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Generating Electricity Price Forecasting Scenarios to Analyze Whether Price Uncertainty Impacts Tariff Performance

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Abstract—A higher share of renewables and electric vehicles increase the risk of congestion in electricity distribution systems. New distribution tariff designs have been proposed to prevent congestion. However, most modeling of tariff performance assumes deterministic price information. This paper proposes a method to assess the impact of price uncertainty for network tariffs, using price forecasting scenarios in a simulation model. Electricity price forecasting scenarios are generated by analyzing autoregressive forecasting errors and recursively generating time-series. The scenarios are used as price forecasting inputs in a model case study of tariff performance in a Dutch context. Results show a reduction in congestion frequency and charging costs using forecasts in this model setup, likely by enabling longer time horizons. Highest peaks however are larger when using forecasts for the fixed and capacity-based tariffs. Overall, this method provides insight into performance of new tariffs in electricity grids, incorporating the impact of price uncertainty.

Index Terms—Network tariffs, distribution networks, demand response, electricity price forecasting, electric vehicles

I. INTRODUCTION

The rapid increase in electric vehicle (EV) usage, combined with the call for flexible electricity demand response (DR), has created the potential for large scale EV-charging price optimization, possibly by means of an EV-aggregator. While flexible EV-demand has a large potential of benefits for national grid-balancing, problems can arise at a regional level. Congestion can occur when too many EV's charge at the same time, reaching the limit of the local transformer capacity. This occurs more quickly with the increasing share of renewables in the energy system [1], [2]. A possible policy solution is the use of new regional tariff schemes, discouraging consumers to charge at times when demand peaks could cause congestion in the energy system. These tariff prices are added on top of the electricity prices and taxes charged to consumers. Various different new tariff schemes and components have been proposed and analysed qualitatively in scientific research [3]–[5]. Most new tariff designs consist of a combination of a volumetric charge for the consumed energy (per kWh), a capacity charge for peak power consumption (per kW), and a fixed charge independent of usage (i.e. per year) [4].

Previous studies have assessed the performance of different tariffs combined with a high share of EV's, see, e.g., [1]. However, most existing research is focused on deterministic decision making for EV-chargers, basing decisions on perfect knowledge of electricity prices. The impact of uncertainty on tariff performance is important as aggregators or charging services providers (CSP's), can use electricity price forecasts to charge more efficiently by using a longer time horizon. However, the uncertainty that comes with these forecasts could possibly affect tariff performance, increasing the amount of congestion [1].

This paper aims to analyze the impact of uncertainty on performance of different proposed tariff structures for congestion prevention. We have studied three different tariff designs: a fixed tariff of 250 euros per year, a volumetric tariff differentiating between day and night and a capacity subscription, where consumers choose a capacity bandwidth charge. Electricity price forecasting scenarios are generated by analyzing the errors of an autoregressive model trained on EPEX-NL¹ day-ahead electricity prices. These scenarios are then used as input in a model scheduling EV's by price-optimization through linear programming. This provides a case study using the proposed methodology in a relevant Dutch policy context.

The focus of this research is not the theory behind tariff design policy, but the quantitative analysis of tariff performance of a selection of proposed frameworks. Other research in the context of tariff design and EV's has been conducted with more emphasis on the social aspect and policy performance, such as [6].

II. METHODOLOGY

A. Forecast Scenario Generation

Scenarios are suitable as input for incorporating uncertainty in optimization problems as they can provide a wide range of different possible outcomes [7]. To generate forecasting scenarios corresponding to realistic behavior of electricity

¹Dutch area power exchange market owner.

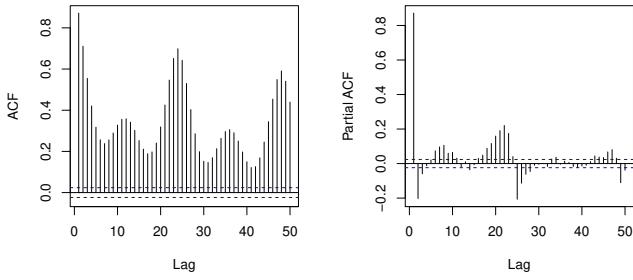


Fig. 1: Auto correlation (ACF) plot (left) and partial auto correlation (PACF) plot (right) of 2018 EPEX-NL day-ahead electricity prices.

price forecasts, forecasting error behavior is used to generate scenarios using an autoregressive model. Statistical methods like autoregressive models are used frequently for forecasting in power systems [8], [9]. A downside of this method is the limitation in adapting for the nonlinear behavior of electricity prices [8]. More advanced and extensive methods for electricity price forecasting scenarios can also be used, for scenario generation such as [10]–[12]. However, this research is not focused on specific forecasting scenario generation techniques but using scenarios in general to assess tariff performance in optimization models.

First, an AR(24) autoregressive time-series model is generated to forecast electricity prices, fitted onto day-ahead EPEX-NL electricity price data of 2018². This AR(24) model produces an estimate for the day-ahead price by looking at the previous 24 hours of electricity prices, calculating the auto correlation and partial auto correlation (figure 1).

An AR(24) time series model can be written as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \phi_3 X_{t-3} + \dots + \phi_{24} X_{t-24} + Z_t \quad (1)$$

Where $\phi_1 \dots \phi_{24}$ are the calculated coefficients and Z_t is the Gaussian innovation, sometimes also called error. In this paper, error will refer only to the difference in realized and forecasted prices.

After fitting the parameters $\phi_1 \dots \phi_{24}$ and Z_t , the model is used to predict blocks of 24 hours ahead of the day-ahead price of 2019. For Z_t , a Gaussian distribution with nonzero mean is chosen for the time series' innovation. The predicted prices are compared to the actual, realized prices and prediction errors are calculated, subtracting the realized price from the predicted price for each hour.

These errors are used to fit a new AR(24) model, describing the auto correlation of prediction errors, and shown in figure 2. This model essentially captures the way prediction errors evolve over time in relation to its own previous values. A Gaussian error with mean zero is used for the time series' innovation, as to only not bias the generated scenarios towards

²Price data retrieved from <https://transparency.entsoe.eu/>

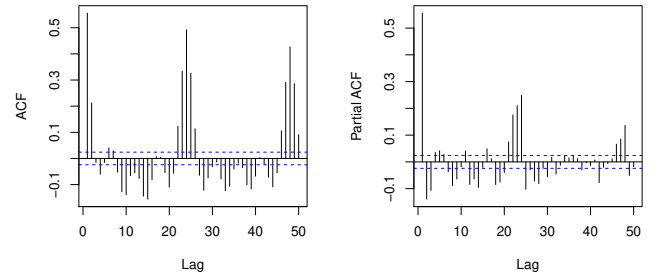


Fig. 2: Auto correlation (ACF) plot (left) and partial auto correlation (PACF) plot (right) of forecast errors of 2019 EPEX-NL day-ahead electricity prices made with the generated AR(24) model.

forecasting higher or lower prices than realized. Executing this model this took a computational time of 147.49 seconds³.

This AR(24) error model is then used to generate error scenarios in MATLAB by recursively applying the autoregressive behavior. Finally, the generated errors are added onto the actual prices of January 2020. For forecasts of n days ahead, the errors are added onto the error of $n-1$ day ahead. The forecast of a day in the future is thus used as the starting point for forecasting the same day one day further in advance. Hence, the forecasts become more accurate as the forecasted day comes closer. The combination of an autoregressive model for errors and a linear error propagation ensure the consistency of forecasting scenarios within and between days of forecasted prices. This approach is chosen as opposed to using a three day forecasting time horizon at once because of the nature of the day-ahead exchange market, where electricity is traded in blocks of 24 hours. Furthermore, an AR(24) model is less suitable for forecasting longer blocks than 24 hours at once, as the autoregressive coefficients only extend back 24 time steps. Other error propagation approaches can be chosen when using different forecasting approaches. A visual representation of scenario generation results can be seen in figure 3. Generating 50 different scenarios took 1.29 seconds, with specifications as specified above in footnote 3.

³Windows based laptop with an Intel@Core™i5-8300H CPU 2.30GHz with 8 GB RAM.

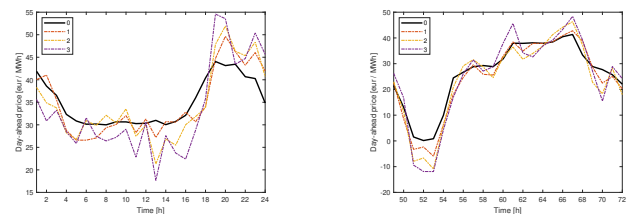


Fig. 3: Results of generated forecast scenarios for two days in the January 2020 data set (January 1 and 3). Forecasted prices are shown 1, 2 and 3 days in advance, together with the actual price (0, black).

TABLE I: Descriptive statistics of generated forecast scenarios 1-3 days in advance.

Days Ahead	MAE	MMAE	RMSE	MRMSE
1	3.11	8.9 %	3.89	11.1%
2	4.34	12.4%	5.45	15.6%
3	5.40	15.4%	6.79	19.4%

Table I provides an overview of descriptive statistics for the generated scenarios, representing the mean of all different seed values used in the case study simulation. Descriptive statistics consist of the mean absolute error (MAE), monthly mean absolute error (MMAE), root mean squared error or st. dev. of the error (RMSE), monthly root mean squared error (MRMSE, a scaled RMSE). The scaled errors are taken by dividing the absolute error by the average EPEX-NL monthly price of January 2020 (35.03 euro / MWh).

These scenarios are generated for 31 days of January 2020 (744 hours). The error size increases with each day forecasted ahead. The one-day day ahead MMAE of 8.9% is higher than values found in literature using the same methods, which are in the range of 6-7% [13], [14]. The scaled one-day ahead RMSE (standard deviation of the error) is equal to 11.1%. This is higher than the value of 8.64% found by [14] for their statistical method of exponential smoothing. The larger error values achieved in this paper resemble the more limited setup used to generate forecasts. Producing high-quality and low-error forecasts for the day-ahead electricity price is beyond the scope of this paper. However, slightly more inaccurate forecasts are not necessarily worse in the model research, as the impact of uncertainty using the forecasts will be more notable.

B. Optimization Simulation Model

The generated electricity price forecasting scenarios are used as input in an optimization model. This model simulates a neighborhood of electricity-consuming households of which a certain share uses electric vehicles. The model has been used before in previous research using deterministic prices [15]. The model works using regular household electricity demand load profiles, upon which the scheduled electric vehicle demand is added for households with an EV. These load profiles are generated using the Load Profile Generator tool, as described in [15]. The regular household load profiles are considered to be inflexible and are static input variables. Scheduled load does not affect the electricity price, effectively making the households purely price takers. Other input variables consist of the number of EV's, the number of households, transformer capacity and the used electricity prices, possibly with forecasts. The forecasts are used without assigning a value to the uncertainty. Hence, EV-chargers perceive the forecasts as entirely accurate regardless of how far into the future prices are.

Scheduled EV demand is the main variable to be calculated by the model. The sum of the EV and regular household loads result in the total load profiles, which can be used

to assess whether congestion occurred and if so, by how much. Additional statistics describing model behavior, such as average charging costs and congestion frequency can be gathered as well. Congestion occurs when more power is demanded in the neighborhood than the transformer capacity allows. No damage is dealt to the network in the model, and actors are not penalized for congestion occurring.

The EV charging pattern profiles are generated using the specifications of a Nissan Leaf BEV car with a range of 352 km, capacity of 60 kWh and a minimum required charge of 40%, as generated in [16]. With these specifications, 25 individual EV-profiles are generated. Combined with the EV assumptions, these lead to 25 driver profiles determining the consumption of electricity for EV charging demand. The driver profiles are assigned randomly to the EV owning households.

The households make their EV charging schedule according to an individual optimization strategy, using a cost-minimization function. Decision variables are the EV charging power in all 15-minute time steps in the chosen time horizon, where households can choose how much to charge. The optimization constraints are determined by the desired battery level after charging of each household, corresponding to their mobility behavior and charging patterns. Different tariff designs are implemented, which are taken into account in the cost-minimization problem.

1) *Tariff designs*: Three different tariff schemes will be used to run the optimization simulation model:

- A **fixed tariff** cost of 250 euros per year, mimicking the current Dutch tariff. This is used as a "base case" for comparing performance of new tariff designs.
- A **volumetric tariff** differentiating between a day and night tariff.
- A **capacity subscription tariff**, where households subscribe to a capacity limit according to their typical consumption. Every kW above the limit is penalized by 0.50 euro / kW.

Details of the tariff implementation can be found in table II. The tariffs are chosen to roughly result in the same cost-recovery for the DSO for the sake of comparison. All tariff designs average 2 cents per kWh for households. These three specific tariffs are chosen to represent a range of different price incentives relevant in the Dutch policy context. Other tariffs such as personal peak pricing or hourly varying time of use

TABLE II: Overview of different tariffs implemented in the simulation model.

Tariff	Fixed charge	Cap. limit	Cap. charge	Vol. charge
Fixed tariff	250	-	-	-
Vol. day / night	-	-	-	0.10 / kWh ^a 0.05 / kWh ^b
2 kW subscription	192	2 kW	0.5 / kW	-
4 kW subscription	252	4 kW	0.5 / kW	-
8 kW subscription	480	8 kW	0.5 / kW	-

^a 6:00 - 23:00

^b 23:00 - 6:00

(ToU) prices are beyond the scope of this paper. Furthermore, yearly and monthly tariff costs are assigned proportionally for the duration of the simulation.

2) *Optimization objectives*: Using a fixed tariff, the cost minimization objective can be formulated as:

$$\min_{l_{i,t}^{\text{ev}}} \sum_t p_t^{\text{DA}} \cdot l_{i,t}^{\text{ev}} \quad (2)$$

Where t indicates the time step, p_t^{DA} is the day-ahead electricity price and $l_{i,t}^{\text{ev}}$ is the to be decided hourly charging schedule of EV i .

In a volumetric tariff where the tariff cost varies over time, the objective function will be:

$$\min_{l_{i,t}^{\text{ev}}} \sum_t (p_t^{\text{DA}} + p_t^{\text{ToU}}) \cdot l_{i,t}^{\text{ev}} \quad (3)$$

With p_t^{ToU} being the added tariff penalty cost dependent on the time of day (*Time of Use*).

For a capacity subscription tariff, this yields:

$$\min_{l_{i,t}^{\text{ev}}} \sum_t p_t^{\text{DA}} \cdot l_{i,t}^{\text{ev}} + p^{\text{penalty}} \cdot \theta(l_{h,t}^{\text{excess}}) \cdot l_{h,t}^{\text{excess}} \quad (4)$$

Where

$$l_{h,t}^{\text{excess}} := l_{h,t}^0 + l_{h,t}^{\text{ev}} - c_h^{\text{sub}} \quad (5)$$

is the load exceeding the subscribed capacity and $\theta(x)$ is the Heaviside theta function that is 0 when $x \leq 0$ and 1 when $x > 0$. The variable $l_{h,t}^0$ indicates the household load, $l_{h,t}^{\text{ev}}$ the EV load per household and c_h^{sub} the subscription capacity. Here, p^{penalty} is the penalty of exceeding the subscription and not dependent on time.

3) *Optimization constraints*: The charging rate of an EV is bound by the maximum capacity of the charger, \bar{l}_i^{ev} . The sum of EV charging and inflexible household load are also bound the connection limit, \bar{l}^{hh} :

$$l_{i,t}^{\text{ev}} \leq \min(\bar{l}_i^{\text{ev}}, \bar{l}^{\text{hh}} - l_{h,t}^0) \quad (6)$$

The charge of the EV battery is bound by the size of the battery:

$$\underline{q}_i \leq q_{i,t} \leq \bar{q}_i \quad (7)$$

Where $q_{i,t}$ is the charge of EV i at time t , $\underline{q}_i = 0$ is the minimum charge and \bar{q}_i the maximum.

The battery charge of an EV is updated based on how much was charged in the previous period. Charges are initialized at the starting charge:

$$q_{i,t} := \begin{cases} q_i^{\text{start}}, & \text{if } t = 0 \\ q_{i,t-1} + \eta_i^{\text{eff}} \cdot l_{t-1,t}^{\text{ev}} \cdot \Delta t_{\text{step}}, & \text{otherwise} \end{cases} \quad (8)$$

With q_i^{start} being the charge at the beginning of the simulation, η_i^{eff} the charging efficiency and Δt_{step} the simulation time step.

EVs can only charge while they're at home at the household:

$$l_{i,t}^{\text{ev}} = 0, \text{ if } t \in [t_i^{\text{dep}}, t_i^{\text{arr}}] \quad (9)$$

Where t_i^{dep} and t_i^{arr} are the departure and arrival times of EV i .

The EV should be charged to the desired charge by the planned departure time:

$$q_{i,t_i^{\text{dep}}} \geq q_i^{\text{target}} \quad (10)$$

Where $q_{i,t_i^{\text{dep}}}$ is the departure charge and q_i^{target} the target charge.

III. MODEL CASE STUDY

A. Setup and Scenarios

The simulation model is used in a case study to analyze the tariff performance in a Dutch policy context. Model settings and tariff designs are as stated in section II-B. For further model configurations, a time span of 17 days is chosen, starting January 1 2020 and ending January 17. Time steps of a quarter are used to schedule demand, resulting in 1536 time steps. The neighborhood consists of 50 households, of which 25 have EV's. Connection limits of households are set to 17.3 kW, and the transformer capacity to 75 kW.

For each of the three tariff designs, three different price knowledge scenarios are used:

- 1) No forecasts, using 1 day of known prices.
- 2) Forecasts, using a time horizon of 4 days, where the first day is known.
- 3) No forecasts, using a perfect-knowledge 4 day time horizon.

This results in 9 different scenarios. Each scenario is ran 50 times, varying the seed for random EV behavior assignment to households and for forecasting scenarios. Three different output variables of the model will be assessed:

- 1) *Timesteps overloaded* (-), describing the number of timesteps the demand is higher than the transformer capacity.
- 2) *Max. overload percentage (%)*, the highest peak relative to the transformer capacity.
- 3) *Average charging costs (eur / kWh)*, the average cost of charging an EV one kWh.

B. Results

Figure 4, 5 and 6 show a graphical view of the results. Running all 450 scenario runs took 4928 seconds, with specifications as described above in footnote 3.

Congestion frequency, described by the average number of timesteps overloaded, is highest in the one-day, no forecasts scenario and decreases sharply when a four-day time horizon is used. The difference between using perfect prices and forecasts however is smaller. For all tariff designs, using forecasts decreases the congestion frequency by about 22%, and using four days of perfect prices decreases the congestion frequency by about 25% compared to the one-day time horizon.

The maximum overload percentage varies more per chosen tariff design. Overload percentages of over 500% are of course unrealistic, but chosen for comparison sake of leaving other input variables equal in all scenario's. In the less restrictive fixed and volumetric tariffs, the highest peaks are highest when four days of perfect prices are used. Using forecasts

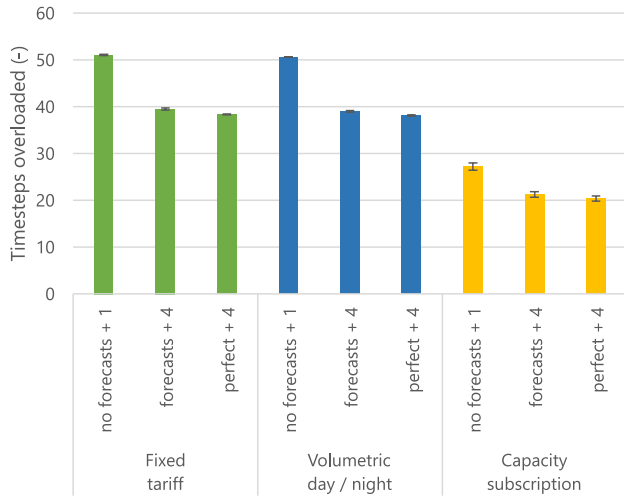


Fig. 4: Model results: average number of timesteps overloaded.

tends to produce lower peaks than using perfect prices for a four day time horizon. However, forecasts perform slightly better in the volumetric day and night tariff compared to the fixed tariff. The capacity subscription tariff in contrast shows higher peaks when forecasts are used. However, the difference is small compared to the one day scenario (2%).

Finally, the average charging costs can be seen as a reflection of the “restrictiveness” of the tariffs. Charging costs show a very similar behavior to congestion frequency in response to changing the price knowledge. Costs decrease when a longer time horizon is used. Using forecasts yields a decrease of about 15% for the fixed and volumetric tariff, and of 9% for the capacity subscriptions. Using perfect price information slightly lowers the prices even further, with a decrease of

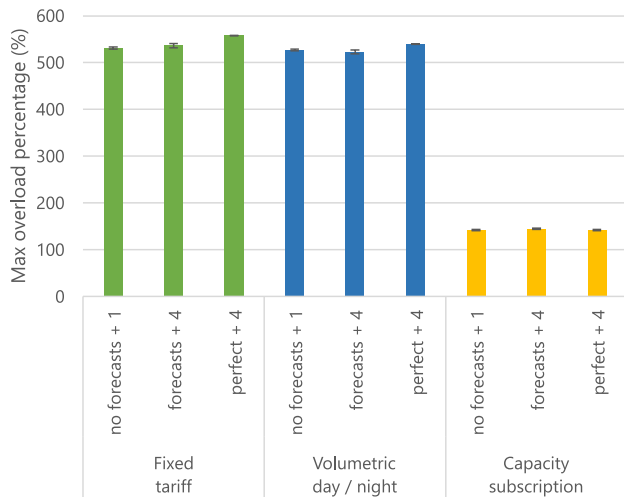


Fig. 5: Model results: maximum overload percentage.

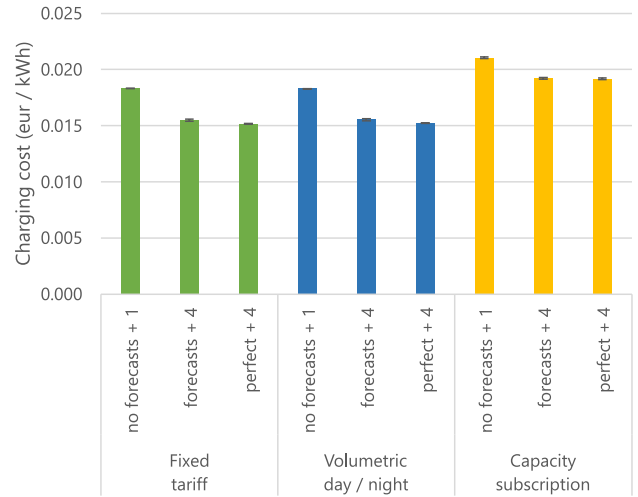


Fig. 6: Model results: average charging costs.

about 17% compared to the one-day scenario for the fixed and volumetric tariff. The capacity subscriptions however respond less to using perfect price knowledge, providing a little bit less charging cost but rounded still 9%.

IV. DISCUSSION

As noted above, the used price forecasting scenarios contain more uncertainty than most real world forecasts would. This could be reduced by choosing other forecasting methods or by scaling error values. As such, an advantage of the used scenario-based approach is the flexibility to use different forecasting methods. Another advantage is the clear interpretation of uncertainty scenarios provide. Furthermore, combined with different random seeds and runs, a broad range of forecasts can be quickly assessed by the model.

Looking at the results of the model case study, a relatively small effect of the added uncertainty can be observed. The used time horizon is a more important factor for tariff performance. This raises the question whether this small effect holds in real world-scenarios, other model research and proposed new tariffs not considered in this research.

The method of generating forecasting price scenarios contain some limitations and directions for further research. First, forecasting scenarios used in this research may not be representative enough of real-world forecasts, as a simple linearly propagated autoregressive prediction model is less suited for forecasting the nonlinear behavior of electricity prices. Second, the absence of extreme events in forecasting can also result in a smaller impact of uncertainty than real-world forecasts would have. Finally, a more extensive research of error propagation of electricity price forecasts could make the rolling time horizon scenario behavior more realistic.

In the optimization model, some points of discussion arise. EV-chargers now attach no value to the uncertainty of the forecasts in this model. This could result in a tendency to

only focus on lower prices, even if they could be perceived as more uncertain by being further in the future. A possible improvement would be to incorporate stochastic optimization techniques. In terms of tariff design, further model calibration could be carried out to have more realistic maximum overload percentages and congestion occurrence for the less restrictive fixed and volumetric tariff. However, it seems unlikely this would drastically change overall model behavior. Furthermore, the absence of additional taxes levied and the assumption of fully price-minimizing rational chargers enlarges the differences in price information scenarios. Moreover, there are more signals and incentives impacting charging behavior and tariff performance than the price signals modeled by uncertainty and the optimization model. Other tariff policy objectives are not assessed in this paper as they are beyond the scope of this research.

Finally, EV-chargers make no assessment of the chance of congestion occurring in the model, and there is no real consequence of congestion when it occurs in the system.

V. CONCLUSIONS

This paper provides an application of electricity price forecasting scenario generation to assess the impact of price uncertainty for network tariffs on a distribution grid level. Electricity price forecasting scenarios are generated using an autoregressive time-series approach, and used as price inputs in an optimization model providing a case study of network tariff performance in a neighborhood with a large share of electric vehicles.

Looking at scenario generation, the main results can be summarized as follows:

- Methodologically, this paper presents a new way to assess tariff performance under more realistic non-deterministic real world behavior. This provides a way to add uncertainty for analyzing the robustness of different tariff designs and policy measures, especially when considering multiple individual actors trying to optimize over uncertain information.

The main insights of the application of scenarios in the model case study can be described as follows:

- In this particular case study, the used time horizon (1 or 4 days) is more relevant than whether forecasts or perfect knowledge of prices is used in for impact on the congestion frequency and charging costs. The advantage of using forecasts in the model appears to lie in their potential to extend the time horizon for price optimization, even if they are not perfectly accurate.
- Of the three chosen tariff designs implemented in the model, charging costs respond less sharply to changes in price information when the more restrictive capacity subscriptions are used. This can likely be explained by the capacity tariffs already limiting charging at the hours where prices are cheapest. Congestion peaks and frequency show the same relative changes, regardless of tariff design. Thus, for the chosen tariffs in this case

study, the tariff performance does not depend critically on whether uncertainty is included in the model or not.

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