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Artificial Neural Networks Application for the Croatian School Maintenance Cost Estimation

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Abstract: The quality of education is associated with the condition of the infrastructure in which the educational process occurs, necessitating the continuous maintenance of these facilities. Limited and often insufficient maintenance funds pose a challenge in this context. Current cost estimates are inaccurate, and data on school and maintenance costs are constrained. More accurate maintenance cost plans would contribute to a better understanding of budget distribution and more efficient financial management. This study aims to investigate the application of artificial neural networks (ANNs) in planning annual maintenance costs for schools in the Republic of Croatia (Primorje-Gorski Kotar County). Using a database and DTREG software, three different ANN models were developed: a multilayer perceptron (MLP), a generalized regression neural network (GRNN), and a radial basis function neural network (RBFNN). Comparisons of the results showed that the GRNN is optimal and achieves the highest accuracy in estimating school maintenance costs. These findings can benefit educational institutions and public bodies in budget planning and decision-making regarding maintenance.

Keywords: artificial neural network; cost estimation; maintenance cost; school buildings

1 INTRODUCTION

Schools are the centres of the educational (and upbringing) system, and the school building is an important indicator of its quality [1-4]. The quality of the school building is mainly ensured by adequate maintenance [5]. School maintenance includes all those activities that retain the desired functions and purposes of the school building during its lifetime [6].

School maintenance is usually divided into ongoing and investment [7]. Ongoing maintenance involves repairing damage caused by the daily use of the building. It includes inspecting the damage, repairing it, and implementing preventive and protective measures and interventions after unplanned events. Investment maintenance involves the implementation of (mostly planned) construction-craft works to improve the conditions of use of the building in the exploitation phase. Usually, it requires larger financial resources [8].

School maintenance is the responsibility of the public authority (state, county, city, municipality), which is in the role of its founder. Public authorities also finance maintenance, and the necessary funds are shown in the financial plans (cost plans). A review of [7, 9], found that these plans are not precise enough and that there is a high level of uncertainty in planning maintenance works and related costs. More accurate estimating of maintenance costs would make it possible to determine the target costs for planned maintenance works and provide information on the limits of available funds. It would give valid cost information to help maintainers make appropriate maintenance decisions [10]. Cost plans are mandatory for efficient cost management [7] and would allow building owners to get value for money spent on maintenance [10].

The public sector covers the costs of educational facilities; therefore, the planning and optimal distribution of these costs, as well as increasing the efficiency of maintenance management, is a significant and valuable goal of broader social interest [7]. Effective management of school maintenance implies planned, organized, and high-quality implementation of maintenance activities with optimal consumption of resources, primarily financial. Effective maintenance ensures the satisfaction of school staff and students by creating conditions that ensure their health and safety, facilitate teaching and learning, and improve school outcomes [11].

In Croatia, there is insufficient comprehensive research addressing the analysis of the expenses associated with maintaining primary and secondary schools, as stated in the available literature [7, 9, 12-14]. School maintenance is often neglected, characterized by a lack of coordination and high financial expenses. Estimates of maintenance costs show insufficient precision [7].

Given all the above, the need to develop a model for estimating the cost of school maintenance is very pronounced. The literature highlights the potential of machine learning for these purposes, using artificial neural networks (ANNs) [7, 15-19]. By using a database and applying computer models, there is the possibility of producing more accurate cost estimates [20].

The main goal of this paper is to investigate the possibility of developing a model for estimating the costs of maintaining school buildings using ANN in the Republic of Croatia. The model will be developed based on a database of school buildings with insight into historical data on actual maintenance costs. The model is intended to provide a more accurate, quick, simple, and structured assessment. The research is limited to Primorje-Gorski Kotar County.

The following research questions were defined;

- Is it possible to create a database on school buildings from Primorje-Gorski Kotar County with insight into historical data on maintenance costs?
- Based on the created database, is it possible to develop an ANN model for estimating the maintenance cost of school buildings with satisfactory accuracy ($R^2 > 0.64$, $MAPE < 30$ %)?
- Is there currently a pronounced inaccuracy in the estimation of maintenance costs, and will the application of the ANN model developed here reduce this inaccuracy?

The application of the developed ANN model should certainly help increase the efficiency of the maintenance process.

The work is organized as follows. The first section is introductory, in which the motives for conducting the research are stated, the main points from the literature review are highlighted, and the goal and research questions are outlined. The second section describes the applied methodology in detail with all the necessary descriptions and explanations. In the third section, the obtained results are presented and discussed. The last fourth section presents the conclusions.

1.1 Theoretical Background

1.1.1 School Building Maintenance Costs and Plans

Authors of [21] define building maintenance as an investment activity throughout the life of the building that ensures a satisfactory level of service. The primary goal of maintaining a school building is to extend its life [22], i.e., to keep it in a satisfactory functional, structural, and aesthetic condition for as long as possible [23, 24]. The lifespan of a building includes all phases of its life cycle, from the design of the building to its demolition. Maintenance costs are often higher than costs incurred in other stages of a building's life and can account for an average of 60% of all costs incurred during its lifetime [25], so it is essential to maintain the building properly, as very uneconomic costs can arise [26].

Building maintenance costs include the costs of labour, materials, equipment, tools, and any other related costs that may be incurred in building maintenance [26]. Maintenance cost estimation includes operation analysis and maintenance cost forecasting.

In the Republic of Croatia, financial needs for the maintenance of primary and secondary education are met for the most part through the Government of the Republic of Croatia, i.e., the Ministry of Science and Education. The main criteria for determining funds per founder include the number of school buildings, departments, and students. A certain financial part can be covered by the founders from their income. The founders are responsible for the distribution of available funds to the schools within their territorial units. The schools themselves analyse their needs, draw up budgets, and submit them to the founders. The founders then consider the reported needs and draw up a maintenance plan with a cost plan. Maintenance costs in all mentioned plans are mostly determined by empirical methods instead of sophisticated techniques. These amounts often do not reflect the actual state of affairs, so continuous updating and revision are necessary to adapt to changes and ensure the proper channelling of funds to prioritized needs [7]. Looking at the average difference between initially planned and actual costs, according to [7], it is very large, often up to 60%. The difference mainly arises due to changes in the scope of works, abandonment of some planned works, or the occurrence of maintenance works that were not foreseen in the plan [7]. The expressed inaccuracy in cost planning can negatively affect maintenance decision-making and the efficient use of the maintenance budget [9]. Therefore, it is necessary to design and develop assessment models that would reduce the level of uncertainty in the maintenance cost planning process.

Cost estimation models are vital for adequate cost determination [10]. According to [18], it should be noted that the maintenance cost model is probabilistic and not deterministic. This highlights the importance of developing innovative models that can assist decision-makers in determining the optimal choice of maintenance activities given the available budgets [27]. A database with insight into historical records can be used as an effective alternative to complement and improve current forecasting approaches [7]. Historical databases for forecasting the maintenance costs of educational buildings can contain various types of important information and data, such as the age of the building, location, area, number of floors, number of elevators, type of founder, number of work shifts, number of students, number of employees, type of heating, last modernization, etc. [7, 12, 14, 16-18]. This information forms a set of independent (predictive) variables based on which costs can be estimated (dependent, target variable). The application of such an approach requires access to data from different cases related to maintenance [28]. ANNs are considered potentially important applied methods for solving cost estimation problems [15] based on historical databases.

1.1.2 ANNs Application for Buildings Maintenance Cost Estimation

ANNs are a simplified mathematical model of processes carried out by networks of nerve cells in living beings. They consist of interconnected artificial neurons that know how to solve a particular problem after a learning process (training) via a database [29]. An ANN is built by arranging neurons in multiple layers, usually comprising input and output layers and one or more hidden layers. The output of one layer serves as the input to the next layer, and the strength of the output is determined by the connection weights between two adjacent layers. ANNs can learn from examples and independently discover the relationships between inputs and outputs [30]. In developing an ANN model, the most critical step is training the network, i.e., learning about the data, followed by testing or validating the network on data that did not participate in the model training.

The ANN consists of network architecture (topology), neuron connection scheme, neuron transfer function, and learning law. The architecture represents a particular arrangement and connection of neurons in the form of a network [31]. Different ANNs differ in architecture, such as Multilayer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN), Generalized Regression Neural Network (GRNN), Temporal Neural Network (TNN), Neuro-Fuzzy, and others [32].

ANNs have proven their applicability in construction over the last few decades and have shown very good solutions to many problems [32]. Several prominent studies focusing on cost estimation have been recognized in building maintenance. Authors of [17] use ANNs to predict maintenance costs for higher education buildings. In their case, the age of the building and the number of floors and elevators are important factors (variables) based on which costs can be estimated very well. Authors of [15] use an ANN to estimate the running costs of high-rise buildings. They identified seven important variables related to the mentioned costs: building type, gross floor area, pitched roof area, flat roof area, external glazing area, and the number of floors above and below ground level. They find that ANNs are a very accurate tool for estimating running building costs. Authors of [19] forecast the maintenance costs of residential buildings based on bills of quantities collected from building authorities. According to them, ANNs are suitable for modelling complex problems of a probabilistic nature and can easily be used for predicting future maintenance projects. Authors of [16] proposed a framework for an ANN model that learns about the maintenance costs of educational institutions. The main finding of this study is that the proposed ANN modelling framework is effective in estimating the maintenance costs of educational facilities. The developed model learns and generalizes claim payout records on the maintenance and repair costs from sets of facility asset information, geographic profiles, natural hazard records, and other causes of financial losses. Authors of [18] use 18 variables to build an ANN model to predict the maintenance costs of hospitals. They found that the ANN model is adequate, and the leading indicator of maintenance costs is the size of the hospital (area, number of patients).

This work is based on the argument that the use of ANNs, as advanced machine learning methods, can help solve the problem of predicting school building maintenance costs. The question arises as to why to use ANNs when using a simpler regression analysis can also obtain satisfactory results [7, 12, 33-38]. Many sources, however, point out that when comparing regression models with ANNs, regression still gives somewhat weaker results [15-17, 19, 38]. Given that building maintenance requires significant financial resources, any increase in the accuracy of the estimation model is essential [38]. Therefore, the application of ANNs in these cases is justified. Modelling techniques, including regression analysis, as well as some more advanced tools (fuzzy logic, genetic algorithms, base reasoning), have a hard time dealing with imprecision, incompleteness, and uncertainty of data and other variables that affect costs and their combinatorial effects and interrelationships. In these problematic areas, ANNs are often very strong [39].

As a result of the theoretical analysis, it can be concluded that the ANN is a promising approach to estimating school maintenance costs. Adopting an ANN to estimate school maintenance costs is doable and can yield satisfactory results.

2 METHODOLOGY

2.1 Study Area Selection

The Primorje-Gorski Kotar County in Croatia was chosen as the study area. The county covers 3 587 km^2 of the inhabited area of Croatia, in which about 7% of the total Croatian population lives. The county seat is located in Rijeka, the third-largest city in Croatia. The county has 14 towns and 22 municipalities, with 536 inhabited localities [40]. In these localities, there are 85 public schools, namely 57 primary and 28 secondary schools. The selected county ranks fourth in terms of the number of school facilities in the country. The location of primary and secondary schools within the selected study area is shown in Fig. 1.

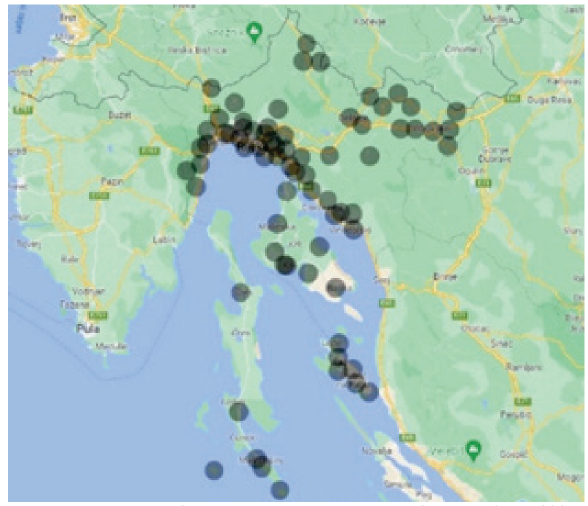


Figure 1 Location of schools within the study area (adapted from [41])

Primorje-Gorski Kotar County was chosen as the study area because of its size and importance for Croatia, a sufficient number of school institutions to create a representative data sample, and the data availability, as the paper's authors live and work in this area.

2.2 Data Collection and Processing

The collected database includes primary and secondary schools. Several documentation groups were used as data sources. Documentation was obtained from school representatives, i.e., from the founders (the City of Rijeka and Primorje-Gorski Kotar County) and the Ministry of Education of the Republic of Croatia. The mentioned documentation includes school work plans and programs, lists of institutions with their characteristics, lists of employees, students, etc. Annual financial reports of schools were also used, in which all receipts and expenses of the institution's operations were categorized. The data collected for this research from all the above documents include the following elements: type of school, type of founder, belonging to cultural property, type of heating, year of construction, total indoor area, number of employees, number of work shifts, number of students, number of classrooms, and realized annual maintenance costs.

In the Republic of Croatia, there was no such comprehensive database on both primary and secondary schools with a focus on maintenance and related costs. Based on the collected documentation, a review of previous research, and analysis, an extensive database was created that includes a set of information, i.e., independent variables considered relevant for defining the cost estimation model. Since there was no usable database, the aim of the research was to investigate a wider range of variables. Therefore, the database contains all those variables for which it was possible to collect data from the available documentation, all with the purpose of determining the impact of individual variables on maintenance costs.

Maintenance costs refer to materials, parts, and services for ongoing and investment maintenance. The period of ten years, i.e., from 2013 to 2022, was observed. Available data on planned maintenance costs for 2022 were also collected to gain insight into the magnitudes of current cost estimation errors. Only schools that operate in one school building and do not share the building with another school (41 of them) were included in the research to avoid the problem of dividing or adding up maintenance costs from financial statements by the institution. If the school operates in several buildings, the problem is also information about the year of construction, belonging to cultural heritage, and type of heating, which can differ from building to building.

The database contains 11 predictive variables (X_1-X_{11}) and one target variable (Y), the average annual maintenance costs in the reference period. The reference period refers to the number of years for which cost data were collected for a specific building.

The average annual maintenance costs (*AAMC*) were obtained by following Ed. (1):

$$AAMC = \frac{1}{n}\sum_{i=1}^{n} PVMC_i. \tag{1}$$

In Ed. (1), *PVMC* refers to the present value of maintenance costs in a certain year, while n represents the reference period. The present value of costs was calculated according to the literature [36, 42, 43], with a discount rate of 3 % as per [44]. This is done because the value of money changes over time. All costs are expressed in euros (€). The set of predictive variables includes four qualitative variables and seven quantitative variables. The results of the statistical processing of the database are shown in Tab. 1 and 2.

Table 1 Characteristics of qualitative variables (sample proportions)

X_1 - School type	Primary	33
	Secondary	8
X_2 - Founder type	City	20
	County	21
X_3 - Cultural heritage	Yes	3
	No	38
X_4 - Heating type	Heating oil	24
	Gas	13
	Heating plant	4

Table 2 Descriptive statistics of quantitative variables

Variables	Mean	Standard Deviation	Min	Max
X_5	82.95	40.89	21	203
X_6	2969.16	1364.95	900	6778
X_7	50.68	16.7	23	93
X_8	1.27	0.45	1	2
X_9	8.15	1.8	5	10
X_{10}	330.17	209.79	30.4	919.8
X_{11}	17.48	8.08	7.33	39.8
Y	12403.08	5975.81	4018.7	25308.04

X_5 – Age to 2022; X_6 – Indoor area (m^2); X_7 – Number of employees; X_8 – Number of work shifts; X_9 – Reference period (RP); X_{10} – Average number of students in RP; X_{11} – Average number of class departments in RP; Y – Average annual maintenance costs (€) in RP

2.3 ANN Models Development

DTREG - *Predictive Modeling Software* was used to develop a model to predict maintenance costs using ANNs. The software offers the possibility to create several types of ANNs, of which MLP, GRNN, and RBFNN are very often used [32, 33, 38, 45, 46], as were employed in this paper. The greatest value of the aforementioned software is that it can self-optimize the parameters of the mentioned ANNs so that they yield the smallest estimation error. Moreover, the application of this software is straightforward and intuitive. Since the relationship between the target variable and the predictor is not known in advance, several ANN models need to be tested to select the best one so that the real data provide the highest accuracy [45]. By applying several types of ANNs, it was desired to test how suitable some of them are for estimating maintenance costs, and by trying several options, the best possible results should be obtained.

The MLP is a feed-forward ANN. It has an input layer of neurons that act as receivers, one or more hidden layers of neurons that compute the data and go through iterations, and finally, an output layer that predicts the output [47]. For training and validation of these networks, an algorithm with backpropagation of errors is used [48], which propagates through the network from the input to the output layer, then determines the error and propagates this error back to the input layer and includes it in the learning formula [49].

The GRNN consists of an input layer, a hidden layer (or pattern layer), an additional invisible layer for summation/division, and an output layer [50]. GRNN uses normalized Gaussian kernels in the hidden layer as activation functions. When training this network, it remembers each data pattern and does not require an iterative training procedure like the MLP network [46].

The RBFNN uses a radially symmetric and radially constrained transfer function in its hidden layer [51]. It consists of input, hidden, and output layers of neurons. The activation function of the hidden neurons is a Gaussian function. Learning the network is done in two steps. First, the weight coefficients of the network are determined from the input to the hidden layer and then from the hidden to the output layer [52].

During the development of the ANN model, different types of data representations were tried, such as originally recorded values and normalized values, to obtain a network model with the lowest estimation error.

For the collected school database to be used within the DTREG software, it first had to be formatted in a format suitable for analysis. The database must be in comma-separated value (CSV) format with values for one case per row and one column for each variable [53].

2.4 ANN Models Performance Comparison

The developed ANN models are evaluated and compared in terms of the magnitude of the estimation error they provide. The model error was measured using the coefficient of determination (R^2) and the mean absolute percentage error (*MAPE*). These two measures are among the most common estimators of model accuracy [54] and have been used in numerous previous studies [8, 32, 33, 38, 45, 54].

The R^2 is a statistical measure that tests the overall fit of the predictive model, i.e., it indicates how much of the changes in the experimental values of the target variable are explained by the obtained model [36, 55]. R^2 values lie in the interval [0,1] [54], and the closer R^2 is to one, the more representative the model is. $R^2 = 0.900$ can be interpreted as follows: about 90.00% of the variation in the response can be explained by the predictor variables, while the remaining 10 % can be attributed to the unknown variables [54].

MAPE is a measure of predictive accuracy and is defined by the following formula [38]:

$$MAPE = \frac{1}{n}\sum\left|\frac{real\ value - estimated\ value}{real\ value}\right| (\%), \qquad (2)$$

where n is number of observations.

2.5 Best-fit Model Selection

The best-fit model will be selected based on the obtained values of R^2 and *MAPE*. According to Tab. 3 and Tab. 4, the interpretation of the selected error indicators is visible regarding the obtained sizes and according to Chaddock's scale [56] and Lewis's scale [57].

Table 3 Chaddock scale for interpreting the R^2 (adapted from [56])

R^2	Interpretation
<0.01	Absence of connection
0.01-0.24	Weak connection
0.25-0.64	Medium strength connection
0.65-0.99	Strong connection
>0.99	Full connection

Table 4 Lewis scale for interpreting the *MAPE* (adapted from [57])

MAPE (%)	Interpretation
<10.00	Very accurate prediction
10.00-20.99	Good prediction
21.00-50.00	Reasonable prediction
>50.00	Imprecise prediction

It is considered that models with R^2 over 0.64 describe the model well; that is, they provide a solid strong connection between actual and estimated values [58]. In cost prediction models, *MAPE* values up to 21% provide good prediction [59]. Some authors state that a *MAPE* of up to 30 % is considered a sufficiently good prediction [8, 38].

In this paper, an attempt will be made to obtain a model that gives $R^2 > 0.64$ with $MAPE < 30$ %, and it will be considered satisfactorily accurate. The goal is always to obtain models with as high an R^2 value as possible and as low a *MAPE* value as possible.

The obtained results of the optimal model will be additionally compared with modelling by regression analysis for the purpose of more significant statistical validation

The purpose of this study is to contribute to the maintenance management process in schools. Maintenance management encompasses a range of decisions, among which the decision-making regarding the maintenance tasks and associated costs holds significant importance. The objective is to effectively manage and optimally allocate these tasks and costs, for which the cost plan is of inestimable importance.

3 RESULTS AND DISCUSSION

The developed MLP, GRNN, and RBFNN models gave the results shown in Tabs. 5, 6, and 7. In addition to the results the developed networks gave based on the data in their original form, the results for R^2 and *MAPE* with normalized quantitative variables are shown in parentheses. The min-max normalization technique was used. The comparison shows that the results are somewhat closer with respect to R^2; however, *MAPE* shows significantly better performance in networks developed on the basis of the original data, so these will be presented in more detail. The reason for this may be the nature of the data. The actual data may already be in an acceptable shape and range, so additional normalization may lead to the loss of specific information or variations in the real data, resulting in reduced performance when applying networks with normalized data.

Table 5 Performance of MLP model

Parameters	MLP	
	Training	Validation
Mean target value for input data	12,331.55	12,698.11
Mean target value for predicted values	12,361.94	9,943.49
Correlation between actual and predicted	0.844	0.903
Proportion of variance explained by model (R^2)	0.713 (0.713)	0.614 (0.614)
MAPE	26.37 (69.29)	22.24 (22.27)
Analysis run time	00:02.84	

Table 6 Performance of GRNN model

Parameters	GRNN	
	Training	Validation
Mean target value for input data	12,331.55	12,698.11
Mean target value for predicted values	12,502.52	11,287.42
Correlation between actual and predicted	0.930	0.945
Proportion of variance explained by model (R^2)	0.862 (0.909)	0.811 (0.603)
MAPE	13.83 (43.74)	20.50 (50.55)
Analysis run time	00:00.67	

Table 7 Performance of RBFNN model

Parameters	RBFNN	
	Training	Validation
Mean target value for input data	12,331.554	12,698.11
Mean target value for predicted values	12,331.55	9,501.80
Correlation between actual and predicted	0.976	0.901
Proportion of variance explained by model (R^2)	0.953 (0.943)	0.542 (0.657)
MAPE	9.34 (31.39)	47.61 (72.50)
Analysis run time	00:01.28	

According to the results, the best model was provided by the GRNN, which demonstrated one of the highest R^2 values and the lowest *MAPE* values. These values indicate satisfactory accuracy during both training and validation. The obtained R^2 values during training and validation reveal a strong relationship between actual and estimated costs. Regarding the *MAPE* value, it is an impressive 13.83 % during training. In validation, the *MAPE* is somewhat weaker, nearing the border, but still within the range of good prediction. The GRNN also exhibited the shortest time for data analysis and model creation. According to [53], it is not uncommon for the GRNN model to outperform MLP and RBFNN models in this type of estimation.

Slightly weaker results were observed with the MLP model, which, as per Tab. 3 and Tab. 4, fall within a reasonable prediction range. As for the RBFNN model, it achieved a commendable result during training, but its performance during validation was not as high. Therefore, among the three models, it may not be the most suitable for estimating maintenance costs. Possible reasons for these differences could be attributed to the nature, composition, and complexity of the database. Machine learning models exhibit diverse performance across different datasets, and the optimal model choice can vary based on the data characteristics and the specific problem at hand. Therefore, exploring multiple models is advisable to determine the most suitable one.

All presented results surpass current estimates. Specifically, during the database collection, data on planned and actual (realized) maintenance costs for the year 2022 were also collected. Planned cost values are reported in financial plans before the start of the fiscal year, while actual costs are reported in financial statements after the end of the observed year.

Such comprehensive data were collected for 20 schools. The comparison of initially planned and actual realized values for the specified accounting year resulted in the graph shown in Fig. 2.

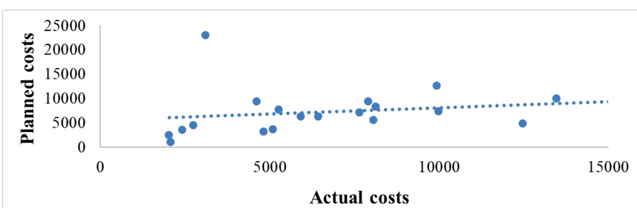
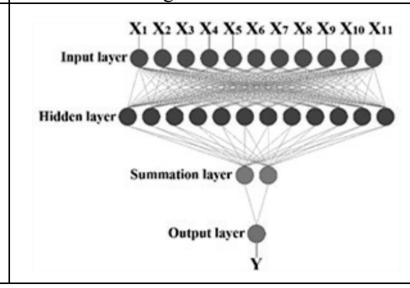


Figure 2 Relationship between actual and planned values of school maintenance costs for 2022

Comparing the planned cost values with the actual realized costs yields a *MAPE* value of 64.03 %, with an R^2 of 0.0484. In practice, planned cost values are typically adjusted based on needs, considering the available funds of the founder and often utilizing empirical methods. In the context of this research, which utilized a historical database for computer modelling with a particular focus on key predictor variables for assessing the target, it is not surprising that the obtained results significantly exceed the accuracy level relative to the actual operational scenario.

Considering the obtained results, the GRNN is acknowledged as the most suitable model for predicting actual annual maintenance costs. The parameters of the developed GRNN from DTREG are presented in Tab. 8. With the selected parameters; the model resulted in the smallest estimation error.

Table 8 Parameters of the developed GRNN

Type of model	General Regression Neural Network (GRNN)
Type of analysis	Regression
Number of neurons in the model	The minimum error occurred with 26 neurons in the model (12 in the hidden layer)
Sigma values for model	Sigma for each variable
Starting sigma search control	Min. sigma: 0.001 Max. sigma: 10 Search steps: 20
Model optimization and simplification	Remove unnecessary neurons Minimize error Retrain after removing neurons
Model testing and validation	Random sampling (20%)
How to handle missing values	Replace missing values with medians
Type of kernel function	Gaussian
Conjugate gradient parameters	Maximum total iteration: 5000 Iterations without improvement: 1000 Min. improvement delta: 1.000e-005 Absolute convergence tolerance: 1.000e-008 Relative convergence tolerance: 1.000e-004
Developed GRNN architecture	

The developed GRNN consists of 4 layers, with the optimal number of neurons in the hidden layer set at 12. DTREG conducts regression analysis within the ANN model, given the continuous nature of the target variable. The sigma values control the radius of influence of each point in the ANN model, and a separate sigma value is calculated for each predictor variable. This choice is recommended as it strikes a good balance between a single sigma and the possibility of a separate sigma for each target category. The initial sigma search control parameters determine the range of sigma values used during the initial search, and once the conjugate gradient method begins, the sigma values can extend beyond this range. DTREG utilizes the conjugate gradient algorithm to compute optimal sigma values and weights between neurons. To optimize and simplify the model, unnecessary neurons were removed, error was minimized, and retraining was performed after neuron removal [53].

Regarding model testing and validation, DTREG offers four options:

- A random percentage of rows is kept out when the model is created. After the model is created, this number of rows is run through the model, and the error is evaluated.
- The control variable is used to select which rows to hold out for validation.
- Cross-validation with the selected number of folds.

- Cross-validation with one omitted row in each model created [45, 53].

In this specific scenario, a random selection method was applied, involving the selection of 20 % of the data from the total database that did not participate in the ANN training process. This methodology, due to its simple implementation, quick performance, and reliability, is often used in similar research, as confirmed by the authorship of various scientists [15-19, 29, 39, 60, 61].

As part of this research, all the mentioned validation methods were checked, showing close results. Nevertheless, the random selection method resulted in slightly improved performance compared to the others, so it was chosen as authoritative.

In case certain values are missing in the database, the developed GRNN model replaces them with medians. However, there were no such values in this study.

The kernel function is used to take data as input and transform it into the required form of data processing. According to [53], the kernel function controls how the influence of a point decreases as the radius increases. In this case, the Gaussian function was applied. A Gaussian function causes the influence of a point to decrease according to the value of a Gaussian distribution cantered on the point. According to [53], Gaussian functions are almost always the best kernel.

The relationship between the actual and predicted values of annual school maintenance costs for the GRNN model is shown in Fig. 3.

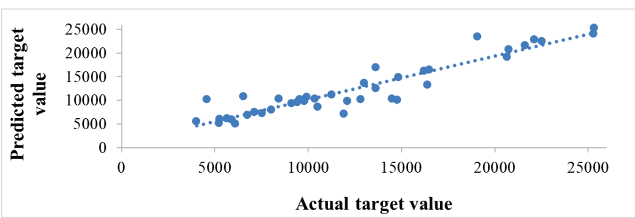


Figure 3 Relationship between actual and predicted values of the target variable (GRNN)

DTREG also calculates the relative importance of each predictor to model quality using sensitivity analysis. Below is the importance to three decimal places for the first five predictor variables:

1) Founder type (100.000 %)
2) Average number of class departments in RP (48.807 %)
3) Heating type (18.250 %)
4) Age to 2022 (8.848 %)
5) Indoor area (2.141 %).

The displayed values represent the percentage importance of each predictor in the model for predicting the target variable. It can be observed that the most crucial predictor for predicting actual maintenance costs is information about the type of school founder (the City of Rijeka or Primorje-Gorski Kotar County), followed by the number of departments, heating method, age, and indoor area. Other predictive variables from the database have an importance below 1 %.

The exceptionally significant importance of the variable "founder type" may reflect the complexity of financial, organizational, and structural factors associated with different types of school founders. The type of founder primarily affects the amount of financial support given their size, income, and maintenance policies. This financial support significantly influences the school's ability to maintain its infrastructure.

The average number of class departments is also crucial because it affects the size, scope, and frequency of maintenance. The number of departments influences the consumption of resources such as water, heating and cooling, use of equipment, etc., which can increase maintenance costs to ensure the proper functioning of all school spaces. Also, the number of departments directly affects the budget that the founders receive from the state to maintain their institutions.

The heating type also has a pronounced impact on school maintenance costs but to a lesser extent than the previous two factors. This variable may be more important than others because different heating types require different levels of attention and resources to maintain. The type of heating can affect the energy efficiency of the building as well as the infrastructure of the building, where all complex and more efficient systems require special maintenance and financial expenses. The specificity of the local environment is particularly important for heating, where local conditions and climate affect heating systems, which can have a significant impact on maintenance costs. Primorje-Gorski Kotar County's climate is characterized by warm summers but dry and extremely windy winters, which requires efficient heating systems.

The age of schools in the context of this research has a certain influence on maintenance costs. The age of the building can affect maintenance costs in terms of the need for modernization, improvement of energy efficiency, and adaptations to modern needs. Regular maintenance and planned investments can help extend the life of the building and reduce overall maintenance costs over time. According to the available information, the vast majority of schools in the observed research sample had a certain form of modernization intervention, so it is not surprising that the age of the building itself did not have a pronounced impact on maintenance costs. Unfortunately, more detailed information about the modernization of the facilities was not available.

According to the results, the indoor area of the school has a certain influence on maintenance costs, but it is the least significant of all the factors listed here. The size of the school affects maintenance costs primarily through the amount of maintenance work that needs to be done. It is possible that in this context, some other factors or specificities compensate or reduce this impact, such as the specificity and structure of buildings, energy efficiency, maintenance method, etc. Another important aspect may be that in the developed model for estimating maintenance costs, the school indoor area is reflected through the number of class departments, which means that the direct influence of the school area may be less pronounced in this specific case.

It should be noted that the obtained relationships of the variables may vary depending on the specifics of the data used in the model and the characteristics of the school facilities.

Additional statistical validation and robustness checks of the developed GRNN model were confirmed through a comparison with multiple regression analysis. Conducting the regression analysis in DTREG, the training results were $R^2 = 0.743$, $MAPE = 23.14$ %, and for validation, $R^2 = 0.440$ and $MAPE = 30.39$ %. These results indicate that the ANN model is a more appropriate choice when estimating maintenance costs and provides estimates with a smaller error.

Considering all the presented results, it can be concluded that the developed GRNN model for estimating the average annual costs of maintaining school buildings is suitable for use in schools in Primorje-Gorski Kotar County.

The developed cost estimation model contributes to increasing the efficiency of the maintenance process. The ANN model enables:

- Simple, quick, and structured planning of maintenance costs for specific time periods.
- A more accurate estimate that provides better insight into the budget, helps allocate funds, and aids decision-making and cost control.
- Reduction of financial losses and the possibility of creating a strategy for mitigating and reducing losses.
- By using the model, the value of the average annual maintenance costs is obtained, which remains constant for each year of maintenance in the observed reference period, allowing for planning over extended periods.
- Defining the characteristics of school buildings that affect maintenance costs and obtaining the necessary information for designing new schools concerning cost rationalization. In this case, the important characteristics are the type of founder, the number of class departments, the type of heating, the age, and the total indoor building area.

The magnitudes of the errors obtained from the GRNN model show that there is still room for progress and the development of more precise estimation models. The results prove that estimating maintenance costs is a demanding undertaking filled with numerous uncertainties. Still, any increase in accuracy in the estimations is of great importance, considering the amount of funds that need to be invested in schools. ANNs learn from input data; therefore, their quality and quantity directly affect the model's accuracy. The possibility of increasing the accuracy of the model can be seen in the expansion of the database with additional variables.

The results of this research can help school institutions and public bodies in planning costs and making maintenance decisions. Applying the ANN model opens up new possibilities for planning the necessary budget for school maintenance, making maintenance more efficient. A more accurate maintenance cost plan provides insight into the budget, helps allocate money, and helps control and monitor these costs. Founders managing school buildings can include in their budget the average required amount spent annually on school maintenance. For school buildings to be maintained, it is first necessary to consider the necessary maintenance activities and then to foresee certain funds for that purpose in the budget, which can be helped by the cost forecasting model developed here.

The main finding of this study is that the proposed ANN is effective in learning the maintenance costs of school facilities, comparable to other previous studies focused on a limited number of factors affecting maintenance costs [15-19].

Comparing the highlighted predictor variables for predicting maintenance costs, the results correlate with different studies where similar results have been obtained. In study [14], the type of founder of the institution and the area of the premises are also mentioned as important variables for estimating maintenance costs. In studies [16, 18, 37], the area of buildings is also highlighted, and in studies [16, 17], one of the important variables for estimating costs is the age of the examined buildings. Considering the quality and coverage of the database, this research further emphasizes the need to consider the number of departments and the type of building heating as relevant variables in the maintenance cost modelling process.

Looking at prominent studies from the Republic of Croatia where a model for estimating the costs of maintaining educational buildings is being developed, two studies stand out, in which, admittedly, regression analysis was used. The author of [12] estimated the costs of use and maintenance of faculty buildings and obtained a model with accuracy indicators of $R^2 = 0.669$ and $MAPE = 27.24$ %. The author of [14] developed a model for estimating primary school maintenance costs and obtained $R^2 = 0.759$, $MAPE = 21.17$ %. In this research, a larger database with both primary and secondary schools was used, and ANNs were applied as more advanced forecasting techniques. The obtained results are, therefore, more precise, indicating that the research is heading in the right direction and contributes to progress in the estimation modelling of the maintenance costs of educational buildings.

The first and basic limitation of the developed ANN model is its applicability to school buildings in Primorje-Gorski Kotar County. Also, since the database consisted only of schools operating in one building, the application is exclusively for such institutions. The limit is also related to the number of years over which school maintenance costs are estimated. The period for which the data was collected ranges from 5 to 10 years, and considering that, it is possible to estimate the costs for a maximum period of 10 years. The values obtained for R^2 and $MAPE$ suggest that there is room for creating models that could give even better results; expanding the database with additional variables is necessary.

Considering the highlighted limitations, it is recommended to expand the research to the entire territory of the Republic of Croatia (or beyond) and develop a model that will not have a regional character and potentially give better results. For this reason, the database should be continuously expanded and updated.

4 CONCLUSION

The subject of this study is estimating the costs of maintaining primary and secondary schools in the Republic of Croatia using ANNs. The study successfully achieved the research goal and provided positive answers to all research questions.

Within the study, a database of school buildings in Primorje-Gorski Kotar County, Republic of Croatia, was created, containing historical data on maintenance costs. A large sample database with data for 41 schools, was utilized for further analysis and modelling. It encompasses 11 predictor variables (characteristics of primary and secondary schools) and one target variable (average annual maintenance costs). Data on maintenance costs were collected for the 5 to 10 years.

Based on the database, an ANN model was developed to estimate the maintenance costs of school buildings with satisfactory accuracy ($R^2 > 0.64$, $MAPE < 30$ %). Initially, three different ANNs were developed: MLP, GRNN, and RBFNN, using the software DTREG. The error of models is expressed using R^2 and $MAPE$, and the values obtained in all developed models are considered satisfactory for this type of assessment. Comparison of results showed that the highest estimation accuracy is achieved by applying GRNN, with a training $MAPE$ of 13.83 % and validation $MAPE$ of 20.50 %. R^2 values are 0.862 and 0.811, respectively, indicating that GRNN is optimal for estimating school maintenance costs.

The study demonstrated that the current inaccuracy in the estimation of school maintenance costs can be reduced by applying the developed ANN model. Specifically, by processing the actual data for the year 2022, it was found that, observing the actual planned and realized costs from the financial documents, the accuracy indicators are $MAPE$ = 64.03 %, with $R^2 = 0.0484$, which is far below satisfactory values.

The application of the developed ANN model can contribute to increasing the efficiency of maintenance. The results can assist educational institutions and public bodies in planning costs and making maintenance decisions. By applying the developed model, it is possible to plan and calculate maintenance costs for a multi-year period in a simple, fast, and structured way. This approach can help reduce losses and develop strategies to mitigate them. Characteristics of schools that significantly affect maintenance costs were also identified, namely the type of founder, the number of school departments, the type of heating, age, and the total indoor area of the building, which can be useful when designing new school buildings.

No significant studies dealing with this topic in the manner approached here have been noted in the literature so far. In the Republic of Croatia, there was a lack of more extensive research analysing the costs of maintaining primary and secondary schools. Estimates of maintenance costs have shown inaccuracy, and the limited studies conducted were based on smaller databases of educational buildings, where cost prediction was reliant on simpler modelling techniques.

There are also some research limitations, such as the regional orientation, the limited database, and the reference period for which the data were collected. In future research, expanding the database and developing new estimation models is recommended to obtain even better results, as there is undoubtedly room for improvement considering the size of R^2 and $MAPE$ obtained.

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