Design Considerations for Artificial Neural Network-based Estimators in Monitoring of Distribution Systems

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***Abstract*—Data-driven approaches based on Distributed Artificial Intelligence (DAI) such as Artificial Neural Networks (ANN) could be used to perform estimation of voltage magnitude in distribution systems for monitoring purposes. These methods may offer high accuracy and yet require relatively few measurement inputs and low computational power compared to conventional state estimation techniques. However, the number of required measurements may vary from system to system depending on several factors. Furthermore, it is important to ensure that these estimators are robust to input noise. Moreover, a factor to be considered in presence of sparse electrical measurements is that other additional inputs may be used to improve the accuracy of estimation. This paper investigates the decisive factors that affect the minimum number of input measurements for an ANN-based estimator. Furthermore, it discusses how the ANN should be designed to handle measurement noise properly in practice. Simulations are performed on benchmark networks to support the discussion.**

Keywords—artificial neural networks; measurement uncertainty; network topology; power distribution; power system measurements; state estimation

I. INTRODUCTION

Ensuring the safe and secure operation, maintenance, identifying the weaknesses, and performing required upgrades in power distribution systems are among the integral responsibilities of distribution system operators (DSOs) [1]. In conventional distribution systems, there has been usually no monitoring system deployed at MV and LV levels. The risks of lack of monitoring systems in these systems were unawareness about the voltage profile and loading of components in the system during different operation times. However, considering that the distribution systems were predominantly passive, i.e. only loads were connected to them, it was a sensible assumption that the voltage profile would simply decrease along the feeder. Therefore, the only concern about the voltage profile was the possibility of excessive voltage drop at the end of the feeders. This meant that the DSO could assure that there is no overvoltage in its system without any monitoring and simply relying on the fact that the voltage would decrease from it maximum value at the substation transformer along the feeder.

With the ever increasing penetration of distributed generation (DG) units at distribution networks, particularly at LV level, the situation has changed and there is a growing concern especially about the overvoltage along the feeders. This means that, although the voltage magnitude may be within the normal range at the substation, it may exceed the allowable limits at some nodes in the downstream network. This could be the case especially during periods with light load levels and heavy generation from DG units, such as PV installations [2], [3]. Such overvoltage may have an adverse impact on the aging of some components and may cause damage to the connected devices. Furthermore, when the voltage magnitude rises above the allowable limits specified by the standards, the inverters of DG units usually disconnect them from the grid as a protection measure and therefore, these units cannot generate the power as expected. As a result, monitoring the actual voltage profile of the distribution system, including the LV parts, has become increasingly important for DSOs to properly manage the operation and planning of their grids.

The idea of performing state estimation at the distribution level has been investigated since 1990s [4]. Its goal is to estimate the state of a system, which includes magnitude and phase of voltage at all nodes and currents in all branches. While such knowledge about the system is very valuable, performing a state estimation using classical, static model-based approaches requires knowledge about system model. In addition, it requires either a significant number of measurements or pseudo measurements from the system [4], [5]. Furthermore, the calculation needed for computation of the state involve operations such inversion of matrices with large dimensions, which are both computationally demanding and could face convergence issues. However, if only a smaller set of information about the system is of interest, rather than the complete system state, it is possible to use an alternative approach, which in turn has less stringent input measurement requirements. This is actually the case for distribution system where the DSO is mainly interested in estimating the voltage magnitude of various buses at its system. The reason is that the critical electrical quantities affecting component stress and

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lifetime are the magnitudes of voltage and current while their phase angle does not play a critical role [6]. So, the effort could be knowingly focused on estimating only these quantities which are more critical for the system operator. In [7], an artificial neural network (ANN)-based method for estimation of voltage magnitudes in the framework of distribution monitoring system has been introduced. It has been shown that using only the voltage and current measurements at the substation, the voltage profile of a simple distribution system could be estimate with very high accuracy for a residential distribution system with a radial topology. However, the presented test case does not include any DG units. Furthermore, the system has a relatively simple structure and the different input data requirements in case of a more complex network structure are not discussed. Finally, the measurements are assumed to be ideal (carrying the “true value”), which is not the case in reality. In this paper, we provide a deeper insight into the ANN-based distribution monitoring approach. For this purpose, the impact of uncertainty in measurements on the estimation accuracy and the approach to limits this impact are discussed. Furthermore, we show how the minimum number of measurement inputs may increase as system topology becomes more complex and DG units are integrated into the system. All these cases are supported by simulation results.

II. MONITORING SYSTEM ARCHITECTURE

In Fig. 1, a low voltage rural distribution network composed of 10 nodes is shown. This network is connected to the medium voltage system via a 20 kV/ 400 V transformer with a rated power of 160 kVA and short circuit voltage of 4%. Each line segment is assumed to have a length of 60 m. In Table I and Table II, a summary of the line parameters and the system loads are presented. It should be mentioned that in this study, the system is assumed to be balanced. In presence of significant unbalances among the three phases, it could be envisaged that the voltage and current for each of the phases is estimated and monitored separately.

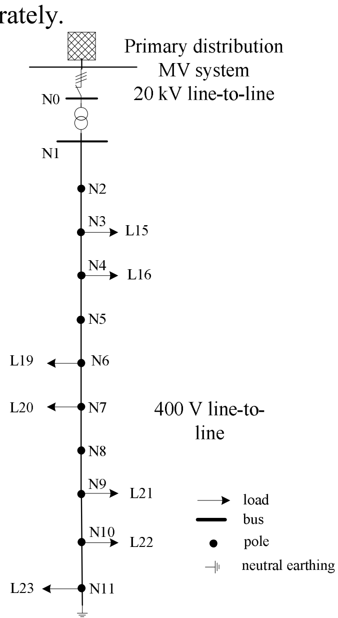

Fig. 1. Topology of the base test distribution system

TABLE I. SUMMARY OF FEEDER LINE PARAMETERS

Rated current (A)	Positive sequence impedance (Ω/km)	zero sequence impedance (Ω/km)
270	0.4910+0.3211j	0.8895+j1.1607

TABLE II. SUMMARY OF FEEDER LINE PARAMETERS

Node	Type of load	Number of households	Peak load of each consumer group (kVA)	Power factor
N3	Water pumps	0	7.5	0.95
N4	Residential	9	13.5	0.85
N6	Residential	6	9	0.95
N7	Water pumps	0	6.75	0.95
N9	Residential	6	9	0.95
N10	Residential	5	8.33	0.95
N11	Water pumps	0	6.75	0.85

A. Base Case

The neural network considered for the estimations has a feedforward structure with 2 hidden layers. The data for the training of the ANN is generated by running power flows in DIgSILENT PowerFactory. The ANN is then trained in MATLAB Neural Network Toolbox using the Levenberg Marquardt (LM) algorithm. To generate sample data, each customer group is assigned a random load value between zero and its peak power at each iteration and then the power flow is run. 1500 samples are generated for training the ANN, 20% of which is used for verifying the trained network. It should be mentioned that this is only a tentative training data set and we intend to take into account correlation between the loads and the fact that they collectively follow statistical profiles in the future.

In the base case, it is assumed that only the magnitude of voltage and the current at the LV side of the transformer are measured. Therefore, the ANN has only two inputs. Similarly, considering that the ANN is expected to estimate the voltage magnitudes at all nodes, it has 11 outputs. After the training the ANN using the generated sample data, it could be used to estimate the voltage magnitude of different nodes for new measurements. Fig. 2 shows the actual voltage magnitude values versus the estimated values obtained using the ANN-based estimator for a sample operating point. The ANN is trained using the values obtained from the simulation, which are the exact values of the quantities with high precision. The inputs used to test the network are also obtained from the simulation, which represent the measured quantities with very high precision. In this case, the ANN can estimate the voltage magnitude of the buses in a very accurate way, with the maximum error in the voltage estimations equal to 0.36% in this example. Although there could be various loading conditions which result in similar voltage and current measurements at the substation transformer, in reality, the error resulting from not being able to differentiate among them is not usually significant and the ANN is still able to make relatively acceptable estimates in most cases.

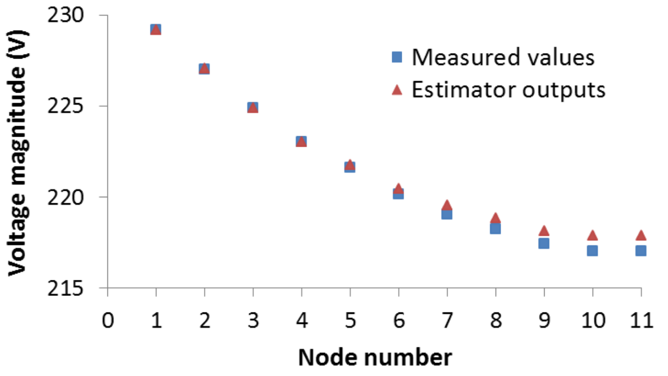

Fig. 2. Actual values and ANN estimates of voltage magnitudes vs node number

III. Impact of Measurement Uncertainty

In practice, measurement devices can measure the quantities only with some limited accuracy, and furthermore in reality a variety of factors affect the measurement resulting in measurement uncertainty. Besides, the input to the ANN-based estimator will contain some noise.

In order to see how the uncertainty in the input propagates to the estimated values in the output of the estimator, a random noise with Gaussian distribution with zero expected value and standard deviation equal to 0.33 % of the nominal value is assumed for both voltage and current measurements. The standard deviation is chosen to be 0.33% of the nominal value so that 99.7% of all measurements fall within ±1% of the actual value, i.e. represent uncertainty of approximately 1%. Fig. 3 shows the distribution of the estimated voltages at nodes N6 and N11 at a sample operating point obtained using the Mont Carlo method. The number of Mont Carlo trials is 1000.

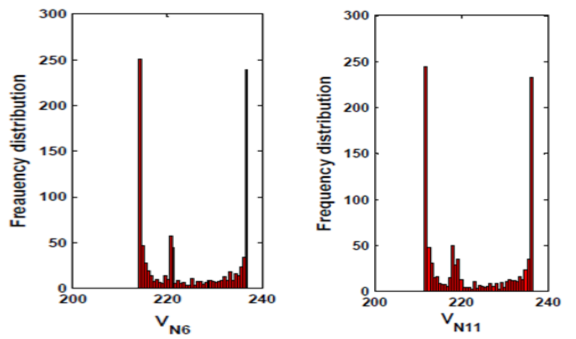

Fig. 3. Propagation of input noise to the output of the ANN-based estimator trained with ideal training data for nodes N6 and N11

From the figure, it can be observed that the estimates from an ANN trained with a set of ideal training data could have significant errors (about 10% in the above example) in presence of uncertainty of about 1%, which is a relatively moderate uncertainty in real word situations. This indicates that the estimations are very sensitive to the measurement uncertainty and this could result in unacceptable error in the overall estimation (i.e. more than 2-3%). It is worth noting that the U-shape distribution in the above figures is a result of saturation of the output values of the ANN for most of the test inputs. The asymmetry of the shape could be due to two reasons: firstly, the number of the training samples is limited and therefore, in this case, most of the training data have been located in the region with heavier loading and therefore higher voltage drops. Therefore, the ANN may tend to consider estimates with voltage magnitudes less than the actual values. Secondly, a relatively low number of test inputs have been considered which cannot result in equal number of samples with positive and negative uncertainties.

To address this issue, training the neural network using noisy input is considered. For this purpose, a random noise is added to those quantities which are considered as the ANN input, namely the transformer voltage and current values. The added noise should be as similar as possible to the uncertainty expected in practice. Therefore, a Gaussian noise with zero mean and standard deviation equal to 0.33% of the nominal values is added to the sample data obtained from power flow calculation. The distribution of estimated values of voltage magnitudes using the newly trained ANN, when its inputs are affected by measurement uncertainty, is show in Fig. 4.

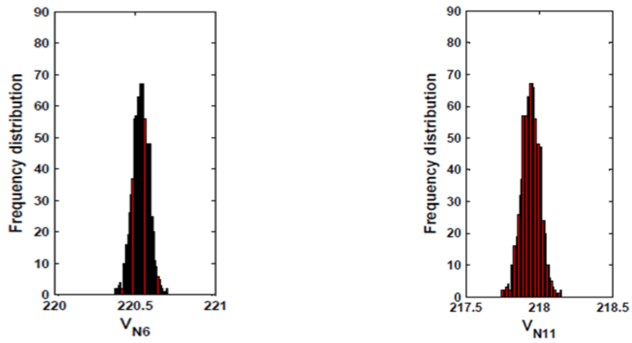

Fig. 4. Propagation of input noise to the output of the ANN-based estimator for trained with noisy training data for nodes N6 and N11

As this figure indicates, training the ANN using noisy input enables it to maintain its accuracy in presence of measurement uncertainty.

IV. Minimum Number of Inputs

The base case in Section II shows that using only 2 measurements, namely transformer voltage and current is sufficient to provide a highly accurate estimation. However, this may not be always the case as the complexity of the network structure increases and the DG units are added to the system. In this section, we will show how these factors could require larger number of inputs for accurate estimation of the voltage magnitudes.

A. Grid Topology

In this part, we consider a more complex network topology compared to the one presented in Fig. 1. This network is basically composed of two parallel feeders with the same length and similar loads as shown in Fig. 5.

In the first case, it is assumed that only two measurements, the voltage and the current at the secondary side of the transformer, are available. The ANN is trained with the same procedure described in the previous section. It is observed that the ANN has a good performance in most cases. However, there are cases in which the ANN is not capable of making an accurate estimation. The reason is that the inputs of the ANN may be the same for two completely different scenarios with significant differences in voltage profiles, which makes it impossible for the ANN to differentiate between them. In Table III, two of such scenarios are shown as an example. It is assumed that both feeders have similar loading conditions but with different scales. More precisely, in the first scenario each load of feeder 1 has four times more power demand than its corresponding load in feeder 2, and vice versa in the second scenario. Therefore, the measured transformer voltage and current for both of these scenarios will be exactly the same. In Fig. 6, the estimated values and the actual values of the voltage magnitude for different nodes of the system are presented. As shown in this figure, there is a significant estimation error in this case, which is as large as 2.50% for the worst estimated node. It should be noted that no matter how well the ANN is trained, it simply cannot differentiate between the two cases. In such cases, provision of additional measurements to the ANN is necessary in order to ensure accuracy of estimations.

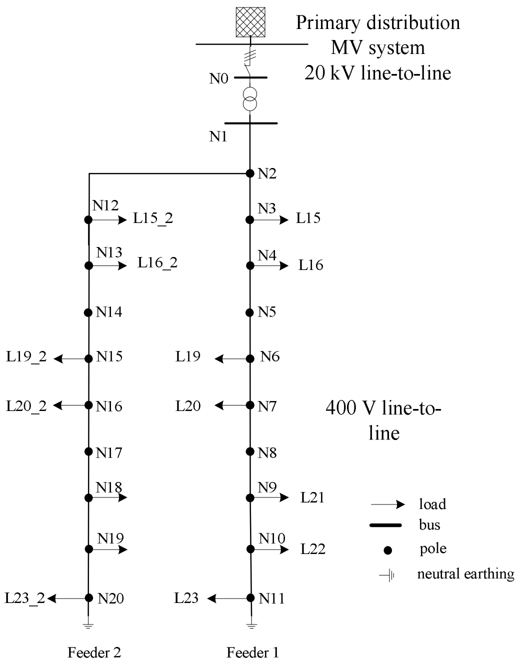

Fig. 5. Test distribution system with two similar feeders connected in parallel

TABLE III. TEST SCENARIOS FOR

Scenario	Share of the total load	
	Feeder 1	***Feeder 2***
1	85 %	15%
2	15%	85%

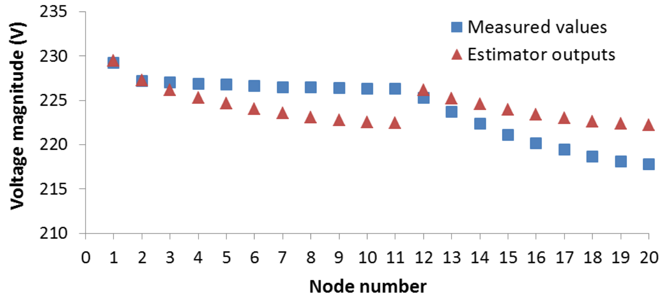

Fig. 6. Estimated versus measured values of the voltage magnitudes for scenarios with 2 measurements available

One additional voltage measurement is now added at the end of feeder 2, namely at node N20. The ANN is then trained using three inputs and the results. Fig. 7 shows the estimated and actual voltage magnitudes for the same scenarios as defined in Table III. It can be seen that the addition of a new voltage measurement at the end of one of the feeders significantly improves the estimation accuracy.

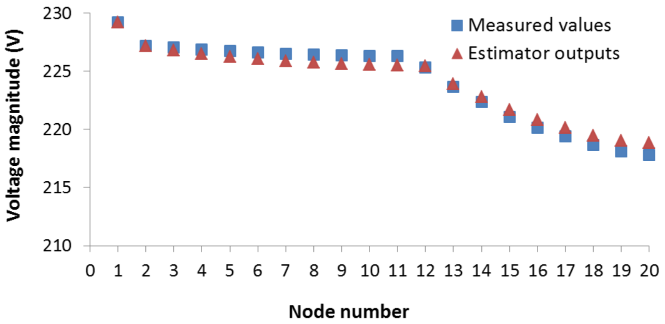

Fig. 7. Estimated and measured values of the voltage magnitudes for scenarios with 3 measurements available

In presence of more parallel feeders, additional measurements for each of the added feeders should be considered. The number of required measurements for each of these feeders depends on their topological complexity and the presence of significant distributed generation in them.

B. Presence of DG Units

Presence of DG units is another factor that can significantly affect the voltage profile in a distribution system. Power injection from DG units in a feeder could compensate all or part of the load demand in that part of the distribution system. In such cases, the current sensor at the substation will only measure the amount of load in the feeder supplied from the upper level grid and will have no means to measure the amount of load supplied by the local generation units. However, transmission of power from the DG units to the load points in the system downstream the transformer will still cause some voltage drops. As a result, the ANN will not be able to differentiate among various cases. Apart from this, in case the power generation of DG units in part of a feeder is higher than the power demand in that section, the power flow could change direction, resulting in the increase of voltage magnitude from the upstream parts of the feeder towards that section. This is another case which may not be detected by an ANN estimator that uses only the measurements at the substation.

To illustrate the above points, it is assumed that a PV unit is added to the last node of the system shown in Fig. 1, i.e. node N11. In the first case, it is assumed that only the transformer voltage and current measurements at the substation are available. The ANN is trained once more considering that the PV unit may inject power to the feeder. Now, three scenarios are considered with different PV generation levels and loads L15 and L23 as defined in Table IV. All other loads are assumed to be the same for these three scenarios:

TABLE IV. THREE SCENARIOS OF LOAD DEMAND AND PV GENERATION VALUES RESULTING IN IDENTICAL MEASUREMENT AT THE SUBSTATION

Scenario	PV power generation (kW)	Load demand of L15 (kW)	Load demand of L23 (kW)
1	0	0	50
2	50	100	0
3	20	70	0

All of these scenarios result in the same voltage and current at the substation. Therefore, the ANN is not capable of performing proper estimation of voltage magnitudes of feeder nodes. In Fig. 8 to Fig. 10, the estimated and the measured values of the voltage magnitude for different nodes of the system in all the three scenarios are presented.

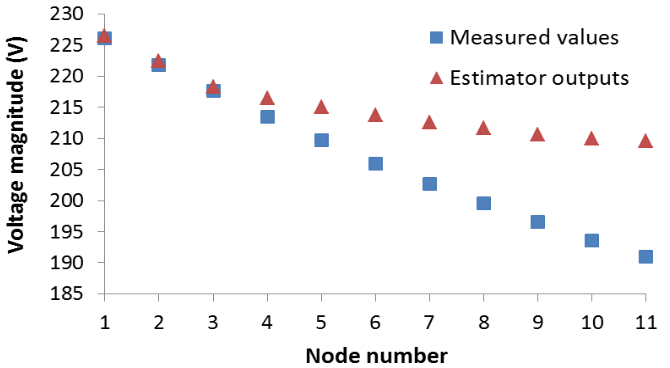

Fig. 8. Estimated and measured values of the voltage magnitudes for scenario 1 with 2 measurements available

In Scenario 1, there is no PV power injected to the grid and active and reactive power is only consumed in the feeder. As a result, there is a continuous decrease in the voltage magnitude along the feeder as shown in Fig. 8. In scenario 2, however, there is a significant power injection at the end of the feeder at L23, which is significantly larger that the power demand at that node. Therefore, the surplus of the injected power from the PV unit flows towards the beginning of the feeder, leading to an increase in the nodes at the end of the feeder. However, the ANN cannot differentiate this scenario with scenario 1 with only voltage and current at the LV side of the transformer and make an incorrect estimation as shown in Fig. 9.

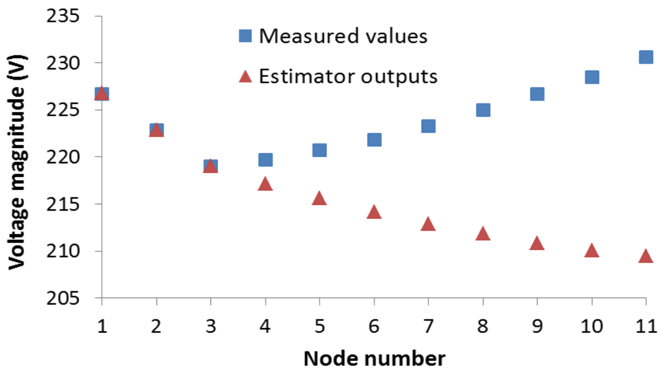

Fig. 9. Estimated and measured values of the voltage magnitudes for scenario 2 with 2 measurements available

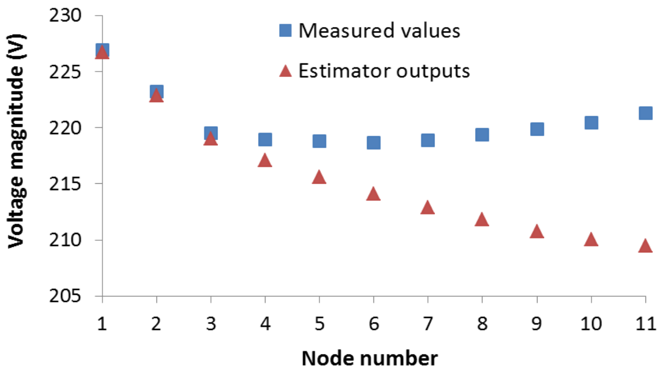

Fig. 10. Estimated and measured values of the voltage magnitudes for scenario 1 as defined in Table IV with 2 measurements available

Scenario 3 represent a situation similar to scenario 2, but it differs in the sense that the injected power by the PV unit and the load at L15 are considerable smaller. As a result, the voltage rise towards the end of the feeder is also less intense.

It is important to note that it is because of significant output of DG units that the estimation error was significant. Otherwise, the error in the estimation is expected to be quite small. The reason is that local generation with power levels relatively small compared to the network load and rated power of feeder cables could not make considerable changes in the power flow and voltage profile in the feeders, respectively. So, if the DG units have a negligible maximum power compared to the loading levels of the feeder they are connected to, they will not increase the number of the required measurement in the grid for an accurate estimation of voltage.

To address this issue, one additional voltage measurement is considered at the end of feeder, namely L11. The ANN is trained once more by considering this measurement as the third input. The trained ANN is then tested for all the scenarios and the results are shown in Fig. 11 to Fig. 13. It can be seen that the ANN can perform the estimations with very high accuracy when this new input measurement is considered. It is worth noting that the new measurement should be placed in a way that it can adequately capture the information not detectable at the LV side of the transformer. For example, placing an additional voltage measurement at the nodes close to the transformer can only convey little additional information about the flow of power along the feeder, while the voltage magnitude at the nodes close to the end can serve this purpose.

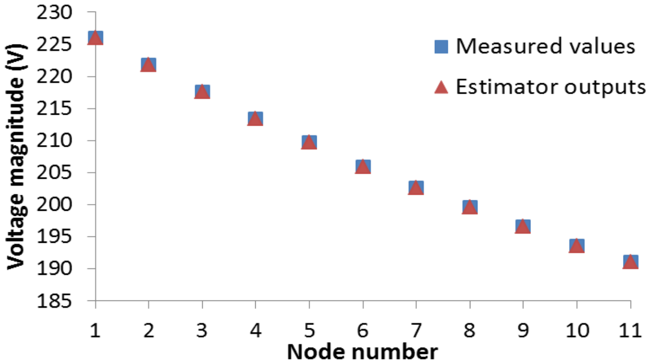

Fig. 11. Estimated and measured values of the voltage magnitudes for scenario 1 with 3 measurements available

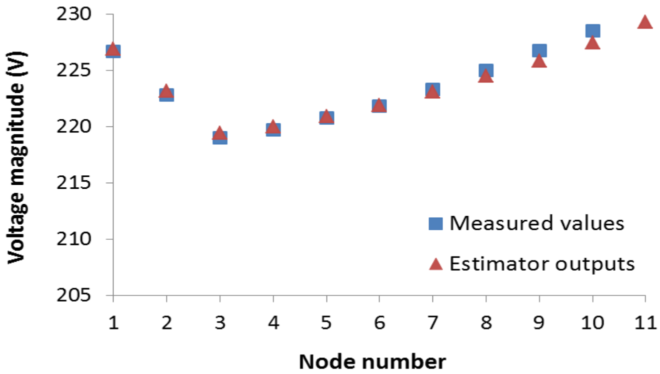

Fig. 12. Estimated and measured values of the voltage magnitudes for scenario 2 with 3 measurements available

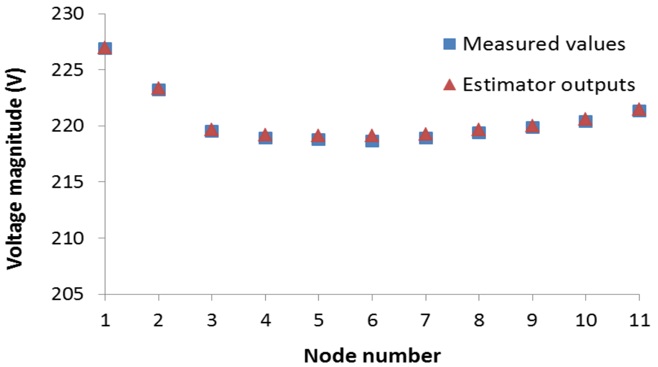

Fig. 13. Estimated and measured values of the voltage magnitudes for scenario 3 with 3 measurements available

It should be also noted that the additional input should not necessarily be a voltage measurement. For example, a current measurement placed properly could provide adequate information allowing the ANN to perform its estimations with enough accuracy. However, unlike the voltage measurement, the current measurement should not be placed at the end of the feeder as its output could not serve as an indicator of the loading of the network in that case. Instead, it should be placed, for example, in the middle of the feeder to capture the flow of the power along the feeder, but the best location to place it may be different from one network to another.

Another consideration that can enhance the estimation accuracy of estimations is to include the information about the actual time and weather condition among ANN inputs. Using this data, the ANN may select weights corresponding to DG outputs and network loading conditions more similar to the actual network situation. In fact, these inputs could help the ANN to better differentiate between many different situations which result in similar voltage and current measurements. These inputs may also reduce the need for additional voltage and current measurements in the event of increased topological complexities and local generation. Having access to these inputs should not be an issue if the estimator communication interface can get updates about local weather conditions.

V. Conclusion

In this paper, the impact of a number of factors on the performance of an ANN-based voltage magnitude estimator is described. In particular, the effect of measurement uncertainties on the voltage estimation and a training method to limit their adverse impacts were discussed. Furthermore, it was shown how the increased topological complexities and significant presence of DG units may increase the number of required input measurements. Additional inputs may be voltage or current measurements which are placed in the network in a way that allow the ANN differentiate among various operating conditions not detectable by other input measurements. Local weather condition as well as actual time could be also considered as helpful information for ANN to make a better estimate. To this end, preparing a library of ANNs each trained for a specific time of year and a given weather condition may improve the performance of ANN-based estimations.

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