JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 3522 - 3528
https://publishoa.com
ISSN: 1309-3452

Based on IoT and Fog Computing, A Machine Learning-Based Predictive Maintenance Approach for Optimal Asset Management in Industry 4.0.

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ABSTRACT

Industry 4.0 enables smart production by allowing technical trends like Big Data Analytics and Machine Learning to be integrated into and blended with existing production processes. By putting IoT sensors on physical sources, intelligent manufacturing systems make utilization of Industrial Internet of Things (IIoT) technology to enhance manufacturing activities. Smart industrial plants can communicate information independently thanks to IoT sensors, which can be used to make smarter business decisions. Smart manufacturing processes give businesses a comparative advantage by allowing them to boost profit margins, cut the cost of maintenance, save fuel, and manufacture higher-quality goods.The data generated by the Industrial Internet of Things (IIoT) facilitates information openness and process control in Industry 4.0. Before a part fails and interrupts the entire manufacturing line, proactive maintenance permits the company administrator to make decisions like whether to repair or replace it. As a result, to optimize work allocations and sustain a predictive maintenance system, Industry 4.0 needs good investment management.A study based on the ancillary vehicle industry is provided to demonstrate a predictive model for predicting abrupt breakdown in industrial equipment, allowing for a more efficient manufacturing and maintenance process. Real-time data and two-class logistic regression are used to create the proactive maintenance architecture using the proposed system.

Keywords— Internet of things, predictive maintenance, industry 4.0, technology, energy consumption.

I. INTRODUCTION

The rapid rise of Communication and Information Technology (TICs) has changed today's industrial output into a disruptive new production paradigm, resulting in the 4th Industrial Revolution, often known as Industry 4.0. The phrase "Industry 4.0" was coined in 2011 to improve Germany's production sector [1]. The promise of a new industrial era is reliant on the convergence of numerous distinct technologies, including CPS and the Iot [2]. The incorporation of CC became a crucial problem due to the real-time volume of data that Industry 4.0 will produce, i.e. Big Data, and its multifold advantages. Processes are more efficient, available, and scalable because of cloud technology.[3] As a result, it is possible to integrate not only the internal manufacturing cycle but also other businesses with one another, allowing for horizontal and vertical integration [4]. However, whereas CC provides worldwide centralization, it is not able of addressing all of the requirements of dispersed IoT-based installations [5], especially given the rapid expansion in the number of sensor devices, which may be limited in terms of time and power. Fog computing [6] is a new emerging computing model that aims to extend cloud applications like storage, processing, and networking.

Minimum latency, energy, and location-based services are all enabled in this fashion. Fog computing, on the other hand, does not have to be a replacement for cloud computing. Combining the two technologies, especially for Big Data analytics purposes, could be extremely helpful [7]. It has proved the utility of machine learning algorithms for forecasting and predicting sensor information [8]. By minimizing end device communications, the proposed approach saves energy. Nonetheless, it is critical to use a protocol that is fast and facilitates communication between devices with limited resources. Lightweight network protocols like MQTT [9] and CoAP [10] are growing in interest as a result of the preceding. As a result, the MQTT protocol stack is the subject of this study.

Cloud computing is considered to be a feasible network system in the context of Industry 4.0 [4], [11], and [12]. Several articles have been released that detail the advantages of cloud computing. 3 use case examples where CC is used for industry solutions are described by the authors in [13]. They suggest a CMfg system in [14] and [15], which is a revolutionary concept that merges cloud computing with industrial output and procedures. In contrast, most previous research has not taken advantage of the capabilities of a fog computing-based system. There is currently just a handful of studies that mix fog computing and Industry 4.0.

To achieve better QoS, the suggested scheme in [14] comprises fog devices and edge services within a Smart Factory. A Wireless Computational Network (WCN) is presented as a fog layer for industrial WSNs. (WSNs). The research described above makes use of a fog-based infrastructure. However, to reduce energy consumption, they do not take into account the prediction of observed data.

Many scholars have developed various prediction methods to achieve the aforementioned goal. [15] To this goal, time series methods like ARMA are commonly utilized. Implementing Kalman Filters, as recommended, is a more advanced option.
The proposed strategy includes fog instruments and edge applications within a Smart Factory to improve QoS. In a fog layer for industrial WSNs is proposed as a WCN. . A fog-based infrastructure is used in the studies mentioned above. They do not, nevertheless, take into account the forecast of observational data to minimize energy use. To attain the abovementioned goal, many researchers have devised various prediction algorithms. Time series approaches like ARMA are widely used to achieve this purpose. A more advanced approach is to use Kalman Filters, as suggested.
To our understanding, this is the first paper to propose an Industry 4.0 architecture that incorporates prediction algorithms into a fog computing-based IoT strategy.As a result, we provide a novel framework that combines the advantages of the above technologies while also providing an energy-efficient option for future industries.IoT has found its way into a variety of industries, including healthcare, industrial, oil and gas, and many others. The goal is to predict problems ahead of time to increase equipment uptime. IoT has found its way into a variety of industries, including healthcare, industrial, oil and gas, and many others. The main aim is to detect equipment breakdowns ahead of time, boosting equipment availability. In today's highly dynamic business world, companies aim to improve manufacturing and operational reliability, worker safety, and financial performance. Due to an absence of smart analytical tools and capabilities, many industrial companies have yet to make use of big data and ML analytics.

II. PROPOSED METHOD

This section provides a full overview of the suggested system design for asset management as well as a resource scheduling method for dealing with incoming activities from IIoT sensors.

2.1. System architecture

The suggested asset management system design is shown in Figure 1. According to their capabilities, the architecture is divided into 5 layers: asset, vision, network, fog nodes, and CC.

2.2. Asset layer

It refers to all of the company's resources that have monetary value and are expected to produce value. The core elements necessary for manufacturing and industrial goods are known as main physical assets. Different production and automation machinery that varies depending on the nature of the sector is the fundamental aspects. The parts that enable and maintain the core production process are known as sustaining physical assets. Through the incorporation of IT software, virtual assets enable digitalization in the business and production processes. Humans who are involved directly in the life span of produced items include workers, vendors, consumers, and end customers.

2.3. The layer of the network

Its job is to send real-time data from sensors to linked devices, fog nodes, and computer platforms. Through satellite communications, business owners with multiple manufacturing locations throughout the world can be connected to a worldwide business. Cable, wireless, and Intranet channels could be used to communicate assets internally.

2.4. Perception layer

It is composed of ISS that gather data on the environment and products. ISS and metres in the gadget can detect and send physical parameters for maintenance forecasts. Vision sensors can read QR codes and barcodes that include sensitive asset data including asset kind, region, and purchase date. Face recognition simplifies human resource management by decreasing time theft and allowing employees to create their own access restrictions.

2.5. The layer of computational fog

It establishes a connection between edge computing devices and cloud data centres. Fog computing is a decentralised, distributed computing technique that permits data to be supplied to a server and analysed on the fly.Cloudlets and micro clouds are small data centers that exist on the network's outskirts. The smart switch enables digital facility management to provide a more environmentally friendly and sustainable workplace. The application host, on the other hand, permits the server to run industry-specific software on its own. Several IIoT applications, like data collecting, smart monitoring, and distribution management, are enabled by the router at fog computing levels.

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2.6. The layer of cloud computing

It provides resource utilization, industrial big data analytics, and IIoT operations. Because of the cloud's versatility, industrial big data pre-processing, training, testing, forecast, and model deployment can all be done at this level. The cloud makes it possible to manage and schedule resources by organizational regulations.

2.7. Scheduling: A resource scheduling strategy based on the Genetic Algorithm (GA).

GA is based on state search and simulates Darwin's evolution, a theory in which the best survive in nature. In nature, fitter organisms have a higher chance of surviving and passing on their genes to the next group through reproduction. This enables the younger, fitter generation to better adapt to their surroundings. GA begins with a set of variables, with the population denoted by the number of chromosomes. New solutions are evaluated based on their fitness value (offspring). GA uses three operators to enhance the solutions in each generation: (1) crossover, (2) mutation, and (3) selection.
The selection entails choosing feature matrices from the same generation as the parents, as denoted by the fitness value. A zero cross rate means that no crossover occurred, and the offspring is a carbon copy of the parents. Because crossover does not provide a new feature vector to the progeny, similar solutions may occur in future generations. To generate random modifications, mutations are introduced into the locus.Because of the following properties, GA can handle resource scheduling problems:

1. In comparison to ABC and PSO, GA has better band selection, smaller size categorization, and testing and training accuracies.
2. GA begins with population points rather than with a single point.
3. GA is a well-known method for global search that avoids local optima trapping.

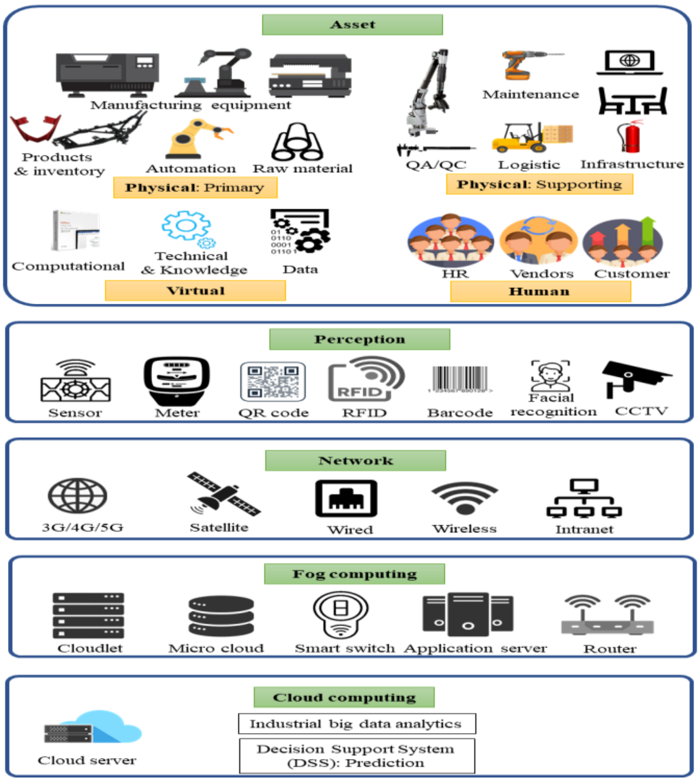

Figure 1 system architecture

2.8. Communication model

We present the proposed communication paradigm in this part, which was created to reduce the energy costs of IoT nodes. As a result, energy consumption can be reduced, partly because data transport consumes more energy than receiving data (Table I). The fog layer can produce a forecasting model that predicts future trends after a training process that involves obtained sensed data (t0, t1, t2,...,tn) from end nodes: allowing detectors to transmit information only when essential.
The predictor broadcasts the estimated data (t3,t4,t5,...,tm) to the associated devices after defining the model. The broker

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continues to execute the model if the gap between the predicted data and the actual data is less than a predetermined value, such as $\hat{t}3 - t3 \leq \gamma$. If the predefined limit is exceeded, on the other hand, the sensor sends the actual measurement to the broker, who then corrects the predictive model. Finally, the design will be more effective if the prediction method is more accurate..

III. SIMULATION RESULTS

The proposed communication model's energy usage is studied and compared to the conventional MQTT method in this section. After that, the results are tailored to real ML techniques.

3.1. Energy consumption analysis

Table I compares the energy usage and effectiveness of 2 wireless protocols: WiFi (IEEE 802.11) [31] and 4G [32]. (Long Term Evolution, LTE)

Table 1 Wireless protocol power usage and performance

Protocol	P_{TX}	P_{RX}	Eff_{TX}	Eff_{RX}
WiFi	396 mW	132 mW	3.6 nJ/bit	1.2 nJ/bit
4G	2.84 W	1.75 W	3.1 μJ/bit	1.9 μJ/bit

The number of bytes required to publish a single MQTT message was calculated using the tcpdump packet sniffer. The cryptographic protocol SSL/TLS was used to conduct the tests, with QoS 0, 1, and 2 enabled. The identical topic and payload were used for all of the messages sent out.Table II shows the results of the experiment.

TABLE 2Messages in the publishing of mqtt (bytes)

QoS	PUB	PUB_{ACK}	PUB_{REC}	PUB_{REL}	PUB_{COMP}	TCP_{ACK}
0	136	-	-	-	-	66
1	138	99	-	-	-	66
2	138	99	99	99	99	66

Figure 2 shows the results for WiFi and 4G technologies. It has been discovered that using a more precise predictor reduces energy use significantly. Because a 4G connection is more expensive in terms of energy, it necessitates higher precision. Furthermore, using higher QoS levels allows for even more energy savings because, because it takes a bigger amount of bytes, the distinction between passing or failing the estimation is more obvious.

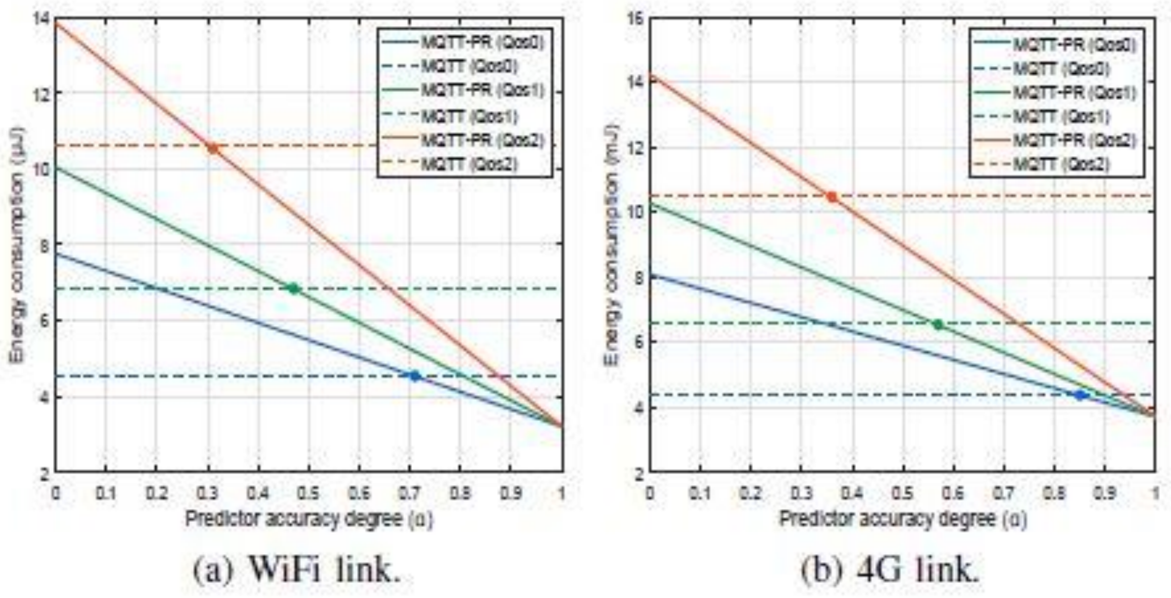

Fig. 2.Comparison of energy usage between MQTT and MQTT-PR for various degrees of accuracy and QoSs.

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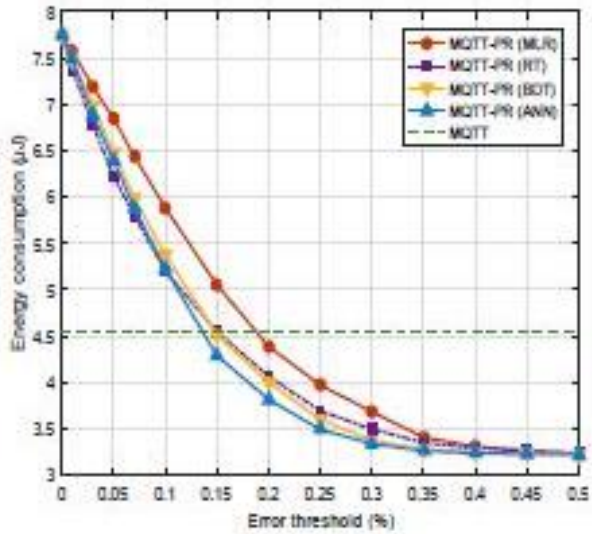
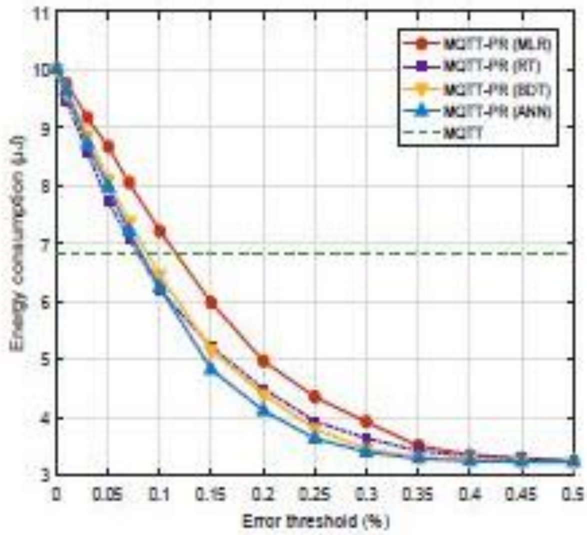
3.2. Simulations based on real data

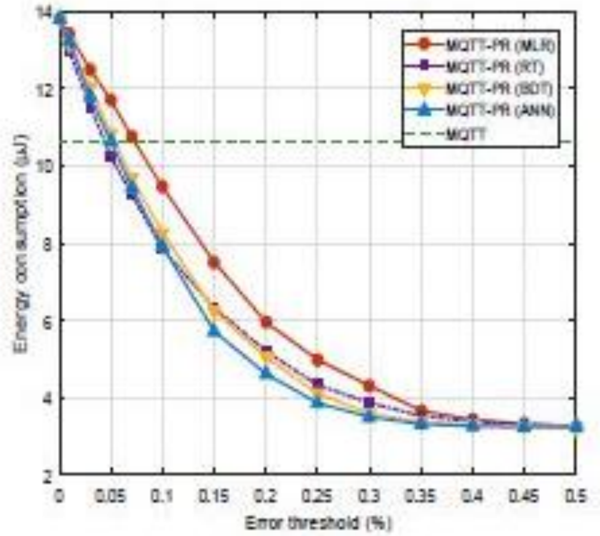
This section looked at four distinct Machine Learning techniques and used them to predict real sensor readings to incorporate genuine prediction approaches into the model. MLR, RT, BDT, and ANN were the approaches chosen. The prediction techniques in this study have been tested on a publicly available dataset that contains observations from an integrated power plant.The models, as in the previous analysis, are based on a comparison of the MQTT protocol's application and the proposed model, both with MQTT's 3 distinct QoS levels. The energy costs are computed for various mistake levels (in this case). Figure 5 depicts the energy use in each situation. Similar to what was seen in Fig. 2, increasing the QoS level improves the model's cost-effectiveness. Except for Linear Regression, which has been proved to be less reliable, the results achieved with various ML methods are similar.



(a) ML algorithms with QoS 0.



(b) ML algorithms with QoS 1.



(c) ML algorithms with QoS 2.

Fig. 3.Using different Machine Learning techniques, compare the energy usage of MQTT with MQTT-PR for various error thresholds and QoSs.

It's worth mentioning that different prediction approaches have varied computational needs. However, because our technique is based on fog computing, it gives the network mobility, so the prediction algorithms can be deployed at either the fog or cloud layer, depending on the accuracy needs.

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3.3. Predictive maintenance accuracy training and testing

To estimate the condition of industrial machinery, equipment proactive maintenance uses two-class logistic regression. With two-class logistic regression, you can get good accuracy while saving time on training. The ROC curve of the testing and training dataset is shown in Figure 4. The AUC of ROC is 0.876 and 0.865, respectively, when the threshold is set to a constant value of 0.5 in both the testing and training data. AUC near 1 indicates a higher level of separability, whereas AUC = 1 indicates that the classifier correctly recognizes all negative and positive classes. The model's testing and training accuracies are 96 percent and 95 percent, respectively. The confusion matrix, as well as their testing and training data metrics, are shown in TABLE 3.

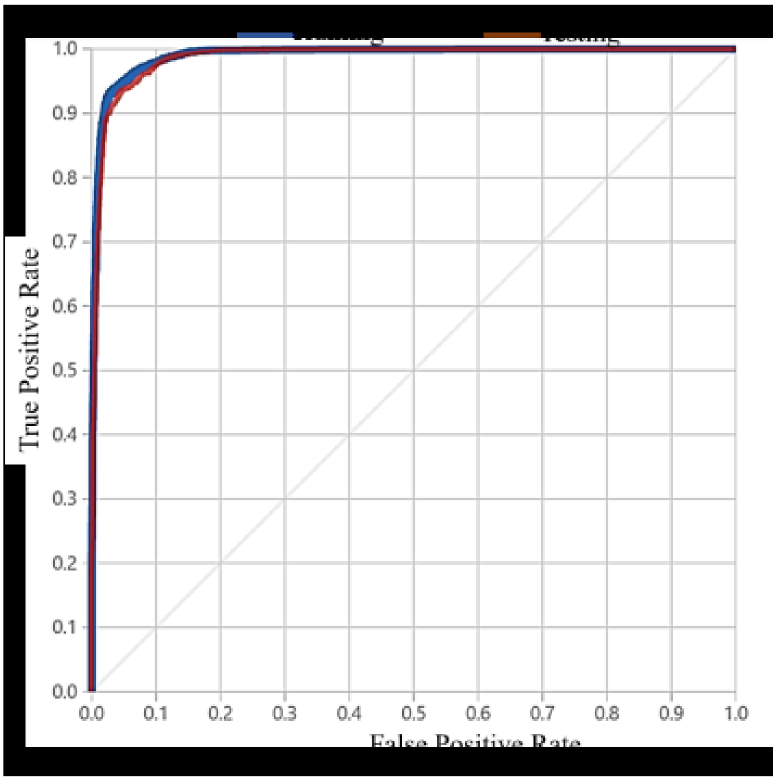

Fig. 4 Training and testing of the two-class logistic regression ROC curve.

TABLE 3Training and testing confusion matrix and measure

Training	TP 4412	FN 274	Accuracy 0.951	Precision 0.952	Threshold 0.5
	FP 223	TN 5228	Recall 0.942	F1 Score 0.947	AUC 0.990
Testing	TP 1844	FN 133	Accuracy 0.945	Precision 0.946	Threshold 0.5
	FP 105	TN 2263	Recall 0.933	F1 Score 0.939	AUC 0.987

IV. CONCLUSIONS

The Genetic Algorithm (GA) was proposed as a method for resource planning in an asset management app for Industry 4.0 in this article. In FogWorkflowsim, GA was compared to MaxMin, MinMin,RoundRobi, and FCFS to demonstrate the usefulness of the suggested technique. The evaluation's performance indicators were implementation time, expense, and power.When compared to the second-best results, the execution time was 0.48 percent faster, the cost was 5.43 percent lower, and the energy use was 28.10 percent lower. Finally, a model for equipment predictive maintenance was created using two-class logistic regression, a supervised machine learning approach.

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He was certified in Microsoft Certified Technology Specialist (MCTS) from Microsoft Corporation, and Certified Ethical Hacker v9 (CEH), and "Paul Harris Fellow" recognition by Rotary International. He is Published more than 10 research papers in various reputed International and national research journals/conferences/ Magazines. He attended 4 national level workshops and participated 3 international workshops; He is also a charted Engineer (Computer Science) from IEI. He is active member of IEEE, ACM, IEI, SHRM, NEN – Bangalore Chapter, HR Sangham – Chennai, CCICI (Cloud Computing), Rotary International Services. He is acting as a reviewer for the High Standard Journals such as Springer, IE, Scopus etc.