Explainable Feature Selection and Anomaly Detection of a Gas Turbine with Variational Autoencoder

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Faults and sudden stops of a gas turbine might be caused by various factors including combustion chamber failures, fuel control valve malfunctions, and exceedance of combustion pressure limits. These faults might decrease the lifespan of high-temperature components in the gas turbine, resulting in significant financial losses. To design a predictive maintenance system by solving these issues, it is necessary to determine which features among the numerous ones associated with the gas turbine should be monitored. This study proposes a novel feature selection and anomaly detection method that addresses a novel deep learning architecture for detecting abnormal states of gas turbines. The proposed method aims to find the optimal feature subset for anomaly detection of gas turbines using variational autoencoder (VAE) with low computational cost. Specifically, feature importance is calculated using the VAE trained on the entire set of features based on feature-wise reconstructed errors in train phase. The optimal feature subset is obtained by performing the recursive feature elimination with the feature importance. In test phase, VAE with the optimal feature subset considers an instance as a failure when its anomaly score exceeds a threshold set at a specific confidence level. If the VAE regards the test data as an anomaly, reconstructed error contribution of features is calculated as explainable results. The effectiveness of the proposed method is validated by using field measurements of a gas turbine generator for nine years. Experimental validation confirms that the proposed method has high true negative rate and low false negative rate, suggesting that the selected features effectively distinguish between normal and abnormal data. The VAE with the optimal feature subset determined by the proposed method outperforms other anomaly detection algorithms. Moreover, the reconstructed error contribution of features is verified in its capability to perform source identification for the gas turbine failures. The proposed method is an effective explainable anomaly detection framework in real-world applications because it determines the optimal feature subset from countless features and provides explainable anomaly detection results with high accuracy and robustness.