Day Ahead Market price scenario generation using a Combined Quantile Regression Deep Neural Network and a Non-parametric Bayesian Network

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***Abstract*—In this manuscript we propose a methodology to generate electricity price scenarios from probabilistic forecasts. Using a Combined Quantile Regression Deep Neural Network, we forecast hourly marginal price distribution quantiles for the DAM on which we fit parametric distributions. A Non-parametric Bayesian Network (BN) is applied to sample from these distributions while using the observed rank-correlation in the data to condition the samples. This results in a methodology that can create an unbounded amount of price-scenarios that obey both the forecast hourly marginal price distributions and the observed dependencies between the hourly prices in the data. The BN makes no assumptions on the marginal distribution, allowing us to flexibly change the marginal distributions of hourly forecasts while maintaining the dependency structure.**

***Index Terms*—Probabilistic electricity price forecasting, scenario generation, deep neural network, non-parametric bayesian networks, quantile regression, probabilistic forecasting, day ahead market, demand response**

I. Introduction

As the transition to renewable energy is progressing, uncertainty plays an increasingly larger role in decision-making. The increasing market penetration of renewables leads to volatile electricity generation, in turn resulting in more volatile electricity prices [1] that are harder to forecast [2]–[5]. Price forecasts benefit Demand Response (DR), allowing consumers to change the timing of energy consumption based on expected prices. In Europe, the main market for short-term trading is the Day Ahead Market (DAM), where energy is traded in hourly blocks and with hourly prices. To purchase electricity on a certain day and hour, market participants make a bid before 12:00 AM the previous day, after which the market closes and the Market Clearing Price (MCP) is decided. The actual price is unknown when making a bid, motivating research in Electricity Price Forecasting (EPF) in the context of the DAM.

Large forecasting errors can lead to sub-optimal dispatching and a loss in both system efficiency and profits for the users and producers. Since electricity prices are becoming increasingly uncertain due to renewable energy penetration, probabilistic forecasting can be of added value since it gives a prediction interval, which is an indication of the forecast uncertainty. It allows for risk management and stochastic bidding/optimisation of assets [6]. Probabilistic forecasting gained track in the energy sector after GEFCOM2014, where the probabilistic forecasts outperformed point forecasting methods [7].

One way of generating probabilistic forecasts is by applying the Combined Quantile Regression Deep Neural Network (CQR-DNN) [8]. The model forecasts multiple quantiles of a response distribution, instead of a single value. The set of forecast quantiles can be used to construct Cumulative Distribution Functions (CDFs), allowing for the estimation of a marginal distribution of the forecast variable (e.g. the hourly electricity price). Since the time of forecast is the same for all hours considered in the forecast, these distributions are considered independent marginal distributions. When applying DR, generally a model predictive control (MPC) approach is applied. When including uncertainty in the MPC problem, price scenarios can be used for optimal expected and risk-based decision making. The CQR-DNN forecasts 24-hourly DAM prices simultaneously, giving 24 marginal CDFs that are conditional to the input of the network. However, when generating scenarios the dependency between hourly DAM prices should be considered in order to create realistic price samples.

A Non-parametric Bayesian Networks (BNs) are probabilistic graphical models that represent complex and high-dimensional dependency structures between variables [9]. BNs describe dependencies between variables according to a user-defined structure, using marginal distributions and bivariate copulae. No assumptions are made about the marginal distributions, making the model flexible with respect to the desired distribution. Using historic data, Spearman's rank-correlation between the hourly DAM prices can be calculated and used to parameterise the bivariate copulae.

In this manuscript, we propose the use of a CQR-DNN to forecast distribution quantiles of hourly electricity prices.

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Forecasts of the model described in [8] are used. A rank-correlation matrix is calculated from the historic DAM data, and applied to fit a BN. The BN is then applied to transform the marginal forecast distributions and generate scenarios that obey both the hourly marginal distribution forecasts and the observed rank-correlation between hourly prices.

II. Methodology

In this section we describe the applied methods for probabilistic forecasting, conditional sampling, and evaluation of the results.

A. Combined Quantile Regression Deep Neural Network

The Combined Quantile Regression Deep Neural Network (CQR-DNN) [8] was developed to lessen the occurrence of the 'crossing quantile problem' [10], compared to ensemble models where every quantile is represented by a separate model. The combined quantile loss function allows for simultaneous training of multiple quantiles in a single DNN by applying a different loss to each output node while minimizing the mean loss over all output nodes. This prevents separate quantile-models from diverging to different local optima because of stochastic sampling during training, leading to non-monotonically increasing quantiles.

The model is trained using a combination of pinball loss functions [11]

$$L_\tau = \max(\tau \cdot e, (\tau - 1) \cdot e), \text{ with} \tag{1}$$

$$e = z - y \tag{2}$$

where L is the loss, τ denotes the quantiles and e the quantile forecast error, with y being the observed value and z 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. Figure 1 shows the CQR-DNN with the separate quantile output nodes. The model trained by minimising the mean of the combined pinball loss of all quantiles

$$L_{CQ} = \frac{1}{N} \sum_{n=1}^{N} L_{\tau_n}, \tag{3}$$

where N is the amount of quantiles to be taken into consideration, and τ_n the n$^{\text{th}}$ quantile.

B. Non-parametric Bayesian Networks

The Non-parametric Bayesian Network (BN) is applied to condition samples based on a user-defined dependency structure. The BN consists of a Directed Acyclical Graph, where nodes and arcs represent uncertain or random variables and their dependency, respectively. Each node without a parent is described by a marginal distribution. Each child node is described by a conditional distribution, capturing the dependency between variables in the BN. BNs have had successful applications in Earth Dam safety assessment, emission source linking, air transport safety the reliability of structures, like

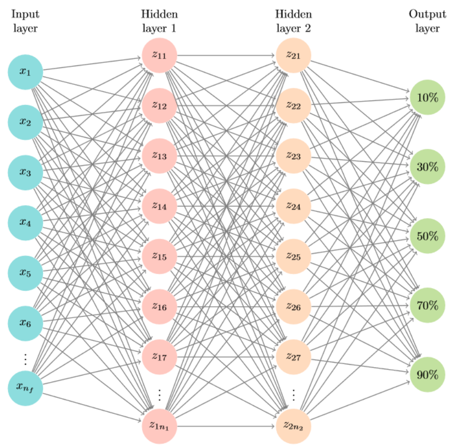


Fig. 1: A Combined Quantile Regression Deep Neural Network with n_f features, n_1 nodes in hidden layer 1, n_2 nodes in hidden layer 2 and 5 quantile output nodes of the same random variable. [8]

flood defence infrastructures or bridge safety assessment [12], [13].

BNs make use of Sklar's theorem, which states that multivariate joint distributions can be described by univariate marginal distributions and a copula that represents the dependency. Bivariate copulae, from now on simply called copulae in this paper, are joint distributions with uniform marginal distributions on $[0, 1]$

$$H(x, y) = C(F_x(x), G_y(y)), \tag{4}$$

where $H(x, y)$ is a joint distribution with marginal distributions F_x and G_y. The function $C(\cdot)$ is a, in our case Gaussian, copula taking values from $I^2 = ([0, 1] \times [0, 1])$.

The joint density of BNs with n variables is factorized as

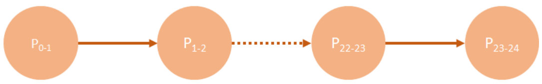
$$f_{1,\ldots,n}(x_1, \ldots, x_n) = f_1(x_1) \prod_{i=2}^{n} f_{i|Pa(i)}(x_i|x_{Pa(i)}), \tag{5}$$

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 $Pa(i) = \{i_1, \ldots, i_{p(i)}\}$. The arcs are assigned one-parameter conditional copulae [14], parameterised by Spearman's rank correlations [12]. 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 amount of variables it is conditional to). The order increases with the amount of parents that have previously been assigned a rank-correlation.

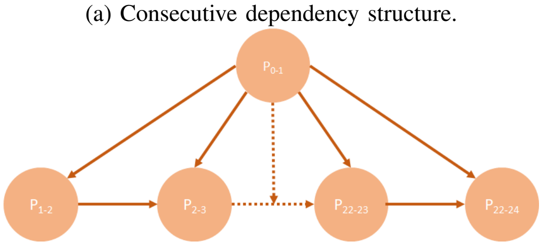
$$\begin{cases} r_{i,i_{p(i)}}, & \text{if } k = 0 \\ r_{i,i_{p(i)-k}|i_{p(i)},\ldots,i_{p(i)-k+1}}, & \text{if } 1 \le k \le p(i) - 1 \end{cases} \tag{6}$$

Generally, $k = 0$ is applied to the parent-node $i_{p(i)}$. As more parents are assigned a (conditional) rank correlation (r_{i,i_m}), k increases and the assigned rank correlation is conditional to the previously assigned parent nodes.

The open-source python package Banshee [15] was used, which applies a Gaussian copula to represent the dependencies. A Gaussian copula does not present tail dependence or other asymmetries between variables [9]. We apply the BN to define the dependency structure between hourly DAM prices based on historic data, while being able to flexibly change the marginal distributions. Therefore, it allows the application of the probabilistic forecast provided by the previously described CQR-DNN. In this paper, we assume a dependency structure where all hours are only conditional to the previous hour except for the first hour of the day as depicted in Figure 2.



(a) Consecutive dependency structure.



(b) Consecutive dependency structure with a shared dependency on the first sample.

Fig. 2: The two considered dependency structures for the Non-parametric Bayesian Network.

III. Electricity Market Data

In this section we briefly describe the data we used for this paper. We apply the CQR-DNN and the BN to generate scenarios for the Dutch DAM. The data used in the model is open-source data from the ENTSO-E transparency platform [16] exclusively. Features were made using the historic DAM prices, historic load, the day-ahead load forecast and the day-ahead renewable generation forecasts. Due to the lacking quality of actual generation data in the Netherlands, the day-ahead generation forecasts are used. The day-ahead forecasts might even contain more information on DAM prices than actual generation, due to the day-ahead market closure of the DAM. We use the model derived in [8], where an elaborate hyperparameter and feature search space was set up to optimise model performance. Market integration features are considered by adding features of the market with highest importance [17] to the search space. For the analysis performed in this paper, data from 2015-2019 was used. Data from 2019 was used to test the models. For the BN, 2018 data was used to parameterise the copulae at each node of the dependency structure.

Using Dutch 2018 DAM data, the correlation matrix as depicted in Figure 3 can be constructed. The matrix shows that hourly prices do indeed mostly correlate with the prices of the surrounding hours, justifying our choice for a consecutive dependency structure. Although there is also some correlation between the first and last hour of the day due to diurnal demand patterns, which we now do not represent in the dependency structure.

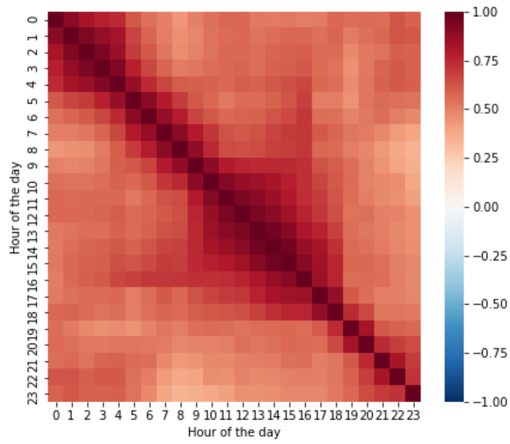


Fig. 3: Correlation matrix for the observed hourly Dutch DAM prices in 2018.

IV. Results and Discussion

In this section we show the results of applying the BN to the forecast distributions by the CQR-DNN. First, we fit parametric distributions on the forecast distributions.

The parametric distributions were fit using a least squares minimisation considering gumbel and normal distributions, where the distribution with the lowest minimisation error was selected. Figure 4 shows the fitted parametric distribution for four hourly marginal forecast distributions.

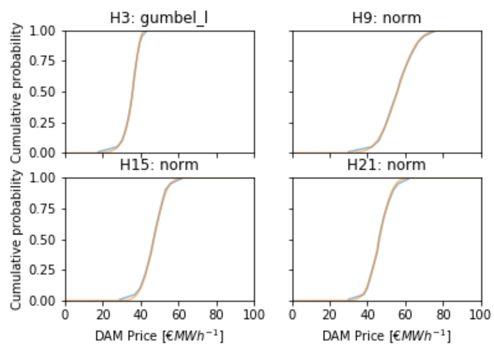


Fig. 4: Fitted parametric distributions on the hourly marginal price forecast distribution.

We can apply the fitted parametric distributions to the BNs with copulae parameterised with the observed market data from 2018. The BN now generates samples that follow both the hourly marginal forecast distributions (Figure 5) and the observed correlation in the data (Figure 6). The largest difference between the samples from the simpler consecutive BN and the data seems to be the correlation between the prices of the begin and end of the day. The second dependency structure which has a shared dependency of all hourly prices with the first does not seem to share this issue.

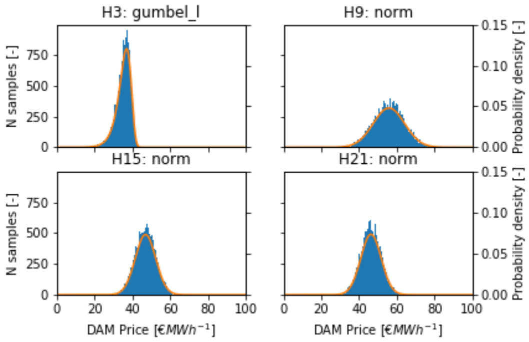


Fig. 5: Generated samples by the BN and the fitted hourly marginal price forecast distribution,

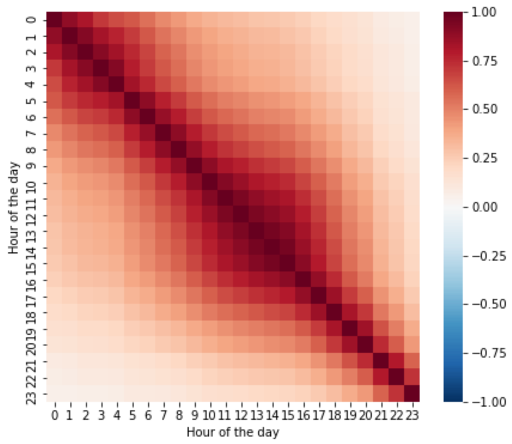
To demonstrate, Figure 7 shows the QR forecast provided by the CQR-DNN, with scenarios sampled by the BN. These scenarios can then be used in a dynamic program, optimising over electricity price scenarios.

V. Conclusions

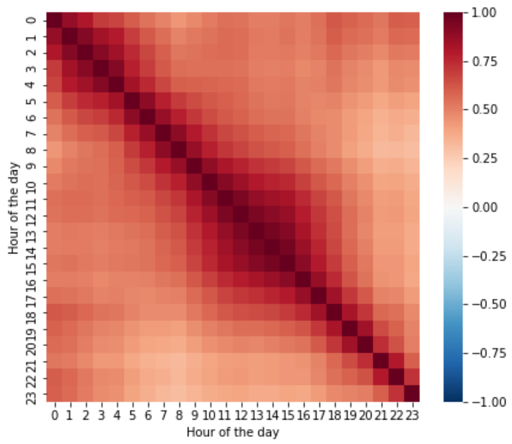
In this paper we proposed the use of a QR forecast provided by a CQR-DNN in combination with a Non-parametric Bayesian Network in order to generate DAM price scenarios to be used in a dynamic program. The CQR-DNN is applied to generate hourly marginal price forecast distributions of future DAM prices, while a BN is applied to sample from these distributions with the observed correlation in the data.

We show that the scenarios generated obey both, while the methodology is flexible and low-cost. The marginal distributions can easily be changed, while the computationally intensive part is the calculation of the rank-correlation matrix.

The structure of the BN was optimised in order to increase similarity between the correlation of the sampled and observed hourly DAM prices. In the Dutch case, connecting all nodes with the first node increased the similarity. The structure of the BN can be changed to include other markets, for example to allow for multi-market scenario sampling.



(a) Consecutive dependency structure.



(b) Consecutive structure with shared dependency on the first sample.

Fig. 6: Correlation matrices of the price samples generated by the BNs.

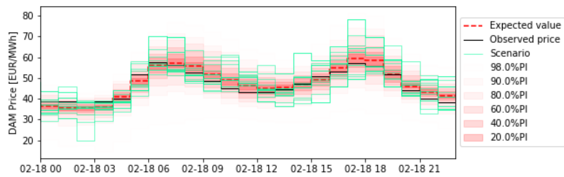


Fig. 7: QR forecast with scenarios generated by the BN.

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