Predicting Completion Time for Production Line in a Supply Chain System through Artificial Neural Networks

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***Abstract*—Completion time in manufacturing sector is the time needed to produce a product through production processes in sequence and it reflects the delivery performance of such company in supply chain system to meet customer demands on time. However, actual completion time always deviated from the standard completion time due to unavoidable factors and consequently affect delivery due date and ultimately lead to customer dissatisfaction. Besides, it is found that little attention has been given in analysing completion time at production line from previous literatures. Therefore, this paper fill the knowledge gap by predicting completion time based on historical data of production line activities and discovers the most influential factor that contributes to the tardiness or a late job's due date from its completion time. A well-known company in producing audio speaker is selected as a case company. Based on the review of previous works, it is found that Artificial Neural Networks (ANN) has superior capability in prediction of future occurrence by capturing the underlying relationship among variables through historical data. Besides, ANN is also capable to provide final weight for each of related variable. Variable with the highest value of final weight indicates the most influential variable and should be concerned more to solve completion time issue which has persisted among entities in supply chain system. The obtained result is expected to become an advantageous guidance for every entity in supply chain system to fulfil completion time requirement as requested by customer in order to survive in this turbulent market place.**

***Keywords*—** *completion time, production line, data mining, ANN.*

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1. Introduction

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 [1], [2]. The entities of a supply chain are commonly represented by suppliers, manufacturers, distributors, retailers and end-use customers [1], [3], [4]. The focus of development in manufacturing sector has increasingly transformed from concerning at competitors' achievements to the performance of each entity in supply chain system [5], [6]. Figure 1 shows the flow of products or services among related entities in a supply chain system.

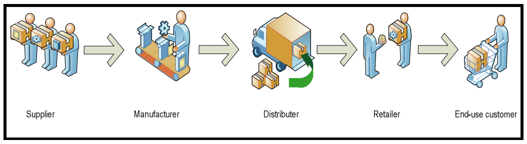

Figure 1 Entities in a supply chain system

Suppliers are providers of raw materials for manufacturers to produce products [2]. Then, raw materials are delivered to manufacturer who utilizes and transforms them to finished products or semi-finished products through their expertise and facilities [7], [8]. The central core of most manufacturing companies is originated from production line activities [9]. After that, finished goods from manufacturer is transported by distributer who perform storage process in order to receive, manage, store, package and deliver products [2]. Products from manufacturer are stored at distribution centre before they are delivered to retailers as entity that sells products directly to the end-use customers to fulfil their demands.

Completion time refers to the required flow time to complete an item in sequence processes from customer order until delivery due date based on production activities [2] and becomes a performance indicator that widely used in supply chain to meet customer delivery demand on time [10], [6], [9]. All the related activities in production systems are performed within standard completion time in order to minimize tardiness or lateness of job's due date from its completion time [11], [12].

If completion for a particular product is beyond the production's due date, normally a certain amount of penalty is imposed to the manufacturer such as air shipment [13] and charge of production line down [14], [15]; which both of the penalties are very costly. However, if the completion time is achieved with minimum tardiness, then a lot of benefits in terms of trustworthiness [16], [17], good reputation [18], [19] and long term business partnership [20], [21] are gained by the manufacturer and other entities in supply chain system to sustain in this competitive marketplace. Graphical representation and elaboration regarding challenges on completion time at production line can be referred in [22]. Realizing that the prediction of completion time which need to inform to related entities is crucially important, this paper predicts completion time based on historical data from production line by implementing ANN method and discover the most influential factor that contribute to the tardiness.

The following section discusses the challenges on completion time at manufacturer site which affects the smoothness of product delivery in supply chain system. After that, the related reviews on completion time, implementation of ANN in production system, and fundamental of ANN are discussed. Then, a framework based on ANN method is presented for predicting completion time. Next, results from learning process of ANN are elaborated. Finally, the conclusion and future work are mentioned in the final section.

2. Challenges in production system

Production systems is a management operation that comprises technological elements such as machine and tools operation [23] while organizational behaviour comprises of manpower and information flow [24], [25]. Several challenges contribute to dynamic and complexity of production system such as inefficient inventory management [1], [9], [26], limitation of manpower [27], [28], machines capacity [7], [29], [30] and materials availability [31], [32], [33], and long lead time [34], [35]. These challenges also consequently affect completion time as activities in production systems are performed within standard completion time.

2.1 Inefficient inventory management

Inventory is a resource of raw materials, in-process products, finished goods to fulfil unexpected demand in the future [1], [2]. Inefficient inventory management could interrupt production process which manufacturers have to struggle in tackling inventory problem for their operation [6], [36]. Hence, strategies in tackling inventory problem should be considered for analysing completion time to avoid disturbance of production operation.

2.2 Limitation of manpower

Manpower is the person who performs specific task at production line [2], [37]. When analyzing completion time, management of production line turns into incontrollable due to limitation of manpower as a human being who possess stress and fatigue [38], [39] which caused by a tight working schedule and a chaotic working environment [27], [28]. Besides, number of manpower also plays an important role for production operation and directly affects completion time of a product [37]. Realizing that manpower factor plays important role in production operation, it should be included in analyzing completion time in order to meet job requirements.

2.3 Materials availability

Many decisions faced by management are subject to material constraint [32]. Late deliveries of materials from appointed suppliers affect the performance of operation management in multi-plant enterprise [6]. This is because flow of materials is one of the important feedbacks among the entities in supply chain [41]. Therefore, material constraint is crucial to be included in analyzing completion time as it gives big impact in production operation and entities in supply chain.

2.4 Machine capacity

Machine constraint can be in terms of machine capacity and becomes one of the limitations at assembly line of production floor [30], [42]. Besides, not only limited to machine resource, machine breakdown also affects stability of initial planning in production system [7], [30]. Therefore, machine constraint must be included in analysing completion time to ensure smoothness of production system from disrupting the initial planning.

2.5 Long lead time

Lead time is defined as length of time needed to manufacturer a product between the placement of orders until the delivery process to warehouse or customer [35]. Lead time comprise of many time elements such as order setup, supplier lead time, completion time and delivery time [34]. The coordination of lead time between the manufacturer and other entities turns to be a frequent problem. Therefore, the different lead time among the entities must be analysed to ensure smoothness of completion time.

3. Reviews on completion time and Artificial Neural Networks

Based on the discussion of previous section, a study on completion time for production system is very crucial since the occurrence of tardiness at manufacturer site affects the smoothness of product delivery in supply chain system. Therefore, reviews of related works on completion time and implementation of ANN in production system are presented.

3.1 Related works on completion time

The study of completion time was initially conducted by Merten and Muller in 1972 which was inspired by the file-organization problem in a computing system [10]. After that, a broad review of completion time was further explored by Cheng and Gupta in 1989 for scheduling research involving due date determination decisions [10]. Then, Zhou and Cai in 1996 conducted a study regarding relationship between completion-time variance (CTV) and waiting-time variance (WTV). In recent times, the study of completion time is extensively studied in various sectors such as multi-plant enterprise and supply chain system as presented by [1], [5], [6], [9] and [12]. However, more works with scientific approach are needed to fill the knowledge gap in analysing completion time at production line.

3.2 Related works on Artificial Neural Networks

Data mining process which commonly performed by ANN, decision tree and regression methods [43], [44] is the extraction process from large sets of data to predict the future or new occurrence [43]. Regression analysis is a statistical process that estimates the relationships between a dependent variable and one or more independent variables [2]. Decision tree is a graphical appearance of a classification of related decisions to be decided under certain risk [43], [45], [46]. ANN is a brain metaphor of information processing [47], a nonlinear data driven, self-adaptive approach and powerful tools especially when the underlying data relationship is unknown [48], [49].

It is found that regression analysis shows low performance for data mining process [43], [50] while decision trees only best be applied when the number of classes is low [51] and for classification purpose [46]. However, ANN serve a lot of advantages for data mining process compared to conventional methods in terms of processing speed, robustness, fault-tolerance, self-learning and self-organization [48], [49], [52].

ANN has gained a tremendous attention for many researchers and popularity from industrial players to solve various problems in production system during the past two decades [43]. Among the studies are part classification and coding [53], [54], planning processes [55], part family and machine-cell [56], [57], production inventory [58], design processes [59], modelling processes [60], [61], and production processes [62], [63].

Based on previous literatures, ANN is mostly implemented for prediction and classification purposes. However, it is found that ANN is also able to provide evaluation weight as the guidance to determine the most influential variable as presented by [28] and [64]. From the output of learning process, variable with the highest value of final weight demonstrates the most influential variable. Based on this finding, it is worthwhile to implement ANN in predicting completion time and determining the most influential variable which contribute to tardiness for operation of production line.

4. The fundamentals of Artificial Neural Networks

ANN mimics the human brain structure for information processing [43]. There is a central processing portion of all neurons or cells called nucleus in human brain [43], [49]. Several terminologies of the relationships between biological neural networks and ANN can be referred in [65] and [66].

ANN paradigm can be classified into two major classes of architectures which are feed-forward network and recurrent network [48], [49], [52]. Both architectures have input layer, hidden layer and output layer. However, feed-forward network has no layer for feedback connections while recurrent network has at least one feedback loop with feedback connection [48], [49]. From previous studies, it is found that feed-forward is a promising architecture that has capability in forecasting of new occurrence in future [43]. Figure 2 shows the example of feed-forward architecture.

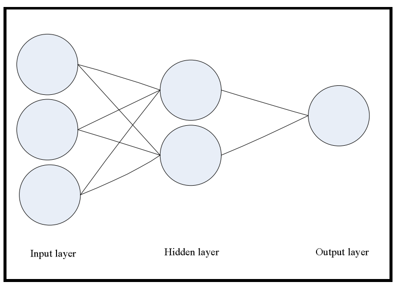

Figure 2. Architecture of feed-forward network

The architecture consists of three layers which known as input layer(s), hidden layer(s) and output layer(s) [43], [48], [49]. There are three nodes for input layer, two nodes for hidden layer and one node for output layer. Signal or raw information is fed into the input layer in the network. After the input layer received the signal, the activity of each hidden layer(s) is determined by the activities of the input layer and the weights of connections between input layer and hidden layer(s) [43], [48], [49]. On the other hand, the activity of the output layer is determined by the activities of the hidden layer(s) and the weights of connections between hidden layer(s) and output layer [43], [48], [49].

5. Framework in analysing completion time

To analyze completion time, a production line from a well-known company in producing audio speaker is selected. Data are collected from the daily reports of Production Department from January, 2015 until Jun, 2015 as shown in Figure 3.

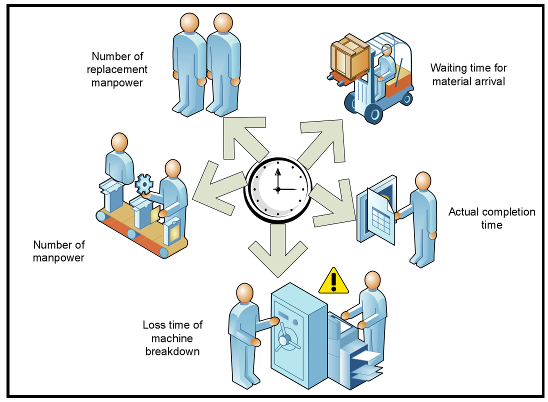

Figure 3. Data for analysing completion time at production line

Based on the discussion with production planner of audio speaker manufacturer, the factors that contribute to the tardiness from its completion time are number of manpower, number of replacement manpower, waiting time for materials and loss time of machine breakdown. Manpower commonly suffers with stress and fatigue which caused by working schedule and working environment [28]. However, only number of manpower and number of replacement manpower are considered in this paper as stress and fatigue factors need a deeper qualitative analysis.

In addition, material constraint in terms of materials availability [32], [33] and late deliveries turns a problematic challenge at production line as it gives a great impact on assembly processes to produce a product. Besides, machine breakdown also contributes to the instability of production system as it interrupts the production planning [7]. In addition, long lead time which required by supplier in delivering raw materials to manufacturer also affects production system as it prolongs the completion time and contribute to the tardiness [2].

The framework for analysing completion time at production line based on ANN method as illustrated in Figure 4. The related phases are historical data collection, data cleaning process, data normalization, determination of ANN paradigm, determination of ANN learning algorithm, determination of initial weight, and percentage of training and validation processes. Finally, ANN learning process is conducted to obtain the final weight of each variable in order to predict completion time.

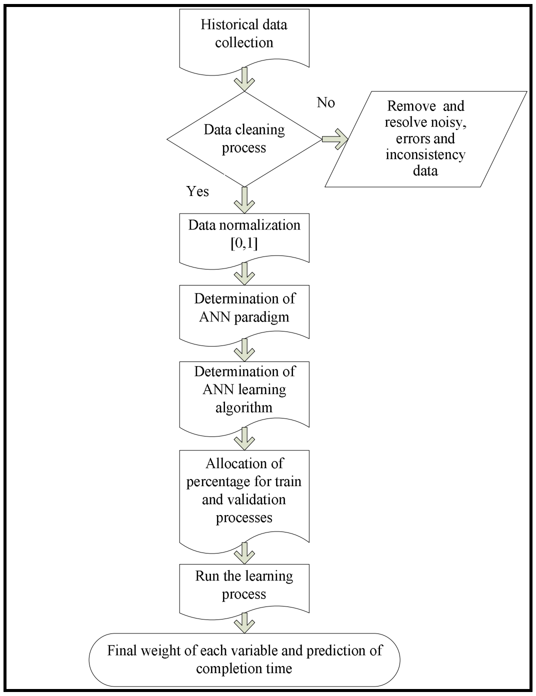

Figure 4. Framework for analyzing completion time based on ANN method

After historical data from the daily reports of Production Department are collected, data cleaning process is performed to ensure the quality of such data for learning process. Data normally have input with incomplete value and inconsistency information that reduce training performance. Hence, data cleaning is required to remove the noise or errors. It can be resolved manually by modeler or alternatively, the system utilizes mean value of available data to fill in the missing values.

After that, the values of each input variables (number of manpower, number of replacement manpower, waiting time for material and loss time of machine breakdown) must fall between interval 0 and 1 [0, 1]. In ANN, inputs in the data are known as attributes. For attribute with value outside the interval, it is required to transform through data normalization. All related attributes in the data set are numerical type and no categorical type is involved. The attributes is normalized by using MIN-MAX formula:

$$\textbf{new value} = \frac{\textbf{original value} - \textbf{minimum value}}{\textbf{maximum value} - \textbf{minimum value}} \qquad (1)$$

The subtraction of minimum value from original value is divided with the subtraction of minimum value from maximum value to obtain a new value within interval 0 and 1. The transformed value is used in the next ANN learning process.

The next step is the determination of ANN architecture or paradigm. In this paper, feed-forward multilayer perceptron (MLP) is selected due to this paradigm is a favorable architecture for predicting purpose as implemented in most of previous studies.

Since MLP is implemented for predicting purpose, back propagation (BP) is the suitable learning algorithm for learning process. This kind of learning algorithm compares initial output with the desired output. Then, the essential alteration is accomplished by BP to adjust the weights until the variance between final output and desired output is minimized.

Learning rate and momentum rate are two types of parameters which involved in BP. Learning rate can have an impact on speed and correctness during learning process while momentum rate slows the learning process for converge purpose. As suggested by [48], learning rate for last layers in MLP paradigm should be allocated with a smaller value than the front layers. On the other hand, the selection of suitable value for momentum should be restricted to the range $0 \leq |\alpha| < 1$ [48, 49].

After that, the data is partitioned accordingly between training set and validation set. Number of manpower, number of replacement manpower, waiting time for material and loss time of machine breakdown are assigned as input variables while actual completion time is assigned as target variable. Training process is conducted to learn the relationship among the attributes while validation process is performed to verify the fully trained set. The percentage of training and validation can be changeable as desired such as 80%:20% or 60%:40%. In this paper, 80%:20% are implemented since by assigning more percentage of data for the training set gives better exposure for the model to mimic the pattern of historical data.

Then, the training process iterates several times during learning process. Iteration with the smallest value of mean squared error is proceeded for validation since the lowest value indicates the model best fit the data in prediction. Then, the validation process takes place after the training process. The network freezes with the final weights once the computed outputs are within satisfactory tolerance of the targeted outputs.

Finally, prediction of completion time based on the learning process of historical data is achieved.

Moreover, the final weight of input variables are evaluated. Variable with the highest value of final weight indicates the most influential variable which much affects the tardiness on completion time.

6. Results and discussion

During learning process, three iterations are generated to obtain final weight for prediction purpose. As the result, the final weight for each input variable is listed in Table 1.

Table 1. Final weight for each variables

Input variables	Final weight
Number of manpower (NM)	0.005
Number of replacement manpower (NRP)	0.123
Waiting time for materials (WTM)	0.208
Loss time of machine breakdown (LTMB)	-0.095

From Table 3, waiting time for materials is the highest final weight (0.208), followed by number of replacement manpower (0.123), number of manpower (0.005) and loss time of machine breakdown (-0.095). It indicates that the most influential factor that contributes to the tardiness of completion time is waiting time for materials while loss time of machine breakdown has less impact on completion time. However, other factors are still significant since the number of final weight among them shows minimal difference.

Based on the final weight of each variable, a new input is implemented to predict completion time. Table 2 shows a new input for each variable to predict completion time.

Table 2. New input for each variables to predict completion time

NM (person)	NRP (person)	WTM (hours)	LTMB (hours)	Prediction of Completion Time (hours)
30	0	0.3	0.1	5
29	1	0.2	0.1	4.8
28	2	0.1	0.2	4.5
29	1	0.1	0.1	4.3

For example, the longest completion time (5 hours) would be taken if waiting time for material is 0.3 hours with 30 persons manpower and no replacement of manpower, 0.3 hours for waiting time of materials and 0.1 hours for loss time of machine breakdown. On the other hand, the shortest completion time (4.3 hours) would be taken if waiting time for material is just 0.1 hours with 29 persons manpower with 1 person for replacement of manpower, 0.2 hours for waiting time of materials and 0.2 hours for loss time of machine breakdown.

In terms of method comparison for the best method in predicting completion time, results from regression and ANN is compared. Decision tree is excluded since the method is just for classification purpose instead of prediction purpose. Table 3 shows mean squared error for each method.

Table 3. Method comparison between Regression and ANN in predicting completion time

Method	Average squared error for test stage	Average squared error for validation stage
Regression	0.046	0.078
ANN	0.024	0.056

Based on the percentage of average squared error for test stage, regression method shows higher value (0.046) compared to ANN (0.024). For validation stage, regression method demonstrates higher value (0.078) compared to ANN (0.056). From the results, it indicates that ANN has better performance for predicting completion time compared to regression since the lower the average squared error, the better the method fits the data in prediction process.

7. Conclusion and future work

This paper presents the implementation of ANN for predicting completion time for audio speaker manufacturer in supply chain system. From the results obtained, it shows that waiting time for materials is the most influential factor compared to other factors as indicated by ANN final weight. Hence, it indicates that management have to concern more on issue that have correlation to material such as delivery from supplier, stock preparation at material warehouse and classification material at production line. Besides, number of replacement of manpower which becomes the second most influential factor also must be emphasized by management as the less skill worker might affect the assembly processes at production line, hence contribute to the tardiness for completion time. It is found that, ANN has better performance in predicting completion time compared to regression method as indicates by value of mean squared error. The implementation of ANN could provide beneficial information for various entities in supply chain system in predicting completion time of manufactured product as necessary plan and preparation could be done before delivery due date. For future work, the final weight of each variable which obtained from the ANN method can be employed in the development of model formulation in system dynamics simulation for further analysing of completion time.

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