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Validation of a robust neural real-time voltage estimator for active distribution grids on field data

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ABSTRACT

The installation of measurements in distribution grids enables the development of data driven methods for the power system. However, these methods have to be validated in order to understand the limitations and capabilities for their use. This paper presents a systematic validation of a neural network approach for voltage estimation in active distribution grids by means of measured data from two feeders of a real low voltage distribution grid. The approach enables a real-time voltage estimation at locations in the distribution grid, where otherwise only non-real-time measurements are available. The method shows robust behavior in all analyzed aspects, which is vital for real world applications. A methodology to select the most relevant input variables and find the best achievable performance for a particular number of inputs is presented. Moreover, the paper shows that the performance is not sensitive to the number of neurons in the hidden layer of the neural network as long as the model is not underdetermined. The paper examines the quantity of historical data needed to establish an adequately functioning model. To accommodate grid evolution and seasonal effects, the impact of different retraining intervals is investigated. Furthermore, the performance of the model during periods of high PV generation is evaluated. The validation shows that accurate voltage estimation models for distribution grids with high share of dispersed generation can be established with approximately one month of historical data. The model has to be retrained every 10–20 days to retain estimation mean squared errors below 0.35 V^2. It was also found that the performance does not decline during times of high PV generation.

1. Introduction

Renewable energy sources (RES) are continuously being installed at all voltage levels in today's electric power systems [1]. A large share is being installed in the distribution grid, even at the lowest voltage level. Distribution feeders are transitioning to host both, energy users and producers and, thus, the power flow of distribution grids changes significantly in the presence of dispersed generation units [2]. Moreover, voltage becomes more volatile with the fluctuating power output of photovoltaics (PV) and increasing number of single-phase charging electric vehicles [3,4]. The operation of distribution grids becomes more challenging as distribution grids transform from traditionally passive behavior to more active behavior with a considerable share of generation. To operate an active distribution system, operators need to increase the observability of distribution grids. Today, observability of distribution systems is generally low due to their large size. Observability usually translates into a need for additional measurement sensors, such as smart meters. Obviously, costs prohibit achieving full observability of distribution grids and, hence, complementary methods must be used. Data driven methods benefit from the availability of offline measurements from different sources and offer a cost-efficient alternative to the installation of additional real-time measurements.

Conventional state estimation approaches, such as [5–7] assume that the network topology and accurate line parameters are given. The state estimation accuracy depends highly on accurate line parameters and topology knowledge and seriously degrades in presence of inaccurate parameters [8,9].

Unlike conventional state estimation approaches, in the approach described in this paper there is no need to model the network as admittance matrix and no iterative process is needed for the estimation after the model has been established. A major differ-

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ence in the application point of view, is also that only variables for which prior measurements are available can be estimated. For this work, it is assumed that the network topology remains constant between training and observation. Similar to conventional state estimation, topology changes have to be detected in parallel and accounted for. This high flexibility paired with higher speed, accuracy and efficiency compared to their conventional counterparts makes data driven approaches interesting for complex problems and development of online applications [10].

A hierarchical bottom-up distribution system monitoring approach using neural networks (NNs) was proposed in [11]. This hierarchical approach in [11] splits up the monitoring problem to each voltage level. Local estimators are trained to estimate the voltage at certain nodes at the lowest voltage level by using voltage and current measurements at the medium-voltage/low-voltage transformer. The estimation results are communicated to the upper-level estimator and, thereby, generating an overall picture of the distribution system.

The authors of [12,13] study how data from phasor measurement units (PMUs) impact the accuracy of NN-based estimation of voltage magnitude and angle. They conclude that the NN-based estimator including input data from PMUs achieves similar results as a classic state estimation algorithm. The current work is based on less expensive non-synchronized measurements.

A NN with two hidden layers and entropy-based selection of input variables is proposed in [14], and it was found that the selection of appropriate input variables is of crucial importance.

The authors of [15] employ a NN voltage estimator to calculate the voltage profile along a feeder. Remote terminal units (RTUs) send the resulting voltage profile to a master controller aiming at enhancing the operation of an on-load tap-changer (OLTC) transformer for voltage regulation.

In the above works and throughout the literature, NN-based voltage estimation approaches are tested and validated by means of simulation models alone. Generally, a large number of different load flow scenarios are simulated and the results of the simulations are divided into training and test set. In contrast, this work focuses on necessary steps towards implementation in real environment by setting the framework for a neural real-time voltage estimator and validation based on actual distribution grid measurements.

This paper builds on the approach proposed in [16] where the conceptual framework and a numerical implementation for a distribution grid model with three feeders including PV generation was implemented and analyzed. It is proposed to estimate the voltage at specific low voltage (LV) buses by use of NNs trained on voltage and power measurements from substation level only. Various generation and consumption scenarios including reverse power flow scenarios are analyzed in terms of estimation accuracy. The results showed the method to be promising for all analyzed scenarios concluding in the need for a validation in real world environment. This manuscript specifically focuses on the validation of the NN-based voltage estimation approach on field data from a real distribution grid, in particular, estimating the phase-neutral voltage magnitudes (U_a, U_b, U_c) at a downstream bus of a distribution feeder based on available measurements from the substation. A general sketch of an active LV distribution grid which includes distributed generation (DG) among loads is shown in Fig. 1. The substation and the downstream measurement are highlighted in red and blue, respectively. In the training phase, historical measurements from the substation and from the downstream bus are used to train the estimator. In the estimation phase, substation measurements are fed into the estimator and the voltages of the downstream bus are calculated in real-time (order of milliseconds on a standard laptop). Voltage angles are not considered because they are typically small in LV grids while the voltage magnitude is from paramount interest [17]. This paper presents the intermediate step towards implementation of a neural real-time voltage estimator (NRTVE) in an operating environment, such as integration into an existing SCADA system. A considered application of the proposed approach is real-time voltage estimation at buses where measurements, such as smart meters, are installed, but data is not available in real-time. For these buses, a real-time estimator could be established to increase the observability of the distribution grid. The provided assessment of accuracy and sensitivity will serve online monitoring well. However, reactive applications such as voltage control would impose further engineering requirements and development steps to be considered.

The key contributions of the manuscript are twofold:

I The framework to establish a highly accurate neural real-time voltage estimator is described.
II The capabilities and limitations of the approach under practical considerations are analyzed, in particular:
  i Methodology to select the most relevant input variables and find the best achievable performance for a particular number of inputs.
  ii It is shown that the performance is not sensitive to the number of neurons as long as the model is not underdetermined.
  iii The quantity of historical data needed to train an adequately functioning model is analyzed.
  iv The impact of the retraining interval on the performance of the model is determined.
  v It is shown that the performance of the model is not sensitive to the level of PV generation.

2. Architecture and training of the neural real-time voltage estimator

Two different phases of the NRTVE are distinguished: training and real-time estimation, as shown in Fig. 2. The NRTVE is established in the training process by use of an suitable training algorithm. Prior to the training, the architecture and number of neurons in the hidden layer have to be defined. After the training process, the NRTVE can be used for real-time voltage estimation at the specific bus. Distribution network operation is characterized by faults, topology changes and outages. The proposed model is exclusively established for normal operating conditions found in the available data. For estimation under abnormal conditions, a separate model would need to be trained and a change detection would have to be implemented as the characteristics of the disturbed grid are different than in normal operation. Moreover, for changing topologies separate models need to be trained. Here, no topology change occurred.

The calculation of a bus voltage with a trained NN is in the order of milliseconds as it can be directly calculated and no further iterations are needed after the training. That computation time is deterministic is crucial for real-time applications, since it has to be accounted for the worst case. All available input and the three output variables are indicated in Fig. 2 . The colors used for the input and output arrows are aligned with the colors in Figs. 1 and 3.

2.1. Architecture

A great number of NN architectures can be imagined [18–22]. As this is a fitting problem, a feed-forward NN with one hidden layer is used as that is sufficient for most fitting problems [23]. A multilayer perceptron with hyperbolic tangent-sigmoid neurons in the hidden layer and linear neurons in the output layer is chosen. Additional hidden layers can be added if the performance is not satisfactory. The term performance refers to the mean squared error (MSE) between the model output and the real measured val-