate modelling comes at the expense of a higher problem complexity as in linear optimization models. To reduce this complexity, some authors use piecewise linear approximations (e.g., Voll et al., 2013, Ghadimi et al., 2014a, or Destro et al., 2016). Furthermore, several authors use a linear approximation and claim that the errors are neglectable. For instance Aguilar et al. (2007) state that "it is possible to fit linear equations representing equipment performance with enough accuracy for preliminary design purposes (i.e., a normal error range of +5%)" (Aguilar et al., 2007: 1137). Varbanov et al. (2004) report maximum linearization errors of 3.8% and a mean error less than 1% for steam turbines. However, both authors investigate the errors isolated for specific CUs but do not investigate the influence on the ECS design or efficiency. To the best of our knowledge, there exists no contribution analyzing the influence of the different part-load efficiency modelling approaches on the ECS design and its efficiency. To fill this research gap, we are going to perform a comparative analysis by comparing nonlinear part-load efficiency modelling with linear part-load efficiency modelling.

2.3 Further aspects and conclusions

Another aspect in literature is the development of robust ECS design approaches tackling uncertainties such as variations in energy demand (cf., e.g., Yokoyama et al., 2014 or Maleki et al., 2016), varying prices (cf., e.g., Carpaneto et al., 2011a or Gibson et al., 2013 or), or equipment failures (cf., e.g., Aguilar et al., 2008, Rad et al., 2016 or Andiappan and Ng, 2016). Most approaches considering uncertainty at all, focus on energy demand uncertainty and use scenario-based robust design approaches (e.g., Aguilar et al., 2008, Carpaneto et al., 2011a, Carpaneto et al., 2011b, or Benam et al., 2015). Stochastic modelling is seldom used (e.g., by Gamou et al., 2002 and Sun and Liu, 2015). To achieve a robust ECS design with regard to variations in energy demand, we generally follow the first approach but do not optimize the ECS design for several scenarios individually and then derive the most suitable ES design, but we integrate the demand scenarios of one year with 240 production days into an AES demand time series and calculate the optimal ECS design for all the integrated scenarios simultaneously.

Most ECS design approaches in the literature are related to specific types of ECSs, mostly cogeneration systems (typically combined heat and power; e.g., see Azit and Nor, 2009, Ghadimi et al., 2014b, Kazi et al., 2015, Sun and Liu, 2015, and Keshavarzzadeh et al., 2020) and trigeneration systems (typically combining cooling, heat, and power; cf., e.g., Chicco and Mancarella, 2007, Kavvadias and Maroulis, 2010, Wang et al., 2010, or Kasivisvanathan et al., 2014). These approaches have been developed for specific environments (e.g., types of AES or CUs) but lack some generality and flexibility as any of these approaches formulate a selection decision based on AES specific CUs (or for instance superstructures) with given characteristics (e.g., Shiun et al., 2012, Carvalho et al., 2014, or Rad et al., 2016). Only a few approaches are independent regarding the type of AES and provide some flexibility (e.g., Voll et al., 2012 or Zhou et al., 2013).

Summarizing the analysis of the planning backgrounds and the most relevant literature, we conclude that—to the best of our knowledge—there exists no flexible and robust ECSD approach addressing the specific needs of manufacturing companies, i.e., that considers the (hierarchical) interdependencies between conversion system (CS) design, CS operation, and PSs as well as highly varying AES demands and operational CU behavior such as partial loads combined with nonlinear part-load efficiencies.

3 A new flexible approach for ECSD

In this section, we first present a comprehensive decision model for ECSD with the objective to maximize the ECS' energy efficiency while considering the most relevant (technical) aspects (regarding manufacturing companies) as examined in section 2 . Afterwards, we describe the aggregation process for preparing the data of the AES demands per period ($AESD_t^{CS}$) as used by the decision model. Source of the data preparation are the cumulated AES demands originating from historical data of the production system or from “simulative” scheduling (cf., section 3.3).

3.1 The model for maximizing the CS’ energy efficiency

The basic task of ECSD as defined in this contribution is to determine the dimension ($MaxL$) and the nominal load ($NomL$) of two CUs. The composition of the ECS by more than one CU is appropriate whenever (strongly) varying AES demands are present. In this case, we can distinguish between the so-called “base-load” share and the “peak-load” share of the AES demand. In consequence, we propose to differentiate CUs by their general characteristics to handle these two basic load types as follows: large scale conversion units (LCUs) to cover “constant” base loads with a high efficiency and flexible conversion units (FCUs) with a large operational range to cover peak loads and/or strongly varying loads (cf., Figure II.C-2, where CU A represents an LCU and CU B represents an FCU). In this contribution, to keep the analyses manageable, we limit the composition of the CS to one LCU and one FCU. Nevertheless, an extension to consider several FCUs would be possible (but using multiple LCUs for covering the base-load is not common in literature and practice). To specify the planning problem at hand most precisely, we present the main aspects by mathematical equations that are also part of the optimization model to be completed in section 4.1.

One part of the decisions to be made are the dimensions of both CUs: $MaxL^{LCU}$ and $MaxL^{FCU}$. These dimensions must be determined in a way that the maximum AES demand $AESD^{MAX} = \max_{t \in \{1,\ldots,T\}} \{AESD_t^{CS}\}$ is covered by the two CUs and the ECS’ energy efficiency is maximized. As we use two CUs to cover the complete AES demand and the LCU operates with maximum efficiency at $NomL^{LCU}$, we would like to run the LCU at its nominal load point for most of the time. To accomplish this, the FCU is dimensioned related to $NomL^{LCU}$ (not to $MaxL^{LCU}$) and $AESD^{MAX}$ (note that if more than one FCU should be integrated in the ECS, the $MaxL^{FCU}$ must be divided between these FCUs):

$$MaxL^{FCU} = AESD^{MAX} - NomL^{LCU} \tag{1}$$

In this context we assume that the nominal load of a CU is different from the maximum load and that for the LCU, the nominal load is relative to its maximum load. Therefore, the nominal load of the LCU is defined by the parameter Δ_{NomL}^{LCU}:

$$NomL^{LCU} = MaxL^{LCU} \cdot \Delta_{NomL}^{LCU} \tag{2}$$

For the FCU, we assume that it exists a given degree of freedom to determine a most sufficient nominal load. Thus, we can decide on the nominal load $NomL^{FCU}$ within given bounds ($ubNomL^{FCU}$, $lbNomL^{FCU}$) related to the FCU`s dimension (on feasible regions, cf., Mavromatis and Kokossis, 1998 or Mitra et al., 2013). These bounds are relatively defined by Δub^{FCU}_{NomL} and Δlb^{FCU}_{NomL}. The $NomL^{FCU}$ is bounded as follows:

$$NomL^{FCU} \leq ubNomL^{FCU} \text{ with } ubNomL^{FCU} = MaxL^{FCU} \cdot \left(1 - \Delta ub^{FCU}_{NomL}\right) \tag{3}$$

$$NomL^{FCU} \geq lbNomL^{FCU} \text{ with } lbNomL^{FCU} = MinL^{FCU} \cdot \left(1 + \Delta lb^{FCU}_{NomL}\right) \tag{4}$$

This second approach for determining the nominal load of a CU could also be used for the LCU if it is technically realizable for large CU of a specific (AES) type. However, this additional degree of freedom increases problem complexity.

Two main differences between LCUs and FCUs are their operational ranges and the related part-load behavior (cf., Figure II.C-2). The operational range of both CU types is defined by their maximum load $MaxL$, which is part of the planning decision, and their minimum load $MinL$, which is a parameter either given by an absolute value (e.g., Azit and Nor, 2009) or a relative value with regard to the maximum load (e.g. Sun and Liu, 2015). Here, we follow the relative approach and use the two parameters Δ^{LCU}_{MinL} and Δ^{FCU}_{MinL} for determining $MinL^{LCU}$ and $MinL^{FCU}$, respectively:

$$MinL^{LCU} = MaxL^{LCU} \cdot \Delta^{LCU}_{MinL} \tag{5}$$

$$MinL^{FCU} = MaxL^{FCU} \cdot \Delta^{FCU}_{MinL} \tag{6}$$

The assumptions and conditions described so far are illustrated by the left side of Figure II.C-3 depicting a load duration curve (LDC) representing the varying AES demands, the main decisions about maximum and nominal loads, and the depending decisions.

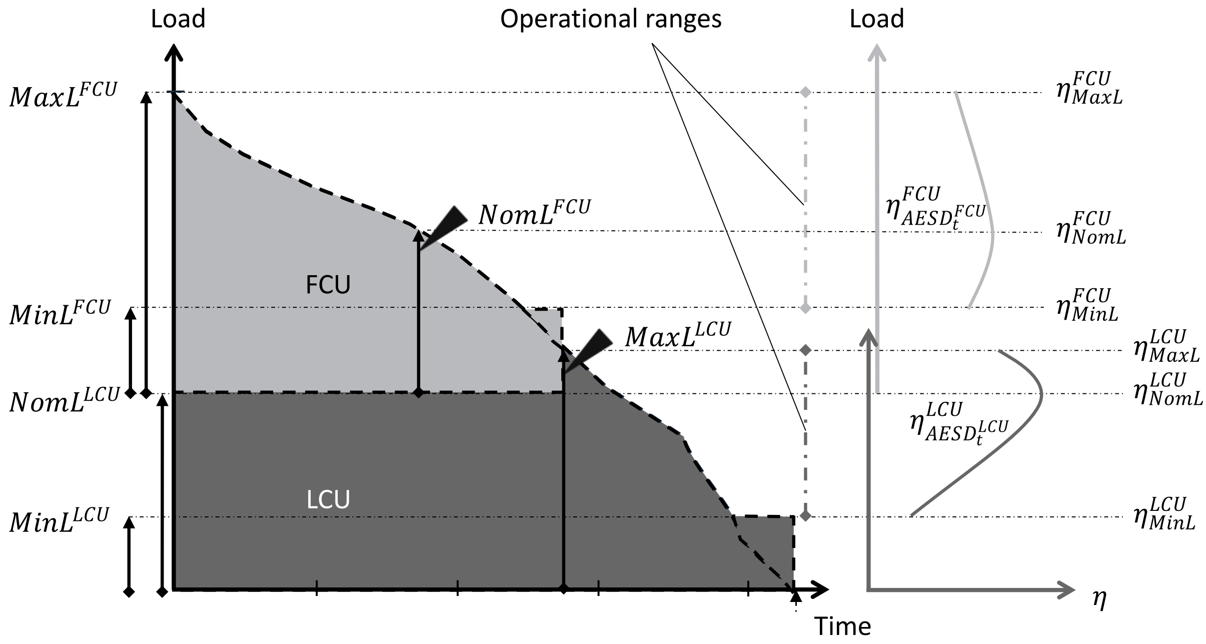


Figure II.C-3: Main decisions and depending decisions illustrated by an LDC

In addition, Figure II.C-3 shows the allocation of load shares of both CUs. The light grey area (restricted by the dotted line) represents the AES demands allocated to the FCU and the dark grey area (restricted by the dashed line) AES demands allocated to the LCU. In consequence of the decision on both dimensions, we have to decide for each time period $t \in \{1,...,T\}$ of the LDC which CU provides how much load share of the required $AESD_t^{CS}$. As we would like to run the LCU at its nominal load for most of the time and to reduce problem complexity (by avoiding the operational decision on the load separation), we propose the following approach for load separation: Whenever $AESD_t^{CS}$ is larger than $NomL^{LCU}$, the LCU operates at $NomL^{LCU}$. The remaining demand is provided by the FCU, except in the case in which the complete AES demand can be provided by the LCU only. In this case, the LCU provides the total AES demand and the FCU load share is zero. This approach of load separation between CUs can also be applied if more than one FCU should be integrated in the ECS design.

To indicate whether the FCU is required to fulfil the AES demand for period t, we use the auxiliary binary variable X_t (with $X_t = 1$ indicating that the FCU is required and $X_t = 0$ otherwise) and the following sets of disjunctive constraints (with M specifying a sufficiently large number; $M = AESD^{MAX}$):

$$AESD_t^{CS} - MaxL^{LCU} \leq X_t \cdot M \qquad \forall t = 1,...,T \qquad (7)$$

$$MaxL^{LCU} - AESD_t^{CS} \leq (1 - X_t) \cdot M \qquad \forall t = 1,...,T \qquad (8)$$

Based on X_t, the individual load shares can be determined. To accomplish this, two sets of auxiliary integer variables ($AESD_t^{LCU}$ and $AESD_t^{FCU}$) representing the load share for each period and the following constraint sets (9) and (10) are used. Hereby, the constraints also guarantee that the LCU operates at the nominal load whenever the FCU is required.

$$AESD_t^{LCU} = X_t \cdot NomL^{LCU} + \left(1 - X_t\right) \cdot AESD_t^{CS} \qquad \forall t = 1,\dots,T \qquad (9)$$

$$AESD_t^{FCU} = \left(AESD_t^{CS} - AESD_t^{LCU}\right) \cdot X_t \qquad \forall t = 1,\dots,T \qquad (10)$$

To respect the technical restrictions of minimal loads, we have to update $AESD_t^{LCU}$ and $AESD_t^{FCU}$ to their "current" admissible values represented by the auxiliary integer variables $cAESD_t^{LCU}$ and $cAESD_t^{FCU}$. The update is assured by the following sets of constraints (constraint set (15) assures that the $cAESD_t^{FCU}$ is equal to zero if the FCU is not required at all):

$$cAESD_t^{LCU} \geq AESD_t^{LCU} \qquad \forall t = 1,\dots,T \qquad (11)$$

$$cAESD_t^{LCU} \geq MinL^{LCU} \qquad \forall t = 1,\dots,T \qquad (12)$$

$$cAESD_t^{FCU} \geq AESD_t^{FCU} \qquad \forall t = 1,\dots,T \qquad (13)$$

$$cAESD_t^{FCU} \geq MinL^{FCU} \cdot X_t \qquad \forall t = 1,\dots,T \qquad (14)$$

$$cAESD_t^{FCU} \leq X_t \cdot M \qquad \forall t = 1,\dots,T \qquad (15)$$

The technical analysis of CUs (cf., section 2.2) has shown that the part-load and conversion efficiency characteristics are a central aspect for the dimensioning of CUs. The relationship of the planning decisions and the resulting partial loads with the corresponding conversion efficiencies is illustrated in the right part of Figure II.C-3. To that, Figure II.C-3 depicts illustrative load-efficiency curves with the corresponding efficiencies for the related loads (within their operational ranges) for the LCU and FCU. To model the increasing efficiency losses of larger deviations from the nominal load most adequately, we use quadratic functions for the determination of the conversion efficiency at a specific partial load (cf., e.g., Ashok and Banerjee, 2003, Savola and Keppo, 2005, Aguilar et al., 2007, Agha et al., 2010, or Denz, 2015). To increase model accuracy even more, we use two functions for each CU: one to determine the part-load efficiencies between the minimum and the nominal load and another one to determine the part-load efficiencies between the nominal and the maximum load of a CU. To ensure that only one of these functions is in use, the binary auxiliary variables Y_t^{LCU} and Y_t^{FCU} are introduced.

The following constraint sets guarantee that if $cAESD_t^{LCU} \geq NomL^{LCU}$, then $Y_t^{LCU} = 1$ (otherwise, $Y_t^{LCU} = 0$) and that if $cAESD_t^{FCU} \geq NomL^{FCU}$, then $Y_t^{FCU} = 1$ (otherwise, $Y_t^{FCU} = 0$):

$$cAESD_t^{LCU} - NomL^{LCU} \leq Y_t^{LCU} \cdot M \qquad \forall t = 1, \ldots, T \qquad (16)$$

$$NomL^{LCU} - cAESD_t^{LCU} \leq \left(1 - Y_t^{LCU}\right) \cdot M \qquad \forall t = 1, \ldots, T \qquad (17)$$

$$cAESD_t^{FCU} - NomL^{FCU} \leq Y_t^{FCU} \cdot M \qquad \forall t = 1, \ldots, T \qquad (18)$$

$$NomL^{FCU} - cAESD_t^{FCU} \leq \left(1 - Y_t^{FCU}\right) \cdot M \qquad \forall t = 1, \ldots, T \qquad (19)$$

To reflect the nonlinear part-load efficiency behavior of the CUs, for each CU, the vertex form of univariate quadratic functions is used. For the LCU and the FCU, the part-load efficiencies per period (η_t^{LCU} and η_t^{FCU}) are determined based on the current load, Y_t^{LCU} and Y_t^{FCU}, and the corresponding basic efficiencies (η_{MinL} , η_{NomL}, and η_{MaxL}) at the extreme points ($MinL$, $NomL$, and $MaxL$). The constraint sets (20) and (21) define the continuous auxiliary variables η_t^{LCU} and η_t^{FCU}. Note that we assume "static" efficiencies for the extreme points $MinL$, $NomL$, and $MaxL$ that are independent of a CU's dimension because at these points, the efficiencies of most types of CUs only minimally depend on the finally determined dimension (cf., e.g., efficiency ranges of steam boilers listed in Robert Bosch (SEA), 2014).

$$\begin{aligned}\eta_t^{LCU} = {} & Y_{lt}^{LCU} \\ & \cdot \left(\frac{\eta_{MaxL}^{LCU} - \eta_{NomL}^{LCU}}{\left(MaxL^{LCU} - NomL^{LCU}\right)^2} \cdot \left(cAESD_t^{LCU} - NomL^{LCU}\right)^2 + \eta_{NomL}^{LCU} \right) \\ & + \left(1 - Y_t^{LCU}\right) \\ & \cdot \left(\frac{\eta_{MinL}^{LCU} - \eta_{NomL}^{LCU}}{\left(MinL^{LCU} - NomL^{LCU}\right)^2} \cdot \left(cAESD_t^{LCU} - NomL^{LCU}\right)^2 + \eta_{NomL}^{LCU} \right)\end{aligned} \qquad \forall t = 1, \ldots, T \qquad (20)$$

$$\begin{aligned}\eta_t^{FCU} = {} & X_t \cdot [Y_t^{FCU} \\ & \cdot \left(\frac{\eta_{MaxL}^{FCU} - \eta_{NomL}^{FCU}}{\left(MaxL^{FCU} - NomL^{FCU}\right)^2} \cdot \left(cAESD_t^{FCU} - NomL^{FCU}\right)^2 + \eta_{NomL}^{FCU} \right) \\ & + \left(1 - Y_t^{FCU}\right) \\ & \cdot \left(\frac{\eta_{MinL}^{FCU} - \eta_{NomL}^{FCU}}{\left(MinL^{FCU} - NomL^{FCU}\right)^2} \cdot \left(cAESD_t^{FCU} - NomL^{FCU}\right)^2 + \eta_{NomL}^{FCU} \right)]\end{aligned} \qquad \forall t = 1, \ldots, T \qquad (21)$$

For the comparative analysis between nonlinear and linear part-load efficiency modelling, for the linear part-load efficiencies we replace the constraint sets (20) and (21) by the following ones:

$$\begin{aligned}\eta_t^{LCU} = Y_{lt}^{LCU} \\ &\cdot\left(\eta_{NomL}^{LCU} + \left(cAESD_t^{LCU} - NomL^{LCU}\right)\cdot\frac{\eta_{MaxL}^{LCU} - \eta_{NomL}^{LCU}}{\left(MaxL^{LCU} - NomL^{LCU}\right)}\right) \\ &+\left(1 - Y_t^{LCU}\right) \\ &\cdot\left(\eta_{NomL}^{LCU} + \left(cAESD_t^{LCU} - NomL^{LCU}\right)\cdot\frac{\eta_{NomL}^{LCU} - \eta_{MinL}^{LCU}}{\left(NomL^{LCU} - MinL^{LCU}\right)}\right)\end{aligned} \qquad \forall t = 1,...,T \quad (22)$$

$$\begin{aligned}\eta_t^{FCU} = X_t \cdot [Y_t^{FCU} \\ &\cdot\left(\eta_{NomL}^{FCU} + \left(cAESD_t^{FCU} - NomL^{FCU}\right)\cdot\frac{\eta_{MaxL}^{FCU} - \eta_{NomL}^{FCU}}{\left(MaxL^{FCU} - NomL^{FCU}\right)}\right) \\ &+\left(1 - Y_t^{FCU}\right) \\ &\cdot\left(\eta_{NomL}^{FCU} + \left(cAESD_t^{FCU} - NomL^{FCU}\right)\cdot\frac{\eta_{NomL}^{FCU} - \eta_{MinL}^{FCU}}{\left(NomL^{FCU} - MinL^{FCU}\right)}\right)]\end{aligned} \qquad \forall t = 1,...,T \quad (23)$$

Of course, we are aware that using a function consisting of two linear functions results in a piecewise linear function, but to strengthen our point regarding different part-load efficiency modelling approaches, we use the differentiation between the nonlinear and the "linear" modelling approach.

To distinguish the two models, each of which represents a different approach of part-load efficiency modelling, we refer to the MINLP using the constraint sets (20) and (21) as model M-NL and the model using the constraint sets (22) and (23) as model M-L.

Because the AES output (required by the PS) of the ECS is given, we maximize the energy efficiency of the manufacturing companies' ECS by input minimization, i.e., the minimization of the amount of totally required final energy sources (TFES):

$$\text{Minimize} \quad \sum_{t=1}^{T}\left(\frac{cAESD_t^{LCU}}{\eta_t^{LCU}} + \frac{cAESD_t^{FCU}}{\eta_t^{FCU}}\right) \qquad (24)$$

In addition to input minimization, techno-economic evaluation approaches based on cost minimization or other monetary criteria such as net present values (for an overview see Biezma and Cristóbal, 2006) would also be plausible. However, since we focus our analysis on technology-related parameters, we are not using these techno-economic approaches to avoid biases by additional (economic) parameters. The input minimization objective is also based on the idea of developing a flexible ECSD approach that is independent of a specific type of AES and specific CUs. To maintain this flexibility, generic cost parameters (e.g., for investment and operational costs) would have to be determined, which is hardly possible to do in a reasonable manner. However, based on the determined size of the CUs, investment costs could be estimated by scaling functions for specific types of CUs (cf., e.g., Peters et al., 2004 or Arcuri et al., 2015) and the required FES determines the main part of the operational costs (combined with corresponding cost factors).

An additional aspect that could be considered is that, due to economic and/or strategic reasons, it might be appropriate (particularly for LCUs) to define a minimum number of periods at which a CU has to operate at its nominal load. This is for example done to achieve 4,500 hours of nominal load operation annually (cf., O'Brien and Bansal, 2000a). Thus, we introduce the parameter $relP_{NomL}^{LCU}$ defining a relative number of periods and derive a corresponding upper bound for $MaxL^{LCU}$ from the LDC:

$$MaxL^{LCU} \leq ubMaxL^{LCU} \text{ with } ubMaxL^{LCU} = \frac{AESD(\lfloor relP_{NomL}^{LCU} \cdot T \rfloor)}{\Delta_{NomL}^{LCU}} \tag{25}$$

In (25), the function $AESD(t)$ returns the AES demand of the LDC at period *t*. In addition to the economic or strategic reasons, this parameter can be used to limit the solution space of the LCU`s maximum load. If $relP_{NomL}^{LCU}$ is set to zero, the upper bound would be greater than the maximum AES demand $AESD^{MAX}$ (as the cumulated AES demands in an LDC are arranged in a descending order of magnitude and $\Delta_{NomL}^{LCU} < 1$) and constraint (25) is not binding.

3.2 Data preparation and aggregation

Basic data of our ECSD approach for manufacturing companies are discrete time series of cumulated AES demands originating from the PS. Each time series $s \in S$ (with set S of all available time series) represents a production period subdivided into a number of time slices ϑ_s^{PS} with a given duration δ^{PS} (i.e., δ^{PS} defines the level of detail for all the time series). The cumulated AES demand per time slice originating from the PS is then given by $AESD_t^{PS}$. Sources of the time series could be historical data from manufacturing execution (O'Brien and Bansal, 2000b) but also the result of “simulative scheduling” (planning predictions) that will be discussed in section 3.3. Both sources can be used alone or in combination. Each time series represents an AES demand scenario representing one production day. Therefore, if an appropriate number of time series (scenarios) is used during ECSD, the resulting ECS design will be robust with regard to uncertain energy demands. We propose using a set S of time series representing the number of production periods within one year (e.g., $|S|=240$ time series, each representing one working day with ϑ_s^{PS} = 480 minutes).

To anticipate load transition characteristics of the ECS (cf., section 2.2), we use an approximate anticipation approach by an "aggregating" model to not further increase problem complexity (cf., Ghadimi et al., 2014b). To that, we consider these characteristics (e.g., maximum or minimum ramping restrictions, minimum durations, and efficiency losses) by estimating their impact and aggregating the original AES demands per time slice ($AESD_t^{PS}$) accordingly. To that, we use a time slice aggregation factor $agg^{PS,CS}$ to determine a number of time intervals for each time series ($\lceil \vartheta_s^{PS} / agg^{PS,CS} \rceil$). An aggregation factor of 10 minutes is used to reflect the varying AES demand on the one side and load transition characteristics (like ramp ups) on the other side. Within each aggregation interval r, restricted by a first time slice f_r and a last time slice l_r, we use the maximum AES demand to guarantee demand fulfilment and to account for conversion efficiency losses during load transitions. The new estimated AES demand ($AESD_t^{CS}$) per time slice within interval r is calculated as follows:

$$AESD_t^{CS} = \max_{t' \in \{f_r, l_r\}} \{AESD_{t'}^{PS}\} \qquad \forall t \in [f_r, l_r] \qquad (26)$$

Note that consecutive intervals that do not have any AES demands in one of their time slices and that are at the end of a time series are excluded from further considerations. Of course, the intervals not at the end of a time series are not excluded (this can be interpreted as operational state "idle" or "hot standby").

3.3 Simulative scheduling

Due to the strong relationship between the ECS and the PS of a manufacturing company, besides historical AES demands, our proposed ECSD approach incorporates the opportunity to consider time series based on simulative (machine) scheduling. Simulative scheduling could mean that historical scheduling problem instances are solved by considering new constraints and/or objectives (variant a.), that anticipated scheduling problem instances are solved by considering existing (traditional) constraints and/or objectives (b.), or that anticipated scheduling problem instances are solved by considering new constraints and/or objectives (c.).

4 Solution methods

For solving the planning problem, we formulate a mixed-integer nonlinear program (MINLP) and evaluate several standard solvers capable to solve MINLPs. To support the solution process, we propose a lower bound on the objective value (TFES, cf., (24)) and a new truncated enumeration heuristic (TEH) to provide an initial solution and an upper bound on the objective value.

According to section 3.2, AES demand time series and their data points are the base for ECSD. To reduce the computational efforts of optimization, we combine all data points of a time series having identical AES demands to AES demand levels (indexed by $l=1,...,L$). These AES demands levels $AESD_l$ combined with the number of aggregated data points (n_l) reduce the number of variables without influencing the result.

4.1 Mixed-integer nonlinear program

The MINLP used for optimization is generally specified by the equations (1) to (25) presented in section 3.1. To reduce computational efforts by using the AES demand levels, $AESD_t^{CS}$ must be replaced by $AESD_l$ (after a corresponding aggregation), all indices t must be replaced by l and the objective function must slightly be adapted to:

$$\text{Minimize} \quad \sum_{l=1}^{L}\left(\frac{cAESD_l^{LCU}}{\eta_l^{LCU}}+X_l\cdot\frac{cAESD_l^{FCU}}{\eta_l^{FCU}+z}\right)\cdot n_l\cdot agg^{PS,CS} \tag{27}$$

In (27), the parameter X_l and the sufficiently small parameter z are only required for solver related, technical reasons ($z=1E\text{-}20$).

To provide an initial approximated lower bound ($lbTFES^{APP}$) on the objective value, we assume that the total AES demand would be provided with maximum efficiency and hence use the following approximation (here, we assume that the efficiency at the nominal load of the LCU is highest):

$$lbTFES^{APP}=\frac{1}{\eta_{NomL}^{LCU}}\cdot\sum_{l=1}^{L}AESD_l\cdot n_l\cdot agg^{PS,CS} \tag{28}$$

For solver selection, the investigated solvers have been evaluated due to their capability to solve general mixed-integer nonlinear programs and have shown a good performance in the analysis of Kronqvist et al. (2019). Preliminary tests based on eight randomly selected problem instances have shown that the solver ANTIGONE outperforms the solvers BARON, DICOPT, and SCIP in terms of solution quality (all solvers are provided within GAMS). In the following, the application of ANTIGONE for solving the MINLP specified by the equations (1) to (25) and (27) to (29) is abbreviated by ANT.

As SCIP provides better lower bounds ($lbTFES^{SCIP}$) on the TFES in a short time, we use this solver to provide an improved lower bound for ANTIGONE:

$$lbTFES^{ANT} = \max\{lbTFES^{APP}, lbTFES^{SCIP}\}.$$

As the preliminary tests have also shown that the maximum load of the LCU should be larger than 30% of $AESD^{MAX}$, we introduce a lower bound for $MaxL^{LCU}$ to reduce the solution space and thus, decrease the computational effort (the minimum function in (29) is used to guarantee feasibility):

$$MaxL^{LCU} \geq lbMaxL^{LCU} \text{ with } lbMaxL^{LCU} = \min\{AESD^{MAX} \cdot 0.3,\ ubMaxL^{LCU}\} \qquad (29)$$

4.2 Truncated enumeration heuristic

The developed heuristic to determine initial solutions is based on a truncated enumeration scheme. Therefore, it is called truncated enumeration heuristic (TEH). It consists of two phases: the first phase determines $MaxL^{LCU}$ and the second phase determines $NomL^{FCU}$.

In the first phase, we start with an incumbent maximum load $incMaxL^{LCU} = ubMaxL^{LCU}$ (cf., (25)) and iteratively decrement it by parameter υ until $lbMaxL^{LCU}$ (cf., (29)) is reached. For the $NomL^{FCU}$, a "fixed" incumbent nominal load $incNomL^{FCU} = \max\{lbNomL^{FCU}, ubNomL^{FCU} \cdot \zeta\}$ is used in the first phase (cf., (3) and (4)). The parameter ζ defines an offset from the upper bound. Based on this decision, all other variables and the objective value are determined according to the MINLP described above. To avoid inefficient iterations, the first phase terminates if the relative objective value degradation of the incumbent solution S' (with regard to the best known solution S^*) becomes larger than a given parameter: $(TFES(S') - TFES(S^*)) / TFES(S^*) > \kappa$. After the termination of the first phase, $MaxL^{LCU}$ of the best solution so far (i.e., with the minimum TFES) is fixed. Thereafter, the second phase starts with $incNomL^{FCU} = ubNomL^{FCU}$ and iteratively decrements $incNomL^{FCU}$ by υ until $lbNomL^{FCU}$ is reached. The heuristic terminates early if the relative degradation becomes larger than κ. The parameters $\upsilon = 0.5$, $\zeta = 0.33$, and $\kappa = 0.1$ have revealed the best results (regarding the trade-off between solution quality and computation time) in preliminary tests.

5 Experimental design

To analyze the interdependencies between the basic planning parameters and their influence on the energy efficiency of an ECS, an appropriate experimental design is necessary.

5.1 The scheduling problem

Because we follow the simulative scheduling variant b. in our analysis (cf., section 3.3), we have to anticipate scheduling problem instances for the simulative scheduling. To keep the analysis straight, we limit the analysis to a production system consisting of identical (unrelated) parallel machines, as we can assume that machines of this type have the same energy characteristics and thus, that the total required AES demand is independent of the job to machine allocation. The basic scheduling task for such a production system is the allocation and sequencing of a set of jobs J (with indices $j=1,...,n$) on a set of identical parallel machines K (with indices $k=1,...,m$). The processing time of a job j is depicted by p_j. Each job can only be processed by one machine at one time, and each machine can only process one job at one time. All jobs are available at time zero, and the preemption of jobs is prohibited. To represent the AES demand of a job, we follow the approaches of Artigues et al. (2013) and Rager et al. (2015) and use discrete AES demand profiles. Therefore, the AES demand of job j is defined by a sequence of energy demands $e_{j,p}$ (with $p=1,...,p_j$). Usually, p_j and $e_{j,p}$ are defined as integers.

To solve the scheduling problem with regard to the two standard scheduling objectives makespan (Cmax) and total flow time (TFT), we use the list scheduling approaches LPT (longest processing time) for Cmax and SPT (shortest processing time) for TFT, as these approaches are very efficient and provide a sufficient solution quality (or even the optimum) for these objectives (cf., Baker and Trietsch, 2009: 204 & 214).

5.2 Scheduling instances and scenarios

To provide a broad testing environment for our analysis, we consider different types of companies to generate company related, anticipated scheduling problem instances. We distinguish companies according to the following production-related parameters: production system size (i.e., the number of machines), job size (i.e., the mean processing times) and variability (i.e., the processing time distribution), energy demand type (i.e., the energy demand course), and energy demand variability (i.e., the energy demand distribution).

With respect to the production system size, we differentiate between two basic settings: small (S) and medium (M). The small (medium) type consists of four (twelve) machines, and for half of the production days, only three (ten) machines are in use (due to less jobs and cost savings, e.g., the cost of machine operators). Each of these company types can produce either many simple (MS) products (with an assumed mean processing time $\tilde{p}=30$ and processing times that are randomly drawn from a discrete uniform distribution restricted by [24, 36]) or few complex (FC) products (with $\tilde{p}=80$ and a discrete uniform distribution restricted by [64, 96]). Altogether, the introduced production parameters define four basic settings (S-MS, S-FC, M-MS, and M-FC) with two types of production days.

Because the AES demand time series represent individual production days with one eight-hour shift, we assume a "target" planning horizon $\tau^{PS} = 480$. This planning horizon together with the actual mean processing time $\bar{p} = 1/n \sum_{j=1}^{n} p_j$ and the number of available machines m is used to approximate the maximum number of jobs $n^{max} = \lceil (\tau^{PS}/\bar{p}) \cdot m \rceil$ to be processed within τ^{PS}. Then, based on n^{max}, the number of jobs n per problem instance is randomly chosen from a discrete uniform distribution restricted by $[\lceil n^{max} - 1.5m \rceil, n^{max}]$.

In addition to the basic production system parameters, companies and their production processes can be further separated due to their energy demand characteristics (for a detailed overview see Gahm et al., 2016). Within our analysis, we concentrate on "job related" and "varying job related" demands and differentiate companies by their job-related energy demand type and their energy demand variability. With respect to the energy demand type, we use four different courses (cf., Figure II.C-4): constant (C), hill (H), iterating (I), and erratic (E). Each of these types represents a specific production process (e.g., the iterating demand course can be found in the dyeing process in the textile industries; see Rager et al., 2015). To represent different energy demand variabilities, we use different intervals for representing a small range of variability (SR) and a large range of variability (LR).

For the constant demand course, the intervals for the two ranges SR and LR are restricted by [80, 120] and [20, 180], respectively, and only a single constant energy demand e_j has to be drawn from the corresponding discrete uniform distribution.

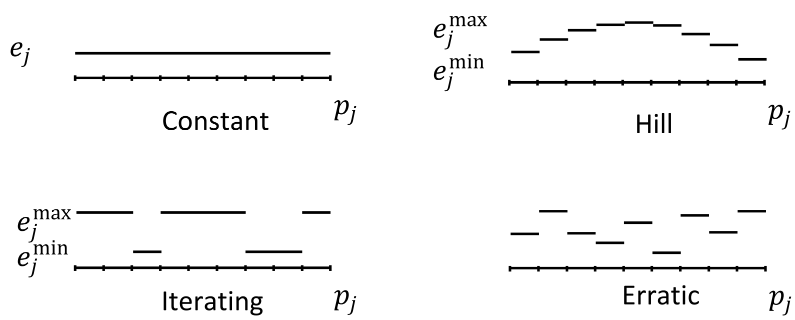


Figure II.C-4: Energy demand course types

For the types H and I, we first have to determine e_j^{min} and e_j^{max} and use the following intervals $e_j^{min} \in [80,90]$ and $e_j^{max} \in [110,120]$ for SR and $e_j^{min} \in [0,90]$ and $e_j^{max} \in [110,200]$ for LR. These intervals are used to guarantee that $e_j^{min} \leq 20 + e_j^{max}$ and thus, to differentiate those types from type C. For type H, we use the function $e_{j,p} = \lceil \alpha \cdot (p - p_j/2 - 0.5)^2 + e_j^{max} \rceil$, with $\alpha = -4 \cdot (e_j^{max} - e_j^{min})/p_j^2$ to determine the AES demand profile. For type I, we additionally draw the number of periods with the same AES demand in sequence from a discrete uniform distribution limited by $[1, \lfloor p_j/2 \rfloor]$ and all jobs start with an AES demand equal to e_j^{max}. With these interval borders, we can guarantee at least one change between e_j^{min} and e_j^{max} and thus, a minimum difference to type C. For type E, we individually draw $e_{j,p}$ from discrete uniform distributions restricted by [80, 120] and [0, 200] for SR and LR, respectively.

Altogether, the four basic production environments (S-MS, S-FC, M-MS, and M-FC) combined with the eight energy settings (C-SR, C-LR, H-SR, H-LR, I-SR, I-LR, E-SR, and E-LR) represent 32 company types. Since our ECSD approach is based on time series which cover one year with 240 production days, a corresponding set of scheduling instances for each company type must be generated. Furthermore, to analyze the scheduling objectives` influence on the ECS efficiency, two sets of time series are calculated for each company type (one with the scheduling objective Cmax and one with TFT). The combination of a company type and a scheduling objective defines the content of a so-called PS scenario. Altogether, a total of 15,360 schedules have to be calculated to provide the 240 time series for the 64 PS scenarios. The complete set of AES demand time series is publicly accessible at – Mendeley Data (*and will be provided within the supplementary material within this doctoral dissertation*).

5.3 CU parameter settings and ECSD scenarios

In addition to PS scenarios, CU parameters are required to completely define an experiment. To create a traceable planning parameter analysis, we use a basic parameter setting for each CU (i.e., LCU-0 and FCU-0) and vary these settings according to the goals of the analysis. The LCU and FCU parameter settings described in Table II.C-1 and Table II.C-2 are then combined to form CS-parameter settings (e.g., LCU-0 and FCU-3 are combined to form CS-0-3) used for analyzing different aspects: The influence of the operational range of LCUs is examined on its own (CS-1-0) and in combination with efficiency losses (CS-2-0 and CS-3-0). Additionally, different LCU efficiency parameters are solely considered (CS-4-0 and CS-5-0). The influence of the bounds restricting the nominal load of FCUs is investigated on its own (CS-0-1) and in combination with efficiency losses (CS-0-2). Again, different efficiency parameters are solely investigated (CS-0-3 and CS-0-4). The complete LCU and FCU parameter settings are listed in Table II.C-1 and Table II.C-2, respectively (changes compared to the basic parameter settings are marked bold). Note that the efficiencies of both CUs considered in our experiments are generally based on boiler data from the literature (cf., Chicco and Mancarella, 2007 and Kavvadias and Maroulis, 2010).

Table II.C-1: LCU parameter settings

	LCU-0	LCU-1	LCU-2	LCU-3	LCU-4	LCU-5
η^{LCU}_{MaxL}	87.0%	87.0%	**85.0%**	**85.0%**	**80.0%**	**91.0%**
η^{LCU}_{NomL}	95.0%	95.0%	95.0%	**93.0%**	**97.0%**	**93.0%**
η^{LCU}_{MinL}	82.0%	82.0%	**80.0%**	**80.0%**	**75.0%**	**86.0%**
Δ^{LCU}_{NomL}	0.95	**0.90**	**0.90**	**0.90**	0.95	0.95
Δ^{LCU}_{MinL}	0.70	**0.60**	**0.60**	**0.60**	0.70	0.70

The combination of a PS scenario with a CS setting defines a complete experiment and is called an ECSD scenario in the following. For the segregated parameter influence analysis, we use a subset of all possible CS-parameter settings (CS-0-0, CS-1-0, CS-2-0, CS-3-0, CS-4-0, CS-5-0, CS-0-1, CS-0-2, CS-0-3, and CS-0-4) and define the ECSD scenario set ESS with 640 experiments (based on 64 PS scenarios and the ten CS-parameter settings).

Table II.C-2: FCU parameter settings

	FCU-0	FCU-1	FCU-2	FCU-3	FCU-4
η^{FCU}_{MaxL}	65.0%	65.0%	65.0%	**60.0%**	**70.0%**
η^{FCU}_{NomL}	84.0%	84.0%	**82.0%**	**86.0%**	**82.0%**
η^{FCU}_{MinL}	60.0%	60.0%	60.0%	**55.0%**	**65.0%**
Δub^{FCU}_{NomL}	0.15	**0.05**	**0.05**	0.15	0.15
Δlb^{FCU}_{NomL}	0.30	**0.10**	**0.10**	0.30	0.30

The (optional) parameter $relP^{LCU}_{NomL}$ is fixed to 40% in our experiments because this value defines a loose upper bound for the maximum load and thus does not restrict the optimum solution but only the solution space (to reduce computational efforts). The parameter $\Delta^{FCU}_{MinL} = 0.15$ is fixed for all experiments.

All experiments have been executed on workstations with an Intel® Xeon® CPU with 3.00 GHz and 64 GB RAM. SCIP was executed with the following settings: limits/gap=1E-12, limits/time=600 (seconds), gams/mipstart=true (an initial solution provided by TEH is used), and misc/printreason=TRUE (checks the feasibility of the initial solution). ANTIGONE was executed with CPLEX (threads=1) for solving relaxations, CONOPT for finding feasible points, a relative stopping tolerance (rel_opt_tol=1E-9), and a time limit of 10 hours (reslim=36000 seconds).

6 Experimental results

In the first part of our analysis, we compare the two part-load efficiency modelling approaches. In part two, we investigate the influences of the CU parameters on the TFES and in the last part, we analyze the most preferable CU parameters per company type, the influence of scheduling objectives, and the effect of decreasing conversion efficiencies.

Note that although the relative differences between objective values seem to be small, the impacts on the ECSs' efficiency should not to be underestimated as the absolute objective values (i.e., the final energy demand of one year) vary between 39,551,151 to 193,720,091 units.

6.1 Nonlinear vs. linear part-load efficiency modelling

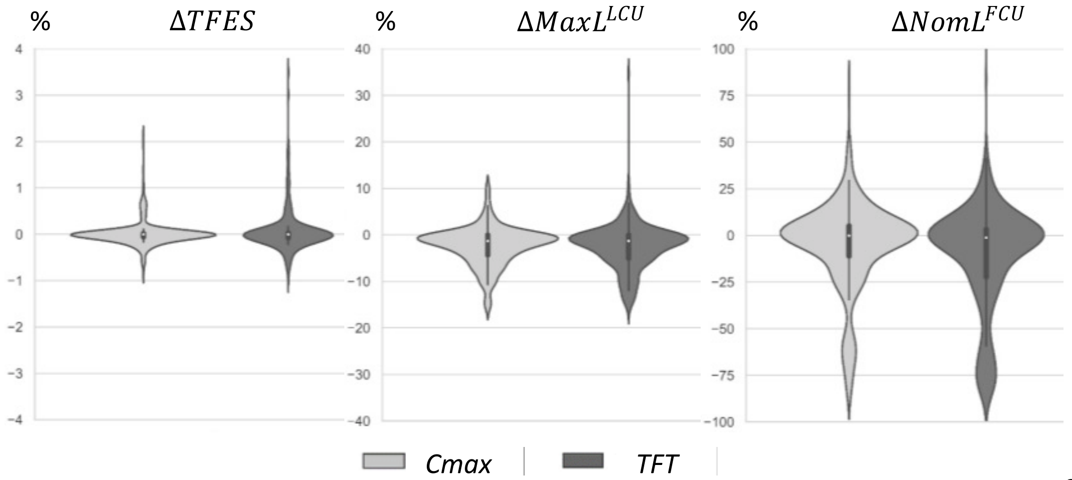
To analyze and compare the influence of both part-load efficiency modelling approaches on the ECS's design, we optimize both models (M-NL and M-L) with TEH and ANTIGONE and afterwards evaluate both solutions with the more accurate, but more complex model M-NL. The consequences of the simplified linear modelling of part-load efficiencies is then measured in terms of the required *TFES* (TFES(NL) vs. TFES(L)). In addition, we analyze the influence of both modelling approaches on the main decisions, i.e., the maximum load of the LCUs ($\text{MaxL}^{\text{LCU}}\text{(NL)}$ vs. $\text{MaxL}^{\text{LCU}}\text{(L)}$) and the nominal load of the FCUs ($\text{NomL}^{\text{FCU}}\text{(NL)}$ vs. $\text{NomL}^{\text{FCU}}\text{(L)}$). To that, we measure the influence of both modelling approaches on the ECS's design by the relative percentage difference of the TFES achieved with M-NL (TFES(NL)) and the TFES achieved with M-L (TFES(L)): $\Delta\text{TFES} = [(\mathit{TFES(L)} - \mathit{TFES(NL)}) / \mathit{TFES(NL)}] \cdot 100$. In addition, the influence on the actual design decisions MaxL^{LCU} and NomL^{FCU} is evaluated by the relative percentage differences $\Delta\text{MaxL}^{\text{LCU}}$ and $\Delta\text{NomL}^{\text{FCU}}$ (defined like ΔTFES).

Table II.C-3 shows the maximum, mean, standard deviation, and minimum relative percentage differences per scheduling objective, aggregated with regard to the 32 company types and the ten CS setting combinations from ESS (positive values mark that TFES(NL) , $\Delta\text{MaxL}^{\text{LCU}}\text{(NL)}$, or $\Delta\text{NomL}^{\text{FCU}}\text{(NL)}$ is smaller than TEFS(L) , $\Delta\text{MaxL}^{\text{LCU}}\text{(L)}$, or $\Delta\text{NomL}^{\text{FCU}}\text{(L)}$, respectively).

Table II.C-3: Aggregated relative percentage differences

	ΔTFES				$\Delta\text{MaxL}^{\text{LCU}}$				$\Delta\text{NomL}^{\text{FCU}}$			
	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min
Cmax	2.15	0.01	0.28	-0.87	10.21	-2.32	4.11	-15.63	78.71	-5.27	4.11	-83.63
TFT	3.50	0.01	0.28	-0.97	34.70	-2.50	3.89	-22.58	83.78	11.23	4.88	-82.98

In Figure II.C-5, the influence of the two part-load efficiency modelling approaches on *TFES*, $\mathrm{MaxL}^{\mathrm{LCU}}$, and $\mathrm{NomL}^{\mathrm{FCU}}$ is illustrated by violin plots (note the different scaling of the three parts).



0

Figure II.C-5: Violin plots of the relative percentage difference key figures

On the one hand, Figure II.C-5 and the values in Table II.C-3 show that the TFES values calculated with the nonlinear modelling approach can be remarkably lower (positive $\Delta\mathrm{TFES}$) for some cases and are also slightly lower on average. On the other hand, the values also indicate that the ECS designs determined with the linear modelling approach can be better (in terms of solution quality). The latter effect can be traced back to the fact that the optimization of model M-NL is more complex compared to model M-L, which was not accounted for in the experiments (because both models had the same time limit for computations). This drawback of the nonlinear modelling approach can be eliminated or at least weakened by extending the computation time limits or by using more efficient solution methods. However, possible savings up to 3.5 % are not insubstantial. In addition, it must be considered that the ECSD planning approach forces the LCU to operate at the nominal load level for most of the time. If relaxing this assumption during ECS operation, the appropriate modeling of part-load efficiencies becomes even more important.

The (remarkably) high differences of $\mathrm{MaxL}^{\mathrm{LCU}}$, and $\mathrm{NomL}^{\mathrm{FCU}}$ (cf., Figure II.C-5 and Table II.C-3) substantiate the previous finding that the way of modelling part-load efficiencies has a not neglectable influence on the ECS's design and therefore, the way of modelling must be chosen wisely.

6.2 Influences of CU parameters

Goal of the ten CS-parameter settings in the ECSD scenario set ESS is to analyze the influence of different CU parameters on the ECS's efficiency. For analyzing the influences, we illustrate in Figure II.C-6 the relative percentage deviation of TFES achieved (by ANT) with each of the corresponding CS-parameter settings compared to the TFES achieved with the reference setting CS-0-0. Note that negative values indicate a lower, improved TFES and that positive values indicate a higher, worsened TFES.

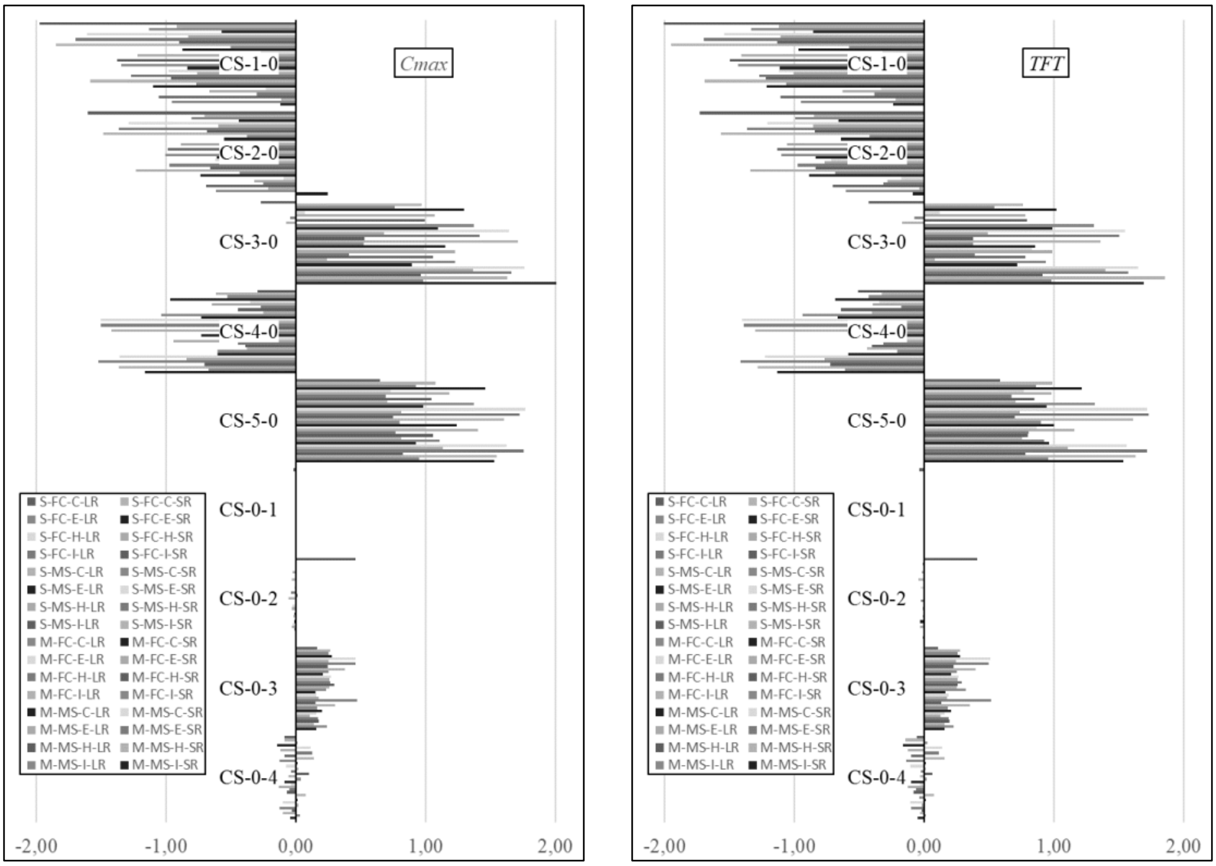


Figure II.C-6: Influence of CU parameters on the TFES

The results in Figure II.C-6 show that the effects of CU-parameters seem to be independent of the scheduling objectives. Furthermore, the results show a larger operational range for LCUs to be preferable (CS-1-0), even if the boundary load efficiencies (η_{MinL}^{LCU} and η_{MaxL}^{LCU}) decrease (CS-2-0), but that a simultaneous decrease of the nominal load efficiency cannot be compensated (CS-3-0). Figure II.C-6 also reveals a high positive influence of an increased nominal load efficiency (CS-4-0) and a high negative influence if boundary load efficiency increases comes along with nominal load efficiency decreases (CS-5-0) for LCUs. Both effects and thus the importance of the nominal load efficiency of an LCU can easily be explained, as the LCU is designed to operate at the nominal load for most of the time (cf., section 3.1, Figure II.C-3, and Table II.C-4).

Table II.C-4: Relative numbers of periods LCUs operate at nominal load

	Cmax	TFT
Mean	57.61 %	58.80 %
Variance	0.74 %	0.87 %

As seen by the results of Figure II.C-6, a greater degree of freedom for the determination of the nominal load of the FCU only slightly increases the CS's efficiency (cf., CS-0-1 and CS-0-2). In contrast to LCUs, for the FCU, the nominal load efficiency is of minor importance compared to the boundary load efficiencies (η^{FCU}_{MinL} and η^{FCU}_{MaxL}) as can be seen by comparing CS-0-3 and CS-0-4.

Generally, we can report that compared to FCU parameters, LCU parameters have a greater influence. This can be traced back to the larger amount of AES provided by the LCUs (cf., Table II.C-5).

Table II.C-5: Relative load share of LCUs

	Cmax	TFT
Mean	88.91 %	88.12 %
Variance	0.29 %	0.36 %

6.3 Most suitable planning parameters per company type

To finally evaluate the influence of the basic planning parameters, we report in Table II.C-6 for each company type the most preferable combination of scheduling objective, LCU parameters, and FCU parameters (here we evaluated all possible compositions of non-dominated CS-parameter settings). For comparing the influence of both scheduling objectives, we depict in column five the relative percentage difference between the most suitable objective and the other objective. In addition, we report the results of a sensitivity analysis simulating decreasing conversion efficiencies (e.g. due to unit aging or other stochastic influences; cf., e.g., Guinot et al., 2015). To that, efficiencies of the most preferable CS parameter settings are adapted after 5 and 10 years (nominal load efficiencies are decreased by 0.6 per "year" and minimum and maximum load efficiencies by 0.4 per "year") and for each company type, further ECS designs are calculated with the reduced CU efficiencies. The resulting relative percentage changes of the (additional) TFES, $MaxL^{LCU}$, and $NomL^{FCU}$ (compared to the unchanged efficiencies) are depicted in the last six columns of Table II.C-6:

Table II.C-6: Most preferable parameters by company type (sensitivity analysis)

Company type	LCU	FCU	Sched. obj.	Rel. TFES diff. [%]	Additional TFES after		MaxL^{LCU} changes after		NomL^{FCU} changes after	
					5 "years" [%]	10 "years" [%]	5 "years" [%]	10 "years" [%]	5 "years" [%]	10 "years" [%]
S-FC-C-LR	LCU-1	FCU-1	Cmax	1.13	3.23	6.64	1.47	1.47	-1.14	-1.14
S-FC-C-SR	LCU-1	FCU-3	Cmax	0.84	3.22	6.68	0.00	0.55	0.00	-3.11
S-FC-E-LR	LCU-1	FCU-3	Cmax	0.97	3.17	6.55	0.38	1.34	0.00	0.30
S-FC-E-SR	LCU-4	FCU-3	Cmax	1.35	3.20	6.62	0.00	0.00	0.00	0.00
S-FC-H-LR	LCU-1	FCU-3	Cmax	0.11	3.20	6.60	3.08	4.98	-2.61	-4.69
S-FC-H-SR	LCU-1	FCU-3	Cmax	0.59	3.21	6.69	0.25	1.26	-0.77	-3.64
S-FC-I-LR	LCU-1	FCU-1	Cmax	0.90	3.21	6.65	0.00	1.22	0.00	-1.20
S-FC-I-SR	LCU-1	FCU-3	Cmax	1.00	3.21	6.64	0.00	0.00	0.00	0.00
S-MS-C-LR	LCU-1	FCU-3	Cmax	0.66	3.18	6.57	1.08	1.62	-1.62	-1.62
S-MS-C-SR	LCU-4	FCU-3	Cmax	0.17	3.21	6.63	0.00	0.00	0.00	0.00
S-MS-E-LR	LCU-1	FCU-3	Cmax	0.05	3.18	6.55	0.74	2.03	1.17	2.59
S-MS-E-SR	LCU-4	FCU-3	TFT	0.01	3.24	6.69	0.14	0.27	-0.53	-1.47
S-MS-H-LR	LCU-1	FCU-3	TFT	1.18	3.18	6.56	0.59	0.98	-0.34	-1.46
S-MS-H-SR	LCU-4	FCU-3	TFT	0.46	3.22	6.65	0.00	0.00	0.00	0.00
S-MS-I-LR	LCU-1	FCU-3	TFT	0.89	3.17	6.54	1.57	1.57	10.06	9.28
S-MS-I-SR	LCU-4	FCU-3	TFT	0.35	3.25	6.68	0.27	0.27	-0.75	-0.75
M-FC-C-LR	LCU-1	FCU-3	Cmax	1.56	3.17	6.58	0.00	3.22	0.00	12.23
M-FC-C-SR	LCU-1	FCU-3	Cmax	1.42	3.21	6.69	0.00	0.97	0.00	-4.94
M-FC-E-LR	LCU-1	FCU-3	Cmax	1.29	3.17	6.55	0.43	2.00	0.55	3.11
M-FC-E-SR	LCU-4	FCU-3	Cmax	1.57	3.18	6.57	0.00	0.00	0.00	0.00
M-FC-H-LR	LCU-1	FCU-3	TFT	0.05	3.24	6.69	1.12	2.23	-3.96	-8.18
M-FC-H-SR	LCU-1	FCU-3	Cmax	1.06	3.17	6.54	0.00	0.00	0.00	0.00
M-FC-I-LR	LCU-1	FCU-3	Cmax	0.79	3.18	6.56	1.10	1.86	-1.38	-2.28
M-FC-I-SR	LCU-1	FCU-3	Cmax	1.10	3.19	6.55	2.01	2.01	-5.01	-5.19
M-MS-C-LR	LCU-1	FCU-3	Cmax	1.13	3.16	6.53	0.00	0.00	-0.35	-0.35
M-MS-C-SR	LCU-4	FCU-3	Cmax	0.65	3.20	6.63	0.00	0.27	-0.31	-2.45
M-MS-E-LR	LCU-4	FCU-1	Cmax	0.30	3.18	6.57	0.00	0.00	0.00	0.00
M-MS-E-SR	LCU-4	FCU-3	Cmax	0.43	3.25	6.67	0.52	0.60	-3.93	-4.72
M-MS-H-LR	LCU-1	FCU-3	TFT	0.84	3.14	6.49	1.65	1.65	-2.76	-3.10
M-MS-H-SR	LCU-4	FCU-3	Cmax	0.09	3.20	6.61	0.00	0.00	0.00	0.00
M-MS-I-LR	LCU-1	FCU-3	TFT	1.45	3.17	6.54	1.14	2.55	1.72	3.14
M-MS-I-SR	LCU-4	FCU-3	TFT	0.27	3.19	6.59	0.00	0.00	-0.23	-0.45
MAX				1.57	3.25	6.69	3.08	4.98	10.06	12.23
MEAN				0.77	3.20	6.60	0.55	1.09	-0.38	-0.63
STD				0.48	0.03	0.06	0.75	1.14	2.37	3.82

Regarding the FCU settings, FCU-3 is most preferable for almost all company types (29 of 32). Nevertheless, FCU-1 (3 times) is more suitable for specific company types. Accordingly, the nominal load efficiency is not the only important parameter for FCUs (cf., Table II.C-2). For the same reasoning as in Section 6.2, LCU-5 is not preferable due to its lower nominal load efficiency (cf., Table II.C-1). However, although LCU-4 has the highest nominal load efficiency, LCU-1 with its larger operational range is preferable for most company types (21 of 32). Therefore, we conclude that next to the nominal load efficiency, the operational range is a second main influencing parameter for LCUs.

Analyzing the influence of the scheduling objective, the values in Table II.C-6 show that the makespan objective is preferable for most company types but that also the TFT objective can be superior. The comparison of both objectives by a two-sided pairwise t-tests (on the ten CS-parameter settings), used to test whether the difference of the objective values (TFES) is statistically significant (≤ 0.05; with degrees-of-freedom df = 9) or not, leads to the following results: mean relative percentage difference = -0.44 (Cmax is superior), mean p-value = 0.009, mean t-value =28.238, and that the differences are significant for 31 of 32 company types. This leads to the conclusion that manufacturing companies can influence their energy efficiency by an appropriate scheduling objective (presumably even more when an energy-oriented scheduling is performed) and that this scheduling objective should be already considered during ECS design.

The increasing TFES values resulting from the decreasing conversion efficiencies are as expected. More interesting are the sensitivity analysis' results concerning the decisions on the maximum load of the LCU and the nominal load of the FCU. The results in Table II.C-6 reveal a very robust dimension of the LCU regarding decreasing conversion efficiencies: if the nominal load efficiency decreases by 3% (6%), the most suitable $MaxL^{LCU}$ only increases by 0.55% (1.09%) on average (maximum increases are 3.08% and 4.98%). Somehow more sensitive is the nominal load of the FCU. The mean decreases of 0.38% and 0.63% are comparable small but for some company types, the "new" adapted nominal load is remarkably higher (e.g., M-FC-C-LR), whereas for other company types, the "new" adapted nominal load is remarkably lower (e.g., M-FC-H-LR). For these cases, an appropriate adjustment of the nominal load of the FCU is advised.

7 Conclusions

In this paper, we presented a new, flexible —AES-type independent— approach for the dimensioning of a manufacturing company's ECS. With respect to the special conditions arising in the context of manufacturing companies (highly dynamic AES demands and the opportunity to directly influence the temporal course of the AES demand by scheduling), our approach not only considers and anticipates the hierarchical interdependencies between ECS design and ECS operation but additionally takes the relationship to the PS into account. To that, the simulative scheduling component of our planning approach is capable to model different types of production systems, constraints, and objectives. In addition, as we propose to consider 240 production days during the ECSD, the resulting ECS design is robust with regard to AES demand uncertainties and also to decreasing conversion efficiencies.

The most important characteristics defining an ECS's energy-related behavior (i.e., size, nominal loads, and part loads with related conversion efficiencies) are explicitly modelled by the proposed MINLP. In this context, our experimental results have shown the advantage of the most accurate modelling of part-load efficiencies by nonlinear functions as it leads to a more efficient ECS design compared to linear modelling approaches (savings up to 3.5 % can be achieved). In consequence of this result, we emphasize the importance of a suitable part-load behavior modelling when designing ECSs for manufacturing companies.

Another essential aspect highlighted by the experiments is the importance of not only the nominal load efficiency but also of the operational ranges and boundary efficiencies for the ECS design (at least for CUs used to cover peak demands).

Furthermore, the possibility of manufacturing companies to directly influence the AES demand course by scheduling can be used to improve the ECS design and its efficiency. Hereby, the usage of energy-oriented objectives or constraints is a promising research topic to further improve energy efficiency.

The final conclusion from the experimental analysis is that, depending on a manufacturing company's characteristics, individual combinations of a scheduling objective and CU parameters are best suited to maximize its energy efficiency.

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II.D Contribution 4: Approximate anticipation of base-level reactions by machine learning techniques used to substitute the solving of complex nesting problems

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Abstract: In hierarchical production planning systems, complex nesting problems (also known as two-dimensional, highly irregular strip packing problems) often constitute a subordinated problem of a superior scheduling problem, e.g., the serial-batch scheduling problem in metal manufacturing. Here, the top-level scheduling decision includes a batching decision, i.e., the determination of a set of small items to be cut out of a large object. To examine the feasibility of a batch, the base-level nesting problem must be solved. Because solving subordinated (nesting) problems is often time consuming even when applying heuristics, it is troublesome to solve it multiple times during solving the superior (scheduling) problem.

Instead, we propose an approximative anticipation of base-level reactions by the application of machine learning techniques (i.e., to approximate the feasibility of a batch by predicting the height of the required strip). To that, we propose a prediction framework to identify the most promising machine learning technique for the prediction (regression) task. For applying these techniques, we propose new feature vectors describing the characteristics of complex nesting problem instances. For training, validation, and testing, we present a new instance generation procedure that uses a set of 6,000 different convex, concave, and complex shapes to generate 88,200 nesting instances. The testing results show that an artificial neural network achieves the lowest expected loss (root mean squared error). Depending on further assumptions, we can report that based on the height predictions, for 98.9% of the nesting instances, the approximate anticipation leads to an appropriate decision regarding batch feasibility.

Keywords: (R) Machine learning, hierarchical planning, anticipation, nesting, irregular strip packing (S) Artificial intelligence, (O) Cutting, (O) Packing, (T) Manufacturing

1. Introduction

The concept of hierarchical production planning is used by almost any manufacturing company applying production planning and scheduling methods. The concept can be traced back to the works of Hax and Meal (1973), Bitran et al. (1981), Bitran and Tirupati (1993) and Schneeweiß (1995) (amongst others). Particularly the conceptual framework of Schneeweiß (1995) describes this essential aspect of actual production planning systems. In this framework, the interdependencies between superior top-level decisions (defining the instructions or top-down influence) and the subordinate base-level decisions are explicitly emphasized (cf., Figure II.D-1). In addition, the anticipation of base-level reactions (bottom-up feedback) by top-level decisions is recommended. This anticipated reaction can be modelled by a so-called anticipation function "calculating" hypothetical reactions of the base-level founded on hypothetical instructions of the top-level. In Schneeweiß (2003), four archetypical types of anticipation functions are described: perfect anticipation (reactive), approximate anticipation (reactive), implicit approximation (reactive), and non-reactive anticipation (further details are discussed in Section 3).

In this paper, we propose to use machine learning techniques for the approximate anticipation of base-level reactions instead of solving complex nesting problems (CNPs; also known as two-dimensional, highly irregular strip packing problems; cf., e.g., Burke et al., 2009 or Leao et al., 2020). Without losing the ambition to propose a general anticipation method, the application context of CNPs provides several advantages: First, CNPs, a special kind of packing/cutting problem, occur in many industrial sectors like metal-processing, carbon fiber, or textile manufacturing and therefore, make our approach relevant in different industrial application fields (Burke et al., 2009). Second, very often nesting problems, or packing/cutting problems in general, constitute a subordinated (base-level) problem of a superior (top-level) decision problem (e.g., a machine scheduling problem) or are at least closely related to it (cf., e.g., Chryssolouris et al., 2000 or Helo et al., 2019). More details on an application case and the hierarchical interdependencies between the planning tasks are described in section 2. Finally, solving CNPs causes high computational efforts, even if heuristics are used (note, that solving CNPs within an iterative solution method for the superior problem would even be troublesome if computation times are only a few seconds; cf., e.g., López-Camacho et al., 2013a). Therefore, the most accurate and efficient approximate anticipation method would be very welcome to improve the solution quality and/or reduce computational efforts of superior planning problems in a broad range of industries.

Our main contribution to literature is the new method for an approximate anticipation of base-level reactions by machine learning used to substitute the solving of complex nesting problems. In contrast to Rohde (2004) who only uses artificial neural networks to anticipate lot-size stocks and setup times in the context of master production scheduling, we recommend to use a broad range of machine learning techniques to improve anticipation accuracy. To that, we propose a prediction framework to identify the most suitable technique. Further contributions to literature are the new instance generation procedure for CNPs (based on real-world shapes and controllable attributes) and the feature vectors to model CNP characteristics used by the machine learning techniques.

The structure of this paper is as follows: After an introductory section and the description of the application case in section 2, we analyze in section 3 the backgrounds and related work of our anticipation approach. The approximative anticipation approach itself is described in section 2 and the prediction framework used for the approximation is depicted in section 3 . Section 4 is dedicated to the evaluation of the proposed anticipation approach and the applied machine learning techniques. Concluding remarks are given in section 5 and a brief summary and outlook on further research is presented in section 6 .

2. Application case

An incisive example of the interdependencies between a top-level decision, i.e., a serial-batch scheduling problem, and a base-level decision, i.e., a complex nesting problem, can be found in the sheet metal manufacturing. Here, customer-specific metal pieces have to be cut out from large metal slides by one or more laser cutting machines. Thereby, the metal pieces (cutting items) should be grouped into batches to avoid machine setups. This batching decision, together with the machine allocation (in the case of multiple cutting machines) and the sequencing decision, defines the (superior, top-level) serial-batch scheduling problem. The serial-batching type (i.e., the processing time of a batch is the total processing time of all items assigned to this batch), the presence of setup times, and the due dates of the items make the batching decision crucial for the overall performance of the scheduling decision (e.g., in terms of delivery reliability). Besides economic reasons, good batching decisions also influence resource efficiency by avoiding waste and thus, a more sustainable production can be achieved.

To evaluate the solution quality of a batch and, more important, to evaluate its feasibility (metal slide dimensions must be respected and items may not overlap), the metal pieces must be packed on the metal slide. This packing task leads to the subordinated complex nesting problem. Actually, the base-level decision problem could be formulated as "two-dimensional bin packing problem" (or "two-dimensional finite bin packing problem"; cf., the typology of Wäscher et al., 2007). Instead, we consider the more general "two-dimensional strip packing problem" having one open (infinite) dimension (cf., e.g., Martello et al., 2003). For this problem, the planning objective is the minimization of the height of the required strip whereas the second dimension (width) is fixed. Then, to evaluate batch feasibility, the calculated height can be compared to any reference height, e.g., the height of standard metal slides or the height of smaller metal slides remaining from previous cutting processes (to increase resource efficiency). Regarding the cutting items, it must be considered that the customer specific items have arbitrary shapes that are typically irregular (also called non-regular; cf., Wäscher et al., 2007; for an overview of relevant application areas see e.g., Dowsland and Dowsland, 1995). Accordingly, the problem is called "irregular strip packing problem" or "nesting problem" (cf., Oliveira et al., 2000; in textile manufacturing, the problem is called "marker-making problem", cf., e.g., Li and Milenkovic, 1995). Burke et al. (2007) use the term "highly irregular" shapes if the item shapes include concavities and/or holes. Complexity further increases if the items can be rotated (at fixed angles, a given number of times, or even arbitrarily). In consequence, for evaluating the feasibility of a batch in the context of serial-batch scheduling in sheet metal manufacturing, the "highly irregular strip packing problem with free rotations" must be solved. For simplicity, we call this problem the "complex nesting problem (CNP)".

The relationship between the theoretical concept of hierarchical production planning and the concrete manifestations of the decision problems (models) of the application case is depicted in Figure II.D-1.

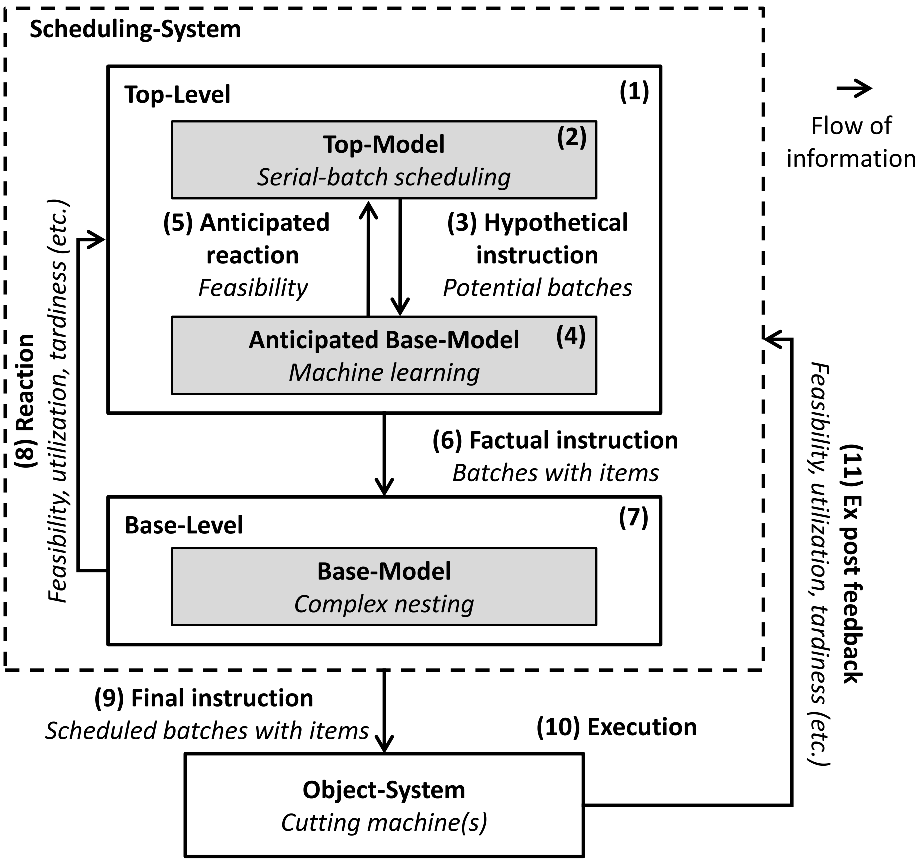


Figure II.D-1. Hierarchical integration of the approximate anticipation by machine learning

The bold terms in Figure II.D-1 represent the abstract concepts and elements as used in literature (cf., e.g., Schneeweiß, 1995 and Schneeweiß, 2003), whereas the italic terms depict the concrete manifestations regarding the sheet metal manufacturing case. The numbers in brackets show the basic course of action. Because we assume the reader to be familiar with the concepts of hierarchical production planning, we omit a detailed explanation here.

3. Background and related work

The literature review to examine related work is divided into three parts. The first part is dedicated to anticipation functions in the context of hierarchical production planning. The second part contains contributions related to the application of machine learning techniques in the area of packing and cutting, whereas the third part introduces major machine learning concepts in general and briefly describes potential techniques appropriate for the height prediction task.

1.1 Basics on anticipation functions

As already described in the introduction, Schneeweiß (2003) differentiates between four archetypical types of anticipation functions. In the case of perfect anticipation, the base-level decision model is completely known and exactly integrated into the top-level model. Only the parameters (information) used by the top-level model might not be known deterministically and change when solving the base-level model. In contrast, approximate anticipation is performed by using some approximative anticipation function (models or methods). For an implicit anticipation, only some (most important) aspects of possible base-level reactions are considered within the anticipation function. Note that for these three anticipation types, explicit anticipation functions are used, whereas for the last type, non-reactive anticipation, no explicit anticipation function is used. Instead, some major aspects of the base-level decision are incorporated within the top-level model. Hereby, these aspects are not (reactively) depending on the top-level instructions. Because the complexity of the top-level model is often already too high, using non-reactive anticipation or even perfect anticipation is not possible. This is particularly the case for the models considered in this paper: the serial-batch scheduling problem (e.g., with minimizing total weighted tardiness as objective, it is NP-hard since it is a reduction from the corresponding NP-hard single machine sequencing problem) and the CNP (already the strip packing problem with rectangular items is NP-hard in the strong sense; cf., Martello et al., 2003). Therefore, we propose to use an approximative anticipation function that has also an implicit anticipation aspect as we only consider the height (representing the major aspect) to decide on batch feasibility and do not require the complete CNP solution.

In literature, different approaches for approximative anticipation functions can be found: for instance, exponential smoothing (Selçuk et al., 2006), clearing functions (cf., e.g., Graves, 1986 or Asmundsson et al., 2006), or simulation (cf., e.g., Venkateswaran and Son, 2005 or Albey and Bilge, 2011). To the best of our knowledge, only Rohde (2004) uses a machine learning technique (artificial neural networks) for anticipation as we propose. Giving a good example for implicit anticipation, Kallestrup et al. (2014) emphasize that for non-perfect anticipations, the actual reaction from the object-system may be quite different from the anticipated reaction and that this problem can be reduced by increasing the quality of the anticipation. Therefore, we are not going to rely our prediction on a single machine learning technique like Rohde (2004) but propose a prediction framework to identify the most suitable technique.

1.2 Machine learning applied to packing and cutting problems

In contrast to the almost non-existing application of machine learning techniques for anticipation purposes, these techniques are commonly used by hyper-heuristics and less frequently as solution method itself. Hyper-heuristics can be defined as "an automated methodology for selecting or generating heuristics to solve hard computational search problems" (Burke et al., 2010; for a similar definition cf., Pappa et al. 2014). To that, the central idea of hyper-heuristics is to learn which heuristic (or operator) will perform best by exploiting information about the current problem instance to solve and/or information from already solved problem instances. In this context, Burke et al. (2010) propose the distinction between online and offline learning. Online learning takes place while a heuristic solves a single problem instance, whereas offline learning aims to gather knowledge (e.g., in form of rules) from a set of training instances and to use this knowledge for solving unknown instances better. For recent advances and an extended classification scheme of hyper-heuristics see Drake et al. (2020). Most relevant publications concerning the development of hyper-heuristics for solving cutting and packing problems are Terashima-Marín et al. (2010), Sim et al. (2012), López-Camacho et al. (2013b), López-Camacho et al. (2014), Segredo et al. (2014), and Gomez and Terashima-Marín (2018). Although these publications have a different scope, they are relevant concerning the prediction task at hand as the authors use features to characterize their problems that are related to CNPs. An explicit performance prediction to estimate minimum reference values for evaluation purposes or as termination criteria of iterative solution methods for the rectangular two-dimensional strip-packing problem is proposed by Neuenfeldt Júnior et al. (2019). Besides the differing prediction purpose, another main difference between their and our prediction task is their limitation to the problem with rectangular shaped items (in contrast to highly irregular ones). Remember, goal of our approach is to predict the height of the strip that would result from the application of the CNP solution method that will be actually used for solving the CNPs defined by the superior scheduling (batching) decision.

Another way of applying machine learning techniques is to use them as autonomous solution method or as a part of a solution method. For instance, to calculate initial solutions for a two-dimensional cutting problem, Han and Na (1996) combine self-organizing feature maps (an unsupervised learning architecture) and fuzzy c-means. Dagli and Poshyanonda (1997) use a back-propagation neural network to generate larger patterns out of smaller input patterns for the nesting of rectangular patterns. Wong and Guo (2010) use a learning vector quantization neural network to classify items in order to select packing rules.

1.3 Major machine learning concepts

Recent advances in machine learning have risen new possibilities for its application. Particularly deep learning (a synonym for deep neural networks; cf., Goodfellow et al., 2017 or Kraus et al., 2020) has become a very powerful technique in the last years. According to Goodfellow et al. (2017), this is due to the rapidly growing computational capabilities, the widespread use of graphical processing units, the increasing amount of available training data (not least due to the emerging idea of the internet-of-things), and the improvements in optimizing the parameters of (deep) neural networks. Besides deep learning and "traditional" artificial neural networks, also other machine learning techniques might be appropriate for the height prediction task at hand. To be appropriate, the technique must be capable to perform a univariate multiple regression for the following reasons: First, as the strip height to be predicted is a single dependent continuous variable ("outcome variable"), classification and clustering models (methods) are not useful but univariate regression models. Second, as we do not expect that the height is related to a single CNP instance characteristic, several independent variables (also called "predictors", "covariates", or "features") must be considered by a multiple regression model. Summarizing, machine learning techniques that are capable to perform univariate multiple regressions and that belong to the class of supervised machine learning methods are basically appropriate. To select and evaluate the most appropriate machine learning method, we will briefly review models and methods in the following. For easier reading, we use the term regression model, regression method, or the abbreviation RM if we refer to corresponding machine learning models and methods in the remainder of this paper.

Because a detailed description of RMs is out of the scope of this paper, we only carve out the main aspects related to the prediction task at hand and refer to several books that are good starting points to deepen the topics. Remark that the basic idea of supervised machine learning is the use of training data (containing training instances or samples comprising independent variables and dependent/response variables) to determine the parameters of a model in such a way that a sufficient generalization is achieved. In the context of machine learning, a sufficient generalization means that a RM performs well on new, previously unseen inputs (cf., Goodfellow et al., 2017) and not only on the training data. Because we are not interested in inference (i.e., understanding the relationship between independent and dependent variables) but in most accurate predictions, the aspect of interpretability is not that important and thus, even very flexible parametric and non-parametric regression models are suitable. An important theoretical result of statistics and also machine learning is that a model's "generalization error" (i.e., its error rate on unknown data; also called "out-of-sample error", "test error", or, related to prediction tasks, "prediction error") consists of three very different errors (cf., Géron, 2019: 196, p. 195): bias, variance, and irreducible error. Accordingly, the challenge is to find a RM for which bias and variance are low (this is referred to as the bias-variance trade-off; cf., e.g., James et al., 2013 or Goodfellow et al., 2017). This is challenging because in general, more flexible RMs have a lower bias but a higher variance compared to inflexible ones. Note that the generalization error is not measured by using the training data but by a special hold-out data set called "test set". This test set may not be used in advance, neither during development, training, nor during the validation (evaluation) of different RMs. For the validation of different models (i.e., the identification of the most suitable RM), a special hold-out set, the "validation set", can be separated from the training data set. Behind this background, we briefly describe some main aspects of appropriate machine learning techniques in the following.

The group of rather inflexible, linear models includes multiple linear regression and regularized linear models like Ridge regression, Lasso regression or Elastic Net. More flexible are non-linear models like polynomial regression (based on non-linear transformations of the predictors; cf., e.g., Géron, 2019) or generalized additive models. Generalized additive models provide a universal framework for extending standard linear models by allowing non-linear functions for each of the variables, while maintaining additivity (cf., e.g., James et al., 2013).

Even more flexible is support vector regression basing on the same principles as support vector machines used for classification tasks (also called support vector classifier). For regression, an ε-insensitive error function is used. Central hyper-parameter (hyper-parameters control the general behavior of a RM, e.g., how the model is trained; in contrast, a "normal" parameter is part of the model and determined during training) of support vector regression is the used kernel: e.g., linear, polynomial with a specific degree, Gaussian RBF, or sigmoid. The kernels are used for "virtually enlarging" the feature space without having the (computational) drawback of an actually large feature space (cf., e.g., Bishop, 2006 or Murphy, 2013).

Another group of regression model bases on decision trees. Besides their advantages (e.g., interpretability or visualizability), decision trees have several disadvantages, i.e. they are non-robust (instable to even small changes in the data; cf., e.g., Géron, 2019) and tend to overfitting. To eliminate these disadvantages, for example bagging regression trees, random patches and random subspaces, random forests (particularly helpful to determine a feature's importance), or boosting (e.g., gradient boosted regression trees) have been developed. Because these RMs use several decision trees to construct a more accurate prediction model, they belong to the group of "ensemble models" where the final prediction is the (weighted) mean value of the individual predictions of the ensemble's members (e.g., decision trees). Generally, the result of an ensemble model has a similar bias but a lower variance than a single prediction model (cf., James et al., 2013). Instead of using the mean value to determine the final prediction, also an additional RM could be used. This type of ensemble model, where one or more layers of RMs are used and the prediction of the preceding layer is the input (feature) of the succeeding layer, is called stacking or blending (cf., e.g., Géron, 2019). An idea that is also used by the following RM.

Artificial neural networks are maybe the most flexible machine learning technique for predicting the strip height, as they do not make any assumptions about the relationship between independent variables and dependent variable (cf., Bishop, 1995). Because we are not going to discuss biological neural networks, we use the term neural networks (or NN) for simplicity in the following. Due to their nonlinear nature, NNs perform very well for modeling complex data structures where the functional form is most likely nonlinear. Basically, NN consist of several layers of processing units (neurons) that are structured and interacting according to a basic network architecture like “feedforward neural networks” (or “multilayer perceptrons”) or “recurrent neural networks” (cf., e.g., Goodfellow et al., 2017). Because the number of NN architectures is almost infinite (a good visualization is provided on www.asimovinstitute.org), we are not going into more detail about all available architectures. In this paper, we concentrate on a “standard” feedforward NN architecture with two hidden layers and evaluate several hyper-parameters like number of neurons per hidden layer and learning epochs. Such a NN with two hidden layers can be seen as a deep learning method.

Summarizing the related work, we conclude that there is no existing approach that uses and evaluates different machine learning techniques for the approximative anticipation of base-level reactions in the context of complex nesting problems.

2 Approximate anticipation by machine learning predictions

Goal of the application of machine learning techniques as approximative anticipation function is a most accurate anticipation of base-level reactions. Regarding the metal-processing application case, the anticipation function is used to predict batch feasibility, i.e., if the items assigned to a batch can be placed on a metal slide. Note that goal of the prediction is not a minimum height or lower bound but to hit the result of the solution method that would be actually used for solving the CNPs. Instead of solving the corresponding CNP, we seek to find an efficient RM and its parameters (used as anticipation/prediction function f^P) that predicts the height $\hat{H}_i$ of a CNP instance I_i based on a set of instance features θ_i such that the prediction error $e_i = H_i - \hat{H}_i$ is minimum. To measure the overall prediction error, we use the root mean squared error (RMSE) because larger errors are penalized stronger and it has the same unit (and scale) as the predicted value. Besides using the RMSE as prediction error measure in the training, hyper-parameter tuning, and validation phase, the RMSE is also used to estimate the overall expected loss of prediction function f^P regarding unknown instances

D. Depending on the purpose, instance set *X* in equation (1) can either be a training data set (*T*), a validation set (*V*), or a test set (*D*):

$$L(X, f^P) = \sqrt{\frac{1}{|X|}\sum_{i \in X}(\hat{H}_i^{f^P} - H_i^{f^{SM}})^2} \tag{1}$$

In (1), $\hat{H}_i^{f^P}$ depicts the height predicted by prediction function f^P and $H_i^{f^{SM}}$ (H_i for readability in the following) depicts the height calculated by solution method f^{SM} for CNP instance I_i: $H_i = H_i^{f^{SM}} = f^{SM}(I_i)$. Note that H_i depicts the known response variable in the regression analysis (also called label in the context of supervised learning).

Before describing three simple approximative anticipation functions and their evaluation in terms of prediction accuracy, further terms and notations are introduced.

2.1 Notations

Basic task of the CNP as considered in this contribution is to position a set $P_i = \{p_{j=1}, \ldots, p_n\}$ of *n* items on a large object (the strip) having a fixed width W_i by minimizing the “used” height of the object. A feasible solution (called “nesting”) is a placement of items without overlaps and with no item outside the object limits. An item p_j is represented by a tuple of polygons $\Psi_j = (\rho_{j,1}, \rho_{j,2}, \ldots, \rho_{j,n_j})$ with $n_j \geq 1$. The first (enclosing) polygon $\rho_{j,1}$ (also depicted by E in the following) defines the enclosing line and thus, separates the “interior” from the “exterior” of an item shape. All other polygons define holes of an item (these are also called difference polygons). Each of the polygons is defined by a tuple of vertices $\Lambda_{j,\rho} = (v_1, v_2, \ldots, v_{k_\rho})$ in $\sim^2$. The edges defined by the vertices of a polygon are given by $\Gamma_{j,\rho}$ and their lengths by $\Omega_{j,\rho}$.

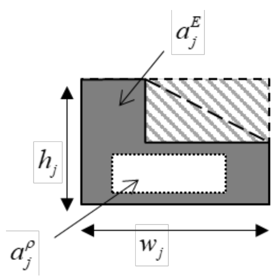


Figure II.D-2: Item shape properties

Basic properties of an item’s shape are the height h_j and width w_j of the shape’s minimum bounding rectangle (MBR; as we allow arbitrary rotations, the naming is not relevant but we use the convention that without rotation, the width of an item is not smaller than its height, i.e., $w_j \geq h_j$). The area of the minimum bounding rectangle is depicted by $a_j^{MBR} = h_j \cdot w_j$, the area of the enclosing polygon by a_j^E (dark grey area plus white area a_j^ρ of polygon ρ in Figure II.D-2), and the area of the convex hull of the enclosing polygon by a_j^{CH}.

2.2 Simple approximation approaches

Based on the "area lower bound" idea proposed by Martello et al. (2003) for the strip-packing problem, three very simple but highly efficient problem-specific approximate anticipation functions can be derived: SA-E (2), SA-CH (3), and SA-MBR (4).

The first function "fills" the strip with the total area of the enclosing polygons and represents an inordinate optimistic anticipation approach:

SA-E:
$$\hat{H}_i^E = \max\{\max_{j\in P_i}\{h_j\}, \sum_{j\in P_i} a_j^E \Big/ W_i\} \quad (2)$$

The second, more conservative approach, fills the strip with the total area of the convex hulls:

SA-CH:
$$\hat{H}_i^{CH} = \max\{\max_{j\in P_i}\{h_j\}, \sum_{j\in P_i} a_j^{CH} \Big/ W_i\} \quad (3)$$

The third, most conservative approach, fills the strip with the total area of the MBR of all items:

SA-MBR:
$$\hat{H}_i^{MBR} = \max\{\max_{j\in P_i}\{h_j\}, \sum_{j\in P_i} a_j^{MBR} \Big/ W_i\} \quad (4)$$

Figure II.D-3 illustrates the three simple approximation approaches compared to a nested solution by an example with 15 items:

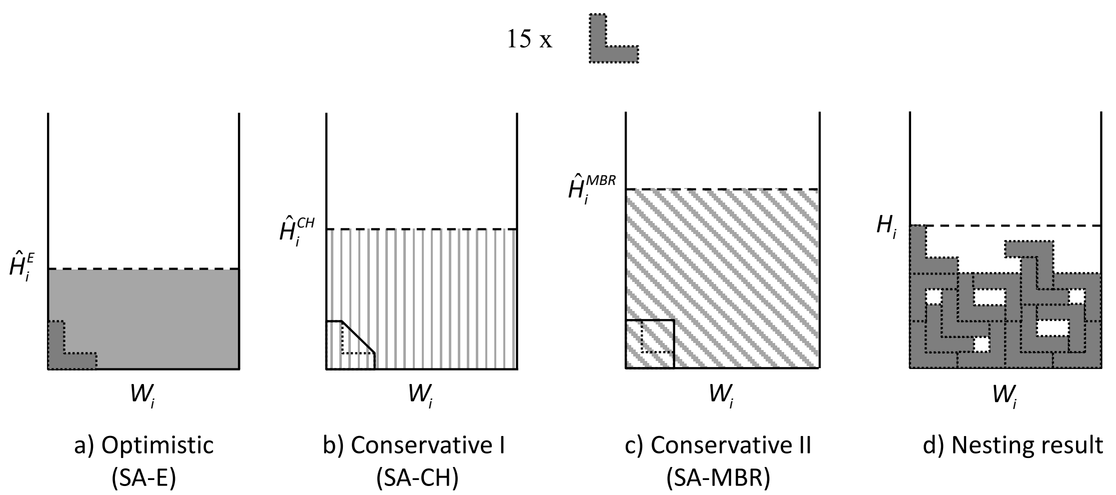
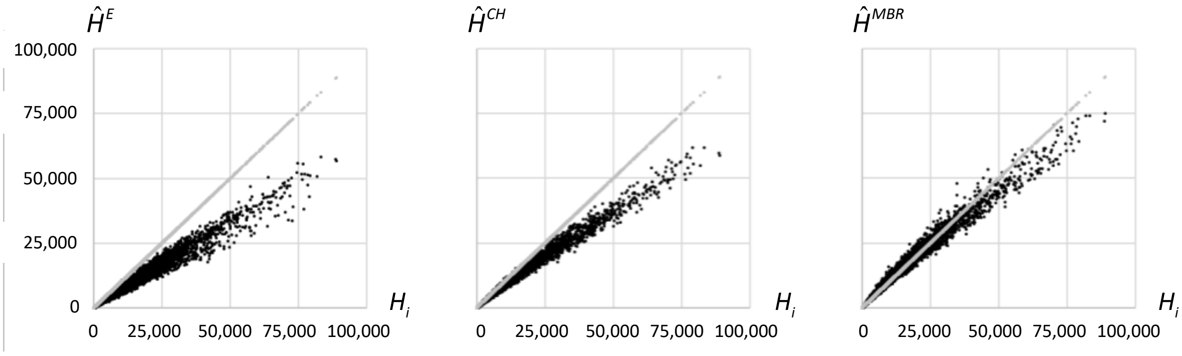


Figure II.D-3. Illustration of simple approximation approaches by a single CNP instance

The low prediction accuracy of the simple approximation approaches is illustrated by the three diagrams in Figure II.D-4. The diagrams show the approximations based on the test data set consisting of 17,640 CNP instances.



a) Optimistic (SA-E)

b) Conservative I (SA-CH))

c) Conservative II (SA-MBR)

Figure II.D-4. Predictions by simple approximation approaches

The diagrams of Figure II.D-4 show that the simple approximation methods are not suitable for an accurate decision on the batch feasibility: SA-E and SA-CH most likely will underestimate the height and lead to infeasible batches, whereas the accuracy of SA-MBR decreases with increasing height. Further details, substantiating the low prediction accuracy of the simple approximation methods are listed in Table II.D-5 (section 4.3). The lack of accuracy of these methods manifest the need for more accurate techniques e.g., from machine learning.

However, the information provided by the simple approximation methods should or can be used by the RMs. One way for integration is to use them as descriptive features (independent variables). Another way is to use one of them for defining a new response variable ΔH_i by the difference between H_i and $\hat{H}_i^{MBR}$: $\Delta H_i = H_i - \hat{H}_i^{MBR}$ ($\hat{H}_i^{MBR}$ is used because it achieved the lowest RMSE of all simple approximation approaches). In this case, the RM is no longer predicting the height but the difference $\hat{\Delta}_i^{f^p}$ to $\hat{H}_i^{MBR}$. Based on this labeling strategy, the following RMSE definition is to be used during training and hyper-parameter tuning:

$$\text{RMSE}(T, f^P) = \sqrt{\frac{1}{|T|}\sum_{i \in T}(\hat{\Delta}_i^{f^p} - \Delta H_i)^2} \tag{5}$$

Note that a height value can easily be derived by $\hat{H}_i^{f^p} = \hat{H}_i^{MBR} + \hat{\Delta}_i^{f^p}$.

3 The prediction framework

For the approximate anticipation, we propose the following framework to identify and apply the most suitable RM for the strip height prediction. Figure II.D-5 illustrates the framework's main components, the flow of information and data, and highlights the relationship between the top-level and the base-level decisions.

To determine the most suitable RM ($\hat{f}^{BEST}$), CNP instances are required for training and validation. These instances, provided by the "Data acquisition" component, can be either acquired "real-world" instances or generated instances that optimally represent "real-world" instances (the latter aspect is described in detail in section 3.1).

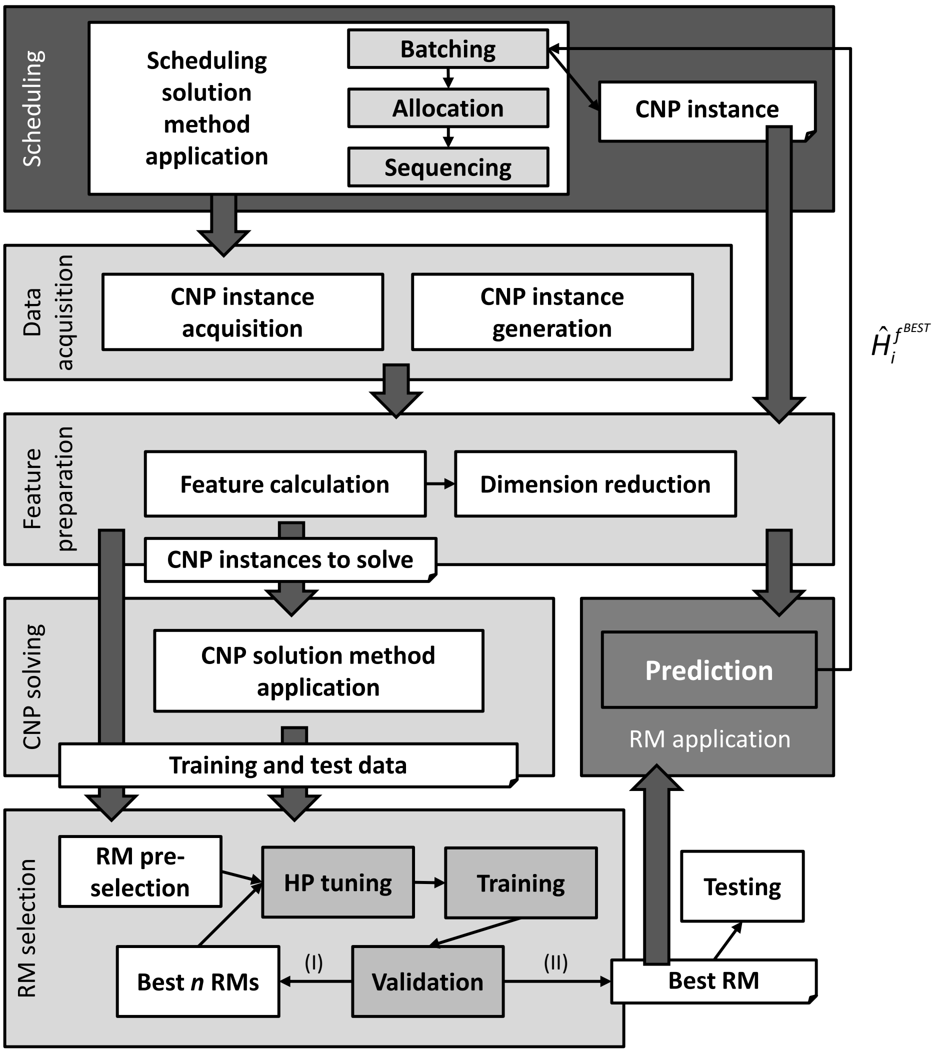


Figure II.D-5. Prediction framework

The component "Feature preparation" is responsible for calculating the descriptive features of the CNP instances (cf., section 3.2.1) which in turn are the base of the following "Dimension reduction" (cf., 3.2.2). Note that these two steps must also be performed when applying $\hat{f}^{BEST}$ for the prediction of the height and therefore, should be very efficient.

For CNP instances that are not yet solved, it is important to calculate the actual heights with the same CNP solution method with which the "real-world" instances are solved. If the solution method changes, all available instances must be solved again by this solution method. This is part of the component "CNP solving". The resulting set of instances with features and labels (height H_i) are then split to training and test data sets.

The component "RM selection" uses these data sets for the RM pre-selection, hyper-parameter tuning (HP tuning), training, validation, and testing (cf., 3.4). Thereby, we recommend to use two cycles of hyper-parameter tuning, training, and validation: In the first phase (I), all generally applicable RMs (cf., section 1.3) are evaluated by means of their RMSE. To reduce computational efforts, this evaluation is based on the half of the training data and a limited set of hyper-parameter settings. In the second phase (II), a selection of the *n* most promising RMs is investigated with a greater set of hyper-parameter settings and the complete training data set. In this way, the complete potential of each promising RM can be exploited and the best RM is identified and trained in an efficient manner.

Component "RM application" contains the final application of the most suitable prediction method, i.e., the RM with the lowest expected loss after phase II.

3.1 Data acquisition and CNP instance generation

If there is no sufficient number of real-world CNP instances for training, validation, and testing of RMs available (not sufficient means that the number of samples is too small and thus, sampling noise is induced), instances can be generated (e.g., also proposed by Feng et al., 2003). To avoid sampling biases, these instances must be representative for the complete, diverse instance space of real-world instances. Therefore, we basically rely on the procedures and aspects discussed by Wang and Valenzela (2001), Wäscher et al. (2007), Silva et al. (2014), López-Camacho et al. (2014) and Neuenfeldt Júnior et al. (2019) for generating instances. In addition, we particularly follow the advice of Smith-Miles and Bowly (2015) to generate instances by controllable characteristics (attributes) to achieve a high instance dissimilarity and method discrimination (instances should elicit different behaviors; cf., Smith-Miles et al., 2014). Note that the following instance generation procedure could be applied or easily adapted to any type of (complex) cutting and packing problems.

Because the quality of the training data is substantial for applying machine learning techniques, we put great emphasize on the instance generation procedure and its description.

3.1.1 Basic item shapes

In contrast to the generation of shapes for regular, rectangular, or (simple) irregular packing and cutting problems, the shapes of CNPs have a high degree of freedom and a completely automated generation of shapes would likely lead to unrealistic shapes and consequently, to unrealistic problem instances. To address this problem, we create shapes based on technical drawings from a sheet metal manufacturer operating several laser cutting machines (cf., Figure II.D-10 in Appendix A-1). In doing so, we take care that the generated instances represent the diversity of real-world shapes. Accordingly, the instances base on 50 elementary item shapes with three basic types $BT \in \{CV, CA, CX\}$: 10 shapes are convex (*CV*; regular and irregular), 20 shapes are concave (*CA*), and 20 shapes are complex (*CX*). These elementary shapes are then used to derive a comprehensive set of diverse item shapes by scaling according to the attributes item widths *IW* and item height *IH* (Figure II.D-6 illustrates the scaling for the shape depicted in Figure II.D-2).

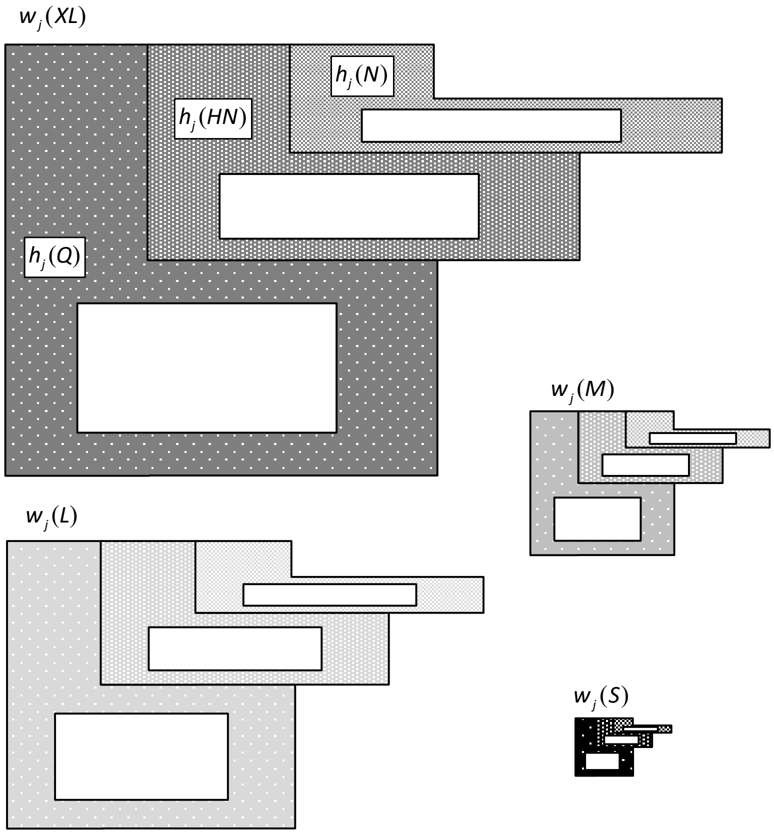


Figure II.D-6. Illustration of the shape scaling mechanism

Based on the item width attribute specified by $IW \in \{S, M, L, XL\}$, the width of an item's MBR is drawn from a uniform distribution with restrictions related to the reference strip width $W^R = 1{,}000$ scaled by parameter ζ: $w_j(IW) \sim U(0.9 \cdot \zeta \cdot W^R, 1.1 \cdot \zeta \cdot W^R)$ with $\zeta = 0.1$, $\zeta = 0.25$, $\zeta = 0.5$, and $\zeta = 0.75$ for *S*, *M*, *L*, and *XL*, respectively.

To reflect the approach of quadratic and narrow items proposed by several authors (cf., e.g., Terashima-Marín et al., 2010 or Silva et al., 2014), we use quadratic, half-narrow, and narrow items. Accordingly, the item height attribute $IH \in \{Q, HN, N\}$ defines how heights are drawn from uniform distributions with restrictions related to the item's width w_j scaled by parameter ψ: $h_j(IH) \sim U(0.9 \cdot \psi \cdot w_j, 1.1 \cdot \psi \cdot w_j)$ with $\psi = 1.0$, $\psi = 0.5$, and $\psi = 0.25$ for *Q*, *HN*, and *N*, respectively.

For each of the 12 combinations of width and height attribute, we derive ten MBRs by drawing w_j and h_j ten times. Then, we scale each of the 50 elementary shapes to fit in the 120 MBRs. This leads to a shape repository of 6,000 different shapes that are separated into 36 categories according to their attributes type $BT \in \{CV, CA, CX\}$, width $IW \in \{S, M, L, XL\}$, and height $IH \in \{Q, HN, N\}$: e.g., the category (*CV*, *S*, *Q*) contains 100 basic shapes or the category (*CA*, *L*, *HN*) contains 200 basic shapes.

3.1.2 Instance attributes and classes

All generated instances are categorized by classes based on several attributes (generation parameters). First attribute of a generated instance I_i is the width W_i of the strip. Here, we use the attributes $OW \in \{SW, MW, LW\}$ with the corresponding widths of $W_i(SW) = 1000$, $W_i(MW) = 2000$, and $W_i(LW) = 4000$. Together with the number of items n and the item related parameters explained in the following, the strip width determines if the strip (or nesting) aspect ratio is basically rather "quadratic" or "narrow" (on the importance of the strip aspect ratio cf., e.g., Neuenfeldt Júnior et al., 2019). Item related attributes used in our generation procedure described in the following section are item type assortment (ITA), item type heterogeneity (ITH), item width assortment (IWA), and item height assortment (IHA).

Before describing these attributes in detail, we introduce the mechanism of "random attribute selection with shuffling" that is used later on (cf., section 3.1.3). As pointed out by Silva et al. (2014), beta distributions with probability density function $f(x, \alpha, \beta)$ should be preferred for instance generation because of their flexibility to model different probabilities depending on the parameters α and β. Since we are going to use beta distributions for selecting specific instance attributes from discrete sets and too similar beta distributions would result in too similar instances (contradicting the request for diverse instances), we propose to use a set *B* of 81 beta distributions based on all combinations of α and β values from set $\{1.0, 1.5, 2.0, 2.5, ..., 5.0\}$. The resulting density functions are illustrated in Figure II.D-7. Then, we randomly select one beta distribution from this set. The drawn distribution is marked by $beta^R$. As the evaluation of the resulting attribute selection by these distributions has shown small undesired accumulations due to the law of large numbers (cf., graphs a) and c) of Figure II.D-11 in Appendix A-2), we enhance the attribute selection by a "shuffling" mechanism, i.e., the assignment of attributes to selection intervals (cf., Figure II.D-7) is randomized. A randomly determined assignment of an attribute to a selection interval is called $\mathrm{attPerm}$ in the following. The positive effect of this mechanism is illustrated by the graphs b) and d) in Figure II.D-11 in Appendix A-2. Summarizing, the "random attribute selection with shuffling - RBetaS" mechanism has two randomly defined parameters: beta^{R} and $\mathrm{attPerm}$.

The parameter item type assortment ITA defines the composition of different items with regard to the elementary shape types convex (*CV*), concave (*CA*), and complex (*CX*): $\mathrm{ITA} \in$ {*CV*, *CA*, *CX*, *CV+CA*, *CV+CX*, *CA+CX*, *CV+CA+CX*}. If more than one type is specified, the selection is done by RBetaS.

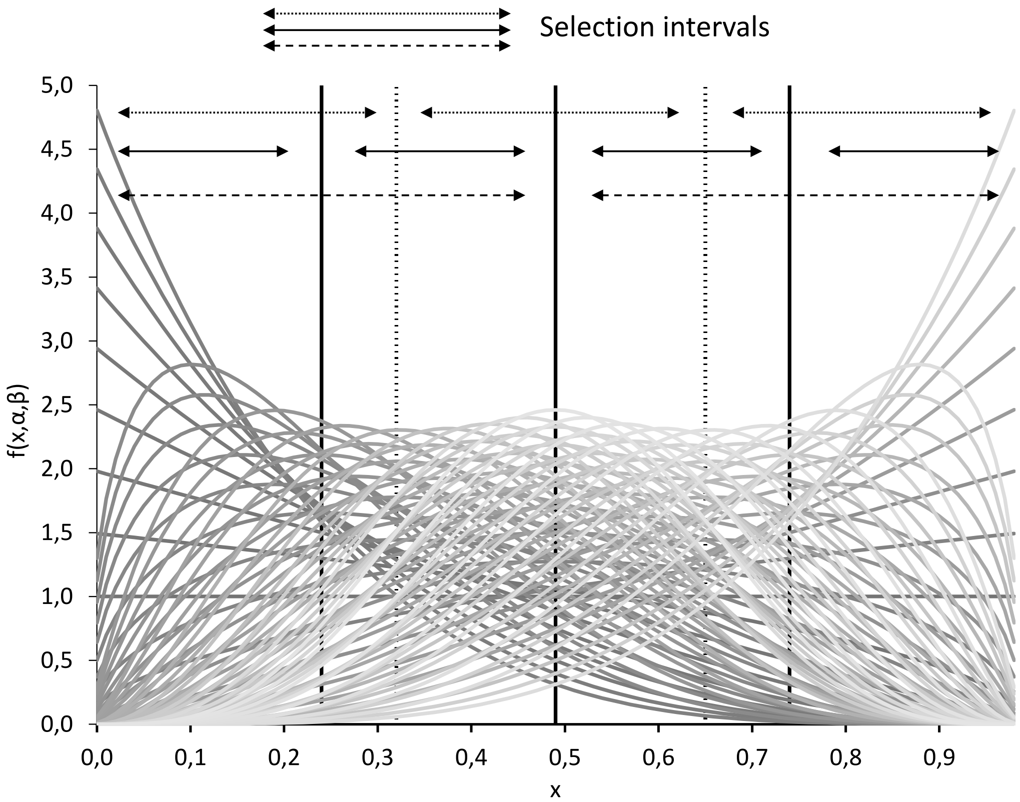


Figure II.D-7. Visualization of selectable beta distributions

To further improve instance dissimilarity, we use the parameter item type heterogeneity $\mathrm{ITH} \in \{\mathrm{WH}, \mathrm{SH}\}$ and only consider randomly defined subsets of all elementary shapes (specified by the other parameters) for selection. Thereby, for *WH* ("weakly heterogeneous") and *SH* ("strongly heterogeneous"), the number of elementary shapes in the subsets is drawn from a discrete uniform distribution restricted by $[0.2 \cdot \upsilon \cdot n_{est}, 0.4 \cdot \upsilon \cdot n_{est}]$ with $\upsilon = 1$ and $\upsilon = 2$, respectively. Here, n_{est} depicts the total number of elementary shapes per type (e.g., $n_{est} = 10$ for convex shapes).

The parameter item width assortment IWA defines the composition of items with different widths according to $\mathrm{IW} \in$ {*S, M, L, XL*}: $\mathrm{IWA} \in$ {*S+M, M+L, L+XL, S+M+L, M+L+XL, S+M+L+XL*}. If more than one type is specified, the selection is done by RBetaS.

The item height assortment parameter IHA defines the composition of items with different heights according to $\mathrm{IH} \in \{\mathrm{Q}, \mathrm{HN}, \mathrm{N}\}$: $\mathrm{IHA} \in \{Q, HN, N, Q{+}HN, Q{+}N, HN{+}N, Q{+}HN{+}N\}$. If more than one type is specified, the selection is done by RBetaS.

According to the attributes *OW*, ITA, ITH, IWA, and IHA, a total number of 1,764 instance classes are available. Each class can be specified by a tuple like (*SW, CV+CX*, *WH, M+L+XL, Q+HN*). Regarding the aspect of weakly and strongly heterogenous items (cf., Wäscher et al., 2007), we classify all instances with item type heterogeneity *WH* and an item width assortment from the subset {*S+M, M+L, L+XL*} to be weakly heterogenous and all others to be strongly heterogenous.

3.1.3 Generation Procedure

The following pseudo-code illustrates the main course of action of the instance generation procedure:

createInstances($\mathrm{N_c}$:= number of instances per class, $\mathrm{lb^n}$, $\mathrm{ub^n}$, *shapeRepository*[ ])

```
For each OW ∈ {SW, MW, LW}
    For each ITA ∈ {CV, CA, CX, CV+CA, CV+CX, CA+CX, CV+CA+CX}
    For each ITH ∈ {WH, SH}
        For each IWA ∈ { S+M, M+L, L+XL, S+M+L, M+L+XL, S+M+L+XL}
            For each IHA ∈ {Q, HN, N, Q+HN, Q+N, HN+N, Q+HN+N}
                For i = 1 to N_c
                    beta^R_ITA := ~U(B); beta^R_IWA := ~U(B); beta^R_IHA := ~U(B);
                    attPerm_ITA := getPerm(ITA);
                    attPerm_IWA := getPerm(IWA);
                    attPerm_IHA := getPerm(IHA);
                    S[ ] := getShapeSubsets (shapeRepository[ ], ITA, ITH, IWA, IHA)
                    n := ~U(lb^n, ub^n)
                    For j = 1 to n
                        basicType_j := getTypeAttribute (beta^R_ITA, attPerm_ITA, ITA); // e.g., CX
                        w_j := getWidthAttribute (beta^R_IWA, attPerm_IWA, IWA); // e.g., L
                        h_j := getHeightAttribute (beta^R_IHA, attPerm_IHA, IHA); // e.g., IH
                        item := selectItemFromSubset (S[ ], basicType_j, w_j, h_j)
                        addItemToInstance (item);
                    Next
    ...
Next
```

Based on this procedure, we generate 50 instances ($N_c = 50$) for each of the 1,764 instance classes, leading to 88,200 CNP instances in total. The lower bound of the number of items per instance ($lb^n = 50$) is derived by the number of items used by instances from literature, whereas the upper bound ($ub^n = 150$) is justified by the application case.

3.2 Feature preparation

The descriptive features used by the RMs are based on aggregated item (shape) properties and further instance related characteristics. Thereby, we use properties and concepts known from literature and new ones, particularly developed to characterize CNPs. Feature selection and combination are part of the feature engineering that has an important influence on the prediction performance of RMs (e.g., on the one hand, too less features can lead to underfitting but, on the other hand, irrelevant features can lead to overfitting; these aspects will be discussed in more detail in section 3.2.2).

Instead of numerically descriptive features used by our RMs, it would be generally possible to use the information how many items with a specific shape are part of an CNP instance: e.g., the instance contains eight items with shape A, 34 items with shape B, 12 items with shape C, and so on. This kind of feature preparation could be very fruitful if item shapes are not varying but constant because using this kind of features, other prediction methods, like bag-of-words models as used in Naive Bayes spam filtering, could be used. Unfortunately, the number of different shapes is anything but constant in most companies and particularly in most sheet metal manufacturing companies. In this case, whenever a new shape has to be cut or packed, new instances for training, validation, and testing would have to be available or generated. As this is not an adequate approach for real-world applications, we use descriptive numerical features as these provide a higher degree of flexibility (regarding new item shapes).

3.2.1 Feature calculation

Besides the basic properties described in section 2.1, further item properties are used to define the descriptive features θ_i of a CNP instance *i*. Some of these properties are obvious, some of them are derived from literature (Wang and Valenzela, 2001, López-Camacho et al., 2013b, López-Camacho et al., 2014, and Neuenfeldt Júnior et al., 2018), and some are newly defined to particularly express highly irregular shapes. The complete set of 43 item properties is listed in Table II.D-7 in Appendix A-3. Based on these item properties, we use the functions *SUM*, *MED* (median), *MIN*, *MAX*, *VAR* (variance), *Q1* (first quartile), *Q3* (third quartile), *P10* (10% percentile), *P90* (90% percentile), and *SKEW* (Fisher-Pearson coefficient of skewness; cf., Zwillinger and Kokoska, 2000) to determine aggregated instance related features. Note that mean values are omitted because they are directly related to *SUM*. In contrast to Neuenfeldt Júnior et al. (2019), we are not using the ratios *Q3/Q1* and *P90/P10* but use the "unrelated" values and leave the combination of both to the RM. Besides these 430 ($43 \cdot 10$) aggregated features (named $\mathrm{SUM}(h_j)$, $\mathrm{MED}(h_j)$ etc. in the following), additional instance related features are listed in Table II.D-1 (features marked by an asterisk * originate from López-Camacho et al., 2013b).

Table II.D-1: Additional instance features

Feature	Description
n	Total number of items
W	Width of the strip
$\hat{H}^{E}$	Predicted height based on the area of the enclosing polygon
$\hat{H}^{CH}$	Predicted height based on the area of the enclosing polygon's convex hull
$\hat{H}^{MBR}$	Predicted height based on the area of the enclosing polygon's MBR
n^{D}	Number of different item categories; two items have a different category if they are not completely identical regarding the combination of the attributes $BT \in \{CV, CA, CX\}$, $IW \in \{S, M, L, XL\}$, and $IH \in \{Q, HN, N\}$.
$MIN^{\#IpC}$	Minimum number of items regarding all item categories
$MAX^{\#IpC}$	Maximum number of items regarding all item categories
$MEAN^{\#IpC}$	Mean of the number of items regarding all item categories
$MED^{\#IpC}$	Median of the number of items regarding all item categories
$VAR^{\#IpC}$	Variance of the number of items regarding all item categories
$SKEW^{\#IpC}$	Skewness of the number of items regarding all item categories
$Q1^{\#IpC}$	First quartile of the number of items regarding all item categories
$Q3^{\#IpC}$	Third quartile of the number of items regarding all item categories
$P10^{\#IpC}$	10% percentile of the number of items regarding all item categories
$P90^{\#IpC}$	90% percentile of the number of items regarding all item categories
n^{LI}	Number of large items ($w_j \geq 0.75 \cdot W$); *
n^{SI}	Number of small items ($w_j \leq 0.25 \cdot W$); *
n^{HR}	Number of items with a high rectangularity ($r_j^E > 0.9$); *
n^{LR}	Number of items with a low rectangularity ($r_j^E \leq 0.5$); *
n^{NCON}	Number of non-convex items (items with $n_j^{XIA} > 0$)
n^{COMP}	Number of complex items (items with $n_j > 1$)

The number of totally 452 features ($43 \cdot 10 + 22$) seems to be quite large and can cause difficulties for some RMs. To that, we use dimension reduction as described in the following section. In addition, we define two sets containing different instance features to evaluate the influence of features on the prediction quality and computational efforts. The first set contains the total number of available instance features (TIF), whereas the second set only contains a reduced number of instance features (RIF). This second set RIF does not contain features having an average-case computation complexity higher than O(n), e.g., O(n log n): *MED*, *Q1*, *Q3, P10, P90*, and *SKEW*. Accordingly, feature set RIF only contains 188 features ($43 \cdot 4 + 16$). Note that because item properties only have to be computed once, their amount influences computation efficiency only minimally.

As many RMs require or perform better on scaled feature values, we use a normalization (min-max scaling) between 0.0 and 1.0 for scaling all features.

3.2.2 Dimension reduction

At first sight, a large number of descriptive features seems to be favorable for characterizing an instance in the best possible way and thus, increase prediction accuracy. This is indeed the case if these features are actually relevant for the prediction. If features are not relevant, the prediction accuracy can get worse. This is because such “noise” features, while increasing the dimensionality, exacerbating the risk of overfitting and adding bias (cf., e.g., James et al., 2013). Even if features are relevant, the variance incurred in determining their coefficients may compensate the benefits that they bring. Furthermore, the increased dimensionality leads to the need for larger data sets due to the curse of dimensionality (cf., e.g., Géron, 2019). To handle the tradeoff between benefits and drawbacks of more or less descriptive features, dimension reduction methods can be very helpful and therefore, are applied and analyzed in detail for the prediction task at hand. Another important aspect to be considered regarding this tradeoff is that dimension reduction can speed up the training of RMs.

One of the most popular dimension reduction methods is the Principal Component Analysis (PCA) belonging to the group of unsupervised machine learning methods. Besides dimension reduction, PCA is used as clustering method (cf., e.g., Anzanello and Fogliatto, 2011), in the context of face recognition and image compression (cf., e.g., Bishop, 2006), and for the visualization and interpretation of high dimensional data (cf., e.g., López-Camacho et al., 2013b). Within the prediction framework, PCA is used to convert a set of features into a set of uncorrelated descriptive variables (called “principal components”) by retaining most of the variance of the original features. Main parameter for the PCA is the number of resulting components. Instead of defining a fixed number, we use the approach to specify a minimum value for the training data set’s variance to be preserved (e.g., PCA(98%); as proposed by Géron, 2019).

Of course, also other dimension reduction methods like “Kernel PCA”, “Locally Linear Embedding”, or “Linear and Quadratic Discriminant Analysis” could be applied.

3.3 CNP solving

Because the RM is used to predict strip heights calculated with one specific CNP solution method, this solution method, that is not only used for solving training instances but also applied on the real CNP instances resulting from the superior scheduling task, must be determined. The CNP solution method used in this contribution is the open source nesting software “deepnest” (https://deepnest.io) that bases on “SVGnest” (https://svgnest.com) which in turn bases on the works of Kendall (2000), Burke et al. (2007), and López-Camacho et al. (2013a). All used sources and libraries are available at github.com. For solving the CNP instances, we used the following parameters: population size = 10, mutation rate = 10, maximum computation time = 180 seconds, optimization ratio = 0, and number of threads = 2.

3.4 RM selection

The determination of the most appropriate RM, its parameters, and hyper-parameters starts with the separation of the available data into training data and test data. Only the training data is used for the next steps of hyper-parameter tuning, model training, and model validation. Final result of these steps is the RM achieving the lowest RMSE with regard to the training data.

3.4.1 Data separation: training and test data

As it is common practice to use at least 20% of the available data for testing, we follow this approach and separate our 88,200 CNP instances into a training data set (T) consisting of 70,560 instances and a test data set (D) of 17,640 instances. Because we use an integrated training and validation method (cf., section 3.4.3), an explicit validation set is not required. To have a greatest possible diversity in the test data set, we randomly select 10 from each of the 1,764 instance classes for the test data set and put the remaining instances into the training data set. This results in a stratified sampling.

3.4.2 RM pre-selection

Because we have only very limited information about previous RM applications related to the prediction task at hand (only Neuenfeldt Júnior et al., 2019 address a similar problem), we have pre-selected a relatively large number of 18 RMs to be evaluated in the first phase of the RM selection process (the pre-selection is based on the different groups of RMs described in section 3): Multiple linear regression (MLR), Ridge regression (RR), Lasso regression (LR), Elastic net (EN), LARS Lasso (LL), Polynomial regression (PR; with the best tuned linear model), Stochastic gradient descent (SGD), K-nearest neighbors regression (KNN), Kernel ridge regression (KRR), Support vector regression (SVR), Decision tree – CART (CART), Bagging regression trees (BRT; uses one of the base estimators PR, SGD, KNN, KRR, SVR, or CART with best hyperparameters), Random forest regressor (RF), Extremely randomized trees (ERT), AdaBoost with R2 (ABR2; uses one of the base estimators PR, SGD, KNN, KRR, SVR, or CART with best hyperparameters), Gradient boosted decision trees (GBDT), Stochastic gradient boosted decision trees (SGBDT), and Neural networks (NN). Because some of the RMs (PR, BRT, and ABR2) base on other RMs, a corresponding sequence of experiments must be respected.

3.4.3 Hyper-parameter tuning, training, and validation

Because hyper-parameter tuning, training, and validation are strongly related to each other, these aspects are explained together.

To determine the best hyper-parameter setting (HP-setting) of a RM, approaches like manual search, grid search, or randomized search are common. In manual search, hyper-parameter values are set manually, in grid search, given value vectors for each hyper-parameter are combined to a full factorial analysis, and in randomized search random combinations of the values given by predefined vectors for each hyper-parameter are used. In all three cases, one RM is iteratively trained and validated to determine the best hyper-parameter setting.

The training and validation of a RM with a specific hyper-parameter setting is performed based on the cross validation technique (cf., e.g., Bishop, 1995 or Goodfellow et al., 2017). This technique is commonly used by learning methods to achieve a good generalization, to compare the performance of several RMs (cf., Wong, 2015), and to estimate prediction errors (cf., Fushiki, 2011). Therefore, for determining the most suitable RM and its parameters, we use grid search and a 5-fold cross-validation with shuffling. Shuffling means that the instances in the training data set are randomly reordered before they are split into the different folds. To reduce computational efforts, we restrict the number of folds to five and do not perform any repetitions as we can assume that our training data set is large enough (35,280 instances in the first phase and 70,560 in the second phase; for discussions about the usefulness of a higher number of folds and repetitions cf., e.g., Bengio and Grandvalet, 2004 or Baets et al., 2012).

The result of the 5-fold cross-validation of a RM is the mean validation RMSE of all five folds. This mean validation RMSE is the major criteria when determining the most suitable RMs in the first phase and the best RM in the second phase. Further criteria are the mean computation times (regarding all folds and the best hyper-parameter setting) and the coefficient of determination (R^2).

3.5 Testing and RM application (prediction)

To evaluate whether a RM generalizes well on new CNP problem instances, we follow the common approach and apply the best RM on the test data set (containing instances the RM has never “seen” before) to determine its expected loss.

The best (most accurate) RM is finally used for the prediction of the strip height, i.e., this trained RM provides a highly efficient anticipation function for the superior scheduling problem to anticipate batch feasibility (and quality).

4 Evaluation

The accuracy of a machine learning technique does not only depend on its basic capabilities (e.g., the possibility to model nonlinear relations) but also on the engineered features, the dimension reduction (parameters), and the labeling strategy. Accordingly, we investigate the influence of the two feature sets RIF and TIF combined with three parameter settings: PCA(98%) combined with the original absolute height label "AbsLab" and the difference label "DiffLab" (as used in equation (5)). A third setting, indicated by "SimApp", uses PCA(90%) and the additional information of the simple height approximations as unscaled features (to compensate the reduced number of principal components) combined with the absolute height label.

The proposed prediction framework is implemented in Python 3.7, instance data, training and test results are persisted in a PostgreSQL database, and statistical analyses are performed by RStudio. For implementing the various regression methods, we use the "scikit-learn" package (Pedregosa et al., 2011) despite for SGBDT and NN. For SGBDT, we use "XGBoost" (xgboost.ai) and for NN, we use "Keras" (keras.io) and "TensorFlow" (www.tensorflow.org). To provide the possibility to reproduce our results, an executable Jupyter-Notebook and the complete set of instance data with instance attributes, features, labels, simple approximations, and the results of our best RM method are provided within the digital supplementary material. Within the supplementary material we also list the evaluated hyper-parameter settings and indicate the best setting of each RM.

All experiments are executed on workstations with Intel Xeon 3GHz CPUs and 64 GB RAM.

4.1 Results of RM selection phase I

In phase I, we evaluate the 18 pre-selected RMs in terms of their mean validation RMSE and with regard to the different settings previously described. Besides the mean validation RMSEs, Table II.D-2 additionally depicts the number of tuned hyper-parameters ("Num. HP") and the number of investigated HP-settings ("Num. HP-settings") for each RM. Note that PR(EN) names Polynomial regression combined with tuned Elastic net, BRT(PR(EN)) names Bagging regression trees with tuned PR(EN), and so on. Unfortunately, not all RMs have been able to produce reasonable results and the return codes have not been meaningful in all cases. Thus, in Table II.D-2, abbreviation OOM indicates "Out-of-Memory" errors and UKE indicate "unknown errors".

The results in Table II.D-2 show that the calculation of all defined instance features (TIF) justifies the additional computational efforts by improved predictions. Particularly when considering the small additional efforts: the RIF instance feature set can be calculated in 0.09 seconds on average and the TIF instance feature set can be calculated in 0.39 seconds on average. However, if computation times are very critical also the RIF set in combination with NN, PCA(98%), and "DiffLab" is an opportunity. The results also show that linear models like MLR or LL are underfitting and thus, are not suitable for the height prediction task. Furthermore, the results clearly indicate the benefit of using the information provided by the simple approximation approaches, especially if $\hat{H}_i^{MBR}$ is used by the "DiffLab" label (cf., equation (5)).

Table II.D-2: RMSEs with regard to RM, feature set, PCA variance, and labeling

RM (Num. HP, Num. HP-settings)	RIF PCA98%-AbsLab	RIF PCA98%-DiffLab	RIF PCA90%-SimApp	TIF PCA98%-AbsLab	TIF PCA98%-DiffLab	TIF PCA90%-SimApp
MLR (0, 1)	6786,6	822,3	788,3	6600,8	750,8	767,5
RR (2, 120)	6786,6	822,3	788,3	6600,7	750,8	767,5
LR (3, 240)	6786,6	822,3	788,3	6600,7	750,8	767,5
EN (4, 2160)	6786,6	822,3	788,3	6600,7	750,8	767,5
LL (2, 120)	6786,6	822,3	788,3	6600,7	750,8	767,5
PR(EN) (5, 1080)	753,1	464,8	443,5	432,3	**389,7**	413,6
SGD (4, 3240)	6818,9	828,2	UKE	6641,8	758,7	UKE
KNN (3, 48)	3550,6	805,8	628,3	4159,0	800,1	628,8
KRR (1-4, 1140)	OOM	OOM	OOM	OOM	OOM	OOM
SVR (3-5, 390)	2447,9	772,0	UKE	OOM	OOM	OOM
CART (5, 256)	2604,1	840,8	727,6	2505,4	826,8	745,5
BRT (PR(EN)) (2, 8)	751,9	462,9	442,8	430,1	**386,4**	410,6
RF (6, 1024)	1684,6	684,1	558,9	1725,4	642,8	550,1
ERT (6, 1024)	1612,8	664,0	541,3	1548,1	609,9	526,8
ABR2 (PR(EN)) (2, 10)	752,2	463,6	442,5	429,8	**386,8**	411,1
GBDT (6, 1536)	1399,8	664,0	553,8	1390,1	577,0	536,8
SGBDT (7, 4608)	1244,0	590,5	550,8	1280,7	552,6	528,3
NN (4, 225)	424,9	389,5	732,4	361,7	**341,7**	725,4

The most promising RMs after this first phase are marked bold in Table II.D-2 and analyzed in detail in Table II.D-3. Besides the RMSE, we report the explained variance (R^2) and the mean computation time ("Mean CT"; mean with regard to the best HP-setting and the five folds including training and validation).

Table II.D-3: Key figures of most promising RMs in phase I (all with TIF, PCA 98%, and "DiffLab")

RM	RMSE	R^2	Mean CT [seconds]
PR(EN)	389.7	0.8813	115.96
BRT(PR(EN))	386.4	0.8833	6,256.07
ABR2(PR(EN))	386.8	0.8831	45,182.49
NN	341.7	0.9088	962.95

Because the solution quality of ABR2(PR(EN)) is similar to that of the other most promising RMs but its mean computation is remarkably higher, we decided to use PR(EN), BRT(PR(EN)), and NN (with TIF, PCA 98%, and "DiffLab") in RM selection phase II.

The results of the RM selection phase I also show the benefit of the proposed prediction framework that emphasizes the evaluation of a broad range of RMs, different feature sets, different labeling strategies, and dimension reduction parameters in order to identify the most suitable ones.

4.2 Results of RM selection phase II

In phase II, we concentrate on the three RMs PR(EN), BRT(PR(EN)), and NN and the two configurations with RIF and TIF combined with PCA(98%) and "DiffLab". Here, we use the complete training data set with 70,560 CNP instances. Table II.D-4 depicts the key figures with regard to RM and feature set, and additionally the percentage changes compared to phase I.

Table II.D-4: Key figures of most promising RMs in phase II (with PCA(98%) and "DiffLab")

RM	RIF			TIF		
	RMSE	R^2	mean CT [seconds]	RMSE	R^2	mean CT [seconds]
PR(EN)	471.58 (1.46%)	0.8383 (0.90%)	42.19 (72.13%)	383.96 (-1.47%)	0.8926 (1.28%)	240.40 (107.31%)
BRT(PR(EN))	470.84 (1.72%)	0.8389 (0.81%)	3,284.89 (149.90%)	383.22 (-0.82%)	0.8930 (1.10%)	17,082.95 (173.06%)
NN	374.96 (-3.73%)	0.8978 (1.88%)	6,135.63 (191.26%)	339.17 (-0.74%)	0.9162 (0.81%)	56,569.90 (5,774.65%)

As we can see by the percentage changes of the mean computation times, computational efforts remarkably increase (particularly for NN) whereas prediction accuracy and explained variance are only slightly improved (despite NN with RIF where we have a larger improvement). Note that remarkably increase of the mean computation time of the NN in phase II can be traced back not only to the larger number of CNP instances in the training set but also to the different best HP-settings: in phase I, we have two hidden layers with 512 and 64 neurons and 200 epochs and in phase II we have two hidden layers with 1024 and 1024 neurons and 500 epochs.

Summarizing the RM selection process, artificial neural networks (with two hidden layers each containing 1024 nodes, a dropout rate of 0.3 for each node in the hidden layers and a L2 weight regularization rate of 0.001 for 500 epochs) are identified to provide the most accurate predictions.

4.3 Testing results

The final testing of the best RM (NN) is used to estimate the overall expected loss of the prediction. The standard test of machine learning techniques to estimate $L(X, f^P)$ bases on the test data set separated from the complete data set before starting training and validation (cf., section 3.4.1). In Table II.D-5, the results of the testing are depicted with regard to the complete test set D and with regard to the different instance classes (in the last four rows, the number in brackets indicates the number of instances).

Table II.D-5. Testing results

f^P		$L(X, f^P)$ SA-E	SA-CH	SA-MBR	NN	R^2 SA-E	SA-CH	SA-MBR	NN
Testing (D)		3,688.03	2,474.07	1,230.48	327.89	0.8286	0.9229	0.9809	0.9986
OW	*SW*	5,918.05	4,062.95	1,931.17	509.31	0.7797	0.8962	0.9765	0.9984
	MW	2,148.95	1,218.10	812.13	217.55	0.8435	0.9497	0.9777	0.9984
	LW	1,078.64	609.66	391.47	125.73	0.8430	0.9498	0.9793	0.9979
ITA	*CV*	3129.45	3129.45	1249.70	275.33	0.8760	0.8760	0.9802	0.9990
	CA	4601.00	1611.84	1146.52	350.19	0.6833	0.9611	0.9803	0.9982
	CX	3149.15	2502.35	1586.27	357.52	0.8932	0.9326	0.9729	0.9986
	CV+CA	3977.66	2424.98	1051.82	303.41	0.7877	0.9211	0.9852	0.9988
	CV+CX	3119.24	2792.69	1251.61	334.86	0.8843	0.9072	0.9814	0.9987
	CA+CX	3949.07	2090.48	1147.13	335.36	0.8030	0.9448	0.9834	0.9986
	CV+CA+CX	3631.07	2478.72	1103.30	331.17	0.8319	0.9217	0.9845	0.9986
ITH	*WH*	3,615.56	2,419.76	1,292.59	356.02	0.8312	0.9244	0.9784	0.9984
	SH	3,759.10	2,527.21	1,165.05	297.11	0.8260	0.9214	0.9833	0.9989
IWA	*S+M*	451.00	270.59	169.20	77.85	0.8356	0.9408	0.9769	0.9951
	M+L	2021.32	1208.99	724.60	225.19	0.8231	0.9367	0.9773	0.9978
	L+XL	6644.81	4589.43	2186.82	506.77	0.7525	0.8819	0.9732	0.9986
	S+M+L	1303.67	752.53	507.64	170.35	0.8440	0.9480	0.9763	0.9973
	M+L+XL	4310.76	2773.85	1415.28	402.00	0.7944	0.9149	0.9778	0.9982
	S+M+L+XL	3589.52	2422.33	1219.77	375.32	0.8140	0.9153	0.9785	0.9980
IHA	*Q*	6352.49	4394.10	2125.28	545.00	0.7792	0.8943	0.9753	0.9984
	HN	2813.26	1737.32	865.29	249.37	0.8066	0.9263	0.9817	0.9985
	N	1108.51	727.32	258.17	133.20	0.7966	0.9124	0.9890	0.9971
	Q+HN	4473.39	2957.50	1504.45	360.63	0.8178	0.9204	0.9794	0.9988
	Q+N	3608.03	2460.09	1232.61	346.02	0.8350	0.9233	0.9807	0.9985
	HN+N	1920.72	1150.45	530.59	182.41	0.8270	0.9379	0.9868	0.9984
	Q+HN+N	2999.24	1967.05	1096.40	304.28	0.8451	0.9334	0.9793	0.9984
50≤ n ≤75 (4547)		2215.57	1429.96	725.22	221.77	0.8221	0.9259	0.9809	0.9982
75< n ≤100 (4396)		3145.23	2032.87	1000.57	289.51	0.8137	0.9222	0.9811	0.9984
100< n ≤125 (4312)		3967.05	2695.10	1331.19	353.93	0.8238	0.9187	0.9802	0.9986
125< n ≤150 (4385)		4922.76	3349.28	1673.09	417.48	0.8208	0.9170	0.9793	0.9987

The results of Table II.D-5 clearly show the remarkable benefit of using NN as anticipation function compared to the simple approximation methods: For any case of instance characteristics, the expected loss achieved with NN is much lower compared to SA-E, SA-CH, and, SA-MBR. However, there are some CNP instance characteristics that make predictions more difficult: e.g., instances with a small strip width (*OW*=*SW*), instances where items with a large or extra-large width constitute the majority of items (*IWA*=*L+XL* or =*M+L+XL*), or instances where items are all more or less quadratic (*IHA*=*Q*).

Furthermore, the results also show that prediction accuracy decreases with increasing number of items.

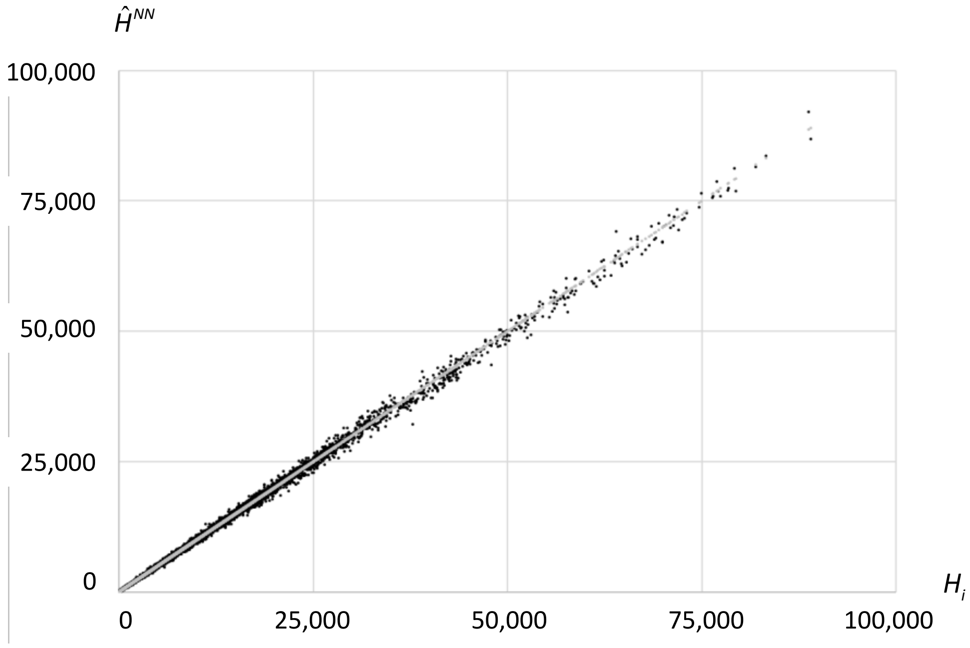


Figure II.D-8. Height predictions by the neural network (test data set)

Summarizing the testing results, the prediction accuracy of the NN is remarkably good (with a mean expected loss – RMSE – of 327.89), particularly when comparing the predictions of the NN illustrated in Figure II.D-8 to the simple approximations methods illustrated by the diagrams in Figure II.D-4 (section 2.2). Note that the mean total response time to predict the height of a CNP instance is sufficiently small: 440.81ms (instance feature calculation: 397.56ms; feature scaling: 0.10ms; PCA computation: 0.09ms; NN prediction: 43.06ms).

Against the background of the hierarchical planning model and the importance of fast anticipation, prediction accuracy could be traded for a lower response time. For that, the RIF features achieve a mean expected loss of 368.46 and a mean total response time of 140.13ms (instance feature calculation: 99.91ms; feature scaling: 0.09ms; PCA computation: 0.09ms; NN prediction: 40.04ms).

5 Conclusions

In this paper, we proposed using machine learning techniques for the approximate anticipation of base-level reactions instead of solving CNPs. Main question yet to be answered is the suitability of our approximate anticipation function to substitute the solving of CNPs. Remember, during solving the superior serial-batch scheduling problem, the predicted height is used to estimate whether or not a created batch is feasible, i.e., a batch is feasible if the predicted height is smaller than the maximum height of any currently available metal slide (H_{max}). In this context, we must be aware of two cases:

false negative feasibility decisions and false positive feasibility decisions (the two other cases, i.e., true positive and true negative, will not cause any problems; cf., Table II.D-6). False negative feasibility decisions mean that the height is overestimated and thus, a batch is declared to be infeasible although it would have been feasible. In this case, we might skip a good, or even the optimum, scheduling solution (i.e., scheduling solution quality is affected). False positive feasibility decisions mean that the height is underestimated and thus, a batch is declared to be feasible although it is infeasible. In this case, the most critical one, not only solution quality but solution feasibility is affected and the scheduling solution might be infeasible.

Table II.D-6. Error type distinction

Overestimation	$H_{max} < \hat{H}_i$	negative	if $H_{max} < H_i$	true negative
			if $H_{max} > H_i$	false negative
Underestimation	$\hat{H}_i < H_{max}$	positive	if $H_{max} < H_i$	false positive
			if $H_{max} > H_i$	true positive

Because we do not have any information about actual available metal slides, we show the benefits of our approach by the following line of arguments. In Figure II.D-9, a histogram depicts 12 classes of relative percentage errors. Thereby, negative errors indicate overestimations and positive errors underestimations. Assuming that false negative decisions are bearable, all overestimations (58.5%) are acceptable. Furthermore, if we can assume that underestimations below or equal 5% only lead to a negligible share of false positive conclusions, in total 93.5% of the overall decisions would be implementable.

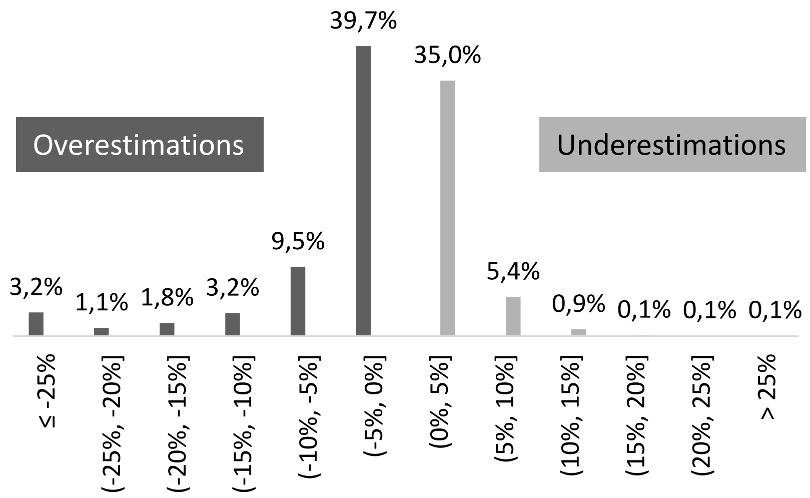


Figure II.D-9. Histogram of relative percentage errors (test data set)

Relaxing this assumption to underestimations below or equal 10%, this value even increases to 98.9%.

6 Summary and outlook

As the conclusions in the previous section show, the approach to use machine learning techniques as approximate anticipation function used to substitute the solving of CNPs is appropriate and suitable. Furthermore, the conclusions underscore the importance of a most accurate height prediction and the testing results, on which the conclusions are based on, demonstrate that the proposed prediction framework is capable to identify, train, and validate the best machine learning technique for the univariate multiple regression task at hand. Regarding the prediction framework, special emphasis has been spent on the completely new data generation procedure and the feature engineering. Potential to further improve prediction accuracy is given for instance by applying deeper neural network architectures or using machine learning stack models. Additionally, providing prediction or confidence intervals quantifying the uncertainty of a prediction would be helpful for the batch feasibility decision. This information could be used to get a better control over false positive conclusions.

Besides the application case sheet metal manufacturing described in section 2, several other areas of application can be found. For example, the emerging area of additive manufacturing constitutes a very similar decision environment: top-level batching and scheduling decisions combined with three-dimensional packing decisions. Here, depending on the additive manufacturing technology, not only the feasibility of a batch is of interest but the processing (build) time of a batch depends on the packing decision (e.g., on the build orientation or on the maximum height of the batch; cf., Griffiths et al., 2019 and Zhang et al., 2020, respectively).

However, the application of machine learning techniques as approximate anticipation function is not restricted to production scheduling but applicable to many other hierarchical decision environments.

7 Appendix

A-1: Elementary item shapes

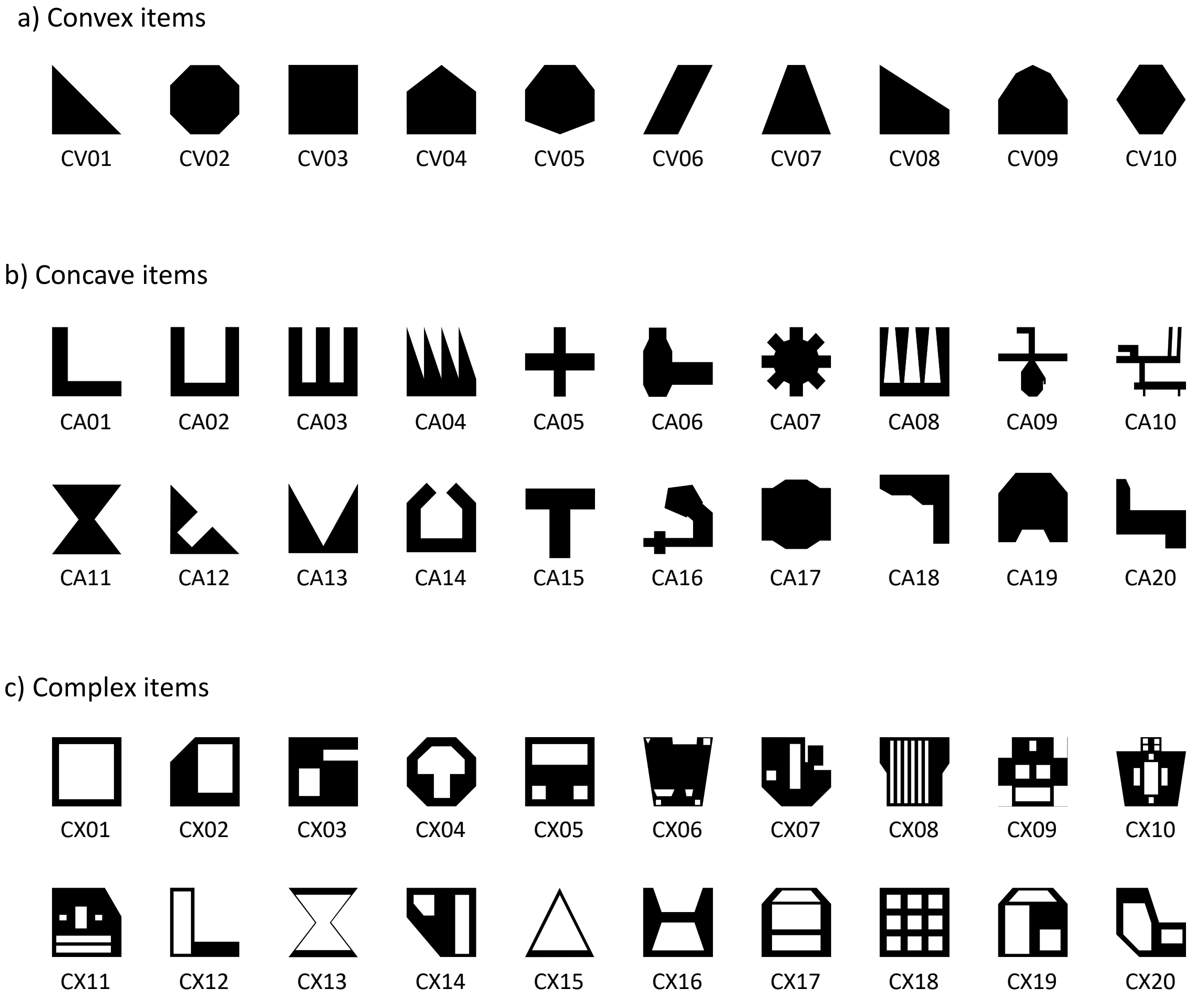


Figure II.D-10. Elementary item shapes (scaled 1:1)

A-2: Visualization of discrete parameter selection

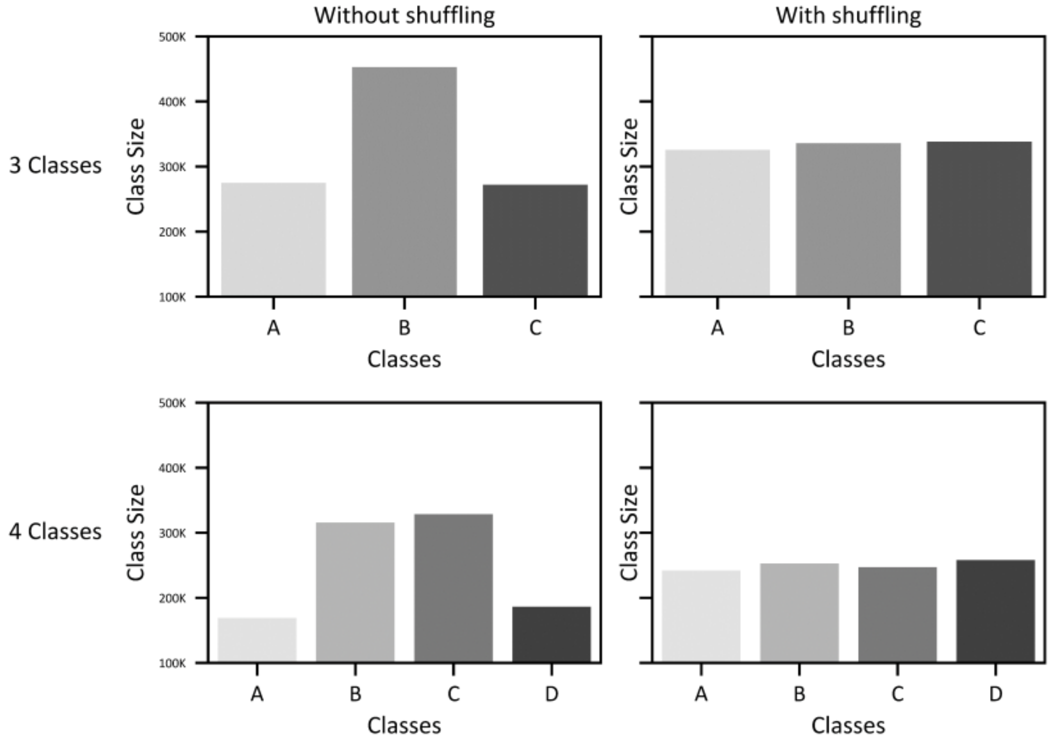


Figure II.D-11: Parameter selection based on the beta distributions without and with shuffling

For the illustration of the shuffling mechanism in Figure II.D-11, a simulation with 1,000 iterations was used. In each iteration, one beta distribution (out of the set of 81) was drawn and based on this beta distribution, 1,000 attributes have been drawn out of three or four classes, respectively. Accordingly, each of the four diagrams in Figure II.D-11 illustrates the distribution of 1,000,000 randomly selected attributes.

A-3: List of item properties

Table II.D-7: Item properties

Property	Description
h_j	Height of the MBR
w_j	Width of the MBR
$r_j^{h,w} = h_j / w_j$	Aspect ratio of the dimensions of the MBR
$r_j^{h} = h_j / d_j$	Ratio between the height and the diagonal of the MBR
$r_j^{w} = w_j / d_j$	Ratio between the width and the diagonal of the MBR
a_j^{E}	Area of the enclosing polygon (including areas of the difference polygons)
a_j^{CH}	Area of the convex hull
a_j^{MBR}	Area of the MBR
$r_j^{D-E} = 1-(a_j^{D} / a_j^{E})$	Filling degree of the shape with $a_j^{D} = \sum_{\rho=2}^{n_j} a_j^{\rho}$ depicting the total area of all difference polygons (a_j^{ρ} depicting the area of a difference polygon ρ ; cf., white area in Figure II.D-2)
$r_j^{O-MBR} = a_j^{O} / a_j^{MBR}$	Filling degree of the MBR with $a_j^{O} = a_j^{E} - a_j^{D}$ depicting the total occupied area
$r_j^{E} = a_j^{E} / a_j^{MBR}$	Elementary rectangularity based on MBR (cf., López-Camacho et al., 2013b; for alternative measures of rectangularity cf., e.g., Rosin, 1999)
$r_j^{CH} = a_j^{CH} / a_j^{MBR}$	Rectangularity of the convex hull
n_j^{E}	Total number of vertices (edges) of the enclosing polygon
l_j^{E}	Total length of the enclosing polygon's edges
$l_j^{MEAN-A,E} = (1/k_E) \cdot \sum_{z=1}^{k_E} l_z$	Mean absolute length of the enclosing polygon's edges
$l_j^{MEAN-R,E} = l_j^{MEAN-A,E} / d_j$	Mean relative length of the enclosing polygon's edges
$l_j^{MED-A,E}$	Median of the absolute lengths of the enclosing polygon's edges
$l_j^{MED-R,E} = l_j^{MED-A,E} / d_j$	Median of the relative lengths of the enclosing polygon's edges
$l_j^{VAR-A,E}$	Variance of the absolute lengths of the enclosing polygon's edges

$l_j^{VAR-R,E} = l_j^{VAR-A,E} / d_j^2$	Variance of the relative lengths of the enclosing polygon's edges
$l_j^{MIN-A,E}$	Minimum absolute length of the enclosing polygon's edges
$l_j^{MIN-R,E} = l_j^{MIN-A,E} / d_j$	Minimum relative length of the enclosing polygon's edges
$l_j^{MAX-A,E}$	Maximum absolute length of the enclosing polygon's edges
$l_j^{MAX,E} = l_j^{MAX-A,E} / d_j$	Maximum relative length of the enclosing polygon's edges
$l_j^C = l_j^E + \sum_{\rho=2}^{n_j} l_j^\rho$	Total cutting length, with l_j^ρ depicting the length of the perimeter of a difference polygon ρ.
n_j^{RIA}	Number of "right" interior angles (between 85° and 95°)
$r_j^{RIA-IA} = n_l^{RIA} / n_j^E$	Relative number of "right" interior angles
n_j^{XIA}	Number of reflex interior angles (angles between 180° and 360°); if $n_j^{XIA} > 0$, the item has an irregular shape
$n_j^{XIA-IA} = n_j^{XIA} / n_j^E$	Relative number of reflex interior angles
n_j	Total number of polygons per item; if $n_j > 1$, the item has a complex shape
c_j^{MAX}	Maximum degree of concavity (cf., López-Camacho et al., 2013b and Wang, 1998)
c_j^{SUM}	Total degree of concavity measured by the sum of concavity of all reflex interior angles (e.g., to reflect star-shaped items)
$d_j^{CE-CMBR}$	Euclidean distance between the centroid of the enclosing polygon c_l^E (defined by the means of the x and y coordinates of all vertices in $\Lambda_{j,E}$) and the centroid of the MBR c_j^{MBR} (cf., Figure II.D-2)
$c_j^{MEAN-A,E} = \mathrm{MEAN}(\delta)$	Mean absolute distance between the enclosing polygon's vertices and centroid c_l^E (with δ depicting the set of all distances between the enclosing polygon's edges and c_l^E)
$c_j^{MEAN-R,E} = c_j^{MEAN-A,E} / d_j$	Mean relative distance between the enclosing polygon's vertices and the centroid c_l^E
$c_j^{MED-A,E} = \mathrm{MED}(\delta)$	Median of absolute centroid distances
$c_j^{MED-R,E} = c_j^{MED-A,E} / d_j$	Median of relative centroid distances
$d_j^{VAR-A,E} = \mathrm{VAR}(\delta)$	Variance of absolute centroid distances
$d_j^{VAR,E} = d_j^{VAR-A,E} / d_j^2$	Variance of relative centroid distances

$c_j^{MIN-A,E} = MIN(\delta)$	Minimum of absolute centroid distances
$c_j^{MIN-R,E} = c_j^{MIN-A,E} / d_j$	Minimum of relative centroid distances
$c_j^{MAX-A,E} = MAX(\delta)$	Maximum of absolute centroid distances
$c_j^{MAX-R,E} = c_j^{MAX-A,E} / d_j$	Maximum of relative centroid distances

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III

Conclusion and research outlook

III.A Added value and findings

This doctoral dissertation advances the research field of ECS design for manufacturing companies with special consideration of the concept of hierarchical planning. In the following section the most important added value and findings are presented.

The added value of Ganschinietz (C1) to the research field is the answer to the first research question RQ1[10] with the concept centric ECS design framework (ECSDF). The ECSDF unifies the understanding of important planning factors crucial for ECS design and forms an easily accessible platform for discussion and collaboration. Furthermore, from a practical perspective, the framework supports the analysis and structuring of individual planning problems and provides a knowledge base for decision makers for identifying relevant design approaches. From a scientific perspective, Ganschinietz (C1) provides the structure for an empirical literature analysis to disclose important research gaps.

Ganschinietz et al. (C2) answer RQ2[11]and extent the ECSDF for the analytical categories “Objective system”, “Solution method”, and “Application case”. They apply the extended ECSDF on findings of a systematic literature search and structure the research field by categorizing 120 scientific articles. Within this categorization process also ECS design approaches with similar assumptions as for manufacturing companies were categorized which shows a more general validity of the ECSDF. Based on the categorized articles the following intensive analysis reveals deficiencies in research concerning ECS design approaches that are flexible regarding the FES supply, AES type, and ECS type. Furthermore, research gaps regarding the operational CU states, CU state transitions, partial load behavior, load transitions, and related conversion efficiencies are pointed out. Concerning the comparability of diverse ECS design approaches, the analysis exposes two problems: First, the lack of suitable benchmark data sets, and second, the broad variety of the used evaluation criteria and underlying time horizons. In addition to the deficiencies in research, there are some points already covered in literature that need to be considered and discussed in more detail: A more thorough explanation of the data used for optimization, the necessity of a more detailed AES demand aggregation level (e.g., minutes instead of hours), and sensitivity to ECS performance degradation over time.

Gahm et al. (C3) add to literature by addressing many of the research gaps identified in Ganschinietz et al. (C2) and by answering RQ3[12], RQ4[13], and RQ5[14]. They develop an AES type independent ECS design approach (RQ3) which proves to be robust to AES demand uncertainties and performance

[10]RQ1: How can the research area of ECS design for manufacturing companies be structured and which planning factors are crucial for an adequate ECS design?
[11]RQ2: Which individual planning problems of ECS design have been addressed thus far or reveal a deficiency in research?
[12]RQ3: How can different complex and individual planning problems of ECS design be addressed to increase energy efficiency?
[13]RQ4: How do the most important planning factors influence ECS design and ECS energy efficiency for manufacturing company?
[14]RQ5: How can the concept of hierarchical planning be incorporated during ECS design?

degradation over time. Gahm et al. (C3) are one of the first in literature who take the relationship of the ECS and the PS into account. This flexible ECS design approach incorporates the concept of hierarchical planning by the anticipation of different base-level production scheduling objectives and aspects of the ECS operation during the design (RQ5). As already stated above, the literature analysis of Ganschinietz et al. (C2) reveals the current lack of suitable benchmark data sets in literature to test and compare different ECS design approaches. Consequently, Gahm et al. (C3) define an experimental setup and describe the generation of the underlying data used for optimization in detail. In line with this setup, they provide generated AES demands from simulative scheduling in the supplementary material. Besides that, Gahm et al. (C3) provide an experimental analysis which investigates the influence of different scheduling objectives, different technical CU parameters, and part-load efficiency modelling approaches on the ECS design and ECS energy efficiency for different company types (RQ4). The analysis shows the advantage of a most accurate modelling of CU partial load behavior combined with nonlinear partial load efficiencies. Compared to linear modelling approaches, FES savings up to 3.5% can be achieved. These savings and the importance of the accurate modelling of partial load behavior can be explained by the high share of partial load operation due to the highly dynamic AES demands in manufacturing companies. Another essential finding is the identification of the CU`s nominal load efficiency, the operational ranges, and the boundary efficiencies as influencing parameters for the ECS design. In addition, the ability of manufacturing companies to directly influence the AES demand per time unit through production scheduling is shown to influence the energy efficiency of an ECS. The final conclusion from the experimental analysis is that, depending on a manufacturing company’s characteristics, an individual combination of a scheduling objective and CU parameters is best suited to maximize energy efficiency.

Gahm et al. (C4) test machine learning techniques as new anticipation functions for the approximation of the base-level reactions, exemplary on a serial-batch scheduling problem with an integrated subordinate complex nesting problem. For the identification and selection of the best approximation method, a prediction framework based on the concept of hierarchical planning is developed. This new approach enables a much more accurate approximation and offers the opportunity to make better scheduling decisions. Against the background of these promising results, they generate insights and lay the foundation to transfer this approach to other hierarchical planning problems. One example is the emerging area of additive manufacturing since it comprises similar decisions to CNP (top-level serial-batch scheduling problem with an integrated subordinate three-dimensional complex nesting problem). And yet, the utilization of machine learning techniques in this context is not limited to production planning but can be transferred to other decision environments. Another added value by Gahm et al. (C4) is the development of a completely new instance generation procedure (of complex item shapes) for CNPs (based on real-world shapes and controllable attributes) and the development of feature vectors to model CNP characteristics. By doing so, they create a much needed benchmark set, and invite future researchers to utilize the defined methods and benchmark set for evaluation and comparison.

III.B Outlook

Besides answering the introduced research questions, this doctoral dissertation discloses opportunities for future research.

Regarding the first contribution (Ganschinietz, C1), the development of the ECSDF is a continuous process, since future applicability of the ECSDF relies on a constant iterative adaption with an evolving research field. Because Ganschinietz et al. (C2) classify ECS design approaches according to the ECSDF that are related to ECS design for manufacturing companies, the ECSDF`s transferability to ECS design in general is conceivable. Nonetheless, this suggestion needs to be tested in future research by applying the ECSDF on ECS design approaches for different application cases (for instance ECSs for households or residential districts). In the case of ECS design, the reactions of the base-level production scheduling and/or the corresponding base-level ECS operation (cf., Figure I.B-4) could be approximated with the techniques investigated in Gahm et al. (C4). These techniques offer the consideration of the additionally needed amount of final energy sources or efficiency losses caused by transitions between CU states and CU loads with an unprecedented approximation accuracy and could enable a further improvement of the overall ECS design and ECS efficiency. The applicability and benefit of using machine learning techniques in this planning context needs to be tested in future research.

Concluding this doctoral dissertation, production processes are accountable for 90% of industrial energy consumption. For this reason, this thesis refines qualitative structuring and quantitative methods for an adequate and energy efficient design of an ECS providing energy for production processes. Besides energy savings achieved by an efficient ECS design, such a design has been identified as one of the most important aspects leading to a cost efficient ECS. Ultimately, this doctoral thesis fosters a simultaneously economic and ecological striving for a cost efficient and environmentally friendly orientation of industry.

III.C References

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