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Predictive maintenance of Base Transceiver Station Power System using XGBoost algorithm. A Case Study of Econet Wireless, Zimbabwe

Research Paper

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ABSTRACT

Faults incurred by Base Transceiver Stations pose challenges to telecommunication organisations. Mostly the faults are due to BTS failures. BTS power system failures can have a significant impact on organizational performance in the telecommunications industry. These failures can cause disruptions in mobile network coverage, leading to dropped calls, slow data speeds, and difficulty connecting to the network. ECONET Zimbabwe has been experiencing unprecedented BTS power system failures for the past five years. Team Data Science Process was the pillar of the study methodology. The XGBoost algorithm was employed to develop a predictive model for the maintenance of Base Transceiver Station power failure. By using Machine Learning techniques to predict power system failures, ECONET Zimbabwe can take proactive measures to prevent disruptions in service, resulting in improved resource utilization and revenue. The number of dropped calls decreases and data speeds increase. The XG Boost algorithm reached 97% accuracy.

KEYWORDS

Predictive maintenance, XGBoost, Base transceiver Station, Econet Wireless.

INTRODUCTION

The telecommunications sector faces a serious problem with Base Transceiver Station power system failure. This is a critical issue in the telecommunications industry as it can result in service disruptions and loss of revenue. The use of machine learning (ML) techniques for predicting power system failures in BTS can help to improve the performance and efficiency of the telecommunications infrastructure. The research identified factors important in predicting Base Transceiver station failures and use them to develop machine learning model to predict the failure. The use of the XGBoost algorithm proved to be capable of predicting the station failure by an accuracy level greater than 95%.

BACKGROUND

The telecommunications sector faces a serious problem with Base Transceiver Station power system failure. This is a critical issue in the telecommunications industry as it can result in service disruptions and loss of revenue. The use of machine learning (ML) techniques for predicting power system failures in BTS can help to improve the performance and efficiency of the telecommunications infrastructure. Globally, the use of ML for predicting and preventing power system failures in BTS has been widely researched. A large portion of the total operating costs of any industry or service provider is devoted to keep their machinery and instruments up to a good level, aiming at ensuring minimal disruption in the production line (Pratap, Samson and Let, 2021). It has been estimated that the costs of maintenance is in the range 15-60% of the costs of good produced (Chen & Chen, 2021). Predictive maintenance attempts to minimise the costs due to failure via regular monitoring of the conditions of the machinery and instruments (Kamat & Sugandhi 2019). Faults incurred by Base Transceiver Stations are a major problem to telecommunications organisations around the world (Balmer, Levin & Schmidt, 2020). According to the Institute of Electrical and Electronic Engineers (IEEE 2020), majority of the faults in the telecommunications industry are due to BTS failures.

Machine Learning is a branch of artificial intelligence (AI) that enables systems to learn and improve from experience automatically without being explicitly programmed (Chen, 2019). ML algorithms are designed to identify patterns and relationships in data, which can then be used to make predictions or decision (Gupta & Shaw, 2019). The application of machine learning model for predicting power system failures in base BTS involves using historical data of the power system failures to train the model (Ebrah & Elnasir, 2019). According to Ritika (2022), a Base Transceiver Station (BTS) is a piece of equipment that is used in mobile telecommunications networks to provide wireless coverage in a specific geographic area. Base Transceiver Stations are an essential component of the telecommunications infrastructure that connects client equipment to the cellular network (Kibatu, 2019). Base Transceiver Station operations may be disrupted due to a variety of causes, including transmission failure, an optical fibre break, a power system malfunction, a natural disaster, and many others (Pal & Ifeanyi, 2017).

To ensure quality of service (QoS) and customer happiness, mobile network operators must now engage in proactive maintenance efforts (Haseltine & Eman, 2017). In China ML is being used to predict the failure of power systems in BTS (Oughton & Mathur, 2021). Similarly, in a study in India on power system failures in BTS, it was found that ML techniques improved the accuracy of failure prediction. In Africa, the use of ML for predicting power system failures in BTS is also an area of ongoing research. A study by Mukundan et al (2019) on BTS power system failures in South Africa found that ML techniques improved the accuracy of failure prediction. Additionally, a study by (Rab, 2022) on BTS power system failures in Nigeria found that ML techniques improved the accuracy of failure prediction.

According to Gupta and Shaw (2019), BTS power system failures can have a significant impact on organizational performance in the telecommunications industry. These failures can cause disruptions in mobile network coverage, leading to dropped calls, slow data speeds, and difficulty connecting to the network (McNemar, 2021). This can result in poor customer satisfaction, increased customer churn, and a negative impact on the overall reputation of the organization (Pal & Ifeanyi, 2017). According to GSM Association, poor network coverage and dropped calls are among the top reasons for customer dissatisfaction with mobile network operators (MNOs) (GSM Association, 2020). Additionally, power system failures can also cause costly network downtime, resulting in lost revenue for the organization (Taufiqurrahman, 2015). Power system failures can also cause costly network downtime, resulting in lost revenue for the organization. A report by Ericsson estimates that the cost of network downtime for MNOs can range from $5,000 to $500,000 per hour, depending on the size and complexity of the network (Ericsson, 2017). Therefore, it is important for telecommunications companies to have robust power systems in place and to implement regular maintenance and testing to minimize the risk of power system failures.

In Africa, the reliability of power supply is a major concern for the telecommunications industry (Haseltine & Eman, 2017). Power outages and power cuts are common occurrences in many African countries, which can cause BTS power system failures (Oughton & Mathur, 2021). This is a major challenge for telecommunications companies in Africa, as they have to rely heavily on backup power systems such as generators and battery banks to keep the BTS running (Nestor & Ogudo, 2018). This can add additional costs and maintenance requirements. In many parts of Africa, the cost of maintaining a reliable power supply for BTS can be high due to a variety of factors. These factors include the cost of diesel fuel for generators, the cost of maintaining and repairing power infrastructure, and the cost of replacing failed equipment (Dixit, 2022). Additionally, frequent power outages can also lead to increased maintenance costs and equipment failures (Sarker, 2021). Thus, the power supply for BTSs in Africa can present significant challenges and costs for mobile network operators (Chen, 2019).

In Zimbabwe, the use of ML for predicting power system failures in BTS is an area of ongoing research. Over the years, the telecoms industry has had the reputation of being most affected by service disruptions among other industries (Dixit, 2022). ECONET Zimbabwe is the largest mobile network operator in Zimbabwe and has the most extensive network coverage in the country. With 2,356 base stations nationwide, the company's BTS services are frequently interrupted by electrical power supply failures. Power system failures in BTS can result in service disruptions and loss of revenue for the company (Cheng & Frangopol, 2022). By using ML techniques to predict power system failures, ECONET Zimbabwe can take proactive measures to prevent disruptions in service, resulting in improved resource utilization and revenue. Some of the critical issues for the mobile network operator is the management, oversight, and resource allocation of the entire system (Nestor & Ogudo, 2018). A lot of effort and resources go into infrastructure maintenance, which should be juggled with corrective maintenance simultaneously. It is against this background that the study was motivated to expound on use of machine learning model for predicting power system failures in BTS at ECONET.

OBJECTIVES

The objectives of the study were to:

1. determine factors which are statistically significant to BTS power system failures at Econet Wireless Zimbabwe.
2. develop a predictive maintenance model for BTS power system at Econet Wireless Zimbabwe.

3. evaluate the developed predictive maintenance model for BTS Power System at Econet Wireless Zimbabwe for model accuracy.

METHODOLOGY

The positivism research philosophy was employed in this study for its strength in separating the researchers from the research data and activities and personal opinions, thereby viewing the data objectively. Team Data Science Process (TDSP) was the pillar of the study methodology. A variation of the TDSP methodology, which incorporates a business-centric focus covering the full life cycle of creating a Machine Learning artefact, was utilised.
Microsoft's Team Data Science Process (TDSP) is a cyclical data science framework. The TDSP is a high-level data science project life cycle and has a standardized data science project structure. Its desired strength was it being an Agile approach and is well-suited for machine learning projects, which often involve building and testing multiple models before finding the best one.

Feature engineering was carried out on the cleaned dataset to create a new, enhanced dataset that simplifies model training. Feature engineering was built on the insights obtained from the data exploration step. Once the data had informative features, the model was trained and evaluated. In order to effectively analyze the multivariate time-series data of Base Transceiver Station (BTS) logs, advanced machine learning algorithms were utilized. Specifically, Long Short-term Memory (LSTM) and Recurrent Neural Networks (RNN) were employed to take into account the temporal sequential component of the data and prevent the loss of information. The dataset, after undergoing feature engineering, was split into training, validation, and testing sets with 70%, 10%, and 20% respectively. Additionally, each feature was standardized to have a mean of zero and a unit variance. Tools used in the research were Python, Pandas, Matplotlib, seaborn, Watson, JupiterLab, and BTS logs

RESULTS

Results from the Exploratory Data Analysis of the dataset were that: out of the total observations, 53,530 were correct and 7,719 were erroneous; the findings show that the mean for the three phase AC was 247.942873V, with the minimum at 247 Volts and a maximum voltage of 248 V. The single phase AC had a mean of 242V with a standard deviation of 1.097983 V. The minimum for the single phase was 238V and the maximum was 243V. This finding is in tandem with the general standard of voltage allowable in a BTS power system (Milani et al., 2017). Results show that the XGBoost model had a high overall performance accuracy of 97.58%, a precision of 93.46%, a recall rate of 90.79%, and an F1 Score of 93.61%. These results suggest that the XGBoost model can effectively predict power system maintenance needs in BTS systems.

The most robust positive correlation existed between fault and bus bar voltage (0.98). Followed by a positive correlation between fault and rectifier working capacity (0.97), working humidity (0.94), AC-single phase (0.87), and AC-three-phase (0.90).

When the Bus Bar voltage is above 53.45V and when it is below 36.66 V faults were recorded signifying power unit system failure. The warning voltage of faults fell between 36.6V and 45.02V while the optimal voltage was between 45.02 and 53.93V. The normal operating range for a bus bar DC voltage is between 36.66 and 53.45V.

The ideal humidity range for the BTS power system was found to be between 36.2% and 49.87%. It was observed that when humidity levels fell below 36.2% or exceed 50%, there were instances of failure in the BTS power system. Recommended humidity range for communication equipment is 40% to 55% (Sarker (2021).

The ideal temperature range for the BTS system was found to be between 200C and 250C. Any temperatures outside of this range were associated with faults.

The study found out the optimum range of AC-single phase to be 241V to 243V, For AC three-phase power was between 247.5V and 248V. Fluctuations of AC in BTS power system were always associated with power system failure.

The optimum working capacity of the rectifier was found to be 80% and above. Thus if the working capacity is below 80% the rectifier will trigger power system failure. The majority of communication equipment is highly susceptible to interference, thus the selection of rectifiers for the BTS system should take into account the equipment's specific requirements.
Four algorithms were employed on data collected from various Base Transceiver Stations from five BTSs location in order to determine the most effective model. Performance metrics, including accuracy, precision, recall, and F1 score, were captured and analysed for each model, specifically for classification tasks.The XGBoost model had the best all round performance with an accuracy rate of 97.58% and a precision of 93.46%, a recall rate of 90.79 and an F1 Score of 93.61%. However all the models performed well by their accuracy was found to XGBoost model 97.58% ,Decision Trees 94.23% respectively, SVM 93.66% and the LSTM model 90.23%.

The recall rate is a metric used to measure the performance of a model in identifying positive outcomes in a dataset. The XGBoost and Decision Tree models performed the best with 93.79% The SVM model 70.49% and LSTM model 54.09%. This means that the XGBoost and Decision Trees models correctly identified 93.79% of all actual BTS power management issues.

The F1 score is a metric that combines precision and recall to provide a single metric for evaluating the performance of a machine learning model. It is defined as the harmonic mean of precision and recall, and is given by:

$$f1 = \frac{2x(Precision\ x\ Recall)}{Precion + Recall}$$

In terms of the F1 score the XGBoost model had the best performance with 92.61%, followed by the Decision Trees model 90.09%, the SVM model 81.90% and the LSTM 68.75%. A high F1 score for the model means that it has a good balance of precision and recall.

CONCLUSION

The study concludes that Bus Bar voltage, working humidity, working temperature, alternate Current (AC) and rectifier working capacity are the major features that contribute to the prediction of BTS power system failure. The model developed indicated that The XGBoost algorithm was the best for predicting the failure of a BTS power system. Thus, utilizing machine learning models significantly improves the ability to predict power system failures in base transceiver stations at ECONET Zimbabwe. Future work may include Handling Imbalanced Data, Model Ensemble, root cause analysis and real time monitoring.

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