ARTIFICIAL NEURAL NETWORK FOR DYNAMIC JOB SHOP SCHEDULING

Muchamad Oktaviandri[1], Adnan Hassan[2], Awaluddin Mohd. Shaharoun[2]

[1]Dept. of Mechanical Engineering, Faculty of Industrial Technology,
Universitas Bung Hatta, Padang, Indonesia.
[2]Dept. of Manufacturing and Industrial Engineering, Faculty of Mechanical Engineering
Universiti Teknologi Malaysia

muchamad_oktaviandri@yahoo.com

Abstract

The dynamics of real manufacturing system are very complex in nature. Schedules developed based on deterministic algorithms are unable to effectively deal with uncertainties in demand and capacity. Significant differences can be found between planned schedules and actual schedule implementation. This study attempted to develop a scheduling system that is able to react quickly and reliably for accommodating changes in product demand and manufacturing capacity. An ANN model was developed and trained using various scheduling scenarios generated by ARENA simulation. The experimental results suggest that the ANN scheduling model can provided moderately reliable prediction results for limited scenarios when predicting the number completed jobs, maximum flowtime, average machine utilization, and average length of queue.

(Keywords: dynamic scheduling, job shop, ANN model, simulation scheduling)

1. INTRODUCTION

The effect of globalization in every sector of the country, such as economic, information technology, communication, transportation, etc. has directly heightened customer expectation. Today's customers expect to be delighted with customized quality, lower price, time delivery, and service satisfaction. These situations have forced manufacturers to adapt changes in technology, among others, automated, flexibility and integrated system, rapid and short run manufacturing have been improved to respond customer expectation [1]. Frequent changes due to the above mentioned factors have meant frequent rescheduling of production operation. Flexibility in reacting to changes in production scheduling has become an important attribute of modern manufacturing system.

One method of increasing the productivity of a manufacturing is by proper production scheduling of the jobs on the available machines/resources so that a high percentage of orders can be completed on time, average waiting time of orders minimized and utilization of the equipment maximized. The production schedulers (people who make scheduling) have to make a production schedule to meet shorten production lead time, to reduce work-in-process (WIP) inventory and to improve machine utilization. Even if he/she has special knowledge and experience for shop floor control, the scheduling job is much too complicated and time-consuming. To solve these problems, schedulers have to use more effective and interactive production schedules.

2. METHODOLOGY

A case study of 6 by 6 job shop scheduling problem from Fisher and Thompson [2] was adapted in this study since the same case study has been widely referred by other researchers. The case study is shown in Table 1. For the purpose of this research, uncertainty elements were added to the original data set. This job shop consists of six machines, labeled as A, B, C, D, E, and F. The tasks were to manufacture six different parts.

This job shop was modeled using ARENA simulation software which run on Pentium IV personal computer. The simulation model was designed to simulate the six-machine with each machine adopting similar dispatching rule. The job to be processed by a machine is selected from its respective queue. The physical system configuration is shown in Figure 1.

Table 1, A case study of 6 x 6 job shop scheduling problem (Fisher and Thompson, 1963).

	Operation No					
Job No.	1	2	3	4	5	6
1	C,3	A,10	B,9	D,5	F,3	E,10
2	B,6	C,8	E,1	F,5	A,3	D,3
3	C,1	D,5	F,5	A,5	B,9	E,1
4	B,7	A,5	C,4	D,3	E,1	F,3
5	C,6	B,11	E,7	F,8	A,5	D,4
6	B,3	D,10	F,8	A,9	E,4	C,9

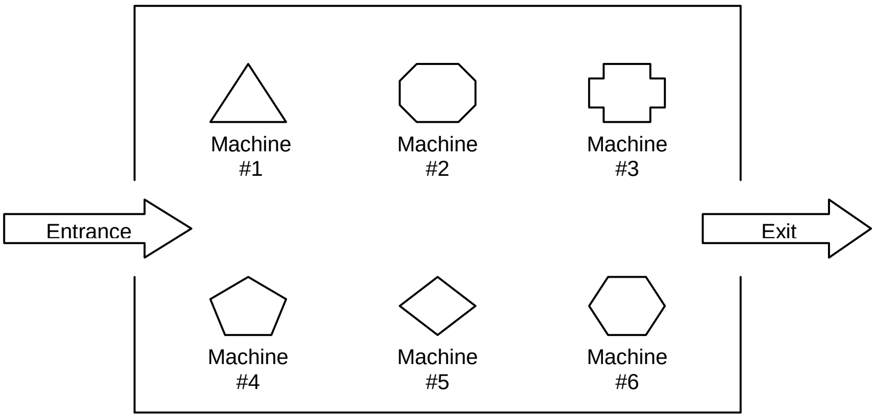

Figure 1, Physical configuration of a six-machine dynamic job shop.

Figure 1 shows each job comes directly through an entrance gate and passes to various machine according to its predetermined route. Each incoming job will posses a specific task characteristic assigned before entering the job shop. The task characteristics for each job are as the following:

- Routings details
- Job processing time on each machine where operation will be performed
- Scheduling rule

2.1 Artificial Neural Network Model

The construction of the artificial neural network (ANN) model involves a learning process. Figure 2 illustrates the neural network model developed for this research. The network was developed using a multilayer perceptron (MLP) architecture and the learning process was based on back-propagation algorithm. The datasets for training and testing were stored in a text file. The ANN learning involves computation of the predicted output against the target output. Adjustment of the weight was made to minimize the mean absolute error (MAE) as shown in Figure 3.

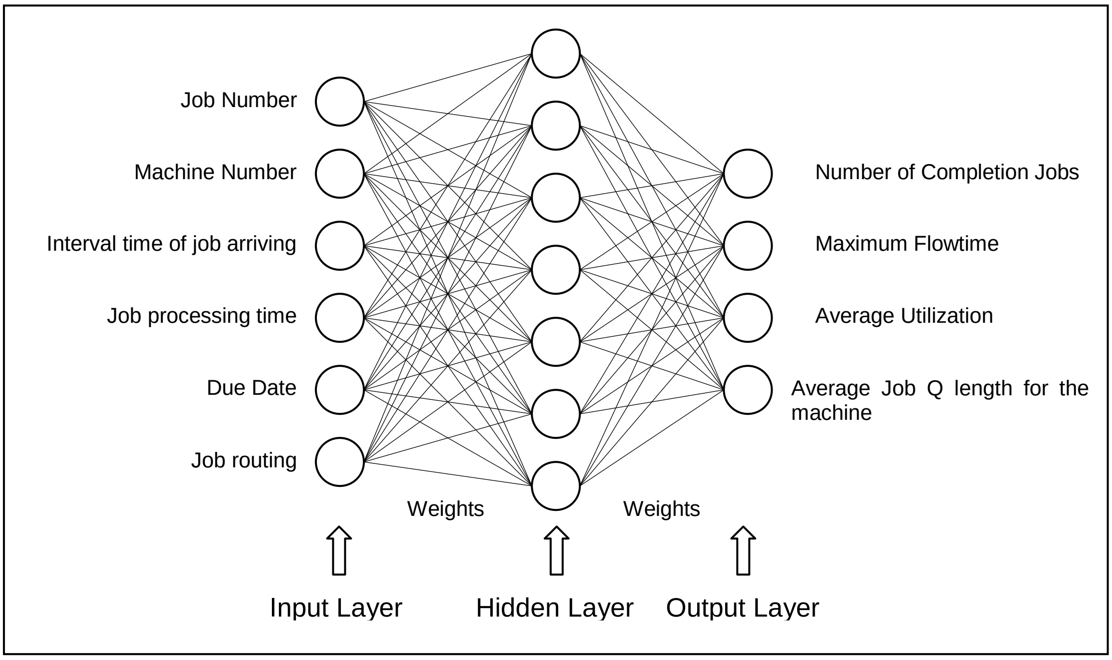

Figure 2, ANN Scheduling Model

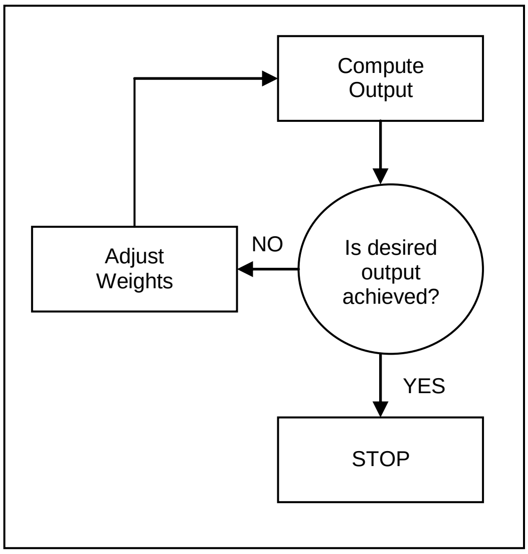

Figure 3, Error Adjusted for ANN model.

2.2 Sequence Codification Scheme (SCS)

The ANN structure with one input layer, one hidden layer, and one output layer as shown in Figure 2 was used in this study. Data representation is an important issue that directly influences the decision on the

ANN architecture, specifically, the number of input neurons. The number of input neurons required to represent any given job sequence depends on the definition of these sequence codification scheme (SCS). The codification rules adopted in this research was based on the guidelines proposed by Lawrence [3].

3. RESULT AND DISCUSSION

3.1 ANN Training Results

The scheduling scenarios evaluated through ARENA simulation provided valuable input data sets [4] and they were used for training the ANN scheduling model. The training parameters used for the ANN model is shown in Table 2. A total of 180 training samples were used with a learning rate = 0.1.

3.2 Parameter used in the BP-MLP

Table 2, Training Parameters.

Parameter	Value
Number of sample	180
Network structure	36-37-24
Stop Condition	
• Maximum Training times	10000
• Error	0.01
Learning Rate	0.1

3.3 The Training Convergent Curve

The Mean Absolute Error (MAE) training convergent curve of the whole training process is shown in Figure 4. According to the curve, it can be seen that the slope decreases significantly prior to 150 training epoch.

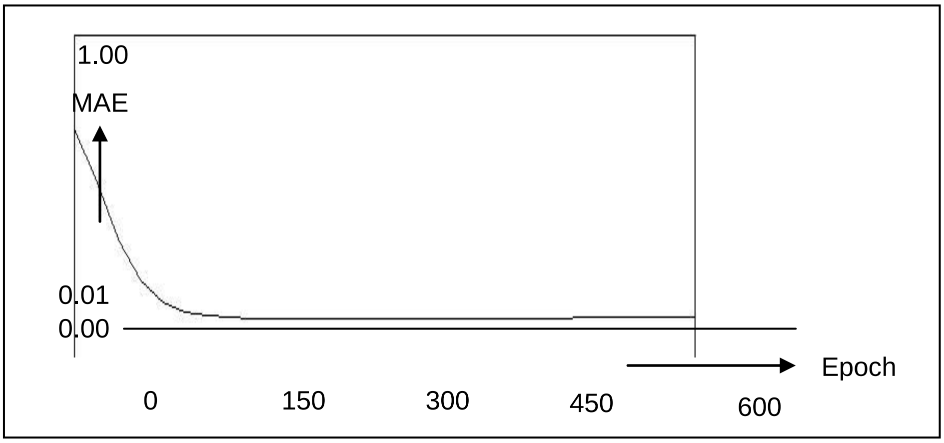

Figure 4, Mean Absolute Error Convergent curve of Training

3.4 Comparison between Simulation Results and Predict Results

Samples of the results are compared graphically between the results from ARENA simulation and the ANN scheduling model. Overall, ANN model resulted in moderately reliable prediction for the following:

(i) Prediction for the number completed jobs for EDD with high job arrival, SPT with medium and high job arrival.
(ii) Prediction for maximum flowtime for SPT with low, and SPT with medium job arrival .
(iii) Prediction for average machine utilization for SPT with medium job arrival.
(iv) Predictions on average length of queue suggest that both techniques gave almost similar patterns.

In general, the above results suggest that the ANN schedule model needs further improvement to provide more consistent results for other scheduling scenarios. High variability in the dynamic job shop environment may have contributed to the difficulty in getting better results.

4. CONCLUSSIONS

In the first phase of this research, a simulation study for various job shop scheduling scenarios were evaluated using ARENA simulation software package. In the second phase, an ANN scheduling model was developed using Multilayer Perceptron model. The ANN model was trained and tested using various scheduling scenarios generated from Arena simulation.

This study has provided better understanding on the complexity of dynamic scheduling. An ANN model to predict various scheduling scenario has been developed. The experimental results suggest that the model can provided moderately reliable prediction results for selected job shop scenario when predicting the number completed jobs, maximum flowtime, average machine utilization, and average length of queue. There were also some scheduling scenarios where the model did not provide good prediction results. The finding suggests that high variability in the dynamic job shop environment and insufficient representative scenarios may have contributed to the difficulty in getting better results. Thus, the present ANN scheduling model needs further improvement to provide more consistent results.

The following are suggestion for further investigation: (i) Fine tune the ANN scheduling model to give more consistent results (ii) Consider more variety of job shop sizes (iii) Incorporate an expert system in realizing an intelligent dynamic scheduling system.

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