Research Article
Journal of Intelligent Systems: Theory and Applications 8(1) (2025) 84-94
DOI: 10.38016/jista.1620633

Due Date Determination in Dynamic Job Shop Scheduling with Artificial Neural Network

Mümtaz İpek[1*], İsmail Hakkı Cedimoğlu[2]

[1] Industrial Engineering Department, Faculty of Engineering, Sakarya University, Sakarya, Türkiye

[2] Department of Information Systems Engineering,Faculty of Computer and Information Sciences, Sakarya University, Sakarya, Türkiye

ipek@sakarya.edu.tr, cedim@sakarya.edu.tr

Abstract
In this study, an artificial neural network approach that is thought to produce better results as an alternative to due date determination methods in dynamic job shop scheduling environment is presented and its feasibility is demonstrated. The performance of the neural network model is compared with five different regression models. An event oriented simulation software is developed for the determination of the coefficients of the regression models and for the generation of data to be used in the training of the neural network model. Back-propagation artificial neural network was used as an artificial neural network model and a software was developed. After the regression models were created and the neural network was trained, the simulation software was run for the shortest processing time and earliest due date priority rules for comparison purposes. In order to compare the models, average absolute deviation from the due date, mean square of absolute deviation from the due date, average tardiness, number of tardy jobs, average earliness and number of early jobs were used as performance metrics. As a result of the study, the artificial neural network model was found to be effective in due date determination. Both the shortest processing time first and the earliest due date first priority rules gave good results in terms of several performance metrics. It was observed that the neural network gave better results in the shortest processing time priority rule in general.

Keywords: Dynamic Job Shop, Due Date Determination, Artificial Neural Networks

1. Introduction

In a production system, activities requiring decision-making occur hierarchically at three levels. These are strategic, tactical, and control level. At the strategic level, production plans are required to meet market demands. At the tactical level, the planned production schedule is coordinated with some shop floor constraints such as inventory, machine capacity, maintenance plan and labour productivity. At the control level, the flow of work is continuously regulated to realise the execution of the planned production schedules and schedules disturbed by unexpected events are immediately updated.

1.1. Dynamic scheduling

The dynamic problem causes difficulties in determining a finite schedule. Unlike make-to-stock production, there is no master production schedule to help predict future workload in a manufacturing facility. Unknown future work fluctuations make it difficult to develop efficient scheduling algorithms. Furthermore, finite scheduling techniques that attempt to detail the future state of jobs within the shop floor may not be appropriate if there is significant uncertainty about processing times.

1.2. Due date determination

The importance of assigning accurate due dates for the delivery of jobs in a production system is well recognised by academic researchers and managers in practice. Due to developments in manufacturing systems and idealised concepts in inventory systems, due dates-based research has attracted attention and a rich literature has been reported in this area (Cheng et al., 1989). In a manufacturing system, each job is assigned a due date before it is released for processing on the shop floor. The literature analysis shows that various decision rules have been proposed for due date assignment. The literature on due date assignment emphasises simple, regression-based approaches to deadline setting for the dynamic multi-machine case (Philipoom, 1994).

* Corresponding Author.
E-mail: ipek@sakarya.edu.tr

Recieved : 15 Jan 2025
Revision : 31 Jan 2025
Accepted : 10 Mar 2025

1.3. Regression analysis

Regression analysis is a statistical analysis technique that is frequently used to determine the relationship between two or more variables that have a cause-effect relationship between them with a mathematical function and to make estimation or prediction about the dependent variable using this relationship (Tarı, 1999, Orhunbilge, 2000). Regression analysis also reveals the structural relationships between variables. It is possible to find cause-effect relationships in most economic, social, and natural events.

After fitting the regression model, checking the adequacy of the model is the most important part of regression analysis. It is necessary to ensure that the applied model is close enough to the correct model and to check whether it meets all the assumptions of the least squares regression analysis. In regression analysis, analysis of variance and multiple coefficient of determination (R^2) are usually used for model adequacy. It is not enough to demonstrate the adequacy of the model by analysis of variance. In addition, the statistical significance of regression parameters should also be investigated by t-tests.

1.4. Artificial neural networks

An artificial neural network (ANN) can be defined as an inference mechanism based on the human brain (Negnevitsky, 2002). In other words, artificial neural networks are planned hierarchical structures with simple elements connected in parallel to each other and interacting with real world objects in the same way as biological nervous systems do (Kohonen, 1987). A general neural network model is characterised by processing elements. A processing element consists of five components:

- Inputs bring information to the processing element. This information is provided by other processing elements or external sources. Sometimes the processing element can provide information itself.
- Weights determine the effect of a certain input on a processing element. It is the weight values that need to be optimised during the training process in order for the network to produce the correct outputs.
- The summation function sums the weighted inputs of the process element. There are various summation functions (Neuralware Inc, 1990). The most common one is to find the weighted sum. Here, each input value is multiplied by its weight and summed (Oztemel, 2003).
- The transfer function determines the output of the processing element by modifying the result of the addition function. Again, there are various transfer functions (Neuralware Inc, 1990). Some of the popular ones are sigmoid function, linear function, and step function.
- The output sends the result of the transfer function to the connected processing elements or to external sources.

The topology of the network is the second feature that characterizes the network. A group of processing elements forms a structure called a layer. A typical neural network contains three interconnected layers. These are the input layer that accepts input from the outside world, the hidden layer (or hidden layers) that processes the information from the input layer and sends it to the output layer, and the output layer that informs the outside world about the decision of the network. Information flows between or within layers of the network.

1.5. Priority rules

Priority rules are used when there is more than one job in the queue in front of a machine and the job needs to be assigned when the machine becomes available. In this study, the shortest processing time and the earliest due date are used as priority rules. Since both priority rules lead to schedules with different flow times, therefore different completion times, separate simulations of the dynamic job shop under study were performed for each rule.

1.6. Performance metrics

Performance measures help comment on the success of a schedule. Therefore, it can be said whether the schedule is good or not according to a performance metric. In this study, an artificial neural network model is proposed for due date determination. The proposed model is compared with the regression models in terms of performance. Since the due dates are in question, the average absolute deviations of the due dates from the actual completion times, the squares of the average absolute deviations, the tardiness and earliness from the actual completion times were selected as performance measures. Comparisons were made on the basis of these metrics. In addition, the number of tardy and early jobs were also calculated for both types of models to give an idea.

1.7. Assumptions

Both real and hypothetical systems are available in the literature for dynamic workshop simulation. Hypothetical systems typically contain a small number of machines (usually less than 10) and some assumptions are made in simulation studies (Baker, 1974, French, 1982).

1.8. Aim

The aim of this study is to demonstrate the feasibility of artificial neural network for deadline determination in dynamic job shop scheduling. For this purpose, an event oriented simulation software using dynamic variables has been developed. A back-propagation artificial neural network software using dynamic variables is also presented for modelling the artificial neural network. The event oriented simulation and the artificial neural network softwares are written in C. The due dates were determined by regression models and artificial neural network and compared according to the selected performance metrics. When determining the due date with regression models, missing data or a possible error may cause the due date information to be calculated very differently from what it should be. Artificial neural network can give appropriate answers in such a situation due to its ability to work with missing data.

2. Literature Review

The production control system for a shop floor can be analysed in a structure consisting of three sequential stages (Philipoom, 1994): Order stage, order release and shop floor stage. In the first stage the customer's work arrives and a due date is assigned. Assigning a due date is the first important task of shop floor control. Due date-related performance is characterised by the quality of the due date assignment rules. Due date assignment and products delivered to the customer on time will provide customer satisfaction and competitive advantage (Sha and Hsu, 2004). In this section, studies on date date assignment in the literature are examined in two groups: numerical and heuristic.

2.1. Numerical methods

In these methods, the problem is defined by mathematical models. These models are solved by mathematical programming techniques and the optimum solution is sought. Mosheiov (2001) studied the due date assignment problem and job shop scheduling in parallel similar machines. He proposed that the cost of a schedule is a function of maximum earliness cost, maximum tardiness cost, and due date cost. The aim of the study is to develop a due date scheduling algorithm that minimizes these three cost functions. Biskup and Jahnke (2001) considered a general due date assignment to jobs and scheduling of jobs on a single machine. They considered that the processing times are controllable. However, in contrast to previous approaches, they emphasised the case where all processing times can be reduced at the same rate. They concentrated on minimising the number of early, tardy, and late jobs as well as due date assignment. They found algorithms that can be solved polynomially. Veral (2001) tried to find out that it is possible to set static due date with flow time analysis. The proposed model has been compared with the TWK (Total Work) model. The comparison was carried out considering light, medium, and heavy shop floor loads. The author's model outperformed the TWK at all three different shop floor loads and performed better in workflow time prediction accuracy. Gupta et al. (2002) studied the permutation flow type problem. In this study, each job centre consists of parallel similar machines. Each job has different release dates and is processed in the same order on machines in different job centres. In the study, 20 jobs and 10 work centres were considered. In addition, the cost of due date assignment was added to the objective function. Wang and Uzsoy (2002) investigated the feasibility of job due dates in batch processing machines used in the metalworking and microelectronics industries when jobs are dynamically sent to the workshop. A genetic algorithm technique was used together with a dynamic programming algorithm. It was concluded that the study showed excellent average performance. Sabuncuoglu and Comlekci (2002) proposed a new flow time estimation method that uses route information about the operations of jobs, such as detailed job, shop floor and machine imbalances. They state that such information is now available in computer integrated manufacturing systems. They measured the performance of their proposed method by simulation under various experimental conditions. They compared with existing flow time estimation methods in terms of various performance measures. They found that the performance of manufacturing systems can be improved by information intensive methods rather than simple methods (TWK). They claimed that the use of detailed information in flow time prediction provides significant improvements over methods that use more integrated information to improve system performance. They stated that the results of the study showed that predicting flow time for each operation is a better approach than traditional job-dependent prediction. Song et al. (2002) stated that the determination of product due dates is an important part of production planning and studied the determination of product due dates in complex multi-stage assembly operations. Product lead times were used to minimise earliness and tardiness. Sha and Liu (2005) argue that although just-in-time production philosophy is gaining importance, the ability to deliver orders on time will increase customer satisfaction and provide a competitive advantage to the organisation. In this study, in order to improve the performance of TWK, which is one of the due date assignment rules, they represented the dynamic workshop conditions with IF-THEN rules and the k coefficient was determined by evaluating the situation in the workshop at the arrival of the job, thus reducing the due date error of the TWK method. As a result, the rule-based TWK method gave better results compared to static and dynamic TWK methods. Shabtay and Steiner (2006) argued that on-time delivery of orders is one of the most important issues in scheduling and supply chain management. The authors aimed to minimise the weighted earliness, tardiness and due date assignment penalties and to minimise the weighted number of late jobs and due date assignment costs for the single machine problem. Zhao (2016) examines a single-machine scheduling problem where jobs have specific release times. The research aims to determine an optimal common due date and scheduling sequence to minimize a cost function that includes the weighted number of tardy jobs and due date assignment costs. The problem is proven to be NP-hard, and the authors propose a dynamic programming algorithm and a fully polynomial-time approximation scheme as solutions. Teymourifar and Ozturk (2018) designed new due date assignment models and dispatching rules for dynamic job shop scheduling problems, developed dispatching rules based on modified and composite characteristics of jobs, and obtained competitive results compared to existing models. Vinod et al. (2019) investigated the interaction between dynamic due date assignment methods and scheduling decision rules in a dynamic job shop with queue-dependent preparations. They developed analytical models based on regression using simulation results and found that the proposed scheduling rules improve the performance with respect to average lateness. Kianpour et al. (2021) introduced an automated model that develops job shop scheduling by integrating Industry 4.0 and project management principles. The model adapts to real-time information about processing times and due dates, aiming to minimise early and late costs by considering rescheduling expenses. Wang et al. (2022) investigates a single-machine scheduling problem that considers due date assignment alongside past-sequence-dependent setup times. Under common, slack, and different due date assignment methods, the objective is to find the optimal sequence and due dates that minimize the weighted sum of lateness, the number of early and delayed jobs, and due date costs, where weights depend on job positions in the sequence. The authors provide optimal properties and propose a polynomial-time algorithm to obtain the optimal solution. Mosheiov and Sarig (2024) addresses a single-machine scheduling and due-date assignment problem incorporating acceptable lead-times. The study combines elements of common and different due-date models, aiming to determine job-dependent due dates. The objective function, of a minmax type, consists of four cost components: job earliness, job tardiness, due-date cost, and due-date tardiness cost. The authors present a simple procedure for identifying different job types and introduce a polynomial-time solution.

2.2. Heuristic methods

In heuristic approaches, the solution is found by narrowing the area to be searched based on the findings obtained from experimental studies. It is called heuristic screening and is based on advanced searching algorithms (Tasgetiren, 1996). Philipoom (2000), who stated that due date determination is a difficult situation for manufacturing managers, examined the trends in the choice of priority rule in a job shop where due dates are determined depending on lead time and tardiness penalties. As a result of his study, he stated that the first rule with the shortest processing time works well for lean tardiness penalties. As the penalty for tardiness increased, he found that priority rules such as first-in-first-out worked well. He stated that the earliest due first rule does not work well due to the interaction between the earliest due date first rule and the parameters of the due date determination rule. Yang and Wang (2001) presented a new adaptive artificial neural network and heuristic hybrid approach for job shop scheduling. The neural network has the ability to adapt the connection weights and bias values of the processing elements during the feasible solution. They presented two heuristics that can be combined with the neural network. One of them was used to speed up the solution of the neural network and to guarantee the approximation of the network. The other one is used to obtain delay-free schedules from the feasible solutions provided by the neural network. Computer simulations showed that the proposed hybrid approach is fast and efficient. Cheng et al. (2002) studied the single machine problem in their study. In their problem, a common due date is assigned to all jobs. The objective is to determine the due date and schedule that will minimise the earliness, tardiness and the total penalty associated with the dur date. The authors claim that they have developed an algorithm that obtains the optimal due date and schedule if the job order is predetermined or if all jobs have the same processing time. Xiao and Li (2002) considered the problem of assigning a general due date to jobs and scheduling jobs on parallel machines by minimising the weighted sums of due date, total earliness, total tardiness and an absolute performance ratio for this heuristic. They presented a better worst-case bounded heuristic for the case with zero earliness penalty. They also developed an approximation scheme that is completely polynomial. They claimed that their heuristic contributes to job shop scheduling and general due date assignment algorithm development. Birman and Mosheiov (2004) studied the due date and scheduling problem in a two-machine flow-type production. They stated that due date scheduling problems have attracted a lot of attention in recent years. The objective of their study was to minimise the maximum earliness, tardiness and due date determination costs. As a result, they claimed that they found a more effective solution with Johnson's algorithm. Min and Cheng (2006) proposed a type of genetic algorithm based on regional coding that determines the optimal scheduling policy to determine the optimal overall due date, the processing sequence and the number of jobs on each machine, and minimises the costs of due date assignment, earliness, and tardiness. For the genetic algorithm, they also added a simulated annealing mechanism and an iterative heuristic fine-tuning operator to construct 3 types of hybrid genetic algorithms with good performance. Focusing on similar parallel machine scheduling and general parallel machine scheduling problem, the numerical computational results show that these algorithms outperform heuristic algorithms and are suitable for large-scale parallel machine earliness, tardiness scheduling problem. In their study, Mosheiv and Oron (2006) wanted to determine the sequence of work, the overall due date and the placement of rapid maintenance activity. Jobs scheduled after or before the due date are penalised according to their early or tardy finish time. The processing time of a job scheduled after the maintenance activity is reduced by a job-dependent factor. The objective is the minimum total earliness, tardiness, and deadline costs. They proposed a polynomial solution for this problem. In this first work, where maintenance scheduling and due date assignment are performed simultaneously, they state that the problem is solvable in polynomial time. In his study, Chen (2007) focused on output time estimation, which is a critical task in a biscuit factory. He proposed an intelligent hybrid system to improve the accuracy of output time estimation. Firstly, he applied the concept of input classification to the Chen fuzzy backpropagation network approach by pre-classifying batches of biscuits with a k-means classifier before estimating their output time with a fuzzy backpropagation network. Examples belonging to different categories were taught by networks with different but identical topology. Secondly, the factory future shipment plan was also included in the intelligent hybrid request. In order to evaluate the effectiveness of the proposed methodology, production simulation was performed to create test cases. According to the experimental results, the prediction accuracy of the intelligent hybrid system is significantly better than other approaches. Baykasoğlu and Gökçen (2009) propose a due date assignment approach for a multi-stage job shop using Gene expression Programming (GEP), a genetic programming technique. Simulation experiments showed that the GEP-based method outperformed several conventional due date assignment models under various test conditions. Yang et al. (2012) considered a job shop scheduling problem involving due dates, aiming to minimise the sum of weighted earliness and tardiness. They proposed an improved genetic algorithm that uses an operation-based scheme to represent schedules as chromosomes. The effectiveness of the algorithm is demonstrated through tests on various job shop scheduling problems of different sizes. Inal et al. (2023) to solve the dynamic scheduling problem, propose a multi-agent system with reinforcement learning aimed at the minimization of tardiness and flow time to improve the dynamic scheduling techniques. The performance of the proposed multi-agent system is compared with the first-in-first-out, shortest processing time, and earliest due date dispatching rules in terms of the minimization of tardy jobs, mean tardiness, maximum tardiness, mean earliness, maximum earliness, mean flow time, maximum flow time, work in process, and makespan. Under a heavy workload, the proposed multi-agent system gives the best results for five performance criteria, which are the proportion of tardy jobs, mean tardiness, maximum tardiness, mean flow time, and maximum flow time.

In addition to the traditional due date setting rules, the use of artificial neural network for prediction is quite common in the literature. The ability of artificial neural network to learn from examples or to reach a conclusion by considering different values related to the workshop can also be used for due date setting. Considering the ability of artificial intelligence to learn from examples and applications in dynamic workshop scheduling, it was deemed appropriate to carry out such a research for due date determination.

3. Due Date Determination

3.1. Regression models

In this study, 5 regression models were used to determine the due date (Philipoom et al., 1994):

1. Total work (TWK):

$$F_i = \mathrm{k}\mathrm{P}_i \tag{1}$$

The predicted flow time (F_i) of job i is a function of the total processing time P_i. k is a coefficient and is calculated by regression.

2. Number of operations (NOP):

$$F_i = \mathrm{k}\mathrm{N}_i \tag{2}$$

Here, the predicted flow time of the job is a function of the number of operations (N_i) of job i. Again k is a coefficient and is calculated by regression.

3. Total work and Number of operations (TWK+NOP):

$$F_i = k_1 P_i + k_2 N_i \tag{3}$$

In this model, both the number of operations and the total processing time are used. k_1 and k_2 coefficients are calculated by regression.

4. Number of jobs in queue (JIQ):

$$F_i = k_1 P_i + k_2 (JIQ_i) \tag{4}$$

When job i arrives at the job shop, the number of waiting jobs in the queues is summed (JIQi). This job shop data is combined with the job characteristic P_i. The coefficients k_1 and k_2 are calculated by regression.

5. Work in queue (WIQ):

$$F_i = k_1 P_i + k_2 (WIQ_i) \tag{5}$$

This model differs from model 4 in that it does not use the number of jobs in the queues but uses the total processing time in the job shop. Again, the coefficients k_1 and k_2 are calculated by regression.

3.2. Due date determination with regression models

In these models, the flow time is estimated (Figure 1). When the ready time (r_i), which is the time when the jobs arrive at the workshop, is added to the estimated flow times, the due date (d_i) can be estimated.

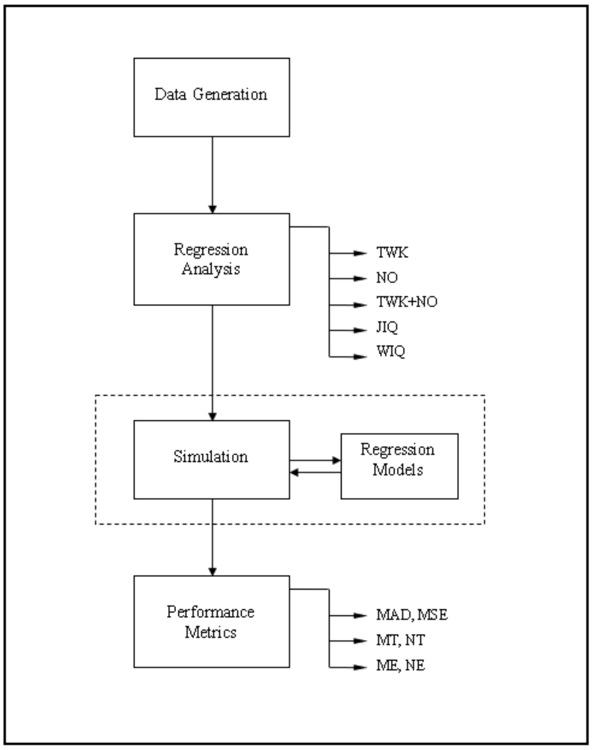

Figure 1. Due date determination with regression models

3.2.1. Data generation for regression analysis

The data required for determining the coefficients of the total processing time of job i, the number of operations of job i, the sum of the number of jobs in the queues when job i arrives at the job shop and the sum of the total processing times of the waiting jobs in the workshop (workload) used in the estimation of the flow time in the 5 regression models mentioned above were obtained by simulation. For SPT (Shortest Processing Time) and EDD (Earliest Due Date) priority rules, 10 simulations were performed, each starting with a different random number. In each simulation run, after a warm-up period of 5000 jobs, the data to be used in the regression models for 10000 jobs were recorded. This resulted in 10 data files with 10000 data in each file. Then, a single data set with 10000 jobs data was obtained by taking the data of one of the 10 jobs from each data file.

3.2.2. Creation of regression models

The k coefficients required for 5 regression models were obtained by linear regression using this data of 10000 jobs (Table 1, Table 2). Regression analysis were carried out for each model, and sample outputs for the SPT first priority rule and the TWK model are given in the appendix.

3.2.3. Due date determination with regression models

After the regression model coefficients were obtained, 10 simulations were performed using SPT and EDD priority rules. In these 10 simulations, different initial random numbers were used from each other and also from the simulations performed to obtain the data set required for the determination of the regression model coefficients. These initial random numbers will be used as the same for the proposed neural network model in the future.

Table 1. Coefficients of regression models (SPT)

Model	**k_1**	**Std. Dev.**	**Sig.**	**k_2**	**Std. Dev.**	**Sig.**
TWK	6,963	0,080	0,000	-	-	-
NOP	50,062	0,867	0,000	-	-	-
TWK+NOP	21,511	0,226	0,000	-143,238	2,124	0,000
JIQ	14,294	0,193	0,000	-17,614	0,428	0,000
WIQ	12,213	0,175	0,000	-0,048	0,001	0,000

Table 2. Coefficients of regression models (EDD)

Model	**k_1**	**Std. Dev.**	**Sig.**	**k_2**	**Std. Dev.**	**Sig.**
TWK	7,336	0,019	0,000	-	-	-
NOP	68,550	0,196	0,000	-	-	-
TWK+NOP	4,184	0,058	0,000	30,960	0,542	0,000
JIQ	3,170	0,025	0,000	6,190	0,038	0,000
WIQ	4,254	0,034	0,000	0,027	0,000	0,000

In these 10 simulations, the due dates are determined when the jobs arrive at the job shop and the due date is determined by adding the flow time estimated using the regression model to the arrival time of the jobs. In each simulation, data were recorded for 10000 jobs after the warm-up period of 5000 jobs.

The mean absolute deviation (MAD) was calculated by taking the absolute differences of the estimated due dates of 10000 jobs from the actual completion times (Ci) and the mean square errors (MSE) were calculated. In addition, the number of tardy jobs (NT), mean tardiness (MT), number of early jobs (NE) and mean earliness (ME) values were calculated. These calculations were made separately for 10 data files. By taking the arithmetic averages of these 10 calculated values, MAD, MSE, NT, MT, NE, and ME values are calculated for the priority rule and regression model to be compared with the proposed model values.

3.2. Artificial neural network model

In this study, an artificial neural network model is proposed for due date determination in job shop type production (Figure 2). The artificial neural network used is a back-propagation neural network. In the previously mentioned regression models, one or more information about the job, job shop or both is used in the equation of that regression model. In the proposed model, in addition to the information used in the regression models, other job and job shop information is used to predict the work flow time of the artificial neural network.

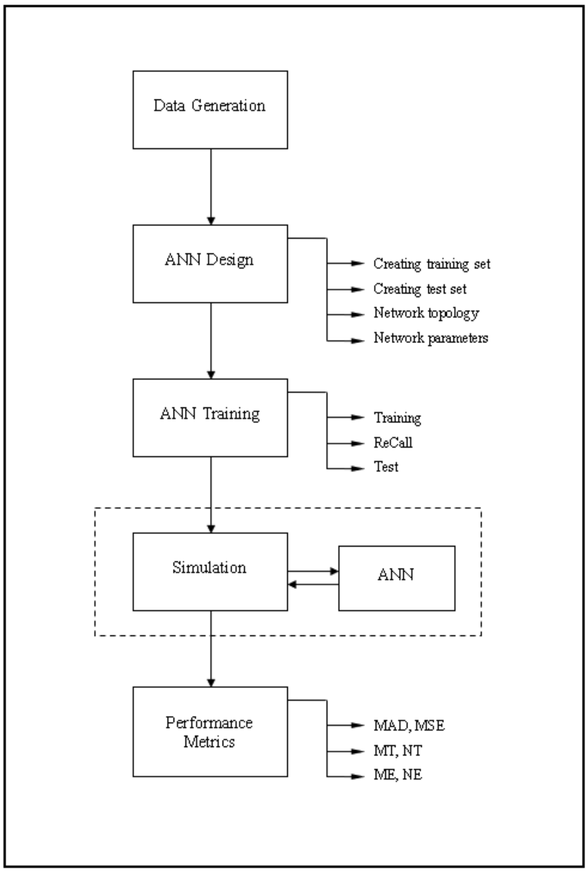

Figure 2. Articial neural network model

The information to be used in the prediction of the flow time and therefore the due date using the artificial neural network is shown in Table 3. This information is the input information of the artificial neural network and its number is 15. Therefore, the number of inputs of the artificial neural network is 15, there are 15 processing elements in the input layer. In the output layer, there is only one processing element, the flow time information.

Table 3. Inputs of artificial neural network

Input	Information
1	Maximum operation time of the work
2	Sum of the operation times of the work
3	Total number of jobs in the workshop
4	Total number of operation of jobs waiting in queues
5	Sum of average lateness times of works
6	Sum of operation times of jobs waiting in queues
7..15	1st, 2nd, ..., 9th operation times of the work

3.2.1. Creation of training set

The samples (input/output) to be used as a training set for the artificial neural network are the same as the dataset produced to determine the coefficients of the regression models. After the warm-up period of 5000 jobs in the regression model, a single dataset of 10000 jobs created by taking one of every 10 jobs from 10 data files obtained as a result of 10 simulations of 10000 jobs was also used for artificial neural network training. There are 2 datasets using SPT and EDD priority rules. Different neural networks were trained for both priority rules. This information in the dataset is not suitable for neural network training. Since sigmoid function will be used as activation function in the neural network, the results will be in the range of 0-1. In other words, it is not possible for the network to produce a value greater than 1 or less than 0 for the flow time (Öztemel, 2003). For this reason, the input and output values of the network were normalised and a scaled dataset was obtained. The output values of the network after training were also reverse normalised to obtain normal flow time values.

The normalisation process was performed according to the following equation:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

The inverse normalisation process is obtained from the normalisation equation as follows:

$$x = x'(x_{max} - x_{min}) + x_{min} \quad (7)$$

In order for the dataset to be ready for the training of the artificial neural network, the dataset should be divided into two parts. Because two sets, training and test, are required for training an artificial neural network. The network already sees all the examples in the training set during training. Until the desired error level is achieved or the desired number of iterations or epochs (the network sees all the examples once) is completed, it calculates output values from the inputs and changes the weight values by looking at the difference between the desired and actual output. Therefore, it cannot be said that the network learnt with a single set. Therefore, the normalised dataset is divided into two sets: training and test. The splitting was done randomly so that 80% of the first dataset was in the training set and 20% in the test set (Philipoom et al., 1994).

3.2.2. Creation of neural network model

Since 15 values will be used as input in the flow time estimation with the artificial neural network, 15 input and one output processing element estimating the flow time are used. For the data obtained using the SPT and EDD priority rule, the artificial neural network was designed as a single hidden layer with 7 and 9 processing elements, respectively. The training process with the data of both priority rules was performed with the same parameters (Table 4).

Table 4. Parameters of articial neural network (SPT, EDD)

Parameter	Value
Learning coefficient	0.2
Momentum coefficient	0.8
Initial weights values	Random between -0.1 and 0.1
Example presentation	Sequential
Number of epochs	2000

3.2.3. Training of artificial neural network

The neural network training was performed in 2000 epochs for both SPT and EDD. Since a training set of 8000 jobs was used during the training, each training was performed as 16000000 iterations. During the training process, absolute deviation and squared error values were calculated and recorded for the output processing element at the end of each epoch. Figure 3 and Figure 4 shows the graphs of the mean deviation squared values of the neural networks.

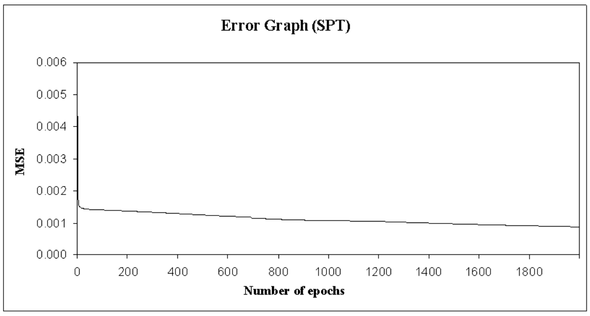

Figure 3. Articial neural network error graph (SPT)

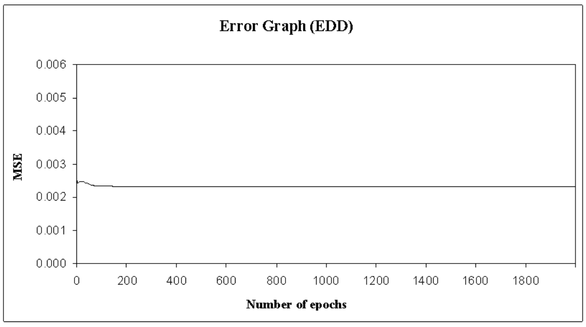

Figure 4. Articial neural network error graph (EDD)

In artificial neural network training, in order to determine whether the network has learnt or not, the training set and the test set that the network has never seen are given as input to the network and the outputs are compared with the actual output values. If the difference is below the acceptable margin of error, the network is said to respond correctly to that input sample, and if it is below, it is said to respond incorrectly. Table 5 shows the training success percentages of both networks.

In artificial neural network training, to determine whether the network has learned, the training set and the test set, which the network has never seen before, are given as input to the network and the outputs are compared with the actual output values. If the difference is below the acceptable error margin, it is said that the network responded correctly to that input sample, if not, it is said to have responded incorrectly. Table 5 shows the training success percentages of both networks.

Table 5. Training performance of artificial neural network

	SPT		EDD	
Epoch	Training set (%)	Test set (%)	Training set (%)	Test set (%)
500	96	96	94	94
1000	97	97	95	95
1500	97	97	95	95
2000	97	97	95	95

3.2.4. Due date determination with artificial neural network

After the training of the artificial neural networks was completed, 10 simulations were performed using SPT and EDD priority rules. In these 10 simulations, different initial random numbers were used from each other and from the simulations performed to obtain the dataset required for the training of the artificial neural networks and also for the determination of the regression model coefficients. These initial random numbers were the same as those used in the simulations in which the due date was decided by using regression models.

In these 10 simulations, the due dates are determined by adding the flow time estimated using the trained artificial neural network to the arrival time of the jobs when the jobs arrive at the workshop. In each simulation, data were recorded for 10,000 jobs after a warm-up period of 5,000 jobs.

The mean absolute deviation was calculated by the absolute deviations of the estimated due dates of the 10000 jobs from the actual completion times (C_i) and the mean absolute deviation squares were calculated. In addition, the number of jobs tardy, mean tardiness, number of jobs early mean earliness values were calculated. These calculations were made separately for 10 data files. By taking the arithmetic averages of these 10 calculated values, MAD, MSE, NT, MT, MT, NE, and ME values are calculated for the priority rules and artificial neural network model to be compared with the values of the previously mentioned regression models.

3.6. Performance metrics of models

In order to compare these simulation results of the proposed artificial neural network model and 5 regression models, arithmetic averages of the performance metric values obtained from 10 simulations were taken and evaluations were made based on these average values. The mean values of the performance metrics obtained for the SPT and EDD priority rules for the regression models and the neural network model are given in Tables 6 and 7.

Based on the statistical analyses (statistical test outputs of the models for the MAD performance metric with the SPT priority rule are given in the appendix as an example), in Table 6, it is seen that the ANN model gives the best result with a value of 211 when the MAD performance metric is considered. This model is followed by the models of TWK+NOP, JIQ, TWK and NOP respectively.

It can be said that the best result in terms of the MSE performance metric is given by the TWK+NOP and ANN model. There is no statistically significant difference between these two models. These models are followed by the NOP, TWK+NOP, JIQ and WIQ models in terms of performance, respectively.

Table 6. Average performance values of models for SPT

Model	MAD	MSE	MT	NT	ME	NE
TWK	377	438156	131	1297	246	8704
NOP	387	567960	192	2190	195	7810
TWK+NOP	308	**305371**	152	4014	156	5986
JIQ	349	394630	142	3049	208	6951
WIQ	669	622800	**75**	**593**	593	9407
ANN	**211**	312044	92	4076	**119**	**5924**

Table 7. Average performance values of models for EDD

Model	MAD	MSE	MT	NT	ME	NE
TWK	396	**439933**	**125**	**1210**	271	8790
NOP	492	596478	162	1564	331	8436
TWK+NOP	446	503898	138	1324	307	8676
JIQ	380	497366	160	1723	220	8277
WIQ	**275**	481953	183	2436	**92**	**7564**
ANN	324	473826	166	1960	158	8040

When evaluated in terms of MT performance metric, the best result is given by the WIQ model. Then, the ANN model gives the second best result. The others, in order of success in terms of this performance metric, are the TWK, JIQ, TWK+NOP and NOP models.

Considering the ME performance metric, based on statistical analyses, it can be said that each model produces different results from each other. The most successful model among these is the ANN model. This model is followed by the models of TWK+NOP, NOP, JIQ and WIQ respectively.

Table 7 shows the performance values of the models using the EDD priority rule. Considering the MAD performance metric, it can be said that each model produces different values from each other with statistical analyses. The best result was produced by the WIQ model. This model is followed by the ANN, JIQ, TWK, TWK+NOP and NOP models, respectively.

It can be said that there are three groups of models that are different from each other considering the MSE performance metric. Of these, the first group of models, namely, the TWK, ANN ve WIQ models, yielded the best results.

When the MT performance metric is analysed, the best result is given by the TWK model. Then, the TWK+NOP model, followed by the third group consisting of JIQ, NOP and ANN, and finally followed by the WIQ model.

Similarly, in terms of the ME performance metric, the statistical analyses show that each model produces different values from each other and the best result is given by the WIQ model. This model is followed by ANN model.

4. Conclusions

In this study, an artificial neural network approach, which is thought to produce better results as an alternative to due date determination methods in dynamic job shop scheduling, is presented and its feasibility is demonstrated. The feasibility of the artificial neural network model in due date determination is demonstrated. In terms of both the shortest processing time first and earliest due date first priority rules, the neural network gave good results in terms of several performance metrics.

It was observed that the artificial neural network generally gave better results in the shortest processing time performance metric. It has been shown that the shortest processing time priority rule gives the best results in terms of mean absolute deviation, mean square error and mean earliness performance metrics. Again, it was seen that the artificial neural network was among the models that gave the best results in terms of the mean square error performance metric together with the earliest due date first priority rule.

In this study, the artificial neural network model used to determine the due date is back-propagation artificial neural network model. Single layer is used as hidden layer. It may be possible to obtain better results by using two or more hidden layers. In addition, a fully connected artificial neural network was used in this study. That is, each process element in each layer is connected with each process element of the next layer. Instead, a semi-connected network model can be used, that is, a network model in which a processing element is connected to only one or a few process elements in the next layer. In this way, better results can be obtained. In the due date prediction of the artificial neural network, various data of the job and job shop were used as input. It may be possible to get better results by using more information about the work and job shop as input or by not using some of the inputs used. The artificial neural network used in this study is a back-propagation artificial neural network. Using other artificial neural network models or deep learning models instead of this network may provide better prediction results.

References

Baker, K. R., “Introduction to Sequencing and Scheduling”, John Wiley & Sons, New York, 1974.

Baykasoglu, A., Gokcen, M., "Gene expression programming based due date assignment in a simulated job shop", Expert Systems with Applications, Cilt 26, Sayı 10, Sayfa 12143-12150, Aralık 2009.

Birman, M., Mosheiov, G., “A note on a Due Date Assignment on a Two Machine Flow Shop”, Computers and Operations Research, No. 31, s. 473-480, 2004.

Biskup, D., Jahnke, H., “Common Due Date Assignment for Scheduling on a Single Machine with Jointly Reducible Processing Times”, International Journal of Economics”, No. 69, s. 317-322, 2001.

Chen, T., “An Intelligent Hybrid System for Wafer Lot Output Time Prediction”, Advanced Engineering Informatics, No. 21, s. 55-65, 2007.

Cheng, T. C. E., Gupta, M. C.,” Survey of Scheduling Research Involving Ddue Date Determination Decisions”, European Journal of Operational Research, No. 38, s. 156-166, 1989.

Cheng, T. C. E., Chen, Z. L., Shakhlevich, N. V., “Common Due Date Assignment and Scheduling with Ready Times”, Computers and Operations Research, No. 29, s. 1957-1967, 2002.

French, S, “Sequencing and Scheduling: An Introduction to the Mathematics of the Job Shop”, John Wiley & Sons, New York, 1982.

Kohonen, T., “State of the Art in Neural Computing”, IEEE First International Conference on Neural Networks, No. 1, s. 79-90, 1987.

Gupta, J. N. D., Kruger, K., Lauff, V., Werner, F., Sotskov, Y. N., “Heuristics for Flow Shops with Controllable Processing Times and Assignable Due Dates”, Computers and Operations Research, No. 29, s. 1417-1439, 2002.

Inal, A., F., Sel, C., Aktepe, A., Turker, A., K., Ersoz, S., “A Multi-Agent Reinforcement Learning Approach to the Dynamic Job Shop Scheduling Problem”, Sustainability, Vol. 15 (10), 8262, 2023.

Kianpour, P., Gupta, D., Krishnan, K., K., Gopalakrishnan, B., “Automated job shop scheduling with dynamic processing times and due dates using project management and industry 4.0”, Journal of Industrial and Production Engineering, Cilt 38, Sayı 7, 2021.

Min, L., Cheng, W., “Genetic Algorithms fort he Optimal Common Due Date Assignment and the Optimal Scheduling Policy in Paralel Machine Earliness/Tardiness Scheduling Problems”, Robotics and Computer Integrated Manufacturing, No. 22, s. 279-287, 2006.

Mosheiov, G., “A Common Due Date Assignment Problem on Paralel Identical Machines”, Computers and Operations Research, N0. 28, s. 719-732, 2001.

Mosheiov, G., Oron, D., “Due Date Assignment and Maintenance Activitty Scheduling Problem”, Mathematical and Computer Modelling, No. 44, s. 1053-1057, 2006.

Mosheiov, G., Sarig, A., “The minmax due-date assignment problem with acceptable lead-times”, Annals of Operations Research, Vol. 343, pp. 401–410, 2024.

Negnevitsky, M., “Artificial Intelligence: A Guide to Intelligent Systems”, Addison-Wesley, 2002.

Neuralware Inc., “NeuralWorks Professional II/Plus: Neural Computing, Pittsburg, 1990.

Orhunbilge, N., “Uygulamalı Regresyon ve Korelasyon Analizi”, Avcıol Basım Yayın, İstanbul, 2000.

Oztemel, E., “Yapay Sinir Ağları”, Papatya Yayıncılık, İstanbul, 2003.

Philipoom, P. R., Rees, L. P., Wıegmann, L., “Using Neural Networks to Determine Internally Set Due Date Assignments for Shop Scheduling”, Decision Sciences, No. 25-5/6, s. 825-851, 1994.

Philipoom, P. R., “The Choice of Dispatching Rules in a Shop Using Internally Set Due Dates with Quoted Leadtime and Tardiness Costs”, International Journal of Production Research, No. 7, s. 1641-1655, 2000.

Sabuncuoglu, I, Comlekci, A., “Operation Based Flow Time Estimation in a Dynamic Job Shop”, Omega, No. 30, s. 423-442, 2002.

Sha, D. Y., Hsu, S. Y., “Due Date Assignment in Wafer Fabrication Using Artificial Neural Networks”, International Journal of Advanced Manufacturing Technology, No. 23, s. 768-775, 2004.

Sha, D. Y., Liu, C. H., “Using Data Mining for Due Date Assignment in a Dynamic Job Shop Environment”, International Journal of Advanced Manufacturing Technology, No. 25, s. 1164-1174, 2005.

Shabtay, D., Steiner, G., “Two Due Date Assignment Problems in Scheduling a Single Machine”, Operations Research Letters, No. 43, s. 683-691, 2006.

Song, D. P., Hicks, C., Earl, C. F., “Product Due Date Assignment for Complex Assemblies”, International Journal of Economics, No. 76, s. 243-256, 2002.

Tarı, R., “Ekonometri”, Alfa Basım Yayım, İstanbul, 1999.

Tasgetiren, M. F., “Atölye Tipi Çizelgeleme Problemi için Bir Uzman-Yapay Sinir Ağı Modeli”, Doktora Tezi, İstanbul Üniversitesi, 1996.

Teymourıfar, A, Ozturk, G., “New dispatching rules and due date assignment models for dynamic job shop scheduling problems”, International Journal of Manufacturing Research, Cilt 13, Sayı 4, 2018.

Veral, E. A., “Computer Simulation of Due Date Setting in Multimachine Job Shops”, Computers and Industrial Engineering, No. 41, s. 77-94, 2001.

Vinod, K., T., Prabagaran, S., Joseph, O., A., “Dynamic due date assignment method: A simulation study in a job shop with sequence-dependent setups”, Journal of Manufacturing Technology Management, Cilt 30, Sayı 6, 2019.

Wang, C. S., Uzsoy, R., “A Genetic Algoritm to Minimize Maximum Lateness on a Batch Processing Machine”, Computers and Operations Research, No. 29, s. 1621-1640, 2002.

Wang, X., Liu, W., Lu, L., Zhao, P., Zhang, R., “Due date assignment scheduling with positional-dependent weights and proportional setup times”, Mathematical Biosciences and Engineering, Vol. 19, Issue 5, pp. 5104-5119, 2022.

Xiao, W. Q., Lı, C. L., “Approximation Algorithms for Common Due Date Assignment and Job Schedulin on Parallel Machines”, IIE Transactions, No. 34, s. 467-477, 2002.

Yang, S. Wang, D., “A New Adaptive Neural Network and Heuristics Approach for Job Shop Scheduling”, Computers and Operations Research, No. 28, s. 955-971, 2001.

Yang, H., Sun, Q., Saygin, C., Sun, S., "Job shop scheduling based on earliness and tardiness penalties with due dates and deadlines: an enhanced genetic algorithm", The International Journal of Advanced Manufacturing Technology, Vol. 61, pp. 657–666, 2012.

Zhao, C., “Common duedate assignment and single-machine scheduling with release times to minimize the weighted number of tardy jobs", Japan J. Indust. Appl. Math., Vol. 33, pp. 239–249, 2016.

Ek (Appendix)

Regression analysis of the TWK regression model with the SPT priority rule:

Regression

Variables Entered/Removed			
Model	Variables Entered	Variables Removed	Method
1	P	.	Enter

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,654	,428	,428	681,26581

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3474552446,846	1	3474552446,846	7486,273	,000
	Residual	4640766870,155	9999	464123,099		
	Total	8115319317,001	10000			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	P	6,963	,080	,654	86,523	,000

Statistical test outputs of the models for the MAD performance measure with the SPT first priority rule:

Oneway

Test of Homogeneity of Variances
OMS

Levene Statistic	df1	df2	Sig.
346,785	5	59994	,000

ANOVA (OMS)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1182740505,285	5	236548101,057	8792,803	,000
Within Groups	1613986659,963	59994	26902,468		
Total	2796727165,248	59999			

Post Hoc Tests

Multiple Comparisons
Dependent Variable: OMS
Tukey HSD

(I) Model	(J) Model	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	-9,75590(*)	2,31959	,000	-16,3663	-3,1455
	3	69,38010(*)	2,31959	,000	62,7697	75,9905
	4	27,87910(*)	2,31959	,000	21,2687	34,4895
	5	-291,60910(*)	2,31959	,000	-298,2195	-284,9987
	6	166,68980(*)	2,31959	,000	160,0794	173,3002
2	1	9,75590(*)	2,31959	,000	3,1455	16,3663
	3	79,13600(*)	2,31959	,000	72,5256	85,7464
	4	37,63500(*)	2,31959	,000	31,0246	44,2454
	5	-281,85320(*)	2,31959	,000	-288,4636	-275,2428
	6	176,44570(*)	2,31959	,000	169,8353	183,0561
3	1	-69,38010(*)	2,31959	,000	-75,9905	-62,7697
	2	-79,13600(*)	2,31959	,000	-85,7464	-72,5256
	4	-41,50100(*)	2,31959	,000	-48,1114	-34,8906
	5	-360,98920(*)	2,31959	,000	-367,5996	-354,3788
	6	97,30970(*)	2,31959	,000	90,6993	103,9201
4	1	-27,87910(*)	2,31959	,000	-34,4895	-21,2687
	2	-37,63500(*)	2,31959	,000	-44,2454	-31,0246
	3	41,50100(*)	2,31959	,000	34,8906	48,1114
	5	-319,48820(*)	2,31959	,000	-326,0986	-312,8778
	6	138,81070(*)	2,31959	,000	132,2003	145,4211
5	1	291,60910(*)	2,31959	,000	284,9987	298,2195
	2	281,85320(*)	2,31959	,000	275,2428	288,4636
	3	360,98920(*)	2,31959	,000	354,3788	367,5996
	4	319,48820(*)	2,31959	,000	312,8778	326,0986
	6	458,29890(*)	2,31959	,000	451,6885	464,9093
6	1	-166,68980(*)	2,31959	,000	-173,3002	-160,0794
	2	-176,44570(*)	2,31959	,000	-183,0561	-169,8353
	3	-97,30970(*)	2,31959	,000	-103,9201	-90,6993
	4	-138,81070(*)	2,31959	,000	-145,4211	-132,2003
	5	-458,29890(*)	2,31959	,000	-464,9093	-451,6885

* The mean difference is significant at the .05 level.