Systems & Control Transactions

Research Article - Peer Reviewed Conference Proceeding
ESCAPE 35 - European Symposium on Computer Aided Process Engineering
Ghent, Belgium. 6-9 July 2025
Jan F.M. Van Impe, Grégoire Léonard, Satyajeet S. Bhonsale, Monika E. Polańska, Filip Logist (Eds.)

PSE PRESS

Electricity Bidding with Variable Loads

Iiro Harjunkoski[a,b]

[a] Aalto University, Department of Chemical and Metallurgical Engineering, Espoo, Finland
[b] Hitachi Energy Research, Mannheim, Germany
* Corresponding Author: iiro.harjunkoski@aalto.fi.

ABSTRACT

Processes increasingly need to consider electricity markets, which shifts the traditional demand side management scope towards a more dynamic nature. Instead of only focusing on day-ahead energy trading, demand-side management scope should be broadened towards being able to support the power grid stability during frequency events. This paper studies an artificial example process, similar to the melt-shop process from the steel industry, highlighting the challenges and opportunities of an energy intensive process. We show the potential benefits of having a battery energy storage system on-site, as well as opportunities in lowering the electricity cost by participating in the bidding process of various ancillary products.

Keywords: Stochastic Optimization, Renewable and Sustainable Energy, Planning & Scheduling, Energy markets, Battery Energy Storage Systems, Price Uncertainties

INTRODUCTION

The ongoing and planned electrification of many industries and processes will increase the interdependencies with the power infrastructure due to the increasing electricity demands. This also results in that all disturbances or changes in production processes will directly require countermeasures at the power grid level to maintain stability. As the electricity infrastructure is already facing increasing volatility on the supply side due to the growing number of renewable energy source (RES) generation units, it is also important to tap the potential of the electrification and the flexibility it can enable. Processes will have a strong impact and can also help compensate for the RES-fluctuations, ensuring that the electricity demand and supply are balanced at all times. This opportunity has already been recognized [1] and in this paper we further elaborate on the concept by adding a battery energy storage system (BESS) to support the balancing between the production targets and grid stability.

Apart from the traditional demand-side management [2], which is often based on a day-ahead production scheduling, acknowledging the next day electricity prices – either based on forecasts or actual market clearing prices – electricity bidding offers more opportunities than only forecasting the electricity price and adapting the load accordingly. Large consumers must actively participate in the electricity markets ahead of time and their energy bids will affect the market clearing. Such consumers are called price makers. This mechanism allows to schedule the power plants to ensure sufficient supply, but with increasing RES participation it becomes a challenge to deliver to promise and here industrial loads could potentially participate, also in helping to maintain the grid stability. The main vehicle to deal with large unplanned supply variations is ancillary services [3], which from the consumer point of view means committing to potentially increase or lowering the energy consumption if called upon. This raises the practical question how much the process industries can plan for such volatility as they primarily need to focus on delivering to customers.

A common option – also seen by many RES unit owners – is to invest in BESS to act as a buffer between the consuming load and the power grid. This can also shield the process owner from unwanted and infeasible power volatilities, which can have an immense effect on critical electricity-dependent processes. With such an energy storage system in place, there is an option to use the BESS for offering ancillary services, as well as participating in energy arbitrage trading [4], i.e. benefiting from buying electricity during low prices and selling it back during high prices. This could also help justifying the investment costs. However, the key question is how to operate such a combined system in a profitable manner, also taking into account the uncertainty over electricity prices. In this paper, we extend the approach in [5], where several energy and ancillary service products are co-optimized taking into account the uncertainty about price developments. The previous approach was targeted at RES/BESS owners, where the forecasted load was relatively stable and mainly consisted of the control system focused on keeping the system running. Here, we change the load behavior to be not a forecasted parameter but a variable and link this to a process schedule, which is co-optimized with the bidding decisions. Much following the concepts in [6], we compare the cases with different combination of products (energy and ancillary products) and different sizes of BESS systems using a simplified stochastic approach, which reduces to a deterministic optimization approach if there is only one price scenario available, which is the case in this paper. The example process is modeled using the resource task network (RTN) [7] approach.

THE EXAMPLE PROCESS

We introduce a steel-plant like energy-intensive process equipped with electric arc furnaces (EAF) and having four processing stages and two parallel units in the first EAF-stage. The process is shown in Figure 1.

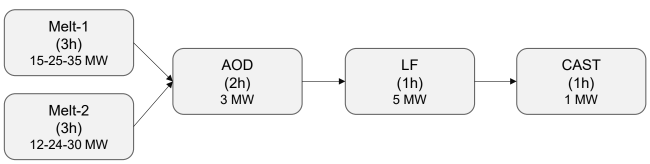

Figure 1. Example four-stage energy-intensive process, inspired by the steel-making process

The process durations and electricity consumptions are shown in the figure. Note that the melting process electricity demand increases along the processing time (e.g. 15 MW for hour 1, 25 MW for hour 2 and 35 MW for hour 3 in Melt-1). We can also see that the two EAFs are not equal. The batch size across the processing stage is 25 tons and constant. This example represents a strongly simplified small steel production process and we e.g. ignore the cooling effect caused by waiting times between process stages. We model the process using the discrete-time RTN approach presented in Castro et al. [8], which considered demand-response aspects of a cement plant. The corresponding RTN graph is shown in Figure 2, where we see all resources represented by circles and tasks by rectangles. The resources are: EAFs, argon-oxygen decarburization unit (AOD), ladle furnace (LF) and continuous caster (CAST) and electricity (ELEC). Intermediate product resources are molten metal (MET), the same after AOD (AODMET) and after LF (LFMET). After the casting, we get the final product (SLAB). We refer the interested reader to further process details described in [9] and [10].

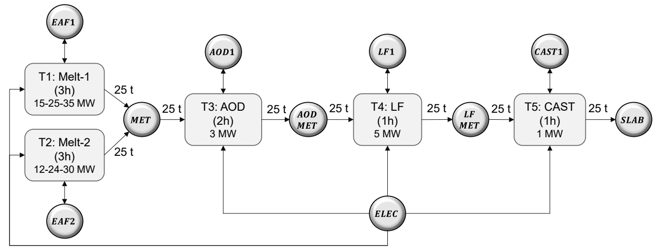

Figure 2. RTN graph of the example process

The RTN diagram can be easily converted into an RTN model, which basically has the following structure. We have a number of processing tasks i, a set of discrete-time points t and the binary variable, $N_{i,t}$, indicating whether a task i starts at time point t. This variable is used in the resource balance equation (1), in which we have ignored the batch size term, as all batches weigh 25 tons. The equation considers the initial resource r amount at time point 1 (R_r^0) and else refers to the previous time point $R_{r,t-1}$.

$$R_{r,t} = R_r^0|_{t=1} + R_{r,t-1} + \sum_{i\in I} \sum_{\theta=0}^{\tau_i} \mu_{i,r,\theta} N_{i,t-\theta} + \Pi_{r,t} \; \forall r,t \quad (1)$$

As we use a time discretization of one hour, the actual processing time is represented by the number of time points (τ_i) needed for processing the tasks. The parameter $\mu_{i,r,\theta}$ tracks how much resource r is consumed or produced at each time point θ. The final variable, $\Pi_{r,t}$, indicates interactions with the environment, e.g. electricity purchase in this case. Each resource must stay within given bounds as shown in Eq. (2).

$$R_{r,t}^{min} \leq R_{r,t} \leq R_{r,t}^{max} \quad \forall r \in R, t \in T \quad (2)$$

For electricity the bound is typically zero, unless we have energy storage units available, since all electricity must be purchased at the time of use. Finally, variable definitions are shown in Eq. (3).

$$\pi_t \in \mathbb{R}, R_{r,t} \geq \mathbb{R}^+, N_{i,t} \in \{0,1\} \quad (3)$$

OPTIMIZING THE PROCESS

In this paper, we focus on a two-day production horizon (48 hours) and assume that the demand of slabs is 500 tons, i.e. 20 batches and that the price per ton (c_{slab}) is 2500 EUR. In this case we assume that material, equipment and labor cost is about 70% of the steel price – before electricity costs (considered by a profit factor, $p_{fact} = 0.3$). This also means that there is not so much flexibility to adapt the production according to electricity price deviations. To make the case, we selected a week where the electricity was relatively expensive (DK-2 spot market on June 28-29th,2023) and assume in this study that the example steel plant is a price-taker and must pay the standard day-ahead market price (normally this is not the case, as will be discussed later). The considered electricity prices are shown in Figure 3 – here we assume "perfect knowledge" and do not involve stochastic elements for the sake of the length of this paper. Note that this corresponds to a maximum of 167 EUR/MWh (about 2-3 times the price of normal industrial energy cost).

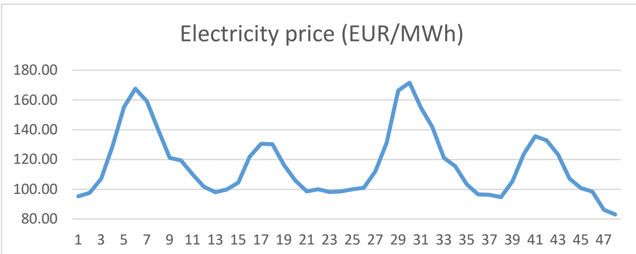

Figure 3. Electricity prices for the studied 48-hour period

Let us first optimize the production without considering the electricity price at all – as well as without any energy storage option (worst case). Specifically, we minimize only the makespan (MS) which is defined as shown in Eq. (4).

$$MS \geq N_{i,t} \cdot (t + \tau_i - 1) \quad \forall i, t \tag{4}$$

This, as expected, results in a schedule that completely ignores the electricity price.

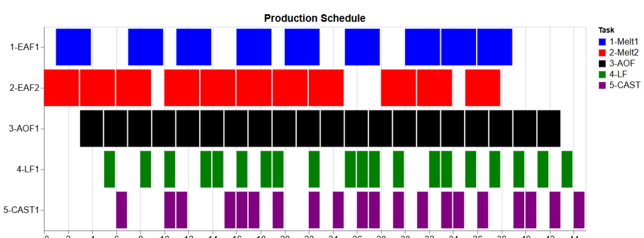

Figure 4. Schedule minimizing the makespan

The corresponding Gantt chart is shown in Figure 4 and while the makespan is 45 hours (3 hours of unused production time), this results in a profit of about 182 kEUR after deducting the electricity costs. Note that we enforce the production of minimum 500 tons. If, however, we include the electricity cost into the scheduling objective (Eq. 5),

$$\max \textstyle\sum_t p_{fact} \cdot c_{slab} \cdot R_{slab,t} - c_{elec,t} \cdot \pi_{elec,t} \tag{5}$$

the results change significantly. The profit increases by 11% to 202 kEUR and the resulting production plan in Figure 5 shows that the full 48 hours are used and the less electricity intensive EAF2 is preferred. Also, one extra batch is produced to increase the profit (total production 525 tons), while simultaneously lowering the electricity costs by 0.6%. This example illustrates that considering the electricity pricing, i.e. doing demand-response has a significant effect on the profitability.

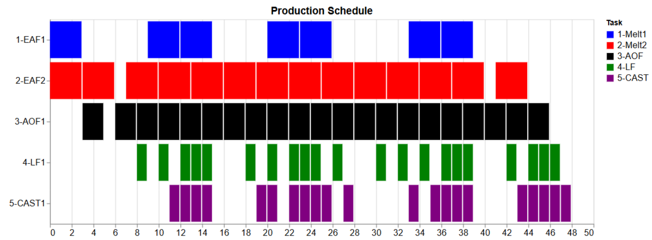

Figure 5. Schedule considering electricity cost

If we allow electricity to be stored i.e. by adapting the parameter $R_{r,t}^{max}$ this changes the situation. Having e.g. a 50 MWh battery energy storage system (BESS) unit, which is initially empty, increases the profit by an additional 4.3% to 210 kEUR with minor changes to the production schedule shown in Figure 6. The main change is the time of purchasing as the previous schedule already operates during the cheapest times.

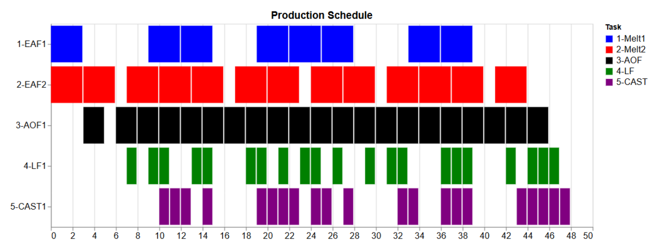

Figure 6. Schedule with a BESS of 50 MWh

The use of the BESS capacity correlates well with the electricity price development, as seen in Figure 7, where the storage is filled up during cheaper prices and emptied during peak prices. This shows that it is worth considering both demand-side management scenarios, as well as investing in a BESS, which can shift the electricity purchases to a more profitable period.

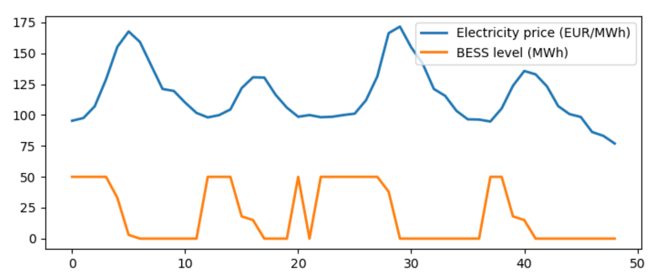

Figure 7. Use of BESS capacity w.r.t. electricity price

Optimization results of using three different BESS-sizes is shown in Table 1. As expected, a larger BESS-size increases the profit through the lowered electricity costs. For the two first cases, the production plan did not deviate from the one shown in Figure 5. Here, we cannot analyze the return of investment, but at least provide a more concrete picture about potential savings (upper bound) of having a BESS installed on site.

Table 1. BESS size impact on profit

BESS size	Profit	Electricity cost
0 MWh	202088.5	191661.5
10 MWh	203615.2	190134.8
20 MWh	205621.7	188128.3
50 MWh	210748.7	183001.3

BIDDING TO ELECTRICITY MARKETS

There exists many literature contributions about bidding into various electricity markets [4,5,6] with or without a BESS. The "traditional" market, where industrial consumers have been participating and bidding to, is the electricity market. Typically, large consumers have various electricity contracts, e.g. time-of-use or fixed base tariffs. As mentioned before, here we assume that the example consumer does not impact the final price ("price taker"). Other options that are becoming increasingly important is to bid into ancillary service markets to help stabilizing the power grids during network disturbances, i.e. when the power frequency exits a given threshold (too low or too high). A key requirement here is that ancillary services are always required to be available but mostly not used (in some markets, only 1-2% of the committed capacity is deployed). Therefore, in many markets it is mandatory that the ancillary service capacity be immediately available, i.e. mostly stored within a BESS. Here we build upon the work presented in [5], which discusses a solar power plant combined with a BESS. In this work, we ignore any renewable sources but focus on the process system, discussed in the previous chapter, having an installed BESS capacity (50 MWh), which allows us to participate in the ancillary markets.

We consider two different ancillary markets, where the market M1 requires bidding 36 hours before start of the trading day and market M2 respectively 12 hours before. The products comprise both up and down regulation of the frequency through either injecting (discharging BESS) or extracting (charging BESS) power to/from the grid. We name the products as follows: P1 (up), P2 (down) and P3 (up & down). Product P3 is symmetric and requires exactly same potential capacity (MW) into both directions. The ancillary service capacity cannot be shared by multiple products. For the energy trading, we use only the day-ahead energy market (DAEN).

The modeling is done as follows. We link the RTN model defined above to the model from [5]. The key is the energy balance equation, which basically implies that the amount of energy bought, x_t^{buy}, and discharged from BESS, $x_{B,t}^{dc}$, must equal the energy sold, x_t^{sell}, charged to BESS, $x_{B,t}^{ch}$, or consumed by a load behind the meter, X_t^{load}, as depicted in Eq. (6).

Here, instead of using a fixed load forecast X_t^{load} as was done in [5], we define the load based on the production schedule, i.e. through Eq. (7).

$$x_t^{buy} + \sum_{B\in BESS} x_{B,t}^{dc} \cdot \Delta_t = X_t^{load} \cdot \Delta_t +$$

$$x_t^{sell} + \sum_{B\in BESS} x_{B,t}^{ch} \cdot \Delta_t \quad \forall t \qquad (6)$$

$$\pi_{elec,t} = X_t^{load} \quad \forall t \qquad (7)$$

This allows us to directly link a very complex bidding model into the variable load of the generated RTN schedule. We add the first term from the profit function in Eq. (5) into the objective function, which might strongly dominate over bidding profits. Nonetheless, we expect to see some indications of the possible benefits of this co-existence. The electricity cost part (second term in Eq. (5)) is already fully embedded into the bidding scheme. We assume again a BESS configuration with the capacity of 50 MWh, and initial state of charge (SoC) of 50% (25 MWh), which can be fully (dis)charged in 2 hours. Using exactly the same information as in [5], but only considering 48 hours instead of 144, we can now optimize the trading.

The profit increases to 417 kEUR, which is a significant improvement (113%). Figure 8 shows the day-ahead energy market price (DAENprice), which was used earlier, with the ancillary product pricing across the three products and two markets discussed above.

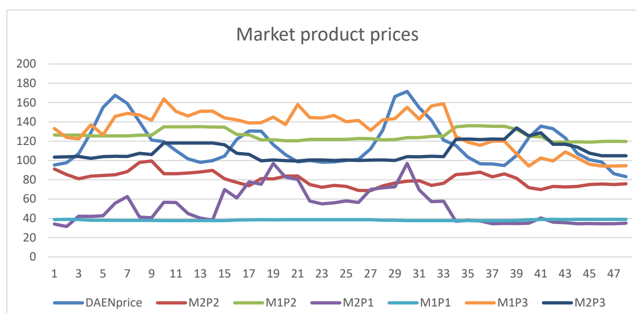

Figure 8. Market prices of different products

Using this approach the production schedule remains unchanged and the Gantt chart in Figure 5 is still valid. The trading volumes are shown in Figure 9. Note that energy trading is done in MWh, whereas ancillary products are mainly traded in MW (power).

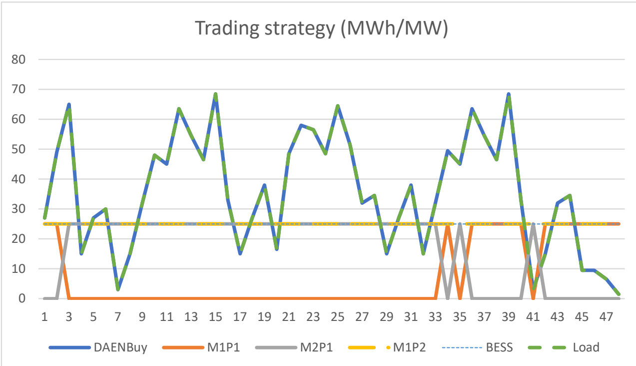

Figure 9. Trading results across multiple markets

Here, we can observe a few facts:

- The energy purchase is 1:1 with the load, i.e. the BESS is not used to shift the electricity demand
- As a consequence, the state of charge (BESS in the figure) is constant and stays exactly in the middle (25 MWh) during the entire planning horizon
- The reason for the above is that the BESS capacity is fully used for trading ancillary services in both directions (25 MW each), which maximizes the trading benefits. Product P3 is not used.

Here we assume the ideal situation that there are no ancillary events, which means that all ancillary trading profits are direct revenues. In this example, the energy purchasing cost is 192 kEUR (as for the 0 MWh case in Table 1) and the earnings from the ancillary service markets 215 kEUR, i.e. the net electricity cost is -23 kEUR. Using the BESS for participating in the ancillary markets would thus completely cover the electricity costs and strongly support the return of investment. However, a more thorough CAPEX estimation would require a more holistic and longer-term studies including seasonal electricity price variations and simulations where ancillary events actually take place, which are out of the scope of this paper.

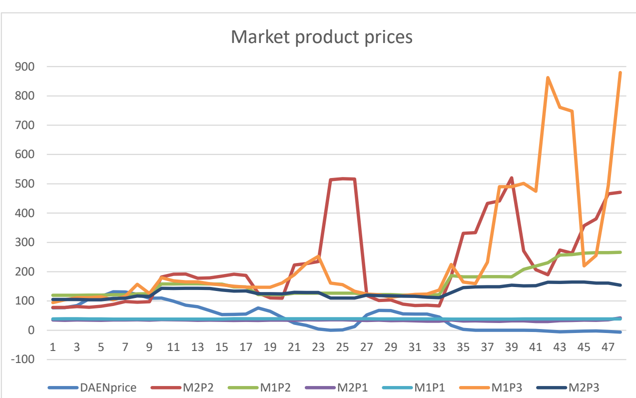

Figure 10. Market prices of the second example

More volatile price profiles

In a second example we study another price profile, which is from the same market but two days later (Figure 10). The volatility of the electricity price (EUR/MWh) is very high (min=-6.62, max=131) and at the end of the time horizon, we can see negative energy prices and very high-prices on the ancillary product P3 (M1P3). Also, compared to the earlier example with an average electricity price of 116 EUR/MWh, in the second example the average price is 45 EUR/MWh, which can be considered more typical.

When running exactly the same problem as earlier, only with the new market prices, the profit increases further by 67% to 696 kEUR. We can also see in Figure 11 that the production schedule is affected and the cheaper or even negative electricity prices at the end of the scheduling horizon are utilized activating the more energy-intensive EAF-1.

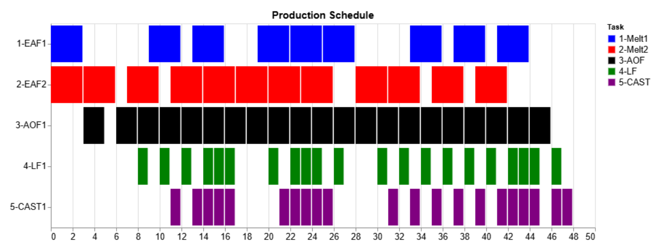

Figure 11. Production schedule of the second example

The trading volumes for this volatile example are shown in **Figure 12**, clearly illustrating that now the symmetric product P3 is used as well, especially towards the end of the schedule. We can further observe that the BESS level is slightly adjusted to maximize the trading profit. In general – maybe surprisingly – the ancillary service revenues are so high and do not involve any corrective actions after a true ancillary event that the optimization is keeping the BESS SoC mainly constant in order to leave sufficient headroom for both up/down directions. Thus, in most cases the energy trading is exactly 1:1 with the load at each point of time.

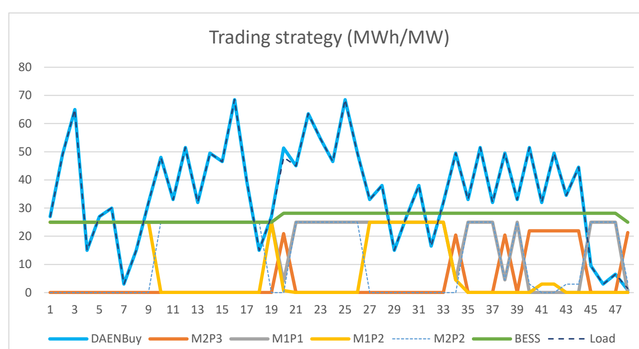

Figure 12. Trading volumes for the second example

CONCLUSIONS

This paper has studied the option of enhancing the traditional demand-side management with BESS utilization and more complex trading schemes, including ancillary services. Both approaches show significant potential. The BESS helps decouple the load and energy purchases, thus reducing trading during the most expensive peak times. If ancillary services are included, the BESS is mainly dedicated to support the enabling of maximum ancillary service trading volumes in both directions. This supports the frequency regulations in various disturbances and ancillary events. The main benefit in the more elaborate trading schemes is that in the two examples ancillary service trading could generate revenues that may fully compensate for the energy costs, making the electricity practically “free”.

However, what we did not address in this short paper were the price uncertainties, which can be easily incorporated into the presented concept. Also, we assumed that all ancillary bids are accepted and did not discuss how an occurring ancillary event would affect the production line and whether e.g. intra-day trading could be used to compensate for these uncertain events. Also, an on-site BESS could also be used to balance possible process disturbances and avoid the resulting demand-peaks. Without having any ancillary events, the production process and energy trading remain practically almost fully decoupled, and one can question the motivation in investing in a BESS. Nevertheless, it is important that future energy-intensive industries also have the capability of, when needed, supporting the grid stability in order to avoid blackouts. As the study shows, this can in ideal situations even be a profitable feature.

ACKNOWLEDGEMENTS

This paper is dedicated to Prof. Pedro Miguel Castro (1973-2024) acknowledging his remarkable contributions within the areas of planning, scheduling and optimization – some of which are reflected in this paper.

REFERENCES

1. X. Tang, R. O’Neill, E. Hale, R. Baldick and M. Baldea, "Demand bidding vs. demand response for industrial electrical loads", Computers & Chemical Engineering, vol. 189 (2024) doi: 10.1016/j.compchemeng.2024.108768
2. L. Merkert, I. Harjunkoski, A. Isaksson, S. Säynevirta, A. Saarela, G. Sand, "Scheduling and energy – Industrial challenges and opportunities", Computers & Chemical Engineering, vol. 72, pp. 183-198 (2015), doi: 10.1016/j.compchemeng.2014.05.024
3. Zheng Wang, Chaojie Li, Xiaojun Zhou, Renyou Xie, Xiangyu Li, Zhaoyang Dong, "Stochastic bidding for VPPs enabled ancillary services: A case study", Applied Energy, vol. 352 (2023) doi: 10.1016/j.apenergy.2023.121918
4. N. Padmanabhan, M. Ahmed and K. Bhattacharya, "Battery Energy Storage Systems in Energy and Reserve Markets," in IEEE Transactions on Power Systems, vol. 35, no. 1, pp. 215-226 (2020) doi: 10.1109/TPWRS.2019.2936131
5. F. Hafiz, I. Harjunkoski, M. Eissa, E. Vallarino and S. Picerno, ”Automated Market Bidding for Battery Energy Storage Systems”, CIGRE Session 2024, Paris, France, August 25-30,2024
6. E. Kraft, M. Russo, D. Keles and V. Bertsch. "Stochastic optimization of trading strategies in sequential electricity markets", European Journal of Operational Research, 308 (1), pp. 400 - 421 (2023) doi: 10.1016/j.ejor.2022.10.040
7. C.C. Pantelides, “Unified frameworks for optimal process planning and scheduling”, Second Conf. on Foundations of Computer-Aided Operations, pp. 253-274 (1994)
8. P.M. Castro, I. Harjunkoski and I.E. Grossmann, "New continuous-time scheduling formulation for continuous plants under variable electricity cost", Industrial and Engineering Chemistry Research, 48 (14), pp. 6701-6714. (2009) doi: 10.1021/ie900073k
9. H.S. Lee, S.S. Murthy, S.W. Haider and D.V. Morse “Primary production scheduling at steelmaking industries”, IBM Journal of Research and Development, 40 (2), pp. 231–252. (1997) doi: 10.1147/rd.402.0231
10. I. Harjunkoski and I.E. Grossmann. ”A decomposition approach for the scheduling of a steel plant production”, Computers & Chemical Engineering, vol. 25, pp. 1647-1660 (2001) doi: 10.1016/S0098-1354(01)00729-3

© 2025 by the authors. Licensed to PSEcommunity.org and PSE Press. This is an open access article under the creative commons CC-BY-SA licensing terms. Credit must be given to creator and adaptations must be shared under the same terms. See https://creativecommons.org/licenses/by-sa/4.0/