Grafenhorst *et al. Energy Informatics* (2024) 7:116
https://doi.org/10.1186/s42162-024-00427-y

Energy Informatics

RESEARCH Open Access

Distribution grid monitoring based on feature propagation using smart plugs

Simon Grafenhorst[1*], Kevin Förderer[1] and Veit Hagenmeyer[1]

*Correspondence:
Simon Grafenhorst
simon.grafenhorst@kit.edu
[1]Institute for Automation and Applied Informatics (IAI), Karlsruhe Institute of Technology, Hermann-von-Helmholtz-Platz 1, Eggenstein-Leopoldshafen 76344, Germany

Abstract
Smart home power hardware makes it possible to collect a large number of measurements from the distribution grid with low latency. However, the measurements are imprecise, and not every node is instrumented. Therefore, the measured data must be corrected and augmented with pseudo-measurements to obtain an accurate and complete picture of the distribution grid. Hence, we present and evaluate a novel method for distribution grid monitoring. This method uses smart plugs as measuring devices and a feature propagation algorithm to generate pseudo-measurements for each grid node. The feature propagation algorithm exploits the homophily of buses in the distribution grid and diffuses known voltage values throughout the grid. This novel approach to deriving pseudo-measurement values is evaluated using a simulation of SimBench benchmark grids and the IEEE 37 bus system. In comparison to the established GINN algorithm, the presented approach generates more accurate voltage pseudo-measurements with less computational effort. This enables frequent updates of the distribution grid monitoring with low latency whenever a measurement occurs.

Keywords Smart grid, Distribution grid monitoring, Smart home, Feature propagation, Measurements

Introduction

New appliances in the distribution grid, such as Electric Vehicle (EV) chargers, heat pumps, and Photovoltaic (PV) systems, lead to a change in infrastructure utilization and possibly the violation of regulatory constraints. For example, the distribution grid can only accommodate a certain amount of photovoltaic generation without violating regulatory constraints (hosting capacity [1, 2]). Other challenges include the optimized control of Distributed Energy Resourcess (DERs), such as controllable heat pumps or schedulable electric vehicle charging infrastructure, as well as Demand-Side Management (DSM) of smart household appliances. As a result, the Distribution System Operator (DSO) must have comprehensive and up-to-date measurement data from the distribution grid. However, upgrading smart distribution grid infrastructure to monitor the live state of the grid or detect bottlenecks is a gradual process [3]. Many legacy grid infrastructures are still in use. They are neither monitored nor equipped with the necessary communications infrastructure and upgrading them is costly and time-consuming. Key components in the distribution grid, such as transformers and cables, have a life expectancy of about 35 years [4], and monitoring the state of the grid with such old equipment is a challenge. However, smart home devices are becoming increasingly popular. In the US, 35.8 % and in the EU, 23.0 % of households had smart home systems installed in 2021 [5]. Smart plugs can turn power outlets on and off remotely, and some smart plugs also include hardware to measure the power consumption of the connected device and the line voltage of the socket outlet they are plugged into. We hypothesize that sufficiently accurate grid monitoring is possible with the use of smart plugs as measuring devices.

Because a DSO usually cannot place measurement instruments at every node in the grid, some measurement data is missing. One way of generating a complete picture of the grid is to use pseudo-measurements as a supplement, for example, generated using neural networks [6]. Furthermore, new measuring devices, such as smart plugs, allow for more measurement data to be recorded at a higher frequency. In order to make use of this data, the monitoring must also be calculated after each new measurement data, preferably with low computing time. These restrictions call for fast algorithms to calculate the pseudo-measurement values for the distribution grid monitoring. However, either typical load profiles or historical data is often necessary for established techniques [7–10]. In instances where a restricted number of measurements are available, pseudo-measurements can be derived from them. Graph-based algorithms can be utilized by constructing a graph from a distribution grid. The graphs representing distribution grids are cycle-free in the test cases we consider, and the nodes have homophilic features. This means that neighboring nodes have similar characteristics and enables the use of algorithms that exploit these properties such as the recently published feature propagation algorithm [11].

In contrast to machine learning methods to generate pseudo-measurement [12], the feature propagation does not rely on historical or statistical data sources. This makes it applicable for changing grid areas, for example, due to increasing renewable generation or EV charging infrastructure. Furthermore, the monitoring results can be computed quickly and are only based on live data, which makes the feature propagation applicable for low-latency monitoring.

As the considered smart plugs are connected to a standard power outlet and monitor the voltage on a single phase, we only aim to monitor a single phase in the distribution grid. However, without loss of generality, the method proposed in the present work can also be applied to all phases of the distribution grid and enable a holistic monitoring solution.

The contributions of the present paper[1] are as follows:

1. It is shown that the measurement inaccuracies of the widely available smart plugs are low enough to be comparable to other distribution grid measuring devices.
2. It is demonstrated how a modified firmware can increase the measurement accuracy and frequency, and the firmware version is released as open-source [14].

[1] This is an extended and revised paper of our previously published work on the use of smart plugs as devices for distribution grid monitoring [13].

3. The feature propagation algorithm presented in [11], and the GINN algorithm presented in [15] are adapted for use in an electricity grid.
4. A novel method to generate pseudo-measurements based on the smart plug data using feature propagation is outlined and evaluated. The feature propagation aspect is new with respect to the previously published algorithm [13] and significantly improves the results of [13].Although the smart plugs have a lower measurement accuracy than a power analyzer such as the Janitza UMG 604EP-PRO [16], they can be a valuable asset for grid monitoring by providing frequent measurement data at a low price. Combined with the feature propagation algorithm presented in the present paper, an accurate distribution grid monitoring with low latency can be realized.

The remainder of the paper is organized as follows: Section 2 summarizes related works on distribution grid monitoring, the development of measuring devices, and the generation of pseudo-measurements. In the first part of Section 3, the data collection method for the selected smart plugs is detailed as previously published in [13]. Afterward, in Section 3.4, the post-processing step to generate measurements for the complete distribution grid is presented. The measurement accuracy of the smart plugs and the monitoring error of our method is evaluated in Section 4. Section 5 presents a case study that illustrates our approach and shows the relationship between an increasing number of measuring devices in the grid and the overall monitoring error. The results and the practical applicability of this research are discussed in Section 6, followed by a final conclusion and outlook in Section 7.

Related work

Distribution grid monitoring

To assess the state of the distribution grid, several articles identify accurate voltage measurements at different nodes in the distribution grid as an important prerequisite [1, 17]. The p.u. (per unit) value describes the factor between the real voltage and the nominal voltage. Different standards define the minimum and maximum p.u. values for different countries. For example, the EN-50160 standard specifies a p.u. of 0.9 to 1.1 as the permissible voltage variation. Therefore, to evaluate the hosting capacity for PV systems in a part of the distribution grid, the minimum and maximum p.u. levels that occur within a predefined period of time need to be known, and thus voltage measurements are needed.

State of the art

In the past, the lack of measurement hardware in the distribution grid led to the exploration of simulations based on sparse measurement data and pseudo-measurements [18–20]. Others have increased the observability of the distribution grid by integrating smart meter data into a state estimation [21–24]. This enables the generation of forecasts [25, 26] or the detection and localization of faults in the grid [27, 28]. Furthermore, network topology reduction techniques can be applied to carry out a grid state estimation with a limited number of smart meters [22]. To increase the accuracy of the state estimation in [23], the unsynchronized measurements of multiple smart meters are filtered, and only the most recent measurements are included. Compared to a state estimation that assumes all smart meter measurements are recorded simultaneously, the proposed method is more accurate [23]. However, smart meters require a professional electrician to install, and most meters only take measurements every 15 minutes [21]. In comparison, the commercially available smart plugs can be installed by anyone and measure the voltage every second with a modified firmware.

Leveraging the Advanced Metering Infrastructure (AMI) already present in the distribution grid saves costs and expenditures at the expense of the timeliness of the data [29], and consequently the accuracy of the grid state estimation at the present time. The lack of measurement hardware also leads to inaccurate load modeling of the distribution grid transformer. To calculate load profiles of the transformer and determine whether new loads could overload the current hardware, AMI can be included in the analysis [30]. Installing monitoring devices on all transformers could also solve this problem, but is not cost effective [30]. To improve the grid model and more accurately estimate the transformer peak load, several other sources of information such as temperature, geographic, customer, and facility management data can also be included. The near real-time optimization of the distribution network with smart grid technology is identified as a significant improvement for the efficient operation of the grid [30].

A smart plug to monitor voltage and frequency in real-time is designed in [31]. The measured values are sent to a smartphone that is connected via Bluetooth. The smartphone then forwards the data to a web server. With their implementation, they demonstrate the feasibility of measuring the voltages at different points in the distribution grid and estimating the live state of the grid based on these measurements. The device is considered a working proof of concept for a low-cost substitute for smart metering hardware, although no measurement accuracy or time delay is specified. Other authors propose using specialized voltage meters to monitor the state of the grid [17]. They synchronize their measurements and analyze the grid state with load flow simulations based on a series of snapshots of the grid. Furthermore, the underlying grid model is extended by learning from the differences between the calculated and measured voltages at different nodes. In [32], a smart plug is designed for DSM. They develop a software that switches the connected load on or off depending on the voltage level and show that the load peaks are shaved off when the designed smart plugs are widely distributed in the grid. However, no communication mechanism is implemented, so the measured values cannot be used for distribution grid monitoring. The hardware is also a prototype design that is not commercially available. To monitor meteorological variables and PV generation, a low-cost data logger device with LoRa wireless communication is developed in [33]. The data is sent to the LoRa Gateway by the data logger and forwarded to an MQTT [34] Broker. The data is stored in the Google Cloud Platform. However, all of these devices are custom-built and cannot be considered widely available, which hinders widespread adoption.

By combining multiple input variables, such as historical data, weather, and day features, distribution grid loads can be forecasted accurately using deep neural networks [12]. The forecasted loads can then be used to derive a grid state. Because of averaging effects, the aggregation of multiple distribution grid participants leads to a less volatile sum of loads than a single household load. However, when a single household's load is of interest, other external inputs such as occupancy behavior and building characteristics need to be considered [12]. Therefore, to monitor a single branch in the distribution grid with only a few participants, a lot of information about the occupants is needed. Manandhar et al. use Kalman filters to estimate different state variables in the distribution grid [35]. Discrepancies between Kalman filter estimates based on a mathematical model for the power grid and measurement data trigger alarms. In their work, Kalman filters are used to detect attacks and faults in the smart grid by describing the relationship between dependent variables and predictor variables [35]. These predictors represent a complete estimate of the distribution grid measurement values and an alternative to conventional distribution grid monitoring.

Distribution grid monitoring relies on sufficient measurement data [36]. Measurement data at nodes that are not equipped with measurement hardware can be derived from other data. For example, Madbhavi et al. use estimates from previous time steps to generate such pseudo-measurements [37].

When typical load profiles for the missing measurement values are known, they can be incorporated into the generation of pseudo-measurements [7]. However, the actual load profiles often significantly deviate from the typical ones, and corrections need to be applied [8]. Other approaches assume that the loads in the distribution grid follow probabilistic density functions and generate pseudo-measurements based on these [9]. The recent publication of Zhang et al. utilizes multiple data sources in a machine-learning approach to generate accurate pseudo-measurements of voltage levels [10]. By combining historical data with up-to-date measurements, the voltage is estimated with high accuracy, and computation only takes a few milliseconds. It is shown that this method is particularly robust in the case of high PV penetration.

Without relying on other time steps, typical load profiles, or statistical load distributions, feature propagation enables the generation of missing features [11]. By diffusing the known features in a graph, the missing features can be reconstructed. Rossi et al. interpret the feature propagation as a low-pass filter and expect it to be especially suitable for homophilic graph data [11]. In homophilic graphs, adjacent nodes tend to have similar features. This is also true for the voltages in the distribution grid, i.e., the voltage values of neighboring nodes are always quite close to each other [38]. Node classification tasks are performed by a Graph Convolutional Network (GCN) on various benchmark datasets to evaluate the feature propagation. A GCN is a Graph Neural Network (GNN), meaning it is either invariant or equivarant to the input data. Therefore, permutations of the input nodes either do not change the output nodes or permute them in the same way, respectively. This allows a GCN to generalize over all node permutations of a graph [39]. Feeding both the propagated and the original features into a GCN, the method proposed in [11] leads to a marginal drop in accuracy of only 4 % with 99 % of features missing. In their evaluation, Rossi et al. show that the feature propagation approach outperforms four other methods to recreate missing features on benchmark datasets, such as Cora, Citeseer, and PubMed [40].

Another approach to estimating missing values in a dataset is presented by Spinelli et al. [15]. They build a similarity graph from the training data that describes the connections between individual features. The weights of the edges are a measurement of the similarity of individual nodes. With this method, creating a graph that represents tabular data is possible. The created similarity graph is encoded as an intermediate graph with a higher dimension using a GCN autoencoder. Another GCN decodes this intermediate representation into data of the original dimension with imputed features. In comparison with other data imputation algorithms, the presented approach archives the best results in most cases. Therefore, we use the GINN algorithm [15] to compare the approach developed in the present paper.

In the present paper, we propose a distribution grid monitoring method using feature propagation. The feature propagation algorithm is strongly inspired by [11]. In contrast to machine-learning approaches [7] or probabilistic mixture models [9] to generate pseudo-measurements, we rely on the homophilic properties of the nodes in the distribution grid. This also eliminates the need to define typical load profiles for grid participants and alleviates concerns about significant deviations from typical load profiles caused, for example, by the increasing number of installed renewable generation components. To the best of our knowledge, such a feature propagation method has not yet been evaluated on electricity grids in literature.

Method

Data collection

Smart plugs connect to a Zigbee (a low-power personal area wireless network) hub, a LoRaWAN (a low-power wide area network) hub, or a WiFi access point. They consist of an outlet that can be turned on and off by smartphone apps or a smart home hub. Some smart plugs also contain hardware to measure the power consumption of the connected device and the line voltage of the socket outlet they are plugged into. The measurement data is typically sent to a device manufacturer's server, allowing customers to monitor the values measured by the smart device via a web service. However, with suitable firmware, some smart devices can connect to IoT gateways other than the manufacturer's server. These gateways can forward the measured data, packaged into standardized messages, to a message broker, thus enabling remote monitoring and logging of the voltage levels and power consumption of connected devices.

Because these smart home devices are not intended to monitor the grid, the manufacturers of these devices do not provide data on the accuracy of the energy measurements. Furthermore, the accuracy and frequency of the measurements can be modified by modifying the firmware of the smart plugs.

In addition, smart home devices may be calibrated differently. Due to manufacturing tolerances and environmental differences between the smart home devices, the measured voltage and current levels can vary between devices from the same manufacturer and production batch. We calculate a constant offset bias for all smart plugs separately by determining the average difference between the measured voltage values and the values measured by a reference meter, a Janitza UMG 604EP-PRO power analyzer [16]. This offset-voltage is removed from the voltage measurements in a pre-processing step. After this step, the average voltage value measured by each smart plug connected to the same constant voltage is identical. The initial measurement of this offset-voltage must be completed for each smart plug before deployment in a live environment.

Communication interface

There are several types of smart home devices available. The main difference is the communication interface available, which can be based on WiFi, LoRaWAN, or Zigbee. All three interfaces have different strengths and weaknesses, as can be seen in Table 1.

For this work, we use WiFi smart plugs. With a customized version of the Tasmota open source firmware [42], it is possible to collect measurements every second and send them directly to an MQTT [34] broker (a message queue with publishers and subscribers). With further modifications, a slightly higher measuring frequency could be realized,

Table 1 Comparison of smart home communication technologies [41]. Depending on the grid topology and availability of an internet connection, different protocols may be preferable

Protocol	Hub needed	Data Rate	Range	Prerequisite
WiFi	No	High	Low	Internet connection available everywhere
LoRaWAN	Yes	Low	High	No available internet connection
Zigbee	Yes	Medium	Medium	Internet connection partially everywhere

but this caused problems during practical tests. Compared to the LoRaWAN and Zigbee smart devices, no hub or gateway device is required other than the WiFi access point. In the test environment, access points are already in place, so no additional hardware is required, making the deployment of WiFi smart plugs the most practical option. In addition, the higher bandwidth allows for more frequent and comprehensive measurement data. With the smart plug used for testing in this paper, the measurements are available in the simulation in less than one second.

Generally, the data sent over WiFi to an access point is not necessarily encrypted. However, the smart plugs evaluated in this paper contain an ESP8266 microcontroller that supports the WPA2 encryption standard. This enables the encryption of the communication between the smart plug and the access point, which protects the transmission of measurements.

The TLS encryption standard is supported by the Mosquitto MQTT broker we use, and the Tasmota firmware for the smart plug also includes basic support for this standard. To enable the ESP8266 to send TLS-encrypted packets, a custom version of the Tasmota open-source firmware must be compiled that includes the very lightweight BearSSL library. Since the smart plugs are configured with the SSL fingerprint of the MQTT broker and a preshared key, a spoofing attack in which the attacker impersonates the smart plug and sends malicious or false data is not trivially possible.

A microservice application is used to subscribe to the MQTT broker. The application creates the adapter between the MQTT messages and the InfluxDB server. Incoming measurement data is mapped to specified fields. This architecture also allows for multiple different measuring devices to write to the same database server and, in this case, to compare voltage measurements recorded by different devices. In addition, metadata can be added to the measurements so that the voltage data is associated with a power phase, a geographic location, and the device manufacturer.

This infrastructure also enables fast integration of new sensors by developing new microservices to map the measurement data messages. Should new smart plugs that do not support the MQTT protocol be introduced, new microservices can be added to inject data into the time-series database without losing support for the existing devices. Furthermore, adding other database servers for specific measurement data only requires the development of another microservice and does not require changes to the existing structures. An overview of the resulting networking infrastructure is shown in Fig. 1.

Measurement hardware

Besides the communication interface, another difference between the smart plugs is the measurement hardware. Popular energy measurement integrated circuits (ICs) for smart plugs are the Shanghai Belling BL0937 and the Shanghai Belling BL0940 [43]. The Nous A1T, Gosund SP1, and Shelly Plug S smart plugs used for testing in this paper contain the BL0937 IC. However, the same measurement hardware is also included in many

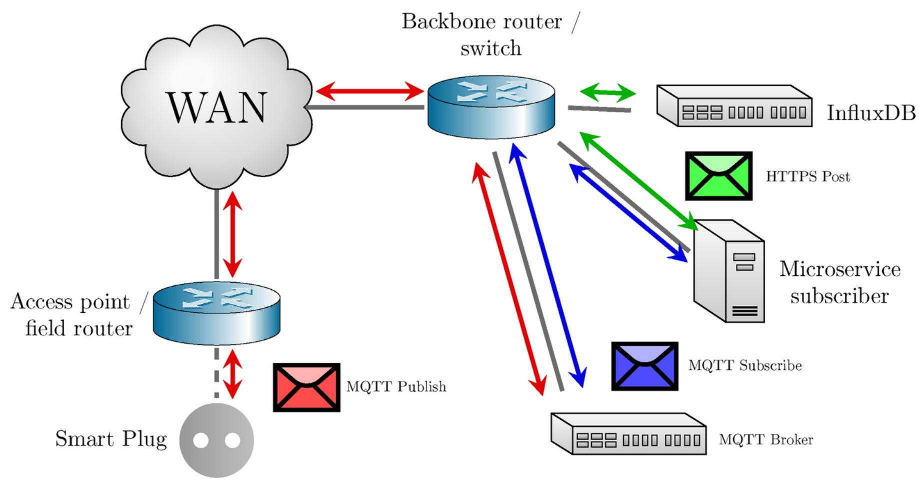

Fig. 1 Network infrastructure between the smart plug and the InfluxDB server

other smart plugs, so the measurement accuracy of the plugs is identical. All tested smart plugs share the same measurement characteristics.

The measurements taken by the smart plugs are compared to the values measured by a Janitza UMG 604EP-PRO power analyzer [16]. This power analyzer implements a measurement process according to IEC 61000-4-30 and is connected to an Influx database via TCP/IP.

Data processing

In order to generate a complete picture of the distribution grid area where the smart plugs are installed, pseudo-measurements are generated. This is undertaken using a feature propagation algorithm, which is adapted from [11]. As this algorithm works on a graph data structure, a graph representation of the distribution grid area must first be created. The following sections describe the graph data structure and the feature propagation algorithm.

Distribution grid graph

A graph is described as $G = (N, E)$, where the set of nodes $N = 1, ..., n$ represents the buses, and the set of edges $E \subseteq N \times N$ represents the lines of the grid. Each node n is a distribution grid participant, such as a building or DER, and has a voltage value assigned to it if a voltage measurement value is available at that node. All edges contain information about the admittance of the distribution grid line they represent. Since the smart plugs only measure voltage, we use a simplified Direct Current (DC) representation of the distribution grid, and all edges have a reactance of $0\,\Omega$. This results in a simple graph of nodes with one feature and edges with one feature.

Feature propagation

In Fig. 2, the input data for the feature propagation algorithm is illustrated. The nodes colored in red do not have voltage values assigned because these nodes are not instrumented in the grid. Reconstruction of the missing features can be conducted using different strategies. As a baseline, filling all missing features with the average of the known features is a straightforward and fast strategy. However, this strategy does not consider

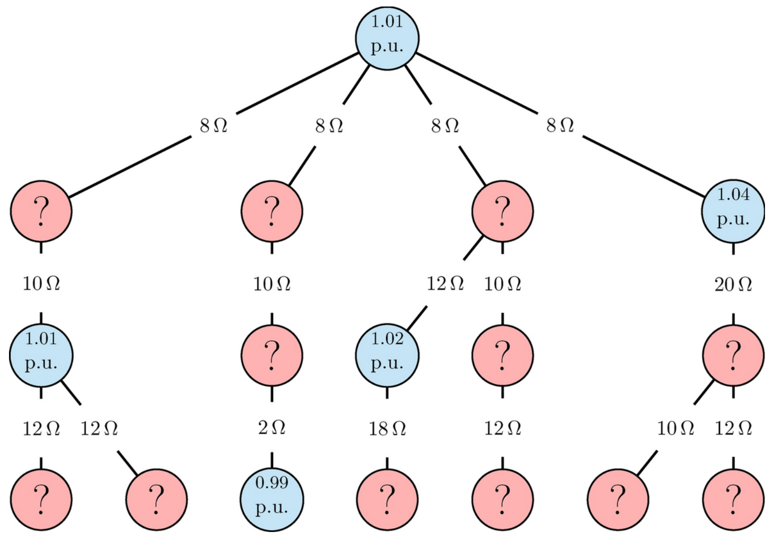

Fig. 2 A diagram illustrating the distribution grid monitoring with missing features. The p.u. values are the node features we aim to reconstruct, and the resistance values in Ω are used as edge weights

the structure of the graph and the underlying data. In order to improve this, a feature propagation similar to heat diffusion is devised. The features are propagated according to the adjacency matrix and the edge weights. This is calculated by multiplying the adjacency matrix with the feature matrix, which results in a new feature matrix. All features are thus propagated by one node. The edge weights represent the line conductance between the nodes and can be interpreted as a measurement of how strongly the neighboring nodes are connected. The adjacency matrix, therefore, is equal to the admittance matrix for a DC grid. After each propagation step, the known features are reset to their original values. In other words, the real measurements are not modified during the feature propagation. For this reason, the measurement errors also remain the same. This process can be interpreted as heat diffusion, where the heat comes from the known features [11]. Between known features, the algorithm creates a gradient with an incline corresponding to the strength of the connections. This algorithm is presented as Algorithm 1.

procedure FEATUREPROPAGATION(x, A)
  $y \leftarrow [0, 0, ..., 0]$
  $y_k(0) \leftarrow x_k$ ▷ Set known features
  while $|y(i-1) - y(i)| > \epsilon$ **do** ▷ While not converged
    $i \leftarrow i + 1$
    $y(i) \leftarrow Ay(i-1)$ ▷ Propagate features according to adjacency matrix
    $y_k(i) \leftarrow x_k$ ▷ Reset known features
  end while
  return $y(t)$
end procedure

Algorithm 1 Feature propagation algorithm as presented by Rossi et al. [11]. x_k contains the known features, and *A* represents the adjacency matrix that contains the edge weights, i.e., the line conductances. In our case, the adjacency matrix equals the DC admittance matrix. The indices of the known features are depicted by $k = \{k_1, k_2, ..., k_n\}$, and *y*(*i*) contains all features after iteration *i*. Each algorithm iteration only requires one matrix multiplication and is, therefore, computationally very cheap.

The number of iterations the feature propagation algorithm needs to converge depends on the number of available measurements, the location of the available measurements, and the distribution grid in question. The algorithm is stopped once the difference delta to the previous iteration is lower than the threshold ϵ. With seven available measurements and $\epsilon = 10^{-5}$, the algorithm stops after 153 iterations on the IEEE bus system 37. The GINN algorithm [15], which we use for comparison, does not use the graph data structure but imputes the missing features based on training data. A training data set consists of the same power grid in different states. The grid remains the same for the training data set, but the voltage measurements change depending on the loads placed in the grid. The internal GCNs learn the relationships between nodes using this training data and do not require the adjacency matrix as an input.

In each iteration of the feature propagation algorithm, a matrix multiplication is performed. The complexity of the feature propagation algorithm is, therefore, directly related to the size of the matrix, which is equal to the number of nodes. This results in a complexity of between about $O(n^{2.38})$ and $O(n^3)$, depending on the algorithm [44]. In the GINN algorithm, a similarity graph is constructed internally, which can be done efficiently [15]. This only needs to be done once for a dataset during training. For the recurring generation of pseudo-measurements, inferring the GCNs is necessary. The inference has a complexity of $O(|E|CF)$ with $|E|$ denoting the number of edges and C and F denoting the number of input and output features of the GCN respectively [15].

Evaluation

The evaluation of the proposed method is split into two parts. First, the accuracy of the measurements of the smart plugs is evaluated. To do so, two smart plugs are installed in a real-world test environment, and the measurements taken by the smart plugs are compared to calibrated professional measuring devices. In the second part, the complete monitoring of the distribution grid area is evaluated.

Smart plug accuracy

Two smart plugs are installed in the real-world test environment to evaluate the accuracy of the smart plug voltage measurements. In our test setup, the power analyzer is configured to send one measurement value per second. Since the smart plugs contain the same measurement IC, the difference in the measured values is only due to the difference between the modified and the unmodified firmware versions.

First, we analyze the measurements of the smart plug with the unmodified Tasmota open-source firmware [43]. With this firmware, the smart plugs output voltage measurements with one decimal place. Therefore, one could assume that the error of a measurement is at most 0.1 V. However, due to rounding errors in the unmodified Tasmota firmware, the measurement error is higher. The smart plug only takes voltage measurements in steps of at least 0.2 V, sometimes even only 0.3 V.

In Fig. 3, the measurement error of the smart plug with the unmodified firmware version is plotted in orange, and the measurement error of the smart plug with the modified firmware is plotted in blue. Since the unmodified firmware version outputs one measurement value every ten seconds and the modified firmware version outputs one value per second, there are exactly ten times as many measurement values of the modified firmware version in the same time span. The Y-axis values are relative to the total number of measurements.

The measurements of the smart plug with the unmodified Tasmota firmware are more spread out than those with the modified firmware, indicating that the standard

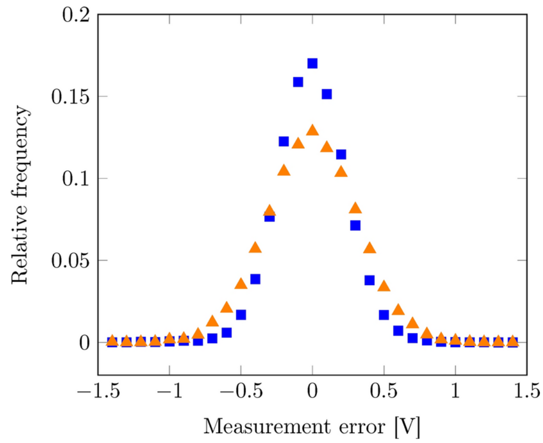

Fig. 3 Relative frequency histogram of the measurement error of smart plugs with the modified firmware (blue) and the unmodified firmware (orange)

deviation of the blue measurements is lower than the standard deviation of the orange measurements. This is indeed the case, as the standard deviation of the smart plug with the unmodified firmware is 0.33 V, and the standard deviation of the smart plug with the modified firmware is 0.27 V.

Neither the Anderson-Darling test [45] for normality nor the Shapiro-Wilk test [46] allow us to reject the null hypothesis that the data are normally distributed. The Anderson-Darling test returns a statistic of 0.44 and a critical value to reject the null hypothesis of 0.57, even at a significance level of 15 %. The Shapiro-Wilk test gives a p-value of 0.54. Therefore, we conclude that the measurement error is likely to follow a normal distribution or some other very similar distribution.

Distribution grid monitoring error

In the context of monitoring the distribution grid, it is of interest to observe the voltage levels at the Point of Common Coupling (PCC). At this point, where the building wiring ends and the distribution grid operator's area of concern starts, the voltage levels must be within a range specified by the regulating authorities. For instance, the standard EN-50160 permits voltage levels between 0.9 p.u. and 1.1 p.u. Consequently, it is advisable to install measuring devices in close proximity to the PCC. In our scenario, we assume that the smart plugs used to measure the voltage levels are installed at an outlet that is in very close proximity to the PCC, such that the voltage level at this point is nearly identical to the level at the PCC. Consequently, only the measurement error of the smart plug itself must be considered in the context of grid monitoring; no additional error has to be attributed to the placement of the smart plug behind the PCC.

In order to evaluate the overall error of the distribution grid monitoring, we calculate the Mean-Square Error (MSE) for multiple test cases. As a baseline comparison, the GINN algorithm presented in [15] is implemented and evaluated. We also compare the results with the basic approach of inserting the mean value of the measured values wherever measurements are missing.

As a test case, the grids "1-LV-rural3–1", "1-LV-semiurb5–2", and "1-LV-urban6–2" from the SimBench dataset [47] are used. All three grids are low-voltage grids with a nominal voltage level of 0.4 kV. They contain PV generation and consist of 118, 104, and 53 nodes, respectively. The power flows for 5000 time steps for each grid are calculated, and the resulting voltage values are used as the ground truth. In order to generate a realistic test case, a percentage of values are removed from the results. The remaining voltage values are modified with a measurement error, following the normal distribution of the measurement error of the smart plugs. The dataset contains between 2 % and 50 % of voltage values for each time step (i.e., 50 %, 80 %, 90 %, 95 %, or 98 % of features are missing). Furthermore, the existing voltage values are offset by a simulated measurement error corresponding to the smart plug measurement error.

In Fig. 4, the MSE of the pseudo-measurement voltage values generated using the GINN algorithm and the feature propagation algorithm are illustrated. The shaded area represents the standard deviation. For this test, 1.000 time steps from the three grids are evaluated. At every time step, a randomized mask is applied to the data, removing a random set of input values and generating a realistic test case with missing features. This dataset, containing incomplete voltage values for the three grids for 1000 time steps, is input into the GINN algorithm or the feature propagation (Algorithm 1).

The GINN algorithm is trained and evaluated separately on the three grids, resulting in a best-case scenario without transfer learning. The algorithm only deals with a single electricity grid in training and testing, and this process is repeated for each grid used for the evaluation.

The feature propagation algorithm is able to reconstruct the missing features relatively accurately, even in cases with 95 % or 98 % of missing features. With more features being present, the GINN algorithm can also generate accurate substitutes. However, the feature propagation that is purely based on the phenomenon that the neighboring nodes have similar characteristics is outperforming the GINN algorithm at every tested percentage of missing values. The feature propagation algorithm is able to reconstruct the missing voltage values with an MSE of $0.43 \cdot 10^{-3}$p.u. with 95 % of voltage values missing in the graph. In a 230 V grid, this equals an MSE of 0.099V. The GINN algorithm produces voltage values with an MSE of $0.64 \cdot 10^{-3}$p.u. when 95 % of the values are missing, which is equal to 0.147V in a 230 V grid. The basic approach of inserting the average

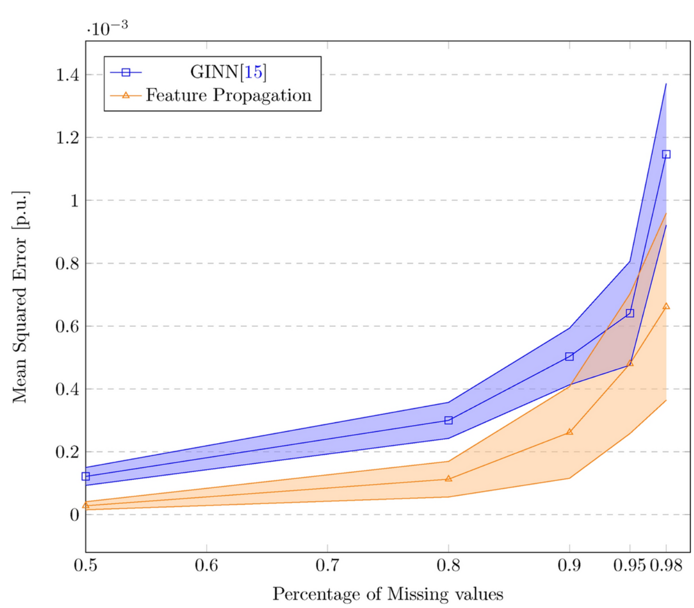

Fig. 4 The MSE between the imputed and true values in the dataset. The shaded area illustrates the standard deviation

measurement value as a pseudo measurement wherever measured values are missing leads to a very high MSE. All results are summed up in Table 2.

Case study

The use of smart plugs as distributed measuring devices in the distribution grid can enable real-time monitoring of voltage levels, allowing operators to detect and address issues promptly. However, measurement errors could be an issue when monitoring the distribution grid accurately. To further explore the impact of the measurement error and the correlation between the number of measuring devices and the accuracy of grid monitoring, this section presents a case study of exemplary distribution grid monitoring.

In the present case study, we simulate the power flow in an IEEE 37 bus system. Smart plugs are emulated by adding a measurement error to all measurements, according to our findings in the previous section. We utilize the feature propagation algorithm presented in Section 3.4.2 and achieve much better results than previously published research [13].

Problem formulation

Distribution grid monitoring and state estimation are becoming increasingly important for DSOs due to the rise in flexible consumption, distributed generation, and the increase of demanding loads such as heat pumps and electric vehicle chargers. However, accurately monitoring the distribution grid and determining the impact of new loads and distributed electricity generation requires many measuring devices. This case study shows how a limited number of smart plugs can provide valuable insight into the voltage levels at different nodes within the distribution grid area. It also outlines the relationship between the number of smart plugs in the grid area and the monitoring accuracy.

Method

In order to evaluate the benefit of smart plug measurements for grid state monitoring, an IEEE 37 bus system is simulated. We implement the grid simulation using pandapower, an open-source tool written in Python for modeling and analyzing power grids [48]. The smart plugs providing the measurements are also simulated. This standardized distribution grid bus system is shown in Figs. 5 and 6.

The transformer **T** is connected to the 20 kV grid on the primary side and the 400 V distribution grid on the secondary side. The nodes in the graph represent the houses in the distribution grid. In this power flow simulation, all the houses are placed 40 m away from each other, and NAYY 4x150 SE lines are used to connect them. These are the most common lines used in Germany [49], and 40 m is a common distance between neighbors in a rural German distribution grid [50]. We assume that the Root-Mean-Square (RMS) voltage at the transformer is constant for this simulation model. To evaluate the impact

Table 2 MSE of the distribution grid monitoring in $10^{-3}\,p.u.$ from 1000 time steps of the grids "1-LV-rural3–1", "1-LV-semiurb5–2", and "1-LV-urban6–2"

Missing rate	Averaging	GINN	Feature propagation
0.5	4.375	0.121	0.030
0.8	6.668	0.300	0.105
0.9	8.019	0.503	0.242
0.95	8.792	0.640	0.431
0.98	11.630	1.146	0.626

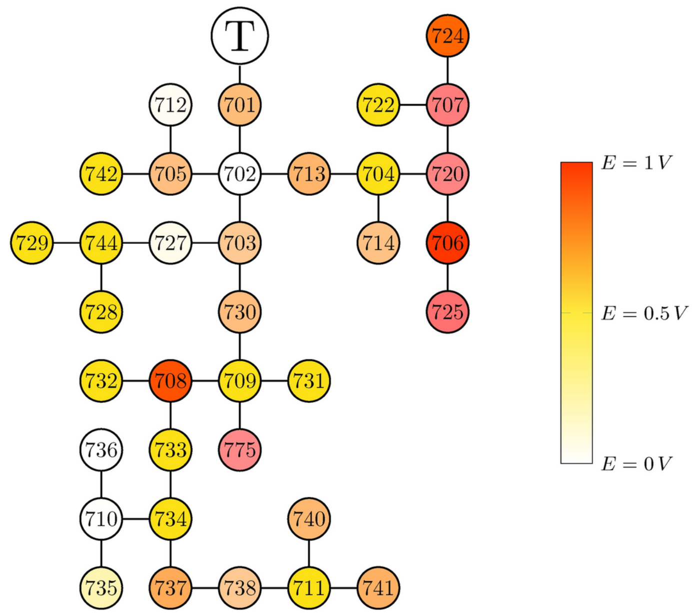

Fig. 5 Graph representation of the IEEE bus system 37 and illustration of the monitoring results at a single time step. Nodes are colored based on the voltage monitoring error at an exemplary time step that results from the feature propagation algorithm. Monitored voltages at white and yellow nodes are similar to the ground truth voltage levels, and monitored voltages at the red nodes differ more from the ground truth voltage levels. In this instance, only two smart plugs are installed at node 736 and node 702. The average monitoring error *E* is about 0.200 V, and the MSE is about 0.044 V

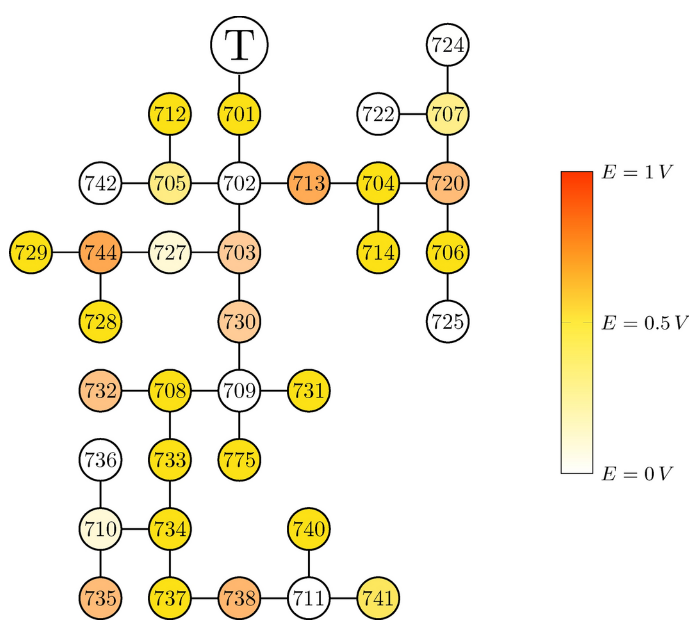

Fig. 6 Graph representation of the IEEE bus system 37 and illustration of the monitoring results at a single time step. Nodes are colored based on the voltage monitoring error at an exemplary time step that results from the feature propagation algorithm. Monitored voltages at white and yellow nodes are similar to the ground truth voltage levels, and monitored voltages at the red nodes differ more from the ground truth voltage levels. In this example, seven smart plugs are installed at nodes 736, 706, 709, 711, 742, 722, and 725. The average monitoring error *E* is about 0.169 V with an MSE of about 0.029 V, and the coloring is consistent with Fig. 5

of the measurement error of the distributed smart plugs on the monitoring of the grid area, we implement several scenarios with different numbers of smart plugs installed in the grid area. We add realistic loads from the SimBench dataset [47] to the nodes, representing household appliances and electric vehicle chargers.

In the case study, we use the voltage levels generated by power flow calculations as the ground truth. We offset them with random values sampled from a normal distribution with the standard deviation calculated in Sect. 4 to model the measurement accuracy of the smart plugs. This results in voltage levels that a DSO could measure in a real-world experiment, and we call them artificial voltage measurements.

In the following, we aim to estimate the true voltage levels at all nodes in the IEEE bus system 37 from the perspective of the DSO with the presented feature propagation algorithm. The artificial voltage measurements represent the features that are present. We assume that the DSO also knows the voltage at the transformer.

The admittance matrix, which the feature propagation algorithm uses as the adjacency matrix, is derived from the bus system lines. By removing the unmonitored nodes from the power flow results and adding a measurement error to the monitored nodes, the input data for the feature propagation algorithm is generated. The algorithm then propagates these measurements during numerous iterations.

Evaluation

In order to evaluate the use of smart plugs as measuring devices in combination with the feature propagation algorithm, we compare the propagated voltage measurements with the true voltage levels. The nodes in Fig. 5 and Fig. 6 are colored based on the difference between the true voltage levels and these propagated voltage measurements. Red nodes represent a greater difference between the true voltage levels and the propagated voltage measurements, and the lighter the nodes are colored, the smaller the monitoring error is. The voltage error is lowest at the nodes where the measuring devices are installed. However, due to the measurement inaccuracy of the smart plugs, even these voltage levels are not perfectly accurate. As a general rule, the further the measurements are propagated by the feature propagation algorithm, the less accurate they are. This means that, especially in large networks, meters should be placed at points that need to be monitored accurately. In the grid shown in Fig. 5, only two smart plugs are used for monitoring. In Fig. 6, seven smart plugs are placed in the grid area. It can be seen that with seven smart plugs, the monitoring error is lower on average. Furthermore, in the experiment with seven smart plugs, the maximum monitoring error is also significantly reduced compared to the monitoring result using only two smart plugs.

The correlation between the number of measuring devices in the grid and the average voltage error in a 230 V grid is illustrated in Fig. 7. This figure also shows the improvement of the feature propagation algorithm compared to the previously used pseudo-measurement generation algorithm from the original version of this paper [13].

In this case study, we utilize typical load profiles drawn from the Simbench dataset to create the ground truth distribution grid state. The aforementioned realistic profiles result in a typical voltage gradient between the feeder and the buses. The further away the buses are from the feeder, the greater the voltage drops. The feature propagation algorithm establishes a similar gradient by diffusing the known measurements

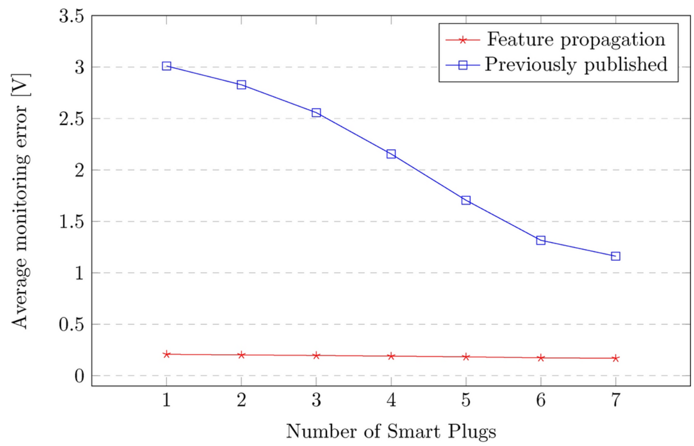

Fig. 7 Correlation between the number of smart plugs in the grid area and the average monitoring error. The blue squares depict the monitoring error of the previously published pseudo-measurement value generation [13], and the red stars depict the monitoring error of the feature propagation (Algorithm 1). The monitoring error of the feature propagation algorithm also decreases the more measuring devices are installed, from 0.210 V with one smart plug to 0.169 V with seven smart plugs

throughout the grid. However, for vastly different load scenarios compared to those evaluated in this case study, the feature propagation algorithm may perform worse.

Discussion

The voltage standard deviation observed in the smart plug measurements with the modified firmware of 0.27 V is well within the range of what is considered acceptable in other publications (0.6 % in [26] and 0.3 % to 0.9 % in [24]). Installing multiple smart plugs in the same distribution grid area further improves the accuracy of the measurements, and monitoring multiple phases in three-phase distribution networks would allow asymmetric loads to be detected. The smart plugs with the modified firmware version allow up to one voltage measurement per second, and they are available almost immediately for a grid state analysis. In contrast, smart meters often take only one measurement every fifteen minutes and transmit the data at intervals of up to six hours [29]. In addition, the deployment of the smart plugs in a real-world test environment can be completed in minutes by configuring the smart plug and connecting it to a nearby WiFi network, and no electrician is required for installation.

Smart meters are typically installed near the point of common coupling. Smart plugs, on the other hand, measure the voltage at the outlet to which they are connected. This means that the voltage drop within the resident's home is included in the smart plug's measurements. This voltage drop depends on the loads within the home's electrical system and is, therefore, not constant. In order to reduce the voltage drop on the local line, it is necessary to install the smart plug as close as possible to the point of common coupling. In addition, the smart plugs monitor only one phase. However, the load in the distribution grid is predominantly symmetrical [51], which results in a symmetrical voltage drop as well.

The approach of using widely available smart plugs to monitor the distribution grid is mainly limited by privacy concerns and the accuracy of the measurements, especially when compared to the measurements from calibrated smart metering systems or power analyzers. Linking the measurement data of the individual smart plugs to a distribution grid customer could reveal daily routines or installed appliances. Installing the smart plugs away from the common coupling point may reduce the validity of the measurements, and the constant offset of each device must be determined and compensated for. However, the frequency of the measurements could permit some compensation for these shortcomings, e.g., employing filters. Another issue for practical implementation in the field is the availability of a WiFi connection to transmit the measurements. Perhaps allowing customers to use the switching function of the smart plug would be an incentive to allow the use of their private WiFi access.

In general, installing a custom firmware to monitor the distribution grid voids the warranty of the smart plugs. The manufacturers of the smart plugs would need to provide a software interface to collect measurement data or connect to a custom server to use the smart plugs without flashing a custom firmware. Without the manufacturer's support for such a feature, the DSO would need to flash the custom firmware before distributing the smart plugs to the customers. The smart plugs used in this paper can be flashed remotely without opening them, making the flashing process scalable. Because of the small amount of data transferred, thousands of smart plugs can connect to the same server. If many more Smart Plugs are installed, the load can also be distributed among several servers.

The presented method to generate pseudo measurements enables the monitoring of the complete distribution grid area with only a few measuring devices being installed. The comparison in Table 2 illustrates that simply replacing the missing values with the average of the measured values does not lead to accurate results. By exploiting the homophily of the neighboring nodes, it is possible to propagate the known features through the graph that represents the distribution grid. This process is computationally inexpensive. On the evaluated test cases, the feature propagation leads to better results than what we can achieve using the GINN algorithm and our previously published algorithm [13]. To the best of our knowledge, this is the first application of this kind of feature propagation in the electricity grid. In the evaluation, we show that the feature propagation can reconstruct the missing measurement values with high accuracy and an MSE of 0.431 p.u., equal to 0.099 V, when 95% of measurements are missing. This approach produces more accurate results than the GINN algorithm published by Spinelli et al. [15], which, in our tests, provided pseudo-measurements with an MSE of 0.640 p.u. or 0.147 V. However, tuning the hyper-parameters of the GCNs might increase the quality of the results. In addition, other algorithms for generating pseudo-measurements may produce even better results, for example, by incorporating typical load profiles. In their publication, Rossi et al. test the feature propagation algorithm on multiple datasets with various levels of homophily [11]. This suggests that other approaches may produce more accurate pseudo-measurements than feature propagation, especially when considering less homophilic distribution grids. These could be distribution grids containing very different types of lines. However, such grids are not included in the SimBench dataset. In scenarios with very high measurement errors or false data, feature propagation will propagate these values. However, such erroneous measurements could be detected by analyzing the gradient of the propagated measurements. This should be investigated in future work.

Because the IEEE bus system 37 is relatively small for a distribution grid and only one line is connected directly to the transformer, the voltage values can be propagated along the lines, and the resulting values are very accurate. The larger SimBench grids used to compare the feature propagation algorithm and the GINN algorithm result in less accurate pseudo-measurements. Depending on the distribution grid topology where this monitoring technique is applied and the accuracy required, different numbers of measuring devices will be needed.

Applicability in the real world In a realistic use case, the distribution grid operator must know the line lengths, line types, and possible connected loads and electricity generation systems at all nodes. With this information, the adjacency matrix - the respective admittance matrix - needed for the feature propagation algorithm can be created. Our evaluation of the presented approach suggests that it is invariant to the location of the known features. With the feature propagation algorithm and the known features being diffused across the graph, randomly located measuring devices in the grid produce good results with a small standard deviation. However, extreme test cases with the measuring devices only being installed at one end of the grid would probably perform worse than evenly distributed measuring devices. Moreover, positioning the smart plugs in proximity to the PCC is crucial for precisely measuring grid voltage levels. In the present paper, the smart plugs are placed at the PCC at every node, representing the optimal location. If the smart plugs are positioned further away from the PCC, the discrepancy between the grid voltage and the measured voltage is amplified. This relationship warrants further investigation in future studies.

Because of the low computational effort of the proposed method, new grid monitoring results can be generated quickly with every incoming smart plug measurement. Accordingly, the monitoring can be accomplished with minimal latency on decentralized devices. This allows devices in the field to monitor the grid autonomously without relying on a central controller.

We show that the feature propagation algorithm yields accurate results for the investigated use cases. However, our evaluation is limited to grids from the SimBench dataset. It does not include very large distribution grids with extreme loads nor bad measurement data, which may significantly impact feature propagation results and require a data clean-up step. There are also country-specific regulatory hurdles, which may impede the real world use of smart plugs as measuring devices.

Conclusion

In this paper, we determine the accuracy of smart plug measurements by comparing the calculated values with voltage readings from a Janitza UMG 604EP-PRO power analyzer. We use commercially available devices in the present work that are able to connect directly to a WiFi network and transmit the measurement data to a server, eliminating the need for a relay. The voltage measurements of the tested smart plugs with the modified Tasmota firmware have a standard deviation of 0.27 V, which is lower than the standard deviation of the measurements taken by smart plugs with the unmodified Tasmota firmware. The modified firmware is published as open-source. We also describe the network structure and the integration of smart plug measurement data into an existing time-series database. Installing the commercially available smart plugs does not require an electrician, the hardware is inexpensive, and the individual configuration of the devices is simple.

By propagating the measured voltage values within the distribution grid using a fast feature propagation algorithm, pseudo-measurement values can be generated. This feature propagation algorithm is based on the heat diffusion equation, and the required number of iterations can be computed with very little effort. Compared to our previously published algorithm and the GINN algorithm, the feature propagation algorithm presented in the present paper leads to a more accurate monitoring result with less computational complexity. In this light, simple smart plugs can help to monitor the distribution grid and provide valuable information to the DSO. Such monitoring can help identify impending congestion in rapidly changing grid areas, for example, due to the growth of distributed renewable generation or the installation of new EV charging infrastructure. Because of the low computational effort, the grid monitoring can be updated with every new smart plug measurement. This also enables the computation of pseudo-measurements on smart grid devices with low computing power at a decentralized location. For example, DERs could monitor the distribution grid and provide ancillary services to the grid without communicating with a central controller but only with local measuring devices. As a result, distribution grid monitoring is more resilient to cyber-attacks and internet connection disruptions.

Future work includes evaluating other electricity grids, more algorithms to generate pseudo-measurements, and real-world tests. In particular, the applicability of the feature propagation algorithm to larger, more complex distribution grids with additional load profiles remains to be investigated. Additionally, the homophilic characteristics of the nodes in the electricity grid could potentially be used not only to propagate voltage features but also to approximate other problem solutions on power grids, such as optimal power flow.

Author Contributions

SG: Conceptualization, Methodology, Programming, Validation, Visualization, and Writing of the original manuscript; KF, VH: Funding acquisition, Supervision, Review, and Editing.

Funding

Open Access funding enabled and organized by Projekt DEAL. The authors gratefully acknowledge funding by the German Federal Ministry of Education and Research (BMBF) within the Kopernikus Project ENSURE "New ENergy grid StructURes for the German Energiewende".

Data Availibility

Not applicable

Declarations

Competing interests

The authors declare that they have no competing interests.

Ethics approval

Not applicable

Consent for publication

Not applicable

Materials availability

Not applicable

Code availability

The feature propagation algorithm is originally developed by Rossi et a. [11] and is available in their repository https://github.com/twitter-research/feature-propagation/tree/main.

Received: 29 August 2024 / Accepted: 31 October 2024

Published online: 12 November 2024

References

1. Fatima S, Püvi V, Lehtonen M (2020) Review on the PV Hosting Capacity in Distribution Networks. Energies 13(18):4756. https://doi.org/10.3390/en13184756. (**Accessed 2022-07-19**)

2. Mulenga E, Bollen MHJ, Etherden N (2020) A review of hosting capacity quantification methods for photovoltaics in low-voltage distribution grids. International Journal of Electrical Power & Energy Systems 115, 105445 https://doi.org/10.1016/j.ijepes.2019.105445 . Accessed 2022-09-12
3. Bundesnetzagentur für Elektrizität (2022) Gas, Telekommunikation. Post und Eisenbahnen: Bericht zum Zustand und Ausbau der Verteilernetze 2021:62
4. Behi B, Arefi A, Pezeshki H, Shahnia F (2017) Distribution transformer lifetime analysis in the presence of demand response and rooftop PV integration. Renewable Energy and Environmental Sustainability 2, 27 https://doi.org/10.1051/rees/2017013 . Accessed 2022-09-07
5. Martin Bäckman: Smart Homes and Home Automation, Smart Buildings 9th Edition. Berg Insight AB (2022)
6. Bernieri A, Betta G, Liguori C, Losi A (1996) Neural networks and pseudo-measurements for real-time monitoring of distribution systems. IEEE Transactions on Instrumentation and Measurement 45(2):645–650. https://doi.org/10.1109/19.492803. (**Accessed 2024-06-07**)
7. Manitsas E, Singh R, Pal BC, Strbac G (2012) Distribution System State Estimation Using an Artificial Neural Network Approach for Pseudo Measurement Modeling. IEEE Transactions on Power Systems 27(4):1888–1896. https://doi.org/10.1109/TPWRS.2012.2187804. (**Accessed 2024-09-16**)
8. Angioni A, Schlosser T, Ponci F, Monti A (2016) Impact of Pseudo-Measurements From New Power Profiles on State Estimation in Low-Voltage Grids. IEEE Transactions on Instrumentation and Measurement 65(1):70–77. https://doi.org/10.1109/TIM.2015.2454673. (**Accessed 2024-09-16**)
9. Singh R, Pal BC, Jabr RA (2010) Statistical Representation of Distribution System Loads Using Gaussian Mixture Model. IEEE Transactions on Power Systems 25(1):29–37. https://doi.org/10.1109/TPWRS.2009.2030271. (**Accessed 2024-09-16**)
10. Zhang J, Zhao J, Yang J, Zhao J (2023) Deep Multi-Fidelity Bayesian Data Fusion for Probabilistic Distribution System Voltage Estimation With High Penetration of PVs. IEEE Transactions on Power Systems, 1–12 https://doi.org/10.1109/TPWRS.2023.3295795 . Accessed 2024-09-18
11. Rossi E, Kenlay H, Gorinova MI, Chamberlain BP, Dong X, Bronstein M (2021) On the Unreasonable Effectiveness of Feature propagation in Learning on Graphs with Missing Node Features. arXiv. Version Number: 3. https://doi.org/10.48550/ARXIV.2111.12128 . Accessed 2024-06-04
12. Vanting NB, Ma Z, Jørgensen BN (2021) A scoping review of deep neural networks for electric load forecasting. Energy Informatics 4(S2):49. https://doi.org/10.1186/s42162-021-00148-6. (**Accessed 2024-10-07**)
13. Grafenhorst S, Förderer K, Hagenmeyer V (2024) Distribution Grid Monitoring Based on Widely Available Smart Plugs. In: Jørgensen, B.N., Da Silva, L.C.P., Ma, Z. (eds.) Energy Informatics vol. 14468, pp. 195–212. Springer, Cham. https://doi.org/10.1007/978-3-031-48652-4_13 . Series Title: Lecture Notes in Computer Science. https://link.springer.com/10.1007/978-3-031-48652-4_13 Accessed 2024-08-09
14. Simon Grafenhorst: Fast + Accurate Voltage Measurements in Tasmota, Karlsruhe (2023). https://github.com/si-gr/Tasmota/commit/0d5170928e4fc09a29421b43731631c5c061f42e
15. Spinelli I, Scardapane S, Uncini A (2020) Missing data imputation with adversarially-trained graph convolutional networks. Neural Networks 129, 249–260 https://doi.org/10.1016/j.neunet.2020.06.005 . Accessed 2024-07-30
16. Janitza electronics GmbH: The New Generation - the UMG PRO Series (2019). https://www.janitza.de/files/download/leaflets/pro-serie/janitza-umg-pro-serie-en.pdf
17. Andreas Abart, Daniel Burnier, Benoit Bletterie, Matthias Stifter, Helfried Brunner, Andreas Lugmaier, Alexander Schenk (2011) Power Snapshot Analysis: A new method for analyzing low voltage grids using a smart metering system, vol. 21st. Frankfurt
18. Dahale S, Karimi HS, Lai K, Natarajan B (2020) Sparsity Based Approaches for Distribution Grid State Estimation - A Comparative Study. IEEE Access 8, 198317–198327 https://doi.org/10.1109/ACCESS.2020.3035378 . Accessed 2022-08-12
19. Primadianto A, Lu C-N (2017) A Review on Distribution System State Estimation. IEEE TRANSACTIONS ON POWER SYSTEMS 32(5):9
20. Akrami A, Asif S, Mohsenian-Rad H (2022) Sparse Tracking State Estimation for Low-Observable Power Distribution Systems Using D-PMUs. IEEE Transactions on Power Systems 37(1):551–564. https://doi.org/10.1109/TPWRS.2021.3094534. (**Accessed 2022-09-09**)
21. Wang Y, Chen Q, Hong T, Kang C (2019) Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges. IEEE Transactions on Smart Grid 10(3):3125–3148. https://doi.org/10.1109/TSG.2018.2818167. (**Accessed 2022-09-11**)
22. Khan MA, Hayes B (2022) Smart Meter Based Two-Layer Distribution System State Estimation in Unbalanced MV/LV Networks. IEEE Transactions on Industrial Informatics 18(1):688–697. https://doi.org/10.1109/TII.2021.3079267. (**Accessed 2022-09-11**)
23. Alimardani A, Zadkhast S, Jatskevich J, Vaahedi E (2014) Using smart meters in state estimation of distribution networks. In: 2014 IEEE PES General Meeting | Conference & Exposition, pp. 1–5. IEEE, National Harbor, MD, USA. https://doi.org/10.1109/PESGM.2014.6939801 . Accessed 2022-09-11
24. Jia Z, Chen J, Liao Y (2013) State estimation in distribution system considering effects of AMI data. In: 2013 Proceedings of IEEE Southeastcon, pp. 1–6. IEEE, Jacksonville, FL, USA. https://doi.org/10.1109/SECON.2013.6567406 . Accessed 2022-09-06
25. Quilumba FL, Lee W-J, Huang H, Wang DY, Szabados RL (2015) Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities. IEEE Transactions on Smart Grid 6(2):911–918. https://doi.org/10.1109/TSG.2014.2364233. (**Accessed 2022-09-12**)
26. Samarakoon K, Wu J, Ekanayake J, Jenkins N (2011) Use of delayed smart meter measurements for distribution state estimation. In: 2011 IEEE Power and Energy Society General Meeting, pp. 1–6. IEEE, San Diego, CA. https://doi.org/10.1109/PES.2011.6039384 . Accessed 2022-09-06
27. Trindade FCL, Freitas W (2017) Low Voltage Zones to Support Fault Location in Distribution Systems With Smart Meters. IEEE Transactions on Smart Grid 8(6):2765–2774. https://doi.org/10.1109/TSG.2016.2538268. (**Accessed 2022-09-09**)
28. Araujo MA, Flauzino RA, Moraes LA, Borges FAS, Spatti DH (2019) Decision Trees Applied to Fault Locations in Distribution Systems with Smart Meters. In: 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I &CPS Europe), pp. 1–6. IEEE, Genova, Italy. https://doi.org/10.1109/EEEIC.2019.8783511 . Accessed 2022-09-09

29. Sanchez R, Iov F, Kemal M, Stefan M, Olsen R (2017) Observability of low voltage grids: Actual DSOs challenges and research questions. In: 2017 52nd International Universities Power Engineering Conference (UPEC), pp. 1–6. IEEE, Heraklion. https://doi.org/10.1109/UPEC.2017.8232008 . Accessed 2022-09-11
30. Lo Y-L, Huang S-C, Lu C-N (2014) Transformational Benefits of AMI Data in Transformer Load Modeling and Management. IEEE Transactions on Power Delivery 29(2):742–750. https://doi.org/10.1109/TPWRD.2013.2280574. (**Accessed 2022-09-07**)
31. Dimitriou P, Leber T, Nagele N, Temmel L, Tessarek C (2014) Voltage and frequency measuring plug: As part of Smart Grids metering system. In: 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 350–355. IEEE, Venice, Italy. https://doi.org/10.1109/SmartGridComm.2014.7007671 . Accessed 2022-08-11
32. Ganu T, Seetharam DP, Arya V, Kunnath R, Hazra J, Husain SA, De Silva LC, Kalyanaraman S (2012) nPlug: a smart plug for alleviating peak loads. In: Proceedings of the 3rd International Conference on Future Energy Systems: Where Energy, Computing and Communication Meet, pp. 1–10. ACM, Madrid Spain. https://doi.org/10.1145/2208828.2208858 . Accessed 2023-01-20
33. Melo GCGd, Torres IC, Araujo IBQd, Brito DB, Barboza EdA (2021) A Low-Cost IoT System for Real-Time Monitoring of Climatic Variables and Photovoltaic Generation for Smart Grid Application. Sensors 21(9), 3293 https://doi.org/10.3390/s21093293 . Accessed 2022-09-09
34. Andrew Banks, Ed Briggs, Ken Borgendale, Rahul Gupta (2019) MQTT Version 5(0). https://docs.oasis-open.org/mqtt/mqtt/v5.0/mqtt-v5.0.html
35. Manandhar K, Cao X, Hu F, Liu Y (2014) Detection of Faults and Attacks Including False Data Injection Attack in Smart Grid Using Kalman Filter. IEEE Transactions on Control of Network Systems 1(4):370–379. https://doi.org/10.1109/TCNS.2014.2357531. (**Accessed 2024-10-07**)
36. Marković M, Bossart M, Hodge B-M (2023) Machine learning for modern power distribution systems: Progress and perspectives. Journal of Renewable and Sustainable Energy 15(3):032301. https://doi.org/10.1063/5.0147592. (**Accessed 2024-06-04**)
37. Madbhavi R, Natarajan B, Srinivasan B (2023) Graph Neural Network-Based Distribution System State Estimators. IEEE Transactions on Industrial Informatics 19(12):11630–11639. https://doi.org/10.1109/TII.2023.3248082. (**Accessed 2024-06-04**)
38. Coster EJ, Myrzik JMA, Kruimer B, Kling WL (2011) Integration Issues of Distributed Generation in Distribution Grids. Proceedings of the IEEE 99(1):28–39. https://doi.org/10.1109/JPROC.2010.2052776. (**Accessed 2024-07-31**)
39. Keriven N, Peyré G (2019) Universal Invariant and Equivariant Graph Neural Networks. In: Wallach, H., Larochelle, H., Beygelzimer, A., Alché-Buc, F.d., Fox, E., Garnett, R. (eds.) Advances in Neural Information Processing Systems, vol. 32. Curran Associates, Inc., ???. https://proceedings.neurips.cc/paper_files/paper/2019/file/ea9268cb43f55d1d12380fb6ea5bf572-Paper.pdf
40. Sen P, Namata G, Bilgic M, Getoor L, Gallagher B, Eliassi-Rad T (2008) Collective Classification in Network Data. AI Magazine 29(3):93–106. https://doi.org/10.1609/aimag.v29i3.2157. (**Accessed 2024-10-08**)
41. Song Y, Lin J, Tang M, Dong S (2017) An Internet of Energy Things Based on Wireless LPWAN. Engineering 3(4):460–466. https://doi.org/10.1016/J.ENG.2017.04.011. (**Accessed 2022-09-08**)
42. Theo Arends et al.: Tasmota (2022). https://github.com/arendst/Tasmota
43. Tasmota (2022) Tasmota Components. https://tasmota.github.io/docs/Components/#tasmota
44. Schwartz O, Vaknin N (2023) Pebbling Game and Alternative Basis for High Performance Matrix Multiplication. SIAM Journal on Scientific Computing 45(6):277–303. https://doi.org/10.1137/22M1502719. (**Accessed 2024-09-24**)
45. Stephens MA (1974) EDF Statistics for Goodness of Fit and Some Comparisons. Journal of the American Statistical Association, 9
46. Shapiro SS, Wilk MB (1965) An Analysis of Variance Test for Normality (Complete Samples). Biometrika 52(3/4):22
47. Meinecke S, Sarajlić D, Drauz SR, Klettke A, Lauven L-P, Rehtanz C, Moser A, Braun M (2020) SimBench-A Benchmark Dataset of Electric Power Systems to Compare Innovative Solutions Based on Power Flow Analysis. Energies 13(12):3290. https://doi.org/10.3390/en13123290. (**Accessed 2023-01-18**)
48. Thurner L, Scheidler A, Schafer F, Menke J-H, Dollichon J, Meier F, Meinecke S, Braun M (2018) Pandapower-An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems. IEEE Transactions on Power Systems 33(6):6510–6521. https://doi.org/10.1109/TPWRS.2018.2829021. (**Accessed 2022-09-11**)
49. Kochanneck S (2018) Systemdienstleistungserbringung durch intelligente Gebäude. PhD thesis, Karlsruher Institut für Technologie (KIT), Karlsruhe
50. Georg Kerber, Rolf Witzmann: Statistische Analyse von NS-Verteilnetzen und Modellierung von Referenznetzen. ew Jg. 107 (2008) vol. 6, 22–26 (2008)
51. Schwab AJ (2017) Elektroenergiesysteme: Erzeugung, Übertragung und Verteilung Elektrischer Energie. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-55316-9 . Accessed 2022-09-12