



AN ARTIFICIAL NEURAL NETWORKS MODEL FOR THE ESTIMATION OF FORMWORK LABOUR

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Abstract. Artificial Neural Networks (ANN) is a problem solving technique imitating the basic working principles of the human brain. The formwork labour cost constitutes an important part within the costs of the reinforced concrete frame buildings. This study suggests a method based on artificial neural networks developed for estimating the required man-hours for the formwork activity of such buildings. The introduced method has been verified in the study with reference to the test conducted involving two case studies. In all cases, the model produced results reasonably close to actual field measurements. The model is a simple and quick tool for the estimators and planners to aid them in their work.

Keywords: Artificial Neural Networks (ANN), Formwork, Labour, Cost, Man-hour, Productivity.

1. Introduction

The estimation and the determination of the final completion date and the budget of a project are among the main objectives of the construction project management. However, both these tasks can only be achieved through a healthy estimate of the material, equipment and labour resources needed. Among these, the quantities of labour resources can only be calculated based on a robust estimation of man-hours needed to perform the unit amount of work, namely the productivity, for each and every construction activity in the project. Similarly, from the contractor's point of view, it is also obvious that an erroneous estimate of the productivities of the work items, and accordingly the total man-hours needed, at the tender stage may cause the loss of a bid or on the contrary may cause getting awarded a contract that will end up with a loss. Hence, estimation of the man-hours needed is a very critical and important issue in the construction business.

To estimate the man-hours, the estimators and planners usually use the data available in the sector specific data bases (RS-Means 2009; Spon's... 2010; Plümecke 2008). The data available in these data bases can be quite detailed. Some of them provide even different productivity data for work items based on the dimensions of each individual element to be constructed. But in this case, each unit element should be estimated, thus making the estimation process quite time consuming. Also, since the data provided for every individual item has some level of safety margin included, the total amount of man-hours estimated can be considerably higher than the actual required amount. At this point, it is also important to note that these data bases in general contain data specific to

one country. Hence, the results may not cover some of the local factors affecting the productivity. Thus, they cannot be used universally.

The productivity of formwork labour is an important factor in the determination of the overall cost of the reinforced concrete frame type buildings. In fact, the formwork labour cost constitutes a major part of the construction cost of these buildings. For instance in Turkey, the cost of formwork labour accounts for 10–15% of the total turnkey cost of this type of structures which are abundantly used in residential and commercial building construction. Formwork productivity is also a major factor that needs to be considered during the planning and scheduling of the site activities of this type of buildings. Yet, the actual man-hours required for the formwork activities in a project is affected by many factors such as the formwork technology selected, building's geometric characteristics, local climatic conditions, local methods of application, local codes and regulations. Among the building's geometric characteristics affecting the formwork labour productivity; the density of columns per floor area, height of the building, floor heights or number of floors can be listed.

Hence, the estimation of formwork labour will require extensive statistical data of past projects. But, it is also quite common that in some countries the necessary detailed statistical data may not be available to aid the estimator and the planners in their endeavours. For instance, in Turkey the labour productivity rates published by the Turkish Ministry of Public Works and Settlement (2010) specifies only a single value for the engineered formwork labour without differentiating any items such as slab, column or beam formwork. Though this approach

can provide an average value on a wide spectrum, it is obvious that estimating on this basis can be highly erroneous. For instance, the productivity rates are considerably different for a villa construction and a high rise office building. Similarly, it is self evident that the productivity rates will differ from floor to floor in a high rise building construction.

The objective of this study is the development of a simple, yet effective, artificial neural networks based model to estimate the productivity of formwork labour for the frame type reinforced concrete buildings.

2. Artificial neural networks

Artificial neural networks (ANN) are based on the principle of how the human brain processes visual data and learns to recognize objects. The concept of artificial neural networks dates all the way back to 1800's when studies started on how human mind and brain performs. However, somewhat owing to the scepticism presented in a study published by Minsky and Papert (1987), research on the field had a slow pace till mid 1980's, when studies started accelerating again, including in the area of construction management (Moselhi *et al.* 1991).

The structure of a typical neural network has input, output and hidden layers. The output layer receives the input and signals flow from the input layer through the hidden layers which are between the output and input layers. The number of hidden layers changes according to the application.

A very common type of neural network is the so called multilayer perceptron. In this type of network, the inputs, x_1 thru x_n as shown in Fig. 1, are fed into the input layer and multiplied by "connection weights" as they are passed from the input layer to the hidden layer. Within the hidden layer, they get summed and then processed by an activation function. This process gets repeated at each hidden layer till the data finally reaches the output layer. At the output layer, the data is multiplied by interconnection weights and processed one last time within the output layer to produce the output.

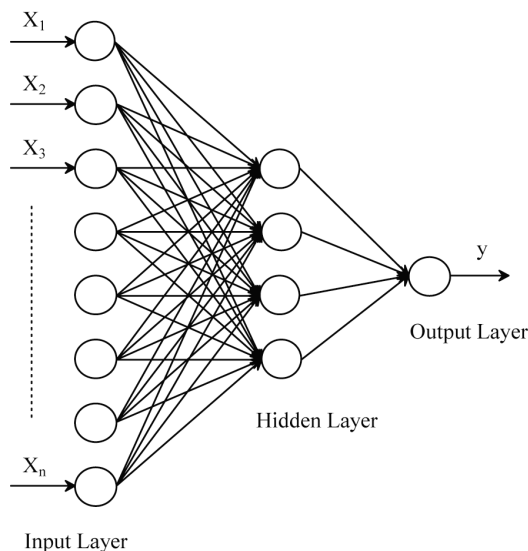


Fig. 1. Typical neural network model

An artificial neural network is configured for a specific application, such as estimation of productivity, voice recognition or data classification, through a learning process. Also, it is worth to mention that artificial neural networks comprise more than one solution method. However, due to space limitations no further explanation will be given here and the readers are suggested to refer to numerous valuable literature available in this field (Elmas 2007; Haykin 1998; Veelenturf 1995; Zurada 1992).

3. Earlier studies

Starting in the second half of 1980's, substantial amount of research has been conducted till today about the use of neural networks in construction management (Adeli and Karim 2005; Boussabaine 1996; Moselhi *et al.* 1991). In that respect much valuable research has been conducted and published about the use of artificial neural networks in the subjects of cost and price estimation, productivity, risk assessment, prediction of profit, time and resource management and prediction of the result of adjudication process (Adeli and Karim 2005; Dikmen *et al.* 2009). A brief summary of the research in the field of ANN's related to the subject of productivity estimation in various construction activities with special emphasis on formwork productivity will be made below.

Portas and AbouRizk (1997) have used neural networks to estimate the productivity of concrete formwork tasks. They used a back-propagation; feed forward ANN with a sigmoid transfer function. The network used by them had an input layer with 55 nodes, a hidden layer with 30 nodes and an output layer with 13 nodes. The model was geared for the prediction of the formwork productivity of a specific task, such as basement wall formwork. The model, besides requiring a rather large number of input data, also requires some subjective data as input such as the skill level of the superintendent, skill level of the formwork crew and the activity complexity.

Neural network modelling was used by Sonmez and Rowings (1998) for the estimation of construction labour productivity of concrete works. They studied the effects of labour productivity factors such as quantity, crew size, humidity, precipitation, temperature and job type on the formwork, concrete pouring and concrete finishing through the use of neural networks. They concluded that the quantity of work being done and the crew size are the most effective parameters on the formwork productivity. According to their findings the rate of increase in productivity for each one person increases in the crew is 0.04 hrs/m^2 .

AbouRizk *et al.* (2001) have used a two stage neural network analysis for the estimation of labour production rates for industrial construction activities. They reported that their method, on an average 84% of the time predicted the efficiency multiplier to 15% of the actual value. They have also concluded that "The most significant (and demanding) aspects of applying artificial neural networks in a practical application within an industrial setting are (1) defining input factors; and (2) collecting sufficient relevant data for training".

ANN was also used by researchers to estimate the productivity of various construction equipment and machinery. Karshenas and Feng (1992), Chao and Skibniewski (1994) and later Ok and Sinha (2006) studied the use of artificial neural networks to estimate the production rate of the earthmoving equipment. Later Hola and Schabowicz (2010), Schabowicz and Hola (2007, 2008) used back propagation networks with conjugate gradient algorithm to study the productivity of earthmoving machinery and estimation of the earthworks execution time. The results obtained in all these studies, indicates that neural networks is a sound tool for the estimation of the production rate of earthmoving equipment and consequently the estimation of earthworks.

In two different studies, Leung *et al.* (2001) and Tam *et al.* (2004) studied the hoisting times and hook times of tower cranes and mobile cranes in Hong Kong. They used 3 different neural network methodologies to predict the hook times of mobile cranes. They reported that the general regression neural network (GRNN) model aided with genetic algorithm (GA) is most promising in describing the non-linear and discrete nature of the hook times.

Zayed (2001), Zayed and Halpin (2004, 2005) had applied neural network method for the assessment of productivity in the construction of cast in situ piles.

4. Proposed Method

As mentioned above the objective of this study is the development of a decision support system for the estimation of formwork labour productivity for reinforced concrete frame type structures.

4.1. Input and output parameters

Often times the ease of use and simplicity are the two important factors for a method's acceptance for use in practice. Hence it is essential that the data required for the use of the method is simple and easily attainable. Otherwise the method will face the risk of remaining purely academic. However, on the other the hand, since artificial neural network method determines the probable solutions through the information obtained from the actual measured quantities, a large number of healthy data sets are essential for the training of the model. In lieu of these facts, it was aimed that the data required for the model developed is simple and easily collectable at construction sites without additional effort or expense.

Currently in the modern world, due to their flexibility and ease of use engineered formwork systems are widely utilized in the construction of reinforced concrete frames. In almost every country there are locally manufactured systems as well as internationally well known brands. One of the major advantages of the engineered formwork systems is the use of preassembled formwork elements for casting beams, columns and shear walls. As a matter of fact this particular advantage is one of the factors that increase the labour productivity. For instance, often times the columns are formed by using two preassembled units. Similarly, large preassembled panels are

used for the formation of shear wall forms. The overhanging portions of beams are also formed in a similar fashion. The preassembled units are then placed by the aid of hoisting equipment such as tower cranes.

Hence taking these characteristics of the engineered formwork systems into account, it can be assumed that the amount of labour necessary for the formation of a column formwork is independent of the column cross section, but instead the column length can be used to characterize the magnitude of column formwork activity. Similarly, regarding the shear walls, surface area of one face of the wall and for the beams the net length of the beams can be used. Regarding the slab formwork the total projection area of the slabs can be used.

The total number of floors to be casted and the height of the floor being worked are the two other factors affecting the formwork productivity. The total number of floors is important. Because by the increasing number of floors casted, the workers get used to the characteristics of the building, i.e. in some sense memorize it. On the other hand, at higher elevations the labour productivity due to various reasons has a tendency to drop. Hence all of these factors are included in the model as input variables.

4.2. Architecture of the neural network proposed

In this section, a presentation of the neural network proposed will be made. For the symbolic presentation of the neural network in a compact written form, the following mathematical notation, which was introduced by Ghaboussi and Sidarta (1997), Ghaboussi and Lin (1998) and Ghaboussi *et al.* (1998) will be used:

$$F = \text{NN}(\{\text{input parameters}\}; \{\text{NN architecture}\}), \quad (1)$$

where the symbol NN denotes the output of a multilayer feed forward neural network and the notation indicates that the vector F is the output of the neural network. The first argument field describes the input to the neural network, while the second argument field describes the neural network architecture, i.e. the number of processing units in the input layer, the hidden layers and the output layer, respectively.

In this study, a feed-forward multilayer error back propagation network has been selected. With respect to the parameters presented above, the input variables are determined as; the total length of columns, the total length of beams, the total area of shear walls, the total slab area, the elevation of the storey, the floor height of the storey and the total number of floors to be constructed in the building are used. The term building here is used to mean any structurally independent section standing alone or separated from the other sections by expansion joints. The output is the total amount of man-hours required for the erection of the formwork for the same storey. Using the notation given in Eq. (1), the neural network proposed can be written as follows:

$$y_e = \text{NN}(\{l_b, l_c, A_w, A_s, e_s, h, n_s\}; \{7, n_h, 1\}), \quad (2)$$

where l_b is total net length of beams, l_c is total length of columns, A_w is total area (one side) of shear walls, A_s is total slab area, E_s is elevation, and h is height of the storey under study.

While n_s is the total number of stories in the building of the storey studied. The output represented by y_e is the estimated total amount of man-hours needed for all the formwork activity, namely columns, beam, walls and slab formwork, to be performed for the storey. The elements of the second argument field indicate the number of input values, number hidden layer nodes (n_h) and the number of output values respectively. The number of hidden nodes, n_h will be determined through a selection process which will be presented in Section 4.5. of this paper. The neural network proposed is also graphically presented Fig. 2.

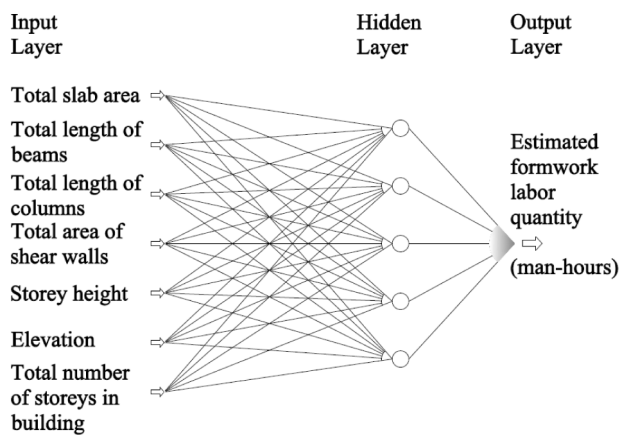


Fig. 2. Form of the selected ANN

4.3. Data

For the purposes of verifying the model 613 sets of data has been compiled from 22 different building projects (Sonmez 2009). All the data used were collected from various construction sites in Istanbul that were realized in different times of the year as well as different years. Hence the data collected represents the average labour productivity in Istanbul as well as the local climatic conditions and local method of applications in Istanbul.

While compiling the data, beam and column lengths and the shear wall and slab areas had been directly calculated from the design drawings. The man-hours spent for the formwork activity for each floor have been obtained from the site records.

The buildings included in the data base range from 1 to 31 stories high including basement floors. They all have different total construction areas and floor areas. The range of the storey areas varied from a minimum of 30.0 m² to a maximum of 1650 m². The storey heights varied between from a minimum of 2.45 m to a maximum of 9.70 m.

4.4. Software

For the training, testing and running the ANN model proposed, software named FANN Tool is selected.

FANN Tool is part of a free open source neural network library named “The Fast Artificial Neural Network Library – FANN” (FANN 2010). It is the graphical user interface (GUI) to the FANN library which allows its easy usage without the need of programming. This tool enables the users to prepare the data in FANN library standard, and design, train, test and run the artificial neural network model.

The reasons of selection of this software are simply its ease of use and its free availability. Thus even the small construction companies with limited information technologies (IT) capabilities can download and start using immediately.

4.5. ANN – Selection, training and testing

For training the neural network an incremental training algorithm has been selected. The algorithm is a standard back propagation algorithm, where the weights are updated after each training pattern. This means that the weights are updated many times during a single epoch (FANN 2010). The algorithm generally exhibits a satisfactory performance when the data sets and the number of input parameters are not too large, such as in this case.

For training the neural network, out of the 613 data sets collected, 551 sets of data were used, while randomly picked 62 sets were kept for testing the model. To observe the effect of the number of neurons in the hidden layer and the activation function, trials have been made by changing these parameters. The absolute error values for each individual set out of the 62 sets in every trial have been calculated per the following equation:

$$E(y_i) = |(y_{ai} - y_{ei})/y_{ai}|, \tag{3}$$

where $E(y_i)$ is the absolute error value of test set i and y_{ai} and y_{ei} are the actual field measured and the neural network model estimated values of set i respectively. Then, the root mean square (RMS) of the error for each trial having n (namely 62 for all trials in this study) number of test sets is calculated using the following equation:

$$RMS(n) = \sqrt{\frac{1}{n} \sum_{i=1}^n E(y_i)^2}. \tag{4}$$

Trials made are summarized in Table 1. The selected model is the trial number 6 shown in the Table. The selected scheme is a back propagation scheme with a sigmoid activation function. In this scheme the maximum single error value obtained is 21.3% and the root mean square (RMS) of the error values is 9.2%.

The number of hidden nodes is determined as 5. Consequently, Eq. (2) can be rewritten to reflect the final form of the network as follows:

$$y_e = NN(\{l_b, l_c, A_w, A_s, e_s, h, n_s\}; \{7, 5, 1\}), \tag{5}$$

where all the variables have the same definitions as in Eq. (2).

The actual values versus the estimated values through the model obtained in this trial are shown in Fig. 3. Taking into account, the uncertainties and the

ambiguities involved in estimating the construction work items, these values can be considered well within the acceptable range.

Table 1. ANN model trials

Trial	Activation Function	No. of hidden layer neurons	Maximum error	RMS of the error Values
1	Sigmoid Symmetric	8	126.8%	21.9%
2	Sigmoid Symmetric	6	119.0%	21.4%
3	Sigmoid-Step	5	90.9%	19.3%
4	Sigmoid-Step	10	127.3%	21.5%
5	Sigmoid	10	80.3%	15.6%
6	Sigmoid	5	21.3%	9.2%

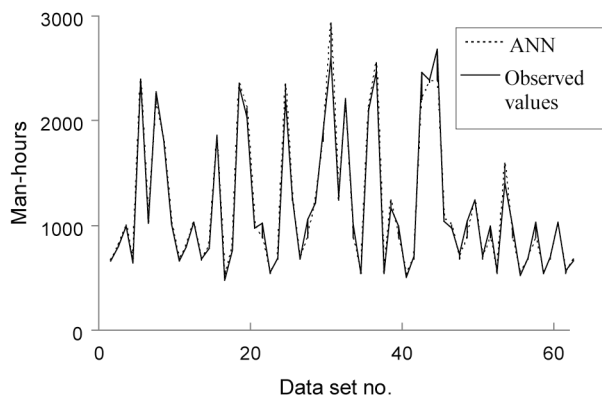


Fig. 3. Comparison of the actual observed values and ANN model calculated values

5. Case studies

The proposed method has been further verified by two case studies with different structural configurations. Both cases are also from the Istanbul area and constructed in the recent years. The cases used in the verification were used neither as the training data nor as the testing data. The results obtained were also compared with the suggested values of the Turkish Ministry of Public Works and Settlement (MP+S).

The first project used for verification is an office building. The building is 6 stories high with a total floor area of 2500 m². The building has 2 basement floors and 4 above ground floors including the ground floor. The floor to floor height is 2.92 m. The spans between the columns vary. The basement floors have reinforced concrete external walls. Other input quantities required by the model are presented in Table 2.

The results obtained using the proposed method and the actual field measurements are summarized in Figs 4a and b. Also the MP+S recommended values are shown in the same figure.

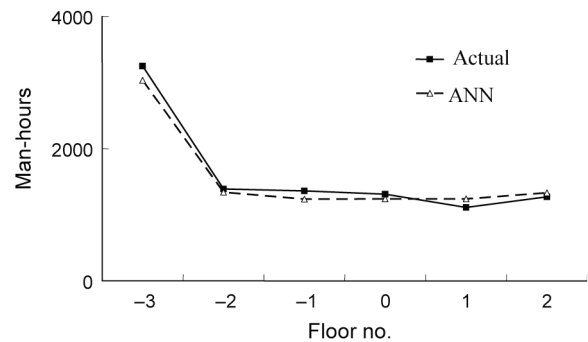
As can be seen from the figure there is a very good match between the measured and the predicted labour quantities. The predicted man-hours, depending on the

Table 2. Office building quantities

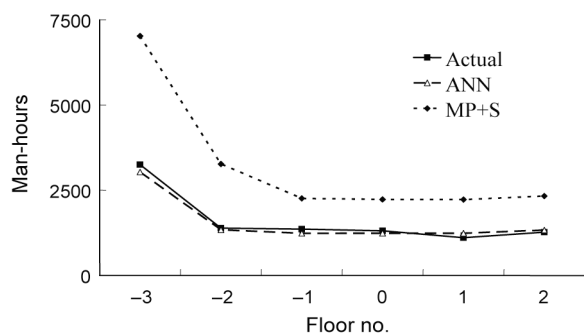
	Total Column Length (m)	Total Beam Length (m)	Total Shear Wall Area (m ²)	Total Slab Area (m ²)
2 nd Basement	41.8	109.6	366.2	531.6
1 st Basement	33.0	61.6	178.2	302.8
Ground fl.	29.7	7.6	18.0	416.8
1 st floor	29.7	7.6	18.0	416.8
2 nd floor	29.7	7.6	18.0	416.8
Roof floor	29.7	7.6	54.0	420.6
Total	193.5	201.5	652.5	2505.4

floor, had an error ranging from 4% to 12% as compared to the actual field recorded values (see Fig. 4a). The error of the total amount of man-hours is only 5% as compared to the total actual man-hours spent. On the other hand, the MP+S recommended labour quantities overestimate the required man-hours over 100% as compared to actual values. Especially, the values recommended by the Turkish Ministry of Public Works and Settlement (MP+S) had produced significantly higher results for the below ground levels (see Fig. 4b).

The second project used to verify the model is a 7 story high residential building. The building has 1 basement and 6 above ground floors. The floor to floor height between the levels is 2.95 m. The total construction area is 1500 m². Due to the architectural layout of the building the column sizes and spans between them vary throughout



a) ANN produced versus actual measured man-hours



b) ANN produced and actual measured man-hours versus MP+S suggested man-hours

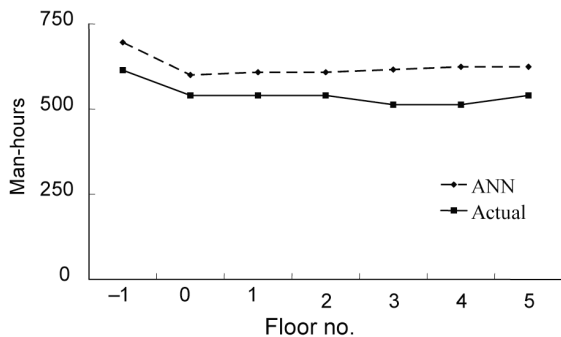
Fig. 4. Office building formwork productivity comparison

the floor. The slabs were designed as ribbed slabs and ribs were formed by using extruded polystyrene blocks as stay-in-place formwork. Thus, a flat ceiling is formed without any beams being visual. This type of construction is quite common in Turkey. The quantities used for the ANN analysis are presented in Table 3.

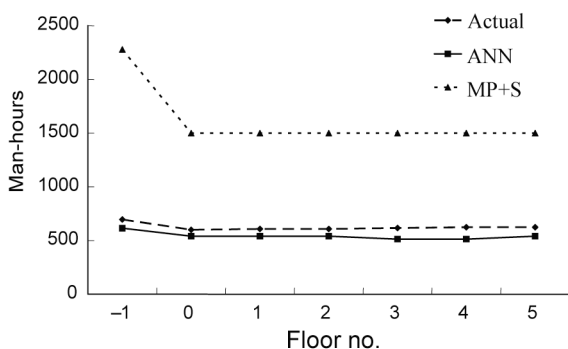
The results obtained using the proposed method is presented in Figs 5a and b. As can be seen from Fig. 4a, the values estimated are about 11% to 22% above the actual field measured man-hours for each individual floor. The difference in total man-hours is calculated as 15%. On the other hand, as presented in Fig. 5b, the total man-hours estimated using the Turkish Ministry of Public Works and Settlement (MP+S) proposed values are much higher than both the actual values and the values estimated by the proposed method. The MP+S suggested values are about 100% to 200% above the actual and estimated values.

Table 3. Residential building quantities

	Total Column Length (m)	Total Shear Wall Area (m ²)	Total Slab Area (m ²)
1 st Basement	5.50	169.5	250.0
Ground fl.	51.30	14.9	250.0
1 st floor	51.30	14.9	250.0
2 nd floor	51.30	14.9	250.0
3 rd floor	51.30	14.9	250.0
4 th floor	51.30	14.9	250.0
5 th floor	51.30	14.9	250.0
Total	333.30	258.9	1500.0



a) ANN produced versus actual measured man-hours



b) ANN produced and actual measured man-hours versus MP+S suggested man-hours

Fig. 5. Residential building formwork productivity comparison

In both cases, the model predicted the total man-hours required with reasonable accuracy. For both cases studied, the results indicate that the proposed method is much more accurate in estimating the field performance than the estimating using the Turkish Ministry of Public Works and Settlement (MP+S) recommended values. Similar conclusion about the Ministry’s values has been reported by Kuruoglu and Bayoglu (2001, 2002). Upon making a series of field measurements they have concluded that the Ministry’s values overestimate the field performance by an average of 70% differing based on the type of formwork activity.

6. Conclusion

In this study an artificial neural networks based method developed for the estimation of the required man-hours for the formwork activity of reinforced concrete frame type buildings. The method has been verified in the study by test cases and also by two case studies. In all cases the model produced results reasonably close to the actual field measurements. As a conclusion the advantages of the method can be listed as follows,

- The model is a simple and quick tool for the estimator to check his/her estimated formwork total labour man-hours in reinforced concrete framed building projects.
- The method requires only a small number of input parameters.
- Both the data to be collected from the field and the data that needs to be measured from the design drawings are very simple and can even be acquired by an inexperienced engineer.
- The model takes into account factors such as building size, climatic conditions, work culture, building height, working height that might have effect on the productivity of formwork labour.
- The data base needed to train and test the model is usually available even at small size construction companies.
- The method is very versatile and can be used by any size construction company including the quite small ones.

References

AbouRizk, S.; Knowles, P.; Hermann, U. R. 2001. Estimating labor production rates for industrial construction activities, *Journal of Construction Engineering and Management* ASCE 127(6): 502–511. doi:10.1061/(ASCE)0733-9364(2001)127:6(502)

Adeli, H.; Karim, A. 2005. *Construction scheduling, cost optimization, and management – a new model based on neurocomputing and object technologies*. Taylor & Francis Group. 178 p.

Boussabaine, A. H. 1996. The use of artificial neural networks in construction management: a review, *Construction Management and Economics* 14(5): 427–436. doi:10.1080/014461996373296

Chao, L. C.; Skibniewski, M. J. 1994. Estimating construction productivity: neural-network-based approach, *Journal of Computing in Civil Engineering* ASCE 8(2): 234–251. doi:10.1061/(ASCE)0887-3801(1994)8:2(234)

- Dikmen, S. U.; Ateş, O.; Akbiyıklı, R.; Sonmez, M. 2009. A review of utilization of soft computing methods in construction management, in *Proc. of the 26th International Conference on IT in Construction & 1st International Conference on Managing Construction for Tomorrow*, Istanbul Technical University, Istanbul Turkey, 1–3 October, 2009, 703–710.
- Elmas, Ç. 2007. *Yapay zeka uygulamaları* [Artificial Intelligence Applications]. Seckin Yayıncılık, Ankara, Turkey. 100 p.
- FANN, Fast Artificial Neural Network Library. 2010 [online], [cited June 19, 2010]. Available from Internet: <<http://leenissen.dk/f/>>.
- Ghaboussi, J.; Sidarta D. E. 1997. New method of material modeling using neural networks, in *Proc. of the International Conference on Numerical Models in Geomechanics*, Montreal, Canada, 393–400.
- Ghaboussi, J.; Lin, J. 1998. New method of generating spectrum compatible accelerograms using neural networks, *Earthquake Engineering & Structural Dynamics* 27(4): 377–396. doi:10.1002/(SICI)1096-9845(199804)27:4<377::AID-EQE735>3.0.CO;2-2
- Ghaboussi, J.; Pecknold, D. A.; Zhang, M.; Haj-Ali, R. 1998. Autoprogressive training of neural network constitutive models, *International Journal for Numerical Methods in Engineering* 42(1): 105–126. doi:10.1002/(SICI)1097-0207(19980515)42:1<105::AID-NME356>3.0.CO;2-V
- Haykin, S. 1998. *Neural Networks: A Comprehensive Foundation*. 2nd Ed. NJ: Prentice Hall, Upper Saddle River. 842 p.
- Hola, B.; Schabowicz, K. 2010. Estimation of earthworks execution time cost by means of artificial neural networks, *Automation in Construction* 19(5): 570–579. doi:10.1016/j.autcon.2010.02.004
- Karshenas, S.; Feng, X. 1992. Application of neural networks in earthmoving equipment production estimating, in *Proc. of the 8th Conference on Computing in Civil Engineering*, ASCE, New York, 841–847.
- Kuruoglu, M.; Bayoglu, F. I. 2001. Yapı üretiminde adam saat değerlerinin belirlenmesi üzerine bir araştırma ve sonuçları [A study and its results on the determination of man-hour values in construction production], in *16th Civil Engineering Technical Congress*, Ankara, Turkey 65: 22.
- Kuruoglu, M.; Bayoglu, F. I. 2002. Yapı üretiminde adam-saat değerlerinin belirlenmesi ve Bayındırlık Bakanlığı'nın değerlerine göre karşılaştırmalı değerlendirmesi, [Determination of man-hour values in construction production and comparison against the values of the Ministry of Public Works and Settlement], in *Civil Engineers Chamber, Istanbul Branch, Bulletin*, Istanbul, Turkey. 62 p.
- Leung, A. W. T.; Tam, C. M.; Liu, D. K. 2001. Comparative study of artificial neural networks and multiple regression analysis for predicting hoisting times of tower cranes, *Building and Environment* 36(4): 457–467. doi:10.1016/S0360-1323(00)00029-9
- Minsky, M. I.; Papert, S. 1987. *Perceptrons: An Introduction to Computational Geometry: Expanded Edition*. Cambridge, MA: MIT Press. 308 p.
- Moselhi, O.; Hegazy, T.; Fazio, P. 1991. Neural networks as tools in construction, *Journal of Construction Engineering and Management* ASCE 117(4): 606–625. doi:10.1061/(ASCE)0733-9364(1991)117:4(606)
- Ok, S. C.; Sinha, S. K. 2006. Construction equipment productivity estimation using artificial neural network model, *Construction Management and Economics* 24(10): 1029–1044. doi:10.1080/01446190600851033
- Plümecke, K. 2008. *Preisermittlung für Bauarbeiten* [Costs of Construction Works]. 26th ed. R. Mueller Verlag. 34 p.
- Portas, J.; AbouRizk, S. 1997. Neural network model for estimating construction productivity, *Journal of Construction Engineering and Management* ASCE 123(4): 399–410. doi:10.1061/(ASCE)0733-9364(1997)123:4(399)
- RS Means cost data. 2009 [online], [cited June 19, 2010]. Available from Internet: <<http://rsmeans.reedconstructiondata.com/>>.
- Schabowicz, K.; Hola, B. 2007. Mathematical-neural model for assessing productivity of earthmoving machinery, *Journal of Civil Engineering and Management* 13(1): 47–54.
- Schabowicz, K.; Hola, B. 2008. Application of artificial neural networks in predicting earthmoving machinery effectiveness ratios, *Archives of Civil and Mechanical Engineering* 8(4): 73–84.
- Sonmez, M. 2009. *Yapay Sinir Aglari Metodu ile Kalip İşlerinde bir Verimlilik ve Adam-Saat Tahmini Modeli* [A productivity and man-hour estimation model for formwork labor by artificial neural networks]. MSc thesis, Istanbul Kultur University, Institute of Sciences, Istanbul, Turkey. 125 p.
- Sonmez, R.; Rowings, J. E. 1998. Construction labor productivity modeling with neural networks, *Journal of Construction Engineering and Management* ASCE 124(6): 498–504. doi:10.1061/(ASCE)0733-9364(1998)124:6(498)
- Spon's Price Books. 2010 [online], [cited June 19, 2010]. Available from Internet: <www.tandfbuiltenvironment.com/pricebooks/series/Spon's_Price_Books>.
- Tam, C. M.; Tong, T. K. L.; Tse, S. L. 2004. Modelling hook times of mobile cranes using artificial neural networks, *Construction Management and Economics* 22(8): 839–849. doi:10.1080/0144619042000202771
- Turkish Ministry of Public Works and Settlement. 2010. Birim Fiyat Listesi 2010 [Unit Price List 2010]. Ankara, Turkey. 66 p.
- Veelenturf, L. P. J. 1995. *Analysis and applications of artificial neural networks*. Prentice Hall ACM, New York, USA. 368 p.
- Zayed, T. M. 2001. *Assessment of productivity for concrete bored pile construction*. PhD thesis. School of Civil Engineering, Purdue University, West Lafayette, India. 411 p.
- Zayed, T. M.; Halpin, D. W. 2004. Process versus data oriented techniques in pile construction productivity assessment, *Journal of Construction Engineering and Management* ASCE 130(4): 490–499. doi:10.1061/(ASCE)0733-9364(2004)130:4(490)
- Zayed, T. M.; Halpin, D. W. 2005. Pile construction productivity assessment, *Journal of Construction Engineering and Management* ASCE 131(6): 705–714. doi:10.1061/(ASCE)0733-9364(2005)131:6(705)
- Zurada, J. M. 1992. *Introduction to Artificial Neural Systems*. West Publishing Company, New York, USA. 19 p.

DIRBTINIŲ NEURONINIŲ TINKLŲ MODELIS, KURIO PASKIRTIS – SKAIČIUOTI KLOJINIAMS SKIRTO DARBO APIMTIS

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Santrauka

Dirbtiniai neuroniniai tinklai (DNT) – tai problemų sprendimo metodas, imituojantis pagrindinius žmogaus smegenų veiklos principus. Statant gelžbetoninius karkasinius pastatus, nemažą sąnaudų dalį sudaro klojinių ruošimas. Šiame tyrime siūlomas dirbtiniais neuroniniais tinklais pagrįstas metodas, kurio paskirtis – apskaičiuoti, kiek žmogaus darbo valandų reikės ruošti klojinius tokiuose pastatuose. Pristatomas metodas tyrimo metu patikrintas remiantis bandymu, susijusiu su dviem atvejo tyrimais. Visais atvejais modelio pateikti rezultatai buvo gana artimi faktiniams matavimams. Modelis – tai paprastas ir greitai naudojamas įrankis, kuris pravers sąmatininkams ir planuotojams.

Reikšminiai žodžiai: dirbtiniai neuroniniai tinklai (DNT), klojinys, darbas, sąnaudos, žmogaus darbo valanda, našumas.

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