Concept of a probabilistic digital twin for the monitoring and control of low-voltage grids

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Abstract

The transition to a climate-neutral energy system has prompted the European Union to promote the expansion of renewable energy sources. This change has had a profound impact on low-voltage (LV) grids, in particular an increase in distributed generation, driven mainly by photovoltaic systems. In addition, the emergence of high-demand technologies, such as electric vehicles and heat pumps, has placed further stress on LV grids. To mitigate potential grid congestion, flexibility options such as energy management systems (EMS) for controllable consumption devices are being investigated. However, the implementation of appropriate control measures requires reliable and accurate grid monitoring, which is currently hampered by the limited metering infrastructure in LV grids. This study presents a probabilistic digital twin (PDT) for LV grid monitoring, designed to integrate grid, meteorological and socio-economic data to address and compensate for uncertainties arising with this lack of measurement data. The probabilistic framework enables the assessment of the grid state in scenarios where real-time feedback from the grid is not available. The PDT calculates the probabilities and likelihoods of specific grid events, eliminating the need for the distribution system operator to collect additional data. By using the grid state assessment provided by the PDT, an EMS can implement preventive grid controls, in opposition to the currently applied reactive controls, to manage load flows and mitigate potential congestion. The effectiveness of the PDT concept is evaluated through a case study of a German low-voltage grid.

1 Introduction

The European Union (EU) has been actively promoting renewable energy sources (RES) as part of its strategy to decarbonize the energy system [1]. In alignment with this objective, EU member states have set ambitious targets for their gross energy generation and consumption. Germany, for example, aims to increase its electricity generation from RES to a targeted 80 % by 2030 [2]. This consequently implies a continued increase in decentralized electricity generation, primarily through the integration of photovoltaic (PV) systems into LV grids. Parallelly, sector coupling has emerged as a critical component of the clean energy transition, encouraging the adoption of technologies such as electric vehicles (EVs) and heat pumps (HPs). While these technologies significantly contribute to the decarbonization of the mobility and heating sectors, their high peak loads place additional strain on distribution grids, potentially pushing existing grid infrastructure to its operational limits [3].

To address these challenges, distribution system operators (DSOs) face a choice between expanding the grid infrastructure or leveraging flexibility options within the grid. While necessary in the long run due to aging infrastructure and ever rising energy demand, grid expansion involves substantial costs and complex planning processes. To postpone these grid expansions, leveraging existing flexibilities in the grid offered by decentral energy resources (DER), through the deployment of intelligent control systems like EMS, have been explored as short-term solutions to mitigate the strain on LV grids. Even in the context of grid expansion, flexibility options are recognized as key technologies to tackle the volatility of RES [4]. Recent works have shown that optimized control of DER like battery energy storage systems (BESS) for grid optimization can be used to minimize peaks in reverse power flow and enhance local photovoltaic (PV) utilization. This is however a substantial shift from traditional reactive grid management strategies to proactive management in LV grids, a transition that introduces additional complexities and risks.

Effective management of load flows within the electrical grid requires comprehensive monitoring of current grid states alongside reliable forecasts of future states [5]. While current grid states can be determined using state estimations and load flow calculations, the assessment of future grid states, which is essential for effective EMS, can only be achieved with forecasts of load and generation. This necessary estimation of future states can be implemented using a digital twin (DT) of the grid, which integrates static data such as grid topology with dynamic data including load and generation forecasts. This approach facilitates near-real-time monitoring of the grid's current state, enables the analysis of potential future states, and provides essential information for EMS-based grid control.

The challenge in setting up such a DT lies however in the limited availability of measurement infrastructure, as a result of the historically developed reactive grid management strategies. This, in turn, complicates the acquisition of empirical data for the creation of an accurate DT or the accurate forecasting of generation and load. The forecasting of load, particularly at the level of individual households, is inherently complex due to the influence of numerous interdependent factors that contribute to uncertainty, such as unpredictable user behavior or unprecedented weather events. A reliable source of information for the development of load forecasts is data from smart meters, both historical and as current measurements. However, in Germany, the smart meter rollout is still in its early stages, resulting in a scarcity of data in most LV grids, which makes sufficiently accurate forecasting of household loads and, in turn, accurate DT representations of the grid infeasible.

To address this limitation, this work proposes a novel method for creating a DT capable of operating under conditions of having neither real-time feedback nor historical data from the grid. The proposed model introduces a PDT which employs probabilistic modelling techniques, to account for the inherent uncertainties in household consumption behavior. By doing so it can provide sufficient grid information to an EMS for reliable load control and congestion management in LV grids. Moreover, the PDT model is designed to be flexible enough to incorporate scenarios with varying grid observability.

This research is part of the project 'ProSeCO – Probabilistic Sector Coupling Optimizer' funded by the Clean Energy Transition Partnership, co-funded by the EU Commission. The paper is organized as follows, in Section 2 the boundary conditions considered during the development of the PDT are outlined, and Section 3 describes the individual components of the PDT and EMS. Finally, a summary of the project's idea is provided in Section 4.

2 Methodology

The concept for grid monitoring and control presented in this paper consists of two core components: the PDT used for the monitoring of the grid and the estimation of future grid states, and the EMS for proactive load flow management. An overview of the individual parts of the monitoring and control concept is given in **Figure 1**. As depicted here, the PDT itself comprises of three parts: a static DT of the grid using the topology, a module for modelling the typical demand based on socio-economic (SE) assumptions, and a probabilistic model for updating the load profiles with short-term load forecasts in a rolling time window.

Unlike traditional deterministic approaches, the PDT generates probabilistic scenarios, allowing the EMS to develop adaptive scheduling strategies based on varying likelihoods of future grid states. By issuing scenario-based forecasts, the PDT ensures that the EMS is not solely optimized for the most likely outcome, but is also prepared for less probable, high-risk scenarios that may cause significant grid instability. This probabilistic approach mitigates the risk of under-preparation in the face of atypical load patterns, thereby enhancing the system's resilience to uncertainties in both consumption behavior and distributed generation.

To evaluate the PDT-EMS framework a LV grid in a German city is adopted as a case study. This grid consists of a 630 kVA transformer, 114 nodes, three HPs, two 11 kW EV charging stations, and five PV systems. The grid currently lacks smart meters or real-time measurement devices; however, voltage and current measurement devices are installed in six cable cabinets to facilitate the

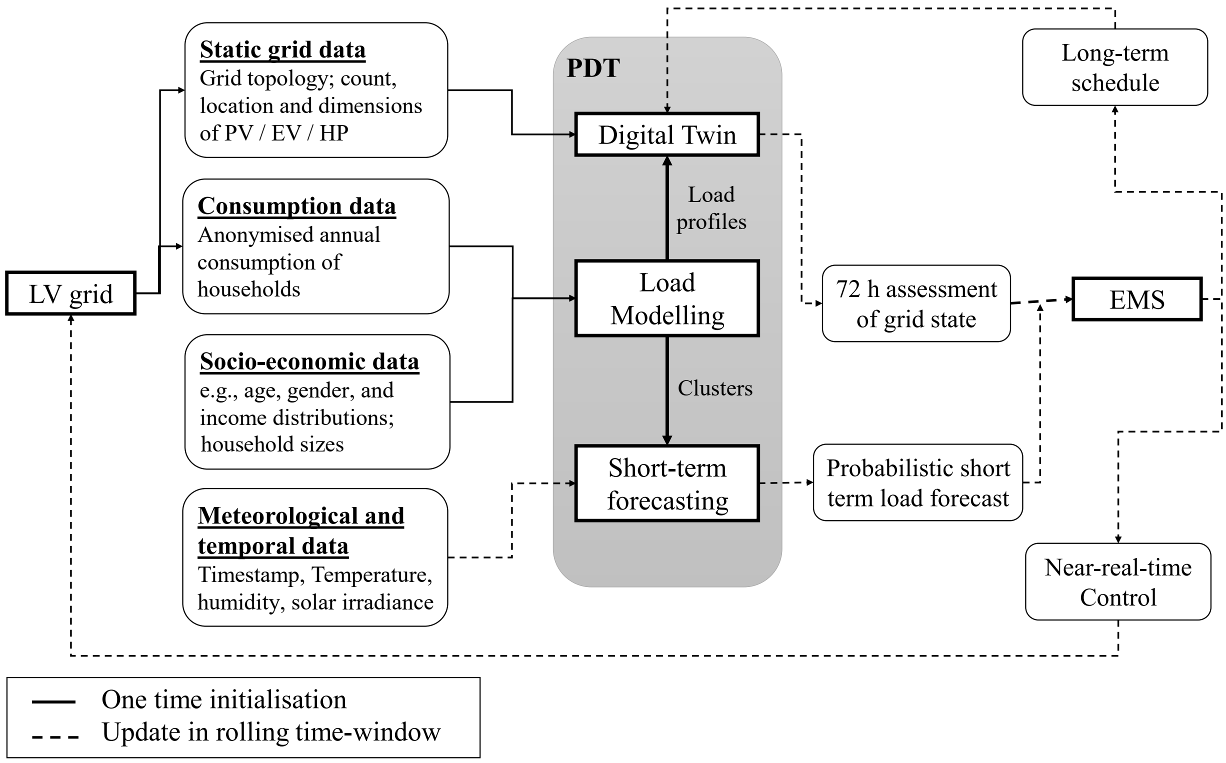

Figure 1 Schematic overview of the proposed concept

validation of the proposed model. This initiative is conducted in collaboration with the local DSO, with who's support the identification and acquisition of available grid data, while ensuring compliance with regional data privacy regulations is possible. The available technical details include the topology of the grid, the count of decentral energy resources (DER), and the anonymized annual consumptions of the households within the selected grid area. Most DSOs have ready access to these data, without need for new infrastructure.
The key components of the PDT-EMS framework and their interfaces are discussed in the following.

2.1 Digital Twin

The static DT is set up using the co-simulation framework BIFROST [6], which consists of a core simulation engine, that drives the dynamic data generation, as well as a 3D web UI, an example of which is depicted in **Figure 2**. The core itself does not produce any data, but provides a data-model for external simulation modules. This data-model lists syntactic (shape of data) and semantic (units of data) characteristics and is freely editable, allowing the introduction of new domains (e.g., SE domain) into the simulation. Simulation values (e.g., power values from load flow solvers) are represented by 'dynamics' within the data-model. External modules can subscribe to the BIFROST core via a REST API. Due to this modular structure, new capabilities as described above (e.g., load flow solvers, control algorithms or the different components of the PDT) can be easily integrated into the simulation environment. The BIFROST UI is capable of building and inspecting settlements, modifying module configurations, starting/stopping simulations and visualizing the results. Therefore, making BIFROST a suitable modelling and simulation environment to not only model the case study but also use it as a simulation testbed for the whole PDT. The simulated results will then be compared to real measurements from the case study grid to validate the developed PDT.

Figure 2 Example of a visualized DT using BIFROST

The static part of the PDT, i.e., the DT of the grid is established using pre-existing modular components from the BIFROST framework. This setup incorporates all pertinent assets and DERs. These components are configured based on the grid topology provided by the DSO. In cases where specific data, such as technical specifications of PV or HP modules, is unavailable, BIFROST utilizes existing databanks containing information collected from comparable real-world assets to supplement the missing data.
Additionally, a built-in forecasting module integrates meteorological predictions to generate DER forecasts. These forecasts are instrumental for the EMS in developing optimized schedules. The forecast window is set to 72 h or 288 datapoints with a 15 min interval, as this is required for reliable scheduling. For the household loads, BIFROST allows the flexibility of using any load profile for configuration. Once the grid model is established, BIFROST can operate as a simulator, generating power values for both controllable and uncontrollable prosumers.

2.2 Probabilistic load modelling

As previously discussed, the development of a deterministic model based on empirical historical consumption data or live grid measurements is often impractical in many LV grids due to the lack of sufficient metering infrastructure. This work therefore, aims to investigate non-technical factors that influence consumption behavior in order to improve demand forecasting. Among these factors, SE distributions and regional climatic and meteorological characteristics have been identified to have significant influence on consumption [7]. SE factors, including household composition, age, gender, and income level, play an important role in shaping consumption patterns [8]. In addition, geographic location and seasonal climatic variations have a strong influence on consumption patterns, particularly in regions such as Central Europe where summer and winter temperatures differ significantly. As these non-technical factors interact with each other in complex ways, their individual effects on consumption cannot be precisely isolated or mapped within a mathematical model.
To explore these relationships, a publicly available smart meter dataset comprising of data collected from 4500 London households between November 2011 and February 2014, is analyzed [9]. This data is also supplemented with associated SE information, categorized using the geodemographic classification system described in [10]. Each household is assigned a SE category based on various SE factors such as income and age, derived from a census data collected from all participating households. Given the high correlation between the individual factors (household composition, age, etc.), further analysis is limited to distinction based on the aggregated SE category, represented by alphabets (A, B, C…).
To begin identifying typical load profiles, the smart meter data set is stratified into the smallest possible homogeneous groups. To accomplish this, households are first divided based on the SE category they belong to. Subsequently, to ensure that households within the SE categories have homogenous, i.e., similar consumption patterns, a k-means cluster analysis is applied on average values for each household of each SE category. **Figure 3** depicts the

average daily consumption curves for the three clusters detected within SE category A using k-means. The curves of cluster 1, 2 and 3 vary distinctively in amplitude, which suggests that even within an SE category, the consumption patterns can vary extensively. This could be because the SE categories do not make clear distinctions based on household sizes, therefore using clustering to further divide the dataset ensures that household sizes are accounted for. Each cluster of each SE category now has a similar curve with varying amplitudes.

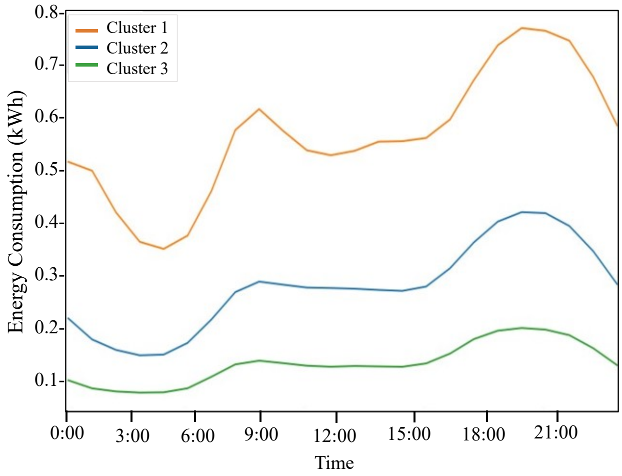

Figure 3: Three typical load curves for SE category A

At runtime of the probabilistic load modelling, the first step is to assign a given household in the real grid or case study to an SE category. As mentioned above, the only input from the real grid for each household is its annual consumption value. Therefore, the annual consumption values of the households in each cluster are calculated in the next stage of the model. By plotting a histogram for each cluster, as shown in **Figure 4**, it is possible to identify the distribution of annual consumption values over the number of households. This then gives an insight into the probability distribution of a particular consumption given a particular SE category. **Figure 4** shows the histogram, its centroid or average and the probability distribution for cluster 2 of SE category A.

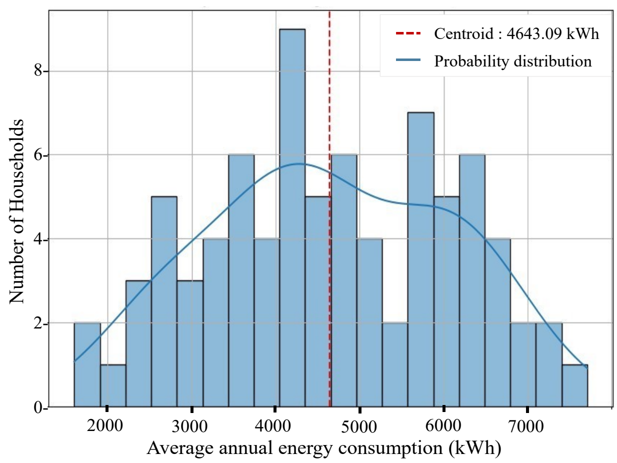

Figure 4: Probability distribution of average annual consumption values for SE Category A Cluster 2

The assignment of households to a specific SE category is implemented using the k-Nearest Neighbors (kNN) algorithm, which performs a Euclidean distance calculation between the given annual consumption value and the annual consumption value of all cluster centroids. The proximity between the actual consumption value and a centroid is associated with the 'likelihood' of the household having the load curve associated with that cluster and SE category. This approach allows for the dynamic assignment of 'm' load profiles, representing 'm' likely probabilistic scenarios.

Once a household has been assigned to a specific cluster (SE category), the second step is to determine the typical load curve for that household. The load curves shown in **Figure 3** are inaccurate and vague, as they only consider SE categories and not other factors such as seasons or working and non-working days. Therefore, after clustering, a further segregation of the smart meter dataset is made based on seasons (summer, winter and transitional period), and working or non-working days. **Figure 5** shows a flowchart of the data segmentation process. At the end of the segregations, each subgroup is homogenous, i.e., the households within each subgroup have similar consumption patterns and hence load curves. Subsequently, an average daily curve is calculated for each homogenous subgroup.

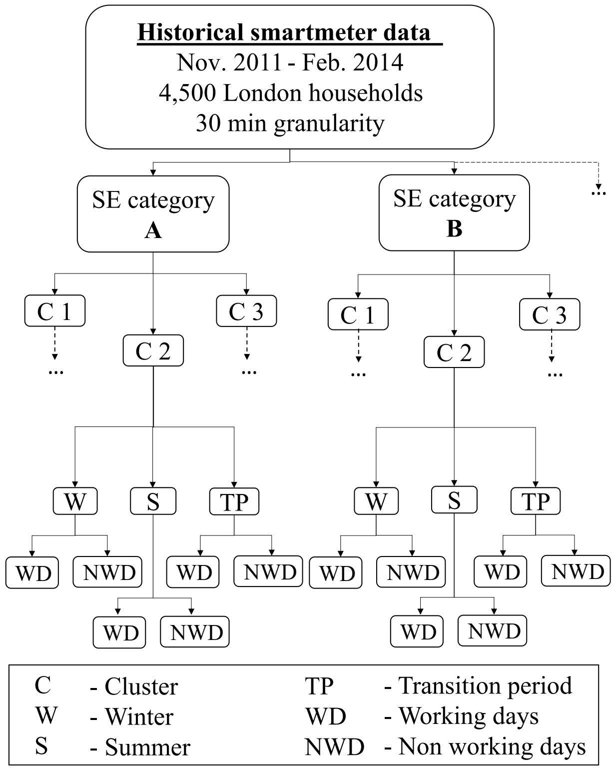

Figure 5: Overview of the smart meter data segmentation

During runtime once the household has been assigned a SE cluster, the model takes the current season and date as input to determine which load profile is to be assigned. **Figure 6** shows the load profiles of three different SE categories (A, F and Q). Here the clusters with the most number of households are depicted for working days in Winter.

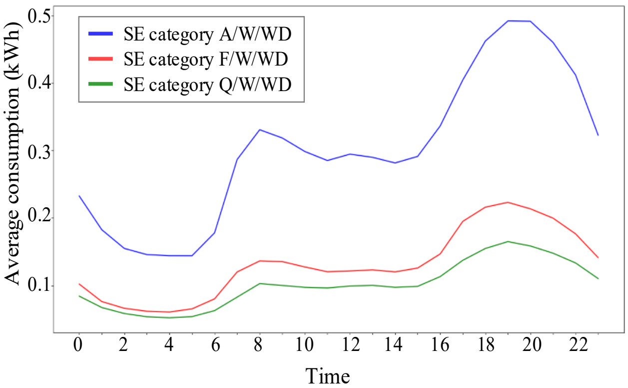

Figure 6: Typical load profile for three different socio-economic categories on working days in Winter

Through this methodology, the load modelling module can use annual consumption values and temporal values to assign load profiles to each household in the real grid. Using the probability distribution, the likelihood of each load profile is accessed and can be further used as probabilistic scenarios.

2.3 Short-term probabilistic load forecast

The load profiles developed in Section 2.2 represent average consumption patterns, which serve as an approximate indicator of actual load at a specific time. While these profiles allow for the extraction of average base load and a rough estimate of real-time consumption, they lack the granularity necessary to accurately capture critical variations, particularly during intervals of extreme consumption (either high or low). These intervals are especially relevant for grid assessments, as they are more likely to result in congestion or potential reverse power flow. The short-term probabilistic load forecast module aims to predict the occurrence and extent of such 'high risk' values. This probabilistic analysis aims to capture peak consumption patterns that might otherwise go undetected in a purely deterministic framework.

As in 2.2., meteorological, temporal, and SE factors are isolated to facilitate a probabilistic estimation of 'high risk' events. Meteorological variable like temperature, humidity and solar irradiance are selected as causal features that influence the occurrence of the 'high-risk' events. The probabilities are derived from the likelihood of 'high-risk' events, assessed across the various publicly available smart meter datasets under specific predefined meteorological and temporal conditions.

The publicly available smart meter data used to develop this module are selected in such a way that they are relatively new compared to the dataset used in 2.2. This is to ensure that new loads like EV and HP are sufficiently represented. Each data set of a household is firstly categorized in clusters according to the method discussed in 2.2. based on the annual consumption values. This ensures that the detection of 'high risk' events is unique to the SE category of the household, season and working/non-working days. A machine learning (ML) model then learns the frequency of 'peaks' and their corresponding meteorological condition for each cluster. In other words, the ML model aims to learn the most frequently occurring load, given a specific temperature, humidity, solar irradiance and time. Additionally, the model captures less frequent, but still relevant, load values by generating a probability distribution based on their observed frequency across the analyzed datasets.

During runtime the trained model receives both the current measurements and forecasts of meteorological data for the next three hours to predict the possible demands for this interval. The short time horizon of three hours is chosen, as the variance of probabilistic forecasts is smaller when it is closer to the current time step. The further the forecast stretches into the future, the higher the variance and the lower the accuracy.

2.4 Energy Management System

For the development of an EMS capable of processing probabilistic outcomes of the PDT, a mathematical model is developed to minimize operational costs while accounting for uncertainties in PV generation and demand scenarios. The model incorporates stochastic optimization techniques, e.g., structured as a two-stage framework, to address both day-ahead scheduling and near real-time adjustments. The rolling window of the PDT's probabilistic forecast is developed to facilitate this. In addition, robust optimization techniques are applied to ensure reliability by preparing for worst-case scenarios, enhancing the adaptability of the system.

Moreover, the EMS is designed to integrate seamlessly with the PDT, leveraging its probabilistic approach/outputs to refine optimization strategies and enable proactive grid management (see **Figure 1**). By aligning optimization processes with the probabilistic outputs of the PDT, the system enhances its predictive capabilities, preventing grid congestion and ensuring cost-efficient operation. The EMS further utilizes probabilistic scenarios to train advanced control algorithms, ensuring scalability and robustness in managing decentralized energy resources.

Building on prior research [11], the optimization framework used for the long-term scheduling of appliances employs an objective function designed for cost minimization:

$$
\begin{aligned}
\min OC = {} & \sum_{t=1}^{T} \sum_{i \in \Omega_{DG}^{d}} p_{i,t}^{DG} \cdot C_{i,t}^{DG} \\
& + \sum_{s=1}^{N_s} \sum_{t=1}^{T} \Big(\sum_{i \in \Omega_{DG}^{nd}} p_{i,t,s}^{DG} \cdot C_{i,t}^{DG} \\
& + \sum_{e=1}^{N_e} p_{e,t,s}^{ESS^-} \cdot C_{e,t}^{ESS^-} \\
& + \sum_{e=1}^{N_v} p_{v,t,s}^{EV^-} \cdot C_{v,t}^{EV^-} \\
& + \sum_{l \in \Omega_{load}^{curt}} p_{l,t,s}^{curt} \cdot C_{l,t}^{curt} \\
& + \sum_{l \in \Omega_{load}^{inte}} p_{l,t,s}^{inte} \cdot C_{l,t}^{inte} \\
& + \sum_{l \in \Omega_{load}^{shift}} p_{l,t,s}^{shift^-} \cdot C_{l,t}^{shift^-} \\
& + \sum_{l=1}^{N_l} p_{l,t,s}^{imb^-} \cdot C_{l,t}^{imb^-} \\
& + \sum_{l=1}^{N_l} p_{l,t,s}^{imb^+} \cdot C_{l,t}^{imb^+} \Big) \cdot \pi(s)
\end{aligned}
\qquad (1)
$$

Here OC represents the total operational cost, considering different energy resources and demand-side flexibility options under uncertain scenarios. The variables p and parameters C denote the power and associated cost for distributed generation, storage systems, load curtailment, load shifting, and imbalances, respectively, across time horizons t and scenarios s with probability $\pi(s)$. A detailed explanation of the model and parameters is provided in [11].

This approach provides a solid foundation for addressing the complexities of modern LV grids while promoting higher integration of RES and other distributed energy sources such as controllable loads or EVs. By combining exact methods, such as two-stage stochastic optimization, with metaheuristic techniques like evolutionary algorithms [12], the EMS aims to balance computational efficiency with solution robustness.

The development and testing of the EMS are supported by scenario-based analysis and validation using real-world grid data. These efforts aim to ensure the system's ability to prevent grid congestion, optimize energy flows, and maximize RES utilization. This work emphasizes the importance of integrating optimization models with probabilistic tools to enable flexible, efficient, and sustainable energy management in the evolving landscape of LV grids [13].

2.5 Communication Architecture

To ensure seamless interoperability between the DT, the load and short-term forecasting models and the EMS, a common interface is essential. While the DT, the load and the short-term forecasting models are designed to communicate within the same framework, enhancing the capabilities of the DT and minimizing the potential for communication errors, the EMS operates as an independent system with external interface, allowing for easy integration with other DT instances or field experiments.

For this, a NATS interface is established, providing an environment-independent, real-time publish subscribe messaging service. NATS is a lightweight low latency implementation, realizing the QoS 0 paradigm and also supporting MQTT [14]. The NATS server is pre-configured for four topics. The simulation environment publishes the state of available controllable devices and their operation station to a dedicated topic, triggered by any changes, while the prediction data for all entities receiving a forecast is published to a separate topic. Control commands and schedule intel can also be handled through NATS and can receive messages from both multiple EMS or controllers, respectively. The NATS server supports both direct control commands and energy management plans so that the interface does not have to be altered even when the simulation backend would be replaced by a hardware-in-the-loop field experiment involving households and power-intensive appliances. The loosely coupled architecture, with NATS serving as middleware, facilitates the seamless replacement of both sensor-actuator systems and control instances. The simulation instance (PDT) or a real appliance can subscribe to the designated schedule and control topics.

3 Conclusion

LV grids are increasingly confronted with the mounting demand of emerging loads, such as HPs, and EV chargers, as well as decentralized RES feed-in from PV systems. This increased volatility poses significant challenges to the LV grid's operation and capacity. To mitigate these challenges, there is a need for reliable and accurate monitoring and control measures. However, the limited metering infrastructure in most LV grids currently hinders the implementation of reliable, proactive grid management concepts. This paper proposes a novel model that aims to enhance LV grid management by integrating a static DT of a grid with a module for load modelling and a module for short-term probabilistic load forecasting. The resulting PDT is capable of issuing probabilistic forecasts, thereby enabling an EMS to adapt control strategies for a range of possible grid states and subsequently reducing the risk of grid congestion. The proposed concept of a PDT and EMS for the monitoring and control of LV grids will be evaluated using a case study of a German LV grid with limited data availability.

The PDT-EMS concept has been developed with the assumption of minimal grid data, and is scalable for various scenarios across countries and regions, which can be simulated on the virtual testbed BIFROST. With smart meter rollouts progressing at varying speeds across the EU Member States, it is essential that LV grids can be monitored and maintained reliably, independent of data availability. Thus, the adaptable PDT framework represents a reliable tool for grid management and congestion mitigation in LV grids.

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