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Forecasting operation times by using Artificial Intelligence

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ABSTRACT

Due to increased competition, companies must reduce delivery and costs on time and provide the desired product characteristics. This study was carried out in a firm that manufactures napkin machines according to the order. The most important problem is that the suppliers cannot deliver to customers on time. For effective production planning, it is necessary to use the correct operation times for each machine used. The times were estimated by using the Artificial Neural Network (ANN) approach and the Taguchi Design of Experiment was used to estimate the optimal combination of ANN parameters. According to the results of the research, it is found that the number of layers and neurons have significant influence. By using the ANN method, the time spent in parameter design is effectively reduced and the efficiency of the algorithm is increased. Estimation performance is compared with the statistical analysis. This model proved to be statistically reliable in estimating operation times. Thus, the operators will be able to estimate the processing times for new designs.

1. Introduction

On Time delivery and selling the product with the desired characteristics is important for the customer satisfaction. And an efficient scheduling should be done by using the right data. Effective production planning is a must in order to avoid problems in the production process. For a proper production planning, it is necessary to use correct data. There are various methods for collecting data. With time study method, time of a job is recorded under certain conditions at a certain working speed. The obtained data is used to calculate the standard work time. These standard times are used in many different areas such as optimization, performance evaluation. ANN is one of the techniques widely used in the field of optimization. Various techniques are used to select appropriate levels of these parameters. Some studies are based on experimental design method or previous studies in the literature. Due to the systematic and scientific, Taguchi method which is the one of the design experiment is used. This application was implemented in a machine manufacturer. The company's biggest problem is that customers cannot make their demands on time. Company records indicate that the average delivery time of the product is 113 days. The main reason of the late delivery is that each of the machines manufactured according to the order has different characteristics and the standard times are unknown. Especially for machines with different characteristics, it is very difficult to estimate the processing times according to experience and mind. Thus, the ANN method is an appropriate tool for predicting irregular and complex systems. In this study, it was researched whether the YSA method has an appropriate modeling approach to estimate the duration of operation. Inputs of the YSA method are factors affecting the duration of operation and also the data determined by experts in the field. In order to obtain training and test data sets, both time study studies and company records were used. An ANN structure for each machine is designed and trained using more than 100 sample groups, tested using thirty-eight datasets. The Taguchi Experiment Design was used to optimize the

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parameters in the method. Hypothesis testing was used to test whether the method was reliable. Thus, the firm will be able to estimate the duration of planning activities of the new designs with the determined factors and the data collection phase, one of the largest time-consuming activities of a company, has been completed effectively. In this paper, firms can give realistic term time to their customers if they determine the factors affecting the delivery time during the workload. Estimating the realistic delivery date provides customer satisfaction. This situation provides a competitive advantage for the company and eliminates the cost penalty resulting from the incorrect deadlines. In section 2, general information about artificial neural networks is given, and ANN's evaluation methods are explained. In section 3, a model has been proposed for estimating the processing times. First, the problem was determined and performance was measured by ANN method. Experimental design method was used for optimization of parameters. Whether the results obtained are meaningful or not is tested using a hypothesis test. In the result section, the data obtained was analyzed and interpreted.

2. Artificial neural networks

Artificial Neural Networks used in classification, prediction and recognition models are a very important tool that imitates the functioning of the human brain. Multilayered MLP structure is the most widely used design in estimation. For MLP design for time series estimation, it is important to identify variables such as input neurons, hidden layer, and output neurons [1]. Artificial Neural Network method is inspired by the human brain [2]. Neuron forms a weighted sum of its inputs. Bias is added as a constant term. This sum is then passed through linear, sigmoid or hyperbolic tangent as a transfer function. Most widely used kind of neural network is Multilayer perceptron [3]. The units are organized in a way that determines the network architecture which has an input layer, one or more hidden layers and an output layer in feed forward networks. To determine the optimal network architecture, too many combinations were computed. These combinations contained transfer functions, hidden layers, units in each layer. Neural networks involve training and learning steps to forecast. Feed forward networks are carried out in a supervised manner in training step. The training set is formed by the historical data, included inputs and the related outputs, which is proffered to the network. The success of training depends on the convenient elected of inputs for neural network training. Neural network arranges an input–output matching, setting the weights and biases at each iteration to minimize error between the outputs and desired outputs in the learning step. Learning requires an optimization process which is replicated until a convenient criterion [4]. In addition, it does not require mathematical models, does not require a rule base, and has the ability to self-learn and organize [5]. ANN method is used in a wide variety of areas. It is possible to give examples such as weather forecasts [6,7,8,9], finance [10,11,12], exchange rates [13,14], energy needs and system [15,16,37], time series [17,18,19,20,21,22], recognition [23,24], cost estimation [25,33-36]. ANN and regression analysis method are used for high manganese steel tool life. The criteria's are different cutting conditions of feed rates, depth of cuts, cutting speeds, surface temperatures [26]. The disassembly time estimation method is used by providing one of several needed metrics for use during product design in this research [27]. Time estimates provide a powerful measure of ease of disassembly when used for comparing alternative designs of the same product. This paper [28] proposes a machining time estimation model using several factors. These are distribution of NC blocks, length, angle, federates, acceleration and deceleration constants, and minimum feed rate. The study estimates the processing times of the machines according to the selected criteria. We tried to end up with an intelligent system for the forecasting of drilling operation times and related subjects. It is not encountered a study on estimation of operation times in literature by ANN method.

2.1 Forecasting evaluation methods

The estimation ability of the samples is evaluated according to the mean absolute error (MAE) in the following:

$$MAE = \sum_{i=1}^{n} \left| P_i - A_i \right| / n \tag{1}$$

Where P_i and A_i are the i_{th} predicted and actual values, respectively, and n is the total number of predictions. In this study, the mean absolute error (MAE) is calculated.

3. Model for Estimation of Operation Times Using Artificial Neural Network

The study was achieved of four sections. In the first section, to obtain the input parameters of Artificial Neural Network, the reasons affecting the drilling times are determined by domain experts with brainstorming. Then the time study was conducted according to specified criteria. In the second section, for ANN parameters which are number of layer, number of neuron, learning coefficient and the coefficient optimization, L16 orthogonal array Taguchi Design of Experiment method is used. In the third stage, training and forecasting data set is determined and ANN is applied according to the level obtained at the end of the design of experiments. In the last section, showing whether the performance of the model is acceptable MAE value and hypothesis value is determined. In the Figure 1 flowchart of the model is given.

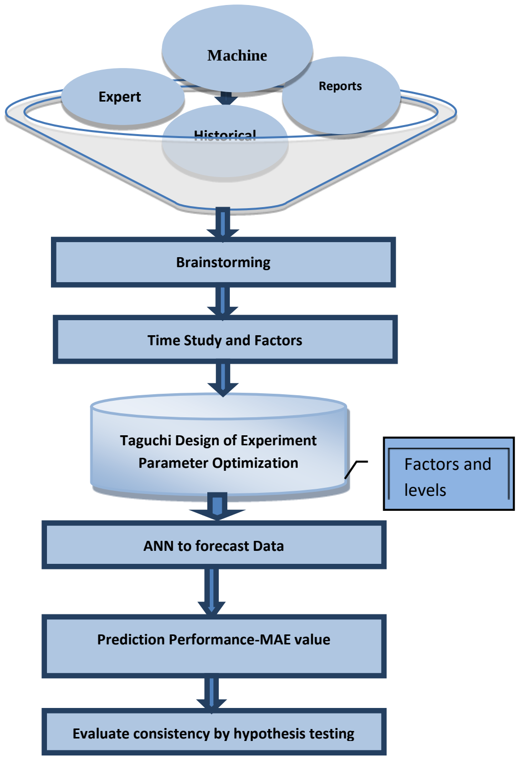

Figure 1. Flow chart of Model

3.1 Problem Definition

This research is studied in a machine production factory which has a problem about the inability of the orders on time. The inadequacy of the operation time of the required parts and the different specifications of the machines cause the delay in the production. To arrange effective timetable and to eliminate congestions, the factory needs to use the reliable operation times for each machine used in production. So in this study it is investigated whether the ANN is an appropriate modeling approach for estimating the operation times or not. For the inputs of the ANN, the factors affecting the drilling times are determined by domain experts:

Material Type: The operation times are affected by the hardness of material. In the company seven types of material is worked: St 37, St 47, S1030, S1040, S1045, S4140, and Aluminum
Dimensions of Material: The material's size big or not is effected manufacturing time
Surface Quality: Small tolerance is increased the manufacturing time. For this reason cutting velocity is fallen down. This increases the production time.
The Number of Holes to be processed: The number of hole on material is affected manufacturing time. If the number of holes is many, the manufacturing time increases.
The number of diameter changes: The holes in different sizes increase the manufacturing time.
The number of surfaces to be processed: It is necessary to know how many surfaces of the part will be processed at the machine and also the drilling lengths. If more than one surface of the part is to be processed, the part is removed from the device. This will increase the preparation time.
Complexity: The difficulty of processing the shape of the piece increases the processing time.

According to above defined factors which are material type, dimensions of material, surface quality, the number of holes to be processed, the number of diameter changes, total depth of drilled holes, the number of surfaces to be processed, complexity ; the time measurement was carried out. Number of layer, number of neuron, learning coefficient, the coefficient of momentum is used for ANN model. Selecting the proper parameters' levels will improve the performance of ANN.

3.2 Design of Experiment

Various techniques are used to select appropriate levels of these parameters. Some studies are based on experimental design method or previous studies in the literature. Due to the systematic and scientific, Taguchi method which is the one of the design experiment is used. This technique which is used properly in engineering analysis to optimize the performance characteristics within the combination of design parameters were developed by Taguchi and Konishi [29]. This technique is composed three-stages. First one is system design which includes the scientific and engineering information that is necessary for producing a part. Second one is parameter design which helps to decide and to analyze parameters about the optimum combinations. Third one is tolerance design which helps to decide and to analyze tolerances about the optimum combinations [15]. By using Taguchi method, the number of experiments which may take a long time and increase the cost, can be reduced. All parameters work with a special array to learn with a small number of experiments. Taguchi offers the use of the S/N ratio for evaluating the performance of the system. The S/N ratio approaches can be called as three types: smaller is better, nominal is best and larger is better [16, 32].

Smaller is better: In case of this case, the ideal target value is zero. S/N ratio is given below.

$$S / N \ ratio = -log(\sum Y^2 / n) \qquad (2)$$

The larger the better: This case is the opposite of the Smaller-is-Better.

$$S / N \ ratio = -10 \, log[\sum(1/Y^2)/n] \qquad (3)$$

The Nominal the best: For this case, target value is the most desirable for the product means that neither the upper nor the lower value.

$$S / N\ ratio = 10\log(\overline{Y^2} / S^2) \quad (4)$$

In this study four factors were chosen and two levels were considered. So, for this research, an L16 orthogonal array was selected. Each run would have five replications and as a result, 16×5 = 80 data values were obtained. The aim of the experiment design is to determine the optimal level of artificial neural network parameters. Four factors have been identified to design the experiment. These are, Number of Layer, Number of neuron, Learning coefficient and the coefficient of momentum. For this study two levels were chosen and shown in Table 1.

Table 1 .Taguchi L16 orthogonal array

	Layer	Neuron	Learning coefficient	Momentum coefficient
1	1	1	0.2	0.6
2	3	1	0.2	0.6
3	1	3	0.2	0.6
4	3	3	0.2	0.6
5	1	1	0.4	0.6
6	3	1	0.4	0.6
7	1	3	0.4	0.6
8	3	3	0.4	0.6
9	1	1	0.2	0.8
10	3	1	0.2	0.8
11	1	3	0.2	0.8
12	3	3	0.2	0.8
13	1	1	0.4	0.8
14	3	1	0.4	0.8
15	1	3	0.4	0.8
16	3	3	0.4	0.8

To study the main objective function, the data from design of experiments were used. Smaller is better is the target function. The S/N ratios were calculated as in the case of smaller is better i.e. Eq. (2).

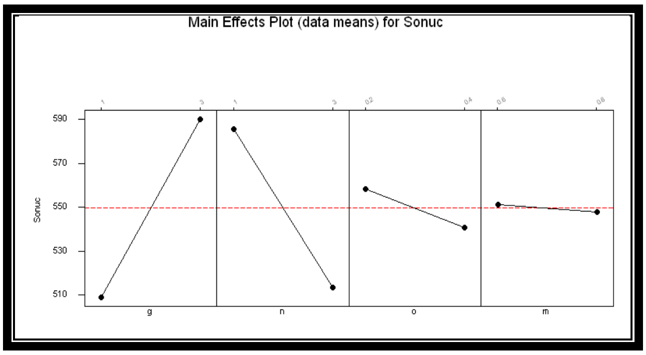

Figure 2. Main Effects of parameters for Means

Figure 2 shows the main effect graph of four selected factors for the Taguchi method and number of layer (g) and Number of neuron (n) followed Learning coefficient (o) are the major factors that affects the response. This effect can be clearly seen in Figure 2 which is resulted as having different slopes in each interval and the optimum levels were: g (number of layer: 1) n (number of layer: 3) and o (Learning coefficient: 0, 4) and m (The coefficient of momentum: 0, 8) respectively. In addition to S/N ratio analysis, main effects of the process parameters on the mean response was analyzed. For each factor the mean response referred to the average value at different levels.

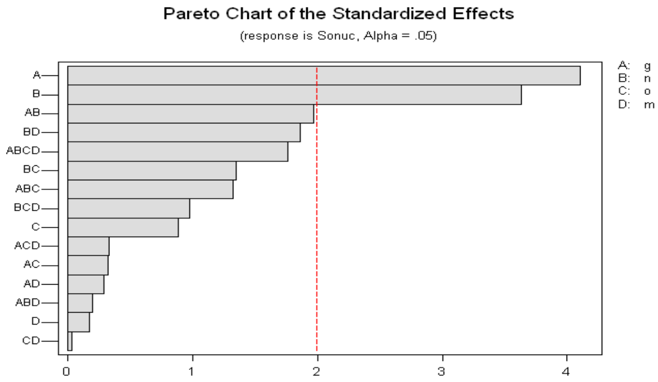

Figure 3. Pareto Chart of Effects

In each experiment, possible combinations of the levels of factors were investigated and the main effects and interactions between the factors were determined. Figure 3 shows the effect of process parameters on average S/N ratio. Thus, better results have been obtained by optimizing the ANN parameters using the Taguchi method.

2.3 ANN Method Applications

For machine, eight factors are determined as ANN inputs. According to these factors, the finished times are determined. Part of the YSA output was taken from company records and the rest was taken from the time study. MATLAB (6.5) toolbox is used for ANN. For network type feed-forward back propagation is used. 8 inputs are used. Inputs ranges are 0-1 (the finished times are normalized). TRAINGDM is used for the training function. TRAINGDM is a network function which updates weight and bias values according to gradient descent with momentum and for adaption learning function .For model learngdm and for performance function, MSE is used (It is a network performance function. It measures the network's performance according to the mean of squared errors). Furthermore absolute deviation is calculated for training and learning data. Architecture and bias weights of proposed model is shown in Figure 4.

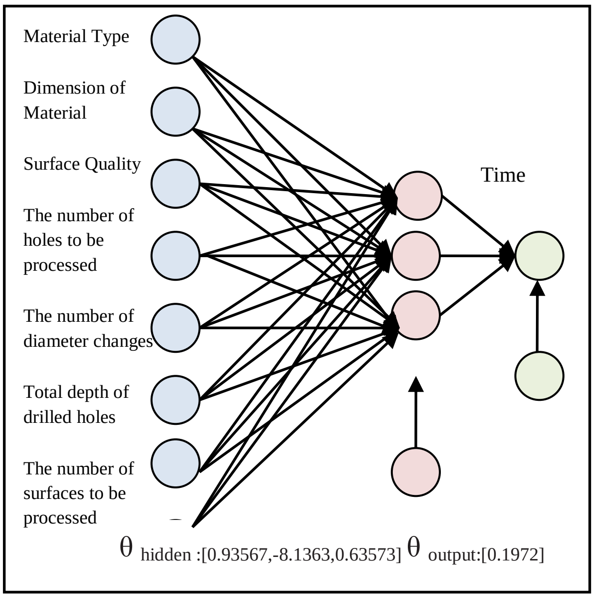

Figure 4. The Architecture and Bias Weights of Model

For hidden and output layers LOGSIGMOID (logsig (n)=1/(1+exp(-n))) (Linear Transfer Function) is used.

3.4 Performance Model

For drill machine about 70 experiments are made. To decide the best structure of the ANN model, the sensitivity of the ANN model can be tested by different neurons. It has been selected as 1, 3 and 5 in the hidden layer. This layer which contains different neuron numbers obtains the best structure of the ANN model. In the hidden layer there are three nodes and the value 0.2 for learning rate and the value 0.8 for momentum coefficients obtains the best structure of the ANN model. Data are subjected to training 1000 epoch and sum of min square error before 100 epoch constant condition and continue decreasing. For training 100 samples are used. The Result Of 1000 epoch performance, minimum square mean 0.00881626 (obtained from normalize data) After Artificial Neural Network the relationships between events are trained, ANN is forecasted manufacturing time samples which has not known before. For test data and actual data are given in Figure 5.

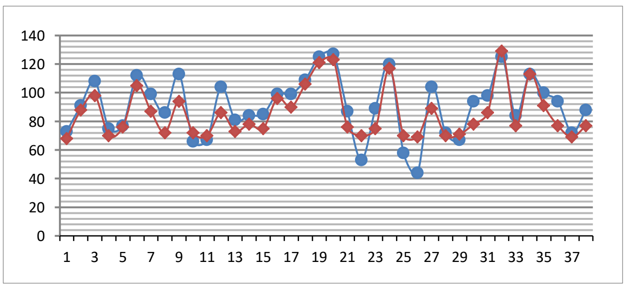

Figure 5. Comparison of Actual and ANN Simulated Data

For test data between Actual Data and Training data absolute deviation 332 minutes are calculated. This is for each manufacturing time approximate 8.74 minutes. (Obtained from ANN's mean is 86 minutes.) Obtained from ANN and actual data has to be consistent, therefore in this study two masses(ANN data and Actual data) are made a comparison and mean value between these masses must be forecasted or for this distinction hypothesis test must be done.

3.5 Hypothesis Test

To make this comparison the necessary knowledge of the each population is obtained from samples. Using sample dataset about two populations mean value is made induction. Table 2 shows H_0 and H_a hypothesis for big samples.

Table 2. Big Sample Z Test For $\mu_1 - \mu_2$

Null Hypothesis	**H_0: $\mu_1 - \mu_2$ = Hypothesis Value**
Test Statistically	$z = \dfrac{\bar{x}_1 - \bar{x}_2 - (\mu_1 - \mu_2)}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}}$
Ha: $\mu_1 - \mu_2$ > **Hypothesis Value**	if z > z critic value H_0 reject (right queue test)
Ha: $\mu_1 - \mu_2$ < **Hypothesis Value**	if -z < -z critic value H_0 ret (Left queue test)
Ha: $\mu_1 - \mu_2$ ≠ **Hypothesis Value**	if z >z critic value or –z < -z critic value H_0 reject

Comparison between the two populations' characteristics is distinguished [30, 31]. In this study μ (the mean of the population) σ (the standard deviation of the population) $\bar{x}$ (the mean of the sample) and s (standard deviation of sample) are shown in Table 3.

Table 3. Symbols of mean, variance, standard deviation

	Mean value	variance	standard deviation	
Pop.1	μ_1	σ_1^2	σ_1	
Pop.2	μ_2	σ_2^2	σ_2	
	Sample Size	**Mean value**	**Variance**	**Standard deviation**
Sample 1	n_1	$\bar{X}_2$	s_1^2	s_1
Sample 2	n_2	$\bar{X}_1$	s_2^2	s_2

$$z = ((\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)) / \sqrt{(s_1^2 / n_1) + (s_2^2 / n_2)}$$
$$z = ((98-86)-0)/\sqrt{(15464/38)+(10938/38)} = 0.185$$

% 95 confidence level (z=1.645) obtained from ANN dataset and actual values don t have differences. That is to say H_0 ($H_{0:}$ $\mu_1 - \mu_2$ =hypothesis value=0) null hypothesis is accepted. To conclusion there is no difference between datasets statistically.

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4. **Conclusion**

On time delivery is an increasingly important strategic factor in the area of global competition. Successful firms seek to introduce products or service early and respond to customer orders punctually. To be successful in competition, new generation firms should have flexible manufacturing, rapid response, product variety and there are too many customers types that have distinct requirements about cost, products, operation time for each product.

In order to schedule and achieve on time delivery, it is very important to forecast the operation time of parts and products in the beginning stage of the product development process. While it is easier to know the operation time for standard products, it is much more difficult to know the operation time and process when the company has a wide and diverse product range. This research is studied in a machine production factory which has a problem regarding the inability of the orders of the customers on time. The inadequacy of the operation time of the required parts and the different specifications of the machines cause the delay in the production. For preparing effective plans and to regulate the production flow of the factory needs to use accurate operation times for each machine which are used in production. This research has been carried out in a firm that cannot deliver orders to customers on time. The processing time of the machine parts is unknown and therefore the delays occurs. For effective planning and production flow, correct operation times should be used for each machine. First of all, machine factors are investigated and eight factors which are material type, dimensions of material, surface quality, the number of holes to be processed, the number of diameter changes, total depth of drilled holes, and the number of surfaces to be processed, complexity are determined. The operation times are forecasted by using ANN approach and ANN is trained by using a sample group with 100 instances and tested with 38 datasets. ANN method parameters may vary depending on different problem types. If it is desired to reach global optimum for the ANN method, it is important to select the appropriate parameters level of ANN. It also impacts the efficiency of ANN. Most users select parameters manually based on the reference values of previous examples. But this trial-and-error method is wasting time, not effective, and often it could not reach the optimal combination. Therefore, this research was studied with optimal parameters using Taguchi experimental design and parameter combination design in ANN. With respect to the research results, number of layer and neuron are the most important parameters of the ANN model. From the research results optimal parameter combination created and confirmation experiment is conducted. It can be seen that if the obtained parameter combination is strong and reliable, the results can be predicted with less error. Also, this research method, increase the algorithm's efficiency, even decrease the time that spent on parameter design using ANN. The findings gained from this study will be used for the new process designs by establishing model to calculate the operation times. Obtained from ANN's deviation dataset is tested %95 confidence level and actual dataset and obtained from ANN's dataset have no difference statistically. So the ANN approach is found to be reliable for forecasting the operation times depending on the statistical analysis. In the study, processing times were estimated for determining specific criteria. Likewise, forecasting can be done by determining the factors affecting the operation of the different machines. Thus, when the operation time is known, better planning can be done, in areas such as capacity planning, product delivery time and the firm can estimate operation times for new design.

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