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A big data approach for worker's performance evaluation in IoT-enabled manufacturing shopfloors

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Abstract

Internet of things (IoT) and Radio Frequency Identification (RFID) technologies are gradually adopted in manufacturing recently. With the aid of them, numerous data is generated from daily manufacturing operations. Big data analytics is used in locating deficiencies and thus improving the productivity of a manufacturing shopfloor. Many studies have also examined the effect of "Blue Monday" and "post-lunch slump" on worker's performance. This paper provides a big data approach on analyzing worker's performance with the data collected from a manufacturing shopfloor. By evaluating the worker's performance at different time periods, a better decision can be arranged for improving overall productivity.

Keywords: IoT-enabled manufacturing; Big data analytics; Performance evaluation

1. Introduction

Internet of things (IoT) and Radio Frequency Identification (RFID) technologies have been increasingly used in manufacturing shop floors in recent years. [1] demonstrated a typical IoT-enabled manufacturing shopfloor, where all the elements involved in manufacturing are connected through IoT technologies. Smart objects are created with RFID tags and their conditions will be updated to the cloud with RFID readers instantaneously. Worker's production scheduling and planning are arranged according to the data in the cloud enhance the overall manufacturing process.

Regarding on IoT-related technologies, Chen and Tsai [2] compared the definitions of Ubiquitous Computing (UC), Ubiquitous Manufacturing and Cloud Manufacturing (CMfg). IoT-related technologies were firstly initiated with the concept of UC introduced by Weiser [3], demonstrating computing should be performed regardless of location. Putnik [4], considered UM as an extension of UC. Huang et al. [5] and Zhang et al. [6] provided a detailed explanation on UM. They consider UM system as an RFID-enabled wireless sensor network in collecting and processing real-time data in manufacturing processes. CMfg is described in Lei et al. [7], demonstrated a cloud sharing platform for managing all manufacturing activities.

RFID is known according to the definition from Want [8]. A RFID tag consists of an antenna and a small chip, which enables identification within a certain distance. RFID technologies were first applied for product tracking and quality management on Ford manufacturing line [9]. Furthermore, there are more studies regarding the applications of RFID technologies in different manufacturing processes [10-13].

In a typical daily operation of an IoT-enabled manufacturing shopfloor, RFID tags and readers are widely used and thus numerous manufacturing data (worker, material, machine, etc.) are created and stored in the cloud or local database. With such a large amount of data generated, which is often called as big data. According to the definition from Jacobs [14], the word "big data" refers to large and complex data sets, which they are difficult to process with the traditional methods. It is discovered

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that useful information could be extracted by evaluating trends, patterns from the manufacturing data [16]. As a result, decision-makers can evaluate and manage the operation and make adjustments to the operational processes respectively, to achieve a more efficient and productive manufacturing process.

"Blue Monday" phenomenon described by Stone et al. [17] that people often have a bad feeling on Monday, which indicates that people's performance will be lower than usual on Monday. "Post-lunch slump", which is also called as "Post-lunch dip" is another effect described in Bes et al. [18], explains that people will easily fall in nap after the lunch.

The above phenomenon demonstrated the fact that workers' performance varies differently at different time periods in a typical daily operation. In this paper, there are two objectives: 1) A comparison of working performance at different time scales and 2) Examine the effect of "Blue Monday" and "Post-lunch slump" with data taken from a real-world factory. The objectives are achieved by evaluating the worker's performance in an RFID-enabled smart manufacturing shopfloor.

This paper is organized as follows. Section 2 reviews the literature related to worker's performance in a different time period (such as "Blue Monday" and "Post-lunch slump") and literature about modern applications of big data analytics in IoT-enabled manufacturing. Section 3 introduces some basic information about the data set. and proposes the methodology adopted when analyzing the dataset. Section 4 reports the results and discussion. Finally, a summary of this paper is given in Section 5.

2. Literature review

2.1. Worker's performance under different time periods

For studies on 'post-lunch dip', Bes et al. [18] discovered that the 'post-lunch dip' is a bi-circadian phenomenon. Monk [20] shows that the 'post-lunch dip' is independent of the lunch. Reyner et al. [19] investigated on the effect in the meal size on driving and discovered that the driver's performance is affected more significantly after heavy meal if those drivers did not have a sufficient sleep last night. This research conducted the experiment for 12 male drivers using the car simulator to examine the effect of meal size on 'post-lunch dip'.

Apart from 'post-lunch dip', there are also studies on a similar phenomenon, which is known as 'postprandial sleepiness'. Orr et al. [21] investigated the relationship between the composition of meals and how they affect 'postprandial sleepiness'. A similar study conducted by Wells et al. [22], investigated how fat and carbohydrate affect postprandial sleepiness, mood, and hormones.

Stone et al. [17] have conducted a study on day-of-week mood pattern with a large-scale survey using telephone. It shows that Blue Monday effect was discovered when Friday is included in a working week. If Friday is not a working day in a week, it is stated that there is no difference in worker's mood between Monday and other weekdays (Tuesday, Wednesday, and Thursday).

The above literature studies the phenomena of 'post-lunch dip', 'postprandial sleepiness' and 'Blue Monday'. The majority of reports are conducted to study how these phenomena change with external factors (e.g. insufficient sleeping) instead of how these phenomena affect the working performance. Some of the studies have a small sample size (around 10-20) and some of them conduct with collect data with questionnaires and perhaps there may be bias due to subjective opinion. This paper will examine those phenomena by big data analytics with data collected by RFID readers.

2.2. Applications of big data analytics in manufacturing.

There are also several pieces of literature demonstrated how big data analytics is used in evaluating datasets. Zhong et al. [23] investigated big data cleansing approach in a multi-dimensional RFID-enabled manufacturing data, which the manufacturing data is represented in the form of RFID-Cuboids. The algorithm detects the cuboids, then removes, inserts, and deletes appropriate data to prepare for further data analysis. [15] also proposed a big data approach in mining the trajectory information from RFID-enabled logistic data, which adopted the RFID-Cuboids cleansing algorithm to extract useful trajectory knowledge from the dataset [23].

[16] perform big data analytics on the Physical Internet (PI)-enabled manufacturing shop floors, which data was then collected under an intelligent environment using RFID technologies. By performing the big data analytics approach, it is believed that the system could be more efficient in logistic scheduling and planning. Another similar study conducted by [24], adopted the big data analytics in evaluating the working processing time of an RFID-enabled manufacturing shop floors. [25] presented a cloud-based adaptive shop-floor scheduling given the available machine tool so as to improve the whole production system.

3. Proposed Methodology

The proposed methodology is presented in Fig. 1 which shows the flowchart of the major procedures. Details will be included in this section.

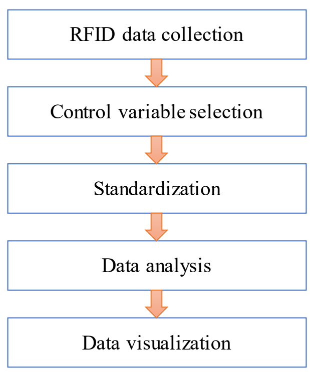

Fig. 1. Proposed Methodology

3.1. Dataset for the research

The dataset used in this paper is collected from RFID tags and readers with 3-months duration, which contains 9 types of the data as shown below:

- ID: An ID generated automatically in the SQL database
- BatchMainID: The ID of a batch of product
- UserID: The ID of a specific worker
- ProcCode: Code of a typical processing (e.g. milling, drilling etc.)
- ProcSeqnum: A number which indicates the sequence of processing
- Quantity: Total number of pieces in a batch
- Good Number: Number of quantities which passes the inspection within a batch
- Time: Time stamp which records the finish time of a processing batch
- Location: An ID number which represents a specific machine

In order to measure the performance of the workers in different time scale, the data are sorted in daily, weekly, and monthly basis. The passing rate after quality check (QC) can be found out by the ratio of quantity and good number.

Besides, some terminologies are defined as follows:

- Good rate: Good Number divided by Quantity within a batch.
- Fail case: Any batch has a good rate below 1.
- Good case: Any batch has a good rate of 1.
- Fail rate: Fail cases divided by total quantity within a certain time period.

Some basic statistics of the Dataset are:

- Total number of complete set of data: 364558
- Total number of Fail cases: 11284

3.2. Big Data approach for evaluation of the workers' performance

To evaluate the performance of workers, the fail rate of workers is analyzed on a daily, weekly, and monthly bases. There are 7 steps when performing data analysis in this paper:

1) Determine the control variable, which is the total number of on-going processes at the same time (daily, weekly, and monthly).
2) For standardization, the rate of change of quantities is calculated by the following formula:

$$Rate\ of\ change\ of\ quantity = \frac{x_2 - x_1}{x_1} \quad (1)$$

where x_2 and x_1 are the quantities in current and previous time, respectively. By calculating the rate of change of quantities, quantities are standardized, and comparison is made between data at a different time (daily, weekly, and monthly) scale.

3) Three sets of quantities and their rate of change is found.
4) The data are grouped by fail and good cases.
5) The data are further grouped at different time scales.
6) The number of fail and good cases are counted and compared at different time scale.
7) Graphs are generated based on the grouped datasets.

To facilitate the calculation, it is assumed that all the workers have the same skill level, same working hours, workload, and the same processing difficulty for all kinds of work.

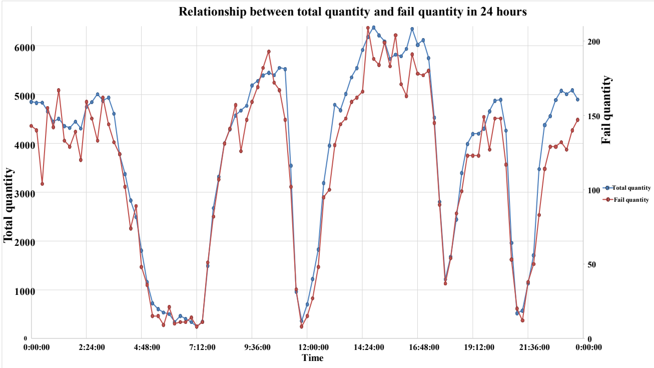

Fig. 2. Relationship between total and fail quantities in 24 hours

4. Results and Discussions

For the data grouped in daily basis from Fig. 2, it is discovered that the peaks appear at around 0:00, 10:00, 15:00, 20:00 and their troughs appear at around 07:00, 12:00, 18:00 and 21:30. It is believed that the trough is the meal and the break time of workers.

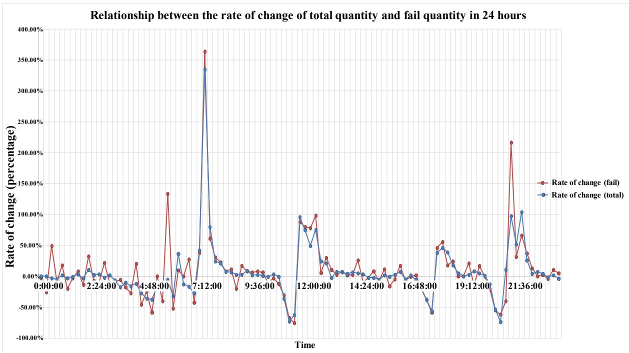

Fig. 3. Rate of change of total and fail quantities in 24 hours

From Fig. 3, the fail curve fluctuates more frequently than the total curve from 00:00 to 04:00. It is anticipated that the workers would be sleepy and tried from midnight to early morning. In addition, the fail curve sometimes decreases after break periods (07:00, 12:00, 18:00 and 21:30). This phenomenon happens in 2 hours after the break period, this perhaps is the effect of the 'post-lunch dip'.

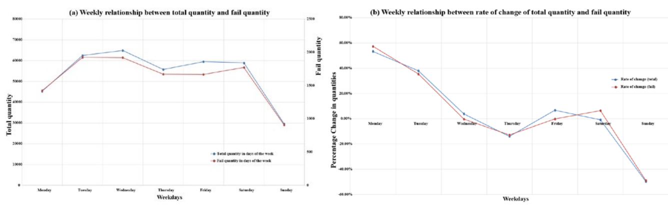

Fig. 4. Experimental Results - 1

For the data grouped in a weekly basis, from Fig. 4 (a), the quantity increases from Monday, there are small fluctuations from Tuesday to Saturday, and a significant drop on Sunday. It is discovered that more work is processed from Tuesday to Saturday and less work is processed on Sunday and Monday.

By considering the shift of workers, full-time workers are anticipated to work from Tuesday to Saturday. Besides, it is likely that part-time workers worked on Monday and Sunday. It is also suggested that there is scheduled shift for workers during weekdays.

From Fig. 4 (b), a decreasing trend is observed from Monday to Sunday. Small fluctuations occur from Wednesday to Saturday and the lowest fail rate occurs on Sunday. From this figure, the working performance is poor on Monday and Saturday. The rate of change of fail case increase more rapidly than total quantity. The highest fail rate occurs on Monday in Fig. 4 (b) while it has a lower fail rate than the other weekdays (except Sunday). This perhaps the 'Blue Monday' effect happens on Monday. For Saturday, it is expected that workers are distracted thus resulted in a lower working performance. For Sunday, where the lowest total and fail quantities happen in Fig. 4 (a), and the lowest fail rate happens in Fig. 4 (b). It is obvious that there are fewer workers thus resulting in a lower failure rate.

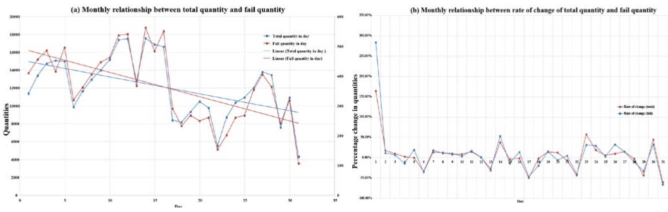

Fig. 5. Experimental Results - 2

From Fig. 5 (a), from the regression of line of the total and fail quantities, the 2 lines intersect in the middle of the month, where a higher fail quantities occur in the first half of the month and lower fail quantities occur at the second half of the month. Moreover, Fig. 5 (a) shows a more fluctuated curve than Fig. 5 (b). One possible reason is that new workers are not familiar with working process in the first half of the month and become familiar with that in the second half of the month. From Fig. 5 (b), only high fluctuations occur in the first few days in a month, small fluctuations appear during the whole month, which the production qualities are stable throughout the whole month. Although small peaks and troughs happen, since there is not enough information about the factories, it is difficult to predict the reasons at this stage.

To sum up the result, for graphs on a daily basis (Fig. 2 and 3), the daily performance and daily working cycle are determined. It is anticipated that workers may feel tired and sleepy from midnight to early morning and suffer from 'post-lunch dip' after break time, resulting in a lower working performance. For graphs on a weekly basis (Fig. 4 (a) and (b)), it is estimated that full-time workers usually work from Tuesday to Saturday, and part-time workers work on Monday and Sunday. The higher fail rate happen on Monday is regarded as 'Blue Monday'. For graphs in monthly basis (Fig. 5 (a) and (b)), it is expected that new workers are employed and started to work in the first few days, and the production quality is stable throughout the rest of the month.

For the limitation, only 3-month data is used in this analysis, there may be bias when considering seasonal factors. Since the working environment is unknown at this stage, workers' performance may also be affected due to the surrounding environment. There are also biases due to the machine condition. In reality, there are different skill levels and production qualities among workers. However, workers are assumed with the same skill level in this paper and the difficulties for different tasks are also different in reality.

5. Conclusion

This paper provides a big data approach in analysing the workers' performance in weekly, monthly, and daily basis. The 'Blue Monday' effect and 'post-lunch dip' effect is examined as well. To achieve the objective of this paper, a 3-month operation data recorded by RFID tags and readers are sorted and analysed with 7 steps proposed in the methodologies under certain assumptions. By analysing the trend of the graphs, it is believed that worker's performance is affected due to the tried and sleepy at midnight and the effect of 'post-lunch dip'. It is also discovered that worker has a lower performance during Monday and Saturday, and the possible reasons are 'Blue Monday effect' and workers' distraction on Sunday. It is discovered that fluctuations are found in the first few days of the graphs on a monthly basis. However, the production quality remains stable throughout the whole month. Some limitations are suggested, which are ignored from the impact from seasonal factors, working environment; machine condition; skill level and workload of workers.

For future studies, data analytics of other parameters should also be performed for an efficient allocation of workforce, such as the effects of working hours, sex and age of the workers. By selecting the better performing workers group and environment, worker's performance will be improved in terms of lowering processing time, higher QC passing rate and eventually a lower cost.

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