Implementing IoT for the Detection of Production Machine Failures

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Abstract

Machine failures are normal and expected events of any manufacturing process. However, they may impact manufacturing negatively. Since these failures are a challenge to any manufacturing process; identifying and preventing them is an essential measure. This paper will focus on the failures of machine and their effects on manufacturing and production. A smart model will be presented that will enhance a fault detection process proposing a smart factory data analytics using cyber physical systems (CPS) and Industrial Internet of Things (IIoTs). This research will explore the statistical relationships among different types of critical failures and their factors and how they are caused. An actual business case for a company is presented with the suggested smart factory model that will monitor and predict critical failures during the production process. This predictive failure control system will create an intelligent machine environment for a smart manufacturing process.

Keywords

IOT, Industry 4.0, MTBF, Smart Factory

1. Introduction

Manufacturing companies hold an essential position in economy. Thus, maintaining operational efficiency during production is important in order to provide high value products. Without operational efficiency, the increase of failures might directly affect the service life of equipment and its production (Wan et al., 2017).Manufactural organization such as company planning, utilization and tool maintenance is also a vital part of the manufacturing process (Raman et al., 2009). Machine failures result in low production rates, have a negative impact on quality and make it challenging for manufacturing to be accomplished. Consequently, an operative failure control system should be applied to ensure flawless production (Shekhar et al., 2017). A strategic and systematic method should be implemented in any manufacturing company to study and detect machine failures along with their associated causes. Some machine failures may be due to internal factors and can lead to breakdowns and hazardous safety issues causing very harmful accidents while others however are caused by external factors. These factors include product demand, global warming, and production breakdowns and could possibly affect production operations (Fernández-Olmos and Ramírez-Alesón, 2017). Machine failures awareness is a valuable contribution for initiating a proficient and productive maintenance program (Carper, 1987).

Facility planning is also important because it clarifies needed repair activities. Strategies should be designed and applied to decrease cost and travelling distances which will subsequently result in a successful manufacturing process with low failure occurrence. The study of machine failures and their effect on production processes is popular among scientists and researchers (Groenevelt et al., 1992), along with the study of manufacturing maintenance policies and their applications (Ahuja and Khamba, 2008; Swanson, 2001). Pandey and Singh, 2000 also discussed testing the homogeneity of critical machine failures such as mean time between failures (MTBF) (Pandey and Singh, 2000). Other studies show that failure analysis could support in building an effective layout model and improve operational efficiency and manufacturing environments (Moua and Russell, 2001; Peters and Yang, 1997). Similarly, the importance of integrating business strategies in any manufacturing maintenance program was researched (Jones and Sharp, 2007) while (Moohialdin and Hadidi, 2016), discussed the effects of failure types on downtime durations.

Machine failure behavior and their associated relations is a common research area. Factorial and fractional factorial experimental techniques were conducted to analyze the machine failure data and presented its research outcomes (Roy and Sutapa, 2004). Shen and Wan studied simulation modelling and evaluated a current manufacturing system for a serial production line in a printed circuit board factory (Shen and Wan, 2009). In order to reduce machine cycle times for the elimination of cycle time unevenness experimental design was used (Adhikary, 2014). The most important factors that contribute significantly to operational problems are also studied by (Chan and Chan, 2003). In another study, factorial design was used to conduct experiments on the flow process of boiling and the factors parameters that influence it were studied (Ek, 2005).

This research will analyze machine failure causes unlike other research studies presented in the literature, which were mostly dedicated to mechanical and electrical failure causes, this study will research the main causes of failures (COF) due to material deficiency and production organizational environment. To conduct this study, an actual case study was done on a manufacturing company where data was collected and analyzed using experimental design methodology and the outcome of the study will support and guide in the prevention of critical machine failures. It will also help in machine failure control with the support of failure prevention strategy.

To incorporate the recent smart manufacturing process technologies, which are proficient at failure prediction rather than prevention strategy, such as Industrial Internet of Things (IIoT) and cyber physical systems (CPS) technologies, a conceptual smart model has been proposed for failure detection. It is a new method which can support a high accuracy failure control system. A smart factory that uses new technologies such as IoT and CPS is proposed in this research to support failure reduction and promote production efficacy. (Haller et al., 2008)

The progression of IoT and other smart sensor technologies allow industries to capture large amounts of data (Jiang et al., 2016) with a low cost. Guo and Qui (Guo and Qiu, 2018) researched the new generation of information technology as cloud computing, big data, IoT, and artificial intelligence (AI) in modern manufacturing processes. Industries have started to implement IIoT to integrate traditional manufacturing process functions with smart technologies. Also known as Industry 4.0., this trend is used by manufacturers for production efficiency and product quality (Wang and Zhang, 2016). Many researchers have recently contributed to the development of smart manufacturing systems and the data analytics using IIoT based solutions for machine condition monitoring and detection of any failures on real-time bases. (Zhong et al., 2017) and (Ahmad et al., 2018) also reviewed the Industry 4.0 concept by describing worldwide movements in intelligent manufacturing.

This paper is organized as follows: Section 1 provides an introduction. Section 2 describes the experimental methodology of the study along with the conceptual framework of the proposed smart factory model. Section 3 discusses the results while section 4 describes the concept of the proposed smart factory model. Section 5 provides the conclusions and recommendations for future research.

2. Methodology

Machine failures slow down any company's performance which therefore causes the disability of continuing their operations in order to meet customer demands on time. This paper studies failure patterns and the source cause of these (critical) failures using root-cause analysis as these critical failures (CFs) affect mean-time-between-failure (MTBF). MTBF is the average time between two machine failures and is normally measured in hours. The higher the MTBF number, the longer the reliability of the system (Lienig and Bruemmer, 2017). Failure times also known as facility downtime is based on the failure type. A factorial design model, which is a well-established analytical approach consisting of experimental analysis of two or more failures (factor), to study the behavior of CFs, is developed. It is the most powerful experimental and statistical technique for conducting research (Ek, 2005). This experimental technique helps the investigator to know the effect of each factor (failure) on the MTBF, as well as the interaction effects that occurred between factors on the response variable.

A smart model will be proposed to solve the issues that will be collected from the case study where the experimental methodology is as follows:

i. **Data Collection:** A large manufacturing company is chosen to provide daily production reports data (secondary) and primary data by conducting interviews with production staff and maintenance crew. The beverage company is in Saudi Arabia and faces different failure types which affect productivity such as mechanical failures, electrical breakdowns, material deficiency failures, production organization failures and planning failures. A research team will be initiated to collect the data.
ii. **Data verification:** This is done by verifying the production reports with the machine's time log sheet data.
iii. **Developing the model:** Testing for normality of the collected data will be done to check and, if appropriate, a mathematical transformation technique will be carried out to solve the issue of non-normality of the data. The research team reviewed the company's production reports to categorize the Failure types into five factors mentioned earlier: mechanical, electrical, material deficiency, production organization, and planning. Hypotheses (H0, H1) were generated to complete the study. H0 stated that different failures had no significant impact on response, i.e. MTBF, while on the other hand hypothesis (H1) stated that at least one of the failures had an impact on MTBF. A significant level of $\alpha = 0.05$ was applied to test the hypotheses using Minitab version 17.1.0. The model implemented has three factors: Product Type (*PT)*, cause of failure , and production line (*PL*).
iv. **Checking model adequacy.** A model adequacy test is will be carried out to conclude whether or not the model is applicable to the data. After successfully testing the model adequacy further analysis can be proceeded.
v. Experimental analysis using full factorial design approach.
vi. Simultaneous testing: multiple comparisons of results are conducted to determine which means (critical failures) are significantly different among each other.
vii. **Validation**: To validate the analysis results by discussing with industry experts and plant management. Results could be revised by the stakeholders if needed.
viii. **Future work**: With the use of smart devices, a smart factory conceptual model is proposed which will help to detect the critical failures more resourcefully and promptly.

A conceptual framework towards a smart manufacturing system is proposed which consists of three levels explained below along with the limitations:

Level 1: Sensory Devices. Level one consists of devices such as sensors and cameras used to detect machine failures and alerting if any abnormality occurs during machine functioning and production operations. For instance, thermal cameras and sensors can detect different temperatures; the cameras will alert when any abnormal action occurs.

Level 2: Data Storage. The second level includes the employment of a cloud platform as a means for large data storage to allow for easier access and sharing. The system provides data channels for information exchange between the levels. The cloud based systems can provide massive storage resources and low cost computing as well as the flexibility of customizing the operating environment (Shu et al., 2016). Therefore, data generated by the equipment can be collected and analyzed and messages are sent to the user level. The optimization unit will need to be preprogrammed by specialized personnel such as programmers (Wan et al., 2016b).

Level 3: User Platform. Level 3 will be a suitable way to interact and communicate as a user platform. For a computer network, a software development system can be installed. To achieve the required mobile services, development of mobile application software must be carried out. The mobile device will need a Wi-Fi or 3G/4G signal to connect to the network and access the cloud service system (Wan et al., 2016a). The proposed system will help in failure reduction and prediction which will in turn decrease MTBF and achieve higher productivity and efficiency. Although these systems are cost effective in the long run, initial investment is a bit high.

Limitations: Limitations in the system could be that workers might not want to learn and use smart systems correctly and precisely. Machine part failures might occur and need on time replacements; meaning that some machines might be unable to deliver production target. Finally, network systems may have outages, which might delay functioning.

3. Results

The results show that at MTBF the three factors (Production Line, Product Type, and causes of failures) were had significant effect because the $P < 0.05$. The relationship between a continuous variable and one categorical factor, rely on value of a second categorical factor. In addition, the result show the is no significant interaction effect between Product Type and Production Line according to their relationship, but according to the relationship between causes of failures and Production Line the interaction between causes of failures and Production Line was significantly for failure of electrical. Similarly, the other 2 factors (Product Type and causes of failures) can be interpreted.
A statistical model is developed as:

$$MTBF = 7.053 + 0.0\,PL\,(1) + 1.808\,PL\,(2) + 0.0\,PT\,(1) - 0.715\,PT\,(2) + 1.052\,PT\,(3) + 0.0\,COF\,(Failure1) + 4.65\,COF\,(Failure2) + 0.78\,COF\,(Failure3) + 1.13\,COF\,(Failure4) + 1.12\,COF\,(Failure5) \quad (1)$$

It represents the relationships and interaction effects between CFs and the causes of failure and an improved model:

$$MTBF = 7.053 + 1.808L2 - 0.715P2 + 1.052P3 + 4.65F2 + 0.78F3 + 1.13F4 + 1.12F5 \quad (2)$$

Note: notations used in (2) are L = Production Line, P = Product Type, F = Causes of failure (Failure).

In addition, there is a main effect for all three main factors. For the first factor that is production line (Production Line), the MTBF in Production Line1 has a lower response when compared with MTBF in Production Line2. In the second factor Product Type Product Type, the MTBF variable shows a significant difference at Product Type 1, Product Type 2 and Product Type 3; nevertheless, from the analysis it shows that at Product Type 3 the highest response was found. In the causes of failure factor, and due to the highest slope the Failure 2 was had the highest main effect on the MTBF.

Use a Tukey test to find the data means that are significantly unlike from each other. If an interval does not contain zero, the corresponding means are significantly different. When get a significant difference that mean the corresponding response will be significantly affected. The results display that Failure 2 had a significant affected on the Failure 1, Failure 3, Failure 4, and Failure 5. From the above results, it can be concluded that Failure 2 are affecting the most to the factors of model (Production Line, Product Type, and causes of failure).

4. Smart System

Machine failures disturb production operations which therefore affect efficient production. Therefore, developing and adopting an appropriate machine failure control system is important in manufacturing companies to make sure that customer demands are being met. This age is the age of technology and since it is a fast growing era, manufacturing factories of the future need to take advantage of such technologies. This new direction is heading towards the inception of fourth industrial revolution called Industry 4.0 (Shrouf et al., 2014).

The main concept of Industry 4.0 era is the use of the Industry Internet of Things (IIoT), (connecting the Internet of computing devices in everyday objects, so that they can send and receive data) to create a smart factory environment. Smart factories are productive and efficient by incorporating IoT technology with computer networks, data integration, and analytics (Lee, 2015; Lee et al., 2014). To implement this smart factory, cyber physical systems (CPS) which is a new and complexly engineered system that integrates embedded computer technologies into the physical world (Gunes et al., 2014).

cyber physical systems have high potential, especially since a CPS-based smart factory can raise efficiency of energy of production systems via equipping them with decision making at level of production management (e.g., management of maintenance and scheduling of production) (Shrouf et al., 2014). based on a survey that published by American Society for Quality (ASQ) in 2014, 82% of administrations that claim to have applied smart manufacturing systems their efficiency was increased, Product defects decreased by 49%, and satisfaction of customer increased by 45%.(BRALEY, 2013).

Controlling production systems and performance data collecting in real time using communication technologies and smart sensor will have affirmative influence on improved efficiency of production and planning of maintenance. For example, using sensors for temperature will allow proactive actions to be taken to prevent breakdown. The same proactive actions can be possessed when consumption of energy is abnormal. This will reduce energy, decrease defective products wastage , and avert the breakdowns of machine. Additionally, IoT-enabled vision devices will enable machines to forecast failures and make maintenance actions immediately. Therefore, manufacturing companies with a smart factory concept will have less failures because of predictive maintenance strategies (Research, 2014; Wang, 2014).

Next, a smart factory design for the case is described using CPS and IoT, however some modifications might be essential to adapt with the existing manufacturing operations. The proposed smart manufacturing system includes three phases with each phase is illustrated in figure 1 and depending on relevant communication technologies (Shrouf et al., 2014) and protocols to communicate with the other phases:

Phase 1: Physical Phase. This phase consists of three different sections which are connected using sensors, telecommunication, and computing (processing; memory) elements in the proposed model. The three different sections are described below:

(i) *Materials*. Materials which are processed in the manufacturing process are of two types:
   a. *Raw Materials*: These are the materials that will be used to manufacture the finished products. The layer needs to make sure for this section that the raw material is a sufficient amount for production and make sure the material is also qualified to be used for manufacturing. Otherwise, the software will alert a signal for raw material shortage to avoid any interruptions during the production process.
   b. *Processed Raw Material*s: These are the materials that have already met quality standards and are being processed so that they can be made into finished products ready to be delivered. Data will be collected and sent to the control unit.

(ii) *Robots*: Robots in the smart system are designed for activities done in the factory so this section should consider developing robot ability so that it can conduct these conduct required tasks with a specific level of knowledge and skills. In this phase, employees of the company are analyzed for skills and abilities and are assigned afterwards to specific machines as per their skills. This guarantees that each machine in the factory will be operated by an expert to avoid any planning failures.

(iii) *Equipment*. All of the machines and devices in the factory will be analyzed by the smart system through sensors and cameras. There will be an alert if any instability is found which will also help to detect and prevent failures.

Phase 2: Control Phase: This phase includes four sections.

(i) *Database*. This unit consists of servers and mirrors to support the data collection, storage and categorization. The data is received from phase 1. All data is stored in case of loss and is sent by IoT devices and can be accessed by the users whenever and wherever the data is needed through Wi-Fi.

(ii) *Analyzing & Optimization Unit*. The data sent from the database unit is analyzed here. The data is read and then the unit decides how to organize it into categories so that whenever the data is needed it can be searched for.
(iii) *Software Unit*. This connects the database and analyzing and optimization unit together through software.

Phase 3: User Platform: All users, through mobile networks or computer networks, will use this phase. This phase needs to be user-friendly so that it can be reliable and easy to use.

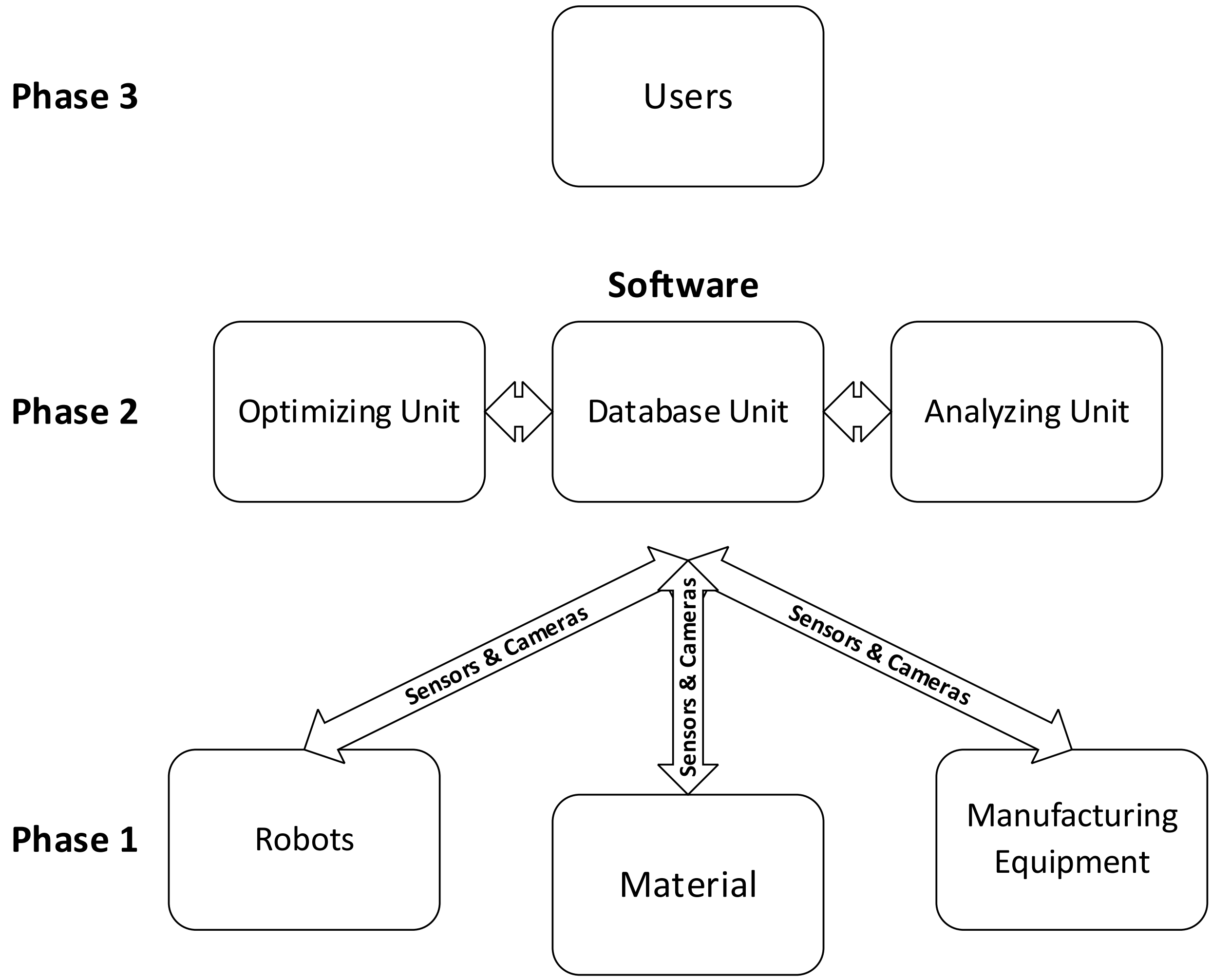

Figure 1. Implementation of the smart manufacturing system layout

5. Conclusion and Recommendations

The occurrence of machine failures in manufacturing is due to different reasons that might affect production and customer satisfaction. In this paper, critical failures and their related causes were identified and investigated by a case study. Real machine failure data from factory production reports and interview with workers was collected. Statistical analysis of the provided data using an experimental design technique is performed. It was found that electrical failures are the most likely to occur among all the others failure types. It was also found that production line failure has a significant effect. On the other hand, the product type failure was not the cause of machine failure. There was no significant interaction between the relationship of production line and Product Type effect while in the relationship between production line and the cause of failures significant interaction effect was visible, particularly for the electrical failure with production line 2.

This research study concludes that manufacturing companies should give attention to preventing critical failures. This can be done by eliminating failure causes and by creating a predictive failure control system. The future is moving towards IoT and smart technology so a productive failure control system has been suggested based on a smart manufacturing factory module and including smart technologies such as sensors and other communication technologies.

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