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# A flexible approach for the dimensioning of on-site energy conversion systems for manufacturing companies

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## A B S T R A C T

### Keywords:

Conversion (utility) systems  
Energy efficiency  
Manufacturing  
Nonlinear programming

Besides electricity, many industrial production processes require other energy sources such as steam or pressure. To transform primary or secondary energy sources into the required energy sources, manufacturing companies often operate their own on-site energy conversion system. Most important parameters determining a conversion systems' overall degree of efficiency are the dimension of its conversion units (CUs) and the design point (nominal load) at which a CU operates with maximum efficiency. In addition, conversion efficiencies at part load are particularly important because strongly varying energy demands from production processes frequently forcing an operation different from the nominal load. The (mostly) nonlinear relationship between part load operation and conversion efficiency makes an adequate consideration of this relationship essential.

To address these factors, we present a new conversion system design approach aligned for manufacturing companies. To maximize energy efficiency, we propose a heuristic and a mixed-integer nonlinear program. In the experimental analysis, we analyze different types of companies, several CU parameter settings, the influence of nonlinear and linear efficiency modelling, and the influence of different machine scheduling objectives on the conversion system design. The results show that all these factors can remarkably influence the design and the energy efficiency of a conversion system.

## 1. Introduction

The sustainable development of a society is strongly related to the sustainable development of its manufacturing companies (Jovane et al., 2008; 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, Pastras, Alexopoulos, and Chrysosolouris, 2014), is an effective measure to guarantee a desired production output at a minimum energy demand.

Improving the energy efficiency of manufacturing companies can be achieved by various measures on different decision levels: e.g., in the short-term, by energy-efficient scheduling (cf., e.g., Biel and Glock, 2016) or in the long-term, by the design of energy conversion systems

(cf., e.g., Sun & Liu, 2015). This paper focuses on the long-term decision level with the goal to improve the energy efficiency of manufacturing companies by optimizing the design of on-site operated energy conversion systems (ECSs). To that, we propose a new flexible approach for ECS dimensioning, i.e., for determining the size (maximum capacity) and related parameters of its conversion units (CUs). The most important of these related parameters is the nominal load, i.e., the load at which the CU operates with maximum efficiency (also called design point). This long-term decision is addressed because an appropriate dimensioning can remarkably reduce conversion inefficiencies. To carve out starting points for avoiding inefficiencies, technical characteristics of ECSs and its CUs are particularly analyzed with regard to manufacturing companies where two special aspects must be considered: First, the energy 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 energy demand by scheduling production processes (cf., Gahm, Denz, Dirr, and Tuma, 2016). Our paper makes the following contribution to literature:

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## Nomenclature

AES	Applied energy sources	$K$	Set of machines
$AESD_l$	Energy demand at level $l$	$L$	Number of levels in an energy demand time series
$AESD_t^{PS}$	Cumulated energy demand per time slice originating from the PS	$l$	Indices of energy demand levels
$AESD_t^{CS}$	Energy demand per period $t$ to be fulfilled by the energy conversion system	$l_t$	Last time slice of an aggregation interval
$AESD_t^{FCU}$	Auxiliary integer variable depicting the load of the FCU in period $t$	$lbMaxL^{LCU}$	Lower bound for the maximum load of the LCU
$AESD^{MAX}$	Maximum energy demand of an energy demand time series (PS scenario)	$lbNomL^{FCU}$	Lower bound for the nominal load of the FCU
$AESD_t^{LCU}$	Auxiliary integer variable depicting the load of the LCU in period $t$	$lbTFES^{ANT}$	Lower bound for the total final energy sources used by the Antigone solver
$agg^{PS, CS}$	Time slice aggregation factor	$lbTFES^{APP}$	Approximated lower bound for the total final energy sources
ANT	Solution method based on the MINLP and the Antigone solver	$lbTFES^{SCIP}$	Lower bound for the total final energy sources calculated by the SCIP solver
BECS	Basic ECS-scenario set	LCU	Large scale conversion unit
C	Constant energy demand	LPT	Longest processing time (dispatching rule)
CS-settings	Combination of LCU and FCU parameter settings	LR	Large range energy variability
CU	Conversion unit	$m$	Number of machines
$cAESD_t^{FCU}$	Updated $AESD_t^{FCU}$	M	Production system size: medium
$Cmax$	Maximum completion time, also known as makespan (scheduling objective)	$M$	Sufficiently large number
$\Delta_{MinL}^{FCU}$	Relative difference between the maximum load and the minimum load of an FCU	$MaxL$	Maximum load at which a CU can operate (i.e., its dimension or maximum capacity)
$\Delta_{NomL}^{LCU}$	Relative difference between the maximum load and the nominal load of an LCU	$MaxL^{FCU}$	Continuous variable for the maximum load of the FCU
$\Delta ub_{NomL}^{FCU}$	Relative difference between the maximum load and the upper bound of the nominal load of an FCU	$MaxL^{LCU}$	Continuous variable for the maximum load of the LCU
$\Delta lb_{NomL}^{FCU}$	Relative difference between the minimum load and the lower bound of the nominal load of an FCU	$MinL$	Minimum load at which a CU can operate
$\delta^{PS}$	Duration of a time slice (defines the level of detail of the time series)	$MinL^{FCU}$	Continuous variable for the minimum load of the FCU
$e_{j,p}$	Energy demand of job $j$ at processing time $p$	$MinL^{LCU}$	Continuous variable for the minimum load of the LCU
$e_j^{max}$	Maximum AES demand of job $j$	MINLP	Mixed-integer nonlinear program
$e_j^{min}$	Minimum AES demand of job $j$	MS	Many simple products
ECS-scenario	Combination of a PS-scenario with a CS-setting	$n$	Number of jobs
$\eta_t^{FCU}$	Continuous variable for the part-load efficiency of the FCU in period $t$	$n_l$	Number of data point represented by an energy demand level
$\eta_t^{LCU}$	Continuous variable for the part-load efficiency of the LCU in period $t$	$n^{max}$	Approximate number of jobs
$\eta_{MaxL}$	Conversion efficiency at maximum load; also, per FCU $\eta_{MaxL}^{FCU}$ and LCU $\eta_{MaxL}^{LCU}$	NLM	Nonlinear part-load efficiency model
$\eta_{MinL}$	Conversion efficiency at minimum load; also, per FCU $\eta_{MinL}^{FCU}$ and LCU $\eta_{MinL}^{LCU}$	$NomL$	Nominal load at which a CU operates with maximum efficiency
$\eta_{NomL}$	Conversion efficiency at nominal load; also, per FCU $\eta_{NomL}^{FCU}$ and LCU $\eta_{NomL}^{LCU}$	$NomL^{FCU}$	Continuous variable for the nominal load of the FCU
ECS	Energy conversion system	$NomL^{LCU}$	Continuous variable for the nominal load of the LCU
E	Erratic energy demand	$p$	Indices of processing time
$f_r$	First time slice of aggregation interval $r$	$\tilde{p}$	Assumed mean processing time
FES	Final energy sources	$\bar{p}$	Actual mean processing time
FC	Few complex products	$p_j$	Processing time of job $j$
FCU	Flexible conversion unit	PS	Production system
H	“Hill” energy demand	PS-scenario	Production system scenario: Combination of company type and scheduling objective
$incMaxL^{LCU}$	Incumbent maximum load of the LCU (used by the TEH)	PU	Production unit
$incNomL^{FCU}$	Incumbent nominal load of the FCU (used by the TEH)	PWM	Piecewise linear part-load efficiency model
I	Iterating energy demand	$r$	Indices of an aggregation interval
$j$	Indices of jobs	$relP$	Relative number of periods the LCU must operate at nominal load
$J$	Set of jobs	$s$	Indices of time series
$\kappa$	Maximum relative degradation (parameter of the TEH)	S	Production system size: small
$K$	Indices of machines	$S$	Set of available time series
		$S'$	Incumbent solution (used by the TEH)
		$S^*$	Best known solution (used by the TEH)
		SM	Small range of energy variability
		SPT	Shortest processing time (dispatching rule)
		$g_s^{PS}$	Number of time slices in time series $s$
		$t, t'$	Indices of time
		$\tau^{PS}$	“Target” planning horizon of scheduling instances
		$T$	Number of periods in an energy demand time series (PS scenario)
		TEH	Truncated enumeration heuristic
		TFES	Totally required final energy sources
		TFT	Total flow time (scheduling objective)

$ubMaxL^{LCU}$	Upper bound of the maximum load of the LCU		maximum load and $Y_t^{FCU} = 0$ otherwise
$ubNomL^{FCU}$	Upper bound of the nominal load of the FCU	$Y_t^{LCU}$	Binary variables with $Y_t^{LCU} = 1$ indicating that the load of the LCU in period $t$ is between the nominal load and the maximum load and $Y_t^{LCU} = 0$ otherwise
$X_t$	Binary variable with $X_t = 1$ indicating that the FCU is required and $X_t = 0$ otherwise	$\zeta$	Upper bound offset (parameter of the TEH)
$\nu$	Decrement value (parameter of the TEH)	$z$	Sufficiently small number
$Y_t^{FCU}$	Binary variables with $Y_t^{FCU} = 1$ indicating that the load of the FCU in period $t$ is between the nominal load and the		

- A flexible ECS design approach which is suitable for almost any type of energy and which is not limited to specific CUs. We achieve this flexibility by considering common CU characteristics.
- Regarding CU characteristics, the explicit consideration of 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 energy demands).
- In addition, we consider the hierarchical relationship between the production system (scheduling) and the ECS during the ECS dimensioning by particularly analyzing the influence of production scheduling objectives on the ECS design.
- Finally, a robust ECS design with regard to uncertain future energy demands is ensured by the consideration of energy demand time series containing the data of a complete production year with 240 production days.

Because the proposed design approach is very different to existing approaches, we would also like to gain insights on the solvability of the ECS design problem at hand and thus, aim at calculating optimum solutions. Accordingly, we present a mixed-integer nonlinear program (MINLP) and a tailor-made heuristic to calculate initial solutions used by the MINLP.

From the perspective of a manufacturing company's decision-maker, the results of our ECS design approach (suitable CU dimensions and several basic parameters) can be used to pre-select the most suitable energy type-specific CUs based on CU-producer data. Then, the pre-selected CUs can be used as input for energy type-specific planning approaches (e.g., based on superstructures) from the literature. From the perspective of a CU-producer, our 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.

The structure of the paper 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 ECS design 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 related work

To provide a general understanding of the organizational and technical backgrounds, we first discuss the interdependencies between the energy-demanding production system (PS) and the ECS and then the most important technical characteristics of CUs. After discussing additional aspects, the section closes with a table that compares existing ECS design approaches and highlights the research gap filled by this paper.

### 2.1. On the interdependencies between PS and ECS

In manufacturing companies, different energy sources (carriers) are

used to run production processes executed by the production units (PUs; e.g., machines or chemical reactors) of the production system (PS). Hereby, energy sources that are directly applied by production units are named applied energy sources (AES). For ease of reading, we will generally use the term energy instead of applied energy sources in the following. According to Gahm et al. (2016), a production system's energy demand is either supplied directly by an external energy provider or it is converted and supplied by an internally operated conversion (utility) system. In the latter cases, on-site energy conversion systems consisting of one or more CUs supply the production system with a specific energy (e.g., steam or pressure) by converting other energy sources (e.g., coal, fuel, or electricity). As soon as the ownership of energy sources is transferred to the manufacturing company (the final energy user), energy sources are referred to as final energy sources (FES; Gahm et al. 2016).

The PUs require specific energy sources to fulfil the process tasks defined by the working plans and as soon as the tasks are scheduled on the PUs, the energy demand per time unit can be determined for most production processes. If several PUs demand for the same type of energy, a cumulated energy demand arises. Fig. 1 a) shows a production schedule with task executions on four PUs. In this Gantt-chart, tasks with a light grey background indicate an energy demand of one unit, whereas tasks with a dark grey background indicate an energy demand of two units. According to these energy demands, the production schedule leads to the cumulated energy demands depicted in Fig. 1 b). In spite of the illustrated interdependency between the PS and the ECS, this interdependency has currently only been considered by energy-efficient scheduling approaches (e.g., by Moon & Park, 2014; Rager, Gahm, & Denz, 2015; Schulz, Neufeld, & Buscher, 2019, or Liu et al., 2020) and ECS operation planning approaches (e.g., by Mignon & Hermia, 1996; Agha, Théry, Hetreux, Haït, & Le Lann, 2010; Zhang, Luo, Chen, & Chen, 2013, or Zulkafli & Kopanos, 2017). To the best of our knowledge, only Denz (2015) considers this relationship in terms of ECS design.

Almost all 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 (cf. Table 1). Such approaches are sufficient for ECS designs related to district heating, building supply, or power generation for grids, but should be adapted in the case of ECS design for manufacturing companies.

The relationship between the long-term design and the short-term operation of ECS is a central aspect for ECS design because the long-term ECS design sets the constraints on the attainable efficiency in the short-term (e.g., Gamou, Yokoyama, & Ito, 2002 or Wakui & Yokoyama, 2014). 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., Forough & Roshandel, 2018 or Alirahmi, Dabbagh, Ahmadi, & Wongwises, 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., Benam, Madani, Alavi, & Ehsan, 2015 or Amusat et al., 2017). Most design approaches consider ECS operation by integrating some operational characteristics and thus, anticipate an ECS's

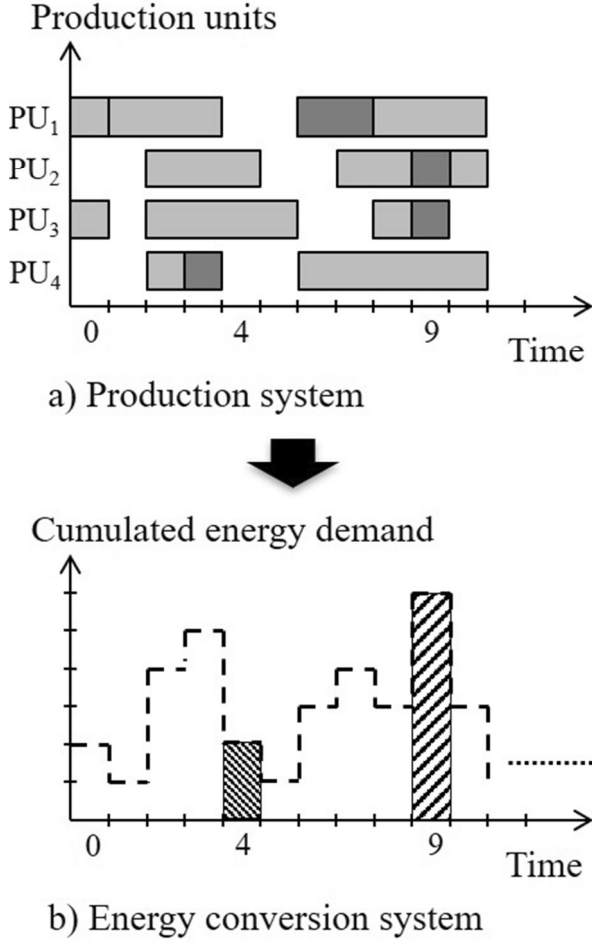


Fig. 1. Interdependencies between PS and the cumulated energy demand to be supplied by the ECS.

operational behavior. Hereby, the ECS operation can be integrated passively, i.e., conversion operations are derived based on design decisions (e.g., by control strategies; cf. Ghadimi et al., 2014 or Andiappan & Ng, 2016) or can be integrated actively, i.e., operation decisions are actively made (e.g., Aguilar et al., 2008 or Gibson et al., 2013).

## 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 characteristics of the conversion units. One of the most important technical CU characteristics is the energy conversion efficiency. 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 part load (cf., e.g., Th  ry, Hetreux, Agha, Ha  t, & Le Lann, 2012 or Darrow, Tidball, Wang, & Hampson, 2017). In principle, literature agrees (for most types of CUs) that conversion efficiencies are lower at part load and that the more the load deviates from the nominal load, the lower the conversion efficiency (cf., e.g., Voll, Lampe, Wrobel, & Bardow, 2012 or Li, Mu, Li, & Ma, 2016). This effect of efficiency loss is particularly relevant for ECSs at manufacturing sites. Because of their varying energy demands, these ECSs will operate at part load for most of the time (e.g., Varbanov, Doyle, & Smith, 2004). The dependency between part-load operation and conversion efficiency is illustrated in Fig. 2 (section 3.1). Although literature in principle 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., e.g., Azit and Nor, 2009 or Arcuri, Beraldi, Florio, and Fragiaco, 2015), the efficiency modelling is very heterogeneous. Some authors even consider constant efficiencies (e.g., Andiappan & Ng, 2016) or discrete efficiencies (e.g., Gibson et al., 2013). Other authors like Arcuri et al. (2015) or 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 the complexity, some authors use piecewise linear approximations (e.g., Voll, Klaffke, Hennen, & Bardow, 2013 or Destro, Benato, Stoppato, & Mirandola, 2016). Furthermore, authors use linear approximations and claim that the errors are neglectable. For instance Aguilar, Perry, Kim, and Smith (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, p. 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 and its 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. To fill this research gap, we perform a comparative analysis by comparing nonlinear part-load efficiency modelling with linear part-load efficiency modelling.

Another aspect related to part-load operation is load transition, i.e., the switching from one load to another. Along with load transitions, two facts must be considered: CUs are not able to execute arbitrarily large load transitions within short time and load transitions always cause efficiency losses (cf., Rager et al., 2015). To handle the former issue, load ramp-ups or ramp-downs can be restricted by so-called ramping constraints or minimum equal load durations are specified. Such constraints are rarely used by ECS design approaches (cf., Pruitt, Braun, & Newman, 2013) but more frequently in the context of ECS operation (e.g., Carrion and Arroyo, 2006 or Mitra et al., 2013). Due to the complexity of the interdependencies between basic conversion processes, CU characteristics, and transition parameters (e.g., start load, direction, and magnitude), efficiency losses due to load transitions are difficult to measure at all and very challenging to consider during ECS design.

## 2.3. Further aspects

Another aspect in literature is the development of robust ECS design approaches tackling uncertainties such as variations in energy demand (e.g., Yokoyama, Fujiwara, Ohkura, & Wakui, 2014), varying prices (e.g., Gibson et al., 2013), or equipment failures (e.g., Andiappan & 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). Stochastic modelling is seldom used (e.g., Benam et al., 2015). To achieve a robust ECS design with regard to variations in energy demand, we generally follow the scenario-based approach but do not optimize the ECS design for several scenarios individually and then derive a most suitable ECS design, but we integrate the demand scenarios of one year with 240 production days into one energy demand time series and calculate the optimal ECS design for all the integrated scenarios simultaneously.

Many ECS design approaches in the literature are related to specific types of ECSs (cf., Table 1), mostly cogeneration systems typically combining heat and power (e.g., Ghadimi et al., 2014 or Kazi, Mohammed, AlNouss, and Eljack, 2015) and trigeneration systems typically combining cooling, heat, and power (e.g., Kavvadias & Maroulis, 2010 or Wang, Jing, & Zhang, 2010). These approaches have been developed for specific environments but lack some generality and flexibility as any of these approaches formulate a selection decision based on

**Table 1**  
Literature analysis.

	Hierarchical integration			Part load consideration			Conversion efficiency modelling					Consi deration		Uncertainty			Basic ECS type			Solution methods			
	PS consi dera tion	ECS operation Top-down with feed back	Antici pation (passive)	Antici pation (active)	Dis crete nuous specified	Con stant	Dis crete	Linear wise linear	Piece wise linear	Non linear sitions	of load tran sitions	Dynamic energy demand	Uncer tain energy de mand	Uncer tain prices	Equip ment failures	Single gene ration	Cogene ration	Tri- and Polyge neration	Flexi ble integer pro gram	Mixed-integer solution (e.g., B&B)	Exact integer solution methods (e.g., Heu ristics)	Meta heuris (e.g., simu lation)	Other
Kazi et al. (2015)			X			X										X							X
Andiappan and Ng (2016)		X													X		X						X
Emadi and Mahmoudi mehr (2019)		X															X						X
Wang et al. (2010)			X									X											X
Carvalho et al. (2014)				X								X							X				X
Maleki, Khajeh, and Ameri (2016)			X									X		X		X							X
Amusat et al. (2017)		X										X		X			X						X
Gannou et al. (2002)			X			X						X		X						X			
Chicco and Mancarella (2007)			X									X											X
Carpaneto, Chicco, Mancarella, and Russo (2011a)			X									X		X		X							X
Chicco, Mancarella, and Russo (2011b)																							
Benam et al. (2015)		X										X		X						X			
Sun and Liu (2015)				X								X		X		X							X
Forough and Roshandel (2018)		X										X				X							X

(continued on next page)

Table 1 (continued)

	Hierarchical integration			Part load consideration			Conversion efficiency modelling					Consi- deration of load tran- sitions	Uncertainty			Basic ECS type			Solution methods										
	PS	ECS operation		Antici- pation (passive)	Antici- pation (active)	Dis- crete	Conti- nous	Not further specified	Con- stant	Dis- crete	Linear- wise		Piece- wise linear	Non- linear sitios	Dynamic energy demand	Uncer- tain energy de- mand	Uncer- tain prices	Equip- ment failures	Single gene- ration	Cogene- ration	Tri- and Polyge- neration	Flexi- ble	Mixed- integer pro- gram	Mixed- integer non- linear (e.g., B&B)	Exact solution methods (e.g., B&B)	Heu- ristics	Meta heuris- tics	Other simu- lation	
		Top- down	Top- down with feed back																										
Gibson et al. (2013)			X		X				X					X		X				X									X
Aguilar et al. (2008)						X				X				X		X		X				X							
Yokoyama et al. (2014)			X					X						X		X					X								
Yokoyama, Shinano, Taniguchi, Ohkura, and Wakui (2015)			X					X						X								X							X
Rad, Khoshgofar Manesh, Rosen, Amidpour, and Hamedei (2016)										X								X		X							X	X	X
Voll et al. (2013)						X				X				X							X								X
Ghadimi et al. (2014)			X					X					X			X					X					X			
Frangopoulos (2004)			X					X						X				X			X							X	
Sanaye, Meybodi, and Shokrollahi (2008)			X					X						X					X								X		
Azit and Nor (2009)			X					X						X							X					X			
Kavvadias and Maroulis (2010)						X				X				X						X								X	
Voll et al. (2012)						X				X				X		X				X								X	
Arcuri et al. (2015)			X					X						X		X										X			
Li et al. (2016)			X			X		X		X			X		X		X			X					X				
This paper			X			X		X		X			X		X		X			X					X				X

specific CUs with given characteristics or superstructures (e.g., Shiun, Hashim, Manan, & Alwi, 2012 or Carvalho, Romero, Shields, & Millar, 2014). Only a few approaches are independent regarding the type of energy and provide some flexibility (e.g., Voll et al., 2012).

#### 2.4. Summary

To summarize the current state of literature tackling similar planning problems like the one addressed in this contribution, we analyzed the literature according to all the aspects previously discussed and additionally regarding applied solution methods. Table 1 depicts this analysis.

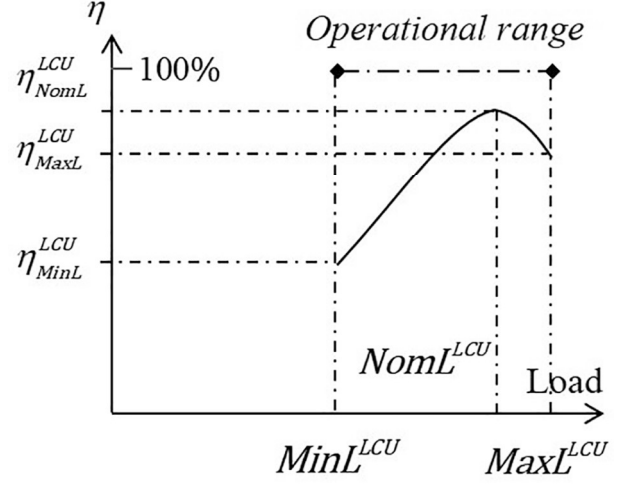
Based on the analysis of planning backgrounds and most relevant literature (cf., Table 1), we conclude that—to the best of our knowledge—there exists no flexible and robust ECS dimensioning approach addressing the specific needs of manufacturing companies, i.e., that considers the (hierarchical) interdependencies between the ECS design, the ECS operation, and the PS. In our approach, we particularly account for the highly varying energy demands of manufacturing companies by directly integrating part-load operations combined with nonlinear part-load efficiencies. In addition, we account for load transitions by their approximate anticipation within the data preparation phase. Furthermore, there exists no contribution that considers nonlinear part-load efficiencies and formulates a nonlinear model to be optimized by a standard solver.

### 3. A new flexible approach for ECS dimensioning

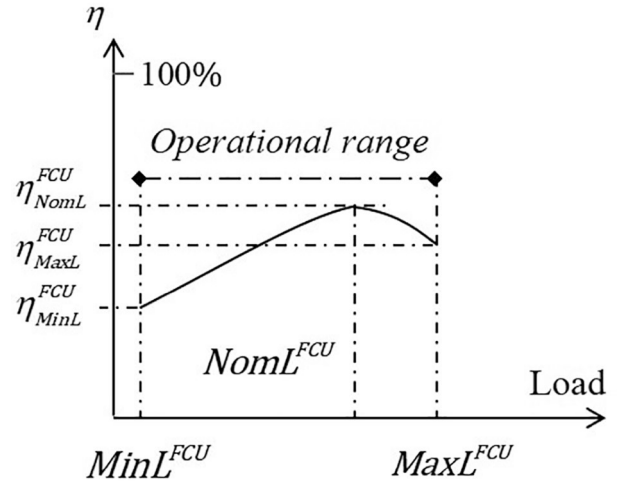
In this section, we first present our new and comprehensive decision model for ECS dimensioning with the objective to maximize the ECS' energy efficiency while considering the most relevant technical aspects regarding manufacturing companies as examined in the previous section. Afterwards, we describe the necessary data of energy demand per period ( $AE\mathcal{S}D_t^{CS}$ ) as used by the decision model and also the aggregation process for preparing the data. The source of the data preparation are cumulated energy demands originating from historical data of the production system or from “simulative” scheduling (cf. section 3.4).

#### 3.1. The model for maximizing the CS' energy efficiency

The basic task of ECS dimensioning, 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 energy demands are present. When energy demands vary, a distinction can be made between the so-called “base-load” and the “peak-load” energy share. To handle these two basic load types, we propose to install complementary CUs with different characteristics: 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. For both types of CUs, Fig. 2 illustrates the dependencies between load and conversion efficiency based on the parameters minimum load  $MinL$ , nominal load  $NomL$ , and maximum load  $MaxL$  as well as the corresponding efficiency parameters  $\eta_{MinL}$ ,  $\eta_{MaxL}$ , and  $\eta_{NomL}$ . Note that for these three load points, the efficiencies can be obtained easily in most cases (e.g., with technical documentations or literature; cf., e.g., Pruitt et al., 2013); Fig. 2 a) exemplarily depicts loads, operational ranges, and the load-efficiency curve of an LCU and Fig. 2 b) of an FCU. Fig. 2 illustrates that LCUs have a smaller operational range (defined by  $MaxL - MinL$ ) and a high nominal load efficiency at the expense of high part-load efficiency losses. In contrast, FCUs have a lower maximum load, a broad operational range, and small part-load efficiency losses at the expense of basically lower efficiencies. The maximum load of both CUs combined to one ECS can be very different, for instance in our numerical study, the relative mean size of the FCUs is about 21% of the



a) Large conversion unit (LCU)



b) Flexible conversion unit (FCU)

Fig. 2. Load-efficiency curves illustrating the relationship between part-load operation and conversion efficiency.

size of the LCUs.

Note that the minimum load greater than zero of LCU and FCU could cause the provisioning of unnecessary energy if the required energy is lower than the minimum load. Thus, the overall efficiency of the LCU and FCU could decrease. The influences of operational ranges and related efficiencies on the ECS design are analyzed in Section 6.2.

In this contribution, to keep the analyses manageable, we limit the composition of the ECS 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 share 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 energy demand  $AE\mathcal{S}D^{MAX} = \max_{t \in \{1, \dots, T\}} \{AE\mathcal{S}D_t^{CS}\}$  is covered by the two CUs while the ECS' energy efficiency is maximized. As we use two CUs to cover the complete energy demand and the LCU operates with the ECS' 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  $AESD^{MAX}$  (cf. Fig. 3).

$$MaxL^{FCU} = AESD^{MAX} - NomL^{LCU} \quad (1)$$

Note that if more than one FCU should be integrated in the ECS, the  $MaxL^{FCU}$  must be divided between these FCUs.

Generally, we assume that the nominal load of a CU is different from the maximum load and that for the LCU, the nominal load is given relative to its maximum load. Thus, the nominal load of the LCU is defined by the parameter  $\Delta_{NomL}^{LCU}$ :

$$NomL^{LCU} = MaxL^{LCU} \cdot \Delta_{NomL}^{LCU} \quad (2)$$

For the FCU, we assume that a given degree of freedom to determine a most sufficient nominal load exists. 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  $\Delta_{ubNomL}^{FCU}$  and  $\Delta_{lbNomL}^{FCU}$ . The  $NomL^{FCU}$  is bounded as follows:

$$NomL^{FCU} \leq ubNomL^{FCU} \quad (3)$$

with  $ubNomL^{FCU} = MaxL^{FCU} \cdot (1 - \Delta_{ubNomL}^{FCU})$

$$NomL^{FCU} \geq lbNomL^{FCU} \quad (4)$$

with  $lbNomL^{FCU} = MinL^{FCU} \cdot (1 + \Delta_{lbNomL}^{FCU})$

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 energy 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., Fig. 2). The operational range of both CU types is defined by their maximum load  $MaxL$ , which is part of the design 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 & Liu, 2015). Here, we follow the relative approach and use the two parameters  $\Delta_{MinL}^{LCU}$  and  $\Delta_{MinL}^{FCU}$  for determining  $MinL^{LCU}$  and  $MinL^{FCU}$ , respectively:

$$MinL^{LCU} = MaxL^{LCU} \cdot \Delta_{MinL}^{LCU} \quad (5)$$

$$MinL^{FCU} = MaxL^{FCU} \cdot \Delta_{MinL}^{FCU} \quad (6)$$

The assumptions and conditions described so far are illustrated by Fig. 3. Fig. 3 depicts a load duration curve representing the varying energy demands (sorted non-increasing), the main decisions about

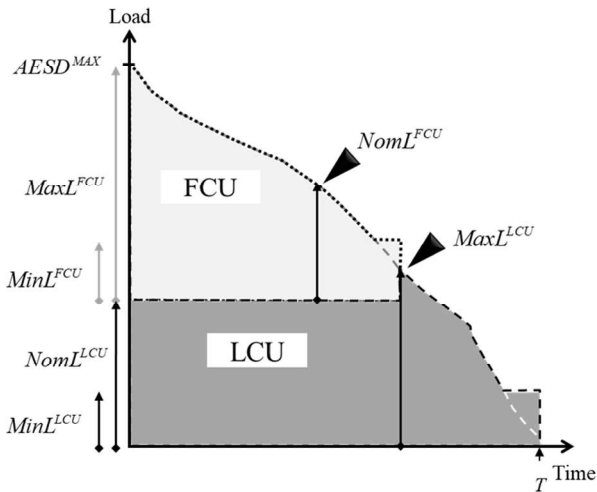


Fig. 3. Main decisions and depending decisions illustrated by a load duration curve.

maximum and nominal loads, and the depending decisions.

In addition, Fig. 3 shows the separation of load shares assigned to both CUs. The light grey area (restricted by the dotted line) represents the energy demands allocated to the FCU and the dark grey area (restricted by the dashed line) the energy demands allocated to the LCU. In consequence of the decision on both dimensions, we have to decide for each time period  $t \in \{1, \dots, T\}$  which CU provides how much of the required energy ( $AESD_t^{CS}$ ). 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 energy demand can be provided by the LCU only. In this case, the LCU provides the total energy demand and the FCU load 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 that the FCU is required to fulfil the energy demand for period  $t$ , we use the auxiliary binary variable  $X_t$  with  $X_t = 1$  indicating that the FCU is required ( $X_t = 0$  otherwise) and the following sets of disjunctive constraints (with  $M$  specifying a sufficiently large number;  $M = AESD^{MAX}$ ):

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

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

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.

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

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

To respect the technical restrictions of minimal loads, we 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) assure that the  $cAESD_t^{FCU}$  is equal to zero if the FCU is not required at all):

$$cAESD_t^{LCU} \geq AESD_t^{LCU} \quad \forall t = 1, \dots, T$$

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

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

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

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

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 main decisions and the resulting part loads with their corresponding conversion efficiencies are illustrated in Fig. 4 and Fig. 5. In these figures, the solid load-efficiency curves illustrate nonlinear part-load efficiencies whereas the dashed curves illustrate piecewise linear approximations.

Both figures depict illustrative load-efficiency curves with the corresponding efficiencies for the related loads (within their operational ranges) for the LCU and FCU, respectively. To model the increasing efficiency losses of larger deviations from the nominal load most adequately, we use parabolic functions to determine the conversion efficiency at a specific part load (cf., e.g., Savola & Keppo, 2005; Aguilar et al., 2007, or Agha et al., 2010). To increase model accuracy even

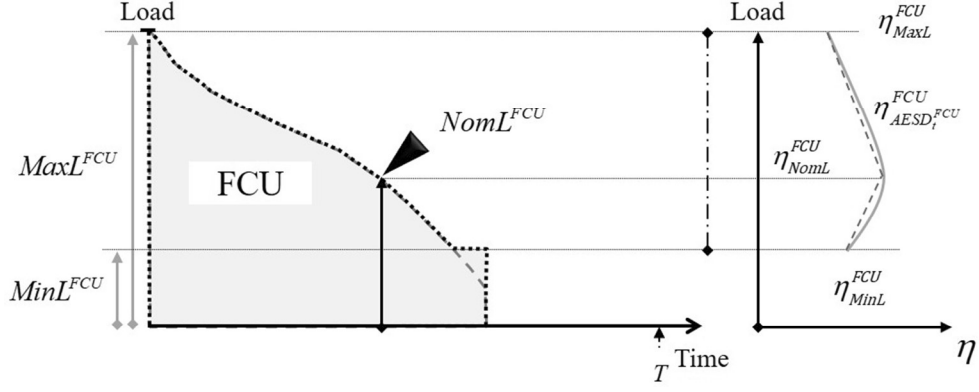


Fig. 4. Illustration of loads and conversion efficiencies for the FCU.

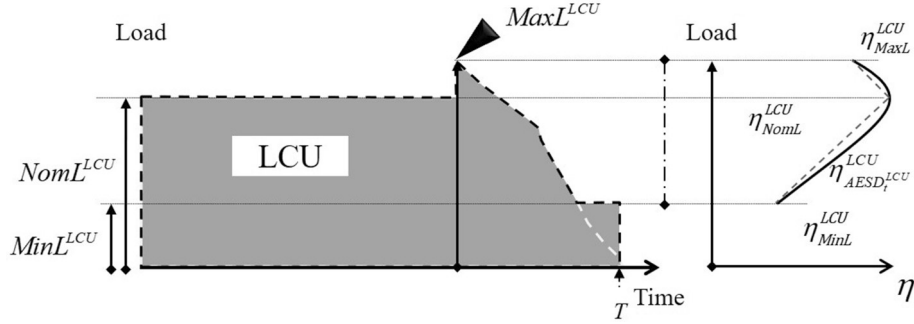


Fig. 5. Illustration of loads and conversion efficiencies for the LCU.

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. This modelling approach is not required for all types of CUs, but reflects the characteristics of many complex CUs. To ensure that only one of these functions is used at one point in time, 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,  $Y_t^{FCU} = 0$ ):

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

$$NomL^{LCU} - cAESD_t^{LCU} \leq (1 - Y_t^{LCU}) \cdot M \quad \forall t = 1, \dots, T \quad (17)$$

$$NomL^{FCU} - cAESD_t^{FCU} \leq (1 - Y_t^{FCU}) \cdot M \quad \forall t = 1, \dots, T \quad (19)$$

To reflect the nonlinear part-load efficiency behavior of the CUs most accurately, for each CU, the vertex form of univariate quadratic functions is used. For the LCU and the FCU, the part-load efficiencies per period ( $\eta_t^{LCU}$  and  $\eta_t^{FCU}$ ) are determined based on the current load,  $Y_t^{LCU}$  and  $Y_t^{FCU}$ , and the corresponding basic efficiencies ( $\eta_{MinL}$ ,  $\eta_{NomL}$ , and  $\eta_{MaxL}$ ) at the extreme points ( $MinL$ ,  $NomL$ , and  $MaxL$ ). The constraint sets (20) and (21) define the continuous auxiliary variables  $\eta_t^{LCU}$  and

$\eta_t^{FCU}$ . 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 [Bosch Thermotechnology Division, 2014](#)).

$$\eta_t^{LCU} = Y_t^{LCU} \cdot \left( \frac{\eta_{MaxL}^{LCU} - \eta_{NomL}^{LCU}}{(MaxL^{LCU} - NomL^{LCU})^2} (cAESD_t^{LCU} - NomL^{LCU})^2 + \eta_{NomL}^{LCU} \right) + (1 - Y_t^{LCU}) \cdot \left( \frac{\eta_{MinL}^{LCU} - \eta_{NomL}^{LCU}}{(MinL^{LCU} - NomL^{LCU})^2} (cAESD_t^{LCU} - NomL^{LCU})^2 + \eta_{NomL}^{LCU} \right) \quad \forall t = 1, \dots, T \quad (20)$$

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

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

Because the energy output of the ECS is defined by the PS, 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):

$$\text{Minimize } TFES = \sum_{t=1}^T \left( \frac{cAESD_t^{LCU}}{\eta_t^{LCU}} + \frac{cAESD_t^{FCU}}{\eta_t^{FCU}} \right) \quad (22)$$

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 ECS dimensioning approach that is independent of a specific type of energy 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, Timmerhaus, & West, 2004](#) or [Arcuri et al., 2015](#)) and the required FES determines the main part of the operational costs (combined with corresponding cost factors).

### 3.2. Extension and piecewise linear part-load efficiency modelling

A further aspect that could be considered during ECS design is that, due to economic and/or strategic reasons, it might be appropriate (particularly for LCU) 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 an absolute number of 4,500 h of nominal load operation annually (cf. [O'Brien and Bansal, 2000a](#)). Instead of an absolute parameter, we introduce the parameter *relP* defining a relative number of periods. For instance, *relP* = 60% means that the LCU should operate at its nominal load for 5,256 h (with regard to one year with 8,760 h). Based on *relP* an upper bound for  $MaxL^{LCU}$  can be derived:

$$MaxL^{LCU} \leq ubMaxL^{LCU} \quad (23)$$

$$\text{with } ubMaxL^{LCU} = \frac{AESD(\lfloor relP \cdot T \rfloor)}{\Delta_{NomL}^{LCU}}$$

In (23), the function  $AESD(t)$  returns the energy demand of period  $t$ , whereby energy demands are sorted non-increasing and  $T$  defines the planning horizon (total number of periods). 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* is set to zero, the upper bound would be greater than the maximum energy demand  $AESD^{MAX}$  (as  $AESD(0) = AESD^{MAX}$  and  $\Delta_{NomL}^{LCU} < 1$ ) and constraint (23) is not binding.

For the comparative analysis between nonlinear and (piecewise) linear part-load efficiency modelling (cf., the discussion in section 2.2), we use the following efficiency approximations:

$$\eta_t^{LCU} = Y_t^{LCU} \cdot \left( \eta_{NomL}^{LCU} + (cAESD_t^{LCU} - NomL^{LCU}) \cdot \frac{\eta_{MaxL}^{LCU} - \eta_{NomL}^{LCU}}{(MaxL^{LCU} - NomL^{LCU})} \right) + (1 - Y_t^{LCU}) \cdot \left( \eta_{NomL}^{LCU} + (cAESD_t^{LCU} - NomL^{LCU}) \cdot \frac{\eta_{NomL}^{LCU} - \eta_{MinL}^{LCU}}{(NomL^{LCU} - MinL^{LCU})} \right) \quad \forall t=1, \dots, T \quad (24)$$

$$\eta_t^{FCU} = X_t \cdot Y_t^{FCU} \cdot \left( \eta_{NomL}^{FCU} + (cAESD_t^{FCU} - NomL^{FCU}) \cdot \frac{\eta_{MaxL}^{FCU} - \eta_{NomL}^{FCU}}{(MaxL^{FCU} - NomL^{FCU})} \right) + (1 - Y_t^{FCU}) \cdot \left( \eta_{NomL}^{FCU} + (cAESD_t^{FCU} - NomL^{FCU}) \cdot \frac{\eta_{NomL}^{FCU} - \eta_{MinL}^{FCU}}{(NomL^{FCU} - MinL^{FCU})} \right) \quad \forall t=1, \dots, T \quad (25)$$

Of course, using a function combining two linear functions results in a piecewise linear function. The functions are illustrated in [Fig. 4](#) and [Fig. 5](#), respectively.

To distinguish the two resulting models, each of which represents a different approach of part-load efficiency modelling, we refer to the optimization model using the nonlinear constraint sets (20) and (21) as model NLM (nonlinear model) and the model using the constraint sets (24) and (25) as model PWM (piecewise linear model) in the following.

### 3.3. Data preparation and aggregation

Basic data of our ECS dimensioning approach for manufacturing companies are discrete time series of cumulated energy 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  $\delta_s^{PS}$  with a given duration  $\delta^{PS}$  (i.e.,  $\delta^{PS}$  defines the level of detail for all the time series). The cumulated energy 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 3.4. Both sources can be used alone or in combination. Each time series represents an

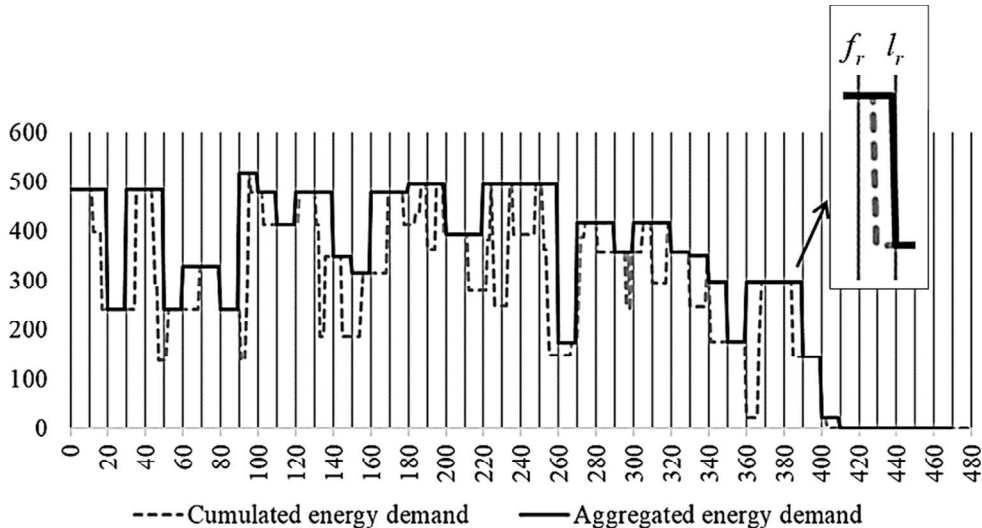


Fig. 6. Illustration of the load transition anticipation for one production day (480 min).

energy demand scenario representing one production day. When an appropriate number of time series (scenarios) is used during ECS design, the resulting design will be robust with regard to uncertain energy demands. To that, 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 480 min:  $\vartheta_s^{PS} = 480$ ).

To integrate load transition characteristics of the ECS (cf., section 2.2) without further increasing problem complexity, we use an approximate anticipation approach in form of an “aggregation” model (cf., Ghadimi et al., 2014). In doing so, we consider load transition characteristics (e.g., maximum or minimum ramping restrictions, minimum durations, and efficiency losses) by estimating their impact and aggregate the original energy demands per time slice ( $AESD_t^{PS}$ ) accordingly. To that, we use a time slice aggregation factor of  $agg^{PS,CS} = 10$  (minutes) to reflect the varying energy demand on the one side and load transition characteristics on the other side. Within a time-slice interval  $r$  that comprises 10 min and is enclosed by a first time slice  $f_r$  and a last time slice  $l_r$ , we aggregate the energy demand for  $r$  to the maximum energy demand between  $f_r$  and  $l_r$ . This maximum is used to guarantee demand fulfilment and to account for conversion efficiency losses during load transitions. The aggregated energy demand ( $AESD_t^{CS}$ ) per time slice within interval  $r$  is calculated as follows:  $AESD_t^{CS} = \max_{t' \in [f_r, l_r]} \{AESD_{t'}^{PS}\}$ , with  $\forall t \in [f_r, l_r]$ . Fig. 6 illustrates, for one production day, the relationship between the original cumulated energy demand (grey dashed line) and the aggregated energy demands (black solid line) that anticipate load transitions.

Note that consecutive intervals that do not have any energy demands in each of their time slices and that are at the end of a time series are excluded from further considerations. Of course, intervals not at the end of a time series are not excluded.

### 3.4. Simulative scheduling

Due to the strong relationship between the ECS and the PS of a manufacturing company, our ECS design approach incorporates the opportunity to consider energy demand time series based on simulative (machine) scheduling besides historical energy demands. It is called simulative because the calculated schedules are not used for actual production execution planning but to generate a comprehensive data basis for the ECS dimensioning. In this context, 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.). In this paper, we use simulative scheduling variant b. This means that we generate new scheduling instances for a specific production system (with identical parallel machines) and use two traditional objectives (makespan and total flow time minimization). More details on the scheduling environment and the scheduling instance generation are described in sections 5.1 and 5.2.

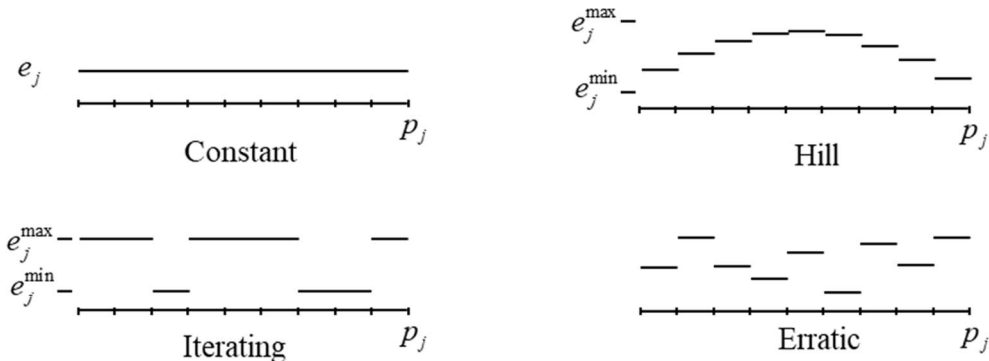


Fig. 7. Energy demand course types.

Table 2  
LCU parameter settings.

	LCU-0	LCU-1	LCU-2	LCU-3	LCU-4	LCU-5
$\eta_{MaxL}^{LCU}$	87.0%	87.0%	85.0%	85.0%	80.0%	91.0%
$\eta_{NomL}^{LCU}$	95.0%	95.0%	95.0%	93.0%	97.0%	93.0%
$\eta_{MinL}^{LCU}$	82.0%	82.0%	80.0%	80.0%	75.0%	86.0%
$\Delta_{NomL}^{LCU}$	0.95	0.90	0.90	0.90	0.95	0.95
$\Delta_{MinL}^{LCU}$	0.70	0.60	0.60	0.60	0.70	0.70

Table 3  
FCU parameter settings.

	FCU-0	FCU-1	FCU-2	FCU-3	FCU-4
$\eta_{MaxL}^{FCU}$	65.0%	65.0%	65.0%	60.0%	70.0%
$\eta_{NomL}^{FCU}$	84.0%	84.0%	82.0%	86.0%	82.0%
$\eta_{MinL}^{FCU}$	60.0%	60.0%	60.0%	55.0%	65.0%
$\Delta_{NomL}^{FCU}$	0.15	0.05	0.05	0.15	0.15
$\Delta_{MinL}^{FCU}$	0.30	0.10	0.10	0.30	0.30

## 4. Solution method

For solving the planning problem at hand, we present a mixed-integer nonlinear program (MINLP) and evaluate several standard solvers to identify the most suitable one (in terms of solution quality and computation time). To support the solution process, we additionally propose a lower bound on the objective value (TFES, cf., (22)) and a new truncated enumeration heuristic (TEH) to provide initial solutions and upper bounds on the objective value. The main course of action is as follows (explanations of the different steps are given in the following sections):

- I. Prepare energy demand levels
- II. Lower bound determination
  - II.1 Approximate lower bound  $lbTFES^{APP}$
  - II.2 Solve the MINLP with the SCIP solver to get lower bound  $lbTFES^{SCIP}$
  - II.3 Select best lower bound  $lbTFES^{ANT} = \max\{lbTFES^{APP}, lbTFES^{SCIP}\}$
- III. Calculate initial solution  $S'$  and upper bound  $ubTFES^{TEH}$  with heuristic TEH
- IV. Solve the MINLP with solver ANTIGONE using  $S'$ ,  $lbTFES^{ANT}$ , and  $ubTFES^{TEH}$

Note that the application of this solution procedure is abbreviated by ANT in the remainder of this paper.

### 4.1. Mixed-integer nonlinear program and standard solver

The developed MINLP forms the core of our solution method and is generally specified by the equations (1) to (23) presented in section 3.1

and section 3.2.

According to section 3.3, energy demand time series are the basis for ECS design. To reduce computational efforts, we combine all data points of a time series having identical energy demands to energy demand levels (indexed by  $l = 1, \dots, L$ ). These energy demands levels  $AESD_l$  combined with the number of aggregated data points per energy demand level ( $n_l$ ) reduce the number of variables without affecting the result. In consequence, the parameter  $AESD_t^{CS}$  must be replaced by  $AESD_l$ , all indices  $t$  must be replaced by  $l$  and the objective function must slightly be adapted to account for the totally required FES:

$$\text{Minimize} \quad \sum_{l=1}^L \left( \frac{cAESD_l^{LCU}}{\eta_l^{LCU}} + X_l \cdot \frac{cAESD_l^{FCU}}{\eta_l^{FCU} + z} \right) \cdot n_l \cdot \text{agg}^{PS,CS} \quad (26)$$

In (26), the parameter  $X_l$  (with  $X_l = 1$  indicating that the FCU is required) and the sufficiently small parameter  $z$  are only required for solver related, technical reasons ( $z = 1E - 20$ ).

To identify a most suitable solver, we investigated solvers that are capable to solve general mixed-integer nonlinear programs and have shown a good performance in the analysis of [Kronqvist, Bernal, Lundell, and Grossmann \(2019\)](#). 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 24.4.5). Consequently, all experimental results are calculated with ANTIGONE.

The preliminary tests have also shown that the maximum load of the LCU should be larger than 30% of  $AESD^{MAX}$ . Thus, we introduce a lower bound for the dimension of the LCU to reduce the solution space and decrease the computational effort:

$$\text{Max}L^{LCU} \geq lb\text{Max}L^{LCU} \quad \text{with } lb\text{Max}L^{LCU} = \min\{AESD^{MAX} \cdot 0.3, ub\text{Max}L^{LCU}\} \quad (27)$$

Note that the minimum function in (27) is used to guarantee feasibility.

In consequence of this additional constraint, the nonlinear model NLM is specified by objective function (26) combined with the adapted constraint sets to (1) to (23) and (27). In the piecewise linear model PWM, constraint sets (20) and (21) are replaced by the constraint sets and (24) and (25). Both models are completely provided in the [supplementary material](#).

#### 4.2. Lower bounds

To provide a basic lower bound ( $lbTFES^{APP}$ ) on the objective value (TFES), we assume that the total energy demand could be provided with maximum efficiency of the ECS ( $\eta_{NomL}^{LCU}$ ) and use the following approximation:  $lbTFES^{APP} = \left( \sum_{l=1}^L AESD_l \cdot n_l \cdot \text{agg}^{PS,CS} \right) / \eta_{NomL}^{LCU}$ . Furthermore, as SCIP has shown the capability to provide good lower bounds ( $lbTFES^{SCIP}$ ) in a short time, we use this solver to provide an improved lower bound ( $lbTFES^{ANT}$ ) for ANTIGONE:  $lbTFES^{ANT} = \max\{lbTFES^{APP}, lbTFES^{SCIP}\}$

#### 4.3. Truncated enumeration heuristic

The developed heuristic to determine initial solutions is based on a truncated enumeration scheme and is called truncated enumeration heuristic (TEH). It consists of two phases: The first phase determines the capacity of the LCU ( $\text{Max}L^{LCU}$ ) and the second phase determines the nominal load of the FCU

( $\text{Nom}L^{FCU}$ ). The following pseudo code illustrates the two phases:

---

```
TEH(AESD[l], n[l], aggPS,CS, v, ζ, κ)
// init reference solution
S* := getSolutionByMINLP(ubMaxLLCU,
                        lbNomLFCU, AESD[l], n[l], aggPS,CS)
(continued on next column)
```

---

(continued)

---

```
TEH(AESD[l], n[l], aggPS,CS, v, ζ, κ)
// phase 1
incMaxLLCU := ubMaxLLCU // cf. (23)
Loop
  incNomLFCU := max{lbNomLFCU, ubNomLFCU · ζ}
  // cf. (4) and (3)
  S' := getSolutionByMINLP(incMaxLLCU,
                          incNomLFCU, AESD[l], n[l], aggPS,CS)
  If (TFES(S') < TFES(S*)) then S* = S'
  incMaxLLCU := incMaxLLCU - v
Until incMaxLLCU ≤ lbMaxLLCU // cf. (27)
  Or (TFES(S') - TFES(S*)) / TFES(S*) > κ
MaxLLCU := getMaxLoadOfLCU(S*)
// phase 2
incNomLFCU := ubNomLFCU // cf. (3)
Loop
  S' := getSolutionByMINLP(MaxLLCU,
                          incNomLFCU, AESD[l], n[l], aggPS,CS)
  If (TFES(S') < TFES(S*)) then S* = S'
  incNomLFCU := incNomLFCU - v
Until incMaxLLCU ≤ lbNomLFCU // cf. (4)
  Or (TFES(S') - TFES(S*)) / TFES(S*) > κ
Return S*
```

---

In the first phase, we start with an incumbent maximum load  $incMaxL^{LCU} = ubMaxL^{LCU}$  (cf., (23))

and iteratively decrement it by parameter  $v$  until  $lbMaxL^{LCU}$  (cf., (27)) 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  $\zeta$  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 (*getSolutionByMINLP*). To avoid inefficient iterations, the first phase terminates before  $incMaxL^{LCU} \leq lbMaxL^{LCU}$  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  $S^*$  (i.e., with the minimum TFES) is fixed. Thereafter, the second phase starts with  $incNomL^{FCU} = ubNomL^{FCU}$  and iteratively decrements  $incNomL^{FCU}$  by  $v$  until  $lbNomL^{FCU}$  is reached. The heuristic terminates early if the relative degradation becomes larger than  $\kappa$ .

The parameters  $v = 0.5$ ,  $\zeta = 0.33$ , 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 3.4), 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 energy 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  $j = 1, \dots, n$ ) on a set of identical parallel machines  $K$  (with indices  $k = 1, \dots, m$ ). 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 energy demand of a job, we follow the approaches of Artigues, Lopez, and Haït (2013) and Rager et al. (2015) and use discrete energy demand profiles. Therefore, the energy demand of job  $j$  is defined by a sequence of energy demands  $e_{j,p}$  (with  $p = 1, \dots, p_j$ ). 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 ( $C_{max}$ ) and total flow time ( $TFT$ ), we use the list scheduling approaches LPT (longest processing time) for  $C_{max}$  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, page 204 and 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  $\bar{p} = 30$  minutes and processing times that are randomly drawn from a discrete uniform distribution restricted by  $[24, 36]$ ) or few complex (FC) products (with  $\bar{p} = 80$  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 energy 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  $\bar{p} = (\sum_{j=1}^n p_j)/n$  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  $\tau^{PS}$ . Then, based on  $n^{max}$ , the number of jobs  $n$  per problem instance is randomly chosen from a discrete uniform distribution restricted by  $\lceil [n^{max} - 1.5m], n^{max} \rceil$ .

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., Fig. 7): 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 two 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.

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 I, we additionally draw the number of periods with an identical energy demand in sequence from a discrete uniform distribution limited by  $[1, \lfloor p_j/2 \rfloor]$  and all jobs start with an energy 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 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 energy demand profile. These formulas were identified by experiments. 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 ECS design 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  $C_{max}$  and one with  $TFT$ ). The combination of one company type and one scheduling objective defines the content of a so-called PS-scenario. Altogether, a total of 15,360 schedules has to be calculated to provide the 240 time series for the 64 desired PS-scenarios. The complete set of energy demand time series is publicly accessible at Mendeley Data (Gahm, 2020).

## 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 Tables 2 and 3 are then combined to form CS-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 2 and Table 3, 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

**Table 4**  
Aggregated relative percentage differences.

	$\Delta TFES$				$\Delta MaxL^{LCU}$				$\Delta NomL^{FCU}$			
	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min
$C_{max}$	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

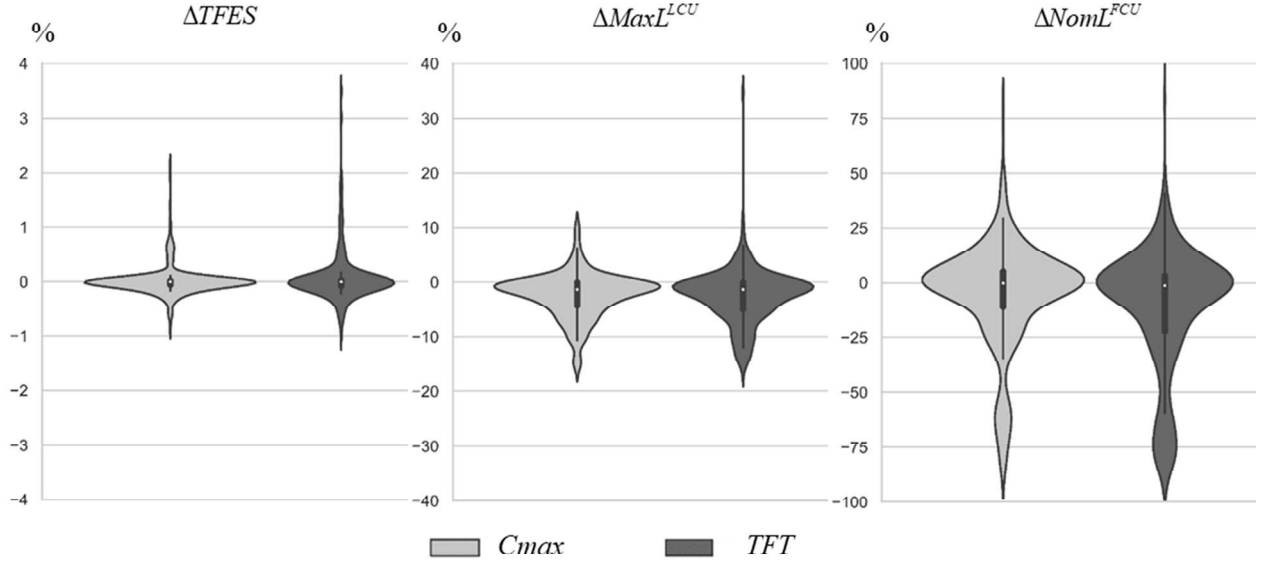


Fig. 8. Violin plots of the relative percentage difference key Figs.

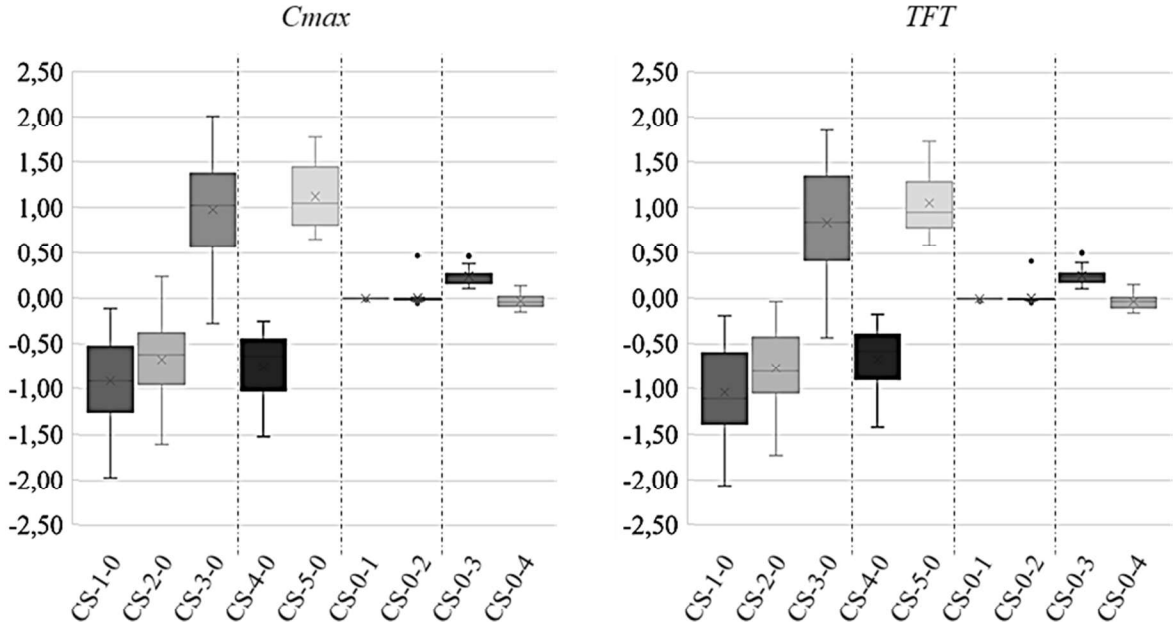


Fig. 9. Influence of CU parameters on the TFES.

Table 5

Relative numbers of periods LCUs operate at nominal load.

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

Table 6

Relative load share of LCUs.

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

Mancarella, 2007 and Kavvadias and Maroulis, 2010).

The combination of a PS-scenario with a CS-setting defines a complete experiment and is called an ECS-scenario in the following.

For the segregated parameter influence analysis, we use a subset out of all possible CS-settings and define the basic ECS-scenario set BECS with 640 experiments (based on 64 PS-scenarios and the ten CS-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).

The (optional) parameter *relP* 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  $\Delta_{MinL}^{FCU} = 0.15$  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 h (reslim = 36000 s).

## 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 total FES demand 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 on the total FES demand.

Note that although the relative differences between objective values seem to be small, the impacts on the ECSs' efficiency should not 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 all instances using ANT and the models NLM and PWM and afterwards evaluate the solutions calculated by PWM with the more accurate but more complex NLM model. The consequences of the simplified piecewise linear modelling of part-load efficiencies are then measured in terms of the required *TFES*: i.e., *TFES(NLM)* vs. *TFES(PWM)*. To that, we use the relative percentage difference of the *TFES* achieved with both approaches:  $\Delta TFES = [(TFES(PWM) - TFES(NLM)) / TFES(NLM)] \cdot 100$ . In addition, we analyze the influence of both part-load modelling approaches on the main decisions, i.e., the maximum load of the LCUs (*MaxL<sup>LCU</sup>(NLM)* vs. *MaxL<sup>LCU</sup>(PWM)*) and the nominal load of the FCUs (*NomL<sup>FCU</sup>(NLM)* vs. *NomL<sup>FCU</sup>(PWM)*) by the relative percentage differences  $\Delta MaxL^{LCU}$  and  $\Delta NomL^{FCU}$  (defined like for  $\Delta TFES$ ).

Table 4 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-settings used in BECS (positive values mark that *TFES(NLM)*,  $\Delta MaxL^{LCU}(NLM)$ , or  $\Delta NomL^{FCU}(NLM)$  is smaller than *TFES(PWM)*,  $\Delta MaxL^{LCU}(PWM)$ , or  $\Delta NomL^{FCU}(PWM)$ , respectively).

In Fig. 8, the influence of the two part-load efficiency modelling approaches on *TFES*, *MaxL<sup>LCU</sup>*, and *NomL<sup>FCU</sup>* is illustrated by violin plots (note the different scaling of the three parts).

On the one hand, Fig. 8 and the values in Table 4 show that the *TFES* values calculated with the nonlinear modelling approach can be remarkably lower (positive  $\Delta TFES$ ) 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 NLM is more complex compared to model PWM, which was not accounted for in the experiments (because both models had the same time limit for computation). 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 ECS design 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 *TFES*, *MaxL<sup>LCU</sup>*, and

*NomL<sup>FCU</sup>* (cf., Fig. 8 and Table 4) between both modelling approaches 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 scenario set BECS is to analyze the influence of different CU parameters on the ECS's efficiency. To that, Fig. 9 illustrates the relative percentage deviation of *TFES* achieved with each CS-setting 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*. The box-and-whisker plot illustrates the aggregated values for the 32 company types with regard to CS-setting and scheduling objective.

The results in Fig. 9 show that the effects of CU-parameters seem to be almost 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 ( $\eta_{MinL}^{LCU}$  and  $\eta_{MaxL}^{LCU}$ ) decrease (CS-2-0), but that a simultaneous decrease of the nominal load efficiency cannot be compensated (CS-3-0). Fig. 9 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 come 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, Fig. 3, and Table 5).

As seen by the results of Fig. 9, 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 FCUs, increasing the nominal load efficiency seems less preferable than increasing the boundary load efficiencies ( $\eta_{MinL}^{FCU}$  and  $\eta_{MaxL}^{FCU}$ ) 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 energy provided by the LCUs (cf., Table 6).

### 6.3. Most suitable planning parameters per company type

To finally evaluate the influence of the basic planning parameters, we report in Table 7 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-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-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<sup>LCU</sup>*, and *NomL<sup>FCU</sup>* (compared to ECSs with the original efficiencies) are depicted in the last six columns of Table 7.

Regarding the FCU settings, FCU-3 is most preferable for almost all company types (29 of 32). Nevertheless, a higher degree of freedom to determine the nominal load of the FCU (FCU-1, 3 times) is more suitable for specific company types. Accordingly, the nominal load efficiency is important, but not the only important parameter for FCUs (cf., Table 3). For the same reasoning as in Section 6.2, LCU-5 is not preferable due to its lower nominal load efficiency (cf., Table 2). However, although LCU-4 has the highest nominal load efficiency, LCU-1 with its larger

**Table 7**

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

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. The fact that the most preferable parameters by company type slightly differ from the results of Section 6.2 indicates, that the combined design of the LCU and FCU is important to maximize the ECS’s overall energy efficiency.

Analyzing the influence of the scheduling objective, the values in Table 7 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-settings), used to test whether the difference of the objective values (TFES) is statistically significant ( $\leq 0.05$ ; 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 7 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 —energy-type independent— approach for the dimensioning of a manufacturing company’s ECS. Hereby, we respected the special conditions arising in the context of manufacturing companies: highly dynamic energy demands and the opportunity to directly influence the temporal course of the energy 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 design 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 ECS dimensioning, the resulting ECS is robust with regard to energy demand uncertainties and also to decreasing conversion efficiencies due to aging.

The most important characteristics defining an ECS’s energy-related behavior (i.e., size, nominal load, 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 piecewise 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 operational ranges and boundary efficiencies for the ECS design.

Based on these results, we conclude that further research should aim on the integration of the analyzed aspects into ECS design approaches. Particularly the consideration of nonlinear part-load efficiencies can be important, and their integration is easily possible when applying heuristic solution methods. Of course, also the development of more effective and/or efficient solution methods for the problem at hand are of interest. Furthermore, the possibility of manufacturing companies to directly influence the energy demand course by scheduling can be used to improve the ECS design, ECS efficiency, and thus, a manufacturing company's overall efficiency. Hereby, the usage of energy-oriented scheduling objectives or constraints is a promising research topic to further improve energy efficiency.

## CRedit authorship contribution statement

**Christian Gahm:** Conceptualization, Methodology, Project administration, Software, Validation, Writing - original draft, Writing - review & editing. **Chantal Ganschietz:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Florian Denz:** Conceptualization, Methodology, Writing - original draft. **Axel Tuma:** Conceptualization, Resources, Writing - original draft, Supervision.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cie.2021.107470>.

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