Research Article

The Estimation of Product Standard Time by Artificial Neural Networks in the Molding Industry

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Determination of exact standard time with direct measurement procedures is particularly difficult in companies which do not have an adequate environment suitable for time measurement studies or which produce goods requiring complex production schedules. For these companies new and special measurement procedures need to be developed. In this study, a new time estimation method based on different robust algorithms of artificial neural networks (ANNs) is developed. For the proposed method, the products that have similar production processes were chosen from among the whole product range within the cleansing department of a molding company. While using ANNs, to train the network, some of the chosen products' standard time that had been previously measured is used to estimate the standard time of the remaining products. The different ANN algorithms are trained and four of them, which are converged the data, are stated and compared in different architectures. In this way, it is concluded that this estimation method could be applied accurately in many similar processes using the relevant algorithms.

1. Introduction

In recent years, due to greater competition in the market, determining the exact standard time of products has become a necessity [1]. It is very difficult to prepare manufacturing plans and programs, short- and long-term forecasts, pricing, and the other technical and managerial activities in a company without true standard time. Unfortunately, direct or indirect work measurement procedures are insufficient in most cases to determine the exact standard time. For example, in addition to complex production scheduling and processes as well as inadequate environmental situations, the cost of time study can be extremely prohibitive. Thus, existing direct or indirect work measurement methods are not deemed feasible for use all companies.

There are some modern measuring methods in the literature, for example, activity sampling, standard data synthesis, analytical estimation, comparison and prediction, and elementary motion standards. The methods are not relevant for all studies or possess some

special adversities for application on the model. Therefore, three methods could be advised for these kinds of problems. One of them, comparison and prediction method (CPM), requires a value assigned according to the experience of the one who has applied the time study that is the reason why it is subjective. As it is a method where all the time effecting factors are not taken into consideration, CPM is not able to provide accurate results in every case.

In searching for an alternative estimation method to compare the results of ANNs, regression analysis appears to be a good choice. When evaluating the results of regression analysis, it seems that there is a significant difference with the real values. The maximum overshoot value is significantly high. It is clear that this would present a great problem in the production planning.

In combating the cost and complexity of the measurement techniques, ANNs have been recognized as a simple and flexible tool for modeling and system analysis. Over the last decade, ANN method has been utilized in many industrial fields. Most of its applications are in marketing, electronic, manufacturing planning and scheduling, supply chains, expert systems, risk theory, software, energy, food, and beverage industries. The studies in what follows can be given as examples in similar applications.

Yarlagadda [2] developed an ANN system to generate the process parameters for the pressure die casting process in production; Laybeygier [3] studied on a constrained hybrid NN model to improve the accuracy of conventional option pricing models; Yahia et al. [4] studied a new model on knowledge processing of expert systems; Mitchell et al. [5] examined the usefulness of perceived risk theory to understand customer's behaviors in package holidays; Brasquet and Cloirec [6] used classical methods of ANN and that experimental study showed the influence of specific parameters of cloths through textile fabrics; Lind and Sulek [7] proposed a NN model approach to prediction of software development completion time taking into account complexity and variability of worker's knowledge and attention span; Joshi and Weng [8] worked on autonomous mental development of robots with two new learning algorithms in robot's vision, audition, manipulation and locomotion; Gestal et al. [9] studied a classification of apple beverages using ANN with some fuzzy characteristics and supply chain of foods; Duran et al. [10] submitted the results of analysis on the particulate matter emissions of biofuels; Celebi et al. [11] used ANNs to approach total computational time for QW laser technology, and Köker et al. [12] studied an ANN based inverse kinematics solution on robotics.

In this study, an alternative ANN based indirect standard time estimation methodology is proposed. The method is specially designed for the selected company in the molding sector using multilayer perceptrons (MLPs) architecture with different types of learning algorithms. The six factors that effect the time are determined and the ANN is used to estimate the standard time based on the variation of these factors. While training the networks, previously completed time study results of guide products of product families are used. The accuracy of the model is tested with these standard times and the divergences are compared among algorithms. Thereby, small software is developed to estimate the complete product family's standard time with decreased cost and time and increased reliability for the cleansing department.

2. The Structure of the Artificial Neural Networks (ANNs)

The obtained ANN model is optimized by using various learning algorithms with different network configurations. A brief explanation of ANNs and the model used is explained below:

ANNs are biologically inspired computer programs designed to simulate the way in which the human brain processes information. An ANN is formed from hundreds of single units, artificial neurons or processing elements connected with weights, which constitute the neural structure and are organized into layers. The power of neural computations comes from weight connection in a network. Each neuron has weighted inputs, transfer function and one output. The behavior of the overall ANNs depends on the transfer functions of its neurons, by the learning rule, and by the architecture itself. The weights are the adjustable parameters and, in that sense, a neural network is a parameterized system. During training, the inter-unit connections are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained and tested it can be given new input information to calculate the output. ANN represents a promising modeling technique, especially for data sets having nonlinear relationships that are frequently encountered in engineering. The various applications of ANNs can be summarized into classification or pattern recognition, prediction and modeling [13–15].

There are many types of neural networks for various applications available in the literature. Radial basis function networks and MLPs are examples of feed-forward networks and both universal approximators. In spite of being different networks in several important respects, these two neural networks are capable of accurately mimicking each other.

MLPs are the simplest and most commonly used ANN architectures which are shown in Figure 1 [16, 17]. As shown in the figure, a MLP consists of three layers: an input layer, an output layer and one or more hidden layers with previously defined number of neurons. The neurons in the input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i, after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, namely

$$y_j = f\left(\sum w_{ji} x_i\right),\tag{2.1}$$

where f is one of the activation functions used in ANN architectures.

Training is completed successfully by optimizing the weights to achieve the desired response with the use of a learning (optimization) algorithm. A learning algorithm gives $\Delta w_{ji}(t)$ in the weight of a connection between neurons i and j at time t. The weights are then updated according to the following formula:

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji}(t+1).\tag{2.2}$$

There are many learning algorithms available in literature [14, 17]. The learning algorithms which give accurate results and used in analysis are briefly summarized below [18]:

Fletcher-Reeves (CGF) algorithm is a second-order method, which restricts each step direction to be conjugated to all previous step directions. This restriction simplifies the computation because it is no longer necessary to store or calculate the Hessian or its inverse [19]. *Broydon-Fletcher-Goldfarb-Shanno (BFG)* algorithm is considered to be the best form of quasi-Newton methods. It uses an update formula derived from the quasi-Newton update of Hessian [13]. *Levenberg-Marquardt (LM)* algorithm represents the simplified versions of Newton's method applied to the problem of training MLP ANNs. Also it is a well-established numerical optimization technique with quadratic speed of convergence [14]. *Bayesian Regularization (BR)* method is the modification of the LM training algorithm to
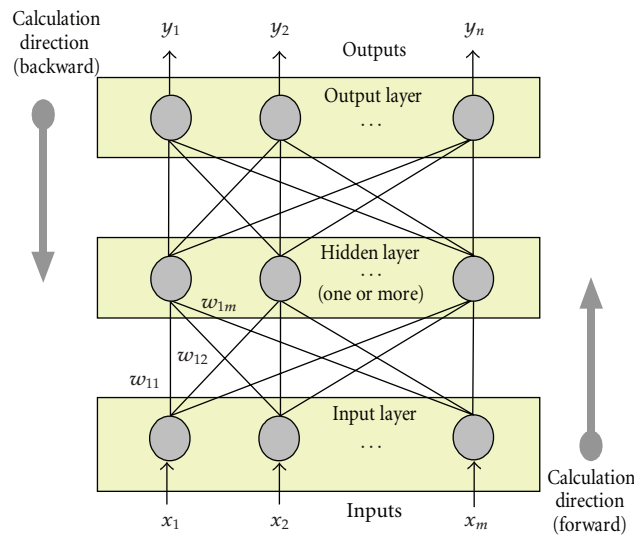
Figure 1: General form of multilayer perceptrons.

produce a well-generalized network. This method can train any network as long as its weight, inputs, and activation function [18].

Although one of the selected algorithms mentioned above could be converged a sample data, there is no convergence guarantee on other data sets. Several trials with different learning algorithms and with different network configurations are necessary to obtain a better performance. If the most suitable network configuration is $A \times B \times C \times D \times E$, this means that the number of inputs is A, the number of outputs is E, and the number of neurons is B for the first hidden layer, C for the second, and D for the third, respectively. This is the common use to designate the architecture [18]. (The numbers of input and output layers are not stated in the following sections. The structure is given with the hidden layers only.)

Before training, the input and the output data tuples are normalized between 0.0 and 1.0 in order to ensure the learning performance since the normalization is an essential step to improve the training process of ANNs. After completing the training process successfully, a test process is carried out for one output parameter.

3. Time Estimation Using ANNs

Time and work measurement studies in recent years have focused on comparing alternative methods, balancing the work force, determining the number of machines that a worker can simultaneously control, manufacturing planning and scheduling, obtaining the machine and worker's performance standards and workshop performance evaluations and calculation of the direct cost of workmanship. Some of the recent studies in the literature are outlined below:

Koelling and Ramsey [20] studied on the effects of multimedia in developing and applying in a work measurement methods, Cohen et al. [21] examined successful integration of automatic speech recognition (ASR) into industrial systems and found that the generation of time standards is a time-consuming process that has always slowed the work measurement task and increased costs, and that by using ASR, it demonstrated a 70% time reduction, and Freivalds et al. [1] tested the effect of work measurement and design systems in
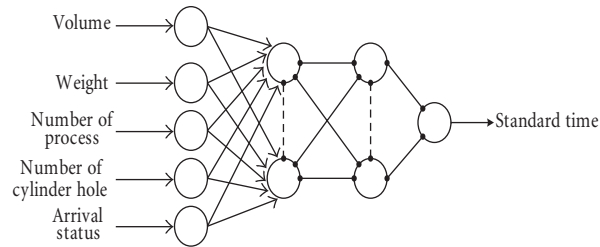
Figure 2: The inputs and outputs of the developed model.

customer satisfaction on future engineers using the 100 industrial engineering programs in US. Praszkiewicz [22] presented the application of ANNs in small lot production in machining with a purpose that is similar to this study. Apart from the fact that there are some studies on the literature which uses genetic algorithms or optimization techniques in the manufacturing systems/flexible manufacturing system processes and they are used for forming materials.

To manage the activities of an establishment effectively, the exact standard time must be known [1]. Activity sampling, standard data synthesis, analytical estimations and elementary motion standards methods are developed to indirect measurement but these methods are not applicable for the determination of standard time in every company or of every product.

In a process, the activities that are the components of processes differ with the facts of the structure of the work piece, machine used, process and environmental conditions. In many companies, it is possible to observe that similar production processes are repeated during manufacturing. It is very expensive or not possible to measure the time in individual or small serial manufacturing, small-sized enterprises, rework activities, or production of a new part [23]. In these circumstances, standard time is estimated rather then measured by past documents but in this estimation method, there is the effect of personal non-objective decisions. The evaluations are subjective during a comparison between known and unknown standard time. There are not only the quantitative differences between the products whose standard time will be estimated but also the products whose standard time was previously known. The qualitative facts that have unknown effects on time, but have important impacts on the duration, need to be considered in time estimation. When the literature is reviewed, it is seen that these qualitative factors are advised to be taken into consideration by the one who performs the time study. This proposal is not an acceptable engineering systematic. It is not possible to explain these qualitative facts by numerical expressions. Thus, the method can not be extended beyond a subjective method.

In this study, a different method that can estimate the standard time objectively by ANN is developed. Different varieties of algorithms are compared. In ANNs, qualitative factors have already been identified. However, quantitative factors are expressed based on predefined numerical scales. The structure of the proposed model is shown in Figure 2.

4. An Application in a Molding Company

The proposed alternative method was applied to Turkey's biggest molding and machining company. Many types of motor blocks were molded, cleaned and tested in CNC machines.

The manufacturing processes of many products of different types and dimension are almost the same to operate in various scheduling with 13 machines in the selected cleansing department. It was reported by the managers that there is a huge amount of products operating and that if is impossible to measure the standard time because of product variations and the environmental conditions.

The proposed method can be outlined as follows:

(i) Firstly, a production system should be selected which manufactures numerous different finished products or spare parts.

(ii) The factors that affect the production time have to be determined. It is necessary to express these factors numerically. In addition to quantitative factors such as length, weight or area etc, there are qualitative factors that can not be measured. These factors can be numerically expressed using Likert scale.

(iii) Then, the production time of some of these products should be measured. The factors that effect the time need to be clearly defined and numerically expressed. These factors are the inputs and the production time will be the output for the system.

(iv) In the last step, by changing the network structure and parameters, the proposed network is trained and tested. If the final network is capable of estimating the time in the desired error band, the same network can be used to estimate the time of other finished products, semiproducts or new products. This method is summarized as a flow chart which is shown in Figure 3.

The most important step in activating the MLP ANN is the determination of the factors. While determining the quantitatively and qualitatively factors, some facts need to be taken into consideration. These are the factors that effect the production time, have the ease of measurement and do not effect the time linearly. For example, it may not be known how much an individual factor affects the time or if it is the only factor. The factors are determined by a decision group which comprised of the company managers, engineers and experts. After time study, these factors are determined to effect time. Therefore, they are selected as the features of the products or semiproducts.

The factors can be divided into two; the ones that are affected by the product specifications and the ones that are based on production method. Increasing the number of the factors (input variables) that affect the standard time could interpret the results better and the affect of each factor on the standard time can be determined more accurately. Therefore, the most important factors examined, six possible factors are identified as most determinant to achieving more reliable results and these are listed as follows.

(i) *Volume.* The volumes of the motor blocks and spare parts to be cleaned are changeable. The bigger parts are carried with forklifts or the biggest ones with cranes which affects the time. The values of the volumes are factored into the model numerically.

(ii) *Weight.* As the same with volume factor, carrying the different weight parts effect the time. The values are also taken into model numerically.

(iii) *Process Number.* There are 13 machines available in this department. Some parts' operating processes follow 4 machines only but some others follow up to 13. The greater number of stations means more time need.
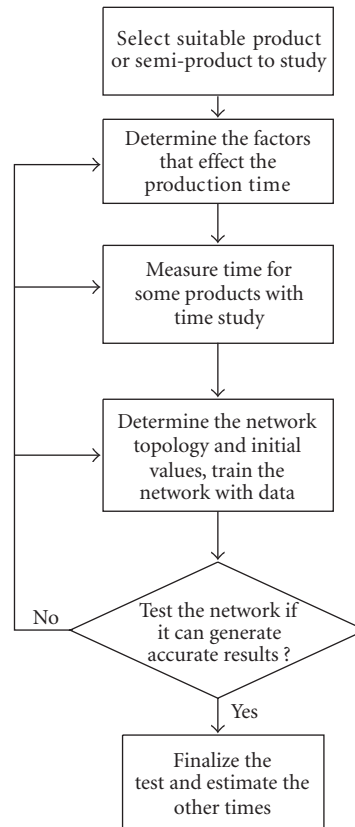
Figure 3: A Flowchart of the proposed method.

(iv) *Cylinder Hole Number.* The holes on the blocks to be cleaned require extra time for detailed work. That's why, the hole numbers are taken into account.

(v) *Arrival Status.* The arrival status condition of the blocks and parts are divided into three types that effect the cleaning time. They are assigned to model "good" as 2, "moderate" as 1, and "bad" as 0.

(vi) *Material Type.* The materials that the parts are made of can affect the cleaning process. However, the materials of all parts are almost the same and the variation is very limited. Therefore, this factor is omitted.

Before training, the input and the output data tuples were normalized between 0.0 and 1.0 to normalize the data to improve the training process of ANNs. Then, a test process provides one output parameter which is the standard time of the work. In the study, time study is done on 50 products. The pre-measured 40 values are used to train the ANN and the randomly selected remain 10 values are used to test if the ANN is generating the correct results. The data was exactly measured with time study in the non-ergonomic area and under unsuitable conditions of the department of the company. The train and test values of the products are given in Table 1.

The MLP ANNs was trained with the four learning algorithms as explained earlier. The ANN parameters, weights, activation functions, number of neurons and the levels of

Table 1: The premeasured train and the test values of the ANNs.

Volume	Weight	Process number	Cylinder hole number	Arrival status	Standard time
310000	118	14	4	good	1094.0
265000	110	14	3	good	896.0
⋯	⋯	⋯	⋯	⋯	⋯
⋯	⋯	⋯	⋯	⋯	⋯
⋯	⋯	⋯	⋯	⋯	⋯
115000	34	6	0	good	369.7
120000	37	6	0	good	389.7*
112000	33	6	0	good	379.3*
98000	41	6	0	good	378.0*
13500	25	7	0	good	365.0*
14000	23	7	0	good	377.3*
14000	23	7	0	good	374.0*
13500	30	7	0	bad	380.3*
12000	28	7	0	good	368.0*
17000	34	7	0	good	354.0*
11000	18	8	0	moderate	430.0*
18000	22	6	0	moderate	354.0
⋯	⋯	⋯	⋯	⋯	⋯
⋯	⋯	⋯	⋯	⋯	⋯
⋯	⋯	⋯	⋯	⋯	⋯
16500	8	5	0	good	245.0
480	8	3	0	bad	83.0
3200	9	5	0	good	293.0
4000	14	7	0	moderate	418.0
4000	18	7	0	moderate	425.0

*Randomly selected 10 standard times are used as test values.

the input and output values were achieved in a small software developed in C++. The training phase takes 15–20 secs for each run on a Pentium IV 2.4 GHz PC with 512 MB of RAM memory.

Several configurations of ANNs are tested with different network configurations. For the proper training system, the model was run several times for each different structure beginning with different random numbers in order to reach the minimum error level. The input and output layers have the linear activation function and the hidden layers have the hyperbolic tangent sigmoid activation function. The epoch number is selected 800 for training. After training, the calculation time is less then a few μs in real time calculation. The neural computation is very fast after training phase. Therefore, ANN can be used effectively in real-time applications.

The result of the two configurations (i.e., $6 \times 4 \times 2$ and $7 \times 5 \times 3$) in order to obtain better convergence with simpler structure to the pre-measured values in four algorithms are stated below:

Table 2 summarizes the comparison between the estimation outputs of algorithms with previously measured standard time for the structure $6 \times 4 \times 2$ and Table 3 summarized for the $7 \times 5 \times 3$. The required error level corresponds to the total difference between the outputs of the network to trained inputs and exact values of the outputs.

Table 2: Comparison of outputs of the MLP ANN algorithms (for the hidden layers 6 × 4 × 2).

No.	Pre measured values	Generated values by CGF	Absolute difference (%)	Generated values by BFG	Absolute difference (%)	Generated values by LM	Absolute difference (%)	Generated values by BR	Absolute difference (%)
1	389.7	384.84	1.25	375.04	3.76	389.35	0.09	401.69	3.08
2	379.3	368.24	2.92	367.05	3.23	379.25	0.01	388.01	2.30
3	378.0	365.79	3.23	364.32	3.62	378.13	0.04	369.81	2.17
4	365.0	304.58	16.55	314.20	13.92	364.67	0.09	307.14	15.85
5	377.3	303.08	19.67	312.45	17.19	377.01	0.08	304.51	19.29
6	374.0	303.08	18.96	312.45	16.46	373.65	0.09	304.51	18.58
7	380.3	507.76	33.51	473.41	24.48	380.38	0.02	444.65	16.92
8	368.0	306.38	16.75	316.03	14.12	368.04	0.01	310.58	15.60
9	354.0	315.65	10.83	325.97	7.92	353.46	0.15	321.76	9.11
10	430.0	493.90	14.86	422.77	1.68	429.73	0.06	463.36	7.76
Train error		$2.24E{-}03$		$2.14E{-}03$		$7.77E{-}04$		$2.59E{-}03$	
Test error		$3.17E{-}03$		$1.84E{-}03$		$6.87E{-}03$		$1.85E{-}03$	

Table 3: Comparison of outputs of the MLP ANN algorithms (for the hidden layers 7 × 5 × 3).

No.	Pre measured values	Generated values by CGF	Absolute difference (%)	Generated values by BFG	Absolute difference (%)	Generated values by LM	Absolute difference (%)	Generated values by BR	Absolute difference (%)
1	389.7	385.75	1.01	446.06	14.46	350.30	10.11	402.12	3.19
2	379.3	368.12	2.95	415.30	9.49	385.63	1.67	388.42	2.40
3	378.0	399.98	5.82	436.44	15.46	449.68	18.96	370.51	1.98
4	365.0	315.42	13.58	278.53	23.69	187.77	48.56	306.98	15.90
5	377.3	307.55	18.49	273.95	27.39	115.89	69.29	304.36	19.33
6	374.0	307.54	17.77	273.95	26.75	115.89	69.01	304.36	18.62
7	380.3	365.49	3.89	615.83	61.93	407.08	7.04	444.74	16.94
8	368.0	326.87	11.18	285.57	22.40	278.50	24.32	310.39	15.65
9	354.0	353.95	0.01	314.61	11.13	395.49	11.72	321.62	9.15
10	430.0	477.81	11.12	453.62	5.49	420.70	2.16	462.88	7.65
Train error		$1.85E{-}03$		$1.48E{-}03$		$3.00E{-}24$		$2.59E{-}03$	
Test error		$1.31E{-}03$		$7.96E{-}03$		$1.46E{-}02$		$1.85E{-}03$	

As seen in Table 2, the developed MLP ANN methods can generate very accurate results with respect to standard time. It was found that the most suitable network configuration is 6 × 4 × 2 with the LM algorithm. The maximum difference observed was lower than 0.5 minutes. This structure gives more accurate results than 7 × 5 × 3. These differences will not affect the managerial and planning activities and could be used as standard time easily. Additionally, it is obvious that when the cost of time study is considered, the results are quite useful and important. In addition, the test and the train errors are quite low.

When Table 3 is examined, it is seen that the best results are obtained from CGF algorithm for the hidden layers 7 × 5 × 3. Although the train and the test errors are quite low, the results are not satisfactory.

Table 4: Comparison of outputs of the regression model.

No.	Premeasured values	Predicted values by regression model	Absolute difference (%)
1	389.7	412.28	5.79
2	379.3	402.16	6.02
3	378.0	374.69	0.87
4	365.0	289.77	20.61
5	377.3	291.86	22.64
6	374.0	291.86	21.96
7	380.3	337.51	11.25
8	368.0	285.42	22.43
9	354.0	289.46	18.23
10	430.0	354.85	17.47

The regression analysis is one of the best alternative methods in the estimation of the standard time. The regression model is constructed using this pre-measured values and the standard time is predicted. The R^2 value is calculated as 0.91. In our sample, this means that 91% of total variation of the values of Y (standard time) is accounted for by a linear relationship with values of X_i's $(i = 1, 2, \ldots, 5)$. The model says that all the factors are effective on model. The comparatively results of the regression model is stated in Table 4.

The absolute differences of values in Table 4 show that the results are not satisfactory. Although the results are better than some algorithms of hidden layer $7 \times 5 \times 3$, this method could not be used in the planning activities.

5. Conclusion and Discussions

The proposed MLP ANN model with a very limited calculation time is very easy to use in the estimation of standard time for any production department of a company. The companies that do not know the exact standard time of their products due to measurement difficulties can easily obtain these time values with the benefits of lower cost, shorter time, and higher accuracy for use in production planning.

The developed method is based on the time affecting factors in similar processes. After experimentation, the best results were obtained from LM learning algorithm for the structure $6 \times 4 \times 2$ and CGF learning algorithm for $7 \times 5 \times 3$. With the developed model, the total train and the test errors of standard time estimation was very low. This accuracy shows that the model is valid with its selected time affecting factors. In other words, it was evident that the determining factors are relevant for the proposed model. Moreover, more accurate results could be obtained by increasing the premeasured data or by trying for several different architectures. However the results are satisfactory consider the limited data obtained from the non-ergonomic working conditions.

In ANN-based time estimation method, many factors effecting the time are taken into consideration and it is possible to deduce the fractions of these factors during time measurements. More accuracy is required to measure more premeasured values in order to increase learning progress. The train errors indicate that sometimes these algorithms are over-trained. When the method is compared with other measurement methods, the following advantages and the benefits to the industry can be listed:

(i) does not require long term experience with the product to estimate time,

(ii) minimizes the amount of time study to avoid time and money consumptions,

(iii) gives high accuracy results with a very limited error band,

(iv) considers all the factors that effect time with the pre-measured values and gives more objective estimations,

(v) allows tracing of factors which have more effect on the standard time.

It is obvious that the method is applicable in many companies economically. When the company develops one of the appropriate ANN methods, they can easily calculate the standard time of their products family. The disadvantages of the method are that it is not easy to apply for every product or semiproduct whose manufacturing processes are quite complex and it is difficult to determine the time effecting factors in every case, and furthermore, determination of the MLP ANN methods, number of hidden layers or parameter sets are required when using the software. In contrast, it is very simple and efficient in the fields where applicable.

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