Optimal microgrid operation considering battery degradation using stochastic dual dynamic programming

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***Abstract*—Intermittent energy sources demand temporal storages to balance generation and load, and batteries stand out as an alternative. However, the lifetime is limited, and cycling depth affects the battery degradation rate. Current stochastic multi-stage methods lack proper representation of battery degradation. This paper proposes a stochastic multi-stage model for optimizing battery operation in a microgrid considering battery degradation with a piece-wise linear cost function with uncertain wind power production and load. The model is solved using Stochastic Dual Dynamic Programming (SDDP) and is demonstrated on a 4-bus test case with limited import and export capacity to illustrate the battery degradation cost's impacts on the battery cycling strategy. The results show that the importance of a stochastic method is more pronounced when battery degradation is modelled.**

***Index Terms*—stochastic dual dynamic programming, battery degradation, microgrid, arbitrage**

I. Introduction

A. Motivation and background

The increasing share of energy conversion from intermittent sources such as photovoltaics (PV) and wind energy conversion systems (WECS) increase the demand for balancing services in the power system. Coordination of energy storages in distribution grids and microgrids are important for reliability of supply as well as optimal economic dispatch [1].

Energy conversion from PV and WECS are uncertain by nature, and smaller energy systems yields larger variation both in generation and load. Optimal operation of storage in a deterministic model will typically provide an overly aggressive utilization of the storage capacity by frequently cycling between maximum and minimum. Unfortunately, this strategy does not account for forecast error, which may cause load shedding or production curtailment. Therefore, the forecast error may increase the operation cost, but also accelerate aging of battery storage [2]. Stochastic methods are effective for balancing cost minimization and risk, and applicable both for planning, operation and control of microgrids [3].

B. Relevant literature

A commonly used stochastic formulation is the two-stage stochastic problem. Reference [4] suggests a two-stage stochastic formulation for minimizing the operational costs including the grid power losses of a microgrid. Similar two-stage formulations are shown in [5]–[7].

A limitation of the two-stage stochastic formulation is the assumption that all uncertainty is revealed at once. For a multi-stage formulation, the uncertainty is revealed stage-wise and the control of the system is updated stage-wise as the uncertainty is revealed. This formulation is widely used in hydropower scheduling [8], and stochastic dual dynamic programming is an efficient technique for solving large scale multi-stage stochastic problems [9].

There are a few proposed methods for managing storages in microgrids based on SDDP in the literature. Reference [10] suggests a microgrid model minimizing procurement cost under uncertain wind generation where load is balanced in terms of purchase and sale to the utility grid, by using load shifting and micro generators. Reference [11] has a similar formulation also including power loss minimization and uncertain price. In [12], the cost is minimized for a private household with battery storage and uncertain PV generation. Reference [13] balances uncertain wind generation with conventional generation and battery storage including a cost associated with varying the battery level.

C. Contributions and organization

Batteries degrade from several factor, among others state-of-charge (SoC), depth-of-discharge (DoD) and operating temperature. A shortcoming among the aforementioned papers are lack of more sophisticated modelling of degradation due to DoD. Batteries will typically have an increasing degradation rate with increasing cycling depth, and [14] shows how to represent this with a piece-wise linear model.

The contributions of this paper can be summarized as follows: i) The microgrid storage coordination problem has been formulated as a multi-stage stochastic problem. Battery degradation has been modelled as a piece-wise linear cost function to assess cycling costs. ii) The proposed method has been applied on a 4-bus test case to demonstrate the impact of battery degradation both for stochastic and deterministic model formulations. The problem has been solved using the SDDP algorithm.

The remainder of this paper is organized as follows. Section II formulates the multi-stage stochastic formulation of the microgrid storage dispatch problem, section III presents a test case including numerical values, and discusses the impact

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TABLE I
NOMENCLATURE

Sets	
T	Time steps
N	Buses
S	Battery segments
Parameters	
η_k^c	Charge efficiency for battery at bus k
η_k^d	Discharge efficiency for battery at bus k
R	Storage replacement cost $€/MWh$
$c_{k,t}^m$	Power price at bus k, time t
$c_{k,s}^b$	Marginal storage aging cost of cycle depth at bus k, segment s
$\bar{e}_{k,s}$	Maximum energy stored in bus k, segment s
WP_k	Wind scale factor at bus k
LP_k	Load scale factor at bus k
$\hat{p}_{k,t}^w$	Normalized wind power forecast at bus k, time t
$\hat{p}_{k,t}^l$	Normalized load forecast at bus k, time t
ϕ^w	Auto-correlation wind forecast error
ϕ^l	Auto-correlation load forecast error
E_k^{max}	Maximum energy storage in battery at bus k
E_k^{min}	Minimum energy storage in battery at bus k
B_k^c	Maximum charge power to battery at bus k
B_k^d	Maximum discharge power from battery at bus k
P_k^s	Maximum sale power to market at bus k
P_k^b	Maximum purchase power from market at bus k
P_k^w	Maximum wind power generation at bus k
Variables	
Δt	Time step length
$e_{k,t,s}$	Energy stored at bus k, time t, segment s
$b_{k,t,s}^c$	Storage charge power bus k, time t, segment s
$b_{k,t,s}^d$	Storage discharge power bus k, time t, segment s
$p_{k,t}^b$	Power purchase in wholesale market at bus k, time t
$p_{k,t}^s$	Power sale in wholesale market at bus k, time t
$p_{k,t}^w$	Wind power generation at bus k, time t
$p_{k,t}^l$	Load at bus k, time t
$\hat{p}_t^w$	Normalized wind power generation at time t
$\hat{p}_t^l$	Normalized load at time t
$\Delta\hat{p}_{k,t}^w$	Normalized wind forecast error at bus k, time t
$\Delta\hat{p}_{k,t}^l$	Normalized load forecast error at bus k, time t
ε_t^w	Normalized wind forecast error noise at time t
ε_t^l	Normalized load forecast error noise at time t
Φ	Battery cycle stress cost
δ	Battery cycle depth

of modelling the battery degradation costs. The algorithm convergence properties are also presented. Conclusions are drawn in section IV.

II. MODEL DESCRIPTION

This section presents a mathematical formulation of the optimal purchase, sale, storage and generation dispatch in a microgrid with uncertain wind power generation and load. The objective is to minimize utility grid power exchange costs, diesel generation costs, and battery cycling degradation costs. Diesel generation is considered as a purchase opportunity with fixed price. Symbols used in the mathematical formulations are shown in the nomenclature in table I.

A. Problem definition

Each stage in the multi-stage problem is given by a linear problem formulation and linear objective terms. Each time step t represents a stage in this formulation, but the formulation may be generalized such that each stage can have multiple time steps. A state variable represents the required information to model the system from present time and onward. A stage problem may contain both current and previous state variables. A control variable is an internal stage variable and represents an action or decision, either implicit or explicit. A noise is a stage-wise independent random variable [15], [16].

In this paper, the state variables are given by the battery level, wind generation forecast error and load forecast error. The battery level must be a state variable since the current level depends on the previous, while the wind generation and load forecast errors are state variables since they are modelled with auto-regressive models. The system noise is the noise terms in the AR-models describing generation and load error. The remaining variables are control variables.

The objective is to minimize purchase costs from the utility grid and minimize battery degradation costs as shown in (1) under exogenous power price.

$$\min \sum_{t\in T}\sum_{k\in N}\left(c_{k,t}^m(p_{k,t}^b - p_{k,t}^s) + \sum_{s\in S} c_{k,s}^b b_{k,t,s}^d\right)\Delta t \quad (1)$$

B. Battery degradation

Some of the factors causing battery degradation are depth-of-discharge (DoD), state-of-charge (SoC) and operating temperature. This paper only considers degradation due to DoD. The cycle depth stress function describes how much the battery degrades as a percentage of its expected lifetime, and is approximated using a quadratic stress function based on the results from [17]. The cycle depth stress function in (2), where δ is the cycle depth percentage, has been used in this paper. It permits 10 000 cycles at 50% DoD before battery must be replaced.

$$\Phi(\delta) = 4 \cdot 10^{-4}\ \delta^2 \quad (2)$$

The battery cycling cost is implemented as a piece-wise linear model as described in [14]. The battery is divided into segments, where the discharge cost is increasing for increasing segment number. This method demands segmentation of the energy storage state variable, and the charge and discharge variables since SDDP is not capable of handling non-linear states. This is a potential drawback with this method as increased accuracy for the cycling cost function demands additional state variables, which again increase the computation time.

To avoid simultaneous charging and discharging of battery one must ensure that loosing power never is profitable. In this case generation curtailment is free, and the power exchange price is always non-negative. Simultaneous charging and discharging may also be avoided by using binary variables, but that is not supported by standard SDDP. The objective function (1) has an individual cost associated with discharging each segment. The low-cost segments will always be charged and discharged first, while deeper cycles also demand use of the

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high-cost segments. The marginal cost of the segment is given by (3) where $\bar{s}$ is the number of segments.

$$c^{b}_{k,s} = \frac{R}{\eta^{d}_{k}}\ \bar{s}\left[\Phi\left(\frac{s}{\bar{s}}\right) - \Phi\left(\frac{s-1}{\bar{s}}\right)\right], s \in 1, \ldots, \bar{s} \quad (3)$$

C. Battery and energy balance

The battery energy balance is given by the charge/discharge and efficiency as shown in (4). Moreover, the charge/discharge is given by the sum of the segment variables as shown in (5). The battery segments are enforced by (7), and the segments have equal size for each storage in our model. The charge/discharge is enforced by (6) limiting maximum battery charge and discharge. The total energy stored at a bus is limited by the battery maximum and minimum limits as shown in (8), and the purchase and sale with the utility grid is limited as shown in (9). The power must balance at every bus in the network, thus the net injection must be zero (10).

$$e_{k,t,s} - e_{k,t-1,s} = \left(b^{c}_{k,t,s}\eta^{c}_{k} - b^{d}_{k,t,s}\frac{1}{\eta^{d}_{k}}\right)\Delta t \quad (4)$$

$$b^{c}_{k,t} = \sum_{s\in S} b^{c}_{k,t,s}, \quad b^{d}_{k,t} = \sum_{s\in S} b^{d}_{k,t,s} \quad (5)$$

$$0 \leq b^{c}_{k,t} \leq B^{c}_{k}, \quad 0 \leq b^{d}_{k,t} \leq B^{d}_{k} \quad (6)$$

$$e_{k,t,s} \leq \bar{e}_{k,s} \quad (7)$$

$$E^{min}_{k} \leq \sum_{s\in S} e_{k,t,s} \leq E^{max}_{k} \quad (8)$$

$$0 \leq p^{s}_{k,t} \leq P^{s}_{k}, \quad 0 \leq p^{b}_{k,t} \leq P^{b}_{k} \quad (9)$$

$$\sum_{k\in N}\left(b^{c}_{k,t} - b^{d}_{k,t} + p^{s}_{k,t} - p^{b}_{k,t} + p^{l}_{k,t} - p^{w}_{k,t}\right) = 0 \quad (10)$$

D. Load and generation uncertainty

The SDDP algorithm is only capable of solving stochastic problems with stage-wise independent uncertainty. However, the uncertainty is introduced as a state variable and modelled as a first order auto regressive model, and the uncertainty is decomposed into a dependent and an independent term [18] as shown in (11).

$$\Delta\hat{p}^{w}_{t} = \phi^{w}\ \Delta\hat{p}^{w}_{t-1} + \varepsilon^{w}_{t} \quad (11)$$

Generation and load are correlated series. However, the uncertainty in this model is not the generation and load but the generation and load forecast error. Since most of the correlation between generation and load is captured by the forecast, the weak correlation between the forecast errors is neglected.

The expression for wind power generation at a specific node is given by (12) and (13) where WP_k is the maximum generation at node k, $\hat{p}^{k}_{t}$ the normalized wind generation forecast and $\Delta\hat{p}^{w}_{t}$ the normalized forecast error. The normalized forecast is computed by dividing the forecast on the historical maximum from the three previous years. To avoid negative production, a slack variable is introduced to capture negative values.

$$p^{w}_{k,t} - p^{w,slack}_{k,t} = WP_{k}(\hat{p}^{w}_{t} + \Delta\hat{p}^{w}_{t}) \quad (12)$$

$$p^{w}_{k,t},\ p^{w,slack}_{k,t} \geq 0 \quad (13)$$

The wind forecast error is modelled as an auto-regressive model of first order (11), which holds under the assumption that the process is weak stationary. This is a common assumption for wind forecasting, for details see [19].

The slack variable may also be used to generate power, hence the cost for using it must be greater than the highest generation cost in the system.

Similar representation is used for load forecast error but with no cost on the slack variable, which implies that load may be added at no cost.

E. Storage end value

If the end value is not included in the objective, the algorithm tends to always empty the storage in the end since there are no incentives for saving the energy for later. In this model, the value of the stored energy in the last stage is set equal to the value of selling all stored energy in the market after the last stage.

F. Stochastic dual dynamic programming (SDDP)

The model has been solved with SDDP, which is a decomposition technique for solving linear multistage stochastic programs. The SDDP algorithm approximates the expected cost-to-go function with piece-wise linear bounds obtained from the dual solutions of the optimization problem at each stage. The SDDP algorithm has two main phases: forward simulation where scenarios are sampled based on the probability distribution of the random variables, and backward recursion where each stage is optimized backwards along the trajectory from the forward simulation. This procedure is repeated until a convergence criteria is reached [9].

The model has been implemented in Julia with SDDP.jl [20] using CPLEX 12.8.0.

III. Case Study

This section presents the results from a case study of a 4-bus test system with storage, generation and load, where both generation and load are subject to uncertainty. The maximum purchase and sale for the system is limited. Figure 1 shows the topology of the test system where the utility grid connection is limited such that the battery and the emergency generator must balance the load and wind power generation.

A. Case numerical data

This case study uses historical time series from ENTSO-E Transparency Platform [21]. The price series is day-ahead for Denmark (DK-2) between 2018-12-15 and 2018-12-18. The corresponding series are used for load and onshore wind generation. The load and wind series has been normalized as described in section II. The AR(1) model parameters are calculated based on normalized historical generation and forecast values from the given time with regression analysis. The historical forecasts are day-ahead forecasts. The shift between old and new forecast at midnight has therefore been removed when doing the regression analysis. The calculated auto-correlation for the normalized series was 0.90 and 0.65

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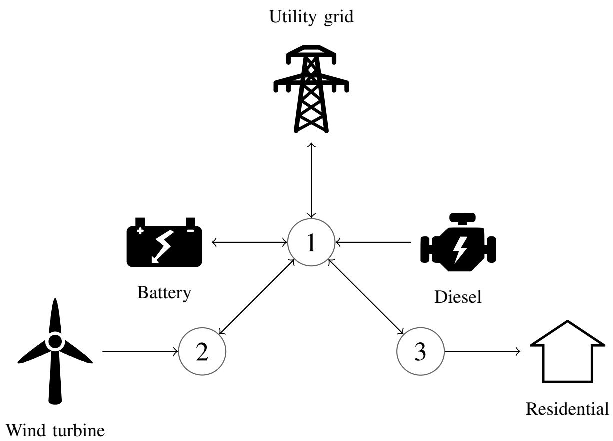
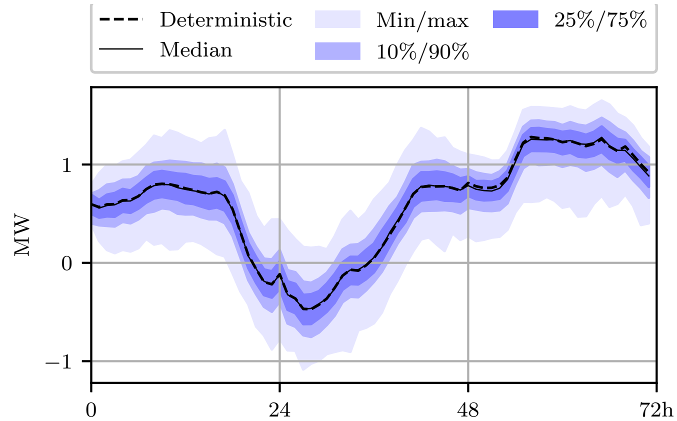


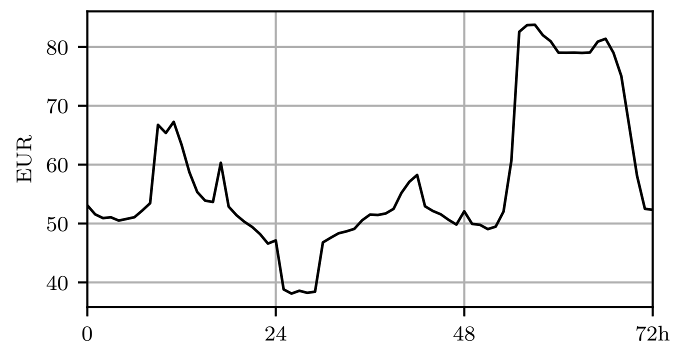
Fig. 1. Test system

TABLE II
CASE PARAMETERS

Utility grid	
Maximum purchase	1 MW
Maximum sale	1 MW
Max purchase/sale violation penalty	600 €/MWh
Storage	
Size	3 MWh
Maximum charge/discharge	1 MW
Efficiency charge/discharge	95%
Replacement cost	100,000 €/MWh
Diesel	
Maximum generation	1 MW
Cost	500 €/MWh
Wind generation	
Maximum generation	2 MW
Forecast error auto-correlation	0.90
Forecast error standard deviation	0.05
Slack variable cost	600 €/MWh
Load	
Maximum load	2 MW
Forecast error auto-correlation	0.65
Forecast error standard deviation	0.05



(a) Net load: Difference between load and generation



(b) Price.

Fig. 2. Sampled load, wind power generation and price.

TABLE III
BATTERY CYCLING MARGINAL COST

Segment	Marginal cost
0-20%	24
20-40%	72
40-60%	120
60-80%	168
80-100%	216

for wind and load respectively, and the standard deviation was 0.02 and 0.0065. Note that these are the statistical properties of the forecast errors. In this case, the standard deviation is increased to 0.05 for both generation and load to demonstrate the capabilities of the method, and to reflect that a smaller population yields greater standard deviation. Each noise variable is sampled into three evenly spaced quantiles such that the number of discrete outcomes for each stage is nine. Other parameters are presented in table II, while net load and price profiles are shown in figure 2. The storage cycling cost function is divided into five segments of equal size, and the segment marginal costs for this particular case is shown in table III.

B. Results and discussion

The presented stochastic solution shows the percentiles of 500 simulations of 72 stages where each hour represents a stage. The results show that the primary objective is to avoid expensive generation from diesel by ensuring high battery level when reaching the period with high net load as seen from around hour 54 where the net load in figure 2a exceeds the maximum purchase limit, and the battery level is 100% in both figure 3a and 3b. Figure 3c and 3d shows that there is no sale for at least 90% of the scenarios despite the very high price, since all the stored energy is used to avoid generation from diesel. Nevertheless, diesel generation is unavoidable in 25-50% of the scenarios as shown in figure 3e and 3f.

The secondary objective, given that the diesel cost always is higher than the price difference, is using battery for arbitrage. The battery level without degradation cost in figure 3a shows arbitrage between hour 0 and 54. This is also shown in figure 3c where there are frequent changes between purchase and sale. However, when including battery degradation costs as shown in figure 3b, there is no sign of arbitrage, and the purchase/sale profile in figure 3d is much more stable. The lowest prices are found between hour 24 and 30 causing two spikes in the deterministic solution in figure 3d to fully charge

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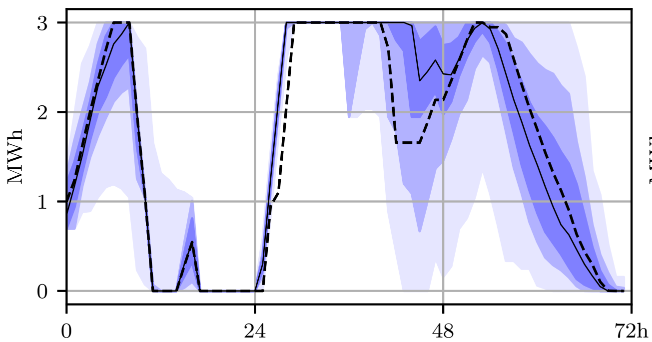
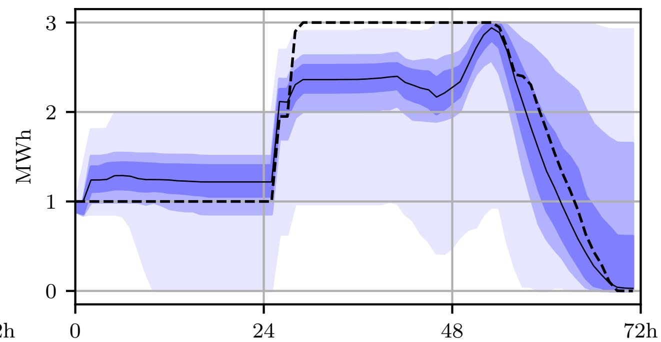
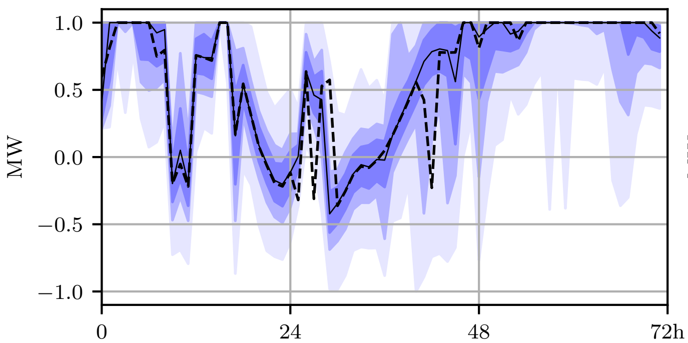


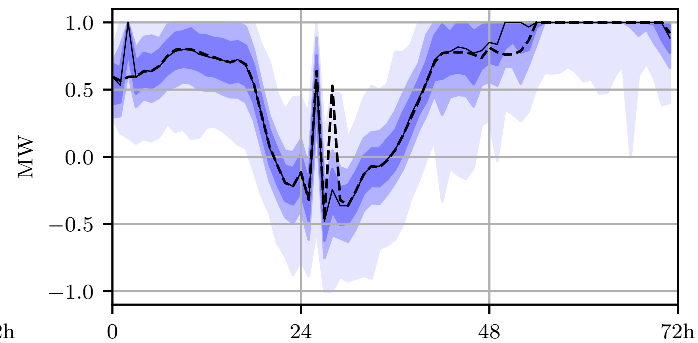
(a) Battery level without degradation.



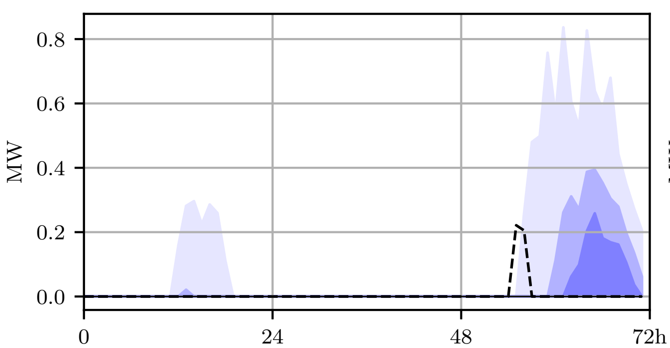
(b) Battery level with degradation.



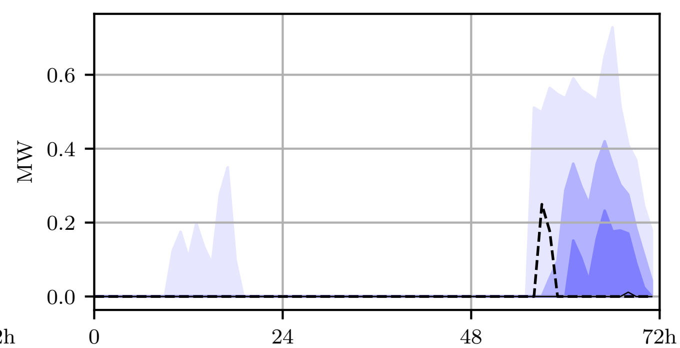
(c) Purchase from utility grid without degradation.



(d) Purchase from utility grid with degradation.



(e) Generation from diesel without degradation.



(f) Generation from diesel with degradation.

Fig. 3. Comparison of optimization without and with battery degradation costs.

the battery in advance to the high load from hour 54.

The difference between the deterministic and stochastic solution is more pronounced when battery degradation costs are included. With no degradation cost, figure 3a shows that the deterministic and the stochastic median solutions have almost overlapping solutions much of the time. In contrast, the solution including battery degradation costs has a more risk averse strategy for the stochastic solution. Instead of charging the battery immediately as the deterministic solution, the storage level is kept below maximum to avoid production curtailment in case the net load should exceed the export limit.

Calculating the value of the stochastic solution is a computationally hard task. Nevertheless, an interesting property with the solution of a SDDP problem is the interpretation of the cuts added by SDDP. For a minimization problem, the cuts are lower bounds for the future cost functions of the problem state variables. These cuts may also be used as boundary conditions for an optimization model with shorter time horizon and possibly different solving methodology.

Note that these analysis has been carried out on a limited case for the purpose of demonstrating the concept. To verify the scalability of the method, it should be tested on a larger case.

C. Algorithm convergence

To check if the algorithm has converged, the lower bound is compared with and upper bound confidence interval as described by [9]. The 95% confidence interval for the upper bound is computed regularly with 200 Monte Carlo simulations, and figure 4 shows how the confidence interval and

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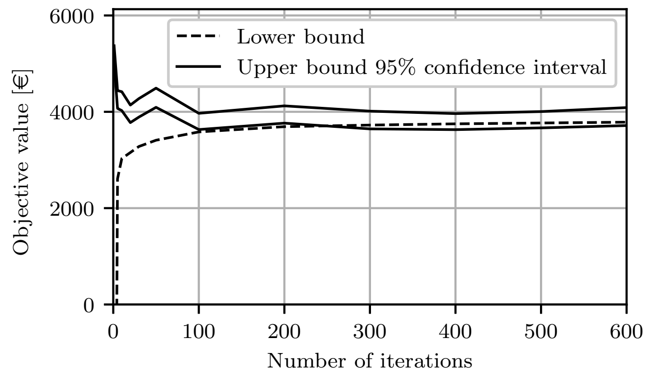

Fig. 4. Algorithm convergence

lower bound develops for the case with degradation costs. The results show that a high number of iterations are required to satisfy the convergence criteria. Testing also shows that if the diesel generation and penalty costs had been closer to the day-ahead price, the algorithm would have converged faster.

IV. Conclusions

The importance of stochastic methods in the microgrid storage coordination problem is more pronounced when including degradation costs incurred by battery cycling. A naive model permits correction of a sub-optimal battery level by charging and discharging at no other cost than the energy price. For a model including battery degradation costs, the stochastic strategy will attempt to avoid correction of a sub-optimal battery level caused by uncertainty by operating farther away from the battery limits than a deterministic solution.

The battery price and cycling cost used in this case also shows that high price differences are necessary to profit on arbitrage with batteries. Since the net demand is correlated with price, the battery is already occupied with load shifting in the hours with the highest arbitrage potential.

Battery degradation has significant impact on the optimal strategy, hence it will be instructive to extend the degradation model to also include SoC in future work. Moreover, it will also be instructive to embed different types of end-user flexibility to compare how they can provide an alternative or supplement to battery storage. Finally, recent developments in SDDP has provided new methods for handling correlated uncertainty in price [22] and integer problems [23] enabling more precise formulations of multi-stage stochastic programs.

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