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Energy Management for Industrial Plants with Thermal Batch Processes

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Abstract

Reducing greenhouse gas emissions is crucial to fight climate change. A key instrument for reducing CO₂ emissions is to increase the share of renewable energies in the power supply. Renewable energy sources, such as wind or solar power plants, have a fluctuating availability and thus lead to a transformation of the electricity market. Power demand management is becoming crucial for frequency control in the power grid, as electricity supply is becoming more volatile. Therefore, attractive economic incentives such as the balancing energy market and flexible electricity prices are gaining importance.

To take full advantage of these incentives, an industrial plant's energy management system (EMS) must meet both timing (e.g., 24-hour electricity demand forecasting) and operational (e.g., short-term electricity demand reduction) requirements.

In addition to meeting the challenges of the modern energy market, modern EMSs must further ensure production reliability and have low implementation costs to be deployed in industrial manufacturing plants. Thermal batch processes are common (e.g., annealing, tempering, pasteurization) but particularly challenging processes for EMSs because they generate peak heat loads and are usually not fully automated, leading to uncertainties in heat load prediction.

Little research has been done in the field of EMSs for industrial plants with thermal batch processes. Therefore, it is the overarching goal of this thesis to design a broadly applicable EMS which enables the optimal operation of ESSs of industrial plants with thermal batch processes considering the modern electricity market, ensuring production reliability, and causing little implementation cost.

According to this goal, multiple methods including a novel EMS-structure, a novel load-prediction method, and a novel parametrization method for EMSs are presented in this thesis. The novel EMS-structure consists of a two-layer mixed-integer linear program (MILP) where each layer has a different sampling time, and an online load predictor (OLP). The two layers of the MILP allow to combine a long prediction horizon with a short sampling time. The OLP utilizes the novel load-prediction method and guarantees production reliability. To reduce implementation cost, the MILP is structured in a component-wise way, enabling a fast adaptation to changes of the ESS. The novel parameterization method further reduces the implementation effort and ensures the optimality of the EMS operation.

These methods have been combined to produce an EMS that realizes all the features required for widespread application in industrial plants with thermal batch processes. Nevertheless, plant operators must have full confidence in the reliability of the methods before predictive and optimization-based EMSs become state of the art in industry. To approach this issue, a laboratory setup was designed to replicate the power systems of industrial plants with thermal batch processes. The laboratory setup was used to emulate two different industrial plants, including heat recovery systems, peaking heat loads, and industrial heat pumps. The EMS was tested, and its performance validated for both plants.

In summary, this thesis presents a validated EMS for power systems considering thermal batch processes at technology readiness level (TRL) 4. It meets the challenges of modern energy markets and facilitates the implementation of renewable energy sources in industrial plants and the power grid. Thus, the thesis provides a significant contribution to the decarbonization of industry.

Kurzfassung

Die Verringerung der Treibhausgasemissionen ist ein entscheidender Faktor im Kampf gegen den Klimawandel. Ein wichtiges Instrument zur Verringerung der CO₂-Emissionen ist die Erhöhung des Anteils der erneuerbaren Energien an der Stromversorgung. Erneuerbare Energiequellen, wie Wind- oder Solarkraftwerke, haben eine schwankende Verfügbarkeit und radikale Änderungen am Strommarkt. Der Stromverbrauch muss an die volatile Stromerzeugung angepasst werden, um die Netzfrequenz zu stabilisieren. Dadurch gewinnen wirtschaftliche Anreize wie der Regenergiemarkt und flexible Strompreise an Bedeutung.

Um diese Anreize in vollem Umfang nutzen zu können, muss das Energiemanagementsystem (EMS) einer Industrieanlage sowohl zeitliche (z. B. 24-Stunden-Strombedarfsprognose) als auch betriebliche (z. B. kurzfristige Strombedarfsreduzierung) Anforderungen erfüllen.

Neben den Anforderungen des modernen Energiemarktes müssen moderne EMS auch Produktionssicherheit und niedrige Implementierungskosten gewährleisten, um in industriellen Fertigungsanlagen eingesetzt werden zu können. Thermische Batch-Prozesse sind weit verbreitet (z. B. Glühen, Anlassen, Pasteurisieren), und stellen eine besondere Herausforderung für EMS dar, da sie Lastspitzen verursachen und in der Regel nicht vollständig automatisiert sind, was zu Unsicherheiten bei der Vorhersage der Wärmelast führt.

Auf dem Gebiet der EMS für Industrieanlagen mit thermischen Batch-Prozessen wurde bisher wenig geforscht. Daher ist es das übergeordnete Ziel dieser Arbeit, ein breit einsetzbares EMS zu entwerfen, das den optimalen Betrieb von ESS in Industrieanlagen mit thermischen Batchprozessen unter Berücksichtigung des modernen Strommarktes ermöglicht, die Produktionssicherheit gewährleistet und geringe Implementierungskosten verursacht.

Um dieses Ziel zu erreichen, werden in dieser Arbeit mehrere Methoden vorgestellt, darunter eine neuartige EMS-Struktur, eine neuartige Lastvorhersagemethode und eine neuartige Parametrisierungsmethode für EMSe. Die neue EMS-Struktur besteht aus einem zweischichtigen gemischt-ganzzahligen linearen Programm (MILP), bei dem jede Schicht eine spezifische Regelfrequenz hat, und einem Online-Lastvorhersageverfahren (OLP). Die zwei Schichten des MILP ermöglichen es, einen langen Vorhersagehorizont mit einer hohen Regelfrequenz zu kombinieren. Der OLP nutzt die neuartige Lastvorhersagemethode und garantiert die Zuverlässigkeit der Produktion. Um die Implementierungskosten zu senken, ist das MILP komponentenweise strukturiert, wodurch eine schnelle Anpassung an Änderungen des ESS ermöglicht wird. Die Parametrisierungsmethode reduziert den Implementierungsaufwand weiter und gewährleistet die Optimalität des EMS-Betriebs.

Durch die Kombination dieser Methoden entsteht ein EMS, welches alle Eigenschaften für einen breiten Einsatz in Industrieanlagen mit thermischen Chargenprozessen erfüllt. Dennoch müssen die Anlagenbetreiber volles Vertrauen in die Zuverlässigkeit der Methoden haben, bevor prädiktive und optimierungsbasierte EMS zum Stand der Technik in der Industrie werden. Zu diesem Zwecke, wurde ein Laboraufbau entwickelt, der die Energiesysteme von Industrieanlagen mit thermischen Chargenprozessen nachbildet. Der Laboraufbau wurde verwendet, um zwei verschiedene Industrieanlagen und die Leistungsfähigkeit des EMS an diesen zu validieren.

Zusammenfassend wird in dieser Arbeit ein validiertes EMS für Industrieanlagen vorgestellt, welches thermische Batch-Prozesse auf dem Technology Readiness Level (TRL) 4 berücksichtigt, den Herausforderungen moderner Energiemärkte gerecht wird und die Implementierung erneuerbarer Energiequellen in Industrieanlagen und im Stromnetz erleichtert. Damit leistet die Arbeit einen wichtigen Beitrag zur Dekarbonisierung der Industrie.

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*”If you thought that science was certain -
well, that is just an error on your part.”*

Richard P. Feynman

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List of Abbreviations

Nomenclature		p	pressure
<i>Abbreviations</i>		P	power consumption
BC	batch consumer	Q	heat
COP	coefficient of performance	RU	ramp up
EMM	energy management in manufacturing	RD	ramp down
EMS	energy management system	S	slack variable
ESS	energy supply system	t	time
HLC	high-level control	t_s	sampling time
HP	heat pump	T	temperature
HS	heat source	U	plant input
HT	heat treatment	u	operation condition
HVAC	heating ventilation and air conditioning	v	start-up integer
LLC	low-level control	V	volume
MILP	mixed-integer linear programming	w	shut-down integer
MPC	model predictive control	<i>Indexes</i>	
OLP	online load predictor	avg	average
RU	ramp-up	C	charge
RD	ramp-down	D	discharge
SOC	state of charge	full	full load
SU	start-up	in	incoming mass flow
SD	shut-down	j	running index
TES	thermal energy storage	k	current time step
<i>Symbols</i>		lhs	left hand side
α, β	linearization coefficients	lim	limit
ϵ_{fix}	fix loss	min	minimum value
ϵ_{SOC}	loss proportional to SOC	max	maximum value
η	compressor efficiency	out	outgoing mass flow
ρ	density	part	partial load
ΔT	temperature difference	rhs	right hand side
ΔN	time-step shift	sink	heat sink of the heat pump
\dot{m}	mass flow	source	heat source of the heat pump
\mathbf{C}	cost coefficient vector in €	<i>General nomenclature</i>	
c	cost factor in e.g. €/MWh	X	scalar variable
c_p	mass-specific heat coefficient	\mathbf{X}	vector variable
n	number of time-steps	\dot{X}	time derivative of X
N_p	prediction horizon	\hat{X}	estimate of X

A) Research Summary

This introduction chapter provides the context of the publications that constitute this thesis and places them in the respective subject areas. First, the challenges for modern energy management systems (EMSs) in the manufacturing industry are summarized. The influence of the increasing share of volatile power sources on the energy market and their implications for energy supply systems (ESSs) in the industry are discussed. Next, known solutions to these challenges - the current state of the art in EMSs - is summarized. In Chapter 2, remaining research gaps are pointed out and research questions are formulated. It is the goal of the thesis to answer these questions. Chapter 3 outlines the methodology which were developed to investigate these questions. The results answering the research questions were published in scientific journals. Therefore, Chapter 4 contains short summaries of these publications comprising the thesis. The introduction chapter is concluded with a description of the scientific contribution of the thesis and an outlook.

1 Problem Statement

The decarbonization of industry is a core objective of the European Green Deal [1] and requires an increasing share of renewable energy sources in electricity generation. The fluctuating availability of electricity generation from wind, solar or hydro power leads to a transformation of the electricity market. This is driven by the mandatory balance between power generation and power consumption, which is required for stable operation of the power grid. Traditionally, power generation is adjusted to balance the grid, but this is no longer sufficient with volatile power sources. Therefore, adjusting the power demand to match power generation is necessary to stabilize the power grid. The actions taken to adjust an industrial facility's power consumption to match power generation are referred to as demand-side management. Incentives such as flexible electricity prices encourage industrial plants to use demand side management. One measure to take full advantage of these incentives is to implement energy management systems (EMSs) that meet the requirements of the modern electricity market. In addition to participating in the modern electricity market, EMSs enable industrial plants to increase energy efficiency and reduce machine wear and emissions by optimally operating the plant's energy supply system (ESS). Nevertheless, EMSs are mainly used in large industrial plants, and widespread application in the manufacturing industry is still hindered by remaining challenges presented in the in the following subchapter.

1.1 Challenges for Energy Management Systems

A major challenge for modern energy management in the industry is the high implementation cost [2]. A predominant part of these costs is caused by the modeling effort [3]. Models of the energy supply systems (ESSs) are indispensable as EMSs rely on predicting the plant's energy demand. Models used for EMSs need to map the energy consumption and the central states of

the ESSs as a function of the production schedule and other factors like the weather. The development of suitable models is challenging. On the one hand, the model accuracy must enable a prediction of the ESS's main states for a prediction horizon of, say, 24 hours; on the other hand, the computational effort to solve the model must be small enough to enable an online optimization. The design and parametrization of sufficient process models is time- and resource-intensive, adding to the implementation cost of EMSs. This challenge is enhanced by the unique character of ESSs in the manufacturing industry. There, ESSs are usually grown structures which are commonly adapted due to changes in the production process or the implementation of renewable energy sources. This individuality of ESSs makes it difficult to implement EMSs in a standardized way and requires repeated adaptation of the model to changes in ESSs [4].

In addition to the model accuracy, the performance of EMSs strongly relies on the accuracy of underlying predictions such as the energy demand, the weather, or the energy price. Reliable forecasts of the energy demand are especially challenging for semi-automated manufactories where human operators greatly influence the processes. The human influence has to be incorporated into the EMSs to avoid critical process state conditions which could harm the production reliability [5].

EMS's possible negative impact on production reliability is another major inhibitor of EMSs in manufacturing plants [2]. The economic impact of inferior products or reduced output often exceeds the savings potential by reducing energy costs many times over. Therefore, EMSs need to ensure production safety. The fear of a negative impact on production reliability is further increased by the lack of validations of EMSs on real ESSs.

A variety of ESS-structures with fundamental differences exist for manufacturing plants mainly depending on the type of production process. The publications this work consists of mainly focus on manufacturing plants, including thermal batch processes. Contrary to continuous processes, where machines constantly operate at specific working points, batch processes induce recurring start and stop maneuvers. While model-based controllers are widespread in continuous processes, they are rarely applied for discontinuous operations [6]. The broader research gap was decisive for focusing on thermal batch processes.

Thermal batch processes frequently occur in manufacturing plants often due to heat treatment (HT) processes. During a HT, a product undergoes specific temperature trajectories to alter the chemical or physical properties of the product. Typical HT are, for example, annealing, tempering, or pasteurization. Typically, HTs include heating phases where the product is brought from a starting temperature to an end temperature causing a short peak-shaped heat demand, as displayed in **Figure 1** [7].

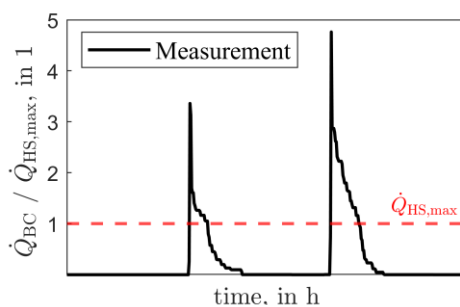


Figure 1: Typical pulse-like heat loads of a batch consumer (BC) compared to the maximum heat production of the heat source (HS). Adapted from **Conference Paper A**.

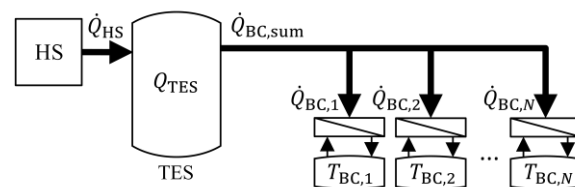


Figure 2: Typical structure of energy supply systems for thermal batch processes. Adapted from **Conference Paper A**.

As indicated in **Figure 1**, the resulting heat demand is usually higher than the maximum continuous heat supply. Therefore, a thermal energy storage (TES) is needed to buffer the high short term energy demand. The typical ESS's basic structure usually looks as shown in **Figure 2** consisting of one heat source (HS), a TES and multiple batch consumers (BC).

Thermal batch processes are often semi-automated and imply require preparation steps. This makes the prediction of heat demands caused by thermal batch processes challenging. The semi-automated nature is also a barrier to implementing scheduling algorithms in EMSs for thermal batch processes. Scheduling enables the synchronization of heat demand with low energy costs. It is a powerful tool to increase the performance of EMSs. Still, it demands a highly automated production process which usually implies cost-intense adaptations of the logistics and production system. Also, logistic reasons like short-term on-demand production, available storage room, and available educts often hinder manufactories from executing scheduling.

In summary, the challenge is to develop a lightweight EMS with low implementation costs and ease of use that ensures production reliability and optimally operates the ESS. Thereby, the decarbonization of manufacturing plants would be enhanced.

1.2 State of the Art

Numerous research groups around the world are working on energy management systems. Therefore, first, an overview of typical different EMS concepts and applications is given. The weighting of the objective function has a strong influence on the ease of use and implementation costs. Therefore, the focus is laid on multi-objective optimization (MOO) and the scalarization and parametrization of multi-objective cost functions. Finally, a summary of recent publications concerning the performance validation of EMSs is given as it is vital to prove that production reliability is ensured with the EMSs.

1.2.1 Energy Management Systems (EMSs)

EMSs are part of the model- and optimization-based methods which are broadly applied to improve manufacturing plants. As the name suggests, model-based methods require appropriate process models. They are used for design optimization, operation optimization, process monitoring, and process control. Depending on the application and investigated process, different model types are applied. Still, for all model-based methods, there are two main counteracting prerequisites for process models. First, they have to describe all relevant effects of the process in a sufficient level of detail. Second, the computational effort has to be small enough to allow optimization in a suitable time. The necessary level of detail and the available optimization time strongly depend on the application. Also, the choice of the model type (state space, linear programming forms, etc.) depends on the ESS.

ESSs in manufacturing plants usually consist of multiple switching components like heat pumps, gas vessels, or combined power and heat plants (CHP). The method of choice to model such components are mixed-integer linear programs (MILP), as the integer variables are used to map the switching behavior. Furthermore, MILP models of the ESS have proven to be easy to implement and easily adaptable [8]. Today, solvers are sufficiently fast and robust to solve reasonable MILP control formulations within fractions of seconds, allowing their use in real-time plant control. MILP optimization problems consist of inputs, a set of constraints, and objectives. Typical

inputs of EMSs are predictions of the energy price, weather conditions, and heat or power demands. The constraints are used to describe the operation limits and energy conversion processes. Among other possible objectives are energy costs, machine wear, and CO₂ emissions.

Beside the concepts of EMS we want to take a look on their fields of application. The scope of the application of EMSs is broad, ranging from urban energy systems [8] and heating, ventilation, and air-conditioning (HVAC) [9]–[12] to energy management for fuel cells [13], to name just a few examples. Also, in large industrial plants, EMSs are becoming more widely used [14]. May et al. [2] give an overview of EMSs in manufacturing plants and identify the main barriers and drivers for EMSs in the industry. They cite the potential negative impact on production performance as the main barrier to the broader adoption of EMSs in manufacturing operations. It is essential that an EMS never violates critical production constraints during operation. Model predictive control (MPC) allows convenient implementation of constraints to ensure production reliability while optimizing (multiple) objectives [15]. Moreover, as its name suggests, MPC can consider predictions during optimization, making it a suitable tool to take full advantage of flexible energy pricing.

This advantage is also a potential weakness of the MPC. The accuracy of the predictions used as input to the MPC is critical to the performance of EMSs [16]. Prediction errors can lead to the violation of important process specifications and thus harm production reliability [5]. This challenge is particularly significant in thermal batch processes for two main reasons: first, the maximum heat flow demand of the thermal heat treatment is usually many times higher than the maximum heat flow that can be supplied continuously by the ESS. As a result, heat demand cannot always be delivered on time but must be stored promptly in the TES. Improper TES management can result in a discharged system which may result in the failure to provide the process heat. Second, thermal batch processes are usually semi-automated, and human operators cause uncertainties in the production schedule.

To avoid impacts on production reliability, EMSs are either not installed at all or operated too conservatively [17], [18]. When EMSs are operated conservatively, the available flexibility of an ESS is not fully utilized, so optimum results are not achieved in terms of reducing energy costs. Methods to avoid the over-conservative operation of EMSs were developed. Still, they either demand elaborate data preprocessing [5], [19], or they are heuristic rules with a narrow field of application [20]. There exists a research gap for EMSs that fully exploit the flexibility of an ESS with broad applicability and little implementation cost.

Implementation costs for EMSs in the industry are mainly caused by the modeling effort, including the estimation of model parameters. Therefore a cost-effective formulation and maintenance of models is crucial [3]. Further, EMSs often demand a high degree of automation and seamless monitoring of the ESSs. These physical adjustments to the ESSs involve implementation costs that are often difficult to offset by reduced energy costs. Therefore, a need for EMSs that optimize existing ESSs without adaptations, which only require little modeling effort exists. A significant challenge for the modeling process is that ESSs are usually grown structures and, thereby, unique [4]. Further, existing ESSs undergo a constant adaptation and development process to comply with changes in the production process. Thus, the model of the ESS needs to be easily adaptable. A modular component-wise formulation of the process model enables a cost-efficient adaption and development of the model. Further, the modular principle enables a broad application to different ESSs. Moser et al. [8] developed a modular EMS for urban multi-energy systems, but no such EMS has been developed for industrial applications. Still, designing the model is only

the first step of EMS implementation. The parameterization of the model and the resulting multi-objective function is equally important.

1.2.2 Multi-Objective Optimization (MOO)

EMSs usually consider different, sometimes contradictory objectives such as increasing production safety, reducing energy costs, and reducing machine wear. In doing so, EMSs minimize several objective functions or an objective function in which several objectives are included. Marler and Arora [21] provide a condensed and comprehensive overview of MOO methods focusing on engineering applications. They classify MOO methods into those with an a priori articulation of the decision makers' preferences and those with an a posteriori articulation of the preferences [21]. The classification differentiates whether the weighting of the goals is executed before or after the optimization. A posteriori articulation of preferences is broadly applied, for example, in the field of combined design and process optimization [22]–[25] but has a decisive disadvantage. Multiple optimization runs with different weight settings must be executed to enable weighting after the optimization. The high computational effort makes the a posteriori articulation of preferences hardly applicable for a real-time application like MPCs.

The most common method for a priori determination of preferences is the weighted sum method, where the different cost functions are combined into a single cost function and weighted by a weighting parameter [21]. The correct choice of the weighting parameters is crucial for the performance of the optimization. Still, a research gap exists, especially on the optimal choice of weight parameters for counteracting objectives [26].

1.2.3 Validation of EMS Performance

Possible negative effects of EMSs on the production process and in particular on production reliability are a major obstacle to the widespread use of EMSs in production plants [2]. Savings in energy costs can rarely compensate for reduced product quality caused by malfunctions of the EMSs. In particular, prediction errors and the lack of countermeasures can cause such malfunctions. Moreover, the solution proposed by a model-based method is never optimal in real applications due to model accuracy [27]. Validation must be performed to prove that the model and EMS are suitable for use in a plant. There is little literature on EMS validation in factories and no experimental validation for plants with thermal batch processes. This lack of validation leads to a lack of confidence in the EMSs by decision makers.

2 Goals

From the state of the art and the outlined research gaps, the main objective was derived: to develop a lightweight EMS that has low implementation costs and can be easily used in industrial plants with thermal batch processes. The EMS must guarantee high production safety and optimize the utilization of the ESS. To condense and structure the goals the overarching objective was formulated:

Overarching Objective:

How to design a broadly applicable EMS which enables the optimal operation of ESSs of industrial plants with thermal batch processes considering the modern electricity market, ensuring production reliability, and causing little implementation cost?

This broad objective is narrowed and subdivided in the following research questions:

- Q1) How can the MILP of such an EMS be designed to meet the time and operational constraints of the modern electricity market?
- Q2) How can the effort of weighting the objective function of the EMS be reduced to lower the implementation costs as much as possible?
- Q3) How can heat loads in thermal batch processes be optimally predicted and measured using data from existing measuring equipment?
- Q4) How can production reliability be ensured when an EMS is used in production facilities with uncertain thermal batch processes?
- Q5) How can a laboratory setup be designed to enable performance validation of such an EMS?

3 Methodology

The core of the methodology is the novel EMS structure shown in **Figure 3** which is presented first [28]. Then, the different components of the EMS are presented, starting with the online load predictor, followed by the HLC and LLC. Then, the volatile energy prices scalarization (VEPS) method is presented. It provides a fast and a priori scalarization and weighting of the multi-criteria cost function of the EMS. Finally, the performance of the EMS is validated using simulation studies and laboratory experiments.

3.1 Energy Management System Structure

The novel EMS structure consists of three major parts:

1. The high-level controller (HLC), which solves a MILP optimization problem to compute optimal trajectories for the main ESS states, considering all objectives (e.g., emissions, energy costs, machine wear).
2. The low-level controller (LLC), which also solves a MILP to calculate the optimal plant inputs for the ESS, considering the trajectories of the HLC and possible disturbances. The main goal of the LLC is production reliability.
3. The online load predictor (OLP), which utilizes the production plan and measurement data to estimate the heat load for the prediction horizon. Further, the OLP deducts a minimal state of charge (SOC) from the load prediction.

Together these parts shall ensure production reliability and utilize the flexibility of the ESS to optimize the operation in terms of all objectives. Further, major goals in the development were to reduce implementation costs, increase production reliability and utilize existing sensors and components optimally to avoid cost intense changes in the ESS. The major parts of the EMS are described in more detail in the following sections.

The separation of the optimization problem into two layers is done mainly due to the high calculation effort. The calculation effort for MILP optimization problems is strongly related to the number of integer variables. At least one integer variable for each time step of the optimization horizon is required to map the behavior of switching behavior. For example, components with switching behavior are supply units like a heat pump or a gas boiler. Also, the charging states of energy storages can induce further integer variables. The modern energy market is structured in

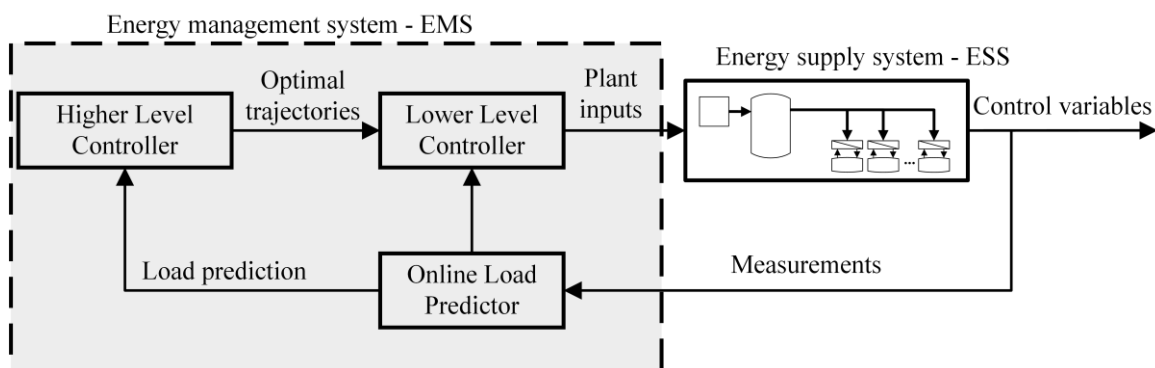


Figure 3: Structure of the developed energy management system (EMS) consisting of an high level controller (HLC), a low level controller (LLC) and an online load predictor. Adapted from **Journal Paper C**.

15 minute intervals, and the day-ahead market demands a prediction of at least 24 hours. Therefore the prediction horizon is at least 96 time steps long.

To react to disturbances and ensure production safety, the EMS needs a shorter sampling interval of about one minute. If the time horizon shall remain at 24 hours, this would cause a prediction horizon of 1440 steps. Considering current mainstream computing power and MILP solver performance, the calculation effort for such a high number of integers would be too high to allow online optimization. The calculation time for a sampling interval of one minute has to be less than one minute. Due to this reason, the optimization problem is split into two problems with different sampling intervals and prediction horizons. The HLC is responsible for fully exploiting the energy market and has a prediction horizon of 96 steps and a sampling interval of 15 minutes $T_{S,HLC} = 15\text{min}$. On the other hand, the LLC is responsible for production safety with a prediction horizon of 60 steps and a sampling interval of one minute $T_{S,LLC} = 1\text{min}$.

The solution of the HLC is incorporated into the optimization problem of the LLC as desired trajectories of the plant inputs and outputs. The LLC tries to follow these trajectories as long as detected disturbances do not endanger production reliability.

Fundamental to the assessment of whether a disturbance endangers the production reliability is the minimal state of charge SOC_{\min} . The SOC_{\min} defines a required minimal amount of heat stored and available in the thermal energy storage, ensuring production reliability. The OLP is responsible for the calculation of the SOC_{\min} bounding trajectory. Therefore, the definition and utilization of the SOC_{\min} is given in Section 3.2.2.

Next to the calculation of the OLP is responsible for detecting deviations between measured and predicted heat load that could cause a violation of SOC_{\min} . Therefore, a load prediction method is utilized, fully exploiting sensors available in most ESSs. Therefore, expensive changes to the ESSs are avoided. As the load prediction and the SOC_{\min} bound are inputs into the optimization problem of the HLC and the LLC, first, the OLP is presented.

3.2 Online Load Predictor (OLP)

The OLP has the following tasks:

1. Predict the heat load caused by thermal batch processes
2. Define the SOC_{\min} which is necessary to ensure production reliability
3. Detect load prediction errors and correct the prediction

3.2.1 Heat Load Prediction

To predict the pulse-like heat load caused by thermal batch processes like heat treatments (HT), the OLP utilizes a prediction method consisting of two steps. First, the integral heat amount of a single heat treatment $Q_{HT,\text{total}}$ is estimated, and then the typical time-domain behavior is the heat-flow $\dot{Q}_{HT}(t)$ is recreated using a first-order delay element.

This method utilizes only the a priori known temperature trajectories of the HTs and the production plan as inputs. As the temperature trajectory is crucial for HTs, it is always known in advance. Further, historical data from a few measurement points are sufficient for the parameterization of the model. **Figure 4** shows the shape of the resulting heat load prediction [7].

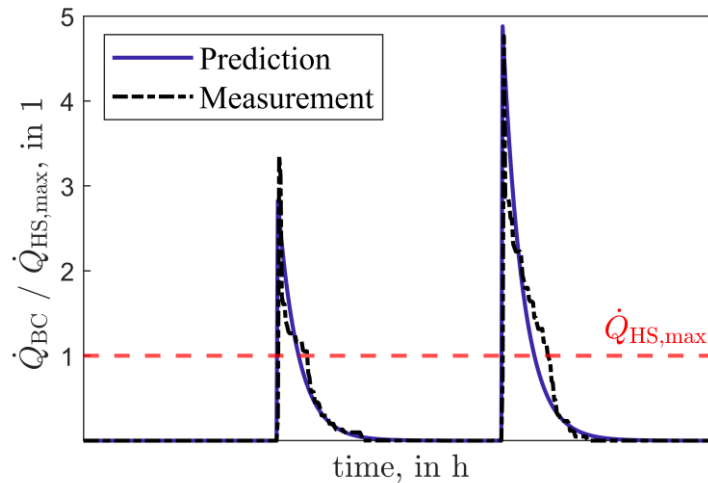


Figure 4: Typical pulse-like heat loads of a batch consumer (BC) and the prediction compared to the maximum heat production of the heat source (HS). Adapted from **Conference Paper A**.

3.2.2 Definition of SOC_{min}

The quantity SOC_{min} is a time-variable minimum state of charge bound for energy storage devices. OLC and LLC consider it as a constraint to ensure production reliability. The SOC_{min} is calculated as enthalpy level and not as temperature. Thereby, different temperature levels can be considered without inherent nonlinearities caused by the mixture of liquids with different temperatures.

The SOC_{min} depends on the maximum temperature and duration of a HT, a safety margin to increase robustness against uncertainties, and a desired minimum temperature difference which ensures the driving force for heat exchange. The EMS is robust to prediction errors smaller than the defined safety margin. The constraint is only active when heat loads occur according to the production plan considering an uncertainty factor. The uncertainty factor increases the robustness of the EMS against differences between the scheduled and the actual starting times. **Figure 5** shows the constraint used in the HLC as red area, the predicted, and the measured SOC .

Implementing the SOC_{min} ensures production safety while maximizing the flexibility of the EMS. The flexibility of electricity demand can be used either for participation in the balancing energy market or in short-term electricity markets such as the intraday market or the day-ahead market.

3.2.3 Prediction Error Compensation

The OLP performs three corrective actions when the measured heat load deviates from the prediction in terms of amount or timing:

1. Shifting the starting time of all HTs to the earliest possible time: The semi-automated nature of thermal batch processes can cause a change in the starting time of a HT. Thereby, the pulse-like heat load may occur before the SOC is high enough. To prevent HT from occurring earlier than predicted, the start times of all HTs are shifted by their maximum possible start time deviations.

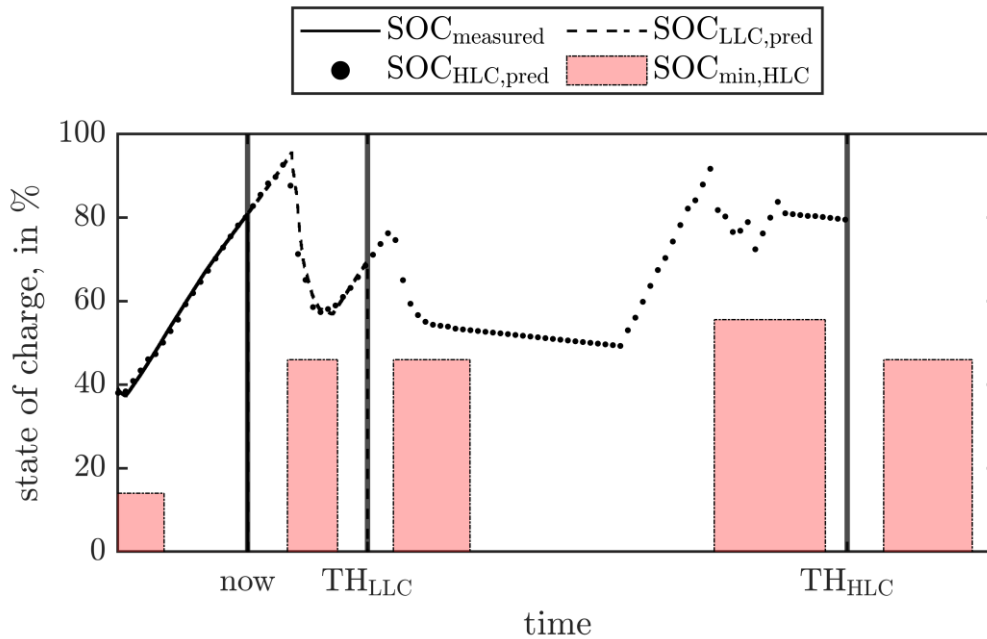


Figure 5: The measured (SOC_{measured}) minimal (SOC_{min}) and the predicted state of charge SOC_{pred} of both optimization layers and the corresponding time horizons (TH). Adapted from **Journal Paper A**.

2. The second measure counteracts the delay of HT. If an expected HT is detected to be delayed, the OLP automatically delays the HT load prediction by one timestep.
3. The third measure corrects the difference between the measured and the predicted heat flows. At each timestep, the difference between measured and predicted heat flows is distributed to the remaining load prediction profile.

Via these three measures, the OLP utilizes online measurement data to correct the load prediction and increase the production reliability for manufacturing plants with thermal batch processes.

3.3 High-level Controller and Low-level Controller (HLC & LLC)

The HLC and the LLC are both based on a component-wise defined MILP. The optimization problem is described component-wise by a set of constraints, inputs, and objectives. To connect the single components to each other, so-called nodes are used. Nodes represent the mass or energy balances that have to be fulfilled for connected components.

The energy balances are interpreted as utilizable enthalpy amounts covering net heat demand on specified temperature layers. Thereby, nonlinearities caused by mixing two fluids with different temperatures are avoided.

Due to this structure, the overall optimization problem can be assembled by stacking all constraints and summing up all objectives into a single MILP. Thereby, the effort of adapting the model due to changes in the ESS is minimized. The main remaining design effort is the correct choice of the weight parameters of the cost function. A novel parametrization method was developed for EMSs which seek to exploit the modern power market as described in the following chapter.

3.4 Volatile Energy Price Scalarization (VEPS) – Parameterization Method

Modern EMSs usually consider multiple different objectives, like the reduction of energy cost, the reduction of machine wear, and the reduction of emissions. A balanced weighting of each objective is necessary to achieve optimal performance in all objectives. Due to the small calculation effort, the weighted sum method is used in the vast majority of MPC applications.

For modular EMSs, each component has its own objective function consisting of one term for each considered objective (e.g., energy cost reduction, machine wear reduction). Thereby the objective function consists of many terms, and scalarization and weighting are necessary to achieve satisfying results.

Existing scalarization and weighting methods are either cost-intensive or do not guarantee good overall performance. Therefore, a new method was developed: the volatile energy price scalarization (VEPS) method. The VEPS method does not rely on previous simulations or test runs, which reduces implementation costs. The method is based on selected metrics which quantify the cost reduction potential caused by volatile energy prices. The definition of the scalarization factor is based on the assumption that ESSs with a given production plan and without energy carrier substitution can only reduce energy costs by storage management.

The VEPS method introduces weighing parameters based on the scalarization factor that are comprehensible, meaningful, and clear to operators or technicians handling an ESS. Thereby implementation costs are reduced, and the optimal performance of the EMS is ensured. Another barrier for the acceptance of EMSs in the manufacturing industry is still low due to the lack of performance and reliability validations.

3.5 Validation

The developed EMS and its methods were validated in various simulation studies and two case studies executed in the laboratory. The vast majority of performance validation of EMSs in literature is executed without a detailed and validated simulation model of an existing plant and even more rarely with real-world hardware [Journal Paper C]. Instead, the optimization model used in the EMS is also used to simulate the plant. Thereby the effect of model errors is neglected during the performance assessment. To close this gap, a validated simulation model of an existing food processing manufacturing plant was developed.

The available publications on EMS for industrial plants only rarely include laboratory applications [2]. To conduct thorough validation experiments, a laboratory setup must be designed to replicate a thermal batch process, including, for example, pulse like heat loads and heat recovery systems. Experiments that adopt the key features of factories with thermal batch processes can increase the confidence and applicability of EMSs in factories. To the best of the authors' knowledge no laboratory experiments for EMSs in manufacturing plants with thermal batch processes are published. Therefore, laboratory experiments with high relevance for industrial plants were executed.

3.5.1 Simulation Study

The simulation study is based on a real-world manufacturing plant that uses thermal batch processes to alter the taste and consistency of food products and increase their shelf life. The structure of the considered production plant is displayed in **Figure 6**. The production line consists of a heat pump with 206kW heat flow at the heat sink, a water tank with a volume of 12.7m³ as

TES, and four batch consumers, which cause pulse-like heat loads. The maximum heat demand is 1367 kW and thereby 6.6 times higher than the maximum continuous heat supply.

Figure 7 shows a validation plot for the simulation model of the plant. Industrial measurement data was used to evaluate the accuracy of the model and to validate the usability of the model for predictive control tasks. The simulation model was built component-wise in MATLAB Simulink®. The component models consider nonlinear effects like valve openings, underlying control architectures, and nonlinear fluid properties. For each time step of the simulation, this detailed plant model calculates the system states for the optimized plant inputs obtained by the EMS. To allow a quantitative evaluation of the EMS performance, each simulation emulates a production plan of one month, including over 100 heat treatments.

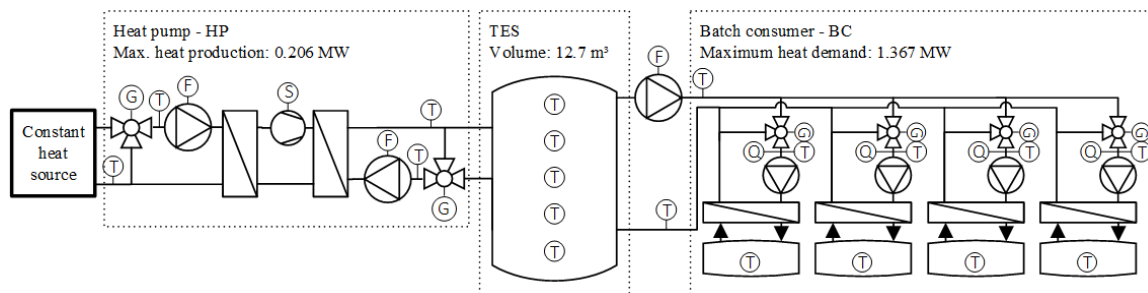


Figure 6: Structure of the investigated production line of the industrial food processing plant from **Journal Paper A**.

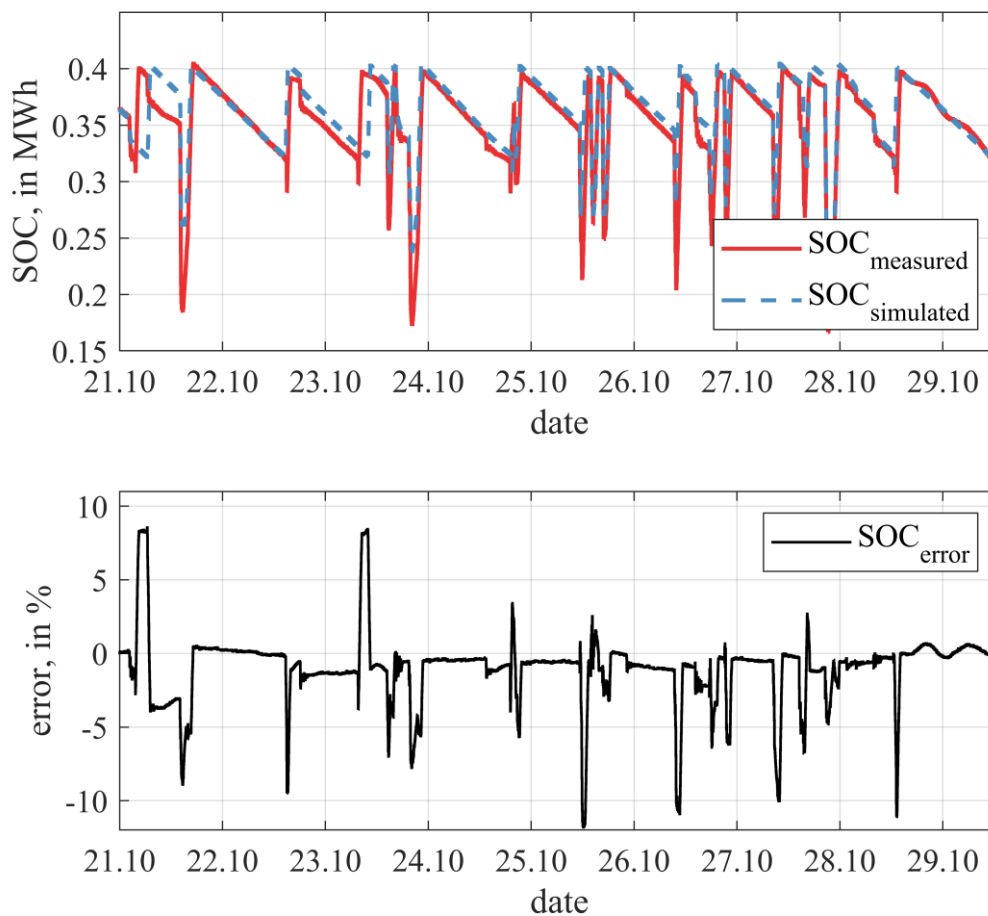


Figure 7: Validation of the simulation model. Adapted from **Journal Paper A**.

3.5.2 Laboratory Validation

To validate the performance of an EMS for manufacturing plants considering thermal batch processes, industrial use cases need to be emulated. Two case studies considering pulse-like heat loads and temporarily available heat sources are created for validation.

The laboratory setup is displayed as a scheme in **Figure 8**, and a picture of parts of the setup is shown in **Figure 9**. The setup consists of a heat pump, a boiler used to emulate heat recovery systems, an electric heater used to emulate different heat sources, a thermal storage and a heat sink enabling the emulation of pulse-like heat demands. To quantify the performance, the EMS is compared to a typical rule-based hysteresis controller.

To enable an assessment of the multi-objective optimization, emission reduction and energy cost reduction are considered objectives. Current values for energy price, emission footprint, and heat loads deducted from industrial measurement data are used to increase the industrial relevance of the experiments.

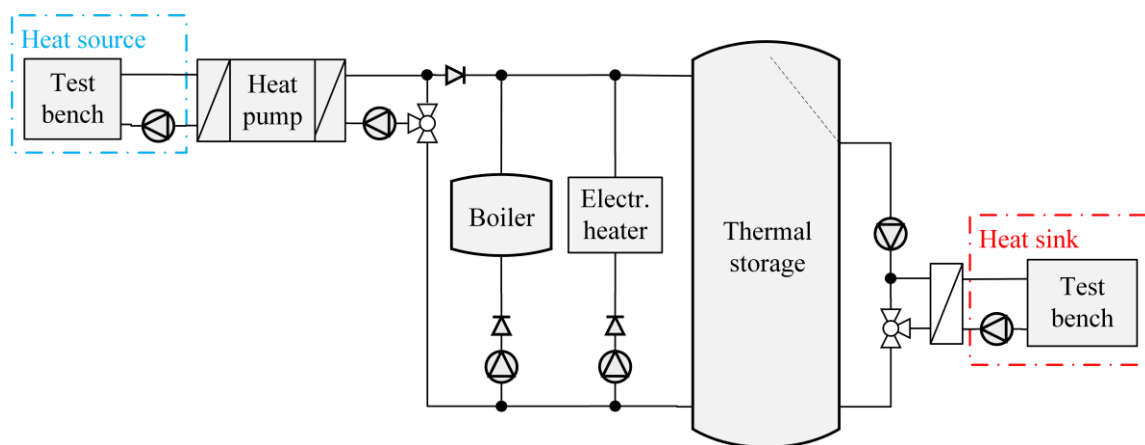


Figure 8: Schema of the laboratory setup. Adapted from **Journal Publication C**



Figure 9: Picture of the laboratory setup from **Journal Publication C**.

4 Summary of scientific approaches

In this chapter, the context and synthesis of the publications which constitute this thesis are given and their results are summarized. The chronological order of publications is chosen as a structure:

4.1 Conference Paper A

The first literature studies showed that the prediction of disturbances is crucial for the performance of EMSs and that no such prediction method exists for heat loads caused by thermal batch processes. Therefore, the first publication, see Section B)5, deals with predicting pulsed heat loads in manufacturing plants caused by heat treatments. The application-oriented method utilizes basic laws of thermodynamics to increase the prediction accuracy and, thereby, the performance of energy management systems. The method can be applied in a straightforward way because historical data from a few measurement points are sufficient for its execution. Thereby, no cost-intensive changes in sensor installations are needed for the application of the method in industrial plants. Furthermore, the method is seen to be insensitive against measurement noise. The method was validated using measurement data from an actual food processing industrial plant. Also, the impact on the performance of a model predictive controller was investigated. The work was also presented as a conference presentation at the IFAC World Congress 2020.

4.2 Conference Paper B

Despite the precise prediction method presented in Conference Paper A), unpredictable inaccuracies in the heat load remain when human operators are involved. Therefore, research was conducted to increase the robustness particularly against such uncertainties and presented in Conference Paper B. The publication, see Section B) 6, presents guidelines for model predictive control dealing with uncertain pulse-like disturbances whose uncertainties are caused by human operators. An efficient solution method based on introducing slack constraints on the minimal state of charge is presented. Further guidelines to calibrate a mixed-integer model predictive controller with industrial operating data are given. The method successfully avoids critical system states caused by uncertain peak-like heat loads. Using measured data from an industrial application, a simulation study is conducted to investigate the control parameters' influence on the controller's robustness and efficiency. The work was also disseminated as a conference presentation at the 30th European Symposium on Computer Aided Process Engineering (ESCAPE30).

4.3 Journal Paper A

During the research for the conference papers multiple different EMS structures were tested in simulation studies and further optimized afterwards. Journal Paper A, see Section B) 2, presents the result: a modular model predictive EMS for production plants with thermal batch processes. Core elements of the EMS are a two-layer mixed-integer model predictive controller and an online load predictor (OLP). The OLP uses real-time measurement data to estimate the typical pulse-like heat loads of thermal batch processes. The OLP uses the prediction method and constraint formulations developed in Conference Papers A and B. Thereby the OLP increases production reliability and maximizes the flexibility of the EMS. The structure of the optimization

problem allows modular, component-by-component definition and parameterization. The modularity allows system integrators to implement the EMS without time- and resource-intensive modeling tasks and parameter tuning.

The proposed methods address the two significant challenges in implementing EMSs in production plants: high implementation cost and reduction of production reliability. The validated simulation model of an actual food processing production plant was used to validate the EMS performance. Since the considered process strongly exhibits the typical characteristics of batch processes, the results can be transferred to other thermal batch processes such as tempering, annealing, or pasteurization.

4.4 Journal Paper B

During the development and validation of the EMS presented in Journal Paper A, the high workload of correctly choosing the weight parameters and the crucial impact of these parameters on the optimization performance became evident. Therefore, Journal Paper B, see Section B) 3, focuses on the efficient parametrization and scalarization of multi-objective EMSs. The volatile energy prices scalarization method (VEPS) is introduced, enabling an intuitive weighting of EMSs participating in modern power markets. The VEPS method is compared to existing methods in the literature. The VEPS method outperforms methods with comparable effort and shows similar results to methods which higher parametrization effort. For comparison, the validated model of an existing food processing manufacturing plant is utilized. The case study also confirms the effectiveness of existing methods using prior simulation studies for tuning the weights. Nevertheless, economic weighting methods such as the VEPS method are helpful for the fast and cost-effective implementation of EMSs in the manufacturing industry.

4.5 Journal Paper C

Despite the validated performance and easy implementation of the EMS developed in the first four publications, further experiments were needed before the EMS could be applied in industry. The trust in the optimality and robustness of the EMS needed to be proven under industry-close conditions. Therefore, Journal Paper C, see Section B) 4, presents the laboratory validation of the EMS developed in Journal Paper A and quantifies the performance benefit for two industrial use cases. The laboratory setup consists of a heat pump, an electric boiler, an instantaneous water heater, a flexible heat sink, and a thermal energy storage system. This setup replicates industrial energy supply systems, including heat recovery systems. The heat sink is used to apply pulse-like heat loads, thus emulating thermal batch processes. Actual values for volatile energy prices, CO₂ equivalent coefficients, and heat loads from a real industrial plant make the laboratory experiments highly relevant to the industrial context. The EMS outperforms the commonly used hysteresis controller by reducing energy costs by 5-15%, reducing CO₂ emissions by 9-42%, and increasing production reliability. With these experiments, the practical applicability of the EMS is tested, and the technology readiness level (TRL) of the EMS is raised to TRL 4.

Summarized, an EMS which meets the challenges of industrial plants with thermal batch processes and the modern power market was developed and optimized throughout the publications. The EMS thereby reached TRL 4 as its performance was validated in the laboratory. During the application of the EMS, yet unseen potential for an enhanced configuration of EMS in different

process control systems was detected. The developed method was hence the basis for a patent application.

4.6 Patent*

A patent application has been filed for a method that enhances the configuration and operation of a model-based optimal energy controller within a process control system. The optimal energy controller optimizes the operation of energy supply systems and reduces energy-related costs of a process plant. The novelty facilitates the implementation of EMSs.

5 Scientific Contribution & Outlook

The scientific contributions of this work, organized according to the research questions and the publications presented in this work, are:

Q1: How can the MILP of such an EMS be designed to meet the time and operational constraints of the modern electricity market?

Journal Publication A presents a novel EMS structure consisting of the two optimization layers, HLC and LLC, and the online load predictor. This structure can satisfy the time constraints of the modern electricity market. Moreover, the MILP formulation of the optimization problem allows convenient implementation of the constraints typical for the modern electricity market. The planning and implementation of the control energy supply is also possible with the presented structure.

Q2: How can the effort of parametrization and weighting of the objective function of the EMS be reduced to lower the implementation costs as much as possible?

The optimization models presented in **Journal Publication A** enable straightforward parameterization based on data sheets, allowing system integrators to implement and configure the energy management system without time-consuming modeling tasks and complex parameter tuning. Furthermore, the VEPS method presented in **Journal Publication B** enables effective design, standardization, and weighting of the multi-objective function of model-based EMSs without the need for prior simulations or test runs. This reduces implementation effort and cost.

Q3: How can heat loads in thermal batch processes be optimally predicted and measured using data from existing measuring equipment?

In **Conference Publication A**, an application-oriented prediction method for peak heat loads is presented based on data from a few data points typically available in industrial facilities. The method is validated and tested for an industrial application.

Q4: How can production reliability be ensured when an EMS is used in production facilities with uncertain thermal batch processes?

The prediction method for peak-shaped heat loads introduced in **Conference Publication A** is incorporated in the online load predictor (OLP) presented in **Journal Publication A**. Therefore, the EMS can fully exploit the existing measurement data to increase the robustness of the optimization performance. Moreover, the definition of a time-dependent SOC_{\min} ensures process reliability while simultaneously maximizing the flexibility of the EMS. In **Conference Publication B**, a case study was conducted to investigate the impact of heat load uncertainties on the performance of the EMS.

Q5: How can a laboratory setup be designed to enable performance validation of such an EMS?

Journal Publication C presents a laboratory setup that allows emulation of an ESS with temporarily available heat sources (i.e., waste heat and renewable energy sources) and pulse-shaped heat demand, both typical of industrial plants with thermal batch processes. The laboratory setup was used to validate the performance of the EMS proposed in **Journal Publication A** for two different experimental setups. The EMS successfully and reliably optimized the operation of the emulated ESS and the results published in Journal Paper C.

In summary, the methods presented in this work allow to implement and operate an EMS for ESSs of industrial plants with thermal batch processes that takes into account the modern electricity market, ensures production safety and has low implementation costs. Thus, the overall objective *Overarching objective* was achieved. The developed EMS has all the features required for wide application in industrial plants with thermal batch processes. Nevertheless, plant operators must have full confidence in the reliability of the methods before predictive and optimization-based EMS become state of the art in industry.

To further increase the confidence and interest of industry decision makers, further validation of the EMS performance is required. The next step in the validation process is an application in industrial facilities. The EMS presented in this paper is currently being implemented in three different manufacturing plants to accomplish this step. In addition, general applicability in various manufacturing processes must be demonstrated. The validation must be extended to other types of plants in addition to thermal batch processes.

The rapid developments in the electricity market and energy markets in recent months have created enormous incentives for industrial plants to focus on improving their energy management. The operation and optimization of the electricity system, ranging from the power plant to the grid to the household and industrial ESS, will be one of the most demanding and interesting challenges for control engineers in the coming decades.

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B) Publications

1 List of Publications

Journal Publication A

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

Model-predictive energy management system for thermal batch production processes using online load prediction

Computers and Chemical Engineering, Volume 163, 2022, Issue 107830.

DOI: [10.1016/j.compchemeng.2022.107830](https://doi.org/10.1016/j.compchemeng.2022.107830)

Journal Publication B

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

Model-based energy management systems : Weighting of multi-objective functions using the Volatile Energy Prices Scalarization (VEPS)

Computers and Chemical Engineering, Volume 169, 2022, Issue 108078.

DOI: <https://doi.org/10.1016/j.compchemeng.2022.108078>

Journal Publication C

Florian Fuhrmann, Bernd Windholz, Alexander Schirrer, Sophie Knöttner, Karl Schenzel, Martin Kozek.

Energy management for thermal batch processes with temporarily available energy sources – laboratory experiments

Case Studies in Thermal Engineering, Volume 39, 2022, Issue 102473.

DOI: [10.1016/j.csite.2022.102473](https://doi.org/10.1016/j.csite.2022.102473)

Conference Publication A

Florian Fuhrmann, Alexander Schirrer, Martin Kozek, Stefan Jakubek.

Prediction of pulsed heat loads in manufacturing plants

IFAC-PapersOnLine, Volume 53, 2020, p. 10449-10454.

DOI: [10.1016/j.ifacol.2020.12.2787](https://doi.org/10.1016/j.ifacol.2020.12.2787)

Conference Publication B

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

MPC for Process Heat Supply Systems: Considering Load Prediction Uncertainty Caused by Human Operators

Computer Aided Chemical Engineering, Volume 48, 2020, p. 1219-1224.

DOI: [10.1016/B978-0-12-823377-1.50204-4](https://doi.org/10.1016/B978-0-12-823377-1.50204-4)

2 Journal Publication A

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

Model-predictive energy management system for thermal batch production processes using online load prediction

Computers and Chemical Engineering, Volume 163, 2022, p.107830.

DOI: [10.1016/j.compchemeng.2022.107830](https://doi.org/10.1016/j.compchemeng.2022.107830)

Applicant's contribution*

- **Florian Fuhrmann:** Conceptualization, Methodology, Software, Validation, Writing – original draft.
- **Alexander Schirrer:** Conceptualization, Writing – review & editing, Supervision.
- **Martin Kozek:** Writing – review & editing, Supervision, Funding acquisition.

*According to the Elsevier CRediT author statement: <https://www.elsevier.com/authors/policies-and-guidelines/credit-author-statement>

Abstract:

Predictive energy management systems (EMS) enable industrial plants to participate in the modern power market and reduce energy cost. In this paper, a novel modular model predictive EMS specifically designed for industrial thermal batch processes is presented. The EMS consists of a two-layer mixed-integer model predictive controller and an online load predictor, and thus solves the main challenges of EMS in industry - high implementation costs and the possible reduction of production reliability. The modular formulation of the optimization problem enables system integrators to implement the EMS without time-consuming modelling tasks and elaborate parameter tuning. The online load predictor estimates the typical pulse-like heat loads of batch processes ensuring both - reliable production and maximal flexibility of the power demand. The utilization of real-time data provides additional robustness against uncertainties caused by human operators. The performance of the EMS is evaluated in a case study of an existing food plant.

3 Journal Publication B

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

Model-based energy management systems: Weighting of multi-objective functions using the Volatile Energy Prices Scalarization (VEPS)

Computers and Chemical Engineering, Volume 169, 2022, Issue 108078.

DOI: <https://doi.org/10.1016/j.compchemeng.2022.108078>

Applicant's contribution*

- **Florian Fuhrmann:** Conceptualization, Methodology, Validation, Investigation, Writing - Original Draft, Visualization.
- **Alexander Schirrer:** Supervision, Conceptualization, Methodology, Writing - Review & Editing.
- **Martin Kozek:** Project administration, Funding acquisition, Writing - Review & Editing.

*According to the Elsevier CRediT author statement: <https://www.elsevier.com/authors/policies-and-guidelines/credit-author-statement>

Abstract:

Predictive energy management systems (EMSs) enable industrial plants to operate the energy supply systems at optimal efficiency, taking account of multiple objectives, including energy cost reduction. The performance of model-based EMSs depends on the appropriate design and correct scalarization of the resulting multiobjective function. This paper introduces the volatile energy prices scalarization (VEPS) method, which effectively designs, standardizes, and weighs the multiobjective function of model-based EMSs without the need for prior simulations or test runs. We present a case study, in which we compare the VEPS method to other state-of-the-art methods, utilizing a validated simulation model from an industrial food plant. The results show that the VEPS method outperforms other weighting methods with comparable tuning effort in this case-study. Moreover, the performance of the VEPS method is close to the Pareto-optimal performance. Economic weighting methods such as VEPS enable a fast and cost-effective implementation of EMS in the manufacturing industry.

4 Journal Publication C

Journal Publication C

Florian Fuhrmann, Bernd Windholz, Alexander Schirrer, Sophie Knöttner, Karl Schenzel, Martin Kozek.

Energy management for thermal batch processes with temporarily available energy sources – laboratory experiments

Case Studies in Thermal Engineering, Volume 39, 2022, p.102473.

DOI: [10.1016/j.csite.2022.102473](https://doi.org/10.1016/j.csite.2022.102473)

Applicant's contibution*

- **Florian Fuhrmann:** Conceptualization, Methodology, Investigation, Software, Validation, Writing - Original Draft.
- **Bernd Windholz:** Conceptualization, Investigation, Writing - Original Draft.
- **Sophie Knöttner:** Writing - Original Draft, Methodology.
- **Karl Schenzel:** Writing - Review & Editing, Methodology.
- **Alexander Schirrer:** Conceptualization, Writing - Review & Editing, Supervision.
- **Martin Kozek:** Writing- Reviewing and Editing, Supervision, Funding acquisition.

*According to the Elsevier CRediT author statement: <https://www.elsevier.com/authors/policies-and-guidelines/credit-author-statement>

Abstract:

Predictive energy management systems (EMS) enable the optimization of industrial energy supply systems (ESS) without cost-intensive structural changes. Despite intensive research on EMS, few publications address industrial applications - and even fewer address practical experiments with industrial EMS in physical laboratory environments. This paper describes the design and usage of a test rig emulating an industrial ESS including temporarily available heat recovery systems and batch-type heat demands. In addition, the performance of a recently proposed modular two-layer EMS is assessed on this test rig. The experimental setup consists of a heat pump, an electric boiler, an instantaneous water heater, and a thermal energy storage system. To emulate an industrial ESS current values of volatile energy prices, emissions footprint and industrial measurement data of heat loads are used. The experiments validate that the test rig can emulate an industrial ESS. Further, the results show that the EMS makes optimal use of the laboratory ESS and takes full advantage of temporarily available energy sources. Bottlenecks in heat supply were avoided, and for this specific setup energy cost-reductions of 5-12% and CO₂-reductions of 9-42% were achieved compared to a hysteresis controller.

5 Conference Publication A

Conference Publication A

Florian Fuhrmann, Alexander Schirrer, Martin Kozek, Stefan Jakubek.

Prediction of pulsed heat loads in manufacturing plants

IFAC-PapersOnLine, Volume 53, 2020, p. 10449-10454.

DOI: [10.1016/j.ifacol.2020.12.2787](https://doi.org/10.1016/j.ifacol.2020.12.2787)

Applicant's contribution

- **Florian Fuhrmann:** Conceptualization, Methodology, Validation, Investigation, Writing - Original Draft, Visualization.
- **Alexander Schirrer:** Supervision, Conceptualization, Methodology, Writing - Review & Editing.
- **Martin Kozek:** Project administration, Funding acquisition, Writing - Review & Editing.

Abstract:

Predictive control is beneficial for effective energy demand management. Precise disturbance prediction is a decisive factor for the performance of predictive control. This paper focuses on the accurate prediction of pulsed heat loads caused by heat treatment in manufacturing industry processes. An application-oriented method to predict heat load peaks is developed utilizing basic laws of thermodynamics, validated with process data from an industrial use case, and tested with a model predictive controller. Two core characteristics of the method enable a straightforward application in industry: 1. Historic data from few measurement points are sufficient. 2. Robustness against measurement noise.

6 Conference Publication B

Conference Publication B

Florian Fuhrmann, Alexander Schirrer, Martin Kozek.

MPC for Process Heat Supply Systems: Considering Load Prediction Uncertainty Caused by Human Operators

Computer Aided Chemical Engineering, Volume 48, 2020, p. 1219-1224.

DOI: [10.1016/B978-0-12-823377-1.50204-4](https://doi.org/10.1016/B978-0-12-823377-1.50204-4)

Applicant's contribution

- **Florian Fuhrmann:** Conceptualization, Methodology, Validation, Investigation, Writing - Original Draft, Visualization.
- **Alexander Schirrer:** Supervision, Conceptualization, Methodology, Writing - Review & Editing.
- **Martin Kozek:** Project administration, Funding acquisition, Writing - Review & Editing.

Abstract:

The aim of this work is to define guidelines for model predictive control dealing with uncertain pulse-like disturbances caused by human operators. Measurement data of an industrial use case is utilized to carry out a simulation study to investigate the influence of control parameters on the robustness and efficiency of the controller. Special focus is laid on an efficient way to introduce suitable slack constraint formulations into the mixed-integer model predictive controller formulation to cope with uncertain peak loads. Methods to calibrate such a control structure with industrial operational data are given.

Curriculum Vitae



Florian Fuhrmann

Process Engineer with special interest for control, simulation, optimization and model-based methods.



12-05-1991
Linz, AUT

PERSONAL INTERESTS

SAVT | Chair of Alumni club 2021
Sindbad | Mentor 2019-2020
Football | play & watch since 1994
Travelling | all around the world

EXPERIENCE

Control Engineer | Wien Energie | since 11 / 2022

- development and implementation of new control concepts
- decarbonisation of the district heating in Vienna
- performance optimization of the district heating in Vienna

Project Assistant | TU Wien | 10 / 2018 – 09 / 2022

- modelling and control of energy supply systems in industry
- teaching at the Institute of Mechanics and Mechatronics
- acquisition & management of projects
- scientific dissemination

Laboratory Assistant | TU Wien | 01 – 06 / 2017

- downstream processing (homogenization, filtration)
- analytics (HPLC, Gel electrophoresis)
- fermentation work (experimental setup, sampling)

Internship | Lackner Consulting | 09 – 12 / 2016

- setup of a photobioreactor including process control for cyanobacteria fermentation
- fermentation work (DoE, sampling, harvesting)
- design of a downstream process for Polyhydroxybutyrate

Internship | Wien Energie | 07-08 / 2015

- shift work in a waste-to-energy plant
- analytics for the wastewater treatment

Civil Service | Red Cross Vienna | 2011 - 2012

- Paramedic

EDUCATION

Doctoral Study | TU Wien | since 2018

Model-based energy management systems for manufacturing plants

MA Process Engineering | TU Wien | 2016 - 2018

Thesis: Model based redesign of Experiments in Bioprocesses

BA Process Engineering | TU Wien | 2012 - 2016

Thesis: Investigation of CO₂ Absorption in K₂CO₃-Solutions

High School for Forestry | Bruck/Mur | 2005 - 2011

A-Levels with excellent success

LANGUAGES

German | native
English | excellent
French | basic

COMPUTER

MS Office | excellent
MATLAB | excellent
CAD | basic
Python | basic