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Closed-loop simulation testing of a probabilistic DR framework for Day Ahead Market participation applied to Battery Energy Storage Systems

1st Ties van der Heijden
Electrical Sustainable Energy
Water Resources
Delft University of Technology
Delft, the Netherlands
T.J.T.vanderHeijden-2@tudelft.nl

2nd Peter Palensky
Electrical Sustainable Energy
Delft University of Technology
Delft, the Netherlands
0000-0003-3183-4705

3rd Nick van de Giesen
Water Resources
Delft University of Technology
Delft, the Netherlands
0000-0002-7200-3353

4th Edo Abraham
Water Resources
Delft University of Technology
Delft, the Netherlands
0000-0003-0989-5456

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***Abstract*—In this manuscript, we test the operational performance decrease of a probabilistic framework for Demand Response (DR). We use Day Ahead Market (DAM) price scenarios generated by a Combined Quantile Regression Deep Neural Network (CQR-DNN) and a Non-parametric Bayesian Network (NPBN) to maximise profit of a Battery Energy Storage System (BESS) participating on the DAM for energy arbitrage. We apply the generated forecast time series to a stochastic Model Predictive Control (MPC), and compare the performance using a point and perfect forecast. For the probabilistic forecasts, we test two control strategies; 1) minimising the Conditional Value at Risk (CVaR) for making costs, and 2) minimising the expected value of the cost. We apply the MPC in a closed-loop simulation setting and perform a sensitivity analysis of the profit by changing the ratio between battery capacity and the max power, the cluster reduction method, and the number of scenarios used by the MPC. We show that the proposed framework works, but the approach does not increase profit compared to a deterministic point forecast. This can possibly be explained by the deterministic forecast capturing the shape of the price curve with less noise than a probabilistic forecast without enough scenarios. We show that the value of a good forecast becomes smaller as the charging time of the battery becomes larger, due to the battery being unable to exploit small price differences optimally.**

***Index Terms*—Demand Response, probabilistic forecasting, scenario generation, stochastic programming, battery energy storage systems, day ahead market**

I. Introduction

As the transition to renewable energy accelerates, uncertainty plays a larger role in decision-making. The increasing market penetration of renewables results in volatile electricity generation, which leads to more volatile electricity prices [1], making them more difficult to forecast [2]–[5]. Price forecasts help Demand Response (DR) by allowing users to adjust their planned energy consumption schedules based on price forecasts. The Day Ahead Market (DAM) is the primary market for short-term trading in Europe, where energy is traded in hourly blocks and with hourly prices. To buy electricity on a specific day and time, market participants must make a bid before 12:00 AM the preceding day, after which the market shuts, and the Market Clearing Price is determined. When placing a bid, the actual price is unknown, driving study in Electricity Price Forecasting in the context of the DAM.

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Large forecasting mistakes can result in suboptimal dispatching and a loss of system efficiency as well as income for users and producers. Because energy production is becoming increasingly unpredictable as a result of renewable energy penetration, probabilistic forecasting can be useful because it provides a prediction interval, which indicates forecast uncertainty. It enables asset risk management and stochastic bidding/optimisation [6].

The Combined Quantile Regression Deep Neural Network (CQR-DNN) [7] is a probabilistic forecasting method where, instead of a single value, the model estimates many quantiles of a response distribution. The collection of forecast quantiles may be utilised to build Cumulative Distribution Functions, allowing for estimating the predicted variable's marginal distribution (e.g. the hourly electricity price). These distributions are independent marginal distributions, since the forecast time is the same for all hours examined in the forecast.

A typical way of applying DR is through Model Predictive Control (MPC). When uncertainty is introduced into the MPC problem, price scenarios may be utilised to make optimal decisions based on financial or physical risk. The CQR-DNN forecasts 24-hourly DAM prices at the same time, yielding 24 marginal Cumulative Distribution Functions (CDFs) that are conditional on the network's input. However, to generate realistic multivariate price samples, the relationship between hourly DAM prices should be considered.

Non-parametric Bayesian Networks (NPBNs) are probabilistic graphical models that express complex and high-dimensional dependencies between variables. NPBNs employ marginal distributions and bivariate copulae to characterise variable dependencies according to a user-defined structure. Since no assumptions are made about the marginal distributions, the model is flexible to the desired distribution. Spearman's rank-correlation between hourly DAM prices is calculated on historical data and then applied to parameterize the bivariate copulae as in [8].

The application of Battery Energy Storage Systems (BESS) in the energy system is an active topic of research [9], [10], where it is shown they can be of great value in providing flexibility. Many mathematical formulations can be found for BESS MPC problems. However, many focus on battery state-of-health and deterministic point and perfect forecasts [11]. The operational performance decrease, due to forecasting errors, is often unknown. The operational performance of an asset using a forecast is perhaps a better metric for price forecasting model performance than classical error-based metrics.

In this work, we test the operational performance decrease of a probabilistic DR framework for DAM participation in a BESS environment. We model a simple BESS to be active on the DAM based on quantile forecasts of the Dutch DAM price and scenarios generated with an NPBN. The scenarios are reduced to be optimally representative of the original scenario set while ensuring computational feasibility. The DR framework is applied in a closed-loop simulation setting, simulating DAM participation in 2019 and 2020 for varying power/storage ratios, using Conditional-Value-at-Risk and Expected Value objective functions. The results are then compared with a point and perfect forecast strategy.

II. Methodology

Our proposed probabilistic DR framework for DAM participation consists of four main steps; forecasting distributions of prices (II-A), generating 48-hourly price scenarios that obey both the forecast distribution and the observed temporal dependencies in the data(II-B), reducing those scenarios for computational feasibility (II-C), and applying the scenarios in a stochastic MPC (II-E).

A. CQR-DNN

To forecast DAM price distributions, we apply the Combined Quantile Regression Deep Neural Network (CQR-DNN) [7]. Compared to ensemble models in which each quantile is represented by a separate model, the CQR-DNN was developed to forecast all quantiles simultaneously. By applying a different loss to each output node while minimising the mean loss across all output nodes, the combined quantile loss function enables simultaneous training of multiple regression quantiles in a single DNN. This prevents separate quantile models from diverging to different local optima during training, significantly reducing the 'crossing quantile problem'.

The CQR-DNN is trained a multiple pinball loss functions [12], a combined quantile loss

$$L_{CQ} = \sum_{\tau \in T} L_\tau, \tag{1}$$

$$L_\tau = \max(\tau \cdot e_\tau, (\tau - 1) \cdot e_\tau), \tag{2}$$

$$e_\tau = z_\tau - y, \tag{3}$$

where L_τ is the loss, T denotes the set of quantiles τ and e_τ the quantile forecast error, with y being the observed value and z_τ the quantile forecast. Due to the asymmetrical penalisation of over- and under-predictions, the model will learn how to regress a variable that is expected to exceed the actual target for a τ fraction of the samples; a quantile. In our case, we apply the CQR-DNN to forecast 13 quantiles $(0.99, 0.95, 0.8, 0.7, 0.6, 0.5, ...)$.

B. Non-parametric Bayesian Networks

In order to efficiently sample multiple hourly prices at once while having realistic temporal dependencies between the hours, we apply a Non-parametric Bayesian Network (NPBN) like in [8]. The NPBN is a Directed Acyclical Graph with nodes and arcs representing uncertain or random variables and their dependencies. A marginal distribution describes each node that does not have a parent. Each child node is described by a conditional distribution, which captures the NPBNs dependency between variables. NPBNs have been previously applied in Earth Dam safety assessment, emission source linking, air transport safety the reliability of structures, like flood defense infrastructures or bridge safety assessment [13], [14].

Within the NPBN, multivariate distributions are described by univariate marginals and a copula to describe dependencies. The joint density of NPBNs with n variables is factorized as

$$f_{1,\dots,n}(x_1, \dots, x_n) = f_1(x_1) \prod_{i=2}^{n} f_{i|Pa(i)}(x_i | x_{Pa(i)}), \tag{4}$$

where $f_{1,\cdots,n}$ denotes the joint density of the n variables, f_i denotes their marginal distributions, and $f_{i|j}$ denotes conditional distributions. Each random variable x_i belongs to node i, where the parent nodes if node i form the set $Pa(i) = \{i_1, \dots, i_{p(i)}\}$. The arcs are assigned one-parameter conditional copulae [15], parameterised by Spearman's rank correlations [13]. The arc from parent-node i_m to node i is assigned a conditional rank correlation, where k denotes the order of the condition (e.g. the number of variables it is conditional to).

In this work, we fit parametric distributions to the hourly forecast quantiles and use these as marginal distributions. The rank correlation is based on the data, and the dependency structure is depicted in Figure 1.

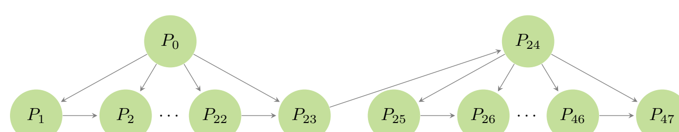

Fig. 1. Bayesian network with consecutive dependency structure and a shared dependency on the first sample of the day. [8]

C. Scenario reduction

We reduce the sampled scenarios by the NPBN to optimally represent the full set of scenarios. Random sampling from the generated set of scenarios might result in the over- or under-representation of certain events or shapes. Therefore we take a large number of samples from the NPBN, and reduce these by clustering them. We apply three methods; first, as comparison, we randomly choose scenarios from the full set of scenarios. Second, we apply the KMeans clustering algorithm [16] to group scenarios into a specified amount of clusters. The KMeans algorithm functions by assigning n forecast timeserie scenarios x with length of 48 hours into cluster sets S in such a way that the in-cluster inertia is minimised

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x \in S_i} ||x - \mu_i||^2, \tag{5}$$

where $k \leq n$, $S \in \{S_1, S_2, ..., S_k\}$, and μ_i is the mean of cluster i. Third, we apply the KMedoids algorithm [17] to cluster data similarly to KMeans, but with centroids being an actual forecast time series in the cluster. An example of the resulting scenarios can be seen in Figure 2. We assign the representative scenarios a probability by dividing the size of the cluster by the size of the initially generated set of scenarios.

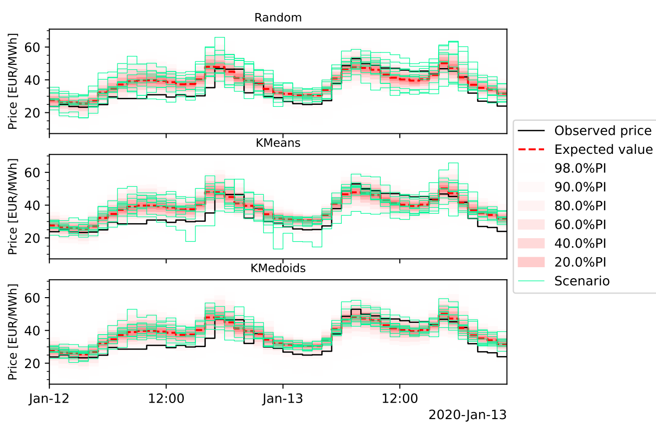

Fig. 2. Quantile forecast of the DAM price and reduced scenarios for each method.

D. Conditional Value at Risk

The Conditional Value at Risk (CVaR) is applied to BESS energy arbitrage in order to reduce the risk of participating in volatile and uncertain markets. CVaR is defined as

$$CVaR_\alpha = \frac{1}{1-\alpha} \int_{f(x,y) \geq \mathrm{VaR}} f(x,y) p(y) dy, \tag{6}$$

which is the mean value of the stochastic variable for the part that is greater than a (predefined) Value at Risk (VaR) with a certain confidence level α [18]. It is also known as the expected shortfall in financial theory, where it depicts the expected return on a portfolio in the worst α% of the cases. The CVaR is a risk measure that describes the whole tail of a distribution, rather than a single cut-off point at the distribution like the VaR. When CVaR is minimised, more conservative choices are made compared to minimising VaR.

E. MPC for BESS DAM participation

We apply a receding horizon MPC to bid on the DAM using the reduced set of scenarios with a prediction horizon of 48 hours. For this study, we apply three strategies and compare them with the theoretical optimum. First, we minimise the expected value (EV) (J_1) of the cost over all scenarios. Second, we minimise the Conditional-Value-at-Risk (CVaR) (J_2) with a 50% and 90% confidence level. We compare the methods with a point forecast and a perfect forecast to estimate the value of a stochastic program. The stochastic program for EV minimisation is formulated as

$$R[s] := \sum_{t=1}^{N} (P_{\text{in}}[t] - P_{\text{out}}[t] \cdot \rho_{\text{out}}) \Delta t \cdot \text{price}[t, s], \tag{7a}$$

$$J_1 := \min \sum_{s \in S} R[s] \cdot p[s], \tag{7b}$$

s.t.

$$C[t] \in [0, C_{\text{max}}], \tag{7c}$$

$$P_{\text{in}}[t] \in [0, P_{max}], \tag{7d}$$

$$P_{\text{out}}[t] \in [0, P_{max}], \tag{7e}$$

$$Z_p[t] \in \{0, 1\}, \tag{7f}$$

$$P_{\text{in}}[t] \leq P_{\text{max}} \cdot Z_p[t], \tag{7g}$$

$$P_{\text{out}}[t] \leq P_{\text{max}} \cdot (1 - Z_p[t]), \tag{7h}$$

$$C[t] = C[t-1] + (P_{\text{in}}[t] \cdot \rho_{\text{in}} - P_{\text{out}}[t]) \Delta t, \tag{7i}$$

where $R[s]$ is the cost function in [€] of scenario s which is part of the set of M scenarios in S, $C[t]$ the storage level at time t in [kWh], $P_{in}[t]$ and $P_{out}[t]$ are the charging and discharging power at time t in [kW], respectively, ρ_{in} and ρ_{out} the charging- and discharging efficiency [-], $p[s]$ is the probability [-] of scenario s, and Z_p the binary indicator for charge- or discharging mode. When a point- or perfect forecast is applied in the simulation, a single scenario with $p[s] = 1$ is introduced.

The stochastic program for CVaR minimisation is formulated as

$$J_2 = \min \ \text{CVaR} := \min \ \text{VaR} + \frac{1}{1-\alpha} \cdot \sum_{s \in S} Z_c[s] \cdot p[s], \tag{8a}$$

s.t. (7c), (7d), (7e), (7f), (7g), (7h), (7i),

$$Z_c[s] \in [0, \infty), \tag{8b}$$

$$VaR \in \mathbb{R}, \tag{8c}$$

$$Z_c[s] \geq R[s] - VaR, \tag{8d}$$

where VaR is the Value-at-Risk in [€] that is implicitly calculated as a variable in the optimisation problem, α the confidence level of the CVaR calculation, and Z_c a deficit variable introduced to calculate the CVaR efficiently [18].

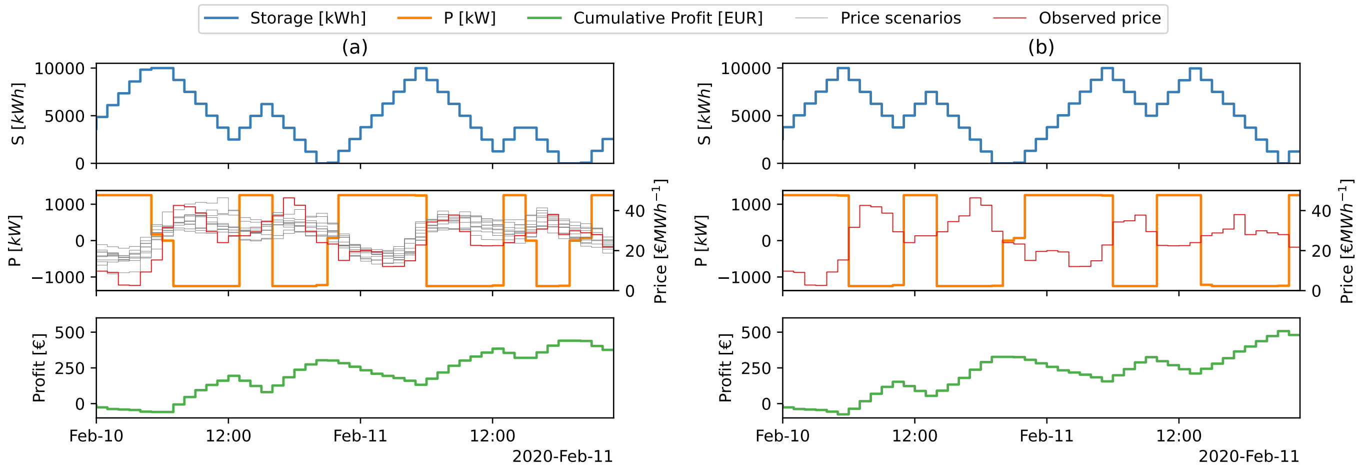

Fig. 3. A depiction of the BESS operations using an MPC with (a) 10 KMedoids selected scenarios with expected value minimisation, and (b) a perfect forecast.

III. Results and Discussion

We assume a battery with 10 MWh storage capacity and varying power/storage ratios. Figure 3 shows the results of the closed-loop simulation for February 10 and 11 in 2019 for (a) the MPC with 10 scenarios selected through KMedoids while minimising the expected value of the cost, and (b) the MPC with a perfect forecast. The decisions made by the MPCs are similar, but the perfect forecast is slightly more optimal, which is expected.

Multiple amounts of scenarios and different scenario reduction techniques are analysed. Figure 4 shows the relative profit for the closed-loop simulation experiments with varying power, objectives, amount of scenarios and scenario reduction technique. The results show that for this case, there is no added value for the use of stochastic programs compared to a point forecast. When enough scenarios are considered, the profit converges to that of a single point forecast consisting of the expected value of the quantile forecast. The results also show that generally, the profit with KMedoids scenario reduction technique converges with fewer scenarios than the Clustered Random or Random approaches.

In this setting, a higher confidence level for the CVaR translates into less profit due to deviation of the plan from the maximum expected profit. As the confidence level decreases, CVaR minimisation of the cost coincides more with the expected value minimisation of the cost. However, for BESS participating solely on the DAM, it seems that a stochastic MPC approach does not lead to extra benefits compared to using a point forecast. This could be due to the nature of CVaR, which is not to maximise profit, but to decrease risk of participation. This could change when local system constraints by (uncertain) demand or generation are taken into account, making it more likely for a point forecasting framework to result in suboptimal results. CVaR can be constrained in the minimisation of the expected value, which could represent the risk of causing imbalance due to insufficient storage left in the battery to supply the local demand. In a multi-market setting, risk acceptance could translate into the frequency of trading, or speculation, on the intraday market. The simulation with the minimisation of the expected value of energy cost converges to a point-forecast performance with enough scenarios. It could be that the point-forecast (i.e. the expected value of the quantile forecast) represents the shape of the price realisation well enough and that the consideration of uncertainty through an insufficient number of scenarios only gives noise to that signal. As the number of scenarios increases, uncertainty is captured more completely, and performance converges to the expected value.

The results show that for a decreasing ratio between power and storage, the accuracy of a forecast starts becoming less valuable. When batteries can charge quickly within the timeslot of the market, small deviations in price have higher impact on optimal results. When a BESS takes multiple market timeslots to charge or discharge, small deviations matter less since (dis)charging covers multiple timeslots.

IV. Conclusions

In this work, we test the operational performance decrease that using a probabilistic DR framework causes for BESS participation in the DAM using quantile price forecasts. We apply 1) a CQR-DNN to forecast price distributions of the Dutch DAM for 2019 and 2020; 2) an NPBN to sample 48h price scenarios with realistic temporal dependencies; 3) scenario reduction techniques based on several clustering algorithms; 4) a stochastic MPC maximize profits due to energy arbitrage based on the forecast price scenarios. A closed-loop simulation is performed with a BESS using the forecast price scenarios and a stochastic program for varying battery parameters, number of scenarios, scenario reduction technique, and control objectives. Results are compared with the BESS participating on the DAM with a single price scenario (point forecast) and the theoretically optimal case with know prices (perfect forecast).

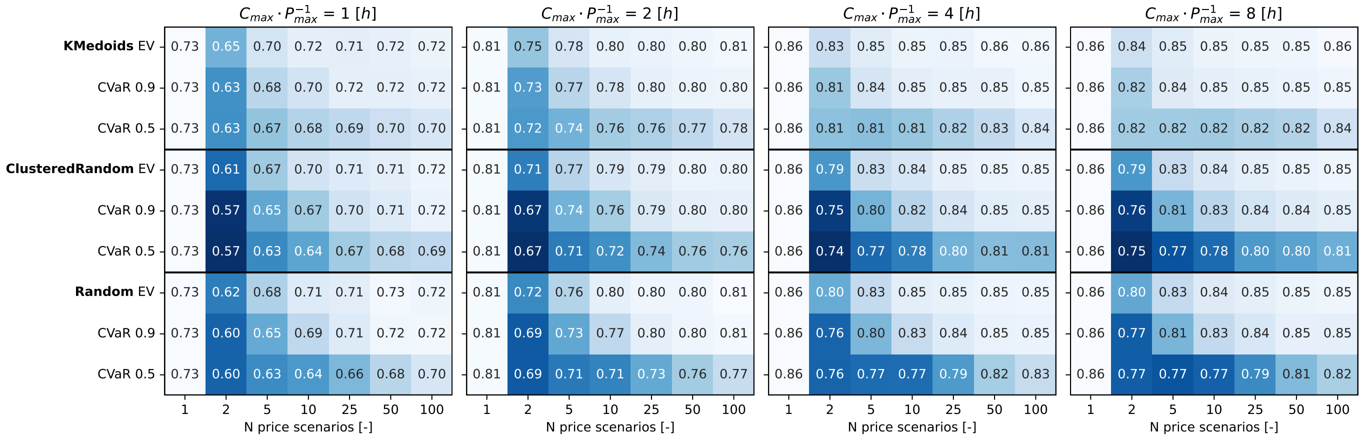

Fig. 4. Relative profit for a BESS system with 10 MWh capacity (C) and varying power. Profits are normalised by the profit from the simulation with a perfect forecast.

The results show that including uncertainty does not lead to improved profit for energy arbitrage on the DAM only compared to a point forecast in this specific case. This can possibly be explained by the fact that the deterministic point forecast consists of the expected value of the probabilistic forecast, making the general shape of the price forecast curves similar. Including a small number of other scenarios would then only introduce noise to the shape. This results is hypothesised to change when multiple markets (e.g. FRR, intraday) are considered in a multi-stage fashion where intraday prices are conditional to the DAM prices, which we leave for future work. Also, when local generation and/or consumption are taken into account, risk-aware decision-making can be of value to ensure the continuation of critical processes, prevent curtailment, or to prevent high imbalance costs by constraining the risk. For market participants without liquidity constraints (e.g. energy traders), a CVaR cost objective is not preferred over an expected value objective. However, when energy trading is secondary in the business model, or when large energy costs could threaten the business model, CVaR minimization of cost can be of value.

We also show that as the BESS takes longer to charge or discharge, profits are closer to the theoretical optimum due to the spreading of market participation over multiple timeslots. Small hourly deviations in price can be exploited less, due to the relatively slow (dis)charging of the BESS, decreasing the value of a good forecast.

We show how the operational performance decrease of the proposed DR framework, and how it would work. The framework can be flexibly changed to accommodate local constraints and objectives resulting from, for example, generation and demand. In future work, we will focus on multi-market scenarios and local consumption and/or generation.

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