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AN ARTIFICIAL NEURAL NETWORK (ANN) MODEL PROPOSAL FOR COST MINIMIZATION AND COST ESTIMATION BASED ON BUILDING DIMENSIONS FOR REINFORCED CONCRETE DUPLEX VILLA IN PRELIMINARY DESIGN

Keywords: Design economics, Optimum structure dimensions, Artificial Neural Network (ANN), Regression Analysis (RA), Unit Price Based Cost (BFY)

Abstract

The primary aim of this study is to create connections / graphs showing the change of different design parameters and unit and average costs for reinforced concrete duplex houses. In this way, optimum cost-effective designs can be achieved. Another objective is to realize a cost estimation model based on a limited number of design parameters. Such a model will contribute to time and time savings in estimating low error rate cost to the preliminary design phase. Study; A model based on Artificial Neural Network (ANN) has been established for the purpose of preliminary estimation of the construction costs of 115 duplex villas. The data set, which was formed by using the existing data, was entered as data into ANNs structured in single and multi-layer, feed-forward, consultant learning features. These residential structures; basement floor areas, ground floor areas, first floor areas, building total areas, building heights, exterior façade areas, exterior façade areas, number of bathrooms, number of wc, number of kitchens, total wet areas, number of balconies, total balcony areas, rooms numbers and hall numbers were used as main evaluation criteria (input vectors) to the network. The cost values of each structure were used as output vectors. Learning, information storage and generalization features of this method; The performance of cost estimates in terms of proximity to reality is investigated. The solutions found by ANN are compared with Unit Price Based Cost (BFY) and Regression Analysis (RA) methods; error rates of cost

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estimates were evaluated. According to the results obtained, the estimated values obtained from the ANN created are closer to reality and applicable than the RA data. As a result of the study, it is understood that ANN modeling approach can be used successfully in the prediction stage of the costs of duplex reinforced concrete residential buildings. With the help of graphs showing the relationship between building dimensions and unit costs, optimum values were determined to reach minimum cost. These graphs can be utilized in the preliminary design phase of similar types of structures.

1. Introduction

Building design; It is the process of drawing a plan, section, appearance and perspective of a whole structure in accordance with the technical drawing rules. It is the process of establishing the relations between the various elements of a structure according to the building standards applied in the country concerned and showing it on a plan. In addition to meeting the necessary functions, building designs for different purposes must be economical. Besides the choice of style and material, one of the important factors that affect the economic structure of a building is its dimensions. In general terms; In order to realize a more economical structure, the size-cost researches made during the design and the design of the cheaper sized buildings determined as a result of these researches can be called as “design economy.. Determining different alternatives without determining the implementation decision and determining the costs of these alternatives is a study that has a first degree effect on project cost. In this study, it is vital to formulate data for the optimization of changes in the different parameters of the structure in question and to decide the dimensions of the structure. Unfortunately, there is not much data in this field. The primary aim of this study is to create connections / graphs showing the change of different design parameters and unit and average costs for reinforced concrete duplex houses. Another objective is to realize a prediction model based on a limited number of design parameters. Such a model will contribute to time and time savings in making low error rate cost estimates to the preliminary design phase.

Considering the intense competitive environment in the construction sector, it is clear that there is a need for fast and efficient methods that can be used by the technical personnel involved in planning and cost control. Various cost models have been developed in construction and production works. Cost models for various purposes are useful for planning, decision making and control issues [1].

The purpose of cost estimation is to define the cost required to provide the desired level of service or product by using the limited resources in the most effective way. Ensuring maximum productivity is possible through the accurate estimation of the costs required to complete the work in question and the effective management of the costs within the accepted cost limits [2].

Adequate estimation of construction costs is a key factor in construction projects [3].

The aim of cost estimating is to forecast, approximate, assess or calculate the probable cost of a project computed on the basis of available information. The process of cost estimating in the whole cycle of a construction project is a matter of high importance as the cost analyses form a basis for lots of decisions important for the success of a project. [4-6]

Both client/owners and constructors need to be informed in advance of the likely costs of construction work. For constructors, successful bidding is critical for survival and this depends to a large extent on estimates of project cost to the constructor [7].

Early stage (as calledpre-design) cost estimation is a crucial element of any construction project. The accurate estimation of the early cost will support the project managers in decision-making process. It allows the managers to choose adequate alternatives and to avoid misjudging of solutions. The cost of a construction project is impacted significantly by the decisions taken at the design phase. At this stage, designers use severel cost estimation methods and techniques for cost estimation at different phases of a project, including; traditional detailed breakdown cost estimation; simplified breakdown cost estimation; cost estimation per activity; cost estimation based on cost functions; index number estimate; expert systems [8].

The importance of decision making in cost estimation for building design processes points to a need for an estimation tool for both designers and project managers [9].

To support the complexity of the modern manufacturing environment it is vital that cost modeling under a collaborating network of companies is developed [10].

As project planners continue to move towards frameworks such as probabilistic life-cycle cost analysis to evaluate competing investments, there is a need to enhance the current cost-estimation approaches that underlie these models to enable improved project selection [11].

Understanding how the building design influences construction costs is a challenging task for estimators. Estimators must recognize the design conditions that affect construction costs and customize the cost estimate accordingly. Estimators have different preferences for how and when to adjust a project's activities, resources, and resource productivity rates that form the basis of a cost estimate. Current tools and methodologies lack ways to help estimators customize construction cost information according to their preferences and the particular features in a given design. Cost estimation is a typical example of a knowledgeintensive engineering task [12].

Practitioners and researchers have recognized theuncertainty of construction cost estimates and the need to improve the capability of cost prediction models[13]. Substantial efforts have been made to addressthis issue, and considerable conceptual cost predictionmodels are currently available in practice based on suchtechniques as probabilistic cost estimation, regression analysis, neural network (NN), fuzzy logic (FL), genetic algorithm (GA), and case-based reasoning (CBR). [14–16].

Nonparametric cost estimation in construction projects with the use of artificial networks is presented as suitable mainly for the early estimates. These conceptual estimates are based on the variables – namely cost predictors that characterize the project or a facility. Data gathered on the basis of completed projects are combined together and applied to the current project cost estimation process [17].

An accurate estimation of construction cost is crucial in construction projects for budgeting, planning, and monitoring for compliance with the client's available budget, time and workoutstanding. In cost estimation, the experience of the estimator and the project information are significant factors. Therefore, parametric cost estimation models are very useful in the early stage of a project's life cycle, when little information is known about the project's scope [18].

A cost estimation model based on the estimator's experience is required because this experience is reflected in the cost estimation process. Since the 1980s, with the greater appreciation of the benefits of user experience and increased research into the potential of artificial intelligence, new approaches to project cost estimation have been introduced [19].

Kim at all, used the construction cost data for 530 residential buildings constructed in Korea between 1997 and 2000 for training and evaluating the performance of their ANN model [20].

Siqueira [21] applied NNs for cost estimation of low-rise prefabricated structural steel buildings in Canada. The data were col-lected from 75 building projects over a 3-month period.

Günaydın and Doğan, investigated the utility of neural network methodology to overcome cost estimation problems in early phases of building design processes. Cost and design data from thirty projects were used for training and testing their neural network methodology with eight design parameters utilized in estimating the square meter cost of reinforced concrete structural systems of 4–8 storey residential buildings in Turkey, an average cost estimation accuracy of 93% was achieved [9].

Conceptual cost estimates, the basis of project evaluation, engineering design, cost budgeting, and cost management, not only play an essential role in construction project feasibility studies, but are fundamental to a project's ultimate success. As practiced today, construction cost estimates generally rely on experts' intuitive experience. Scientific methods should be developed and employed during project planning and design stages in order to raise conceptual cost estimate accuracy [22].

Regression analysis represents a traditional alternative [23-33], an inherent disadvantage of which is its requirement of a defined mathematical form for cost functions. In addition, traditional methods are hampered in estimating accurate project costs due to the large number of significant variables and the interactions thereof. Thus, traditional methods have limited applicability.

A cost model that provides effective cost control needs to have some features. Such a model; it should be appropriate for the process (s) to be used. The information to be entered into the model must be accurate and attained a certain level, it should be entered in time and updated to ensure that this information is not affected by the time factor. The model should be available to all groups (employer, construction company, subcontractor, etc.) [34]. The result of the cost estimate can be accurate, low, or high. Accurately calculated projects are the most economically realized projects, while low or high estimates lead to more spending [35].

When determining the cost of the land, the size of the building, planning adequacy, plan form, height, floor height, grouping of buildings, constructability, structural details, final arrangements in the building and so on. factors have a direct impact on the expenditure of any project and should not be overlooked during the economic assessment of the structure [36].

Artificial Intelligence and Artificial Neural Networks

Artificial intelligence science includes the studies aimed at learning computers based on human thinking structure. According to a wider definition, artificial intelligence; computer systems equipped with capacities specific to human intelligence such as information acquisition, perception, vision, thinking and decision-making [37].

Artificial intelligence, which tries to understand human thinking and to develop computer processes that will reveal the same; is the thought initiative of a programmed computer. According to a broader definition; computers equipped with capacities specific to human intelligence, such as thinking and decision-making [38].

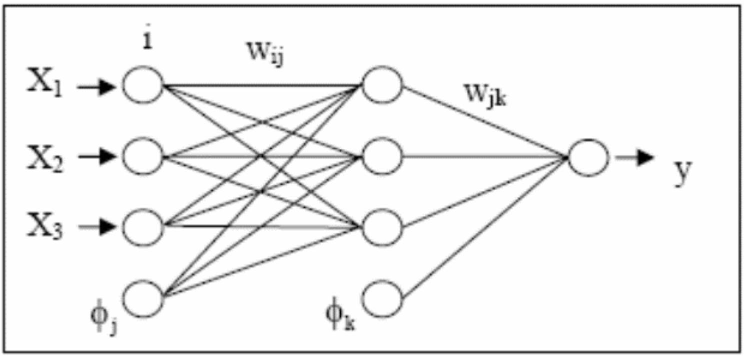
Artificial neural networks (ANNs), which are the sub-branches of artificial intelligence, are computer systems that are developed and inspired by the human brain. ANN was affected by the biological nervous system and showed us that computers can learn [39].

The basic philosophy of ANN is to learn the relationships between the inputs and outputs of the event using the actual examples about an event and to determine the outputs of the new samples that will be formed according to these relations.

ANN is a computer system developed to automatically realize the capabilities of the human brain such as learning, generating and discovering new information through learning without any assistance [39]. ANN can be defined as a computer program written for the purpose of a mathematical formula that enables the adaptation of parameters with the help of a set of samples [40]. Technically, the main task of an ANN is to determine an output set that can correspond to an input set shown to it. In order to do this, the network is given the ability to generalize by learning (learning) with examples of the relevant event. This generalization determines the output sets corresponding to similar events [39]. An artificial neural network consists of a plurality of interconnected artificial neural cells. Artificial nerve cells are a simple model of biological nerve cells [41].

Figure 1 shows a diagram of the structure of a simple artificial neural network. In the figure, the input values enter the processing element from the left. The first step in the process is to weight each of these input values with their respective weights w. A neuron usually receives a large number of inputs simultaneously. Each input has its own relative weight. These weights have the same function as the changing synaptic efficacy of biological neurons. In both cases, some inputs become more important than others. Thus, they are more effective in the process of generating a neural response of the processing element. In addition, weights are adaptive coefficients that determine the strength of the input signal. That is, a measure of the connection strength of the input. These connecting forces can be changed according to various training sets [42].

Fig. 1. Structure of Artificial Neural Networks



After weighting, these modified inputs are sent to the addition function. In the addition function, as the name implies, the addition process is generally performed. However, many different process types can be used for addition functions. In addition to the sum of these simple products, the addition function can be the minimum, maximum, mode, multiplication, or any of the various normalization operations. The algorithm that will combine the entries will usually depend on the selected network architecture. These functions can produce different values and then forward these values. In addition, the practitioner can create his own function and use it as a collection function. Some addition functions perform additional operations on the results before they are transmitted to the transfer function. This process is called the activation function. The purpose of using an activation function is to ensure that the output of the addition function changes over time [42].

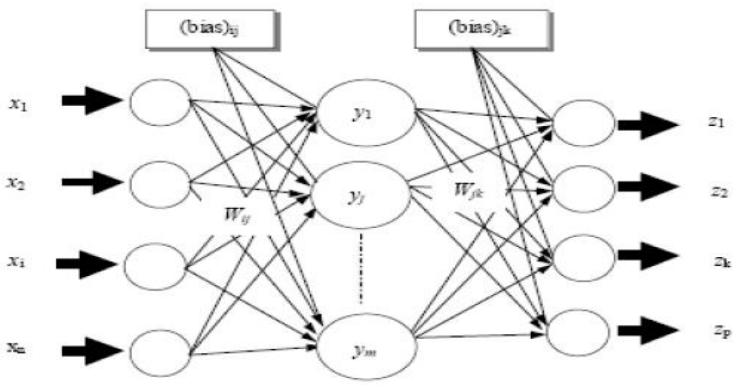
In the next step, the output of the summation function is sent to the transfer function. This function converts the value into an actual output with an algorithm. The transfer function is usually a nonlinear function. Linear functions are generally not preferred, because in linear functions the output is proportional to the input [43].

2. Method

In this study, it is aimed to estimate the cost of reinforced concrete duplex residential buildings by ANN and to obtain data for cost minimization during the preliminary design phase. For this purpose, construction costs of similar two-storey villa projects with reinforced concrete bearing system were calculated. Basement floor areas, ground floor areas, 1st floor areas, building total areas, building heights, facade areas, exterior space areas, bathroom numbers, wc numbers, kitchen numbers, total wet space areas, balcony numbers determined on the projects of these buildings, the total balcony areas, the number of rooms and the number of living rooms consisting of single and multi-layer, feedback, advisory learning features are entered as ANN data (input vectors). Each project's construction cost, "the Republic of Turkey Ministry of Environment and Şahircilik Unit Price Fair 2016" is calculated on the basis of the output vector is introduced as a network.

In the network architecture given in the example of ANN in Figure 2, instead of x1, x2, … xn entries; basement floor areas, ground floor areas, 1st floor areas, building total areas, building heights, exterior façade areas, exterior façade areas, bathroom numbers, wc numbers, kitchen numbers, total wet area areas, balcony numbers, total balcony areas, room numbers and hall numbers are entered. The unit cost-based construction cost values of each project have been entered in response to the Zi values that constitute the outputs of the network.

Fig. 2. Back-spread network architecture with a single hidden layer [42].



It is expected that the consultant learning process carried out in ANN will show the project data allocated for testing to the network and estimate the output vector. The cost estimates were compared with the unit price based estimation method and regression analysis and the performance of ANN method was evaluated. Neural Power and Neural Designer programs were used to create the network. SPSS program was used for regression analysis. According to the results obtained, the usability of ANN was evaluated and the closeness of the cost values to the truth was interpreted according to the results.

Creating Data Set

Basement floor areas (m2), ground floor areas (m2), 1st Floor areas (m2), total building areas (m2), building heights (m), exterior areas (m2), exterior space areas determined over the projects of the buildings (m2), bathroom numbers (pcs), wc numbers (pcs), kitchen numbers (pcs), total wet area areas (m2), balcony numbers (pcs), total balcony areas (m2), room numbers and number of halls (pcs) and the single and multi-layered, feedback, advisory learning features. The costs of each project, calculated on the basis of 2016 Unit Price Values, have been entered in the network as an output vector. The data set obtained from the projects belongs to 115 duplex villas. 105 of these data were used for networking and training; 10 of them were separated as control group.

Following the teaching process, the data allocated for the test with the same characteristics were entered into ANN and cost estimates of these test data were made. These estimates were compared with the cost estimations made by Unit Price Method and Regression Analysis method and the performance of ANN method was evaluated.

In addition, graphs showing the variation of average costs with each input vector (structure dimension feature) were obtained. Each graph was evaluated and determinations were made for optimum dimensions.

3. Application

Different network structures corresponding to different versions of variables such as number of intermediate layers, network function, learning algorithm, momentum coefficient, stop criterion have been formed. Trial and error procedures were applied on these network structures and their performance was evaluated.

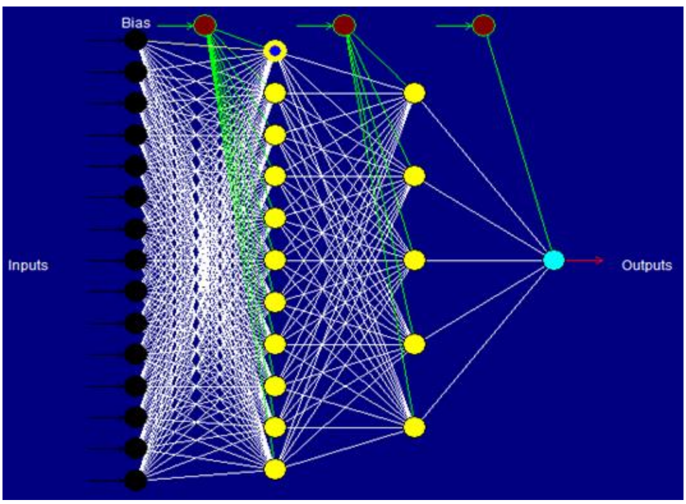
With the help of the control group; The results have been selected from those with the lowest characteristic and predicted error rates. The data for these networks are shown in Table 1.

Table 1. Artificial neural network average (%) error rates

				(%) Error			
Number of samples	A	B	C	D	E	F	G
1	97.08	98.35	90.85	-8.26	98.70	98.52	90.86
2	29.61	31.83	29.82	-6.74	34.48	28.78	30.13
3	71.84	71.52	71.21	-0.44	72.98	71.20	70.66
4	16.51	18.67	21.20	11.91	18.95	17.76	17.67
5	-30.94	-28.79	-30.16	4.56	-26.18	-29.42	-30.56
6	-12.80	-10.79	-17.02	36.61	-10.36	-12.54	-12.18
7	-15.19	-6.99	-12.47	43.98	-3.45	-8.92	-12.93
8	-12.92	-11.99	-15.71	23.64	-12.24	-8.15	-11.86
9	68.17	68.86	68.53	-0.48	68.16	68.26	68.12
10	-97.79	-111.20	-84.74	-31.23	-97.79	-101.29	-84.46
Mean Error	**11.36**	11.95	12.15	13.71	14.33	12.42	12.55

The most suitable performance (error rate 11.36%) and the network structure (A) which is the basis for the study is given in Figure 3.

Fig. 3. Network architecture and connection ranges used



Importance Degrees of Input Vector Parameters

One of the data obtained as a result of the analysis of ANN calculations is the graphical expression of the significance of the input parameters. In the graph in Figure 4.16., the biggest weight value is 21.07 with basement floor area while calculating the building cost, followed by the number of bathrooms, number of halls, number of rooms and exterior area respectively. The number of kitchens, the number of WCs, the ground floor area, the total building area and the total wet area area affect the weight values close to each other. The height of the building, total area of the building, exterior space area, first floor area and number of balconies are followed. Table 2 lists the values of the input vector parameters.

Table 2. Values of input vector parameters

Input items	İmportance (%)
Basement floor area	21.07
Number of balconies	11.01
Number of halls	10.13
Number of rooms	7.565
Exterior area	6.988
Number of kitchens	5.728
Number of WC	5.099
Ground floor area	5.091
Total building area	5.078
Total wet space area	5.072
Building height	4.967
Building Total Area	4.871
Exterior cavity space	3.135
1st floor area	2.789
Number of bathrooms	1.408

Accordingly, the effect of the basement floor area on the unit cost of construction corresponds to 21.07%. It can be concluded from here that the input parameter that affects building unit cost the most is the basement floor area.

The data of the regression equation was calculated based on the results of the Regression Analysis applied to the same data in order to test the results of ANN method.

Table 3. Regression equation coefficients

Constant	-25868,299
Basement floor area	-997,375
Ground floor area	-551,190
Firs floor erea	-750,854
Building Total Area	934,871
Building height	5746,619
Exterior area	233,124
Exterior space	66,153
Number of bathrooms	2903,177
Number of WC	15550,332
Number of kitchens	-16727,472
Total wet space area	-56,566
Number of balconies	-1866,246
Total balcony area	844,150
Number of rooms	-5586,261
Number of halls	26842,847

The performance of multiple linear regression equation based on these data; the same control group data (See Table 4.). Error rates are calculated for each duplex villa. The average of these error rates is given in the last line.

Table 4. Cost Estimation Results with Regression Analysis

Test No	**Cost estimate**	**Actual cost**	**Disparity**	**Error (%)**
1	356077.322	316492.7	39584.59	11.12
2	365213.796	238735	126478.8	34.63
3	719705.599	541164	178541.6	24.81
4	314269.412	321260.3	-6990.92	-2.22
5	300804.228	188254	112550.2	37.42

Test No	**Cost estimate**	**Actual cost**	**Disparity**	**Error (%)**
6	308109.569	237204.6	70905.02	23.01
7	273033.548	170070.1	102963.5	37.71
8	353024.09	183120.2	169903.9	48.13
9	404902.418	531215	-126313	-31.20
10	277993.389	117000	160993.4	57.91
Average error				**%24.13**

The error rates for the examples are given in Table 4. The arithmetic mean of these values corresponds to 24.13%. Although the average error value seems to be low, the fact that the error value of sample 10 is slightly more than 2 times the average error value has a decreasing effect on the reliability of the results obtained with this method.

The value of R = 0.687 among the data of the regression analysis indicates that the calculation can be used, and R2 = 0.472 indicates that fifteen input vectors are made using a 47.2% of all factors affecting the cost of construction. This value obtained by determination coefficient; the data set itself does not achieve the desired level of compliance, or that increasing the number of data may contribute to lower errors.

According to these findings, modeling with ANN is more reliable than the error rate of 24.13%, which is 11.36% error rate and regression analysis.

4. Findings about Optimum Buildıng Dimensions

As a result of the studies, the effect of each input parameter on the total structure unit cost was determined with the help of graphs. The information obtained is as follows. (In the graphs, unit costs are vertical; structure dimension parameters are shown on horizontal axes.)

Relationship between basement floor area and building unit (m2) cost

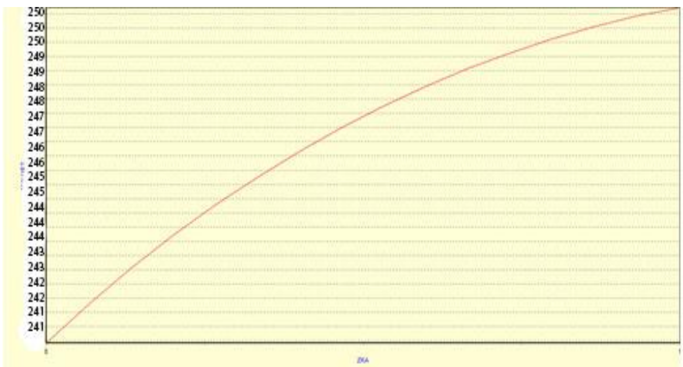
Figure 4 shows the relationship between basement floor area and building unit (m2) cost. The cost of the building, which initially showed a linear increase with the increase of the basement floor area, decreased after 67.63 m2. While the basement area is 67.63 m2, it can be inferred that the maximum unit cost will be.

Fig. 4. The relationship between the basement floor area and the building unit (m^2) cost

Relationship between ground floor area and building unit (m^2) cost

Figure 5 shows the change in the cost of building unit (m2) with the increase of the ground floor area. 52.40 m2 to 280 m2 unit (m2) values received by the costs are as shown in the figure. From this, it can be inferred that in general the ground floor area and unit (m2) costs have increased very close to linear.

Fig. 5. The relationship between ground floor area and cost of building unit (m^2)



Relationship between first floor area and building unit (m^2) cost

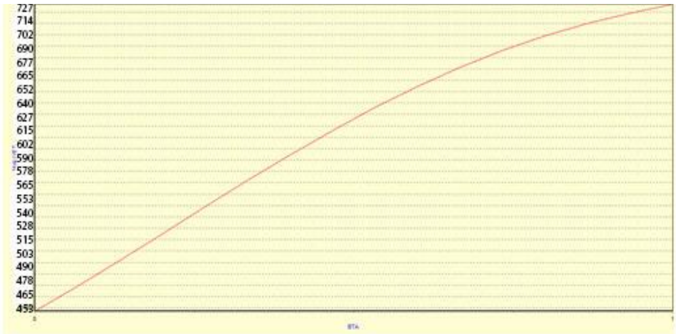
Figure 6 shows the change in the cost of building unit (m2) with the increase of the first floor area. When the values taken by the costs are examined for first floor areas ranging from 50 m2 to 280 m2; While a linear increase is observed between 50 - 198.24 m2 values, it is understood that the cost increases of the structural unit (m2) corresponding to the increase of the first floor area after 198.24 m2 show a curvilinear structure with a slightly lower slope. From this, it can be inferred that the cost of the first floor area and building unit (m2) generally increases very close to linear.

Fig. 6. The relationship between the cost of the first floor area and the building unit (m^2)

Relationship between total building area and building unit (m^2) cost

Figure 7 shows the change in the cost of building unit (m2) with the increase of the first floor area. When the values taken by building unit (m2) costs compared to the total area of buildings ranging from 104.42 m2 to 726.93 m2; While a linear increase was observed between 104.42 and 468 m2, it is understood that the cost increases corresponding to the first floor area increase after 468 m2 show a curved structure with a slightly lower slope. From this, it can be inferred that the overall total area of the building and the cost of the building unit (m2) are very close to linear.

Fig. 7. The relationship between the total area of the building and the cost of the building unit (m^2)



Relationship between building height and building unit (m^2) cost

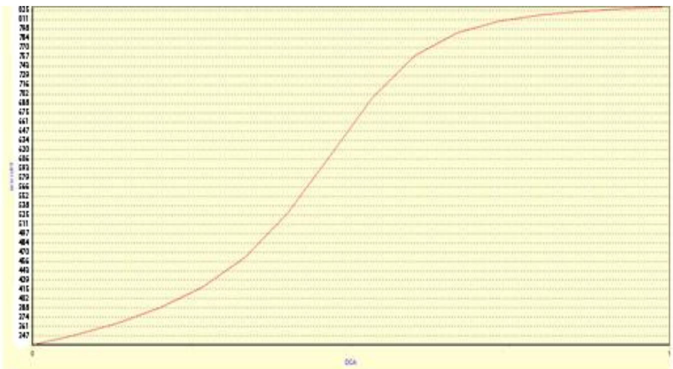
Figure 8 shows the relationship between building height and building unit (m2) cost. Initially, as the building height increases, the cost of building unit (m2), which is close to linear, increases with a decrease after 8.40 m. Therefore, it can be said that the building will have the highest unit cost at 8.40 m. In architectural designs where it is more than 8.40 m, it can be determined that lower unit costs will be approached and the increase in building height more than 9.98 m will decrease the effect on unit costs. According to this graph, the building height value of 9.98 m corresponds to the most expensive unit cost.

Fig. 8. The relationship between building height and cost of building unit (m^2)

The relationship between exterior area and building unit (m^2) cost

In Figure 9, the relation between the exterior area and the cost of the building unit (m2) is given. Initially, with the increase of the façade area, the cost value of the building unit (m2), which is close to linear, increases and decreases after a certain value. Therefore, it can be determined that in architectural designs where the exterior area is 441.86 m2 and more, lower unit costs will be approached and the increase of exterior area more than 524.29 m2 will decrease the effect on unit costs.

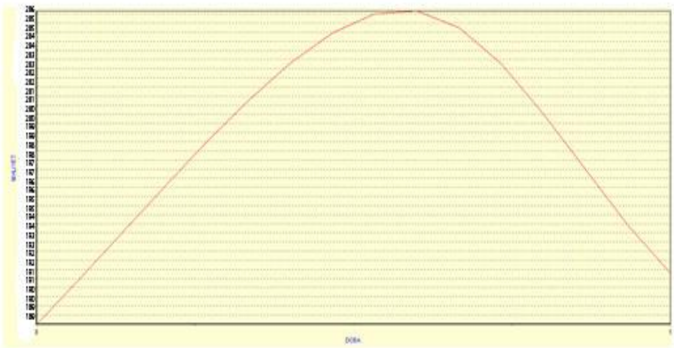
Fig. 9. The relationship between the external facade area and the cost of building unit (m^2)



Relationship between external cavity area and building unit (m^2) cost

Figure 10 shows the relationship between the external cavity area and the cost of the building unit (m2). The cost of the building unit (m2) increases linearly up to 101.63 m2 with the increase of the outer cavity area. After this value, the cost of the building unit (m2) decreases with the increase of the façade space. Based on these data, it can be stated that the cost of building unit (m2) will be lower after 101.63 m2. The exterior area of 101.63 m2 corresponds to the most expensive unit cost.

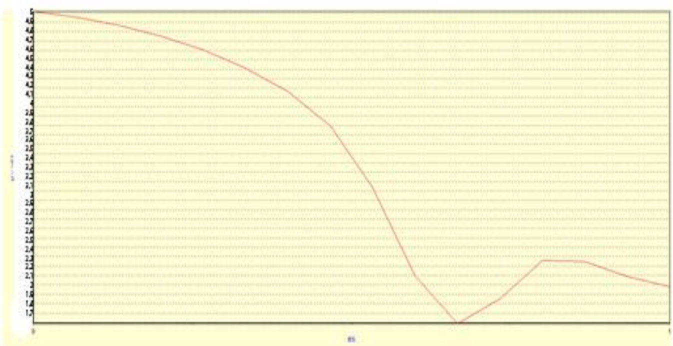
Fig. 10. The relationship between the external space and the cost of the building unit (m^2)



Relationship between the number of bathrooms and the cost of building units (m^2)

Figure 11 shows the relationship between the number of bathrooms and the cost of building units (m2). As the number of bathrooms increases to a certain value, the building cost decreases, after a certain value the building cost increases and then decreases again. When these data are taken into consideration, it can be said that the cost of building 4 units (m2) will be in the optimum direction.

Fig. 11. The relationship between the number of bathrooms and the building unit (m^2)



The relationship between the number of WC and the cost of building unit (m^2)

Figure 12 shows the relationship between the number of wc and the cost per unit (m2). As the number of wc increases, it can be said that the cost of the building unit (m2) will increase linearly. It can be said that the construction of 1-2 wc for the building would be ideal in terms of the cost of building unit (m2).

Fig. 12. The relationship between the number of WCs and the cost of building units (m^2)

The relationship between the number of kitchens and the cost of building units (m^2)

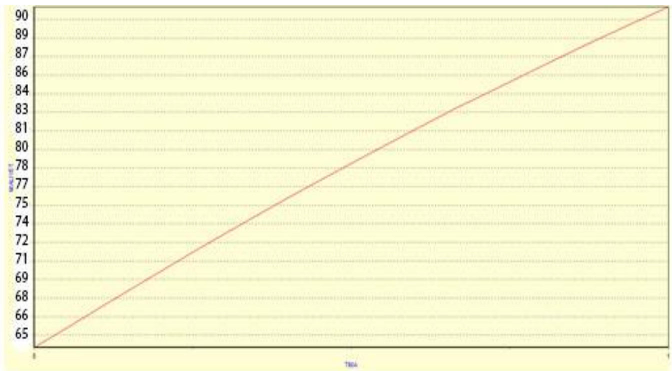
Figure 13 shows the relationship between the number of kitchens and the cost of building units (m2). While the cost decreases to a certain value of the number of kitchens, after a certain value, the building cost increases and then decreases again. When these values are taken into consideration, it can be stated that the construction of one kitchen in the building would correspond to the value of the optimum unit cost of building (m2).

Fig. 13. The relationship between the number of kitchens and the cost of building units (m^2)

Relation between total wet area area and building unit (m^2) cost

Figure 14 shows the relationship between the total wet area area and the cost per unit (m2). The value of the cost per unit unit (m2) increases linearly with the increase of the total wet area area between 4 m2 and 152.71 m2. From this it can be inferred that the total wet area area and construction unit (m2) cost increases linearly.

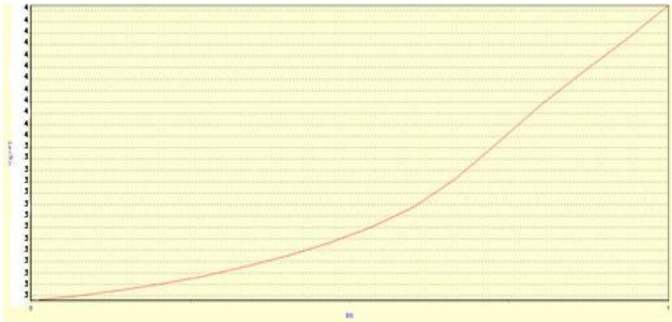
Fig. 14. The relationship between the total wet space area and the cost of the building unit (m2)



The relationship between the number of balconies and the cost of building units (m^2)

Figure 15 shows the relationship between the number of balconies and the cost of building units (m2). With the increase in the number of balconies, it can be inferred that the cost of building units (m2) also increases. Considering these data, it can be said that having a balcony in the building is the most economical in terms of cost.

Fig. 15. The relationship between the number of balconies and the cost of building units (m2)



Relationship between total balcony area and building unit (m²) cost

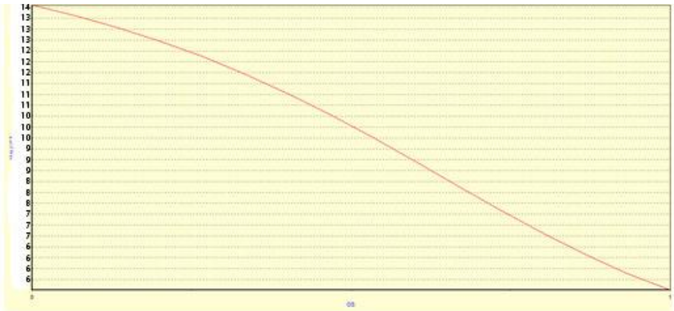
Figure 16 shows the relationship between the total balcony area and the cost of the building unit (m2). The graph increases linearly to 74 m2 and then parabolically decreases and increases again after 44.50 m2. Taking these data into consideration, it can be stated that the balcony area will take the value of optimum building unit (m2) cost at 44.50 m2.

Fig. 16. The relationship between the total balcony area and the cost of the building unit (m2)

The relationship between the number of rooms and the cost of building units (m²)

Figure 17 shows the relationship between the number of rooms and the cost of building units (m2). As the number of rooms in the building increases, the cost of the building unit (m2) decreases in a linear manner. Based on these data, the ideal number of rooms is between 3 and 5.

Fig. 17. The relationship between the number of rooms and the cost of building units (m²)



Relationship between the number of halls and the cost of building units (m²)

Figure 18 shows the relationship between the number of halls and the cost of building units (m2). Building unit (m2) cost up to a certain value of the number of halls shows a linear increase. The cost of the building unit (m2) will increase as the number of halls decreases at a certain value and then increases. Based on these data, the construction of 2 halls is the most optimal value in terms of unit cost.

Fig. 18. The relationship between the number of halls and the cost of building units (m²)

In the preliminary design stage, it is possible to reach the optimum cost dimensions by making use of the above data.

5. Conclusions and recommendations

It is understood that ANN can make cost estimation with less errors according to Regression Analysis. (11.36% <24.13%). According to these data, since the RA data is more than 2 times the average error value of ANN data, data can be estimated with ANN.

The process of preparing the data used in both ANN method and Regression Analysis is the same. In the artificial neural network approach, the input and output parameters can be shown to the network at one time and the network is expected to learn the relationship between these parameters. However, in the Regression Analysis, the relationship of each output parameter with the input set must be determined separately. When the methods used were examined from this point of view, it was seen that the time spent for tests and result evaluation was much more at the end of the Multiple Linear Regression Analysis.

It has been demonstrated that ANN approach for cost estimation can be used as a fast and efficient method in the pre-design phase of construction projects.The results obtained in this study show that the continuation of similar studies in this field will provide positive returns.

Similar cost estimation studies in this direction will result in more realistic and lower error results by using different network architectures and adding different input parameters. However, determination of the most appropriate and useful one is possible with the knowledge and experience of the accountants. The higher the amount of data used in the application of the Artificial Neural Network method, the higher the quality of modeling will be. The number of samples used in this study is of a certain limit value and further studies with more samples will be beneficial in achieving more qualified results.

Increasing the number of ANN simulation softwares, not having high license fees, having the opportunity to make transactions easily and quickly with personal computers in cases where there is not much data and not having complexity, there are positive points in using this method and more specific purpose software may be needed for strengthening the hardware. Efforts should be made to achieve optimum building dimensions with similar optimization studies to be carried out during the preliminary design phase of construction projects. The primary priority in architectural design should not be in the economy; integrated models should be developed in which function and aesthetics are taken into consideration.

References

1. Uğur, L.O. (2007), “Analysis of building costs with artificial neural networks” Gazi University, Institute of Science and Technology, Ph.D. Thesis, Ankara.
2. (Steaward, 1992).

3. Gwang-Hee Kim, Sung-Hoon An, Kyung-In Kang, Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning, Building and Environment 39 (2004) 1235 – 1242
4. P.M.M. Foussier: From Product Description to Cost: A Practical Approach, vol. 1: The Parametric Approach, Springer, Berlin, 2006.
5. A. Layer, E.T. Brine, F. Van Houten, H. Kals, S. Haasis: Recent and future trends in cost estimation, International Journal of Computer Integrated Manufacturing, 15 (6) (2002) 499–510.
6. R.D. Stewart, R.M. Wyskida: Cost Estimator's Reference Manual, Wiley, New York, 1987.
7. Skitmore, R.M. (1989) Contract Bidding in Construction: Strategic Management and Modelling. Longman Scientific and Technical, Harlow, Essex.
8. Mohammed Arafa, Mamoun Alqedra, Early Stage Cost Estimation of Buildings Construction Projects using Artificial Neural Networks, Journal of Artificial Intelligence 4 (1): 63-75, 2011
9. H. Murat Günaydın, S. Zeynep Doğan, A neural network approach for early cost estimation of structural systems of buildings, International Journal of Project Management 22 (2004) 595–602
10. Qing Wang, Artificial neural networks as cost engineering methods in a collaborative manufacturing environment, Int. J. Production Economics 109 (2007) 53–64
11. Omar Swei, Jeremy Gregory, Randolph Kirchain, Construction cost estimation: A parametric approach for better estimates of expected cost and variation, Transportation Research Part B 101 (2017) 295–305
12. Sheryl Staub-Frencha, Martin Fischer, John Kunzc, Boyd Paulson, A generic feature-driven activity-based cost estimation process, Advanced Engineering Informatics 17 (2003) 23–39
13. K. Bala, S.A. Mustani, B.S. Waziri, A computer-based cost pre-diction model for institutional building projects in Nigeria, J. Eng.Des. Technol. 12 (4) (2014) 518–529.
14. R. Sonmez, Review of conceptual cost modeling techniques,AACE Int. Trans. (2005) EST.07.1–EST.07.4.
15. G.-H. Kim, S.-H. An, K.-I. Kang, Comparison of construc-tion cost estimating models based on regression analysis, neuralnetworks, and case-based reasoning, Build. Environ. 39 (10)(2004) 1235–1242.
16. R. Sonmez, Conceptual cost estimation of building projects withregression analysis and neural networks, Can. J. Civil Eng. 31 (4)(2004) 677–683.

17. Michał Juszczyk, The Challenges of Nonparametric Cost Estimation of Construction Works With the Use of Artificial Intelligence Tools, Procedia Engineering 196 (2017) 415 – 422
18. Hegazy T, Ayed A. Neural networkmodel for parametric cost estimation of highway projects. Journal of Construction Engineering and Management 1998;124(3):210–8.
19. Khosrowshahi F, Kaka AP. Estimation of project total cost and duration for housing projects in the UK. Building and Environment, 1996;31(4):373–83.
20. Gwang-Hee Kim, Jie-Eon Yoon, Sung-Hoon An, Hun-Hee Cho, Kyung-In Kang, Neural networkmodel incorporating a genetic algorithm in estimating construction costs, Building and Environment 39 (2004) 1333 – 1340
21. I. Siqueira, Neural Network-based Cost Estimating (Master the-sis), Concordia University, 1999.
22. Min-Yuan Cheng, Hsing-Chih Tsai, Wen-Shan Hsieh, Web-based conceptual cost estimates for construction projects using Evolutionary Fuzzy Neural Inference Model, Automation in Construction 18 (2009) 164–172
23. P.A. Bowen, P.J. Edwards, Cost modeling and price forecasting; practice and theory in perspective, Construction Management and Economics 3 (1985) 199–215.
24. M.Y. Cheng, C.H. Ko, Computer-aided decision support system for hillside safety monitoring, Automation in Construction 11 (4) (2002) 453–466.
25. M.Y. Cheng, C.H. Ko, Object-oriented evolutionary fuzzy neural inference system for construction management, Journal of Construction Engineering and Management 129 (4) (2003) 461–469.
26. M. Gen, R. Cheng, Genetic Algorithms and Engineering Design, Wiley, New York, 1997.
27. H. Ghezelayagh, K.Y. Lee, Training neuro-fuzzy boiler identifier with genetic algorithm and error back-propagation, IEEE Power Engineering Society 2 (1999) 978–982.
28. M.B. Gorzalczany, P. Gradzki, A neuro-fuzzy-genetic classifier for technical applications, Proceedings of IEEE International Conference on Industrial Technology 1 (2000) 503–508.
29. I. Hayashi, M. Umano, T. Maeda, A. Bastian, L.C. Jain, Acquisition of fuzzy knowledge by NN and GA, IEEE International Conference on Knowledge-based Intelligent Electronic Systems, 1998, pp. 69–78.

30. S. Haykin, Neural Networks: A Comprehensive Foundation, Prentice-Hall, New York, 1999.
31. T. Hegazy, A. Ayed, Neural network model for parametric cost estimation of highway projects, Journal of Construction Engineering and Management 124 (3) (1998) 210–218.
32. J.H. Holland, Adaptation in Neural and Artificial Systems, The University of Michigan Press, Ann Arbor, 1975.
33. I. Jagielska, C. Matthews, T. Whitfort, An investigation into the application of neural networks, fuzzy logic, genetic algorithms, and rough sets to automated knowledge acquisition for classification problems, Neurocomputing 24 (1–3) (1999) 37–54.
34. Akınbingöl, M. ve Gültekin, A.T., (2005), “A Cost Management Model for Cost Planning And Control in the Building Production Phase ”Gazi University, Faculty of Engineering and Architecture Journal, vol.: 20, no: 4, pp: 449-505.
35. Phaobunjong, K., (2002), “Parametric cost estimating model for conceptual estimating of building construction projeckts, Fakulty of Graduate School of Texas at Austin, USA.
36. Ashworth, A. (1999), Cost Studies of Buildings, Longman Scientific & Technical, Harlow, p. 14, England.
37. Elmas, Ç., (2007), “Artificial Intelligence Applications”, Seçkin Yayıncılık, Ankara.
38. (Altuntaş vd. 1998).
39. Öztemel, Ercan., (2006), ““Artificial Intelligence” Papatya Yayıncılık, İstanbul.
40. Güneş, M., “Estimation of Lake Water Levels with Artificial Neural Network-Wavelet Model of Sultan Sazlığı”, Master Thesis, Erciyes University, Institute of Science and Technology, Kayseri, 81s, 2010.
41. Baş, N., (2006), “Artificial Neural Network Approach and an Application” Mimar Sinan Fine Arts University, Graduate School of Natural and Applied Sciences, Master Thesis, İstanbul.
42. Yurtoğlu, E., "Forecasting with artificial neural network modeling methodology: in Turkey for some macroeconomic variables", Thesis, State Planning Organization, General Directorate of Economic Modeling and Strategic Research, Ankara, 3-43 (2005).
43. (Minsky M., Papert, S. “Perceptrons” MIT Press, Cambridge, 231-232 (1969).