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Impact of Pseudo-Measurements Generation on Distribution System State Estimation

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***Abstract*—The evolving structural changes in power networks have a significant impact on the management of monitoring and control applications. Among them, Distribution System State Estimation (DSSE) faces inherent limitations due to uncertainties arising from these transformations, which often lead to a degradation in the quality of measurements and pseudo-measurements used in state estimation routines. To mitigate these challenges, Machine Learning techniques are increasingly recognized as effective solutions to improve the performance of monitoring applications. In this context, this paper aims to assess how the prediction of active and reactive powers obtained through a Multi-Layer Perceptron (MLP) neural network and compared with simple benchmark models, affects DSSE performance. Firstly, starting from real data collected from the Forschungszentrum Jülich campus, the MLP model has been characterized and, finally, DSSE has been evaluated by means of several numerical simulations. The preliminary exploratory results have suggested that the proposed model shows promising potential in improving the accuracy of DSSE. These initial results suggest that it may be worth investigating more complex neural models in the future, with the aim of further enhancing DSSE performance and providing system operators with increasingly reliable monitoring and control tools.**

***Index Terms*—Distribution System State estimation, Machine learning, Multi-Layer Perceptrons, Pseudo-measurements, Observability, Measurement accuracy.**

I. Introduction

The ongoing transformation of electrical power systems, driven by the integration of renewable energy sources, the increased integration of distributed generation, and the evolution towards prosumer-based models, is reshaping the structure and operation of modern distribution networks. This paradigm shift leads to increased complexity in grid management, characterized by higher variability, bidirectional power flows, and a greater need for flexibility and resilience. This structural change poses challenges for network monitoring, control, and voltage stability [1], [2]. Accurate measurements are essential to enable real-time control actions, detect anomalies and identify faults. However, the limited instrumentation available in distribution networks, makes real-time observability a challenge. One of the key tools to overcome this limitation is Distribution System State Estimation (DSSE).

DSSE provides a real-time snapshot of the electrical conditions across the network, typically estimating voltage magnitudes and phase angles at various nodes, by combining real-time measurements and, for full observability, synthetic or estimated data. The latter, known as Pseudo-Measurements (PMs), are often based on historical patterns, forecasts, or Machine Learning (ML) techniques [3]. Employing effective PMs enhances grid management, especially in networks with low observability where real-time measurements are sparse or scarcely available. However, generating PMs requires balancing trade-offs between accuracy, robustness, and computational complexity.

The application of PMs in DSSE has significantly evolved since the 1990s. Initially, methods addressed the lack of real-time data by incorporating PMs based on nominal values, historical averages or forecasted load values [4], [5]. However, these traditional PMs often exhibited high variance and low temporal resolution, leading to potential inaccuracies [6]. To address this, statistical approaches such as Monte Carlo (MC) simulations, Bayesian inference, and Gaussian Mixture Models (GMMs) have been introduced [7]–[10], offering probabilistic representations of unmeasured quantities and improving the handling of uncertainty.

More recently, ML techniques have emerged as powerful tools for PM generation. Artificial Neural Networks (ANNs) have been used to model non-linear relationships between historical consumption, time-based features, and load patterns [6], [11], [12]. These models allow for the creation of more accurate and context-aware PMs. For instance, ANNs have been trained to predict active and reactive power injections using substation measurements and limited field data, showing improved generalization across different operating conditions [13].

Building on these developments, the primary objective of this work is to evaluate the potential benefits of incorporating accurate PMs of active and reactive power absorption into the DSSE process. These PMs are generated using different models, including an ANN trained on real consumption data, extending the methodology presented in [3]. While many studies focus mainly on improving PM generation accuracy, the direct impact of PM quality and nature on DSSE performance remains relatively unexplored. Therefore, this study explicitly investigates how different PM generation strategies, from simple approaches to data-driven models, influence DSSE performance when applied to real-world data.

Following this introduction, in Section II the fundamentals of DSSE are offered. In Section III and IV the problem formulation and the models used for PM generation are shown. In Section V the simulation scenario is presented. In Section VI the results are provided and finally, in Section VII the conclusions are drawn.

II. Distribution System State Estimation

DSSE is a mathematical technique used to estimate the most likely state of a power system given a particular set of measurements. Among the approaches used to solve the State Estimation (SE) problem, the most common one is the Weighted Least Squares (WLS) method, which has proven to be a well-established solution for DSSE.

Considering a single-phase power distribution system with N_b buses and L_{br} branches, it is possible to define, for each measurement instant, t, the vector of state variables $\mathbf{x}(t)$ of size $2N_b$:

$$\mathbf{x}(t) = [V_1, \theta_1, ..., V_{N_b} 0, \theta_{N_b}]^{\mathrm{T}} \tag{1}$$

In (1), the superscript "T" indicates the transpose operator. For the generic bus k, V_k and θ_k represent the voltage magnitude and phase, respectively.

DSSE relies on the following measurement model:

$$\mathbf{z}(t) = \mathbf{h}(\mathbf{x}(t)) + \mathbf{e}(t) \tag{2}$$

where $\mathbf{z}(t)$ and $\mathbf{e}(t)$ represent the measurement vector and the errors of the corresponding measurements, respectively, while, $\mathbf{h}(\cdot)$ represents the vector of the measurement functions linking $\mathbf{x}(t)$ with $\mathbf{z}(t)$. A typical assumption about the vector $\mathbf{z}(t)$ is to have uncorrelated measurements. Nevertheless, depending on the specific requirements, more advanced formulations can be adopted [14]. The estimated state vector $\hat{\mathbf{x}}(t)$ is obtained via WLS method minimizing the following objective function:

$$J(\mathbf{x}(t)) = [\mathbf{z}(t) - \mathbf{h}(\mathbf{x}(t))]^T \mathbf{W} [\mathbf{z}(t) - \mathbf{h}(\mathbf{x}(t))] \tag{3}$$

In (3), $\mathbf{W}$ is a weighting matrix, chosen as the inverse of the covariance matrix of measurements, and thus depending on the information available on measurement accuracy (e.g., on the datasheet information of the measurement devices) and also on PMs uncertainty. The minimization of the objective function in (3) can be obtained, for instance, by applying the Gauss–Newton method until the convergence of the procedure is achieved.

III. Problem Formulation

The problem at hand is framed in a realistic scenario where PMs serve as virtual sensors, enhancing network observability in distribution systems that lack full real-time monitoring. This approach reflects the common situation in low and medium-voltage grids, where measurement infrastructure is often sparse or incomplete.

The proposed model could be used to generate PMs for all nodes in the grid that lack real-time measurements. In general, the model can be applied to any node, provided that historical estimations of active and reactive power data are available. In the absence of real-time data, PMs ensure complete system observability, thus supporting a consistent and reliable SE process. A schematic representation of the overall system is shown in Fig. 1.

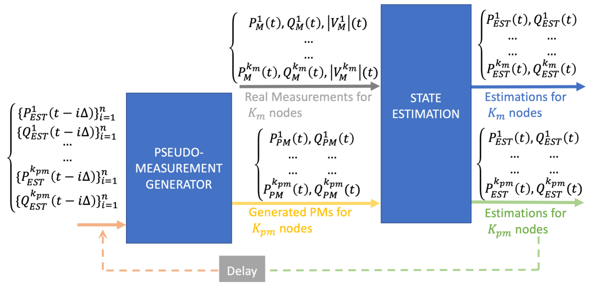

Fig. 1. Scheme of the overall system at the time instant t.

Assuming a total of K nodes in the network (comprising the slack node), the nodes are divided as follows:

- K_m nodes are monitored nodes, i.e., they are equipped with real-time measurements of active and reactive power and voltage magnitude (P, Q, and $|V|$, respectively);
- the remaining $K_{pm} = K - 1 - K_m$ nodes are unobserved but are covered by the PMs Generator (PMG) block, which process historical time series of the estimated active and reactive power values (P_{EST}, Q_{EST}).

The generated PMs, together with the real-time measurements from the monitored nodes, are provided as input to the SE algorithm.

The SE algorithm processes all these inputs to produce estimated active and reactive power values (P_{EST}, Q_{EST}) across the network. Notably, the estimated values for the K_{pm} nodes are then fed back into the PMG block, where they are used iteratively to refine the PMs. This iterative loop ensures that the system continuously improves the accuracy of its PMs based on the latest state estimations.

It is important to note that, for the purpose of developing and validating the PM models in this study, simulations are carried out using actual power consumption data from the nodes of interest, treated as if they were historical estimations produced by the DSSE process.

A. Database

The data used in this study comprises electrical power measurements recorded from two buildings within the Forschungszentrum Jülich (FZJ) campus. The first building is primarily comprised of office spaces, with electrical loads of equipment such as computers, monitors, and similar devices. It also includes recreational rooms, which introduce non-typical office loads such as dishwashers, microwave ovens, refrigerators, and water heaters. The second building is a cafeteria, which serves as a dining area for the campus community. It accommodates various food preparation and consumption activities, contributing to the overall power consumption with loads associated with kitchen equipment, refrigerators, and other appliances typical of food service facilities. The complete set of data spans a period of three and a half years, from 2017 to mid-2020. Upon analyzing the data, it was observed that during the initial phase of the COVID-19 pandemic, from

March to June 2020, office consumption remained consistent with previous years, whereas the cafeteria experienced a significant decline in usage. To ensure a coherent and homogeneous dataset, it was therefore decided to include only the data from January 1st, 2017 to February 29th, 2020, just before the onset of the pandemic.

The original database includes Root Mean Square (RMS) values of voltages and currents, power factor values, and total active power, collected via Smart Meters compliant with class 1 of the standard IEC 61036 [15] with a reporting rate of one value every minute.

For the purposes of evaluating the PMs, a dataset containing only active power values (from the original data) and reactive power values (derived from the other quantities, i.e., the power factor) was created, sampled at 15-minute intervals. The dataset then underwent cleaning by removing duplicates, handling missing values, and identifying outliers.

As in a previous work using the same data [3], the analysis of the temporal structure of the data revealed the importance of distinguishing between working days and holidays or weekends, due to their markedly different load profiles. Consequently, this study also focused exclusively on working days. Following the same methodology, datetime features, such as hour of the day, day of the week, month of the year, and day of the year, were encoded using sine and cosine transformations to preserve their cyclical nature.

IV. PSEUDO-MEASUREMENTS GENERATION

This work investigates the impact of different PM generation methods on the accuracy and robustness of the SE. Specifically, three approaches are considered: Naïve PMs, historical average profiles, and ML-based PMs generated through ANNs. The analysis aims to quantify how the quality and nature of PMs influence both system observability and the overall performance of the estimation process.

A. Artificial Neural Networks for PMs generation

ANNs represent a particularly effective solution for load forecasting tasks. Their selection in this work is motivated by their ability to capture non-linear relationships between input features and load values, their flexibility in handling a wide variety of input data, and their rapid inference times once training is completed. The latter characteristic is especially critical within the proposed framework, where load forecasting operates in a closed-loop configuration with the SE process.

ANNs are composed of artificial neurons organized into interconnected layers. Each neuron performs a mathematical operation on its input data, and information is propagated through the network layer by layer.

In this work, the load forecasting problem has been addressed using a Multi-Layer Perceptron (MLP), a model known for its ease of training and strong generalization capabilities. The implemented MLP architecture consists of three layers: an input layer, a single hidden layer and an output layer. Each neuron is fully connected to all neurons in the subsequent layer. This architecture enables the network to effectively model the non-linear relationship between the input features and the corresponding output. In line with standard procedures, the dataset was divided into training, validation, and test sets, with the final 9 months reserved for testing and a random subset of the training data allocated for validation. Through a cross-validation process, the hyperparameters, including the number of input features, the number of hidden neurons, the number of training epochs, were selected as those yielding the best model generalization.

Distinct MLPs were developed to forecast P and Q values. The decision to create two distinct models was based on the results of a series of tests conducted on various configurations, including using a single model to predict both active and reactive power. However, the best results were obtained when the models were trained separately. To preserve generality, both models were designed with identical input structures, comprising:

(i) **Eight time-related variables**: the hour of the day, the day of the week, the day of the year, and the month, all encoded in a cyclical manner using sine and cosine transformations. This encoding captures the periodicity in daily, weekly, and yearly consumption patterns.

(ii) **Two historical power consumption variables**: the average of P and Q for the same weekday within the same month, calculated from the training data. The ultimate choice of the average of the same weekday and month was made after testing various averages with different time windows, i.e., all working days, days of the same season, days of the same month, same weekday.

(iii) **Previous power consumption values**: each model uses historical values of active (P) or reactive (Q) power to predict the corresponding output. They allow the models to capture short-term temporal dependencies in power consumption. The P and Q input values range from 15 to 60 minutes prior to the prediction time, meaning from 1 up to 4 inputs. The optimal number of preceding inputs was determined through a series of tests, progressively adding one previous step at a time. The final number of inputs was chosen as the best performing among all. A sliding window approach was used during training, where for each prediction instant t, the model inputs consist of power values at fixed 15-minute intervals preceding t. The model predicts a single time point at instant t.

Note that the time-related variables and historical averages described above are always included, so there are at least 10 input features in every model configuration.

B. Other PMs generator models

In this study, in addition to the ML-based model, referred to as Neural, four alternative PMG models were implemented to compare their performance under various operating conditions. These simpler baseline methods serve as references to assess the benefit of more advanced forecasting techniques.

The models considered are detailed as follows:

- $\mathbf{PMG_{Na\ddot{\i}ve}}$: predicts the next time step's consumption as equal to the previous time step (15 minutes earlier).

- **PMG$_{\text{Seasonal}}$**: averages historical values for the same time of day and weekday within the same month.
- **PMG$_{\text{Mean-raw}}$**: uses the average consumption computed over the entire historical dataset.
- **PMG$_{\text{Min/max}}$**: estimates consumption as the midpoint between historical minimum and maximum values.

C. Performance of the PMG Models

The performance of the developed PMG models was evaluated to assess their accuracy in predicting both active and reactive power. The evaluation focused on the ability of the models to generate reliable power consumption estimates that can be effectively used in the subsequent DSSE process. Given that the two buildings studied have significantly different power consumption ranges, a relative metric rather than an absolute one was preferred for performance evaluation. The primary metrics used to evaluate model performance is the Root Mean Squared Percentage Error (RMSPE), which was calculated using the formula:

$$\text{RMSPE} = 100\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\hat{v}_i - v_i}{v_i}\right)^2} \tag{4}$$

where, for each node, v_i represents the observed power consumption values, either the active power P or the reactive power Q, $\hat{v}_i$ represents the corresponding predicted values, and n is the number of training, validation and testing samples. RMSPE is a widely used relative metric that provides a normalized measure of forecasting accuracy, it expresses errors as a percentage of the actual values, making it easier to interpret the magnitude of errors in relation to the actual data.

It is important to note that the validation set was used to fine-tune model parameters and to prevent overfitting. However, for the sake of simplicity and clarity in result presentation, only the performance metrics obtained on the training and test sets are reported here, as the evaluation of the validation results was globally consistent with the training performance, confirming the models' stability and generalization capability.

Table I reports the RMSPE values obtained by the Neural PMG models for both active and reactive power. Each model was implemented with a single hidden layer comprising 20 neurons. The table reports also the number of inputs, which specifically refers to the number of preceding power consumption values used as model inputs, in addition to the 10 time-related and historical average variables always included.

TABLE I
RMSPE VALUES OF ML-BASED MODELS FOR ACTIVE AND REACTIVE POWER

	Load	# Inputs (preceding values)	Train	Test
Active Power	Offices	4	10.2	9.4
P [%]	Cafeteria	2	14.2	13.4
Reactive Power	Offices	3	6.9	6.2
Q [%]	Cafeteria	3	10.3	9.1

Although RMSPE was adopted as the primary evaluation metric, Mean Absolute Percentage Error (MAPE) was evaluated. The results for the office building showed that MAPE was approximately 2% lower than the corresponding RMSPE for both active and reactive power, while for the cafeteria building, MAPE was about 5% lower. This indicates that, while most of the model's errors are reasonably small, a few larger errors are inflating the RMSPE.

Table II shows RMSPE values for the other PMG models. Among them, the Naïve and Seasonal models consistently achieve lower errors for both P and Q across offices and cafeteria loads. These results suggest that models leveraging recent or seasonal patterns better capture power consumption dynamics than those based on simple historical averages or extremes. As shown, the ML-based model exhibits best performance in forecasting power consumption both for the office and cafeteria buildings.

TABLE II
RMSPE VALUES FOR PMG MODELS USING DIFFERENT GENERATION STRATEGIES

	Load	Naïve		Seasonal		Mean-raw		Min/max	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
P	Offices	13.1	11.4	12.9	13.5	35.7	30.8	82.1	68.8
[%]	Cafeteria	15.1	15.3	17.2	15.7	65.2	61.5	148.9	142.1
Q	Offices	9.1	7.1	8.0	10.1	24.1	19.8	38.7	29.3
[%]	Cafeteria	14.5	12.2	11.4	10.0	20.4	16.8	65.6	57.7

V. SIMULATION STUDY

The network used in this study to test PMs impact on DSSE is a single-phase 19-bus Medium-Voltage (MV) distribution network (shown in Fig. 2), specifically designed as a facsimile of part of the actual electrical network supplying the FZJ campus. Due to security, confidentiality, and practical constraints, the real network topology cannot be publicly disclosed. However, the test system maintains structural and operational characteristics representative of the original infrastructure, ensuring the relevance and applicability of the simulation results.

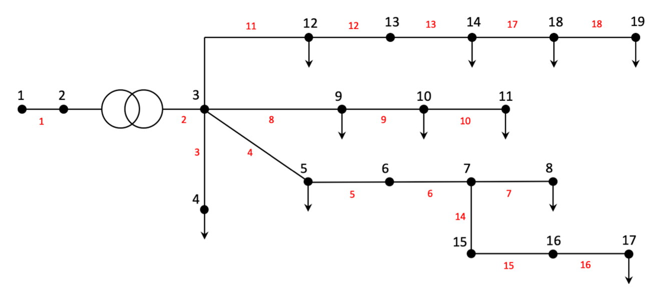

Fig. 2. MV distribution system under test.

The network in Fig. 2 was simulated considering single-phase distribution lines with a rated voltage of 10 kV.

Since the main purpose of the work is to investigate the impact of a broader adoption of the proposed ML-based PM on distribution systems, the loads in the test network indicated with black arrows were simulated using the same predictions generated by the PMG models for the cafeteria and office buildings. To avoid identical load profiles, the generated data were appropriately scaled for each replicated load, introducing variability while preserving the overall consumption patterns. As a result, the test grid includes 7 office-type loads and 4 cafeteria-type loads, allowing for a more comprehensive evaluation of the impact and potential benefits of ML-based PMs on DSSE performance. Given the large scale of the FZJ campus, replicating these two types of loads poses no significant issue, as it helps to simulate a wider range of scenarios and assess the effectiveness of the predictions.

The 19-bus network under test includes 19 nodes and 18 branches, with some real measurement points available in the system, placed at specific observation points in the grid. Ten measurement points have been assumed on the network, specifically: active and reactive power flow measurements on branches 4, 13, and, magnitude voltage measurements on buses 1, 2, 3, 6, 7, 13, 15, 16 along with the corresponding active and reactive power measurements. All other power inputs to the DSSE process rely on the PMs [16] as shown in Fig. 2.

VI. Results

The results of the study are presented below to demonstrate the performance differences between the tested ML-based method and others methods derived from PMG models described in Section IV-B. The DSSE is supposed to run every 15 minutes, according to the database structure outlined in Section III-A. Additionally, the test set-up allows for simulating realistic conditions and measurement uncertainties, whose specific details are summarized below:

- Active and reactive power measurements,assumed to be available from Supervisory Control And Data Acquisition (SCADA) systems, are assumed to have maximum errors of 3 % (for both nodal and branch powers), while, as for magnitude voltage measurements, they are assumed to have maximum errors of 2 %. The errors for each DSSE instant have been randomly extracted from uniform distributions.
- For the baseline estimators as well as the other estimators, PMs were assumed to follow uniform distributions, with a maximum variability of $\pm 50\,\%$.
- The performance of all state estimators was evaluated considering all working days in the test set, i.e., from June 24th, 2019, to February 28th, 2020.

To establish the ground truth for evaluating the DSSE algorithms, the Newton-Raphson power flow method was employed. This solver was run at each time instant using the actual load values at each node of the test network to compute the exact system state, which serves as the reference for comparison with the estimated states. RMSPEs have been also used as evaluation metric of the quality of the DSSEs.

As a first representation of the impact of the generation of PMs with MLP on DSSE, RMSPE values for active and reactive powers (recalculated from the results of the DSSEs) are compared. In Figs 3 and 4, RMSPE values among the relevant nodes of the network are shown, considering the comparison between $\text{DSSE}_{\text{Neural}}$ and the four baseline methods previously presented.

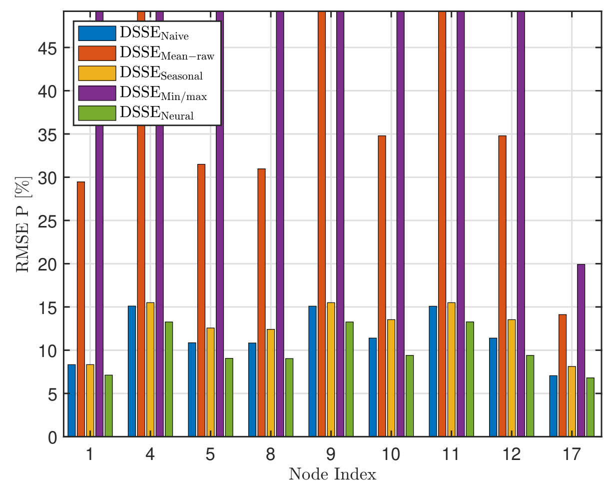

Fig. 3. Comparison of RMSPEs for nodal active powers.

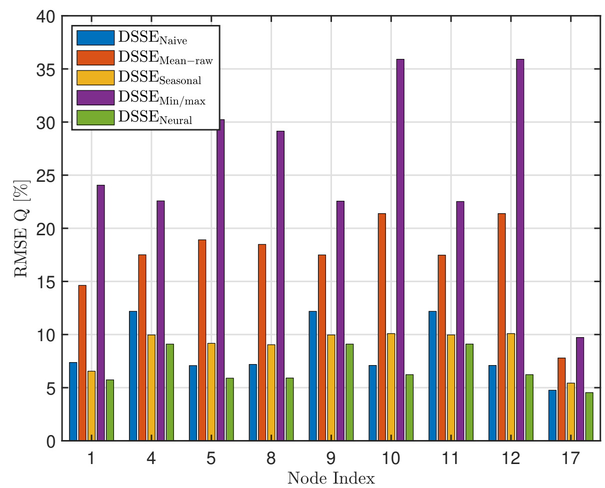

Fig. 4. Comparison of RMSPEs for nodal reactive powers.

Focusing on the results for active and reactive powers on nodes 4, 5, $8-12$ and 17 (which are the only relevant ones), it is evident that, due to the nature and the occurrence of the DSSE problem faced in this paper, and depending on the node under analysis, the performance of $\text{DSSE}_{\text{Naïve}}$ (e.g., for the active powers on nodes 5 and 10) and $\text{DSSE}_{\text{Seasonal}}$ (e.g., for the reactive power on node 4) get close to $\text{DSSE}_{\text{Neural}}$. Nevertheless, $\text{DSSE}_{\text{Neural}}$ has always the best RMSPE results, reaching, for instance, a maximum improvement for active and reactive powers of about 18 % and 25 % and of about 31 % and 38 % when $\text{DSSE}_{\text{Naïve}}$ and $\text{DSSE}_{\text{Seasonal}}$ are considered as a comparison method, respectively. At this point, it is interesting to move to other results and, specifically, the results of branch current estimates. To this purpose, Fig. 5 shows the RMSPEs of current magnitudes across the relevant branches of the grid in Fig. 2. Also in this case, it is possible to notice that the improvement brought by the ML-based PMs on DSSE results is clearly noticeable. For example, considering branches not directly affected by additional power flow measurements (for instance, branches with indexes $1-3$, $7-11$, $14-16$), $\text{DSSE}_{\text{Neural}}$ confirms once again to be the best solution for improving the results. In particular, to sum up the key outcomes from Fig. 5, Table III shows the achievable improvements in terms of the average, maximum and minimum relative improvements of $\mathrm{DSSE}_{\mathrm{Neural}}$ with respect to the other methods. Focusing on the closest competitors (thus excluding $\mathrm{DSSE}_{\mathrm{Mean\text{-}raw}}$ and $\mathrm{DSSE}_{\mathrm{Min/max}}$) in Table III, it is possible to notice that $\mathrm{DSSE}_{\mathrm{Neural}}$ has always the best performance improving, on average, $\mathrm{DSSE}_{\mathrm{Naïve}}$ and $\mathrm{DSSE}_{\mathrm{Seasonal}}$ of about 10.7 % and 18.9 %.

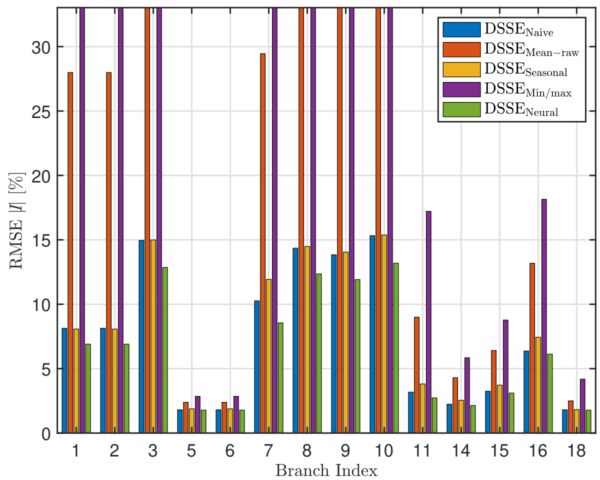

Fig. 5. Comparison of RMSPEs for magnitude branch currents.

TABLE III
COMPARISON OF RELATIVE IMPROVEMENT OF $\mathrm{DSSE}_{\mathrm{NEURAL}}$ WITH RESPECT TO THE OTHER METHODS FOR BRANCH CURRENT MAGNITUDE RMSPE VALUES

Method	Average [%]	Min [%]	Max [%]
$\mathrm{DSSE}_{\mathrm{Naïve}}$	10.7	3.8	16.7
$\mathrm{DSSE}_{\mathrm{Mean\text{-}raw}}$	66.0	50.3	77.6
$\mathrm{DSSE}_{\mathrm{Seasonal}}$	18.9	14.3	28.3
$\mathrm{DSSE}_{\mathrm{Min/max}}$	79.4	63.4	91.0

VII. CONCLUSIONS

In this paper, the inclusion of a neural model for PM generation and its impact on DSSE algorithms has been evaluated by means of several simulations. It has been demonstrated that leveraging these models can be helpful in improving the accuracy of DSSE and, in this regard, that these models can be a promising tool for improving monitoring and control applications. Future research will focus on refining these models to enable their application to general types of loads and exploring the feasibility to build, from these neural models, other types of PMs (possibly on all the nodes of the grid, thus helping the actual monitoring infrastructure).

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