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Distribution System Topology Identification for DER Management Systems Using Deep Neural Networks

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Abstract—For DER management systems (DERMS) to manage and coordinate the DER units, awareness of distribution system topology is necessary. Most of the approaches developed for the identification of distribution network topology rely on the accessibility of network model and load forecasts, which are logically not available to DERMS. In this paper, the application of deep neural networks in pattern recognition is availed for this purpose, relying only on the measurements available to DERMS. IEEE 123 node test feeder is used for simulation. Six switching configurations and operation of two protective devices are considered, resulting in 24 different topologies. Monte Carlo simulations are conducted to explore different DER production and load values. A two-hidden layer feed-forward deep neural network is used to classify different topologies. Results show the proposed approach can successfully predict the switching configurations and status of protective devices. Sensitivity analysis shows that the positive and negative sequence components of the voltage (from DER units and substation) have the most contribution to discrimination among different switching configurations.

Index Terms—Deep neural network, distributed energy resources management systems, distribution networks, topology identification.

I. INTRODUCTION

In traditional distribution systems, where the main responsibility of Distribution Management System (DMS) is to supply loads, different applications e.g. topology processing and state estimation have been developed to facilitate the management of system; however, increasing penetration levels of DERs has fundamentally changed the logic of these applications [1], so that with the current state of the art, gaining benefit from the full capabilities of DERs in the management of distribution systems is unattainable [2]. To address this issue, recently a software-base solution has been developed, referred to as DER Management System (DERMS), that covers the gap between managing the distribution system as a whole entity and managing each individual DER [3].

The main objective of DERMS is to organize, manage and

control the DER units in a distribution system in order to gain maximum grid support [1]. To achieve this goal, DERMS should be aware of the topology of distribution system [1], which is subject to continuous changes due to switching and operation of protective devices [4]. For this purpose, developing a function for capturing the real-time network topology is crucial for DERMS.

Up to now, different approaches have been suggested for the identification of distribution network topology. In [4] the network configuration prediction is implemented by evaluating the error between the estimated states and real time measurements in different possible configurations and use of a recursive Bayesian approach subsequently. In [5], [6] a fuzzy logic model is applied to predict the operation of protective devices in a distribution system. This approach employs the short circuit current, changes of active power at the substation and some information about the system maintenance. This approach is however, not applicable for identifying the status changes of network's switches. A mixed integer quadratic programming approach is presented in [7] to identify the distribution network topology, based on minimization of the weighted square of state estimation error, while in [8] this is achieved by implementing an event-triggered topology identification stage to the state estimation process.

As it is noted, most of the approaches proposed for topology identification in distribution systems rely on state estimation, which requires access to load forecast and network model. Since these approaches have been developed originally for DMS, having access to this information is applicable. DERMS on the other hand, logically do not have access to this information, but only a simplified hierarchy model of the distribution network [1], [3].

The main objective of this paper is to develop a function for the identification of distribution network topology to be applied by DERMS. This function relies only on measurements available to DERMS. The application of deep neural networks in pattern recognition is employed for this purpose. The results show that the proposed approach can successfully predict the status of switches and protective devices. Sensitivity analysis

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is conducted to discern which measurements have the most contribution to the network topology identification.

The rest of the paper is organized as follows. Section II describes the proposed approach; the test system is introduced in Section III; results are presented in Section IV. This section also describes the results of sensitivity analysis; Section V concludes the paper.

II. METHODOLOGY

As it was mentioned, for the proposed function to be applicable by DERMS, it should only rely on the measurements available to DERMS (from DER units and substation). The distribution system can be unbalanced and contain both the three and one-phase parts. It might also contain auto-regulators (which makes the identification process more arduous). The DER and HV/MV substation are supposed to be equipped with PQV sensors (that measures the active power (P), reactive power (Q) and connecting voltage in the case of DER and voltage of the MV side in the case of substation (V)).

Since network topologies are distinctive, topology identification is basically a classification problem. Classification techniques are categorized into statistical and artificial intelligence techniques [9]. Considering the successful applications of deep neural networks in state estimation of distribution systems [10]–[13], in this paper deep neural networks are used for this purpose.

A. Inputs to deep neural network

Without loss of generality, it is assumed that DER units operate under constant power factor (Irish regulations [14]) and therefore, the DER reactive power does not contain new information; also, since the network is unbalanced, the negative sequence component of DER voltage is important in discerning the correct network topology. As a result, three measurements from each DER units are considered in this approach: P_{DER-k} (active power generation of the k th DER), V_{DER-k}^+ and V_{DER-k}^- (positive and negative sequence components of the k th DER voltage, respectively) and four measurements from the HV/MV substation: P_{sub} and Q_{sub} (active and reactive power of the substation MV side, respectively) and V_{sub}^+ and V_{sub}^- (positive and negative sequence components of voltage in the substation MV side, respectively). Therefore, $3n + 4$ measurements are used cumulatively as the inputs to deep neural network for classification (n the number of DER units which are equipped with PQV sensors).

B. Deep neural network architecture

A typical neural network consists of one input layer, one or more hidden layers and one output layer, as in Fig. 1. A neuron is a mathematical function that passes the weighted average of its input through an activation function. Let y be the neuron's output, m be the number of neuron's inputs, $x = [x_1, x_2, \dots, x_m]$ be the neuron's inputs from the neurons of another layer, $w = [w_0, w_1, w_2, \dots, w_m]$ be the weight factor, net be the weighted average sum of the neuron's inputs and f

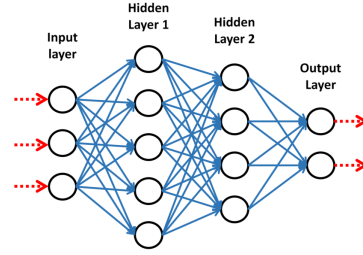


Fig. 1. A typical feed-forward neural network with 2 hidden layers, 3 inputs and 2 outputs.

be the activation factor. Equation (1) presents the mathematical representation of a neuron.

$$\begin{aligned} net &= w_0 + w_1x_1 + w_2x_2 + \dots + w_mx_m \\ y &= f(net) \end{aligned} \quad (1)$$

For the application of neural networks in pattern recognition, fully-connected feed-forward networks are used, in which each layer feeds its following layer [15]. In addition, normalized exponential function is used as the output layer neurons' activation function, which evaluates the posterior probability of each sample belonging to each of the classes ($prob(class = n)$). Suppose net is the input to activation function, equation (2) defines the normalized exponential function (f_n) for the n th output neuron (and hence, the n th class) as [15]:

$$f_n(net) = e^{\beta_n net_n} / \left(\sum_{i=1}^N e^{\beta_i net_i} \right) \quad (2)$$

where β_n is the n th function parameter, which is typically calculated by maximum a-posterior estimation [16] and N is the total number of classes. For the hidden layers' neurons, the hyperbolic tangent sigmoid [17] is used as the activation function in this approach.

III. TEST SYSTEM

The IEEE 123 node test feeder is used as test system [18]. This system operates at a nominal voltage of 4.16 kV and contains 3-phase and 1-phase overhead and underground lines, four shunt capacitor banks and four voltage regulators. Loads are unbalanced with constant current, impedance and power. This system contains 16 switches, five of which are used for load transferring: S_{13-152} , S_{60-160} , S_{97-197} , $S_{151-300}$ and S_{18-135} . Two protective devices are also considered at buses 18 and 72 (PD_{18} and PD_{72}). Fig. 2 depicts the circuit diagram of this test system.

To consider a high DER penetrated distribution system, this system was modified by adding six DER units at buses 8, 18, 44, 57, 76 and 105 (DER1 to DER6 respectively) with mean active power generation of 100, 100, 70, 200, 300 and 80 kW, respectively. Defining a load transferring zone as an artificial area located between each two switching devices, the DER units are placed such that in each zone at least one DER (and hence one measuring point) exists. It will be discussed

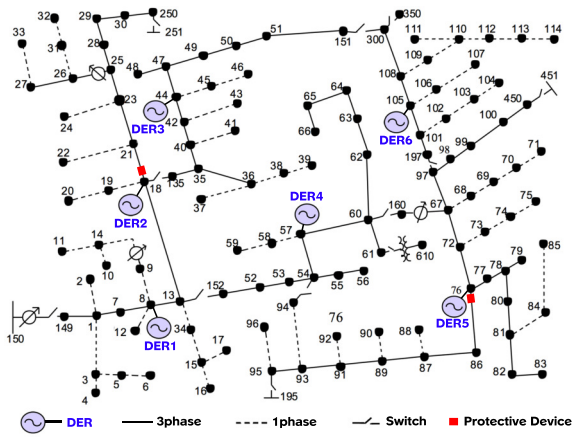


Fig. 2. IEEE 123 node test feeder.

TABLE I
DIFFERENT NETWORK TOPOLOGIES.

Switches	Switching configurations					
	C1	C2	C3	C4	C5	C6
S_{13-152}	0 ^a	0	1	0	0	0
S_{60-160}	0	0	0	1	0	0
S_{97-197}	0	0	0	0	1	0
$S_{151-300}$	1	0	0	0	0	0
S_{18-135}	0	0	0	0	0	1
P. devices	Status of p. devices					
	Cx-00	Cx-01	Cx-10	Cx-11		
PD_{18}	0	0	1	1		
PD_{76}	0	1	0	1		

^a0 represents close; **1** represents open.

later that this model is still potent to identify the switching configurations in case the latter assumption is neglected; also, since DERMS is purposeful for a distribution system with noticeable penetration of DER units, this assumption is practical.

Considering the switches, six possible configurations can be considered for load transferring which do not lead to interruption of any load. These configurations are labeled as configuration 1 (C1) to configuration 6 (C6). Table I describes the details. Only in one of the configurations (C2) the network is weakly-meshed, while in the other five the network is radial. In each of the switching configurations, four statuses can be assumed for the two protective devices, resulting in total of 24 possible topologies to be identified by the proposed approach. Monte Carlo simulations with mean of 1 and standard deviation of 0.3 are employed to simulate 6000 different load values and DER generations per topology (144000 simulations cumulatively). For each simulation, the DERs PQV values and substation measurements were noted to build a model bank to train, validate and test the neural network. 70% of the simulations were used for training, 20% for validation and 10% for test (per configuration).

Scaled conjugate gradient back-propagation method is used to train the network, as it generally converges faster than the basic back-propagation algorithm [19]. To determine the number of the hidden layers, the cross-entropy index [20] was

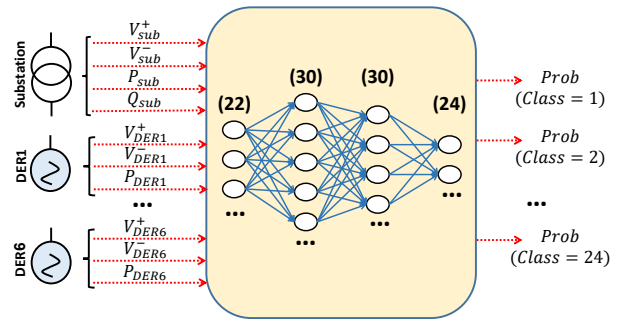


Fig. 3. A schematic diagram of the proposed neural network.

TABLE II
SUCCESS RATE OF IDENTIFYING THE CORRECT NETWORK TOPOLOGY.

Correct(✓)/Incorrect(✗)	Success/Failure Rate (%)					
	C1-00	C2-00	C3-00	C4-00	C5-00	C6-00
Network Topologies						
SC ✓ ^a – PDS ✓ ^b	91.65	91.45	94.24	88.86	94.29	93.17
SC ✓ – PDS ✗ ^c	8.28	8.31	5.76	11.14	5.71	6.04
SC ✗ ^d	0.05	0.24	0.00	0.00	0.00	0.79
Network Topologies	C1-10	C2-10	C3-10	C4-10	C5-10	C6-10
SC ✓ – PDS ✓	90.40	92.83	88.02	91.55	89.83	94.79
SC ✓ – PDS ✗	9.60	6.96	11.98	8.45	10.17	3.42
SC ✗	0.00	0.21	0.00	0.00	0.00	1.79
Network Topologies	C1-01	C2-01	C3-01	C4-01	C5-01	C6-01
SC ✓ – PDS ✓	95.74	95.07	97.74	93.88	97.62	95.71
SC ✓ – PDS ✗	4.26	4.81	2.26	6.12	2.38	4.17
SC ✗	0.00	0.12	0.00	0.00	0.00	0.12
Network Topologies	C1-11	C2-11	C3-11	C4-11	C5-11	C6-11
SC ✓ – PDS ✓	91.21	92.55	92.56	84.38	90.00	95.24
SC ✓ – PDS ✗	8.79	7.40	7.44	15.62	10.00	4.43
SC ✗	0.00	0.05	0.00	0.00	0.00	0.43

^aSC✓: Correct identification of switching configuration

^bPDS✓: Correct identification of protective device status

^cPDS✗: Misidentification of protective device status

^dSC✗: Misidentification of of switching configuration

used to evaluate the network performance over 1000 training iterations. Results show the two-hidden-layer configuration will come to a lower cross-entropy index. Passing 30 consequent successful validation checks with the maximum of 1000 training iterations was used as the stopping criteria to select the optimum number of neurons in the hidden layers, starting from 20 in ascending order. Results show that 30 neurons in each of the hidden layers will pass this condition. Fig. 3 depicts the schematic diagram of the proposed neural network.

IV. RESULTS AND SENSITIVITY ANALYSIS

Table II presents the results of the proposed approach. In this table, for each topology, the first row shows the percentage of successful topology identification, but misidentification of the correct topology has been divided into two categories: first, when the model has predicted the correct switching configuration but incorrect status for one or both of the protective devices (for example prediction of either C1-00, C1-10, or C1-11, where the correct configuration is C1-01), the percentage of which has been shown in the second row; and second, when the model has predicted the wrong switching configuration (for example confusing C1-01 with C2-01, C2-11, C3-00, or etc.), the percentage of which has been shown

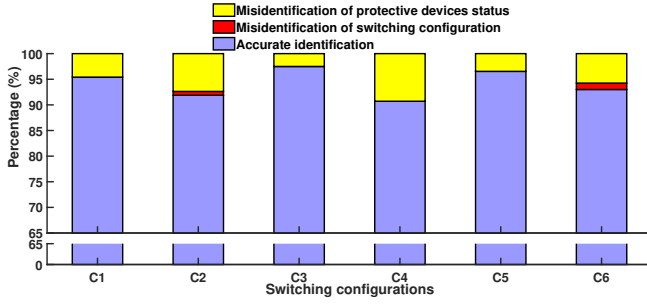


Fig. 4. Success rate of identifying the correct distribution network topology.

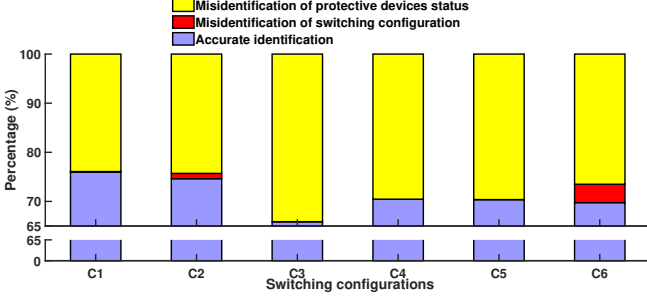


Fig. 5. Success rate of identifying the correct distribution network topology, without substation measurements.

in the third row.

To facilitate the assessment of the results, they were combined, such that topologies with the same switching configurations be considered together (for example the results of C1-00, C1-01, C1-10, and C1-11 are combined to form C1). Fig. 4 presents the results. According to this figure, the proposed approach has successfully predicted the switching configuration with less than 0.16% error on average (less than 0.02% error for configurations C1, C3, C4 and C5 and less than 0.78% error for C2 and C6). In addition, the model has predicted the status of protective devices with less than 7.3% error on average (10% error in the worst case, C4).

A. Most contributing features to discrimination among different network topologies

As it was discussed, 22 measurements were used to predict the distribution network topology. Here, sensitive analysis is conducted to discern the most contributing measurement signals to the discrimination among different network topologies. First, the unavailability of HV/MV substation measurements is simulated. In this regard, the neural network is trained and tested without the following measurements: P_{sub} , Q_{sub} , V_{sub}^+ and V_{sub}^- . Fig. 5 presents the results. It can be noticed that the proposed approach is still potent to predict the correct switching configuration with high accuracy (less than 3.5% error in the worst case, C6), but the approach's success rate in identifying the correct status of protective devices has noticeably deteriorated.

Afterwards, neural network is trained and tested without the following signals in each step: step 1 - positive sequence

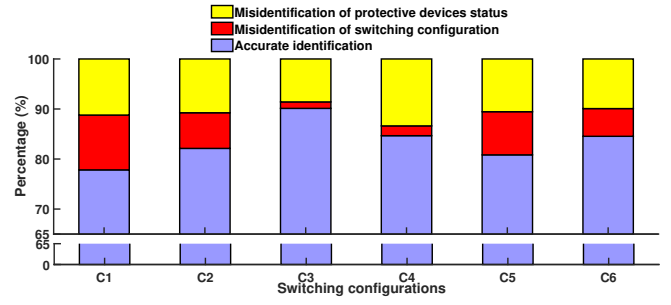


Fig. 6. Success rate of identifying the correct distribution network topology, without positive sequence component of DER units and substation voltage.

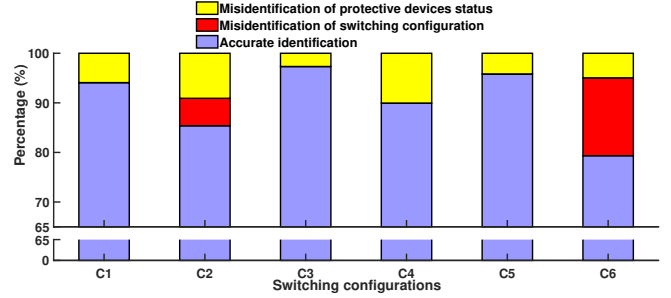


Fig. 7. Success rate of identifying the correct distribution network topology, without negative sequence component of DER units and substation voltage.

component of voltage, from the substation and all the DER units (V_{DER}^+ and V_{sub}^+); step 2 - the negative sequence component of voltage, from the substation and all the DER units (V_{DER}^- and V_{sub}^-); and step 3 - the active power generation of all the DER units. Figs. 6, 7 and 8 present the results, respectively. The results demonstrate that in regard to discern the correct switching configuration, the positive and negative sequence components of voltage have the most contribution, while the impact of DER units' active power generation is insignificant; however, in regard to discerning the correct status of protective devices, DER units' active power generation has the most contribution, while the impact of the negative sequence component of voltage is negligible.

B. The impact of measurement areas on the success of identification

As it was mentioned, it was assumed that between each two switching devices, at least one DER is present. At this stage, it is investigated how much the violation of this assumption will impact the performance of this approach. For this purpose, the neural network is trained and tested without the measurements from one of the DER units at each step. The results are presented in Fig. 9. It can be noticed that, without the measurements from one of the DER units, the average percentage of misidentification is still below 2%, showing that the proposed approach performs satisfactory, even when there is no measurements in one of the switching areas. In addition, it can be concluded that DER3 and DER6 have the most contribution to network configuration identification,

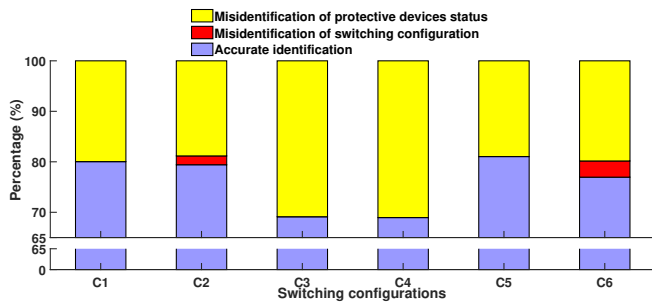


Fig. 8. Success rate of identifying the correct distribution network topology, without active power generation of DER units.

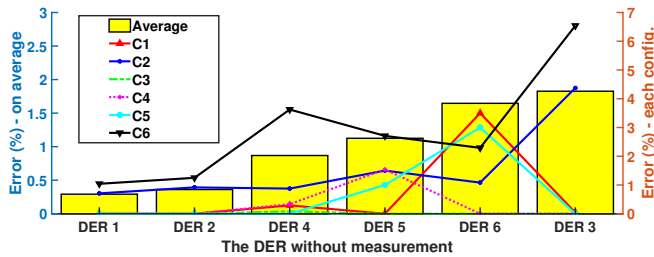


Fig. 9. Percentage of misidentification of switching configuration, without the measurements from one of the DER units. Right axis shows the percentage for each configuration, while the left axis shows the average percentage.

which emphasizes the importance of measurements in these areas. The rate of misidentification of C6 is higher than the other configurations almost in all the cases (except when DER6 measurements are missing), showing that this switching configuration is the hardest to be distinguished.

V. CONCLUSIONS

The main purpose of this paper is to develop a function to be applied by DERMS to identify the distribution network topology, which relies only on the measurements available to DERMS. The application of deep neural networks in pattern recognition was employed for this purpose. Results on modified IEEE 123 node test feeder show that the proposed approach can successfully predict the switching configuration and the status of protective devices. The positive and negative sequence components of the voltage of substation and DER units have the most contribution to discrimination among the switching configurations; however, to discern the correct status of protective devices, DER units' active power generation is the most important feature. It was also shown that without access to measurements from one of the DER units or substation, the model is still potent in predicting the correct network switching configuration with high accuracy.

It should be noted that for each distribution network, a unique neural network should be trained and for that, preparing a model bank is necessary. There are two ways to provide this model bank: 1- To use the electrical model of the network in a simulation software and run Monte Carlo simulations; 2- To use the outputs of the DMS topology processor function to predict the switch statuses. It should be considered that while

the DMS topology processor can predict the switch statuses, to maintain the modularity of DERMS and to provide the ability for DERMS to work independently from DMS, the outputs of DMS functions should only be used for preparing the model bank.

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