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A Neuro-Adaptive Learning (NAL) Approach about Costs of Residential Buildings

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The artificial neural networks and fuzzy logic models are two well-known branches of artificial intelligence and have been broadly and successfully used to simulate input–output systems. Over the last two decades, a different modeling method based on fuzzy logic or neural networks has become popular and has been used by many researchers for a variety of engineering applications. Nowadays, for reducing the amount of experiment costs, modeling methods based on artificial neural networks and fuzzy logic systems have become more popular and have been used by many researchers for many civil engineering management applications. In this study a neuro-adaptive learning approach about costs of residential buildings was designed. As a result, NAL can be an alternative approach for the evaluation of the cost estimations of residential buildings construction.

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1. Introduction

Construction cost estimation for tendering is important for both tenders and bidders in construction projects and needs to be strictly complied with corresponding standards so that quantities and prices from different bidders are comparable [1]. Construction cost models in general reflect experiences unique to a construction organization for a certain project type [2]. Cost estimates are fundamental to all project-related engineering and greatly influence planning, design, bidding, cost management/budgeting and construction management [3]. Construction cost overrun is a common problem in construction industries [4]. Cost estimation techniques can be classified into qualitative and quantitative techniques [5]. Qualitative cost estimation techniques utilize past historical cost data and expert experience to subjectively estimate project costs [6]. Since relevant past historical information shares characteristics with the project to be estimated in terms of design, process, data, and knowledge, it can help in forecasting project costs [7]. Despite these shortcomings, qualitative assessments offer a useful reference for experienced users. In contrast, quantitative techniques not only rely on previous data and expert knowledge, but can also analyze project designs, processes, and distinctive attributes. Analytic methods are used to explore cost functions and the total costs of resources used in project activities (items) to determine the approximate project costs [7–20]. Although these techniques obtain estimates that closely approximate actual costs, they require time to gather sufficient data or obtain relevant information during initial project stages. Ibadov investigated duration and work costs of buildings in Polish market [21]. Once learning process has been completed, the results become available in real time [22].

In this study a neuro-adaptive learning (NAL) approach about costs of residential buildings was designed. Different reinforced concrete, multilayer, residential apartments projects some parameters used for the neuro-adaptive learning (NAL) fuzzy model as input data. A fuzzy logic model was designed for estimating of the costs of these buildings.

2. Application

At the beginning of study, 78 different reinforced concrete, multilayer, residential apartments projects were found and their quantities and costs have been calculated. After than these buildings some parameters; total apartments (TA), maximum high (Hmax), floor space (FS), front area (FA) and front blank surface (BS) used for the NAL fuzzy model as input data. One of them, actual cost (C), is used as output data. Some statistics values of these data are given below in Table I.

TABLE I

Statistic values of the data.

	Hmax [m]	TA	FS [m^2]	FA [m^2]	BS [m^2]	C [TL]
min	11	–125035	181	–4374	85	–141449
max	776721	52	158785	3724	1945155	3022523
med	16	18	432	821	381	690537

Data of 5 different apartments were allocated for testing the model. Then other 73 blocs' data were used for the model. The process, applied for making the model fuzzy, is conversion of all information given to the model as input, to a fuzzy structure by assigning a membership value to each of them. The conformity of handled membership functions during fuzzification process to the structure and aim of the problem is a point to be emphasized in terms of the success of the model. The developed model has 5 inputs and one output. Membership function parameters of inputs and output of the model are given in Fig. 1.

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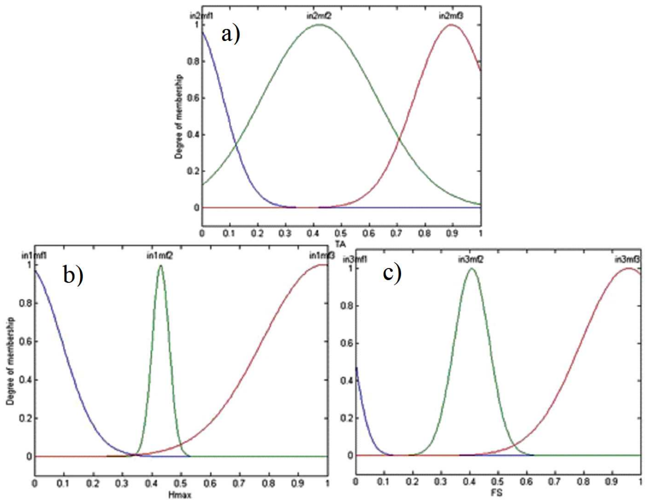

Fig. 1. Membership function of parameters (a) TA, (b) Hmax, (c) FS.

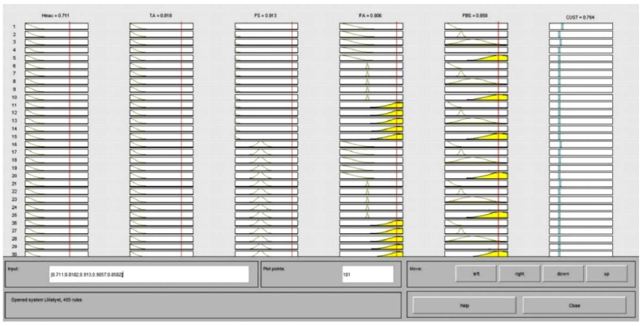

Fig. 2. Block diagram used for fuzzy modelling (rule base of ANFIS).

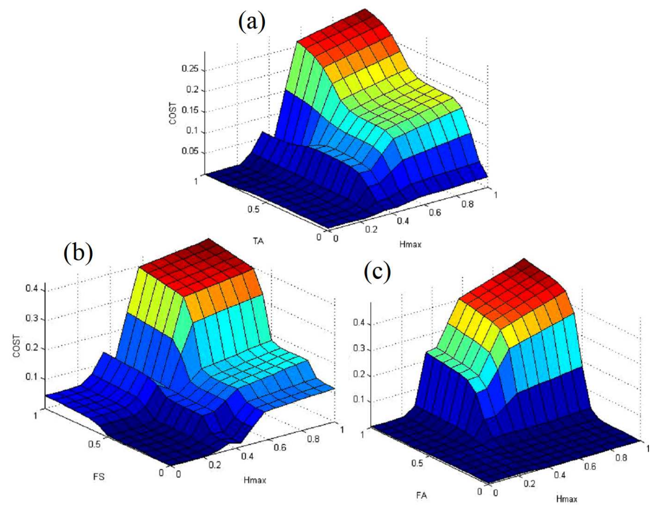

Fig. 3. Some inputs correlations with actual cost, (a) TA and Hmax, (b) FS and Hmax, (c) FA and Hmax.

The graphical demonstration of the contribution share percentage calculation of the fuzzy implication system of the model created is shown below. Block diagram (the rule base of ANFIS) used for NAL fuzzy modelling is given in Fig. 2.

In other literature studies obtained related with membership function selection, each function type is used in separate education data set so that the function type with the least error value was found to be suitable for the education of the established model. Some inputs correlations with AC are given in Fig. 3a–c.

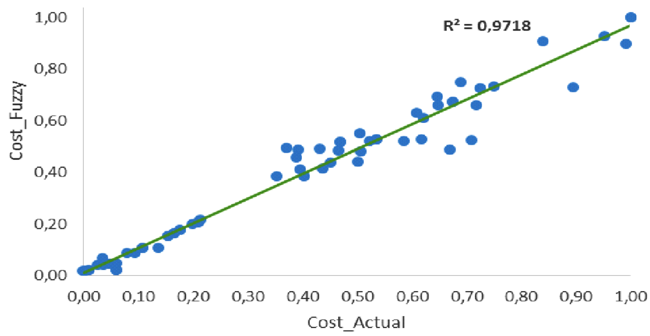

Fig. 4. NAL fuzzy model training results.

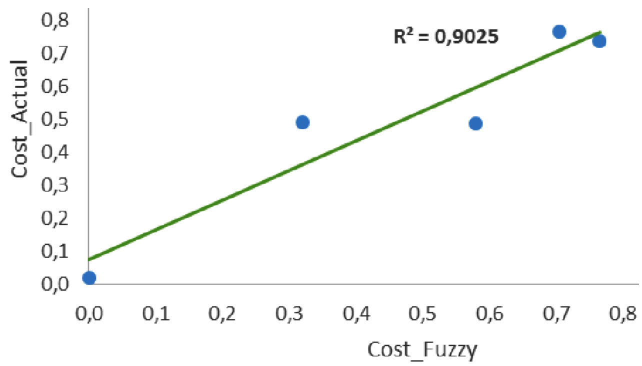

Fig. 5. NAL fuzzy model test results.

After the models learning has finished, a test was exerted with the 5 allocated apartments data. The NAL fuzzy model training and test results are given in Fig. 4 and Fig. 5. Their determination factors R^2 values are near the "1". This means both training and test results are acceptable to use.

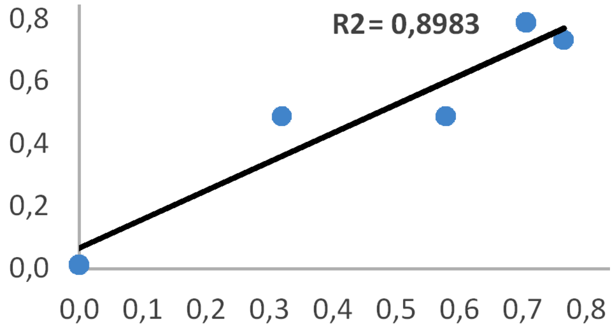

Fig. 6. Regression model test results.

For comparing the model success, a regression analysis (RA) has made. The result of this analysis is given in Fig. 6. It can be understood from Figs. 4–6 that determination factor value of fuzzy model is nearer than the regression model. This means that the fuzzy model, which was designed, is more achievable than the regression model.

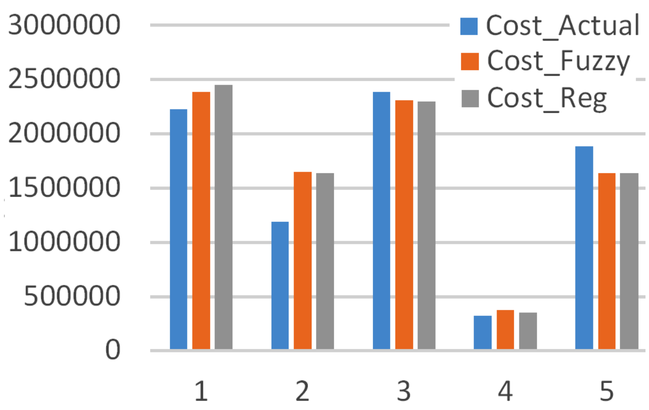

Fig. 7. Actual costs with fuzzy and regression models costs.

Figure 7 shows the actual costs (TL) and the estimates of both fuzzy and regression models.

3. Conclusions

The NAL fuzzy model training and test results' determination factors ($R^2 = 0.97$) values are near the "1". This means both training and test results are acceptable to use. For comparing the model success, a regression analysis (RA) has made. This model determination factor is $R^2 = 0.89$. Determination factor value of fuzzy model is nearer than the regression model. This means fuzzy model which was designed, is more achievable than the regression model. As a result, NAL can be an alternative approach for the evaluation of the cost estimations of residential buildings construction. NAL can be an alternative approach for the evaluation of the cost estimations of residential buildings construction. NAL are efficient for predicting the compressive evaluation of the cost estimations of residential buildings construction. Comparison between NAL and regression analysis in terms of R^2 showed that NAL provides better results than the RA.

As a result, it is considered that the fuzzy logic suggested in this study is a model that makes successful estimations and that the model estimations will be very close to real value in the future when control is realized with more sample data. This approach can also be used for controlling the approximation of the studies made for cost calculation to reality.

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