A NEURAL NETWORK MOBILE LEARNING APPLICATION FOR AUTONOMOUS IMPROVEMENT IN A FLEXIBLE MANUFACTURING ENVIRONMENT

by

SIEW JIT PING

Thesis submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy

August~~July~~ 2016

Formatted: Line spacing: single

Formatted: Justified

Formatted: Justified, Indent: First line: 0"

Formatted: Font: 18 pt

ACKNOWLEDGEMENTS

I would first like to express my gratitude to both my advisors, Professor Dr. Low Heng Chin and Dr. Teoh Ping Chow, for their support and dedication to this research project. Dr. Teoh, as my field supervisor, has been instrumental in providing the seed and growth of this research. Dr. Low, as Deputy Dean for Industrial Networking, gave critical guidance needed to ensure the success of this project. The outstanding quality I experienced in this research was the openness to new ideas in the application of mobile learning, which led to the design of this mobile learning system that was implemented as a pilot study in a manufacturing facility, which will be briefly known as MF in this report. It was like a trip into the unknown, with no precedence as reference. The effort was rewarded, when a call was received on September 8th, enquiring if the mobile learning system could be replicated to other manufacturing lines.

I would like to express my gratitude to the management at MF, who graciously hosted this research project, who shared pertinent knowledge on the manufacturing processes, and provided useful ideas that led to the development of this mobile learning system.

I would like to express my gratitude to CREST (www.crest.my), and to Institute for Research and Innovation (WOU) for sponsoring this research project.

Last but not least, my gratitude to my parents for their unrelenting support throughout the trying times of this study, and my wife for the years that we lived in frugality when the outcome and future is yet uncertain.

TABLE OF CONTENTS

Formatted: Font: Bold

Formatted: Centered

195

LIST OF ~~TABL~~TABLES~~ES~~

LIST OF FIGURES

LIST OF NOTATIONS

Andon	Signal, meant for visual warning
ANN	Artificial neural network
AOI	Automated optical inspection
BE	Back end
BGA	Ball grid array
CID	Operator identification number
CP	Component placement
DMAIC	Define, Measure, Analyse, Improve, Control
ETL	Extraction, transformation, and loading
FE	Front end
Gemba	Place where the activity took place
GPT	General purpose technologies
ICT	Information and communication technologies

ISN	Inferior-superior-neutral
IT	Information technology
LCD	Liquid crystal display
ML	Mobile learning
MF	A manufacturing facility in Penang
Nnet	Neural network algorithm
OLAP	Online analytics processing
PCB	Printed circuit board
ppm	part per million
Poka-yoke	Mistake proofing
SID	Shift identification (Shift A or B or C)
SMT	Surface mount technology
SPP	Stencil printing process
TPM	Total productive maintenance
ULE	Ubiquitous learning environment
UDS	Unbalanced data set

~~LIST OF PUBLICATIONS~~

~~1. Siew, J.P., Low, H.C. and Teoh, P.C. (2014). Towards Zero Defects in Solder Paste Printing. *2014 Motorola Solutions Penang Technical Expo,* Equatorial Hotel Penang, 6 Nov 2014. [Online] Available at Motorola internal website, paper reference : TS14MA0033.~~

~~2. Siew, J.P., Low, H.C. and Teoh, P.C. (2015). Characterizing Performances of Solder Paste Printing Process at Flexible Manufacturing Lines. *Proceedings of the 2nd ISM International Statistical Conference 2014(ISM-II),* MS Garden Hotel, Kuantan, Pahang, 12 – 14. AIP Conference Proceedings, 1643: 341-348. [Online]. http://dx.doi.org/10.1063/1.4907418.~~

~~3. Siew, J.P., Low, H.C. and Teoh, P.C. (2016). An Interactive Mobile Learning Application Using Machine Learning Framework in a Flexible Manufacturing Environment. *International Journal of Mobile Learning and Organisation,* **10**(1) : 1-24.~~

APLIKASI PERANTI MUDAH ALIH DENGAN RANGKAIAN NEURAL UNTUK PENINGKATAN AUTONOMI DALAM PERSEKITARAN KILANG PEMBUATAN YANG FLEKS~~X~~IBEL

ABSTRAK

Kajian ini memberi tumpuan kepada inovasi berasaskan telekomunikasi dan teknologi komputer di kilang pengeluaran "MF" untuk menjanakan pulangan nilai yang lebih tinggi. Process pembuatan moden merupakan industri yang sangat kompetitif, dan kos kerugian daripada kecacatan dalam pengeluaran produk adalah tinggi. Berdasarkan kaji selidik aktiviti process pembuatan, proses percetakan stensil (SPP) telah dipilih sebagai kawasan kajian. Keputusan ini berdasarkan ulasan kesusasteraan yang menunjukkan bahawa sekurang-kurangnya 50% daripada kecacatan dalam pemasangan papan litar bercetak berasal dari SPP, dan data kecacatan sebenar yang dikumpul semasa penyiasatan. Memandangkan persekitaran kerja sambil berdiri oleh krew pengendali mesin yang terus menerus bergerak, cabarannya adalah untuk memberi keupayaan autonomi melalui pengetahuan mengenai prestasi kerja mereka dengan penggunaan aplikasi pembelajaran mudah alih. Untuk mencapai objektif ini, peranti mudah alih dimuatkan dengan sebuah

aplikasi Android yang digunakan untuk menyampai maklumat yang diproses oleh algoritma rangkaian neural. Algoritma rangkaian neural digunakan untuk menganalisis sejarah prestasi setiap krew berbanding dengan tugas-tugas yang dilakukan dalam persekitaran pembuatan yang fleksibel, dan membuat ramalan prestasi yang dijangka untuk setiap tugas. Teras aplikasi pembelajaran adalah dalam penggunaan grafik jadual dua hala, yang diperkenalkan sebagai matrik inferior-superior-neutral (ISN). Dengan memperkasakan pengetahuan yang berdasarkan pengalaman kerja krew pembuatan, dua peningkatan dalam prestasi SPP dicapai. Pertama, krew B mencapai kecacatan produk sifar selepas perlaksanaan projek selama 9 bulan, manakala kadar kecacatan bagi krew A dikurangkan hampir 90%. Kedua, perbezaan antara kadar kecacatan krew A dan krew B yang dianalisa oleh model regresi menunjukkan kurangkan secara mendadak. Ini membuktikan bahawa aplikasi pembelajaran mudah alih telah berjaya mengurangkan jurang pengetahuan dan membolehkan prestasi yang konsisten antara kedua-dua krew.

A NEURAL NETWORK MOBILE LEARNING APPLICATION FOR AUTONOMOUS IMPROVEMENT IN A FLEXIBLE MANUFACTURING ENVIRONMENT

ABSTRACT

This study is focused on how an innovation based on telecommunication and computer technologies at a manufacturing facility "MF" is implemented to generate higher value returns. Modern manufacturing has evolved into a very competitive industry and wastages resulting from process defects are very costly. Based on a survey of the manufacturing floor activities, the stencil printing process (SPP) was selected as the area of research. This decision was based on literature reviews which indicated that at least 50% of defects in the printed circuit board (PCB) assembly originated from SPP, and actual defects data collected during the survey. Given the standing work environment of the machine operators who are continuously on the move, the challenge is therefore, to empower them with knowledge on their performances relative to defects with a mobile learning application, and to stimulate an autonomous process improvement. To attain this objective, a mobile device loaded with an Android app is used to present information that is processed by a neural network algorithm. The neural network algorithm is used to analyze the past performances of each crew relative to the tasks that are performed in a flexible

manufacturing environment, and make prediction on the expected performance for each task. The core of the learning app is in the use of a graphical two-way table, introduced as an inferior-superior-neutral (ISN) matrix. This empowerment of knowledge, which leveraged on the extensive work experience of the manufacturing crews, led to two improvements in the SPP performance. Firstly, crew B achieved zero defects after 9 months of project implementation, while defect rates for crew A reduced by almost 90%. Secondly, the divergence between defect rates of crew A and B, as indicated by the regression model, reduced dramatically. This proved that the mobile learning application has been successful in reducing the knowledge gap and enabled a consistent performance between the two crews.

CHAPTER 1

INTRODUCTION

1.1 Background

General purpose technologies (GPT) is a term used to describe a new method of producing and inventing that is important enough to have a protracted aggregate impact (Jovanovic and Rousseau, 2005). Examples of GPT are the steam engine, semiconductor, electric motor, and they are characterized by its pervasiveness, inherent potential for technical improvements, innovational complementarities, and giving rise to increasing returns-to-scale (Bresnahan and Trajtenberg, 1995). Pervasiveness is defined as the widespread use of the GPT, as in the examples mentioned prior. Besides being widely used, the GPT must also demonstrate capabilities in complementing inventions of new products or processes, leading to the term “innovational complementarities” used. Finally, when the GPT enables an increase in output by more than the proportional change in input, it gives rise to increase in returns-to-scale. With the introduction of internet, and with wireless technologies that enable connections from computers, tablets and smartphones, information and knowledge transfers become instantaneous and at a level of unprecedented accessibility. These phenomena led Lipsey *et al.* (2005) to specify 24 technologies in history that can be classified as true GPT, of which, included the internet and computers. These technologies in combination, also known as information and communication technology (ICT), have been credited with productivity gains since comparative studies started in 1870 (David and Wright, 1999).

This study was conducted at a manufacturing facility named as “MF”, which is a large multinational corporation where the adoption of ICT has become a necessity for efficiency in resource utilization. Modern manufacturing is a very competitive industry, where losses from defects are very costly. Surveys from the surface mount technology (SMT) industry indicated that at least 50% of defects in the front-end of printed circuit board (PCB) assembly originated from the stencil printing process (SPP). Due to the complexity and miniaturization of circuit components, majority of the defects are not known until the circuit board testing phase, where the PCB is already fully populated with components. This incurs a loss in productive time, as well as costs in analyzing the defects, in repair works, in component replacement, and in maintenance of repair facilities. Although the stencil printing in MF is performed by precision and automated machines, it operates in a flexible manufacturing process where recurring configuration changes performed by machine operators, called “changeovers”, are required. Based on statistical study of the defects, they generally are repetitive, and unequal across all 3 crews who operate in shifts over 24 hours.

Leveraging on the extensive usage of IT infrastructure at MF, this research explores the use of mobile learning as a GPT for improvement in the manufacturing process. Data collection in this study has been facilitated by the availability of Oracle database engine that stores huge amount of information on relevant aspects of manufacturing processes. The next section shall discuss on the concept of flexible manufacturing to further describe the background of this research.

1.2 Flexible manufacturing, mobile learning and neural network

The IT infrastructure at MF covers the entire manufacturing floor, linking all manual processes and automated manufacturing equipments with the central Oracle database. The database serves as an information repository, as process analytics tool, as online tracking of piece parts and progress of product assembly, known as work in progress (WIP), and as support for various process monitoring programs. The objective of the infrastructure is to enable productivity in manufacturing operations. There are 23 manufacturing lines with unique piece-parts and process flow. The products that MF produces are communication devices, grouped in product families, where there are 34 product families as surveyed in August 2013, and each product family contains variations of the product identified by a model number. The variations are essential due to product pricing according to the model features, customer custom configurations, and country regulations governing communication devices. Each of the 23 manufacturing lines is capable of flexible manufacturing. Product families with approximately matching printed circuit board (PCB) sizes, component sizes, and number of components are grouped and run on selected manufacturing lines. The main advantage of flexible manufacturing is the flexibility in adjusting to the customer demand, in terms of the shortest lead time to delivery, and to the quantity as required. The disadvantage of not having a fixed manufacturing line for each product family is the frequent equipment configuration change, termed as “changeover”. Equipment changeovers are a manual process, and from conversations with MF process engineers, changeover is one of the contributors to increase in manufacturing defects, and a source of variation in overall process performance. This information led to the use of Six Sigma methodology, where the overall objective is about reduction in process variation to achieve customer satisfaction (Pyzdek, 2003).

In this study, mobile learning is used to empower the operation crews on very specific knowledge of their performance over time, to create a metric of that performance, and to prioritize actions required for process improvement. Since the subject of learning is based in an environment of flexible manufacturing, the learning content will dynamically change over time in accordance to the models that are produced. The main advantage of using a handheld mobile device as a learning tool is in the learning of the subject at the immediate place of work and learning whenever it is needed, which supports informal learning of the operation crews towards job proficiency, self-improvement, and problem solving (Huang *et al*., 2008).

To process large amount of information that is available ~~in~~ from the Oracle database, a neural network learning algorithm was utilized to model the specific manufacturing process. The intention of the learning algorithm is to built an expert system that will give guidance towards process improvement efforts by the manufacturing crew. An expert system is defined as a computer program designed to model the problem solving ability of the human expert, both in terms of content and structure (Feigenbaum 1977). In effect, the expert system is the encoding of the knowledge and problem solving skills of a human expert. This expertise gained from learning of the specific manufacturing process will then be used to assist the manufacturing crew in process improvement.

The neural network learning algorithm was selected based on two criterias which were judged to be most important. First, it is the amount of time needed to process the information and build the machine learning model, and secondly, the accuracy of the resulting model in predicting unseen datasets. The neural network algorithm was inspired by the biological processes of the human brain. Among the earliest papers which discussed on the mathematical model of the brain neuron was by McCulloch and Pitts (1943). This was followed by the “Perceptron” model by Rosenblatt (1962), which defined the neuron model used today. Further developments by Rumelhart *et al.* (1986), which introduced the backpropagation algorithm and multi-layered perceptron model, simulates the brain approach to information processing by using multi-layered neurons connected to each other as in a networked system.

1.3 The Six Sigma methodology

This study began with a general direction towards an application in mobile learning, which can be integrated into the manufacturing operations at MF. In addition, the mobile learning application as a GPT, must lead to increasing returns-to-scale, which is expected to be in the form of gains from defect reduction, productivity increase in manpower, and reduction in lead time of delivery to customer. In the search for a process that is suitable for implementing mobile learning the Six Sigma methodology (Pyzdek, 2003) was used due to the statistical modeling approach. It is also the standard approach for process improvement in MF as a way towards process improvements. The Six Sigma methodology consists of five phases, which are Define, Measure, Analyse, Improve, and Control. A summary of the methodology is illustrated in a flowchart (Figure 1.1).

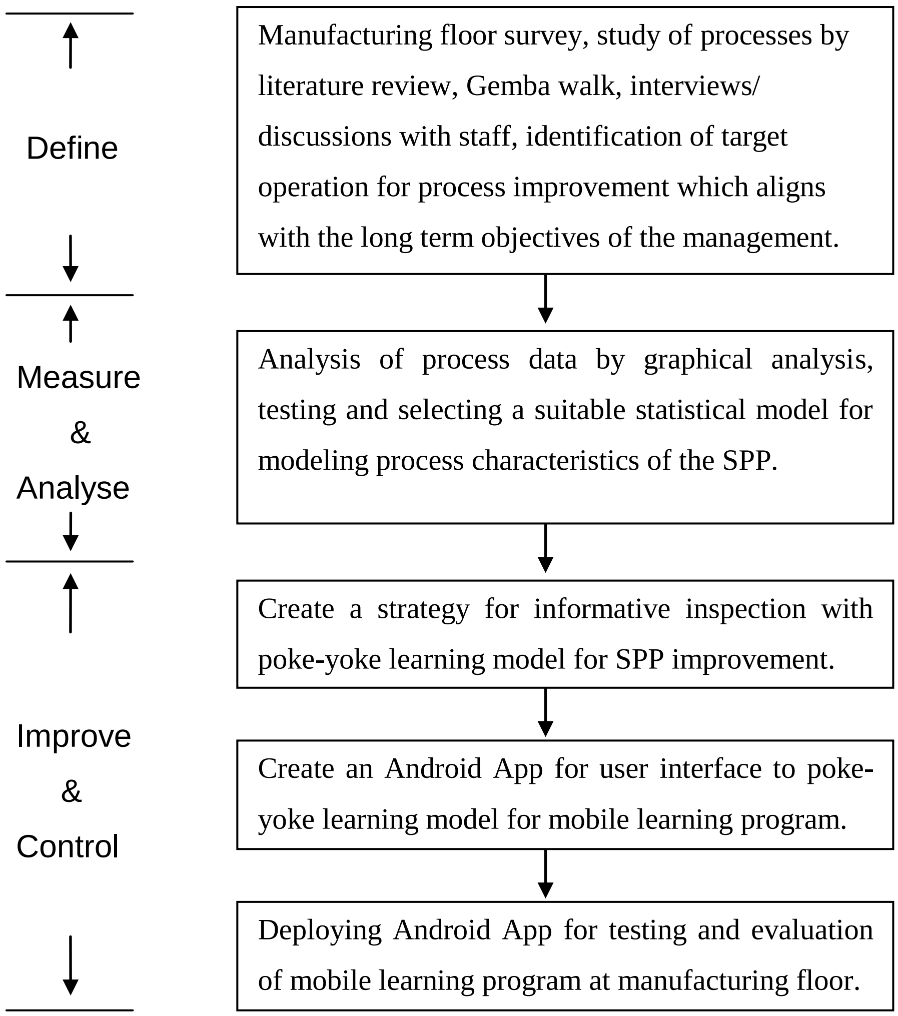

Figure 1.1. Flowchart of Six Sigma methodology.

In the first phase which is Define, the research project is constructed by evaluating the strategic focus of the organization, the long term objectives and the priorities to justify a business case for the project. This is due to the fact that all projects consume resources, and those resources must be justified in the form of investment returns to the organization. Typical areas for high impact projects include high volume processes, high defect rate products, consistent customer returns or warranty claims, and large budget items. Clearly, such projects are connected to the business priorities of the management, and will receive support and approval. The outcome of the evaluation is a problem statement that specifies an area of focus that meets the interests of the organization. When the area of focus is identified, the project must be defined in scope to set the boundaries in which to match the complexity to the approximate length of the study. This is followed by defining the metrics of measurements in the area of focus, which sets the baseline and target for improvement as a final delivery towards project completion.

In the second phase which is Measure, data is collected from areas that are related to the research for measurements on the process performances. In addition, mathematical models as the physical process will be built to understand the influences of various factors towards the outcome of the process. Mathematical function such as these enable an unbiased and objective study of the process (Vapnik, 1995; Pyzdek, 2003; Hastie *et al.*, 2013). The general function to be modelled can be given as

$$Y = f(x_1, x_2, ..., x_n) \tag{1.1}$$

where

Y is the output variable of interest from the process, which may be continuous or discrete (binomial, multinomial), and

x_i for i = 1,2,…,n, are the input variables of the process.

The approach in Six Sigma in the measurement phase is to take as many measurements of relevant input variables as possible, and to gradually reduce those towards a critical few through hypotheses testing for variable significance (Pyzdek, 2003).

In the third phase which is Analyse, the statistical model of the process is used to predict outcomes with the objective of improving the process. Michie *et al.* (1994) introduced two general divisions of statistical modelling, one being classical statistics, the other being modern statistics. Generally, classical statistics is based on certain parametric distributions of the dataset, but modern statistics make no assumptions on the underlying distribution of the dataset. The value of the statistical model of the process is first, to evaluate the effects of predictor variables including their interactions where permissible by the model, and secondly, to learn the characteristics of the process performance over time. Therefore, the Analyse phase forms the core of the process improvement study, which sets the platform for the next phase in improving the process. This approach is similar to several other studies, where data are collected and modelled with various statistical models to determine the characteristics of the process (Ho *et al*., 2001; Zhang and Luk, 2007; Barajas *et al*., 2008; Tsai and Chen, 2009; Tsai, 2012,), with the exception that the processes are not done in a flexible manufacturing environment. Due to the frequent changeovers required, this study will have to include, in the statistical model, the effect of changeover activities on the stencil printing process (SPP).

The Improve phase is the implementation of a solution to the problem statement first stated in the Define phase. The solution is found through a statistical model of the process, where significant predictive variables are identified. Majority of literatures on SPP focus on machine parameters under experimental conditions (Ho *et al*., 2001; Zhang and Luk, 2007; Jianbiao *et al*., 2004; Aravamudhan *et al*., 2004; Yang *et al.*, 2010), and some on actual production run conditions (Huang *et al*., 2004; Tsai and Chen, 2009; Tsai, 2012). None of these studies on SPP improvement involved flexible manufacturing, where human factor in equipment set-up changes to accommodate changing product models in manufacturing runs is evaluated. In addition, the validation on the quality of SPP is performed using automated inspection machine, whereas in this study, the quality of SPP is performed using human as the inspector. Since the parameters for the stencil printing machine has been optimized and programmed to be used for each specific product model in production, the improvement method study will be focused on the human factors that determine the quality of SPP. One of the ways to achieve that would be to compare several manufacturing lines and to use the best SPP performer as a standard. This will then be followed by the use statistics to achieve a SPP quality that will be just as good or better than the best performing manufacturing line.

Finally, the Control phase in a standard Six Sigma project involves documenting the improvements made and concludes with a Control Plan (Pyzdek, 2003). The Control Plan is a plan to ensure that the process improvements are sustained throughout the lifetime of the process. In this study, an innovative approach has to be found as a substitute, as the operation crews are hands-on personnel, and do not respond well to documentations. A common approach towards sustaining the process performance is in the use of control charts (Montgomery, 2004; Hung and Sung, 2011) as part of the institutional memory of what has been learned in the past. This method, however, will be difficult to implement due to multiple product models in the manufacturing process, and aggregating multiple models into a single chart will invariably introduce a bias towards the product model that is the majority, or highest in production volume in the analysis. Even though ~~the~~ challenges exist due to flexible manufacturing, a control method that is based on SPP evaluation over period of time was thought to be the best way in sustaining the process improvement.

1.4 Problem statement

One of the major challenges of manufacturing is of productivity, and the foundations have been laid since the days of Henry Ford, the inventor of assembly line production (Ford and Crowther, 1922). This translates to a maximization on the use of resources to obtain the highest possible output. However, no manufacturing process is perfect, and process defects, leading to rework, or reject, is a constant challenge. Five percent of the factory floor space in MF is dedicated to repair and rework of product defects originating from the production line. Teams of technicians work 24 hour shifts to handle the flow of defects, whose objective is to minimise sub-assembly rejection, where each carries costs of manhours and of piece parts. The challenge presented is wide in scope, and must be narrowed down for this research project. Therefore, the first problem is to determine the main source of failures where the research should be focused on. Secondly, when the area of focus is identified, what will be the strategy for process improvement. Thirdly, how can the infrastructure of MF be leveraged to support the implementation of the process improvement, which is to allow the improvement method to be integrated into the existing IT system.

1.5 Objectives of the research

The three primary objectives of this research are:

1. To identify a process suitable for implementation of mobile learning that aligns with the objective of the top management at MF towards zero manufacturing defects.
2. To learn the process characteristics and to construct a strategy in process improvement that can be integrated into manufacturing operations.
3. To create an effective mobile learning application for the operation crews as a process improvement tool towards the goal of zero defects within the scope of the selected process.

In summary, with consultation from the top management at MF, a viable research project on a manufacturing process will be selected. Evidences of viability shall be collected in the form of historical data from the manufacturing process. The analysis of the data shall then used as a business case to justify returns to the company when the project is implemented in actual production runs.

1.6 Organisation of the thesis

The rest of this thesis is organized as follows: Chapter 2 provides a literature review and discussion of related work in Lean and Six Sigma methodology, SMT stencil printing, data mining, statistical learning methods, artificial intelligence, and mobile learning. Chapter 3 presents the approach in selecting the process suitable for implementing the mobile learning application. Chapter 4 illustrates the stencil printing process (SPP), the pre-processing of SPP information extracted from Oracle database, the mathematical modeling of the process output characteristics based on the input variables, and the construction of information lookup table for Android app. Chapter 5 details the mobile learning application development. Chapter 6 presents the mobile learning system deployment and results, while Chapter 7 presents the conclusion and possible future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of relevant literature that forms the basis of this study. Since the research started with only a general direction, the review of literature begins with subjects consistent with the manufacturing policy and objectives of MF which are Lean manufacturing, and the continuous improvement methodology of Six Sigma. This is followed by a review of literature that focuses on the subject of stencil printing process, the process identified for implementation of mobile learning. Subsequently, literature pertaining to statistical modeling is reviewed, followed by literature on mobile learning.

2.2 Application of Lean and Six Sigma methodologies

Henry Ford lived during a time where resources are scarce, and financing for new business start-up is difficult to come by. He detailed his chronicles in a self-biography, as a learning to be passed on to anyone who is interested (Ford and Crowther, 1922). Ford was credited with the invention of the car assembly line, a huge success which is the embodiment of his ideas on productivity. He defined waste from work involving man and machine as "due largely to not understanding what one does, or being careless in doing of it", and illustrated in detail that prices of products can be lowered by elimination of wastes and not by cutting of worker wages.

Henry Ford's philosophy on manufacturing spread to the east and greatly influenced an engineer by the name of Taiichi Ohno, who was credited with the development of Toyota production system (Ohno, 1988). This concept was introduced to the world as "Lean Manufacturing" (Womack *et al.*, 1990). He refined the concept of waste from Henry Ford into 7 categories, of which, manufacturing defect is one of the elements. In addition, he developed a manufacturing system for small numbers of many different kinds of automobiles, in contrast to Western practice of producing large numbers of similar vehicles (Imai, 1986), which led to the use of the term "flexible manufacturing" (Dessouky *et al*., 1995).

Shigeo Shingo, a consultant to Toyota who worked with Taiichi Ohno, implemented a method to achieve zero defect in manufacturing process known as "Poka-yoke" system (Shingo, 1986). In the system, Shingo categorized 3 types of inspections, which are judgment inspection, informative inspection, and source inspection. Judgment inspection is defined as an inspection to discover defects, which is of no value as it does not contribute towards continuous improvement. Informative inspection leads to gradual reduction of defect rates by an immediate feedback loop, in conjunction with statistical quality control, to correct the work process. Source inspection, used in conjunction with poka-yoke device, leads to elimination of defects.

To integrate all work methods in all aspects of operations to achieve high productivity in Lean Manufacturing, a total productive maintenance (TPM) program is utilized. It is a program that involved all levels of employees through motivation management (McKone *et al.*, 1999; Kodali and Chandra, 2001; Jadhav *et al.*, 2013). The term "autonomous", defined by Merriam-Webster online dictionary (2015) as self-government and independent, is used to describe one of the eight pillars of TPM, which is “autonomous maintenance” (Rajput and Jayaswal, 2012). In line with this usage, the term “autonomous improvement” is proposed as self-motivated, self-governing and independent initiative by the production crews towards process improvement.

Quality control for inspection of manufactured products was first introduced by Walter A. Shewhart (Shewhart, 1931). It was quickly adopted by a host of industries as an economical way of controlling process variations (Blount, 1953; Montgomery, 2004; Cozzucoli, 2009; Marques *et al*., 2015), and was promoted by Shingo (1986) for process continuous improvement. Control charts are essential tools in Six Sigma methodology, where they serve as process monitoring, diagnostics, as well as a historical record of the learning process in continuous improvement (Pyzdek, 2003). Even though the selection of analytical tools used is not rigid, the methodology is to follow the Six Sigma DMAIC model. Since the selection of analytical tools are flexible, certain Six Sigma studies do not contain any analysis with control charts at all (Valles *et al*., 2009). Due to this flexibility, many industries have adopted the methodology in improving critical processes to reduce costs, and to meet or exceed customer expectations (Sokovic *et al*., 2006; Hung and Sung, 2011).

However, in environment where processes have very low levels of nonconformities, the use of standard control charts is not recommended as it leads to false alarms (Steiner and MacKay, 2004; Chang and Gan, 2001; Cheng and Thaga, 2008). Since the Six Sigma methodology is flexible, other methods must be found to mitigate this shortcoming in control charts as a quality tool towards continuous process improvement.

2.3 The stencil printing process (SPP)

SPP is part of the process in manufacturing printed circuit board (refer to Section 3.2 for detailed description). SPP has been a challenge on printed circuit board (PCB) manufacturing, evident by the proliferation of solder paste inspection equipment, or substituted by rigorous non-value added activity of manual inspections. It is a process of applying solder paste onto the surface of PCB solder pads, and has been characterized as a process that is challenging, with 45 important controllable variables that will influence the quality of the stencil print (Jianbiao *et al*., 2004). Given the ever decreasing size of components, the paste printed must be very precise in position, thickness and volume. Process variations lead to defects in the form of solder shorts and unsolders, which forms the majority of defects observed in SPP (Huang *et al*., 2004, Ooi *et. al*., 2004, Ooi *et. al*., 2012).

The component placement (CP) process is the next process after SPP if solder paste inspection equipment is not present. CP process places all the components that are required by design onto the PCB, and it must do so at high speed to attain the economy of volume. Front-end defects for SPP versus CP are found by practitioners to be in the range of 50%-80% (Aravamudhan *et al*., 2002; Jianbiao *et al*., 2004; Zhang and Luk, 2007; Ufford and Mohanty, 2009; Yang *et al*., 2010). Even though the SPP literature provide detailed study into the characteristics of the process (Jianbiao et al., 2004; Huang *et al*., 2004), by design of experiments (Aravamudhan *et al.*, 2002), and automated inspection equipment evaluation (Ooi *et al.*, 2006), these studies are all done under ideal operating circumstances, or "controlled conditions".

2.4 Statistical learning using machine learning algorithms

Statistical learning refers to a set of tools for modeling and understanding complex datasets (Hastie *et. al.*, 2013). It is a recently developed area in statistics and blends with parallel developments in computer science and, in particular, machine learning. Machine learning is an implementation of statistical learning using automatic computing procedures based on logical or binary operations, that learn a task from a series of examples (Michie *et al*, 1994). They have all attempted to derive procedures that would be able:

a. to equal, if not exceed, a human decision-maker's behaviour, but have the advantage of consistency,
b. to handle a wide variety of problems and, given enough data, to be extremely general,
c. to be used in practical settings with proven success.

The goal is to apply a statistical learning method to the training data in order to estimate the unknown function f such that $Y \approx \hat{f}(X)$ for any observation (X, Y). Therefore, supervised statistical learning involves building a statistical model for predicting, or estimating, an output based on one or more inputs (Hastie *et. al.* 2013). The earliest examples on techniques for statistical learning, or learning from data are from Legendre and Gauss on the method of least squares (M.Merriman, 1877), and Nelder and Wedderburn on generalized linear models (Nelder and Weddeburn, 1972). These are exclusively linear models because fitting non-linear relationships were computationally infeasible at that time. With the development of computing technology in the 1980's, non-linear statistical learning became prominent. Among the first non-linear statistical learning models to be introduced was the classification and regression trees (Breiman *et. al.*, 1984), followed by the Neural Network (Rumelhart *et al.*, 1986), Support Vector Network (Cortes and Vapnik, 1995), AdaBoost (Freund and Shapire, 1996), and Random Forests (Breiman, 2001).

The prominence of classification and regression decision tree model is attributed to model interpretability (Hastie *et. al*, 2013). Trees are directed graphs beginning with one node and branching to many. They are fundamental to computer science (data structures), biology (classification), psychology (decision theory), and many other fields. Decision trees classify instances by sorting them down the tree from the root to some leaf node, which provides the classification of the instance. Each node in the tree specifies a test of some attribute of the instance, and each branch descending from that node corresponds to one of the possible values for this attribute (Mitchell, 1997).

In an effort to improve the accuracy of decision tree, a technique called "boosting" is introduced by Freund and Shapire (1996). "Boosting" is a general method for improving the performance of any learning algorithm. In theory, boosting can be used to significantly reduce the error of any "weak" learning algorithm. Boosting works by repeatedly running a given weak learning algorithm on various distributions over the training data, and then combining the classifiers produced by the weak learner into a single composite classifier. Therefore, AdaBoost is an implementation of decision tree classification algorithm that learns from the training data iteratively to generate a superior solution when compared to a single decision tree algorithm (Shapire *et al.*, 1998).

Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest (Breiman, 2001). The generalization error for forests converges to a limit as the number of trees in the forest becomes large. The generalization error of a forest of tree classifiers depends on the strength of the individual trees in the forest and the correlation between them. Using a random selection of features to split each node yields error rates that compare favorably to Adaboost (Freund and Shapire, 1996) but are more robust with respect to noise.

The support-vector network was introduced as a new learning machine for two-group classification problems by Cortes and Vapnik (1995). The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high dimension feature space. In this feature space a linear decision surface is constructed, where special properties of the decision surface ensures high generalization ability of the learning machine. The algorithm was initially restricted to cases where the training data can be separated without errors. This capability was later extended to non-separable training data (Cortes and Vapnik, 1995).

The development of Neural Network first began as an enquiry by Socrates on what qualifies an expert to be an expert (Plato, 2001). Since then, capturing the essence of expert's knowledge has been a popular topic under the study of knowledge engineering. Early attempts to construct models based on rules and heuristics of a specialist were time consuming and tedious (Felgenbaum, 1977). One of the obstacles faced was in the representation of large amount of knowledge in a fashion that permits their effective use and interaction (Goldstein and Papert, 1977). Early studies into the modeling of human brain as a neural network of information processing functions were slow in progress (McCulloch and Pitts, 1943; Rosenblatt, 1962) due to absence of computing technology. In 1986, a breakthrough came with the introduction of the backpropagation algorithm, which enabled the Perceptron model first proposed by Rosenblatt, to be viable for approximating general functions (Rumelhart et al., 1986). The modern neural network consist of layers of interconnected nodes, each node producing a non-linear function of its input. The input to a node may come from other nodes, or directly from the input data, and some nodes are identified with the output of the network. The complete network therefore represents a very complex set of interdependencies which may incorporate any degree of nonlinearity, allowing very general functions to be modeled (Michie *et al*, 1994). With the advent of low cost computers and widespread use of internet, the open source community of R contributed over a hundred algorithms on machine learning where statistical models could be built, and are available as open source (R Core Team, 2014). In the R program installation, a Neural Network algorithm (Nnet) contributed by Venables and Ripley, is available as a default installation. It is one of the most flexible algorithms, where predictor variables can be in the form of nominal or continuous variable (Venables and Ripley, 2002). Michie *et. al.* (1994) named the neural network algorithm as the best overall classifier base on a comprehensive evaluation of 20 algorithms over 20 different types of datasets, where performances of various algorithms are compared with respect to accuracy.

2.5 Mobile learning

The motivations behind development of mobile learning in a flexible manufacturing environment are mobility, self-paced learning, user friendly interface, autonomous improvement, and networked communication capabilities of the handheld device. Mobile learning is a new way of learning which refers to the use of mobile and handheld IT devices, such as mobile telephones, tablet, in training, learning, and teaching, that may take place anywhere and anytime (Sarrab *et al*., 2012). Mobile learning is defined as the union of mobile computing technologies and electronic education technology, where learners are able to access to the learning materials from anywhere at anytime (Vinu *et al*., 2011). Mobile learning contents are broadly classified into fixed content and dynamic content. Examples of fixed contents designed using fixed learning objects as building blocks are in educational fields (Chang *et al*., 2012; Paulins *et al*., 2014). A simple example of dynamic content learning are location based self-paced mobile learning, where the contents change based on user location (Li *et al*., 2013).

A more advanced form of dynamic learning content is found in ubiquitous learning environment (ULE) of multiple handheld devices capable of computing and communication with each other and with objects embedded with devices containing source data (Vinu *et al*., 2011, Jones and Jo, 2004; Yahya *et al*., 2010). The intent of ULE is to create an intelligent learning environment to enable the user to connect directly to the relevant objects in the context of learning, and within the surroundings of other users with handheld devices. This development led Pontefract (2013) to define the phenomenon as pervasive learning, where learning takes place at the speed of need through formal, informal and social learning modalities. The idea of informal education is not new, with the first study published in 1950 by Knowles (1950). A comprehensive survey by the US Bureau of Labor Statistics found that informal learning is a significant factor in career development in the work environment, where it leads to greater wage growth for workers whose tenure is 2 years or greater (Loewenstein and Spletzer, 1998). This led to a learning and development model of 70-20-10 proposed by Lombardo and Eichinger (2000), where 70% of the learnings are in the workplace context by challenging assignments and job experiences, 20% through relationships, network and feedback, and 10% through formal training process. Informal learning is best defined by Bell and Dale (1999) as "Learning which takes place in the work context, relates to an individual's performance of their job and/or their employability, and which is not formally organised into a programme or curriculum by the employer. It may be recognized by the different parties involved, and may or may not be specifically encouraged."

The Android driven mobile device is efficient in memory management and comes with well developed programming classes (Murphy, 2008). It has variety of user interface templates for rapid program development with good documentation, and above all, being open source. Since the raw data is sourced from Oracle database, the learning content that is displayed by the mobile learning application is dynamic (Li *et al.*, 2013), where information feedback on performance of the operation crews varies according to the tasks that are performed. Taking advantage of the mobile device light weight mobility, learning can take place on the manufacturing floor, right next to the relevant activities, termed as "situated" learning (Traxler, 2005). By bringing the learning to the workstation of the operation crews, the learning becomes personalized, self-learning and self-paced at the discretion of the team (Teoh *et al*., 2012). In addition, the advantages of mobile learning at the manufacturing floor based on the concept of ubiquitous learning (Huang *et al*., 2008) are as follows :

a. Enhancing availability and accessibility of information networks.
b. Engaging operation crews in learning-related activities in diverse physical locations.
c. Supporting of project-based group work.
d. Improving of communication and collaborative learning.
e. Enabling quick content delivery.

In terms of design of the mobile learning content, Elias (2011) suggests 8 universal instructional design (UID) principles, which will be discussed here in conjunction with the use of Android operating system and user interface (Murphy, 2008; Lehtimaki, 2013);

a. Equitable use – to enhance mobility and for use with multiple devices wireless connection to the cloud server is necessary for instant sharing of latest information updates across all devices. This design feature will be invaluable for implementation across the manufacturing floor, according to techniques for large scale implementation and just-in-time delivery of information (Traxler, 2009).
b. Flexible use – learning to be packaged in small chunks. However, with the advent of Android tablet devices, this limitation is mitigated, especially large tablets with screen sizes at and above 10 inches.
c. Simple and intuitive – unnecessary complexity should be eliminated and course design to be rendered simple and intuitive. Android menu driven

features are standard across all apps (Lehtimaki, 2013), and therefore the designer has only to focus on the flow of information presentation.

d. Perceptible information – recommendation to add captions, descriptors and transcriptions.
e. Tolerance for error – to minimize hazards and adverse consequences for errors in software operation by designing learning environments with a tolerance for error. Android programming recommends error handling and recovery as part of the standard subroutine to avoid application crash (Murphy, 2008).
f. Low physical and technical effort – relates to the physical effort in user interaction and assistive technologies. Android user interface has well developed touch and gesture features that make user interaction a breeze (Lehtimaki, 2013).
g. Community of learners and support – to include study groups or group learners in the learning program.
h. Instructional climate – to focus on instructor's course delivery and generate interest in the learning content.

The above UID elements were found to be consistent with other literature (Connell *et at*., 1997; Scott *et al*., 2003) and were included in the design of the mobile learning program.

2.7 Summary

Mobile learning is a form of information delivery through a mobile device, where the objective varies across different environments. In education, objective is