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RESEARCH ARTICLE

Predictive Maintenance using Machine Learning with the Support from Smart Sensors and Supply Chain Management using Blockchain

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Abstract

Objectives: The objective of the research is to study the existing predictive maintenance solutions, find more efficient solutions that can help industries improve their efficiency, and study the advantages of decentralized supply chains. The efficiency of predictive maintenance systems can be improved by multiple sensor inputs. Also, a user-defined safe limit value system will improve the efficiency of the predictive maintenance system. **Methods:** Time-series data is used in our machine-learning-based forecasting operations on Google Collaboratory. Long Short-Term Memory (LSTM) and Prophet models are used in our study for time-series forecasting. **Findings:** For the predictive maintenance system, multiple sensor inputs will lead to more efficient results. Instead of predicting a single sensor value, we can take the idea from Google's weather forecast to predict future assets' health by taking multiple inputs. **Novelty:** Predicting maintenance systems lack the feature of a user input for safe or unsafe state. By giving a user input for safe or unsafe state the system will understand the failure. Improvements can be done on predictive maintenance systems by giving multiple sensor inputs.

Keywords: Blockchain; Corrosion; Maintenance; Machine Learning; Predictive maintenance

1 Introduction

Predictive maintenance[1] has made great progress in recent years, due to technical developments and increased data availability. Artificial intelligence (AI) and machine learning (ML) algorithms have played a critical role in effectively predicting equipment failure through the analysis of large amounts of sensor data and historical records. The integration of IoT devices and sensor technology has enabled real-time data collection, allowing for continuous monitoring of asset health and performance. This data, when combined with big data analytics, enables rapid processing and extraction of useful insights, arming maintenance staff with actionable information to improve maintenance plans and avoid costly downtime. One limitation of predictive maintenance systems is that the systems are less accurate to predict failure in advance. The accuracy of the predictive maintenance system can be improved by increasing the input sensor data. Taking single sensor input and predicting value will predict the sensor value only. For example, taking a temperature value of an asset from a sensor will predict the temperature value but one has to analyze the result and have to check whether the predicted value is in a safe range. Limitations of the traditional supply chain are transparency and security. This can be overcome by using a decentralized structure to store supply chain data. By using a decentralized structure, the transparency of the supply chain will improve due to the decentralized structure.

The primary reasons behind sensor-based predictive maintenance systems' inefficiency is that it uses a single sensor input to anticipate sensor value rather than failure.

We proposed to develop a web application that take sensor data as input to predict the possibility of failure of machines. This will be done by:

1. Creating a machine learning time-series forecasting model and putting it in a pickle format to make it simple to deploy as a web app. Collecting multiple sensor data
2. Data collection from several sensors, which will be used as input for the prediction model. Creating a two-column time-series dataset for time and state column
3. Taking human input for each sensor's safe limit, allowing customization depending on unique requirements. In this way, a new time-series data of time and state can be created
4. Creating a two-column time-series dataset comprised of time and machine state
5. When a sensor exceeds the safe limit, the status column is marked as "unsafe" at the corresponding time instances using the Sheets API.
6. This technique creates a new time-series dataset with time and state information that reflects the occurrence of hazardous circumstances.
7. The new dataset can be used to train the machine learning model and forecast whether the system is safe or unsafe.
8. Finally, the trained model can be made available as a web application for easy access and use.

A centralized server outage or technological faults have the ability to disrupt the entire supply chain, resulting in substantial operational and financial losses. In centralized supply chains, dependence on a single authority for information management frequently results in a lack of transparency. Participants are forced to submit their data to the central authority, raising privacy and data ownership concerns. As a result, the centralized nature of these systems creates dangers to the supply chain's smooth operation and data governance.

1.1 Literature review

1. IEEE 2019 Predictive Maintenance 4.0 as next evolution step in industrial maintenance development P. Poór, J. Basl, D. Zenisek talks for possibilities for a "new" kind of maintenance associated with Industry 4.0, namely Predictive Maintenance.
2. IEE 2020 Modeling Time Series Data with Deep Learning: A Review, Analysis, Evaluation and Future Trend. Ang, J.S., Ng, K.W., Chua, F.F. gives a review and discuss the benefits and drawbacks of various models, evaluation strategies, upcoming developments, and approaches for using DL to solve time series problems.
3. IEEE 2022 Blockchain based Supply Chain Management. Nirantar, K., Karmakar, R., Hiremath, P., Chaudhari, D. discuss the contrasts between a non-blockchain supply chain with a supply chain that uses blockchain-based solutions.

2 Methodology

2.1 Dataset

Time-series data is critical in predictive maintenance because it captures temporal patterns and provides useful insights for equipment monitoring and preventive maintenance. It detects early warning indicators and deviations from usual behavior, allowing for prompt maintenance steps to avoid costly breakdowns. Time-series data is used to build predictive models like LSTM and Prophet, which allow for precise predictions of equipment states, failure rates, and remaining useful life. It aids decision-making by giving information for maintenance planning and resource allocation. Continuous time-series data monitoring provides real-time evaluation of equipment health and proactive maintenance measures. Organizations can drive continuous improvement, optimize maintenance practices, and improve equipment reliability while minimizing downtime and costs by analyzing time-series data.

2.2 Machine-learning models

In predictive maintenance, LSTM and Prophet are quite important. LSTM networks are particularly good at collecting complicated temporal connections and long-term memory in time-series data, allowing for accurate predictions and comprehension of equipment behavior. Prophet is an expert at dealing with seasonal patterns and trends, providing significant insights into maintenance requirements. Both methods provide interpretability and flexibility in data management, allowing different formats and facilitating performance evaluation. Using LSTM with Prophet results in better maintenance strategies, preemptive measures, reduced downtime, and increased asset reliability, all of which contribute to cost savings.

3 Results and Discussion

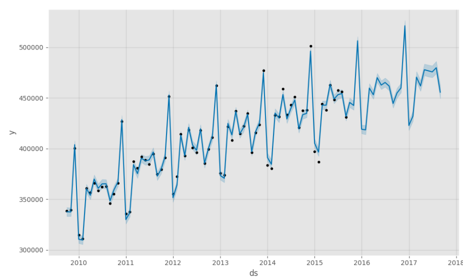

Fig 1. Time-series forecasting using prophet

Table 1. Root mean square value comparison table in a time-series sales data

Model	Root mean square value
Prophet	3319
Prophet (our work)	3319

3.1 Comparison of time-series forecasting on energy consumption time-series data

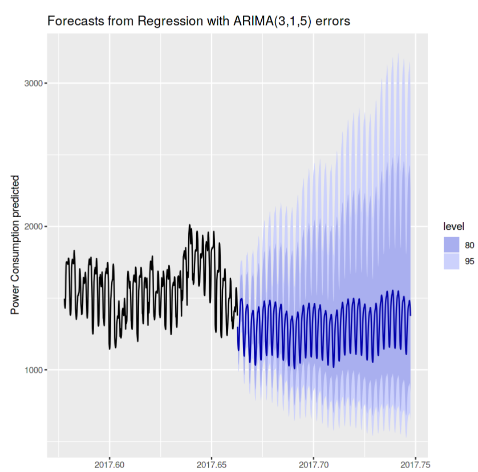

Fig 2. Energy Consumption — Time Series Forecasting in ARIMA

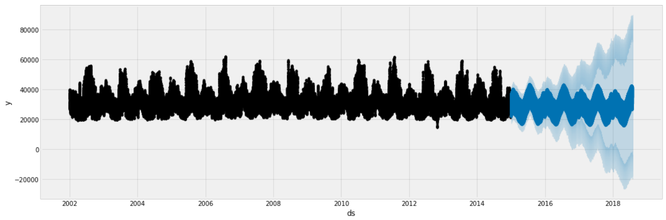

Fig 3. Time-series forecasting with prophet

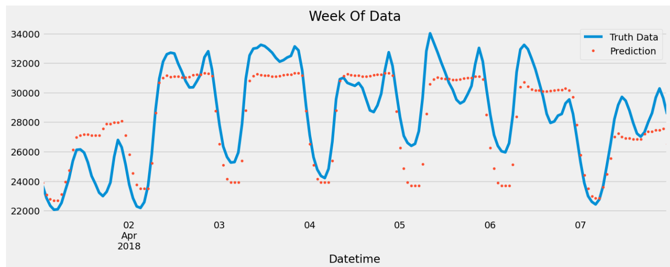

Fig 4. Time-series forecasting using xgboost

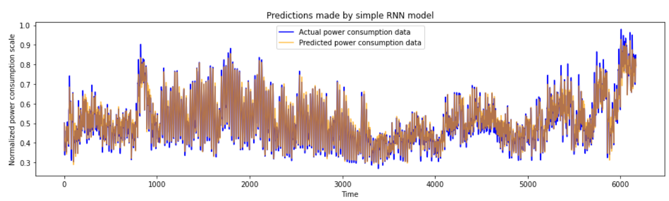

Fig 5. Time-series analysis using RNN

Table 2. Comparison of root mean square value

Model	Root mean square value
ARIMA	162.6
Prophet	43854192
xgboost	3682.3
RNN	0.9489354361425067

4 Conclusion

The results are displayed graphically, with the X-axis representing time and the Y-axis representing the values in time-series forecasting, demonstrating how the values vary as time passes and allowing for the observation of changing trends. These findings provide useful insights for decision-making as well as a clear understanding of asset behavior. The graphs aid in trend analysis, which is critical for making educated decisions, and the anticipated values can be used to construct sophisticated tactics. Furthermore, the predicted values can be compared to the real values and visualized using comparison graphs, emphasizing the disparities between the actual and anticipated values. Time-series forecasting is the cornerstone for many applications, including demand forecasting, sales forecasting, and pricing forecasting.

- **Trends in time-series forecasting**

The long-term direction or pattern noticed in the data over time is referred to as the trend in time series forecasting. It represents the series' underlying growth or decline and can provide useful information for anticipating future values.

- **Corrosion rate calculation for corrosion rate forecasting system**

Four elements influence the corrosion rate in an amine regeneration unit: the concentration of corrosive acid, the temperature, the fluid velocity, and the anion concentration in the heat-stable salt (HSS). Corrosion rate = f (acid gas concentration, temperature, velocity, and HSS anion concentration) can be written as a function of these elements using the equation: corrosion rate = f(acid gas concentration, temperature, velocity, and HSS anion concentration). These variables have a substantial impact on the rate of corrosion within the amine system. This can be used to build a corrosion rate forecasting system [(2)].

- **Pipeline health forecasting in remote areas**

The proposed pipeline health forecast system makes use of the MQTT protocol, sensors, a satellite link, and machine learning techniques. Sensors acquire real-time data on pipeline parameters, which is then transferred via MQTT. The data is processed by the central monitoring system using machine learning algorithms to discover patterns and potential problems. The system generates health projections, warns stakeholders in real-time, and provides visualizations for thorough monitoring. This integrated method offers remote monitoring, proactive maintenance, and informed decision-making for pipeline integrity and reliability. MQTT can be implemented in a low-power mode, allowing it to run for extended periods of time, such as up to ten years, on a single battery. This efficient power consumption allows for long-term connectivity and data transmission in IoT (Internet of Things) devices and applications, reducing the need for frequent battery replacements and improving the overall sustainability and cost-effectiveness of MQTT-based systems.

- **Combination of IoT, and Blockchain in the supply chain**

There are various advantages to combining IoT, machine learning, and blockchain [(3)] in supply chain systems. It increases transparency by documenting transactions on an immutable blockchain, boosts efficiency through real-time data collecting and analysis, and protects data with cryptographic mechanisms [(4)]. These solutions promote supply chain trust and collaboration, enabling product provenance and quality assurance, streamlining auditing and compliance processes, and improving supply chain operations. The convergence of IoT, machine learning, and blockchain advances supply chain management innovation, resilience, and sustainability.

4.1 Advantages of the blockchain-based supply chain

- ***Improved Traceability***: Blockchain creates a transparent and immutable ledger in which every transaction or data exchange is recorded. This allows for complete product tracking across the supply chain. Each link in the network can record and verify goods movement, ensuring authenticity and preventing counterfeit products from entering the supply chain [(5)].
- ***Increased Transparency***: With blockchain, all stakeholders have access to a synchronized and shared record of transactions. This transparency reduces knowledge asymmetry and boosts trust among members. It improves teamwork and accountability by boosting visibility into the movement of products and decreasing delays and disagreements.
- ***Supply Chain Integrity***: The immutability of blockchain maintains the integrity of data recorded on the ledger. It provides a tamper-proof and auditable transaction history, lowering the risk of fraud or unauthorized record changes. This characteristic is especially important in businesses where the provenance and quality of goods are critical, such as food and pharmaceuticals.
- ***Enhanced Security***: Due to its decentralized architecture and cryptographic techniques, blockchain is extremely safe [(6)]. Transactions are encrypted and linked together in a chain on the blockchain, making it extremely impossible for bad actors to alter or manipulate the data. This strong security feature guards against counterfeit goods, unauthorized access, and data breaches.

5 Declaration

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