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A Final Cost Estimating Model for Building Renovation Projects

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Abstract: The construction sector in Greece has been developing radically in the field of building renovations. The foremost problem for projects in the building construction industry is producing an accurate and reliable cost estimate at the onset of construction. The artificial neural network (ANN) approach, using data available at the early stages of the project, can help resolve or prevent any kind of difficulty that could make the successful completion of a building less likely. ANNs have been highly efficient in gaining results which could prevent the failure of building constructions projects. The ultimate goal is to highlight the usefulness of the adoption of ANNs models to predict the final cost of a building renovation project. Thus, construction companies could avoid financial failure, provided that the gap between cost prediction and final cost for renovation projects is minimized. This paper presents an artificial neural network (ANN) approach for predicting renovation costs in Greek construction projects. The study, based on a comprehensive literature review and real renovation data from construction companies, employs IBM SPSS Statistics software to build, train, and test the ANN model. The model, which uses initial cost, estimated time, and initial demolition cost as inputs, is based on the radial basis function procedure. The model presents high performance with up to 2% sum of squares error and near zero relative error, demonstrating the ANN's effectiveness in estimating total renovation costs.

Keywords: artificial neural network models; ANN; cost prediction models; cost estimation; building construction projects; building renovation projects

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1. Introduction

Construction projects always differ from manufacturing initiatives. Consequently, there are always risks and unknowns when estimating building costs [1–3]. Cost projection is additionally made difficult by the absence of a trustworthy database of building costs, as well as the contractors' reluctance to supply accurate cost information.

Additionally, each country has a distinct legal structure for project procurement and payment processes [4] which are typically based on insufficient budget estimation techniques.

As found by Antoniou et al. [4], on a global level, researchers have delved deeply into providing scientifically based construction cost estimate models for a variety of projects such as buildings, transportation infrastructure (roads, bridges, tunnels, metro stations), and utility and power networks. In their thorough analysis of the literature, they also demonstrated that the most popular techniques used in recent years for the creation of cost prediction models include linear regression (LR), Gaussian process regression (GPR), artificial neural networks (ANNs), support vector machines (SVMs), gradient boosting machines (GBMs), and building information modeling (BIM).

To help in this respect, researchers in Greece have attempted to collect data from infrastructure procurement authorities to provide cost estimation tools to public authorities during their initial funding seeking stages. By taking advantage of the abundance of material quantity and unit cost data available to the researchers from the Egnatia Motorway, a major European Union (EU)-funded motorway project, cost estimate models using both ANNs and LR have been provided to researchers and practitioners [5–7]. The independent variables in these studies were the ground conditions, the overburden height and the cross-section area for tunnels and deck width, deck length, pier height, and theoretical volume for bridges, and finally net width, net height, and the height of the overburden for culvert construction costs.

Trying to secure construction companies' prosperity, many researchers developed models using artificial neural networks (ANNs) which are a subset of the artificial intelligence (AI) field. Due to their demonstrated accuracy and effectiveness in control, estimation, optimization, decision making, and numerous other applications, ANNs are the most prevalent and widely used AI technology. They have the potential to be used to accelerate sustainable development in the construction industry. A wide range of ANN technique applications have been shown by Ahmed et al. [8] to assist the construction industry's sustainable growth. It may be stated that a comprehensive research strategy using information from all construction stages and industry segments is required for the sustainable growth of the construction sector.

The purpose of this paper is to introduce an ANN-based tool for cost prediction aimed at building renovation projects in Greece since, following an extensive literature review, it was found that, to the best of the authors knowledge, no such models exist.

The lack of an established model emphasizes the necessity of an innovative approach. The goal is to provide reliable cost estimates to support management decisions in the process of building renovations. There is not an available model to predict the final cost of building renovation projects; therefore, a new model will be introduced to predict the final cost. In order to develop such a cost estimation model, data should be gathered from previous renovation initiatives. By taking into account past project data, ANN models are able to produce forecasts that are more accurate since they are able to recognize patterns and connections. Even in the early stages of a project, they can adjust when there are few project details available. Adequate use of data, model training, and model validation are required when introducing an ANN model to estimate renovations costs. After an ANN model's implementation and identification, the optimum model could benefit contractors and engineers by making realistic predictions. There is currently no such model based on a specific group of work packages.

To contribute to this gap in scientific research, a significant dataset of actual project cost data was gathered from a Greek contractor engaged in building renovations. The acquired data were categorized, analyzed, and appropriately encoded for the creation of ANN models for cost prediction. To develop, train, and test the network, IBM SPSS Statistics software 28.0.0.0, was implemented. The final cost is the dependent variable. The independent variables include initial renovation cost estimate (tender offer), contractual duration, and estimated initial demolition cost as defined by the contract. The procedure followed is the radial basis function. The model's performance during training and testing was evaluated and discussed, showing high effectiveness with up to 2% sum of squares error and nearly 0% relative error in the training sample, which is almost 70% of the whole sample. Thus, it has been demonstrated that ANNs are a highly effective method for estimating overall cost, particularly in building renovation projects.

The present article is structured into the following sections: In Section 2, a thorough literature review about ANNs as a tool in the construction field in general and specifically for building projects is provided. In Section 3, data gathering and analysis procedures for the creation of the ANN models in order to forecast the final building renovation costs are developed. The findings are provided in Section 4 and discussed in Section 5. Section 6 includes findings and suggestions for further research.

2. Systematic Literature Review

2.1. Artificial Neural Networks as a Tool in Construction Field

As seen from the following, ANN models have been shown to be an effective tool for construction organizations in achieving accurate cost estimates for construction projects, particularly in building construction projects, and preventing them from failing.

The interest of researchers in using ANNs for estimating has risen enormously in the past two decades. Even from 1998, Zhang et al. [9] strongly believed that although ANNs offer a lot of potential, they also include a lot of unknowns. The implications of important elements on the prediction effectiveness of ANNs remains unclear to researchers. Nevertheless, ANNs have been widely used in construction research [10], as described in the following paragraphs.

Adeli [11] tried to show various applications of ANNs. The structural engineering, construction engineering, and management sectors were the focus of the ANNs. A substantial portion of ANN applications in civil engineering are built on the straightforward backpropagation procedure. The current study also focused on the integration of ANN with other computing paradigms, such as wavelet, fuzzy logic, and genetic algorithms. These combinations provided added value to the efficiency of ANN models.

Buscema [12] asserts that ANNs reflect multidimensional, complex, dynamic phenomena that are unexpected and uncontrolled in the sense of conventional cause and effect. Therefore, they are probably nonlinear in their core. They state that it is possible to use inadequate intervention strategies and draw erroneous inferences about what transpired when linear-based paradigms are used for planned intervention with nonlinear processes.

In the construction sector, ANNs have proven to be essential. Three different categories of issues have been addressed through ANNs: Prediction, classification, and time series. For this to happen, it is necessary firstly to train the ANN. There is an established method since ANNs, by virtue of their properties, do not necessitate a formal learning process. Multilayer perceptrons are the most prevalent type of ANNs. Their adaptability has been verified in many cases [13]. Interestingly, there are additional supervised ANNs that employ supervised machine learning (ML), performing as a nonlinear classification algorithm, such as radial basis function networks, a sort of supervised ANN. Nonlinear classification methods employ complex functions to do more in-depth analysis than basic ones.

There are many sectors in the construction field that have benefited from the use of ANN models, such as construction claims prediction [14–19], prediction of construction duration of highway projects [20], forecasting of construction project safety behavior [21], material quantity consumption prediction [22], cost prediction in pavement construction [23], estimation of life-cycle costing of a construction project [24], initial cost projections of constructing road tunnels [25], determining the cost and material quantities for underground metro stations [7], and many others.

2.2. Application of ANNs to Cost Estimation in the Particular Field of Building Construction

The most popular construction project type, for which many cost prediction models exist, remains by far buildings. In the relevant literature review carried out by Hashemi et al. [26], it became apparent that 40 out of 92 studies analyzed referred to buildings. Additionally, in their review, Antoniou et al. [7] found another 31 out of 51 studies, published in 2021 and 2022, providing construction cost estimation models for building projects. Out of these 31 studies, 11 employed ANNs in their models. Following a demonstrative, non-exhaustive content analysis of those found to provide construction cost estimates for buildings using ANNs, the following studies stood out as noteworthy.

Chua et al. [27] acknowledged that it is important for project owners, contractors, and designers to identify and understand specific characteristics that could contribute to the successful completion of a building project. They consequently employed an ANN technique in an effort to discover the important project management traits linked to effective budget performance. They suggested several variables, including the number of organizational ranks between the project manager and craft workers, the amount of comprehensive planning completed prior to construction, the frequency of control meetings during the construction phase, the frequency of budget updates, the use of a constructability scheme, team turnover, the amount of money spent on project management, and the technical experience of the project manager. Chua et al. [27] utilized 75 buildings construction projects, 48 from contractors and 27 from owner organizations. After training, the final model was utilized as an estimator to anticipate the extent to which a buildings construction budget would perform. This method enables the budget performance model to be developed even while the functional relationships between the inputs and outputs are not explicitly established [27].

ANNs predicting the total construction cost were used by Emsley et al. [28], based on data from 300 buildings. The data collected were project files, the building cost information, and the results of a widely disseminated questionnaire survey. Since their data included final account totals, their resulting model could also assess the entire cost to the client, including, apart from the construction costs, the client's external and internal expenditures. In order to assess the ANN models, they further employed models developed via LR approaches, thus reaching the conclusion that the primary positive aspect of the ANN approach was its propensity to simulate nonlinearity in the data. The strongest model produced a mean absolute percentage error (MAPE) of 16.6% that took client changes into account to an unknown extent. This contrasts well with conventional estimation, where values of MAPE have been determined to range from 20.8% to 27.9%.

The efficacy of ANN procedures to resolve cost estimating issues in the first stages of building design processes was studied by Günaydin and Doğan [29]. An ANN-based model with eight design variables designed to estimate the square meter cost of a building's reinforced concrete structural systems for four to eight story residential structures in Turkey was developed and verified utilizing cost and design data from 30 projects achieving a 93% accuracy rate.

Examining the performance of three cost estimation models, Kim et al. [30] also attempted to demonstrate that accurate cost prediction is a crucial element in building projects. Using historical cost data for 530 buildings, they applied ANNs, multiple regression analysis (MRA), and case-based reasoning (CBR). The residential buildings were completed by general contractors between 1997 and 2000 in Seoul, Korea. The CBR estimating model outperformed the ANN estimating model in terms of long-term usage, accessible information from results, and time alongside accuracy tradeoffs, even though the most efficient ANN estimating model provided more accurate estimating results than either the MRA or the CBR estimating models.

Cheng et al. [31] suggested using the Evolutionary Fuzzy Neural Inference Model (EFNIM), an AI procedure, to increase cost estimation accuracy. As such, the beneficial characteristics of ANNs, genetic algorithms, and fuzzy logic have been integrated into the EFNIM, enabling the model to identify viable options in challenging situations. The combination of these techniques maximized each method's positive attributes and helped compensate for their inherent weaknesses when utilized individually. Genetic algorithms were used for optimization; fuzzy logic dealt with uncertainties and approximate inferences; and ANNs were employed for fuzzy input–output mapping. As a result, Cheng et al. [31] offered two models that could calculate conceptual building costs at the commencement of projects.

Arafa and Algedra [32] implemented a model employing ANNs to determine the cost of building initiatives at an early stage. A database of 71 construction initiatives in the Gaza Strip was utilized. The aforementioned type of projects was non-governmental and governmental buildings, schools, kindergartens, and residential buildings. At the pre-design stage of the project, a number of critical parameters were determined for the construction cost of the buildings structure that could be acquired from the engineering drawings and data available. Seven variables were included in the input layer of the ANNs; the usual floor size, the number of stories, the number of rooms, the ground floor area, the type of foundation, the number of columns, and the number of lifts. The created ANN model had seven input neurons, one hidden layer, and a single output neuron that represented an early estimate of the building's construction cost. The trained model's findings demonstrated that ANNs could estimate the initial stages cost estimation of structures using just rudimentary project information, without the requirement for a more intricate design. The number of stories, the ground floor area, the type of foundation, and the number of lifts were found to be the most influential factors on early estimations of building costs.

An interesting point of view came from Wang et al. [33], who innovated by creating models utilizing support vector machines and ANNs to forecast project cost and schedule success using early planning data as model inputs. They discovered that early planning status may be successfully applied to predict project success by utilizing ANNs after collecting early planning and project performance data from a total of 92 building projects through a relevant industry questionnaire survey. A total of 12 retrofits and 80 new construction projects comprised the 92 building projects, out of which 32 projects were public and 60 were private. In comparison to models produced from single ANNs, those built using bootstrap-aggregated ANNs were shown to be more accurate and reliable.

For Shehatto and El-Sawalhi and Shehatto [34,35], ANN models for accurate building construction project cost estimates and cost data for each different construction stage were identified using a combination of quantitative and qualitative procedures based on a repository of 169 completed building projects in the Gaza Strip. The constructions utilized as data were historical cases of building projects from municipalities, government ministries, engineering institutions, contractors, and consultants. Eleven important factors were taken into account as independent input variables, and the project cost was regarded as the dependent output variable. The models that were developed were trained utilizing the NeuroSolutions application. Once again, their ANN models demonstrated that an ANN could properly estimate construction project costs without requiring substantial definitive designs since the average error for the upgraded model was generally satisfactory, less than 6%. The outcome of the sensitivity analysis indicated that the standard floor size and the number of stories had the most significant influence on building cost, according to the sensitivity analysis. They came to the conclusion that 11 factors should be regarded as independent inputs that affect project cost.

Elfaki et al. [36] strongly believed that cost estimation in building projects fluctuates due to variety of distinct variables. These considerations may be divided into two separate categories: (1) Variables particular to estimators, and (2) variables specific to designs and projects. They concentrated on the need to create a projection of costs strategy that could account for all estimating components from every perspective and contained a usual validation approach that could be used to gauge the degree of accuracy of cost estimation proposal.

Also, Ongpeng et al. [37] utilized an ANN model with the objective to forecast the entire structural cost of construction projects in the Philippines. They employed information from 30 construction projects, which were gathered and separated into three parts: 60% for training, 20% for verifying performance, and 20% for a totally autonomous test of network generalization. The number of stories and basements, the total ground area, the concrete volume, the formwork area, and the reinforcing steel mass were the six independent variables they incorporated in their ANN model that was implemented in MATLAB for simulation. The superior model for the overall structural cost was created using the feedforward backpropagation approach. Six variables used as inputs, six hidden layer nodes, and one output node completed the most efficient ANN structure. After adequate training, the resultant ANN model correctly forecasted the overall building construction costs. The researchers suggested that variables like surface area, number of floors and basements, concrete volume, formwork area, reinforcing steel mass, post-tensioned area, pile volume, etc., all determine the structural or civil engineering cost. On the other hand, other building costs include the architectural costs that depend on the style and caliber of the materials used for the floor, walls, ceiling, doors, windows, painting, etc. Finally, water and sewage networks, electrical installations, air-conditioning and heating systems, and the installation of lifts complete the whole engineering cost of the building.

It is important to note that the most popular method for stakeholders in the construction industry to determine the preliminary costs of building is the Unit Area Cost Method (UACM). The predicted costs using this technique, considering only construction area, differed significantly from real costs, as Bayram et al. [38] observed. They nonetheless compared the cost estimates derived using the widely utilized ANN techniques of multilayer perceptron (MLP) and radial basis function (RBF). Additionally, the outcomes of the MLP and RBF were measured and compared with the ones from the UACM. After analyzing data from 232 public buildings completed in different regions in Turkey from 2003 to 2011, it was found that the predicted values using both techniques were greater than the actual values with a 0.28% variance when using the RBF and a 1.11% variance when using the MLP. With a variation of 28.73%, the estimated costs from the UACM are significantly higher than the actual expenses. It was discovered that RBF outperformed MLP, while both ANN algorithms performed better than the UACM [38].

During the pre-design stage, Ambrule and Bhirud [39] tried to examine and address issues with cost estimation at the initial phase of building development, and attempted to utilize ANNs for cost forecasting of building projects. A graphical user interface (GUI) model of cost estimation for enhanced concrete buildings was also created and tested during the preliminary design period. Ambrule and Bhirud [39] determined that the ANN GUI model may help managers in making recommendations about project implementation in the very beginning stages of the engineering process.

Another mathematical model based on ANN was developed by Abd and Naseef [40] to estimate total building construction costs based on the initial estimates of the cost of 25 construction elements. Their data were derived from 501 Iraqi building projects built between 2005 and 2015 and included the total amount spent on foundation excavation, landfill construction, filling with sub-base construction, construction of moisture proof layer, construction of components, typical concrete for paths, structural concrete foundation, etc. The correlation coefficients between the factor findings were approximately 100%, the error rate was around 5.81%, and the degree of accuracy was 94.19%, indicating that the algorithm used for the ANN performed extremely well in estimating the expenses for a construction building endeavor in Iraq.

Researchers in India also attempted to develop an ANN model for construction cost prediction of buildings. Specifically, Chandanshive and Kambekar [41] obtained quantity and cost data from 78 buildings, which included small- and medium-sized residences and bungalows constructed between 2017 and 2019, built in or around Mumbai (India), via questionnaires and the opinions of building designers and building specialists. Eleven independent variables related to quantities of specific construction works were included: ground floor area, typical floor area, number of floors, structural parking area, volume of elevator walls, volume of exterior walls, volume of exterior plaster, flooring area, number of columns, foundation type, and number of households. The only output parameter was the total cost of the project in Indian national Rupees. For their model, they created a multilayer feedforward ANN model that had been programmed using a backpropagation procedure. Early ending and Bayesian regularization algorithms were used to improve the ANN's efficiency for generalization and prevent excessive fitting. The Bayesian regularization methodology's ability to perform was determined to be superior than early halting during the building cost prediction. The trained ANN model's findings demonstrated that it was capable of successfully foreseeing the total building construction cost [41].

In another emerging economy, this time that of Yemen, a study was carried out to provide a cost prediction tool based on ANN models by Hakami and Hassan [42], based on historical data from 136 buildings constructed from 2011 to 2015. They included 17 independent variables to be implemented in their model to produce a preliminary total construction cost estimate. The 17 independent variables were project category, number of stories, area of floors, type of groundwork, number of elevators, exterior finishing type, interior decoration, conditioning system type, HVAC, electrical work type, mechanical work type, basement floor, floor height, slab type, site area, tile type, and project location. They created, trained, tested, and ran evaluations of sensitivity on the structure utilizing the NeuroSolutions 6 application. The outcomes of the educating, evaluating and sensitivity examination were highly acceptable, with high efficacy and validity, and less than 1% error.

The only cost forecast model found for public buildings alone was provided by Sitthikankun et al. [43], who explained that there are two commonly employed techniques for estimating public building expenses: a preliminary estimation with an advantage of a quick cost estimate and a disadvantage of a high final cost variance, and an exhaustive prediction with the benefit of a more precise cost estimate but negative effects related to the need for a definitive completion and the associated need for time to complete, thus missing set funding deadlines. In their study they utilized data from 50 public building projects completed in 2020 in Thailand. The 11 independent variables used were total usable floor area, average perimeter length, average story height, total building height, number of floors, total roof area, total bathroom area, ground floor slab area, total area of openings, type of roof, and type of slab structure. The findings were forecasted using the ANN approach. Two hidden layers with ten and eight nodes each, respectively, formed the final method, with a root mean squares error (RMSE) value of 0.331 million Thai Baht. After the most recent data source was validated, the correlation factor R^2 was found to be 0.914, demonstrating the preciseness of the modelling approach as a substitute for public bidders to minimize tolerances and spend less time estimating building expenses more effectively.

All of the aforementioned studies attempted to provide cost estimation models for the construction of new buildings. One study was found that investigated the cost–performance of building reconstruction, also called renovation projects; Attalla et al. [44] tried to investigate this challenging environment and proposed a model based on ANN to calculate a cost performance index based on data known at the beginning of the construction phase. In their study, data was gathered about the causes of excess expenses and low-quality work from 50 reconstruction schemes via a poll of industry specialists. Each project-related real expenditure variance from projected values and the specific project control methods that were implemented were documented. Overruns in fees to the client and the expense of repairs to the building contractor were utilized as two indicators of financial variance. Eighteen independent variables were finally chosen out of thirty-six that were believed to have an effect on the cost performance all related to project management tools and techniques, including cost, schedule, quality, safety, communication tools, and techniques, as well as scope definition, and tendering and project completion procedures. They employed an ANN (Neuro Shell2) and statistical analysis (Systat) to create their models. Although the performance of both approaches was comparable, the model generated by the ANN was more susceptible to a wider range of factors. It was this study that inspired this research work to develop an ANN model for actual cost prediction of building renovation projects based on cost and schedule estimates known at the start of construction in order to predict final cost deviations. To the best of the authors' knowledge, this is the first published ANN model for final cost prediction of building renovation projects.

A summary of the above techniques, data sources, etc. used by the aforementioned researchers are summarized in the following table (Table 1).

In the following section, the valuable knowledge from the extended review mentioned above is used and an effort is made to develop an ANN model in order to have more accurate cost estimation in building renovation projects.

Table 1. Summary of ANN approaches for building cost estimation found in the existing literature.

Publishing Year	Authors/Ref.	Country	Data Base Source	Data Size	Data Type	Inputs	Outputs/Research Object	ANN Architecture/Training Algorithm	ANN Tools
1997	Chua et al. [27]	Singapore, USA	Questionnaires	75 buildings	Qualitative	8 independent variables: Project manager and craft workers' organizational ranks, quantity of finished detailed design at the initial phase of construction, frequency of the phase-of-construction control meetings, total amount of funding spent on managing a project, team rotation, constructability scheme usage, financial updates on a continuing basis, and project manager's expertise	Project budget performance–cost estimation	MLP/BP	Neural Works Professional II/PLUS
2002	Emsley et al. [28]	UK	Real project data, questionnaires	288 buildings	Quantitative and qualitative	6 Project strategic variables: Building standards, type of commitment, procurement approach, procurement methodology, time frame, goals 4 Site-related variables: Geographical features, location access, specific type of place, site typology 31 Design-related variables: Internal doors, rooftop characteristics, cooling systems, interior walls, ceiling coatings, structural variety, specific installations, interior wall completes, electrical infrastructure, types of stairways, number of elevators, surroundings, quantity of stories over ground, exterior doors, subsystem, number of stories under the surface, the external walls, structural units, additional floors, mechanical installations tasks, finishes on floors, piling, wall-to-floor proportion, frame technique, windows, preventive structures, functionality of structures, rooftop structure, height, roofing finishes, and GIFA	Construction cost estimation and client's external and internal expenditures	MLP, RBF, and GRNNs.	Trajan NN Simulator Release 4.0E
2003	Attalla and Hegazy [44]	Canada	Questionnaires	50 buildings	Quantitative and qualitative	18 independent variables: Concept of the reconstruction project, as-built designs, expenditures and baseline for spending plan, boards for design, requirements and criteria for quality, prior qualification of contractors, unit costs, cash disbursements, coordinating timetable, bar diagrams, critical path technique, augmental benchmark, variance in costs, independent evaluation companies, frequent site meetings, efficient reaction system, collaborative health and safety committee, evaluation by the customer, maintenance, and operator	Cost estimation of reconstruction projects	Statistical analysis and ANN/MLP/BP	Neuro Shell 2 and. Systat software

Table 1. *Cont.*

Publishing Year	Authors/Ref.	Country	Data Base Source	Data Size	Data Type	Inputs	Outputs/Research Object	ANN Architecture/Training Algorithm	ANN Tools
2004	Kim et al. [30]	South Korea	Real project data	530 buildings	Quantitative	9 independent variables: Cross floor area, stories, duration, roof types, fdn types, total unit, utilization of basement, actual costs, finishing grades	Project cost estimation	ANN/MLP (GAs)/BP	Neuro Solutions for Excel Release 4.2, NeuroDimension, Inc., Gainesville, FL, USA
2004	Gunaydın and Dogan [29]	Turkey	Real project data	30 buildings	Quantitative and qualitative	8 independent variables: Total area of the building, ratio of the typical floor area to the total area of the building, number of floors, ratio of ground floor area to the total area of the building, console direction of the building, foundation system of the construction, location of the core of the building, floor type of the structure	Cost estimation of reinforced concrete structural systems of four–eight storey residential building	Feedforward ANN/BP	NeuroSolutions by NeuroDimensions Inc.
2009	Cheng et al. [31]	Taiwan	Real Project data	28 buildings	Quantitative and qualitative	6 Quantitative factors: total floor area, floors underground, floors above ground, number of households, household in buildings, site area 4 Qualitative factors: Soil condition, seismic zone, electromechanical infrastructure, interior decoration	Project cost estimation	Evolutionary Fuzzy Neural, MLP, inference System mechanisms (EFNISM) and process of developing construction cost estimators ((EWCCE)/BP	EWCCE system via World Wide Web
2011	Arafa and Alqedra [32]	Palestine	Real project data	71 buildings	Quantitative and qualitative	7 independent variables: Number of stories, number of rooms, usual floor size, ground floor area, type of foundation, number of columns, number of lifts.	Early building cost estimation	MLP/BP	Matlab v.2009b
2012	Wang et al. [33]	Taiwan	Questionnaires	92 buildings	Quantitative	Early planning data and project performance data	Final cost estimation Schedule success	SVMs and ANNs * ensemble techniques	1. NeuroSolutions TM by NeuroDimension, 2011, 2. LS-SVMlab
2014	Roxas and Ongpeng [37]	Philippines	Real project data	30 buildings	Quantitative	6 independent variables: Number of stories, total ground area, number of basements, concrete capacity, reinforcing steel mass, and formwork area	Project cost estimation	MLP/BP, weights and bias values updated according to Levenberg–Marquardt	Matlab (R2010a)
2014	El-Sawalhi and Shehatto [35]	Gaza	Questionnaire, interviews, literature review	169 buildings	Quantitative and qualitative	11 independent variables: Type of project, number of floors, area of typical floor, type of foundation, type of slab, type of external finishing, type of air-conditioning, type of electricity, type of tilling, type of sanitary, and number of elevators	Total cost estimation	MLP/BP (Tanh transfer function and momentum learning rate)	NeuroSolutions 5.07
2016	Bayram et al. [38]	Turkey	Real project data	232 buildings	Quantitative	5 independent variables: Approximate cost, contract value, entire constr. zone, number of floors, and structure height	Project cost estimation	MLP and RBF	Matlab v.7.9.0

Table 1. *Cont.*

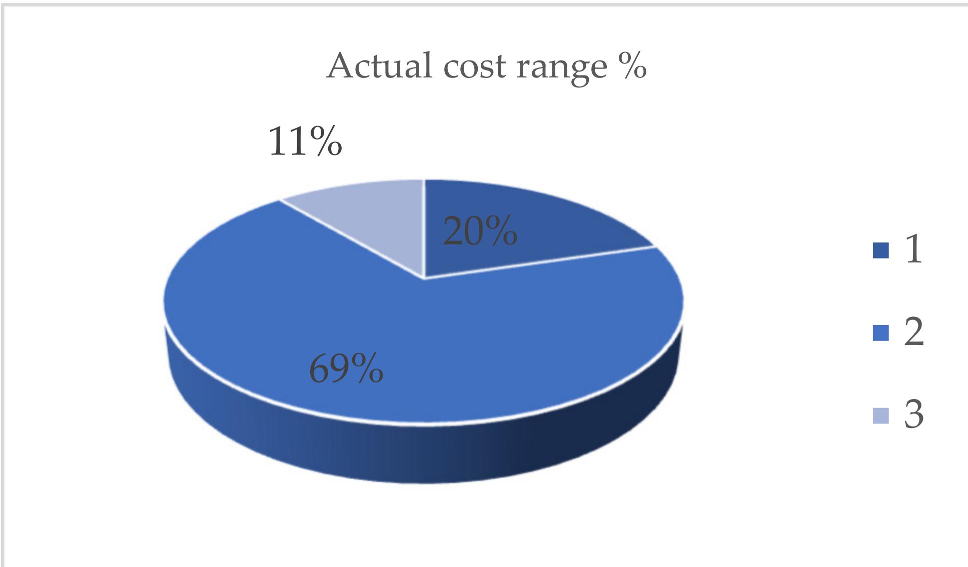
Publishing Year	Authors/Ref.	Country	Data Base Source	Data Size	Data Type	Inputs	Outputs/Research Object	ANN Architecture/Training Algorithm	ANN Tools
2017	Amprule and Bhirud [39]	India	Not specified	Not specified	Not specified	Not specified	Early cost estimation	ANN GUI model in general	Not specified
2019	Abbas Mahde Abd et al. [40]	Iraq	Real project data	501 projects	Quantitative and qualitative	25 independent variables: Excavation the groundwork works, filling with foundation workings, landfill works, construction works under moisture proof layer, construction works above moisture proof layer, building works of sections, ordinary concrete for walkways, reinforced concrete foundation, reinforced concrete column, reinforced concrete lintel, reinforced concrete slabs, reinforced concrete beams, reinforced concrete stair, reinforced concrete for the sun bumper, plaster finishing workings, cement finishing workings, plastic paints, pentolite paints, pigment color, stone packaging, workings of placing marble, ceramic works for floor, ceramic works for walls, flattening (2 opposite layers), tiling	Project cost estimation	ANN not specified	Matlab
2019	Chandanshive et al. [41]	India	Questionnaires	78 buildings	Quantitative and qualitative	11 independent variables: Ground floor zone, typical floor zone, quantity of floors, structural parking zone, size of elevator walls, size of exterior walls, size of exterior plaster, flooring area, number of columns, foundation category, and amount of households	Project cost estimation	MLP/BP Bayesian regularization Levenberg–Marquardt	Matlab v.R2015a
2019	Hakami and Hassan [42]	Yemen	Real project data, literature review	136 buidings	Quantitative and qualitative	17 independent variables: Project type, number of stories, area of floors, type of groundwork, quantity of elevators, external finishing type, inner decoration, conditioning system category, HVAC, electrical work category, mechanical work type, basement floor, flooring height, slab category, site zone, tile type, and project position	Project cost estimation	MLP/BP	SPSS IBM v.19.0-NeuroSolutions v.6
2021	Sitthikankun et al. [43]	Thailand	Real project data	50 buildings	Quantitative and qualitative	11 independent variables: Whole usable floor area, average perimeter length, average story height, total building height, number of floorings, total rooftop area, whole area of openings, entire rest room area, ground flooring slab area, category of rooftop, and kind of slab structure	Project cost estimation	A 2 hidden layers (10 and 8 nodes) ANN structure	Rapid Miner Studio

Note: ANN for artificial neural network; MLP for multilayer perceptron; RBF for radial basis function; BP for back propagation (algorithm); GA for genetic algorithms; GRNNs for generalized regression neural networks; M3 for square meter; SVM for support vector machine; LRV for logistic regression model; GUI for graphical user interface, when not specified by the relevant researcher. * Bootstrap aggregating and adaptive boosting ANNs classifiers.

3. Methodological Approach

In the current paper, an effort was made to produce ANN models. A sample of 52 building renovation projects were collected from a single construction company specializing in building renovations. The aforementioned company holds a lot of experience in structure renovations, so it is a great opportunity to retrieve functionally accurate data from their knowledge base. The projects were selected as the company followed the same system of structural analysis in each of their works. They all were private projects. An analytical cost was the result of a survey and detailed measurement of each building project. The initial cost was sanctioned by both parties, constructor and proprietor. The total cost of each project was based on the current prices of the Greek financial and construction fees.

According to Figure 1, the data source including 52 building renovation projects was the main source of information for the current research. As foreseen, the major portion of that category of projects (69%) had a cost range up to EUR 50,000. Nevertheless, 20% of those projects only reached EUR 20,000 and 11% went up to EUR 450,000. Thus, the information from such a cost variety of building renovation projects was an opportunity to examine the accuracy of an ANN to estimate the cost in both low- and high-budged building renovation projects.



Definitions

1. Up to EUR 20,000 (11 projects)
2. EUR 20,000–50,000 (35 projects)
3. EUR 50,000–450,000 (6 projects)

Figure 1. Range of initial cost values.

Acknowledging the above notions, a database including initial renovation cost estimate (tender offer), contractual duration, and demolition costs as defined by the contract, were created. IBM SPSS Statistics software [45] was used to create a database with the above technical parameters. The structures are mostly residential apartment buildings in urban areas, mainly in the Municipality of Thessaloniki. The key motive for the renovations was the demand for energy upgrading, but other reasons included modernization, redesigning, and, rarely, change of use. The buildings are often plus several years of age, especially those that were in the center of the city. The projects started in 2018 and were completed in 2023.

Initially, a correlation analysis was performed. The results are presented in Table 2.

Table 2. Correlation analysis.

		Tender Offer	Project Contract Duration	Initial Demolition Cost per Contract
Final Renovation Cost	Pearson Correlation	0.989	0.826	0.479
	Sig. (1-tailed)	0.000	0.000	0.000
	N	54	54	54

According to Table 2, there is a considerable correlation between the final renovation cost and the tender offer and project contract duration variables. A medium correlation exists between final renovation cost and demolition cost per contract. The correlation between tender offer and project contract duration is important, due to the fact that the relationship between these two parameters remains directly proportional. The longer the duration of the project, the higher the cost of its construction. Thus, the final cost of the renovation project would be affected. The initial demolition cost is one of many categories in a building renovation project that could have a significant role in determining the final cost. Demolition is the main initial stage of renovation constructions and an accurate initial estimation would have a significant impact on the project's final cost. Thus, its contribution to the final project's cost estimation depends on its magnitude and accuracy of prediction. In addition, the amount of demolition work that will be required on a project has a significant variation depending on the size of the project and the type of work the client requested, and also the building's age and condition. Thus, the following model that will be created will be based on these correlated variables.

The dependent as well as independent variables are defined. The model was created, trained, and tested using IBM SPSS application. The radial basis function was the method adopted. In accordance with the company's records, the dependent variable is the final renovation cost of each project. The independent variables include initial renovation cost estimate (tender offer), contractual duration, and demolition costs as defined by the contract. A total of 38 projects were chosen for the training sample and 14 for the testing sample. The relationship of 70% of the project sample for training and 30% of the project sample for testing is an acceptable percentage according to the above-mentioned literature review and the results obtained. Changes are focused on the number of neurons (units) within the hidden layer. The analysis initiates with a single neuron and continues by adding one neuron with each consecutive time and analysis. The radial basis function, which connects the values of the units in one layer to those in the next, is the activation function for the hidden layer. The activation function for the output layer is the identity function; as a result, the output units are just the weighted sums of the hidden units. In the present model's architecture, the activation function for the hidden layer is the normalized radial basis function, which employs the SoftMax activation function to normalize all concealed unit activations such that they add up to 1. The multiplier applied to the radial basis functions' width is the overlapping factor. The overlapping factors were automatically calculated. The value is 1+0.1d, wherein d is the amount of input data.

The study reached an ANN with 50 neurons in the hidden layer. In essence, the research produced 50 models. The analysis revealed that, based on sum of squares error and relative error, the ANN with 40 neurons in the hidden layer provided the best results. The trained model's gathered information indicated that the ANN approach was efficient in forecasting the expenditure prediction of structures utilizing minimal project data and without the requirement for a more extensive design. Figure 2 presents the flowchart of the proposed methodological approach.

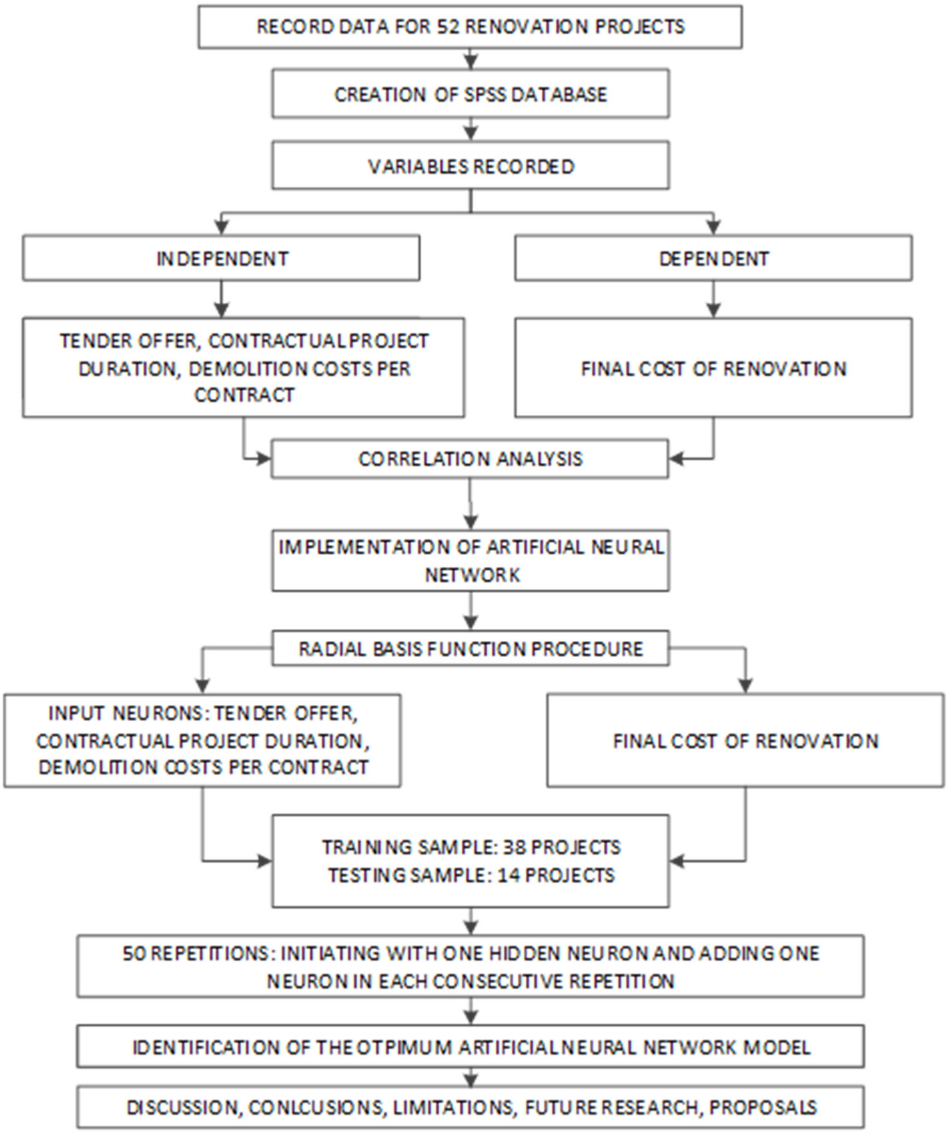


Figure 2. Proposed methodological approach.

4. Results

A total of 52 distinct projects were included in the data collection. This extensive collection of data provided the structure for the testing process that had been established in place in the network. This test procedure's main goal was to make it simpler to compare the actual costs utilized for these kinds of projects with the cost estimates produced by the artificial neural network model.

This dataset's projects each represented a distinct instance with a unique set of variables and results. These projects' actual costs were thoroughly collected and assembled, offering the testing process a solid and trustworthy baseline.

In Figure 3, the predicted final cost in comparison to actual cost in the training sample had a respectable performance. The actual costs of the sample projects ranged significantly. As a result, the effort of the ANN to produce prediction models was really challenging. As seen below in Figures 4 and 5, the sum of squares error and the relative error in the training sample remained low.

The analysis revealed that according to the training sample and based on the sum of squares error and the relative error, the ANN with 40 neurons in the hidden layer had the best performance. In this ANN model, the sum of squares error remains at 2% and the relative error is near to 0 at the training phase of the model, as presented in Figure 4.

In Figure 5, it can be seen that the relative error remains near to 0. Thus, according to the training sample and based on the relative error, the ANN with 40 neurons in the hidden layer still provided the optimum results.

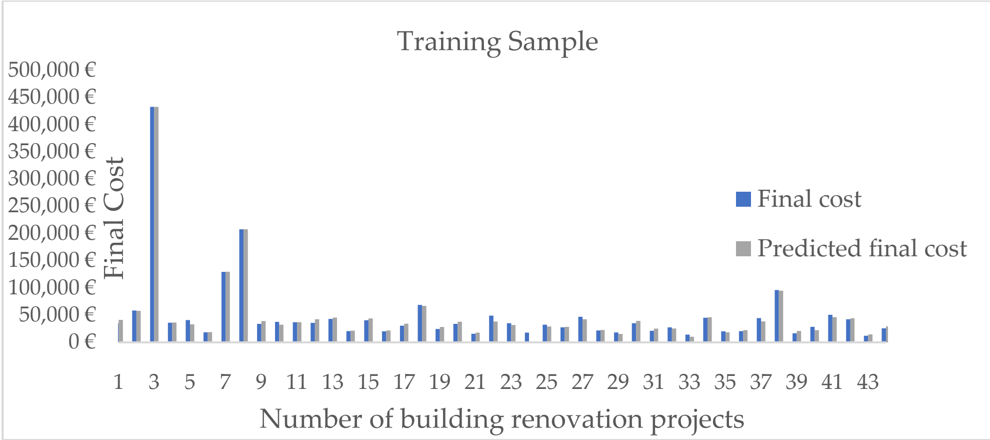


Figure 3. Final cost and predicted final cost (testing sample).

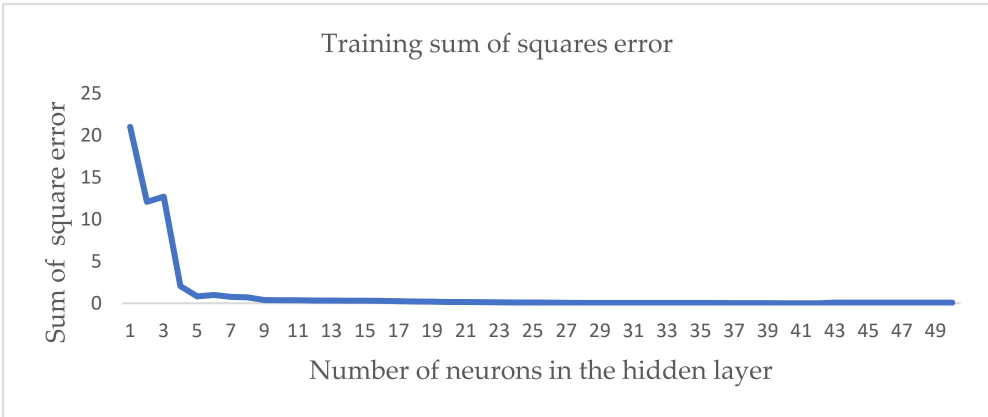


Figure 4. Training sample sum of squares error based on the number of neurons within hidden layer.

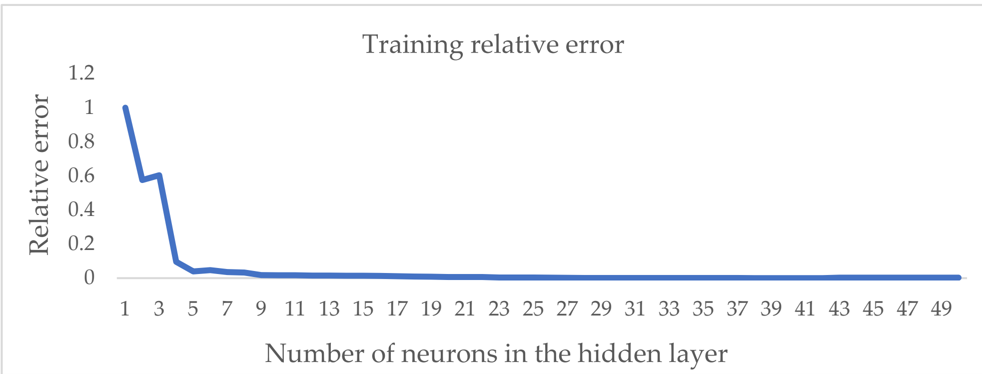


Figure 5. Training sample relative error based on the number of neurons within hidden layer.

5. Discussion

The present research focuses on the usage of ANN models, specifically the radial basis function procedure, when implemented as a technique for forecasting costs in the building construction sector. This approach concentrated on the field of renovation in order to pre-estimate the total cost of a construction project.

The current paper is based on extensive literature review, concerning the implementation of ANNs in construction projects. Additionally, a noteworthy amount of actual data regarding renovations has been collected from the construction field in Greece. The data from 52 construction projects are solely in the field of building renovation projects that have been performed within the last 5 years, precisely from 2018 to 2023. The gathered data were categorized and processed in accordance with ANN restrictions. Network construction, training, and testing were done with IBM SPSS Statistics software. The dependent variable is the final cost. The independent variables include initial renovation cost estimate (tender offer), contractual duration, and demolition costs as defined by the contract. The method followed was the radial basis function. A total of 70% of the sample was chosen for training and 30% for testing. The models' performance was carefully assessed during the training phase. According to the parameters utilized to assess the models' performance, the evaluation showed a high level of effectiveness. The sum of squares was discovered to be as high as 2%. Figure 4's low error rate shows that the model was able to predict the outcomes with slight variance based on the input data. It was also evaluated the model's performance using the relative error in addition to the sum of squares error. Figure 5 illustrates the relative error, which was found to be almost 0. The model's superb precision is further demonstrated by this almost zero relative error, illustrating that the ANN can produce forecasts that precisely correspond to the resultant data.

It is indispensable not to overlook, though, that the current study's scope was rather constrained. In particular, this study only included components that were easily recognized in the early stages of planning. This indicates that some variables or elements that might have surfaced later in the projects were left out of this model. This method allowed researchers to remain concentrated on the most easily accessible data, but it additionally indicates that not all possible variables on the project results may be properly accounted for in the model.

In summary, even though this particular model has proved to be highly effective in the training phase, more thorough research that considers new variables and aspects that are apparent in the latter stages of project planning and execution may prove advantageous in subsequent studies.

6. Conclusions and Future Research

It may be inferred from the research and discussion that ANNs have been highly effective in their implementation for cost estimates with a substantial degree of accuracy. The Greek construction sector might employ this method to more quickly and reliably estimate the expenses of their construction projects. Additionally, this proposed approach may be adopted by other countries, which would greatly benefit. The quantity and quality of independent variables—in this study, the initial renovation cost estimate (tender offer), contractual duration, and demolition costs as defined by the contract—are just a few of the many uncertainties that the ANN model has to face. The data used in the present research was collected over the last five years.

The construction sector, in particular, uses ANNs as useful tools for cost estimation. Reliability and the number of cases, finished projects in this case, are important factors that affect an ANNs capacity to predict expenses.

An ANN's capability to learn from a grander amount of data, which improves prediction accuracy, increases with the dependability and quantity of successfully completed projects. This is so that they can develop forecasts for the future using the principle of machine learning from historical data. Thus, an ANN's performance is directly impacted by both the quantity and quality of the data it receives.

However, reliable and high-quality expenditure data is essential for the ANN to learn and produce accurate forecasts. Since there are many variables that might have a significant effect on construction costs, this information should cover structures in diverse situations. The building's location, the materials utilized, and the design's complexity are a few examples of these variables.

With a large and varied dataset, researchers may experiment with various modelling and prediction strategies. This enables scientists to optimize ANNs, enhancing their potential to forecast project costs with greater accuracy. Essentially, the ultimate objective is to create an accurate building cost forecast model, which can be very helpful with financial and budgetary management in the construction sector.

For instance, researchers could use this data to perform in-depth analyses and investigations. They may look at patterns, pinpoint recurring problems, and provide creative answers. This could result in the creation of more cost-effective building methods, the identification of potential cost savings, or the enhancement of project management procedures.

In addition, such databases could be very beneficial to construction companies. They might learn more about the real expenditures and schedules connected with comparable projects if they have access to data from previous initiatives. They might be able to anticipate their own projects more precisely as a result, which would lower the possibility of delays or cost overruns.

Furthermore, not only would the databases hold unprocessed data, but they would also provide input for models of artificial neural networks (ANNs) and other computational techniques. By analyzing the data and drawing conclusions from it, these models might produce forecasts for future initiatives. This could greatly improve the cost estimate accuracy for upcoming building projects, resulting in more dependable planning and budgeting.

Under this situation, building firms could become more proficient in carrying out their projects. If they were allowed access to precise budgets and schedules, they could better use their resources and finish their projects on schedule. This might boost the construction industry's profitability and level of competition.

Furthermore, anticipating a project's ultimate cost or even its cashflows could help avert possible financial disaster. Businesses could make sure they have adequate funds to pay for the expenses, refrain from taking on initiatives they may not afford, and choose the best financing solution in their favor. This could be beneficial to help companies maintain their financial stability and see their projects through to completion.

In conclusion, the evolution of databases that are accessible to the public and contain information from finished state projects has the potential to completely transform the building sector. It might help construction companies and researchers tremendously, make accurate cost estimations easier, increase productivity, and shield businesses from financial ruin. In terms of using data to the advantage of the construction sector, it is a major advancement.

The reliability and number of cases (completed projects) have a significant impact on the cost estimation performance of an ANN model, since ANNs learn from them. Therefore, there is a need for trustworthy and high-quality expenditure information of buildings of various circumstances in order to explore modelling and prediction approaches and establish an accurate forecast model of building expenses.

The effectiveness of an ANN model depends on the type and structure of the ANN that was used, the training procedure, and the way that data are organized and interpreted, in addition to the quality of the training data.

In the present research it has been observed that it was not required to place great emphasis on correlation testing between the independent input parameters (initial renovation cost estimate (tender offer), contractual duration, and demolition costs as defined by the contract) and the dependent parameter (estimated final cost). The above parameters are related analogously as parameters of the same projects. Thus, their correlation is significant and their inclusion in the model will lead to improving the model's efficacy. Data that have been used in the current study required a lot of research since databases are often unavailable or unreliable. It should be noted that a holdout sample was not created or used in the current study.

It was pointed out that ANNs have been utilized to address issues that are challenging to solve with conventional mathematical techniques. With respect to traditional ANNs, findings from the integration of ANNs with additional approaches such as genetic algorithm, fuzzy logic, ant colony optimization, artificial bee colony, and particle swarm optimization showed greater performance. This was especially true when attempting to predict the costs associated with building initiatives.

Furthermore, another important step forward would be the creation of publicly accessible databases, including information from State-completed initiatives. For many different stakeholders, these databases may be a veritable information gold mine.

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