Cost Sensitivity Analysis to Uncertainty in Demand and Renewable Energy Sources Forecasts

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***Abstract*—Addressing uncertainty has become a necessity when modeling modern power systems. Many state-of-the-art methods suffer from either poor uncertainty characterization or a high computational burden. This paper proposes a model that is easy to implement, fast to compute, and effective in addressing uncertainty. It is based on the model predictive control algorithm with the addition of uncertainty parameters optimization. For demonstration purposes, the model is applied to a microgrid consisting of a wind turbine, a local load, and battery energy storage. The model seeks to satisfy the local demand at the lowest cost by procuring energy from the battery energy storage, the wind turbine (in its portfolio), or the wholesale market, where wind power output, local demand, and market prices are uncertain parameters. In the presented case study, the upper bounds obtained using our model are close to the perfect information deterministic model values. Hence, this model has a great potential for practical use.**

***Index Terms*—uncertainty, model predictive control, battery energy storage, renewable energy sources**

I. Introduction

A. Motivation

The world is in the midst of enormous changes concerning energy production and consumption. The decades of rapid industrial progress at the expense of environmental pollution are taking their toll. Luckily, world leaders are gradually embracing the problem, and society, in general, is becoming more environmentally conscious. In that manner, conferences such as the 26th UN Climate Change Conference of the Parties (COP26) in Glasgow [1] are to gear countries around the globe towards clean and sustainable energy solutions (e.g. India's 2070 net-zero promise [2]). The European Union (EU) may be regarded as the leader in setting ambitious goals with its Clean Energy Package that promotes energy performance in buildings, renewable energy sources (RES), energy efficiency, and modern electricity market design [3]. Accelerated integration of RES, the distributed paradigm, and the active role of previously passive consumers (now – prosumers) bring challenges in maintaining a reliable and secure energy supply [4], [5]. Thus, researchers are motivated to propose modeling approaches that will ease the integration of RES and the transition towards sustainable and environmentally friendly energy production and supply. The focus is on uncertainty, which RES in the modern power system paradigm inevitably cause [6].

B. Literature Review

Modeling of modern power systems includes in most cases, among other, RES and energy storage systems. As one step further from the deterministic optimization, stochastic programming is a widely used strategy to address the uncertainties in predictions and decision-making processes [7]. Kazempour and Pinson [8] in their two-stage stochastic optimization model consider the uncertainty of RES. Leterme et al. [9] use electric vehicles' batteries to balance wind power production including wind power forecast errors, while Covic et al. [10], in addition to the photovoltaic generation uncertainty, use stochastic optimization to capture the local load, primary reserve market and day-ahead market prices to decide on optimal PV and battery investment. Similarly to [10], in [11] the authors use stochastic optimization to model the day-ahead market, the balancing market, and the proposed distribution-level flexibility market price uncertainties, while the intraday market uncertainty is addressed using robust optimization. However, the curse of dimensionality is the main disadvantage in multistage stochastic scenario-based optimization problems. Hafiz et al. [12] have thus proposed a method, using an algorithm that avoids it, where they proposed a multi-stage stochastic optimization model to use a plug-in electric vehicle for load shifting with load demand uncertainty.

According to Powell, [13], it is possible to create a unified framework for all sequential decision problems. Stochastic optimization, as a type of sequential decision problem, perfectly fits under the proposed framework. Furthermore, he defines four policy function classes that encompass all sequential decision-making problems, namely:

- Policy function approximations (PFA);
- Cost function approximations (CFA);
- Value function approximations (VFA);
- Direct lookahead policies (DLA).

PFAs and CFAs are policies based on policy search, while VFAs and DLAs are policies based on the lookahead approximations [14]. The policy search comes down to finding a class

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of functions that fits the needs of the problem and tuning its parameters, while the lookahead approximations come down to constructing policies by approximating the impact of a decision made now on the future [13]. Furthermore, Ghadimi et al. [15] claim that common industry practice is to use a deterministic approximation of the future, which is easier to understand and solve than methods usually used in academia such as dynamic and stochastic programming. The authors argue that their proposed parameterized lookahead model as a form of the policy for solving stochastic-based models offers all the perks of stochastic optimization while avoiding approximations associated with scenario trees. Hence, we are motivated to develop a model based on their findings, compare it with the base model and present several case studies.

C. Paper Contribution and Structure

We implemented an Model Predictive Control (MPC) model which determines the optimal operation of a microgrid consisting of that needs to satisfy the demand using wind power, battery energy storage, and wholesale market. The MPC model considers updated forecasts of uncertain parameters, which are wind production, demand, and market prices. The forecast values are modified with different forecast uncertainty parameters to identify low-risk and low-cost arbitrage policies. This concept is easy to implement, fast to compute, and effective in addressing uncertainty, which is why it is attractive for application in the industry. The case study presents the uncertainty parameter analysis and evaluates the effectiveness of the presented MPC algorithm.

The rest of the paper is structured as follows. The mathematical formulation of the MPC is given in Section II. The results are discussed in section III. Firstly, the uncertainty parameter analysis is performed for various wind profiles, after which the model performance is compared to a perfect-information deterministic model, with and without battery energy storage installed. Lastly, the work is concluded in Section IV.

II. Mathematical Formulation

A microgrid consists of a battery energy storage (BES), a wind power plant, and a load. The goal is to reduce the cost of purchasing electricity from the grid, while constantly maintaining the power balance of the observed system. To address uncertainties in the market prices, the wind production, and the consumption, system behavior is modeled using a hybrid of CFA and DLA proposed in [13]. More precisely, MPC is designed with additional parameters to better capture the uncertainty of the forecasts. The optimization is performed T times, once for each period of the day. Each optimization uses the known data at the starting time period and the predicted data for the subsequent periods, each time shifting the starting point for one. Also, at each starting point, the forecasts for the uncertain parameters for the following periods are updated. The final result of all optimizations are the decisions made at each starting period while considering the predictions in subsequent periods. The forecasts are marked with tilde in the following mathematical formulation. E.g. $f^{\lambda}_{t,t'}$ represents market price at time period t' forecasted at time period t.

The objective function (1) minimizes the cost of electricity purchased from the grid in periods with known information p_t^{gu} and with forecasted information on the uncertain parameters (under the sum). The importance of the decisions made based on predicted parameters, $\tilde{p}^{\mathrm{gu}}_{t,t'}$, can be diminished by a factor γ which is less than 1 and diminished with $t'-t$. This way, the predicted decisions at time t' that can be far from the moment when the forecast was made (thus the lower forecast accuracy), are less penalized in the objective function.

$$\min_{p_t^{\mathrm{gu}},\tilde{p}^{\mathrm{gu}}_{t,t'}} p_t^{\mathrm{gu}} \cdot \lambda_t + \sum_{t'=t+1}^{T} \gamma^{\mathrm{t'-t}} \cdot \tilde{p}^{\mathrm{gu}}_{t,t'} \cdot f^{\lambda}_{t,t'}, \quad \forall t \tag{1}$$

Wind power output, $p_t^{\mathrm{w,u}}$ may be curtailed if necessary, but may not exceed the maximum possible $P_t^{\mathrm{w,max}}$ at time period t:

$$p_t^{\mathrm{w,u}} \leq P_t^{\mathrm{w,max}}, \quad \forall t \tag{2}$$

Inequalities (3) and (4) are battery charging and discharging constraints. Charging p_t^{ch} and discharging p_t^{dis} cannot occur at the same time, which is ensured by the binary variable x_t and must not exceed the maximum installed capacity of the storage $P^{\mathrm{s,max}}$.

$$p_t^{\mathrm{ch}} \leq P^{\mathrm{s,max}} \cdot x_t, \quad \forall t \tag{3}$$

$$p_t^{\mathrm{dis}} \leq P^{\mathrm{s,max}} \cdot (1-x_t), \quad \forall t \tag{4}$$

Constraints (5) and (6) describe the propagation of the state of energy soe_t and its limits. In time period t, the state of energy depends on the state of energy (SoE) in the previous time period $t-1$ increased by the amount of the charged energy and reduced by the amount of the discharged energy. Coefficients η_{ch} and η_{dis} (lower than 1) describe the losses during the charging/discharging process, due to which less energy enters the battery than is taken from the grid and less energy enters the grid than is discharged from the battery.

$$\begin{aligned} soe_t = soe_{t-1} + \eta^{\mathrm{ch}} \cdot p_t^{\mathrm{ch}} \cdot x_t \cdot \Delta t \\ - \frac{p_t^{\mathrm{dis}} \cdot (1-x_t)}{\eta^{\mathrm{dis}}} \cdot \Delta t, \quad \forall t \end{aligned} \tag{5}$$

$$soe_t \leq SOE^{\mathrm{max}}, \quad \forall t \tag{6}$$

Power balance constraint (7) ensures that the demand P_t^{d} is met at every time period t. Since the objective of the observed system is to maintain the power balance valid, it is only allowed to buy the energy from the grid and not to sell it. In this way, the battery storage is motivated to behave optimally to ensure constraint (14), rather than to make a profit.

$$p_t^{\mathrm{w,u}} - p_t^{\mathrm{ch}} + p_t^{\mathrm{dis}} - p_t^{\mathrm{g,u}} = P_t^{\mathrm{d}}, \quad \forall t \tag{7}$$

The previous constraints model decision making at time t at which the values of all uncertain parameters ($P_t^{\mathrm{w,max}}, \lambda_t, P_t^{\mathrm{d}}$) are known. The latter constraints, (8) – (13), model the making of the same decisions, but for periods in which only forecasted uncertainty values are known ($f^{\mathrm{w,max}}_{t,t'}, f^{\lambda}_{t,t'}, f^{\mathrm{d}}_{t,t'}$). Forecasted values may vary depending on the forecast accuracy, which is modeled with parameters θ^{w} and θ^{d}. Different values of these parameters (and forecasts) can show the influence of the forecast on decisions and consequently the value of objective function.

$$\tilde{p}^{\mathrm{w,u}}_{t,t'} \leq \theta^{\mathrm{w}} \cdot f^{\mathrm{w,max}}_{t,t'}, \quad \forall t, t' = t+1, ..., T \tag{8}$$

$$\tilde{p}^{\mathrm{ch}}_{t,t'} \leq P^{\mathrm{s,max}} \cdot \tilde{x}_{t,t'}, \quad \forall t, t' = t+1, ..., T \tag{9}$$

$$\tilde{p}^{\mathrm{dis}}_{t,t'} \leq P^{\mathrm{s,max}} \cdot (1 - \tilde{x}_{t,t'}), \quad \forall t, t' = t+1, ..., T \tag{10}$$

$$\begin{aligned} \tilde{soe}_{t,t'} &= soe_t + \eta^{\mathrm{ch}} \cdot \tilde{p}^{\mathrm{ch}}_{t,t'} \cdot x_{t,t'} \cdot \Delta t \\ &- \frac{\tilde{p}^{\mathrm{dis}}_{t,t'} \cdot (1 - x_{t,t'})}{\eta^{\mathrm{dis}}} \cdot \Delta t, \quad \forall t, t' = t+1 \end{aligned} \tag{11}$$

$$\begin{aligned} \tilde{soe}_{t,t'} &= \tilde{soe}_{t,t'-1} + \eta^{\mathrm{ch}} \cdot \tilde{p}^{\mathrm{ch}}_{t,t'} \cdot x_{t,t'} \cdot \Delta t \\ &- \frac{\tilde{p}^{\mathrm{dis}}_{t,t'} \cdot (1 - x_{t,t'})}{\eta^{\mathrm{dis}}} \cdot \Delta t, \quad \forall t, t' = t+2, ..., T \end{aligned} \tag{12}$$

$$\tilde{soe}_{t,t'} \leq SOE^{\mathrm{max}}, \quad \forall t, t' = t+1, ..., T \tag{13}$$

$$\begin{aligned} \tilde{p}^{\mathrm{w,u}}_{t,t'} - \tilde{p}^{\mathrm{ch}}_{t,t'} + \tilde{p}^{\mathrm{dis}}_{t,t'} - \tilde{p}^{\mathrm{g,u}}_{t,t'} &= \theta^{\mathrm{d}} \cdot f^{\mathrm{d}}_{t,t'}, \\ \forall t, t' &= t+1, ..., T \end{aligned} \tag{14}$$

$$p^{\mathrm{w,u}}_t, p^{\mathrm{ch}}_t, p^{\mathrm{dis}}_t, p^{\mathrm{g,u}}_t, \tilde{p}^{\mathrm{w,u}}_{t,t'}, \tilde{p}^{\mathrm{ch}}_{t,t'}, \tilde{p}^{\mathrm{dis}}_{t,t'}, \tilde{p}^{\mathrm{g,u}}_{t,t'} \geq 0, \quad \forall t \tag{15}$$

Decisions at time period t are influenced by the uncertainty at time periods t'. however, the final sequence of decisions that causes the actual cost is the set of decisions at time t in all T optimizations.

III. Case Study

The case study is divided into two subsections. The first one shows the impact of the forecast uncertainty parameters θ^{d} and θ^{w} on the actual energy procurement costs for different wind forecast scenarios. The second subsection shows the benefit of using the updating-forecasts MPC optimization scheme by comparing it to the least possible costs using the perfect information deterministic optimization.

The uncertain parameters analysis is performed using the grid search method covering a total of 100 points in two-dimensional θ^{d} and θ^{w} space where each parameter ranges from 0.5 to 1.5. In all cases the BES circular charging and discharging efficiencies are assumed to be 0.92, maximum SoE is 15 MWh, installed BES power is 9 MW, while weight factor γ is 1.

Scenarios only differ in wind realizations and wind forecasts. However, forecasts updated with each hour are more accurate near the time of realization. Wind, demand, and energy prices are taken for a geographically small, but a wind-power-rich area in Croatia. At the beginning of the day market prices take values below 20 €/MWh, but increase 3 to 4 times after hour 8.

Simulations were done by using Gurobi 9.1.2 with an AMD Ryzen 7 4700U CPU, 16 GB of RAM at 3733 MHz.

A. DLA-CFA uncertainty parameter analysis

1) End-day high wind scenario (CS1):

All 24 wind forecasts are shown in Figure 1. Each line represents one forecast, and since the forecasts are made in each time period t for all subsequent periods until the end of the time horizon, there are more lines toward the end of the day. The smallest forecast errors occur near the beginning of the day since those time periods are close to the realization time for all forecasts. In this case study, there is high wind near the end of a day, with a peak wind realization of 28.0 MW.

Parametric grid search results are displayed in Figure 2. Since there is almost no wind production until hour 18, little difference is observed in the BES operation. At most times (until hour 18), energy needs to be purchased from the grid to meet the demand. However, periods when wind production starts to change make a significant difference in the overall cost for that day. Purple area (low cost) in Figure 2 represents the cost for underestimated demand and overestimated wind. When the demand is underestimated for the following time periods at time period 18, the BES is allowed to almost fully discharge due to high wind production (compared to the demand) until the end of the day, as given in Figure 3. As the end of the day and the reduction of wind production approaches, the need for recharging is observed to maintain the power balance in the last time period. On the other hand, the yellow area representing high cost periods is the result of the more conservative behavior of BES at hour 18 when it is not fully discharged to provide a sufficient amount of energy at the end of the day. In that case, the forecast at hour 18 for hour 24 shows that wind production will not be sufficient to meet the demand (demand is overestimated), and prices up to that period are not favorable for performing arbitrage, so the BES does not discharge. The increase in costs for extremely underestimated consumption and overestimation of production is due to a poor preparation of the BES for the decline in wind production at the end of the day, which is why a larger amount of energy must be purchased from the grid during this period. The optimization execution time was 54.11 seconds.

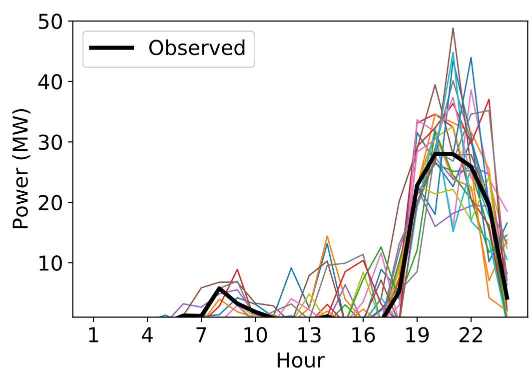

Fig. 1. Wind profile in CS1

2) Wind profile follows load profile (CS2):

Wind profile in this scenario, displayed in Figure 4, resembles the load profile curve. The actual realised maximum and

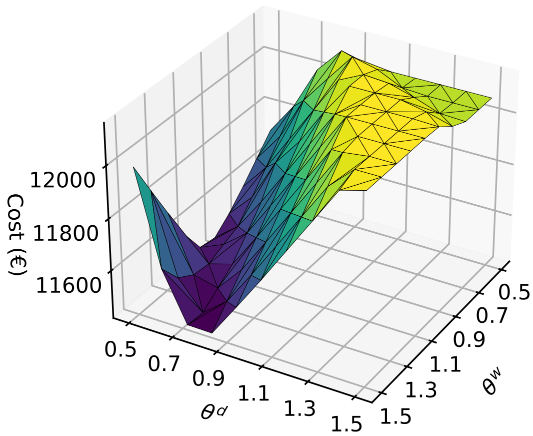

Fig. 2. Cost sensitivity on thetas in interval [0.5, 1.5] in CS1

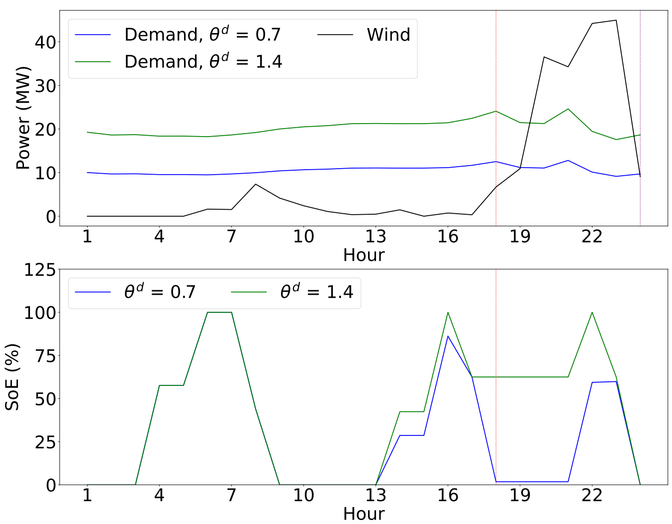

Fig. 3. Upper figure shows the forecast made at time period 18 for (θ^d, θ^w) = (0.7, 1.2) and (θ^d, θ^w) = (1.4, 1.2) combinations. The lower graph shows battery operation for both θ combinations. Due to demand underestimation at hour 24 with the first θ combination, the battery fully discharges at hour 18 and therefore it generates an income. In the second case, the the energy is saved for the last hour of the day.

minimum wind productions are 13.88 MW and 10.51 MW, respectively.

The results are displayed in Figure 5 and show that the most favorable costs are achieved with underestimated wind production and overestimated demand. The plot displays two cost saturation planes. The yellow one represents the periods of high cost when forecasted wind exceeds or is equal to the predicted demand, and therefore no BES charging/discharging is scheduled. However, at the time of realization, there is not enough power to meet the actual demand, hence more energy needs to be purchased from the grid resulting in higher cost. The purple saturation plane represents the periods of low cost, when the forecasted demand exceeds the predicted wind power production. The BES is then scheduled to operate optimally considering the market prices, as well as taking into account the need to satisfy the power balance equation. Although BES operation is optimized for the forecasted demand and wind production, actual demand cannot be met with actual wind production, which is why any battery operation is beneficial to the microgrid cost, because it allows for reduced grid purchases. The costs in case of CS2 are significantly lower than in cases CS1 and CS3, because of the constantly available wind production during the day which allows for reduced grid purchases. The optimization execution time was 55.23 seconds.

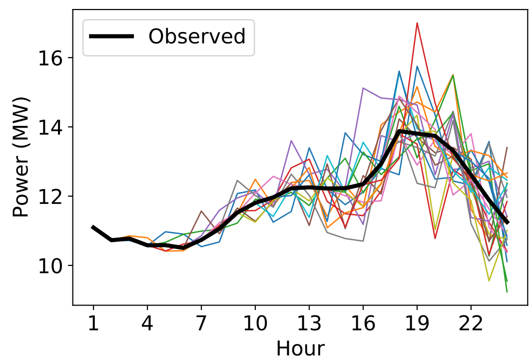

Fig. 4. Wind profile in CS2

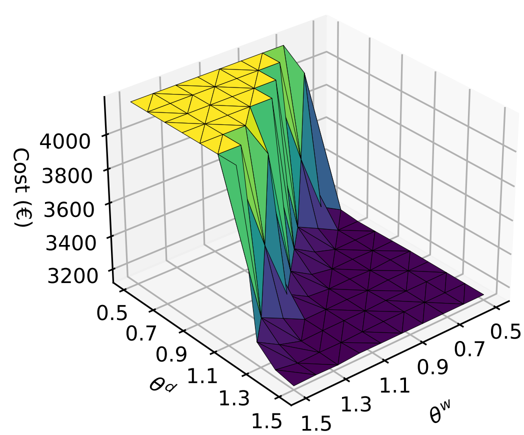

Fig. 5. Cost sensitivity on thetas in interval [0.5, 1.5] in CS2

3) Early-day high wind scenario (CS3):

Wind profile in this scenario is displayed in Figure 6. There is high wind at the start of the day, but almost no wind at the end of the day when the demand is generally high.

Figure 7 show the results of the forecast uncertainty parameter analysis for this scenario. As in the previous subsection, where wind profile followed the demand profile, during the most of the day there is enough wind to meet at least some demand and therefore to partly avoid purchasing energy from the grid. The lowest costs are realized when the demand is equal to or overestimated in comparison to the wind production. The optimization execution time was 63.18 seconds.

B. Benefits of MPC rolling forecast optimization – model comparison

This part of the case study compares the MPC optimization scheme with updating forecasts with the best possible achievable costs, i.e. perfect information deterministic optimization.

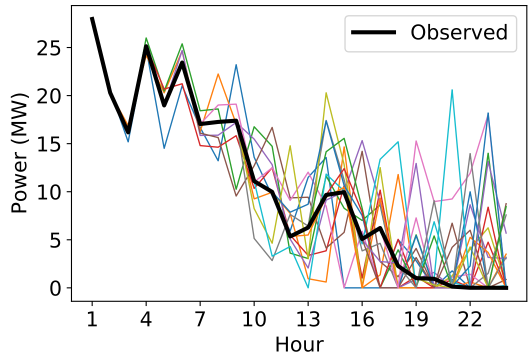

Fig. 6. Wind profile in CS3

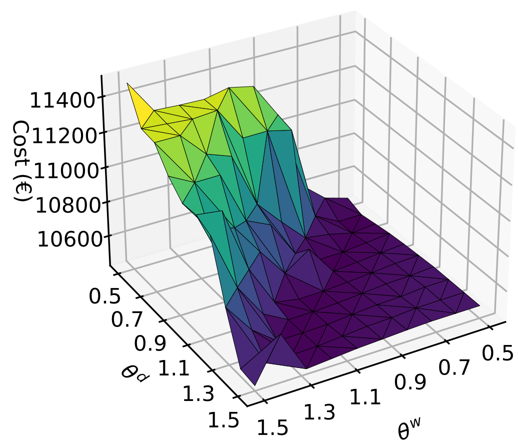

Fig. 7. Cost sensitivity on thetas in interval [0.5, 1.5] in CS3

The perfect information case exactly knows the actual realized wind, demand and prices and thereby makes the perfect decisions. MPC optimization scheme is run with the best and the worst uncertainty parameters as determined in the previous case study.

Table I shows the actual worst and best bounds for the DLA-CFA method for the previously presented three case studies compared to the Perfect-information deterministic approach. The best DLA-CFA results refer to the lowest costs with all considered forecast uncertainty parameters θ^{d} and θ^{w}, while the worst column refers to the worst costs of all the parameters within the grid search area. In all cases, the best DLA-CFA results are close to the perfect information case with maximum difference of 1.47% occurring in scenario CS2, where the wind profile follows the load profile. The worst case results differ from perfect-information case 6.08% in the CS1 to 26.21% in the CS2, while the difference in CS3 is 11.43%. The cost without the use of BES and wind production (20,967.92 €) emphasizes their importance in reducing the cost of the microgrid.

IV. Conclusion

In this paper, we modelled a hybrid of CFA and DLA motivated by the research presented in [13]. The proposed MPC model with the updated forecasts of uncertain parameters captures their uncertainty while remaining computationally

TABLE I
The best and worst cost value for DLA-CFA approach compared to the Pefect-information deterministic model

Cost	DLA-CFA		Perfect-information deterministic
	Worst	Best	
CS1	12,142.89	11,428.34	11.404,00
CS2	4,193.58	3,139.51	3,094.12
CS3	11,493.33	10,444.73	10,401.48

tractable and easy to implement. The results indicate that the importance of the uncertain parameters is dependent on the wind and demand profiles with an important note that without BES, there is no need to consider uncertainty as the demand may only be satisfied from the grid. However, it is fair to conclude that the lowest costs are realized when the demand is equal to or overestimated in comparison to the wind production. The model's worst performance considering all case studies differs no more than 27% from the perfect-information deterministic model. However, it can be reduced with the proper (optimal) choice of the uncertain parameters, which is one of the future research directions. On the other hand, the proposed model's best results are close to the perfect-information deterministic results. Hence, the credibility and importance of the model is proven. Future work shall also include the analysis of other data-driven methods that present higher implementation challenges as compared to the one presented in this paper.

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