



Predictive Maintenance of Industrial equipment using Temporal Graph Neural Networks: A step towards Novelty

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ABSTRACT

Predictive maintenance is important for improving industrial activities and achieving minimum downtime. The most common methods focuses on temporal features that are static and extracted from a set of sensors which may not account for the dynamic of time evolution in the degradation of the equipment .In this paper , we develop a Temporal Graph Neural Networks (TGNN) model to address the limitations. Since sensor data comprises of temporal data which can be structured as graph with time points as nodes and relationships between time points as edges, TGNN can learn advanced timing configurations to enhance accuracy of the model's forecast. The method has been tested on dataset, which has a real industrial applications and conducted a comparison of its result with the traditional system. Our findings confirm that TGNN are effective than other baseline methods and thus, generalising the type of tasks for predictive maintenance.

Keywords : Predictive maintenance ,Temporal Graph Neural Networks (TGNN), Industrial operations, Sensor data analysis, Equipment degradation, Time-series forecasting, Graph-based modelling, Dynamic temporal features, Downtime reduction, Machine learning in maintenance

1 Introduction

Predictive maintenance is essential in industrial activities that attempt to predict the future state of the equipment and try scheduling its maintenance accordingly. This practice may lead to a minimization of outage time, maximization of techniques such as SVM, Random Forests, and deep learning-based approaches. Time-series models like LSTM, GRU have also been applied to predict the times when equipment is likely to fail. These models however cannot capture structural interdependencies between different components, and therefore, in complex systems, tend to fail.

1.1 Graph Neural Networks (GNN)

GNNs have been applied in many fields, such as social network analysis, molecular chemistry, and recommendation systems, among others. The extension of GNNs to TGNN provides a framework to consider both temporal sequences and graph structure in one go. Many works have been done on the application of TGNNs in predictions such as traffic and



recommendation, but very little has been explored on PdM.

2 Recent Works

Older systems depend mainly on a few fixed attributes recognized in sensor records such as mean value, its variance and standard deviation. But any equipment functionality loss is a complicated evolution of events episodically coupled in time. The performance of predictive maintenance techniques heavily relies upon the ability to capture such dependencies.

TGNNs have proven to be efficient and effective in the predictions of dynamic graph-structured data. Sensor data can be presented as a graph consisting of time step's nodes and temporal relationship's edges. With such graph representation, TGNNs are able to appropriately learn the complex temporal patterns. This attribute renders them appropriate for predictive maintenance tasks. This paper proposes another approach to predictive maintenance using TGNNs. First, we create a graph from sensor data: time steps are perceived as nodes and time steps that are next are connected to each other. We then predict the probability of equipment failure after training the TGNN model on the graph to understand the temporal relationships. Such effectiveness of the proposed approach is demonstrated on a real case study in which the dataset comprised of an industrial equipment sensor.

2.1 Graph Neural Networks (GNN)

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2.2 Problem Definition

Predictive maintenance thus can be viewed as a time-series forecasting problem, in this case, that aims to predict the likelihood of failure within a specified future time window. However, industrial systems have reality in them, in the sense that the components are interconnected and hence the failure of one could easily impact the others. To capture these relationships effectively, the PdM task can be conceptualized as a graph-based problem where the nodes are components, and edges represent relationships in the form of physical connections, usage dependencies, or shared environmental conditions, to name a few.

3 Proposed Approach: Temporal Graph Neural Networks (TGNN)

Node Features: Here node features would include sensor readings, historical maintenance data, and other operational parameters.

Evaluation Metrics: The models are evaluated using standard metrics for classification and regression tasks, namely accuracy, F1score, precision, recall and root mean square error (RMSE).



Edge Features: All such relations between the components, such as sharing working conditions or physical proximity, can be represented as edge features.

Temporal Modeling: This module captures the system's temporal evolution using recurrent layers such as (e.g., LSTM) integrated within the GNN framework. In that way, the model learns to capture temporal dependency as well as the graph structure.

Prediction Layer: The model outputs the probability of failure for every component at future time steps.

3.1 GNN Architecture

In this paper, the model applied will be TGNN, consisting of the following:

Graph Representation: As every industrial equipment is considered a node, the representation is in terms of a graph where edges depict the dependencies among them.

3.2 Training and Loss Function

For TGNN model, it was supervised training based on historical event data that had labels corresponding to failure, the loss function was therefore defined with objectives of minimizing the error in a prediction while discouraging the model to fail between healthy and at-risk components.

3.2 Data Preprocessing

The raw data coming from the sensor equipment are preprocessed for extracting features while normalizing them. The graph construction is performed based on the relationship between components that could be defined either based on expert knowledge or learned from data.

4 Results and Discussion

Dataset

The model will be tested on a publicly available industrial equipment dataset containing sensor readings and operational parameters and failure records of a set of machines.

Baseline Models

Baseline Comparison

Results

The performance of the proposed TGNN model is benchmarked against several baseline models, namely,

- Time-series models: LSTM, GRU
- Graph-based models: Static GNN, GCN
- Machine learning models: Random Forest, SVM

The TGNN model outperforms the baseline models on all of the evaluation metrics. This should represent its ability to capture both the temporal and structural information in predicting equipment failures, thus proving superior to these baseline models.



Superior performance of the TGNN model in early fault detection is also very critical in PdM applications.

Discussion

This outcome depicts the capability of TGNN to manage complex, interconnected industrial systems for predictive maintenance tasks. This capability certainly supersedes existing time-series models and typical machine learning approaches since it learns both temporal patterns and relational structures.

5 Conclusions

This paper presents a new direction of applying TGNNs for predictive maintenance on industrial equipment. The model leverage graph representation of equipment and incorporation of temporal dependencies significantly improve predictions and fault detection at early times. Future work would involve developing unsupervised learning techniques that improve feature extraction.

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