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Demand response potential of industrial processes considering uncertain short-term electricity prices

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Abstract

Time-varying electricity prices on the day-ahead and intraday market incentivize demand response of industrial processes. In prior work (Schäfer et al. *AIChE J.* 2020;66:1-14), we studied the demand response potential with a generalized process model, but neglected the intraday market. Extending our prior investigation, we account for uncertain intraday prices in a mixed-integer linear stochastic programming-based scheduling, that is, we minimize expected cost and conditional value-at-risk in a bi-objective optimization. We find that for very broad variations of the generalized process parameters, the conditional value-at-risk can be reduced significantly without drastically increasing the expected cost. Furthermore, simultaneously improving multiple process parameter leads to synergetic benefits. Moreover, the savings of three electrolysis processes can be more than doubled by marketing flexibility on the intraday market in addition to the day-ahead market. Overall, our model allows for a rapid early assessment of the demand response potential considering the two markets.

KEYWORDS
conditional value-at-risk, demand response, electricity price uncertainty, production scheduling, stochastic programming

1 | INTRODUCTION

Wind and solar electricity are key elements of sustainable energy systems, but their volatile availability causes short-term imbalances between electricity supply and demand.[1] These imbalances have to be counteracted to stabilize the power grid, for example, by short-term load and generation adjustments incentivized through the electricity market.[2] Particularly, the day-ahead (DA) and intraday (ID) spot markets allow for electricity trading 1 day prior to and during the day of commitment, respectively.

Industrial consumers can adjust their production schedule to time-varying electricity prices by means of so-called demand response (DR).[3] DR can be economically attractive for flexible, electricity-intensive production processes, for example, air separation,[4] chlor-alkali electrolysis,[5] electric arc steelmaking,[6] aluminum electrolysis,[7] cement production,[8,9] seawater desalination,[10] pulp,[11] and electrolytic copper refining.[12] Cost-optimal DR for such processes attempts to shift load from high-priced hours to low-priced hours which generally correspond to hours with low and high share of renewable electricity production, respectively.[13,14] Thus, DR is not only economically attractive for process operators but DR is also beneficial for the further integration of renewable electricity into the power mix.[15–17]

The DR potential of a process design under uncertainty can be maximized by means of the flexibility index, that is, a scalar measure representing the size of the feasible operational space,[18] for example, in a three level formulation using existence constraints.[19] In contrast, the DR potential for a fixed process design can be characterized by the savings of flexible operation compared to inflexible operation, particularly accounting for time-varying electricity prices. The generalized DR potential for a wide range of power-intensive processes can be evaluated via a generalized process model[3,20–22] that is not based on a specific flow sheet but rather characterizes an electricity-intensive process by means of basic process parameters such as process oversizing, ramping limits, and product storage capacities. In our prior work,[21] we used such a generalized process model to quantify the DR potential of industrial processes in Germany by considering its economic and environmental benefits. Solely accounting for the German DA market and assuming perfect foresight of DA prices, the analysis neglected the ID electricity market that allows for last-minute demand and supply adjustments.

Future realizations of ID prices are particularly uncertain due to strong correlations between prices and renewable electricity generation.[23,24] Price uncertainty can be tackled in DR scheduling optimization by means of stochastic programming (SP)[4,25,26] that comes at the cost of computational expense which calls for reduced-order modeling and tailored solution methods such as progressive hedging or Benders decomposition, see, for example references 27-29. Typically, SP optimizes the expected cost[30] and has been used for various applications in scheduling under price uncertainty, see, for example references 4,27,31-34. Alternatively, SP can optimize a risk measure such as the conditional value-at-risk (CVaR)[35,36] that allows to consider financial risks associated to worst case scenarios. Expected cost and CVaR can be considered simultaneously in a bi-objective optimization to facilitate risk-averse scheduling under price uncertainty, see, for example references 28,29,37,38. Risk-averse SP-based scheduling has been found to significantly outperform the computationally cheaper benchmark expectation of expected value (EEV) considering the optimal objective value[28,29] and has been applied in the context of, for example, electricity procurement of large consumers,[37] trading strategies of wind power producers,[38] as well as DR of selected industrial processes like air separation[28] and steel production.[29] To the best of our knowledge, the generalized DR potential of industrial processes has, however, not been studied in combination with SP-based scheduling under price uncertainty.

We extend our prior work[21] to assess the economic benefit of DR flexibility considering the DA and ID market while particularly accounting for short-term price uncertainty. We optimize the process operation for the next day based on the German DA and ID market in a two-stage stochastic program and analyze the trade-off between the expected electricity cost and the CVaR in a bi-objective scheduling optimization. By systematically varying parameters of the generalized process model, we compare the impact that the process parameters have on the scheduling objectives and the economic gain of additional ID market participation. Finally, as an illustrative example, we assess the potential savings of three industrially relevant electrolysis processes, that is, the copper electrolysis, the aluminum electrolysis, and the chlor-alkali electrolysis.

The remainder of this article is structured as follows: In Section 2, we present the employed electricity market model. We then discuss the generalized process model, the stochastic scheduling objectives, and the solution and evaluation approach in Section 3. In Section 4, we assess the DR potential of the generalized process by bi-objective scheduling optimization, evaluate the impact of price volatility, and investigate three illustrative electrolysis processes. Finally, Section 5 concludes our work.

2 | ELECTRICITY MARKET MODEL

Time varying electricity prices on the spot markets incentivize short-term load adjustments that are essential for DR. We consider the example of the German spot market[39] as Germany has a relatively high share of renewable electricity[40] as well as energy-intensive industries. The German spot market uses auction systems to settle electricity trades. On the DA market, electricity is traded at market clearing price at noon on day prior to the delivery. On the continuous ID market, electricity is traded on a pay-as-bid basis, that is, distinct prices for matching buy- and sell-orders, up to 5 min before delivery. On both markets, participants have to submit their bids and thus commit to the purchase before the final electricity prices are fixed. For an extended description of a detailed market model, we refer to Dalle Ave et al.[41]

Figure 1 provides an overview of the market model which we use in our SP-based scheduling. Considering short-term trading for the next day, we make use of the following assumptions on market participation and market prices similar to existing work.[27,42] First, the participant is a price-taker who does not influence market prices, neither on the DA nor on the ID market. Second, electricity on the DA market can be purchased at market clearing price by conservative bidding[43] using existing, sufficiently reliable electricity price forecasting methods.[44] Therefore, we assume DA prices for the next day to be known in our SP-based scheduling. Note that when committing to the DA trading, the ID prices for the same scheduling horizon are yet unknown, as the ID market is strongly affected by short-term forecasting errors of renewable electricity generation.[23] Our third key assumption therefore is that we can represent the uncertain ID prices

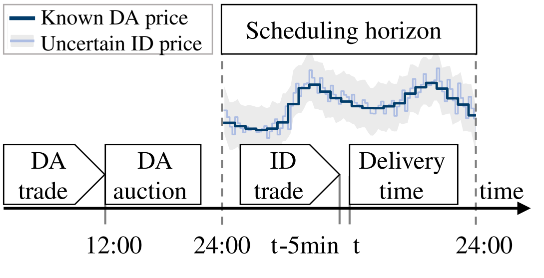
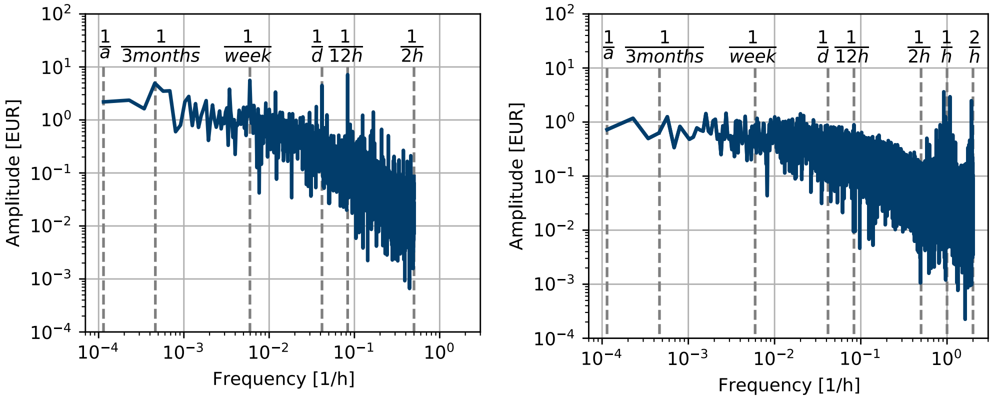


FIGURE 1 Market model for SP-based scheduling: Considering the scheduling for the next day, hourly blocks of electricity are traded on the DA market assuming known DA prices. The DA trading ends the prior day at noon with the DA auction. Afterwards, quarter-hourly blocks of electricity are traded on the ID market until 5 min before delivery. ID prices are uncertain when participants commit themselves to their DA bids.



(A) Frequency spectra of DA prices
(B) Frequency spectra of market deviation between DA and ID prices

FIGURE 2 Discrete Fourier transform of German electricity market data from 2019: The discrete Fourier transform shows fluctuation patterns of the market data considering the DA market and the price deviation between the DA and ID markets.

by a set of scenarios and assume the participant can buy or sell at index price on the ID market, that is, the weighted-average price, for the according delivery time. This assumption leads to a two-stage stochastic program, which is introduced in Section 3. Note that the two-stage stochastic program approximates a multistage stochastic problem,[45] as in reality, ID electricity can be traded up to 5 min before delivery in response to both updated ID prices and past trading decisions, opposed to having fixed ID decisions for each price scenario. The two-stage stochastic approximation leads to an upper bound on the expected cost of the original multistage program.[45] On the DA and ID market, hourly and quarter-hourly blocks of electricity can be traded, respectively.

To model representative 24 h-price profiles and scenarios, we use historic hourly DA market clearing prices and quarter-hourly ID index prices of 2019.[46] Similar to Rahimiyan and Baringo,[47] we assume that the market deviation, that is, the difference between the DA and ID prices, is uncorrelated to the DA market price. Following our previous paper,[21] we identify dominant price fluctuation patterns by means of a discrete Fourier transform to assess the seasonality of the price data. Figure 2A indicates that major frequencies of the DA market prices are 1/(3 months), 1/week, 1/day, and 1/(12 h), implying seasonal, weekly, daily, and half-daily patterns. In contrast, the market deviations (Figure 2B) are characterized by major frequencies around 1/h and 1/(30 min) and do not reveal significant daily, weekly, or seasonal patterns.

We use historical market data of 2019 from Energy-Charts[46] to create ID price scenarios. Here, we consider the 201 workdays (Monday through Thursday, excluding national public holidays) of 2019 and omit Fridays, Saturdays, and Sundays, as price profiles differ on weekends including Friday.[14] First, we retrieve one average DA price profile thus averaging over any seasonal or weekly patterns. Next, we add the historical market deviation to the average DA price profile and retrieve 201 ID price scenarios. Figure 3 shows the resulting average DA price profile and the mean and standard deviation of the ID price scenarios. Note that by omitting Fridays through Sundays, we focus on the DR potential on a typical workday. Alternatively, an evaluation of the weekday-specific DR potential could be conducted by considering weekday-specific average DA prices and ID scenarios.

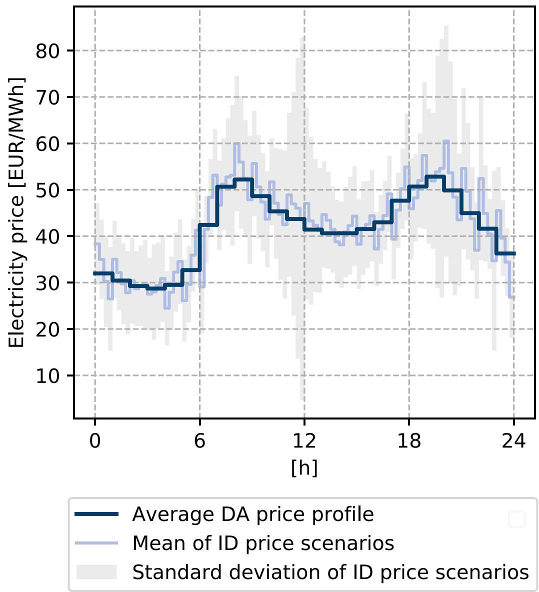


FIGURE 3 Electricity price profile and scenarios based on working days (Mon-Thu) of 2019 excluding German public holidays: In case of ID price scenarios, the historical market deviation is added to the average DA price profile, resulting in 201 price scenarios. The mean and standard deviation of the ID price scenarios are indicated. All price data is taken from Energy-Charts.[46]

3 | STOCHASTIC SCHEDULING WITH GENERALIZED PROCESS MODEL

In the following, we introduce the SP-based scheduling with the generalized process model. First, we revisit the generalized process model of our prior work[21] and extends it to the quarter-hourly ID market. Then, we discuss the scheduling objectives. Finally, we specify the solution and evaluation approach.

TABLE 1 Parameters of the generalized process model: The parameters θ_{add}, θ_{min}, S, R, and ζ are given in relation to the nominal power intake P_{nom}.

Parameter	Description	Unit
P_{nom}	Nominal power intake	[MW]
θ_{add}	Process oversizing	[%]
θ_{min}	Minimal part-load	[%]
S	Product storage capacity, that is, time to fill empty storage	[h]
R	Ramping limit between two consecutive time steps	[%/h]
ζ	Efficiency loss at minimal part-load compared to P_{nom}	[%]
τ_{off}	Maximum consecutive down-time	[h]

3.1 | Generalized process model

In the following, we revisit the generalized process model used in our prior work[21] and adapt it to simultaneous participation on DA and ID markets. The model is characterized by the process parameters given in Table 1 and the model equations are based on the source code provided in the supporting information of Schäfer et al.[21]

The generalized process model is an ideal storage-type customer with flexible operation and a product storage.[3] We assume quasi-steady-state operation within any time interval of the discrete scheduling horizon. The process flexibility is characterized by the nominal power intake P_{nom}, the process oversizing θ_{add}, the minimal part-load θ_{min}, the product storage capacity S, and the ramping limit R. The process model is defined by the following set of equations:

$$P_{nom}\theta_{min} \le p_{s,t} \le P_{nom}(1+\theta_{add}) \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}, \tag{1}$$

$$p_{s,t} = q_{DA,\lfloor\frac{t-1}{4}\rfloor+1} + q_{ID,s,t} \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}, \tag{2}$$

$$P_{nom}\, T = \sum_{t=1}^{T} r_{s,t} \quad \forall s \in \mathbb{S}, \tag{3}$$

$$r_{s,t} = p_{s,t} \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}, \tag{4}$$

$$-P_{nom}\, R \le \frac{p_{s,t+1}-p_{s,t}}{\Delta t} \le P_{nom}\, R \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T-1\}, \tag{5}$$

$$l_{s,t+1} = l_{s,t} + (r_{s,t} - P_{nom})\Delta t \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}, \tag{6}$$

$$0 \le l_{s,t} \le P_{nom}\, S \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}, \tag{7}$$

$$l_{s,1} = l_{s,T+1} = 0.5\, P_{nom}\, S \quad \forall s \in \mathbb{S}. \tag{8}$$

In Equations (1)–(8), $\boldsymbol{p}_s \in \mathbb{R}^T$ denotes the power intake, $\boldsymbol{q}_{DA} \in \mathbb{R}^{\lfloor T/4 \rfloor}$ and $\boldsymbol{q}_{ID,s} \in \mathbb{R}^T$ are the purchases from the DA and ID market, $\boldsymbol{r}_s \in \mathbb{R}^T$ is the effective production rate, $\boldsymbol{l}_s \in \mathbb{R}^T$ is the storage level, $\mathbb{S}$ denotes the set of ID price scenarios, T is the number of quarter-hourly steps, and $\Delta t = 0.25$ h is the time step size. The nominal power intake P_{nom}, the process oversizing θ_{add}, and the minimal part-load θ_{min} restrict the power intake and, thus, the electricity purchase decisions (Equations 1 and 2). The flexible operation has to produce as much as a steady-state nominal production would achieve in the 24 h scheduling horizon (Equation 3). The production depends on the effective production rate $\boldsymbol{r}_s$ which is equal to the power-intake $\boldsymbol{p}_s$ when neglecting efficiency losses (Equation 4). The ramping limit R restricts the change of power intake between consecutive time steps to enforce safety and process constraints (Equation 5). We consider an ideal product storage that is filled by the effective production and has to meet a continuous, constant product demand corresponding to the nominal production (Equation 6). Here, the product storage capacity S corresponds to the time necessary to fill an empty storage at nominal production P_{nom} and, thus, restricts the storage level (Equation 7). Furthermore, initial and final storage levels are fixed to enforce a cyclic behavior and prevent the product storage to be emptied at the end of the scheduling horizon (Equation 8). Note that for a process that is not constrained by a product storage, Equations (6)-(8) can be removed from the process model. Furthermore, Section 1 of the supporting material proves that Equations (6) and (8) implicitly enforce the production goal (Equation 3). Thus, Equation (3) is redundant but has to be explicitly added to the model in case of processes without storage constraints.

The total amount of purchased electricity is restricted by Equations (1) and (2) for each time step. Additionally, we restrict the DA purchases by means of

$$0 \le q_{DA,t} \le P_{nom}(1+\theta_{add}) \quad \forall t \in \{1,\dots,\lfloor T/4 \rfloor\} \tag{9}$$

in order to not exceed the possible process power intake and, thus, take the position of an electricity consumer with process-limited trading capacity. We want to point out that Equations (1) and (2) implicitly allow for selling purchased DA electricity on the ID market as long as the power intake $\boldsymbol{p}_s$, that is, the sum of the purchases, is feasible.

For a model considering efficiency losses at off-design operation, Schäfer et al.[21,32] estimate the effective production rate $r_{s,t}$ from a cubic function of the power intake $p_{s,t}$:

$$r_{s,t} = \left(1 - \zeta\left(\frac{P_{nom} - p_{s,t}}{P_{nom} - P_{nom}\theta_{min}}\right)^2\right) p_{s,t} \quad \forall (s,t) \in \mathbb{S}\times\{1,\dots,T\}. \tag{10}$$

Here, the process parameter ζ characterizes the relative loss of production efficiency at minimal part-load θ_{min} compared to P_{nom}. Following Schäfer et al.,[21,32] we embed efficiency losses into the process model by means of a piecewise linear approximation with a set of equidistant support points $\{(p_i, r_i)\}$. Instead of using the formulation of Schäfer et al.[21,32] with equality constraints and binary variables, we apply a reformulation into a set of inequality constraints without binary variables as suggested by Varelmann et al.[48] Thus, for a process with efficiency losses, Equation (4) is replaced by

$$r_{s,t} \leq b_i + s_i p_{s,t} \qquad \forall (i,s,t) \in \mathcal{I} \times \mathbb{S} \times \{1,\ldots,T\} \quad (11)$$

$$\text{with } b_i := r_i - s_i p_i, \quad (12)$$

$$s_i := \frac{r_{i+1} - r_i}{p_{i+1} - p_i}, \text{ and} \quad (13)$$

$$r_i := \left(1 - \zeta\left(\frac{P_{\text{nom}} - p_i}{P_{\text{nom}} - P_{\text{nom}}\theta_{\min}}\right)^2\right) p_i, \quad (14)$$

where b_i and s_i denote the linearization parameters intercept and slope, respectively, for the set of linearization intervals $\mathcal{I}$. Note that the reformulation Equations (11)-(14) only holds due to the concave curvature of Equation (10) in the interval $p_{s,t} \in [P_{\text{nom}}\theta_{\min}, P_{\text{nom}}(1+\theta_{\text{add}})]$.[48] When considering efficiency losses, we therefore limit the maximum operational range to ±50% P_{nom} by means of $\theta_{\min}$ and θ_{add} to ensure an adequate linearization by five linearization points.

Production during peak priced hours can be completely avoided by allowing for temporary shutdowns. Shutdowns with a maximum down-time τ_{off} (in [h]), that is, consecutive hours with a turned-off process, are modeled by:

$$y_{t+\overline{\tau}_{\text{off}}} \geq z_{\text{off},t} \qquad \forall t \in \{1,\ldots,\lfloor T/4 \rfloor - \overline{\tau}_{\text{off}}\}, \quad (15)$$

$$z_{\text{on},t} - z_{\text{off},t} = y_{t+1} - y_t \qquad \forall t \in \{1,\ldots,\lfloor T/4 \rfloor - 1\}, \quad (16)$$

$$z_{\text{on},t} + z_{\text{off},t} \leq 1 \qquad \forall t \in \{1,\ldots,\lfloor T/4 \rfloor\}, \quad (17)$$

$$-y_{\lfloor \frac{t}{4} \rfloor + 1} P_{\text{nom}} R - \left(1 - y_{\lfloor \frac{t}{4} \rfloor + 1}\right) \frac{P_{\text{nom}}\theta_{\min}}{\Delta t} \leq \frac{p_{s,t+1} - p_{s,t}}{\Delta t} \qquad \forall (s,t) \in \mathbb{S} \times \{1,\ldots,T-1\}, \quad (18)$$

$$\frac{p_{s,t+1} - p_{s,t}}{\Delta t} \leq y_{\lfloor \frac{t-1}{4} \rfloor + 1} P_{\text{nom}} R + \left(1 - y_{\lfloor \frac{t-1}{4} \rfloor + 1}\right) \frac{P_{\text{nom}}\theta_{\min}}{\Delta t} \qquad \forall (s,t) \in \mathbb{S} \times \{1,\ldots,T-1\}, \quad (19)$$

$$y_{\lfloor \frac{t-1}{4} \rfloor + 1} P_{\text{nom}}\theta_{\min} \leq p_{s,t} \leq y_{\lfloor \frac{t-1}{4} \rfloor + 1} P_{\text{nom}}(1+\theta_{\text{add}}) \qquad \forall (s,t) \in \mathbb{S} \times \{1,\ldots,T\}. \quad (20)$$

In Equation (15), $\overline{\tau}_{\text{off}} := \tau_{\text{off}}/\text{h}$ denotes the maximum number of turn-off hours and is introduced for correct indexing. The binary variable $\boldsymbol{y} \in \{0,1\}^{\lfloor T/4 \rfloor}$ specifies whether the process is turned on or off. The binary variables $\boldsymbol{z}_{\text{on}} \in \{0,1\}^{\lfloor T/4 \rfloor}$ and $\boldsymbol{z}_{\text{off}} \in \{0,1\}^{\lfloor T/4 \rfloor}$ indicate a transition from off to on and vice versa. Equation (15) forces the process to run again after at latest τ_{off} hours after having been turned off. Equation (16) links the transitions $\boldsymbol{z}_{\text{on}}$ and $\boldsymbol{z}_{\text{off}}$ to the process being on or off. The solutions $z_{\text{on},t} = z_{\text{off},t} = 1$ and $z_{\text{on},t} = z_{\text{off},t} = 0$ both indicate an unchanged on/off state of the process, that is, $y_{t+1} = y_t$. Equation (17) breaks this symmetry of Equation (16), that is, Equation (17) reduces the feasible space by removing the solution $z_{\text{on},t} = z_{\text{off},t} = 1$.

Following reference 21, we assume that process operation is limited to the minimal part-load $\theta_{\min}$ prior and subsequent to a shutdown and, thus, adapt the restrictions on the power intake and ramping (Equations 1 and 5) accordingly to obtain the integer formulation in Equations (18)-(20).

For the analysis in Section 4, we model shutdowns by means of *hourly*, *first-stage* discrete decisions. Note that considering shutdown decisions on the *second* stage of the stochastic program would allow for the most flexible process operation but would strongly increase the computational burden of solving the optimization problem due to the resulting large number of binary variables, that is, one per scenario and quarter-hourly time step.

3.2 | Scheduling objectives

In the scheduling under price uncertainty, we minimize the expected cost $\text{E}[C]_{\text{SP}}$ and the conditional value-at-risk CVaR_{SP}. Both objectives are shown for an exemplary probability distribution in Figure 4. In the scheduling, we use the set of scenarios $\mathbb{S}$ that describes possible realizations of uncertain ID electricity prices. Note that we consider operational electricity cost only and thus neglect investment and maintenance cost due to flexibilization measures. The expected cost

$$\text{E}[C]_{\text{SP}} = \sum_{s \in \mathbb{S}} \pi_s C_s(\boldsymbol{q}_{\text{DA}}, \boldsymbol{q}_{\text{ID},s}) \quad (21)$$

is the weighted sum of the cost of all scenarios. For our set of historical scenarios, the weights are equi-probable, that is, $\pi_s = 1/|\mathbb{S}|$, but in principle π_s could vary, for example, as result of clustering[49] or probabilistic forecasting.[50] The electricity cost C_s with hourly DA prices $\boldsymbol{c}_{\text{DA}} \in \mathbb{R}^{\lfloor T/4 \rfloor}$ and quarter-hourly ID prices $\boldsymbol{c}_{\text{ID},s} \in \mathbb{R}^T$ in [EUR/MWh] is defined as

$$C_s(\boldsymbol{q}_{\text{DA}}, \boldsymbol{q}_{\text{ID},s}) = 4\Delta t \cdot (\boldsymbol{c}_{\text{DA}} \cdot \boldsymbol{q}_{\text{DA}}) + \Delta t \cdot (\boldsymbol{c}_{\text{ID},s} \cdot \boldsymbol{q}_{\text{ID},s}) \quad (22)$$

with $\Delta t = 0.25$ h.

In addition to $\text{E}[C]_{\text{SP}}$, we minimize CVaR_{SP} to account for the high cost associated with worst case scenarios. Generally, CVaR

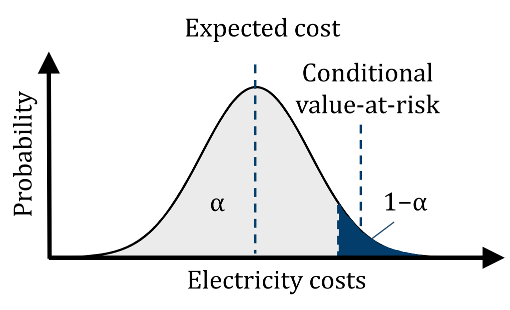


FIGURE 4 Expected cost E[C] and conditional value-at-risk CVaR of an exemplary probability distribution: CVaR is the expected electricity cost of the $(1-\alpha)$-probable worst outcomes of the probability distribution.

corresponds to the expected value of the $(1-\alpha)$-probable worst outcomes for a given probability distribution and a chosen confidence level α.[35,36] A linear programming-based optimization of $\mathrm{CVaR}_{\mathrm{SP}}$ is possible by means of the constraints

$$\mathrm{CVaR}_{\mathrm{SP}} = \psi + \frac{\sum_{s \in \mathbb{S}} \pi_s \phi_s}{1-\alpha} \tag{23}$$

and

$$C_s\left(\boldsymbol{q}_{\mathrm{DA}}, \boldsymbol{q}_{\mathrm{ID},s}\right) - \psi \leq \phi_s \forall s \in \mathbb{S} \tag{24}$$

with the continuous auxiliary variables $\psi \in \mathbb{R}$ and $\phi \in \mathbb{R}^{|\mathbb{S}|}_{\geq 0}$.[35] If the cost C_s of a scenario s exceeds ψ, ϕ_s equals the difference between the scenario cost C_s and the variable ψ. Otherwise, ϕ_s equals zero.

3.3 | Solution and evaluation approach

For the analysis in Section 4, we fix the following parameters: For the piecewise linear approximation of the efficiency losses, we use five equi-sized intervals. $\mathrm{CVaR}_{\mathrm{SP}}$ is optimized at confidence level $\alpha = 0.9$. To perform the bi-objective optimization of $\mathrm{E}[C]_{\mathrm{SP}}$ and $\mathrm{CVaR}_{\mathrm{SP}}$, we determine the Pareto curve by the ϵ-constraint method[51] using 10 Pareto optima that are equidistant with respect to $\mathrm{CVaR}_{\mathrm{SP}}$. The optimization is a two-stage stochastic program with $\boldsymbol{q}_{\mathrm{DA}}$ and ψ as first-stage variables and $\boldsymbol{q}_{\mathrm{ID},s}$ and ϕ_s as second-stage variables. The stochastic program is formulated in terms of the deterministic equivalent and the resulting MILPs are solved using Gurobi 9.1.1[52] with default solver settings on an Intel Core i5-8265U processor and 24GB RAM.

For benchmarking, we also compute the wait-and-see solution (WS) and the expectation of expected value (EEV). WS assumes perfect foresight of uncertain events and allows for individual first stage decisions for each scenario.[53,54] Thus, WS serves as an Utopian lower bound for the SP-based scheduling. The difference between WS and the stochastic program is defined as the expected value of perfect information. To compute the EEV, the problem is first optimized with a single expected-value scenario, that is, the mean of the ID price scenarios, followed by a second optimization with all scenarios but fixed first-stage decisions.[55] The difference between the stochastic program and the EEV is defined as the value of stochastic solution. For more detailed information on WS and EEV, we refer to Birge and Louveaux.[30] Note that, we evaluate both $\mathrm{E}[C]$ as well as the CVaR of WS and EEV based on their respective optimal schedules.

As a reference, we consider the cost of inflexible operation as well as the cost of a DA-only scheduling as in our prior work.[21] The DA-only scheduling cost refers to the cost of flexible process operation with purchases from the DA market only and thus without consideration of the ID market. The inflexible operation cost refers to the cost of *steady-state operation* at P_{nom}, where again only the DA market is used for electricity procurement. The inflexible operation cost and the DA-only scheduling cost allow us to evaluate the relative economic gain of ID market participation:

$$\text{Relative economic gain} = \frac{\text{Minimal } \mathrm{E}[C]_{\mathrm{SP}} - \text{Inflexible operation cost}}{\text{DA-only scheduling cost} - \text{Inflexible operation cost}}. \tag{25}$$

4 | ANALYSIS OF DEMAND RESPONSE POTENTIAL

In this section, we assess the DR potential of simultaneous DA and ID market participation. In particular, we analyze the impact of the process parameters introduced in Section 3.1 on the scheduling objectives. First, we discuss the influence of individual process parameters, whereas in the subsequent section, we focus on the interplay of the parameters. Next, we evaluate the impact of electricity price volatility on the ID market. Finally, we provide an illustrative example on how the MILP-based scheduling formulation can be used to perform a rapid early assessment of the DR savings potential in case of a specific, industrially relevant process.

4.1 | One-at-a-time variation of process parameters

In the following, we evaluate the impact of the individual process parameters on the expected cost $\mathrm{E}[C]_{\mathrm{SP}}$ and the conditional value-at-risk $\mathrm{CVaR}_{\mathrm{SP}}$ and draw a comparison to the three benchmarks

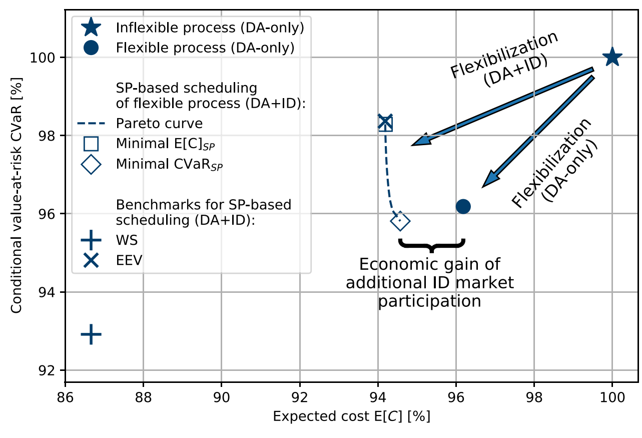


FIGURE 5 SP-based scheduling objectives and benchmarks for an illustrative reference process: The Pareto curve of the SP-based scheduling shows the trade-off between the minimal $\mathrm{E}[C]_{\mathrm{SP}}$ and the minimal $\mathrm{CVaR}_{\mathrm{SP}}$. The properties of the illustrative reference process are $\theta_{\mathrm{add}} = 20\%$, $\theta_{\min} = 50\%$, $S = 3$ h, $R = 25\%$/h, $\zeta = 0\%$, and $\tau_{\mathrm{off}} = 0$ h. In contrast to the SP-based scheduling, DA-only scheduling of the flexible process allows purchases only from the DA market. The expectation of expected value (EEV) neglects ID price uncertainty. The wait-and-see solution (WS) considers perfect foresight of the ID price uncertainty. All values are normalized to the cost of inflexible operation.

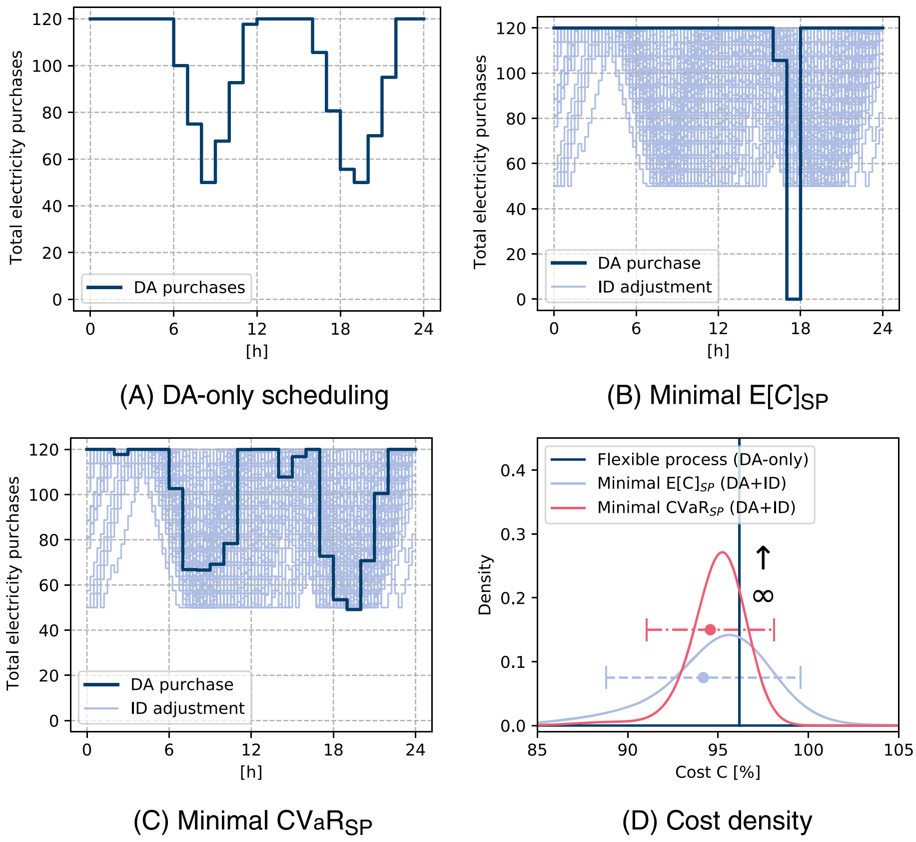


FIGURE 6 Market decisions and estimated cost density for the illustrative reference process ($\theta_{add} = 20\%$, $\theta_{min} = 50\%$, $S = 3$ h, $R = 25\%$/h, $\tau_{off} = 0$ h, $\zeta = 0\%$): The market decisions, that is, DA purchases and ID adjustments relative to the nominal power intake P_{nom}, are given for the (A) DA-only scheduling, (B) minimal E[C]$_{SP}$, and (C) minimal CVaR$_{SP}$. (D) The probability distribution of the electricity cost is estimated by means of the kernel density estimation for the minimal E[C]$_{SP}$ and minimal CVaR$_{SP}$. The horizontal bars reflect the mean value and the standard deviation.

(DA-only, WS, and EEV). To this end, we assume a flexible illustrative reference process with oversizing $\theta_{add} = 20\%$, minimal part-load $\theta_{min} = 50\%$, storage capacity $S = 3$ h, ramping limit $R = 25\%$/h, efficiency loss $\zeta = 0\%$, and a maximum allowed down-time $\tau_{off} = 0$ h and perform a one-at-a-time variation of the process parameters.

Figure 5 shows the Pareto curve for the SP-based scheduling and its relation to the benchmarks. The economic gain of ID market participation is the difference between the expected cost of DA-only scheduling and SP-based scheduling. Note that for the DA-only scheduling, E[C] equals CVaR as no price uncertainty is present. We observe that the bi-objective SP-based scheduling returns a Pareto curve resembling a hockey stick, that is, CVaR$_{SP}$ can be reduced significantly with only minor increases in E[C]$_{SP}$. Per definition, the Pareto curve is framed by the minimal E[C]$_{SP}$ and minimal CVaR$_{SP}$. It can be noted that the EEV and the minimal E[C]$_{SP}$ are particularly similar but not identical with respect to both E[C] and CVaR, indicating a very small value of stochastic solution. Furthermore, the Utopian WS solution indicates major additional savings could be attained with perfect foresight of the ID electricity prices, thus indicating a large expected value of perfect information.

Figure 6A–C shows the market decisions for the DA-only scheduling, minimal E[C]$_{SP}$, and minimal CVaR$_{SP}$. The DA-only scheduling and the minimal CVaR$_{SP}$ show very similar DA purchase decisions, that is, both avoid the price peaks in the DA market (compare to Figure 3) in the morning (6-10 h) and evening (17 h-21 h). In contrast, minimal E[C]$_{SP}$ leads to an oversupply of DA electricity, that is, maximal-allowed purchases of 120%, allowing for last minute sales on the ID market. The ID adjustments of both minimal E[C]$_{SP}$ and minimal CVaR$_{SP}$ suggest similar total electricity purchases, tend to increase production during night hours (0-6 h, 23-24 h) with overall low electricity prices, and generally show a strong scenario dependency. Figure 6D shows expected value, standard deviation, and a probability distribution of the electricity cost for the different schedules. The probability distribution is estimated based on kernel density estimation using the build-in functionality of the Python package Pandas[56] with standard settings. For the DA-only scheduling no price uncertainty is present, leading to an infinite density at the expected cost. While minimal E[C]$_{SP}$ has a lower expected cost than minimal CVaR$_{SP}$, its estimated cost distribution and standard deviation is much broader. Furthermore, a significant quantile of the distribution resulting from minimal E[C]$_{SP}$ is above the DA-only scheduling cost and the inflexible operation cost (100%). In contrast, the distribution of minimal CVaR$_{SP}$ has a much smaller quantile above the DA-only scheduling cost and an insignificant quantile above the inflexible operation cost. Overall, minimizing E[C]$_{SP}$ may result in DA electricity purchases that disregard price peaks in the DA price signal and has a relatively high probability of leading to electricity cost larger than the DA-only scheduling cost or the inflexible operation cost. In contrast, minimal CVaR$_{SP}$ shows a strong response to the DA price signal and rather narrow cost distribution with less cases above the DA-only scheduling cost.

Figure 7 shows the impact of the individual process parameters on the minimal E[C]$_{SP}$ and reveals that the process oversizing generally has the largest impact, that is, process oversizing allows the strongest cost reductions due to flexibilization in the reference process.

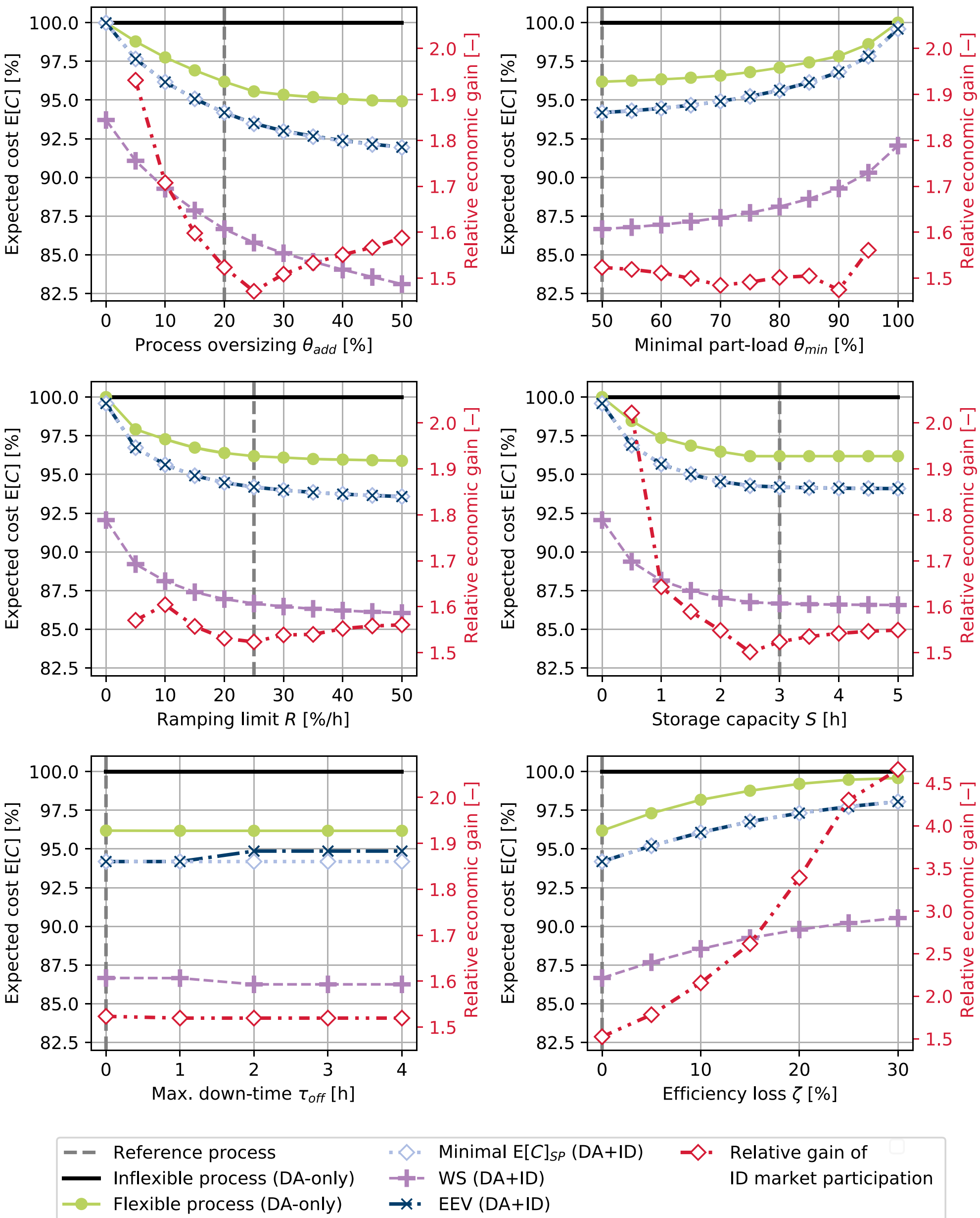


FIGURE 7 One-at-a-time variation of the process parameters for the illustrative reference process ($\theta_{add} = 20\%$, $\theta_{min} = 50\%$, $S = 3$ h, $R = 25\%/\text{h}$, $\tau_{off} = 0$ h, $\zeta = 0\%$): The expected cost $E[C]$ are given relative to the inflexible operation cost. The relative economic gain of ID market participation is evaluated as defined in Equation (25). Only the marked points are optimization results. The lines have been added to guide the eye of the reader.

The impact of minimal part-load, ramping limits, and storage capacities are somewhat smaller and similar to each other in magnitude. The small but noticeable gradients between 50% and 60% minimal part-load and 40% and 50% ramping limitations suggest that cost can be reduced even further with lower minimal part-load or even looser ramping. In contrast, no additional benefit can be gained from product storage capacities larger than 3 h due to the restrictive 24 h scheduling horizon and the cyclic constraint for initial and final storage level. Varying the maximum allowed down-time has only a minor impact, which is further discussed in the following subsection. In contrast to the other process parameters, the shape of the efficiency loss curve is concave due to the cubic definition of the efficiency losses (Equation 10). Particularly for processes with large efficiency losses, ID market participation can significantly lower the minimal $E[C]_{SP}$, whereas DA-only scheduling would hardly allow for any savings in such a case. Large efficiency losses lead to an overall larger energy consumption as a result of flexible operation, but still allow for profitable marketing of flexibility by exploiting price differences in the two markets.

The relative economic gain of ID market participation as defined in Equation (25) (right axis in Figure 7) does not follow a monotonous trend, for example, the relative gain decreases for a process oversizing between 0% and 25% but increases again beyond 25%. Nevertheless, we observe that for less flexible processes the relative economic gain of ID market participation tends to be larger than for more flexible processes. Thus, ID market participation can be particularly attractive for processes with less room for flexibilization. Moreover, we observe that for processes with large efficiency losses, the relative gain increases most drastically.

Assuming perfect foresight of ID prices, the WS solution in Figure 7 suggests that significant cost reductions by ID market participation are possible even for inflexible processes, that is, WS cost for processes with no flexibility ($\theta_{add} = 0\%$, $\theta_{min} = 100\%$, $R = 0\%/h$, or $S = 0$ h) are approximately between 92% and 94% of the expected cost of operation with purchases only on the DA market. These savings can be explained by arbitrage opportunities that are possible as the constraints Equations (1), (2) and (9) allow the electricity consumer (i) to make excessive purchases on the DA market and then re-sell the excessive electricity on the ID market and (ii) to not cover electricity consumption on the DA market but purchase electricity on the ID market instead. In addition to the WS solution, processes with restricted minimal part-load, ramping limitations, or storage capacity show a slight arbitrage effect with respect to the minimal $E[C]_{SP}$. Note that the electricity purchase restriction (Equation 9) does not allow an inflexible non-oversized process to make excessive purchases on the DA market. Thus, its arbitrage potential is generally smaller.

EEV and minimal $E[C]_{SP}$ differ noticeably for maximum downtimes larger than 2 h. As the binary on/off decisions have to be made before the uncertain ID prices are realized but have large consequences, consideration of price uncertainty by means of SP-based scheduling is particularly important to optimize profitability. For all other process parameter variations, the difference between EEV and minimal $E[C]_{SP}$ is found to be insignificant.

Table 2 shows the maximal computation times for the subproblems of the one-at-a-time variations. For the DA-only scheduling, EEV, and the WS solution, the maximal computation times are significantly lower compared to the minimal $E[C]_{SP}$, as the respective problem sizes are much smaller. For all scheduling approaches, the computational times for the basic process model, that is, the case where only variations in the process oversizing, minimal part-load, ramping limitations and storage capacity are considered, are the lowest, followed by models with efficiency losses and, finally, models with shutdown capabilities. Particularly the consideration of shutdowns increases computational times significantly due to the introduction of binary variables. Note that modeling binary decisions on the second stage could potentially decrease the electricity cost further, but would involve discrete recourse decisions on the second stage, leading to strongly increasing solution times.

In contrast to Figure 7, Figure 8 focuses on both E[C] and CVaR, where CVaR is the expected cost of the 10% worst case scenarios, and shows the impact of process oversizing and efficiency loss variations. Varying the other process parameters leads to similar conclusions. The corresponding figures can be found in Section 2 of the supporting material. Our analysis shows that the SP-based scheduling consistently leads to a Hockey stick curve, that is, significant reductions of $CVaR_{SP}$ can be achieved without strongly increasing $E[C]_{SP}$.

TABLE 2 Maximal computation time in seconds and problem size of a single optimization run in the one-at-a-time variation: All points on a Pareto curve of the SP-based scheduling have the same degrees of freedom and constraints and, hence, their computational times can be represented by the times of minimal $E[C]_{SP}$.

	DA-only	Min. $E[C]_{SP}$	EEV (1)	EEV (2)	WS
Basic process model	0.049 s	25.660 s	0.065 s	0.067 s	0.051 s
W/efficiency losses	0.026 s	47.243 s	0.316 s	0.217 s	0.253 s
W/shutdowns	0.763 s	204.319 s	1.433 s	0.326 s	0.617 s
Degrees of freedom	24	$24+96\cdot\lvert\mathbb{S}\rvert$	$24+96$	96	$24+96$
Number of problems	1	1	1	$\lvert\mathbb{S}\rvert$	$\lvert\mathbb{S}\rvert$

Note: For EEV, the times of (1) the single expected-scenario optimization and (2) the optimization with all scenarios and fixed first-stage decisions are stated separately. For WS and EEV (2), the maximal average time of the $\lvert\mathbb{S}\rvert$ independent problems is reported.

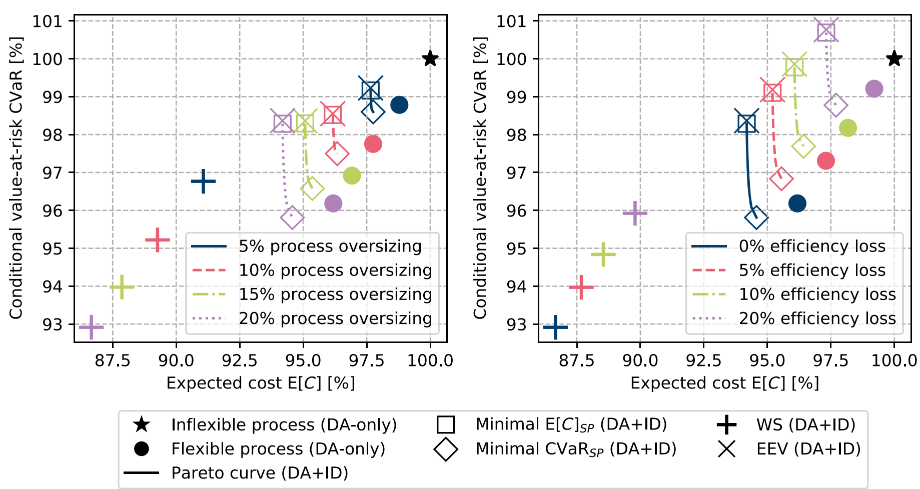


FIGURE 8 Impact of one-at-a-time variation on both E[C] and CVaR for the illustrative reference process ($\theta_{add} = 20\%$, $\theta_{min} = 50\%$, $S = 3$ h, $R = 25\%/h$, $\tau_{off} = 0$ h, $\zeta = 0\%$): The impact of varying process oversizing is shown left, whereas the impact of varying efficiency losses is shown right.

Furthermore, EEV and minimal $E[C]_{SP}$ are always highly similar. While process oversizing allows to decrease $E[C]_{SP}$ significantly, the largest Pareto-optimal $CVaR_{SP}$ hardly changes, indicating that the financial risk for lowest expected cost cannot be reduced considerably (Figure 8, left). This observation does not extend to the efficiency loss variation (Figure 8, right) which affects both $E[C]_{SP}$ and $CVaR_{SP}$ to a similar degree. Interestingly, $CVaR_{SP}$ of processes with large efficiency losses can become larger than the cost of inflexible operation. In contrast, the minimal $CVaR_{SP}$ is always much lower than the cost of inflexible operation. The large $CVaR_{SP}$ observed for some parameter combinations therefore motivates a bi-objective scheduling optimization where financial risk and expected operational cost can be traded off.

Overall, we observe significant savings due to ID market participation. Furthermore, the relative economic gain suggests that ID market participation is particularly attractive for processes with only a modest amount of flexibility or significant efficiency losses. Independent of the process parameters, the Pareto curve resembles a Hockey stick curve, thus allowing to significantly reduce $CVaR_{SP}$.

4.2 | Two-at-a-time variation of process parameters

In the following, we study the impact of varying two process parameters at a time. We consider the same illustrative reference process as in the prior subsection and discuss the effects on minimal $E[C]_{SP}$ and the relative economic gain of ID market participation for an exemplary combination of process parameters. Results for all binary combinations can be found in Section 2 of the supporting material.

Figure 9A shows the impact of concurrent process oversizing and minimal part-load variations. The two-at-a-time variation suggests a synergetic benefit, that is, the gained benefit of varying two parameters exceeds the sum of the gains resulting from single parameter variations, as exemplified in the red rectangle in Figure 9A. In fact, synergy can be observed across all binary parameter combinations, which suggests that significant savings can be achieved by leveraging multiple process parameters instead of maximizing the flexibility of any single process parameter.

Figure 9B shows a significant relative economic gain of marketing flexibility on the ID market for any combination of process parameters. In contrast to the minimal $E[C]_{SP}$ in Figure 9A, no combinatorial effect or clear trend can be observed, that is, no monotonous in- or decrease. Therefore, the relative economic gain depends on the specific combination of the process parameters and the optimization results cannot be predicted from the one-at-a-time assessments.

Figure 10 shows the particular interplay between minimal part-load and maximum down-time. The shutdown constraints (Equations 18 and 19) involves the minimal part-load θ_{min}, as we assume that the process can only shut down from and restart to the state of the minimal feasible part-load. A significant impact of shutdowns can only be observed for minimal part-loads above 70%, where minimal $E[C]_{SP}$ may change significantly between a maximum down-time of 1 and 2 h. Each hour of down-time requires the process to catch up the

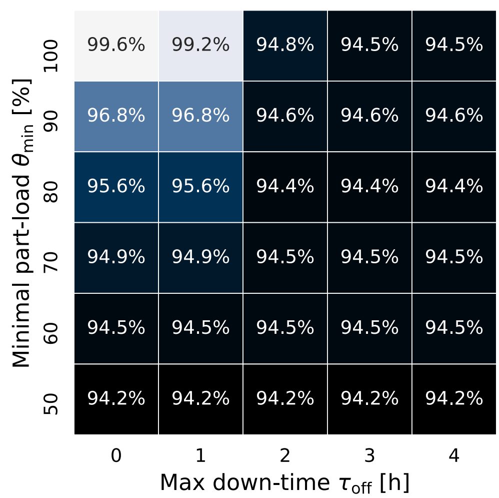


FIGURE 10 Impact of minimal part-load and shutdown capabilities on minimal $E[C]_{SP}$ for the illustrative reference process ($\theta_{add} = 20\%$, $S = 3$ h, $R = 25\%/h$, $\zeta = 0\%$) relative to the inflexible operation cost

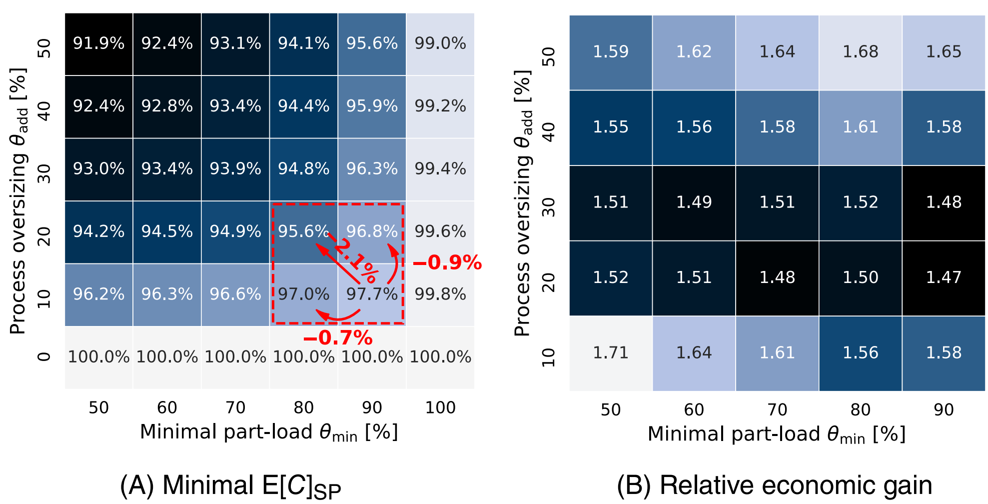


FIGURE 9 Impact of two-at-a-time variation of process oversizing and minimal part-load for the illustrative reference process ($S = 3$ h, $R = 25\%/h$, $\tau_{off} = 0$ h, $\zeta = 0\%$): Minimal $E[C]_{SP}$ is given relative to the inflexible operation cost. The relative economic gain is evaluated as defined in Section 3.3. The red rectangle exemplifies the synergetic behavior of parameter combinations considering minimal $E[C]_{SP}$.

lost production in advance or later on, while being restricted to the minimal part-load θ_{min} prior and subsequent to the shutdown. Therefore, only processes with specific characteristics, for example, high minimal part-load, can profit from down-times. Furthermore, the 24 h scheduling horizon restricts shutdown opportunities such that the impact of shutdowns is insignificant compared to the results from our prior work[21] where we considered a 1-year scheduling horizon.

Overall, the synergetic benefit of changing multiple parameters at once suggests that flexibilization efforts ideally target more than one process parameter. Furthermore, we observe a significant, but non-trending relative economic gain of ID market participation, demonstrating the value of the proposed MILP stochastic scheduling in use-case specific evaluation. Moreover, shutdown capabilities are beneficial only for specific processes with a high minimal part-load, given the 24 h scheduling horizon.

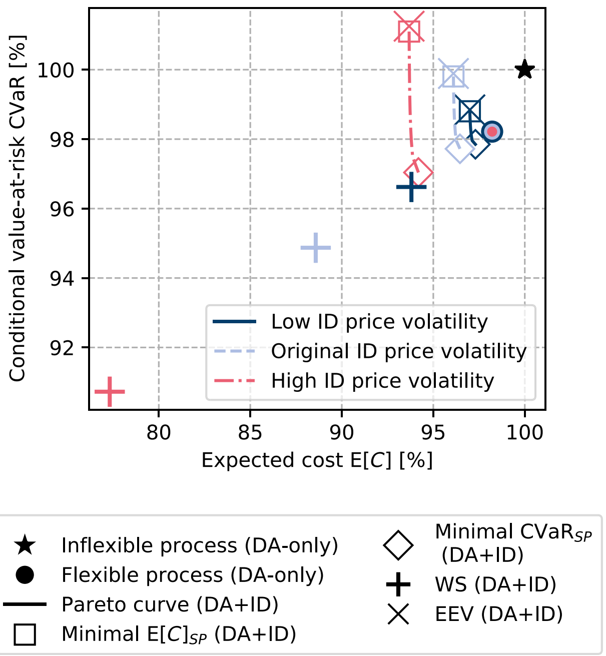


FIGURE 11 Impact of price volatility on scheduling objectives and benchmarks for an illustrative process with 10% efficiency loss ($\theta_{add} = 20\%$, $\theta_{min} = 50\%$, $S = 3$ h, $R = 25\%$/h, $\zeta = 10\%$, $\tau_{off} = 0$ h): The ID price scenarios have been scaled such that their standard deviation is halved and doubled for low volatility and high volatility scenarios, respectively.

4.3 | Impact of electricity price volatility

In the following, we analyze the impact of electricity price volatility on the scheduling objectives. To this end, we vary the volatility of the ID price scenarios by scaling the standard deviation of ID price scenarios by a factor of two. Note that this scaling leads to an increased number of hours with negative ID prices. Negative electricity prices already occur in the German market[57] and their occurrence is expected to increase until 2030 due to an increasing share of renewable electricity.[58] We slightly modify the reference process from the one-at-a-time and two-at-a-time assessment as we now consider a non-idealized process with 10% efficiency loss ($\theta_{add} = 20\%$, $\theta_{min} = 50\%$, $S = 3$ h, $R = 25\%$/h, $\zeta = 10\%$, and $\tau_{off} = 0$ h).

Figure 11 shows the impact of ID price volatility on the DR potential. Note that the values for the DA-only cost are unaffected since only the ID price scenarios are scaled. As expected, higher ID price volatility generally makes marketing of flexibility on the ID market more economically attractive. Importantly, high ID price volatility can cause $CVaR_{SP}$ to rise significantly above the inflexible operation cost, that is, for the 10% worst cases flexible operation is on average more expensive than inflexible operation. Therefore, consideration and optimization of $CVaR_{SP}$ are particularly interesting for electricity markets with high ID price volatility.

4.4 | Application to three illustrative electrolysis processes

In the following, we apply the process model to three illustrative power-intensive processes of industrial relevance to exemplify how our approach can be used as an early-stage screening method for investigation of flexibilization measures of a given process. Based on our prior work, we have deduced the key parameters given in Table 3 for the copper electrolysis,[12] the aluminum electrolysis,[32] and the chlor-alkali electrolysis.[59]

TABLE 3 Overview of electrolysis process properties based on Röben et al.,[12] Schäfer et al.,[32] and Brée et al.[59]: Assuming infinite storage capacity, that is, no scheduling-relevant storage constraints exist, the influence of the storage constraints can be effectively removed from the optimization problem in case of the copper electrolysis.

Process	P_{nom}	θ_{add}	θ_{min}	S	R	ζ	τ_{off}
Copper electrolysis	14.97 MW	10.5%	0%	(∞ h)	400%/h	(0.0%)	(0 h)
Aluminum electrolysis	90 MW	25%	75%	24 h	400%/h	1.0%	(0 h)
Chlor-alkali electrolysis	2.34 MW	13%	42%	3 h	142%/h	a	(0 h)

Note: Instantaneous ramping, that is, 400%/h given the 0.25 h time step size, is assumed to be possible for copper and aluminum electrolysis. Values in parenthesis have not been assessed in our prior work.

[a]The relationship between power intake and production rate for the chlor-alkali electrolysis has a different form than Equation (10). The appropriate integration into the model can be found in Section 3 of the supporting material and does not require a specification of an efficiency loss ζ.

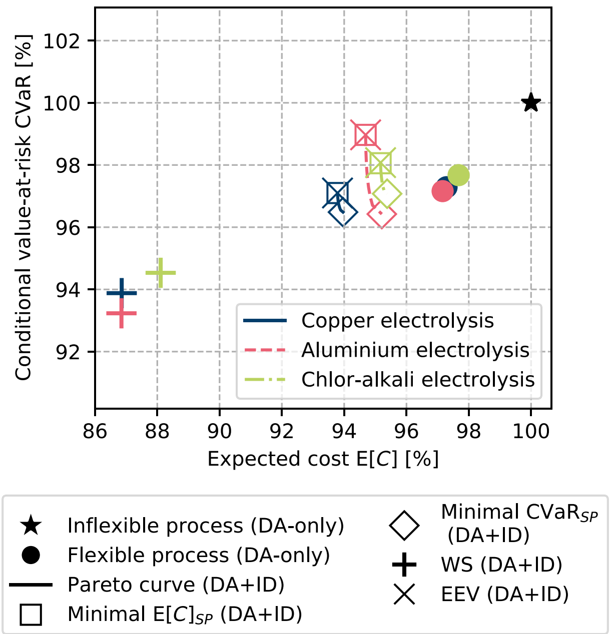


FIGURE 12 Pareto curve and benchmarks of SP-based scheduling for three illustrative electrolysis processes (Table 3)

TABLE 4 Relative economic gain of ID market participation

Process	Relative economic gain
Copper electrolysis	2.29
Aluminum electrolysis	1.87
Chlor-alkali electrolysis	2.08

Figure 12 shows the impact of marketing flexibility on DA and ID markets for the three processes. All three processes can gain significantly by additional participation on the ID market as indicated by the large relative economic gain (Table 4). Copper electrolysis is a particularly promising candidate as it has the largest relative economic gain, that is, its savings of marketing flexibility on the DA market alone can be more than doubled by ID market participation. On the contrary, the chlor-alkali electrolysis has the least savings potential due to more restricted process oversizing, storage constraints, and ramping limitations. For the DA-only cost, the savings for the aluminum and copper electrolyses are very similar, as the aluminum electrolysis has large headroom due to large process oversizing while the copper electrolysis is assumed to have unrestricted minimal part-load capabilities. It shall be noted that we observe significant potential for cost savings, although we use simple, historic ID price scenarios instead of any more sophisticated ID price forecasting method. Overall, the generalized process model allows for a rapid first assessment of the DR potential of any given process whose behavior can be described with the generalized process model (Equations 1-9 and 11-20). Thus, the approach allows exploring the potential of different flexibilization measures without the need to perform time-consuming process modeling.

5 | CONCLUSION

In this article, we have extended our prior assessment of the DR potential of industrial processes using a generalized process model.[21] Specifically, we have considered the opportunity of additionally marketing flexibility on the intraday (ID) electricity market. To this end, we have optimized the DR scheduling of a generalized process model with known DA and uncertain ID prices by means of mixed-integer linear stochastic programming. The generalized process model is characterized by key process properties, namely process oversizing, minimal part-load, product storage capacity, ramping limitation, efficiency losses, and temporary shutdowns. In a bi-objective scheduling optimization, we minimized expected cost and conditional value-at-risk (CVaR) and visualized the resulting trade-offs as Pareto curves.

Our analysis reveals that process oversizing has the most significant impact on the expected cost. Furthermore, processes with large efficiency losses can hardly benefit from marketing flexibility on the DA market but may significantly lower their operational cost by ID market participation. Increasing flexibility through multiple process parameters leads to synergetic benefits, that is, the economic gains exceed the additive effects brought by the individual measures. The relative economic gain of ID market participation in relation to DA-only scheduling does not follow a clear trend but depends on the specific process parameter combinations. In general, however, the results suggest that less flexible processes can gain relatively more from ID market participation compared to more flexible processes. For the three investigated processes, that is, copper electrolysis, aluminum electrolysis, and chlor-alkali electrolysis, our analysis suggests that more than twice the savings can be achieved by also marketing flexibility on the ID market compared to exclusive consideration of the DA market.

Studies on stochastic DR scheduling of specific processes under electricity price uncertainty have unanimously reported insignificant values of stochastic solution when optimizing the expected cost only.[27–29,33] Zhang et al.[28] attribute this behavior to presumably similar scheduling decisions in stochastic and deterministic approaches due to reoccurring trends in the price scenarios. Our work confirms and generalizes the finding of insignificant value of stochastic solution as we could show that the expectation of expected value (EEV) is always very close to the minimal expected cost $E[C]_{SP}$, independent of the investigated process parameter, with the exception of shutdown times where binary on/off decisions must be made before the uncertain ID prices are realized. However, our results suggest that $CVaR_{SP}$ can be significantly reduced without strongly increasing $E[C]_{SP}$ by bi-objective stochastic scheduling, as the Pareto curve always resembles a Hockey stick curve, independent of the investigated process parameter combinations. Furthermore, the maximal Pareto-optimal $CVaR_{SP}$ can become larger than the inflexible operation cost, particularly in case of processes with large efficiency losses and in markets with high electricity price volatility.

In an industrial setting, the amount of flexibility a process can provide is defined by technical feasibility, safety requirements, and also investment decisions. Adjustments of process parameters, for example, by retrofitting a storage unit, thus always require further process-specific investigations. However, the particular value of our work is that it allows for *a priori* estimation of the effects such changes might exert on the DR potential. Our model can therefore be used for rapid early screening of possible flexibilization measures. Future research could address the (semi-)automatic deduction of key process parameters from flow sheet or resource-task-network models as well as the deduction of a scalar metric similar to the flexibility index[18] that would represent the size of the feasible operational space as a function of the generalized process parameters. Furthermore, an integration of the 24 h stochastic scheduling into a longer-term scheduling is essential to utilize larger storage capacities and shutdown capabilities. Finally, we have found significant cost saving potential using basic, historic ID price scenarios. However, the wait-and-see solutions suggest that probabilistic price forecasting methods[50] could offer significant further economic benefit by using information such as price seasonality or renewable energy generation forecasts. Along the same lines, the impact of weekday-specific price profiles on the DR potential could be investigated by using weekday-specific average DA profiles and ID scenarios opposed to focusing on workday-specific price profiles as done in this article.

AUTHOR CONTRIBUTIONS

Sonja H. M. Germscheid: Conceptualization (lead); investigation (lead); methodology (lead); software (lead); visualization (lead); writing – original draft (lead). **Alexander Mitsos:** Conceptualization (supporting); funding acquisition (equal); supervision (equal); writing – review and editing (supporting). **Manuel Dahmen:** Conceptualization (supporting); funding acquisition (equal); supervision (equal); writing – review and editing (lead).

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CONFLICT OF INTEREST

We have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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