Medium-term forecasting of active power curtailment from MV/LV transformer loadings with an increasing capacity of PV panels

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***Abstract*—Driven by the energy transition, the electricity generated by photovoltaic panels connected by customers behind-the-meter is annually increasing. This is expected to lead to congestion of medium to low voltage (MV/LV) transformers because the related capacity is unable to be reinforced fast enough to accommodate all these PV panels. Based on medium-term load forecasts of an MV/LV transformer with an annual increasing capacity of installed PV panels behind-the-meter, active power curtailment (APC) necessary to prevent congestion and related compensation costs to owners of these PV panels is forecasted. First, a month-ahead load forecast of the studied MV/LV transformer with an annual increasing capacity of installed PV panels behind-the-meter is performed multiple times based on weather conditions measured during the same month but in previous years. Second, each of these month-ahead load forecasts is used to forecast the related APC and compensation costs. Subsequently, the distribution in forecasted APC and compensation costs due to annual variation of weather conditions over a month is analyzed. In addition, APC duration curves are calculated for all these forecasts to analyze the distribution of the amount and duration of alternative solutions, such as demand-side management to reduce necessary APC and the local mismatch between supply and demand.**

***Index Terms*—active power curtailment, behind-the-meter PV generation, medium-term, net load forecasting, supervised machine learning**

I. Introduction

Driven by the energy transition to reduce the number of carbon emissions, the share of electricity generated by renewable energy sources (RES) is increasing. The introduction of RES has changed the traditional top-down oriented way of operating, where generators are connected to transmission networks and delivered to customers through distribution networks. The electricity generation can be controlled to balance supply and demand. However, due to the intermittent properties of many RES, such as photovoltaic (PV) panels, electricity generation can not be controlled. Additionally, many PV panels are connected to distribution networks unlike traditional generators typically connected to transmission networks. Consequently, this may lead to congestion and voltage violations in distribution networks when electricity generated by solar PV exceeds demand [1]. Active power curtailment (APC) of PV panels during periods of peak generation is widely studied to prevent these issues, which is increasingly applied in practice in different countries already [2].

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Many real-time applications of APC to prevent voltage violations in distribution networks have been proposed, as extensively reviewed in [3], [4]. In addition, [2], [5] also describe studies that aim to apply APC for congestion management. However, APC is usually considered to be a loss given that PV panels are not generating electricity at their full potential, which is therefore aimed to be minimized [2]. Many studies have also proposed mechanisms to fairly compensate owners of PV panels being curtailed, see for example [6], [7]. However, proposed methodologies so far are unable to forecast APC in advance and only load profiles including the application of APC are known afterward. References [8], [9] propose new methodologies to overcome this issue. Both methodologies enable the estimation of electricity that would have been generated without APC afterward. Based on the difference between measured load profiles with APC and the estimated load profile which would have been without APC, the APC is estimated to compensate owners of PV panels.

Being limited to estimating APC afterward has several disadvantages. First of all, responsible distribution system operators (DSOs) are unable to indicate expected costs due to the application of APC beforehand. As a consequence, applicability for network planning is limited and comparing the costs and benefits of APC with other solutions aiming to prevent related network congestion or voltage violations is not possible. Secondly, being able to evaluate APC to prevent congestion beforehand enables studying alternative solutions, such as demand-side management (DSM) to reduce necessary APC. To reflect on APC beforehand, the current development of the advanced metering infrastructure enables DSOs to measure loads of assets in distribution networks, such as medium to low voltage (MV/LV) transformers and low-voltage (LV) feeders. Together with the development of machine learning (ML), these measured load profiles can be used to forecast the need for APC to prevent congestion of assets in distribution networks due to the annually increasing capacity of installed PV panels behind-the-meter (BTM). As discussed in [10], most studies focus on short-term or long-term forecasting. Short-term forecasts up to a week ahead are too short to reflect on the impact of increasing installed PV capacity. Long-term forecasts up to many years ahead are generally focused on the impact on a specific day with peak generation without reflecting on the varying impact due to seasonal differences. Therefore, [10] proposed a medium-term forecasting (MTF) methodology to study this varying impact of an increasing installed PV capacity due to seasonal differences. However, PV panels are typically installed by end-customers on rooftops BTM. As a consequence, only net loads of MV/LV transformers are measured, which is the sum of all load profiles and generated electricity by connected PV panels BTM. Therefore, [10] described a methodology to improve the MTF of an MV/LV transformer loading when the capacity of PV panels installed BTM is rapidly increasing without having to disaggregate the net load into load and generation profiles first. However, it does not consider the forecast of APC and related compensation costs to owners of these PV panels based on this MTF of the MV/LV transformer loading.

This study applies a month-ahead MTF of APC necessary to prevent congestion of an MV/LV transformer due to an increasing capacity of PV panels based on the MTF of an MV/LV transformer loading proposed in [10]. The main contributions of the proposed methodology are

- to forecast the total amount of APC and related compensation costs a month-ahead to prevent congestion of an MV/LV transformer caused by an increasing capacity of installed PV panels BTM
- to forecast the amount and duration of required APC a month-ahead
- to enable evaluation of the impact of annually varying weather conditions on the distribution of the forecast of APC using historical weather data

II. Methodology

This paper proposes a two-step approach to forecast the APC a month-ahead aiming to prevent congestion of MV/LV transformers due to an annual increasing capacity of installed PV panels BTM. An overview of the proposed methodology is shown in Fig. 1. The first step performs an MTF of the net load of an MV/LV transformer using a supervised machine learning model. The second step applies the MTF of the net load to forecast congestion and related APC. Based on the APC forecasts, related compensation costs for owners of BTM PV panels connected to the MV/LV transformer are estimated assuming that they receive equal compensation for every kWh of electricity being curtailed which they otherwise would have received through feed-in tariffs.

A. Load Profile Generator

To perform the proposed methodology described in Fig. 1, first the net load of the studied MV/LV transformer is synthesized for a residential neighborhood. Individual load profiles of households $L_h(t)$ are first synthesized using the load profile generator. Load profile generator is a modeling tool, which enables the generation of household load profiles for customers with different types of load profiles [11].

B. Solar PV Generation

To calculate the net load profile N_h [kW] of a household with installed PV panels BTM, the synthesized load profile of a household $L_h(t)$ is summed with a synthesized generation $G_{PV,h}(t)$ [kW] profile according to:

$$N_h(t) = L_h(t) + G_{PV,h}(t). \tag{1}$$

These generation profiles of PV panels are synthesized as described in Ref. [10] using local measured temperature [°C] and irradiation [W/m^2] [12]. To represent the increasing capacity of installed PV panels BTM, these synthesized generation profiles are not summed with load profiles of all households simultaneously, but every year, the number of households to which generation profiles are added increases. Thereby, a varying installed capacity of PV panels per household is applied between 5.5 kWp and 6.7 kWp in steps of 0.3 kWp. Finally, synthesized net load profiles of all households H are summed to synthesize the net load of the MV/LV transformer $T_{net}(t)$ [kW] at each timestep t according to:

$$T_{net}(t) = \sum_{h=1}^{H} N_h(t). \tag{2}$$

C. Medium-term Forecast

Once the net load of the MV/LV transformer is synthesized as described in sections II-B and II-C, the net load of the MV/LV transformer is decomposed into daily $T_d(t)$, weekly $T_w(t)$ and yearly $T_y(t)$ stationary time series and one residual non-stationary time series $T_r(t)$ according to:

$$T_{net}(t) = T_d(t) + T_w(t) + T_y(t) + T_r(t). \tag{3}$$

All these decomposed time series are first separately forecasted a month-ahead. Subsequently, the net load of the MV/LV transformer is forecasted a month-ahead by summation of all stationary and non-stationary time series [10], [13].

To accurately forecast the net load of the studied MV/LV transformer $T_{\mathrm{net}}(t)$, [10] showed that the forecasting algorithm of the non-stationary time series $T_r(t)$ does not require the exact generation profiles of all connected PV panels BTM. Important is an estimation of generation profiles using the installed capacity of PV panels BTM. In addition, the proposed forecasting algorithm requires the same category of weather-related features, which are temperature, global irradiation, sunshine, and rain duration. However, these features are unknown a month-ahead as well. Therefore, the forecasting algorithm applies historical weather data measured during the same period of the forecast as shown in Fig. 1.

D. Active Power Curtailment Forecast

Based on the net load forecast $T_{net}(t)'$, the congestion $C(t)$ [kW] of the MV/LV transformer is calculated according to:

$$C(t) = T_{net}(t)' - Cap_T, \tag{4}$$

in case when:

$$T_{net}(t)' > Cap_T, \tag{5}$$

where Cap_T [kW] is the capacity limit of the studied MV/LV transformer.

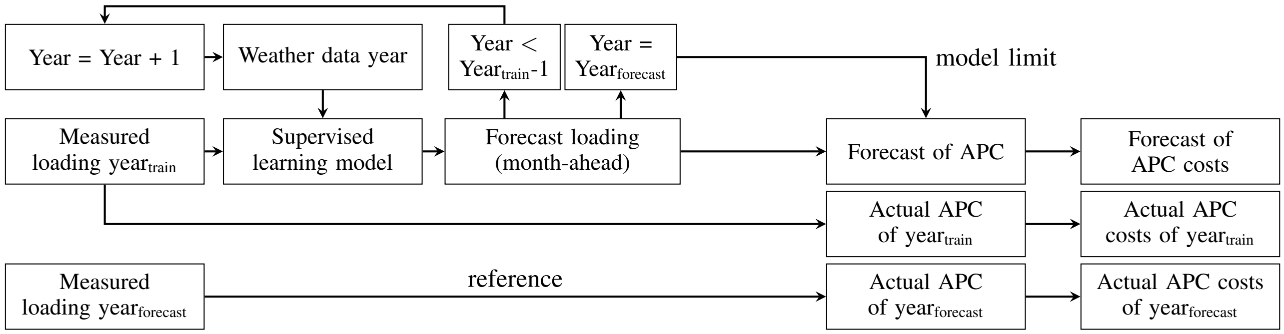

Fig. 1: Proposed methodology to forecast the APC and its related costs.

The amount of APC $A(t)$ $[kW]$ to avoid congestion of an MV/LV transformer is equal to $C(t)$. In addition, the relative APC $A_{rel}(t)$ $[\%]$ is calculated to enable efficient comparison between MV/LV transformers with different capacities using:

$$A_{rel}(t) = \frac{A(t)}{Cap_T} \cdot 100. \tag{6}$$

Based on the net load exceeding the transformer capacity, it is calculated how much electrical energy must be curtailed E_{curt} $[kWh]$ during each forecasting period to avoid congestion according to:

$$E_{curt} = \sum_{i=1}^{I} A(t) \cdot T, \tag{7}$$

where I represents the total number of time intervals t within each forecasting period and T $[min.]$ represents the duration of each individual time interval t. Finally, the curtailed amount of electrical energy, E_{curt} is used to estimate the related compensation costs c [€] during each forecasting period according to:

$$c = E_{curt} \cdot \alpha, \tag{8}$$

where α [€/kWh] is average unit-price per kWh of electrical energy during the period of forecast.

E. Error evaluation

First of all, the limit of the forecasting algorithm is calculated if the actual weather data of 2020 are applied using the normalized root mean squared error ($NRMSE$) according to:

$$NRMSE\ [\%] = \frac{\sqrt{\frac{1}{T}\sum_{i=1}^{T}(T_{net}(t)' - T_{net}(t))^2}}{T_{max} - T_{min}}, \tag{9}$$

where T_{max} and T_{min} represent maximum -and minimum values of the synthesized net load during the period of forecast [14]. However, analyzing results if historical weather data are applied using commonly applied point-wise error metrics, such as the $NRMSE$ may reflect upon the accuracy of MTFs incorrectly. Point-wise error metrics only take into account the difference between the forecast value and actual value at the same time step to determine the error. Due to annual variation of weather, the forecast algorithm may forecast the size and duration of generation peaks of the profile given the applied historical weather data accurate, but the timing on days during the forecasting period may be different. As a consequence, point-wise error metrics penalize the accuracy of the forecast twice. Therefore, an MTF using historical weather data which forecasts the size and duration of generation peaks of a profile consistently too low may result in a lower forecast error using point-wise error metrics compared with an MTF that is able to forecast the size and duration of generation peaks of the profile better, but on different days during the forecast period [15]. Therefore, a boxplot for each month is used to calculate the distribution of the total forecasted amount of curtailed energy E_{curt} and related compensation costs c compared with the actual calculated curtailed energy E_{curt} and compensation costs c using equations (6) and (7). Next to the forecast of the total amount of APC and related compensation costs, duration curves are calculated for $A(t)$ and $A_{rel}(t)$ to gain insight into the distribution of amount and duration of APC. These APC duration curves are calculated by sorting all forecasts of $A(t)$ and $A_{rel}(t)$ from chronological order into descending order.

III. IMPLEMENTATION AND VALIDATION OF THE PROPOSED MODEL

The implemented forecasting algorithm is described in detail in [10]. The supervised learning model based on an extreme gradient boosting algorithm is used to forecast the non-stationary time series, while an autoregression model is used to forecast the stationary time series with a training set of two years and a forecast period of a month.

A. Load Profile Generator

For this study, load profiles of twenty households are synthesized from 01-03-2018 until 31-08-2020 with a 15-minute time resolution using load profile generator. Load profiles from five different groups of households are synthesized to represent a variety of different end-customers. From each group of households, four load profiles are randomly generated. The first group represents a household with two children and one parent working, the second group a household with two children and both parents working, the third group a household with a couple without children, the fourth group a household with one single adult, and the last group a household with a retired couple [11].

B. Solar PV Generation

The generation profile of each household is synthesized with the measured temperature [$°C$] and irradiation [W/m^2] at the weather station located in Arcen, the Netherlands from 01-01-2018 until 31-08-2020 [12]. To avoid that all households are synthesized with exactly the same generation profile, the constant temperature parameter is varied in a range from [0.023, 0.038] together with the installed capacity as explained in section II-C [16].

C. Medium-term Forecast

To forecast the non-stationary time series $T_r(t)$, the forecasting algorithm applied the measured temperature [$°C$], global irradiation [W/m^2], sunshine [*min./hour*] and rain duration [*min./hour*] from 01-01-2018 until one day before the month to forecast starts. Typically, weather data measured at a station nearby is strongly correlated with unknown local weather conditions on the location of the studied MV/LV transformer, but it does not match exactly. Therefore, generation profiles applied as features for the forecasting algorithm are synthesized with the measured temperature [$°C$] and global irradiation [W/m^2] at another weather station nearby located in Volkel, the Netherlands [12]. The PV generation is estimated using the same calculations as described in section II - C. The weather-related and PV-related features used by the forecasting algorithm are historical weather data from 2008 until 2017 during the same period of the forecast, assuming actual weather data a month-ahead is unknown at the moment of forecasting. Additionally, analyzing the impact of annual varying weather conditions over the period to forecast provides more insight into possible variations in generation peaks. For each month-ahead forecast, the maximum and minimum amount of estimated PV generation that occurred before 2008 is applied to the forecast as well. The forecasting algorithm also forecasts $T_r(t)$ with the actual weather-related features from 2020 to indicate the limit of the forecast. Altogether, each month from March until August is forecasted 13 times using different measured weather data.

D. Active Power Curtailment

Based on the 13 forecasts for each month from March until August, the values of $A(t)$ and E_{curt} are calculated using equations (4)-(6). The capacity Cap_T of the studied MV/LV transformer is 55 kW. To calculate related compensation costs c, the average price-unit α is estimated at 0.22 *€/kWh* for this study, based on the average price of electrical energy per kWh from March until August from 2018 until 2020 for end-customers in the Netherlands [17].

E. Error evaluation

After all the forecasts are performed, the related NRMSE is calculated using (9) in the case when the forecast is carried out with the actual weather data of 2020. For the forecasts based on the historical weather data, the described boxplots and duration curves as described in section II.E are calculated for each month from March until August.

TABLE I: Calculated NRMSE for each month-ahead net load forecast from March until August 2020.

Month	NRMSE [%]
March	4.56
April	4.07
May	4.49
Jun	4.68
Jul	4.70
Aug	5.20

IV. Results and Discussion

A. Medium-term Forecast

The synthesized net load of the MV/LV transformer, the month-ahead net load forecast, curtailed net load forecast and the capacity limit are shown in Fig. 2. The synthesized net load used as the training set is shown in Fig. 2.A. The synthesized net load, the month-ahead net load forecast, the curtailed net load forecast, and the capacity limit of the MV/LV transformer during the subsequent period are shown in Fig. 2.B. The synthesized net load in Fig. 2 clearly indicates the expected seasonal pattern of electricity generation by PV panels, which is annually increasing due to the increasing installed capacity of PV panels BTM. Relatively small generation peaks causing congestion appear in 2019 from April until August, while significantly larger generation peaks causing congestion appear from March until September in 2020. The results shown in Fig. 2.C and 2.D show the same profiles, but for the months of March and June specifically. The shown results in Fig. 2 applied the actual weather conditions of 2020 as features to the forecasting algorithm. Fig. 2.C and 2.D also show that the forecast follows the size and duration of generation peaks rather accurately. However, the forecasting algorithm tends to underestimate the size of daily generation peaks, especially during March and April when the average electricity generation is increasing. Thereby, it has difficulty to forecast irregularly occurring large generation peaks, because there are also fewer similar generation peaks in the training set. Using (9), the $NRMSE$ of each month-ahead net load forecast is shown in Table I, which varies from 4.07 % until 5.2 %.

B. Active Power Curtailment

Fig. 3 shows a boxplot of the total amount of forecasted APC and related compensation costs per month from March until August if historical weather data are used as features to forecast the net load. It also shows the total amount of APC and related costs per month based on the synthesized net load and the forecast in the case when the measured weather data of 2020 are used. To indicate the impact of increasing capacity of installed PV panels BTM, Fig. 3 also shows the total amount of APC and related compensation costs based on the synthesized net load of 2018 and 2019. Fig. 3 clearly indicates the large error if APC is estimated based on the net load of previous years and the increase of installed PV panels BTM is neglected. The boxplots in Fig. 3 also indicate the distribution of APC and related compensation costs per month due to the impact of annual variation in weather conditions. However, the actual amount of APC and compensation costs

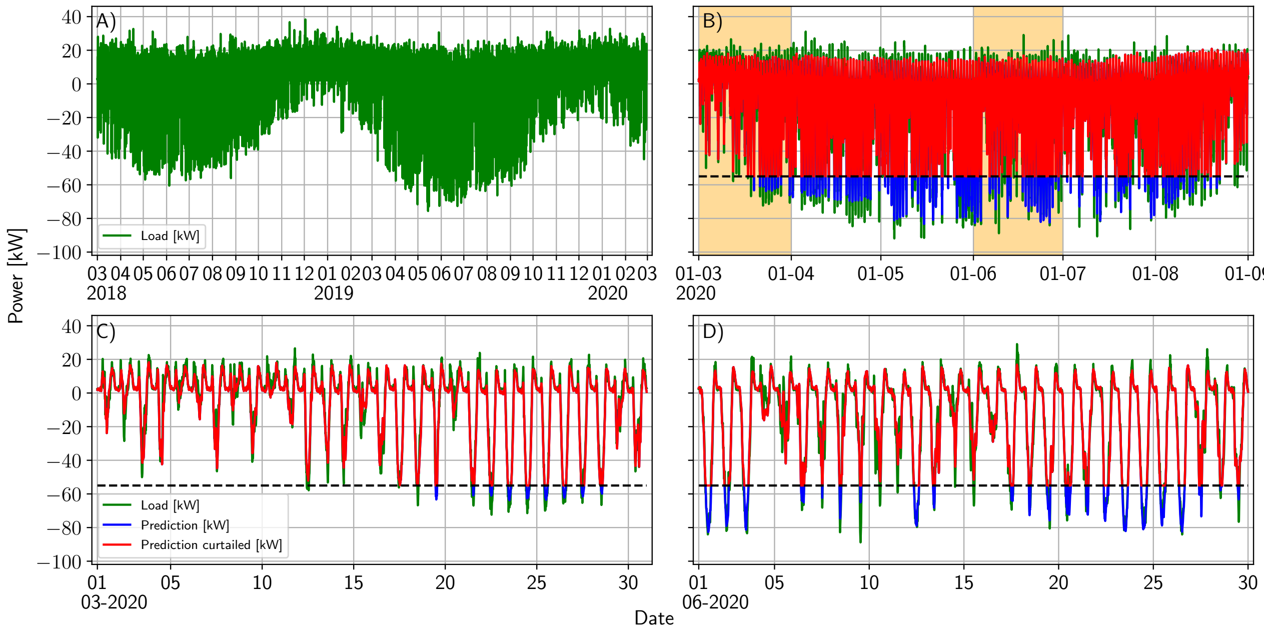

Fig. 2: Subfigure A shows the synthesized net load of the studied MV/LV transformer loading from 01-03-2018 until 28-02-2020 (green), subfigure B shows the synthesized net load (green), month-ahead net load forecast (blue), curtailed net load forecast (red) and the capacity limit (black). Subfigures C and D show the same profiles for the month of March and June specifically.

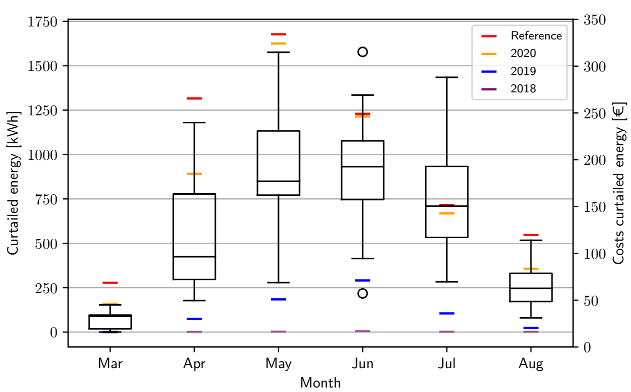

Fig. 3: Total forecasted APC per month using historical weather data (boxplot) and the measured weather data from 2020 (orange). The actual APC based on the synthesized MV/LV transformer loading in 2018 (purple), 2019 (blue) and 2020 (red/reference) are also shown.

does not fit within the boxplot every month. This supports the observation of Fig. 2 that the forecasting algorithm tends to underestimate generation peaks, especially during the period when the average electricity generation is increasing and if less frequently occurring large generation peaks are observed.

Based on all forecasts of the MV/LV transformer loading, APC duration curves for each month from March until August are calculated. Fig. 4 shows the APC duration curve of the synthesized net load, the APC duration curve of the forecasted net load using the actual weather of 2020 and the distribution interval of all duration curves based on the forecasted net loads using historical weather data. The distribution interval is calculated using the minimum and maximum values at each duration, which is caused by the annual variation in weather conditions. Although Fig. 4 provides no direct insight into the exact timing of required APC, APC duration curves support analysis to study the amount and duration of DSM to reduce the necessary application of APC.

The similarity between the forecast using the actual weather conditions of 2020 and the synthesized net load reflects the limit of the forecasting algorithm, which is the highest for June and July. The forecasts for other months appear to be consistently lower, which is expected based on the results of Fig. 2. For April and May, the difference is rather small for duration >50 hours, but the difference starts to increase at shorter durations. However, the latter can be expected which is also observed for all other months, although less significant. If the duration decreases, the change that related peak generations occur also decreases. As a consequence, the change that a similar peak generation occurred in the training set is lower and the forecasting algorithm has fewer data available to train and predict such large generation peaks. Generally, the steeper the slope gets for shorter durations, the harder it becomes to accurately forecast.

Fig. 4 also indicates that the actual synthesized net load does not fit within the distribution interval for all months. On the one hand, this can be due to the tendency of the forecasting algorithm to underestimate generation peaks. On the other hand, monthly weather conditions are correlated with previous years, but it is not limited to these weather conditions. Thus, weather conditions from March until May may have enabled a higher amount of electricity generation in 2020 compared with previous years.

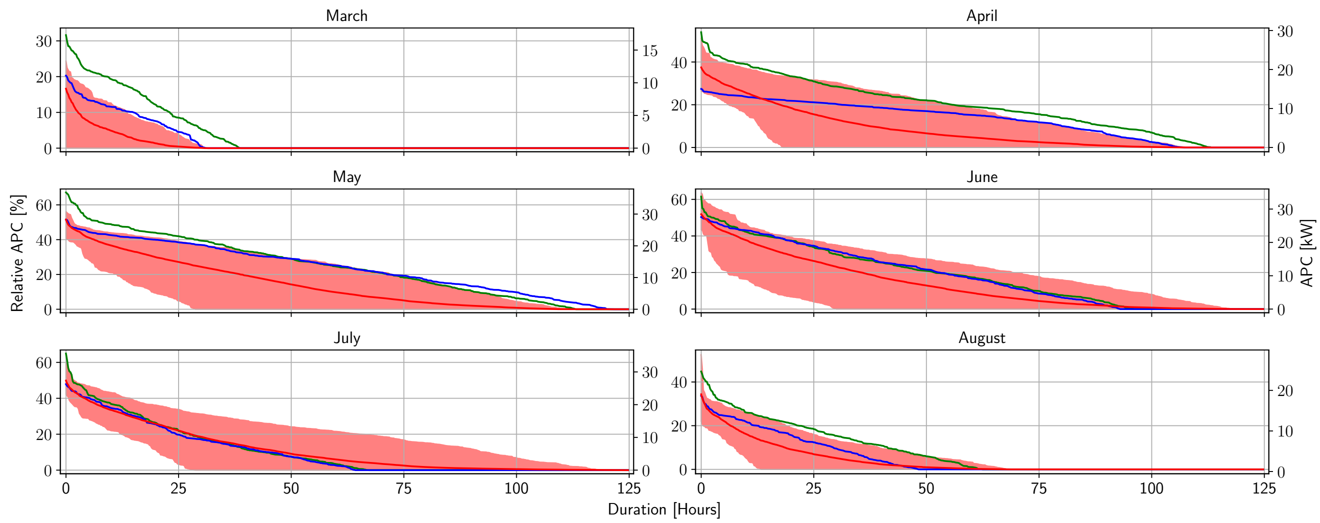

Fig. 4: Monthly APC duration curves of the actual synthesized net load (green), predicted net load using actual weather data of 2020 (blue) and historical weather data (red).

V. Conclusion

A methodology has been proposed to forecast APC and compensation costs to prevent congestion of an MV/LV transformer caused by an increasing capacity of PV panels installed BTM. Thereby, the impact of annual variation in weather conditions on APC and compensation costs is included.

First, a supervised machine learning model was used to forecast the net load of an MV/LV transformer. The limit of this forecasting model indicated the accuracy given actual weather conditions. Then, historical weather data during the same period from previous years was used to analyze the distribution of the sum of APC and related compensation costs due to annual variation of weather conditions. Finally, APC duration curves were calculated to analyze the distribution of amount and duration of APC. These results can be applied to analyze the amount and duration of DSM to reduce necessary APC and the local mismatch between supply and demand.

References

[1] R. Bernards, J. Morren, and H. Slootweg, "Statistical modelling of load profiles incorporating correlations using copula," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Torino, Italy, 2017, pp. 1–6. [Online]. Available: https://doi.org/10.1109/ISGTEurope.2017.8260181

[2] E. O'Shaughnessy, J. R. Cruce, and K. Xu, "Too much of a good thing? Global trends in the curtailment of solar PV," *Solar Energy*, vol. 208, no. September, pp. 1068–1077, 2020. [Online]. Available: https://doi.org/10.1016/j.solener.2020.08.075

[3] N. Mansouri, A. Lashab, J. M. Guerrero, and A. Cherif, "Photovoltaic power plants in electrical distribution networks: A review on their impact and solutions," *IET Renewable Power Generation*, vol. 14, no. 12, pp. 2114–2125, 2020. [Online]. Available: https://doi.org/10.1049/iet-rpg.2019.1172

[4] S. Paudyal, B. P. Bhattarai, R. Tonkoski, S. Dahal, and O. Ceylan, "Comparative Study of Active Power Curtailment Methods of PVs for Preventing Overvoltage on Distribution Feeders," in *IEEE Power and Energy Society General Meeting*, Portland, USA, 2018. [Online]. Available: https://doi.org/10.1109/PESGM.2018.8585526

[5] A. T. Procopiou and L. F. Ochoa, "Asset congestion and voltage management in large-scale MV-LV networks with solar PV," *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 4018–4027, 2021. [Online]. Available: https://doi.org/10.1109/TPWRS.2021.3067838

[6] A. Tomar, A. N. Haque, and P. Nguyen, "Compensation mechanism for active power curtailment in LV distribution networks," in *IEEE PES Innovative Smart Grid Technologies Conference Europe*, The Hague, Netherlands, 2020, pp. 759–763. [Online]. Available: https://doi.org/10.1109/ISGT-Europe47291.2020.9248836

[7] N. Stringer, N. Haghdadi, A. Bruce, and I. MacGill, "Fair consumer outcomes in the balance: Data driven analysis of distributed PV curtailment," *Renewable Energy*, vol. 173, pp. 972–986, 2021. [Online]. Available: https://doi.org/10.1016/j.renene.2021.04.020

[8] R. Fonteijn, P. H. Nguyen, J. Morren, and J. G. Slootweg, "Baselining flexibility from pv on the dso-aggregator interface," *Applied Sciences*, vol. 11, no. 5, pp. 1–25, 2021. [Online]. Available: https://doi.org/10.3390/app11052191

[9] E. Scolari, F. Sossan, and M. Paolone, "Photovoltaic-model-based solar irradiance estimators: Performance comparison and application to maximum power forecasting," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 1, pp. 35–44, 2018. [Online]. Available: https://doi.org/10.1109/TSTE.2017.2714690

[10] G. Rouwhorst, P. Nguyen, and H. Slootweg, "A hybrid supervised learning model for a medium-term MV / LV transformer loading forecast with an increasing capacity of PV panels," in *2021 IEEE Madrid PowerTech*, Madrid, Spain, 2021. [Online]. Available: https://doi.org/10.1109/PowerTech46648.2021.9494854

[11] N. D. Pflugradt, "Modellierung von Wasser-und Energieverbräuchen in Haushalten," Ph.D. dissertation, 2016.

[12] KNMI, "KNMI - Uurgegevens van het weer in Nederland - Download." [Online]. Available: https://daggegevens.knmi.nl/klimatologie/uurgegevens

[13] S. J. Taylor and B. Letham, "Forecasting at Scale," *The American Statistician*, vol. 72, no. 1, pp. 37–45, 2018. [Online]. Available: https://doi.org/10.1080/00031305.2017.1380080

[14] A. Cini, S. Lukovic, and C. Alippi, "Cluster-based Aggregate Load Forecasting with Deep Neural Networks," in *Proceedings of the International Joint Conference on Neural Networks*, Glasgow, UK, 2020. [Online]. Available: https://doi.org/10.1109/IJCNN48605.2020.9207503

[15] S. Haben, J. Ward, D. Vukadinovic Greetham, C. Singleton, and P. Grindrod, "A new error measure for forecasts of household-level, high resolution electrical energy consumption," *International Journal of Forecasting*, vol. 30, no. 2, pp. 246–256, 2014. [Online]. Available: http://dx.doi.org/10.1016/j.ijforecast.2013.08.002

[16] Y. Wang, N. Zhang, Q. Chen, D. S. Kirschen, P. Li, and Q. Xia, "Data-Driven Probabilistic Net Load Forecasting With High Penetration of Behind-the-Meter PV," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 3255–3264, 2018. [Online]. Available: https://doi.org/10.1109/TPWRS.2017.2762599

[17] CBS, "Gemiddelde energietarieven voor consumenten." [Online]. Available: https://www.cbs.nl/nl-nl/cijfers/detail/84672NED