Energy Forecasting at the Secondary Substation Level for DSO Participation in Residential Local Flexibility Markets

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Overview

The transition toward decarbonization, along with the increasing integration of Distributed Energy Resources (DERs), and the growing penetration of Renewable Energy Sources (RES) has led to the active incorporation of explicit flexibility within Local Flexibility Markets (LFMs). This flexibility is crucial for ensuring grid stability, minimizing thermal losses, and preventing critical network contingencies [1]. Explicit flexibility, defined as the proactive commitment of participants to modify their energy consumption or generation in response to signals from a Flexibility Service Provider (FSP), following a request from the Distribution System Operator (DSO), is a key mechanism in LFMs [2]. In recent years, the participation of low-voltage (LV) consumers through an aggregator has been proposed as a viable solution to enhance the volume of available flexibility in the distribution network. However, the effectiveness of this approach depends on accurate power demand forecasting [3], which is essential for performing power flow analyses, calculating the required flexibility, and submitting the respective flexibility request to the FSP. Furthermore, once a flexibility request is accepted, a baseline must be established to validate the dispatched flexibility.

To assess the challenges of forming flexibility requests from the side of a DSO in an intra-day LFM with LV residential users, we examined the process of identifying and forming flexibility requests to address voltage violation issues and define a baseline for validating the flexibility dispatch. Given the stochastic nature of consumer behavior, accurately forecasting individual household loads is highly challenging. Therefore, we adopted an aggregated approach by performing energy forecasting using machine learning techniques on secondary substation energy consumption data. The resulting forecasted energy time series were utilized for grid analysis to assess potential voltage violations within an LFM experimental setup in Mesogeia, Greece. To mitigate the identified constraints and restore voltage levels, the minimum load reduction required was determined through grid optimization, forming the basis for a flexibility request.

Methods

In this study, real-world energy consumption and production data were obtained from telemetered secondary substations of the Hellenic Distribution Network Operator (HEDNO), the Greek DSO, focusing specifically on residential consumers. The metering devices used (DinRail 3-Phase Advanced by Meazon, Greece) provide both energy consumption and power quality data. To enable a direct comparison with the consumption data of individual residential users, the baseline was forecasted in energy units with 15-minute intervals (Market Time Units, MTUs). For this purpose, a Long Short-Term Memory Neural Network (LSTM NN) was employed to perform the forecasting [4]. To enhance predictive accuracy, the raw data undergoes several preprocessing steps. Initially, we enrich the dataset with external weather variables (temperature and cloud-coverage), retrieved from Open Meteo (https://open-meteo.com/). The enriched data are normalized and separated to multiple fixed-length train and test sequences based on the specific experimental settings, such as input sequence length and prediction sequence length. The Mean Absolute Percentage Error (MAPE) was used as metric to evaluate the results.

The forecasted energy time series for the telemetered substations were converted to active power and used for grid flow analysis with the commercially available simulation software PowerFactory (version SP5, DIgSILENT GmbH, Germany). The power factor for the analysis was set to 0.95, obtained as the average of the historical metering data. For the remaining substations in the grid (Fig. 2), a load factor of 80% and a power factor of 0.95 were applied. A Newton-Raphson power flow analysis was then conducted to assess the grid's operating conditions.

Results

Eight weeks of energy and weather data were used to train an LSTM model with two hidden layers, designed to predict the 6th Market Time Unit (MTU). Figure 1 presents a comparison between the metered and forecasted data over a 48-hour period. The MAPE was calculated as 0.085. Since the forecasting process runs iteratively for the next

six MTUs, the forecasted values for the 6th MTU were used for the power flow analysis to allow for one hour to realize the market bidding processes. To review the process of forming flexibility requests we simulated an undervoltage issue at the specific telemetered substation located in an urban area, which propagated to adjacent nodes, further exacerbating voltage instability in the surrounding network (Fig. 2). To address this issue, a flexibility optimization algorithm was applied to the node where the LFM participants are connected, determining a required flexibility demand of 84 kW. This power adjustment would be requested from the residential consumers to alleviate the undervoltage problem and maintain grid stability. The dispatch will be validated based on the forecasted value at the substation.

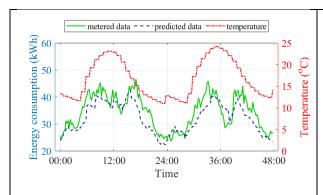


Fig.1 Energy forcasting results (dotted line), the actual metered data (solid line) and the respective temperature data (dash-dot line) over a 48-hour period with 15-minute intervals.

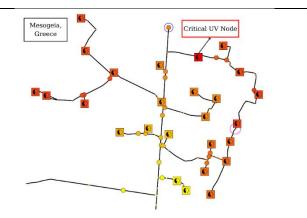


Fig. 2 Grid analysis results for the Medium Voltage Network, with a color-coded representation highlighting undervoltage levels.

Conclusions

This study explores how AI-driven load forecasting, combined with power system analysis and flexibility optimization, can enhance grid reliability and operational efficiency. By applying LSTM-based energy forecasting at the secondary substation level, the proposed approach enables DSOs to proactively identify and address grid stress conditions, such as undervoltage propagation in urban areas. Integrating forecasted flexibility requests into grid simulations allows DSOs to dynamically procure the necessary flexibility, effectively mitigating voltage violations. This work is part of an ongoing effort by our research group. The next steps include incorporating additional features into the LSTM models to enhance their robustness. Furthermore, we aim to develop a mechanism to replace metered data with forecasted baselines during demand-response events, ensuring that the normal energy consumption patterns of consumers remain unaffected.

Fundina

This project has received funding from the European Union's Horizon Europe research and innovation program under the Grant Agreement number 101136216. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

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