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Scheduling coordination of multiple production and utility systems in a multi-leader multi-follower Stackelberg game

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ABSTRACT

Large industrial sites commonly contain multiple production and utility systems. In practice, integrated optimization is often not possible because the necessary complete information cannot be exchanged between the systems. Often, industrial sites optimize the operation of production and utility systems sequentially without any feedback, which leads to suboptimal operation.

In this paper, we propose a method to coordinate between production and utility systems in a multi-leader multi-follower Stackelberg game. The proposed method does not require complete information exchange. The only information exchanged in one feedback loop is the energy demand and demand-dependent energy cost.

In two case studies, the method reduces the total production cost by 7.6% and 3.4% compared to the common sequential optimization. These cost savings correspond to 84% and 88% of the potential cost savings by an integrated optimization. In summary, the proposed method reduces cost significantly, while only incomplete information is exchanged between production and utility systems.

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1. Introduction

Large industrial sites often consist of multiple production systems. Energy for the production systems is normally supplied by on-site utility systems. Most often, each system on the industrial site is operated by a different company or business unit. As a result, the operation is optimized for each system individually (Engell et al. 2015). The individual optimizations are commonly performed sequentially: First, each production system schedules its production plan which also defines its energy demand. Subsequently, the utility systems individually optimize their operation to fulfill the energy demand.

In the last decades, major advances have been achieved in scheduling of either production systems or utility systems (see the review by Castro et al. (2018)). For production systems, research has also tackled different energy-consumption-related issues, e.g., heat integration (Pinto et al., 2003; Seid and Majozi, 2015), time-sensitive electricity prices (Hadera et al., 2015). For utility systems, new challenges arise from increasing electricity production from renewable energy sources, e.g., design with time-dependent grid emissions (Baumgärtner et al., 2019) or operation with time-dependent electricity prices (Kumbartzky et al., 2017; Mitra et al., 2013). However, common approaches optimize production and utility systems still individually and sequentially. Consequently, potential synergetic effects are missed leading to suboptimal operation and cost in general.

The minimal cost can be achieved by the integrated optimization of all production and utility systems. Agha et al. (2010) integrate scheduling for one production and utility system. Zulkafli and Kopanos (2016) incorporated unit performance degradation and Leenders et al. (2020) the provision of control reserve in balancing markets. The present authors extended the integrated scheduling to the integrated design of both systems (Leenders et al., 2019b).

However, integrated optimization is often not desired or even prohibited if systems are operated by different companies since integrated optimization requires that all systems share all information on their optimization problems. In practice, the systems often

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cannot exchange all information. In game theory, this situation is called incomplete information. Still, the exchange of incomplete information can be beneficial. The challenge is to identify the relevant information such that the resulting schedule is almost as good as solving an integrated optimization.

Professor Engell, to whom this special issue is dedicated, has recognized this important practical problem and proposed first solution approaches that use incomplete information to coordinate between systems in an industrial site: Maxeiner et al. (2017) coordinate between interconnected systems and use resource-prices as incomplete information exchanged between the systems. In the method, shared resources are allocated by a central site manager. The problem is solved iteratively by price-based coordination. Wenzel et al. (2020) coordinate between different production systems. They decompose the integrated optimization problem into optimization problems for each production system. The solutions of each production systems optimization problem are approximated and the systems are coordinated by a hierarchical market-like coordination algorithm.

Recently, Allman and Zhang (2020) also addressed the cooperative demand response of an industrial process and its customers. The industrial process can benefit from time-varying electricity prices by shifting its production. For this purpose, the industrial process coordinates with the customers to shift their product demand. The algorithm by Allman and Zhang (2020) is based on the alternate direction method of multipliers. As incomplete information, only product demand and price information are exchanged between the industrial process and its customers.

The above reviewed coordination methods decompose the integrated optimization into individual optimization problems for each system. However, in practice, often a hierarchical structure exists between the systems. For example, the production systems announce their energy demands first and, subsequently, the utility systems optimize their operation to fulfill the announced energy demands. If both systems have different objectives, this hierarchical structure cannot be described by an integrated optimization problem.

However, hierarchical structures can be described by game theory. In particular, Stackelberg games model the hierarchical structure between different parties (von Stackelberg, 2011). In Stackelberg games, the parties are either leaders or followers. Leaders decide first and followers optimize based on the leader's decisions.

If the leader has complete information on the follower, the Stackelberg game can be described and solved as bilevel problem (Sinha et al., 2018). Bilevel problems are challenging to solve and are proven to be NP-hard (Jeroslow, 1985; Bard, 1991). However, promising solution algorithms have been developed to solve bilevel problems (Djelassi et al., 2019; Mitsos, 2010).

If the leader has only incomplete information on the follower, commonly, tailor-made methods are applied. In the following, Stackelberg games are briefly reviewed for both cases where the leader has either complete or incomplete information. Wang et al. (2016) solve a Stackelberg game between the product-family architecture (leader) and the supply-chain configuration (followers). The single-leader multi-follower Stackelberg game is solved iteratively by exchanging the solutions of each follower with the leader and vice versa. Because only the solution is exchanged, the optimization uses incomplete information. Yue and You (2017) propose a solution algorithm for the supply-chain optimization with complete information in a single-leader single-follower Stackelberg game. The algorithm solves the resulting mixed-integer bilevel problem.

Stackelberg games are also widely applied in energy applications. For a smart grid, Yu and Hong (2016) iteratively solve a single-leader multi-follower Stackelberg game. In their Stackelberg game, an utility company is the leader and multiple customers are the followers. The leader minimizes the variations in the generated electricity. The followers minimize the payments for consumed electricity as well as maximize the satisfaction by consumed electricity. An iterative solution algorithm is applied based on incomplete information exchanged: electricity prices and power demands. Motalleb et al. (2018) model a single-leader multi-follower Stackelberg game for a real-time demand response market with an exchange of incomplete information. In their Stackelberg game, the utility company (leader) regulates powers and prices by announcing the electricity price and trading power quantity. Demand response aggregators (followers) announce their bids for buying or selling electricity. For a smart grid, Maharjan et al. (2013) solve a multi-leader multi-follower Stackelberg game iteratively. The solution approach is based on incomplete information exchange where the utility companies (leader) announce the energy prices and end-users (followers) respond with their energy demand.

Yokoyama et al. (2019) model a Stackelberg game between a central power-utility system as the leader and a distributed co-generation system as the follower. The Stackelberg game is modeled as a bilevel mixed-integer linear program assuming complete information exchange. The bilevel problem is solved based on the Karush–Kuhn–Tucker reformulation. Ramos et al. (2018) proposed a single-leader multi-follower and a multi-leader single-follower Stackelberg game for the utility-network design of eco-industrial parks. The authority of the eco-industrial park is the single leader / follower and the enterprises are the multi follower / leader. In the eco-industrial park, the enterprises are continuously operating production plants. The bilevel problem is solved for the single-leader multi-follower Stackelberg game by replacing the followers' problems by the Karush–Kuhn–Tucker reformulation. The bilevel problem for the multi-leader single-follower Stackelberg game is solved by a previously proposed method by the authors (Ramos et al., 2016).

The reviewed literature shows different methods to solve Stackelberg games for both complete or incomplete information exchange. However, the reviewed literature does not tackle Stackelberg games to schedule production and utility systems with incomplete information exchange. In an earlier publication, the authors proposed a method to coordinate a single batch production and a single utility system in a single-leader single-follower Stackelberg game (Leenders et al., 2019a). The method considers incomplete information exchange based on demand-dependent energy cost. This paper extends the method to multiple production and utility systems in a multi-leader multi-follower Stackelberg game. The resulting challenge is that we not only have to coordinate between an upper (production systems) and a lower level (utility systems), but also within each level. Thus, we need to coordinate multiple systems within each level. As a result, three coordination methods need to be devised: on the upper level, on the lower level, and between the levels. Thus, we propose novel coordination methods for the upper level (production systems) and the lower level (utility systems). The coordination methods need to reflect the available and exchangeable information. Thereby, we can extend the method from Leenders et al. (2019a) to multiple production and utility systems.

The concept was already proposed in a conference paper (Leenders et al., 2019c). Due to the page limitation, the conference paper presents only parts of the method. This paper refines the method and includes more detail and an additional case study is provided. In particular, we present a method for reallocation of the demand-dependent energy cost. Furthermore, in this paper, we present the full methods for: the coordination among the production systems and among the utility systems, as well as the optimization problem of the energy price minimization. The remainder of the paper is organized as follows. In Section 2, the proposed method is presented in detail. In Section 3, the method is applied

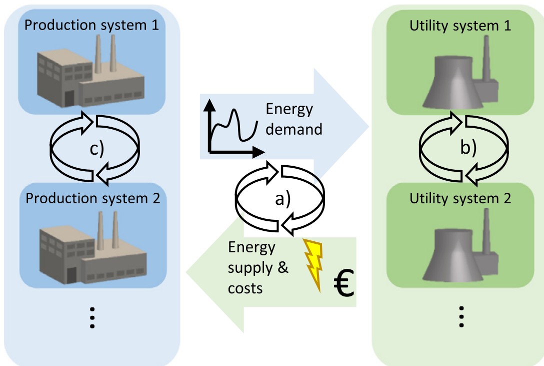

Fig. 1. Problem setup for coordination between production and utility systems illustrated for two production systems and utility systems. The production systems announce their energy demand. The energy demand is allocated to the utility systems. The utility systems announce the energy cost for the supply of the energy demand. The three problems to be solved are: (a) How to coordinate between utility systems and production systems? (Section 2.1) (b) How to coordinate the utility systems? (Section 2.2) (c) How to coordinate the production systems? (Section 2.3)

to two case studies and the result are compared to both integrated and sequential optimization. Finally, in Section 4, conclusions are given.

2. Coordination of multiple production and utility systems

For the proposed method, we consider the following setup of the Stackelberg game (Fig. 1): Multiple production systems are operated on an industrial site. The production systems are supplied with energy by multiple utility systems. The energy supply is organized in 4 steps:

1. The production systems (leader) announce their energy demands based on fixed energy prices to the utility systems (follower), e.g., hourly energy demands for one day.
2. The utility systems (follower) respond by announcing the associated hourly energy cost. The energy cost depends on the operation of the utility systems to supply the energy demand.
3. The production systems (leader) reschedule their operation with the knowledge of their energy cost, also leading to a rescheduled energy demand.
4. The utility systems (follower) adapt their operation to the rescheduled energy demand and announce the associated hourly energy cost.

Ideally, the production systems would know all details of the optimization problems of the utility systems. In this case, total production cost could be minimized since the production systems could directly account for the optimization problems of the utility systems in their decision-making process. The production systems would have complete information on the utility systems and could solve the resulting bilevel optimization problem. However, as discussed in the introduction, the exchange of complete information is often not possible. Thus, here, we propose a method to coordinate multiple production and utility systems in a multi-leader multi-follower Stackelberg game using only incomplete information. Still, with only incomplete information available, our method reduces cost significantly.

In our method, all systems optimize themselves. Thus, each production system and each utility system schedule itself. The systems are coordinated based on incomplete information corresponding to (1) energy demands of the production systems and (2) energy cost announced by the utility systems. Thus, information on the announced energy demands and on energy cost is shared in the industrial park. The coordination can be performed by an authority or any participating production or utility system. For an even higher degree of confidentiality, an aggregator can anonymize the data and can pass it to a coordinator, as proposed by Wenzel et al. (2020).

The proposed method for coordination has to solve 3 problems (Fig. 1):

- Problem a): Coordination between utility systems and production systems (Section 2.1)
  - How to exchange incomplete information for potential demand-side management?
- Problem b): Coordination of the utility systems (Section 2.2)
  - How to identify the amount of energy supplied by each utility system?
  - How to condense individual demand-dependent energy cost to overall demand-dependent energy cost?
- Problem c): Coordination of the production systems (Section 2.3)
  - How to allocate the demand-dependent energy cost to the individual production systems?
  - How changes in the energy demand of the individual production systems affect the overall demand-dependent energy cost?

2.1. Coordination between production systems and utility systems

The operation of production and utility systems needs to be coordinated because each system's operation is affected by the operation of the other systems. The production systems schedule their production for minimal cost. Their cost result from both running the production processes and from the energy cost. In industry, energy cost is often not simply proportional to the energy demand, because the energy costs depend on the operation of the utility systems.

The proposed method coordinates among all systems, while only incomplete information is exchanged. For a single production and a single utility system, the authors previously proposed a coordination method (Leenders et al., 2019a). The incomplete information shared was demand-dependent energy cost. These demand-dependent energy cost are also used in this work.

The coordination of multiple production and utility systems is performed in 4 steps (left-hand side of Fig. 2):

- Step ①: The production systems schedule their production. For the cost of energy, constant prices are assumed. Step ① determines the energy demand as input for Step ②.
- Step ②: The utility systems schedule their operation (details in Section 2.2). In Step ②, the utility systems coordinate how much energy is supplied by each utility system. The coordination aims for a minimal energy price. Furthermore, each utility system calculates its demand-dependent energy cost based on Leenders et al. (2019a). Afterwards, the demand-dependent energy costs of all utility systems are aggregated. This aggregated demand-dependent energy cost is the input for Step ③.
- Step ③: The production systems re-schedule their production (details in Section 2.3). The energy cost of each production system is identified. For this purpose, aggregated demand-dependent energy costs from Step ② and the energy demands from the re-scheduling are used as incomplete information. The rescheduled energy demand of the production systems is passed to the utility systems as the input for Step ④.
- Step ④: The utility systems reschedule their operation to identify the final energy cost (details in Section 2.2). As in Step ②, the utility systems coordinate how much energy is supplied by

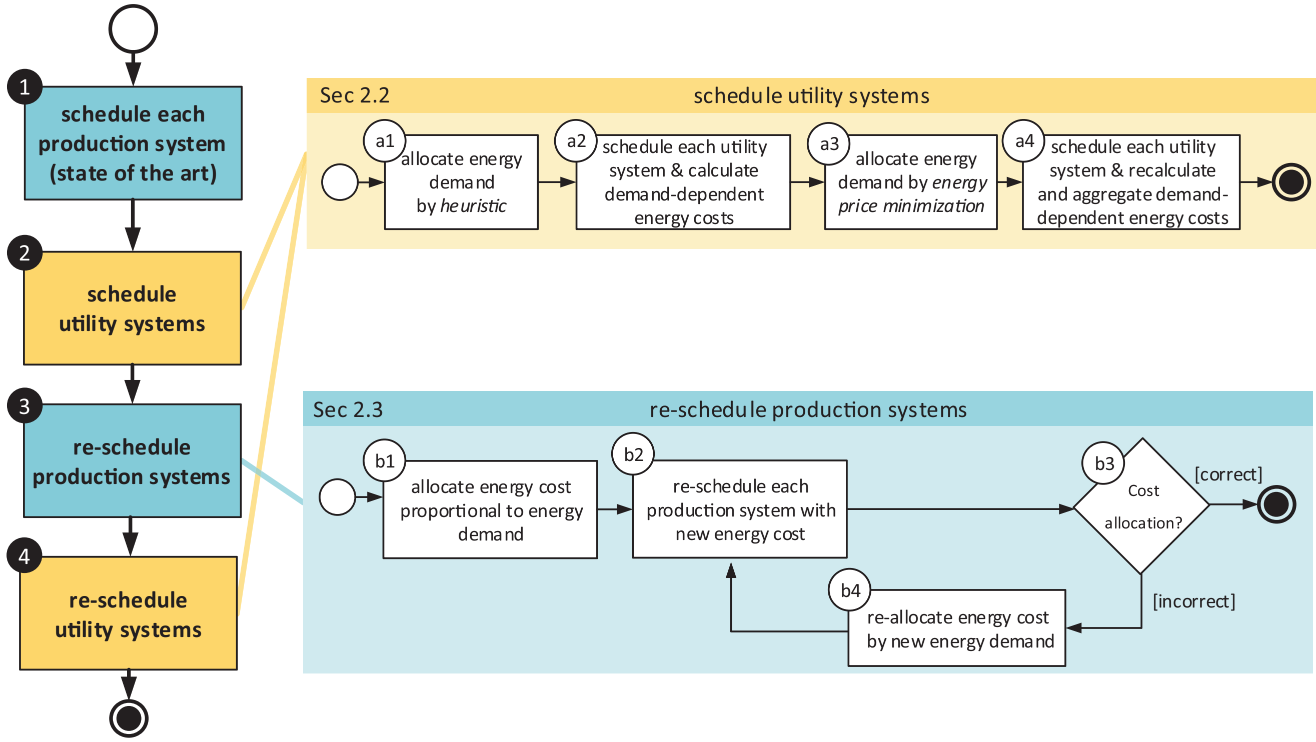

Fig. 2. Method to solve the multi-leader multi-follower Stackelberg game by coordination between multiple production and utility systems. Two inner algorithms are employed to schedule utility systems (Step ②+④) and production systems (Step ③).

each utility system. The result of Step ④ is the energy cost to be paid by the production systems.

The steps ②, ③, and ④ use inner algorithms to coordinate the systems. The inner algorithms are explained in the following Sections 2.2 and 2.3.

A crucial element of the method is the demand-dependent energy cost that is determined by each utility system. Commonly, energy cost increase/decrease nonlinearly when the energy demand is changed. The underlying idea of the demand-dependent energy cost is to capture the typically nonlinear increase/decrease of energy cost by piecewise-linear functions and without computing the full cost curve. As an approximation, 4 price ranges are defined (Fig. 3): 1. small increase, 2. large increase, 3. small decrease, 4. large decrease. A small increase/decrease is defined by the operating range of the current set of operating units. The energy cost of a large increase/decrease is defined by adding 1 additional operating unit or switching off 1 operating unit, respectively.

Following this definition, the demand-dependent energy cost is obtained from the energy cost for the current energy demand and 4 additional energy demands (Fig. 3). The 4 additional energy demands are located where additional units might be switched on or operating units might be switched off. The demand-dependent energy cost is then obtained by interpolating the energy cost between these 4 energy demands. Beyond these energy demands, we extrapolate the energy cost. The demand-dependent energy cost has been described in more detail in Leenders et al. (2019a). Here, multiple utility systems are considered.

Therefore, coordination is necessary for the utility systems. The coordination is presented in the following section.

2.2. Coordination among utility systems: Step ② + ④

The energy demand of the production systems is fulfilled by multiple utility systems. The utility systems compete for the amount of energy that each utility system supplies to the production systems. The coordination has to identify how much energy is supplied by each utility system. We assume that the coordination among the utility systems aims for the minimum energy cost. Thus, the coordination allocates the energy demand according to its objective of the coordination is to reach the minimal cost of energy supply.

For each utility system, the cost of energy supply has not one fixed value but depends on the energy demand. This dependence needs to be captured by the coordination method. For this purpose, we use the concept of demand-dependent energy cost from Leenders et al. (2019a) that are a piecewise-linear representation

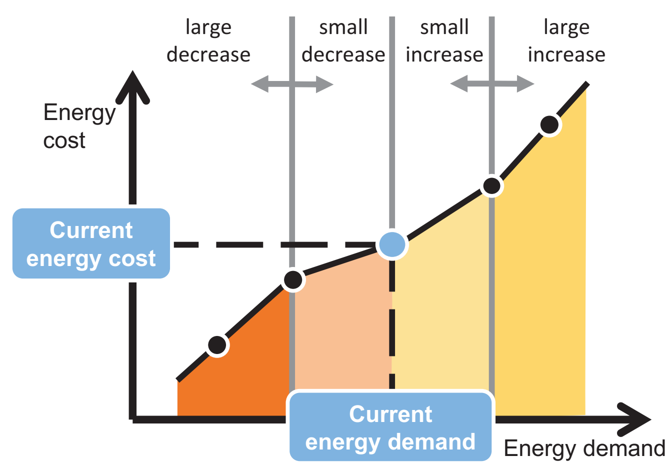

Fig. 3. Demand-dependent energy cost introduced by Leenders et al. (2019a) is a piecewise-linear function. The specific energy cost, i.e., the energy prices, are constant within each linear section. The constant energy prices are calculated by interpolation between 5 energy demands marked by dots and the corresponding energy cost for every time step.

of energy cost as a function of the energy demand. The demand-dependent energy cost is specific for every time step, since time-dependent parameters can be in the utility systems optimization, such as electricity prices.

To reach the minimal energy price, the coordination between the utility systems is performed in 4 substeps (Fig. 2; a1–a4):

- Substep a1: The energy demand is allocated to the utility systems. In Step ②, the allocation is proportional to the maximum capacity of each utility system. In Step ④, the allocation is based on the amount of energy provided by each utility system, as calculated in Step ②.
- Substep a2: Each utility system schedules itself to fulfill the allocated energy demand from Substep a1. Furthermore, each utility system calculates its demand-dependent energy cost.
- Substep a3: The coordinating system solves the optimization problem to minimize the energy price. The optimization problem reallocates the energy demand. As a result, the amount of energy provided by each utility system is determined. The details of the optimization problem are given below.
- Substep a4: As in Substep a2, each utility system is scheduled, but with the reallocated energy demand from Substep a3. Based on the new schedule, each utility system recalculates its demand-dependent energy cost. Subsequently, all demand-dependent energy costs are aggregated to one aggregated demand-dependent energy cost, such that the lowest energy cost is reached. This aggregated demand-dependent energy cost is a merit-order curve for the energy supply.

In Step ② of the main method, the output of the coordination is the aggregated demand-dependent energy cost and the energy cost of the current energy demand. In Step ④, the output of the coordination is the energy cost to fulfill the energy demand.

Energy price minimization in Substep a3

The coordination between the utility systems allocates how much energy is supplied by each utility system. This allocation of the energy demand uses demand-dependent energy cost from Substep a2 to represent the energy cost of each utility system. Thus, only incomplete information is exchanged. The objective of the allocation is to minimize the energy price.

The energy demand is allocated by an optimization problem with the following structure:

- Objective: Minimal energy price
- Subject to: Energy balances and demand-dependent energy cost of each utility system

The optimization problem is performed separately for every energy form e, e.g., heat, electricity. In the following, the equations of the optimization problem are given. The objective is to minimize the energy price c_e of energy form e:

$$\min \quad c_e \tag{1}$$

The main constraints are the energy balances. In the previous Substep a2, each utility system calculated its demand-dependent energy cost for the current energy demand. Thus, the current energy demand is already fulfilled by the utility systems. Consequently, if one utility system supplies additional energy, the remaining utility systems have to supply less energy by the same amount. Thus, the sum of differences in provided energy $\Delta E_{i,e}$ by all utility systems equals zero:

$$\sum_i \Delta E_{i,e} = 0 \tag{2}$$

$\Delta E_{i,e}$ is the difference of energy provided by utility system i compared to Substep a2.

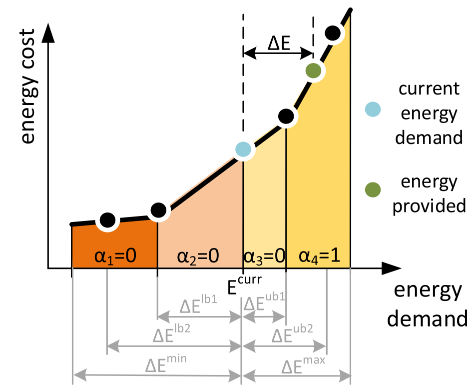

Fig. 4. Nomenclature of the linear sections and declaration of the parameters of the demand-dependent energy cost. The binary variable α_s indicates in which linear section the energy demand $E^{curr}_{i,e} + \Delta E_{i,e}$ is located

The energy cost of each utility system is considered by its demand-dependent energy cost. The demand-dependent energy cost is a piecewise-linear function with 4 sections (Fig. 4). For utility system i, the range of each linear section is defined by the difference of the energy supply $\Delta E_{i,e}$ (Fig. 4):

Linear Section 1(large decrease):

$$\alpha_{i,e,1} \cdot (E^{min}_{i,e} - E^{curr}_{i,e}) \leq \alpha_{i,e,1} \cdot \Delta E_{i,e} \leq \alpha_{i,e,1} \cdot \Delta E^{lb1}_{i,e} \quad \forall i \in I \tag{3}$$

Linear Section 2 (small decrease):

$$\alpha_{i,e,2} \cdot \Delta E^{lb1}_{i,e} \leq \alpha_{i,e,2} \cdot \Delta E_{i,e} \leq 0 \quad \forall i \in I \tag{4}$$

Linear Section 3: (small increase)

$$0 \leq \alpha_{i,e,3} \cdot \Delta E_{i,e} \leq \alpha_{i,e,3} \cdot \Delta E^{ub1}_{i,e} \quad \forall i \in I \tag{5}$$

Linear Section 4 (large increase):

$$\alpha_{i,e,4} \cdot \Delta E^{ub1}_{i,e} \leq \alpha_{i,e,4} \cdot \Delta E_{i,e} \leq \alpha_{i,e,4} \cdot (\Delta E^{max}_{i,e} - E^{curr}_{i,e}) \quad \forall i \in I \tag{6}$$

$\alpha_{i,e,s}$ identifies the section s in which the new energy demand $(E^{curr}_{i,e} + \Delta E_{i,e})$ is located. $E^{curr}_{i,e}$ is the current energy demand.

The energy price in each section s is determined by interpolation between the 4 energy demands used to determine the linear sections. The 4 energy demands are defined by adding an additional operating unit or switching off an operating unit from the set of operated utility units to fulfill the current energy demand (Fig. 4):

- $(E^{curr}_{i,e} + \Delta E^{lb2}_{i,e})$ is the energy demand in Section 1 (large decrease). $\Delta E^{lb2}_{i,e}$ is the difference in the energy demand, if the smallest utility unit operated can be switched off and the second smallest operated utility unit just cannot be switched off.
- $(E^{curr}_{i,e} + \Delta E^{lb1}_{i,e})$ is the lowest energy demand in Section 2 (small decrease). $\Delta E^{lb1}_{i,e}$ is the difference in the energy demand, if just no utility unit currently operated can be switched off.
- $E^{curr}_{i,e}$ is the current energy demand and separates Section 2 (small decrease) and Section 3 (small increase).
- $(E^{curr}_{i,e} + \Delta E^{ub1}_{i,e})$ is the highest energy demand in Section 3 (small increase). $\Delta E^{ub1}_{i,e}$ is the difference in the energy demand, if the utility units currently operated operate at their maximal capacity.
- $(E^{curr}_{i,e} + \Delta E^{ub2}_{i,e})$ is the energy demand in Section 4 (large increase). $\Delta E^{ub2}_{i,e}$ is the difference in the energy demand, if all utility units currently operated and the smallest idle utility unit are operated at their maximal capacity.

The energy demand cannot be negative. The non-negativity of the energy demand is ensured by limiting the decrease in the energy demand ($-\Delta E_{i,e}$) to the current energy demand $E_{i,e}^{curr}$ as follows:

$$\alpha_{i,e,0} \cdot \Delta E_{i,e} \leq -\alpha_{i,e,0} \cdot E_{i,e}^{curr} \quad \forall i \in I \tag{7}$$

$$\Delta E_{i,e} \geq -E_{i,e}^{curr} \quad \forall i \in I \tag{8}$$

The binary variable $\alpha_{i,e,0}$ equals 1, if the energy demand is 0.

The energy demand can only be located in one section s, thus, $\alpha_{i,e,s}$ is 1 in only one section:

$$\sum_{s=0}^{4} \alpha_{i,e,s} = 1 \quad \forall i \in I \tag{9}$$

The objective of the optimization problem is the minimization of the overall energy price c_e to fulfill the energy demand (Eq. (2)). Thus, the energy price of each utility system i needs to be lower or equal to the overall energy price c_e.

In the following equations, we calculate the energy price of each utility system i. We rearranged the equations to avoid a possible division by an energy demand of 0: section 1 (large decrease):

$$c_e \cdot (\Delta E_{i,e} + E_{i,e}^{curr}) \geq \alpha_{i,e,1} \cdot \left[\frac{C_{i,e}^{lb2} - C_{i,e}^{lb1}}{\Delta E_{i,e}^{lb2} - \Delta E_{i,e}^{lb1}} \cdot (\Delta E_{i,e} - \Delta E_{i,e}^{lb2}) + C_{i,e}^{lb2} \right] \quad \forall i \in I \tag{10}$$

section 2 (small decrease):

$$c_e \cdot (\Delta E_{i,e} + E_{i,e}^{curr}) \geq \alpha_{i,e,2} \cdot \left[\frac{C_{i,e}^{lb1} - C_{i,e}^{curr}}{\Delta E_{i,e}^{lb1}} \cdot \Delta E_{i,e} + C_{i,e}^{curr} \right] \quad \forall i \in I \tag{11}$$

section 3 (small increase):

$$c_e \cdot (\Delta E_{i,e} + E_{i,e}^{curr}) \geq \alpha_{i,e,3} \cdot \left[\frac{C_{i,e}^{ub1} - C_{i,e}^{curr}}{\Delta E_{i,e}^{ub1}} \cdot \Delta E_{i,e} + C_{i,e}^{curr} \right] \quad \forall i \in I \tag{12}$$

section 4 (large increase):

$$c_e \cdot (\Delta E_{i,e} + E_{i,e}^{curr}) \geq \alpha_{i,e,4} \cdot \left[\frac{C_{i,e}^{ub2} - C_{i,e}^{ub1}}{\Delta E_{i,e}^{ub2} - \Delta E_{i,e}^{ub1}} \cdot (\Delta E_{i,e} - \Delta E_{i,e}^{ub1}) + C_{i,e}^{ub1} \right] \quad \forall i \in I \tag{13}$$

The energy price of each utility system i is determined with the energy cost from the demand-dependent energy cost [square brackets] divided by energy supplied by each utility system (round brackets). The energy price is defined to be greater 0:

$$c_e \geq 0 \tag{14}$$

$C_{i,e}^{\sim}$ is the energy cost for the energy demand ($\Delta E_{i,e}^{\sim} + E_{i,e}^{curr}$). Because the two continuous variables energy price c_e and difference of energy demand $\Delta E_{i,e}$ are multiplied, the optimization problem is a mixed-integer nonlinear program (MINLP).

The result of the energy-price minimization is the allocation of how much energy is supplied by each utility system ($\Delta E_{i,e} + E_{i,e}^{curr}$). Based on the allocation, the demand-dependent energy cost is recalculated and aggregated in Substep a4. The aggregated demand-dependent energy cost is the input of Step ③. Step ③ is explained in more detail in the following section.

2.3. Coordination among production systems: Step ③

In Step ①, the production systems scheduled their production assuming fixed energy prices. For the resulting energy demand, in Step ②, the utility systems optimized their operation and determined the energy cost for the given energy demand. In Step ③, the production systems reschedule their production. As a price signal, the utility systems now provide demand-dependent energy cost. The aggregated demand-dependent energy cost approximates the energy cost for changing energy demands. Here, the costs of all utility systems are aggregated into a single cost curve. This aggregated demand-dependent energy cost is considered in Step ③ to reschedule the production systems.

In Step ③, each production system reschedules the production independently. For this purpose, each production system needs to know its demand-dependent energy cost. Thus, we need to allocate the aggregated demand-dependent energy cost to the individual production systems. For this purpose, we perform substeps in Step ③ such that each production system assumes the correct energy cost while rescheduling only its own production.

This coordination occurs 4 Substeps b1–b4 (Fig. 2):

- Substep b1: The energy costs from Step ② are allocated according to the current energy demand of each production system. Thus, the specific energy price for the current energy demand is the same for each production system, but the energy cost differs due to the different current energy demands. Consequently, each production system has an individual base of the demand-dependent energy cost (Fig. 3). The linear sections of the aggregated demand-dependent energy cost, e.g., from $E_{i,e}^{curr}$ to ($E_{i,e}^{curr} + \Delta E_{i,e}^{lb1}$), are equally allocated to all production systems (Fig. 5). Thus, all production systems have linear sections of the same size but with different current energy demands.
- Substep b2: Each production system reschedules the production considering its allocated demand-dependent energy cost from Substep b1.
- Substep b3: The coordination is finished if no production system changed its energy demand compared to the previous iteration or the maximum number of iterations is reached. Otherwise, Substep b4 is performed.
- Substep b4: Substep b4 removes potential errors from the allocation used in Substep b2. In Substep b2, every production system rescheduled independently and, consequently, the energy demands have changed independently. Each production system calculated the energy cost based on its allocated demand-dependent energy cost from Substep b1. However, the sum of energy cost calculated by each production system individually might not be consistent with the energy cost from the non-allocated demand-dependent energy cost. To achieve consistent cost, the allocation from Substep b1 is revised in Substep b4. Details on the reallocation are explained at the end of this section.

The output of Step ③ is the energy demand of all production systems.

2.3.1. Reallocation of demand-dependent energy cost (Substep b4)

In Substep b2, the production systems reschedule their production based on the demand-dependent energy cost. In the rescheduling, each production system calculated its energy cost independently. However, these energy costs might not be the same as obtained by summing all energy demands and using the aggregated demand-dependent energy cost. This inconsistency is fixed in Substep b4.

The potential inconsistency is illustrated in Fig. 6. In this example, the energy demand of production system 1 does not change by the rescheduling, while the energy demand of production system 2

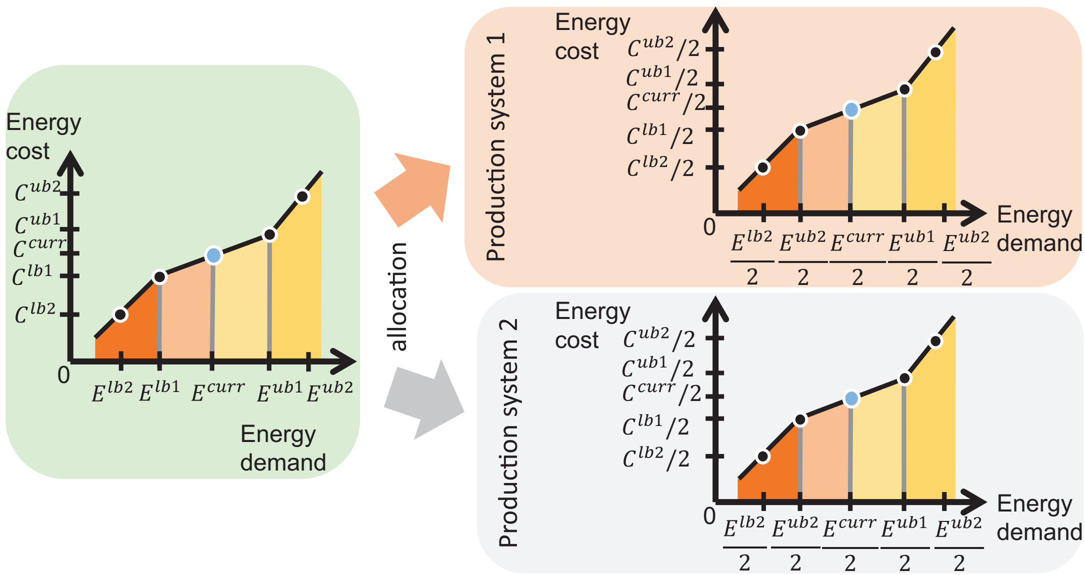

Fig. 5. Allocation of aggregated demand-dependent energy cost to two production systems with equal energy demands. On the left hand, the aggregated demand-dependent energy cost is shown. The energy cost is allocated proportionally to energy demand. Since, both production systems have the same energy demand, the aggregated demand-dependent energy cost is split in half (right). Here, we illustrate the allocation for an aggregated demand-dependent energy cost with only 4 linear sections and, thus, one utility system. Generally, the aggregated demand-dependent energy cost has 4 times as many linear sections as utility systems are present.

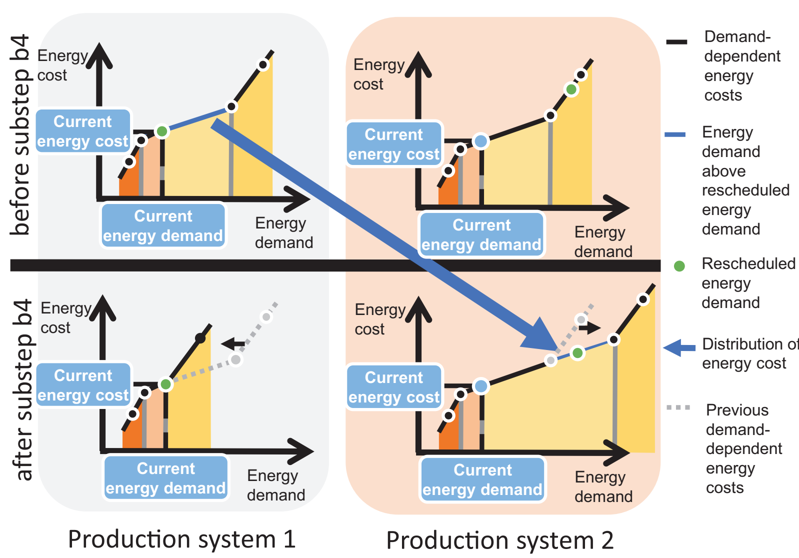

Fig. 6. Example for the reallocation of the demand-dependent energy cost for two production systems (Substep b4). In the upper part of the figure, the demand-dependent energy cost of both production systems is shown. Both demand-dependent energy costs are equal. The energy demand of production system 1 (left) is not changed. The energy demand of production system 2 (right) is increased strongly and exceeds the section for small increases in the energy demand. Thus, in Substep b4, the linear section for small increases of production system 1 is shortened to the rescheduled energy demand. The shortened part is transferred to production system 2.

increases strongly. The rescheduled energy demand of production system 2 is located in the linear section for large increases in energy demand. Thus, production system 2 assumes to pay a high cost for its energy demand. However, if the energy demands of production system 1 and 2 are added and the energy cost are determined with the non-allocated demand-dependent energy cost, the actual energy cost of production system 2 is lower. The energy cost is lower because the energy demand is now correctly located in the linear section for a small increase.

We fix this inconsistency by reallocating the demand-dependent energy cost as follows: For production system 1, we limit the linear section for small increases to the rescheduled energy demand. The available energy supply with the lower energy price is distributed equally among the other production systems where the rescheduled energy demand increased strongly. The redistribution is also illustrated in Fig. 6. By this redistribution, the energy cost calculated independently by each production system equals the energy cost from the non-allocated demand-dependent energy cost. Thus, the cost allocation is consistent. The same principle for reallocation is used for decreasing the energy demand.

3. Case studies

The proposed method to coordinate the scheduling of multiple production and utility systems is applied to 2 case studies. In Case study I (Section 3.1), we model 2 production systems and 2 util-

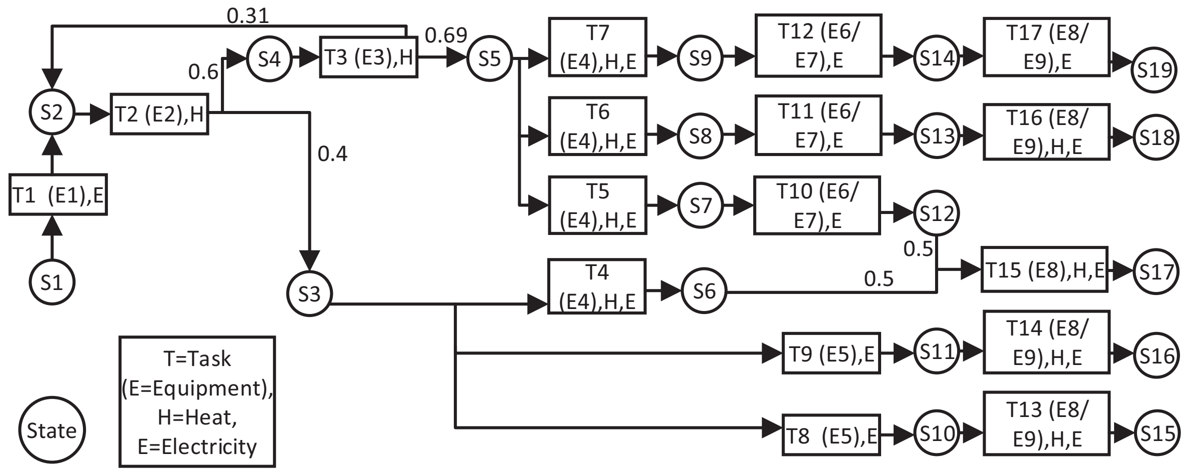

Fig. 7. Production system from Kallrath (2002). The figure is adapted from Leenders et al. (2019a).

ity systems. In Case study II (Section 3.2), we apply our method to a larger case study by modeling 4 production systems and 2 utility systems. Furthermore, we generate 10 instances of both case studies. We apply our method to the instances and, thereby, show the benefits of the proposed method more generally. Our method is compared to sequential and integrated optimization. Sequential optimization represents the benchmark approach. A second benchmark is introduced by the integrated optimization that employs the total cost for the operation of the production system and the energy supply. Integrated optimization represents a best case that would require the exchange of complete information and the control of the production systems over the operational decisions of the utility systems. For a Stackelberg game, the minimal achievable cost under complete information sharing would require the solution of a bilevel problem. The solution of the resulting mixed-integer linear bilevel problem would require a dedicated solution algorithm. The development of such a solution algorithm is part of current research.

In both case studies, we propose that the utility systems pass their utility cost on to the production systems without an additional profit margin. Thus, the overall cost is the sum of production cost and utility cost. The sequential optimization minimizes production cost. The proposed methods might increase production cost while reducing utility cost such that the overall cost is decreased. This decrease is beneficial for the production systems, while there are currently no incentives for the utility system in the given setting to decrease the utility cost. Thus, in reality, the production systems have to share their profit from the proposed method with the utility systems. Alternatively, the utility system might not share all cost reduction with the production system. In the case studies, we do not propose a method to share profits since we want to present the changes in production and utility cost without the impact of a concept for profit sharing. However, as overall cost decreases while still supplying the same amount of product, the situation with profit share should be mutually beneficial for all parties.

3.1. Case study I

3.1.1. Description

In this case study, we model an industrial site with 2 production systems and 2 utility systems. The production systems are based on the case studies from Kallrath (2002) (Fig. 7) and Kondili et al. (1993) (Fig. 8). For each task of the production systems, we added electricity and heat demands. The product demand of the production systems is fixed at the time horizon of 30 h.

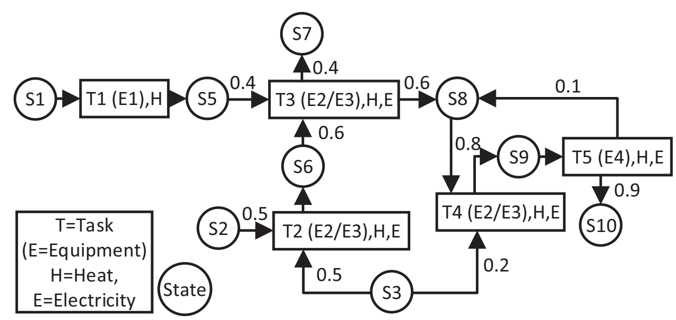

Fig. 8. Production system from Kondili et al. (1993). The figure is adapted from Leenders et al. (2019a).

Production system 1 (Kallrath, 2002) has the following product demand: 20 t of State 16; 20 t of State 17 and 20 t of State 19 (Fig. 7). Production system 2 (Kondili et al., 1993) has the following product demand: 300 t of State 7 and 550 t of State 10 (Fig. 8).

Both utility systems are based on the model by Voll et al. (2013). Utility system 1 has 2 boilers (3 MW, 1 MW) and 1 combined-heat-and-power engine (3 MW) for the energy supply. Utility system 2 has 3 boilers (4 MW, 1.5 MW, 0.5 MW) and 2 combined-heat-and-power engines (each 1.5 MW) for the energy supply. The utility systems can buy electricity from the grid for 0.16 €/kWh, sell electricity for 0.1 €/kWh and buy gas for 0.06 €/kWh. For the sequential optimization, each production system is supplied by only one utility system. Utility system 1 supplies production system 1 and utility system 2 supplies production system 2. A sequential optimization with an integrated optimization of the production systems and an integrated optimization of the utility systems would be slightly beneficial but is not considered here.

All optimization problems are formulated in GAMS 24.7.3 (Development Corporation, 2016). The scheduling problems of the production and utility systems (MILP) are solved with CPLEX 12.6.3.0 (IBM Corporation, 2015). The time limit to schedule the production systems is set to 7200 s and the optimality gap is set to 0.5%, and the maximal number of iterations in Step ③ is set to 10. The time limit of the integrated optimization is set to 86,400 s. For the instances, the time limit of all optimization problems is set to 5000 s. The scheduling of the utility systems is solved within few seconds to optimality. The optimization problem for the energy price minimization (MINLP) is solved with DICOPT

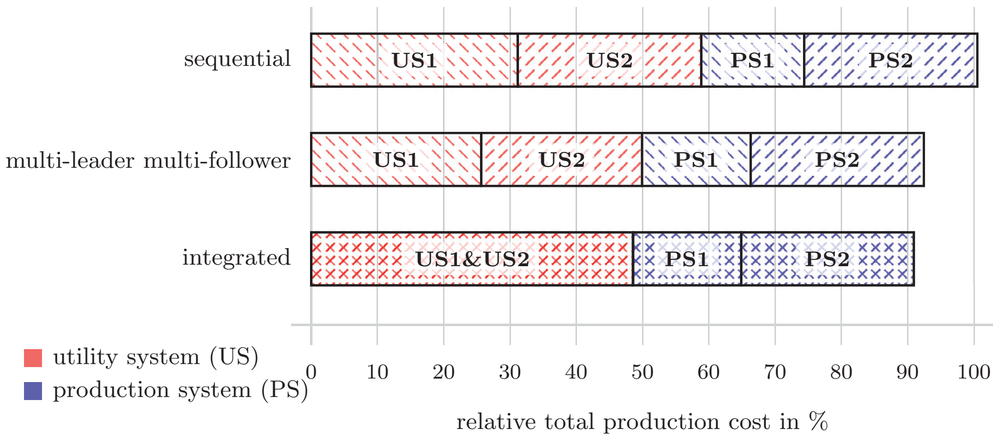

Fig. 9. Cost in Case study I for the different optimization approaches: The common sequential optimization between each production system and the corresponding utility system (benchmark: sequential = 100%), the multi-leader multi-follower Stackelberg game solved by the proposed coordination method (multi-leader multi-follower) and the integrated optimization of all systems (integrated). In the integrated optimization, the cost of the utility systems cannot be assigned to the different systems, because the cost for additional electricity cannot be allocated unambiguous.

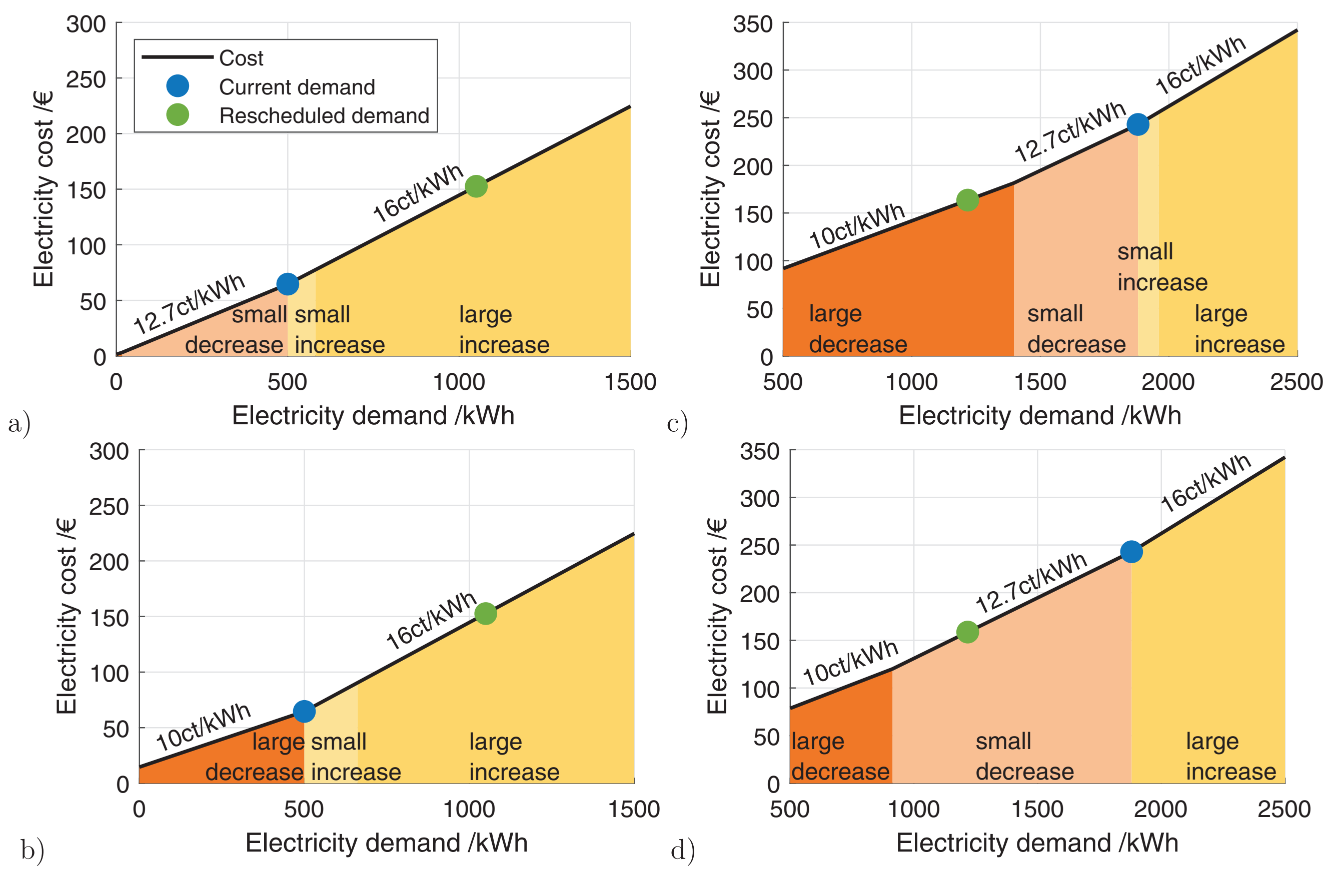

Fig. 10. Case study I: Demand-dependent electricity cost in time step 5 during iteration 1 (a,c) and 2 (b,d) of Step ③. Demand-dependent electricity costs of production system 1 are shown in (a) and (b) and demand-dependent electricity costs of production system 2 are shown in (c) and (d). From iteration 1 to iteration 2, production system 2 decreases the electricity demand such that the electricity demand extends the section for *small decreases*. Thus, the linear section for *small decreases* is increased for production system 2 since production system 1 increases it's electricity demand. By this extension of the linear section for *small decreases*, the electricity cost for production system 2 decreases. For production system 1, the linear section for *small increases* is extended similar since the electricity demand increases such that the electricity demand extends the section for *small increases*.

(Kocis and Grossmann, 1989) using CONOPT 3.17A (Drud, 1996) for solving the NLPs and CPLEX 12.6.3.0 for solving the MILPs.

3.1.2. Results

In Case study I, the proposed method saves 7.6% of total production cost compared to the sequential optimization (Fig. 9). In the sequential optimization, first, the production systems are scheduled and the energy demand is determined. Subsequently, the corresponding utility systems are scheduled for the given energy demand. The integrated optimization saves 9.1% compared to the sequential optimization (Fig. 9). Thus, the proposed method reaches 84% of the potential cost reduction by an integrated optimization.

The proposed method decreases total cost by decreasing energy cost. The energy cost is 15.2% lower than in the sequential optimization, while the production cost increases by 3.3% (Fig. 9). In sum, the overall cost decrease.

The reduction in energy cost results from different energy demands in the proposed method and the sequential optimization (Fig. 11): The proposed method decreases the peak demand for electricity by 23.7% compared to the sequential optimization. The peak of the heat demand increases by 8.2%. Furthermore, the overall electricity demand decreases by 17.9%, while the heat demand increases by 7.8%. In absolute numbers, the sum of heat and electricity demand only changed slightly (-2%). The energy demand is shifted from electricity to heat by choosing different tasks to produce the desired products. The decreased electricity demand results in a lower share of electricity from the electricity grid: In the sequential optimization, 31.9% of the electricity is supplied by the electricity grid compared to only 7.4% in the proposed method. The integrated optimization even reduces the electricity supply from the electricity grid to 0.8%.

The proposed method proceeded as follows: In Step ①, the production systems are scheduled while assuming fixed energy prices. In this case study, we assumed the grid price for electricity and the gas price for heat. In Step ②, the utility systems optimize their operation for the energy demand from Step ①. Initially, (Substep a2 of Step ②) the energy demand is heuristically allocated to the utility systems. Optimization leads to overall cost that is already 3.1% lower than in the sequential optimization. In the following Substep a3, the energy demand is allocated based on an energy price minimization. For the newly allocated energy demand, the utility systems reoptimize their operation in Substep a4, leading to overall cost savings of 3.3% compared to the sequential optimization. Thus, the main savings of Step ② are already obtained in Substep a2 because the heuristic allocation of the energy demand works already well in this case study. Here, the heuristic allocation is based on the maximum capacity of the utility systems. For applications to other utility systems, the energy-price minimization might have a larger impact because in this case study, we use the same component models and thus similar efficiency curves for the components in the utility systems. If the utility systems have different components, the savings from the energy-price minimization in Substep a3 are expected to increase.

The results of Step ② are the demand-dependent energy costs in each time step. The demand-dependent energy costs reflect the prices for heat and electricity paid from the production systems to the utility systems. For each time step, we obtain demand-dependent energy costs. On average, the electricity price for a small increase in demand is 0.129 €/kWh and for a small decrease 0.121 €/kWh. For heat, the average price for a small increase is 0.059 €/kWh and for a small decrease 0.058€/kWh. Thus, on average, the price signal incentives demand reduction and emphasizes electricity over heat demand.

In Step ③, the production systems are rescheduled in 6 iterations. Within these iterations, the demand-dependent energy cost is reallocated until the production systems do not change their energy demand anymore. We exemplary show the reallocation of the demand-dependent energy cost of production system 1 and 2 from iteration 1 to iteration 2 in time step 5 for electricity (Fig. 10). From iteration 1 to iteration 2, production system 2 decreases the electricity demand by 663 kWh, while production system 1 increases the electricity demand by 550 kWh. The decrease of production system 2 is larger than the range for small decrease (483 kWh) in iteration 1 and thus corresponds to a large decrease (cf. Fig. 3).

However, overall, there is no large decrease in energy demand since production system 1 increases its demand. In iteration 2, the cost ranges are therefore reallocated. In particular, the range for small decreases not used by production system 1 is transferred to production system 2. Thereby, the linear section for small decreases increases for production system 2 by 483 kWh and thus, ranges over 966 kWh in iteration 2. By this extension of the linear section for small decreases, the electricity cost for production system 2 decreases. For production system 1, the linear section for small increases is extended similar since the electricity demand increases such that the electricity demand extends the section for small increases.

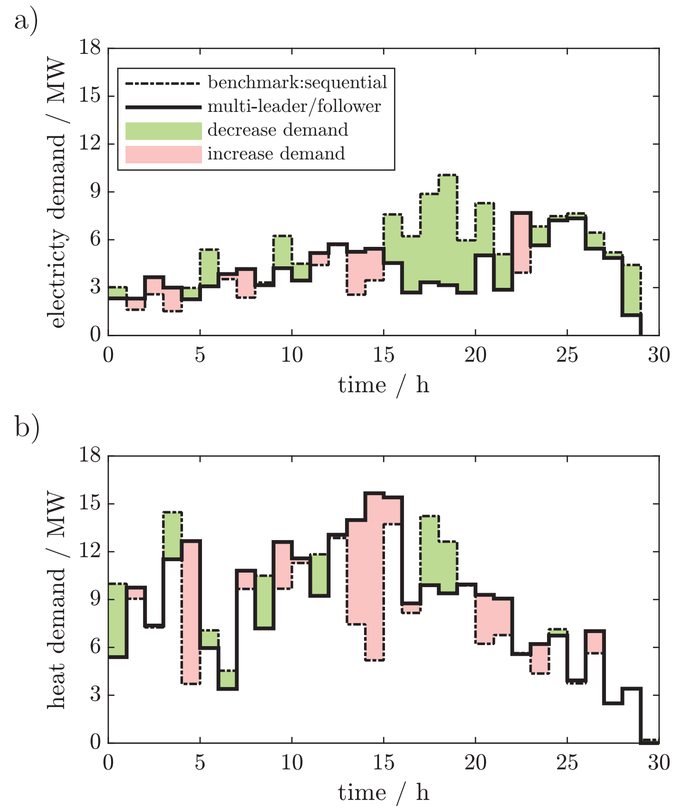

Fig. 11. Case study I: Energy demand of the production systems for the sequential optimization and for the proposed method to coordinate the multi-leader multi-follower Stackelberg game (electricity (a) and heat (b) demand).

In Fig. 10, we also present the specific demand-dependent electricity cost. For small decreases in electricity, the specific cost is 0.127 €/kWh. For large decreases in electricity, the specific cost is 0.1 €/kWh, which is equal to the price of selling electricity to the grid. For small and large increases in electricity, the specific cost is 0.16 €/kWh, which is the price of purchasing electricity from the grid. Thus, the demand-dependent electricity cost resolve at which point the system switches to buying or selling from/to the grid and where internal electricity generation determines the cost.

The actual cost savings resulting from Step ③ are calculated in Step ④, since Step ③ employs only the approximate demand-dependent energy cost. In Step ④, the utility systems optimize again for the rescheduled energy demand, leading to final overall cost savings of 7.6% compared to the sequential optimization. Thus, the largest cost savings (4.3%) are reached by the rescheduling and coordination of the production systems in Step ③ in combination with the rescheduling of the utility systems. Hence, the demand-dependent energy costs enable the main cost savings by rescheduling and coordinating the production systems. The proposed method solves the multi-leader multi-follower Stackelberg game in 1791 s. Therein, step ③ needs 6 iterations which takes 1433 s. The integrated optimization is solved in 728 s. The similar short calculation time shows that the proposed method can be implemented in daily scheduling.

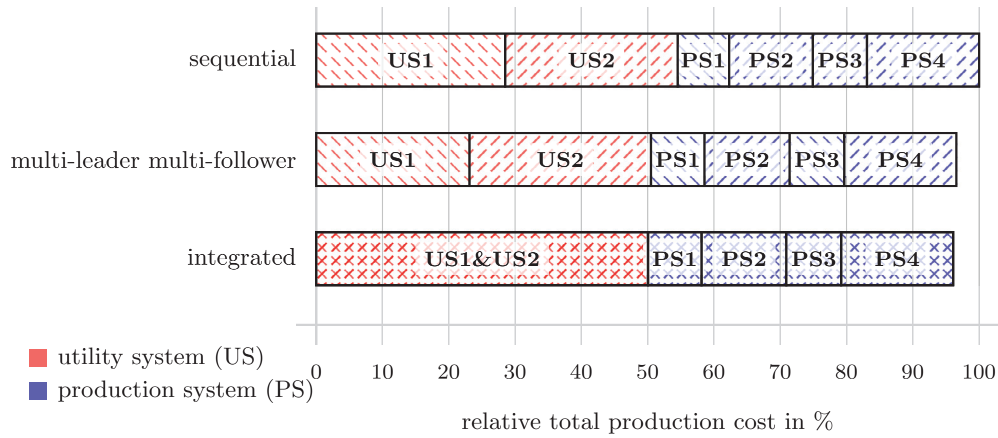

Fig. 12. Cost in Case study II for the different optimization approaches: The common sequential optimization between each production system and the corresponding utility system (benchmark: sequential = 100%), the multi-leader multi-follower Stackelberg game solved by the proposed coordination method (multi-leader multi-follower) and the integrated optimization of all systems (integrated). In the integrated optimization, the cost of the utility systems cannot be assigned to the different systems, because cost for additional electricity cannot be allocated unambiguous.

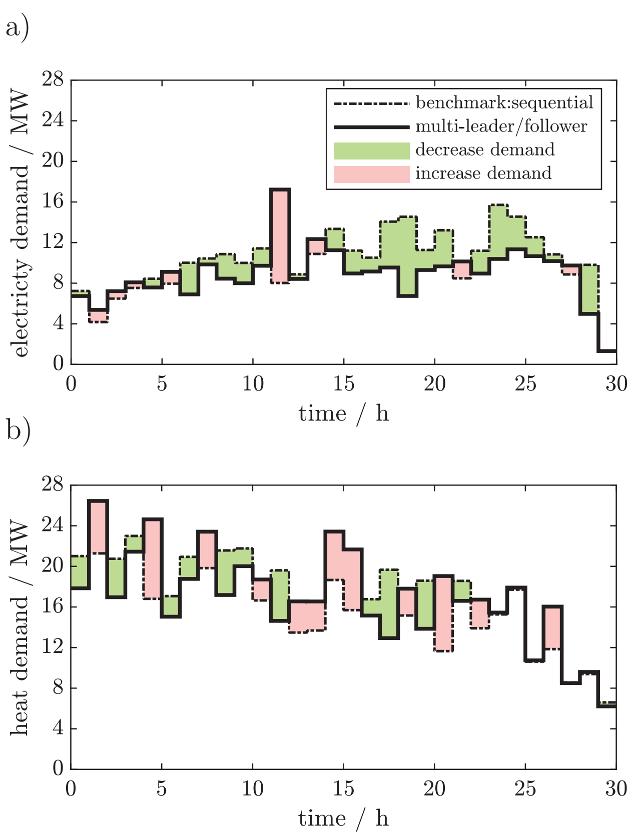

Fig. 13. Case study II: Energy demand of the production systems for the sequential optimization and for the proposed method to coordinate the multi-leader multi-follower Stackelberg game (electricity (a) and heat (b) demand).

In Case study I, we generated 10 instances with Latin-hypercube sampling (McKay et al., 2000) if constant electricity prices are present. The instances are generated with variations of ±20% around the original energy demands of the production systems. For these 10 instances, the proposed method reduces the total production cost on average by 9.1% compared to the sequential optimization (Table 1). The cost savings even correspond to 90% of the integrated optimization (10.2%). Thus, the proposed method largely exploits the potential for cost reductions while only exchanging incomplete information.

Additionally, to the constant electricity prices, we also applied our method for time-of-use electricity prices are present. For this purpose, we used the time-variation of the electricity prices from the German spot market. We used data starting at 15.7.2020, 0 a.m. (Bundesnetzagentur | SMARD.de 2020). The results are similar to the case with constant electricity prices. The proposed method results in cost savings of 7.4% compared to the sequential optimization. The integrated optimization saves 8.4% compared to the sequential optimization. Thus, for Case study I, the proposed method is even closer to the integrated optimization if we apply time-of-use electricity prices.

3.2. Case study II

3.2.1. Description

In this case study, we apply the proposed method to a large industrial site with 4 production systems and 2 utility systems. Production systems 1 and 3 are based on the case study from Kallrath (2002) (Fig. 7) and production systems 2 and 4 are based on the case study from Kondili et al. (1993) (Fig. 8). Similar to Case study I, we added electricity and heat demands to the tasks.

The product demands in Table 2 have to be fulfilled at the end of the time horizon of 30 h. The models of the two utility systems are again based on the model by Voll et al. (2013). Utility system 1 has 4 boilers (3.5 MW, 3 MW, 2 MW, 1 MW) and 2 combined-heat-and-power engines (3 MW, 2 MW). In the sequential optimization, utility system 1 supplies production systems 3 and 4. Utility system 2 has 6 boilers (5 MW, 4 MW, 1.5 MW, 1.5 MW, 0.5 MW, 0.5 MW) and 4 combined-heat-and-power engines (2.5 MW, 1.5 MW, 1.5 MW, 1 MW). In the sequential optimization, utility system 2 supplies production systems 1 and 2. The prices to buy gas, buy electricity and sell electricity are the same as in Case study I. The optimization problems are also formulated in GAMS 24.7.3 and solved with the same solvers as Case study I (Section 3.1.1). The maximal number of iterations in Step ③ is set to 10.

3.2.2. Results

The proposed method saves 3.4% in cost compared to the sequential optimization (Fig. 12) and is solved within 58,094 s. The integrated optimization reaches the time limit of 86,400 s with a remaining gap of 1.2%. If we evaluate the integrated optimization after the solution time of the proposed method (58,094 s), the integrated optimization saves 3.8%. However, a better solution is found after the time limit of 86,400 s with cost savings of 3.91%

Table 1
Cost savings of different optimization approaches in % compared to sequential optimization for the instances of Case study I.

instance	1	2	3	4	5	6	7	8	9	10	⌀
integrated	9.86	10.71	10.46	10.31	9.95	10.15	10.25	10.65	10.42	8.72	10.15
proposed method	9.21	10.51	9.94	9.56	8.61	8.34	8.81	9.84	9.14	7.06	9.11

Table 2
Product demand of the production systems in Case study II.

Production system	1	2	3	4
Product demand	State 16: 20 t State 17: 20 t State 19: 20 t	State 7: 300 t State 10: 550 t	State 15: 20 t State 17: 20 t State 18: 20 t	State 7: 500 t State 10: 250 t

Table 3
Cost savings of different optimization approaches in % compared to sequential optimization for the instances of Case study II. All integrated optimization problems reached the time limit before reaching the optimality gap.

instance	1	2	3	4	5	6	7	8	9	10	⌀
integrated	4.04	3.54	5.38	3.62	4.63	4.07	4.32	3.81	4.00	4.47	4.19
proposed method	2.75	1.84	4.76	2.18	4.75	2.54	4.82	1.22	5.00	3.48	3.33

(Fig. 12). Thus, the proposed method is near the cost savings of the integrated optimization (88%). Again, the cost savings results from large savings in energy costs by 7.4%, while production cost increase by 1.3% (Fig. 12). As in Case study I, the total production cost is decreased as a sum of energy cost and production cost.

The proposed method changes the total energy demand compared to the sequential optimization (Fig. 13): The peak demand for electricity is increased by 9.6%, the peak demand for heat is increased by 15%. Again, the overall electricity demand decreases (12%) while the heat demand increases (2.8%). Since the heat demand is much higher than the electricity demand, the overall energy demand changes only slightly (−2.8%). The shift from heat to electricity is possible because the production systems change their production schedules to produce the desired products. Again, the electricity supply by the electricity grid decreases (sequential 8.1%; proposed method 3.2%). Thus, the utilization of the on-site utility system increases.

For Case Study II, after Substep a2 in Step ②, we reach cost savings of 1.7% compared to the sequential optimization. After Substep a4, the cost savings are nearly similar (1.7%). Thus, as in Case study I, the allocation by the heuristic already provides a good solution. Still, we believe step a4 is crucial for settings with energy systems that are very different in size and employed technologies. After coordination between the production systems using the demand-dependent energy cost (Step ③ and ④), the overall cost savings are 3.4%. Thus, as in Case study I, the rescheduling and coordination of the production systems in Step ③ and the rescheduling of the utility systems enable additional cost savings. Consequently, Steps ① and ② are the basis for expanding the cost savings in Steps ③ and ④.

Again, we generated 10 instances of the energy demands by Latin-hypercube sampling (McKay et al., 2000) if constant electricity prices are present. The instances are generated with variations of ±20% around the original energy demands of the production systems. For the instances, the proposed method reduces the cost on average by 3.3% (Table 3) and, thus, is close to the integrated optimization (4.2%). Consequently, 79% of the potential cost reduction by integrated optimization is reached. All integrated optimization problems reached the time limit before proving optimality. In 3 instances, the proposed method results in even higher cost savings than the integrated optimization which did not solve to optimality within the time limit. The solution of the proposed method lies within the remaining gap of the integrated optimization.

Also, for Case study II, we applied our method for time-of-use electricity prices. Again, we used German spot market's electricity prices, starting at 15.7.2020, 0 a.m. (Bundesnetzagentur | SMARD.de 2020). With these time-of-use electricity prices, the proposed method saves 3.0% of the overall cost compared to the sequential optimization. The integrated optimization saves 3.9%. Thus, the proposed method also reaches a large share of the potential cost savings of the integrated optimization in case of time-of-use electricity prices.

The case studies show the benefits of the proposed method. However, since the proposed method is a heuristic that cannot guarantee the optimal solution, the proposed method's benefits differ for both case studies. In Case study II, the additional production systems supply products not demanded in Case Study I. Furthermore, the utility systems have more and different components. Still, in both case studies, improved production schedules are identified that result in energy demands with significantly lower energy cost. The lower energy cost outweighs the slightly increased production cost. Although both case studies are different, the cost savings in the instances are high with 90% on average in Case study I and 79% on average in Case study II.

4. Conclusions

Commonly, the operation optimization of production and utility systems in industrial sites is sequentially performed without feedback iterations. In this paper, we proposed a method to reduce the total production cost of multiple production systems in a multi-leader multi-follower Stackelberg game. The method exchanges only incomplete information. Thus, the method can be employed for the practical situation in which the systems are operated by different companies. The incomplete information exchanged is the energy demand and demand-dependent energy cost. The method employs energy cost in one feedback iteration.

The method is tested for two case studies. In the case studies, the total production cost is reduced by 7.6% and 3.4% compared to the common sequential optimization. The method realizes 84% and 88% of the potential cost reduction by an integrated optimization based on complete information exchange. The cost savings by the proposed method are obtained by revised production schedules. The revised production schedules lead to slightly increased production cost, but significantly decreased energy cost. The proposed method is further validated by large computational studies of 10 instances for both case studies. The computational studies show an average benefit of the proposed method by cost savings of 90% and 79% of the integrated optimization.

The proposed method significantly reduces total production cost, while only exchanging incomplete information between production and utility systems in one feedback iteration. Thus, the method is well suited for practical applications.

Declaration of Competing Interest

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

CRediT authorship contribution statement

Ludger Leenders: Writing - original draft, Conceptualization, Methodology, Software, Investigation, Visualization, Data curation, Project administration. **Kirstin Ganz:** Methodology, Investigation, Visualization, Software, Data curation. **Björn Bahl:** Writing - review & editing, Methodology, Visualization, Funding acquisition. **Maike Hennen:** Writing - review & editing, Visualization. **Nils Baumgärtner:** Writing - review & editing, Visualization. **André Bardow:** Conceptualization, Writing - review & editing, Supervision, Resources, Funding acquisition.

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