

Abstract

Anomaly detection in the oil and gas industry is a crucial step in maintaining operational smoothness, safety, and efficiency. This study aims to develop and compare two Recurrent Neural Network (RNN) architectures, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), in detecting anomalies in operational time-series data for oil and gas production. The dataset used is derived from operational records from 2015–2016, with four main variables relevant to pipeline operational conditions: PRESSURE, TEMPERATURE, ENERGY_RATE, VOLUME_RATE.

The research stages included data exploration (EDA), preprocessing (handling missing values, normalization using RobustScaler, and windowing), training the LSTM and GRU models, and evaluation using error value metric. Anomaly detection is performed by determining a threshold based on the 95th percentile of the prediction error distribution, where error values above this threshold are categorized as anomalies.

Test results show that the GRU model performs better. Visualization of the detection results shows that anomalies occurred frequently during the period April–May 2016, which may have been influenced by instrument malfunctions or sudden operational changes. This study contributes to the design of an unsupervised anomaly detection system utilizing two RNN architectures for comparison, as well as documentation of the data analysis process in the oil and gas industry, which can serve as a reference for developing automated operational monitoring systems.

Keywords: *Anomaly Detection, LSTM, GRU, Time-Series, Oil and Gas Industry.*
