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.

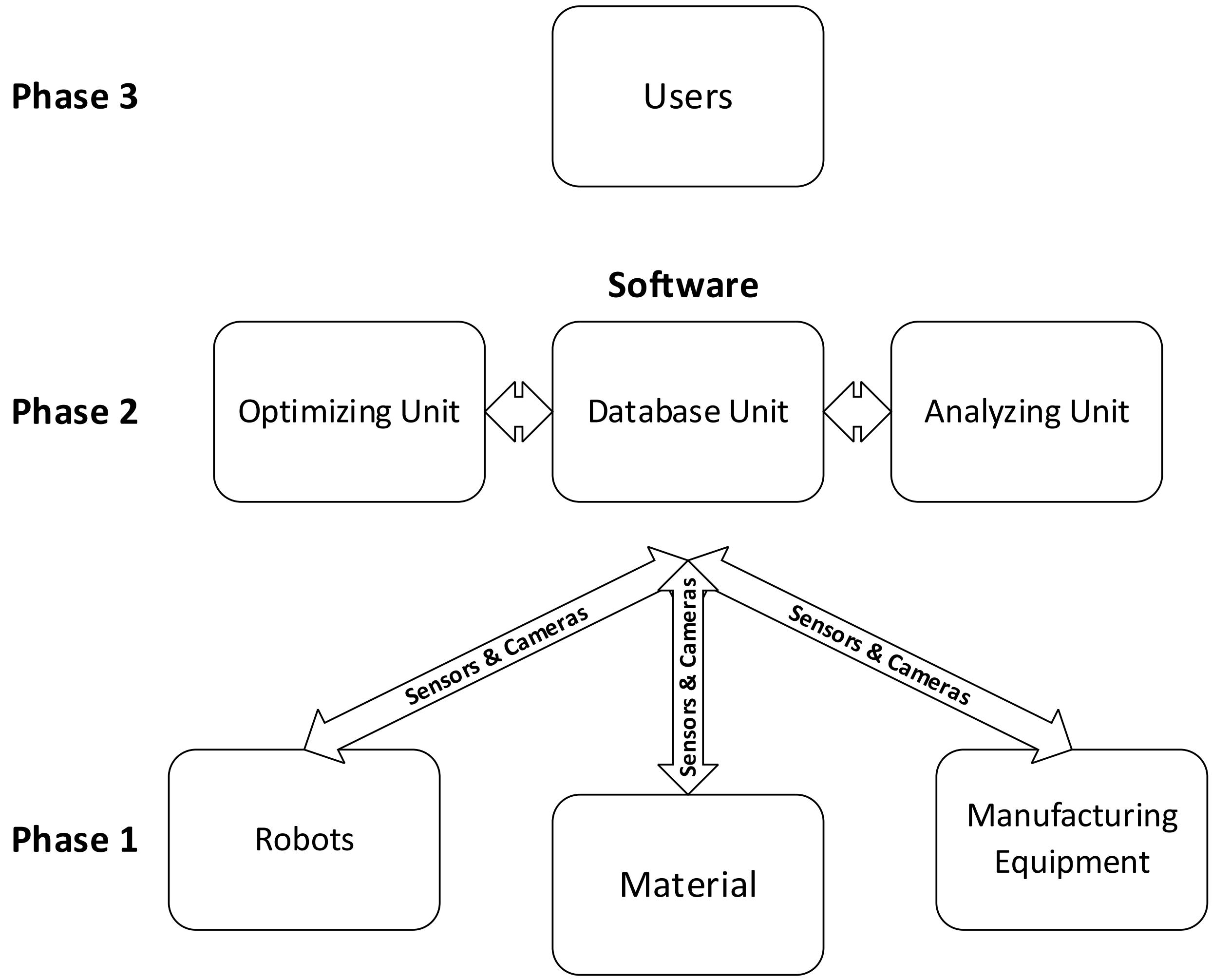

Figure 1. Implementation of the smart manufacturing system layout

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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Biographies

Ahmed Badwelan is a Researcher and PhD Student in Industrial Engineering Department, College of Engineering, King Saud University, Saudi Arabia. He received his B.Sc. degree in mechanical engineering from the University of Aden, Faculty of Engineering in 2012. He received the M.S in Industrial Engineering from King Saud University, Saudi Arabia. His area of expertise is Manufacturing Systems. His main research interests include manufacturing, production and quality.

Moath Alatefi is a Master Student in Industrial Engineering Department, College of Engineering, King Saud University, Saudi Arabia. His area of expertise is Industrial systems. He received the BSc in Industrial Engineering from University of Taiz, Taiz, Yemen.

Atef M. Ghaleb is a Researcher and PhD Student in Industrial Engineering Department, College of Engineering, King Saud University, Saudi Arabia. His area of expertise is Human Factors. He received the M.S in Industrial Engineering from King Saud University, Saudi Arabia , He received the BSc in Industrial Engineering from University of Taiz, Taiz, Yemen.

Prof. Ali M. Al-Samhan has a B. Sc. and M.Sc. Degrees in Mechanical Engineering from King Saud University, Riyadh, KSA. He obtained his Ph. D. from School of manufacturing and mechanical engineering, Birmingham University, United Kingdom. Currently, he is a Full Professor and chairman of the Industrial Engineering Department, King Saud University. Prof. Al-Samhan served as a vice dean of scientific research at King Saud University. He also serves as a consultant for leading manufacturers in Saudi Arabia and member of SASO committee for industrial standardization. Also, he assist local manufactures, as R & D consultant, in developing more than 30 products introduced to Saudi market for 20 years ago. Also, he develop two BSc teaching laboratories in Industrial Engineering Department, for metal forming and manufacturing automation using PLC courses. His research interests focus on engineering materials and manufacturing processes, monitoring and controlling of manufacturing systems using artificial intelligence, product design and development, automation and mechatronics, and biomechanical engineering. Prof. Al-Samhan has many registered patents and published papers in leading journals of Industrial and Manufacturing Engineering. He is leading a number of funded projects from different organization in Saudi Arabia.

Shafiq Ahmad has over 25 years of experience in Engineering and Business Colleges in Australia and Saudi Arabia, coupled with more than a decade long professional experience in reputed multinational organizations in Asia, Australia and Europe, currently his working as Associate Professor at the department of industrial engineering, college of engineering King Saud University Riyadh, Saudi Arabia. His doctoral research is in statistical quality control and operations research area with key focus on performance analysis of engineering and business processes.