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Retraction

Retracted: A Stochastic Rolling Horizon-Based Approach for Power Generation Expansion Planning

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Mathematical Problems in Engineering has retracted the article titled "A Stochastic Rolling Horizon-Based Approach for Power Generation Expansion Planning" [1], as substantial overlap has been identified with a manuscript by different authors which had previously been submitted to another journal and has since been published [2].

References

[1] H. Wang, T. Wang, X. Wang, B. Li, and C. Ye, "A Stochastic Rolling Horizon-Based Approach for Power Generation Expansion Planning," *Mathematical Problems in Engineering*, vol. 2021, Article ID 6635829, 11 pages, 2021.

[2] E. F. Bødal, A. Botterud, M. Korpås, "Capacity Expansion Planning with Stochastic Rolling Horizon Dispatch," *Electric Power Systems Research*, vol. 205, 2022.

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Review Article

A Stochastic Rolling Horizon-Based Approach for Power Generation Expansion Planning

Hanyun Wang,[1] **Tao Wang**,[1] **Xinyi Wang**,[2] **Bing Li**,[2] **and Congmin Ye**[2]

[1]*Huzhou Power Supply Company of SGCC, Huzhou 313000, China*
[2]*North China Electric Power University, Beijing 102206, China*

Correspondence should be addressed to Xinyi Wang; 120171010324@ncepu.edu.cn

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Variable renewable energy sources introduce significant amounts of short-term uncertainty that should be considered when making investment decisions. In this work, we present a method for representing stochastic power system operation in day-ahead and real-time electricity markets within a capacity expansion model. We use Benders' cuts and a stochastic rolling-horizon dispatch to represent operational costs in the capacity expansion problem (CEP) and investigate different formulations for the cuts. We test the model on a two-bus case study with wind power, energy storage, and a constrained transmission line. The case study shows that cuts created from the day-ahead problem gives the lowest expected total cost for the stochastic CEP. The stochastic CEP results in 3% lower expected total cost compared to the deterministic CEP capacities evaluated under uncertain operation. The number of required stochastic iterations is efficiently reduced by introducing a deterministic lower bound, while extending the horizon of the operational problem by persistence forecasting leads to reduced operational costs.

1. Introduction

The increasing penetration of variable renewable energy (VRE) sources is introducing new challenges in modern power systems. Central to these challenges is the increased level of the short-term uncertainty and the need for more flexibility in operation [1, 2]. To balance supply and demand for electricity in the power system, we need a certain share of flexible resources that can reliably change their energy output in a few seconds or minutes to counteract variations in VRE electricity production [3]. The level of VRE that can be integrated into a power system in a cost-effective manner is directly dependent on the level of flexibility in the system [4].

The need for more flexibility, changes in market structures, and operational rules have been evident in countries which are integrating large amounts of VRE such as Denmark, China, Ireland, and Spain [5, 6]. As power systems are aspiring to increase the share of clean energy sources towards 100%, even more and cleaner flexible sources are needed.

Traditionally, the long-term power system capacity expansion problem (CEP) focuses on long-term uncertainties in investment costs, yearly electricity demand, and policy decisions, but neglect short-term uncertainties [7]. In fact, all kinds of uncertainties must be accurately captured and reasonably described to ensure the rationality of planning [8]. This can lead to inaccurate results as using a deterministic representation of operations in investment models overvalues fluctuating VRE [9] and undervalues flexible resources and can also lead to insufficient investments for both thermal generation [10] and transmission capacities [11]. In these types of models, short-term uncertainties from VRE are often implicitly accounted for by using deterministic reserve constraints based on forecast errors [12, 13]. Representing the short-term uncertainty explicitly in the model as a stochastic parameter is expected to give significantly better results compared to using reserve constraints [14], but there are few long-term models for the CEP that do this as it is much more computationally demanding.

The computational complexity of stochastic CEPs can be reduced by either reducing the number of scenarios

[13, 15, 16] or reducing the time dimension by using representative operational periods [17]. Reducing the time dimension from a full year to some representative periods of one to several days is a common approach and allows for more detailed operational models that include the uncertainty in wind and solar power [9, 18]. However, studies show that the temporal resolution and chronology is especially important in CEPs with large shares of VRE [19] where simple operational representations might lead to overinvestments in solar and underinvestments in wind and natural gas. Furthermore, the chronology will become more important as energy storage becomes more relevant as a flexible asset due to reduced storage costs and increasing VRE integration. Evidently, insufficient representation of short-term uncertainty, temporal resolution, and chronology can be significant factors in undervaluing flexibility and overestimating the optimal VRE levels in power systems [20].

In power system applications, rolling-horizon frameworks are extensively used in operational models and case studies that focus on short-term VRE uncertainty and flexibility, for example, to study VRE integration, for large-scale battery operation [21] and for local energy storage in proximity to VRE electricity production [22]. Models using this framework are suitable for representing the short-term uncertainty in an accurate and realistic way and can therefore capture the need for flexibility during operation.

Stochastic rolling-horizon dispatch (SRHD) models are formulated by a series of two-stage economic dispatch problems integrated in a rolling-horizon framework [23], thereby accounting for operational details such as market products, time stages, and uncertain VRE power production. SRHD within the CEP is previously used for assessing the effect of VRE on different CO_2-emission policies [24]. It has also been used for assessing VRE and storage investments in microgrids, using various heuristic methods [25, 26]. To the knowledge of the authors, the work of Fortenbacher et al. (2018) is the only study where a SRHD has been integrated in the CEP using Benders' cuts [27]. The CEP model corresponds to a large-scale MILP problem, which is difficult to solve directly in mathematics, due to its heterogeneous nature in variable types and large number of decision variables involved. The benders' cuts method is dedicated to solving large-scale MILP problems by decomposing them into a master problem and multiple subproblems. Generally, the master program is an integer problem, and subproblems are the linear programs. This reformulation makes the whole problem to be easily manageable by using iterative-based methods. In addition, through the Benders' decomposition, the lower-bound solution of the master problem may involve fewer constraints, which makes the computational complexity, and the time for solving the problem can be significantly reduced, as compared to conventional algorithms. Because of the abovementioned advantages, the benders' cuts method can be highly suitable to be used in CEP studies, which is helpful to improve the computational efficiency of the proposed problem.

In this work, we formulate a model for the CEP with SRHD, focusing on the representation of the operational decisions in both the day-ahead and real-time markets. The market representation is an important difference compared to [27] as we model that generators commit to a schedule in the day-ahead market that can be adjusted in the real-time market. This market representation resembles the market representation used by Pineda et al. (2016), who use forecast errors and duration curves to study the impact of the short-term uncertainty on the CEP [28]. We improve on the dispatch strategy of [27] by including a perfect information deterministic model in the algorithm that gives end-of-horizon storage values and accelerate the decomposition algorithm by providing a lower bound to the operational costs. The operational model in this paper is based on the existing works in [29, 30].

Compared with the extant literatures, the main contributions of this paper are as follows:

(a) We propose an algorithm for representing two-stage stochastic rolling-horizon dispatch in CEP using Benders' cuts, where a lower bound for the operational problem is derived from a deterministic model

(b) We investigate different approaches for using Benders' cuts to extract operational values in the context of day-ahead and real-time electricity markets

(c) We evaluate the impact of the short-term uncertainty and forecast horizon for operations on optimal investments in a realistic case study

The rest of the paper is organized as follows: in Section 2, we describe the investment model with the rolling-horizon operation. Section 3 presents a case study, and we present the corresponding results in Section 4, and finally, the conclusions are drawn in Section 5.

2. Methods

The mathematical formulation of the CEP with energy storage is shown in equations (1)–(10). Investment and operational costs are minimized as formulated in the objective function in equation (1). Operational costs consist of fuel, load shedding, and exchange costs for power traded with market nodes (system boundary). Investments in power plants and storage are limited by an upper threshold in equations (2) and (3). The sum of electricity production and curtailment is equal to the production capacity for each power plant as stated in equation (4). Equation (5) keeps track of the energy level in the storage, accounting for losses. The storage level is limited by the installed storage energy capacity in equation (6). Storage charge or discharge is limited by the storage power capacity in equation (7). The energy balance in equation (8) accounts for the balance between energy injected and extracted from the bus. Curtailment of demand may occur during shortages, but at a significant cost:

$$\min \sum_{i\in R} C_i^w w_i^{\max} + \sum_{i\in\varepsilon}\left(C_i^s s_i^{\max} + C_i^e e_i^{\max}\right) + \sum_{t\in T}\left[\sum_{i\in P} O_i^f p_{ti} + \sum_{n\in B} O^s r_{tn} + \sum_{n\in M} O_{tn}^{ex} P_{tn}^{ex}\right], \tag{1}$$

$$w_i^{\max} \le W_i^{\text{Pot}}, \quad \forall i \in R, \tag{2}$$

$$s_i^{\max} \le S_i^{\text{Pot}}, e_i^{\max} \le E_i^{\text{Pot}}, \quad \forall i \in S, \tag{3}$$

$$p_{ti} + c_{ti} = P_{ti} w_i^{\max}, \quad \forall t \in T, \forall i \in P, \tag{4}$$

$$s_{ti} = s_{(t-1)i} + \eta e_{ti}, \quad \forall t \in T, \forall i \in \varepsilon, \tag{5}$$

$$s_{ti} \le S_i^{\max}, \quad \forall t \in T, \forall i \in \varepsilon, \tag{6}$$

$$e_{ti} \le e_i^{\max}, \quad \forall t \in T, \forall i \in \varepsilon, \tag{7}$$

$$\sum_{j\in P_n} p_{tj} - p_{\text{tis}}^{ex} + r_{ti} + \sum_{j\in\varepsilon_n} e_{tj} = D_{tn}, \quad \forall t \in T, \forall n \in N, \tag{8}$$

$$p_{\text{tns}}^{ex} = \sum_{m\in C_n} B_{nm}\left(\delta_n - \delta_m\right), \quad \forall t \in T, \forall n \in B, \tag{9}$$

$$-T_{nm} \le B_{nm}\left(\delta_n - \delta_m\right) \le T_{nm}, \quad \forall t \in T, \forall n \in B, \forall m \in C_n. \tag{10}$$

Equation (9) states the nodal balance, where the net exchange with other buses equals the flow on all the lines connected to the bus. The line flow is represented by the linearized power-flow equation and is equal to the difference in the voltage angle between the buses and proportional to the susceptance of the transmission line. The power flow on the transmission lines is constrained by the transmission capacity, as shown in equation (10).

3. Benders' Decomposition for the Discussed Problem

A common method for solving the CEP is to decompose investments and operation into two different parts [31], a master problem and a subproblem, which is solved by iterating between them until the upper and lower bounds of the problem converge. We formulate the master problem, as shown in equations (11), (12), (2), and (3):

$$\min \sum_{i\in R} C_i^w w_i^{\max} + \sum_{i\in\varepsilon}\left(C_i^s s_i^{\max} + C_i^e e_i^{\max}\right) + \alpha, \tag{11}$$

$$\alpha \ge \alpha^k + \sum_{i\in P} \pi_i^k P_i\left(w_i^{\max} - W_i^k\right) + \sum_{i\in\varepsilon} \beta_i^k\left(s_i^{\max} - S_i^k\right) + \gamma_i^k\left(e_i^{\max} - E_i^k\right), \quad \forall k \in K, \tag{12}$$

s.t. equations (2) and (3).

In the master problem, the operational costs are estimated by α, which is constrained by Benders' cuts in equation (12) [32]. For a given solution of the investments in the master problem, the subproblem becomes as stated in equations (13)–(16), in addition to equations (5) and (8)–(10). Here, the capacities are no longer variables but fixed parameters, W_i^k, S_i^k, and E_i^k:

$$\min \sum_{t\in T}\left[\sum_{i\in P} O_i^f p_{ti} + \sum_{n\in B} O^s r_{tn} + \sum_{n\in M} O_{tn}^{ex} p_{tn}^{ex}\right], \tag{13}$$

$$p_{ti} + c_{ti} = P_{ti} W_i^k \pi_{ti}, \quad \forall t \in T, \forall i \in P, \tag{14}$$

$$s_{ti} \le S_i^k \beta_{ti}, \quad \forall t \in T, \forall i \in \varepsilon, \tag{15}$$

$$\underset{e}{\overset{ti}{}} \le E_i^k \gamma_{ti}, \quad \forall t \in T, \forall i \in \varepsilon, \tag{16}$$

s.t. equations (5) and (8)–(10).

The cuts in the master problem consist of the optimal objective value of the subproblem, the installed capacities used in the operational model for the current iteration, and the dual of the capacity constraints in equations (14), (15), and (16) summed over all times. The upper bound is the objective of the best solution found so far calculated by summing up the values from the master and subproblem according to the original objective function in equation (1). The lower bound is the best solution that can be found and is the same as the objective of the master problem in equation (11).

4. Stochastic Rolling-Horizon Dispatch

To include the short-term VRE uncertainty, we substitute the deterministic operational subproblem with a stochastic rolling-horizon dispatch (SRHD). The basic element of the SRHD is a two-stage problem which is implemented in a rolling-horizon framework as illustrated in Figure 1, where parameters are updated as new information becomes available.

In the rolling-horizon framework, we introduce day-ahead schedules for energy production and storage. In the first stage, a fixed day-ahead schedule has to be followed. In the second stage, a schedule is created (day-ahead) for the real-time operation in the following two-stage model. One day-ahead schedule is made considering a range of scenarios for VRE production and passed on to the first stage of the next instance of the two-stage model, typically the next day, in the rolling-horizon framework. Deviations from the day-ahead schedules have a cost which is representing a ‘premium-of-readiness’ for changing production close to real time [33]. This is analogous to how the electricity markets are currently organized, illustrated in Figure 1, where a day-ahead schedule is made the day before in the day-ahead market (second stage of the first two-stage model), and deviations from this plan is accounted for continuously in the real-time market (first stage of the second two-stage model).

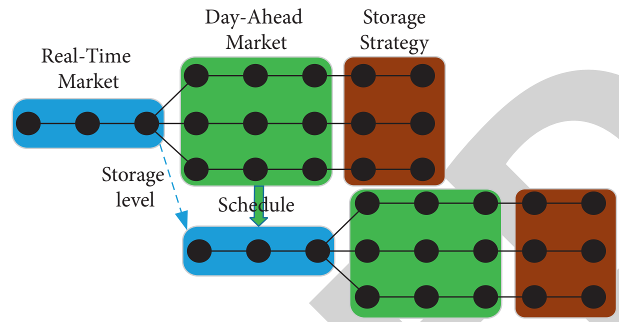

Figure 1: Illustration of the two-stage stochastic operation subproblem of the SRHD.

The two-stage operation subproblem is formulated in equations (17)–(27). The new features compared to the deterministic model in equations (13)–(16) is the day-ahead schedules enforced by equations (19) and (20), where positive and negative deviations incur equal costs in the objective. Additionally, we have the scenario index, s, defining the two-stage structure where S1 is the realized first-stage “scenario” and S2 is the set of future scenarios for the second stage. In the objective function described by equation (17), we add the value of the remaining energy in the storage at the end of the two-stage model horizon (calculated externally by the deterministic model):

$$\min \sum_{s\in S}\sum_{t\in T_s}\left[\sum_{i\in P} O_i^f p_{tis} + \sum_{n\in B} O^s r_{tns} + \sum_{n\in M} O_{tn}^{es} p_{\text{tns}}^{ex} + \sum_{i\in P,\varepsilon} O_{ti}^r\left(d_{\text{tis}}^m + d_{\text{tis}}^p\right)\right] - \sum_{i\in\varepsilon} V_T s_{\text{Tis}}, \tag{17}$$

$$p_{\text{tis}} + c_{\text{tis}} = P_{\text{tis}} W_i^*, \quad \forall t\in T_s, \forall i\in P, \forall s\in S, \tag{18}$$

$$p_{\text{tis}} - d_{\text{tis}}^n + d_{\text{tis}}^p = P_{ti}^{\text{sch}}, \quad \forall t\in T_s, \forall i\in P, \forall s\in S_1, \tag{19}$$

$$p_{\text{tis}} - d_{\text{tis}}^n + d_{\text{tis}}^p = P_{ti}^{\text{sch}}, \quad \forall t\in T_s, \forall i\in P, \forall s\in S_2, \tag{20}$$

$$s_{0is} = S^{\text{prev}}, \quad \forall i\in\varepsilon, \forall s\in S, \tag{21}$$

$$s_{\text{tis}} \le S_i^*, \quad \forall t\in T_s, \forall i\in\varepsilon, \forall s\in S, \tag{22}$$

$$s_{\text{tis}} = s_{(t-1)is} + e_{\text{tis}}, \quad \forall t\in T_s, \forall i\in\varepsilon, \forall s\in S, \tag{23}$$

$$e_{\text{tis}} \le E_i^*, \quad \forall t\in T_s, \forall i\in\varepsilon, \forall s\in S, \tag{24}$$

$$\sum_{i\in P_n} p_{\text{tis}} - p_{\text{tns}}^{ex} + r_{\text{tns}} + \sum_{i\in\varepsilon_n} e_{\text{tis}} = D_{tn}, \quad \forall t\in T_s, \forall i\in N, \forall s\in S, \tag{25}$$

$$p_{\text{tns}}^{ex} = \sum_{m\in C_n} B_{nm}\left(\delta_{\text{tns}} - \delta_{\text{tms}}\right), \quad \forall t\in T_s, \forall i\in B, \forall s\in S, \tag{26}$$

$$-T_{nm} \le B_{nm}\left(\delta_{\text{tns}} - \delta_{\text{tms}}\right) \le T_{nm}, \quad \forall t\in T_s, \forall i\in B, \forall m\in C_n, \forall s\in S. \tag{27}$$

5. Rolling-Horizon Dispatch in Capacity Expansion with Benders' Decomposition

Benders' decomposition has slow convergence if initialized with an inaccurate description of the operational costs in the master problem [34]. A good lower bound on operational costs can greatly improve the solution time of the algorithm by reducing the number of iterations. This is especially important if solving the operational problem is time consuming such as for the SRHD. The algorithm for solving the investment problem with SRHD operation is illustrated by the flowchart in Figure 2. It consists of two loops solved in sequence, first L1 and then L2. The deterministic operations' problem with perfect foresight can be considered a relaxation of the SRHD, as the problems are identical except for the constraints in (19) and (20) and the short-term uncertainty. Thus, solving the decomposed deterministic CEP (D-CEP) first in L1 creates cuts for the investment problem that are a good lower bound for the operational costs in the SRHD (L2). This significantly reduces the computational time for the algorithm as it requires fewer iterations of L2.

In L2, the deterministic operations' problem from L1 is included to reduce the impact of the limited horizon of the two-stage problem by providing end-of-horizon storage values obtained from the duals of the storage balance in equation (5). This enables the SRHD to operate storage with dynamics beyond the horizon of the VRE forecasts. The impact of the end-of-horizon storage values on real-time and day-ahead operations is low if the two-stage model horizon is sufficiently long compared to the storage types considered.

The implementation of SRHD-CEP introduces three main challenges: (1) cut generation in the context of short-term commitments and overlapping time stages, (2) end-of-horizon effects in the two-stage model, and (3) accurate representation of expected wind power production by forecasts over time. We investigate the impact of these challenges (especially 1 and 2) on the performance of the SRHD-CEP and the effect of the short-term wind power uncertainty on investments in a two-bus case study.

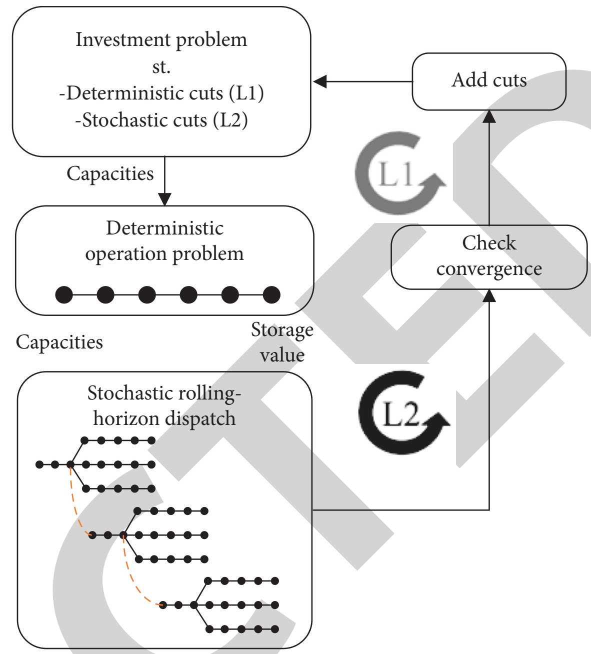

Figure 2: Flowchart of the solution algorithm.

6. Case Study

We use the SRHD-CEP to find the optimal capacity expansion in a two-bus case study where local electricity demand is served by a combination of wind power, energy storage, and a transmission line, as shown in Figure 3(a). The transmission line has limited capacity and is connected to the electricity market, represented by a price series as illustrated in Figure 3(b). A combination of energy storage and wind power is needed to supply the electric load as the transmission capacity of 130 MW is not large enough to supply all the electricity (1000 GWh/year) needed for the load in the winter, as shown in Figure 3(c).

We use a technology cost scenario for 2050 for new investments [35], as shown in Table 1. In this scenario, we assume that the transmission line capacity cannot be expanded, and energy storage costs are sufficiently low to make storage an interesting alternative to transmission line upgrades. Other important parameters include losses of 5% for both charging and discharging and a value of lost load (VOLL) of 10 000 \$/MWh.

Data series for wind and load are obtained from northern Norway where wind power is well suited to supply the electric load as the wind-load seasonal correlation is high. However, the wind power plant has significant short-term variation and uncertainty in power output. Storage can be valuable to alleviate these issues by balancing and improving security of supply. We assume that load, wind power, and energy storage are balancing their power collectively as one unit, which results in one aggregate day-ahead schedule for exchange with the market bus. Thus, the storage can be used for internal balancing that might be less costly than purchasing balancing power from the market. We assume a real-time balancing premium at 30% of the spot price for the power exchanged over the transmission line, which is higher than the current market prices but in line with expectations for future systems with high VRE shares [36].

Forecasts of the future wind power production are essential for efficient dispatch to ensure that sufficient storage levels are maintained ahead of time to avoid load shedding in deficit situations and wind power curtailment in surplus situations. Wind power scenarios are created by using historical weather forecasts and historical wind power production to create quantile forecasts for each day [37]. From the quantile forecasts, we sample 90 scenarios for each day [38], which is reduced to 30 scenarios using SCENRED2 [39].

We use this case study to investigate how to best calculate the parameters for the Benders' cuts, by selecting dual and operational costs from the different stages of the SRHD, resulting in two different cut types: (a) cuts obtained from expected (day-ahead) values; (b) cuts obtained from the average of realized (real-time) and expected values (day-ahead).

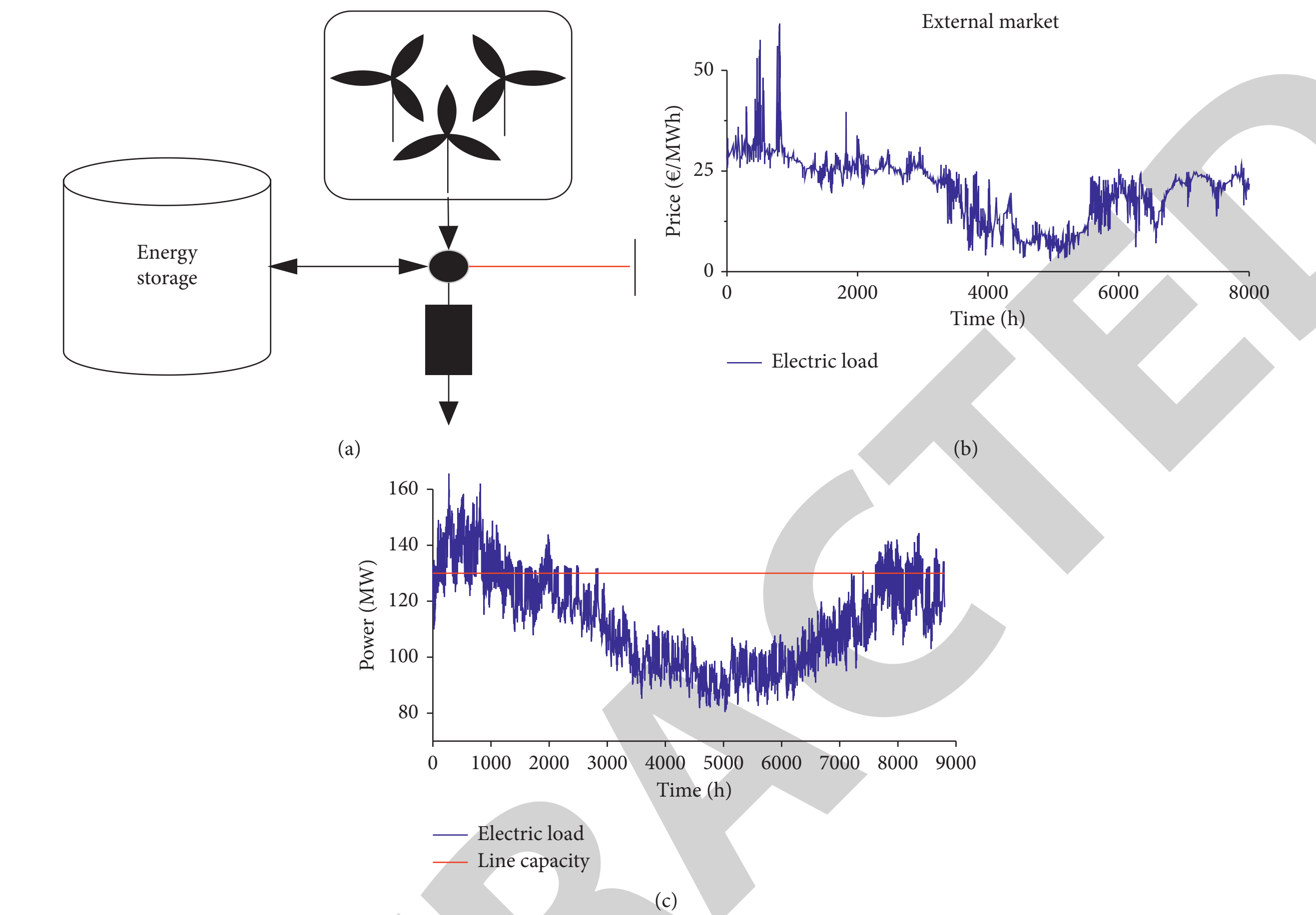

Figure 3: Information of the test system. (a) System structure. (b) Price series of the external market. (c) Load profile and capacity limit of the transmission line.

Table 1: Wind power, storage costs, and unit size.

	Investment cost (€/kW)	O&M cost (€/kW·yr)	Size (MW/unit)
Wind power	930	30	3
Storage power	250	6	1
Storage energy	80	2	10

Cut type b is similar to the cuts used in [27], where they generate cuts from the weighted values of the cut parameters from all the time stages. However, the market commitments used in our model will affect the dual values in the first stage. Thus, type a cuts are introduced to investigate the significance of these commitments on the optimal investments.

The models are implemented in Python using the PYOMO modeling framework [40] and the Gurobi solver. The simulations are performed on a shared server with 28 cores and 56 logical processors of the type Intel Xeon E5-2690 v4 at 2.6 GHz.

7. Results

7.1. Impact of Uncertainty and SRHD Horizon on Investments. We find the realistic D-CEP operating costs by running the SRHD model with the optimal capacities from the D-CEP. The resulting total cost of the D-CEP/SRHD is compared against the SRHD-CEP solutions for the two cut types and different SRHD horizons. The pure D-CEP solution (with the deterministic operation) is used as a benchmark as it has perfect information of the future and is a lower limit for the total realized costs. The total costs are shown in Figure 4 as the percentage increase from the benchmark. The operational costs are calculated by two different metrics from the SRHD, on the left by realized costs (first stage) and on the right by expected costs (expected value of the second-stage scenarios).

It is not surprising that the D-CEP/SRHD result in the lowest total realized costs, 2.3–3.9% more than the benchmark, as the D-CEP investments are optimized with perfect information. In contrast, the two SRHD-CEP solutions result in realized total costs of 4.4–13% higher than the benchmark. However, the better metric for the operational

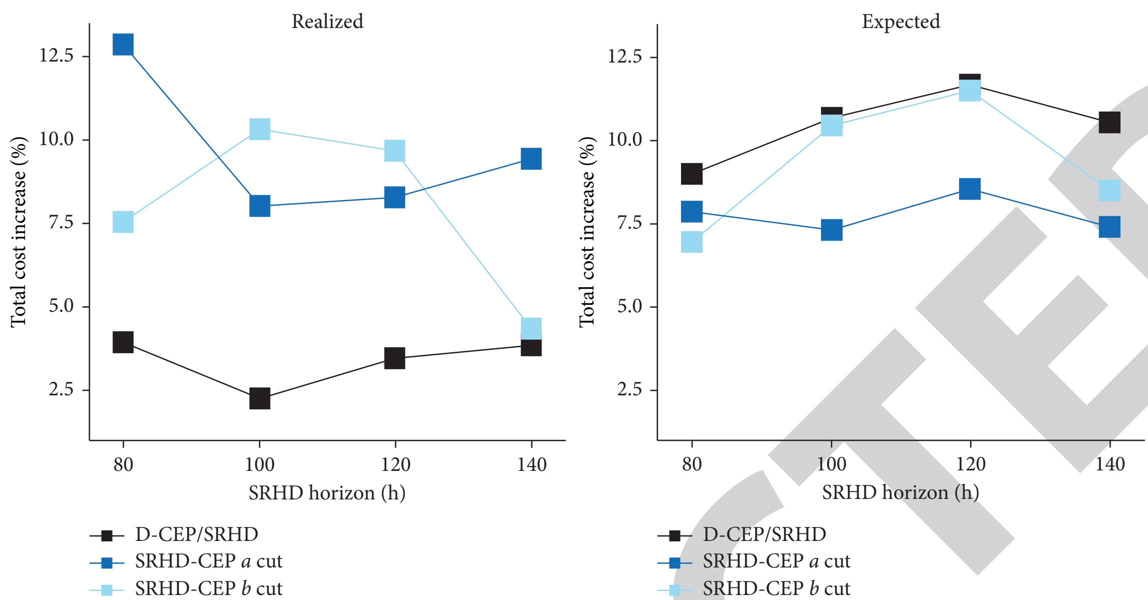

Figure 4: Total costs for D-CEP and the two cases of SRHD-CEP.

costs in a CEP is the expected value, as the operational costs will be close to the expectation across the 30 scenarios over time. The D-CEP/SRHD gives significantly higher expected total costs, 9–11.6% above the benchmark, because the D-CEP expansion plan results in operations close to the capacity limits and have a higher risk of load shedding. The expected cost is clearly lowest for the SRHD-CEP with *a* cuts with total costs of 7.3–8.5% relative to the benchmark. The SRHD-CEP expansion plans result in similar realized and expected costs as the capacities are higher which is better for robust operation under realistic conditions, which generally guarantees a safer operating condition.

A sufficiently long SRHD horizon is important for the storage strategy and gives a more realistic storage value in the presence of the significant wind power uncertainty than the end-of-horizon value given by the deterministic model. In Figure 4, we evaluate the impact of the SRHD horizon by adding persistence forecasts, in increments of 20 hours, at the end of the 80 hours given by the weather forecasts. Note that the persistence forecast extends each of the scenarios for the next x hours with the average of the last x hours of the original scenario. Extending the horizon to 100 hours is beneficial for the D-CEP/SRHD and the SRHD-CEP with *a* cuts as it results in a better storage strategy and lower realized costs. For the SRHD-CEP with *a* cuts, better storage handling in the first stage result in lower expected costs. Longer horizons over 100 hours are less beneficial as the persistence forecasts are not accurate, and it is better to use the end-of-horizon storage value.

The optimal capacities from the D-CEP and the two versions of the SRHD-CEP with a horizon of 100 hours are shown in Figure 5. The wind power capacity in the D-CEP is 60 MW, while the capacities are dependent on the cut type in the SRHD-CEP, 69 MW at *a* cut and 54 MW at *b* cut. The SRHD-CEP results in more storage capacity than the D-CEP due to the higher risk of load shedding when the uncertainty is accounted for in the operation. The storage power capacity is increased from 32 MW in the D-CEP to 36 MW at *a* cut and 58 MW at *b* cut in the SRHD-CEP, whereas the energy capacity increased from 930 MWh to 1120 at *a* cut and 1340 MWh at *b* cut.

The type of cuts used in the SRHD-CEP makes a significant difference for the investments, where *a* cuts give more wind power capacity and *b* cuts give more storage energy capacity (see Figure 5). For *b* cuts, fixed day-ahead schedules lead the first stage to give the wrong investment signal which skews investments from wind power to storage as it can be used for internal balancing (no regulation penalty). The *a* cuts represent the operational costs without taking into account the first stage, instead it obtains the dual values only from the second stage where day-ahead schedules are variable. In general, *a* cuts are superior to *b* cuts because (1) fixed day-ahead schedules will not distort investments and (2) capacities should be built to minimize the expected operational cost. In this case, where the transmission grid is constrained without an option to expand the transmission capacity, the D-CEP also underinvests in wind power contrary to less constrained case studies in the literature.

7.2. Representation of Stochastic Operation. The cutting planes used to represent operational costs in the investment model are shown for the wind-storage energy dimension in Figure 6, where the storage power is fixed at the D-CEP solution of 32 MW. The operational costs estimated by the D-CEP are shown in grey (L1 in Figure 2), while the estimation from the SRHD *a* cuts (L2) are shown in a red-blue color gradient. Points in the red-blue plane indicate where operational costs are calculated by the SRHD-CEP. In Figure 6, the differences between the stochastic (black/solid) and deterministic (red/dotted) planes are highlighted by lines of fixed storage energy capacity. Points indicate the

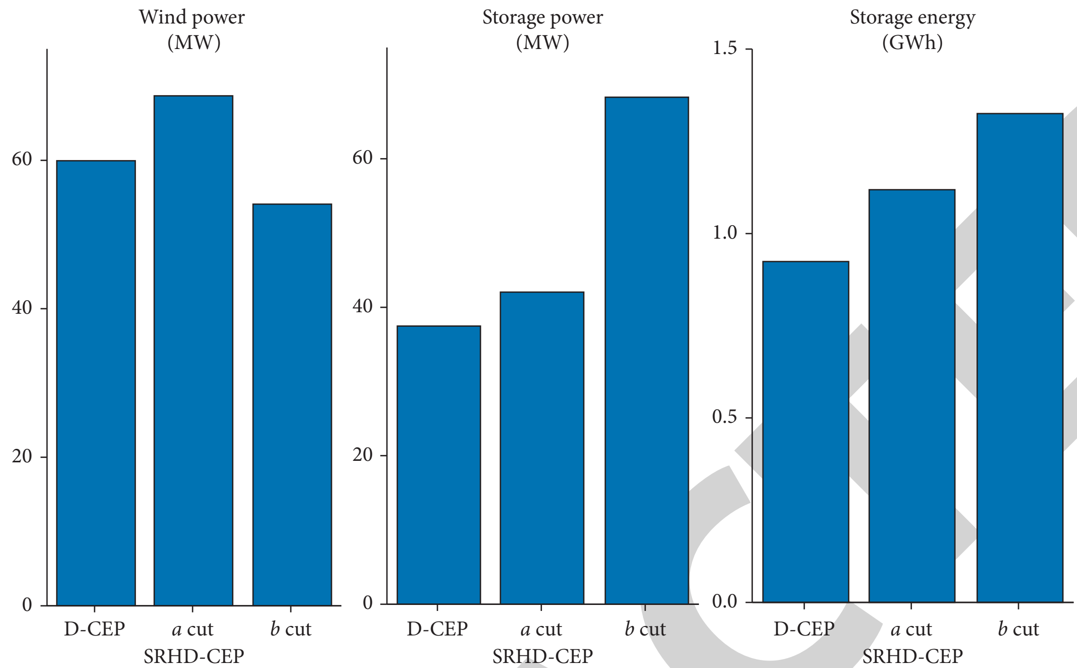

FIGURE 5: Optimal investments for D-CEP and SRHD-CEP models with L2 cuts and 100-hour SRHD horizon.

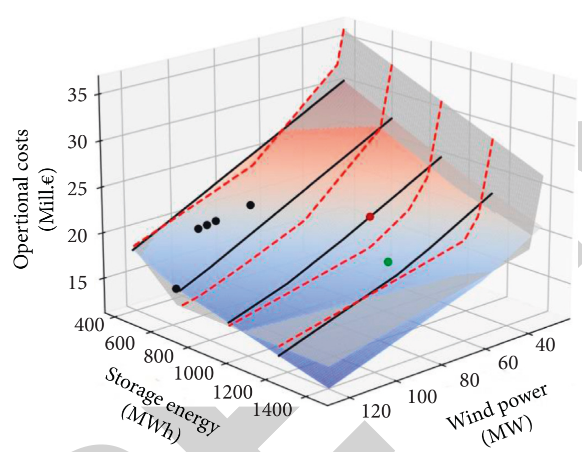

FIGURE 6: Cutting planes show the difference between the stochastic (red-blue) and deterministic (grey) operational cost as a function for the storage energy and wind power capacity.

capacities searched by the SRHD-CEP, where the D-CEP (red) and SRHD-CEP (green) solutions are highlighted.

Figure 6 shows that the operational costs are underrepresented by the cuts from the D-CEP compared to SRHD-CEP. The differences between the two planes are especially large around the optimal D-CEP solution (red point), where the wind power capacity is relatively low and the storage energy capacity is high. This leads the SRHD-CEP to search for alternative solutions with more wind power and less energy storage capacity that potentially gives lower operational costs (black points). However, these solutions prove to be more costly, and the SRHD-CEP solution (green point) is found closer to the D-CEP solution but with higher wind power and storage energy capacity.

Initializing the algorithm with a lower bound from the deterministic cuts helps to significantly reduce the area that is searched when using SRHD for cut generation, resulting in only 7 additional iterations to find the SRHD-CEP solution, thereby saving significant computational time. The operational costs are higher at every point where the operational costs are calculated by the SRHD compared to deterministic operation, which supports the use of the deterministic operational model as a lower bound.

Figure 7 shows the result comparison between deterministic operation and SRHD for the first 20 days of the year using the capacities from the SRHD-CEP solution (*a* cut and 100-hour horizon). The SRHD is represented by the realized values (start of each two-stage problem is marked with a point), and day-ahead scenarios are illustrated by the 50% and 95% confidence intervals. The wind power uncertainty is significant, while realized production is the same for both deterministic operation and SRHD. On the contrary, storage operation is much more restricted in the SRHD than under deterministic operation, where the SRHD leads to slower storage charge/discharge and generally does not operate as close to the capacity limits due to the higher risk of load shedding arising from uncertain wind power production. System operation between hours 250 and 300 is defining for the system capacities as wind power production is low, while demand is high, leading to constraints on the transmission line (Figure 7(c)) and maximum discharge from the storage. In the SRHD, an extension of the horizon from 80 to 100 hours is critical for obtaining a sufficient storage level and avoiding load curtailment. Using the deterministic model to set an end-of-horizon storage value in the SRHD with an 80-hour horizon does not give the sufficient storage strategy as indicated by the realized costs in Figure 4.

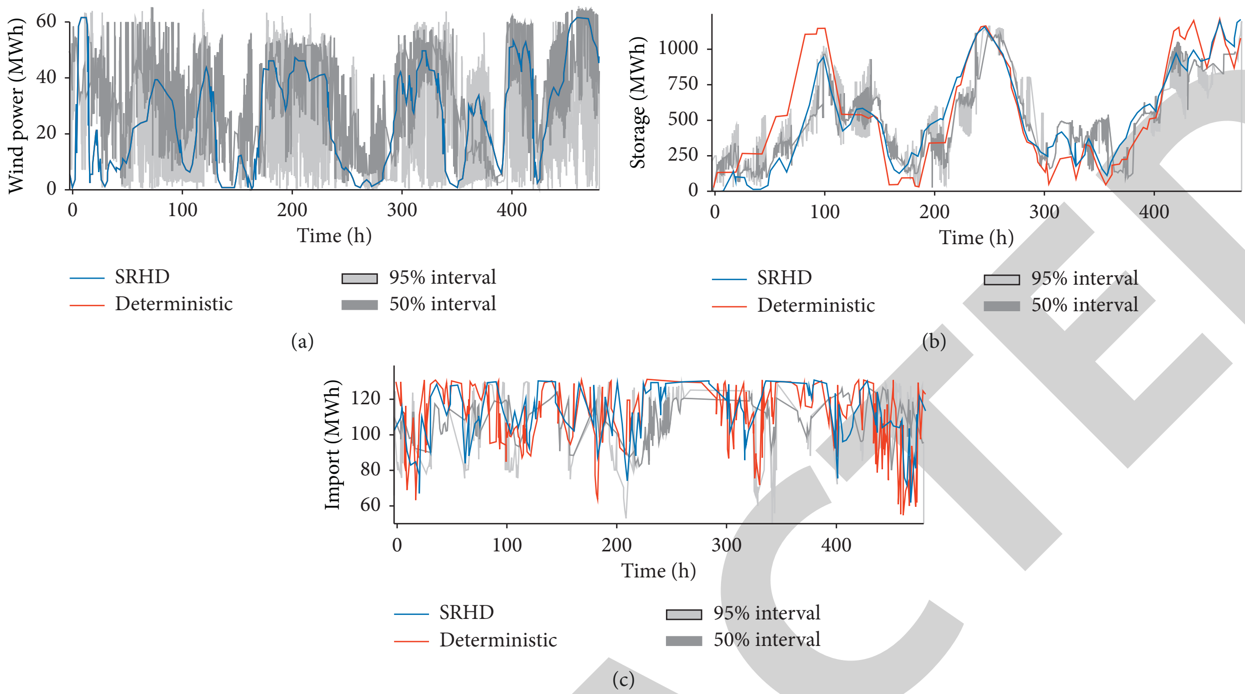

Figure 7: Deterministic and SRHD system operation for the first 20 days of the year and SRHD-CEP investments are represented by the following. (a) Wind power. (b) Storage level. (c) Import from the market bus.

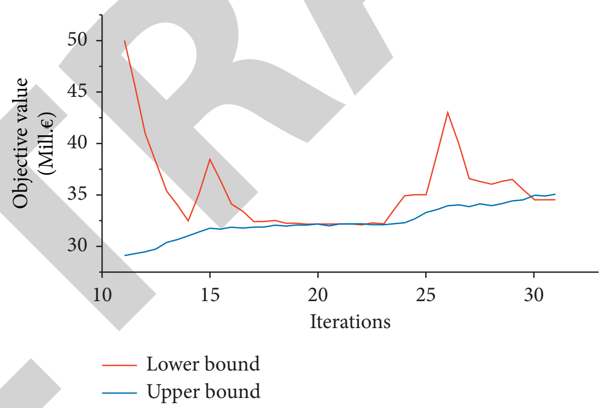

Figure 8: Convergence of the proposed algorithm.

Table 2: Computation efficiency for different SRHD horizons.

SRHD horizon (h)		80	100	120	140
Conventional Benders' decomposition method	Stochastic iterations	86	95	106	114
	Total time (hours)	14.8	18.5	24.8	30.1
Proposed method	L1 time (sec/itr)	31	31	32	30
	L2 time (min/itr)	42	57	75	94
	L2 iterations	7	8	9	11
	Total time (hours)	5.1	7.8	11.4	17.5

7.3. Performance of the Applied Algorithm. The convergence performance of the proposed algorithm is shown in Figure 8, which depicts the upper bounds and lower bounds of each iteration. The deterministic solution in L1 is found after 22 iterations, while an additional 7 iterations are needed to obtain the stochastic solution in iteration 30 (iteration 23 and 31 are redundant and are only used to confirm convergence). The computational time and iterations of conventional Benders' decomposition and our proposed method have been shown in Table 2, which indicates our algorithm spends much less time required for the stochastic iterations which ranges from 42 to 94 minutes depending on the SRHD horizon compared to the conventional Benders' cut method. A longer SRHD horizon also leads to more iterations, thus resulting in larger increase in SRHD-CEP computational times than the increased SRHD times indicate.

8. Conclusions

This paper proposes a new methodological framework to include SRHD with a representation of the real-time and day-ahead electricity markets in CEP, in which the impact of the short-term VRE uncertainty on optimal capacity expansion has been explicitly captured and considered. Through the simulation results from numerical studies, we showed how to link the operational model to the investment model in the presence of short-term market commitments by using Benders' cuts derived from the day-ahead values. The expected total costs are reduced by 2.5–3% compared to a deterministic investment model without stochastic representation of operation. The resulting capacities of wind power, storage power, and storage energy from the SRHD-CEP are 12.5–20% higher than in the deterministic case. The model is initialized by a lower bound generated from a deterministic operational model, which reduces the number of iterations with the more time-consuming SRHD.

In the future work, the capacity expansion with stochastic operations should be tested on a larger system with more sources of uncertainty to see if the effects of including the short-term uncertainty results in larger differences from the deterministic solution in a more complex setting. For larger systems, it could be beneficial to also decompose the two-stage operational model in order to avoid prohibitive increases in computational times.

Nomenclature

Indices and Sets

i: Index of power plants in set P
j: Index of energy storage in set ε
k: Index of cuts in set K
n and m: Indices of system buses in set B
s: Index of scenarios in set S
t: Index of time steps in set T.

Parameters

ρ_s: Probability of renewable power scenario
B_{nm}: Susceptance between bus n and m (p.u.)
$C^{w/s/p}$: Investment cost for wind (w), storage energy (s), or power (p) (€/MW, €/MWh)
D_{tn}: Electricity demand (MW)
E_i and S_i: Storage power and energy capacity (MW/MWh)
$O^{w/s/p}$: Operational cost for fuel (f), regulation (r), load shedding (s), or exchange (ex) (€/MWh)
P_{tis}: Power profile (MW)
T_{nm}: Transmission capacity from bus n to m (MW)
V_T: End-of-horizon storage value (€/MWh)
W^{Pot}: VRE resource capacity (MW).

Variables

α and α^k: Estimated/actual operational cost (€)
β_{tis} and γ_{tis}: Dual values of storage energy and power constraints
δ_{tns}: Voltage phase angle
π_{tis}: Dual values of production constraints
c_{tis}: Curtailment of VRE (MW)
$d_{tis}^{-/+}$: Negative or positive regulation (MW)
e_i^{max}/s_i^{max}: Storage power/ energy capacity (MW/MWh)
e_{ti}: Energy from or to the energy storage (MWh)
p_{tns}^{ex}: Power exchange with other buses (MW)
p_{tis}: Power production (MW)
r_{tns}: Curtailment of load (MW)
w_i^{max}: Installed generation capacity (MW).

Data Availability

The data used to support the findings of this study are included within this article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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