IoT and Fog Computing based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 using Machine Learning

Journal:	*IEEE Internet of Things Journal*
Manuscript ID	IoT-14100-2020.R1
Manuscript Type:	Special Issue on Next-generation IoT for FinTech: Trends and Challenges
Date Submitted by the Author:	09-Dec-2020
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Keywords:	Application Platform < Sub-Area 3: Services, Applications, and Other Topics for IoT, Cloud Services < Sub-Area 3: Services, Applications, and Other Topics for IoT, Other Services and Applications Topics < Sub-Area 3: Services, Applications, and Other Topics for IoT, Efficient Communications and Networking < Sub-Area 2: Communications and Networking for IoT

IoT and Fog Computing based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 using Machine Learning

Yyi Kai Teoh, Sukhpal Singh Gill, and Ajith Kumar Parlikad

***Abstract*— The assets in Industry 4.0 are categorised into physical, virtual and human. The innovation and popularisation of ubiquitous computing enhance the usage of smart devices: RFID tags, QR codes, LoRa tags, etc. for assets identification and tracking. The generated data from Industrial Internet of Things (IIoT) eases information visibility and process automation in Industry 4.0. Virtual assets include the data produced from IIoT. One of the applications of the industrial big data is to predict the failure of manufacturing equipment. Predictive maintenance enables the business owner to decide such as repairing or replacing the component before an actual failure which affects the whole production line. Therefore, Industry 4.0 requires an effective asset management to optimise the tasks distributions and predictive maintenance model. This paper presents the Genetic Algorithm (GA) based resource management integrating with machine learning for predictive maintenance in fog computing. The time, cost and energy performance of GA along with MinMin, MaxMin, FCFS, RoundRobin are simulated in the FogWorkflowsim. The predictive maintenance model is built in two-class logistic regression using real-time datasets. The results demonstrate that the proposed technique outperforms MinMin, MaxMin, FCFS, RoundRobin in execution time, cost and energy usage. The execution time is 0.48% faster, 5.43% lower cost and energy usage is 28.10% lower in comparison with second-best results. The training and testing accuracy of the prediction model is 95.1% and 94.5%, respectively.**

***Index Terms*—Fog computing, Industry 4.0, Internet of Things, predictive maintenance, resource management**

I. Introduction

THE exponential growth of new generation computing such as cloud edge computing, Internet of Things, big data, cyber-physical system (CPS) etc., contributes substantially in the manufacturing industry to accomplish a more proficient, competing and smart manufacturing. Smart manufacturing represents as a future-condition of manufacturing, where the ongoing transmission and analysis of data from shop floor produces manufacturing knowledge, which has a positive effect over all parts of activities. The Industrial Internet of Things (IIoT) is an extension of the Internet of Things (IoT) to use in industrial sectors. IIoT mainly gathers the massively interconnected sensors industrial data at the shop floor to produce information, knowledge and control manufacturing system [1]. The utilisation of IIoT incorporates infrastructure, maintenance, process control and supply chain.

GE Intelligent Platform reports that a health care product manufacturer creates 5,000 samples each 33 milliseconds, likeness 4 trillion of samples each year [2]. Manufacturing factory with one hundred machines tools and ten cameras generate 72 TB of data per year [3]. Conventional in-house servers with constraining resources, i.e. storage, memory, processing power are not fit for processing the new challenging due to scalability and computational complexity and shall deploy in cloud datacentre. However, simulation research in [4] concludes that cloud data centre potentially experiences higher latency and network usage due to the vast geographical distance between IIoT devices and cloud data centre. Fog computing as an expansion of cloud computing to the edge of system networking consists of cloud and edge resources that reduces the latency and network congestion. Therefore, latency-sensitive applications can be executed in fog computing.

A distributed system refers to multiple systems that are interlinked while appearing as a single system to the user to enhance resource sharing [5]. Resource management in a distributed system is a fundamental process that involves resource scheduling and allocating resources to applications [6]. Genetic Algorithm (GA) has been generally applied to improve and optimise the resources allocation, and GA is one of the most dependable and promising metaheuristics [7]. GA is part of the evolutionary algorithm, where it is inspired by the evolutionary theory and nature process selection.

The assets in the manufacturing sector include physical asset, human asset, and virtual asset. The reduction of tag cost and infrastructure cost greatly enhance the usage of RFID, 1D barcodes, QR codes, BLE tag, and LoRa tag in assets management. Open Platform Communications United Architecture (OPC UA) is the primary data exchange standard for industrial communication recommended by Reference Architecture Model for Industry 4.0 (RAMI 4.0). OPC UA allows the primary physical assets (manufacturing equipment)

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to communicate with each other or to exchange information with the gateway.

A. *Motivation and our contributions*

Industry 4.0 enhances the productivity of manufacturing technologies through collection and analysis of real-time data. The ease of communication in IIoT enables real-time tracking and identification of assets within businesses originating from IIoT sources and information services. Industrial big data generated from IIoT sensors promotes information visibility. One of the critical applications in manufacturing is to predict the condition of manufacturing equipment. Therefore, there is a requirement of an efficient and effective resource management technique to handle the generated data. To this end, Genetic Algorithm (GA) seems a promising approach as GA is favourable in band selection, smaller size classification, training and testing accuracies compared to existing works.

The ***main contributions*** of this research paper are:

1. Proposed resource scheduling technique: Genetic Algorithm (GA) for assets management in Industry 4.0.
2. Simulated GA with various scheduling techniques, namely MinMin, MaxMin, FCFS and RoundRobin. The performance metrics are time, cost, and energy.
3. Optimised the Decision Support System (DSS) in the production line by implementing predictive maintenance.
4. Presented a detailed case study of manufacturing equipment predictive maintenance using (GA) and two-class logistic regression.
5. Proposed promising future directions for this research paper.

B. *Article organisation*

The rest of the paper is organised as follows. Section II presents the literature review of existing techniques. Section III describes the proposed resource management technique. The experimental setup and case study are presented in Section IV. Section V presents the results of the evaluation. Section VI concludes the paper and further work.

II. RELATED WORKS

Institute of Asset Management (IAM) built up a theoretical model for physical, virtual and human asset management. IAM assembled the six key subjects for assets management, to be specific, (1) strategy and planning, (2) asset management decision making, (3) lifecycle delivery, (4) asset information, (5) organisation and people, (6) risk and reviews [8].

Authors proposed a novel classification for multi-unit systems asset management into the fleet and portfolio according to a variety of assets and intervention options [9]. Fleet referred to as a system of homogeneous assets while portfolio was a system of the heterogeneous asset. The dependencies in multi-unit systems are categorised into performance, stochastic and resource. Then the authors concluded that safety and reliability for multi-unit systems were complex models that involved various criteria from various dimensions.

Service placement policy, namely MinRE introduced with the aims to supply high QoS for IoT devices and to lower energy consumption in fog computing [10]. Authors classified the services into critical and normal. The goal of critical service was to reduce the responding time while normal service to lower energy consumption. MinRE organised the services in ascending order based on the deadline and priority was given based on the classified services. The policy was evaluated through simulation experiment and the results evidenced that MinRE outperformed cloud-only, edge-ward and resource-aware.

Denial of Service (DoS) attack prevention and energy conservation was an essential concern in IoT [11]. Received Signal Strength (RSS) was introduced to prevent DoS and conserved energy. RSS measured the receiving signals power to determine if the attacker on the same network using Teaching-learning-based optimization (TLBO) algorithm. Simulation results suggested that RSS was able to locate attacker within 12cm and the false alarm probability was 0.7%.

Load balancing mechanism depends on Jena architecture and Contract-Net Protocol (CNP) to manage the smart manufacturing equipment at the floor level posited by [12]. Firstly, resources ontology model was introduced to collect and visualise the knowledge for sharing, reusing and reasoning. Jena reasoning inputted the base model from ontology to extract the hidden information and decided the operating mode. CNP received the input from Jena reasoning to distribute the resources through three mechanisms (1) open tender, (2) bidding, (3) winning mode.

Containerisation for resource allocation in the fog computing instead of virtual machine (VM) application proposed by [13]. This was due to the container was more lightweight and had higher efficiency compared to VM. The concept was supported with simulation experiments where the container outperformed the VM. The authors proposed a novel task scheduling algorithm based on threshold evaluation to amplify the jobs in fog nodes and to diminish the jobs delays. However, this research did not take consideration of the fitness of cloud resources and neglected the cloud computation time.

Lightweight architecture system with cloud and edge, namely, SERENA, to implement predictive analytics platform [14]. SERENA collected the sensors data in edge gateway and processed the information in the hybrid cloud. SERENA managed the deployment in Docker service and utilised the load balancing from Docker to distribute the tasks. SERENA enabled the predictive analytic service to examine the condition of manufacturing equipment using three different machine learning algorithms: (1) decision tree, (2) gradient boosted tree, (3) random forest.

A. *Critical analysis*

TABLE 1 shows the comparison of the proposed resource management technique with existing works. All of the current work only considered physical assets without considering virtual and human assets except [8]. Physical, virtual and human assets are equally crucial for the growth of business in Industry 4.0. Predictive maintenance model enables the team to fix the problem before equipment failure. However, only [14] highlights equipment predictive maintenance and resource scheduling in their work. None of the existing literature

TABLE 1 Comparison of proposed resource management technique with existing work.

Work	**Asset**			**Equipment prediction maintenance**	**Fog/ cloud/ Local**	**Performance metrics**			**Method**
	Physical	Virtual	Human			Time	Energy	Cost	
[8] (Backman et al. 2016)	✓	✓	✓		Local				N/A
[10] (Hassan et al. 2015)	✓				Fog	✓	✓		Policy: MinRE
[11] Ghahramani et al. 2020)	✓		✓		N/A				N/A
[12] (Wan et al. 2018)	✓				Cloud		✓		Load balancing based on Jena reasoning and CNP
[13] (Yin et al. 2018)	✓				Fog	✓			Containerisation
[14] (Panicucci et al. 2020)	✓			✓	Fog				Load balancing
This work (proposed)	✓	✓	✓	✓	Fog	✓	✓	✓	GA-based

considered all the three performances metrics: time, energy and cost in their proposed resource management technique for physical, virtual and human assets. Owning to the reasons mentioned above, current literature becomes inefficient when solving real-life Industry 4.0 manufacturing problem where Industry 4.0 links automation, equipment, labour and software altogether and requires fog computing for low latency.

Therefore, it is necessary to build up a resource management technique that comprises of physical, virtual and human assets for Industry 4.0. Time, cost and energy of the resource management technique should be taken into consideration. The industrial big data from IIoT sensors shall be fully utilised in the predictive maintenance application. This paper addresses the challenges of existing resource management technique.

III. PROPOSED TECHNIQUE

This section presents a detailed description of the proposed system architecture for assets management and resource scheduling technique to handle the incoming tasks from IIoT sensors. Especially in this paper, the question is being responded: How to manage the assets in Industry 4.0 effectively using GA and astutely utilise the industrial big data to minimise manufacturing equipment failure through supervised machine learning?

A. System architecture

Fig. 1 presents the proposed system architecture of assets management. The architecture consists of five layers: asset, perception, network, fog computing and cloud computing according to their functionalities.

Asset layer contains all the resources with economic values owned by the business with the expectation to produce value. The assets are identified as primary physical, supporting physical, virtual, and human. Primary physical assets are the central elements that required for manufacturing and the manufactured products. The central elements are different manufacturing equipment and automation equipment that varies according to the nature of the industry. Supporting physical assets are the elements that enable and keep the primary manufacturing process going. Virtual assets enable digitalisation in the business and manufacturing process through the integration of IT software. Humans such as employees, vendors, customers, and end customers are the parties that directly involved in the life cycle of manufactured products. Employees are necessary to conduct manual operation, maintenance, problem-solving that cannot be replaced by automation equipment.

Perception layer consists of industrial smart sensors to gather the environmental and product information. Industrial smart sensors and meters installed in the equipment are able to detect and send physical parameters for prediction maintenance. Vision sensors are able to read the QR code and barcode which contains vulnerable information such as asset type, location, date of purchase etc. about the assets. Facial recognition eases human resource management by reducing time fraud and employees' access control.

Network layer is in charge of transmitting the real-time date from sensors to network devices, fog computing and computing layers. Business owners with multiples manufacturing plants in the whole world can be linked together to a global business through satellite communications. Wired, wireless and intranet connections allow the communication of assets within the business.

Fog computing layer creates communication between edge devices and the cloud datacentre [15]. Fog computing is a distributed decentralised system and allows the data to send to the server to process locally. Fog computing enables real-time assets analytic applications due to the nature of low latency and bandwidth connections compared to the cloud. Cloudlet and micro cloud are small scale data centres situated at the edge of the network. The smart switch allows digital facilities management to create sustainability and greener environment. Meanwhile, the application server allows the server to run industry-specified software individually. The router at fog computing levels enables several IIoT applications such as data acquisition, smart metering and distribution automation.

Cloud computing layer allows resources management, industrial big data, and IIoT tasks processing [15]. Pre-processing, training, testing, prediction and model deployment of industrial big data are performed at this level due to the cloud offer flexibility: pay as you go. Cloud allows resources management and scheduling according to the policies of the business.

B. Scheduling: Genetic Algorithm (GA) based resource scheduling technique

Genetic Algorithm (GA) mimics Darwin's theory of evolution, where the fittest survive in nature and GA works based on state-space search. In nature, the fitter organism has a higher survival rate and able to possess their genes to the next generation through reproduction. This allows the new and fitter generation better to adapt themselves in nature. GA starts with a set of variables, where the number of chromosomes denotes as population. Their fitness value assesses new solutions (offspring). GA utilises three operators: **(1) selection**, **(2)**

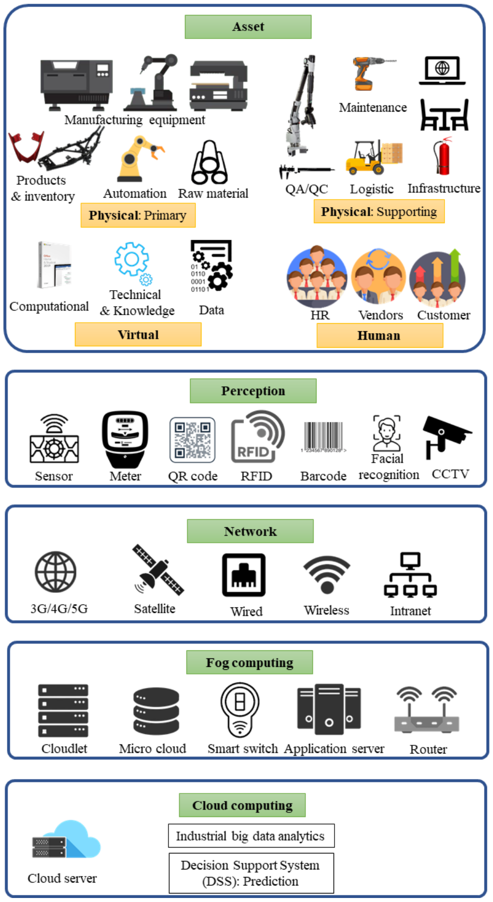


Fig. 1 System architecture.

crossover, **(3) mutation** to improve the solutions in each generation. The **selection** includes picking the parents' feature vectors from the same generation as indicated by the fitness value. Meanwhile, the main objective of **crossover** is to ensure the parents' genes are exchanged, and the offspring inherits the combined genes of parents. Zero cross rate implies no crossover has taken place and the offspring is an exact copy of parents. Crossover alone does not introduce a new feature vector to the offspring and possible to lead to similar solutions in the new generations. **Mutations** are introduced to cause random changes in the locus (positions in the chromosome). The offspring are then being placed in the new generations until the end condition is fulfilled. GA can solve resource scheduling problem due to the following characteristics:

1. GA is favourable in band selection, smaller size classification, training and testing accuracies in contrast to ABC and PSO.
2. GA initialises the search from population points instead of a single point.
3. GA is a direct method for global search and thus avoid trapping in local optima.

TABLE 2 presents the detailed terminology used in this research paper.

IV. PERFORMANCE EVALUATION

To show the practicality of the proposed strategy, this section executes and deploys a case study on the present reality physical asset: manufacturing equipment predictive maintenance on FogWorkflowSim[1] and Microsoft Azure Machine Learning Studio.

TABLE 2 GA terminology.

GA Terminology	Description
Population size	The number of job requests from IIot sensors and devices. Represented by the number of chromosomes in one iteration/ generation.
Number of iterations	The number of generations
Cross rate	The probability of accepting a new feature vector of a job
Mutation rate	The random probability where the elements inside the feature vectors are flipped or changed. Changes caused by errors while copying parents' feature vectors.
Gene	Contained inside the feature vector

Algorithm 1 GA based resource scheduling technique

Begin
Input: utilisation metrics as feature vectors
Output: scheduling decision
generate n population
t=0
while (not terminating condition) do
  begin
    compute fitness function
    t=t+1
    select two parents' feaure vectors
    apply crossover to feature vectors to generate offspring
    apply mutation to offspring
    replace previous population
  end
return best offspring from population
end while
End

A. *Case study: Manufacturing equipment predictive maintenance*

In the manufacturing industry, manufacturing machine such as die casting machine, laser cut machine, plasma cutting machine etc. are the essential equipment to produce goods for customers. However, unforeseen machine failure and components failure can lead to production line stoppage. The domino effects of unplanned production stoppage include delay in delivery, industrial consequences links to processes, and financial losses.

The arrival of Industry 4.0 and industrial big data has created a contemporary opportunity for manufacturing equipment predictive maintenance. Predictive maintenance utilises the IIoT sensors to collect, evaluate and analyse the real-time condition of the manufacturing equipment. The benefits of predictive maintenance include maintaining high Overall Equipment Efficiency (OEE), early warning of anomalies, and awareness of the health condition of the equipment.

This case study runs on a desktop computer with configurations as described below:

- Processor: Intel Core i9-9960X CPU@ 3.10 GHz
- RAM: 64 GB
- System type: Windows 10 64-bit OS

[1] FogWorkflowSim -https://github.com/ISEC-AHU/FogWorkflowSim

B. Datasets

The datasets used in this research paper are available at:
Original (Highly imbalance): https://bit.ly/2VyZY5i
Amended (Under-sampling technique): https://bit.ly/37uVGS9

The datasets used for this case study is created by Fidan Boylu Uz. Due to corporate confidentiality and intellectual property, the data of attributes are represented by general word and numerical number. The dataset contains eleven attributes that identify the condition of manufacturing equipment: **(1)** datetime: recorded date and time, **(2)** machineID: physical assets identification number, **(3)** errorID: the error code, **(4)** volt: electrical voltage in Volt, **(5)** rotate: rotational speed, **(6)** pressure: measured pressure, **(7)** vibration: measured vibration, **(8)** comp: components replaced **(9)** model: type of equipment, **(10)** age: age of the equipment **(11)** failure: 0 or 1. However, the dataset is highly imbalance, where it contains 6,663 samples (2.28%) of class '1' and 285,006 samples (97.72%) of class '0'. The imbalance dataset will result in high accuracy model even without training.

The dataset is then processed with the under-sampling technique to overcome the imbalance issue. Under-sampling technique randomly reduces the majority class to match the number with minority class. Consequently, the total amount of samples has reduced to 14,482, where 6,663 samples of class '1', and 7,819 samples of class '0'.

C. Implementation of the proposed techniques in FogWorkflowSim

In the FogWorkflowSim, the simulation environment considers four end devices (voltage sensors, pressure sensors, vibrational sensors, rotational sensors), five fog nodes (cloudlet, micro cloud, smart switch, application server, smart router) and one cloud server for this case study. The MIPS values and the execution cost of each device are as suggested in [16].

The selection of the parameters, especially cross rate and mutation rate in the GA algorithm are problem dependent. The parameters shown in TABLE 5 are tuned carefully according to previous studies [16]–[19] to optimise the performance matrices such as time, energy and cost. The performance metrics are obtained from equations (1-6) [20], [21]. The population size and number of iterations are fixed to keep the computational time low.

Execution time, t: $t_i^{total} = t_i^{tran} + t_i^{exe} + t_i^{rec} + t_i^{mig}$ (1)

t_i^{tran} denotes transmission time from end devices to fog server, t_i^{exe} represents execution time at fog server, t_i^{rec} is transmission time from fog server to end device and t_i^{mig} refers to task migration time to different fog server because of the motion of the end device.

Cost, C: $C_i^{total} = T_i^{fog} \times C^{fog} + T_i^{cloud} \times C^{cloud}$ (2)

Where T_i^{fog} is workflow task at fog server, T_i^{cloud} is workflow task at cloud server, C^{fog} denotes unit price per second in fog server and C^{cloud} represents a unit price per second in cloud computing.

Energy usage, E: $E_i^{total} = E_i^x + E_i^y + E_i^z$ (3)

$$E_i^x = \frac{Data\ transmission}{Bandwith} \times P_{transmission} \quad (4)$$

$$E_i^y = \frac{Task\ workload}{Task\ processing\ speed} \times P_{idle} \quad (5)$$

$$E_i^z = \frac{Task\ workload}{Task\ processing\ speed} \times P_{end} \quad (6)$$

E_i^x represents transmission energy from end devices to fog server, E_i^y denotes idle energy utilisation of the end devices, E_i^z is the load energy utilisation.

The purpose of scientific workflow is to show the dependencies between tasks and manage the data flow. Montage workflow with 60 jobs is found to be able to optimise the performance matrices.

TABLE 3 Fog environment setting in FogWorkflowSim

Parameters	End Device	Fog Nodes	Cloud Server
Number of devices	4	5	1
Million instructions per **second (MIPS)**	1,000	1,300	1,600
Execution Cost (C$)	0	0.48	0.96

TABLE 4 Genetic Algorithm (GA) setting in FogWorkflowSim

Parameters	Value
Population size	50
Number of iterations	100
Cross rate (%)	85
Mutation rate (%)	1

TABLE 5 Workflow setting in FogWorkflowSim

Parameters	Input
Workflow type	Montage
Total job	60

TABLE 6 Parameters for two-class logistic regression in 70:30 data splitting.

Parameters	Values
Optimisation tolerance	0.000100009
L1 **Regularisation** weight	0.10009
L2 **Regularisation** weight	0.10009
Memory size **(MB)**	11
Quiet	True
Use threads	True
Allow unknown levels	True
Random number seed	12345

TABLE 3 illustrates the configuration settings in the FogWorkflowSim. TABLE 4 shows the GA settings, while TABLE 5 describes the type of workflow and total job.

D. Two-class logistic regression equipment predictive maintenance in Microsoft Azure Machine Learning

The purpose of this case study is to predict the condition of manufacturing equipment using two class logistic regression algorithm, where 0 implies healthy equipment; meanwhile, 1 denotes equipment failure. The dataset is obtained from section IV(B). The attributes that determined the failures are: errorID, volt, rotate, pressure, vibration, comp, age. The dataset is divided into training and testing set in the ratio of 70:30. The training dataset is used for building up the prediction algorithm while testing dataset enabled the model assessment on the real-time data. TABLE 6 describes the best parameters for two-class logistic regression after tuning. For deployment, the maintenance team can predict the equipment condition based on the real-time data input through RESTful API or Microsoft Excel. The complete workflow for this case study is available at https://bit.ly/2I5uP6u.

V. Experimental results

A. Performance of GA in FogWorkflowSim

Fig. 2 compares the (a) execution time, (b) operating cost, (c) energy usage of GA with MinMin, MaxMin, FCFS, RoundRobin scheduling algorithm.

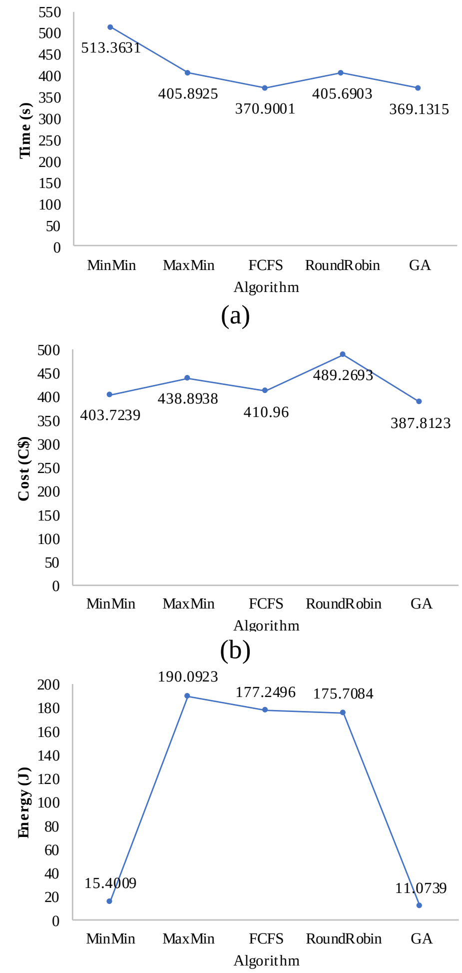
(a) *Execution time:* The execution time of GA is 28.1%, 9.1%, 0.5%, 9% faster compared to MinMin, MaxMin, FCFS, RoundRobin respectively. The execution time of GA is much lower is due to the flexibility of parameters tuning. Crossover is the most important operation and enables the good characteristics of the individual parents to recombine. The algorithm can discover the solution more efficiently throughout the acceleration in each generation and has the lowest execution time among all. Furthermore, the execution time of GA is lower than heuristic algorithm e.g. RoundRobin despite the complexity of GA is due to job scheduler in CloudSim. When the user sends a high number of job requests to the cloudlet simultaneously, CloudSim is not able to execute them and job scheduler places the requests in a queue system. Job scheduler positions and executes the job request from the lowest execution time to the highest and send back to the user. This leads to lower execution times of the GA method.

(b) *Cost:* The cost of GA is 28.1%, 94.2%, 93.8%, 93.7% lower compared to MinMin, MaxMin, FCFS, RoundRobin respectively. GA optimises the distribution of tasks and has a better fitness value. Thus this further reduces the executing cost.

(c) *Energy usage:* The energy usage of GA is 3.9%, 11.6%, 5.6%, 20.7% lesser compared to MinMin, MaxMin, FCFS, RoundRobin respectively. Montage workflow allows label-based clustering, where the same tasks in the workflow can cluster together. Instead of executing individual workload, clustered workload minimises the network traffic and further reduces energy usage. Furthermore, GA strategy tends to club computationally expensive tasks in resource-intensive cloud nodes and simpler tasks in edge devices. This leads to a reduction in energy usage.

B. Training and testing accuracy of predictive maintenance

The equipment predictive maintenance employs two-class logistic regression to predict the health of manufacturing equipment. Two-class logistic regression allows good accuracy with fast training time [22]. Fig. 3 depicts the Receiver Operating Characteristic (ROC) curve of training and testing dataset. Setting the threshold as a constant value of 0.5 in both training and testing dataset, the Area Under Curve (AUC) of ROC is 0.990 and 0.987, respectively. AUC closer to 1 represents a better measure of separability, whist AUC = 1 is where classifier impeccably recognises all positive and negative classes accurately. The training accuracy and testing accuracy of the model is 95.1% and 94.5%, respectively. TABLE 7



(c)

Fig. 2 Evaluation results for MinMin, MaxMin, FCFS, RoundRobin, GA: (a) Time, (b) Cost, (c) Energy

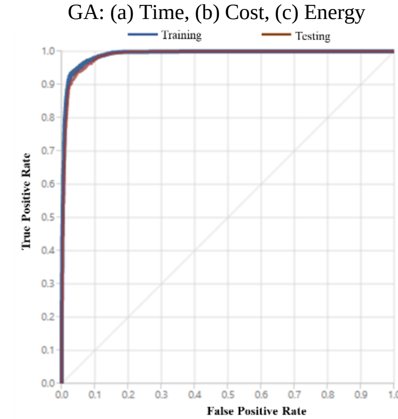


Fig. 3 Training and testing of two-class logistic regression ROC curve.

TABLE 7 Confusion matrix and measure of training and testing.

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

shows the confusion matrix along with their measures of training and testing dataset.

VI. CONCLUSIONS AND FUTURE WORK

This paper proposed the Genetic Algorithm (GA) as the technique for resource management in assets management application for Industry 4.0. Proposed system architecture contains 5 layers, including (1) assets, (2) perception, (3) network, (4) fog computing and cloud (5) computing. GA was evaluated along with MinMin, MaxMin, FCFS and RoundRobin in FogWorkflowsim to show the effectiveness of the proposed technique. The performance metrics for the evaluation were execution time, cost and energy. Extensive simulation experiment evidenced that GA outperformed MinMin, MaxMin, FCFS and RoudRobin in terms of having the lowest execution time, cost and energy. The execution time was 0.48% faster, the cost was 5.43% lower and energy usage was 28.10% lower in comparison to second-best results. Lastly, a model for equipment predictive maintenance had been deployed using a supervised machine learning algorithm, two-class logistic regression. The model was able to predict if the manufacturing equipment failing and produced an early warning alert for the production line. The training accuracy and testing accuracy for the model were 95.1% and 94.5% each.

A. Future work

In spite of the fact that the proposed resource management technique demonstrated efficiency and able to distribute the tasks effectively, it very well may be additionally enhanced in a broader scope followed by the accompanying viewpoints:

1. *Reliability and security communication*: There is a need to ensure up-to-date industrial security communication among the devices to prevent cyberattacks.
2. *Performance metrics*: The performance metrics of the simulation can further include network latency, network bandwidth, jitter.
3. *Extending to varies domains*: Current paper focuses on the manufacturing industry. This can be extended to varies domains of Industry 4.0 such as construction, oil and gas, chemical due to the beneficial of asset usage, quality control, supply chain management, product monitoring, work environment wellbeing.

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Summary of Changes
Revised version of IoT-14100-2020

Dear Prof. Honggang Wang,

We would like to thank the editor, area editor and anonymous reviewers for their valuable comments and suggestions to help and improve our submission. Our summary of changes addresses all comments of esteemed reviewers and have highlighted all changes from the previous manuscript (except for any spelling mistakes or improving sentence grammar) in blue. Hopefully, the revised version is fully acceptable for publication in IEEE IoT Journal.

Please find the attached 'Summary of Changes' which described the revision.

We would be happy to provide any further information and clarification to any items within this submission.

We look forward to hearing from you in the near future.

Best Wishes,
Yyi, Sukhpal and Ajith

Reviewer 1

No.	Comments (C) and Actions (A)
1	C: Dataset and experimental setup: The authors should discuss the origin and collection data collection strategy. The authors should also discuss features in dataset and reasons of choice of these features (mentioned in Section IV B). Moreover, the Microsoft dataset should be cited in the paper giving reasoning on the similarity and differences between the experimental setup used in the paper and that used to generate the dataset. The authors should also give a more exhaustive metric values of each fog node in the testbed. A: Thank you very much for your comment. The origin and collection strategy have been updated. (Please see p.5) Features and reasons of choice: The characteristics and reasons of choice have been provided (Please see p. 5) For the fog nodes, those are the only input values that are required in the FogWorkflowsim. Microsoft data has been cited and provided the differences. (Please see p.5)
2	C: Discussion of results: The authors should also add a brief discussion of results describing the reasons of improved performance and give some analysis of the

	graphs. Furthermore, the authors should mention metrics like energy and cost in abstract instead of prediction accuracy. A: Thank you very much for your comment. Abstract has been updated.
3	C: English: There are minor grammatical inconsistencies and typos in the manuscript. The authors are suggested to carefully proof read their submission. A: Thank you very much for your comment. This updated paper has been proof read to minimize grammatical errors and typos.
4	C: Definitions in table2: the definitions in table are need to reflect the terminology used in computer science. Current ones are misleading. Moreover, the authors should specify the input and output at each scheduling interval for the GA algo. The current representation in Algo 1 is very vague and ambiguous. A: Thank you very much for your comment. Table 2 GA Terminology- The terminologies are updated according to computer science terminologies. Algorithm 1: GA based resource scheduling technique- Input and output at each scheduling interval are specified. (Please see p.4)

Reviewer 2

No.	**Comments (C) and Actions (A)**
1	C: Authors considered GA. Can you please explain why the authors considered GA for PSO/ABC, etc.? A: Thank you very much for your comment. The reason of GA is more favorable than PSO/ABC has been described in detail. (Please see p.4)
2	C: Related work is extensive concerning the other content of the paper, can be reduced, and discusses only related works. Some recent related works can also be added like "Priority, network and energy-aware placement of IoT-based application services in fog-cloud environments" and 'RSS: An energy-efficient approach for securing IoT service protocols against the DoS attack.' A: Thank you very much for your comment. The two suggested papers have been added and recent references have been added. (Please see pp.2-3)
3	C: Table 1 needs to discuss more critically. Please fix it. A: Thank you very much for your comment.

	The discussion for Table 1 has been updated according to the suggestion. (Please see pp.2-3)
4	C: Problem definition can be added at the starting of section 3, which will create some foundation for the rest of the sections. A: Thank you very much for your comment. Problem definition has been defined in section 3. (Please see p.3)
5	C: The authors can add more implementation details, which will help future readers reproduce this work. A: Thank you very much for your comment. Direct URLs to original datasets, amended datasets, FogWorkflowSim github and ML workbook have been added. In FogWorkflowsim github, there is instructions available to run the program in Java and the parameters configurations are exactly similar with Table 3 – 5. Users just need to download github project and run according to table 3-5. For ML part, user can click on the direct link and the workbook with instructions is available. Users can directly run the simulation over there. (Please see pp.4 – 5)
6	C: There could be some future direction of how this proposed model can be used for other domains? A: Thank you very much for your comment. This proposed model is mostly suitable for manufacturing industry (Industry 4.0). However the discussion for other domains have been added accordingly. (please see p.7)

Reviewer 3

No.	Comments (C) and Actions (A)
1	C: Motivation needs some latest references, which will help readers to connect with similar past work. A: Thank you very much for your comment. A three more newer papers have been added to enable readers to connect with similar past works. (Please see pp.2-3)
2	C: In related work, authors are not mentioning name of the authors, for ex: “[19] proposed Operating………”, which could be better if they will write like “LastName et al. [19] proposed Operating………” Or you can write reference number at the end of the line.

	This comment is for every related work discussed in Section 2. I found many papers in Table 1, which are very old like year 2010, 2013. I advise please discuss only latest papers in the related work such as year 2018/19/20. A: Thank you very much for your comment. The reference style has been updated according to IEEE standard, where the number is at the end of line. Very old papers have been removed in order to provide space for three latest papers. (Please see pp. 2-3)
3	C: Fig 3 need more description to understand. A: Thank you very much for your comment. We have added more description on Fig.3 (Please see p.6)
4	C: Please double check the GA terminology given in the Table 2. A: Thank you very much for your comment. Table 2 GA Terminology- The terminologies are updated according to computer science terminologies. (Please see p.4)
5	C: In Tables 3-6, some units are missing, can you please fix it? A: Thank you very much for your comment. Missing units have been added. (Please seep.5)
6	C: Conclusions need to be fully focused on what authors have done in briefly. A: Thank you very much for your comment. Conclusions have been updated and discussed everything briefly. (Please see p.7)
7	C: There are 51 references, which consumes 1.5 pages. I advise, please consider very relevant papers only and use rest of the space to explain other things in the detail. A: Thank you very much for your comment. The number of references has been reduced to 22. (Please see p.7)

Reviewer 4

No.	Comments (C) and Actions (A)
1	C: The terms should be consistent and accurate. For example, in the conclusion, the authors mentioned that GA is a framework, however, GA is a technique. A: Thank you very much for your comment. The terms have been checked carefully and updated accordingly to ensure consistency/ accuracy.

2	C: The discussion of the related work can be improved. The introduction of some related works are not quite relevant to the topic that the authors focused on. More tight connections with the background should be provided. A: Thank you very much for your comment. Related works have been updated and 3 related papers have been newly cited. (Please see p.2)
3	C: I suggest to update the layers of Fig. 1. The layers from the bottom to top can be cloud->Fog->Network->Perceptions->Assets. As Cloud computing is regarded as the infrastructure, generally it is put at the bottom layer. A: Thank you very much for your comment. Fig.1 has been arranged according to the suggestion layer. (Please see p.4)
4	C: In the experiments, how the energy is modelled should be provided. Some equations representing the models should also be provided. A: Thank you very much for your comment. Energy equations have been added according to the comment. (Please see p.5)
5	C: In the related work, one difference compared with existing work is considering the human part, however, in the experiments, the human part is not represented, which undermines the novelty of the proposed work. A: Thank you very much for your comment. The human aspects have been considered in the FogWorkflowSim framework by modelling the dynamic non-stationary goal specifications of "end-users" for adaptive improvement leveraging the GA approach.
6	C: The motivation of using GA algorithm is not quite clear. Without the GA, the prediction approach can still be working. A: Thank you very much for your comment. The motivation of using GA in resource scheduling has been mentioned. (Please see p.4)
7	C: What kind of machine leaning algorithms are used in Azure should be introduced. A: Thank you very much for your comment. The introduction of two-class logistic regression in Microsoft Azure Machine Learning has been added accordingly. (Please see p.5)
8	C: It is strange to see the execution time of GA-based algorithm is less than heuristic algorithms, as the algorithm complexity of GA is much higher than Random or RR algorithms. More analysis should be provided. A: Thank you very much for your comment. We have added further analysis and explanation in section IV. (Please see p.6)

School of Electronic Engineering and Computer Science
Queen Mary University of London, UK

Dear Prof. Honggang Wang,

I am here submitting a revised article titled "IoT and Fog Computing based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 using Machine Learning" "Special Issue on Next-generation IoT for FinTech: Trends and Challenges" for possible publication in IEEE IoT-Journal.

Declaration

We declare that this work has been submitted as an MSc project dissertation in partial fulfillment of the requirements for the award of degree of ***Master of Science*** submitted in ***School of Electronic Engineering and Computer Science*** of Queen Mary University of London, UK is an authentic record of research work carried out by Yyi Kai Teoh (Student ID: 190814258) under the supervision of Dr. Sukhpal Singh Gill and refers other researcher's work which are duly listed in the reference section. This MSc project dissertation has been checked using Turnitin at Queen Mary University of London, UK and submitted dissertation has been stored in repository for university record. Dr. Ajith Kumar Parlikad (Cambridge University) is an expert in this area and has been contributed externally to improve the quality of paper. We followed IEEE Plagiarism Policy strictly.

We can confirm that this paper is currently not under review in any other publication or venue. If you require any additional information or alterations, we would be happy to provide.

I look forward to hearing from you in the near future.

Best wishes

Yyi Kai Teoh
Queen Mary University of London, UK