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A Distribution Network Topology Detection Technique Based on a One-Dimensional Convolutional Neural Network

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Abstract

Distribution network state estimation is based on distribution network (DN) topology identification (TI). The connection of high-penetration renewable energy, on the other hand, makes TI of DN more difficult. This manuscript therefore proposes an active distribution network (ADN) TI method based on a one-dimensional convolutional neural network. The characteristics of the nodes are analyzed in light of the sensitivity of node voltage to DN topology changes in order to select the key nodes where the distribution network phasor measurement unit (DPMU) should be placed. This can save money on investment and make model training less redundant. Using photovoltaic (PV) units and a modified IEEE-33 bus DN, a number of tests are carried out. Under limited DPMU measurement, the results demonstrate that the proposed distribution network topology identification method can achieve high accuracy TI in ADN.

Keywords: Active Distribution Network • Topology Identification • DPMU • Node Characteristics

Introduction

The topology of DN may change frequently as a result of various events like grid reconfiguration, facility maintenance, and failures. A crucial function of the distribution network management system (DMS) is the ongoing monitoring of the network topology in order to guarantee the control and monitoring of the DN. It is critical to ensure that the topology of DN is substantial as the active demand response level rises and DN is developed intelligently. As a result, the DN TI has attracted more and more attention. The supervisory control and data acquisition data system (SCADA) was previously responsible for carrying out the topology analysis of DN. Some data, like the node voltage amplitude and other data, can be collected by SCADA based on the data of node injection power flow. To estimate topology, some academics have proposed the residual method and the transfer power flow method [1,2].

Description

The residual method in uses the residual value of the state estimator and the DN's real-time measurement to estimate the topology, while the transfer power flow method in and use the sensitivity of the transfer power flow to estimate the DN's changing topology. However, high-precision sampling data are required to support the high-precision TI of DN. In the meantime, access to distributed energy resources also complicates its operating environment, making the issue more difficult. High-precision TI of DN is made possible by the widely used distribution network phasor measurement unit (DPMU) [8]. The DPMU's real-time voltage phase angle data are used in to realize the TI of DN; however, this approach only takes into account the topology generated by the tie switch change in DN. In a topology voting strategy is described. The topology with the highest joint probability is selected as the final TI result by each DPMU from the set of topology probabilities it provides. In SCADA and DPMU collaborate to realize DN's TI. In the nonlinear relationship between DN's topology and operating parameters is modeled using the Bayesian network. A reliable TI result for DN can be obtained using its TI model. However, the issue of DPMU placement is not taken into account by this method [3,4].

This manuscript presents a TI DN method based on DPMU sampling data, including voltage power, amplitude, and phase angle, driven by a one-dimensional convolutional neural network. The sensitivity of node voltage to changes in DN topology is used to examine the characteristics of nodes in light of the issue of insufficient measurement equipment in DN. In addition, the key nodes that will house the DPMU are chosen carefully, which saves money and cuts down on model training redundancy. Finally, the photovoltaic (PV) unit-simulated IEEE-33 bus network is used to test the viability of the proposed TI strategy [5].

The admittance matrix generally defines the topology of the DN, and the admittance matrix influences the system's power flow change. As a result, the DN's structure and the power flow variable share a particular relationship or rule. The remaining information regarding injected power, voltage amplitude, and phase angle of partially nodes can be calculated using power flow with the assistance of information gathered by SCADA and DPMU in DN. The TI of DN will be built upon these data. Branch switches in DN are limited in practical engineering. As a result, the number of structural types for a particular DN after the change is limited, allowing deep learning and other techniques to fit the relationship between DN's measured data and calculated topology [6].

The recent research generally selects nodes that have more adjacent nodes when installing DPMU. Additionally, a node's degree can be used to describe the number of adjacent nodes. However, there may be some nodes in a DN system with many nodes that share the same degree; selecting these nodes is a problem that must be resolved. A method for selecting node features that takes into account the voltage-topology change sensitivity of the node is proposed in this paper. The DPMU is preferentially placed on the node with the highest sensitivity out of all nodes with the same degree [7].

In most cases, a TI with fewer features can better meet actual requirements. In order to allow the model to be trained with fewer feature categories, the sensitivity of the node voltage to the topology change of DN is evaluated, and the feature categories are successively reduced in proportion to the significance of the sensitivity features. The amplitude and phase angle of the node are included in the test. The sensitivity index is then calculated in the manner depicted [8,9].

The topology change makes the voltage phase angle fluctuation more

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apparent, as depicted in Figure. As a result, sorting the node sensitivity index is based on the voltage phase angle. The best approach is determined by the sensitivity of the nodes when the placement of DPMU is determined by the degree of nodes. The placement of DPMUs in various numbers of DPMUs is carried out in conjunction with the method of the maximum degree and the identification effect of the model is depicted [10].

Conclusion

The fact that the proposed model achieves an accuracy of at least 90% across a variety of measurement noises demonstrates that the 1DCNN approach is capable of successfully achieving the TI of DN. Additionally, it is evident that the shallow structure of SVM makes it difficult to extract features from data, resulting in a low identification accuracy; While DNN is a deep network structure, it has limited feature extraction capabilities, making it less accurate than the proposed method for identifying topologies.

Acknowledgement

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Conflict of Interest

None.

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