AN INTEGRATED APPROACH OF ARTIFICIAL NEURAL NETWORKS AND SYSTEM DYNAMICS FOR ESTIMATING PRODUCT COMPLETION TIME IN A SEMIAUTOMATIC PRODUCTION

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Abstrak

Penentuan masa siap dalam penghasilan produk baru menjadi salah satu indikator yang penting kepada pengilang bagi penghantaran barangan kepada pelanggan. Kegagalan menepati penghantaran pada masanya, atau dikenali sebagai kelewatan, menyumbang kepada kos penghantaran melalui udara yang tinggi serta ketidakupayaan pengeluaran oleh rantaian bekalan. Ketidakpastian masa siap menyebabkan masalah besar kepada pengilang yang menghasilkan produk audio pembesar suara melalui saluran pengeluaran separuh automatik. Justeru, objektif utama kajian ini adalah untuk membangunkan model tergabung dengan mempertingkatkan penggunaan kaedah rangkaian neural buatan (ANN) dan system dinamik (SD) bagi menganggarkan masa kitaran. Sebanyak tiga jenis model berasaskan perseptron berbilang lapisan (MLP) telah dibangunkan dengan perbezaaan senibina rangkaian untuk menganggarkan masa kitaran. Tambahan, satu persamaan kadar momentum yang telah diformulasi adalah dicadangkan untuk setiap model bagi memperbaiki proses pembelajaran yang mana rangkaian 3-2-1 muncul sebagai rangkaian terbaik dengan nilai kesilapan min kuasa dua yang terkecil. Seterusnya, keputusan anggaran oleh rangkaian 3-2-1 disimulasikan melalui model SD yang dibangunkan untuk menilai pencapaian masa siap dari segi jumlah produk, keletihan operator pengeluaran dan skor beban kerja pengeluaran. Kejayaan model tergabung ANNSD yang disarankan juga bergantung kepada perkaitan pengkali yang dicadangkan untuk gambarajah bulatan penyebab (CLD) bagi mengenalpasti punca yang paling berpengaruh ke atas masa persiapan. Hasilnya, model tergabung ANNSD yang dicadangkan memberi panduan yang bermakna kepada pengilang dalam menentukan faktor yang paling berpengaruh ke atas masa siap yang mana masa diguna untuk melengkapkan produk audio baru dapat dianggarkan dengan tepat. Kesannya, penghantaran barangan menjadi lancar dan tepat pada masa manakala permintaan pelanggan dapat dipenuhi dengan jayanya.

Kata Kunci: Rangkaian neural buatan, Sistem dinamik, Masa siap, Kadar momentum, Pengeluaran separuh automatik.

Abstract

The determination of completion time to produce a new product is one of the most important indicators for manufacturers in delivering goods to customers. Failure to fulfil delivery on-time or known as tardiness contributes to a high cost of air shipment and production line down at other entities within the supply chain. The uncertainty of completion time has created a big problem for manufacturers of audio speakers which involved semiautomatic production lines. Therefore, the main objective of this research is to develop an integrated model that enhances the artificial neural networks (ANN) and system dynamics (SD) methods in estimating completion time focusing on the cycle time. Three ANN models based on multi-layer perceptron (MLP) were developed with different network architectures to estimate cycle time. Furthermore, a proposed momentum rate equation was formulated for each model to improve learning process, where the 3-2-1 network emerged as the best network with the smallest mean square error. Subsequently, the estimated cycle time of the 3-2-1 network was simulated through the development of an SD model to evaluate the performance of completion time in terms of product quantity, manpower fatigue and production workload scores. The success of the proposed integrated ANNSD model also relied on a proposed coefficient correlation of causal loop diagram (CLD) to identify the most influential factor of completion time. As a result, the proposed integrated ANNSD model provided a beneficial guide to the company in determining the most influential factor on completion time so that the time to complete a new audio product can be estimated accurately. Consequently, product delivery was smooth for on-time shipment while successfully fulfilling customers' demand.

Keywords: Artificial neural networks, System dynamics, Completion time, Momentum rate, Semiautomatic production.

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List of Abbreviations

ABS	Agent Based Simulation
ANN	Artificial Neural Networks
ART	Adaptive Resonance Theory
BP	Backpropagation
CBR	Case Based Reasoning
CLD	Causal Loop Diagram
DES	Discrete Event Simulation
EOL	End-of-life
MLP	Multilayer Perceptron
MSE	Mean Square Error
MWH	Material Warehouse
SFD	Stock Flow Diagram
SOM	Self-Organizing Maps
SVM	Support Vector Machine
VSM	Viable System Model

CHAPTER ONE
INTRODUCTION

In today's competitive manufacturing environment, completion time is crucial for manufacturer in reflecting the delivery performance on time (Zhou & Chai, 1996; Behdani, Lukszo, Adhitya & Srinivasian, 2007; Mussa, 2009; Aslam, 2013; Wang & Jiang, 2017). Time is one of the most important dimensions of service quality for manufactured products that a customer demands (Mussa, 2009; Albrecht & Steinrücke, 2017). In order to ensure delivery due date can be fulfilled, production operation that minimally disruptive becomes a vital task (Leus & Herroelen, 2007). Failure in fulfilling distribution date on time will ultimately result in the interruption of production processes. Consequently, the interruption will cause delays in delivery which may incur high costs of shipment (such as by air shipment to rush delivery), and may eventually tarnish the image of the manufacturer.

1.1 Importance of the Manufacturing Sector

The manufacturing sector has been recorded as the most crucial sector (as compared to other industries) and contributed almost RM 70.4 billion to the Malaysian economy in the first quarter of 2018 through export activities (Department of Statistics Malaysia [DOSM], 2018). Thus, a rapid transformation is progressively carried out by the Malaysia government in strengthening the manufacturing sector, especially to cope with the challenges of the Industrial Revolution 4.0 (IR 4.0); a smart and flexible manufacturing operation through the integration of computational and physical processes (Bortolini, Ferrari, Gamberi, Pilati, & Faccio, 2017; Li, Hou,

& Wu, 2017; Ooi, Lee, Tan, Hew & Hew, 2018) which had gained much attention from the industrial community.

The transformation of the manufacturing sector into a smart operation requires a shorter completion time in the production of products to remain competitive in the new marketplace (Weyer, Schmitt, Ohmer & Gorecky, 2015; Saeed, Malhotra & Abdinnour, 2018). In response to meeting customers' orders promptly, improvements in the manufacturing operations has shifted from only being concerned about their competitors' achievements to the performance of the internal entities in the supply chain (Behdani et al., 2007; Mussa, 2009; Aslam, 2013; Paulraj, Chen & Blome, 2017). Thus, these entities play a significant role in the manufacturing sector.

1.2 Supply Chain in the Manufacturing Sector

A supply chain is defined as the involvement of facilities, functions and activities of a product or service in producing and delivering processes from suppliers to customers (Russell & Taylor, 2011). The role of the supply chain is to manage the flow of customer orders and to provide quality products and services (Paulraj et al., 2017). Figure 1.1 shows the flow of products and services in a supply chain of the manufacturing sector.

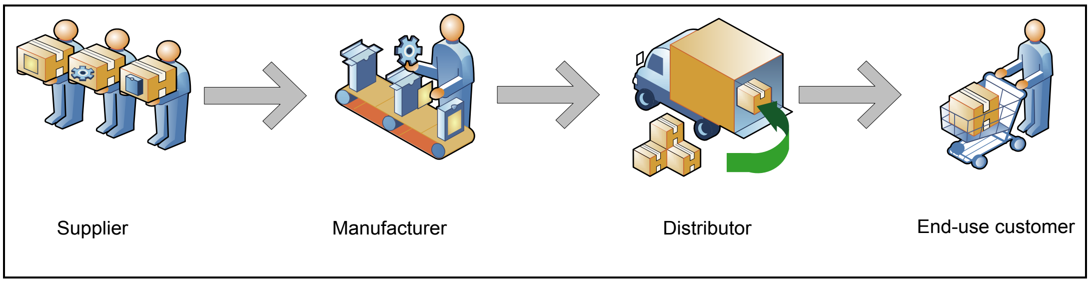


Figure 1.1. Flow of products and services in a supply chain
Source: Russell and Taylor (2011)

The entities of a supply chain are commonly represented by suppliers, manufacturers, distributors, retailers and end-use customers (Disney & Towill, 2003; Samanarayake, 2005; Wai, 2009; Ghafour, Ramli, & Zaibidi, 2017). The elaboration of each entity, i.e., supplier, manufacturer, distributor and end-use customer are further discussed in the following subsections 1.2.1, 1.2.2, 1.2.3 and 1.2.4, respectively.

1.2.1 Supplier as a Basic Entity

A supplier is a provider of raw materials for a manufacturer to produce the products (Paydar & Saidi-Mehrabad, 2017). The function of a supplier in a supply chain is crucial in the procurement activity with the manufacturer due to the supplier being the source of materials in the supply chain (Huber & Sweeney, 2007; Strong, Kay, Conner, Wakefield & Manogharan, 2018). The deferment of material delivery affects the completion time of a product. Hence, the role of suppliers should be taken into consideration as they are the primary entity for manufacturing.

1.2.2 Manufacturer as a Product Maker

A manufacturer is a product maker in a supply chain that transforms raw materials to finished products through its expertise and facilities (Aslam, 2013; Ahmarofi et al., 2017). A manufacturer normally produces products from a production site (Trkmanet et al., 2007; Seth, Seth & Dhariwal, 2017). The high volume of various products at the production site involve numerous activities performed by workers (Leus & Herroelen, 2007). In order to manage the variety of production activities, a product layout is constructed by the manufacturer to ultimately produce a particular product.

A product layout, or commonly known as assembly line, is an arrangement of production activities in sequence (Moreira, Pastor, Costa & Miralles, 2017) equipped with a conveyor that moves along the line (Rehman, Tahir & Lim, 2017). Typically, an assembly line is constructed in fully automatic and semiautomatic structures to ensure the smoothness of workflows within the required completion time (Fisel, Arslan & Lanza, 2017; Sridhar & Anandaraj, 2017). A fully automated production line is a product layout that is equipped with machines but needs no or minimal manpower to handle the machines (Kamath & Rodrigues, 2016; Sikora, Lopes & Magatão, 2017). On the other hand, a semiautomatic production line is a product layout with a combination of an almost equal percentage of manpower and machines to perform the production operations (Russell & Taylor, 2011; Ahmarofi, Abidin & Ramli, 2017; Hager, Wafik & Faouzi, 2017).

A high number of manufacturers in Malaysia and other developing countries still run their operations by applying the semiautomatic production line. A survey by the Federation of Malaysia Manufacturer (FMM) reported that 49 percent of manufacturers were unable to fulfil customer orders due to their production operation which still depended on manpower to perform various tasks (Sivanandam, Rahim & Tan, 2016; Ahmarofi et al., 2017). The low cost of manpower in developing countries (Araujo, Silva, Campilho & Matos, 2017) and high initial cost to setting up an automation line (Nayak & Padhye, 2018) are the reasons why manufacturers in developing countries prefer to operate their production in a semiautomatic structure. Thus, the semiautomatic production line is vital for manufacturers in Malaysia and other developing countries to utilise the semiautomatic structure as their dependency on manpower is high. Figure 1.2 shows an example of a workflow process at a semiautomatic line set up by the manufacturer to produce a product.

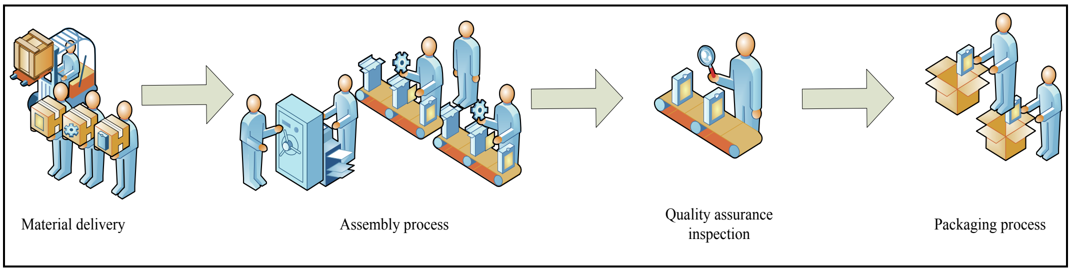


Figure 1.2. Workflow of production operation through semiautomatic line
Source: Author's observation at a case company

Based on the workflow at the line, material from the supplier is delivered to production for further assembling processes such as soldering, magnetising and gluing. Subsequently, an inspection procedure is conducted on the products at the end of the line for quality assurance. Finally, a packaging process is carried out before the product is delivered to customers through distributors.

1.2.3 Distributor for Product Delivery

A distributor is an entity to receive, manage, store, package and deliver the products (Russell & Taylor, 2011; Shadkam, & Bijari, 2017). Products from manufacturers are stored at the distribution centre before being distributed to end-use customers (Wai, 2009; Kadambala, Subramanian, Tiwari, Abdulrahman & Liu, 2017). In today's competitive market, the related processes of distribution should consider speediness as one of the quality attributes in satisfying customer needs (Mussa, 2009; Ahmarofi et al., 2017). Hence, the role of distributors is vital to deliver products from manufacturers to end-use customers in the market.

1.2.4 End-use Customer

An end-use customer is a consumer that purchases and consumes products once it is available in the market (Lambert, Cooper & Pagh, 1998; Wai, 2009; Aslam, 2013). The demand from customers signifies the trend of current order (Singla, Ahuja, & Sethi, 2017) and becomes a target for marketing (Ramanathan, Subramanian & Parrott, 2017). Thus, their requirement must be fulfilled at the appointed completion time when demanded by them (Bag, Anand, & Pandey, 2017). However, there are some challenges that hinder the smoothness of completion time for producing the products as further elaborated in the following section.

1.3 Challenges on Completion Time in the Production Operation

Completion time (also known as flow time) refers to the length of time required to complete a product in sequence during production operation (Behdani et al., 2007; Mussa, 2009; Ahmarofi et al., 2017). Production operation is a system that transforms inputs into outputs (Russell & Taylor, 2011). The workflow process at the production line are performed within the expected completion time (Aslam, 2013; Ahmarofi et al., 2017). Completion time is one of the indicators that is widely used by manufacturers to measure performance (Zhou & Chai, 1996; Behdani et al., 2007; Schafer, Chankov & Bendul, 2016). Figure 1.3 shows an example of a general workflow in a production line which is related to completion time.

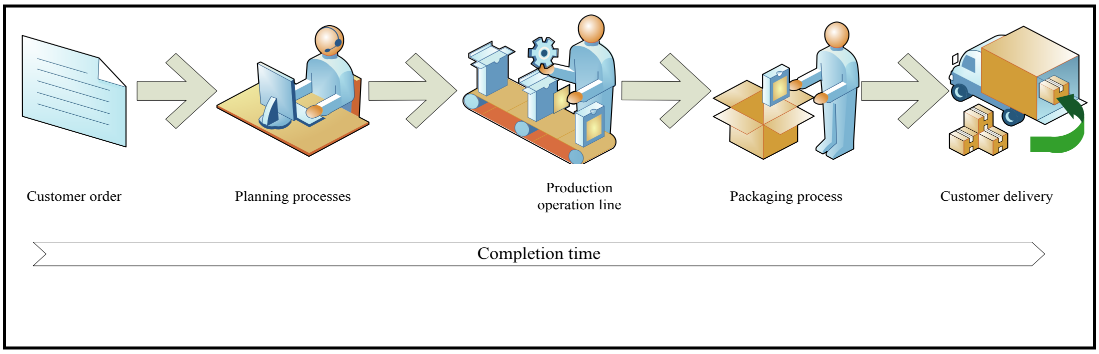


Figure 1.3. Activities considered in the completion time at a production line
Source: Schafer et al. (2016)

Once a customer places an order for product, planning for the production process is arranged to meet the customer's request within the required completion time (Framinan & Perez-Gonzalez, 2017). Several factors may hinder the smoothness of completion time before the product is completely assembled and distributed to customers. These factors which may be considered as challenges to manufacturers are described in the following subsections 1.3.1 until 1.3.4.

1.3.1 Manpower Shortage

Manpower (also known as an operator) is a person who performs a specific task at a production assembly line (Sarif, 2010; Ebrahim & Rasib, 2017). The function of manpower is to perform a specific task as a product operator (Rabbani, Akbari & Dolatkhah, 2017). The management of the production assembly line becomes unmanageable and more complex when there is a shortage of manpower (Sarif, 2010; Gwavuya, 2011; Stynen, Jansen & Kant, 2017). Hence, the number of manpower is strictly observed in managing a semiautomatic production line as it affects completion time.

1.3.2 Material Availability

A material is a physical resource which is provided by the supplier (Mansfield, 1995; Hitomi, 2017). Materials are used in the production of a finished good. Insufficient material availability becomes a significant interruption to production operation and could prolong the time in delivering the product to customers (Gunasekara, 2009; Alglawe, Kuzgunkaya & Schiffauerova, 2016; Segerstedt, 2017). In this regard, material preparation is crucial and should be regularly monitored as it considerably affects the smoothness of completion time.

1.3.3 Machine Constraint

A machine is a mechanical facility which assists the product assembly process (Chakraborty, Giri & Chaudri, 2009; Singhal, Gupta & Singh, 2017). However, the occurrence of machine breakdown contributes to the constraint at the production site which defers the completion time in production (Chakraborty, Giri & Chaudri, 2009; Singhal, Gupta & Singh, 2017). Thus, a machine breakdown must be handled promptly due to the extra time required for rearrangement of the production processes.

1.3.4 Cycle time of a Specific Task

Cycle time is defined as the length of time needed to process a product with specific tasks at the production line (Russell & Taylor, 2011; Seth, Seth & Dhariwal, 2017). The uncertainty of cycle time due to manpower performance, material availability and machine constraint could affect the efficiency of completion time (Hariga & Bendaya, 1999; Lee, 2005; Bülbül & Şen, 2017). Hence, the cycle time of a specific task must coordinate efficiently to ensure the smoothness of production operation.

1.4 Tardiness in Customer Delivery

The challenges of manpower shortage, material availability, machine constraint and cycle time are the factors which contribute to tardiness, which is the delay of a job's due date from its completion time (Kasuma & Maaruf, 2015; Schafer et al., 2016). Consequently, the actual completion time at a production site has typically a high percentage of not meeting the expected completion time (Tyagi, Tripathi & Chandramouli, 2016). In this regard, a proactive solution to overcome these challenges is required for the manufacturer to ensure customers' orders are accomplished on-time.

In determining completion time with on-time delivery, the uncertain cycle time which resulted from related factors, namely, manpower shortage, material availability and machine breakdown becomes a big problem for the management (Bülbül & Şen, 2017). Thus, predicting cycle time is an essential issue in production operation and is deemed crucial to be foreseen. Furthermore, it is also vital to evaluate the expected cycle time and other factors using various strategies through a risk-free experiment, i.e., a technique that can mimic the production operation without any interruption on the real system. As a result of this technique, a policy on completion time at a particular semiautomatic production line can be improved for the best completion time without tardiness.

However, various techniques can be utilised to predict cycle time and evaluate the completion time of a production operation. These techniques are summarised next in Section 1.5 and are further elaborated discussions are presented in sections 2.3 and 2.4.

1.5 Summary of Prediction and Evaluation Techniques for Production

Prediction of uncertain cycle time which results from manpower shortage, material availability and machine breakdown is crucial since it affects overall completion time. In previous studies, researchers implemented various prediction techniques for production operation such as regression analysis (Adembo, Meisn & Toyin, 2012; Ismail, Mir & Nazir, 2018), decision tree (Su & Shiue, 2010; Robert et al., 2017), fuzzy logic (Saleh, 2008; Kahraman, Onar, Cebi & Oztaysi, 2017), support vector machine (SVM) (Hong & Hua, 2013; Saraswathi, Srinivasan & Ranjitha, 2017), case-based reasoning (CBR) (Dalal et al., 2013; Faia et al., 2017) and artificial neural networks (ANN) (Mehrjerdi & Aliheidary, 2014; Wang & Jiang, 2017).

Regression analysis (which includes linear regression, logistic regression and multiple regression), is a statistical model that estimates the association between independent (target) variable and dependent (input) variables when changes are made (Chan et al., 2009; Russell & Taylor, 2011). It shows a low performance for data mining process (Carbonneau, Laframble & Vahidov, 2007; Turban, Sharda & Delen, 2011; Eyduran et al., 2017; Nguyen et al., 2017). A decision tree is defined as a mathematical flowchart in a graphical tree structure (Chien, Wang & Cheng, 2007; Pradeepkumar & Ravi, 2017). It is only best to be implemented when the number of classes is low (Wang, 2007; Chaurasia & Pal, 2017) and for classification purposes (Chien et al., 2007; Wang, Xia & Wu, 2017).

In addition, fuzzy logic, a logically consistent technique of reasoning uncertain information (Saleh, 2008; Kahraman, Onar, Cebi & Oztaysi, 2017), has a limitation where it is hard to supply membership information by the modeller (Suresh et al., 1999; Turban et al., 2011; Sharda & Delen, 2011; Kahraman, Onar, Cebi & Oztaysi, 2018). Case-based reasoning (CBR), is an inference technique derived from historical cases (Fu & Fu, 2012; Dalal et al., 2013; Faia et al., 2017) is difficult in representing cases among different types of various incidents (Hong & Hua, 2013; Tawfik et al., 2018). Support vector machine (SVM), a generalised linear technique based on the value of the input (Hong & Hua, 2013; Saraswathi et al., 2017), shows less performance to achieve true generalisation during the testing phase (Carbonneau, Laframboise & Vahidov, 2008; Saraswathi et al., 2017).

On the other hand, artificial neural networks (ANN) is a brain metaphor model of historical data processing (Venugopal & Narendran, 1992; Kiang, Kulkarni & Tam, 1995; Wu & Jen, 1996; Suresh et al., 1999; Azadeh, Shoushtan, Saberi & Teimoury, 2014; Wang & Jiang, 2017). ANN shows superior capability in prediction with high accuracy as compared to other techniques due to its ability to capture the relationship of various variables toward output through multiple stages in the learning processes such as network structure, learning algorithm, momentum rate and momentum rate (Wang, Tang & Roze, 2001; Turban et al., 2011; Pham, Bui, & Prakash, 2017). Thus, the capability of ANN is suitable to be explored for predicting cycle time in this research.

Subsequently, completion time is determined and evaluated from the predicted cycle time with other factors through a mimic production operation. Due to the complexity and risk of production operation, the mathematical programming technique is deemed incompatible to tackle the evaluation of production operation (Russell & Taylor, 2011; Sumari, Ibrahim, Zakaria & Hamid, 2013; Inam, Adamowski, Halbe & Prasher, 2015). In this regard, simulation technique which is a process of designing a model that resembles a real system in a graphical appearance (Sterman, 2000; Chen, 2016), provides a risk-free experimentation without any interruption on the actual system (Aslam, 2013; Garcia, 2016; Ahmarofi et al., 2017). However, variants of simulation techniques had been studied earlier. These variant techniques which are implemented in a production operation are agent-based simulation (ABS) (Behdani et al., 2007; Mashhadi, Esmaeilian & Behdad, 2015), discrete event simulation (DES) (Komoto, Tomiyama, Silvester, & Brezet, 2011; Hosseini & Tan, 2017) and system dynamics (SD) (Aslam, 2013; Ahmarofi et al., 2017).

However, the ABS technique, which is an individual-centric model (Behdani et al., 2007; Brintrup, 2010; Macal, 2016) is not flexible in terms of explaining the performance of production as many functions are needed to be assigned to the agents to reflect their behavioural rules (Mussa, 2009; Sumari et al., 2013; Baustert & Benetto, 2017). In addition, the DES technique, which models the operation of a system as an isolated time of a selected event model (Ding, Benyoucef, & Xie, 2006; Komoto et al., 2011; Robert et al., 2017), is less concern with the cause-effect relationships and feedback (Aslam, 2013; Sumari et al., 2013; Hoad & Kunc, 2018). On the other hand, the SD technique, a thinking system over time function model (Wai, 2009; Mussa, 2009; Aslam, 2013; Inam et al., 2015) has the capability to understand the complexity of a production environment and is superior to improve the production operation policy by integrating the relevant cause-effect relationships of various factors in a dynamics behaviour (Wai, 2009; Garcia, 2016; Sapiri, Zulkepli, Ahmad, Abidin & Hawari, 2017). Hence, the SD is potentially useful to be explored in the modelling of production operation for evaluating completion time.

1.6 Problem Statement

In the manufacturing sector, completion time is one of the performance indicators that customers are concerned about (Behdani et al., 2007; Schafer et al., 2016). However, the actual completion time at a production site has typically a high percentage of not meeting the expected completion time. This consequently contributes to tardiness as highlighted by Tyagi et al. (2016). Therefore, this research examined the factors that affect tardiness of completion time.

However, among these factors (namely manpower shortage, material availability, machine constraint and cycle time), manpower constraint is more critical in a semiautomatic production line due to its structure that is still manpower-dependent as emphasised by Hager et al. (2017). Nonetheless, due to the high initial cost to set up a fully automatic line as suggested by Nayak and Padhye (2018), the semiautomatic line is still the choice for many manufacturers. As such, this research is deemed essential by filling the gap in focusing on completion time at a semiautomatic production line.

In determining the completion time at a semiautomatic production line, the uncertain cycle time appears problematic for the management as emphasised by Bülbül and Şen (2017) since it could affect the tardiness of completion time. Consequently, cycle time is deemed crucial to be predicted as it is also supported by Schafer et al. (2016). Thus, in this research, the uncertain cycle time at the semiautomatic line was anticipated.

Among all the prediction techniques discussed earlier, the ANN technique shows excellent performance in solving prediction problems. In addition, the ANN technique has a momentum rate to slow down the ANN learning process. However, the momentum rate for the ANN learning process was randomly determined in the previous studies such as in Azadeh et al. (2014) and Wang and Jiang (2017). The selection of a suitable parameter for the momentum rate has no restriction as it is commonly based on the experiment with different values. Hence, a formulation of a momentum rate for the ANN learning process was proposed in this research to achieve the desired output.

Subsequently, the predicted cycle time based on the ANN technique is utilised to determine completion time at the semiautomatic production line. However, the most influential factor (among the four identified factors) needed to be identified in the cause-effect relationship on completion time, only then the cause to minimise tardiness is captured effectively. However, previous studies such as in Pai, Hebbar and Rodrigues (2015) and Inam et al. (2015) did not identify the most influential factor among their related factors. Therefore, this research extended the cause-effect relationship on completion time by introducing a technique to identify this influential factor.

The cause-effect relationship of the identified influential factor on completion time is deemed vital to be evaluated in improving a policy of production operation for the best completion time with minimum tardiness. Based on the reviews on evaluation techniques, SD offers the most suitable solution technique for evaluating the production operation since it can resemble a complex and risk production operation as recommended by Pai et al. (2015) and Inam et al. (2015). However, both these studies only utilised SD in tackling the production operation problem. As such, this research enhanced their studies via the integration of the SD and ANN in evaluating the completion time at a semiautomatic line through various strategies based on the SD technique.

1.7 Research Questions

Based on the problem statement, five key research questions addressed in this research as follows:

i. What are the critical factors considered in the prediction of cycle time and evaluation of completion time at a semiautomatic production line?

ii. How can the momentum rate equation be formulated to improve the learning process of ANN?

iii. How can the most influential factor among related factors towards the completion time be determined?

iv. How can the proposed integrated ANNSD model be validated?

v. How are the interventions of the proposed integrated ANNSD model evaluated?

1.8 Objectives of the Research

The main objective of this research is to develop an integrated model that enhance the ANN and SD techniques in predicting cycle time, and subsequently, evaluate completion time at a semiautomatic production line. Thus, five specific objectives of this research are strategised to achieve the main objectives as follows, which are to:

i. Identify the crucial factors in predicting cycle time and evaluating completion time at a semiautomatic production line.

ii. Formulate a momentum rate equation based on equalization learning speed that can improve the ANN learning process.

iii. Determine the most influential factor among related factors towards the completion time based on the highest coefficient correlation value.

iv. Validate the proposed integrated ANNSD model via structural and behavioural assessments.

v. Evaluate the interventions of the integrated ANNSD model through various intervention strategies or what-if analysis.

1.9 Scope of the Research

In order to predict cycle time and evaluate completion time at a semiautomatic production line, a global business manufacturer in the automotive sector which produces audio speakers as its main product was selected as the case company. Related data were collected from the company from January until March 2016 based on the judgement and advise from company experts according to their customers' demand trend at the time.

However, only one production line was selected among all other production lines since it was the main line that produced the highest number of product demands from customers. Furthermore, the selected line can provided a large set of data as required for this research since the line was entirely operated almost every day.

1.10 Summary of Research Contributions

This research presents six distinctive contributions as the outcomes from the research objectives, where the first three contributions are related to the body of knowledge while the following three contributions are related to the managerial aspects of the manufacturing company. Discussion of these contributions are further elaborated in section 6.3 of Chapter Six. A summary of these contributions is as follows.

i. Development of the proposed integrated ANNSD model provides significant parameter values for the input variables in the stock flow diagram (SFD) from the predicted cycle time. Thus, the developed SFD in resembling a real production operation is more robust for evaluating completion time.

ii. This research enhances the formulation of the momentum rate in slowing down the ANN learning process. Therefore, the convergence of the ANN learning process is improved for a better prediction result.

iii. This research provides the formulation of the correlation coefficient to identify the influential factor among all related factors. As a result, the influential factor enhances the cause-effect relationship for a dynamic causal loop diagram (CLD).

iv. The proposed integrated ANNSD model minimises frequent pre-production process of a new audio product at a semiautomatic production line since the developed ANN model can predict the cycle time from historical data of existing product while the constructed SD model is capable of evaluating the completion time for producing a new audio speaker product.

v. The proposed integrated ANNSD model assists production planners to safely evaluate completion time in terms of the number of manpower, waiting time for material, machine breakdown rate and the cycle time through risk-free experimentation via various scenario strategies or what-if analysis. Hence, the operation of the actual production line is not interrupted.

vi. The proposed integrated ANNSD model guides the manufacturer of the audio product in coordinating an efficient production schedule and smooth customer delivery within the supply chain system through a simulation of a production operation and the management of a big data.

1.11 Organization of the Thesis

Chapter One provides a discussion on the background of the problem and the significant challenges on completion time at the production site. Various techniques that can be utilized to predict cycle time and evaluate completion time of a production operation are briefly discussed in this chapter. Furthermore, the problem statements is presented along with the research questions and objectives. The scope of this research and research contributions are explained at the end of this chapter.

Chapter Two provides a discussion on the problem of completion time from previous studies. In addition, a discussion on factors which contribute to tardiness of completion time are elaborated by a review of predictive techniques that are implemented in solving prediction problems in production operation. Subsequently, simulation techniques that had been applied in previous studies in evaluating production operation are further elaborated.

Chapter Three discusses the essential concepts and theories related to the SD and ANN techniques. An in-depth discussion of the theories of the SD technique in terms of its framework and modelling process is provided. The chapter ends with a discussion on the theories of the ANN in terms of its architecture and learning process.

The research methodology for this research is provided in Chapter Four. The methodology was designed to achieve the objectives of the research as stated in Chapter One. Furthermore, this chapter explains the structure of the research and specific research activities. Specifically, the development of the proposed integrated model of SD and ANN are presented. An in-depth discussion on the validation and evaluation procedures are also included.

Chapter Five presents the results and discussions based on the proposed integrated model. The cycle time of a new audio product is predicted while the completion time is simulated through the developed model. Moreover, the structure and simulation behaviour of the integrated model are validated. Subsequently, several strategies are experimented to select the best scenario. Finally, the best scenario is proposed to the management of the manufacturing company for policy improvement on the completion time at the semiautomatic production line.

Finally, the conclusions of this research are presented in Chapter Six. In addition, a summary of the accomplishment of this research objectives are discussed. The research limitations are discussed, as well as recommendations and suggestions for future research.

CHAPTER TWO

COMPLETION TIME IN MANUFACTURING SECTOR

This chapter provides an overview of previous studies related to the completion time in a production operation. In addition to that, the factors that hinder the smoothness of the completion time in production operation are also discussed. As described in section 1.4 of Chapter One, the uncertain cycle time is a big issue for production operation. Thus, the predictive techniques as presented by previous studies are discussed. The predictive techniques are regression, decision tree and artificial neural networks (ANN). Subsequently, the predicted cycle time and other factors are deemed vital to be evaluated using a risk free experiment that resembles the production operation in determining the completion time. In this situation, the simulation process is most suitable to be utilized. As a result, various simulation techniques need to be reviewed as well. Simulation techniques that have been studied in the production operation are agent based simulation, discrete event simulation and system dynamics (SD). Furthermore, integration of ANN and SD model are elaborated as presented by previous studies. Finally, the significant of ANN and SD in predicting the cycle time and simulating completion time, respectively, are concluded at the end of this chapter.

2.1 Overview of Completion Time in Manufacturing Sector

Completion time or also known as flow time (Russell & Taylor, 2011; Wang & Jiang, 2017) refers to the time required to complete an item in sequence processes (Mussa, 2009; Ahmarofi et al., 2017). From the manufacturing perspective, completion time is the time a given order needs to wait before its production process can be run until delivery due date (Behdani et al., 2007; Yang, Li, Hackney, Chao & Flanagan, 2017).

Completion time is one of the performance indicator that is widely used by various companies in manufacturing sector to fulfil customer delivery on time (Zhou & Cai, 1996; Aslam, 2013; Schafer et al., 2016) and to ensure product movement in supply chain is smooth (Leus & Herroelen, 2007; Donato & Simas, 2011). Thus, completion time is the ultimate target for production site to meet the customers demand and satisfy their order.

The study of completion time has been carried out for almost half a century. It was introduced by Merten and Muller in 1972 which was inspired by the file-organization problem in a computing system (Zhou & Cai, 1994). Since then, a comprehensive study on completion time in manufacturing sector was further enhanced in production operation as presented by Zhou & Cai (199) and Woon and Salim (2004). However, their studies only addressed the completion time problem in a small scale operation that focusing only on machine constraint. Moreover, the nature of production system operates in a dynamic environment with various unpredictable disturbances.

In this regard, many researchers have expended their studies on completion time in medium and larger scale of production by considering dynamic environment such as material availability, machine breakdown, cycle time and supplier delivery lead time as presented by Behdani et al. (2007), Mussa (2009), Aslam (2013) and Azadeh et al.

(2014). Furthermore, recent studies on completion time have been focusing on make-order-production or assigning completion time before production process can be run (Paulraj, Chen & Blome, 2017; Saeed, Malhotra & Abdinnour, 2018) as the current practice nowadays. This is due to a lot of product varieties (Vinod & Sridarand, 2011; Wang & Jiang, 2017) as presented by Luo, Luo, Goebel and Lin (2017). Hence, the determination of completion time is more complex and significant.

It is found that the completion time has been associated with dynamic environment due to unpredictable factors. This consequently contribute to late delivery or tardiness (Huang, Yang & Huang, 2010; Schafer et al., 2016; Tyagi et al., 2016) and ultimately led to customer dissatisfaction and penalties in terms of production line down (Smytka & Clemens, 1993; Coffey & Thornley, 2006) and air shipment chargers (Wu, 2010). Thus, the factors that affect the smoothness of completion time are discussed in the following section 2.2.

2.2 Factors Influencing Completion Time in Production Operation

Production operation is a system that transforms input into output (Russell & Taylor, 2011; Dzakiyullah, 2015). The function of production operation is to produce valuable product from input within stipulated time (Gunasekara, 2009; Saiz, 2015). The smoothness of completion time is affected by several factors in production operation. These factors are number of manpower factor (Mehrjerdi & Aliheidary, 2014; Lembang, 2015; Stynen, Jansen & Kant, 2017), materials preparation time (Zhao & Kathehakis, 2006; Gunasekara, 2009; Dalal et al., 2013; Ahmarofi et al., 2017), machines breakdown rate (Kumar & Viswanadham, 2007; Leus & Herroelen, 2007; Donato & Simas, 2011; Luo et al., 2017) and the cycle time (Lee, 2005; Bülbül & Şen, 2017) as further discussed in the following subsections 2.2.1, 2.2.2, 2.2.3 and 2.2.4, respectively.

2.2.1 Number of Manpower

Number of manpower is the amount of available worker to perform specific task (Masnan, 2004; Lembang, 2015). Manpower has significant role in production line especially at semiautomatic production line due to most of the production tasks such as soldering, magnetizing and packaging are performed by them (Ahmarofi et al., 2017). Thus, several studies highlighted that shortage of manpower directly affect completion time of a product as highlighted by Topaloglu and Ozkarahan (2003), Jamil and Razali (2016) and Stynen et al. (2017).

Jamil and Razali (2016) found that 91% of completion time problem is contributed by the shortage of manpower. In fact, several studies found that stress and fatigue are easily experienced by workers (Sarif, 2010; Gwavuya, 2011; Stynen et al., 2017) due to insufficient manpower to complete production task. Consequently, a tight working schedule and chaotic working environment are created, thus could prolong completion time of a product as highlighted by Mehrjerdi and Aliheidary (2014) and Lembang (2015). Realizing that manpower factor plays important role in production operation, the number of manpower is seriously considered as one of the factor that affects completion time.

2.2.2 Materials Preparation

Material preparation is an arrangement of resource to produce a product (Aslam, 2013; Alglawe, Kuzgunkaa & Schiffauerova, 2016). Material preparation determine the readiness of production operation which consequently affect the completion time of a product as observed by Gunasekara (2009), Aslam (2013), Dalal et al., (2013) and Saiz (2015). Hence, sufficient quantity of material prepared within specified time is crucial for assembly process.

Furthermore, preparation time of material at warehouse could affect completion time significantly. Mussa (2009) highlighted that disruption of material preparation time could prolong completion time of a product at production line up to 83 percent. The finding by Mussa (2009) also supported by Costa et al. (2016) as they found that material lead time from supplier could affect completion time up to 80 percent. Therefore, material preparation time is widely considered as one of the factor that is able to deviate the completion time at production line.

2.2.3 Machine Breakdown

Machine breakdown is defined as a failure of mechanical operation during production process (Donato & Simas, 2011; Yang et al., 2016). Machine breakdown contributes to the instability of product assembly at production site during assembly process (Leus & Herroelen, 2007; Donato & Simas, 2011). Therefore, the occurrence of machine breakdown disrupts the initial planning to complete the product assembly on time.

This problem is considered by many researchers due to a lot of assembly processes are completed by machines as conducted by Woon and Salim (2004), Ruiz-Torres et al. (2006) and Singhal, Gupta and Singh (2017). It is found that production rate could decrease to 30 percent if machine breakdown frequently occurred as highlighted by Singhal et al., (2017). Therefore, machine breakdown is one of the major factor that influences the completion time of product assembly processes.

2.2.4 Cycle Time

Cycle time is the time required by manpower to complete specific task (Schafer et al., 2016; He, Li & Yoon, 2017). Cycle time affects the performance of completion time since the cycle time is measured during pre-production by considering number of manpower (Lembang, 2015), material preparation (Dalal et al., 2013) and machine breakdown (Donato & Simas, 2011). Pre-production is a test run of several pieces of product before accepted to run as an actual production run (Russel & Taylor, 2011). Thus, the cycle time is ultimately contribute to the determination of completion time in processing a product.

However, the expected cycle time is uncertain at semiautomatic production line due to unforeseen performance of manpower as human being experiences fatigue and stress during production run as highlighted by Mehjerdi and Aliheidary (2014). Furthermore, several studies also found out that the completion time of a product always deviated which caused by the uncertain cycle time as presented by Pfeiffer, Gyulai and Monostori (2017), thus contribute to tardiness. Hence, the cycle time appears as a frequent problem and considered as a crucial factor on completion time.

In sum, number of manpower, material preparation time, machine breakdown and cycle time contribute to the deferment of completion time. It is found that the uncertain cycle time of a new product which influenced by number of manpower, material preparation time and machine breakdown rate affect the overall completion time. Thus, it is crucial to use predictive techniques to predict uncertain cycle time, while the predicted cycle time and other factors are deemed necessary to be evaluated in production operation to determine the best completion time. The previous studies related to predictive techniques are further discussed in the following section 2.3, while simulation techniques are elaborated further in section 2.4.

2.3 Prediction Techniques for the Uncertain Cycle Time

Prediction is referred as the action of forecasting the future and uncertain cases (Mehrjerdi & Aliheidary, 2014; Samarasinghe, 2016). The predictions of both cases are normally extracted from a vast of historical data which is known as data mining process through predictive technique (Kumar, 2013; Dzakiyullah, 2015).

A predictive technique is the process of making inferences from a dataset (Russell & Taylor, 2011; Kumar, 2013). It is found that predictive techniques are categorized as machine learning techniques to solve prediction problems which are further elaborated in the following section 2.3.1. However, techniques such as regression analysis, decision tree and ANN also appear to be frequently implemented in many previous studies which is predictive in nature. Therefore, the reviews on these techniques in relation to solving the uncertain cycle time in production operation are presented in subsections 2.3.2, 2.3.3 and 2.3.4.

2.3.1 Machine Learning Technique

A machine learning technique is an artificial intelligence method which mainly concerned with the development of algorithms that enable computers to perform learning process based on historical data (Turban et al., 2011). The applications of machine learning technique for forecasting in manufacturing sector provide good performance in data mining process (Carbonneau, Laframble & Vahidov, 2007). According to Turban et al. (2011), machine learning techniques are capable to support computer operation by automating the learning process in utilizing knowledge from sets of data that reflects the historical occurrences. Fuzzy logic (Saleh, 2008; Kahraman, Onar, Cebi & Oztaysi, 2017), support vector machine (SVM) (Hong & Hua, 2013; Saraswathi, Srinivasan & Ranjitha, 2017), case-based reasoning (CBR) (Dalal et al., 2013; Faia et al., 2017) are categorized as machine learning techniques. Figure 2.1 shows a structure categorizing the machine learning techniques as depicted from Turban et al. (2011).

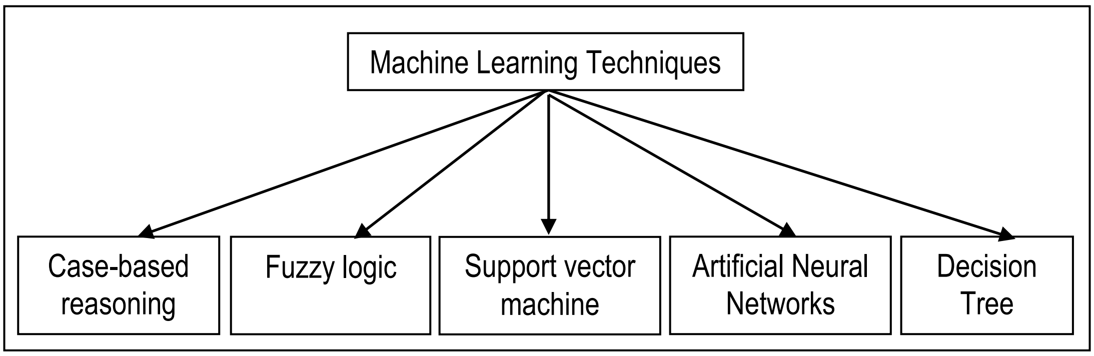


Figure 2.1. Methods under machine learning techniques (Source Turban et al., 2011)

CBR is a problem-solving tool where previous similar cases are retrieved to solve new problem from historical data (Fu & Fu, 2012), while fuzzy logic is a logically and consistent technique of perceptive reasoning that is able to cater to uncertain information (Turban et al., 2011). SVM is a classification and regression based decision technique which relies on the linear combination of input values (Turban et al., 2011). On the other hand, decision tree is a graphical appearance of a classification of related decisions to be decided under certain risks (Turban et al., 2011).

Among these techniques, fuzzy logic has limitation where it is hard to supply membership information by experts or modeler (Suresh et al., 1999; Turban et al., 2011; Kahraman, Onar, Cebi & Oztaysi, 2018), specifically the membership information to the various cycle time. On the other hand, CBR is difficult in representing different cases (Hong & Hua, 2013; Tawfik et al., 2018) especially with numerous circumstances of the cycle time at production line, while SVM is less compatible to be applied on the cycle time due to limitation in achieving true generalization (Carbonneau, Laframboise & Vahidov, 2008; Saraswathi et al., 2017), which in turn the development, training and testing of the technique tend to be time consuming (Suresh et al., 1999; Azadeh et al., 2013).

As a result, it is concluded that the uncertain cycle time is hard to be predicted through fuzzy logic technique, CBR and SVM due to their respective limitations as discussed earlier. However, decision tree and ANN are found to be useful in solving prediction of uncertain cycle time in production operation as suggested by Ahmarofi et al. (2017) and Robert et al. (2017). Moreover, several works also applied regression analysis to solve prediction of uncertain cycle time in production operation. Although it is not categorized under machine learning techniques, regression analysis is capable to perform data mining process which are proved by Turban et al. (2011), Jamil and Shaharanee (2015) and Karam et al. (2016). Hence, a structure on these three major predictive techniques, i.e., regression analysis, decision tree and ANN to solve the uncertain cycle time in production operation is presented in Figure 2.2.

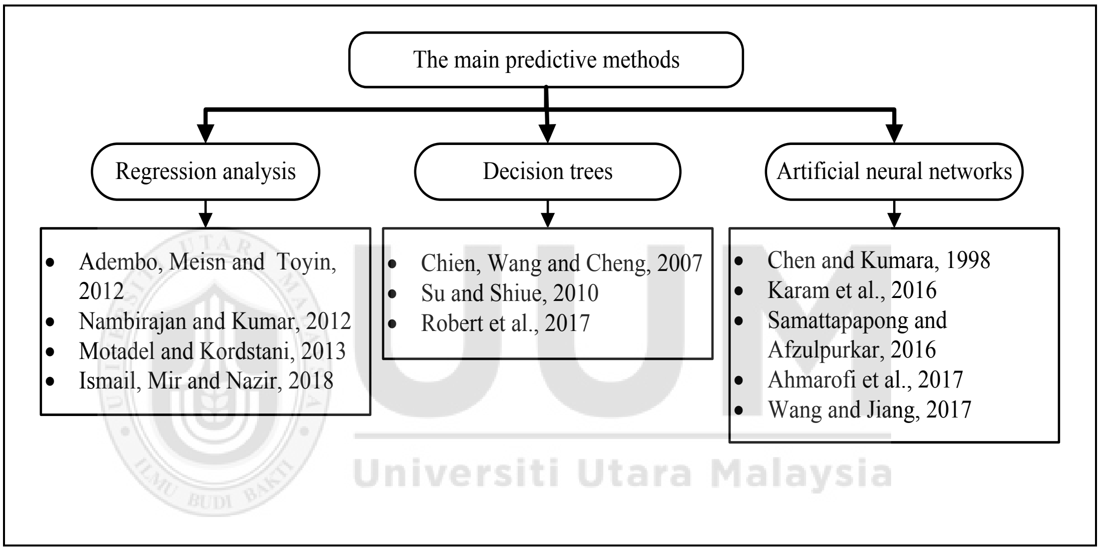


Figure 2.2. Predictive techniques to predict the cycle time in production

Subsequently, these three major predictive techniques are elaborated in subsections 2.3.2, 2.3.3 and 2.3.4, respectively.

2.3.2 Regression Analysis

As defined earlier, regression analysis is a statistical model that estimates the value of dependent (target) variable based on the value of dependent (input) variables when changes are made (Chan et al., 2009). The function of regression technique is to analyze the relationship between dependent and independent variables, i.e., the value of dependent variable changes when any one of the independent variables are varied, while the other independent variables are fixed (Winston, 2004; Russell & Taylor, 2011). Linear regression, logistic regression and multiple regression are different types of regression analysis (Jamil & Shaharanee, 2015). Several studies that implemented regression analysis in predicting the cycle time are presented in Table 2.1.

Table 2.1
Regression analysis to predict cycle time in production operation

Techniques	**Source**	**Dependent variable(s) to predict the cycle time**
Multiple regression	Adembo, Meisn and Toyin, 2012	Delivery lead time from various suppliers
Multiple regression	Nambirajan and Kumar, 2012	Material delivery time and production productivity
Multiple regression	Motadel and Kordestani, 2013	Material delivery time from various suppliers and multi plan productions
Linear regression	Ismail, Mir and Nazir, 2018	Order quantities from customers

In Adembo, Meisn, and Toyin (2012), cycle time is predicted using multiple regression based on material lead time from various suppliers. They claimed that material delivery in supply chain can be improved through the predicted cycle time. However, Nambirajan, and Kumar (2012) improved the estimation of the cycle time by including production productivity in their study that also used multiple regression. This strategy is useful as they claimed that the predicted cycle time increased production competitiveness compared to other manufacturers.

Not only limited to supplier entity, material delivery time is also considered in multi productions to predict the cycle time through multiple regression as presented by Motadel and Kordestani (2013) for production of carpet product. The predicted cycle time successfully improved delivery performance in carpet supply chain. Meanwhile, the linear regression is also implemented in agriculture production line to estimate cycle time based on customer orders as recommended by Ismail, Mir and Nazir (2018). They found that the predicted cycle time is able to meet customer demand of agriculture products on-time.

Even though regression models in those studies are able to solve prediction of the uncertain cycle time, regression analysis shows low performance in data mining process (Carbonneau, Laframble & Vahidov, 2007; Turban et al., 2011; Eyduran et al., 2017; Nguyen et al., 2017). Therefore, a predictive technique with deeper knowledge in learning the relationship among the related factors is deemed necessary to predict a cycle time.

2.3.3 Decision Tree

Specifically, a decision tree (DT) is a flow-chart-like tree graphical structure between identified factors or rules and output (Chien et al., 2007; Wang, 2007; Pradeepkumar & Ravi, 2017). The function of DT is to classify the related rules towards target output (Wang, Guo, Chiang & Wong, 2007; Zhu, Dhokia & Newman, 2017). Only a limited number of studies are found in regards to implementing DT to predict cycle time at production site as presented in Table 2.2.

Table 2.2
Decision tree technique to predict cycle time in production

Technique	Source	Factors considered in predicting cycle time
Decision tree	Chien et al, 2007	Various machining time processes such as grinding and drilling for semiconductor part
	Su and Shiue, 2010	Part and machining processes
	Robert et al., 2017	Production processing time for agriculture product

In the prediction of cycle time for semiconductor part, various machining time processes such as grinding and drilling are considered in the study by Chien et al., (2007) on implementing DT. They managed to predict cycle time which consequently improve the time to repair the defect of semiconductor product. Later, Su and Shiue (2010) combined part and machining processes in predicting cycle time through their developed DT model. Their attempt is useful to support shop floor control system (SFCS) to achieve on-time delivery. In addition, the prediction of cycle time in agriculture production can be solved by considering product processing time as done by Robert et al. (2017). They found out that the predicted cycle time was able to improve Indian agriculture product delivery to related customers through their developed DT model.

It is found that the limited studies on DT in predicting cycle time is caused by the main drawback of DT as the technique is only best to be implemented for classification purposes (Chien et al., 2007; Wang et al., 2017). Furthermore, DT is only efficient when the number of classes or factors is low (Wang, 2007; Chaurasia & Pal, 2017). Hence, DT technique portrays less capability to learn from a large number of data of various factors in predicting the cycle time.

2.3.4 Artificial Neural Networks

The ANN can also be defined as a mathematical estimation tool inspired by the human biological neuron in the brain with learning parameters and network architecture for information processing (Venugopal & Narendran, 1992; Kiang et al., 1995; Wu & Jen, 1996; Suresh et al., 1999; Azadeh et al., 2014; Wang & Jiang, 2017). ANN is also further defined as a biologically inspired statistical tool for data mining (Kumar, 2013; Samarasinghe, 2016). The function of ANN is to forecast or predict the new occurrence based on a learning process of data (Kumar, 2013; Mehrjerdi & Aliheidary, 2014). Historically, ANN is developed by McCulloch and Pitts in 1943 through experiments and observations of biological human brain (Turban et al., 2011). It is found that ANN has been an explosion of interest for many researchers to predict uncertain cycle time in production operation as presented in Table 2.3.

Table 2.3
Artificial neural networks to predict cycle time in production

Technique	Source	Factors to predict cycle time
Artificial neural networks	Chen and Kumara, 1998	Machining parameters for grinding process
	Karam et al., 2016	Machining processing time
	Samattapapong and Afzulpurkar, 2016	Machining processing time and material availability of hard drive product
	Ahmarofi et al., 2017	Number of manpower, machine breakdown rate and material delivery
	Wang and Jiang, 2017	Machining processing time such as milling and boring

In predicting the cycle time for grinding process, machining parameters were considered in the study of Chen and Kumara (1998) through ANN with backpropagation (BP) learning algorithm. The predicted cycle time in their study was able to fulfill desirable process within stipulated time to meet production target. In addition, Karam et al. (2016) considered machining processing time in order to predict cycle time of grinding tool. By comparing the actual grinding process at production line, the predicted cycle time was able to determine the grinding tool life by implementing the ANN with BP algorithm. Furthermore, Wang and Jiang (2017) also considered machining processing time such as milling and boring processes to predict cycle time of radio frequency product through their developed ANN model. This study successfully improved completion time for producing product at production site.

Instead of machining processing time, Samattapapong and Afzulpurkar (2016) included material availability to predict cycle time. As a result, they claimed that the respond on material resources was smooth based on the predicted cycle time by implementing their developed ANN model. On the other hand, Ahmarofi et al. (2017) enhanced the factors on cycle time by considering number of manpower, machine breakdown and material delivery to predict cycle time through the ANN model with BP algorithm. Consequently, the predicted cycle time was able to fulfill customer demand on-time.

Several works show that the smallest measurement error had been achieved in their proposed ANN models in terms of mean square error compared to regression and DT techniques as highlighted by Mehrjerdi and Aliheidary (2014), Ahmarofi et al.,

(2017) and Wang and Jiang (2017). Thus, the prediction of uncertain cycle time at production site is improved in their studies. Furthermore, the uncertain cycle time problems are successfully predicted by ANN technique due to its capability to capture the relationship between various variables and output through its learning processes as proved by Karam et al. (2016), Samattapapong and Afzulpurkar (2016) and Ahmarofi et al. (2017). Moreover, it has also been demonstrated that when ANN trained with a lot of training samples, the technique is able to produce corresponding target values (Haykin, 2009; Kumar, 2013; Samarasinghe, 2016). Therefore, ANN technique is apparently the best predictive method to predict the cycle time in production operation.

Subsequently, the completion time is evaluated from the predicted cycle time through a technique that is able to resemble the complexity and risk of production operation. In this regard, simulation technique which is a process of designing a model that resembles a real system in a graphical appearance (Sterman, 2000; Chen, 2016) provides a risk free experimentation without any interruption on the actual system (Aslam, 2013; Garcia, 2016; Ahmarofi et al., 2017). The variants of simulation techniques being studied earlier for evaluating the completion time are further discussed in section 2.4.

2.4 Simulation Technique in Evaluating the Completion Time

Simulation refers to a technique for conducting experiments on a virtual model that resembles a real system with the aid by a computer (Sterman, 2000; Sapiri et al., 2017). The main purpose of a simulation technique is to evaluate the behavior of the system over a time function (Rossetti, 2010; Pai, Hebbar & Rodrigus, 2015).

It is difficult to solve the complexity and risk of production operation using mathematical formulations (Russell & Taylor, 2011; Sumari et al., 2013). Therefore, simulation provides an effective modelling technique to mimic the real production scenario. This is because simulation offers a tool that is easier to understand with an integration of mathematical formulation and graphical representation (Aslam, 2013; Olaya, 2015) and a risk free tool to analyze without interrupting the real production system (Taylor, 2004; Garcia, 2016).

There are three major techniques in simulation which are agent based simulation (ABS), discrete event simulation (DES) and system dynamics (SD) to evaluate production operation in determining the best completion time (Mussa, 2009; Sumari et al, 2013; Aslam, 2013; Sapiri et al.,2017). In relation to that, overviews of simulation techniques for evaluating production operation in determining completion time from previous studies are presented in Figure 2.3.

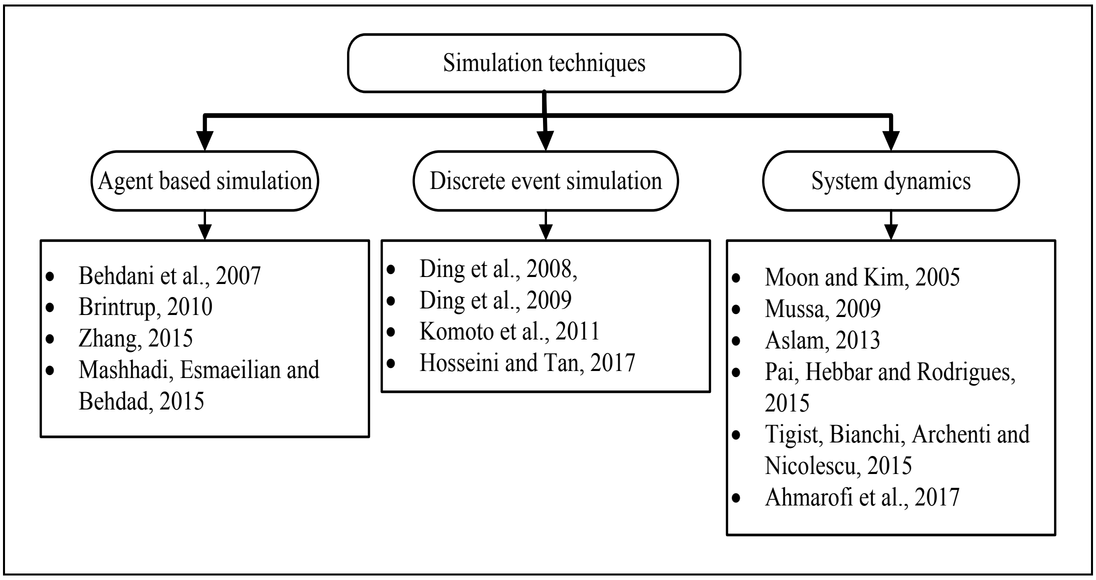


Figure 2.3. Simulation techniques in evaluating the completion time

These three simulation techniques are further discussed in the following subsections 2.4.1, 2.4.2 and 2.4.3, respectively.

2.4.1 Agent Based Simulation

ABS is a simulation technique based on individual-centric approach with developed agents or entities (Behdani et al., 2007; Brintrup, 2010; Macal, 2016). The function of ABS is to decentralize the agents or entities in a system to describe their respective activities (Bintrup, 2010; Zhang, 2015). ABS technique was introduced in the early of 1990's as an academic topic but gain an acceptance and popularity among researchers in 2000 (Sumari et al., 2013). However, limited studies are found on implementing ABS in production operation related to the completion time as presented in Table 2.4.

Table 2.4
ABS technique to evaluate completion time in production operation

Technique	Source	Developed agents
Agent based simulation	Behdani et al., 2007	Suppliers, manufacturer and retailers
	Brintrup, 2010	Suppliers, manufacturer and retailers
	Mashhadi, Esmaeilian and Behdad, 2015	Suppliers, manufacturer and customers
	Zhang, 2015	Suppliers and manufacturer

Behdani et al. (2007) developed ABS model by considering suppliers, manufacturer and retailers in producing lubricant product to determine the completion time. In their study, they were able to improve the product delivery on-time. Moreover, ABS technique also capable to minimize tardiness of completion time as highlighted by Bintrup (2010). In his study, Bintrup (2010) also considered the same agents, i.e., suppliers, manufacturer and retailers as Behdani et al. (2007).

On the other hand, the study by Zhang (2015) contradicted with Bintrup (2010) as Zhang (2015) only considered suppliers and manufacturer agents in producing chemical product through the developed ABS. However, Zhang (2015) claimed that his study was successfully reduced tardiness for chemical production. Meanwhile, Mashhadi et al., (2015) considered suppliers, manufacturer and customers in the developed ABS model. In their attempt, product flow among the entities in supply chain was improved to fulfill product delivery as requested by customer.

It is found that the ABS technique in their studies require a lot of interactions on the related agents to describe their respective functions in modelling production operation as summarized by Sumari et al. (2013). Furthermore, ABS is not flexible in terms of explaining the performance of production as a lot of functions needed to be assigned to the agents to reflect their behavioral rules (Mussa, 2009; Sumari et al., 2013; Baustert & Benetto, 2017). Therefore, ABS technique is less user friendly in mimicking a real production operation for determining the completion time in a holistic view.

2.4.2 Discrete Event Simulation

Discrete event simulation (DES) is a simulation technique that focuses on changes at discrete or isolated points of an operation (Ding, Benyoucef, & Xie, 2006; Komoto et al., 2011; Robert et al., 2017). The function of DES is to evaluate the event at the selected isolated point over time (Rossetti, 2010; Sumari et al., 2013). Several previous studies on implementing DES to determine the completion time in production operation are presented in Table 2.5.

Table 2.5
DES technique to evaluate completion time in production operation

Technique	Source	Related events
Discrete event simulation	Ding, Benyoucef and Xie, 2008	Machining processes, material availability and supplier lead time
	Ding, Benyoucef and Xie, 2009	Machining processes, material availability and supplier lead time.
	Komoto et al., 2011	Machining processes and material availability.
	Hosseini and Tan, 2017	Buffer stock, production operations

In modeling production operation to determine the completion time, Ding et al., (2008) developed DES model by including machining processes, material availability and supplier lead time in producing textile product. They claimed that their DES model was able to reduce tardiness in producing product. Subsequently, Ding et al., (2009) extended their work by considering the same entities in automotive production line in their DES model. Once again, their model successfully reduced tardiness in producing automotive product as achieved in their previous work.

Furthermore, DES is also able to reduce tardiness as proved in a study by Komoto et al. (2011). However, the study by Komoto et al. (2015) is different from Ding et al. (2008) and Ding et al. (2009) as Komoto et al. (2015) only considered machining processes and material availability with inclusion of product cost. Meanwhile, Hosseini and Tan (2017) considered buffer stock in the developed DES model. As a result, they claimed that their proposed ABS model was able to determine minimum buffer capacity for a smooth completion time of production flow.

From their studies, DES has shown its ability in evaluating production performance to determine completion time. However, these DES models are less suitable to be applied in semiautomatic production line due to difficulty of DES in measuring qualitative element (Mussa, 2009; Aslam, 2013; Sapiri et al., 2017) especially related to manpower factor such as fatigue (Garcia, 2016; Ahmarofi et al., 2017). Moreover, DES is less concern with the cause-effect relationships and feedback (Aslam, 2013; Sumari et al., 2013; Hoad & Kunc, 2018). Therefore, the lack of measuring qualitative aspect is the limitation of DES in determining the completion time which involves human factor.

2.4.3 System Dynamics Simulation

SD is a simulation technique which is based on system thinking approach over time function and cause-effect relationships (Wai, 2009; Mussa, 2009; Aslam, 2013; Inam et al., 2015). The function of SD is to evaluate the performance of complex system or environment over time through what-if analysis or known as scenario strategies (Richmond, 1994; Azadeh et. al, 2014; Garcia, 2016). Historically, SD is created by a well-known founder, Jay W. Forrester from Massachusetts Institute of Technology (MIT) in the middle of 1950s with the first application in inventory control system for hiring employees and managing inventory of General Electric Company (Forrester, 1989). Then, the framework of SD has been further developed in Industrial Dynamics in 1958 (Forrester, 1961), Urban Dynamics and World Dynamics (Forrester, 1971). Since then, the application of SD has been widely implemented in various fields including production operation as presented in Table 2.6.

Table 2.6
SD technique to evaluate completion time in production operation

Technique	Source	Developed strategies
System dynamics	Moon and Kim, 2005	Customer order, production operation and product sales in supply chain
	Mussa, 2009	Material delivery lead time from supplier, machine operations and customer order in lubricant multi production
	Aslam, 2013	Material delivery lead time from supplier, production cycle time and machine operations, and distributor delivery lead time in supply chain
	Pai et al., 2015	Material availability and previous order from customer.
	Tigist, Bianchi, Archenti and Nicolescu, 2015	Various machining processes and respective cycle time in producing automotive engine
	Ahmarofi et al., 2017	Material availability at warehouse, number of manpower, cycle time and machine breakdown rate at audio speaker production

Completion time has successfully been evaluated based on several strategies in production operations through SD technique. In this regard, the study by Moon and Kim (2005) was useful to evaluate the completion time based on their developed SD model by including the strategies of customer order, production operation and product sales. Consequently, Moon and Kim (2005) highlighted that customer order trend and product sales growth were improved. In multi productions of lubricant product, Mussa (2009) considered strategies of material delivery lead time from supplier, machine operations and customer order to evaluate the completion time through SD technique. As a result, Mussa (2009) claimed that the completion time of lubricant product was improved to 83 percent through the policy improvement on material delivery lead time.

Furthermore, various strategies on production operation was enhanced by Aslam (2013). In his attempt, Aslam (2013) managed to determine the completion time by implementing the SD model through several strategies on material delivery lead time from supplier, production cycle time, machine operations and distributor delivery lead time. In addition, he claimed that bulkiness of work in process (WIP) and tardiness were successfully reduced. Meanwhile, Pai et al. (2015) proposed strategies on material availability and previous order from customer in their SD model to evaluate the completion time. Based on that developed strategies, they found that product delivery should not be postponed more than two days in order to meet customer demand on-time.

Moreover, the strategies on machining processes and related cycle time were established in the developed SD model as presented by Tigist et al. (2015) to evaluate the completion time of automotive engine. Consequently, they found out that production productivity was increased by seven percent. However, the study by Ahmarofi et al. (2017) is different from other studies as discussed since they proposed their own developed SD model with strategies on number of manpower, material availability at warehouse, cycle time and machine breakdown rate to evaluate the completion time. Moreover, they claimed that the policy on material preparation time should be improved to avoid manpower fatigue and tardiness.

It is found that the effectiveness in improving policy of production operation as presented by related previous studies is driven by the advantage of SD technique in integrating the relevant cause-effect relationships of various factors in a dynamics behavior (Wai, 2009; Garcia, 2016; Sapiri et al., 2017) through feedback process

(Angerhofer & Angelides, 2000; Olaya, 2015), time delays (Sterman, 2000; Inam et al., 2015) and nonlinearity in a dynamic and complex environment (Sterman, 2000; Garcia, 2016;). Moreover, SD is able to measure qualitative aspect (Mehrjerdi & Aliheidary, 2014; Sapiri et al., 2017) such as manpower fatigue during production operation for determining the completion time as presented by Ahmarofi et al. (2017). Therefore, SD can be assumed as the most widely employed technique in production operation to evaluate the completion time successfully as discussed in those previous studies.

2.5 Integration of Artificial Neural Networks and System Dynamics

To the best of our knowledge, there are limited studies that integrate the ANN and SD techniques related to the production operation, while no attempt has been made to predict the cycle time and evaluate the completion time simultaneously. However, among these limited studies, Azadeh et al. (2014) presented the integration of ANN and SD model in their proposed viable system model (VSM) for Iranian broiler production. The function of VSM model is to predict the import tariff of raw materials from suppliers. Subsequently, the predicted import tariff is substituted in their developed SD model to evaluate the price of chicken meat production for the upcoming years. Similarly, a study by Mehrjerdi and Aliheidary (2014) integrated SD with ANN techniques to evaluate job satisfaction in production operation. In their study, Mehrjerdi and Aliheidary (2014) developed the ANN model to predict the most influential factor on job satisfaction including fatigue of manpower. They found that reward factor is the most influential factor and consequently simulated in SD model to evaluate the productivity.

The integration of ANN and SD seems to provide an effective base for the purpose of predicting and evaluating a complex scenario simultaneously. Although the two studies only included one factor from the ANN model to substitute in the SD model, there are still more areas that can be explored in the integration strategy.

2.6 Summary

Throughout this chapter, the implementation of predictive and evaluation techniques to predict the cycle time and evaluate the completion time in related studies have been discussed. The ANN has proved its ability to solve the uncertain cycle time in production operation and becomes superior predictive model as compared to the machine learning, regression analysis and DS techniques. Furthermore, it is also identified that the ANN has good capability to capture the relationships among various variables through a learning process on dataset to provide a better prediction result.

On the other hand, the simulation technique has shown promise as the most effective technique in mimicking a real production operation and then evaluating the completion time. Evidently, the SD offers an effective capability to determine the completion time by considering both quantitative and qualitative elements that exist in the real scenario of production operation line as compared to ABS and DES techniques.

Based on the advantages of SD and ANN, both techniques are highly recommended for the development of integrated model in predicting the cycle time and evaluating the completion time in producing a product at semiautomatic production line which involves element of manpower factor. In this regard, our research can be different from those Azadeh et al., (2014) and Mehrjerdi and Aliheidary (2014) as there are four important factors, i.e., number of manpower, material preparation time and machine breakdown based on the predicted cycle time from ANN technique shall be considered as the input variables for the SD model in simulating the production operation. Thus, the completion time of a new audio production is able to be evaluated. Subsequently, the theories and concepts of the ANN and SD techniques are discussed further in Chapter Three.

CHAPTER THREE

REVIEW ON CONCEPTS AND THEORIES OF ARTIFICIAL NEURAL NETWORKS AND SYSTEM DYNAMICS

As discussed in Chapter Two, ANN and SD are found as the best techniques for integrated model for predicting cycle time and determining completion time in producing audio speaker at semiautomatic production line. Hence, this chapter discusses the concepts and theories behind the ANN and SD techniques in two isolated sections. The first section begins with discussion on the theories and concepts of ANN as a predictive technique. Subsequently, the second section discusses the concepts and theories of SD as an evaluation technique. Finally, the summary of theories and concepts of the ANN and SD techniques are concluded at the end of this chapter.

3.1 Concepts and Theories of Artificial Neural Networks

Artificial neural networks (ANN) is a network structure which resembles a human brain for processing information (Haykin, 2009; Kumar, 2013; Samarasinghe, 2016). Neural is a computing term which refers to development of a computer networks that operate in the way of neuron function (Rahman, 2002; Turban et al., 2011). On the other hand, neuron is a cell of biological human brain to process information (Mehrjerdi & Aliheidary, 2014; Karam et al., 2016). Hence, as the name implies, ANN is developed through a connection of artificial neurons in a simple network which resembles a human brain function to process information.

Historically, ANN is developed by McCulloch and Pitts in 1943 through experiments and observations of biological human brain (Turban et al., 2011). The relationship between biological neuron and ANN are further elaborated in the following subsections.

3.1.1 Relationship between Biological and Artificial Neurons

There are several terminologies in ANN which is inspired by the biological neuron of a human brain. Figure 3.1 shows several terminologies between a biological neuron networks and ANN as elaborated by Zahedi (1993) and Medsker and Liebowitz (1994).

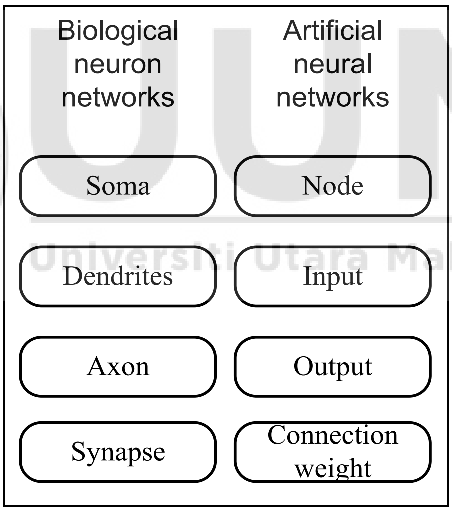


Figure 3.1. The terminologies between biological neuron and ANN

In ANN, the function of a node resembles with the function of a soma in human brain. A node is a processing element for input and output in ANN structure whereas a soma is a processing element for dendrites in human brain to receive input and axon to provide output in human brain (Samarasinghe, 2016). On the other hand, the connection weight is a relative strength in a mathematical value in ANN which resembles the function of synapse in transferring information (Haykin, 2009; Kumar, 2013; Azadeh et al., 2014).

3.1.2 ANN Learning Process for Prediction Purpose

ANN has great capability to solve prediction problem based on a learning process from data collection (Chen et al., 2011; Mehrjerdi & Aliheidary, 2014; Karam et al., 2016). A learning process in ANN is based on mathematical formulation for training ANN in obtaining a desired output (Esfe et al., 2015; Lekamalage, Song, Huan, Cui & Liang, 2017), hence the prediction performance is improved.

In solving prediction problem, a learning process is conducted to teach ANN on how to reach output target. The major steps in the learning process of ANN in solving prediction problem are illustrated in Figure 3.2 as follows:

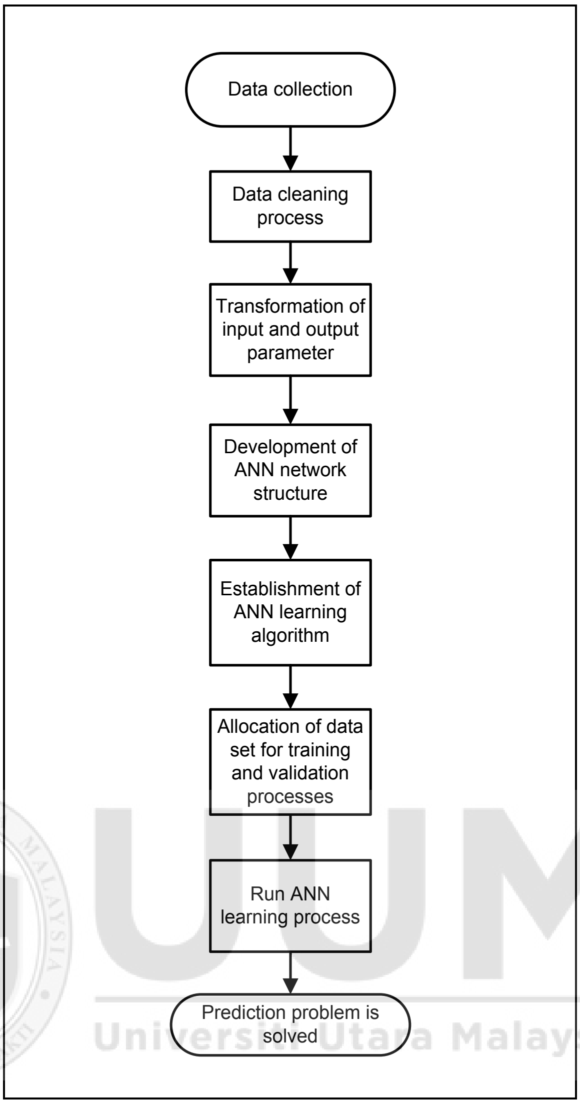


Figure 3.2. Steps in learning process of Artificial Neural Networks

Before predicting the future occurrence of a new case, data is collected for the preparation of ANN learning process (Huang, Chen & Siew, 2006; Turban et al., 2011; Zhang, 2017). Subsequently, several steps in the learning process are conducted to solve prediction problem. Thus, data cleaning process, data transformation, development of network structure, establishment of learning algorithm, and allocation of data for training and validation processes are considered as the major steps in ANN learning process and are discussed further in the next section.

3.1.3 Data Cleaning for ANN Learning Process

The capability of ANN in solving prediction problem is based on the preprocessing data collection through data cleaning (Rahman, 2002; Kumar, 2013). Data cleaning is a process of removing inconsistent and missing values within the data (Rahman, 2002; Jamil & Shaharanee, 2015). Thus, the occurrence of inconsistent and missing values contributes to a biased prediction result (Samarasinghe, 2016).

The missing and inconsistent data are normally replaced with actual values by referring the source of the data (Azadeh et al., 2014; Samarasinghe, 2016). Alternatively, an arithmetic mean formula is formulated to replace the missing and inconsistent data (Mehrjerdi & Aliheidary, 2014). An arithmetic mean formula is the sum of all of the items in a data and divided by the number of the items (Russell & Taylor, 2011; Zhang, 2017). However, arithmetic mean formula would modify the input distribution, thus reducing prediction performance (Ahmarofi et al., 2017). Hence, the completed data without modification value is important to ensure that the prediction result has better performance.

3.1.4 Transformation Function for ANN Input and Output Parameters

Once the collected data is cleaned from missing and inconsistent data, the data is transformed through a transformation function, which is a formulation to normalize the large input parameter and output parameter to small value for a smooth learning process (LeCun et al., 1998; Ismail, 2002; Zhang, Gao & Zhao, 2017). The input parameter, *input*, and output parameter, *output*, are transformed to the range between the interval 0 and 1 or normally presented by [0, 1] (Rahman, 2002; Mehrjerdi & Aliheidary, 2014). The most common transfer function for transforming input and output parameters is MIN-MAX function (Kumar, 2013; Karam et al., 2016) as expressed in the following equation:

$$input_{transformed} = \frac{input_{ori} - input_{min}}{input_{max} - input_{min}} \quad (3.1)$$

where

$input_{transformed}$ = transformation value for *input*

$input_{ori}$ = original value for *input*

$input_{min}$ = minimum value for *input*

$input_{max}$ = maximum value for *input*

$$output_{transformed} = \frac{output_{ori} - output_{min}}{output_{max} - output_{min}} \quad (3.2)$$

where

$output_{transformed}$ = transformation value for *output*

$output_{ori}$ = original value for *output*

$output_{min}$ = minimum value for *output*

$output_{max}$ = maximum value for *output*

The transformation function is able to reduce time consumption and effort in calculation due to its smaller value compared to original value (Rahman, 2002; Lekamalage et al., 2017). Subsequently, the transformed input and output parameters are utilized in the ANN learning process through development of network structure as further discussed in the section 3.1.5.

3.1.5 ANN Network Structure

A learning process to solve the prediction problem is conducted within a network structure or architecture. A network is an arrangement of interconnected structure in a system (Haykin, 2009; Kumar, 2013; Esfe et al., 2015). The ANN network structure is classified into two types which are feed-forward multilayer perceptron network (MLP) and recurrent network (Wang et al., 2001; Rahman, 2002; Zhang et al., 2017). However. the MLP network has a better prediction performance as compared to the recurrent network (RN) due to the MLP network has multiple layers of structure which is able to do forward and backward propagation for input and output, respectively. On the other hand, RN has at least one feedback loop with a chaotic structure (Turban et al., 2011; Lekamalage et al., 2017; Wang & Jiang, 2017). Thus, MLP network is more suitable for training process in solving prediction problem based on its architecture.

The MLP network is a structure to transfer input value from input layer to output layer through hidden layer (Rahman, 2002; Haykin, 2009; Kumar, 2013). On the other hand, perceptron is an association among input, hidden and output layers in MLP network (Turban et al., 2011; Samarasinghe, 2016). The structure of MLP network is illustrated in Figure 3.3 as follows.

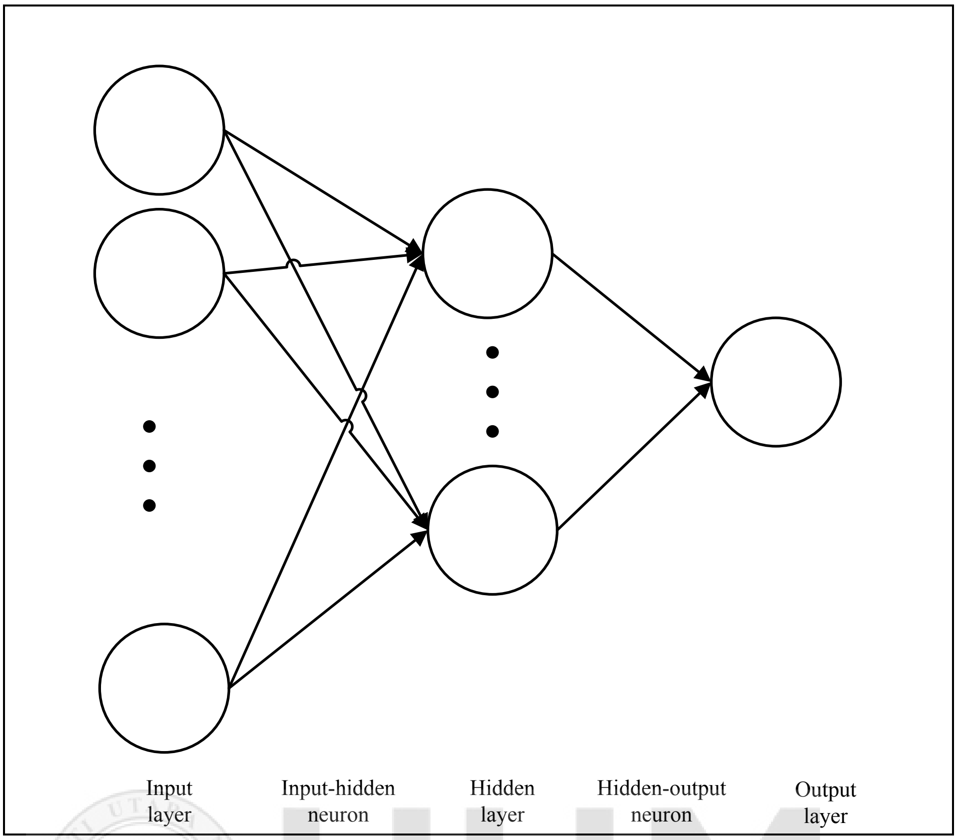


Figure 3.3. Network structure of feed-forward multilayer perceptron
Source: Turban et al. (2011)

The structure of MLP network contains three layers which are input layer, hidden layer and output layer (Wang et al., 2001; Samattapapong & Afzulpurkar, 2016). Each of the layers consists of several nodes. A node is a processing center of information for each layer (Ismail, 2002; Chen et al., 2011). On the other hand, the connection among input, hidden and output nodes are termed as neuron (Haykin, 2009; Azadeh et al., 2014). The function of neuron is to pass input value from one node to another node, hence the learning process within the network is interconnected.

The function of the input node is to receive and process input value to the network (Kumar, 2003; Dzakiyullah, 2015). On the other hand, the function of the hidden node is to transfer input value from input node to output node through a learning process (Haykin, 2009; Ahmarofi et al., 2017). Finally, the function of the output node is to transfer an input from hidden node to output node through a learning process for prediction result (Azadeh et al., 2014; Dzakiyullah, 2015). The learning process at input, hidden and output nodes is aimed to match the prediction target. Therefore, the learning process needs to be supervised to keep the MLP structure on the right track towards the targeted output.

Supervised learning is a learning technique to guide the network towards the targeted output through a training set of collected data (Kumar, 2013; Samarasinghe, 2016). The training set is a group of input value with corresponding to the desired output value from collected data (Haykin, 2009; Zhang, 2017). On the other hand, unsupervised learning is a learning technique with no guidance towards output target but learns through an image exposure (Turban et al., 2011), hence it is unsuitable for prediction purpose. The learning processes through supervised learning are illustrated in Figure 3.4 as follows.

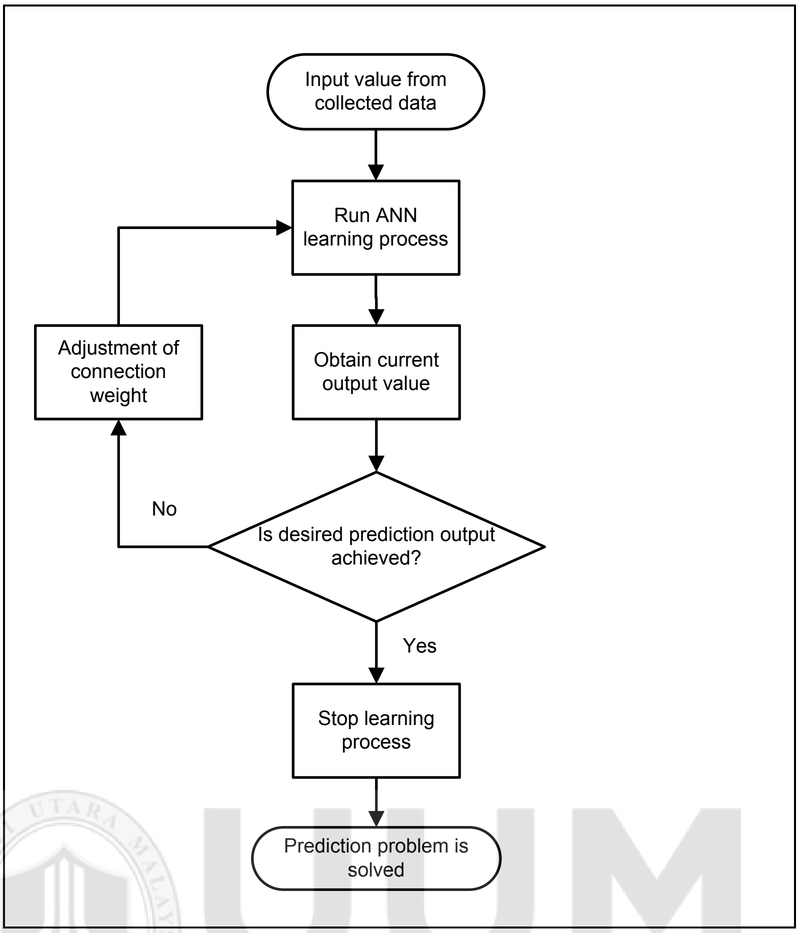


Figure 3.4. Supervised learning process of Artificial Neural Networks

The output value from the MLP network is compared with the desired output value to determine how close both outputs were in solving the prediction problem (Karam et al., 2016; Samarasinghe, 2016). The comparison between the values of the output network with the desired output is measured through a connection weight based on formulation of learning algorithm (Mehrjerdi & Alihidary, 2014; Dzakiyullah, 2015). Hence, learning algorithm is essential to obtain the desired output as further elaborated in section 3.1.6.

3.1.6 Learning Algorithm for ANN Network Structure

The learning process of MLP network is conducted through an appropriate learning algorithm. Learning algorithm is a step of calculation rule to solve a problem (Russell & Taylor, 2011; Jamil & Shaharanee, 2015). In ANN, the learning algorithm is formulated to determine how the connection weights should be corrected to solve prediction problem (Samarasinghe, 2016). The connection weight is corrected based on the difference between the value of MLP network output and desired output (Haykin, 2009; Kumar, 2013). The taxonomy of ANN learning algorithms is based on Medsker and Liebowitz (1994) is presented in Figure 3.5.

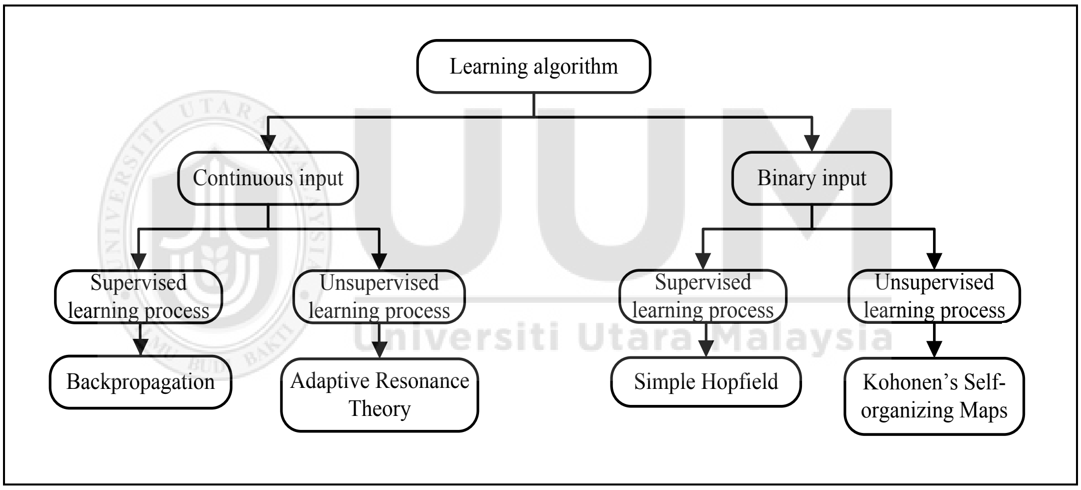


Figure 3.5. Taxonomy of learning algorithm in Artificial Neural Networks

There are several types of learning algorithms for ANN and the most popular are Simple Hopfield, Adaptive Resonance Theory (ART), and Kohonen's Self-organizing Maps (SOM) (Haykin, 2009; Samarasinghe, 2016). Simple Hopfield is a learning algorithm for a problem with objective function and subjected to a number of constraints and suitable in solving optimization or mathematical programming problem (Wang & Jiang, 2017). On the other hand, ART is a learning algorithm with self-learning without input value provided to the network towards the correct target and suitable for clustering analysis (Karam et al., 2016). SOM is a learning process that represents multidimensional data and is suitable to be implemented in visualizing identification such as in image processing (Haykin, 2009; Turban et al., 2011).

Hopfield network is a complex structure in terms of determining the correct measurement of the interconnection weight as well as suffers in finding the global optimum solution as found in the study Venugopal and Narendran (1992) and Wang and Jiang (2017). Besides, SOM network is only suitable for clustering or grouping of various images from database as presented by Chakraborty and Roy (1993) and Karam et al., 2016). Therefore, Hopfield and SOM networks are not suitable to solve prediction problems.

However, most of the previous works are successfully implemented backpropagation learning algorithm (BP) in their studies to predict cycle time at production site as presented by Azadeh et al. (2014), Mehrjerdi and Alheidary, (2014), Karam et al. (2016) and Samattapapong and Afzulpurkar (2016) and Wang and Jiang (2017). BP is a supervised learning algorithm which propagates back the error between the value of output network with desired output (Dzakiyullah, 2015; Samarasinghe, 2016). BP algorithm is suitable for MLP network structure for prediction purpose (Ismail, 2002; Latif, 2009; Karam et al., 2016). Therefore, BP apparently becomes the most widely used learning algorithm in production process for solving prediction problems as further discussed in the subsection 3.1.7 as follows.

3.1.7 Learning Parameters in Backpropagation Learning Algorithm

BP has several suitable learning parameters which are connection weight, summation function, sigmoid function, square error function, learning rate and momentum rate to forward input value within the MLP structure (Ismail, 2002; Latif, 2009; Kumar, 2013). The formulation of major learning parameters for BP algorithm are further discussed in the following subsections for prediction performance.

3.1.7.1 Connection Weight for Input-Output Relative Strength

The most important learning parameter for BP learning algorithm is connection weight (Azadeh et al., 2014; Karam et al., 2016). Connection weight, *w*, is a relative strength in a mathematical value within connections of neurons from layer to layer (Haykin, 2009; Wang & Jiang, 2017). The function of connection weight is to represent the importance of each input towards desired output through repeated adjustment during learning process. Hence, the network is able to learn the solution for prediction problem.

However, to the best of our knowledge, there is no rule of thumb to determine the value of weight rather than iterative adjustment for trial and error during learning process in the range of 0.1 to 100 as presented by Latif (2009), Azadeh et al. (2014), Mehrjerdi and Aliheidary (2014) and Karam et al., (2016) and Ahmarofi et al. (2017). Subsequently, the connection weight is accumulated with input value at each node through summation function and sigmoid function as discussed in the following subsection.

3.1.7.2 Summation and Sigmoid Transfer Functions during Learning Process

The input value at each node is accumulated with connection weight through summation function. Summation function is a formulation to compute the sum of all connection weights with input value at each node (Haykin, 2009; Karam et al., 2016). At the hidden node, *b*, the connection weight which allocated to each input-hidden node is multiplied with respective input value (Feng, Huang Ling and Gay, 2009; Esfe et al., 2015). Then, all multiplied values are summed up by summation function to obtain total weighted sum for *b*th hidden node. The calculation for summation function at hidden node, *b*, is expressed as follows:

$$sum_b = \sum_{a=1}^{A} w_{ab} trans_{input} \tag{3.3}$$

where

sum_b = the weighted sum for *b*th hidden node

w_{ab} = the connection weight for the *a*th input node and *b*th hidden node

$trans_{input}$ = transformation value of *input*

Subsequently, the total weighted, sum_b, is transformed to a nonlinear form through sigmoid function (Haykin, 2009; Samarasinghe, 2016). Sigmoid function is an S-shaped nonlinear function within the range of 0 to 1 or [0, 1] (Russell & Taylor, 2011; Esfe et al., 2015). Nonlinear is a pattern of output value which varies with the input value. Thus, as highlighted by Kumar (2013) and Samarasinghe (2016), the transformed value in a nonlinear form is important for enabling BP algorithm to possibly conduct learning process in MLP network structure from input layer to output layer.

The formulation of the sigmoid function for *b*th hidden node is expressed as follows:

$$sig_b = \frac{1}{(1 + e^{sum_b})} \tag{3.4}$$

where

sig_b = the sigmoid value of *b*th hidden node

sum_b = the weighted sum of *b*th hidden node

e = the base of natural logarithm with a constant value, 2.71828

After that, the sigmoid value, sig_b, is forwarded to the output node, *c*, for summation process through summation function. At the output node, the connection weight which allocated to each hidden-output node is multiplied with sigmoid value of hidden node, sig_b. Thus, the summation function at the output node, *c*, is expressed as follows:

$$sum_c = \sum_{b=1}^{B} w_{bc} sig_b \tag{3.5}$$

where

sum_c = the weighted sum of *c*th output node

w_{bc} = the connection weight for the *b*th hidden node and *c*th output node

sig_b = the sigmoid value of *b*th hidden node

After that, the total weighted of output node, sum_c, is transformed to a nonlinear form through sigmoid function (Kumar, 2013; Lekamalage, 2017). Thus, the sigmoid transfer function for the output node, *c*, is expressed as follows:

$$sig_c = \frac{1}{(1 + e^{sum_c})} \tag{3.6}$$

where

sig_c = the sigmoid value of *c*th output node

sum_c = the weighted sum of *c*th output node

e = the base of natural logarithm with a constant value, 2.71828

The sigmoid value of *c*th output node, sig_c, is then substituted in the formulation of square error function. Thus, the indicator to stop the learning process is achieved through square error function (Mehrjerdi & Aliheidary, 2014; Jamil & Shaharanee, 2015) as elaborated in the following subsection.

3.1.7.3 Square Error Function between MLP Output and Desired Output

The value of sigmoid transfer function, sig_c, which produced by output node, *c*, of MLP structure is transmitted to square error function. Square error function, *E*, is a formulation to calculate the error between output value of MLP network with desired output value (Mehrjerdi & Aliheidary, 2014; Dzakiyullah, 2015). The purpose of square error function is as a stopping criterion for BP algorithm to accomplish learning process once minimum error is achieved (Huang et al., 2006; Zhang et al., 2017). Thus, the minimum error is obtained by comparing the difference between the value of MLP network output i.e. the sigmoid value of output node, sig_c, with desired output i.e. transformation value of $output, output_{transformed}$. The calculation of square error function is expressed as follows:

$$E_o = \frac{1}{2}([sig_c]_o - output_{transformed})^2 \quad \forall o = 1,2,\ldots O \tag{3.7}$$

where

E_o = the square error of oth iteration

sig_c = the sigmoid value of cth output node i.e. the MLP network output value

$output_{transformed}$ = the transformation value of *output*

Moreover, the square error has a gradient, *d*, which is a slope of the error between the output value of MLP network with the desired output value (Feng et al., 2009; Wang & Jiang, 2017). Gradient is necessary in learning process to indicate how much to descend into the slope of the error with respect to modification of connection weight until the network has minimum error (Huang et al., 2006; Zhang et al., 2017). As highlighted by Dzakiyullah (2015), the descent of gradient is generated by derivation function between square error function, *E*, and the connection weights for *a*th input node and *b*th hidden node, w_{ab}, and *b*th hidden node and *c*th output node, w_{bc}. The derivation of both connection weights i.e. w_{ab} and w_{bc} are expressed as follows:

$$[d_{w_{ab}}]_o = \frac{\partial E_o}{\partial w_{ab}} \quad \forall o = 1,2,\ldots O \tag{3.8}$$

where

$[d_{w_{ab}}]_o$ = the gradient value for weight of *a*th input node and *b*th hidden node of *o*th iteration

∂E_o = the derivation for square error function of *o*th iteration

∂w_{ab} = the derivation for weight of *a*th input node and *b*th hidden node

$$[d_{w_{bc}}]_o = \frac{\partial E_o}{\partial w_{bc}} \quad \forall o = 1,2,\ldots O \tag{3.9}$$

where

$[d_{w_{bc}}]_o$= the gradient value for weight of *b*th hidden node and *c*th output node of *o*th iteration

∂E_o = the derivation for square error function of *o*th iteration

∂w_{bc} = the derivation for weight of *a*th input node and *b*th hidden node

Subsequently, during the descent of the slope error with respect to modification of connection weight, the descent's direction is controlled by several parameters. Hence, a learning rate and momentum rate are considered to control how much of the value of previous connection weight is required to modify in every iteration, *o*, of the learning process.

3.1.7.4 Learning Rate for Adjusting Connection Weight

Once the derivation of square error is obtained, the increment of connection weight is adjusted by learning rate. Learning rate is a parameter for controlling the speed of learning process in BP learning algorithm (Feng et al., 2009; Gaud et al., 2016). The function of learning rate is to control the speed of the learning process (Huang et al., 2006; Samattapapong & Afzulpurkar, 2016). Thus, the increment of weight based on learning rate parameter is expressed as follows:

$$\Delta w_o = -\varepsilon d_o \quad \forall o = 1,2,\ldots O \tag{3.10}$$

where

Δw_o = the increment for a connection weight of *o*th iteration

ε = learning rate

d_o = the gradient value of oth iteration

However, to the best of our knowledge, there is no rule of thumb in determining the learning rate value. A high value of the learning rate contributes to too much correction for connection weight value due to the BP algorithm go back and forth among possible values without reaching optimal value (Haykin, 2009; Dzakiyullah, 2015). In contrast, a low value of the learning rate contributes to too slow learning process and long training times (Huang et al., 2006; Feng et al., 2009; Esfe et al., 2015). On the other hand, Shiang (2009), Chen et al. (2011) and Karam et al., (2016) highlighted that the suitable value of learning rate is within the range of 0.1 to 1.0 during learning process. Hence, the selection of learning rate value is crucial to correct connection weight for optimal value.

According to Kumar (2013), researcher normally tests with various learning rate value to obtain optimal learning process. On the other hand, Samarasinghe (2016) emphasized that there is no direct way to set the value of learning rate other than by trial and error as presented by Rahman (2002), Azadeh et al. (2014) and Ahmarofi et al., (2017). Hence, any of the heuristics approaches is suitable to implement in determining the value of learning rate since none of the practices are claimed as the best technique.

3.1.7.5 Momentum Rate

After the speed of learning process is controlled by learning rate, the increment of connection weight is subsequently adjusted by momentum rate. Momentum rate is a parameter for stabilizing the speed of learning process (Rahman, 2002; Gaud et al., 2016). The function of momentum rate is to slow the learning process. Thus, the learning process is gradually guided to reach the optimal value of connection weight (Leung, Lam, Lim & Tam, 2003; Zhang et al., 2017). The subsequent weight increment during *o*th iteration is expressed as follows:

$$\Delta w_o = \mu \Delta w_{0-1} - (1-\mu)\varepsilon d_o \tag{3.11}$$

where

Δw_o = the increment for connection weight of *o*th iteration

μ = momentum rate

Δw_{o-1} = the increment of connection weight of previous *o*th iteration

ε = learning rate

d_o = the gradient value of *o*th iteration

According to Rahman (2002), Latif (2009), Shiang (2009), Chen et al. (2011) and Azadeh et al. (2014), the selection of a suitable value for momentum parameter in ANN has no restriction as it is commonly based on experimenting with various different values. According to LeCun et al. (1998) and Haykin (2009), the value of momentum should be restricted to the range $0 \leq |\mu| < 1$. In addition, Kumar (2013) also highlighted that momentum should be less than 1. Hence, the range between 0 and 1 is the suitable value for momentum rate in a learning process.

In previous literatures, Rahman (2002) employed training pseudo code in his experiment in order to get value of momentum rate randomly while Latif (2009), Chen et al. (2011) and Gaud et al. (2016) applied different values of momentum rate in their experiment and selection was made based on the result with high percentage of test accuracy or low square error value. Since none of the approaches are claimed as the best practice, therefore, the determination of suitable value for momentum rate is based on the results of one's own personal experience through heuristics approach.

3.1.8 Data for Training and Validation Processes

Besides learning rate and momentum rate, the training process is also necessary to adjust the connection weight value. Training process in ANN is a procedure to train a set of data for learning algorithm to adjust the connection weight (Latif, 2009; Karam et al., 2016). Subsequently, validation process in ANN is a procedure to validate the optimal value of connection weight through another set of data (Leung et al., 2003; Samattapapong & Afzulpurkar, 2016). Normally, the collected data are randomly allocated to the training process and validation process (Rahman, 2002; Latif, 2009; Gaud et al., 2016). However, the training process is crucial for ANN to learn the relationship among variables from historical data (Ismail, 2002; Azadeh et al., 2014; Jamil & Shaharanee, 2015). Hence, more data are allocated to the training process compared to validation process since more data can ensure better exposure during learning process.

3.1.9 Prediction Result of MLP Network for Prediction Purpose

Finally, BP algorithm with related learning parameter is ran within MLP network to search the optimal connection weight with minimum error to solve prediction problem. Thus, the equation of prediction result is expressed as follows:

$$y_{predict} = \sum_{a=1}^{A} [w_{ab}]_o input_{transformed} + \sum_{b=1}^{B} [w_{bc}]_o \, sig_b \tag{3.12}$$

where

$y_{predict}$ = predicted output value

$[w_{ab}]_o$ = final connection weight for *a*th input node and *b*th hidden node of *o*th iteration

$input_{transformed}$ = the transformed value of *input*

$[w_{bc}]_o$ = final connection weight for *b*th hidden node and *c*th output node of *o*th iteration

sig_b = the sigmoid function value of *b*th hidden node

3.2 Concepts and Theories of System Dynamics

System dynamics (SD) is a computer simulation technique in understanding behavior of a complex and dynamic system over time (Sterman, 2000; Garcia, 2016). Computer simulation is a technique for conducting experiment with an aid of computer in visualizing a real system through graphical structure and mathematical formulation (Mussa, 2009; Sumari et al., 2013; Dan & Yisheng, 2017). Furthermore, the dynamic behavior in SD is the occurrence of changes within a system at various times in a nonlinear form (Sterman, 2000; Olaya, 2015). On the other hand, complexity behavior is a characteristic of various elements in multiple ways within a system (Aslam, 2013; Sapiri et al., 2017). Hence, complexity and dynamic are two important behaviors in describing the modeling process of a system within SD as further discussed in the following subsections.

3.2.1 Modelling Process in System Dynamics

Modeling process of SD is created by Jay W. Forrester from Massachusetts Institute of Technology through Industrial Dynamics in 1958 (Forrester, 1961). Then, the framework of SD has been further developed by Forrester in Urban Dynamics and World Dynamics (Forester, 1971) which emphasized on the nonlinear control system for hiring employees and managing inventory (Forrester, 1989). Since then, SD is widely implemented in various fields such as healthcare (Dangerfield & Abidin, 2011), manufacturing Mehrjerdi & Aliheidary, 2014), education (Goyol & Dala, 2014) and investment (Dan & Yisheng, 2017).

The purpose of modelling in SD is to improve decision making in solving a problem based on a hypothesis or working theory (Sumari et al., 2013; Garcia, 2016). As illustrated in Figure 3.6, there are five stages in the modelling process of SD which are problem articulation, model conceptualization, model formulation, model testing and finally, model evaluation and policy improvement as highlighted by Sterman (2000).

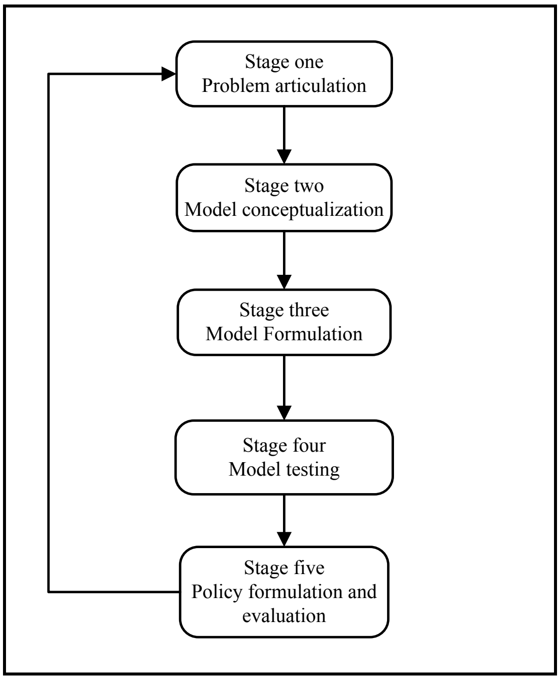


Figure 3.6. The development of system dynamics modelling process
Source: Sterman (2000).

In SD modelling process, the iteration may happen continually until the structure and behavior of the model mimic the real system (Sterman, 2000). Problem articulation, model conceptualization, model formulation, model testing, policy improvement and model evaluation are five important stages in the development of SD modelling to behave as the real system (Chen et al., 2011; Azadeh et al., 2014; Inam et al., 2015). The five stages in the development of SD model are elaborated in the following sections.

3.2.2 Problem Articulation

A specific problem is focused clearly in this stage. Problem articulation is the process of recognizing the scope of the problem under research (Sterman, 2000; Ruth & Hannon, 2004; Tigist et al., 2015) while personal interviews and brainstorming sessions with those individuals who have the most experience with the problem is a common practice (Forrester, 1971; 1980). The purpose of problem articulation is to set a clear objective to solve the problem (Aslam, 2013; Dan & Yisheng, 2017). The clear objective is established from preliminary information, data collection and perspectives of various sources such as journals, articles and expert opinion (Sterman, 2000; Inam et al., 2015; Sapiri et al., 2017). Hence, a specific problem is addressed rather than considering the entire system in detail.

Besides, reference mode and time horizon are important to consider during the stage of problem identification (Mussa, 2009; Aslam, 2013). Reference mode is a data set of important variables related to a problem under research within a certain period (Sterman, 2000; Azadeh et al., 2014). The purpose of determining reference mode is to provide an understanding regarding behavior of the problem over a period (Mussa, 2009; Shadmanpoor & Nikbaht, 2017). On the other hand, time horizon is a boundary of time for upcoming occurrence of the problem (Sapiri et al., 2017). The purpose of selecting time horizon is to ensure the developed SD model is able to capture how the problem emerged. Hence, the determination of reference mode and time horizon is able to provide as much information as possible to the modeler to define the problem effectively.

Subsequently, the identified problem is further conceptualized to capture the cause and effect relationship among the main variables. Hence, model conceptualization is further developed towards the problem in capturing the cause and effect relationship of variables as discussed in the following section.

3.2.3 Model Conceptualization as a Dynamic Hypothesis

The elements related to the identified problem are graphically represented through model conceptualization. Model conceptualization is a dynamic hypothesis or a working theory on how the problem under research arose (Olaya, 2015; Garcia, 2016). The purpose of model conceptualization is to provide a clear picture of relationship between cause and effect relationship of variables (Inam et al., 2015; Hoseini & Tan, 2017). Therefore, discussion of the problem and related theories regarding the cause and effect relationship of main variables are categorized under endogenous or exogenous explanation as highlighted by Sterman (2000) and Inam et al. (2015).

The endogenous variable is a variable which arise from within the problem under research (Olaya, 2015; Garcia, 2016). On the other hand, exogenous explanation is a variable which arise from outside the problem under study (Pai et al., 2015; Hoseini & Tan, 2017). Endogenous variable has high impact towards the problem while exogenous variable has less impact on the problem (Tigist et al., 2015; Sapiri et al., 2017). However, the importance of exogenous variable is not neglected during discussion to have a clear understanding of the problem in as a whole.

A variety of tools are available to assist the modeler in representing the structure of model conceptualization. Several tools as highlighted by Sterman (2000) are presented in Figure 3.7. There are stock and flow maps, model boundary chart, subsystem diagram, policy structure diagrams and causal loop diagrams (Sterman, 2000; Garcia, 2016).

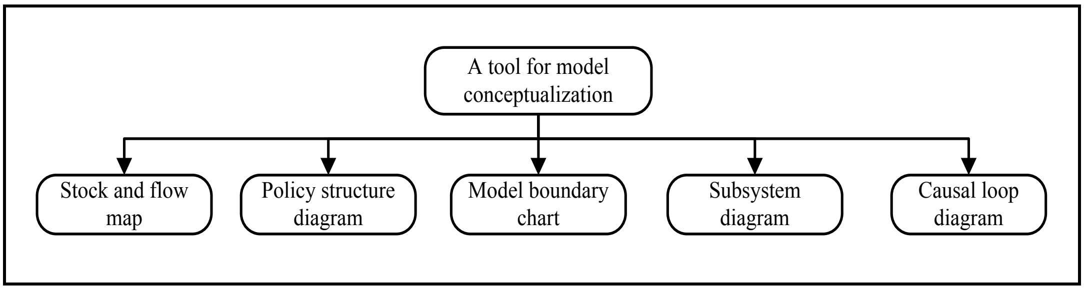


Figure 3.7. A common structure of a tool for model conceptualization
Source: Sterman (2000)

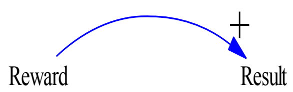
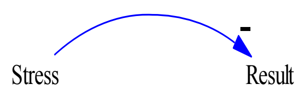
Stock and flow map is a physical drawing of stock and flow which plot the feedback structure of a problem (Sumari et al., 2013; Hoseini & Tan, 2017). On the other hand, policy structure diagram is a causal structure with time delays (Moon & Kim, 2005; Inam et al., 2015) while model boundary chart is a chart that separately show endogenous, exogenous variables and excluded variables of the problem (Sterman, 2000). Subsystem diagram is a diagram of mind mapping that shows the architecture of overall flows for related information in the system by including endogenous and exogenous variables (Garcia, 2016).

In contrast, causal loop diagram (CLD) is a structure of feedback loop diagram from a cause variable to an effect variable (Goyol & Dala, 2014; Olaya, 2015; Inam et al., 2015). It is found that most of the previous literature developed CLD to conceptualize problem based on brainstorming session with experts as presented by Aslam, (2013), Goyol and Dala (2014), Mehrjerdi and Aliheidary (2014), Inam et al. (2015) and Shadmanpoor and Nikbaht (2017) since CLD quickly captures a dynamic hypothesis of the cause and effect relationship of the problem. However, it is found that the previous works are lack of determining the strongest relationship among exogenous variables towards the problem under research as found in Aslam, (2013), Goyol and Dala (2014), Mehrjerdi and Aliheidary (2014), Inam et al. (2015) and

Shadmanpoor and Nikbaht (2017). Hence, the improvement for dynamic hypothesis is required to consider in the development of CLD for an effective working theory towards a problem under research.

In developing CLD, a curved line with arrow is created to represent causal relationship among variables. Causal relationship is an information feedback which link one variable to another variable to represent cause and effect relationship (Goyol & Dala, 2014; Olaya, 2015; Ahmarofi et al., 2017). Every link in the diagram is required to be labeled with link polarity while the related variable should be termed in meaningful and proper noun (Olaya, 2015; Sapiri et al., 2017). A link polarity is a polarization symbol between related variables, whether positive (+) or negative (-). The purpose of creating link polarity is to describe the effect of changing a variable parameter towards another variable parameter. Table 3.1 explains the example of causal relationship with link polarity in the development of CLD.

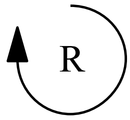
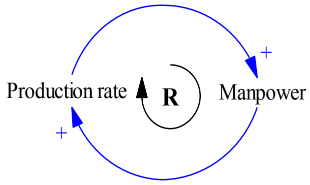
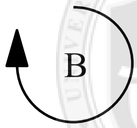
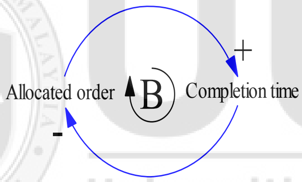
Table 3.1
Link polarity in the development of causal loop diagram

Example of causal relationship	**Explanation for the example of causal relationship**
	The (+) sign within an arrow indicates that if parameter of *reward* variable increases, then the parameter of *result* variable also increases. On the other hand, if the parameter of *reward* variable decreases, so does the *result*.
	The (-) sign within an arrow indicates that if parameter of *stress* variable increases, then parameter of *result* variable decreases. In contrast, if the parameter of *stress* variable decreases, then the parameter of *result* variable increases.

Subsequently, the curved line with arrow among variables is linked until a closed loop is obtained. A closed loop is a feedback loop in circular shape with a cause and effect relationship among variable connections (Inam et al., 2015; Hoseini & Tan, 2017). The purpose of a closed loop is to create a dynamic behavior for a problem under research (Sterman, 2000; Sapiri et al., 2017). Thus, the behavior of a closed loop is determined through loop polarity.

Loop polarity is a characterization of a closed loop, whether in a reinforcing loop (positive) or balancing loop (negative) (Tigist et al., 2015; Ahmarofi et al., 2017). The purpose of reinforcing loop is to modify variable in two conditions whether to increase or decrease value (Mussa, 2009; Pai et al., 2015). On the other hand, the purpose of balancing loop is to create stability for a variable in case a parameter of the variable away from initial target (Inam et al., 2015). If the number of negative (-) link polarity is even, then the loop polarity is positive or categorized as reinforcing loop (R) (Sapiri et al., 2017). In contrast, if the number of negative (-) link polarity is odd, then the loop polarity is negative or categorized as balancing loop (B) (Sapiri et al., 2017). Table 3.2 explains the reinforcing loop and balancing loop polarities applied in this study.

Table 3.2
Description of loop polarity in the causal loop diagram

Symbol of loop polarity	Example of loop polarity	Description for example of loop polarity
		*Manpower* has same direction or positive relationship *with production rate* and vice versa. If the number of *manpower* decreases (increases), then the value of *production rate* also decreases (increases), accordingly. If the value of *production rate* decreases (increases), then the number of *manpower* also decreases (increases), accordingly.
		*Completion time* has contrary direction or opposite relationship to *allocated order* from customer. If the value of *completion time* increases (decreases), then the number of *allocated order* from customer should be decreased (increased) by management to avoid over capacity (excess capacity). However, *allocated order* has positive relationship with *completion time*. If the number of *allocated order* increases (decreases), then the value of *completion time* also increases (decreases) to fulfill customer request.

Subsequently, the establishment of CLD is accomplished once the connection of each variable is clearly captured in showing the cause and effect relationship among the variables. However, the parameter of each variable is required to measure since CLD is a qualitative tool. Hence, the established CLD is transformed into model formulation to measure the parameter of each variable as described in the following section.

3.2.4 Model Formulation based on Stock and Flow Concept

The qualitative analysis in CLD is transformed to model formulation to measure quantitative effect. Model formulation in SD is a structural diagram based on stock and flow concept or known as stock flow diagram (SFD) (Aslam, 2013; Azadeh et al, 2014). Stock is a reservoir to accumulate quantities and describe behavior of formulated model (Garcia, 2016; Shadmanpoor & Nikbaht, 2017). In contrast, flow is a rate function to increase or decrease the value of stock (Moon and Kim, 2005; Chen, 2016). The function of stock is to accumulate the quantities over time which resulted by the difference between flows rate (Sterman, 2000; Mehrjerdi & Aliheidary, 2014). On the other hand, flows are divided into two types which are inflow and outflow variables (Hoseini & Tan, 2017; Sapiri et al., 2017). The function of inflow variable is to add parameter to the stock variable over time while outflow variable is to subtract parameter from the stock variable over time. Hence, the formulation of stock and flow variables enables SFD as a quantitative tool to measure the parameter of each variable during simulation process.

In model formulation, there are no specific rules to transform CLD to SFD (Sapiri et al., 2017). However, a noun such as people, animal, productivity, to name a few, which are involved in a system is considered as stock (Garcia, 2016). On the other hand, an element contributes to the variation of the stock parameter over time such as person/hour, litters/day, to name a few, is considered as flow. As an analogous, a bathtub concept is a clear example to describe stock and flow concept as presented by Sterman (2000) and Garcia (2016) through Figure 3.8 as follows:

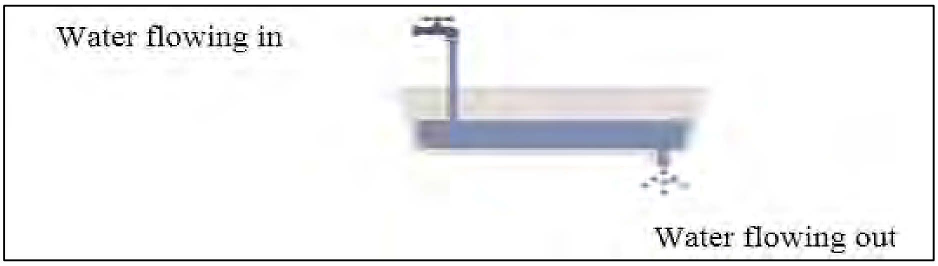


Figure 3.8. Bathtub diagram to illustrate the concept of stock and flow

Based on the bathtub concept, the inflow water fills stock of water in the tub while the water is drained through the outflow. As a result, the quantity of water (stock) in bathtub over time is accumulated by the rate of water flowing in through tap (inflow) and less the rate of water flowing out through the drain (outflow).

In SD modeling, the general structure of stock and flow is represented by development of SFD. SFD is a structural diagram with mathematical equations that quantify the parameter of each variable through stock and flow function. The formulation of equation for variable in SFD involves nonlinear function, $y= f(x)$ (Aslam, 2013; Hoseini & Tan, 2017). Nonlinearity is a chaotic condition which characterized by random and unpredictable behavior between dependent, y, and independent variables, x (Russell & Taylor, 2011). Hence, in the formulation of SFD, stock is considered as the dependent variable while inflow and outflow are considered as the independent variables.

The following equation expresses a flow which changes the stock resulting from inflow minus outflow:

$$flow = inflow - outflow \tag{3.13}$$

Besides, the net change in *stock* through rate between *inflow* and *outflow* over time, t, is equivalent to differential equation as follows:

$$\frac{d}{dt}\, stock = flow = inflow(t) - outflow(t) \quad (3.14)$$

On the other hand, the accumulation function of *stock* is determined by flows integration. Hence, the accumulation of stock function through *inflow* and *outflow* from initial time, t_0 to current time, t is expressed in the integral equations as follows:

$$stock(t) = \int_{t_o}^{t} [inflow(t) - outflow(t)]d(t) + stock(t_o) \quad (3.15)$$

Moreover, the auxiliary variable and constant variable are also formulated in the development of SFD. Auxiliary variable is an intermediate variable with equation while constant variable is a variable with constant value over time (Mussa, 2009; Houghton, 2016). The purpose of formulating auxiliary and constant variables is to break the inflow and outflow equation into smaller part (Tigist et al., 2015; Garcia, 2016). However, some variables are dimensionless since the variables have no applicable physical units (Sapiri et al., 2017). Therefore, the formulation of auxiliary and constant variables richer the dynamic behavior of SFD in simulation process.

Subsequently, the structure of SFD is developed through a formal diagraming icon for running computer simulation. Table 3.3 illustrates the formal diagraming icons involved in constructing SFD for enabling computer to run simulation as implemented by Dangerfield & Abidin (2011), Azadeh et al., (2014), Dan and Yisheng (2017), Zhang et al., (2017), to name a few.

Table 3.3
Formal diagramming icons of stock flow diagram

Elements	**Diagraming icon**
Stock	stock
Flow (inflow or outflow)	flow
Connector	

Referring to Table 3.3, stock, inflow, outflow and connector are diagraming icons in the development of SFD. An example of development SFD for computer simulation is illustrated in Figure 3.9.

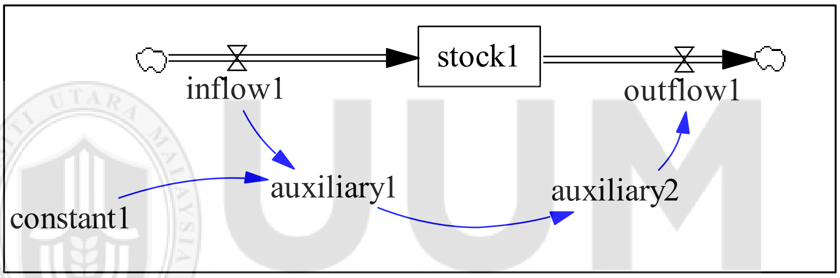


Figure 3.9. Example of developed stock flow diagram

Based on the example of Figure 3.9, the net change of *stock1* resulted from rate of *inflow1* minus rate of *outflow1* as expressed by Equation 3.16. Moreover, the accumulation of stock function through *inflow1* and *outflow1* from initial time, t_0 to current time, t is based on integral equations as expressed by Equation 3.18. On the other hand, the *auxiliary1* and *auxiliary2* are the intermediate variables linked by connector to show the cause and effect relationship between *inflow1* and *outflow1*. Besides, *constant1* is also connected to *auxiliary1* to provide constant value over time.

Besides, to capture the nonlinear relationship between auxiliary variables, a lookup table or table function is developed in SFD as presented by Oliva (1996), Aslam (2013) and Ahmarofi et al. (2017). The table function is established by including dependent variable as the input while independent variable as the output. Hence, by developing table function, the relationship of nonlinear value between the independent and dependent variables is able to be determined.

Subsequently, the equation and structure of stock, inflow, outflow, auxiliary and constant variables in the development of SFD are required to be validated before simulating the real system. Hence, a validation process is established with several tests to verify the ability of SFD in simulating the operations of real system as further discussed in the following section.

3.2.5 Validation of SFD Simulation

The capability of the developed SFD to mimic a real system is validated through a validation procedure. In SD, model validation is a process of establishing confidence in using the developed SFD (Mussa, 2009; Azadeh e al., 2014; Houghton, 2016). Therefore, the developed SFD is required to validate through structure and behavior assessments as highlighted by Barlas (1994), Sterman (2000), Mehrjerdi and Aliheidary (2014) and Hoseini and Tan (2017).

Structure assessment is a process of validating the diagram structure within developed SFD in terms of variable's connection, equation and parameter (Barlas, 1994; Houghton, 2016). The purpose of structure assessment is to validate the structure of developed SFD with the knowledge of a real system (Forrester & Senge, 1980; Ahmarofi et al., 2017). On the other hand, behaviour assessment is a process of validating the pattern of simulation output generated by SFD structure (Barlas, 1994; Mehrjerdi & Aliheidary, 2014; Houghton, 2016). The purpose of behaviour assessment is to validate the dynamic pattern of simulation output between the developed SFD and the real system (Forrester & Senge, 1980; Aslam, 2013). The validation procedure for conducting behavior and structure assessment of developed SFD as adopted from Forrester and Senge (1980) and Barlas (1996) are highlighted in Table 3.4 as follows.

Table 3.4
Types of assessment to validate stock flow diagram

Major Assessment	Types of Assessment	Description
Structure assessment	Structure verification assessment	To validate the construction of the developed model through the comparison with the real system based on the expert judgment or related previous works.
	Parameter assessment	To verify the consistency of parameter values of variables through comparison with relevant quantitative data of the real system or expert judgment.
	Extreme value condition	To test whether the related equation run normally under risk condition by varying input with extreme values (for example no manpower, no material).
	Dimensional assessment	To verify each equation is consistent with the real system by inspecting the equivalence of units on both sides of related equations.
Behavior assessment	Behavior reproduction	To test whether the model simulated the pattern of real system by comparing SFD output with the actual data of the real system.
	Behavior anomaly test	To examine the SFD result when assumption of the model changed by modifying the relationship of variables.

The selection of assessment is not restricted since no test is sufficient and it always based on the purpose of the research (Sterman, 2000; Azadeh et al., 2014; Sapiri et al., 2017). Besides, in behavior assessment, a base run simulation is conducted on the developed SFD. Base run is a current simulation result from developed SFD without changes on parameter or adding new variable(s) (Sterman, 2000; Mussa, 2009; Garcia, 2016). The purpose of conducting base run simulation is to validate current SFD result with actual data. In this regard, the simulation output is validated if the mean square error (MSE) is less than 10 percent (Sterman, 2000).

Once the developed SFD is validated through behavior and structure tests, a new policy to a system is proposed. However, the proposed policy from the developed SFD is required to evaluate. Hence, several strategies are developed to evaluate the effectiveness and sensitivity of policy formulation as discussed in the following section.

3.2.6 Policy Formulation based on Evaluation Procedure

The validated SFD is subsequently evaluated to improve policy of a system. Policy is a strategy and decision rule of a system in achieving long term goal (Sterman, 2000; Houghton, 2016). In SD, policy evaluation is a process of evaluating the sensitivity of developed SFD on uncertainties in terms of changing model parameter and structure (Aslam, 2013; Azadeh et al., 2014; Dan & Yisheng, 2017). However, the purpose of policy evaluation is not only about changing value of parameter and structure but also includes the development of intervention strategies and restructure of previous operation (Mehrjerdi & Aliheidary, 2014; Garcia, 2016). Hence, the policy formulation from the developed SFD is evaluated through two tools which are sensitivity test (Mussa, 2009; Aslam, 2013; Zhang et al., 2017) and optimization test (Dangerfield & Roberts, 2009).

Sensitivity test is an assessment procedure to evaluate a model responsiveness by changing the parameter through intervention strategy or known as what-if analysis

(Sterman, 2000; Azadeh et al., 2014). Intervention strategy is the action to eliminate or reduce the problem of a real system (Mussa, 2009; Zhang et al., 2017). The purpose of conducting intervention strategy is to determine the sensitive parameter which has a major impact on the model behaviour when changes are made (Houghton, 2016). Intervention strategy is created through various scenarios by varying certain input parameters while other parameters are constant (Kie, 2010; Sapiri et al., 2017). Alternatively, adding new variable(s) is also considered for intervention strategy (Houghton, 2016). Subsequently, the result of intervention strategy is compared with the base run to observe the impact on model behaviour. Therefore, by conducting sensitivity test, the developed SFD is able to identify the sensitive parameter for effective policy in solving problem on a real system.

On the other hand, optimization is a process of identifying the best possible solution to a problem (Dangerfield & Roberts, 2009). The purpose of optimization test is to determine optimal parameter which has an influence on the objective function (Sterman, 2000; Dangerfield & Roberts, 2009; Garcia, 2016). The optimization test is developed through formulation of objective function. Hence, the parameter value that maximizes and minimizes the objective function of a problem is able to be determined.

The selection of evaluation technique between intervention strategy, and optimization depends on the purpose of the model (Mussa, 2009; Sapiri et al., 2017). As a result, the best formulated policy that is potentially capable in solving a problem is proposed to management or related parties in dealing the cause of the problem. Consequently, the performance of their operation is improved.

3.3 Summary

This chapter elaborates the theories and concepts of ANN as a predictive technique and SD as an evaluation technique. Both techniques are considered as the integrated model to predict cycle time and in simulating production operation to determine completion time in producing audio speaker product at semiautomatic production line. However, it is found that previous studies related to ANN are lacking of formulating momentum rate for ANN learning process. Besides, previous studies related to SD are lacking in determining the influential variable in the development of CLD. In this regard, these requirements are considered in the research methodology for developing the integrated SD and ANN model as further discussed in the next chapter.

CHAPTER FOUR
RESEARCH METHODOLOGY

Chapter Four discusses the methodology to conduct this research. The methodology was designed to achieve the research objectives as discussed in Chapter One. Firstly, this chapter explains the research design, research processes and research framework. Secondly, the development of the proposed integrated Artificial Neural Networks (ANN) and System Dynamics (SD), ANNSD model is discussed to predict cycle time and simulate completion time of a new audio product at a semiautomatic production line. Finally, a summary of the research methodology is provided at the end of this chapter.

4.1 Research Design

This research aims to integrate the ANN and SD techniques for predicting cycle time and evaluating completion time of a new audio product at a semiautomatic production line. It was accomplished through seven stages which are articulation of a problem, literature review, data collection, development of an integrated ANNSD model, model validation, model evaluation, and policy improvement.

For a problem articulation, a manufacturer that produced a new audio product with at a semiautomatic production line was identified. Both primary and secondary data were collected. Primary data were gathered from experts in the Production Control Department and Production Department while secondary data were collected from daily reports from both these departments. These data were analysed in the development of an integrated ANNSD model. The proposed model was then validated by structure and behaviour assessment. Subsequently, the integrated

ANNSD model was evaluated through various scenarios of intervention strategy in production operation. As a result, a policy for improvement of the production operation was proposed to eliminate tardiness.

4.2 Research Processes

In order to obtain a clear idea to conduct this research, Figure 4.1 shows the stages involved in the research process, namely, articulation of a problem, reviews of the literature, data collection, development of an integrated ANNSD model, model validation and model evaluation, and policy improvement. A detailed discussion of the development of the proposed integrated ANNSD model is provided in Section 4.6.

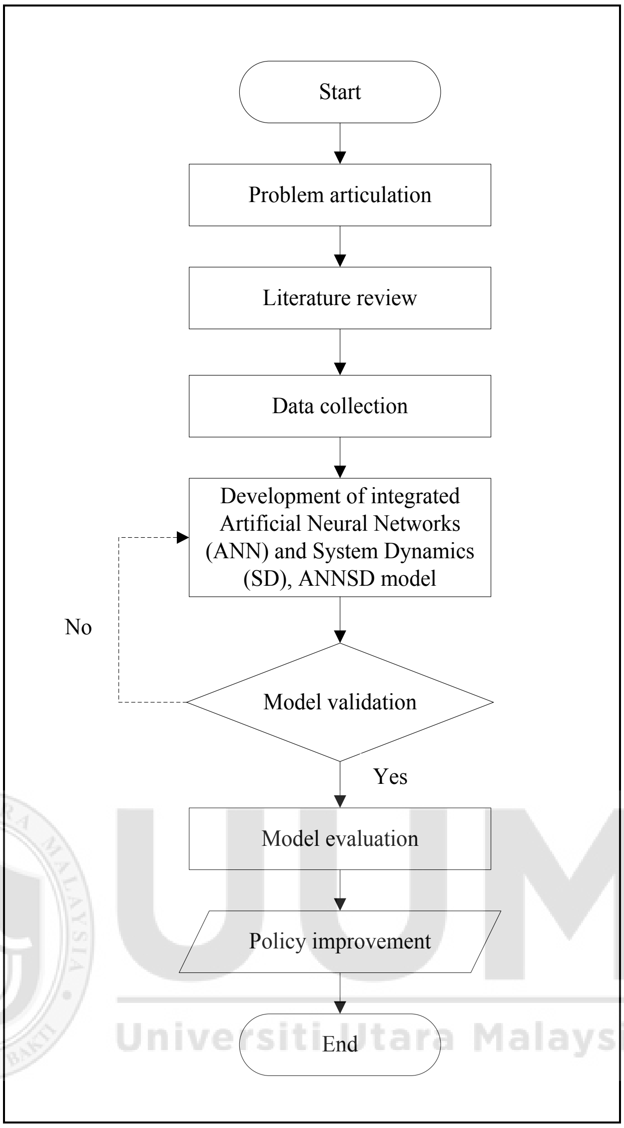


Figure 4.1. General flow of the research process

These stages are specified as phases of research activities carried out to achieve the research objectives (see Figure 4.2). It elaborates the structure of these research activities with the related methods on how to accomplish each particular objective. Furthermore, model validation and evaluation levels were merged in the same phase since both levels had the same purpose, which was to develop confidence of an integrated ANNSD model in mimicking the actual production operation.

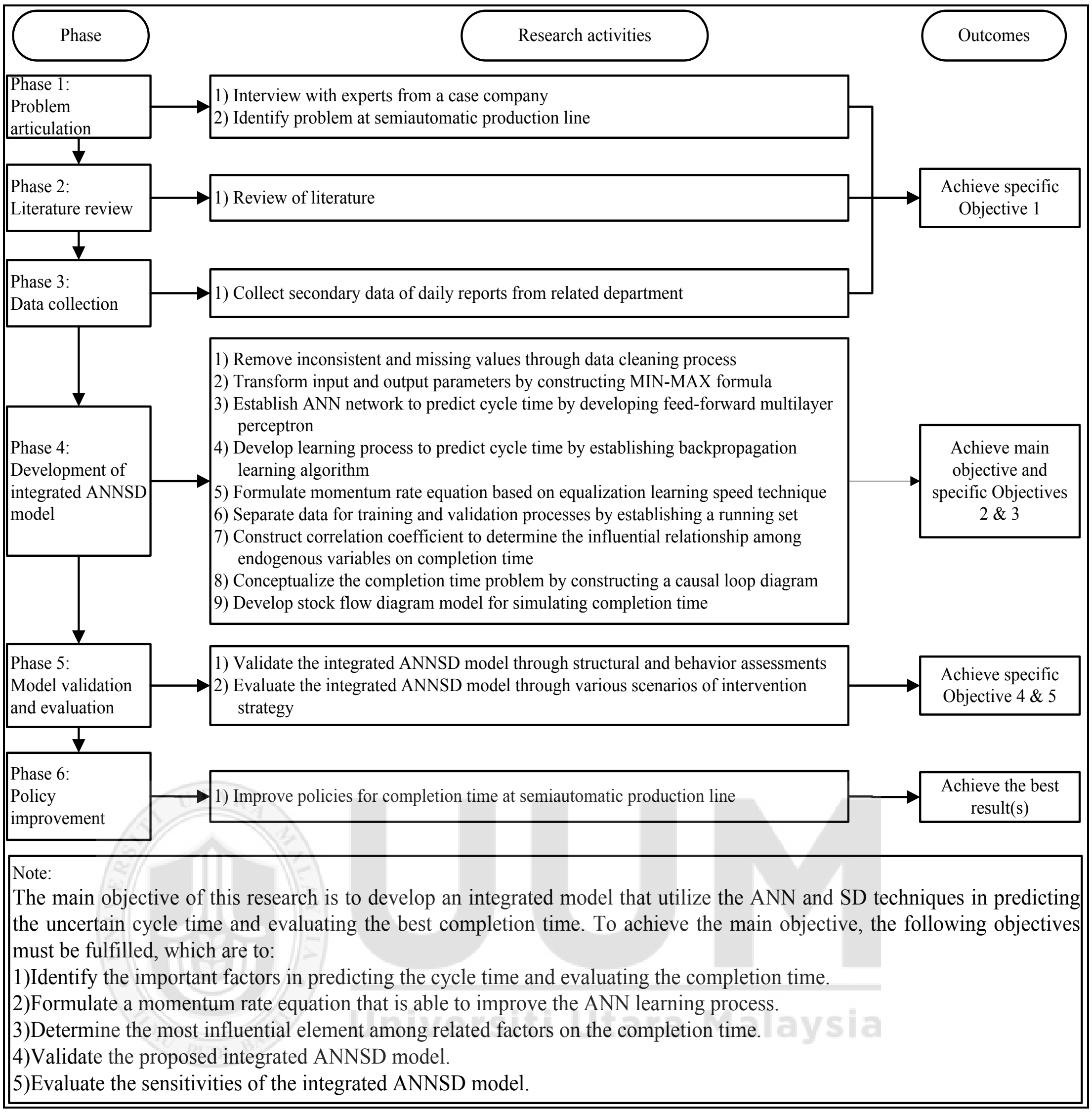


Figure 4.2. Detailed structure of research activities

4.3 Research Framework

Based on the problem statement and the research activities, a research framework was proposed as shown in Figure 4.3. In this framework, Phase 3 (data collection), Phase 4 (development of the integrated ANNSD model), Phase 5 (model validation and evaluation) and Phase 6 (policy improvement) are emphasized to exhibit a more strategic approach in achieving the research objectives. In addition, Phase 1 (problem articulation) is further explained in section 4.4, while phase 2 (literature review) was elaborated in Chapter 2. The framework highlights the data, function of the integration between the ANN and SD techniques, and policy improvement as the final outcome.

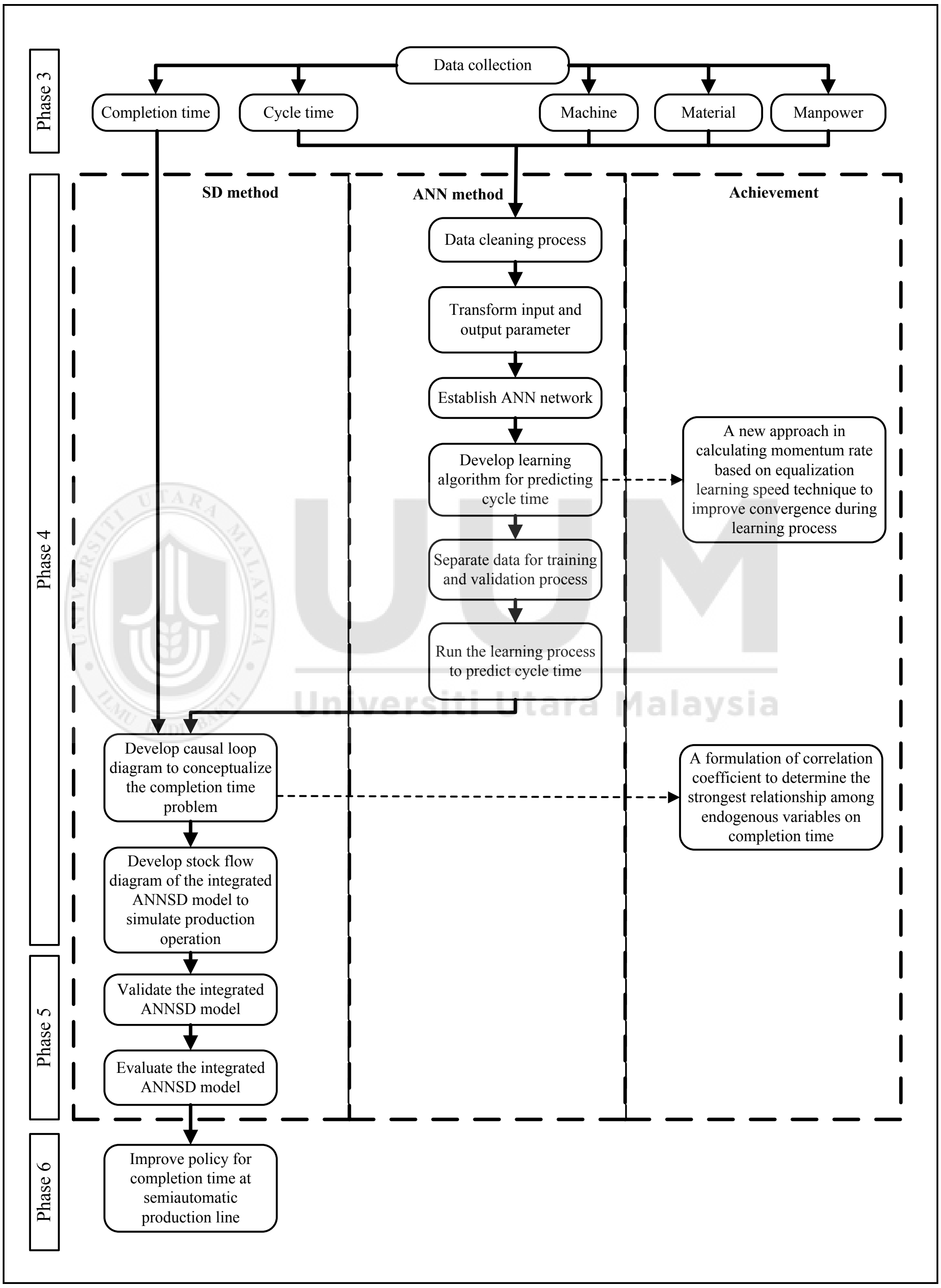


Figure 4.3. Research framework for predicting the cycle time and evaluating the completion time

4.4 Articulation of Problem

In order to develop the proposed integrated ANNSD model, a problem based on a real company situation was considered. The company is a global business manufacturer for audio products in the automotive sector for both the local and international markets. The company produced a new audio product to replace end-of-life (EOL) products in meeting customer requirements with the latest technology and upgraded features.

However, the company was facing an issue with uncertain cycle time of the new audio products at its semiautomatic production line based on a number of factors, which were manpower, material preparation time and machine breakdowns. As a result, the completion time of the new product was affected which contributed to tardiness, thus the production site was unable to fulfil customer delivery on-time. In addition, it is crucial to evaluate manpower fatigue, schedule pressure and production workload during production operation to avoid an unhealthy working environment. This situation has persisted frequently and the management was facing difficulties to overcome the problem. As a consequence, failure in fulfilling delivery on-time had ultimately resulted in production line down and air shipment which were costly for the manufacturer.

4.5 Data Source and Collection

Data on manpower, material, machine, cycle time and completion time were collected to identify factors related to cycle time and completion time. Data was recorded during the test runs of the new audio product and the production of existing audio products from January to March 2016. However, data for completion time was only available for the existing audio products while for the new audio product, the completion time was not recorded due to small quantity runs of less than 50 pieces.

Both primary and secondary data were used in this research. Primary data was gathered from interviews with experts of the company, namely the Production Planner from the Production Department, and the Production Control Executive from the Production Control Department. Each of them has over ten years of working experience and are experts at their job. Hence, their opinions regarding the factors related to cycle time and completion time through these interviews ensured that the collected data were related to the identified problem in fulfilling the first objective of this research. The open-ended interview questions are included in Appendix A. The primary data comprised of the factors related to the tardiness of completion time at semiautomatic production line in terms of manpower, material, machine, cycle time, and completion time.

Daily reports from the Production Control Department and Production Department were used as secondary data. Table 4.1 shows the sources of secondary data collected from the department.

Table 4.1
Sources of secondary data

Secondary data	Source
1.The number of manpower (in person)	Production control document
2.Waiting time for materials (in hours)	Production daily report
3.Machine breakdown rate (in 1 per pieces)	Production daily report
4.Cycle time of a specific task (in seconds)	Production daily report
5.Completion time of existing audio product (in hours)	Production daily report

In terms of ethical and legal considerations for data collection, some important matters were practiced during the time of research. Firstly, permission from the head of department from sselected departments were obtained in order to have permissible data. Secondly, data manipulation was strictly not allowed in order to maintain its originality and trustworthiness. Finally, confidentiality of high risk documents and photos was preserved within the organization in order to avoid any information leakage to outsiders or other manufacturers who are competitors in the marketplace. The following sections elaborate each of the data used in this research.

4.5.1 Number of Manpower

Number of manpower refers to the number of workers who performed a specific task at the semiautomatic production line. Example of specific tasks for an assembly process at the production line are wire soldering, part assembling, magnetizing, inspecting for audio quality, stamping and packaging. They are fully-skilled workers who serve at the semiautomatic line including a supervisor and two line leaders. In the production site, only one type of semiautomatic line is operated while the other three lines are fully-automated. In this research, the number of workers is expressed as the following notation:

$$manpower_n = B_n$$

where $n = 1,2,..., N$ and B is the number of manpower of nth production lot measured in persons. In terms of data collection, it was obtained from the company's production control document.

4.5.2 Waiting Time for Material

Waiting time for materials refers to the periods taken by the material warehouse to prepare materials after being unloaded by suppliers for the production line to produce audio products at the semiautomatic production line. Materials such as metal frames, plates, cone papers, dampers, dust caps, magnets, terminals and voice coils are transferred from the material warehouse to the production site for assembly processes. In this research, the waiting time for material is measured in hours as the following notation:

$$material_n = C_n$$

where $n = 1,2,\ldots,N$ and C is the waiting time of material of nth production lot measured in hour. The data related to the waiting time of material was collected from the production daily report.

4.5.3 Machine Breakdown Rate

Machine breakdown rate refers to the occurrence of machine malfunction at the production line. Machine such as frame and plate caulking, dust cap gluing, cone paper aging and magnetizing are monitored by the production technicians and line supervisor. However, due to the rapid utilization by manpower during operation, the machines could malfunction. In this research, the machine breakdown is measured in terms of rate, which is the occurrence of one breakdown on the pieces of audio product as expressed in the following equation:

$$machine_n = \frac{1}{r_n} \qquad n = 1,2,\ldots,N$$

$$r = 1,2,\ldots,R \tag{4.1}$$

where r is the quantity in pieces of audio product of nth production lot. In terms of data collection, it was obtained from the production daily report.

4.5.4 Cycle time of a Specific Task

Cycle time refers to the time needed to complete a single specific task by a manpower at the production line. Cycle time was recorded during the pre-production test run for the new audio products at the semiautomatic line before it was run in a huge quantity as the existing audio products. In this research, the cycle time of a single specific task is expressed as the following notation:

$$cycle_n = E_n$$

where $n = 1,2,..., N$ and E is the cycle time of nth production lot measured in seconds for r_n pieces of audio products. Information related to cycle time was obtained from the production daily report.

4.5.5 Completion Time of the Existing Audio Product

Completion time refers to the time required in producing a complete piece of audio speaker product through the entire specific tasks. In this research, completion time is expressed as the following notation:

$$completion_n = F_n$$

where $n = 1,2,..., N$ and F is the completion time of nth production lot measured in hours for producing r_n pieces of the existing audio product. The $completion_n$ is only considered for the existing audio products while no data was recorded for the new audio product since only a small number of pieces were assembled during the pre-production test run. In this research, data for completion time was obtained from the production daily report.

4.6 Development of Integrated ANNSD Model

The development of a proposed integrated Artificial Neural Networks and System Dynamics (ANNSD) model are elaborated in the following 10 steps to meet the main objective of this research.

- Step 1: Data for $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ are cleaned through a data cleaning process to increase the ANN prediction performance while data for $completion_n$ is not involved in data cleaning since the data is conceptualized in the development of a causal loop diagram (CLD) through the SD technique.
- Step 2: Data for $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ are transformed as the input and output parameters through MIN-MAX formula for the ANN learning process.
- Step 3: An ANN feed-forward multilayer perceptron (MLP) network is developed for predicting cycle time of the new audio product.
- Step 4: A backpropagation (BP) learning algorithm is established for learning process of the MLP network.
- Step 5: Data were allocated randomly between training and validation process.
- Step 6: The learning process through the BP learning algorithm within the MLP network is run to predict cycle time.
- Step 7: After predicting cycle time, $completion_n$ is conceptualized through the development of a CLD according to the SD technique to inspect the cause and effect relationship on completion time.

- Step 8: A stock flow diagram (SFD) is developed to simulate completion time of the new audio product at semiautomatic production line with the inclusion of predicted cycle time.
- Step 9: The integrated ANNSD model is validated through structure and behaviour assessments as suggested by Forrester and Senge (1980), Barlas (1996) and Mehrjerdi and Aliheidary (2014).
- Step 10: The output performance of the integrated ANNSD model was evaluated through various scenarios.

The 10 steps for the development of the integrated ANNSD model in predicting cycle time and simulating completion time at a semiautomatic production line is illustrated in a flowchart as shown in Figure 4.4. Subsequently, section 4.6.1 until 4.6.10 further describe the 10 steps for developing the integrated ANNSD model.

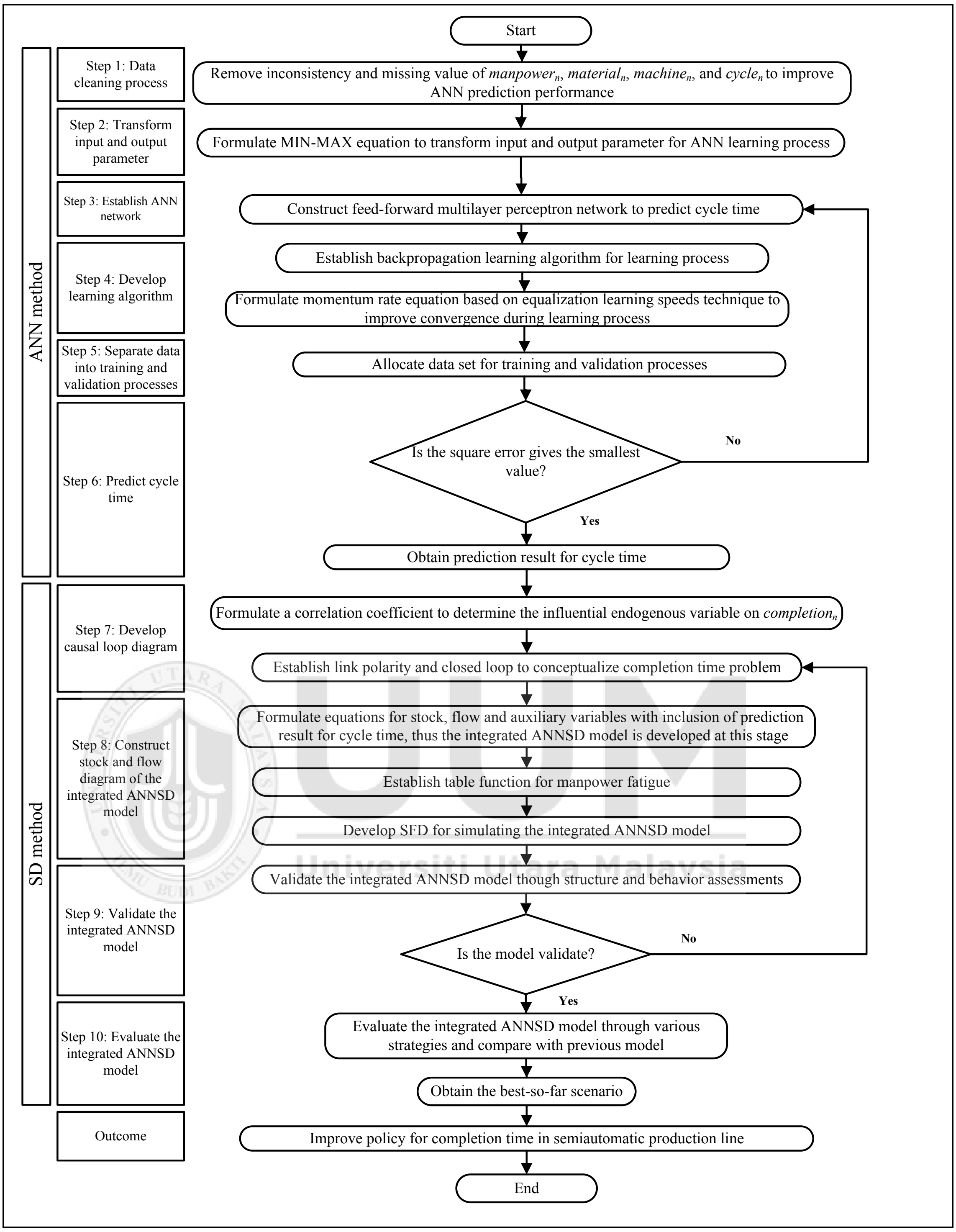


Figure 4.4. Flowchart for development of integrated ANNSD model

4.6.1 Data Cleaning Process

The first step in the development of an integrated ANNSD model was data cleaning to remove inconsistent and missing values. Thus, the quality of data were improved for the ANN learning process as further discussed in section 4.6.4.

In this phase, four types of data for *manpower*$_n$, *material*$_n$, *machine*$_n$, and *cycle*$_n$ were cleaned. The missing and inconsistent data were replaced by actual values from the source of secondary data, which were the production daily report and production control document as presented in Table 4.1. This approach of replacing data by actual value is adopted from suggestion by previous works which were mentioned in section 3.1.3. Thus, a graph for each data, i.e., *manpower*$_n$, *material*$_n$, *machine*$_n$, and *cycle*$_n$ were constructed to observe for any abnormalities as presented in section 5.2. Therefore, a biased prediction for cycle time was eliminated.

4.6.2 Transformation of Input and Output Parameter

The cleaned data for *manpower*$_n$, *material*$_n$, *machine*$_n$, and *cycle*$_n$ were then used as the input parameter and output parameter for ANN learning process. The input and output parameter were transformed from large value to small value between the interval of 0 to 1 or normally presented by [0, 1] as discussed in section 3.1.4. Therefore, the ANN learning process is smooth with small input and output value.

During this stage, *manpower*$_n$, *material*$_n$ and *machine*$_n$, were considered as the input parameters. Thus, the input parameters are transformed between the interval of [0, 1] through MIN-MAX formulation as follows:

$$x_{B_n} = \frac{B_n - B_{miv}}{B_{mav} - B_{miv}} \tag{4.2}$$

where,

B_n = original number of *manpower* for *n*th production lot

x_{B_n} = transformation value for number of *manpower* for *n*th production lot

B_{miv} = minimum number of *manpower*

B_{mav} = maximum number of *manpower*

$$x_{C_n} = \frac{C_n - C_{miv}}{C_{mav} - C_{miv}} \tag{4.3}$$

where,

C_n = original waiting time of *material* for *n*th production lot

x_{C_n} = transformation value for waiting time of *material* for *n*th production lot

C_{miv} = minimum waiting time of *material*

C_{mav} = maximum waiting time of *material*

$$x_{D_n} = \frac{D_n - D_{miv}}{D_{mav} - D_{miv}} \tag{4.4}$$

where,

D_n = original breakdown rate of *machine* for *n*th production lot

x_{D_n} = transformation value for breakdown rate of *machine* for *n*th lot

D_{miv}= minimum breakdown rate of *machine*

D_{mav}= maximum breakdown rate of *machine*

On the other hand, $cycle_n$ is considered as the output parameter. The output parameter was converted to a numerical value between the interval of [0, 1] through MIN-MAX formulation as follows:

$$y_{E_n} = \frac{E_n - E_{miv}}{E_{mav} - E_{miv}} \tag{4.5}$$

where,

E_n = original time of *cycle* for *n*th production lot

y_{E_n} = transformation value of *cycle* for *n*th production lot

E_{miv} = minimum time of *cycle*

E_{mav}= maximum time of *cycle*

The transformed input parameters, i.e., $manpower_n$, $material_n$, and $machine_n$ with the transformed output parameter, i.e., $cycle_n$ were substituted into the learning process of the ANN for predicting the cycle time of the new audio product. An elaboration of the ANN network is further explained in the following section.

4.6.3 Establishment of ANN Network

The transformed input and output parameters were subsequently substituted in the learning process within the ANN. Thus, a feed-forward multilayer perceptron (MLP) network was established for the learning process to predict cycle time based on Azadeh et al., (2014) as elaborated in section 3.1.5. However, the network of MLP to predict cycle time is different from Azadeh et al., (2014) since the number of input node, *i*, hidden node, *j*, and output node, *k*, were varied as illustrated in Figure 4.5.

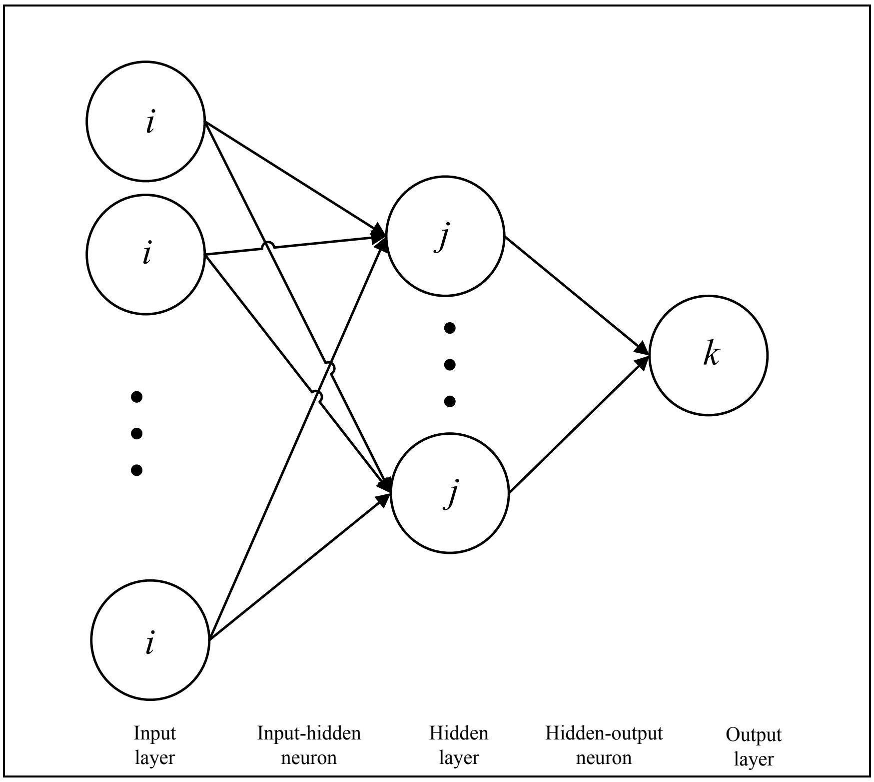


Figure 4.5. The network of feed-forward multilayer perceptron

where,

i = the number of input node at the input layer where $i = 1,2, \dots, I$

j = the number of hidden node at the hidden layer where $j = 1,2, \dots, J$

k = the number of output node at the output layer where $k = 1,2, \dots, K$

In the development of an MLP network to predict completion time, three layers were established which were the input, hidden and output layers. The input node, *i*, hidden node, *j*, and output node, *k* were separated by the input, hidden and output layers, respectively, as discussed in section 3.1.5. Each of the input and output layers are established with a single layer while the number of hidden layers were varied in a single layer.

The input parameters, i.e., *manpower*$_n$, *material*$_n$, and *machine*$_n$, to the network were substituted in respective input node, *i*. The input parameters from the input layer were then transformed in a nonlinear pattern by hidden node, *j* and transferred to the output layer. Subsequently, the nonlinear input from hidden node was transformed by output node, *k*, to produce a network output. Finally, the error between the network output and actual output parameter or desired output was compared for predicting cycle time. All nodes were linked with input-hidden neuron and hidden-output neuron to pass input parameters, i.e., *manpower*$_n$, *material*$_n$, and *machine*$_n$, hence the learning process within the MLP network was interconnected.

Moreover, three types of the MLP network were established in this research with the number of hidden nodes varied from one node until three nodes to find the best-so-far network in predicting cycle time. The three types of MLP network were categorized accordingly based on the number of input node-the number of hidden node-the number of output node, *i-j-k*. Subsequently, a learning algorithm was developed as a learning process for the MLP network to predict cycle time as discussed further in the following section.

4.6.4 Development of BP Learning Algorithm

The learning process within the established MLP network was guided through the development of a learning algorithm to obtain a desired cycle time as elaborated in section 3.1.6. The MLP network was trained by the developed BP learning algorithm to circulate back at different value between output network and desired output as recommended by Mehrjerdi and Aliheidary (2014) as described in section 3.1.6. Figure 4.6 demonstrates the steps of developing the BP learning algorithm for the

MLP network to predict cycle time. Each step is further discussed in the following subsection.

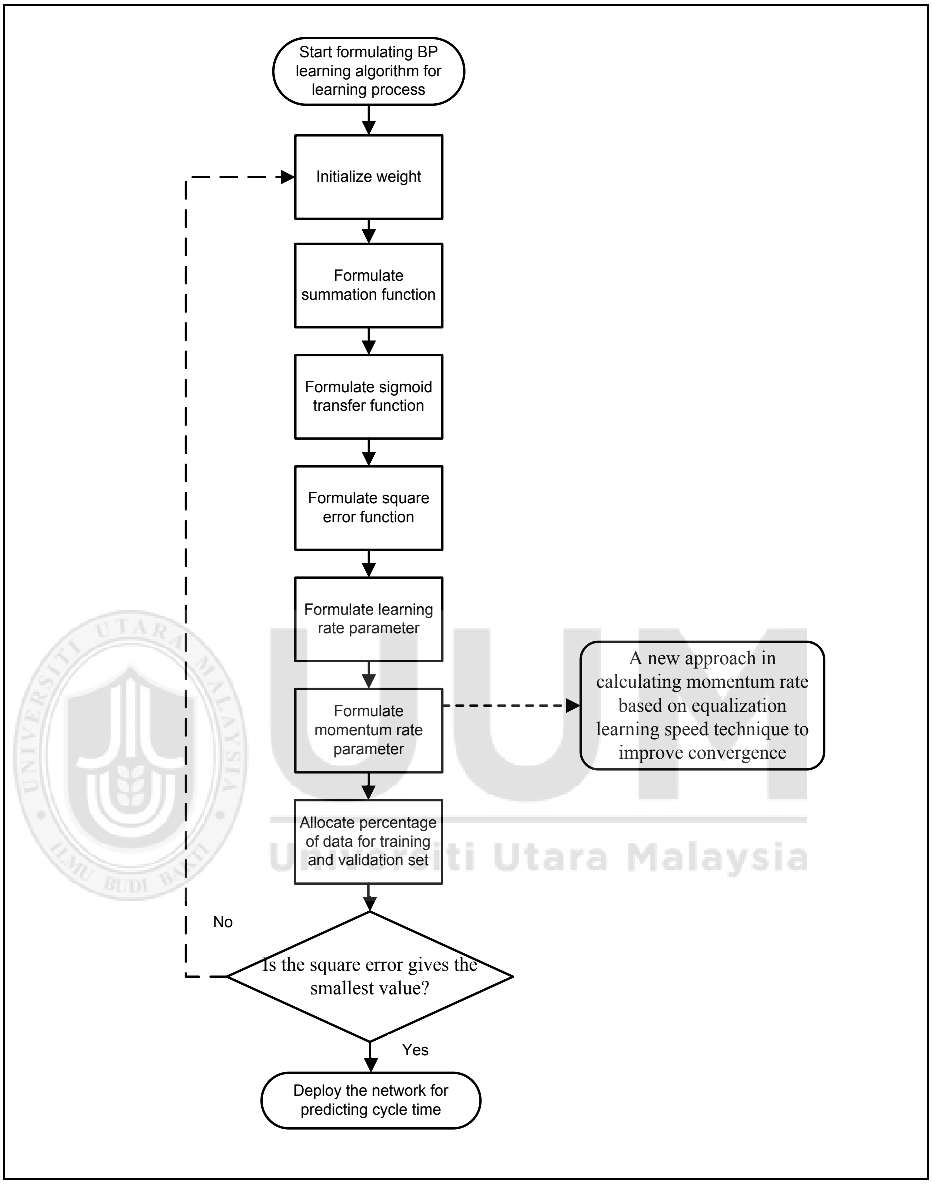


Figure 4.6. The flowchart of backpropagation learning algorithm

4.6.4.1 Initialization of Connection Weight

The learning process of a BP learning algorithm was generated by the initialization of connection weight. The connection weight value was initialized at this stage in representing the importance of each input parameters, i.e., *manpower*$_n$, *material*$_n$, and $machine_n$ towards desired output, i.e., $cycle_n$ during the learning process as elaborated in section 3.1.7.1. Therefore, the connection weight was corrected gradually according to a desired output value.

The value of the connection weight was initially set to a random value and no restriction of formulating the connection weight in a learning process as described in section 3.1.7.1. Thus, the value of the connection weight between the *i*th input node and *j*th hidden node in the MLP network to predict cycle time was formulated as the following equation:

$$w_{ij} = W_{IJ} \tag{4.6}$$

where,

i = the number of input node at the input layer where $i = 1,2, \dots, I$

j = the number of hidden node at the hidden layer where $j = 1,2, \dots, J$

On the other hand, the value of the connection weight between *j*th hidden node and *k*th output node was formulated as follows:

$$w_{jk} = W_{JK} \tag{4.7}$$

where,

j = the number of hidden node at the hidden layer where $j = 1,2, \dots, J$

k = the number of output node at the output layer where $k = 1,2, \dots, K$

Figure 4.7 illustrates the flow of each step during the learning process within the feed-forward MLP network to adjust the connection weight.

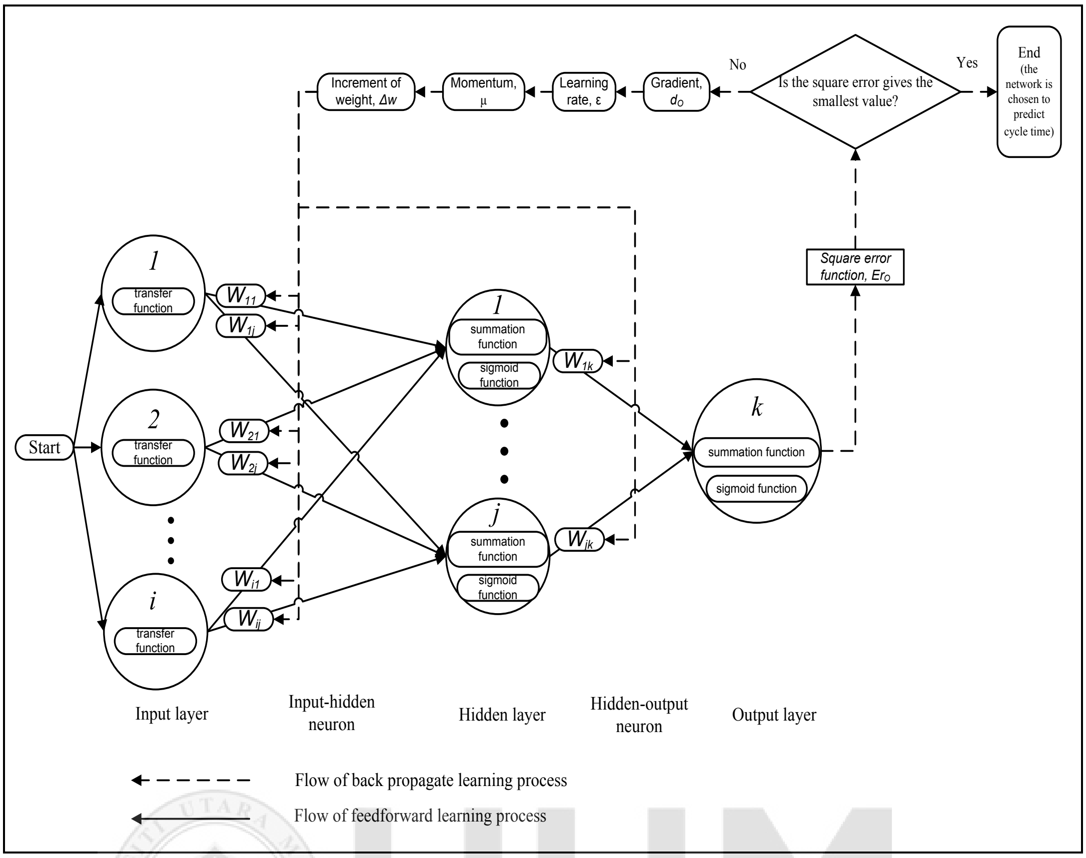


Figure 4.7. The flow of learning process within the multilayer perceptron network

The flow for the learning process in the MLP network was generated in two directions which are feed forward and back propagate. Both of the learning processes were iterated until the desired output of cycle time was achieved. After that, several learning parameters, i.e., summation function, sigmoid transfer function, square error function, learning rate parameter, and momentum rate parameter were formulated to adjust the connection weight as discussed in section 3.1.7. Finally, the smallest value of square error, *E*, between the value of network output from sigmoid function of *c*th output node and desired output of cycle time was selected for predicting cycle time. Thus, the connection weights were adjusted gradually to obtain the desired output in predicting cycle time through summation and sigmoid functions as further explained in the following subsection.

4.6.4.2 Summation and Sigmoid Transfer Functions

The connection weights, w_{ij} and w_{jk} were subsequently multiplied with the transformation value of the respective input parameters through summation function and converted to an S-shaped form through sigmoid function. During this stage, a summation function was formulated to compute the weighted sums of all the input parameters from the previous layer as adopted from Kumar (2013) in section 3.1.7.2.

On the other hand, a sigmoid function is formulated to produce an S-shaped nonlinear form as elaborated in section 3.1.7.2. Thus, the value of summation function from the previous node to the network output was converted within the interval of [0, 1]. Therefore, the input parameter of $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ are preserved in the form of a non-linear S-shaped.

The formulation of summation function and sigmoid function was first established for hidden node, *i*, and subsequently followed by output node, *j*. The summation function for *i*th hidden node is formulated based on Equation (3.3) as discussed in section 3.1.7.2 as follows:

$$sum_j = \sum_{i=1}^{I} w_{ij} trans_r \tag{4.8}$$

where,

sum_j = the weighted sum of *j*th hidden node

w_{ij} = the connection weight for the *i*th input node and *j*th hidden node

$trans_r$= transformation value for respective input parameters where $\forall r = 1,2,\dots,R$ as

r =1 for $manpower_n$, r =2 for $material_n$ and r =3 for $machine_n$

The sigmoid transfer function of *j*th hidden node is formulated based on Equation (3.4) in section 3.1.7.2 as follows:

$$sig_j = \frac{1}{(1 + e^{sum_j})} \tag{4.9}$$

where,

sig_j = the sigmoid value of *j*th hidden node

sum_j = the weighted sum of *j*th hidden node

e = the base of natural logarithm with a constant value, 2.71828

Once again, the summation function for the *k*th output node is constructed based on Equation (3.5) as explained in section 3.1.7.2 as follows:

$$sum_k = \sum_{j=1}^{J} w_{jk} sig_j \tag{4.10}$$

where,

sum_k= the weighted sum of *k*th output node

w_{jk} = the connection weight for the *j*th hidden node and *k*th output node

sig_j = the sigmoid value of *j*th hidden node

Similarly, the sigmoid transfer function for the *k*th output node is formulated based on Equation (3.6) as elaborated in section 3.1.7.2 as follows:

$$sig_k = \frac{1}{(1 + e^{sum_k})} \tag{4.11}$$

where,

sig_k = the sigmoid value of *k*th output node

sum_k= the weighted sum of *k*th output node

e = the base of natural logarithm with a constant value, 2.71828

Consequently, the sigmoid value of *k*th output node, sig_k, became the value of the MLP network output. The value between MLP network output and desired output value, i.e., transformation value of *cycle* for *n*th production lot, y_{E_n} was compared to obtain the smallest error value. Thus, the error between the value of the MLP network output and desired output is discussed further through formulation of square error function in the following subsection.

4.6.4.3 Formulation of Square Error Function

The difference between the output value of the MLP network from the sigmoid function of *k*th output node, sig_k, and the desired output of cycle time of *n*th production lot, y_{E_n} was calculated through the formulation of square error function as described in section 3.1.7.3. The square error function of *o*th iteration, Er_o, was formulated at this stage to compute the difference between the sig_k and y_{E_n}. Thus, the equation of square error function is formulated based on Equation (3.7) as follows:

$$Er_o = \frac{1}{2}([sig_k]_o - y_{E_n})^2 \quad o = 1,2,...O \tag{4.12}$$

where,

Er_o = the square error of *o*th iteration

sig_k= the sigmoid value of *k*th output node, i.e., the MLP network output

y_{E_n} = the transformation value of cycle time, *E*, for *n*th production lot, i.e., desired output

Subsequently, the square error value, *Er_o,* was propagated back to correct the previous connection weight until the network has a minimum error value to accomplish learning process. Hence, by having a minimum Er_o, a learning process to predict cycle time is terminated.

The final connection weights, w_{ij} and w_{jk} were adjusted through gradient descent with respect to the connection weight until the network has a minimum error as described in section 3.1.7.3. Thus, the descent of gradient is formulated through derivation function between square error function, Er_o, and the connection weights, w_{ij} and w_{jk}, according to Equation (3.8) and (3.9) as elaborated in section 3.1.7.3 as follows:

$$[d_{w_{ij}}]_o = \frac{\partial Er_o}{\partial w_{ij}} \quad o = 1,2,\ldots O \tag{4.13}$$

where,

$[d_{w_{ij}}]_o$ = the gradient value of the connection weight for ith input node and jth hidden node of oth iteration

∂Er_o = the derivation value for square error function of oth iteration

∂w_{ij} = the derivation value for the connection weight of ith input node and jth hidden node

$$[d_{w_{jk}}]_o = \frac{\partial Er_o}{\partial w_{jk}} \quad o = 1,2,\ldots O \tag{4.14}$$

where,

$[d_{w_{jk}}]_o$ = the gradient value of connection weight for jth hidden node and kth output node of oth iteration

∂Er_o = the derivation value for square error function of oth iteration

∂w_{jk} = the derivation value for connection weight of jth hidden node and kth output node

Moreover, several parameters were formulated to guide the descent of slope error. Therefore, learning rate and momentum rate parameters were formulated to control the descent of the slope, hence the adjustment of final connection weights, w_{ij} and w_{jk} were corrected accordingly.

4.6.4.4 Formulation of Learning Rate Parameter

Based on the derivation of square error function with respect to the connection weight, the descent direction during learning process is controlled by learning rate. The suitable value of learning rate is within the range of 0.1 to 1.0 during learning process as discussed in section 3.1.7.4. Thus, the formulation of learning rate parameter is expressed with the understanding on Equation (3.10) in section 3.1.7.4 as follows:

$$\Delta w_o = -\varepsilon d_o \quad o = 1,2,\ldots O \tag{4.15}$$

where,

Δw_o = the increment of a connection weight after the *o*th iteration

ε = learning rate

d_o = the gradient value of the *o*th iteration

4.6.4.5 Formulation of Momentum Rate Parameter

The adjustment of connection weight is then adjusted by momentum rate once the speed of learning process is controlled by learning rate. In this stage, momentum rate is formulated for slowing down the speed of learning process based on the discussion in section 3.1.7.5. Furthermore, the selection of suitable value for momentum parameter in the MLP network has no restriction as it is commonly based on experiments with various different values.

Besides, the value of momentum is within the range of $0 \leq |\mu| < 1$ as highlighted by Kumar (2013). Therefore, in this research, a new approach in determining momentum value is proposed. The approach taken in calculating the momentum rate is motivated from the equalization learning speeds concept as mentioned by Haykin (2009) such that for a given neuron, the process of learning should be inversely proportional to the square root of connections to the neuron between the input node and hidden node. However, generally, this concept is only suggested for a learning process. As such, a similar formulation suitable for the momentum rate in the learning process is introduced in this research. Hence, the convergence of the learning process in the MLP network is controllable.

The motivation of formulating this method for momentum rate is to observe its potential with other methods from previous literature, thus fulfilling the second objective of this research. Hence, the formulation of a proposed equation for determining momentum rate value for this research is formulated as follows:

$$\mu = \frac{1}{\sqrt{f_{ij}}} \tag{4.16}$$

where,

μ = momentum rate

f_{ij} = the number of neuron between ith input node and jth hidden node

On the other hand, the new increment of connection weight for oth iteration is formulated according to Equation (3.11) as described in section 3.1.7.5 as follows:

$$\Delta w_o = \mu \Delta w_{0-1} - (1-\mu)\varepsilon d_o \tag{4.17}$$

where,

Δw_o = the increment for a connection weight of *o*th iteration

μ = momentum rate

Δw_{o-1} = the increment of previous connection weight of *o*th iteration

ε = learning rate

d_o = the gradient value of the *o*th iteration

By substituting Equation (4.20) into Equation (4.21), the equation for adjusting the increment of connection weight is formulated as follows:

$$\Delta w_o = \left(\frac{1}{\sqrt{f_{ij}}}\right)\Delta w_{o-1} - \left(1 - \left(\frac{1}{\sqrt{f_{ij}}}\right)\right)\varepsilon d_o \tag{4.18}$$

Subsequently, the increment of the connection weight for the next iteration is adjusted. Then, the feed forward learning process is repeated as shown in Figure 4.7 of section 4.6.4.1. Therefore, the learning process is iterated until the network has a minimum value of square error, *Er*.

4.6.5 Separation of Data into Training and Validation Set

The increment of connection weight is not only adjusted by learning rate and momentum rate but also modified by training process. At this stage, a training process is established to adjust the connection weight from a set of data through learning algorithm as described in section 3.1.8. Subsequently, the connection weight value from the training process for predicting cycle time is validated through a different set of data during the validation process. Hence, the data are separated between training and validation processes with the allocation percentage as formulated in the following equation:

$$train_s = 100 - valid_s \quad s = 1,2,\ldots S \tag{4.19}$$

where,

$train_s$ = the percentage of data allocated for training process of sth set

$valid_s$ = the percentage of data allocated for validation process of sth set

In order to train and validate the learning process for BP algorithm, the related data, i.e., $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ are allocated separately for training set and validation set. By assigning a higher percentage of data to the training set, the MLP network gives a better prediction performance result in data learning process since the more the data are trained, the stronger the predictive relationship it has as discussed in section 3.1.8. Therefore, 80% of data is allocated for training process while 20% are allocated for validation process. Hence, by allocating a higher percentage for training in the ANN learning process, the performance of the network in predicting cycle time is better.

4.6.6 Prediction Cycle Time

The learning process of the MLP network is run iteratively according to the allocated data until the network has a minimum value of square error, *Er*. As a result, the predicted cycle time with the final connection weight w_{ij} and w_{jk} on the oth iteration of learning process is determined. Therefore, the predicted cycle time is formulated with reference to Equation (3.12) as described in section 3.1.9 as the following equation:

$$ct_n = [w_{ij}]_o x_{B_n} + [w_{ij}]_o x_{C_n} + [w_{ij}]_o x_{D_n} + \sum_{j=1}^{J} [w_{jk}]_o \, sig_j \tag{4.20}$$

where,

ct_n = predicted cycle time of *n*th production lot

$[w_{ij}]_o$ = final connection weight for *i*th input node and *j*th hidden node of *o*th iteration

x_{B_n} = transformed value of B_n, i.e., number of manpower for *n*th lot

x_{C_n} = transformed value of C_n, i.e., waiting time of material for *n*th lot

x_{D_n} = transformed value of D_n, i.e., machine breakdown rate for *n*th lot

$[w_{jk}]_o$ = final connection weight for the *j*th hidden node and *k*th output node of *o*th iteration

sig_j = the sigmoid value of *j*th hidden node

Subsequently, the predicted cycle time, i.e., ct_n of the new audio product and respective input parameters, i.e., $manpower_n$, $material_n$, and $machine_n$ based on corresponding transformation value of x_{B_n}, x_{C_n}, x_{D_n} are then considered as input variables in the development of an SFD. The completion time for the new audio product at the semiautomatic production line is measured through an SFD from initial time, t_{init}, to current time, t_{cur} as a time horizon. Moreover, production workload and manpower fatigue are considered to improve manpower performance.

However, before an SFD is developed, the completion time problem is conceptualized for a working theory. Hence, a CLD is established to conceptualize the completion time problem at semiautomatic production line as discussed further in the following section.

4.6.7 Development of a Causal Loop Diagram

Once the predicted cycle time is obtained, the completion time is conceptualized through a CLD based on Inam et al. (2015) as described in section 3.2.3. In this case, Inam et al. (2015) justified that a clear picture of a cause and effect relationship of variables is obtained through CLD. Thus, the cause and effect relationship among $manpower_n$, $material_n$, $machine_n$, $cycle_n$ on completion time are captured through a CLD as discussed further in the following subsections.

4.6.7.1 Formulation of Coefficient Correlation

Since a CLD is a qualitative tool, the establishment of a CLD in this research is based on the brainstorming session with experts as recommended by Inam et al. (2015). In this case, Inan et al. (2015) justified that a clear picture of cause and effect relationship is obtained through a CLD. Thus, the brainstorming session to develop a CLD is conducted with the Production Planner and Production Control Executive.

The variables, which in their judgment relate to completion time were categorized into either endogenous or exogenous variables as shown in Table 4.2. A variable which occurred within the semiautomatic line is categorized as endogenous if it has a major impact on completion time while a variable which occurs outside the line and has a minor impact on completion time is categorized as exogenous discussed in section 3.2.3. Therefore, both endogenous and exogenous variables were considered in the development of a CLD to conceptualize $completion_n$.

At this stage, $manpower_n$, $material_n$, $machine_n$, $cycle_n$ are considered as endogenous variables. However, the strength of the relationship of the endogenous variables, i.e., $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ towards completion time is undetermined. The variable with the strongest relationship on completion time is considered as the most influential endogenous variable. Hence, a correlation coefficient is formulated to identify the strength of the relationship among the endogenous variables on completion time, thus fulfilling the third objective of this research.

A correlation coefficient is formulated to measure the strength of the relationship between the independent and dependent variables as suggested by Russell & Taylor (2011). The endogenous variables, i.e., $manpower_n$, $material_n$, $machine_n$, $cycle_n$ of the existing audio product are considered as the independent variables. On the other hand, $completion_n$ of the existing audio product is considered as dependent variable. The existing audio product is selected in the formulation of correlation coefficient since the new audio product has no data on completion time due to the small number of products, i.e., less than 50 pieces during the pre-production test run as highlighted in section 4.5. The coefficient correlation is formulated for the existing audio product as follows:

$$corr_{endo} = \frac{num \sum sum_{endo} sum_{com} - \sum sum_{endo} \sum sum_{com}}{\sqrt{[num \sum sum_{endo}{}^2 - (\sum sum_{endo})^2][num \sum sum_{com}{}^2 - (\sum sum_{com})^2]}} \quad (4.21)$$

where,

$corr_{endo}$= correlation coefficient of respective independent variable, i.e., $manpower_n$, $material_n$, $machine_n$, and $cycle_n$

num = the number of data

sum_{endo} = summation value of respective independent variable, i.e., $manpower_n$, $material_n$, $machine_n$, and $cycle_n$

sum_{com} = summation value of $completion_n$

The variable with the highest correlation coefficient, $corr_{endo}$ being the most influential endogenous variable on completion time. Thus, the variable is selected for establishing a closed loop in the development of a CLD as elaborated later in subsection 4.6.7.2.

However, $manpower_n$, $material_n$, $machine_n$, $cycle_n$ are renamed to *number of* $manpower_n$, *material preparation* $time_n$, *machine breakdown* $rate_n$, *cycle* $time_n$, respectively, for a meaningful and proper noun as recommended by Sapiri et al. (2017). Furthermore, *production completion* $time_n$ is created to differentiate $completion_n$ since $completion_n$ is the actual completion time recorded in production daily report for the existing audio product while *production completion* $time_n$ is a simulation output from the developed SFD for the new audio product.

Moreover, equations and units were not formulated for the endogenous and exogenous variables since a CLD is a qualitative tool for problem conceptualization as explained in section 3.2.3. The computation of related endogenous and exogenous variables is formulated in subsection 4.6.8.2. Table 4.2 shows the list of endogenous and exogenous variables related to the semiautomatic production line for establishment of a CLD.

Table 4.2

List of endogenous and exogenous variables for development of a CLD

Variable	Description	Type of variable
adjustment material on order$_n$	the amount of adjustment for material on order for n^{th} production lot	endogenous
attendance rate$_n$	the rate of manpower attendance on that working day for n^{th} production lot	endogenous
available material$_n$	the amount of available material for production operation for n^{th} production lot	endogenous
cycle time$_n$	the time required to complete specific task by manpower at each station for n^{th} production lot	endogenous
delivery rate$_n$	the delivery rate of audio products from finished goods warehouse for n^{th} production lot	exogenous
desired completion rate$_n$	the required rate of completing WIP audio in one hour for n^{th} production lot	endogenous
desired material order rate$_n$	the amount of material desired by the company for n^{th} production lot	endogenous
desired production start rate$_n$	the rate of required material for starting production process for n^{th} production lot	endogenous
effect of fatigue on productivity$_n$	the level of manpower fatigue during working time at production line for n^{th} production lot	endogenous
effect of schedule pressure$_n$	the effect of production workload during working hour for n^{th} production lot	endogenous
finished goods inventory$_n$	the amount of completed audio products at finished goods warehouse for n^{th} production lot	endogenous
machine breakdown rate$_n$	the rate of machine breakdown during production process for n^{th} production lot	endogenous
material availability ratio$_n$	the ratio between the amount of available material in warehouse and desired material for starting production process for n^{th} production lot	endogenous
material order rate$_n$	the rate of material ordered by the company for n^{th} production lot	endogenous
material preparation rate$_n$	the rate between available material and preparation time for n^{th} production lot	endogenous
material preparation time$_n$	the time required for material preparation at material warehouse for n^{th} production lot	endogenous
material reject rate$_n$	the rate of material reject for n^{th} production lot	endogenous
material supply rate$_n$	the rate of material supplied by supplier for n^{th} production lot	endogenous
material usage perunit$_n$	the amount of material required to produce one unit of audio for n^{th} production lot	endogenous
material warehouse inventory$_n$	the amount of available material in warehouse for n^{th} production lot	endogenous

Variable	Description	Type of variable
number of manpower per hour$_n$	the available number of manpower for n^{th} production lot	endogenous
number of manpower$_n$	the required number of manpower at production line to perform production process for n^{th} production lot	endogenous
potential completion time$_n$	the potential time for completing a unit of audio for n^{th} production lot	endogenous
production completion time$_n$	the time taken to complete production process in producing r_n audio product for n^{th} production lot	endogenous
production start rate$_n$	the rate of receiving material from warehouse to start production process for n^{th} production lot	endogenous
production utilization$_n$	the rate between schedule pressure and actual working time of a manpower for n^{th} production lot	endogenous
reorder material$_n$	the amount of material reorder for n^{th} production lot	endogenous
schedule pressure$_n$	the level of production workload which caused by desired completion rate for n^{th} production lot	endogenous
shipment rate$_n$	the rate of shipment for n^{th} production lot	exogenous
standard completion rate	the rate between standard working hour and cycle time for n^{th} production lot	endogenous
standard working hour in seconds$_n$	the standard working time of a manpower at production line in seconds for n^{th} production lot	endogenous
standard working hour$_n$	the standard working time of a manpower at production line for n^{th} production lot	endogenous
supplier lead time delivery$_n$	the time required by supplier to delivery material for n^{th} production lot	exogenous
target completion hour$_n$	the target time to complete WIP of audio for n^{th} production lot	endogenous
time per task$_n$	the standard time set by management for a manpower to perform specific task on one unit of audio for n^{th} production lot	endogenous
work in process$_n$	the amount of work in process (WIP) of audio at production line for n^{th} production lot	endogenous

Subsequently, the cause and effect relationships are developed for the related endogenous and exogenous variables. Therefore, link polarities were constructed to capture the cause and effect relationship among the variables as described in the following subsection.

4.6.7.2 Formation of Link Polarity and Closed Loop

The relationship of endogenous and exogenous variables are subsequently constructed by link polarity and closed loop. The formation of link polarity and closed loop for developing a CLD is shown in Figure 4.8.

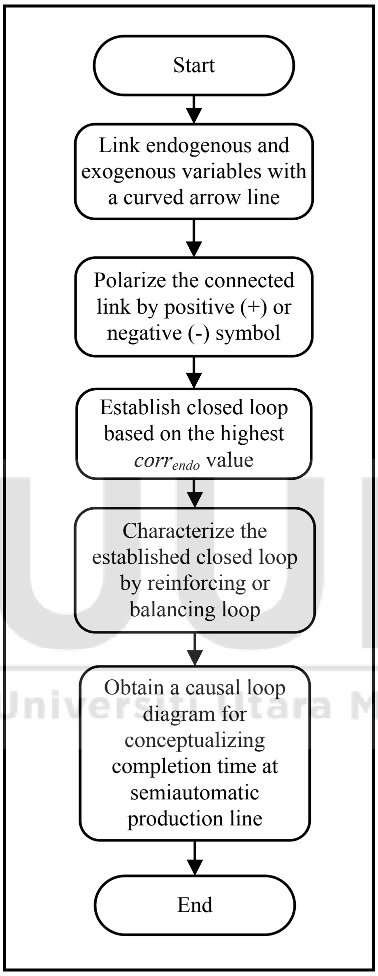


Figure 4.8. The flowchart of establishing link polarity and closed loop for CLD

The cause and effect relationship among endogenous and exogenous variables is established by a curved arrow line while a link polarity is labelled to the connection by a positive (+) or negative (-) symbol as described in Table 3.1 of section 3.2.3. The variables are linked through a connection arrow until a closed loop is obtained.

The variable with the highest correlation coefficient is selected for the formation of a closed loop in a CLD as the most influential element on completion time problem as discussed in subsection 4.6.7.1. Subsequently, the behavior of a closed loop is characterized by loop polarity, whether in a reinforcing loop (positive) or balancing loop (negative) as elaborated in section 3.2.3. However, the cause and effect parameter of each variable is unquantified since a CLD is a qualitative tool. Hence, the CLD is transformed into development of a SFD to measure the parameter of each variable quantitatively as elaborated in the following section.

4.6.8 Development of Stock And Flow Diagram

The developed CLD is transformed an SFD for quantifying the variable parameter since a CLD is a qualitative tool. Thus, a structural diagram to quantify the parameter of each variable through stock and flow concept was developed through an SFD as discussed in section 3.2.4. The variables were classified into stock, inflow, outflow and auxiliary with the establishment of table function for manpower fatigue. The development of an SFD is described further in the following subsections.

4.6.8.1 Formulation of Equation for Stock and Flow Variables

The structural diagram of an SFD is developed through the formulation of stock and flow variables. Stocks are formulated to accumulate quantities within the SFD and are represented by rectangles. The value of a stock is increased or decreased through a flow rate function and represented by valve-like symbol. The stock equation is formulated based on an integral equation. Thus, the general integral equation of inflow and outflow for stock accumulation from initial time, t_{init} to current time, t_{cur}, is formulated based on Equation (3.15) as described in section 3.2.4:

$$stock(t_{cur}) = \int_{t_{init}}^{t_{cur}} [inflow(t_{cur}) - outflow(t_{cur})] d(t_{cur}) + stock(t_{init}) \qquad (4.22)$$

During this stage, initial *material warehouse inventory*$_n$, *work in process*$_n$, and *finished goods inventory*$_n$, are considered as stocks in the developed SFD. Thus, the development of stocks and related flows are presented in Figure 4.9, Figure 4.10 and 4.11 with formulated equations as follow:

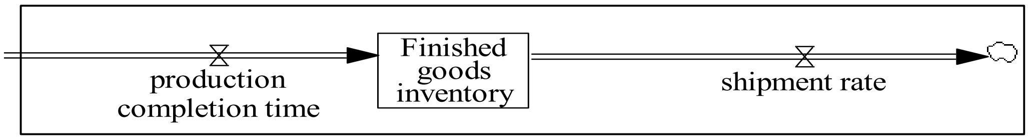


Figure 4.9. The developed SFD for finished goods inventory

$$finished\ goods\ inventory_n = \int_{t_{init}}^{t_{cur}} production\ completion\ time_n - shipment\ rate_n \qquad (4.23)$$

Unit: pieces

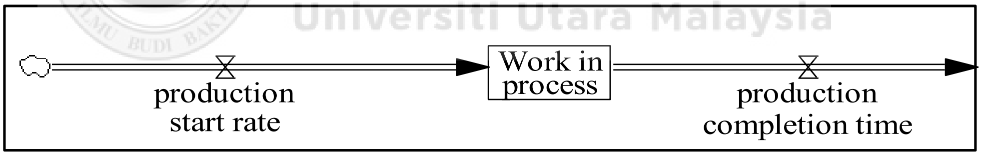


Figure 4.10. The developed SFD for work in process

$$work\ in\ process_n = \int_{t_{init}}^{t_{cur}} production\ start\ rate_n - production\ completion\ time_n \qquad (4.24)$$

Unit: pieces

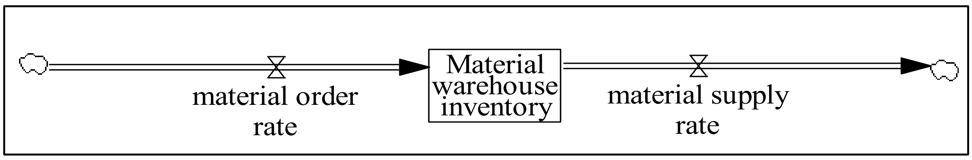


Figure 4.11. The developed SFD for material warehouse inventory

$$material\ warehouse\ inventory_n = \int_{t_{init}}^{t_{cur}} material\ order\ rate_n - material\ supply\ rate_n \qquad (4.25)$$

Unit: pieces

In addition, the inflow and outflow variables are linked with an intermediate variable to clarify the formulation of flow in detail. Hence, the auxiliary variables are formulated as discussed in the following subsection 4.6.8.2.

4.6.8.2 Formulation of Equations for Auxiliary Variables

The formulated stock and flow variables are subsequently connected with auxiliary variables to clarify the flow variables into small partition. Thus, auxiliary variable is formulated as an intermediate variable with the equation as described in section 3.2.4.

The parameter value for *number of manpower*$_n$*, material preparation time*$_n$*, machine breakdown rate*$_n$, and *cycle time*$_n$ is based on the values of B_n, C_n, D_n, and E_n,, respectively, were substituted into the developed SFD. The values of B_n, C_n, D_n, and E_n correspond to the values of x_{B_n}, x_C, x_{D_n} and ct_n, which was obtained in prediction output as resulted in Equation (4.24) of section 4.6.6. Hence, the integrated ANNSD model is formed at this stage.

Furthermore, some variables were dimensionless since the variables had no applicable physical units as suggested by Sapiri et al. (2017) as discussed in section 3.2.4. The formulation of related variables in the ANNSD model are expressed as follows.

$$number\ of\ manpower_n = B_n \tag{4.26}$$
Unit: person

$$material\ preparation\ time_n = C_n \tag{4.27}$$
Unit: hour

$$machine\ breakdown\ rate_n = D_n \tag{4.28}$$
Unit: 1 per pieces

$$cycle\ time_n = E_n \tag{4.29}$$
Unit: second per pieces

$$target\ completion\ hour_n = \in_n \tag{4.30}$$
Unit: hour

$$standard\ working\ hour\ in\ seconds_n = \beta_n \quad \beta = 1,2,\ldots,\infty \tag{4.31}$$
Unit: second

$$standard\ working\ hour_n = \gamma_n \quad \gamma = 1,2,\ldots,\infty \tag{4.32}$$
Unit: hour

$$attendance\ rate_n = \delta_n \quad \delta = 1,2,\ldots,\infty \tag{4.33}$$
Unit: dimensionless

$$time\ per\ task_n = \alpha_n \quad \alpha = 1,2,\ldots,\infty \tag{4.34}$$
Unit: person × hour per pieces

$$delivery\ rate_n = \rho_n \quad \rho = 1,2,\ldots,\infty \tag{4.35}$$
Unit: hour

$$material\ usage\ per\ unit_n = \exists_n \quad \exists = 1,2,\ldots,\infty \tag{4.36}$$
Unit: dimensionless

$$desired\ production\ start\ rate_n = \tau_n \quad \tau = 1,2,\ldots,\infty \tag{4.37}$$
Unit: pieces

$$material\ reject\ rate_n = \vartheta_n \quad \vartheta = 0,1,\ldots,\infty \tag{4.38}$$
Unit: dimensionless

$$supplier\ lead\ time\ delivery_n = \varphi_n \quad \varphi = 1,2,\ldots,\infty \tag{4.39}$$
Unit: hour

$$adjustment\ material\ on\ order_n = material\ warehouse\ inventory_n + reorder\ material_n \tag{4.40}$$
Unit: pieces

$$desired\ material\ order\ rate_n = \frac{adjustment\ material\ on\ order_n}{supplier\ lead\ time\ delivery_n} \tag{4.41}$$
Unit: pieces per hour

$$material\ availability\ ratio_n = \frac{material\ warehouse\ inventory_n}{desired\ production\ start\ rate_n} \tag{4.42}$$
Unit: dimensionless

$$material\ preparation\ rate_n = \frac{material\ availability\ ratio_n}{material\ preparation\ time_n} \quad (4.43)$$

Unit: 1 per hour

$$available\ material_n = \frac{material\ supply\ rate_n}{material\ usage\ per\ unit_n} \quad (4.44)$$

Unit: pieces per hour

$$schedule\ pressure_n = \frac{desired\ completion\ rate_n}{standard\ completion\ rate_n} \quad (4.45)$$

Unit: dimensionless

$$standard\ completion\ rate_n = \frac{standard\ working\ hour\ in\ seconds_n}{cycle\ time_n} \quad (4.46)$$

Unit: dimensionless

$$effect\ of\ schedule\ pressure_n = \frac{schedule\ pressure_n}{standard\ working\ hour_n} \quad (4.47)$$

Unit: hour

$$production\ utilization_n = \frac{effect\ of\ schedule\ pressure_n}{standard\ working\ hour_n} \quad (4.48)$$

Unit: dimensionless

$$number\ of\ manpower\ per\ hour_n = \frac{number\ of\ manpower_n \times attendance\ rate_n}{standard\ working\ hour_n} \quad (4.49)$$

Unit: person per hour

$$potential\ completion\ time_n = \frac{number\ of\ manpower \times machine\ breakdown\ rate \times effect\ of\ fatigue\ on\ productivity_n \times effect\ of\ schedule\ pressure_n}{time\ per\ task_n}$$

(4.50)

Unit: pieces per hour

4.6.8.3 Establishment of Table Function for Manpower Fatigue

A table function was established to determine the functional relationship between *production utilization*$_n$ (independent variable) and *effect of fatigue on productivity*$_n$ (dependent variable) as elaborated in section 3.2.4. Hence, the formulation for *effect of fatigue on productivity*$_n$ is expressed as follows:

$$\textit{effect of fatigue on productivity}_n = \text{table function } (\textit{production utilization}_n) \qquad (4.51)$$

unit: dimensionless

The established table function between *production utilization*$_n$ and *effect of fatigue on productivity*$_n$ is a simple approximation yet a beneficial guide as suggested by company representatives regarding manpower fatigue at the production site. Table 4.3 shows the table function between *production utilization*$_n$ (independent variable) and *effect of fatigue on productivity*$_n$ (dependent variable).

Table 4.3

Table function for production utilization and effect of fatigue

production utilization$_n$	***effect of fatigue on productivity***$_n$
0	1.2
0.8	1.2
1	1
1.3	0

According to Equation (4.52), the *production utilization*$_n$ is related to the *effect of schedule pressure*$_n$ over *standard working hour*$_n$. On the other hand, *the effect of schedule pressure*$_n$ is a result from *schedule pressure*$_n$ over *standard working hour*$_n$, as in Equation (4.51), while *schedule pressure*$_n$ is caused from *desired completion rate*$_n$ over *standard completion rate*$_n$, as in Equation (4.49). Thus, based on the formulation, if the value of *production utilization*$_n$ is 1, it indicates that the amount of *desired completion rate*$_n$ is equivalent to *standard completion rate*$_n$, hence manpower is fully utilized to achieve production productivity within their capability.

Based on their experience, the Production Planner and Production Control Executive suggested that if *production utilization*$_n$ is below 1, i.e., from 0 to 8, it indicates that the amount of *desired completion rate*$_n$ is less than *standard completion rate*$_n$ or not fully utilized. Consequently, *the effect of fatigue on productivity$_n$* should be higher than 1, i.e., up to 1.2 (the maximum scale) which indicates that manpower has more energy due to less work at the production line.

Furthermore, based on their judgment, if *production utilization$_n$* is more than 1, i.e., up to 1.3 (the maximum scale), it indicates that the amount of *desired completion rate$_n$* has increased more than the *standard completion rate$_n$*. Thus, the value of *effect of fatigue on productivity$_n$* gradually approaches 0 which indicates that manpower regularly experienced production overload with more work to complete beyond their capability. As a result, the graph of the established table function between *production utilization$_n$* and *effect of fatigue on productivity$_n$* based on Equation (4.55) is illustrated in Figure 4.12 as follows:

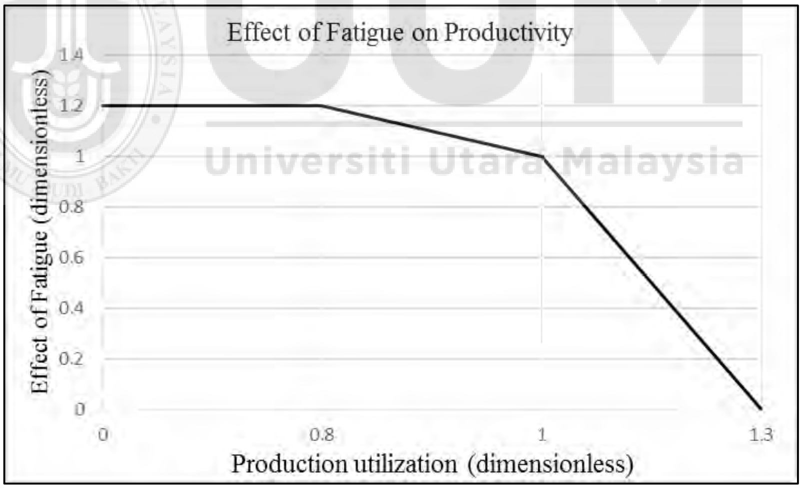


Figure 4.12. Graph for effect of fatigue on productivity

4.6.8.4 Development of SFD for Simulating the Integrated ANNSD Model

The formulated stock, inflow, outflow, auxiliary equations and established table function are structured in the proposed integrated ANNSD model. The formulated equations and established table function are coded and programmed appropriately in a computerized simulation. Subsequently, the integrated ANNSD model is simulated through SFD to mimic the real production system on *production completion time*$_n$.

However, before the ANNSD model is simulated through the developed SFD, the equation and structure of stock, inflow, outflow, auxiliary variables and table function are validated first. Hence, the integrated ANNSD model is validated through several assessments to verify the ability of the ANNSD model in simulating the actual production operation as discussed further in the following section.

4.6.9 Validation of Integrated ANNSD Model Structure and Behaviour

The proposed integrated ANNSD model is validated on its structure and behaviour in resembling a real production operation as described in section 3.2.5. Hence the capability of the integrated ANNSD model for simulating completion time at the semiautomatic production line is validated, thus fulfilling the fourth objective of this research. The validation of structure and behavior of ANNSD model is described in Figure 4.13 as follows.

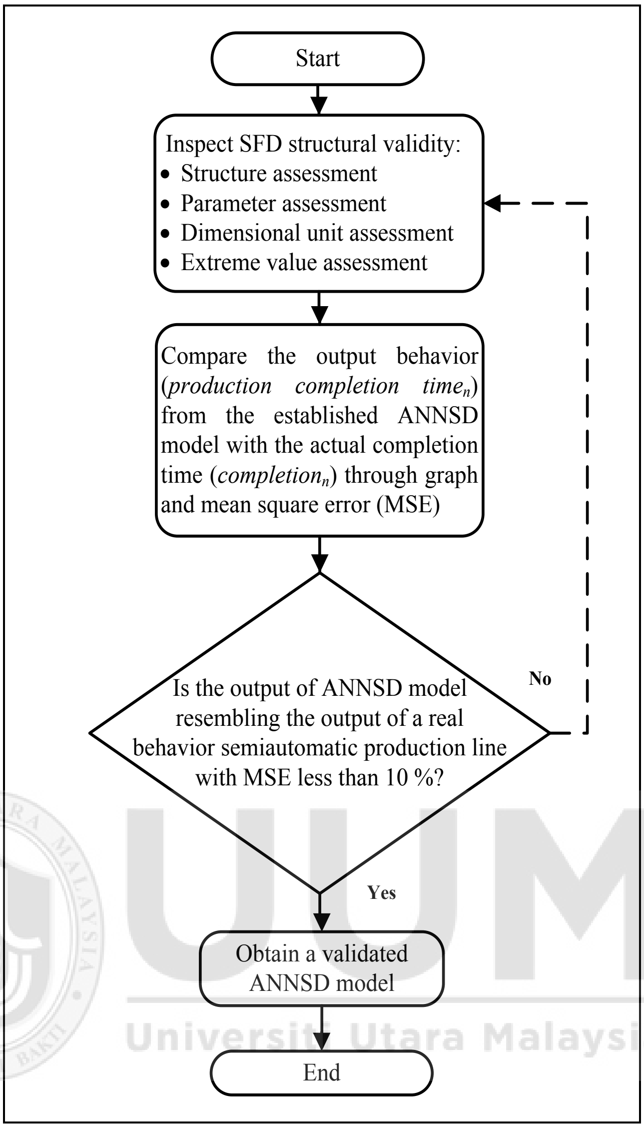


Figure 4.13. Flowchart for validating the integrated ANNSD model

4.6.9.1 Structural Validity

At this stage, the structure of the established SFD was validated through structure, parameter, dimensional unit and extreme value assessments to mimic a real production operation as elaborated in Table 3.4 of subsection 3.2.5. Thus, the confidence in simulating the ANNSD model was improved since contradiction and faulty model structure with the actual production operation are avoided.

The structure of the developed SFD was compared directly with the real structure of production operation that the model represented based on reviews from company experts and related literature. Subsequently, the parameters of each variable in the developed SFD were also compared with the secondary data as provided by the company experts. In conjunction with the parameter assessment, the dimensional units of stock, flow and auxiliary equations were compared by checking the equivalence of units on the related equations in the developed SFD. The dimensional units were compared through a built-in unit consistency checking feature of the SD computer simulation to identify any errors that might be present in the related equations.

In contrast, the extreme value assessment was experimented by setting input value of *number of manpower*$_n$ and *material preparation time*$_n$, with zero, i.e., manpower was unavailable while materials were not prepared. Furthermore, *cycle time*$_n$ was set to 1 second which indicated that manpower must accomplish their tasks within an impossible shortest time. In this regard, *work in process*$_n$ and *production completion time*$_n$ were observed in validating the integrated ANNSD model to resemble real production operation. The expected outcome for extreme value assessment is elaborated in Table 4.4 as follows.

Table 4.4

Expected observation for extreme value assessment

Extreme value condition	Expected observation output
number of manpower$_n$ is set to zero.	If no manpower is operated, no *production completion time*$_n$ is recorded while *work in process*$_n$ is increased.
material preparation time$_n$ is set to zero.	If no material is prepared, no *work in process*$_n$ is produced and consequently, no *production completion time*$_n$ is recorded.
cycle time$_n$ is set to 1 second.	If cycle time set to 1 second, no *production completion time*$_n$ is recorded while *work in process*$_n$ is increased.

Consequently, the output of the developed ANNSD model was validated by behaviour assessment once the SFD fulfilled the extreme value assessment as discussed further in the following section.

4.6.9.2 Behaviour assessment

Behaviour assessment was conducted through a base run simulation by comparing the ANNSD output (*production completion time*$_n$) with the actual completion time (*completion*$_n$) recorded in the production daily report as reference mode. During the base run simulation to obtain *production completion time*$_n$, the initial input parameters, i.e., *number of manpower*$_n$, *material preparation time*$_n$, *machine breakdown rate*$_n$ and *cycle time*$_n$ were based on the valtues of B_n, C_n, D_n, and E_n which corresponded to the value of x_{B_n}, x_{C_n}, $x_{D_n}$and ct_n, respectively, as in Equation (4.24) in section 4.6.6. Furthermore, the difference between ANNSD output (*production completion time*$_n$) and the actual completion time (*completion*$_n$) from the production daily report was measured in terms of mean square error (MSE) formulated as follows:

$$mse_{production\ completion\ time} = \frac{1}{2}\sum(production\ completion\ time_{t_{cur}} - completion_{t_{cur}})^2 \quad (4.52)$$

where,

$mse_{production\ completion\ time}$ is the mean square error of *production completion time*

$production\ completion\ time_{t_{cur}}$ is the completion time from the ANNSD model of *t*th current time

$completion_{t_{th}}$ is the actual completion time of *t*th current time

Based on Equation (4.56), the MSE is validated if the value is less than 10% as emphasized by Sterman (2000). Furthermore, the MSE value is also validated based on the judgment of the company experts in resembling the pattern of actual completion time. Subsequently, the validated *production completion time$_n$* is evaluated with variation of input parameters on the *number of manpower$_n$, material preparation time$_n$, machine breakdown rate$_n$* and *cycle time$_n$*. Hence, the evaluation of the ANNSD model was established to observe the sensitiveness of *production completion time$_n$* as discussed in the following section.

4.6.10 Evaluation of Integrated ANNSD Model through Intervention Strategy

For the final stage in the development of a proposed integrated ANNSD model, the simulation output was evaluated once the ANNSD model was validated. The performance of the integrated ANNSD was evaluated through establishment of an intervention strategy or similar to a what-if analysis to observe model responsiveness towards uncertainty incidents discussed in section 3.2.6. The performance of the integrated ANNSD model was evaluated in two phases, namely, intervention strategy and comparison of the best-so-far scenario with the results from previous work. The evaluation procedure of the ANNSD model on completion time at the semiautomatic production line is shown in Figure 4.14.

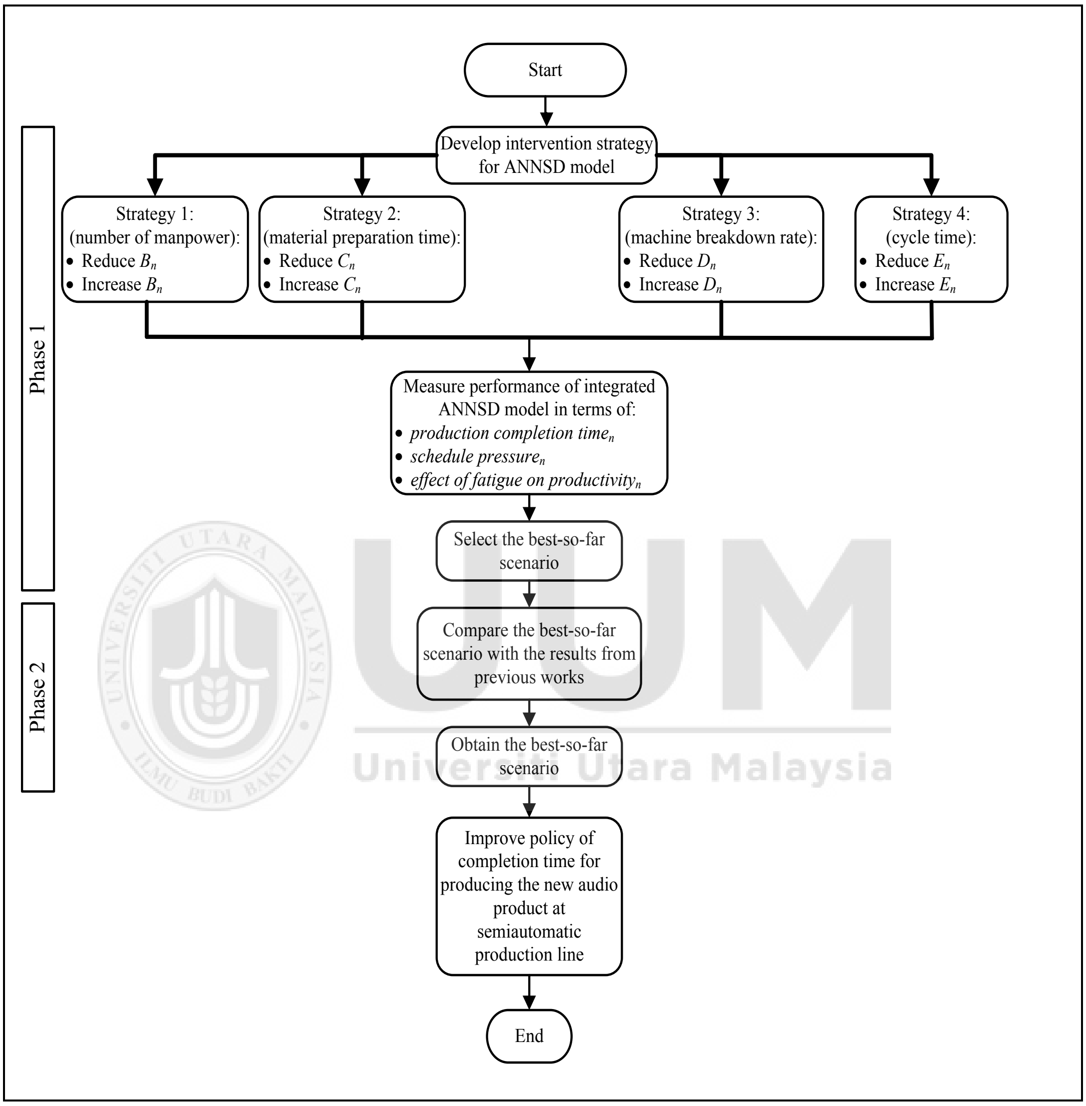


Figure 4.14. The flowchart for evaluating the integrated ANNSD model

At this stage, four strategies were developed to evaluate the sensitiveness of *production completion time*$_n$ through the variation of the input parameters, i.e., *number of manpower*$_n$, *material preparation time*$_n$, *machine breakdown rate*$_n$, *cycle time*$_n$, thus meeting the fifth objective of this research. The performance of the ANNSD model for each of the strategy was measured in terms of *production* *completion time$_n$*, *schedule pressure$_n$* and *effect of fatigue on productivity$_n$*. Consequently, the best-so-far scenario is selected based on the highest percentage deviation of completion time from base run.

The highest percentage deviation was measured through subtraction of total product produced by intervention strategy from total product produced by base run. After that, the different number of product was divided by total product produced from base run multiplied by 100. Hence, the calculation of deviation percentage is measured as follows:

$$DP_n^{IS} = \frac{[total\ product_n^{IS} - \ total\ product_n^{BR}]}{total\ product_n^{BR}} \times 100 \qquad (4.53)$$

where,

DP_n^{IS} is the deviation percentage of intervention strategy for *n*th lot

$total\ product_n^{IS}$ is the total product produced by intervention strategy for *n*th lot

$total\ product_n^{BR}$ is the total product produced by base run for *n*th lot

Subsequently, the highest percentage deviation as the best-so-far scenario was compared with previous work related to production operation. Evaluation of the ANNSD model is the final step in the development of the integrated ANNSD model. Hence, the best-so-far scenario was selected for policy improvement as discussed further in the following section.

4.7 Policy Improvement on the Completion Time

Based on the four experimented strategies and in comparison to previous work, the best-so-far scenario is obtained for policy improvement as discussed in section 3.2.6.

As a result, the best-so-far scenario for *production completion time$_n$* with acceptable *schedule pressure$_n$* and *effect of fatigue on productivity$_n$* is further elaborated in section 5.13. Subsequently, the best-so-far scenario was proposed to the management for improving the policy on completion time at the semiautomatic production line. Therefore, the occurrence of tardiness is reduced allowing the company to be on-time in fulfilling deliveries to their customers, while production workload and manpower fatigue are controllable.

4.8 Summary

In the initial stage, factors related to cycle time and completion time at the semiautomatic production line were identified through data collection from a selected manufacturing company to fulfill the first objective of this research. A proposed integrated ANNSD model was then developed to predict cycle time and simulate completion time. The development of the integrated ANNSD model met the main objective of this research. In the development of the ANN learning process, the equation of a momentum rate was formulated to improve the learning process of the ANN to meet the second research objective. Furthermore, a correlation coefficient was formulated to determine the most influential element on the completion time to fulfill the third research objective. Subsequently, the structure and behavior of the integrated ANNSD model was validated, thus achieving the fourth research objective. Finally, the integrated ANNSD model was evaluated through several scenarios and VSM model from previous work to accomplish the fifth research objective. The expected results of this research are discussed in Chapter 5.

CHAPTER FIVE
RESULTS AND DISCUSSIONS

Chapter Five presents the results and discussions of the proposed ANNSD model. Predicted cycle time of a new audio product is obtained through an established MLP network. Subsequently, the predicted cycle time is substituted in a developed SFD, thus the proposed integrated ANNSD model is established to evaluate completion time. Moreover, the integrated ANNSD model is validated through structure and behaviour assessments. Finally, the best-so-far scenario is obtained through an evaluation phase and was proposed to the company to improve its policy of completion time at the semiautomatic production line.

5.1 Data for Predicting the Cycle Time and Evaluating the Completion Time

Before predicting cycle time and evaluating completion time through the proposed integrated ANNSD model, data for number of manpower, waiting time for materials, machine breakdown, cycle time and completion time were recorded during January 2016 until March 2016 at the identified production site of company. The data from production lot n = 1 until n = 100 were recorded for new audio products since the number of pre-production test run is 100 lots. However, completion time was unavailable for the new product since the number of products is less than 50 pieces, thus completion time is insufficient to be calculated. However, the exact quantity of the new product could not be revealed by the company due to confidential status. On the other hand, production lot for n = 101 until n = 120 were recorded for the existing audio products. The existing products was selected since the product had almost the same specification with the new products. Thus, the data presented in

Table 5.1 fulfilled the first research objective, which is to identify the crucial factors in predicting the cycle time and evaluating the completion time

Table 5.1

Data for predicting the cycle time and evaluating the completion time

Produc-tion Lot number n^{th}	**Number of manpower (person)** $manpower_n$	**Waiting time of material (hours)** $material_n$	**Machine breakdown rate (1 per pieces)** $machine_n$	**Cycle time (seconds)** $cycle_n$	**Quantity of product produced (pieces)** r_n	**Comple-tion time (hours)** $completion_n$
1	30	1.0	0.0013	4		
2	30	1.0	0.0013	4		
3	30	1.3	0.0013	5		
4	30	1.0	0.0013	4		
5	30	1.0	0.0020	5		
6	30	1.0	0.0013	4		
7	30	1.2	0.0013	4		
8	29	1.0	0.0013	5		
9	30	1.3	0.0013	4		
10	30	1.5	0.0013	4		
11	29	1.1	0.0013	4		
12	30	1.0	0.0013	4		
13	30	1.0	0.0013	5		
14	30	1.5	0.0025	4		
15	30	1.0	0.0013	4		
16	30	1.0	0.0013	4		
17	30	1.0	0.0013	4		
18	30	1.2	0.0013	4		
19	30	1.4	0.0013	4		
20	28	1.0	0.0013	4		
21	30	1.0	0.0013	4		
22	30	1.0	0.0013	4	Not available	Not available
23	30	1.0	0.0020	4		
24	29	1.2	0.0025	4		
25	30	1.0	0.0013	4		
26	30	1.0	0.0013	4		
27	30	1.0	0.0013	4		
28	30	1.1	0.0013	4		
29	30	1.0	0.0025	4		
30	30	1.0	0.0013	4		
31	30	1.0	0.0013	4		
32	30	1.0	0.0013	4		
33	30	1.0	0.0013	5		
34	30	1.3	0.0020	4		
35	28	1.0	0.0013	4		
36	30	1.5	0.0013	4		
37	30	1.0	0.0013	4		
38	30	1.0	0.0013	4		
39	30	1.0	0.0013	5		
40	30	1.0	0.0013	4		
41	30	1.0	0.0013	4		
42	30	1.0	0.0013	4		
43	30	1	0.002	4		
44	30	0.75	0.0013	5		

Production Lot number n^{th}	Number of manpower (person) $manpower_n$	Waiting time of material (hours) $material_n$	Machine breakdown rate (1 per pieces) $machine_n$	Cycle time (seconds) $cycle_n$	Quantity of product produced (pieces) r_n	Completion time (hours) $completion_n$
45	30	1	0.0013	5	Not available	Not available
46	30	1.0	0.0013	5		
47	30	1.0	0.0013	5		
48	30	1.0	0.0013	5		
49	29	1.0	0.0013	4		
50	30	1.0	0.0013	5		
51	30	1.0	0.0013	5		
52	30	1.3	0.0013	5		
53	30	1.0	0.0013	5		
54	30	1.0	0.0013	5		
55	30	1.0	0.0013	4		
56	30	1.0	0.0013	5		
57	30	1.3	0.0013	5		
58	30	1.0	0.0013	5		
59	30	1.0	0.0013	5		
60	30	1.2	0.0013	5		
61	30	1.0	0.0025	5		
62	30	1.0	0.0013	5		
63	30	1.0	0.0013	4		
64	30	1.0	0.0013	4		
65	30	1.4	0.0013	5		
66	30	1.0	0.0013	5		
67	30	1.0	0.0013	5		
68	30	1.0	0.0013	5		
69	30	1.0	0.0013	5		
70	30	1.0	0.0013	5		
71	30	1.5	0.0013	5		
72	29	1.3	0.0013	5		
73	30	1.0	0.0013	5		
74	30	1.0	0.0025	5		
75	30	1.0	0.0013	5		
76	30	1.0	0.0013	5		
77	30	1.0	0.0013	5		
78	30	1.3	0.0013	5		
79	30	1.0	0.0013	5		
80	30	1.0	0.0013	5		
81	30	1.0	0.0013	4		
82	30	1.0	0.0013	4		
83	30	1.0	0.0025	4		
84	30	1.0	0.002	4		
85	30	1.1	0.002	5		
86	29	1.0	0.0013	5		
87	30	1.0	0.0013	5		
88	30	1.0	0.0013	5		
89	30	1.2	0.0013	5		
90	30	1.0	0.0013	5		
91	30	1.0	0.0013	5		
92	30	1.0	0.0013	5		
93	30	1.1	0.0013	5		

Production Lot number n^{th}	Number of manpower (person) $manpower_n$	Waiting time of material (hours) $material_n$	Machine breakdown rate (1 per pieces) $machine_n$	Cycle time (seconds) $cycle_n$	Quantity of product produced (pieces) r_n	Completion time (hours) $completion_n$
94	30	1.3	0.0013	5		
95	30	1.0	0.0013	5		
96	30	1.0	0.0013	5		
97	29	1.3	0.0013	5	Not available	Not available
98	30	1.0	0.0013	5		
99	30	1.0	0.0013	5		
100	30	1.0	0.0013	5		
101	30	1.0	0.0013	4	722	1
102	30	1.0	0.0013	4	720	1
103	30	1.2	0.0013	4	699	1
104	29	1.0	0.0013	4	717	1
105	30	1.0	0.0013	4	720	1
106	30	1.0	0.0013	5	710	1
107	30	1.0	0.0013	4	723	1
108	29	1.0	0.0020	4	709	1
109	30	1.0	0.0013	5	715	1
110	30	1.1	0.0013	4	723	1.2
111	30	1.1	0.0013	4	720	1
112	30	1.0	0.0013	4	719	1.1
113	29	1.5	0.0020	4	718	1.2
114	30	1.0	0.0013	4	712	1
115	30	1.3	0.0013	4	740	1
116	30	1.0	0.0013	4	719	1.1
117	28	1.0	0.0013	4	707	1
118	30	1.0	0.0013	4	723	1
119	30	1.2	0.0013	4	700	1
120	30	1.0	0.0013	5	716	1.2

Based on Table 5.1, the cycle time of 4 and 5 seconds are considered as uncertain parameters especially when it involves a lot of manpower, i.e., almost 30 manpower at the production line as it will give negative effects to the overall completion time. In terms of an appropriate number of data for predicting cycle time, the best prediction result is obtained from adequacy of relevant data as recommended by Samarasinghe (2016). As presented in Table 5.1, 120 data of production lots are sufficient and significant based on the judgment by experts from the company in predicting cycle time. Thus, the sufficient number of data as in Table 5.1 ensure the learning process of MLP network is simple and not operated in a complicated manner.

5.2 Cleaned Data

Once the factors for predicting cycle time and evaluating completion time were identified, data for *manpower*$_n$, *material*$_n$, *machine*$_n$, and *cycle*$_n$ of the new audio products were cleaned as discussed in section 4.6.1. On the other hand, data for *completion*$_n$ was not involved in the data cleaning process since it was conceptualized in the developed CLD as elaborated in section 4.6. Data were cleaned through constructed graph (i.e., Figure 5.1 until Figure 5.4) for each data to observe any abnormalities and missing values as elaborated in section 4.6.1. No software was used in this process. Cleaned data for *manpower*$_n$, *material*$_n$, *machine*$_n$, and *cycle*$_n$ were recorded and presented in Figure 5.1, Figure 5.2, Figure 5.3, and Figure 5.4, respectively, as follows.

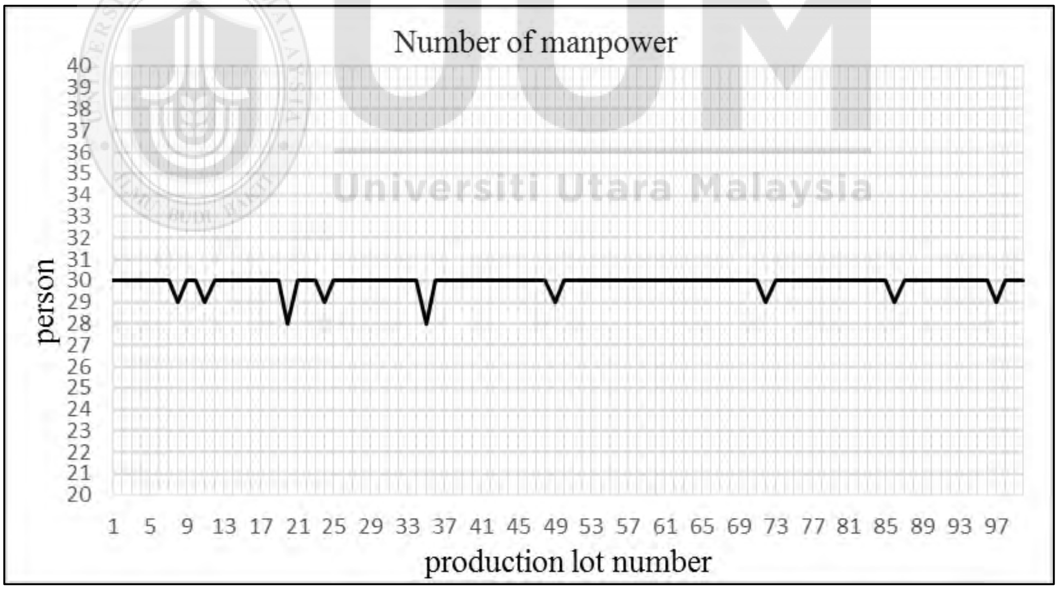


Figure 5.1. Number of manpower for production lot n = 1 until n = 100

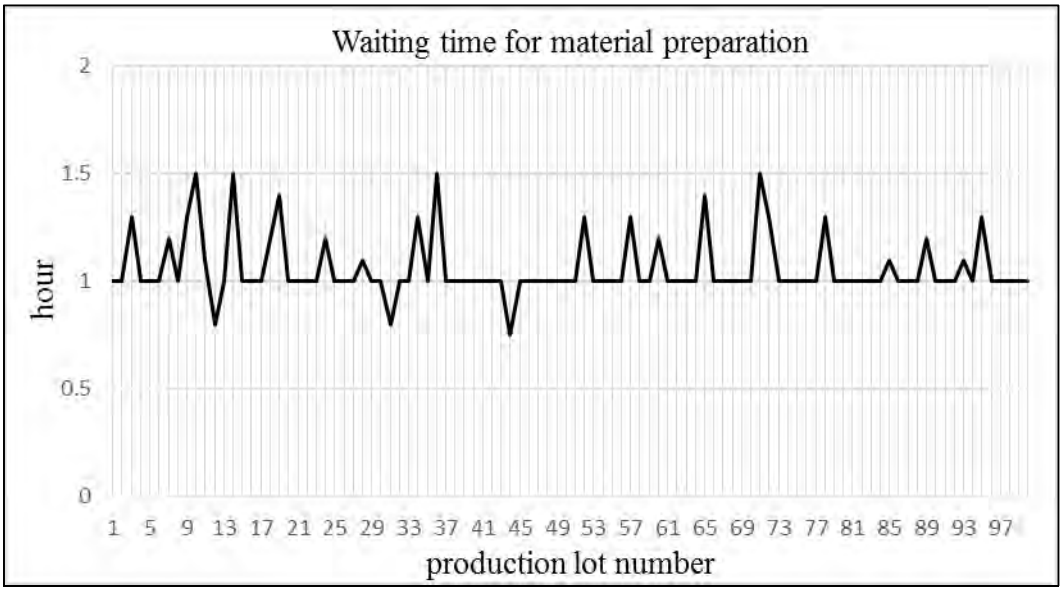


Figure 5.2. Waiting time for material for production lots n = 1 until n = 100

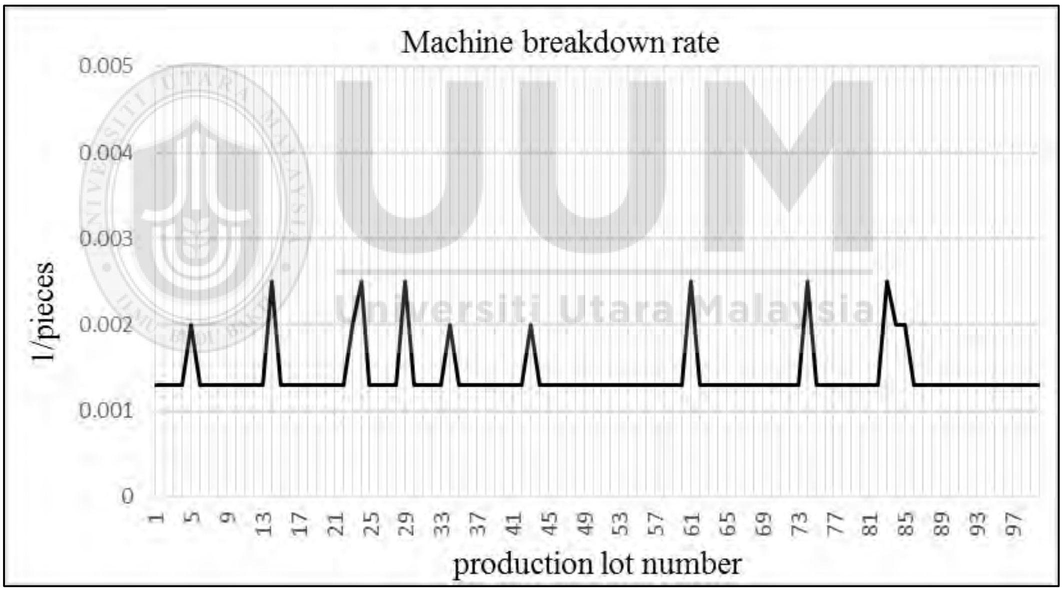


Figure 5.3. Machine breakdown rate for production lots n = 1 until n = 100

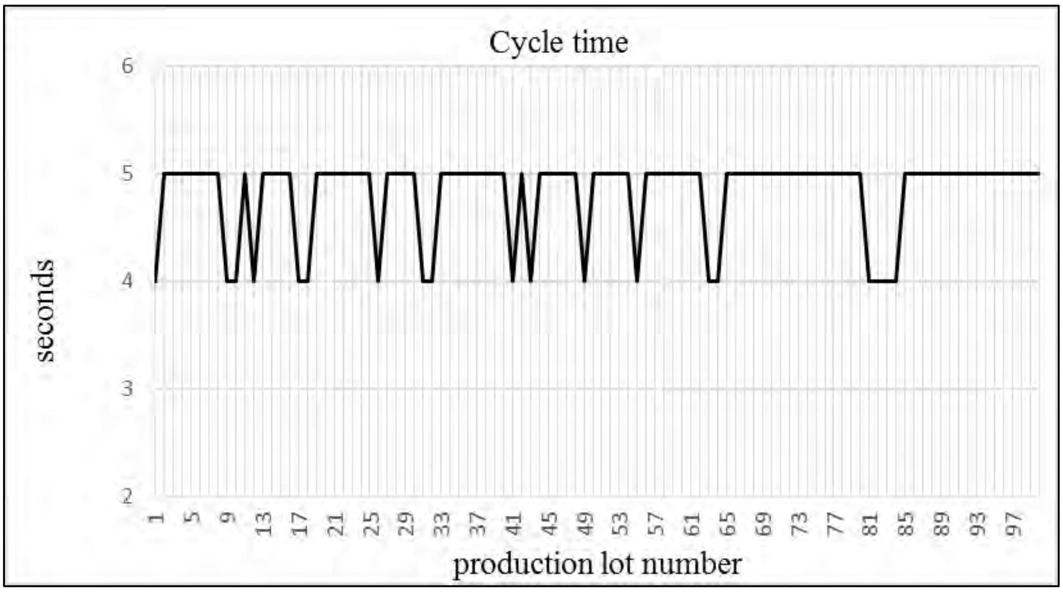


Figure 5.4. Cycle time of the new audio product for lots n = 1 until n = 100

From Figures 5.1, 5.2, 5.3 and 5.4, the pattern of data show normal fluctuation. The figures clearly showed that the data have no extreme increasing or decreasing trend. With no abnormality or missing values, thus the data was acceptable to be utilized in an integrated ANNSD model. The transformation of the input and output parameters from the cleaned data is presented in the following section.

5.3 Input and Output Parameter for ANN Learning Process

The cleaned data was transformed through MIN-MAX formula as described in section 4.6.2. The input parameters, i.e., $manpower_n$, $material_n$, and $machine_n$ were transformed between the interval values of 0 to 1 through formulated MIN-MAX based on Equation (4.2), (4.3) and (4.4), respectively. The sample results of transformed values for $manpower_n$, $material_n$, and $machine_n$ of the first production lot, i.e., n = 1 are presented in Table 5.2.

Table 5.2

Transformation value of input parameters from formulated MIN-MAX

Input parameter	MIN-MAX formulation			Transformed value
	$\boldsymbol{B_1}$	$\boldsymbol{B_{miv}}$	$\boldsymbol{B_{mav}}$	$\boldsymbol{x_{B_1}}$
manpower$_1$	30	28	30	1
	$\boldsymbol{C_1}$	$\boldsymbol{C_{miv}}$	$\boldsymbol{C_{mav}}$	$\boldsymbol{x_{C_1}}$
material$_1$	1	0.75	1.5	0.333
	$\boldsymbol{D_1}$	$\boldsymbol{D_{miv}}$	$\boldsymbol{D_{mav}}$	$\boldsymbol{x_{D_1}}$
machine$_1$	0.0013	0.003	0.002	0

Table 5.2 showed 30 manpower is equivalent to 1 as a transformed value, while an hour of material preparation time is equivalent to 0.333. Moreover, the output parameter, $cycle_n$, is also transformed between the interval values of 0 to 1 through formulated MIN-MAX as Equation (4.5). The sample result of transformed value for $cycle_n$ of the first production lot (n = 1) is presented in the Table 5.3.

Table 5.3

Transformation value of output parameter from formulated MIN-MAX

Output parameter	MIN-MAX formulation			Transformed value
	$\boldsymbol{E_1}$	$\boldsymbol{E_{miv}}$	$\boldsymbol{E_{mav}}$	$\boldsymbol{y_{E_1}}$
cycle$_1$	4	4	5	0

Based on Table 5.3, four seconds of cycle time is equivalent to 0 as a transformed value. Subsequently, the transformed input and output parameters were substituted in the ANN learning process. The predicted cycle time was obtained through three different types of the developed feed-forward MLP network that varied in terms of the number of hidden node, j, as elaborated in section 4.6.3. Furthermore, the values of connection weight, learning rate and momentum rate were varied to obtain the best-so-far network for predicting cycle time as discussed in the following section.

5.4 MLP Networks for 3-1-1, 3-2-1 and 3-3-1

At this stage, the MLP networks are developed based on the number of input node-the number of hidden node-the number of output node, *i-j-k*, as elaborated in section 4.6.3. Each type of networks is different in terms of the number of hidden node, *j*. On the other hand, the number of input node, *i*, and output node, *k*, are constant as there were only three input parameters ($manpower_n$, $material_n$, and $machine_n$) and one output parameter ($cycle_n$), respectively. Therefore, three types of established MLP network are experimented to predict the cycle time.

The first type of established MLP network is illustrated in Figure 5.5.

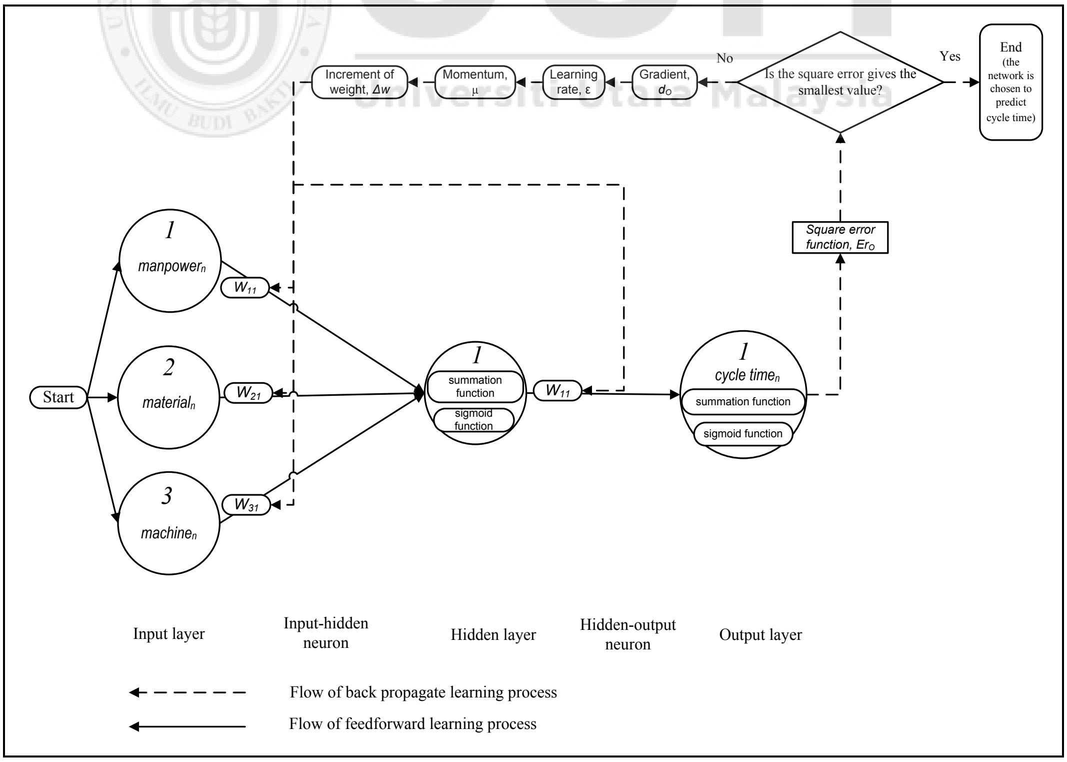


Figure 5.5. Structure of MLP for the 3-1-1 network

For the first MLP network, three layers were established which were input layer, hidden layer and output layer for a learning process. Besides, three input nodes, one hidden node and one output node were constructed within the network. Hence, the first network is a 3-1-1 MLP network.

The second type of established MLP network is illustrated in Figure 5.6.

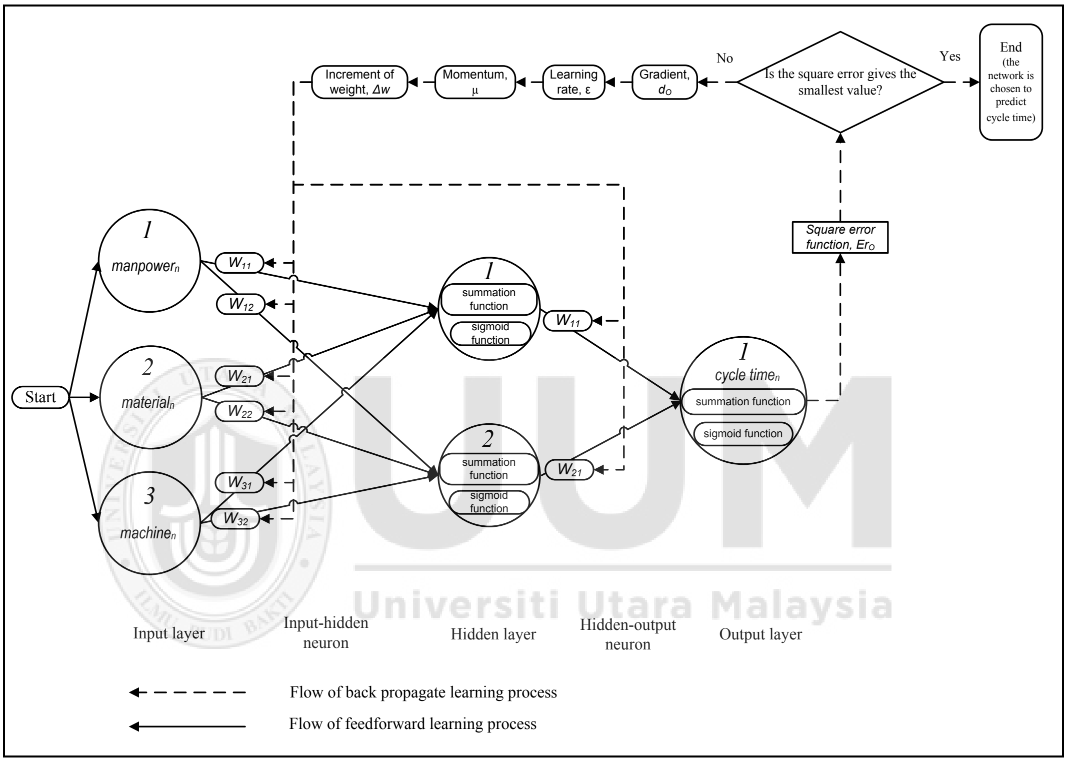


Figure 5.6. Structure of MLP for the 3-2-1 network

For the second network, three layers were established which were input layer, hidden layer and output layer for a learning process. However, the hidden layer for the second MLP network has two nodes as illustrated in Figure 5.6. Therefore, the second type network is a 3-2-1 MLP network.

The third type of established MLP network is presented in Figure 5.7.

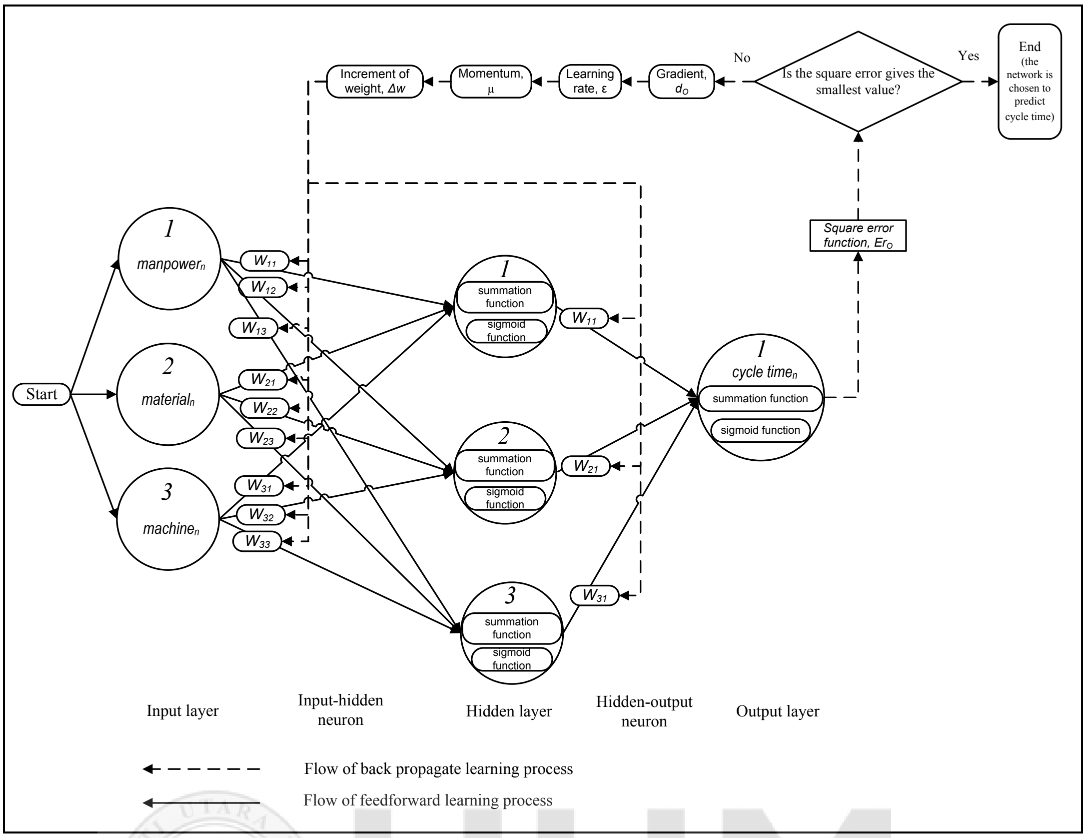


Figure 5.7. Structure of MLP for the 3-3-1 network

For the third network, three layers were established which were input layer, hidden layer and output layer for a learning process. In contrast, Figure 5.7 shows that the hidden layer has three nodes. Hence, the established network is a 3-3-1 MLP network.

Subsequently, the learning process for each type of the MLP network, i.e., 3-1-1, 3-2-1, and 3-3-1 was conducted through the developed BP learning algorithm to predict cycle. Results of predicting cycle time from the developed BP learning algorithm are presented in the following section.

5.5 BP Learning Algorithm for 3-1-1, 3-2-1 and 3-3-1 MLP Networks

The developed BP learning algorithm based on the procedures as described in section 4.6.4 was used in experimenting the three different MLP networks on their error values, i.e., between the output value of the MLP network and the desired output of cycle time as elaborated in section 4.6.4.3. This error value was measured in terms of square error function, Er_o. Thus, each types of the developed 3-1-1, 3-2-1, and 3-3-1 MLP networks from Figures 5.5, 5.6 and 5.7, respectively, were experimented using the developed BP learning algorithm.

The connection weights for the *i*th input node to the *j*th hidden node, w_{ij}, and the *j*th hidden node to the *k*th output node, w_{jk}, were initialized with random values since determination of weight had no restriction in a learning process as discussed in subsection 4.6.4.1. However, the value of summation and sigmoid functions are not presented in this section since both functions were formulated to obtain square error function, Er_o, as elaborated in subsections 4.6.4.2 and 4.6.4.3.

Besides, the value of learning rate, ε, was set randomly to 0.2 since the value is in the range of 0.1 to 1.0 as described in subsection 4.6.4.4. Furthermore, the value for momentum rate, μ, is set to random value since its parameter had no restriction and commonly based on experiment as discussed in subsection 4.6.4.5. Moreover, the proposed formulated momentum rate based on Equation (4.16) as elaborated in section 4.6.4.5 was also experimented for each type of the 3-1-1, 3-2-1, and 3-3-1 MLP networks.

Subsequently, the data from production lots n = 1 until n = 100 were randomly separated into 80% (80 production lot numbers) and 20% (20 production lot numbers) between the $train_1$ set and $valid_1$ set for each of the MLP network since the more data were allocated for training, the stronger the predictive relationship it has as discussed in section 4.6.5. Finally, the iteration of learning process, o, for each of the MLP network is accomplished once the result of square error, Er_o, gives the smallest value as discussed in subsection 4.6.4.3.

Consequently, each of the developed 3-1-1, 3-2-1, and 3-3-1 MLP networks were experimented with two experiments through BP learning algorithm. The value of w_{ij} and w_{jk} were varied (0.1, 0.3, 0.5, 0.7, 0.9, 1 and 1.5) while the value of ε and μ were set to 0.2 and 0.5, respectively, for both experiments. However, the proposed formulated momentum rate based on Equation (4.16) was used for the second experiment for each of the MLP network. Thus, there are six different experiments were conducted for the developed MLP networks at this stage.

The value of final Er_o for the first experiment of the 3-1-1 network (with variation of w_{ij} and w_{jk} while $\varepsilon = 0.2$ and $\mu = 0.5$) are presented in Table 5.4.

Table 5.4

The Er_o of the 3-1-1 network for the first experiment with random μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iterati-on**	**Square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	$train_1$	$valid_1$	o	Er_o
3-1-1 network	0.1	0.1	0.2	0.5	80%	20%	58	0.0164
	0.3	0.3					60	0.0373
	0.5	0.5					61	0.0671
	0.7	0.7					59	0.0934
	0.9	0.9					63	0.1898
	1	1					67	0.0676
	1.5	1.5					74	0.0786

According to Table 5.4, the smallest Er_o for the 3-1-1 MLP network is 0.0164 during the 58th iteration of learning process which was obtained through the input-hidden node connection weight, $w_{ij} = 0.1$ and the hidden-output node connection weight, $w_{jk} = 0.1$.

On the other hand, the proposed formulated momentum rate, μ, based on Equation (4.16) for the 3-1-1 MLP network is calculated as follows:

$$\mu = \frac{1}{\sqrt{f_{ij}}}$$
$$= \frac{1}{\sqrt{3}}$$
$$= 0.577$$

Hence, with the proposed formulated momentum rate (μ = 0.577), the value of final Er_o for the second experiment of the 3-1-1 network are presented in Table 5.5.

Table 5.5
The Er_o of the 3-1-1 for the second experiment with formulated μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iteration**	**Square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	$train_1$	$valid_1$	*o*	Er_o
3-1-1 network	0.1	0.1	0.2	0.577	80%	20%	56	0.0153
	0.3	0.3					61	0.0360
	0.5	0.5					59	0.0609
	0.7	0.7					60	0.0905
	0.9	0.9					61	0.1898
	1	1					62	0.0677
	1.5	1.5					74	0.0785

Table 5.5 shows that the smallest Er_o for 3-1-1 MLP network with formulated momentum rate is 0.0153 during the 56th iteration of learning process which is obtained from $w_{ij} = 0.1$ and $w_{jk} = 0.1$.

Furthermore, the value of final Er_o for the first experiment of the 3-2-1 network (with variation of w_{ij} and w_{jk} while $\varepsilon = 0.2$ and $\mu = 0.5$) are presented in Table 5.6

Table 5.6

The Er_o of the 3-2-1 network for the first experiment with random μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iteration**	**Final square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	$train_1$	$valid_1$	o	Er_o
3-2-1 network	0.1	0.1	0.2	0.5	80%	20%	65	0.0367
	0.3	0.3					65	0.0354
	0.5	0.5					66	0.0589
	0.7	0.7					78	0.0743
	0.9	0.9					56	0.0945
	1	1					45	0.0234
	1.5	1.5					78	0.0156

Based on the result of Table 5.6, the smallest Er_o for the 3-2-1 MLP network is 0.0156 during 78th iteration of learning process as obtained from $w_{ij} = 1.5$ and $w_{jk} = 1.5$.

The proposed formulated momentum rate based on Equation (4.16) for the 3-2-1 MLP network is calculated as follows:

$$\begin{aligned}\mu &= \frac{1}{\sqrt{f_{ij}}}\\ &= \frac{1}{\sqrt{6}}\\ &= 0.408\end{aligned}$$

Thus, based on the value of proposed formulated momentum rate ($\mu = 0.408$), the final Er_o for second experiment of the 3-2-1 MLP network are presented in Table 5.7.

Table 5.7

The Er_o of the 3-2-1 for the second experiment with formulated μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iteration**	**Final square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	***train₁***	***valid₁***	***o***	Er_o
3-2-1 network	0.1	0.1	0.2	0.408	80%	20%	53	0.0154
	0.3	0.3					60	0.0357
	0.5	0.5					59	0.0612
	0.7	0.7					60	0.0102
	0.9	0.9					62	0.1878
	1	1					61	0.0608
	1.5	1.5					72	0.0753

Table 5.7 shows that the smallest Er_o for the 3-2-1 MLP network with formulated momentum rate is 0.0102 during the 60th iteration of learning process which is obtained from w_{ij} = 0.7 and w_{jk} = 0.7.

Furthermore, the value of final Er_o for the first experiment of the 3-3-1 MLP network (with variation of w_{ij} and w_{jk} while the value of ε and μ is 0.2 and 0.5, respectively) are presented in Table 5.8.

Table 5.8

The Er_o of the 3-3-1 network for the first experiment with random μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iteration**	**Final square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	***train₁***	***valid₁***	***o***	Er_o
3-3-1 network	0.1	0.1	0.2	0.5	80%	20%	49	0.0290
	0.3	0.3					58	0.0458
	0.5	0.5					66	0.0786
	0.7	0.7					74	0.0456
	0.9	0.9					50	0.0234
	1	1					48	0.0453
	1.5	1.5					84	0.0734

Table 5.8 shows that the smallest Er_o for the 3-3-1 MLP network is 0.0234 during the 50th iteration of learning process which is obtained from w_{ij} = 0.9 and w_{jk} = 0.9.

The proposed formulated momentum rate based on Equation (4.16) for the type 3-3-1 MLP network is calculated as follows:

$$\mu = \frac{1}{\sqrt{f_{ij}}}$$
$$= \frac{1}{\sqrt{9}}$$
$$= 0.333$$

Therefore, based on the value of proposed formulated momentum rate (μ = 0.333), the final Er_o for second experiment of the 3-3-1 MLP network are presented in Table 5.9.

Table 5.9
The Er_o of the 3-3-1 for the second experiment with formulated μ

MLP network	**Connection weight**		**Learning rate**	**Momentum rate**	**Separation of data from production lot number**		**Iterati-on**	**Final square error**
i-j-k	w_{ij}	w_{jk}	ε	μ	$train_1$	$valid_1$	o	Er_o
3-3-1 network	0.1	0.1	0.2	0.333	80%	20%	34	0.0271
	0.3	0.3					45	0.0462
	0.5	0.5					56	0.0371
	0.7	0.7					50	0.0482
	0.9	0.9					56	0.0945
	1	1					63	0.0627
	1.5	1.5					68	0.0418

From Table 5.9, the smallest Er_o for the 3-3-1 MLP network with formulated momentum rate is 0.0271 during the 34th iteration of learning process which is obtained from w_{ij} = 0.1 and w_{jk} = 0.1.

Based on the results of Table 5.4, Table 5.5, Table 5.6, Table 5.7, Table 5.8 and Table 5.9, the smallest value of Er_o is 0.0102 as obtained from the 3-2-1 network with formulated momentum rate, μ = 0.408, while w_{ij} = 0.7, w_{jk} = 0.7 and learning rate, ε = 0.2 during iteration, o = 60 as described in Table 5.7. Thus, the result of the smallest Er_o, i.e., 0.0102 shows that the proposed formulated momentum rate is slightly better for predicting cycle time compared to random momentum rate, hence the second objective of this research was achieved at this stage. Consequently, the 3-2-1 MLP network with the proposed formulated momentum rate is selected for predicting cycle time of the new audio product at the semiautomatic production line as presented in the following section.

5.6 Predicted Cycle Time

The predicted cycle time of the new audio products at the semiautomatic production line was calculated through the 3-2-1 MLP network with proposed formulated momentum rate as the best network based on the smallest Er_o, i.e., 0.0102 during iteration, o = 60 as shown in Table 5.7. Subsequently, if the company would like to predict the cycle time of the new audio products for the next production lot, n = 121 with the available number of manpower, $manpower_{121}$ = 30 persons, waiting time of material, $material_{121}$ = 1 hour and machine breakdown rate, $machine_{121}$ = 0.0013, the predicted cycle time of the new audio products in transformed output value during the 121st production lot, $\boldsymbol{ct_{121}}$ is expressed based on Equation (4.20) as follows:

$$ct_{121} = [0.161]_{56} x_{B_{121}} + [0.654]_{56} x_{C_{121}} + [0.246]_{56} x_{D_{121}} + [0.201]_{56} sig_1$$

As a result, the best predicted cycle time, E_{121}, for the new audio products during 121st production lot based on the transformed values, i.e., $x_{B_{121}}$, $x_{C_{121}}$, $x_{D_{121}}$ and ct_{121}, respectively, is 5 seconds as presented in Table 5.10.

Table 5.10

The best predicted cycle time based on transformed inputs and outputs

Input parameters	Transformed input value		Corresponding input value		Transformed predicted cycle time ct_{121}	Correspon-ding predicted cycle time E_{121}
$manpower_{121}$	$x_{B_{121}}$	1	B_{121}	30 persons		
$material_{121}$	$x_{C_{121}}$	0.333	C_{121}	1 hour	1	5 seconds
$machine_{121}$	$x_{D_{121}}$	0	D_{121}	0.0013		

Subsequently, the number of manpower, material preparation time, machine breakdown rate and predicted cycle time as presented in Table 5.10 are considered as the inputs to determine the completion time in producing the new audio product from initial time, $t_{init} = 0$ to current time, $t_{cur} = 9$ (in hours) during working period at the semiautomatic production line of the company. Therefore, the developed SFD with inclusion of the best predicted cycle time was simulated to measure completion time for the new audio products as described in section 4.6.8.

However, before conducting the simulation on the SFD, the cause and effect relationship among endogenous and exogenous variables on completion time at the semiautomatic production line is conceptualized. Results of the conceptualization of completion time through the developed CLD (refer to section 4.6.7) is presented in the following section.

5.7 CLD with Correlation Coefficient

The input parameters, i.e., $manpower_n$, $material_n$, $machine_n$ and output parameter, i.e., $cycle_n$ are considered as endogenous variables in the developed CLD. However, the strength of the relationship of the endogenous variables and completion time is undetermined as discussed in subsection 4.6.7.1. Hence, during this stage, the strength of the relationship between the endogenous variables on completion time is identified through a formulated correlation coefficient.

The endogenous variables $manpower_n$, $material_n$, $machine_n$, $cycle_n$ are considered as independent variables while $completion_n$ is considered as dependent variable. The data for $manpower_n$, $material_n$, $machine_n$, $cycle_n$ and $completion_n$ were selected from production lots n = 111 until n = 120 of existing audio products since the completion time of the new audio products, i.e., n = 1 until n = 100 was not available due to the small number of products of less than 50 pieces during the pre-production test run. Thus, the $corr_{endo}$ for $manpower_n$, $material_n$, $machine_n$, and $cycle_n$ on $completion_n$ are presented in Table 5.11 based on Equation (4.21) as follows:

Table 5.11

The correlation coefficients for the independent variables

Variables	**Number of data** num	**Summation value of independent variables** val_{endo}	**Summation value of dependent variable** ($completion_n$) val_{com}	**Correlation coefficient** $corr_{endo}$
$manpower_n$	20	595	20.8	-0.000719
$material_n$		21.4		0.000239
$machine_n$		26.9		-0.000155
$cycle_n$		83		-0.000164

Based on Table 5.11, $material_n$ has the highest value of correlation coefficient indicating that waiting time for material has a strong relationship on completion time. Therefore, the determination of the relationship of endogenous variables on completion time has been fulfilled for the third objective at this stage.

Consequently, waiting time for material was selected for establishing a closed loop of the developed CLD as illustrated in Figure 5.8. The purpose of establishing a closed loop is to create a dynamic condition for completion time at the semiautomatic production line. Moreover, *manpower*$_n$, *material*$_n$, *machine*$_n$, *cycle*$_n$ variables are renamed to *number of manpower*$_n$, *material preparation time*$_n$, *machine breakdown rate*$_n$, *cycle time*$_n$, respectively, for a meaningful and proper nouns as described in section 4.6.7.1. Besides, *production completion time*$_n$ was created to distinguish *completion*$_n$ since *completion*$_n$ was the actual completion time in producing the existing audio products while *production completion time*$_n$ is a simulation output for producing the new audio products as described in section 4.6.7.1. Results of the developed CLD with other variables are further discussed in the following section.

5.8 Structured Link Polarity and Closed Loop in CLD

The cause and effect relationship among exogenous and endogenous variables (as listed in Table 4.2 of section 4.6.7.1) is structured through link polarity and a closed loop within a CLD. The constructed CLD is illustrated in Figure 5.8 to conceptualize the completion time problem at the semiautomatic production line as described in Figure 4.11 of subsection 4.6.7.2 as follows.

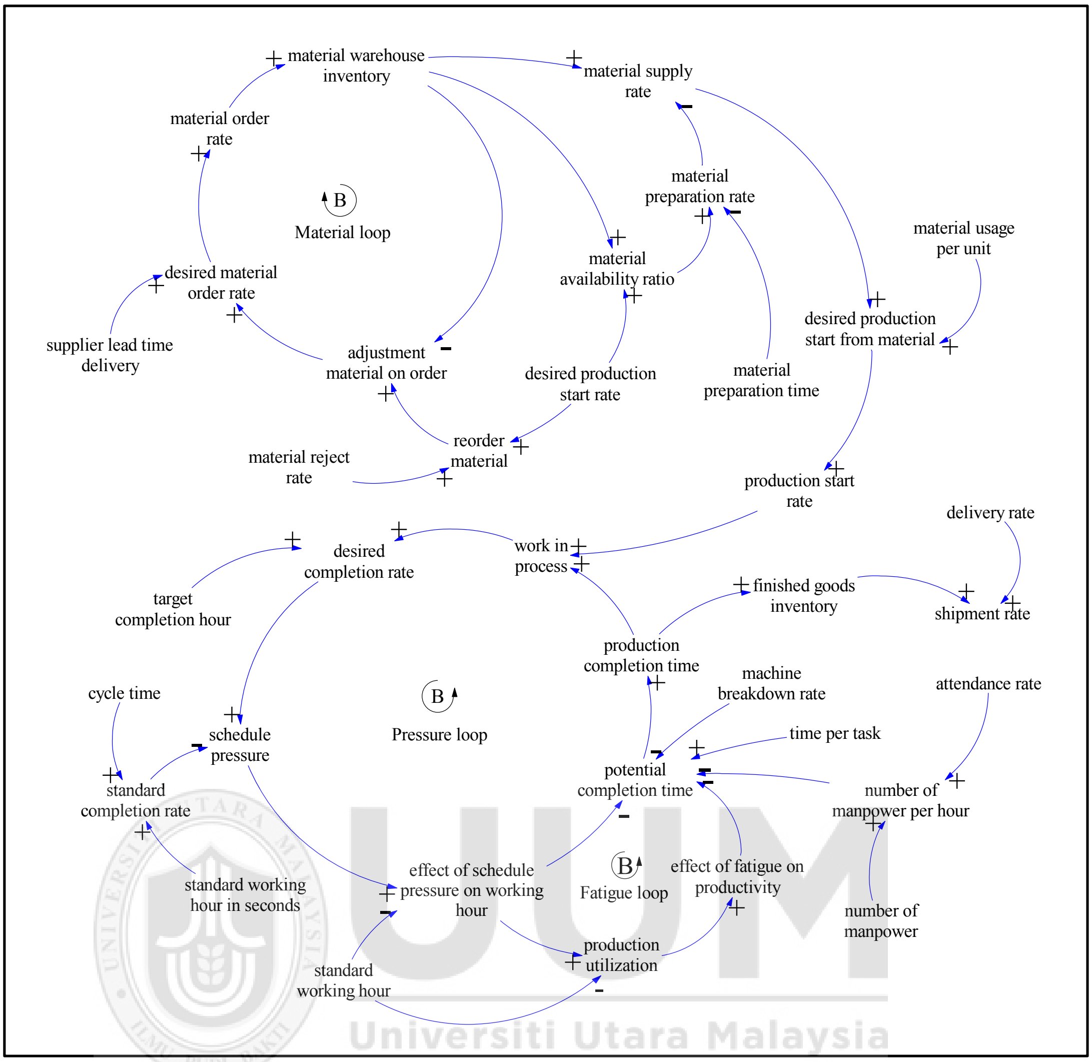


Figure 5.8. Causal loop diagram for conceptualizing the completion time problem

Three loops were established in the developed CLD which are material, pressure and fatigue loops. Although correlation coefficient were not formulated for schedule pressure and effect of fatigue on productivity as these data were unrecorded in daily production report, both variables contributed to a dynamic condition on completion time in the judgment of the company's representatives. Hence, pressure and fatigue loops were established to enhance the dynamics of the developed CLD.

The material loop is indicated with balancing loop (B) that potentially increases or decreases parameters of related variables within the loop. Furthermore, balancing loop (B) for pressure and fatigue loops indicate that both have the tendency to increase or decrease parameters of related variables in the loops.

The related variables in the material loop are *material warehouse inventory*$_n$*,* *adjustment material on order*$_n$*,* *desired material order rate*$_n$ and *material order rate*$_n$. Once material is completely loaded by supplier, the *material warehouse inventory*$_n$, *material supply rate to production*$_n$, and *material availability ratio*$_n$ at the manufacturer site are increased. Consequently, the *adjustment material on order*$_n$ to supplier is decreased. However, if *adjustment material on order*$_n$ increases, *desired material order rate*$_n$ and *material order rate*$_n$ increase as well. Moreover, if the time required by the supplier to deliver material, i.e., *supplier lead time delivey*$_n$ takes longer than usual, the *desired material order rate*$_n$ also increases. Besides, if *desired production start rate*$_n$ increases, *material availability ratio*$_n$*,* *reorder material*$_n$ and *adjustment material on order*$_n$ also increase. Furthermore, an increase in *material reject rate*$_n$ contributes to an increase in *reorder material*$_n$. On the other hand, if *material preparation time*$_n$ increases, *material preparation rate*$_n$ and *material supply rate*$_n$ decrease. However, an increase in *material supply rate*$_n$ contributes to an increase in *desired production start from material*$_n$ and *production start rate*$_n$, and *work in process*$_n$ at the semiautomatic production line.

In the pressure loop, if *work in process*$_n$ increases, the *desired completion rate*$_n$ also increases. Furthermore, an increase in *desired completion rate*$_n$ influences the *schedule pressure*$_n$, which in turn increases the *effect of schedule pressure on working hour*$_n$ while decreasing *potential completion time*$_n$. Besides, *schedule pressure*$_n$ is influenced by *standard completion rate*$_n$ as required by management. On the other hand, increases in *cycle time*$_n$ and *standard working hour in seconds*$_n$

contribute to the increment in *standard completion rate$_n$*. Consequently, a decrease in potential completion timen contributes to the increment in *production completion time$_n$* and *work in process$_n$* as more output, r_n, are accomplished.

In the fatigue loop, *production utilization$_n$* has a positive influence on *effect of fatigue on productivity$_n$*. Therefore, when *production utilization$_n$* gets higher, the *effect of fatigue on productivity$_n$* becomes lower as manpower needs rest due to the longer working hours. Consequently, the lower the *effect of fatigue on productivity$_n$*, the higher the *potential completion time$_n$* to accomplish production process.

Moreover, the *machine breakdown rate$_n$*, *number of manpower$_n$* and *time per task$_n$* also have an impact on *potential completion time$_n$*. As *number of manpower$_n$* and *machine breakdown rate$_n$* increase, the *potential completion time$_n$* decreases. On the other hand, if *time per task$_n$* becomes high, so does the *potential completion time$_n$*. Finally, an increase in the number of products, r_n, produced by *production completion time$_n$* contributes to the increment in *finished goods inventory$_n$* and therefore, it drives the *shipment rate$_n$* higher as well.

It is found that the established CLD provides only the cause and effect relationship among variables related to completion time at the semiautomatic production line since CLD is a qualitative tool. Therefore, the parameter of each variable was quantified through simulations of a SFD as presented in the following section.

5.9 SFD with Formulated Stock, Flow and Auxiliary Variables

The formulated stock, flow and auxiliary variables are structured in the developed SFD as described in subsection 4.6.8.1 and 4.6.8.2. At this stage, the parameters for number of manpower, material preparation time, machine breakdown rate, cycle time for the next production lot, n = 121, based on the values of B_{121}, C_{121}, D_{121}, and E_{121} as obtained from the predicted cycle time in Table 5.10 were substituted in the developed SFD. Thus, the proposed integrated ANNSD model was formed at this stage. The parameters for related auxiliary variables for the next production lot, n = 121, are discussed in Table 5.12.

Table 5.12

Parameter value for related auxiliary variable in the developed SFD

Auxiliary variable	**Parameter value**	**Units**
number of manpower$_{121}$	30	number of person
material preparation time$_{121}$	1	hour
machine breakdown rate$_{121}$	0.0013	1 per pieces
cycle time$_{121}$	5	second per pieces
target completion hour$_{121}$	1	hour
standard working hour in second$_{121}$	3600	second
standard working hour$_{121}$	1	hour
attendance rate$_{121}$	1	dimensionless
time per task$_{121}$	0.41667	person × hour per pieces
delivery rate$_{121}$	1	hour
material usage per unit$_{121}$	7	dimensionless
desired production start rate$_{121}$	5040	pieces
material reject rate$_{121}$	0	dimensionless
supplier lead time delivery$_{121}$	1	hour

From Table 5.12, the parameter value for *target completion hour*$_n$ is set to 1 hour based on the requirement by the production site to complete the work in process audio products. On the other hand, *standard working hour in second*$_n$ is set to 3600 since 1 hour is equal to 3600 seconds. Besides, *standard working hour*$_n$ is set to 1 hour based on time step of working period at the semiautomatic production line from initial time, t_{init} = 0 to current time, t_{cur} = 9 hours.

Moreover, *attendance rate*$_n$ is set to 1 based on the assumption that there was no absenteeism among manpower. Furthermore, *time per task*$_n$ is set to 0.41667 as a tolerance for production utilization set by experts. The parameter for *material usage per unit$_n$* is set to 7 since 1 piece of the new audio product requires seven pieces of material for assembly process while the *desired production start rate$_n$* is set to 5040 pieces based on the ideal amount of materials to enter the production site. Besides, *material reject rate$_n$* is set to 0 based on the assumption that all related materials are in good condition. Finally, *delivery rate$_n$* is set to 1 hour based on the time required to distribute products to customers.

5.10 SFD for Simulating the Integrated ANNSD Model

Subsequently, the completion time at the semiautomatic production line is simulated through the integrated ANNSD model as illustrated in Figure 5.9. Thus, the integrated ANNSD model for predicting cycle time and simulating completion time has been accomplished at this stage.

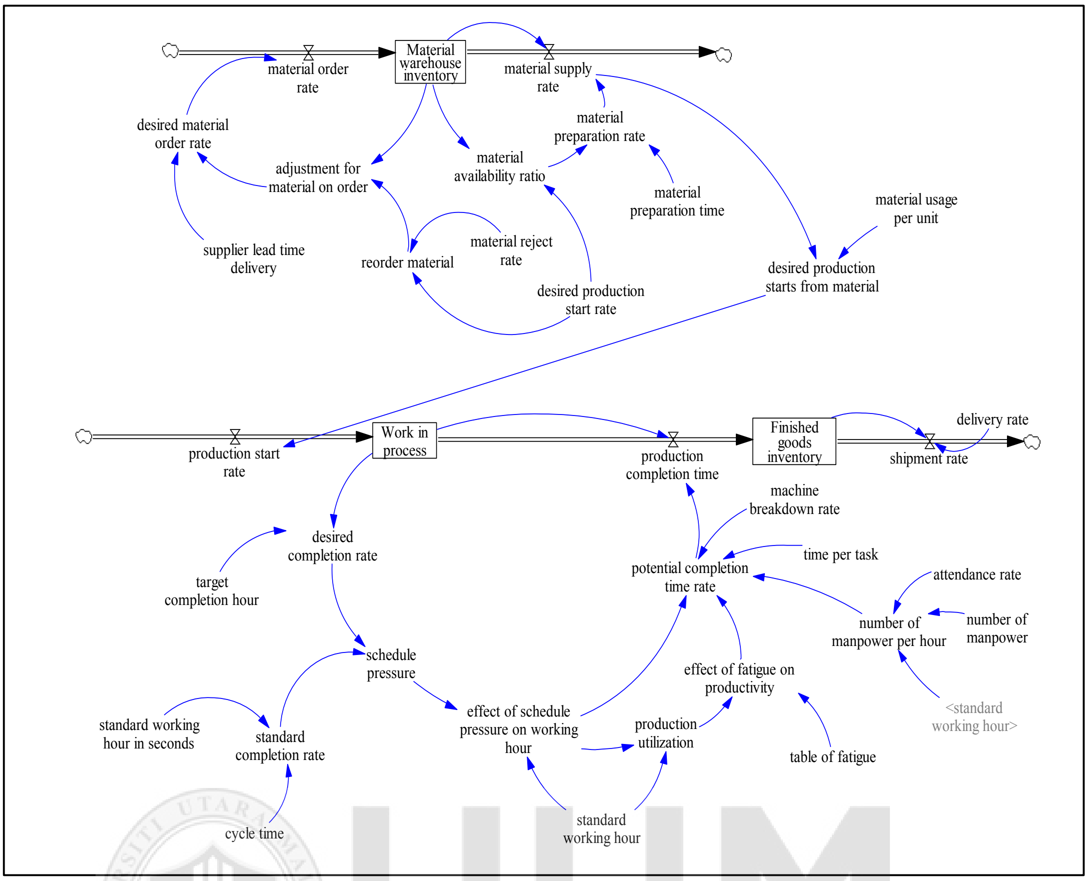


Figure 5.9. The developed SFD of integrated ANNSD for production operation

However, before simulating the completion time through the developed SFD, the equation and structure of stock, inflow, outflow, auxiliary variables and table function of the proposed integrated ANNSD model are validated as discussed in section 4.6.9. Results of the validated integrated ANNSD model in simulating the production operation are further discussed in the following section.

5.11 Validated Structure and Behaviour of the ANNSD Model

The proposed integrated ANNSD model is validated through structure and behaviour assessments as a part of the validation process (see section 4.6.9). The structure of the developed SFD is validated through structure, parameter, dimensional unit and extreme value assessments as discussed further in subsections 5.11.1, 5.11.2, 5.11.3

and 5.11.4, respectively, while validated of SFD behaviour is discussed in section 5.11.5.

5.11.1 Validated SFD Structure

The structure of the developed SFD is compared with the actual production operation of the company based on the reviews of production planner and executive. The validated structure from the experts is obtained through interviews as indicated in Appendix B.

Furthermore, the SFD structure is also compared with the SFD model related to production operation including number of manpower, material preparation, machine breakdown and cycle time as constructed by Sterman (2000) and Garcia (2016). Therefore, the developed SFD is structurally validated and consistently corresponding to the real production operation.

5.11.2 Validated Parameter

Through parameter validation, the developed SFD model is compared with the secondary data, i.e., production control document and production daily report (see Table 4.1 in section 4.5). Furthermore, the related parameters are also validated based on the judgment of production executive and planner through primary data as discussed in section 4.5. It is found that, all parameters for related variables as presented in Table 5.12 are within the acceptable range of values as validated by the company experts (see Appendix B). Hence, the SFD parameters is validated since the parameters correspond conceptually and numerically to the real production operation.

5.11.3 Validated Dimensional Unit

In the dimensional unit validation, the equivalence of units from stock, flow and auxiliary equations are compared in the developed SFD. As a result, the dimensional units are validated as indicated by the built-in unit consistency checking feature of the SD computer simulation in Figure 5.10.

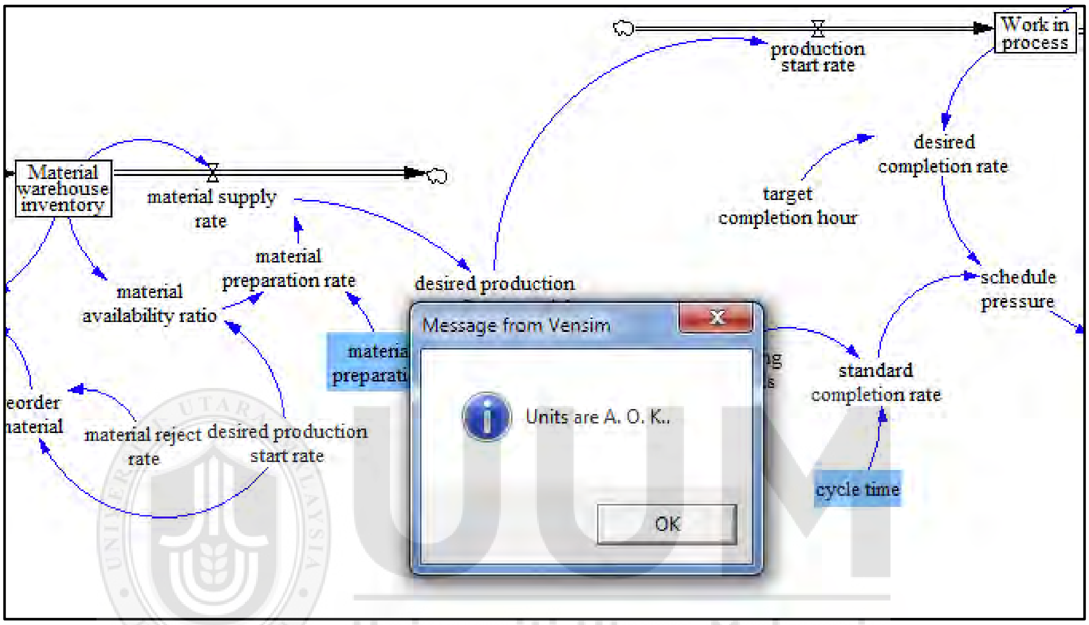


Figure 5.10. Successful of validated dimensional unit

Referring to Figure 5.10, the related units in the developed SFD are validated due to being dimensionally consistent among equations. In this sense, the developed SFD has no faulty model structure in resembling the real production operation of the semiautomatic line.

5.11.4 Validated Extreme Value

Furthermore, the extreme value on number of manpower, material preparation time and cycle time is set to a value of zero during the working period from initial time, t_{init} = 0 to current time, t_{cur} = 9 (in hours) as discussed in Table 4.4. The results of extreme value on work in process and production completion time are described in Table 5.13.

Table 5.13

Observation output for extreme value on the integrated ANNSD model

Type of assessment	**Extreme value condition**	**Observation outputs**
Extreme value	1. number of manpower is set to zero.	No production completion time is obtained while work in process is consistently increased.
	2. material preparation time is set to zero.	No work in process and production completion time are obtained.
	3. cycle $time_n$ is set to 1 second.	No production completion time is obtained while work in process is consistently increased.

Table 5.13 shows that the observation outputs are aligned with the expectation as elaborated in Table 4.4. Thus, the observation outputs on each extreme value as described in Table 5.13 are validated for manpower, material preparation and cycle time as shown in Figure 5.11, 5.12, 5.13, 5.14, 5.15 and 5.16.

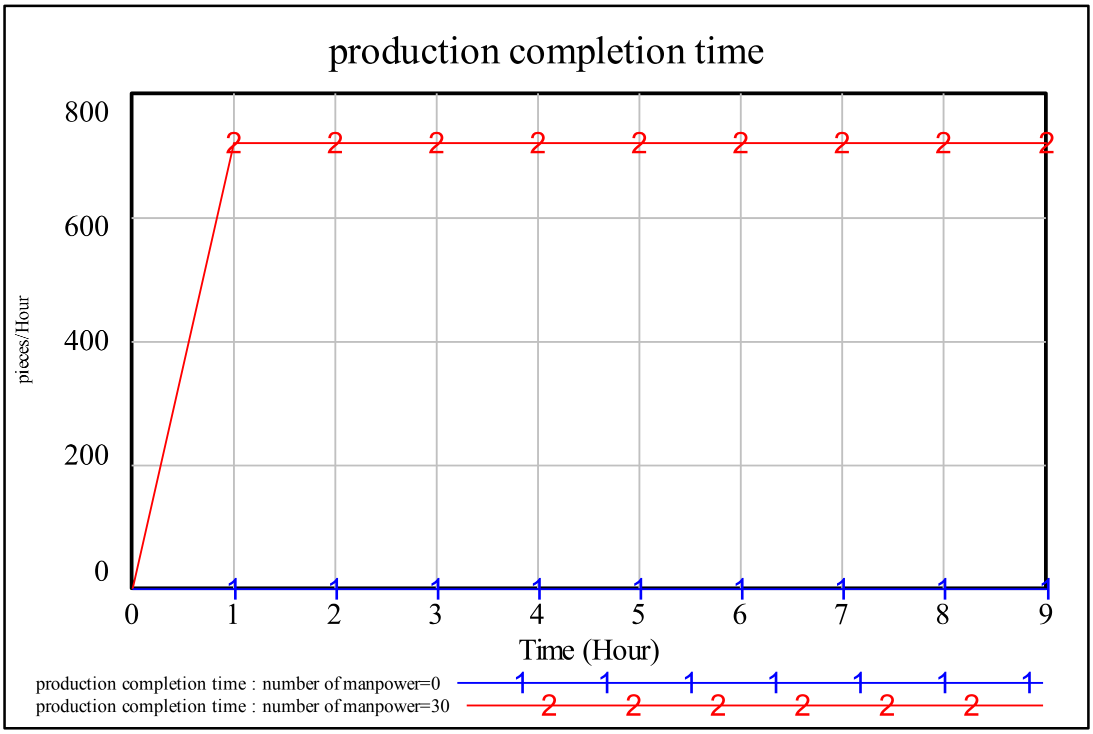


Figure 5.11. The behaviour of the completion time based on the extreme value

Referring to Figure 5.11, if the number of manpower is set to 30, the completion time is consistently achieved 720 pieces per hour. However, if the number of manpower is set to zero, the completion time falls to zero since no assembly task is performed at the production line. Consequently, work in process increases tremendously due to pending items at the production line as presented in Figure 5.12.

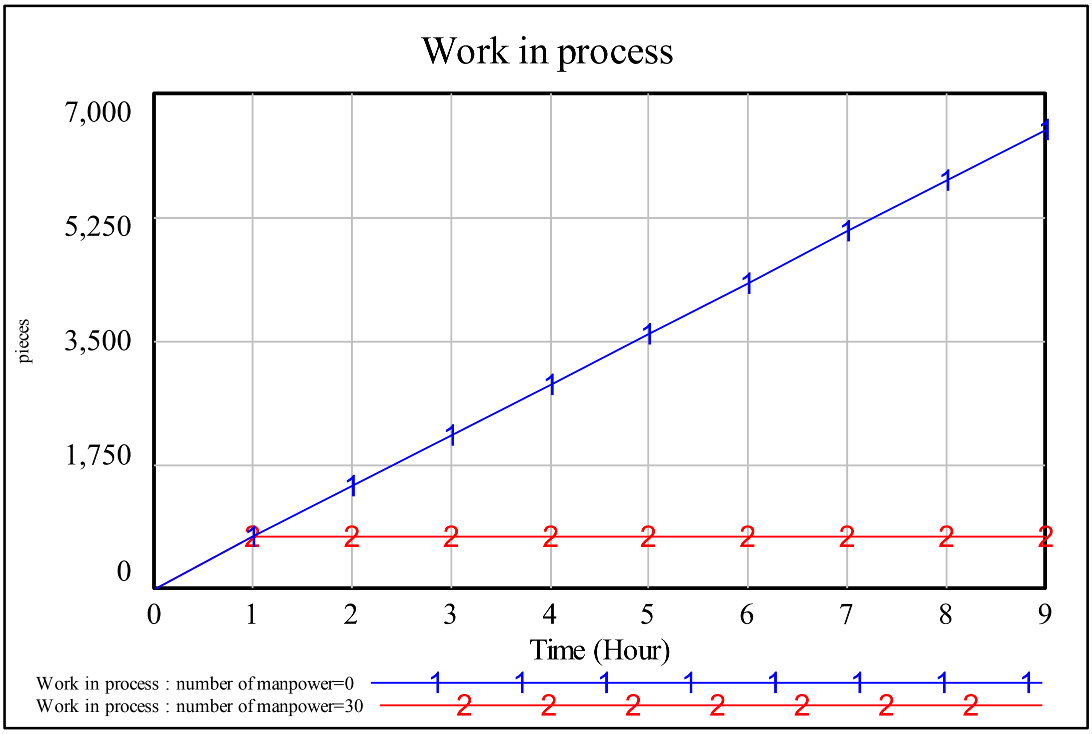


Figure 5.12. The behaviour of work in process based on the extreme value

Based on Figure 5.12, for example, work in process for zero number of manpower could exceed more than 3500 pieces at the 5th working hour, $t_{cur} = 5$ due to pending material since no manpower is performing the assembly task, while work in process for 30 manpower is stable during the entire working hours, i.e., 720 pieces. Therefore, the developed SFD structure is validated based on the result of the extreme value on the number of manpower.

The observation output for extreme value on material preparation time is presented in Figure 5.13.

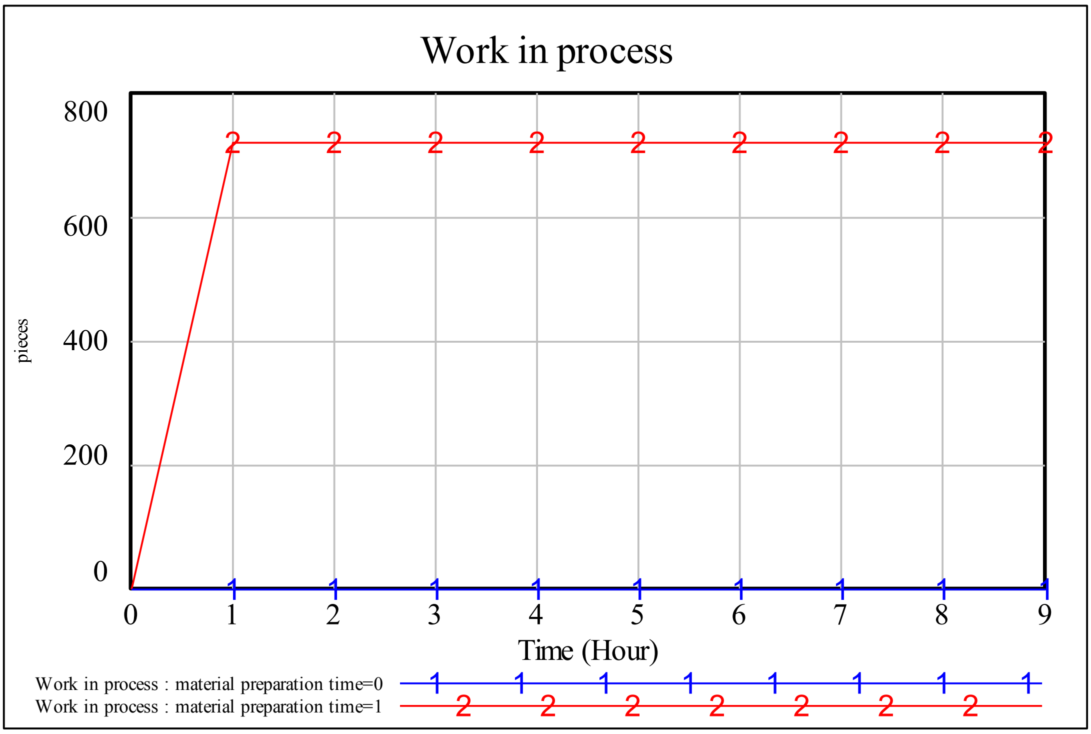


Figure 5.13. The behaviour of work in process based on the extreme value

Based on the Figure 5.13, if material preparation time is set to 1 hour, 720 pieces of product are recorded for very hour. However, if material preparation time is set to zero as the extreme value, no completion time is recorded since materials are not prepared at all. As a result, no completion time is recorded if material preparation time is set to zero, i.e., materials are not prepared as shown in Figure 5.14.

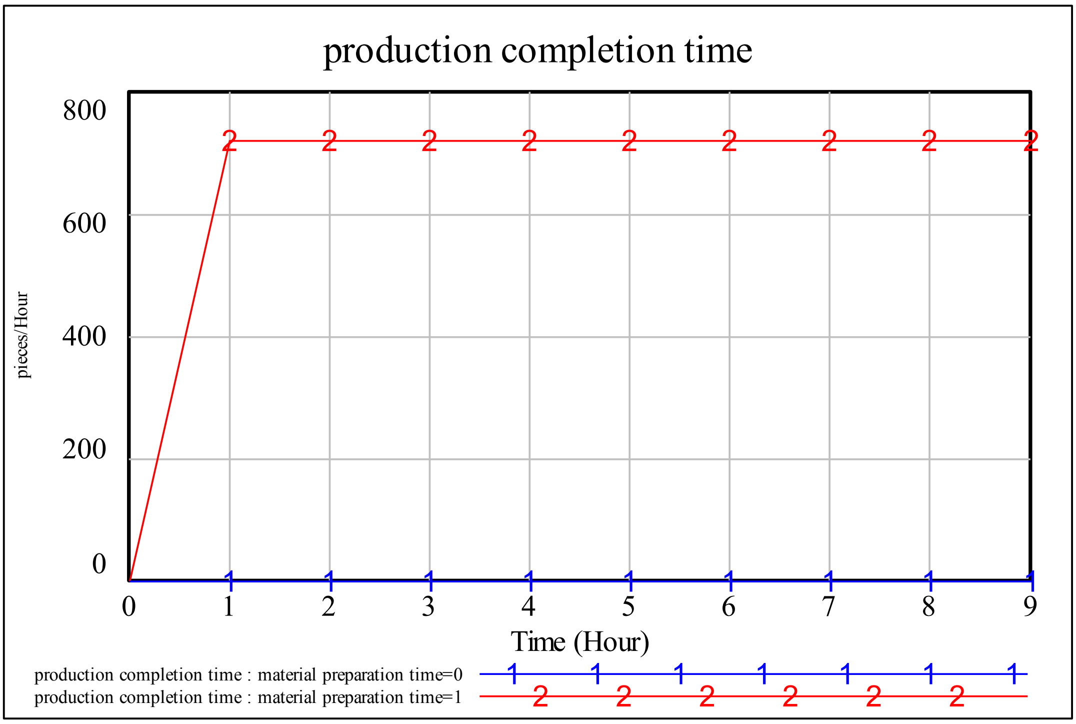


Figure 5.14. The behaviour of the completion time based on the extreme value

Referring to Figure 5.14, the completion time consistently recorded 720 pieces if material preparation time is set to 1 hour. Hence, the developed SFD structure is validated based on the result of extreme value on the material preparation time.

The observation output for extreme value on cycle time is shown in Figure 5.15.

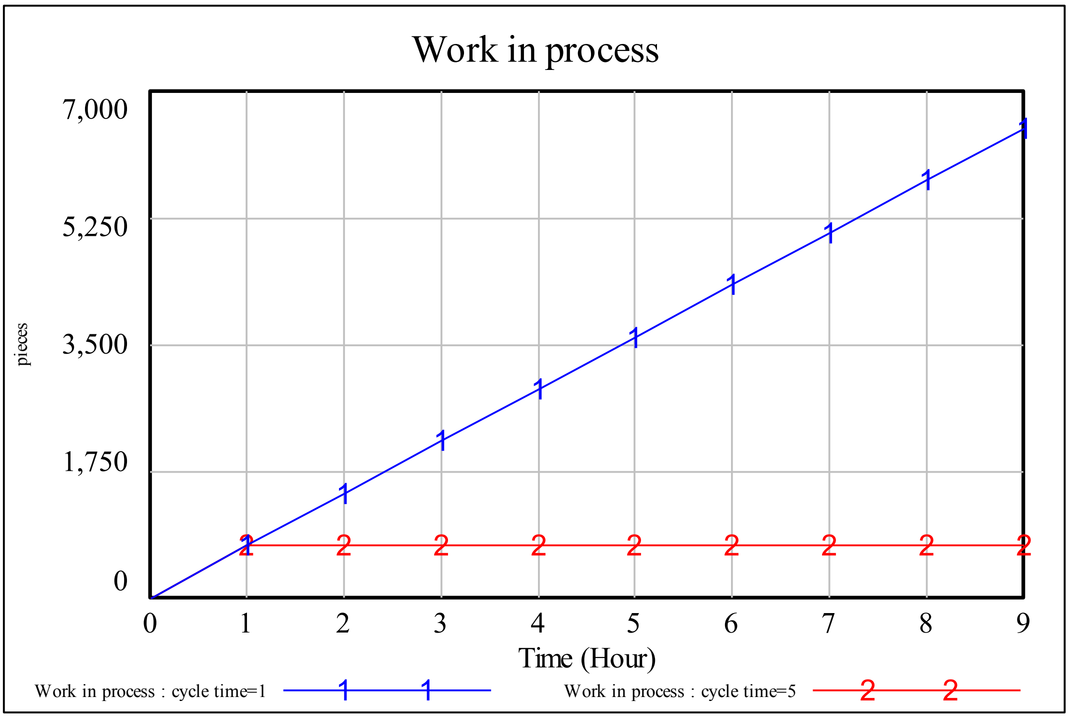


Figure 5.15. The behaviour of work in process based on the extreme value

Referring to Figure 5.15, 720 pieces of product are recorded for every hour if the cycle time is set to 5 seconds. However, work in process increased tremendously if the cycle time is set to 1 second since the materials that enter into the production line are not assembled due to the extreme short time imposed on manpower to complete their task. Consequently, no completion time is recorded for *cycle time*$_n$ = 1 as presented in Figure 5.16.

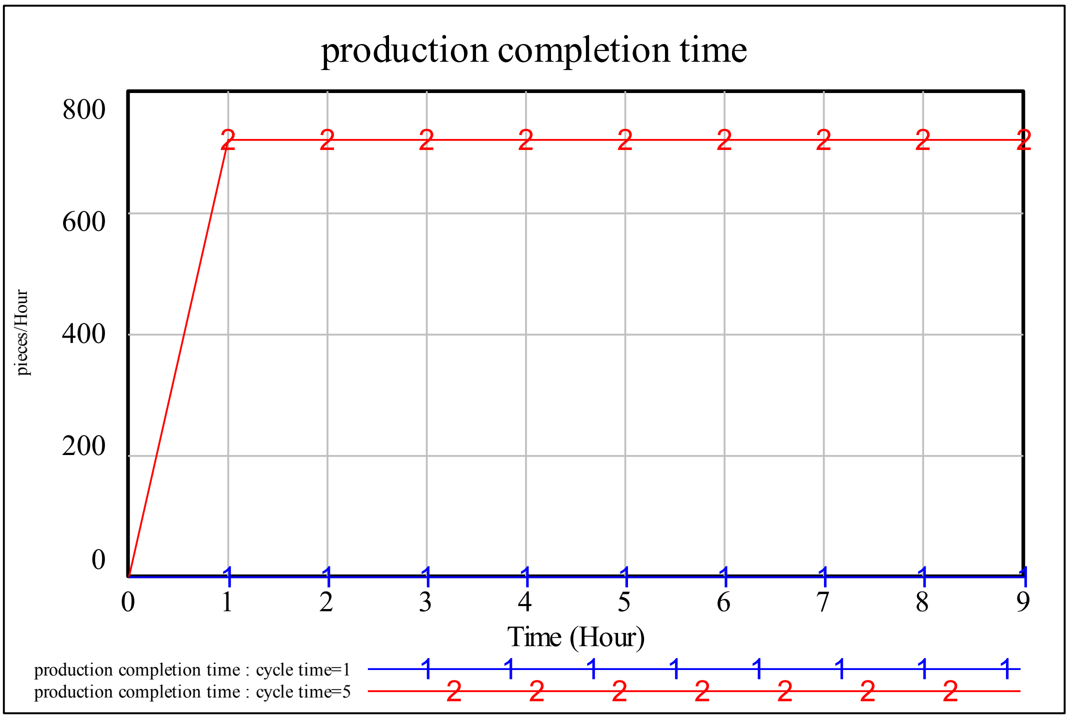


Figure 5.16. The behaviour of the completion time based on the extreme value

Referring to Figure 5.16, no product is produced for every working hour if the cycle time is set to 1 second since manpower experience extreme fatigue to cope with the shortest cycle time. However, 720 pieces of product are produced if the cycle time is set to 5 seconds. Thus, the developed SFD structure is validated through the result of extreme value on the cycle time.

Based on the results of extreme value on number of manpower, material preparation time and the cycle time, the simulation output of the integrated ANNSD model is relevant with the real production operation. The validated output behaviour of the integrated ANNSD model is further discussed in the following section.

5.11.5 Validated Behaviour of ANNSD Output

The behaviour of the ANNSD output is validated by comparing the model simulation output, i.e., *production completion time$_n$* with the actual completion time, i.e., *completion*$_n$ which were recorded in the production daily report as elaborated in section 4.6.9.2. In order to obtain simulated production completion time, a base run is simulated on the integrated ANNSD model with the initial input parameter on number of manpower, material preparation time, machine breakdown rate, cycle time and all other variables as presented in Table 5.12 of section 5.9.

On the other hand, the actual completion time from n = 101 until n = 109 production lots (see Table 5.1) are considered as reference mode since the lots were run sequentially with stable completion time at the semiautomatic production line on the same day. Hence, the simulation result of the simulated production completion time and the actual completion time during working period from initial time, t_{init} = 0 to current time, t_{cur} = 9 (in hours) at the semiautomatic production line is presented in Figure 5.17.

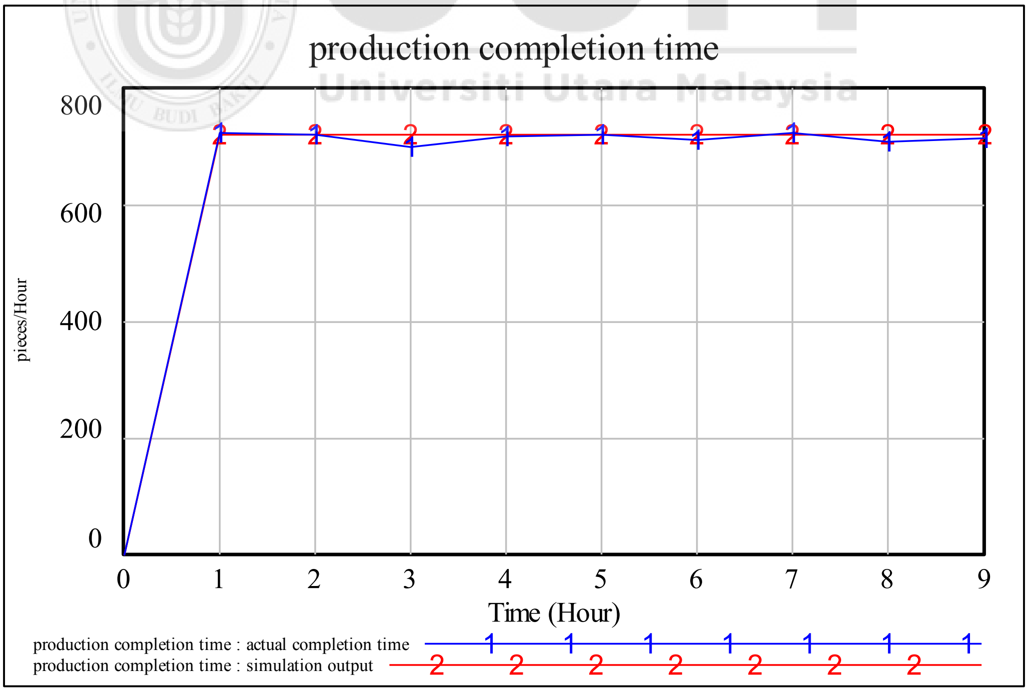


Figure 5.17. Simulated and actual behaviour of the production completion time

Figure 5.17 shows that 720 pieces is consistently produced through the simulated output as observed during work period from t_{init} = 0 until t_{cur} = 9 hours. The comparison between the simulated production completion time and the actual completion time during work period t_{init} = 0 until t_{cur} = 9 hours are measured in terms of MSE (refer Equation 4.52) as shown in Table 5.14.

Table 5.14
Mean square error of production completion time

Behavior assessment test	**Number of pieces for the new audio product from current time, t_{cur} = 1 until t_{cur} = 9 (hour)**									**Mean square error of production completion time**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	$MSE_{production\ completion\ time}$
production completion time$_{121}$	720	720	720	720	720	720	720	720	720	0.0164
completion$_{121}$	720	720	699	720	720	710	720	709	715	

Based on the judgment of experts from the company, the MSE for the *production completion time$_n$*, i.e., 0.0164 or 1.64% is acceptable due to less than 10% as recommended by Sterman (2000). It indicated that 720 pieces of the new products are recorded during t_{cur} at 1, 2, 4, 5 and 7 hours, for both *production completion time$_n$* and *completion$_n$*. However, the small discrepancy between *production completion time$_n$* and *completion$_n$* are recorded only for t_{cur} at 3, 6, 8 and 9 hours.

Based on the result of behaviour assessment, the simulation output of the integrated ANNSD model, i.e., *production completion time$_n$* resembles the actual completion time. Hence, according to the judgment of the company experts, the integrated ANNSD model is validated to simulate the production operation in measuring *production completion time$_n$*, thus the fourth objective has been accomplished at this stage. The simulation output of the ANNSD model was evaluated through various scenarios as well as comparison of the best-so-far scenario with the results from previous works are discussed in the following sections.

5.12 Scenario Analysis for the Completion Time

Several scenario analyses which also known as what-if analyses were carried out to evaluate the completion time. Once the proposed integrated ANNSD model is validated, the *production completion time$_n$* base run simulation is evaluated with four strategies by varying parameters B_n, C_n, D_n, and E_n on the number of manpower, material preparation time, machine breakdown rate, and cycle time, respectively, as discussed in section 4.6.10. Moreover, the results of schedule pressure and effect of fatigue on productivity are measured to avoid over production workload and extreme manpower fatigue, respectively, as shown in Table 5.15.

Table 5.15

The scenarios and strategies on the integrated ANNSD model

Description of scenario	Base run input value	Description of strategy	Observation of performance output
Strategy 1: Parameter B_{121} for *number of manpower$_n$* is altered	B_{121} = 30 persons	i. B_n is reduced to 29 persons ii. B_n is increased to 31 persons	
Strategy 2: Parameter C_n for *material preparation time$_n$* is altered	C_{121} = 1 hour	i. C_n is reduced to 0.75 hours ii. C_n is increased to 1.5 hours	i. *production completion time$_n$* ii. *schedule pressure$_n$* iii. *effect of fatigue on productivity$_n$*
Strategy 3: Parameter D_n for *machine breakdown rate$_n$* is altered	D_{121} = 0.0013	i. D_n is increased to 0.002 (0.2 %)	
Strategy 4: Parameter E_n for *cycle time$_n$* is altered	E_{121} = 5 seconds	i. E_n is reduced to 4 seconds	

For strategy 1, parameter B_n for number of manpower is increased to 31 persons since the management would like to evaluate whether the production process would require additional manpower to speed up production output, or otherwise decrease to 29 persons for operational cost down. For strategy 2, parameter C_n for material preparation time is increased to 1.5 hours since the management would like to evaluate the effect of waiting time on production operation due to a problem with material preparation. On the other hand, parameter C_n is reduced to 0.75 hours due to the management plans to improve the time in preparing material for production operation.

For strategy 3, parameter D_n for machine breakdown rate is increased to 0.002 (0.2%) as the production site was interested to evaluate the influence of machine breakdowns on production output while no decrease rate is tested since parameter below than 0.0013 (0.13%) is beyond the machine capability. For strategy 4, parameter E_n for cycle time is reduced to 4 seconds since the production site would like to evaluate the effect of adjusting the production conveyor on production output, schedule pressure, i.e., production workload and the effect of manpower fatigue. Therefore, the results of these scenario strategies based on variations on input parameters for the number of manpower, material preparation time, machine breakdown rate, and cycle time towards production completion time, schedule pressure and effect of fatigue on productivity are discussed further.

5.12.1 Strategy 1 for the Number of Manpower

Strategy 1 was conducted by reducing the number of manpower to 29 person and increasing the number of manpower to 31 persons. The scenario performance is observed on production completion time as shown in Figure 5.18.

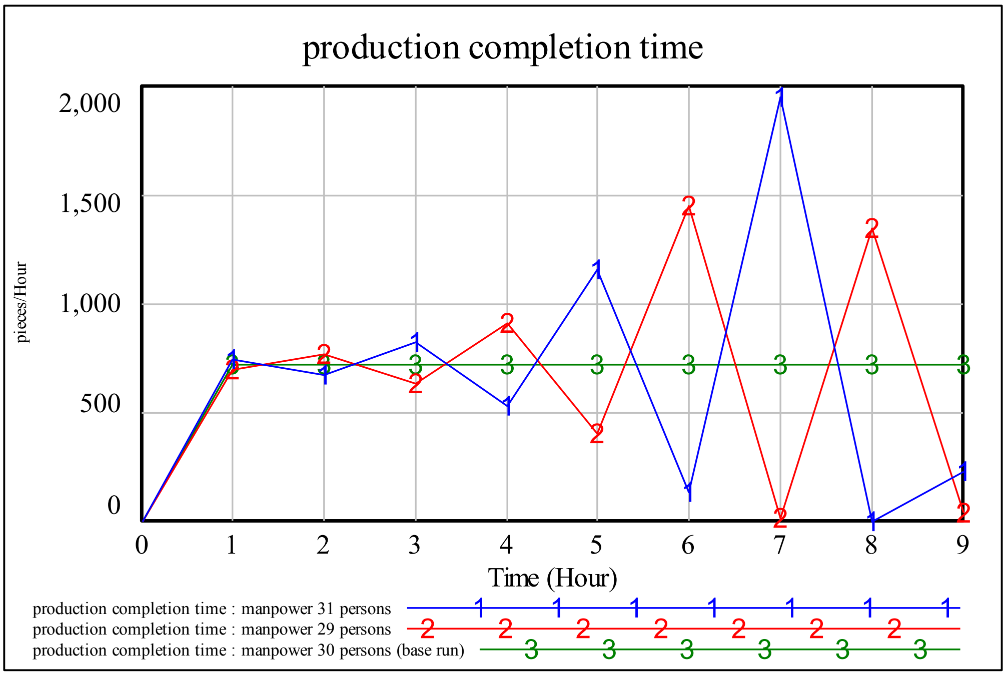


Figure 5.18. Production completion time at different number of manpower

Based on the result of Figure 5.18, the production completion time for 31 and 29 persons of manpower show a rapid fluctuation compared to 30 persons of manpower. The fluctuation of production completion time for 29 persons is due to a lesser number of manpower to accomplish the desired completion rate. On the other hand, the fluctuation of production completion time shows obvious up and down for 31 persons due to an excess number of manpower to fulfill the desired completion time.

Subsequently, a description of production completion time in producing the new audio products based on a variation in the number of manpower during work period t_{init} = 0 until t_{cur} = 9 hours at the semiautomatic production line is shown in Table 5.16.

Table 5.16

Description of completion time based on different number of manpower

number of manpower$_{121}$	**production completion time of the new audio product from initial time, t_{init} = 0 to current time, t_{cur} = 9 hours**										**Total of new audio product (pieces)**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
31 persons	0	744	672	821	530	1151	129	1949	0	226	6222
29 persons	0	696	768	629	910	398	1451	13	1343	38	6246
30 persons (base run)	0	720	720	720	720	720	720	720	720	720	6480

Referring to Table 5.16, 30 manpower contributed the highest number of new audio product, i.e. 6480 pieces. However, only 6222 pieces of new audio product is produced by 31 manpower, while 6246 pieces is achieved from 29 manpower. This performance are observed on the schedule pressure and effect of fatigue on productivity as shown in Figure 5.19 and Figure 5.20, respectively.

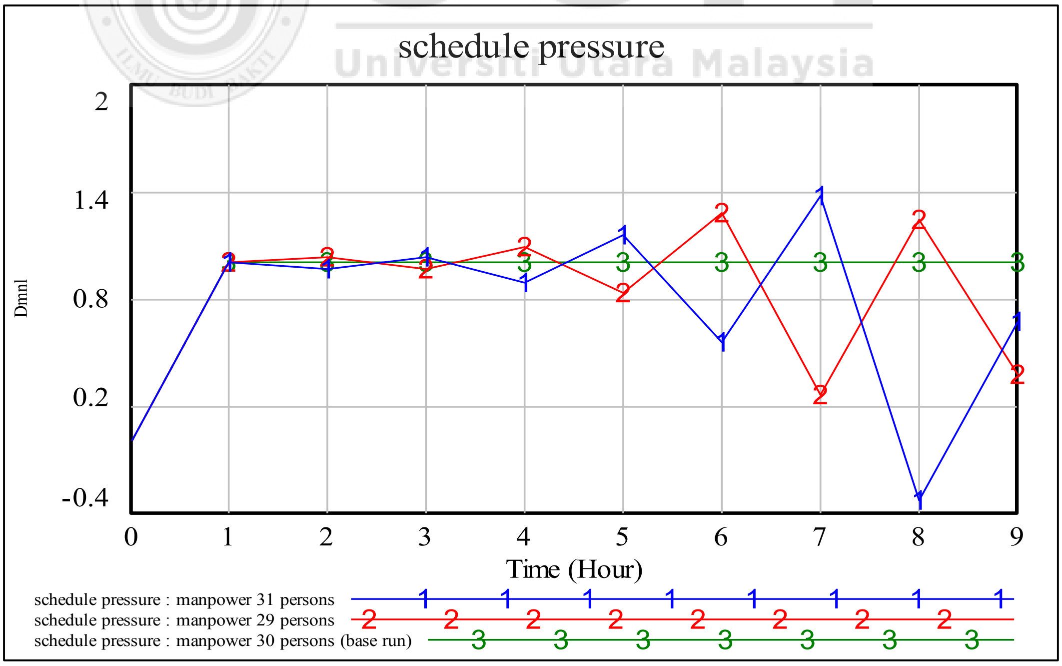


Figure 5.19. Performance of schedule pressure at different number of manpower

Referring to Figure 5.19, 31 and 29 manpower contributed to an unstable schedule pressure, i.e., performance of more than 1 indicates that schedule pressure exceeds allowable production utilization while less than 1 indicates that schedule pressure has a low production utilization. The negative value at vertical axis of Figure 5.19 is due to the effect of table function, i.e., *effect of fatigue on productivity$_n$*, as elaborated in subsection 4.6.8.3. The simulation coding of SFD is also included in Appendix C for reference. Consequently, the unstable schedule pressure for 31 and 29 manpower affect the manpower fatigue as shown in Figure 5.20

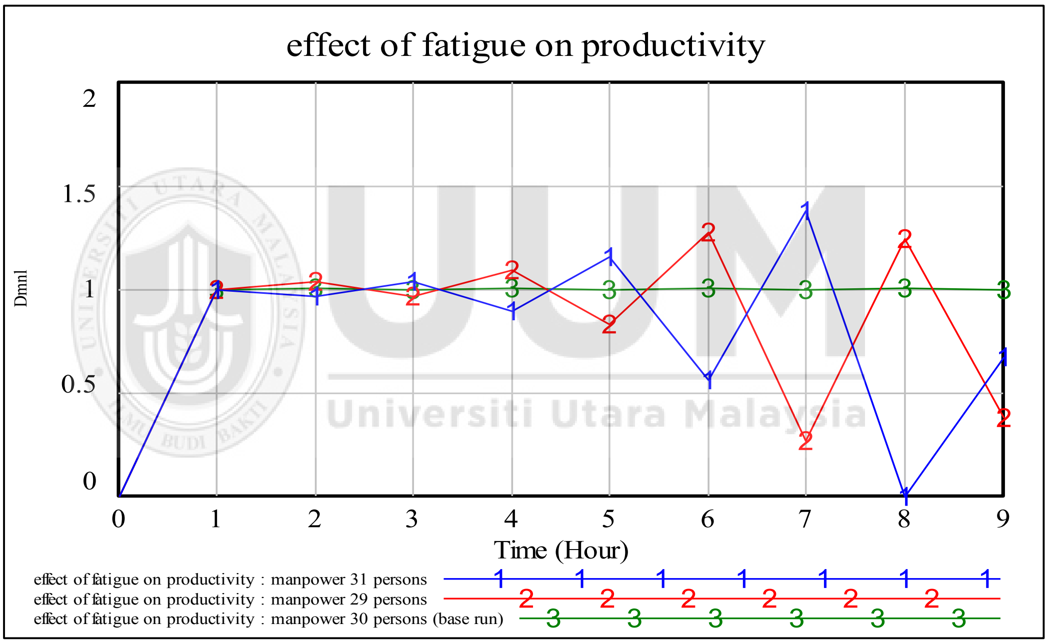


Figure 5.20. Fluctuation of effect of fatigue at different number of manpower

The effect of fatigue on productivity of more than 1 as indicated by Figure 5.20 shows that it is an unhealthy situation for manpower performance since more task is done at the production line. Moreover, the effect of fatigue on productivity of more than 1 for 29 persons are recorded four times during t_{cur} = 2, 4, 6 and 8 as shown in Figure 5.20. On the other hand, the effect of fatigue on productivity of more than 1 for 31 persons is resulted from the large quantity of product during t_{cur} = 3, 5 and 7 (see Table 5.16), hence manpower experienced fatigue.

Besides, it can be induced that 29 persons of manpower create a higher effect of fatigue on productivity. On the other hand, increasing the number of manpower has not speed up the production output since the total number of new audio product produced by 31 persons shows the smallest quantity which is 6222 pieces. Besides, it contributed to an additional cost of hiring manpower as compared to the existing number of manpower, i.e., 30 person of base run. Hence, the result of production completion time indicated that the ideal number of manpower is 30 persons since the schedule pressure and effect of fatigue on productivity are stable.

5.12.2 Strategy 2 on Parameter of Material Preparation Time

Strategy 2 was conducted by reducing the material preparation time to 0.75 hours and increasing it to 1.5 hours. The scenario performance are observed on production completion time, schedule pressure and the effect of fatigue on productivity as illustrated by Figure 5.21, Figure 5.22 and Figure 5.23, respectively.

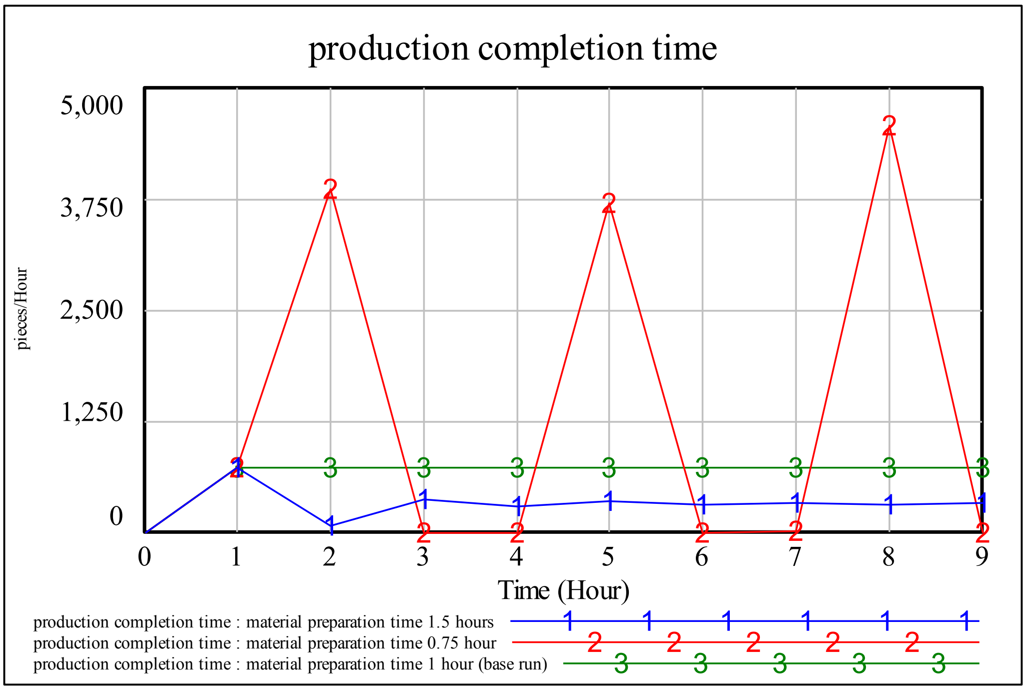


Figure 5.21. Production completion time at different material preparation time

Referring to Figure 5.21, the production completion time for 0.75 hours of material preparation time showed a sharp fluctuation of completion time as compared to 1.5 hours and 1 hour. Apparently, the high number of the new audio product is produced during t_{cur} = 2, 5 and 8 of working time, which are 3868 pieces, 3698 pieces and 4564 pieces, respectively. The reason for the high number of new audio product produced during that period is due to a high rate of receiving material at production line which resulted from acceleration of material preparation time to 0.75 hours compared to 1.5 hours and 1 hour. Table 5.17 shows the production completion time for the new audio products based on variation of material preparation time during working period from initial time, t_{init} = 0 until current time, t_{cur} = 9 hours at the semiautomatic production line.

Table 5.17

Description of completion time at different material preparation time

material preparation time$_{121}$	**production completion time for the new audio product from initial time, t_{init} = 0 to current time, t_{cur} = 9 hours**										**Total of new audio product (pieces)**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
1.5 hours	0	720	63	370	282	348	299	335	308	329	3054
0.75 hour	0	720	3868	0	0	3698	0	0	4564	0	12,850
1 hour (base run)	0	720	720	720	720	720	720	720	720	720	6480

Based on Table 5.17, production completion time for 0.75 hour is only recorded at t_{cur} = 2, 5 and 8 of work period. The performance of completion time resulted from 0.75 hour is due to high schedule pressure recorded on the mentioned period as indicated by Figure 5.22. Similarly as in Figure 5.19, the negative value at vertical axis of Figure 5.22 is due to the effect of table function, i.e., *effect of fatigue on productivity$_n$*, as elaborated in subsection 4.6.8.3. The simulation coding of SFD is included in Appendix C for reference. Consequently, the effect of fatigue on productivity as presented in Figure 5.23 higher than 1 which indicates that the situation is unhealthy for manpower performance since more task must be accomplished at the production line.

On the other hand, production completion time for 1.5 hours shows the lowest number of the new audio product, i.e., 3054 pieces due to delays in material preparation time. As a result, schedule pressure is recorded at lower than 1 which indicates that production utilization is not fully utilized and thus, the effect of fatigue on productivity is also lower than 1. However, the production completion time for base run, i.e., 1 hour of material preparation time shows stable schedule pressure and fatigue for the entire working period due to consistent material preparation time.

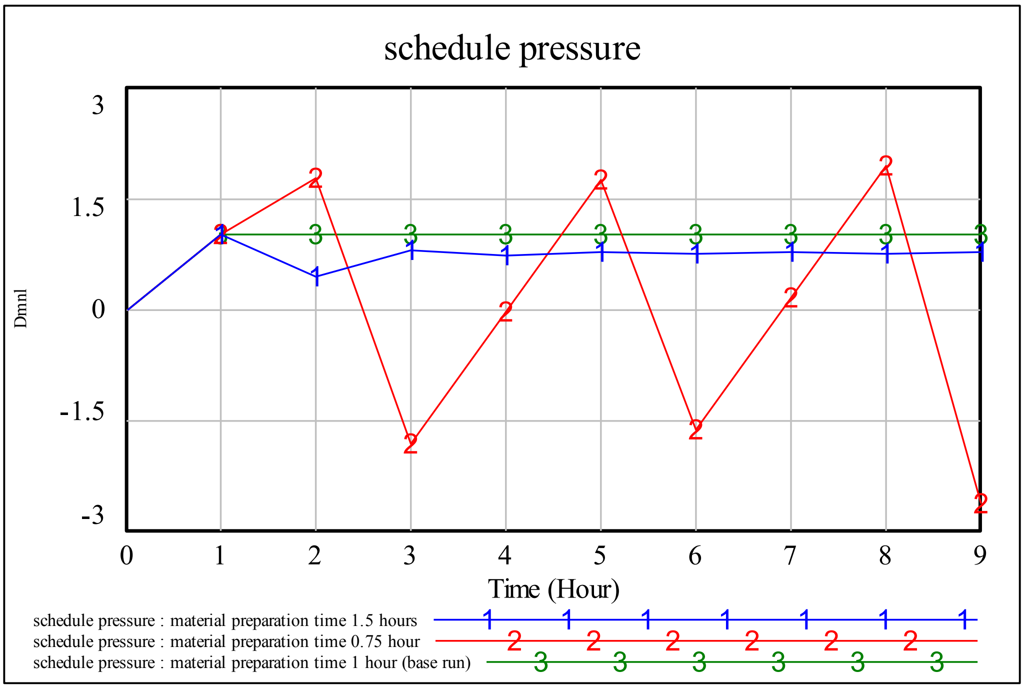


Figure 5.22. Schedule pressure at different material preparation time

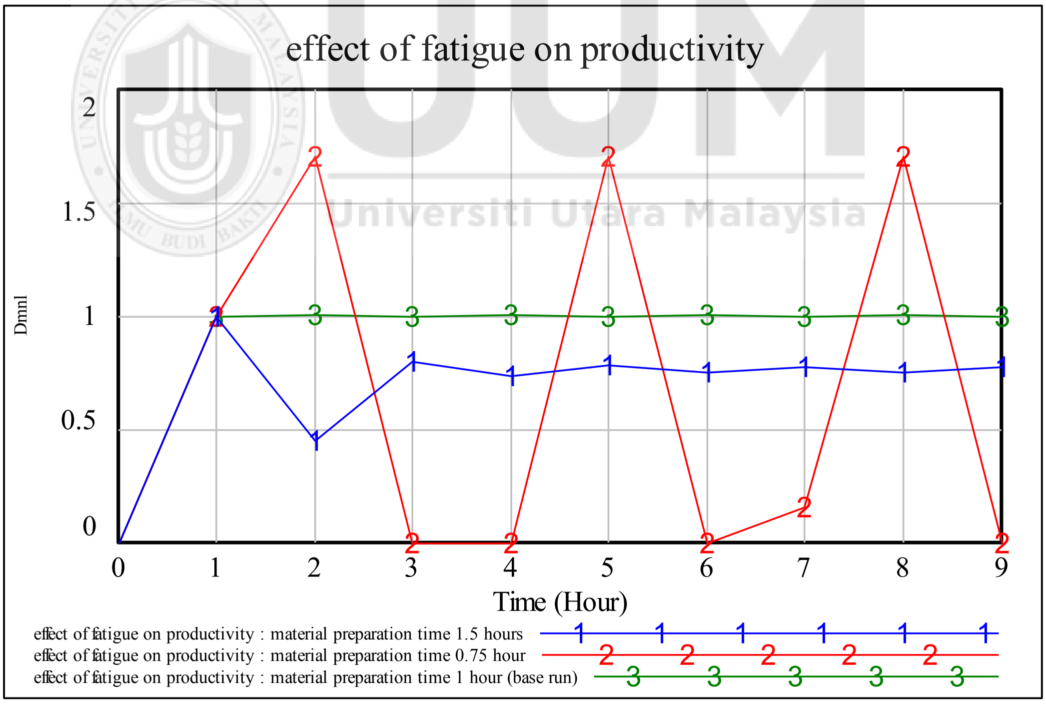


Figure 5.23. Effect of fatigue at different material preparation time

From the results of interventions on material preparation time, it can be induced that acceleration of material preparation time, i.e., 0.75 hour contributes to extreme fatigue to manpower as they are only able to sustain their work in the second hour of working period before continuing the fifth working hour. On the other hand, an increase of material preparation time, i.e., 1.5 hours contributes to the material shortage and low production utilization, thus producing the lowest output. Hence, the result indicates that the ideal material preparation time is 1 hour since the production completion time, schedule pressure and effect of fatigue on productivity are stable.

5.12.3 Strategy 3 on Parameter of Machine Breakdown Rate

Strategy 3 was conducted by increasing the machine breakdown rate to 0.002 (0.2 percent). The scenario performances are observed on production completion time and effect of fatigue on productivity as presented by Figure 5.24 and 5.25, respectively.

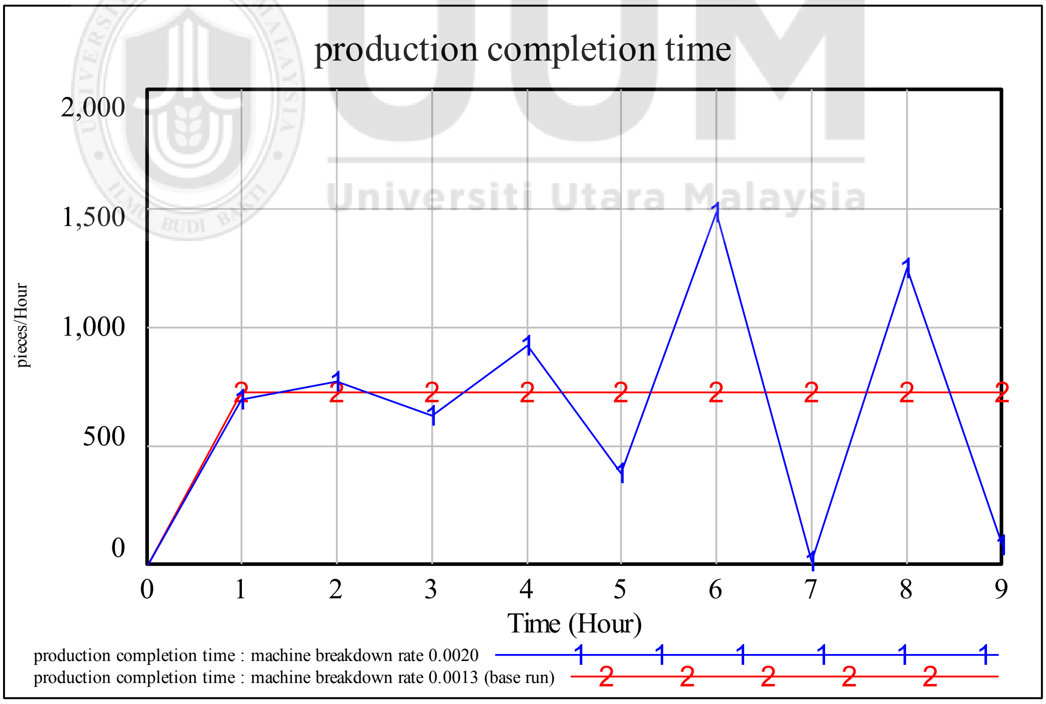


Figure 5.24. Completion time at different machine breakdown rate

Based on Figure 5.24, when the machine breakdown rate was increased to a higher rate, which is 0.002, the output of the new audio product was unstable with sharp fluctuations. Moreover, Table 5.18 presents the completion time in producing the new audio product based on variations in material preparation time during working period from initial time, t_{init} = 0 until current time, t_{cur} = 9 hours at the semiautomatic production line.

Table 5.18: Description of Completion Time at Various Machine Breakdown Rate

machine breakdown rate$_{121}$	**production completion time for the new audio product from initial time, t_{init} = 0 to current time, t_{cur} = 9 hours**										**Total of the new audio product (pieces)**
	0	1	2	3	4	5	6	7	8	9	
0.002	0	695	771	624	920	384	1483	8	1250	77	6212
0.0013	0	720	720	720	720	720	720	720	720	720	6480

Referring to Table 5.18, machine breakdown rate at 0.0013 (0.13%) contributes the highest total number of new audio product, i.e. 6480 pieces. However, only 6212 pieces of new audio product is produced when machine breakdown rate was increased to 0.002. This performance are observed on schedule pressure and effect of fatigue on productivity as shown in Figure 5.25 and Figure 5.26, respectively.

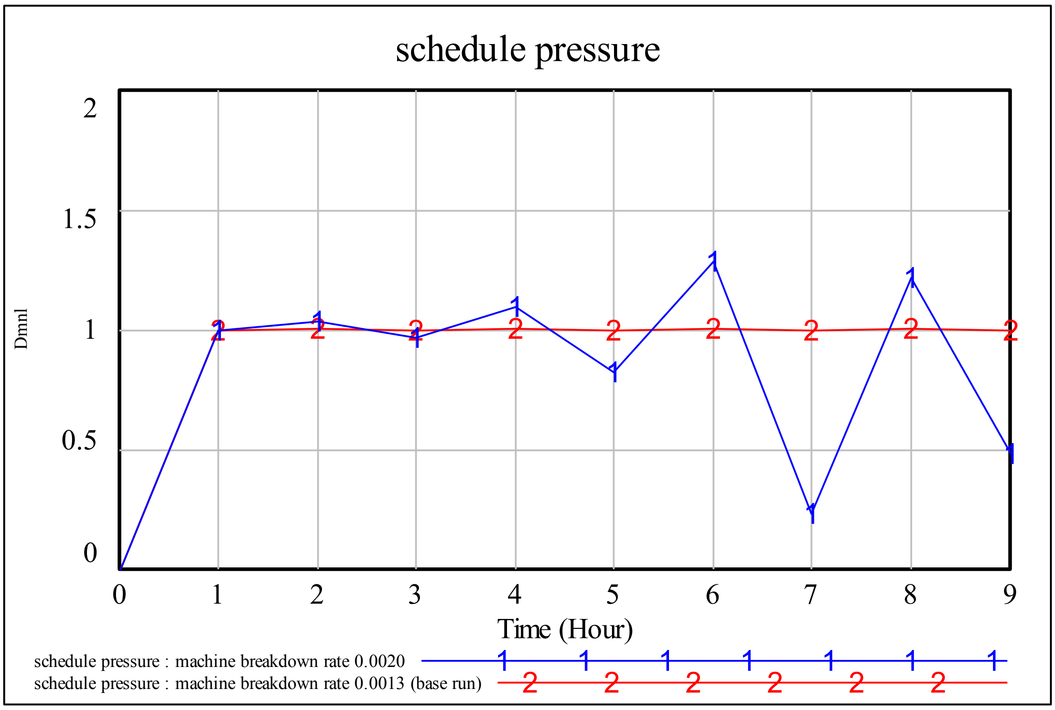


Figure 5.25. Fluctuation of schedule pressure at different machine breakdown rate

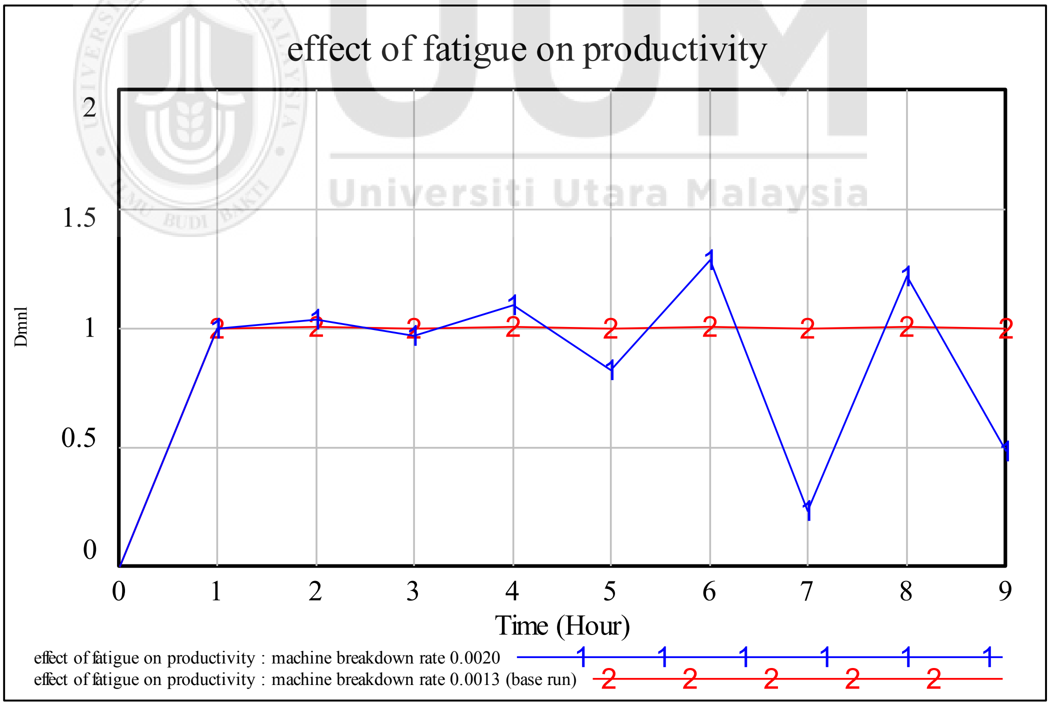


Figure 5.26. Fluctuation of effect of fatigue at different machine breakdown rate

The schedule pressure and effect of fatigue on productivity (see Figure 5.25 and Figure 5.26, respectively) indicate the unbalanced value from t_{init} = 0 to t_{cur} = 9 hours of working period if the machine breakdown rate reaches 0.2%. On the other hand, if the machine breakdown rate is maintained at 0.13%, the production completion time and effect of fatigue on productivity are stable.

From the results, it can be induced that if the machine breakdown rate is higher than 0.13%, production is still able to operate but with unstable schedule pressure and manpower fatigue on productivity. Consequently, it leads to a shortage of production output. Hence, the result indicates that the ideal machine breakdown rate is ideally at 0.13% since the production completion time schedule pressure and effect of fatigue on productivity are stable.

5.12.4 Strategy 4 on Parameter of the Cycle Time

Strategy 4 was conducted by reducing the cycle time to 4 seconds. The scenario performances are observed on production completion time, schedule pressure and the effect of fatigue on productivity as illustrated by Figure 5.27, Figure 5.28 and Figure 5.29, respectively.

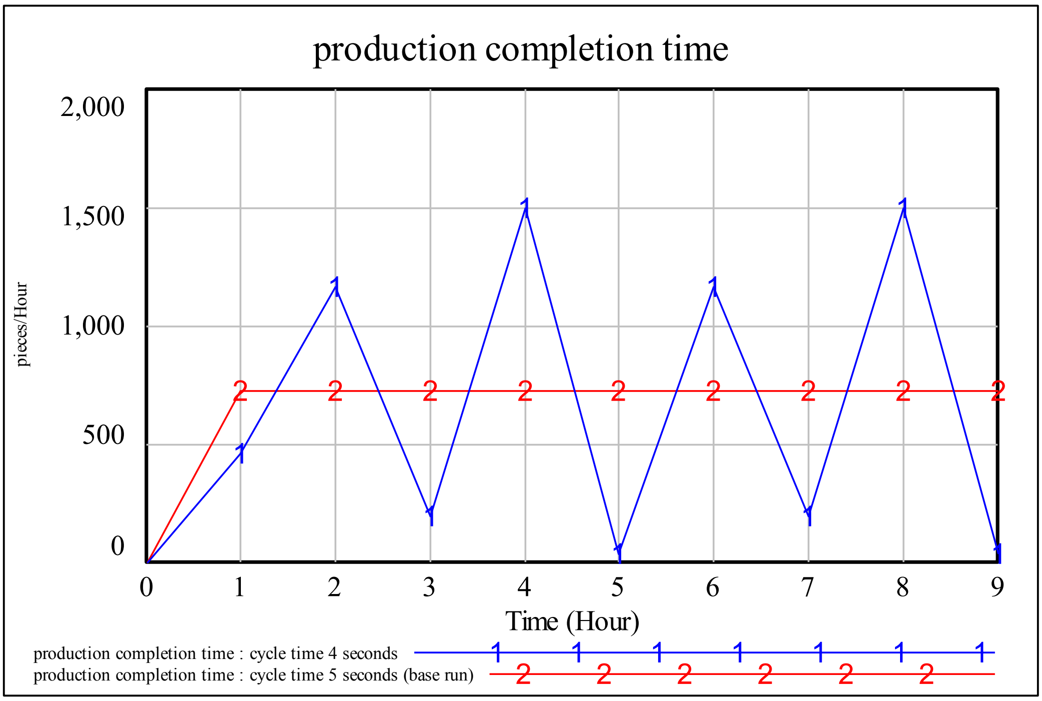


Figure 5.27. Performance of production completion time on different cycle time

Referring to Figure 5.27, the production completion time of the new audio product is unstable if the cycle time is decreased to 4 seconds. The cycle time of 4 seconds is considered as sensitive parameter especially when it involves 30 manpower at production line since it affects the overall completion time which has been mentioned in section 1.5. Consequently, the behaviour of production completion time based on 4 seconds is fluctuated.

Table 5.19 shows the production completion time of the new audio product based on variations of cycle time during working period from initial time, t_{init} = 0 until current time, t_{cur} = 9 hours at the semiautomatic production line.

Table 5.19

Description of production completion time at different cycle time

cycle time$_{121}$	**production completion time for the new audio product from initial time, t_{init} = 0 to current time, t_{cur} = 9 hours**										**Total of the new audio product (pieces)**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
4 seconds	0	461	1159	194	1494	31	1166	189	1495	30	6219
5 seconds (base run)	0	720	720	720	720	720	720	720	720	720	6480

According to Table 5.19, a time of 4 seconds was insufficient for the manpower to complete specific tasks during the production process as compared to 5 seconds. As a result, schedule pressure is recorded higher than 1 during t_{cur} = 2, 4, 6 and 8 of working time as indicated by Figure 5.28, which indicates production is over utilized.

However, t_{cur} = 1, 3, 5, 7 and 9 show lower schedule pressure, i.e., below than scale 1 which indicates poor production utilization. Consequently, the effect of fatigue on productivity as presented in Figure 5.29 shows a scale higher than 1 which indicates that the situation is unhealthy for manpower performance since more task is done at production line.

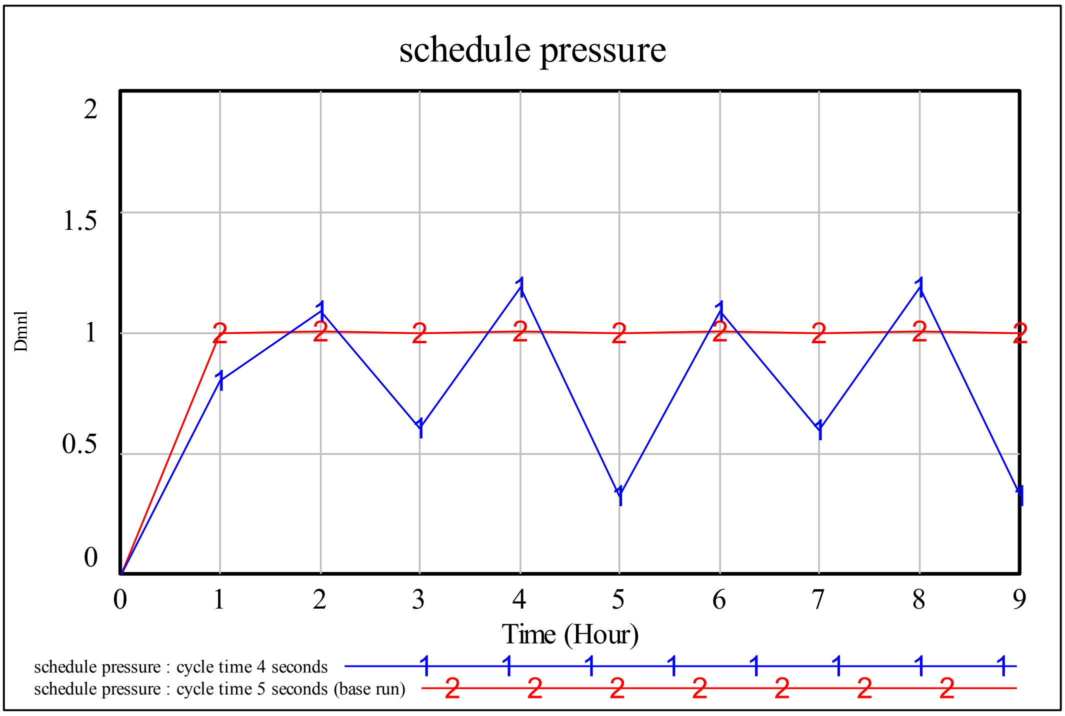


Figure 5.28. Fluctuation of schedule pressure at different cycle time

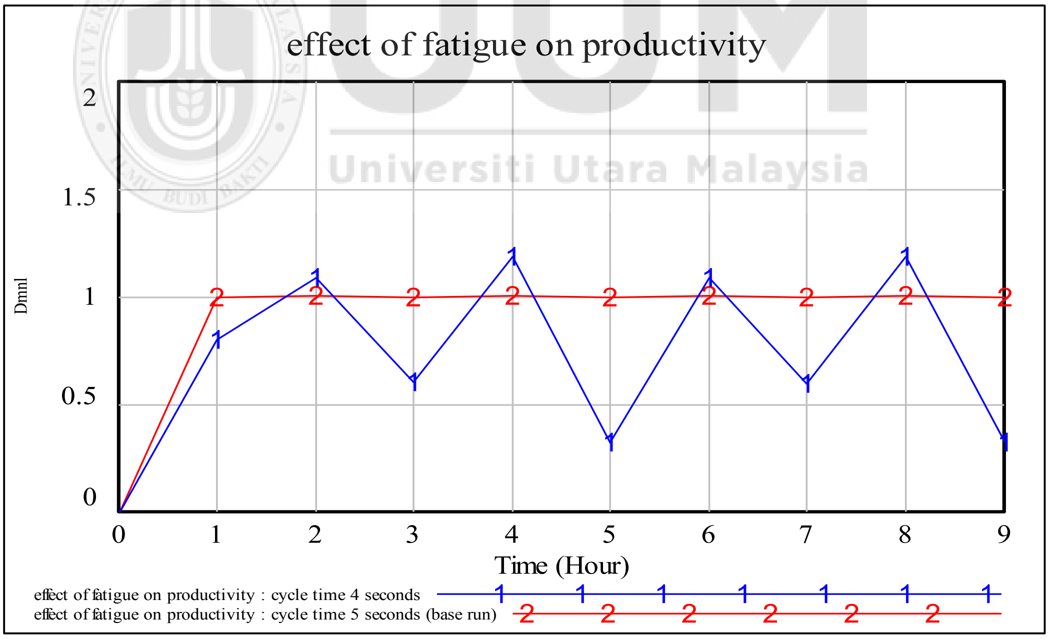


Figure 5.29. Fluuctuation of effect of fatigue at different cycle time

From the performance of different cycle time, there is no requirement of adjusting the production conveyor by decreasing the cycle time to 4 seconds. A cycle time of 4 seconds creates an unstable production utilization that led to a high schedule pressure, thus manpower experience extreme fatigue to complete their task. Hence, the result indicates that the ideal cycle time is 5 seconds since the production completion time, schedule pressure and effect of fatigue on productivity are stable.

Based on the results of these four strategies, i.e., variations of input parameters on number of manpower, material preparation time, machine breakdown rate, and cycle time, it was found that the changes on the material preparation time contributes the highest deviation from the base run. As indicated by Table 5.17, if material preparation time consumed 1.5 hours, i.e., more than 1 hour, the semiautomatic line could only produce 3054 pieces compared to 6480 pieces which obtained from the base run. Moreover, if material preparation time consumed 0.75 hours, i.e., less than 1 hour, the semiautomatic line could produce 12,850 pieces compared to 6480 pieces which obtained from the base run. Consequently, material preparation time appears as the best-so-far scenario compared to other four strategies.

At this stage, scenario performances of the integrated ANNSD model towards production completion time, schedule pressure and effect of fatigue on productivity, are evaluated, therefore the fifth objective has been achieved. Subsequently, the best-so-far scenario, i.e., material preparation time is chosen for policy improvement as further discussed in the following section.

5.13 The Best-so-far Scenario for Policy Improvement

Based on the scenario analysis on the completion time, the highest deviation percentage recorded by number of manpower, material preparation time, machine breakdown rate and cycle time are presented in Table 5.20 as follows.

Table 5.20

The deviation percentage from the completion time base run

Description of strategy	The highest deviation percentage on completion time
Increase number of manpower to 31 person	3.98 %
Reduce material preparation time to 0.75 hours	98.3 %
Increase machine breakdown rate to 0.002 (0.2 %)	4.14 %
Reduce cycle time to 4 seconds	4.03 %

Referring to Table 5.20, as elaborated in section 4.6.10, the highest percentage deviation is measured through Equation (4.53). As a result, the highest deviation percentage, DP_{121}^{IS}, was recorded through material preparation time, which was 98.3% since reducing material preparation time to 0.75 hours could produce 12,850 pieces of audio product as compared to 6480 pieces from base run (see Table 5.17). Moreover, decelerate material preparation time to 1.5 hours contributed 52.87% deviation percentage since only 3054 pieces were produced as compared to 6480 pieces from the base run (see Table 5.17).

Similarly, the highest deviation percentage recorded by number of manpower is 3.98% if manpower increased to 31 person since 6222 pieces of audio products was produced as compared to 6480 pieces obtained from base run (see Table 5.16). Subsequently, the highest deviation percentage for machine breakdown rate is 4.14% since increasing the rate to 0.2% could produce 6212 pieces of audio products compared to 6480 pieces from base run (see Table 5.18). Moreover, the highest deviation percentage for cycle time is recorded to 4.03% due to decrease the time to 4 seconds could produce 6219 pieces of audio product compared to 6480 pieces from base run (see Table 5.19). Apparently, the intervention on the material preparation time is the best-so-far scenario on the completion time since material preparation time contributes the highest percentage of deviation from the base run compared to number of manpower, machine breakdown rate, and cycle time. Therefore, a policy on the material is proposed to ideally prepared within one hour in producing 720 pieces per hour (refer to Table 5.17) as a production completion time at semiautomatic line.

Moreover, the acceleration and deceleration of the material preparation time must be carefully observed as it is significantly influences the effect of fatigue on productivity and schedule pressure. Material preparation of below than 1 hour, i.e., 0.75 hours could create extreme fatigue to manpower as they struggled to cope to the desired completion rate while decelerate more than 1 hour, i.e., 1.5 hours could create low production utilization, thus contribute to the lowest production output, i.e., 3054 pieces (refer to Table 5.17).

For the ideal production completion time, which is to consistently produce 720 pieces of the new audio products for every one hour, 5040 pieces of materials should well prepared within one hour for the semiautomatic production line to operate since seven pieces of materials are required to produce a new audio product. Moreover, the ideal production completion time for semiautomatic production line to produce 6480 pieces of the new audio product is 9 hours of working period with 30 persons, while machine breakdown rate is ideally 0.0013 while cycle time is set to 5 seconds.

Based on the best-so-far scenario, material preparation time could be suggested to the top management of the company. With the policy improvement on completion time for producing the new audio products at the semiautomatic production line, the occurrence of manpower fatigue and tardiness may be avoided, hence manpower performance is improved and customer orders are met on-time.

5.14 Discussions on Overall Performance of the Integrated ANNSD Model

In the development of the MLP network, the smallest square error is achieved through the 3-2-1 network with formulated momentum rate as discussed in section 5.5. The smallest square error indicates that the proposed formulated momentum rate for the 3-2-1 network is slightly better for predicting cycle time compared to random momentum rate as presented in Azadeh et al. (2014).

Subsequently, the material preparation time emerged as the factor with the strongest relationship on completion time which is determined through a proposed formulated correlation coefficient for establishing a closed loop in the development of a CLD as discussed in section 5.7. The proposed correlation coefficient is able to determine the most influential factor in developing a CLD as compared to the CLD as developed by Inam et al. (2015) which is without the influential factor.

Furthermore, the highest percentage of deviation from the base run as recorded by material preparation time in the scenario analysis as discussed in section 5.12 is in line with the result from the study of Pai et al. (2015) where material shortage contributes the highest disruption of product delivery. The finding of material preparation time as the best-so-far scenario on the completion time is also supported by Costa et al. (2016) which emphasized that material lead time from supplier could 80% of the time affect the completion.

However, the percentage of time deviated from the base run of the completion time through material preparation time in this research is 98.3% since the scenario analysis was experimented in the semiautomatic production line, while Costa et al. (2016) conducted their study on an automation line. Nevertheless, the material preparation time is proven to be the most influential factor for the deviation of completion time as in this best-so-far scenario. Furthermore, this finding is verified by the experts at the company (refer to Appendix B).

5.15 Summary

In this chapter, the factors involved in predicting cycle time and simulating completion time are identified through data from an identified company selected as a case problem. In the development of ANN model, three types of MLP networks were established which were the 3-1-1, 3-2-1 and 3-3-3 networks. The experimented results through BP learning algorithm show that the 3-2-1 MLP network with formulated momentum rate has the smallest square error, thus the network is selected for predicting the cycle time. Subsequently, the material preparation time emerged as the variable with the strongest relationship on completion time which was determined through a proposed formulated correlation coefficient for establishing a closed loop in the development of a CLD. Then, the developed CLD is transformed into a constructed SFD while the result of predicted cycle time is substituted as the input. Thus, the integrated ANNSD model is established. Through structure and behaviour assessments, results show that the integrated ANNSD model is validated to simulate production operation. Subsequently, four strategies were experimented on the integrated ANNSD model to measure performance of completion time. As a result, the material preparation time showed the highest deviation from the base run since it has the highest impact on completion time. This scenario has been presented to the top management of the company as an initiative for their policy improvement.

Therefore, tardiness and manpower fatigue were eliminated in meeting on-time deliveries to customers.

CHAPTER SIX
CONCLUSION

As discussed in the previous chapter, the cycle time of a new audio product is predicted based on historical data through ANN model. Subsequently, the predicted cycle time with inclusion of related factors, i.e., number of manpower, material preparation time and machine breakdown are substituted in SD model to evaluate the completion time through simulation of production operation from a case company. Thus, the proposed integrated Artificial Neural Networks and System Dynamics (ANNSD) model was developed to fulfil the objectives of this research. The summary of the proposed integrated ANNSD model is concluded in the following section 6.1. Subsequently, the accomplishment of research objectives are mentioned in the following section 6.2. Then, the research contributions are emphasized in the subsequent section 6.3. Finally, the research limitations are highlighted and suggestion for future works are mentioned in the last section.

6.1 Summary of the Integrated ANNSD Model

The integrated ANNSD model was developed to predict the cycle time and evaluate completion time for producing a new audio speaker product at a semiautomatic production line of selected company. The data related to the number of manpower, waiting time of material and machine breakdown were considered as the input parameter, while the cycle time of a new audio product was considered as the output parameter for ANN learning process. The input and output parameters were transformed using MIN-MAX formula. Subsequently, three types of MLP network were developed which are the 3-1-1, 3-2-1 and 3-3-1 networks. Then, BP learning algorithm was established for learning process with a proposed formulated momentum rate to improve convergence of ANN learning process. Finally, the predicted cycle time was obtained through the 3-2-1 network with the smallest square error.

After predicting the cycle time, the completion time for producing the new audio speaker product at a semiautomatic production line was conceptualized through development of CLD to inspect the cause and effect relationship among endogenous and exogenous variables. A coefficient correlation equation was formulated to determine the most influential element on the completion time. Next, SFD was developed to simulate the completion time and it is validated through structure and behavior assessments, whereas the simulation results were evaluated through the intervention strategy or similar to what-if analysis. As a result, the best-so-far scenario from the intervention strategy has been presented to the top management of the company for improving the completion time. Thus, the achievement in proposing a new policy to improve the completion time reflects that the steps of developing the proposed integrated ANNSD model were constructed in a proper and effective manner. The accomplishments of the developed integrated ANNSD model based on the research objectives are further emphasized in the following section 6.2.

6.2 Accomplishment of Research Objective

The main objective of this research is to develop the integrated ANNSD model for predicting cycle time and evaluating completion time for a new audio product at a semiautomatic production line. The development of the proposed integrated ANNSD model is presented in section 4.6. The results of predicted cycle time is presented in section 5.6 and obtained through the 3-2-1 network with formulated momentum rate.

Moreover, the evaluation of the completion time has been accomplished in section 5.12 through simulation of SFD.

Furthermore, this research successfully achieved five specific objectives in order to fulfil the main objective as described in Chapter One. The first objective of this research is to identify the important factors in predicting the cycle time and evaluating the completion time at semiautomatic production line. The data types and collection in this research are discussed in section 4.5 gathered from selected company. As a result, the data of number of manpower, waiting time of material, machine breakdown, the cycle time of a new audio product and completion time of an existing model are presented in Table 5.1 of section 5.1. Hence, the first research objective has been fulfilled in identifying the important factors related to prediction of cycle time and evaluation of the completion time.

The second objective of this research is to formulate a momentum rate that is able to improve ANN learning process. The equation of momentum rate is formulated in section 4.6.4.5 to slow down the learning process, hence the convergence of a learning process is improved. Consequently, the result of the smallest square error value shows that the proposed formulated momentum rate is slightly better for predicting the completion time compared to random momentum rate as obtained in section 5.5. Therefore, the second objective of this research has been achieved in improving the ANN learning process.

The third objective of this research is to determine the most influential element among endogenous variables towards the completion time. The equation of coefficient correlation is formulated in subsection 4.6.7.1 to determine the relationship of number of manpower, waiting time of material, machine breakdown and the cycle time of a new audio product on the completion time. As a result, waiting time for material preparation has strong relationship on the completion time as obtained in section 5.7. Thus, the third research objective which is determining the most influential element among endogenous variable, is fulfilled.

The fourth research objective is to validate the developed SFD in simulating the completion time. The validation process is established as elaborated in section 4.6.9 through structure and behavior assessment. As a result, the developed SFD was validated as presented in section 5.11. Thus, the validation of the developed SFD in evaluating the completion time has been achieved for the fourth research objective.

Finally, the fifth research objective is to evaluate the simulation of SFD. The evaluation process is constructed as elaborated in section 4.6.10 through various scenarios of intervention strategy. As a result, the evaluation of SFD output was obtained as presented in section 5.12. Thus, the evaluation of SFD simulation output has been achieved for the fifth research objective.

The achievement of five research objectives indicated that the proposed integrated ANNSD model is effective for predicting the cycle time and evaluating the completion time of a new product. Thus, the occurrence of tardiness is able to be minimized for a smooth delivery to customer premises. Subsequently, the contribution of the research is further emphasized in the following sections.

6.3 Contribution of the Research

This research has contributed to the prediction of the cycle time and evaluation of completion time for a new audio speaker product at semiautomatic production line, which has also enriched the literature in the related areas. The contributions of this research are divided into two significant parts: (i) the contribution to the body of knowledge, and (ii) the contribution to the management of the audio speaker manufacturer as emphasized in the subsequent sections 6.3.1 and 6.3.2, respectively.

6.3.1 Contribution to the Body of Knowledge

The main fundamental contribution of this research is the development of improved integrated ANNSD model for predicting the cycle time and evaluating the completion time. The proposed integrated ANNSD model provides the input parameter values for the endogenous variables in the developed SFD through the predicted cycle time. Consequently, the integrated ANNSD model contributes more visible cause and effect relationship among related variables, i.e., number of manpower, waiting time of material and machine breakdown rate. Therefore, the simulation behavior of the developed SFD in resembling the real production operation is more robust.

Secondly, the proposed integrated ANNSD model provides the enhanced formulation of momentum rate for the ANN learning process. The formulated momentum rate is able to slow down and improve the convergence of the ANN learning process within the established MLP networks. To the best of our knowledge, none of the approaches from previous studies can be considered to be the best practice in determining the momentum rate since it is based on the results of one's own personal heuristics approach. Therefore, our 3-2-1 MLP network with formulated momentum rate is another alternative predictive model to predict the cycle time based on the smallest square error as compared to the other established networks. Hence, the proposed formulated momentum rate is able to provide a better prediction result instead of being randomly determined.

Thirdly, the proposed integrated ANNSD model provides the formulation of correlation coefficient. The formulated correlation equation identifies the most influential element among the endogenous variables in the constructed CLD. The highest value of correlation coefficient is selected as the most influential element for establishing a closed loop in CLD. As a result, the material preparation time is indicated as the most influential element on the completion time. Therefore, the determination of the most influential element in establishing a closed loop for CLD based on the highest value of the proposed correlation coefficient enhances the dynamic condition of the completion time at a semiautomatic line.

6.3.2 Contributions to the Management of the Audio Speaker Manufacturer

The proposed integrated ANNSD model could reduce frequent pre-production process at semiautomatic production line. A frequent pre-production process is time consuming for the experts to regularly observe the assembly process and disrupts the smoothness of production operation. To overcome such problem, the proposed integrated ANNSD model assists production planner in predicting cycle time from historical data of existing product and evaluating completion time for producing new audio speaker products. Hence, it is able to reduce the occurrence of tardiness efficiently and fulfill customer delivery on-time.

Secondly, the proposed integrated ANNSD model assists production planner to conduct a risk free experimentation on production operation related to the number of manpower, material preparation time, machine breakdown rate and the cycle time through various scenarios of intervention strategy or similar to what-if analysis. If the desired completion time is not achieved, they can identify the root causes through what-if analysis without disrupting the real production operation. As a result, the cycle time and the completion time is determined effectively for a convenient working environment.

Thirdly, the integrated ANNSD model is able to guide the Malaysian workforce in coordinating production schedule efficiently and product delivery smoothly within supply chain system through a simulation of a production operation and the management of big data. Consequently, increase in knowledge and skill of the industrial community in simulation and big data management is in line with the requirement of the Industrial Revolution 4.0 of this sector.

6.4 Research Limitations

Although this research is carefully prepared, there are some unavoidable limitations. First, in terms of data availability, the access to related information is limited due to company policies and restrictions for outsider and unauthorized person. Therefore, this research only considered four factors related to the completion time, while other factors such as quality assurance, rework process, inventory and equipment setup time are not considered.

Second, in terms of the number of product involved in this research, it is limited to only 100 types of active audio speakers instead of the current 2800 products in the production line. The 100 products are chosen based on customers' demand trend within the period of data is collected, i.e., from January, 2016 until March, 2016. The selected products may experience end-of-life (EOL) which is normally active within a minimum of three years as demands from customer rapidly change from time to time. Hence, the finding from this research are applicable in the condition and period when the data is collected.

Third, the determination of connection weight and learning rate values are normally randomly selected for the ANN learning process. Similarly in this research, the value of connection weight is also randomly selected between the range of 0.1 to 1.5 as being described in section 3.1.7.1 and experimented in section 5.5, while the value of learning rate is heuristically selected value of 0.2 based on the lowest square error as elaborated in section 3.1.7.4. Furthermore, to the best of our knowledge, there is no rule of thumb to determine the value of connection weight and learning rate but rather using the iterative adjustment for trial and error during learning process. Therefore, the prediction result may not be optimal for the cycle time of a new product.

6.5 Future Work

The finding and limitations of this research suggest that the present research could be extended to include other factors related to the completion time in producing a new product at a semiautomatic production line such as quality assurance, rework process, inventory and equipment setup time. Thus, the working theory of model conceptualization is more dynamic, while the cause and effect relationship among variables can be more meaningful.

Moreover, the number of product types could be increased by prolonging the period of collecting data. However, it depends on the permission granted by the respective company to the unauthorized person as the related information are protected under company policies. Therefore, by increasing the number of product types, the findings related to the completion time is more meaningful.

Finally, the determination of connection weight and leaning rate values for ANN learning process could be enhanced by integrating other artificial intelligence (AI) methods such as Evolutionary Algorithm (EA) and Ant Colony Algorithm instead of randomly selected. The integration of AI in ANN is currently gaining much attention from researchers as AI has capability to select the best-so-far solutions among possible candidates for the optimal connection weight and learning rate values.

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APPENDIX A
OPEN-ENDED QUESTIONS

The list of open-ended questions given to Senior Planners, Executive and Supervisor from the Production Control Department and Production Department.

1) What is the challenge(s) facing by management to fulfil customer demand on-time?

____

____

____

2) What is the factor(s) contributes to tardiness of completion time in the semiautomatic production line?

____

____

____

3) How the factors are recorded/ documented?

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APPENDIX B
VALIDATION FROM THE EXPERTS OF A COMPANY

FLEXI ACOUSTICS SDN. BHD. 974200-K

(Formerly Known as Onkyo Jitra Malaysia Sdn. Bhd.)
Plot 105, Kawasan Perusahaan Darulaman, Bandar Darulaman, 06000 Jitra, Kedah Darul Aman.
Tel: +604-9175688 Fax: +604-9175788 Email: sales@flexi-acoustics.com
Website: www.flexi-acoustic.com

26-May, 2017

To whom it may concern,

We hereby verify that the Phd candidate, Ahmad Afif Ahmarofi, from School of Quantitative Sciences, Universiti Utara Malaysia has conducted several consultations with person in charge (PIC) from Department of Control Production and Department of Production of this company for his research thesis.

During the consultation, he had interviewed us with several questions regarding the operation and management of semiautomatic production line concerning completion time problem as well as other factors associated with it. Moreover, he had proposed some of the scientific approaches such as system dynamics and artificial neural networks to overcome the problems as highlighted during the session.

We found that his finding and solutions in scientific approach are acceptable and practical as a beneficial contribution towards the completion time problem which could improve our performance. In addition, the session is a good exposure to the management in industrial sector to tackle the rapid challenges in nowadays market place.

Thank you.

Yours sincerely,

Puspa a/p Ramiah
(Executive of Production Control Department)

Nor'aini Bt. Saad
(Planner of Production Control Department)

Ida Rahaiza Bt. Abd. Rahim
(Executive of Human Resource Department)

FLEXI ACOUSTICS SDN. BHD.
Plot 105, Kawasan Perusahaan Darulaman,
Bandar Darulaman, 06000 Jitra,
Kedah Darul Aman.
Tel: 04-9175688 (Hunting Line) Fax: 04-9175788

APPENDIX C

SIMULATION CODE OF SFD IN VENSIM

desired material order rate=adjustment material on order/supplier lead time delivery
~Unit: pieces/Hour

supplier lead time delivery=1
~Unit:Hour

Finished goods inventory= INTEG (STEP(production completion time-shipment rate,0),0)
~Unit: pieces

Work in process= INTEG (production start rate-production completion time,0)
~Unit: pieces

number of manpower=30
~Unit: person

number of manpower per hour=(number of manpower*attendance rate)/standard working hour
~Unit: person/Hour

attendance rate=1
~Unit: Dmnl |

cycle time=5
~Unit: second/pieces

standard working hour in seconds=3600
~Unit: second/Hour

standard completion rate=standard working hour in seconds/cycle time
~Unit: pieces/Hour

effect of schedule pressure on working hour=schedule pressure*standard working hour
~Unit: Hour

production utilization=effect of schedule pressure on working hour/standard working hour
~Unit: Dmnl

delivery rate=1
~Unit: Hour

time per task= 0.0416667
~Unit: person*Hour/pieces

production completion time=potential completion time*Work in process
~Unit: pieces/Hour

shipment rate=Finished goods inventory/delivery rate
~Unit: pieces/Hour

standard working hour=1
~Unit: Hour

potential completion time= (number of manpower per hour*machine breakdown rate*effect of schedule pressure on working hour*effect of fatigue on productivity)/time per task
~Unit: pieces/Hour/pieces

table of fatigue([(0,0)-(1.7,2)],(0,0),(1,1),(1.25,1.25),(1.7,1.7))
~Unit: Dmnl

machine breakdown rate=0.00138889
~Unit: 1/pieces

effect of fatigue on productivity=table of fatigue(production utilization)
~Unit: Dmnl

schedule pressure=desired completion rate/standard completion rate
~Unit: Dmnl

desired completion rate=Work in process/target completion hour
~Unit: pieces/Hour

target completion hour=1
~Unit: Hour

reorder material=desired production start rate*material reject rate
~Unit: pieces

adjustment material on order=Material warehouse inventory+reorder material
~Unit: pieces

material supply rate=Material warehouse inventory*material preparation rate
~Unit: pieces/Hour

material availability ratio=Material warehouse inventory/desired production start rate
~Unit: Dmnl

material preparation=1
~Unit: Hour

material reject rate=0
~Unit: Dmnl

material preparation rate=material availability ratio/material preparation
~Unit: 1/Hour

material order rate=desired material order rate
~Unit: pieces/Hour

production start rate= STEP(desired production start from material,0)
~Unit: pieces/Hour

desired production start rate=5040
~Unit: pieces

desired production start from material=material supply rate/material usage per unit
~Unit: pieces/Hour

material usage per unit=7
~Unit: Dmnl

Material warehouse inventory= INTEG (material order rate-material supply rate,5040)
~Unit: pieces

```
********************************************************

.Control
********************************************************~
		Simulation Control Parameters

FINAL TIME  = 9
	~	Unit: Hour
	~	/The final time for the simulation/

INITIAL TIME  = 0
	~	Unit: Hour
	~	/The initial time for the simulation/

SAVEPER  = TIME STEP
	~	Unit: Hour [0,?]
	~	/The frequency with which output is stored/
	|

TIME STEP  = 1
	~	Unit: Hour [0,?]
	~	/The time step for the simulation/

\\\---/// Sketch information - do not modify anything except names
V300  Do not put anything below this section - it will be ignored
*View 1
$192-192-192,0,Times New Roman|16||0-0-0|0-0-0|0-0-255|-1--1--1|-1--1--1|96,96,65,0
10,1,Material warehouse inventory,179,344,47,28,3,131,0,0,0,0,0,0
12,2,48,-147,327,10,8,0,3,0,0,-1,0,0,0
1,3,5,1,4,0,0,22,0,0,0,-1--1--1,,1|(81,329)|
1,4,5,2,100,0,0,22,0,0,0,-1--1--1,,1|(-59,329)|
11,5,48,24,329,6,8,34,3,0,0,1,0,0,0
10,6,material order rate,24,363,66,26,40,131,0,0,-1,0,0,0
12,7,48,539,332,10,8,0,3,0,0,-1,0,0,0
1,8,10,7,4,0,0,22,0,0,0,-1--1--1,,1|(428,328)|
1,9,10,1,100,0,0,22,0,0,0,-1--1--1,,1|(271,328)|
11,10,48,322,328,6,8,34,3,0,0,1,0,0,0
10,11,material supply rate,322,362,79,26,40,131,0,0,-1,0,0,0
10,12,adjustment material on order,37,466,75,23,8,3,0,0,0,0,0,0
10,13,desired material order rate,-131,418,70,23,8,3,0,0,0,0,0,0
1,14,1,12,1,0,0,0,0,64,0,-1--1--1,,1|(138,425)|
1,15,12,13,1,0,0,0,0,64,0,-1--1--1,,1|(-48,475)|
1,16,13,6,1,0,0,0,0,64,0,-1--1--1,,1|(-73,340)|
10,17,desired production start from material,594,446,82,23,8,3,0,0,0,0,0,0
10,18,desired production start rate,394,587,82,23,8,3,0,0,0,0,0,0
10,19,material usage per unit,603,529,64,23,8,3,0,0,0,0,0,0
1,20,19,17,1,0,0,0,0,64,0,-1--1--1,,1|(616,492)|
1,21,11,17,1,0,0,0,0,64,0,-1--1--1,,1|(462,362)|
10,22,Work in process,1117,195,40,20,3,3,0,0,0,0,0,0
12,23,48,719,190,10,8,0,3,0,0,-1,0,0,0
1,24,26,22,4,0,0,22,0,0,0,-1--1--1,,1|(994,190)|
1,25,26,23,100,0,0,22,0,0,0,-1--1--1,,1|(814,190)|
11,26,48,906,190,6,8,34,3,0,0,1,0,0,0
10,27,production start rate,906,217,50,19,40,3,0,0,-1,0,0,0
1,28,17,27,1,0,0,0,0,64,0,-1--1--1,,1|(650,276)|
1,29,1,10,1,0,0,0,0,64,0,-1--1--1,,1|(250,296)|
10,30,material availability ratio,262,454,72,23,8,3,0,0,0,0,0,0
10,31,material preparation rate,396,419,69,23,8,3,0,0,0,0,0,0
10,32,material preparation,486,510,54,29,8,131,0,4,0,0,0,0,-1--1--1,128-192-255,|12||0-0-0
```

1,33,1,30,1,0,0,0,0,64,0,-1--1--1,,1|(199,409)|
1,34,32,31,1,0,0,0,0,64,0,-1--1--1,,1|(461,451)|
1,35,31,11,1,0,0,0,0,64,0,-1--1--1,,1|(377,348)|
1,36,30,31,1,0,0,0,0,64,0,-1--1--1,,1|(333,461)|
10,37,reorder material,147,559,36,23,8,3,0,0,0,0,0,0
10,38,material reject rate,257,590,63,23,8,3,0,0,0,0,0,0
1,39,37,12,1,0,0,0,0,64,0,-1--1--1,,1|(126,485)|
1,40,38,37,1,0,0,0,0,64,0,-1--1--1,,1|(226,543)|
1,41,18,30,1,0,0,0,0,64,0,-1--1--1,,1|(373,505)|
1,42,18,37,1,0,0,0,0,64,0,-1--1--1,,1|(240,655)|
10,43,Finished goods inventory,1716,203,51,30,3,131,0,0,0,0,0,0
1,44,46,43,4,0,0,22,0,0,0,-1--1--1,,1|(1560,193)|
1,45,46,22,100,0,0,22,0,0,0,-1--1--1,,1|(1300,193)|
11,46,220,1449,193,6,8,34,131,0,0,1,0,0,0
10,47,production completion time,1449,224,72,23,40,131,0,4,-1,0,0,0,-1--1--1,0-255-0,|12||0-0-0
1,48,22,46,1,0,0,0,0,64,0,-1--1--1,,1|(1181,153)|
10,49,desired completion rate,1028,310,69,23,8,3,0,0,0,0,0,0
10,50,target completion hour,878,359,73,23,8,3,0,0,0,0,0,0
12,51,48,1951,188,10,8,0,3,0,0,-1,0,0,0
1,52,54,51,4,0,0,22,0,0,0,-1--1--1,,1|(1893,194)|
1,53,54,43,100,0,0,22,0,0,0,-1--1--1,,1|(1800,194)|
11,54,48,1840,194,6,8,34,3,0,0,1,0,0,0
10,55,shipment rate,1840,213,58,13,40,3,0,0,-1,0,0,0
10,56,schedule pressure,1100,439,39,23,8,3,0,0,0,0,0,0
10,57,standard completion rate,963,529,69,23,8,3,0,0,0,0,0,0
10,58,effect of schedule pressure on working hour,1258,511,89,34,8,3,0,4,0,0,0,0,-1--1--1,0-255-0,|16||0-0-0
10,59,standard working hour,1361,620,60,23,8,3,0,0,0,0,0,0
10,60,production utilization,1441,515,48,23,8,3,0,0,0,0,0,0
10,61,potential completion time,1471,344,72,23,8,3,0,0,0,0,0,0
10,62,number of manpower per hour,1717,404,85,23,8,3,0,0,0,0,0,0
10,63,time per task,1658,319,55,13,8,3,0,0,0,0,0,0
10,64,machine breakdown rate,1600,259,65,19,8,3,0,4,0,0,0,0,-1--1--1,128-192-255,|12||0-0-0
10,65,table of fatigue,1648,541,34,23,8,3,0,0,0,0,0,0
10,66,effect of fatigue on productivity,1532,455,84,23,8,3,0,4,0,0,0,0,-1--1--1,0-255-0,|16||0-0-0
1,67,22,49,1,0,0,0,0,64,0,-1--1--1,,1|(1045,238)|
1,68,49,56,1,0,0,0,0,64,0,-1--1--1,,1|(1036,380)|
1,69,56,58,1,0,0,0,0,64,0,-1--1--1,,1|(1170,485)|
1,70,58,60,1,0,0,0,0,64,0,-1--1--1,,1|(1350,534)|
1,71,59,60,1,0,0,0,0,64,0,-1--1--1,,1|(1425,576)|
1,72,60,66,1,0,0,0,0,64,0,-1--1--1,,1|(1499,501)|
1,73,65,66,1,0,0,0,2,64,0,-1--1--1,|16||0-0-0,1|(1618,481)|
1,74,66,61,1,0,0,0,2,64,0,-1--1--1,|16||0-0-0,1|(1525,393)|
1,75,58,61,1,0,0,0,0,64,0,-1--1--1,,1|(1398,461)|
1,76,64,61,1,0,0,0,0,64,0,-1--1--1,,1|(1530,276)|
1,77,63,61,1,0,0,0,0,64,0,-1--1--1,,1|(1569,310)|
1,78,62,61,1,0,0,0,0,64,0,-1--1--1,,1|(1627,359)|
1,79,61,47,1,0,0,0,0,64,0,-1--1--1,,1|(1480,282)|
1,80,50,49,1,0,0,0,0,64,0,-1--1--1,,1|(921,306)|
1,81,57,56,1,0,0,0,0,64,0,-1--1--1,,1|(991,450)|
1,82,43,54,1,0,0,0,0,64,0,-1--1--1,,1|(1786,145)|
10,83,delivery rate,1896,131,53,13,8,3,0,0,0,0,0,0
1,84,83,54,1,0,0,0,0,64,0,-1--1--1,,1|(1895,161)|
12,85,0,416,67,378,28,3,135,0,12,-1,0,0,0,-1--1--1,128-192-255,|30||0-0-0
INPUT FROM ANN PREDICTION RESULT
12,86,0,447,128,409,24,3,135,0,12,-1,0,0,0,-1--1--1,0-255-0,|30||0-0-0
OBSERVATION OF PERFORMANCE OUTPUT
10,87,number of manpower,1879,411,49,22,8,131,0,4,0,0,0,0,-1--1--1,128-192-255,|12||0-0-0
10,88,standard working hour,1834,504,71,26,8,130,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128

1,89,87,62,1,0,0,0,0,64,0,-1--1--1,,1|(1789,383)|
1,90,88,62,1,0,0,0,0,64,0,-1--1--1,,1|(1753,456)|
1,91,59,58,1,0,0,0,0,64,0,-1--1--1,,1|(1295,582)|
10,92,cycle time,946,632,43,18,8,131,0,4,0,0,0,0,-1--1--1,128-192-255,|12||0-0-0
10,93,standard working hour in seconds,800,516,75,23,8,3,0,0,0,0,0,0
1,94,93,57,1,0,0,0,0,64,0,-1--1--1,,1|(866,477)|
1,95,92,57,1,0,0,0,0,64,0,-1--1--1,,1|(965,594)|
10,96,attendance rate,1827,341,46,23,8,3,0,0,0,0,0,0
1,97,96,62,1,0,0,0,0,64,0,-1--1--1,,1|(1747,351)|
10,98,production completion time,744,680,78,23,8,130,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128
10,99,supplier lead time delivery,15,589,72,23,8,3,0,0,0,0,0,0
1,100,99,13,1,0,0,0,0,64,0,-1--1--1,,1|(-83,525)|
\\\---/// Sketch information - do not modify anything except names
V300 Do not put anything below this section - it will be ignored
*View 2
$192-192-192,0,Times New Roman|12||0-0-0|0-0-0|0-0-255|-1--1--1|-1--1--1|96,96,100,0