A Mobile Production Monitoring System Based on Internet of Thing (IoT) and Random Forest Classification

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***Abstract*—Production variations are crucial factors that cause the reduction of production efficiency. These variations are often unpredictable and difficult to be interpreted directly from the production activity of the working station. Automated diagnostic of the causes to variations is therefore the key to overcome the issue. The system should also detect and diagnose variations for all the machines which are placed in the same manufacturing line at the same instance to prevent misaligned of production volume. To achieve this, Internet of thing (IoT) technology is proposed. The technology enables automatic data transfer without the need of human intervention. Through IoT, manufacturers are able to keep track the production activity and resolve problems encountered immediately. In addition, a typical random forest classification model is developed to analyze the production patterns and subsequently identify the causes to the unwanted variations. To the best of authors' knowledge, this paper presents a first-time work on implementation of a mobile production monitoring system based on IoT and random forest classification. The methodology and technical matter to realize the implementation are highlighted and discussed. Overall, the proposed system has been tested accordingly and visualized through a developed mobile application.**

***Index Terms*—Internet of Thing (IoT), Mobile monitoring, production control chart, production monitoring, random forest classification**

I. Introduction

Manufacturing industry is one of the major sectors which constitute the largest profit for the developed countries [1]. Despite being the crucial pillars for world economies, current manufacturing platform lacks connectivity of machines and cloud storage facility [2]. With the absent of machines networking, monitoring of machines can only be conducted manually. In the case of machine failure, prompt handling of the machine is rendered impossible thus creating unwanted idle time and hence loss of efficiency [3]. In this context, a real-time remote monitoring system to observe and provide feedback control to production stations is essential to ensure efficient management of the manufacturing processes.

In the advent of Industry 4.0, modern manufacturing is shifting to this technological advancement for competitive advantages. The fourth industrial revolution lies on digitization of physical devices communicated to the cyber world and is often being related to internet of thing (IoT) [4]. Nowadays, with the increasing amount of data generated throughout the manufacturing processes, manual monitoring and control of manufacturing processes are considered non-ideal. On the other hand, IoT technology allows data acquisition and interface of production analytics to user in real-time. Manufacturers that incorporate IoT aim to improve schedule stability, product quality and efficiency of the production stations. Till date, applications of IoT span from production scheduling [5] to health monitoring [6], monitoring of agricultural product [7], force monitoring of grippers [8] and to applications of intelligent manufacturing.

In recent years, a study on cloud monitoring of machines has been conducted by Zhong *et al*. [9] on IoT basis. Nevertheless the work merely implemented networking to milling machines and to monitor mainly information on vibration. Furthermore, the architecture was also in short of a decision-making function to interpret data within the IoT model. Motivated by this, the objective of this work is to design and implement an IoT based remote monitoring system integrated with decision-making support for feedback control of production stations. Nevertheless, a mobile monitoring platform is essential to feedback information in real-time to manufacturer without the need of manual look up on the production status of the machines. Under this scope, the IoT model is categorized into four processes: data acquisition, data processing, data analysis or computation, and application interface.

Data acquisition: Measurements recorded by sensors are collected as data transmitted to the server. The sensors installed on the manufacturing model include temperature sensor, humidity sensor, transmitter and receiver installed on each machine stations.

Data processing: Through a microcontroller module, the raw data acquitted can be preprocessed to fit into appropriate format for data computing in the later stage. Generally, this stage is responsible for extraction, filtering, and conditioning on the raw measurements collected from the sensors in previous stage.

Manuscript received November 5, 2020; revised December 20, 2020; accepted January 3, 2021.
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doi: 10.18178/ijeetc.10.4.243-250

Data computation: A decision-making model is applied to analyse the processed data. The model employs machine learning or artificial intelligence to simulate and compute the analysis of the manufacturing system. Final process of this stage observes a decision of operation inferred from the computation and the feedback command is updated back to the machine stations through application interface.

Application interface: A mobile monitoring platform can be applied to display the computed data. The interface serves as a remote channel for monitoring and visualization of the manufacturing operation in real-time.

In this paper, an internet of thing based remote monitoring system is presented for visualization of manufacturing status based on activity of machines. The IoT model is implemented by networking physical devices to a server hosted on Raspberry Pi. Overall, the remote monitoring process consists of data acquisition, data processing and data analysis for interpreting the production data. Visual interpretation of the manufacturing operation is interfaced via a mobile monitoring platform. As a summary, the developed monitoring system is able to visualize process control chart, environment condition, and overall equipment effectiveness of the machine in real-time.

The remainder of this paper is structured as follows: Section II outlines the related works. Section III describes the initial implementation of the monitoring system. Section IV evaluates the performance of the prototype and the information processed is being displayed via mobile monitoring platform. Section V draws the conclusions, limitations and future improvements of the work.

II. Related Works

The aim of this research is to develop a mobile visualization system to monitor the manufacturing status based on production activity of machines. The study of monitoring system based on IoT has been conducted by several researchers. In 2015, the monitoring of water quality in IoT environment was studied by Vijayakumar and Ramya [10]. The proposed IoT monitoring platform can be used to measure conductivity, temperature, turbidity and pH of water in real-time. A year later, Grgic *et al.* [11] developed a web based monitoring system to monitor the temperature and moisture level of an agricultural drying process. The methodology allowed real-time tracking and display of the sensing parameter using Message Query Telemetry Transport (MQTT) protocol. During the same year, F. Zhang *et al.* [12] developed IoT based online monitoring platform to determine status of steel casting. The model encompassed data processing, data filtering and data conversion. Often, the process requires integration of wireless sensor network for effective communication between the physical devices and the cloud platform [13]. Besides drying process, IoT technology can be adapted to monitor cultivation of oyster mushroom [7]. In 2018, an IoT based energy monitoring framework was presented by Chen *et al*. [14] for machining workshop. By collecting information from the machine in real-time, the optimum cutting parameters can be adjusted corresponding to the designated efficiency. Similar framework has also been observed in IoT based power monitoring of sewing work [15].

The IoT based remote monitoring system enabled automatic data transfer in real-time and remote troubleshooting of machine in advance. Subsequently, the resources can be well managed and thus the efficiency of production increased. In view of the potential benefit brought by the advancement of IoT, the application of the technology in health monitoring can also be found. In 2018, a wireless electrode system to detect pain expression was integrated into an IoT model by Yang *et al*. [16]. The proposed system was merged with cloud and was able to display the signal to a graphical user interface (GUI) in real-time. In addition to pain expression, IoT based monitoring system can be integrated with data analytics to monitor and diagnose diseases [17], [18].

On top of this, some researchers have demonstrated the application of decision-making feature in IoT platform. In 2018, Boveiri *et al*. [19] developed a probabilistic based decision-making model to compute the task of the variables for task scheduling. An IoT based monitoring system to detect severity in health was proposed by Pathinarupothi *et al*. [20]. Nevertheless, the data on severity were mapped to a particular alert level based on the proposed Critically Measure Index (CMI). S. Park *et al*. [21] applied machine learning to classify casting condition based on quality and parameters of die casting. The machine learning such as support Vector Machine (SVM), K-Nearest Neighbour (K-NN) and Multi-Layer Perception (MLP) have been integrated to IoT to identify diseases [17]. According to the experimental finding, Kaur *et al*. claimed that random forest technique scored the highest accuracy among other machine learning techniques in recognizing dermatology related diseases. Based on the literature review, it can be observed that the application of IoT based monitoring system varied with the algorithm and methods employed. To extract the fullest potential of IoT technology in remote monitoring, proper architecture to address the data transfer scheme is required. The performance of IoT based monitoring system lies on its latency and throughput and as such the IoT framework then become the key restriction for efficient information transfer between the physical devices and the cloud platform [1].

III. Proposed Methodology

The work proposes the development and implementation of a mobile production monitoring platform based on internet of thing technology. In this study, Huawei Nova 2i was used for running the developed mobile application and the proposed system was tested at Automation Laboratory of the affiliated institution. Under the project scope, the prototype should monitor the production status based on activity of machines. For simplicity, physical devices such as laptop and computer (PC1 and PC2) were implemented as data transferring machine for the application. Essential information such as machine run time, quantity of products, and measurements of physical environments are transferred from the devices to the server. The architecture of the proposed system is illustrated in Fig. 1.

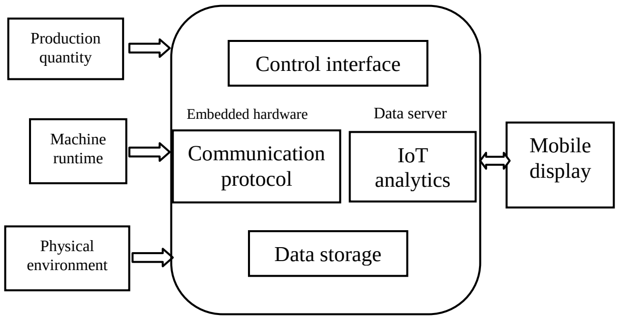

Fig. 1. System architecture of the proposed mobile production monitoring platform.

TABLE I: ENVIRONMENT MEASUREMENT OF THE TESTING SITE

Features	Normal condition		Abnormal condition	
	Mean	STD	Mean	STD
Temperature, (Celcius)	24.6784	0.2209	27.5272	1.4189
Humidity, (%)	81.1525	1.0481	80.2975	1.3040
Air quality index, (PPM)	323.6937	14.8081	399.3327	10.6785

During data acquisition, physical devices treated as manufacturing stations in a particular manufacturing layout are networked to an embedded (Raspberry Pi) server. Information such as production runtime and quantity are transferred from the devices to the server for data interpretation. In this work, Texas Instruments LM 35 temperature sensor, Adafruit LLC DHT22 humidity sensor, and MQ135 air quality sensor are applied for monitoring the conditions of the physical environment. The measurements are sent to the server hosted in Raspberry Pi through a networking development board, WeMos. Table I presents the physical environment measurement of the testing site.

Overall, the data acquisition methodology follows HTTP protocol in which the physical device is required to transfer a coded signal namely HTTP POST request to acknowledge the server for data transfer. Upon successful data transmission, the server then return the HTTP code to the physical device to complete the operation. Should there be any unsuccessful connection to the server or invalid HTTP header, data transfer from the physical devices to server are then repeated. Next, all the data collected are then processed and stored in MySQL database hosted on the Raspberry Pi server. The server can be remotely configured with virtual network computing viewer on a local PC via secure shell (SSH) protocol. The server apply a basic data size filtering function to the data collected before being stored in the database. This prevents processing of outlier data in the database and therefore ensures validity of the measurements recorded.

The production information is then displayed on a mobile application developed with ANDROID STUDIO in real-time. Similar to the data acquisition process, the server transmits HTTP POST header signal to the mobile device to acknowledge the data retrieval operation. However, since the data retrieved are in JSON format, data conversion using JSON parser is required to process the transferred data. Likewise, exception handler will be triggered to re-establish the connection of device and to prompt the system for successful data parsing.

For the analysis part, random forest classification attains much higher accuracy in pattern recognition compared to other techniques as mentioned in previous section. The classification technique allows easier interpretation of the possible factors causing unwanted production variations. In real world production, reasons for the unwanted variations are often difficult to be interpreted and mapped to the production status accordingly. Especially for large scale production, the manufacturing line can be affected by more than one variations. Through random forest classification, 1 or more production characteristic can be set as training factor and freely reorganized in the tree hierarchy. This allows step by step verification of the classification rule in determining the best optimizing route for the production recognition mentioned above. For simplicity, possible variations and the classification rules should be freely trained to optimize the recognition outcome and hence random forest classification was chosen per the advantage mentioned earlier. The acquired data on production quantity were transferred in specific time simulating the actual machine run time from the physical devices to an embedded server incorporating the classification algorithm for later recognition purpose. The production information in this study is obtained from online sources (Kaggle), and among the obtained data, about 5 sets were applied as training sets and 45 sets were applied for experimental or testing of the random forest classification. Experimental design of the random forest classification is discussed in the following section.

IV. RESULT AND DISCUSSION

A. Random Forest Classification

The main focus of data analysis is to identify process variations to maintain and improve the quality of production. Development of this system is essential to feedback possible causes of variations to manufacturers and subsequently allows them to take necessary action promptly. In this work, random forest decision tree was implemented to classify the pattern of production variations. Under this context, the variations of production are mapped to specific sets of production patterns plotted with the quantity of product. This production chart is also called as process control chart or in simpler term, control chart. Therein, corresponding causes of the particular inconsistency can be identified and resolve the matter.

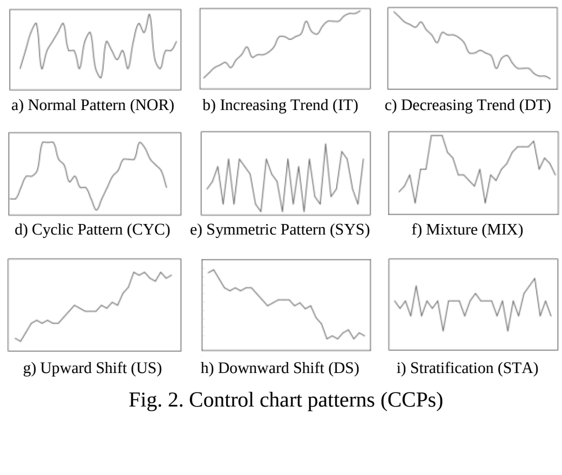

Fig. 2. Control chart patterns (CCPs)

Based on Fig. 2, only the normal pattern is of preference as it indicates consistent performance of production under controlled variations [22]. In this work, the determination of production patterns is worked out through computations of the 7 shape features as follow.

1) Gradient of best-fit line (using least square regression)

$$M = \sum_{i=1}^{N} y_i \left(t_i - \bar{t}\right) \Big/ \sum_{i=1}^{N} (t_i - \bar{t})^2 \quad (1)$$

where M is the gradient of best-fit line, N is the size of observation window, y_i is the collected value from the process at ith time point, t and $\bar{t}$ is the sampling time interval and the mean value of the sampling time interval respectively. A linear relationship is established when a line of best fit is free to map the data point collected. If M >>0, the chart pattern is identified as increasing trend (IT) or upward shift (US) and in contrast M<<0 indicates potential decreasing trend (DT) or downward shift (DS). For the remaining control chart patterns (CCPs), best-fit line with M about 1 are observed.

2) Area between the overall pattern and the best-fit line (ALSPI) per interval of standard deviation

$$\text{ALSPI} = \frac{1}{\text{SD2}} \frac{\text{AUG} + \text{ALS}}{N-1} \quad (2)$$

$$\text{SD2} = \sum_{i=1}^{N} \frac{(y_i - \bar{y})^2}{N-1} \quad (3)$$

where $\bar{y}$ is the mean of the collected values in the observation window. The area under control chart (AUG) and area under best-fit line (ALS) are computed using trapezoid formula. The summation of AUG and ALS is then further divided with standard deviation (SD2) of the data collected. The value of standard deviation defines how the data points spread out from the centerline (mean), thus sliding the value (AUG + ALS) with SD2 helps to discriminate the fluctuation level of control chart. Theoretically, the stratification (STA) chart pattern should result in the highest values of ALSPI as the points are usually lying near to the mean rather in uniform manner compared to the others. On the other hand, the lowest value of ALSPI indicates potential symmetric pattern (SYS).

3) Ratio between variance of control chart and mean sum of square error of best-fit line (RVE)

$$\text{RVE} = \frac{\left[\dfrac{1}{N-1}\displaystyle\sum_{i=1}^{N}(y_i - \bar{y})^2\right]}{\dfrac{1}{N-2}\left[\displaystyle\sum_{i=1}^{N}(y_i - \bar{y})^2 - \dfrac{\left(\sum_{i=1}^{N} y_i \left(t_i - \bar{t}\right)\right)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2}\right]} \quad (4)$$

Variance of a particular control chart is calculated by averaging the squared distance of each point with respect to the mean value. Therefore, further distance will compute a greater variance value and vice versa. Especially for the CCPs of IT, DT, US and DS, the variance values are observed to be larger. In short, trending and shifting pattern should observe RVE value of more than 1, otherwise less than 1.

4) Proportion of sum of crossovers to the mean and best-fit line (PSMLSC)

$$\text{PSMLSC} = \frac{\sum_{i=1}^{N-1}\left(O_i - \bar{O}_i\right)}{2N} \quad (5)$$

Here O_i is 1 if $(y_i - \bar{y})(y_{i+1} - \bar{y}) < 0$, indicating the one of the point is lying above the average mean and another below the line. Similarly, $\bar{O}_i$ is 1 if $(y_i - y_i')(y_{i+1} - y_{i+1}') < 0$ as observed with respect to the values on best-fit line, y', otherwise O_i and $\bar{O}_i$ are zero.

Therefore, symmetric pattern (SYS) in which data points are situated well above and underneath the centerline in interval manner and fall far away from the mean, should observe the highest PSMLSC value. On the other hand, PSMLSC of normal (NOR), STA, IT, DT and mixture (MIX) are intermediate, and cyclic pattern (CYC) should observe the lowest value of PSMLSC.

5) Range of slope of line passing through midpoints of four equal segments on observation window (SRANGE) among six pairwise combinations

In this extraction, the control chart should be observed in four equal sub-windows. This can be achieved by assigning starting values and dividing the observation windows by 4. Then, the midpoints of segment (MPS) are determined for each sub-windows through equation below:

$$\text{MPS} = \left(\sum_{i=k}^{k+(N/4)-1} \frac{t_i}{(N/4)},\ \sum_{i=k}^{k+(N/4)-1} \frac{y_i}{(N/4)}\right) \quad (6)$$

A straight line is assumed to form between every two MPSs based on the following six pairs of possible combinations {j, k} = {1, 2},{1, 3},{1, 4},{2, 3},{2, 4},{3, 4}. The gradients of slopes, s are computed accordingly, and the maximum and minimum values are identified to determine the range of slope (SRANGE).

$$\text{SRANGE} = \max\left(s_{jk}\right) - \min\left(s_{jk}\right) \quad (7)$$

This shape feature can effectively determine trending and shifting patterns for low index of SRANGE. In contrast, for pattern containing fluctuation at low resolution, especially for CYC, highest value of SRANGE is observed.

6) Ratio of mean sum squares of error of best-fit line and average mean sum squares of error in window segments (REAE)

$$\text{REAE} = \frac{\text{MSE}_t}{\sum_{j,k}\left(\text{MSE}_{j,k}\right)\big/6} \quad (8)$$

Similar to the case of finding SRANGE, the control chart is divided into four equal sub-windows. The mean sum squares of error (MSE) for all the divided sub-windows are then computed and averaged. Next, a ratio between overall mean square error (MSE_t) and average

MSE is determined. Among the CCPs, trending patterns should observe REAE value of more than 1, while the MIX should observe the lowest value. The uncertainty in the pattern such as asymmetry fluctuations, trending and shifting accounts much higher MSE errors found particularly in every segment respect to the best-fit line.

The random forest classification differentiates the pattern of control chart in accordance to the computed parameters above. The categorization is performed for few instances and the instance which the control chart is categorized to will be further classified till the production is recognized. This recognition scheme was originally proposed by D. T. Pham and M. A. Wani [23] and has been actively applied for CCPs recognition [22], [24], [25] ever since. To establish the classification system, the priority of evaluation rules is significant and directly affecting the accuracy of the random forest classification. Therefore, to determine the evaluation sequences, the values of every shape features are extracted and further normalized with the local maxima (indexed higher than 80%) as highlighted (bordered) in Table II below. The higher the computed indexing number, the higher the possibility the pattern of control chart is matched. This local maxima is used as starting reference in the following evaluation sequences. In contrast, the local minimum is highlighted (shaded) and acts as supplementary factors.

TABLE II: NORMALIZED VALUES OF SHAPES FEATURES AMONG THE CCPS

Index (%)	*M*	ALSPI	RVE	PSMLSC	SRANGE	REAE
NOR	18.04	25.93	56.86	58.62	11.87	57.59
STA	6.82	100.00	56.18	58.62	10.05	20.45
SYS	34.15	4.76	56.34	100.00	55.71	18.79
IT	95.49	16.71	100.00	41.38	19.63	98.48
DT	-47.43	20.91	65.73	56.89	9.82	100.00
US	100.00	10.98	83.10	46.55	100.00	26.79
DS	-86.17	11.74	78.10	53.45	63.47	56.57
CYC	-3.58	9.73	55.38	37.93	12.78	0.90
MIX	10.54	5.01	55.46	46.55	51.71	2.10

Based on the observation, shape features of ALSPI and PSMLSC are stand-out characteristics compared to the others, and considered as primary features. ALSPI can effectively discriminate STA pattern with confident level of about 74.07%, while PSMLSC can identify SYS pattern with confident level of 41.38%. The secondary feature for the control chart is RVE. RVE index is meaningful to differentiate the trending and shifting pattern (IT, DT, US and DS) from the rest, with confident level of 8.87%.

The tertiary-level features are SRANGE and *M*. SRANGE is helpful in further discrimination between trending and shifting pattern, with confident level of 43.84% at the decision boundary. However, it can be observed that the shape feature of REAE has the similar ability to perform differentiation between shifts and trends, but with slightly lower confident level of 42.21%. Meanwhile, *M* index can determine the growth direction of the chart dependent to the sign of the computed value (positive value indicates IT and US; negative value indicates DT and DS).

Apart from that, it is noticeable that CYC pattern yields the lowest value among the four particular shape features, which are *M*, RVE, PSMLSC and REAE. Therefore, when the four mentioned shape features are applied as evaluation rules, the computation of CYC should be sequenced at bottom-most of the categorization tree.

Lastly, the NOR and MIX pattern can be differentiated by three shape features, which are ALSPI, SRANGE and REAE. As a comparison, NOR has relatively higher ALSPI and REAE index, in which the confident levels is of 20.92% and 55.49% respectively. Nevertheless, MIX has higher SRANGE value and the confident level is 39.84%.

It is found that the identification of types of control chart pattern can be achieved with decision tree which consists of at least 6 levels of evaluation rules, and throughout the sequences, some of the parameters (shape features) are involved in multiple evaluation processes, in order to classify all the nine control chart patterns. Nevertheless, the initial decision tree was implemented with 8 nodes albeit having accuracy at about 74%. From experimental try-out, the number of decision nodes in the random forest should be increased for improved accuracy and in optimum to avoid sacrificing the computation time.

Throughout the evaluation process, the accuracy of the decision tree shown in Fig. 3 has observed about 16% higher accuracy compared to the initial design. All of the control chart patterns have been successfully classified by the random forest besides NOR, IT and DT due to the lack of dataset on the particular patterns. Based on the outcome, the derived random forest is chosen to implement pattern recognition of control charts. In reference to the control chart patterns, possible causes of the production variations can be induced accordingly [26]. This could help manufacturers to effectively track the causes of variations and subsequently maintain the production status of the manufacturing stations promptly. Table III tabulates the possible causes of production variations with respect to the CCPs.

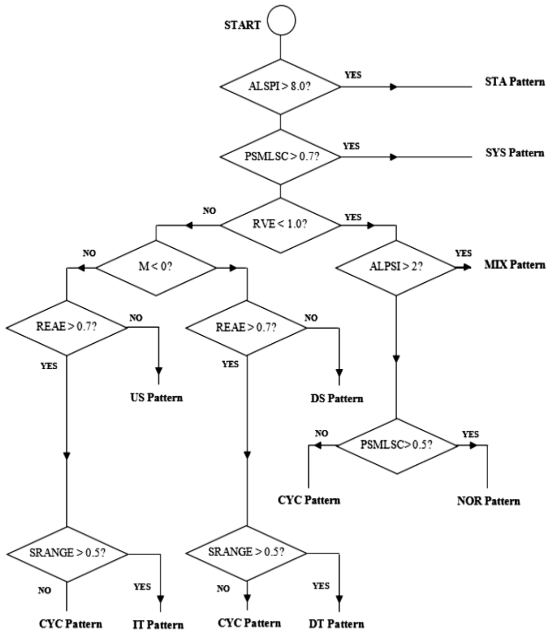

Fig. 3. Decision tree for recognizing the pattern of control chart

TABLE III: POSSIBLE CAUSES MAPPED TO THE PATTERNS OF CONTROL CHART

Control chart patterns	Possible causes of variations
Shifts	• Change of shift workers • Incorrect assembly or setup • Measurement error • Procedure not completed • Electricity failure • Station breakdown • Low or defective material quality • Maintenance not completed
Trends	• Wearing of tools or moving parts • Fracture caused by continuous heating and cooling effects • Broken hardware or lack of maintenance
Mixtures	• Mixture of errors or possible causes.
Stratifications	• Combination of certain groups or all possible causes or errors.
Cyclic and Symmetry	• Interchanging raw materials • Configuration errors • Incorrect or hampered hardware settings

With the extracted production quantity, a subsidiary artificial neural network (ANN) can be implemented to predict the passing rate of the products fabricated. The input data are activated through sigmoid function with randomized weightage matrices upon training. Then the data are fed into a hidden layer of 100 nodes and back propagated till a satisfactory value of accuracy is achieved. In accordance to the experimental finding, the optimum training cycle to reach the highest accuracy is found at around the 2000th iteration. After executing the ANN, it was found that deep learning may not be suitable to be implemented on mobile monitoring due to the additional latency incurred from the long iterations being executed. Furthermore, since the output node only designed to predict one outcome, the use of multiple hidden layer with large number of neural nodes for prediction may not necessarily be required. It may be needed to shrink the size of the ANN in the future to avoid excessive network charges and overloading the data transfer rate of the remote visualization system. Whereas random forest classification predicts the patterns of control chart by feeding the data to series of classification rules, optimum training cycle does not apply to random forest compared to ANN.

B. *Mobile Visualization*

In this section, experimental results in mobile visualization of production activity are presented. The mobile application was developed using Android Studio to present the production data in real-time. The Wi-Fi for networking was implemented with the mobile network service provided by local internet service provider (ISP). The developed system has been tested and the visualization of the monitoring system is shown in Fig. 4 and Fig. 5. The respective overall equipment effectiveness (OEE) can then be calculated using the expression below:

$$\mathrm{OEE}(\%) = \mathrm{Availability} \times \mathrm{Utilization} \times \mathrm{Efficiency} \quad (9)$$

Fig. 4. Mobile production monitoring system; environment and production monitoring (Left) and OEE performance page (Right).

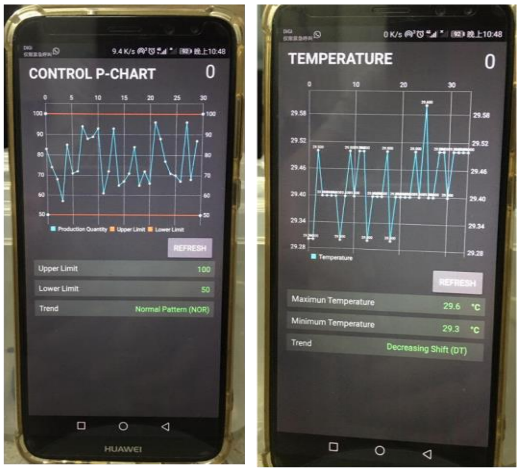

Fig. 5. Mobile production monitoring system; process control chart page (Left) and physical environment display page (Right).

Availability is the actual time that the machine is occupied for production, or in another word, the run time of machine in fabricating products exclusive of downtime:

$$\mathrm{Availability} = \frac{\text{Run time}}{\text{Planned production time}} = \frac{\text{Planned production time} - \text{Stop time}}{\text{Planned production time}} \quad (10)$$

Utilization measures the usage of the machine in the production:

$$\mathrm{Utilisation} = \frac{\text{Net run time}}{\text{Run time}} = \frac{\text{Ideal cycle time} \times \text{Total production}}{\text{Run time}} \quad (11)$$

Efficiency indicates the yield rate achieved by the machine in fabricating defect-free products:

$$\mathrm{Efficiency} = \frac{\text{Pass proudction}}{\text{Total production}} = \frac{\text{Total production} - \text{Fail production}}{\text{Total production}} \quad (12)$$

By merging (9) to (12), the OEE expression can be simplified to the expression below:

$$\mathrm{OEE}(\%) = \frac{\text{Ideal cycle time} \times \text{Pass proudction}}{\text{Planned production time}} \tag{13}$$

Time latency for uploading data to the server and downloading the data to mobile device is studied to evaluate the performance of the developed system. In this work, the latency is measured as a round-trip time (RTT) in which the time taken for a data packet transferred to a target destination till the acknowledgement of the data received and the transfer is successfully performed. The latency measurement for the data processing should be recorded at the instance a return code from the destination has been received. The work flow of the upload (data acquisition) and download (application interface) operation has been mentioned in the system implementation section.

Based on Fig. 6, the network delay for WeMos increases as the data size transferred increases. It takes approximately 1.4s for the sensor to transfer 1000 bytes of data to the server. However, for the case of PC1 and PC2, the latency only increases slightly with the increased of data size transferred. The difference of latency is due to the larger number of sensors WeMos is interfaced to, as the sensors were interfaced in serial to WeMos, it takes considerable more time to communicate all the sensors to WeMos and then to the server. On the other hand, based on Fig. 7, the retrieval of data to mobile device recorded slightly higher latency at about 1.7s for the 1000 bytes transferred. Similarly, the latency for transferring content to mobile device increases with the data size.

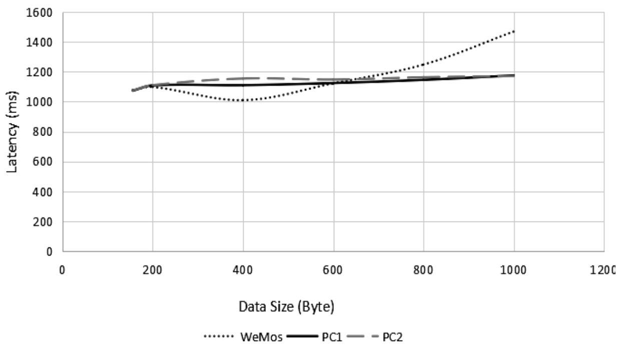

Fig. 6. Latency graph on data acquisition from physical devices to the server.

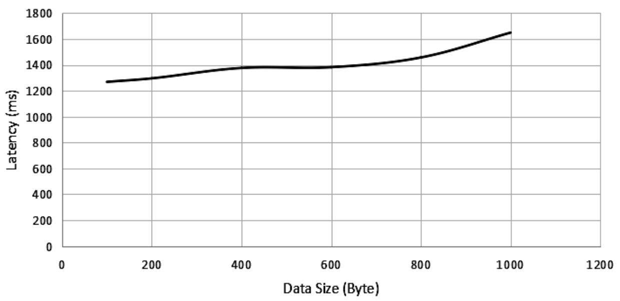

Fig. 7. Latency graph on data retrieval from server to mobile device.

The above work presents the development of an interactive mobile based production visualization system. There are two important contributions; 1) IoT enabled real-time production visualization, 2) the development of random forest classification for smart production feedback. This work serves as an importation reference in merging the proposed IoT system with random forest classification for production analytics. The functionality of the implemented system are tested and discussed. Despite that, the work at this stage are experimented on simple networking interface covering only few devices, in order to standardize the use of IoT and machine learning in the manufacturing industry, a larger scale of sensor networking is anticipated for its future development. The proposed system will help to improve production efficiency and provide instant feedback to cope the production variations. In addition, the proposed strategy could help to promote work safety and quality of life of the employee meanwhile offering an autonomous remote feedback system to guarantee production quality to the employer. Overall, the proposed system is fully automated and applicable for practical use.

V. Conclusion

The work presented in this paper proposes a production monitoring system based on IoT and a developed classification system. The proposed system will help improve the productivity and efficiency of manufacturing stations. An implementation of the mobile monitoring platform has been made and experimental testing of the system developed has been conducted. Overall, accuracy of 86% have been achieved in data analysis using random forest classification. It is expected that the accuracy can be improved with the approach of feeding more datasets for training. In the future, the work can be expanded to include various features such as failure diagnostic and data mining. Development of digital twin for advanced monitoring and data analytics is also part of the research interest.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Qiu Yu Wong carried out the implementation and experimental validation of the work and edited the paper. Yih Bing Chu designed the experiment, conducted the research and wrote the paper.

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