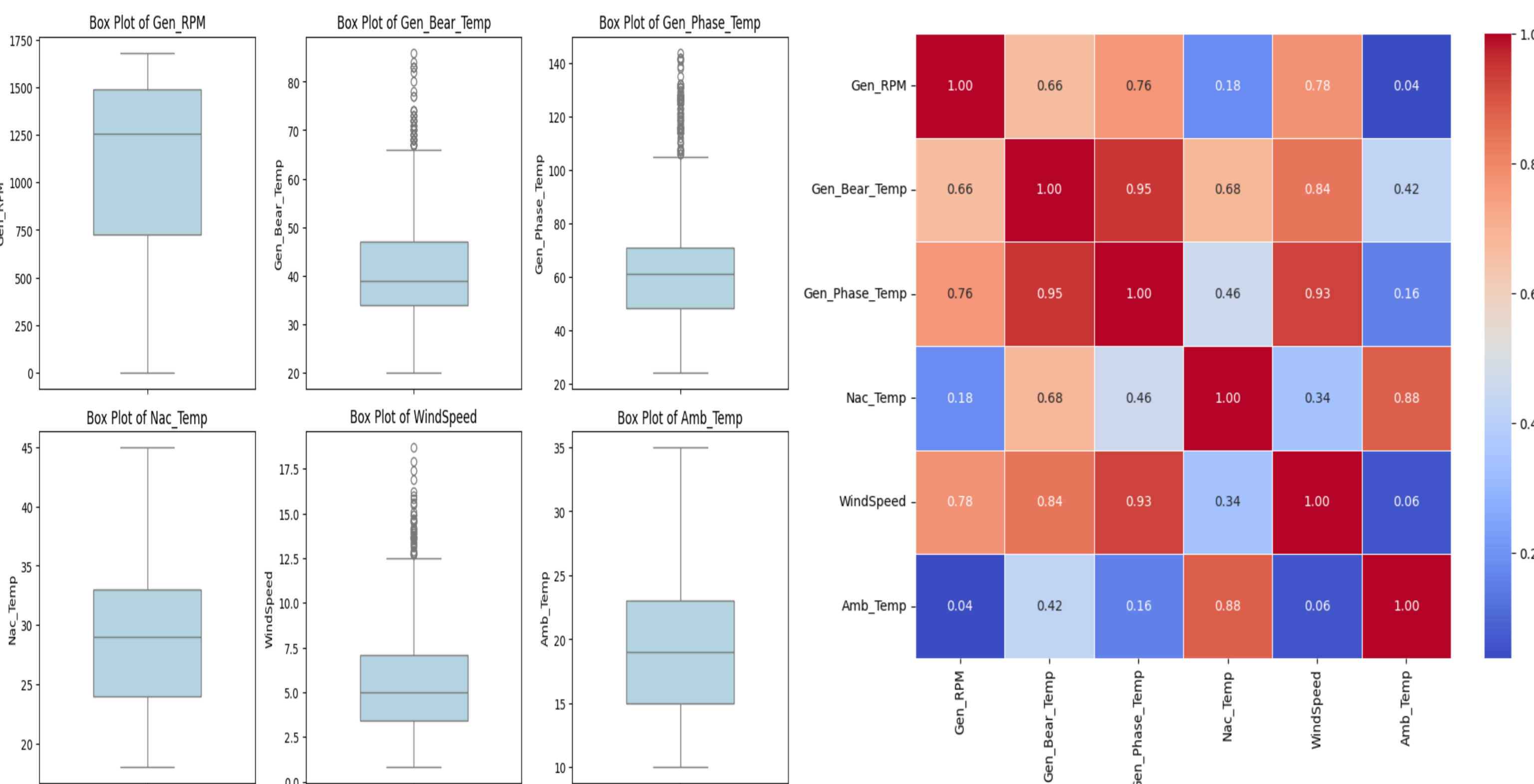


Introduction

Fault detection in wind turbine generator bearings is essential for maintaining the reliability and efficiency of wind turbine systems. Traditional fault detection methods often rely primarily on sensor data and conventional machine learning models, which may not fully capture the complex interdependencies between various system parameters. This research introduces a novel approach that integrates knowledge graph (KG)-based embedded data with traditional feature data to enhance performance of machine learning models for fault detection. By leveraging the structured domain knowledge embedded in KGs, this framework improves the model's predictive accuracy and robustness, offering a more comprehensive and accurate method for detecting bearing faults in wind turbines.

Exploratory Data Analysis

The box plot for the wind turbine data helps identify potential outliers across key parameters, highlighting unusual values that may indicate abnormal behavior or failures. The correlation heatmap reveals the strength and direction of relationships between these parameters, providing valuable insights into how changes in one parameter may affect others, which is crucial for detecting patterns and understanding system behavior.



Box plot for input signals

Correlation matrix for input signals

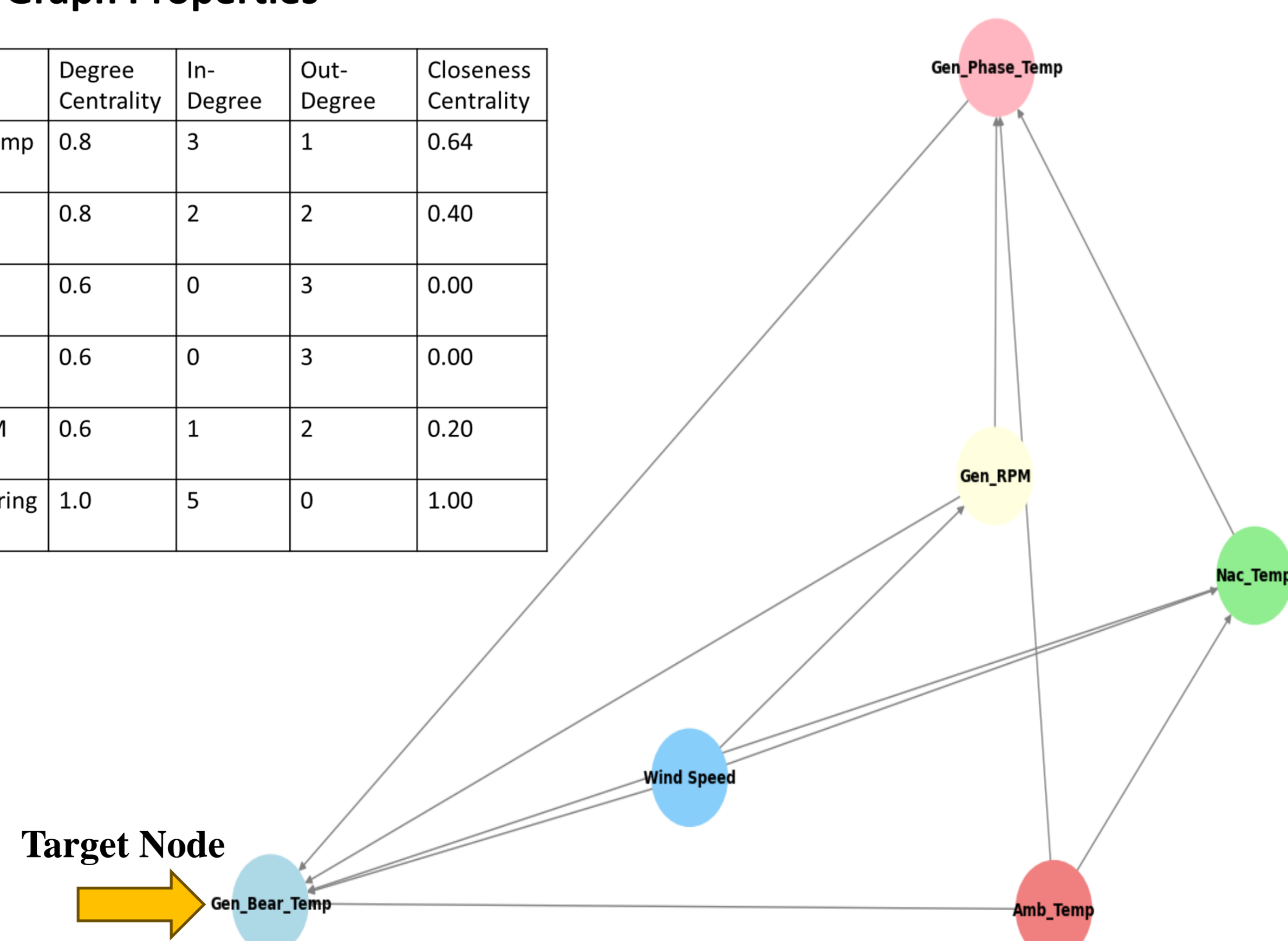
Data & Knowledge Graph (KG) Construction

The study utilizes SCADA data of the offshore wind turbine.

- Entities includes: Wind Speed, Generator RPM, Nacelle Temperature, Ambient Temperature, Generator Bearing Temperature and Generator Phase Temperature.
 - Entity Relations: E.g.,
 - Generator RPM ↔ Generator Phase Temperature (Direct correlation through mechanical and electrical load)
 - Nacelle Temperature ↔ Generator Phase Temperature (Environmental influence on internal temperature)
 - Wind Speed ↔ Generator RPM (Direct correlation through blade speed)
 - Wind Speed ↔ Nacelle Temperature (Affects operational heat and cooling)
 - Ambient Temperature ↔ Nacelle Temperature & Generator Phase Temperature (Affects cooling efficiency and risk of condensation)
- Knowledge Graph Representation: This knowledge graph serves as a foundation for understanding complex interactions within wind turbine parameters.

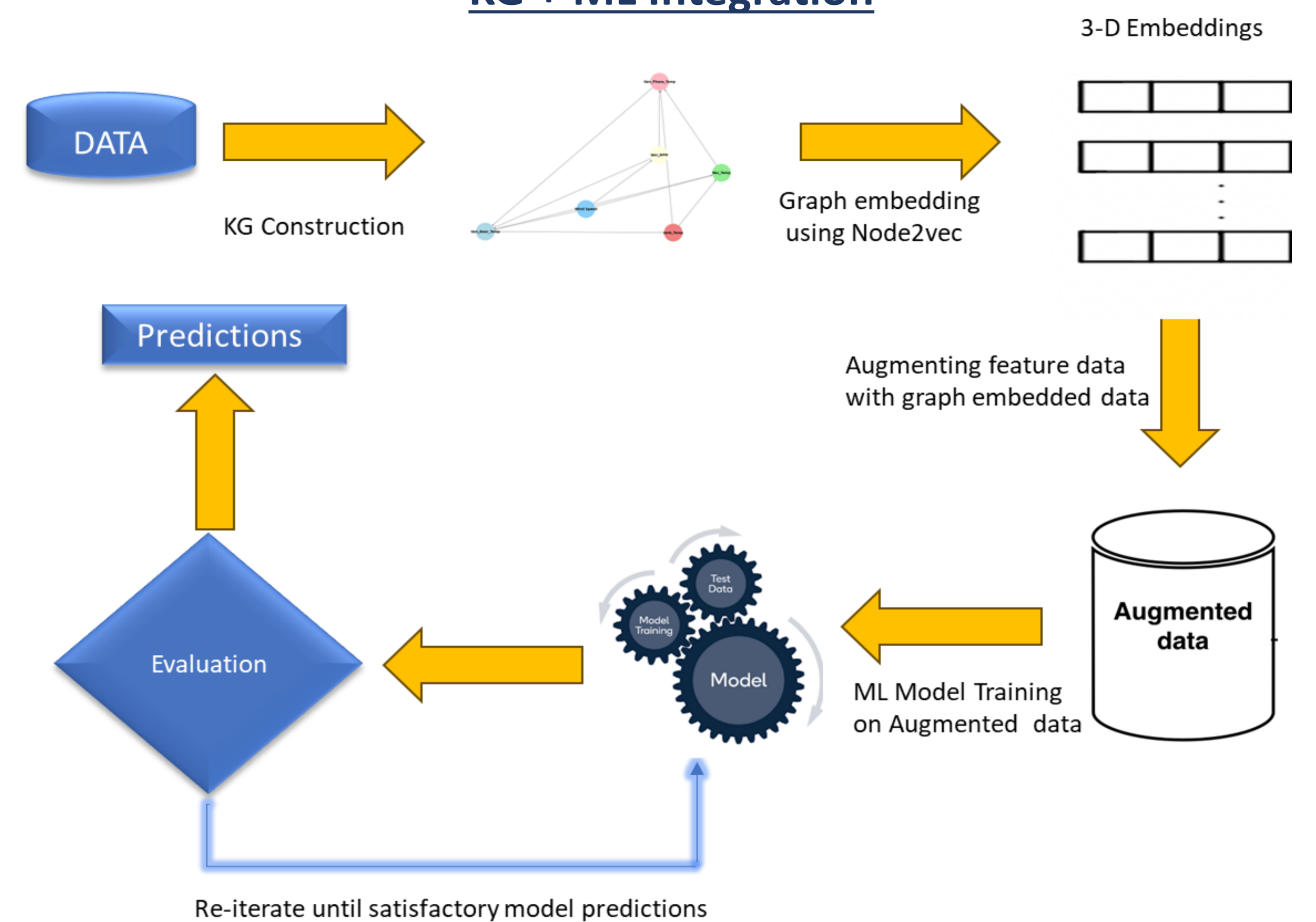
Graph Properties

Node	Degree Centrality	In-Degree	Out-Degree	Closeness Centrality
Gen_Phase_Temp	0.8	3	1	0.64
Nacelle Temp	0.8	2	2	0.40
Ambient Temperature	0.6	0	3	0.00
Wind Speed	0.6	0	3	0.00
Generator RPM	0.6	1	2	0.20
Generator Bearing Temperature	1.0	5	0	1.00

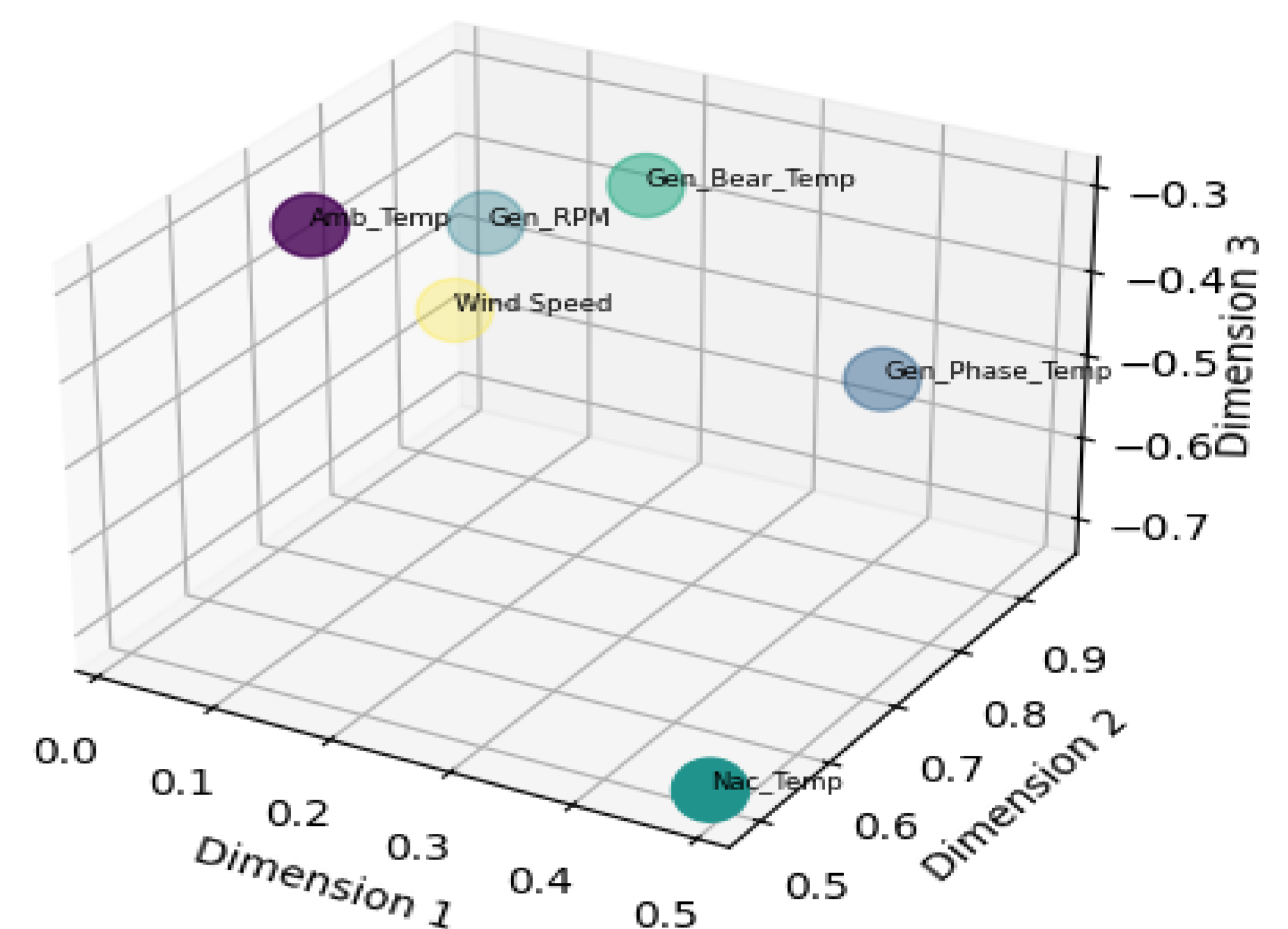


Knowledge Graph for wind turbine parameters

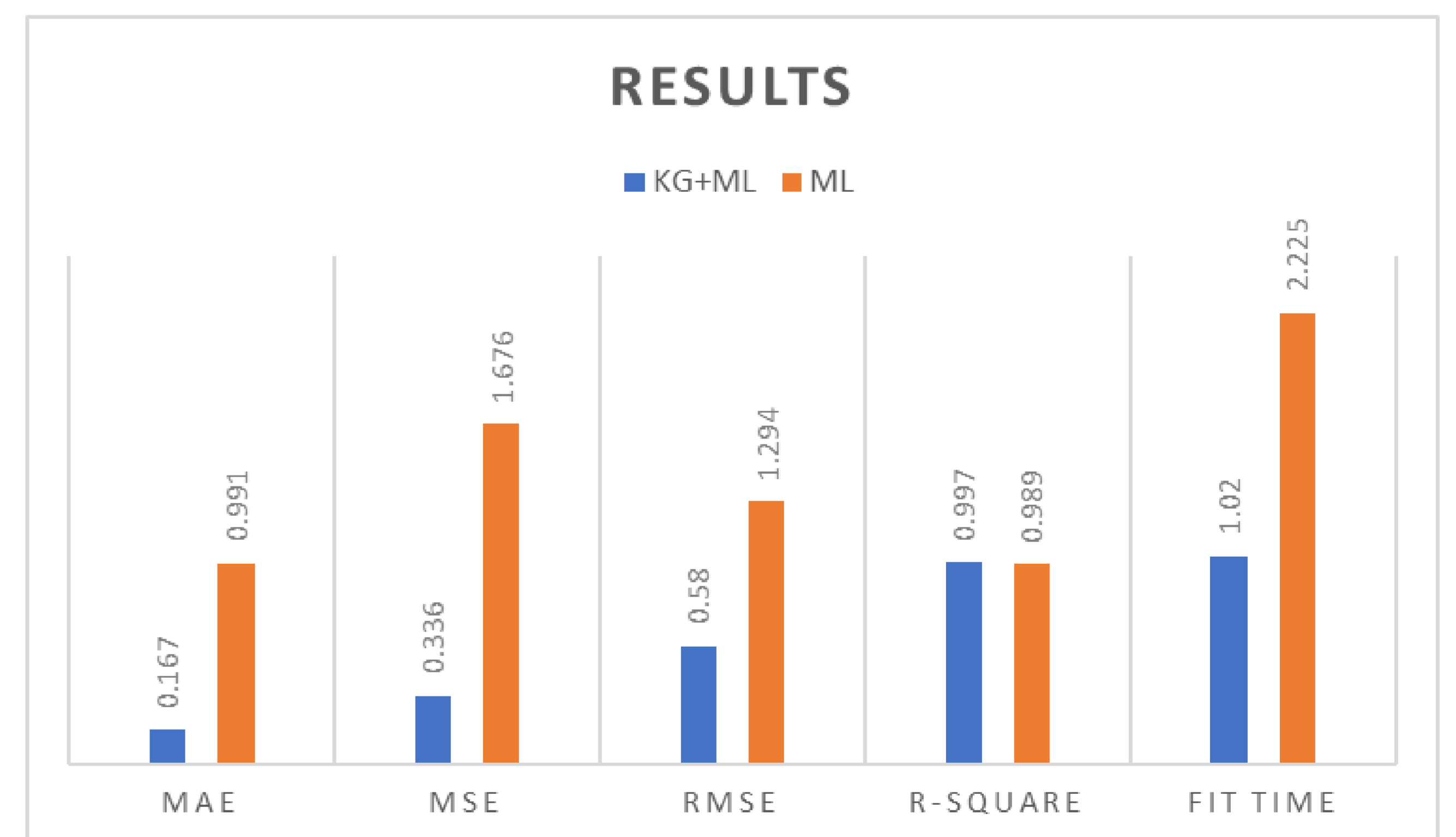
KG + ML Integration



3D Scatter Plot of Node Embeddings



Results & Key Metrics



Using graph-embedded data (KG+ML) significantly improves model performance across all metrics (MAE, MSE, RMSE, R-Square) and reduces fit time compared to using non-embedded data (ML).

Conclusions

This study demonstrates the efficacy of integrating knowledge graphs with machine learning for fault detection in wind turbine generator bearings. By capturing the interdependencies among wind turbine parameters, the approach improves detection accuracy and empowers domain experts to make informed decisions. In this work, we performed node embedding, and future work will focus on real-time deployment, scaling the framework to other critical infrastructure systems, and exploring edge embedding for further improvements..

References

- Bindingsbø OT, Singh M, Øvsthus K and Keprate A (2023), Fault detection of a wind turbine generator bearing using interpretable machine learning. Front. Energy Res. 11:1284676. doi: 10.3389/fenrg.2023.1284676
- Mitropoulou, K., Kokkinos, P., Soumplis, P. et al. Anomaly Detection in Cloud Computing using Knowledge Graph Embedding and Machine Learning Mechanisms. J Grid Computing 22, 6 (2024). <https://doi.org/10.1007/s10723-023-09727-1>