Anomaly Detection of Renewable Energy Systems by Unsupervised Graph Neural Networks

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EXTENDED ABSTRACT

Deep machine learning methods can provide better performance of anomaly detection in Renewable Energy Systems (RESs) than traditional methods [1]. Their actual deployment is challenged by the intrinsic complexity of the detection task, due to: *i*) the interconnections among subsystems and components, which cause complex spatio-temporal correlations among the measured signals, and cascading effects on different parts of the system; *ii*) the variability of the operational and environmental conditions of RESs, which influence and modify the systems behavior and the correlation among signals; *iii*) the presence of control systems that hide anomalies in the signals patterns by actuating on control variables; i*v*) the scarcity of data collected during anomalous conditions, which limits the applicability of supervised learning approaches. This work illustrates the use of Graph Neural Networks (GNNs) to address some of these challenges. GNN is a type of neural network specifically designed to deal with graph-structured data [2]. GNN receives in input graphs whose nodes represent sensors and edges represent relationships among them, and it can be trained to capture correlations among signals (challenge *i*) distinguishing changes caused by anomalies from those caused by different operational and environmental conditions and control actions (challenges *ii* and *iii*). Here, we propose a GNN model based on a combination of Gated Recurrent Units and Graph Convolutional Networks [3], organized in an autoencoder. The model is trained using only normal condition data (challenge *iv*) to reconstruct the signal values expected in normal conditions. Then, in operation, when the residual, i.e., the difference between the signal measurement and the reconstruction is larger than a predefined threshold, the occurrence of an anomaly is detected. The developed GNN is applied to data simulated using the wind turbine model presented in [4], which allows reproducing the system behavior in different operational and environmental conditions, under normal conditions and anomalous ones due to failures of sensors and mechanical components. The proposed method is shown to outperform state-of-the-art methods in terms of missed and false alarms, and delay in detection.

Keywords — Renewable Energy Systems, Wind Turbine, Unsupervised Anomaly Detection, Graph Neural Networks.

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