Article

A Novel Framework for Estimation of the Maintenance and Operation Cost in Construction Projects: A Step Toward Sustainable Buildings

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Abstract: Building maintenance and operation costs represent a significant portion of the life cycle costs (LCC) of construction projects. The accurate estimation of these costs is essential for ensuring the long-term sustainability and financial efficiency of buildings. This study aims to develop a novel framework for predicting maintenance and operation costs in construction projects by integrating an emotional artificial neural network (EANN). Unlike traditional models that rely on linear regression or static machine learning, the EANN dynamically adapts its learning through synthetic emotional feedback mechanisms and advanced optimization techniques. The research collected input data from 313 experts in the field of building management and construction in Ha'il, Saudi Arabia, through a comprehensive questionnaire. The integration of expert opinions with advanced machine learning techniques contributes to the innovative approach, providing more reliable and adaptive cost predictions. The proposed EANN model was then compared with a classic artificial neural network (ANN) model to evaluate its performance. The results indicate that the EANN model achieved an R^2 value of 0.85 in training and 0.81 in testing for buildings aged 0 to 10 years, significantly outperforming the ANN model, which achieved R^2 values of 0.78 and 0.72, respectively. Additionally, the Root Mean Squared Error (RMSE) for the EANN model was 1.57 in training and 1.60 in testing, lower than the ANN's RMSE values of 1.82 and 1.90. These findings show that the superior capability of the EANN model in estimating maintenance and operation costs.. This led to more accurate long-term maintenance cost projections, reduced budgeting uncertainty, and enhanced decision-making reliability for building managers.

Keywords: building; life cycle cost; construction; maintenance and operation cost; questionnaire; emotional artificial neural network; sustainability

1. Introduction

The life cycle of a building begins from its construction and lasts until the end of its life [1–3]. The costs in the life cycle period, such as operating costs (energy and consumed resources), maintenance costs, and salvage value, are known as life cycle costs (LCCs) [4–6]. A building's LCCs can occasionally exceed its initial price. Maintenance involves a combination of technical activities and management implementation throughout the life cycle of equipment with the goal of saving or returning it to its required performance level [7]. Except for maintenance and repair costs, all of the costs associated with performing these tasks, whether as preventive measures to avoid damage or as repairs and/or removal of damages, are practically the same [8]. Maintenance expenditures are important to consider when examining and measuring the effectiveness of building maintenance and repair activities [9]. The process of repairing and maintaining a building is performed to avoid harm as well as to restore damage that has already occurred. The building operation and maintenance phase is the most time-consuming and costly part of a building's life cycle [10,11]. The cost of this phase far exceeds the overall cost of initial design and construction, planning, and

optimal management. The costs of operations, repair and maintenance, renovation, and cumulative support can all help to reduce the total cost of ownership [12].

Maintenance is regarded as an auxiliary tool for improving building safety, effectiveness, and environmental compatibility, and it is critical in ensuring that systems function properly [13,14]. Building reconstruction can be performed in a variety of ways and for various types of buildings, such as residential, office, and commercial. Building maintenance and repair are critical, and neglecting them can result in irreparable costs [15,16]. Examining maintenance costs and developing appropriate models are critical for improving the economic culture of construction projects. Given that most building maintenance and repair costs are the result of poor management, it is critical to consider human and organizational factors carefully [17,18].

Building managers should allocate this budget to restore the structural integrity of the facility to a predefined standard, thereby preventing further degradation or functional failure [19]. This includes restoring operational performance based on specific criteria, replacing components at the end of their life cycle using advanced engineering models, conducting temporary repairs to address critical health, safety, and security concerns, and mitigating the impacts of natural disasters while ensuring comprehensive building assessments [20].

Building maintenance is essential for both functional integrity and ensuring residents' safety and quality of life [21,22]. As a result, poor maintenance can not only cause the building's functional and physical deterioration, but it can also waste money, time, and effort on building repairs [23,24]. To solve this problem, systematic management should begin as soon as the building is completed. The first step in building management is to accurately estimate the maintenance cost of its components because it is possible to create prevention through maintenance measures by allocating the cost and forecasted budget for building maintenance [24]. As a result, it is necessary to estimate the cost of maintenance that causes building damage prior to the onset of problems. However, an insufficient budget for building maintenance or repair has hampered the ability to forecast and support regular maintenance management. This lack of forethought may reduce the building's productivity and real estate value while also endangering residents' safety [25].

Numerous studies have been conducted to develop comprehensive frameworks for accurately estimating the LCCs associated with building maintenance, aiming to optimize resource allocation and ensure the long-term sustainability of infrastructure assets. Han et al. [26] evaluated a model for determining the optimal component combination to achieve the lowest LCCs. The authors used a optimization algorithm to determine the best combination based on the objective function of minimizing LCCs. Initial, operating, and maintenance costs are all part of the LCC. The annual energy consumption must be estimated in order to calculate operating costs. The results revealed that the initial costs and operation accounted for the majority of the building's LCCs and that if the considered life cycle is longer than 30 years, the operation cost will exceed the initial cost. The framework presented in this study is based on user input, which adds complexity and error to the calculation of LCCs. Islam et al. [27] presented a framework for optimizing LCCs and the environmental impact of conventional buildings in Australia. Several types of wall, ceiling, and floor elements were evaluated for their environmental impact and LCCs. Then, to estimate LCCs and environmental effects, two objective functions were determined, and the linear programming method was used to find the optimal combination of components for the lowest LCCs and environmental effects. The performance of the framework presented in this research was investigated. The optimal combination of components with fixed LCCs, the building's environmental impact can be reduced by 20%. Li and Guo [28] conducted a study to demonstrate how to develop a maintenance and repair cost forecasting for educational buildings in Taiwan, using historical maintenance data for model prediction. It utilizes three linear regression methods. This study used simple linear regression (SLR), multiple regression, and an artificial neural network. Krstić and Marenjak [29] investigated a model of the cost of maintenance for university buildings. A questionnaire survey was

conducted to gather information on the building's operational characteristics, age, number of floors, floor area, employees, students, shifts, and observation period, as well as maintenance and operating costs for a 12-year period, including inspection, replacement, periodic works and repairs, active repairs, and operational costs. Statistical and regression analyses were used in this study to create a database of independent and dependent variables.

Jayawardana et al. [30] found that prefabricated construction reduces greenhouse gas emissions by 8.06% compared to traditional methods, based on an LCA of a Sri Lankan office building. Environmental savings were achieved across all impact categories, with optimal benefits observed within a 120 km transport range. Using green concrete reduced emissions by up to 12.05%. Wang et al. [31] developed a BIM-based LCA framework to assess demolition waste disposal strategies, including landfill, reuse, and recycling, focusing on environmental impacts like resource use and human health. Chen et al. [32] explored the integration of building information modeling in smart building by analyzing the barriers that influence its implementation. They developed a combination evaluation model based on 104 expert samples using exploratory factor analysis and a modified snowball sampling method. The model, which incorporates 18 evaluation indicators, was found effective in assessing the benefits, efficiency, and quality of smart buildings, contributing to the continuous optimization of building energy consumption. The cumulative contribution rate of the common factors exceeded 80%. Stamatopoulos et al. [33] introduced a framework to assess climate resilience in buildings, focusing on their ability to withstand and recover from climate-related events. The framework incorporates climate exposure analysis and benchmark building resilience across different typologies. Applied to buildings in Athens and Helsinki, the study demonstrates the framework's adaptability to various climates, highlighting its role in promoting climate-resilient practices and supporting decision-making against climate risks.

A review of existing literature reveals that, despite all efforts to analyze the building LCCs, there is a lack of a comprehensive method for evaluating the costs of building maintenance, which account for a significant portion of the LCC. This issue may also call into question a structure's useful life. In addition to a lack of appropriate tools for estimating a building's LCCs, one of the most significant challenges for LCC analysis in the construction industries is a lack of sufficient and reliable information about LCCs, including repair, maintenance, and operation. To ensure proper management for new cities, it is necessary to estimate the building LCCs with the least amount of error using modern tools and designing a suitable method.

The primary goal of this study is to develop a robust framework that accurately estimates maintenance and operation costs in construction projects, thereby supporting sustainable building management practices. This framework employs an emotional artificial neural network (EANN). The EANN model incorporates a simulated 'emotional feedback' system, which adjusts neural weights dynamically to mimic adaptive responses. By integrating synthetic feedback loops that act as 'emotional states', the EANN enhances its ability to navigate complex, non-linear relationships. Additionally, the model incorporates 'hormonal modulation', a mechanism inspired by biological systems, where synthetic 'hormones' adjust the sensitivity and strength of neural connections based on data complexity and prediction errors. This feedback adjusts learning rates and weight updates, enabling the EANN to refine its predictive outputs more precisely. When combined with advanced optimization techniques such as the Levenberg–Marquardt algorithm, this modulation enhances the model's predictive accuracy and reliability in forecasting maintenance costs over a building's life cycle. The EANN model's adaptive learning structure is designed to capture the intricate patterns in cost data, ensuring that maintenance and operational activities align more closely with sustainability. A questionnaire was used to determine the input data of the model according to 313 experts in the field of building management and construction in Ha'il, Saudi Arabia. The integration of experts' opinions with a machine learning approach could give reliable results regarding the prediction of building maintenance and operational costs. Meanwhile, the results of the proposed model have

been compared with the results of the classic artificial neural network (ANN) model. The goal is to provide building managers and stakeholders with reliable, data-driven insights for long-term planning, thus optimizing cost efficiency and contributing to the overall sustainability of infrastructure assets. In this paper, an attempt was made to provide building managers and stakeholders with reliable, data-driven insights for long-term planning, thus optimizing cost efficiency and contributing to the overall sustainability of infrastructure assets.

2. Materials and Methods

This section explains the cost of the period of use, the importance of considering repair and maintenance costs, and the factors that influence these costs. The background factors that contribute to cost generation are then examined.

According to the goal of the research, which is to evaluate the possibility of estimating the cost of repairing and maintaining residential buildings in Ha'il, Saudi Arabia, according to Morgan's table [34], the total population is 383 experts, of which only 313 experts are accurate and reliable enough to answer the questions. As a result, the data obtained from the reliable questionnaire respondents was analyzed and examined. This study used simple random probability sampling. Being independent means that the choice of one member has no bearing on the choices of other members of the society.

To determine the scale of the questionnaire, a five-point Likert scale was used to assess the attitudes of the beneficiaries. The Likert scale requires a minimum of 11 respondents to determine the reliability of the questionnaire, after which the number of people is estimated. A size has been accepted within this range of degree distances. A Likert scale was used to assess the importance of each variable's title. During the building's operational period, the cost evaluation questionnaire is graded from low to high on a 1 to 5 scale. This questionnaire covers topics such as the cost of facility repair, maintenance, and replacement.

2.1. Questionnaire Validity and Reliability

2.1.1. Validity

The content validity of the questionnaire was investigated using two key component: the Content Validity Index (CVI) and the Content Validity Ratio (CVR). The CVI measures the degree to which the items in the questionnaire are relevant to the study objectives, as judged by experts in the field. The CVR, on the other hand, assesses the necessity of each item by determining whether it is essential for measuring the intended construct [35]. The CVI was calculated using Equation (1).

$$CVI = \frac{\text{Number of experts who rated the item as relevant}}{\text{Total number of experts}}, \tag{1}$$

For the CVR, Lawshe's formula was applied (Equation (2)).

$$CVR = \frac{n_e - \frac{N}{2}}{\frac{N}{2}}, \tag{2}$$

where, n_e is the number of experts who rated the item as essential. N is the total number of experts. Items with CVR values above the critical threshold (based on the number of experts) were retained for the final version of the questionnaire.

2.1.2. Reliability

To assess the reliability of the questionnaire, Cronbach's Alpha was utilized (Equation (3)). This measure indicates the internal consistency of the questionnaire, reflecting how well the

items correlate with each other [36]. A Cronbach's Alpha value of 0.7 or above is generally considered acceptable for demonstrating reliability.

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}},\tag{3}$$

where, N is the number of items in the questionnaire. $\bar{c}$ is the average covariance between item pairs. $\bar{v}$ is the average variance of each item.

2.2. Emotional Artificial Neural Network (EANN)

Machine learning models are regarded as effective tools for analyzing and modeling nonlinear relationships [37]. Artificial neural networks are mathematical models that can demonstrate complex nonlinear functions in multidimensional spaces. The EANN model advances traditional neural networks by integrating a feedback-based modulation system, where simulated 'emotional states' adjust each neuron's activation and weight updates. This system, inspired by mechanisms of adaptive behavior, allows the model to respond to complex, variable input data more dynamically than traditional static neural networks. [38]. These hormones act as feedback signals that modify the parameters of the neural connections based on the inputs and outputs of the neurons [39]. The hormonal factors adapt dynamically in response to environmental changes, adjusting the model to achieve better performance. Unlike typical feedforward neural networks, which propagate information in one direction, EANN allows information to flow bidirectionally and integrates hormonal signals [40]. The emotional system within EANN is conceptualized as a regulatory feedback loop, where 'emotional signals' modulate the neural network's sensitivity to input data fluctuations. Unlike fixed-weight adjustments in conventional models, this approach enables an adaptive recalibration of weights based on the perceived complexity or uncertainty of the input data, thus mimicking adaptive, emotion-like responses in the network.

In this model, each neuron can receive and generate hormonal outputs, mimicking human emotional responses. Three hormone glandities (denoted as H_a, H_b, and H_c) govern the hormonal adjustments for each neuron, which in turn influences the network's outputs. The hormone levels, represented by H_h, are calculated as a summation of inputs and the associated weights (Equation (4)) [41–43].

$$\begin{aligned} H_h &= \sum_i H_{i,h}(h=a,b,c) \\ H_{i,h} &= glandity_{i,h} \times Y_i \end{aligned}.\tag{4}$$

2.2.1. Hormonal Modulation

The hormonal system is crucial for adjusting the network's response. For each neuron, the hormonal feedback modifies the weight of the connections, enhancing the system's learning capacity. The neurons update their internal states based on the dynamic weights Y_i, influenced by both neural activity and hormonal feedback. The overall hormonal level H_h determines the adjustment of these weights (Equation (5)) [44–46].

$$Y_i = \underbrace{\left(\gamma_i + \sum_h \partial_{i,h} H_h\right)}_{} \times f\left(\sum_j \left[\underbrace{(\beta_i + \sum_h \chi_{i,h} H_h)}_{} \times \underbrace{(\alpha_{i,j} + \sum_h \Phi_{i,j,k} H_h)X_{i,j}}_{} + \underbrace{(\alpha_i + \sum_h \chi_{i,h} H_h)}_{}\right]\right),\tag{5}$$

where, f is the function activator, ∂, ζ, Φ, and χ are the weight activation values, and γ, β, θ, and α show the neuron weights. γ controls the sensitivity of each neuron to incoming inputs, effectively modulating the strength of activation. Higher values of γ increase the network's responsiveness to small changes in input, making it more sensitive to fluctuations in data. α adjusts the learning rate of the network based on the simulated 'emotional' feedback. By modulating the learning rate, α helps balance the model's stability and flexibility, ensuring that weight updates are neither too rapid nor too slow (which could lead to overfitting or impede learning). β controls the rate of weight decay, or regularization, within the network. By preventing excessive weight growth, β contributes to the stability

and generalization of the model. Through this decay mechanism, the network avoids overfitting by gradually reducing the influence of weights that contribute little to overall accuracy. The input, hidden, and output neurons are denoted by the letters j, h, and I, respectively. H_h represents the hormonal levels and $X_{i,h}$ are inputs influenced by the hormones. This formulation integrates hormonal dynamics into the network's structure, allowing the EANN to adjust based on changing circumstances.

2.2.2. EANN Backpropagation and Learning

The EANN model is trained using an advanced form of backpropagation. In this training phase, the neural network learns by minimizing the error between the predicted and actual values, as in standard ANN models. However, in EANN, the learning rate is influenced by hormonal factors, meaning that errors not only affect the neural weights but also adjust the hormonal feedback, creating a dynamic learning process [47]. During each iteration of backpropagation, the weight update is applied (Equation (6)).

$$w_{i,j}^{(t+1)} = w_{i,j}^{(t)} - \eta_t \cdot \frac{\partial L}{\partial w_{i,j}} + \Delta H_h, \tag{6}$$

where, η_t is the learning rate influenced by hormones, and ΔH_h is the hormonal adjustment factor. This allows the model to learn more efficiently by incorporating both neural and emotional feedback into the learning process.

2.2.3. Levenberg–Marquardt Algorithm for EANN Training

The Levenberg–Marquardt (LM) algorithm is an advanced optimization technique widely employed for training neural networks, particularly in situations where higher accuracy and faster convergence are required, such as in the EANN model. This algorithm strikes a balance between gradient descent and the Gauss–Newton method, making it an ideal choice for training networks with a large number of parameters, which is often the case in EANNs where emotional feedback mechanisms are involved. In EANN, the feedback loop functions as a pseudo-emotional system that continuously recalibrates neural pathways based on prior input–output patterns. This adjustment mechanism allows for a learning approach that resembles adaptive responses, maximizing predictive accuracy in scenarios with high data variation. The LM algorithm works by adjusting the weights in a manner that allows for both fast convergence and effective minimization of the error function [48]. The weight update rule in the LM algorithm is expressed as Equation (7).

$$w_{k+1} = w_k - \left[J^T J + \lambda I \right]^{-1} J^T e, \tag{7}$$

where, w_k is the vector of weights at the k-th iteration. J is the Jacobian matrix containing first-order partial derivatives of the error with related to the weights. e is the error vector. λ is the damping factor (or regularization parameter) that controls the transition between gradient descent and the Gauss–Newton method. I is the identity matrix.

In the context of EANN, where hormonal feedback plays a significant role in modulating the network's behavior, the LM algorithm ensures that both the emotional feedback loop and the neural learning process are optimized in tandem. The hormonal parameters are dynamically adjusted during each iteration as the error is backpropagated, and the weights are updated accordingly. For each neuron, the backpropagation process calculates the gradient of the loss function concerning the weights, which is influenced by the emotional hormones H_h (Equation (8)).

$$w_{k+1} = w_k - \left[J^T J + \lambda I \right]^{-1} J^T (e + \Delta H_h), \tag{8}$$

where, ΔH_h is the change in hormonal feedback affecting the weight adjustment, providing a more holistic approach to the learning process. This factor represents a feedback

mechanism that adjusts the model's sensitivity to errors based on the perceived data complexity and input patterns. Unlike traditional ANNs, where the learning rate remains static or changes according to a fixed schedule, the EANN uses ΔH_h to dynamically alter the learning rate during training. When the network detects high variability or complexity in the input data, ΔH_h increases the learning rate, allowing the model to respond more aggressively to errors and learn from rapidly changing patterns. Conversely, in periods of data stability, ΔH_h reduces the learning rate, promoting gradual weight adjustments to refine predictions without overreacting to minor fluctuations. Figure 1 shows the study flowchart based on building maintenance and operational cost analysis.
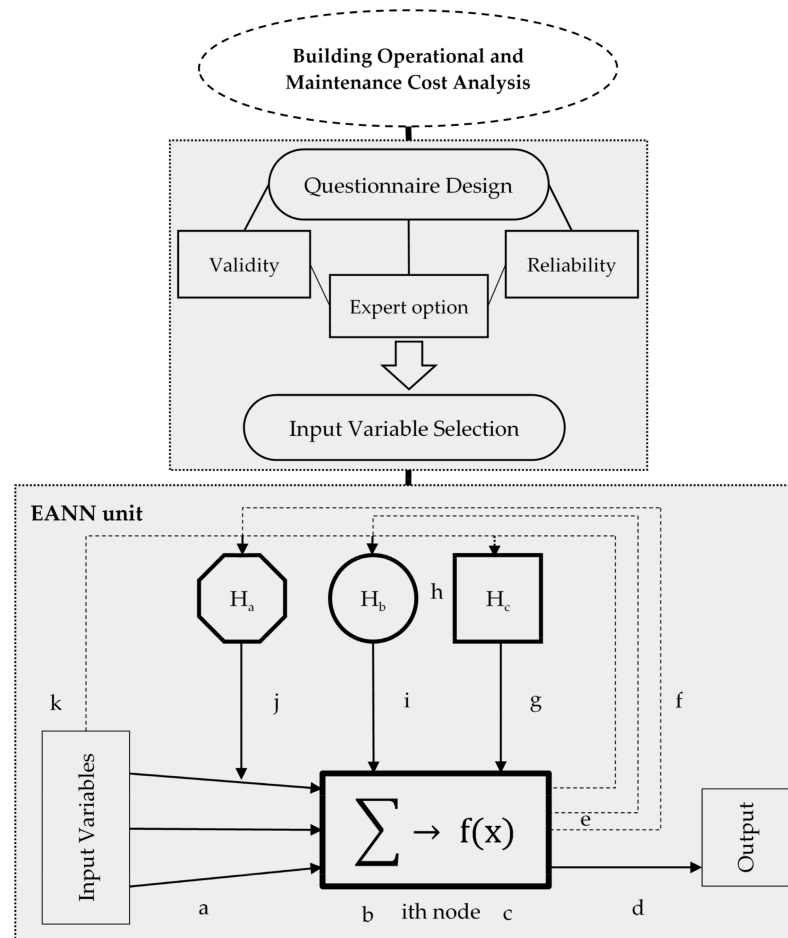

Figure 1. The flowchart of the building operational a maintenance cost estimation.

2.3. Model Evaluation Criteria

The formula for calculating Pearson correlation coefficient (R) between two variables, is given by Equation (9) [49].

$$R_{xy} = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}}, \tag{9}$$

where, X_i and Y_i are the individual data points for variables X and Y, respectively. $\bar{X}$ is the mean of the X values, and $\bar{Y}$ is the mean of the Y values. n is the number of data points. The numerator represents the covariance between X and Y, while the denominator normalizes it by the product of the standard deviations of X and Y.

The Coefficient of Determination (R^2) evaluates the goodness-of-fit of a model, indicating how well the model explains the variability of the response data around its mean (Equation (10)) [50].

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2},$$

(10)

where, Y_i is the actual observed value for observation i. $\hat{Y}_i$ is the predicted value for observation i. $\overline{Y}$ is the mean of the actual data.

The Root Mean Squared Error (RMSE) represents the square root of the average of squared differences between actual and predicted values (Equation (11)) [51].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}.$$

(11)

The Mean Squared Error (MSE) and Mean Absolute Error (MAE) are defined as Equations (12) and (13), respectively [52,53].

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2,$$

(12)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left|Y_i - \hat{Y}_i\right|$$

(13)

3. Results and Discussion

Questionnaire questions are divided into two sections: questions about cognitive population and questions about different dimensions of hypotheses, which are examined and analyzed using descriptive and inferential statistical methods. The questionnaire is divided into two parts. Demographic questions include respondents' general information and demographics, as well as specialized questions, such as questions about the dimensions of building repair and maintenance cost (Figure 2). While this study focused on factors directly related to building characteristics and maintenance histories, external variables such as geographical location, climate conditions, and policy environments could also play a critical role in influencing maintenance and operational costs.
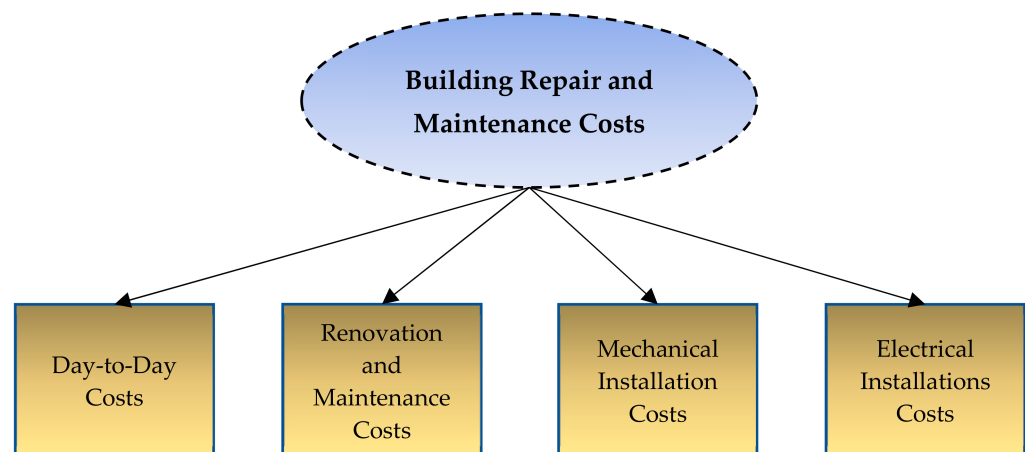

Figure 2. Building repair and maintenance cost items.

To ensure the validity of the survey instrument, the CVI and CVR were calculated for each survey item. The results are presented in Figure 3, providing CVI and CVR values alongside average relevance scores and essentiality ratings for each item. Each item was assessed for relevance and essentiality to the study objectives. The CVI for each item exceeded the acceptable threshold of 0.79, ranging from 0.82 to 0.91, indicating a high degree of item relevance to the research goals.
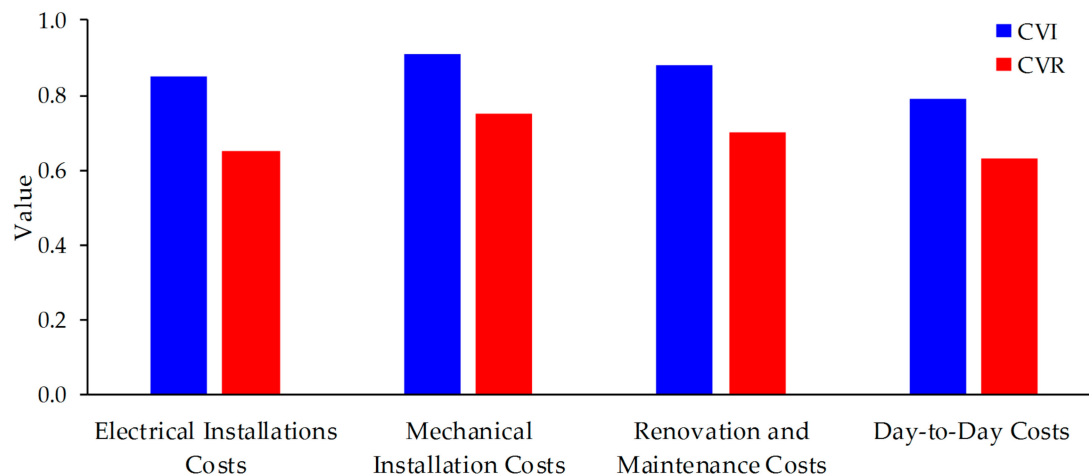
Figure 3. CVI and CVR value for each research item based on expert option.

For CVR calculations, experts were asked to indicate whether each item was essential to the instrument. A threshold of 0.59, based on Lawshe's method, was used to determine item retention. All items achieved CVR values between 0.63 and 0.76, meeting or surpassing this requirement, thereby confirming that the experts deemed each item essential.

To determine the questionnaire's reliability, it was first distributed to 15 respondents. To evaluate the reliability of the survey instrument, Cronbach's Alpha was calculated for internal consistency, yielding a value of 0.87. In this context, a Cronbach's Alpha above 0.70 is acceptable, while values above 0.80 indicate a high level of reliability, particularly in social sciences and applied research. Therefore, a value of 0.87 suggests strong internal consistency among the survey items.

To further substantiate this reliability measure, a 95% confidence interval for Cronbach's Alpha was calculated, resulting in a range of 0.83 to 0.90. This interval reflects the stability and precision of the reliability estimate, indicating that the true reliability of the survey instrument is likely to fall within this range. The narrow confidence interval suggests minimal variability in the reliability estimate, providing confidence that the survey items are consistently measuring the intended constructs.

3.1. Variables Selection

The characteristics of the studied statistical sample based on the gender, educational degree, work experience, building type in which experts work, building age, building area, structure type, number of owners, and type of heating and cooling system variable are shown in Table 1. Most of the respondents are men (271 people). In fact, 13% of the studied statistical sample are female and 87% of the statistical sample are male. Additionally, 50% of the statistical sample have a professional education, 31% of the statistical sample have an advanced professional education, and 13% of the statistical sample have a doctorate and higher education. Most of the respondents had more than 10 years of experience (44%).

Table 1. Characteristics of the study based on respondents and variables.

Respondents Gender		
Male	**Female**	**Total**
271 (87%)	42 (13%)	313

Respondents educational degree			
Diploma	**Bachelor**	**Master of science**	**doctorate and higher**
18 (6%)	158 (50%)	97 (31%)	40 (13%)

Table 1. *Cont.*

		Respondents work experience (year)		
Less than a year	**1 to 5**	**5 to 10**	**Over 10**	
34 (12)	51 (16%)	89 (28%)	139 (44%)	
		Building type		
Concrete	**Steel**	**Masonry**	**Other**	
41%	33%	25%	1%	
		Building Age (year)		
0 to 10	**10 to 20**	**20 to 30**	**30 to 40**	
28%	49%	16%	7%	
		Building Area (m^2)		
Less than 100	**100 to 300**	**300 to 500**	**Over 500**	
8%	32%	34%	26%	
		Heating System		
Natural gas heater	**Central heating**	**Heating package**	**Underfloor heating**	**roof heating**
22%	20%	41%	12%	5%
		Cooling System		
Evaporative air coolers	**Air Conditioner**	**Fan coil**	**Chiller**	**Split duct**
34%	39%	9%	15%	3%

Table 2 shows the correlation coefficient test for 313 samples from different annual periods, as well as the total.

Table 2. Pearson correlation coefficient results for statistical samples.

Variable	Cost 0 to 10 Years	Cost 10 to 20 Years	Cost 20 to 30 Years	Cost 30 to 40 Years	Cost 0 to 40 (Total)	*p*-Value
Building age	0.70	0.61	0.53	−0.62	0.32	< 0.05
Building area	0.52	0.12	0.13	−0.18	0.19	0.680
Structure type	0.37	0.32	0.38	0.22	0.31	0.089
Number of owners	−0.07	−0.04	0.04	−0.01	−0.03	1.18
Heating System	0.33	0.12	−0.11	0.37	0.21	0.29
Cooling System	0.38	0.24	0.18	0.25	0.26	0.38

According to Table 2, the R value of the variables are considered influential. This demonstrates how strongly this parameter and maintenance costs are correlated. With *p*-values < 0.05, the results in this section show that there is a correlation between the parameters as determined by *p*-value and correlation analysis. However, due to the low correlation, the variable "number of owners" was removed from the machine learning model entries. While low correlation alone was not the sole determinant, this variable also showed limited theoretical relevance to maintenance and operational cost estimation, minimal predictive impact on model performance, and an absence of significant multivariate interactions with other predictors.

3.2. EANN Results

This section examines the prediction ability of the EANN model and the ANN model for each period. First, the cost of maintaining 100 buildings has been accumulated. Machine learning models consider five inputs and one output. Building age, building area, structure type, and heating and cooling system type are all considered inputs. Output includes building maintenance costs. Figure 3 compares the predictive ability of machine learning models over the age range of 0 to 10 years. Figures 4–6 show the same results for building ages 10–20, 20–30, and 30–40 years.
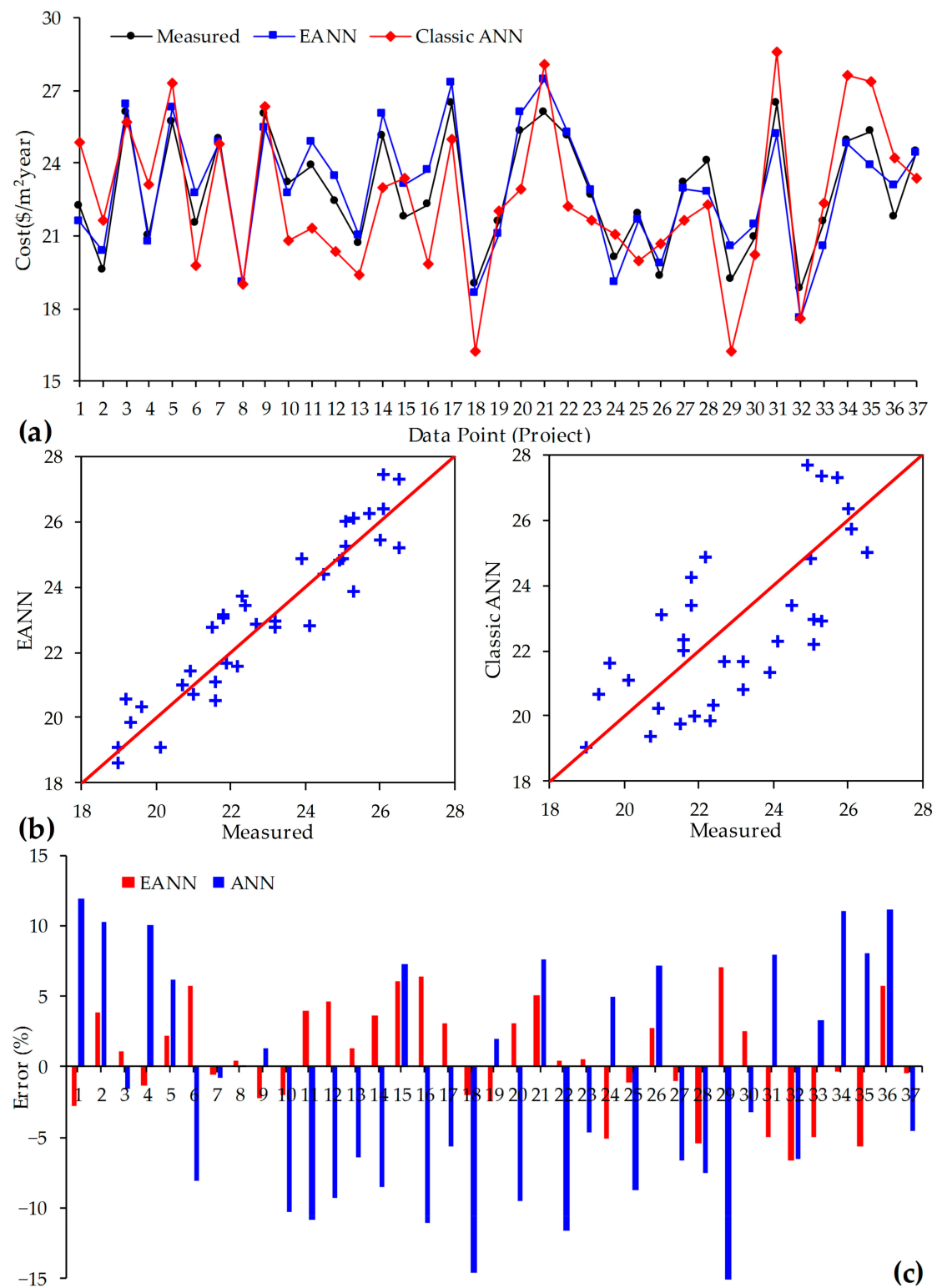
Figure 4. Machine learning models evaluation for building age 0 to 10 years (**a**) cost analysis of the prediction models, (**b**) scatter plot of measured data and predicted results, and (**c**) machine learning error evaluation.
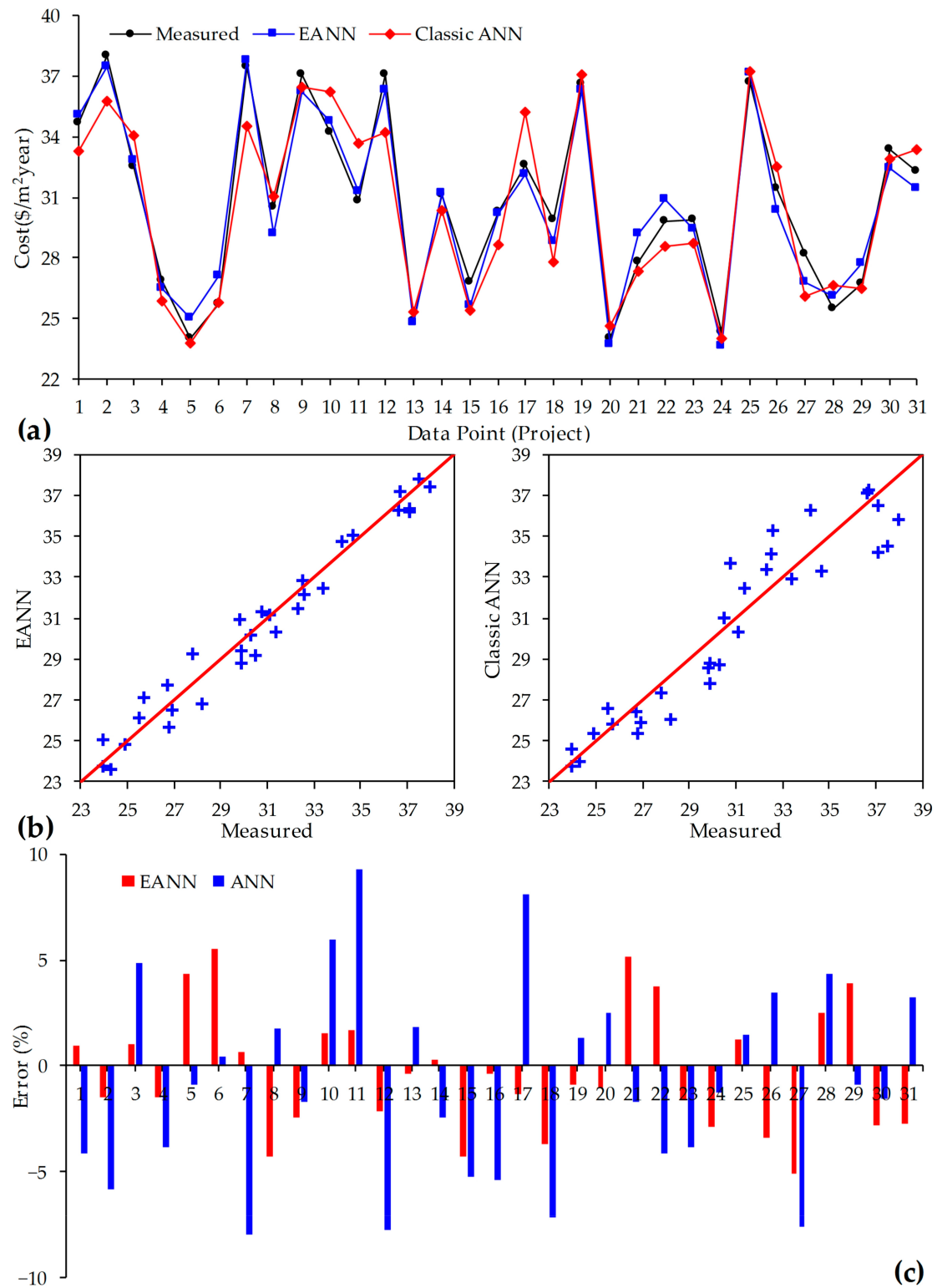
Figure 5. Machine learning models evaluation for building age 10 to 20 years (**a**) cost analysis of the prediction models, (**b**) scatter plot of measured data and predicted results, and (**c**) machine learning error evaluation.
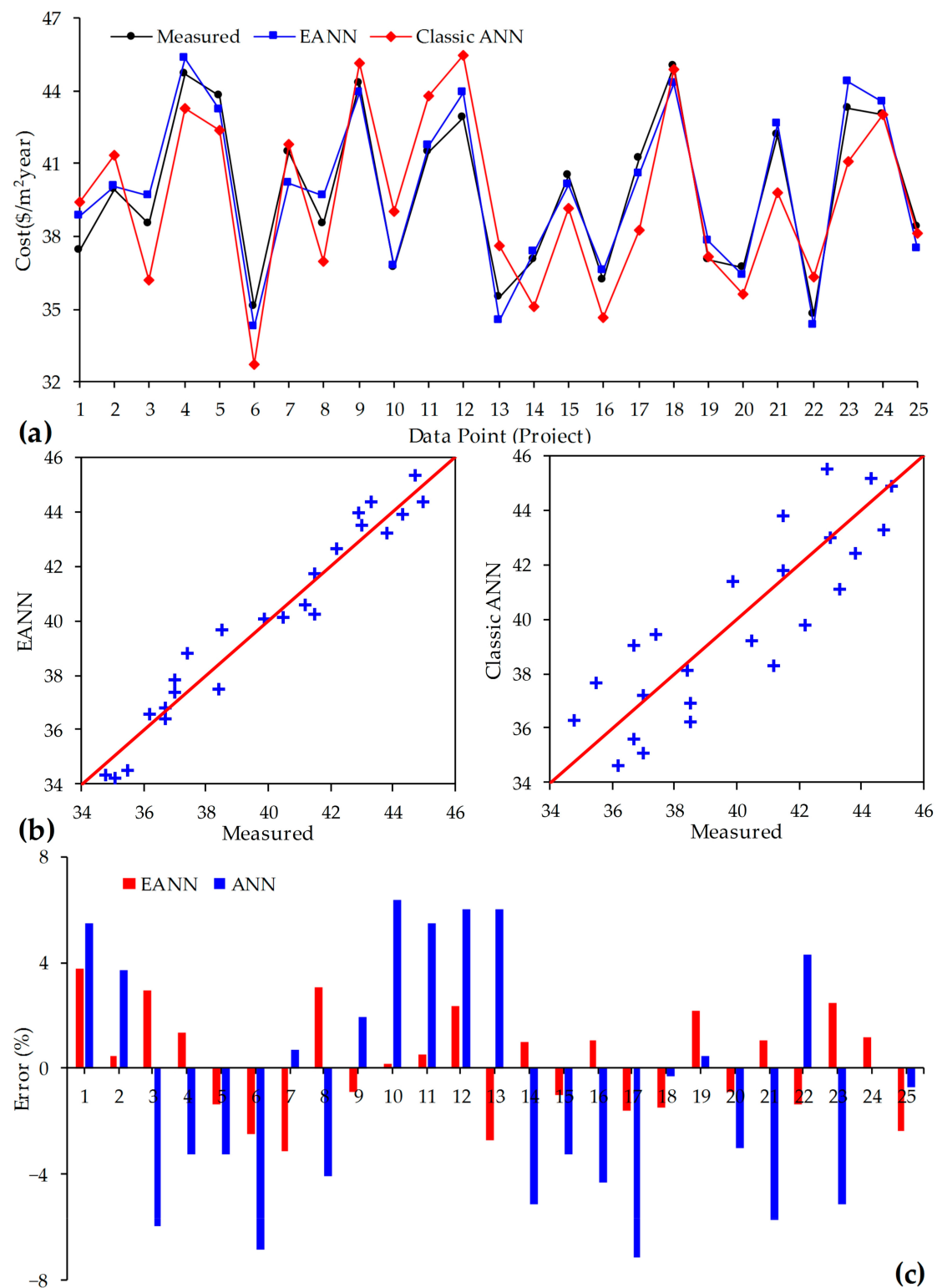
Figure 6. Machine learning models evaluation for building age 20 to 30 years (**a**) cost analysis of the prediction models, (**b**) scatter plot of measured data and predicted results, and (**c**) machine learning error evaluation.

The dataset was divided into k = 10 folds to evaluate the models cross-validation. The average performance metrics (R^2, RMSE) across all folds were calculated to assess the model's overall generalization ability. Table 3 shows the results of K-fold cross-validation. The EANN model achieves a higher R^2 and a lower RMSE compared to the ANN model.

Table 3. K-fold cross-validation (k = 10) results.

Metric	EANN Model (Mean ± Sd)		ANN Model (Mean ± Sd)	
	Training	**Testing**	**Training**	**Testing**
R^2	0.88 ± 0.01	0.84 ± 0.02	0.81 ± 0.03	0.78 ± 0.04
RMSE	1.60 ± 0.05	1.65 ± 0.06	1.80 ± 0.06	1.92 ± 0.08

Figure 4 shows the evaluation of models used for predicting building maintenance and operation costs over a range of 37 data points (representing different projects). In Figure 4a, the measured costs are plotted against the predictions made by the EANN and the Classic ANN models. The vertical axis represents the cost values, ranging from approximately USD 15 to 30 per square meter per year. The EANN model shows a closer match to the measured data throughout the range of data points, particularly in the middle region, between data points 18 and 28, where the predicted values nearly overlap with the actual costs. This indicates a higher accuracy in the EANN's predictive capability. On the other hand, the Classic ANN model exhibits larger deviations, particularly around data points 20 to 28, where its predictions often miss the actual trend.

Figure 4b shows the scatter plots of the models. The EANN predictions are plotted against the measured costs, and the points align closely along the 45-degree reference line. This implies that the EANN model has a high degree of accuracy in its cost predictions. The Classic ANN predictions against the measured data show more dispersion of points away from the reference line. This pattern suggests that the Classic ANN predictions have greater error and are less consistent with the actual measured data compared to the EANN model.

Figure 4c displays the percentage error for both models across all data points. The EANN consistently shows lower error percentages, with most data points exhibiting errors within a small range. In contrast, the Classic ANN model demonstrates significantly larger error values for several data points, indicating that its predictions are less reliable. Notably, in some instances, the Classic ANN's error exceeds 10%, while the EANN's error remains below 5% in most cases. This error analysis highlights the superior predictive performance of the EANN model in terms of minimizing the discrepancy between predicted and measured costs.

Figure 5 demonstrates the evaluation of models for predicting maintenance and operation costs for buildings aged between 10 and 20 years based on 31 different project data points. In Figure 5a, the actual measured costs are compared with the predictions of the EANN model and the Classic ANN model. The cost values range from USD 23 to 40 per square meter per year, and the EANN model shows an overall closer alignment with the measured data compared to the Classic ANN. Specifically, the EANN consistently captures the fluctuations in costs across the different data points. This indicates that the EANN model provides more accurate predictions than the Classic ANN, which deviates more notably from the measured costs.

In Figure 5b, the scatter plots further illustrate the accuracy of the models. The plot for the EANN model shows data points clustering closely around the 45-degree reference line. The points' proximity to the line demonstrates that the EANN provides reliable predictions for various costs. The scatter plot for the Classic ANN shows greater variability, with several data points diverging further from the reference line, particularly for higher cost values. This suggests that the Classic ANN model underperforms in predicting more extreme cost values, leading to larger discrepancies between the predicted and actual data. Figure 5c provides an error analysis for both models. For most data points, the EANN model has smaller error margins, remaining under 5%, especially in the critical middle range of data points. In contrast, the Classic ANN model displays larger error values for numerous points, often exceeding 5%, and in some cases, errors approach or exceed 10%. This comparative analysis highlights the superior accuracy of the EANN model in predicting maintenance and operation costs.

Figure 6 illustrates the evaluation of machine learning models for predicting maintenance and operation costs in buildings aged between 20 and 30 years across 25 different project data points.

In Figure 6a, the actual measured costs are compared with the predictions from both the models. The cost values range from USD 34 to 47 per square meter per year. The EANN model shows closer alignment with the measured values across the entire range of data points, especially for points 5, 12, 19, and 22, where it more accurately captures the fluctuations. In contrast, the Classic ANN model exhibits larger deviations, particularly noticeable in points 7 and 15, where its predictions diverge significantly from the measured costs.

Figure 6b presents scatter plots of the measured versus predicted values. The EANN model's scatter plot shows data points clustering near the 45-degree reference line. This reflects the model's accuracy for both low- and high-cost values. The scatter plot for the Classic ANN model shows a larger spread of points, especially in the higher cost range (40 and above), where the predictions consistently fall below the reference line. This suggests that the Classic ANN model struggles with higher cost predictions, leading to increased error margins.

In Figure 6c, the error analysis compares the percentage errors for both models. For most data points, the EANN model demonstrates smaller error margins, with errors generally falling within $\pm 3\%$. In contrast, the Classic ANN model shows higher error percentages, especially around points 7, 15, and 23, where errors exceed 5%.

Figure 7 presents an evaluation of machine learning models for predicting costs associated with buildings aged 30 to 40 years. The analysis is divided into three parts: cost analysis, scatter plots of predicted versus measured data, and error evaluation. Figure 7a displays cost data across 17 projects, showing that both models closely follow the measured values, with slight variations that are visually apparent. Similarly to Figures 3–5, the proposed model seems to provide predictions more aligned with the measured data compared to the Classic ANN, suggesting improved model accuracy. Figure 7b illustrates the relationship between measured data and model predictions. Both plots indicate a positive correlation, where the data points are closely aligned along the line of equality, signifying that both models are capable of reasonably accurate predictions. The EANN demonstrates a tighter clustering of data points along the 45-degree line, reinforcing its superior performance over the Classic ANN in this context.

Figure 7c illustrates that while the EANN model maintains relatively low prediction errors across data points, the Classic ANN model shows a broader error range, with several data points exceeding 5% error. The Classic ANN model's higher errors are especially pronounced for buildings, where maintenance needs tend to become more irregular and costly. Another contributing factor to the Classic ANN's wider error range may be its inability to process nuanced interactions among variables, such as the combined effects of building age, area, and specific structural characteristics, which can significantly influence maintenance costs. Furthermore, evaluating the errors and improved performance of the EANN model results when compared to the standard ANN model demonstrates that it may offer acceptable predictions with a limited and small amount of data. Additionally, despite the errors, it accurately recognizes the data's trend. This result is consistent with the findings of Sharghi et al. [42].

Figure 8 evaluates the performance of two models, the classical ANN and the EANN, for four different building age groups. The performance is assessed based on various metrics including the R^2, the R, and the RMSE for both training and testing phases. For buildings aged 0 to 10 years, the EANN results demonstrates superior performance across all indices compared to the ANN model. The R^2 value for EANN in the training phase is 0.85, which is higher than 0.78 for ANN, indicating better predictive accuracy. In the testing phase, EANN also outperforms ANN with an R^2 of 0.81 compared to 0.72. Similarly, the correlation coefficient (R) for EANN is higher, reaching 0.91 in training and 0.93 in testing, while ANN shows 0.84 and 0.85, respectively. In practical considerations, this level

of accuracy could represent substantial savings in maintenance budgeting, particularly for large-scale projects where even minor error reductions can translate into significant financial benefits. Additionally, the RMSE for EANN is lower, signifying less prediction error (1.57 in training and 1.60 in testing) compared to ANN's higher error values (1.82 and 1.90).
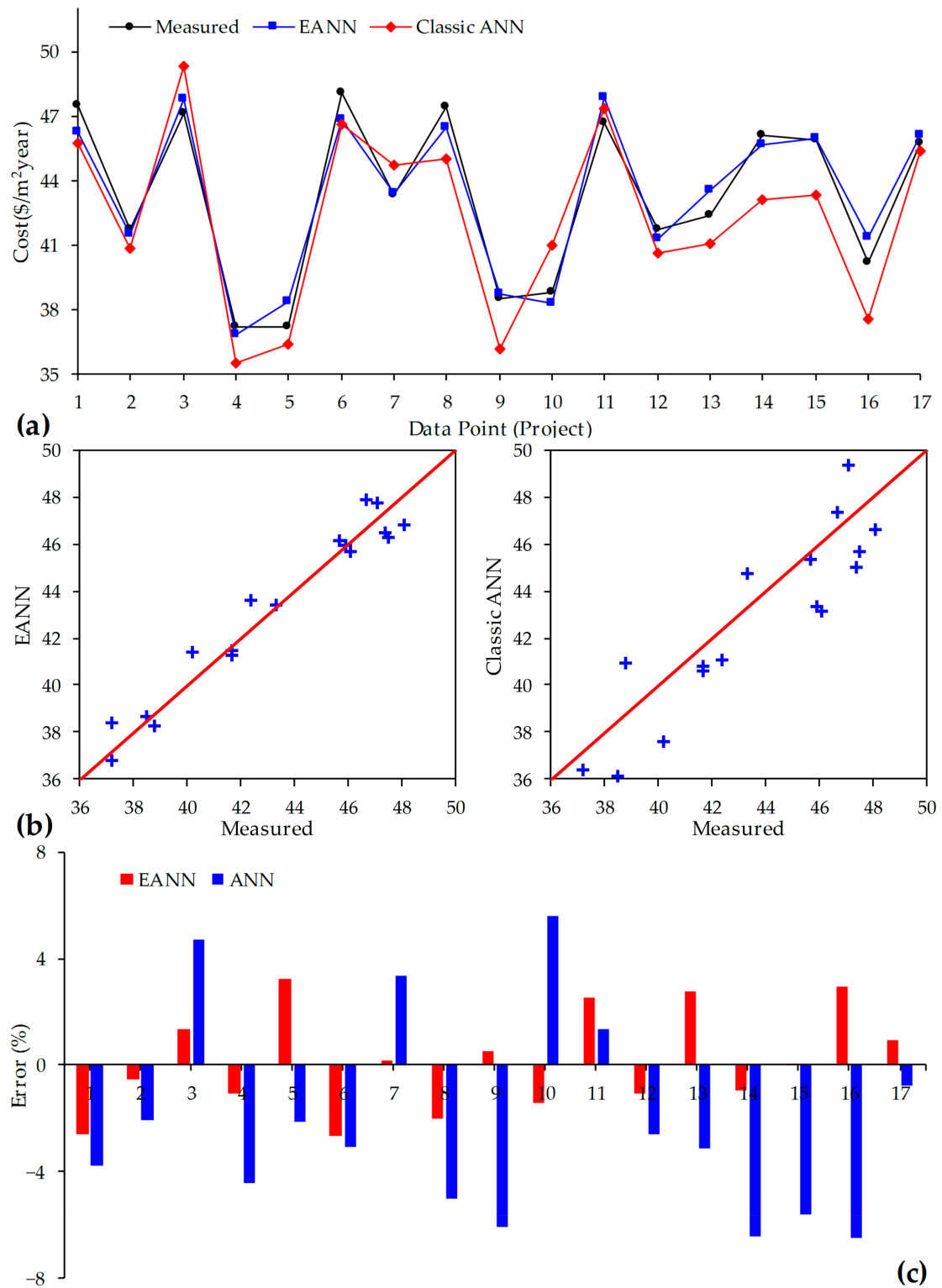

Figure 7. Machine learning models evaluation for building age 30 to 40 years (**a**) cost analysis of the prediction models, (**b**) scatter plot of measured data and predicted results, and (**c**) machine learning error evaluation.
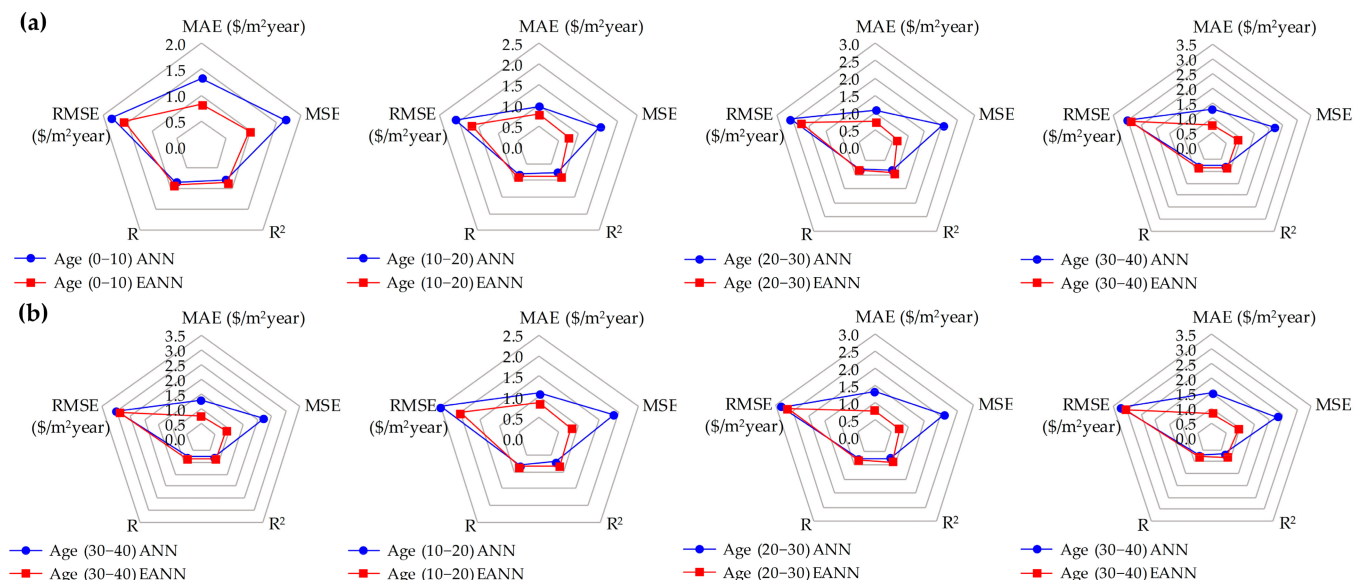
Figure 8. Machine learning models statistical evaluation for various buildings (**a**) training phase (**b**) testing phase.

In the 10- to 20-year age group, a similar trend is observed, with EANN outperforming ANN. EANN achieves an R^2 of 0.88 in training and 0.82 in testing, while ANN lags behind with 0.76 and 0.69, respectively. For stakeholders, a higher R^2 means that the model accounts for the complex factors influencing costs more effectively, reducing the uncertainty in budgeting and planning for maintenance. The correlation coefficients follow the same pattern, with EANN (0.88 in training, 0.83 in testing) again showing stronger results than ANN (0.81 and 0.80). The RMSE values further confirm EANN's better performance, with lower errors in both phases (1.70 for training and 2.00 for testing) compared to ANN's RMSE (2.10 and 2.50). The lower RMSE across all age groups suggests that the EANN model is more adaptable to fluctuations in maintenance costs, which is critical for buildings in mid-to-late lifecycle stages where unexpected repairs and increased maintenance are common. This adaptability allows building managers to make more accurate long-term cost projections, reducing the risk of maintenance budget evaluation. In this scenario, compared to the Classic ANN model, the EANN demonstrated a 15% improvement in predictive accuracy. This level of precision allowed property managers to allocate maintenance budgets more effectively, avoiding both overestimation, which could lead to resource wastage, and underestimation, which might result in delayed repairs and higher long-term costs.

For buildings aged 20 to 30 years, the gap between EANN and ANN remains evident. EANN achieves an R^2 of 0.92 in the training phase and 0.88 in the testing phase, while ANN shows lower values of 0.81 and 0.75. The R values for EANN are slightly higher in testing (0.82 for training and testing) compared to ANN (0.79 for training and 0.77 for testing). The RMSE values are lower for EANN (2.27 for training and 2.64 for testing) than for ANN (2.59 and 2.83). For the final age group (30 to 40 years), EANN continues to show better performance. In the training phase, EANN achieves an R^2 of 0.83, compared to 0.77 for ANN. In the testing phase, EANN's R^2 is 0.82, higher than ANN's 0.70. The correlation coefficient for EANN in training is 0.83, and in the test phase, it is 0.79, while ANN has lower R values of 0.77 and 0.75, respectively. The RMSE for EANN remains lower (2.89 in training and 3.08 in testing) compared to ANN's RMSE (3.01 and 3.24). The lower prediction errors enabled building managers to prioritize critical repairs and optimize resource distribution. This application highlights the EANN's ability to adapt to irregular cost patterns commonly observed in older buildings.

EANN consistently outperforms ANN across all building age groups in terms of accuracy (R^2 and R) and error minimization (RMSE). The EANN model's ability to pro-

vide better predictive performance across both training and testing phases highlights its potential as a more reliable tool for cost prediction in the context of different building ages. The reduction in RMSE, particularly in testing, demonstrates EANN's robustness and generalization capabilities compared to the Classic ANN model (Figure 8).

To further substantiate this performance difference, a statistical comparison of RMSE values was conducted, calculating 95% confidence intervals for the difference in RMSE between the two models. Table 4 summarizes the RMSE values for each age group, along with the 95% confidence intervals for the RMSE differences.

Table 4. RMSE statistical analysis of the EANN and ANN models by 95% confidence interval consideration.

Building Age	RMSE Difference Between EANN and ANN Model	95% Confidence Interval for RMSE Difference
0–10	−0.25	[−0.32, −0.18]
10–20	−0.40	[−0.47, −0.34]
20–30	−0.32	[−0.40, −0.25]
30–40	−0.12	[−0.18, −0.05]

The confidence intervals for the RMSE differences indicate that the EANN model achieves statistically significant lower RMSE values across all age groups, as the intervals do not cross zero. For example, in the 10–20-year age group, the RMSE difference of −0.40 (95% CI: [−0.47, −0.34]) confirms that the EANN model consistently outperforms the Classic ANN in terms of predictive accuracy for this group. The narrower confidence intervals in the 0–10- and 10–20-year groups highlight more pronounced performance differences, while the smaller difference in the 30–40-year group suggests diminishing returns for older buildings (Table 4).

In order to compare the results of the model prediction with other studies, the reader can refer to the study by Chandanshive and Kambekar [54]. In this study, the authors predicted the construction costs by examining 78 construction projects in Mumbai, India, using the support vector machine model. In the best case, their model had an R^2 of 0.94. Their results are very close to the prediction results of the EANN model proposed in the present study, with an R^2 of 0.92 for the buildings group aged 20–30 years.

4. Conclusions

This study presented an innovation technique for predicting maintenance and operation costs in construction projects through the integration of the EANN. This research lies in the incorporation of synthetic emotional feedback mechanisms into the learning process, allowing the model to adjust its predictions in address to complex and nonlinear relationships.. This capability surpasses the limitations of traditional models that rely on static machine learning or linear regression methods, providing a more adaptive and context-aware framework for cost estimation. By utilizing data from 313 experts in the field of building management and construction in Ha'il, Saudi Arabia, the model integrates expert knowledge with advanced machine learning techniques, offering a reliable and scalable solution for cost forecasting in the construction sector. The key contribution of this framework lies in its ability to integrate expert knowledge with advanced machine learning techniques, providing precise and context-aware cost forecasts. By capturing subtle patterns in data and responding dynamically to variability, the EANN supports better resource allocation, minimizes prediction errors, and reduces the risk of underestimating or overestimating budgets. These improvements are particularly significant for buildings with variable maintenance needs, such as mid-to-late lifecycle structures, where traditional models often struggle to provide accurate predictions.

The proposed EANN model was thoroughly evaluated and compared with a Classic ANN model. The results demonstrated that the EANN consistently outperformed the ANN in both accuracy and efficiency. For buildings aged 0 to 10 years, the EANN achieved an R^2

value of 0.85 during the training phase and 0.81 during testing, compared to 0.78 and 0.72 for the ANN model. Furthermore, the RMSE for the EANN model was lower, with values of 1.57 in training and 1.60 in testing, while the ANN model recorded RMSE values of 1.82 and 1.90, respectively. These results underscore the superior predictive capability of the EANN, particularly in capturing the cost fluctuations over different building life cycles.

Although the EANN model demonstrated superior predictive performance over the Classic ANN in this study, several limitations should be acknowledged. First, the EANN model was tested using a specific set of input variables relevant to maintenance and operational cost prediction in construction projects. Incorporating a broader range of variables could provide a more comprehensive understanding of the model's predictive capabilities and help identify any potential interactions that might influence cost predictions. Additionally, the current model was developed and validated on a single type of building dataset, with age groups categorized into four distinct ranges. Meanwhile, the performance of EANN may vary when applied to datasets from other regions or different building types, where environmental and socio-economic factors could influence maintenance costs differently. While EANN showed strong performance across these categories, there may be variability in accuracy when applied to different building types, such as commercial or industrial structures, which may have unique cost drivers and maintenance patterns. Testing the model on a more diverse set of building types would be beneficial in assessing its generalizability. Future research could explore several specific optimization techniques and technological advancements to enhance the EANN model's applicability and predictive accuracy. One promising avenue is the integration of advanced optimization models for hyperparameter tuning. Additionally, incorporating transfer learning techniques could improve the model's generalizability across different datasets. By pre-training the EANN model on large datasets from diverse geographic locations, followed by fine-tuning on specific project datasets, transfer learning could help the EANN adapt more readily to variations in regional construction practices, environmental factors, and building regulations. Meanwhile, future research could conduct separate analyses for different building types, such as commercial, industrial, and public buildings. Each category presents unique maintenance challenges and cost drivers. Applying the EANN model to these contexts could help identify patterns and predictive factors specific to each building type.

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