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Job shop flow time prediction using neural networks

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Abstract

In this paper we investigate the use of Artificial Neural Networks (ANN) for flow time prediction and, consequently, to estimate due dates (DD) in a hypothetical dynamic job-shop. The effectiveness of the proposed ANN based DD assignment model is evaluated comparing it performance with the performance of two dynamic DD assignment rules proposed in the literature: Dynamic Total Work Content, and Dynamic Processing Plus Waiting. Results show that ANN based DD assignment models are more effective than, not only available static DD assignment rules, as concluded by other researchers, but also than the more effective Dynamic DD assignment rules.

Keywords: Dynamic job shop, Dynamic due date assignment rules, Simulation, Artificial Neural Networks, Dispatching rules.

1. Introduction

With increasing globalization, competitiveness and current emphasis on costumers-oriented markets, companies are facing more challenges than ever. In order to gain competitive advantages in the intense market competition, companies must be able to provide customers with better quality, reduced lead time and reliable due dates [1]. The importance of meeting promised due dates (DD) is highlighted in [2] where the authors claim that it not only

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increases the customer service but also improves the resources utilization by making it more efficient. Thus, DD assignment as been pointed out as a key task in shop floor control [3].

The dynamic job shop system has been widely used in DD assignment problem research since it provides a more accurate representation of the operating conditions of a real-world environment [4]. In this kind of environment, the DD assignment problem consists in making an estimation of a job flow time, when it arrives to the shop, and setting a completion date based on that estimation [5], for example by adding an external lead time buffer to the estimated flow time. However, flow time prediction is a challenging task since every arriving job has its own processing needs, in different machines and it will experience different congestion levels which will, consequently, alter the flow of the jobs through the shop [6]. Moreover, as stated in [7], if the shop dispatching rule is not First in First Out, the arrival of a new job can change the processing sequence and thus the expected completion date of a job already in the system.

The general flow time estimation, for a given job i, arriving to a shop, can be represented by equation (1).

$$f_i = r_i + p_i + k_i \tag{1}$$

where f_i, r_i, p_i and k_i are the flow time estimation, the arrival time, the total processing time and the allowance factor for job i, respectively. The arrival time and the processing time of a job are known upon it arrival to the shop, thus the only variable that needs to be estimated is the allowance factor k. The flow allowance is a variable used to control the tightness of the DD which reflect the waiting time that a job will experience in the shop. Choosing the appropriate allowance factor is a trade-off between the tightness of the DD and the job earliness/tardiness. If the allowance factor provides a looser DD, it may be possible to complete all the jobs on time. However, this will lead to a higher number of jobs completed before the DD (earliness). On the other hand, tighter flow allowance will lead to a higher amount of jobs completed after the DD (tardiness). The literature provides a wide variety of methods to estimate job flow times. The main difference among them is the number and type of factors considered to estimate the allowance factor k.

Earlier studies on the DD assignment problem focused in the use of simple rules for flow time estimation. Five examples of this kind of rules: Constant (CON), Number of Operations (NOP), Slack (SLK), Total Work Content (TWK) and Processing Time Plus Waiting (PPW) are presented in Table 1.

Table 1. Examples of DD assignment rules.

DD Assignment rule	DD prediction
CON	$d_i = r_i + k$
NOP	$d_i = r_i + km_i$
SLK	$d_i = r_i + p_i + q$
TWK	$d_i = r_i + kp_i$
DPPW	$d_i = r_i + kp_i + q$

where d_i is the DD of job i, m_i is it number of operations and pi it total processing time. In this class of assignment rules, the constants k and q, the allowance factor and the slack allowance respectively, are determined by linear regression based on historical data.

In this class of rules, the same degree of flow time allowance is given to all the jobs and, for this reason, they are known as static rules. The accuracy of these rules depends on the determination of the most appropriate flow allowance for all the jobs [8]. The main issue stated for this class of rules is that by given the same allowance factor to all the jobs, the shop load is not being taken into account for DD prediction. Yet, the shop load influences the time that a job will experience in the system. If the shop load is heavy a higher flow allowance should be assigned and, in the other hand, if the shop load is moderate, a lower flow allowance should be considered [9].

To overcome the limitation of the static rules for DD assignment, two dynamic DD setting rules were proposed by Cheng and Jiang [9]. In these rules: (1) Dynamic Total Work Content (DTWK), based on the TWK static rule and Dynamic Processing Plus Waiting (DPPW), based on the PPW static rule, the allowance factor is dynamically updated as a job arrives to the shop. These two DD assignment rules are capable of adjusting dynamically the flow time estimation by using feedback information on current shop load information. The authors, using simulation results, demonstrates that the proposed dynamic models are significantly better than their static counterparts in reducing missed DD. Similar results were found by several other authors, see for example [8, 10].

DD estimation using the DTWK and DPPW rules are made following equations (2) and (3) respectively:

$$d_i = r_i + max\left[1, \frac{N_{st}}{\lambda \mu_p \mu_g}\right] \sum_{j=1}^{m_i} p_{ij} \tag{2}$$

$$d_i = r_i + \sum_{j=1}^{m_i} p_{ij} + \frac{N_{qt} m_i}{\lambda \mu_g} \tag{3}$$

where, d_i is the DD estimate for job i, r_i it arrival time; p_{ij} the processing time of the jth operation of job i; m_i is it total number of operations; N_{st} is the number of jobs in the system at time t; λ denote the average job arrival rate; μ_p and μ_g represents the mean operation processing time and the average number of operations per job, respectively; and N_{qt} is the number of jobs in the queues at time t.

All parameters needed for equations 2 and 3 are available each time a job arrives to the shop and, thus, the DD can be determined based on both job file and shop status information.

Artificial Neural Networks (ANN) are computational models inspired on biological functions of the human brain that have the ability to learn and generalize from particular scenarios. An ANN consists in layers, processing elements (nodes) and connections between nodes. This characteristic can be useful in situations where the complexity of the data makes the design of such function by hand unattainable. The ANN has been broadly employed in multiple areas, such as manufacturing, medicine, finances and accounting [11].

As stated previously, flow time prediction is a difficult task due to the number of non-linearly related aspects that can affect it. Thus, some authors have proposed ANN-based DD assignment rules, see for example [9, 12]. In both these studies the ANN-based DD assignment rules effectiveness is compared with static DD assignment rules like TWK and JIQ (Jobs In Queue). Both studies conclude that ANN-based assignment rules can outperform conventional static DD assignment rules and are worthy of further experimentation. To the best of our knowledge ANN-based assignment rules have not been tested against the more effective dynamic DD assignment rules like DTWK or DPPW.

In this paper, an ANN-based due date assignment rule is proposed and it effectiveness is tested by comparing it to two dynamic DD assignment rules: DTWK and DPPW.

2. Research methodology

To address the question on how ANN can be used as a DD assignment method and how well it can predict due dates when compared to the dynamic due date assignment methods, we developed a dynamic job shop simulation model (described on Section 2.1) and an ANN-based assignment model (described on Section 2.2). The simulation model serves two purposes: to generate and provide the necessary data set for modelling the DD assignment rules and generate the necessary input data to train and test the ANN. Due to its influence in flow time prediction, two dispatching rules were considered to prioritize the jobs: FIFO and SPT. Two dynamic DD assignment rules – DTWK and DPPW - were chosen for flow time prediction and to be compared with the proposed ANN-based rule. The performance measures used to evaluate the flow time prediction of the DD assignment rules are: mean absolute lateness (MAL), mean squared lateness (MSL), percentage of tardy jobs (PT) and mean tardiness (MT). The dynamic job shop model was implemented using the simulation software Simul8®, and the ANN-based model was built using the Artificial Neural Network Toolbox of Matlab®.

2.1. Dynamic job shop simulation model

In order to achieve our objective, a simulation model of a hypothetical job-shop was developed. The simulated job shop consists in six non-identical work centers under constant utilization, performing six different operations. The following assumptions were considered:

- All the machines have the same probability of being visited;
- Each machine can perform only one operation at a time on any job;
- Pre-emption is not allowed;
- There are no machine breakdowns, each machine is continuously available for production;
- All the required materials are continuously available;
- There is no restriction on queue lengths at any machine and all jobs are accepted for production;
- Setup times are considered in the processing time and no transportation time are considered.

Jobs arrive to the system following an exponential distribution with a mean of 0.648 time units which leads to a 90% utilization level. This utilization level corresponds to a heavy shop utilization. Each job consists in a set of operations to be performed on the machines in the shop. The routings of the jobs are made by random assignment and a machine will be included only once in the routing. Therefore, a job cannot visit the same machine more than once. Each machine has the same probability to be the first in the routing sequence. The number of operations of each job is uniformly distributed in the range 1-6, which mean that a job can have a number of operations that can be between 1 and 6. Operations processing times follows an exponential distribution with a mean of 1time unit.

2.2. ANN-based DD assignment rule

In this study we use a multilayer feed forward network architecture, Figure 1, in which:

- Input Layer – It is the first layer of the ANN which receives the input data generated in simulation. It has as many neurons as the number of features that are used to train and serve as input to the model;
- Hidden layer – It is a layer connecting the input to the output layer. The number of neurons on hidden layers can be set by empirical estimation although there is a general rule of thumb that consists in defining the number of neurons as the average between the number of input and output neurons. In our study we use one hidden layer composed by 15 neurons;
- Output Layer – It is the last layer of the ANN that returns a class label or a value. In the proposed ANN-based assignment rule, the output layer is composed by a single neuron which will return the job flow time prediction.

The ANN is trained (supervised learning) with labeled data generated by simulation. For this purpose, the network is fed with a set of inputs in order to produce a set of predictions for the data. This is accomplished by having both input x and the associated target output y obtained from the simulation model described in the previous section. For the proposed ANN-based DD assignment model, the input x will be the job characteristics and shop condition at the time that each job i arrive to the shop, see Table 2. The output will be the flow time prediction for each job i. Similar datasets have been used in previous studies, see for example [9, 12].

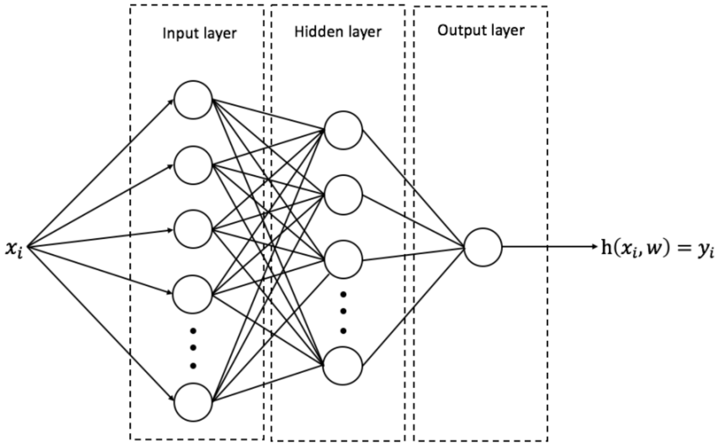

Fig. 1. General architecture for an ANN model.

Table 2. ANN based DD assignment rule input data set.

Main class	Sub class	Number of features
Job information	Number of operations	1
	Total processing time	1
	Processing time in each machine	6
	Processing sequence	6
Shop status	Number of jobs is each queue	6
	Total number of jobs in the queues	1
	Total number of jobs in the system	1

The Matlab® Neural Network Toolbox has already an implementation of a regression/fitting network which uses linear regression as activation function and the Levenberg-Marquardt backpropagation algorithm as learning algorithm. The objective of this training algorithm is to minimize the error (the difference between the actual and expected results) by estimating the weight on forward process and update those weights on the backwards process.

3. Results

To train the ANN we generated a set of jobs using the simulation model described in section 2.1. The simulation model was run for 2000 time units and the first 200 jobs arriving after time 1500 were selected to collect the required data to feed the ANN model. The job information for the 200 selected job and the shop status upon their arrival were used to feed the input layer and the conclusion date of the jobs were given to the ANN model.

Then, a new set of 200 jobs, obtained in a similar way, was used to test the ANN model. The data corresponding to this new job set were used to estimate the DD using the ANN model and the two selected dynamic DD assignment models: DTWK and DPPW. The DD estimation obtained by each of the three models were compared with the achieved conclusion data obtained from the simulation model to calculate the selected performance measures: Mean Absolute Lateness (MAL), Mean Squared Lateness (MSL), Percentage of Tardy jobs (PT) and Mean Tardiness (MT). The results are summarized in Table 3.

Analyzing Table 3, and considering only the results from the two dynamic DD assignment rules (DTWK and DPPW) it is possible to conclude that when the FIFO rule is applied, the DPPW achieves better results for all the performance measures. However, when the SPT rule is applied, the DPPW rule stills achieves the best results when considering the percentage of tardy jobs (PT), but is outperformed by the DTWK rule for both MAL and MSL. These results are in line with the ones presented in [9] and reinforce the idea that the performance of DD assignment rules relies greatly on the integration of job dispatching and DD determination methods.

Table 3. Performance measures comparison.

	FIFO			SPT		
	DTWK	DPPW	ANN	DTWK	DPPW	ANN
MAL	15,5	9,5	7,0	13,4	15,6	10,8
MSL	6359,4	164,6	94,3	1713,2	2108,3	860,6
PT	58,0 %	52,5 %	50,5 %	22,0 %	16,5 %	39,0 %
MT	7,6	5,1	3,9	6,4	7,4	3,4

Regarding the ANN based DD assignment model, it is possible to observe that, under a FIFO dispatching rule, it outperforms both considered dynamic DD assignment rules for all the considered selected performance measures. When considering the SPT dispatching rule, the ANN model leads to a larger PT. Nevertheless, for the other performance measures: MAL, MSL and MT, the ANN model achieve better results than the two tested dynamic DD assignment rules. Many researchers have focused on the tardiness aspect of the DD related performance, giving impression that earliness is acceptable. But, for modern operations management, with emphasis on the Lean concept and, consequently, on waste reduction, it is important to meet target DD as closely as possible, avoiding both earliness and tardiness.

Taking this into account, we can affirm that the ANN based DD assignment rule can be considered a good option, even when considering the SPT dispatching rule. In fact, these results show that, despite the number of tardy jobs is larger with the ANN model, the tardiness of each job is lower than when considering DTWK and DPPW rules. Moreover, the number of early jobs, and their earliness, is decreased under the use of the ANN prediction model.

Moreover, a detailed analysis of the tardiness obtained for each job allows to conclude that, for DTWK and DPPW, the lateness of jobs with large processing time is much higher than the ones obtained for jobs with smaller processing times. This is due to the fact that larger jobs tend to be delayed under the SPT dispatching rule. Nevertheless, this behavior is not present when the ANN based DD assignment rule is in place. In this case the standard deviation of lateness is considerably reduced when compared to the one obtained using the dynamic DD assignment rules to predict the flow time. This means that a shorter external lead time buffer can be applied to obtain a certain level of delivery performance.

In general, results obtained so far with this ongoing project, seems to indicate that ANN based DD assignment rules can lead to better DD estimates, not only when compared with static DD assignment rules, as referred in [9, 12], but also when compared with the more effective dynamic DD assignment rules.

4. Conclusion

In this paper we investigate the use of ANN for flow time prediction and, consequently, to estimate due dates in a hypothetical dynamic job-shop. The effectiveness of the proposed ANN based DD assignment model is evaluated comparing its performance with the performance of two dynamic DD assignment rules proposed in the literature (DTWK and DPPW) and considering two dispatching rules (FIFO and SPT). Preliminary results show that under a FIFO dispatching rule the ANN model outperform both dynamic DD assignment rules, for all the considered performance measures (MAL, MSL, PT and MT). Under an SPT dispatching rule, both dynamic DD assignment rules provide better results than the ANN model in terms of percentage of tardy jobs. Nevertheless, if penalties are considered for both earliness and tardiness, i.e., when jobs due date differ from the actual job completion time, then the ANN model is more effective than DTWK and DPPW. Thus, we can conclude that ANN based DD assignment models are, in general, more effective than, not only available static DD assignment rules, as concluded by other researchers, but also than the more effective Dynamic DD assignment rules.

This paper presents results from an ongoing project and further work is envisaged.

Results used to compare the DD assignment rules consider a single data set constituted by 200 jobs. To reinforce the conclusions obtained so far we intend to generate new data sets, by simulation, and use appropriate statistical tools to compare the performance of the DD assignment rules.

So far, only results considering a heavy shop utilization level (90%) which, according to other authors is the worst case scenario for flow time prediction, were analyzed. We intend to change the jobs inter arrival time in our simulation model to obtain data sets for a lighter shop utilization level (80% and 70%) and investigate the performance of each DD assignment rules under these conditions.

Finally, in this study the DD assignment rules performance was analyzed considering only two different dispatching rules, FIFO and SPT which are not DD dependent. Knowing that the combination of a DD assignment rule and a dispatching rule can have a major impact on the performance criteria based on missed DD, we intend to compare the DD assignment rules using other dispatching rules. We are considering to use three more dispatching rules, which are DD dependent: Earliest Due Date (EDD), Modified Operation Due date (MOD) and Critical Ratio (CR).

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References

[1] Li, M., Int. J. Bus. Manag. 4 (2009) 136-141.
[2] Sha, D.Y., Liu, C.H., Int. J. Adv. Manuf. Tech. 25 (2005) 1164-1174.
[3] Thürer, M., Stevenson, M., Silva, C., Land, M. Int. J. Prod. Res. 51 (2013) 4502-4516.
[4] Sha, D.Y., Storch, R.L., Liu, C.H., Int. J. Prod. Res. 45 (2007) 65-82.
[5] Joseph, O.A, Sridharan, R. J. Manuf. Syst. 30 (2011) 28-40.
[6] Hsu, S.Y., Sha, D.Y., Int. J. Prod. Res. 42 (2004) 1727-1745.
[7] Ragatz, G.L, Mabert, V.A., Int. J. Prod. Res. 22 (1984) 685-695.
[8] Baykasoglu, A., Goçken, M., Unutmaz, Z.D., Eur. J. Oper. Res., 187 (2008) 31-45.
[9] Cheng, T.C.E., Jiang, J., Comput. Ind. Eng. 34 (1998) 297-307.
[10] Vinod, V., Sridharan, R., Int. J. Prod. Econ. 129 (2011) 127-146.
[11] Patil, R.J., Int. J. Prod. Res. 46 (2008) 6009-6027.
[12] Philipoom, P.R., Ress, L.R., Decision Sci. 25 (1994) 825-847.