Advances in Civil Engineering

Advances in Construction Life-Cycle Cost Management

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Research Article

Neural Network-Based Model for Predicting Preliminary Construction Cost as Part of Cost Predicting System

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A model for early construction cost prediction is useful for all construction project participants. This paper presents a combination of process-based and data-driven model for construction cost prediction in early project phases. Bromilow's "time-cost" model is used as process-based model and general regression neural network (GRNN) as data-driven model. GRNN gave the most accurate prediction among three prediction models using neural networks which were applied, with the mean absolute percentage error (MAPE) of about 0.73% and the coefficient of determination R^2 of 99.55%. The correlation coefficient between the predicted and the actual values is 0.998. The model is designed as an integral part of the cost predicting system (CPS), whose role is to estimate project costs in the early stages. The obtained results are used as Cost Model (CM) input being both part of the Decision Support System (DSS) and part of the wider Building Management Information System (BMIS). The model can be useful for all project participants to predict construction cost in early project stage, especially in the phases of bidding and contracting when many factors, which can determine the construction project implementation, are yet unknown.

1. Introduction

The complex cost estimation problem in the field of building construction is the problem which is traditionally burdened by lack of data, uncertainties, and risks, but at the same time very important for the success of a construction project. Due to all of these, numerous construction projects are faced with significant cost overruns, which are elaborated extensively in the paper. The causes of this condition are complex and are the subject of research presented in this paper and supported by data. One of the causes, which is to be particularly emphasized, is the focal point of this paper. This important cause is an early initial cost prediction, which is often of unsatisfactory accuracy. The reason is the lack of information in the initial stages and the desire to get results in a short time, not going too far into its accuracy and the extent of the consequences such data could have on the project. Such a superficial and inaccurate assessment results in a number of further steps in the project, resulting in multiple negative consequences that could jeopardize the implementation of project goals. The desire of the parties to come up with information about the costs as soon as possible is understandable and will always be present, regardless of the type of project or of its size. Therefore, there is a need to create a reliable cost prediction system.

The unsatisfactory and uncertain cost prediction [1] and their overrun in construction projects are a very frequent [2–4] and not easily solvable problem. Due to the uniqueness, diversity, complexity of projects, and the ever-present risks, establishing the model for enough accurate assessment of the project costs is doubtless a challenging task. That is why for many researchers this problem is often the subject of their research, whereby they use different approaches and methods often for a certain type of buildings and structures [1, 5–16]. The aim is to establish as accurate a cost estimation model as possible that would be applied in the initial project phases. The fact that the contracted costs are often exceeded is also evidence of the claim that the cost prediction is in a lot of projects inadequate. The cause may be "... a heavily experience-based process" according to Alex et al. (2010) as it is cited in [1], which means that the estimation is not based on scientifically proven methods, then the application of low-accuracy models or inadequate models for the case under consideration, or even intentional miscalculations [3]. Data on cost overruns of completed projects that are the subject of numerous scientific studies are the evidence of a previous claim of the frequency of cost overruns [2–4]. As stated by Žujo et al. [2], one of the reasons is "...the absence of a thorough expert analysis of conditions, circumstances, and possible risks when concluding a contract."

There are numerous reasons why research often focuses on construction cost. Cost is factor that can be expressed quantitatively and unambiguously. When conducting research regarding construction costs in different countries, numerous researchers indicate frequent significant cost overruns of many construction projects [3, 4, 17, 18]. Hence, for example, Baloi and Andrew [19] have presented the results of the Morris and Hough [20] research resulting in significantly exceeded costs in 63% of the 1778 projects financed by the World Bank, constructed between 1974 and 1988.

The authors in [19] state that cost overrun is more a rule than an exception. Moreover, according to the reports from the World Bank in 2007, road construction in India suffers about 25% of contracted price overrun [21]. According to the research conducted in China [22], where various types of reconstructed structures were considered, the construction contracted price overrun of more than 10% was recorded at 26.39% of the structures and 5–10% at 55.56% of the structures.

In Slovenia, a research was conducted on a sample of 92 traffic structures built in the period from 1993 to 1998. The average contracted price overrun was 51% [23]. A similar study was conducted in Australia in the period from 1992 to 1999. 93 structures were analyzed and the cost overrun was recorded in 21 or 22.58% of structures [24].

Within the scientific research project conducted in Croatia [25], 333 structures were investigated in the period from 1996 to 1998. Price overrun at 81% of structures was recorded.

A similar research was conducted in Bosnia and Herzegovina on 177 structures built from 1995 till 2006. The results indicated that the contracted date was not met in 51.40% of structures and the contracted price was not met in 41.23% of structures [26].

It can be concluded that construction cost overrun is present not only in underdeveloped countries and developing countries but also in developed countries. This was also confirmed by Baloi and Andrew [19], stressing that "... in most developing countries ... the problem is more acute." Reasons are surely multifaceted and multilayer and deserve a deeper analysis of the issue.

Therefore, estimating construction costs already in the initial stages of the project is the subject of special attention of the researchers, which does not lose on the actuality. In doing so, the special attention of the researchers is focused on modeling the interdependence of costs and other variables, primarily on the duration of the construction.

Considering the complexity and the significance of the problem, other opportunities should be explored, which have a greater potential for solving such complex tasks, which are undoubtedly integrated management information systems whose prediction cost system should be an integral part.

2. The Main Objectives and the Research Framework

One of the main objectives of the research is to evaluate the results of applying the proposed combined process-based and data-driven cost estimation model, that is, hybrid model, and compare its accuracy with the results of simple models. The second objective is to propose a basic concept of cost prediction system (CPS) as a part of a Building Management Information System (BMIS), with a more detailed elaboration of NNs module which includes also hybrid models.

The recommendation about applying the results of the considered case of the proposed hybrid model in CPS will also be presented.

Steps in researching, implementing, and displaying the results are as follows:

(1) Review of the existing references on cost prediction in construction projects.

(2) Review of the existing references on CPS ontology basics.

(3) Creating a proposal for cost prediction system ontology.

(4) Predicting construction costs by using a hybrid process-based and data-driven model.

(5) Recommendations for the results' integration into the CPS.

3. Literature Review: Construction Cost Prediction

The Australian Bromilow was the first to investigate financial execution in relation to construction time for a total of 329 structures in the building construction area (built in Australia between 1963 and 1967). The research resulted in establishing the so-called "time-cost" model (hereinafter BTC or TC model) [27, 28]. The simple linear regression analysis method was applied whose suitability was also proven in numerous later researches [18, 29]. Despite being originally a "time-cost" model, it also served as a template for examining the interdependence between construction costs and construction time. It was noted that construction cost prediction and also cost interdependence with time (as quantitative factors) can be mathematically modeled according to Bromilow "time-cost" model by using simple linear regression [2, 29]. Furthermore, scientific studies indicate that there is a dependency between the contracted construction price/cost and time at various construction markets [3, 4, 17, 18, 30].

However, the researchers did not only rely on modeling the interdependence of building time costs but have also introduced new predictors, for example, number of floors, gross floor area, type of facility, and type of client. In their research, some researchers emphasized the risk factors that cause cost overruns. Thus, Le-Hoai et al. [4] apply the factor analysis technique to categorize the causes. Ranking of causes in terms of occurrence and severity was conducted. "Poor site management and supervision, poor project management assistance, financial difficulties of owner, and financial difficulties of contractor are ranked as the first problems." Spearman's rank correlation tests do not point out differences in ranking the main causes among three groups of respondents (owners, contractors, and consultants).

Multiregression analysis is also applied as a mathematical method. Hence, Alshamrani [5] developed a multiregression model for conceptual initial cost estimation of conventional and sustainable college buildings in North America. The obtained model can predict the initial cost in USD/ft^2 in dependence on the following predictors: height of one floor, building space, number of floors, sustainability index (1 for conventional and 2 for sustainable), and structure type.

Multiple regression analysis is also used by authors [6] to develop an early parametric model, that is, a model for early cost estimation. The research was based on data for thirty-three real-constructed road tunnel projects. It was concluded that the employed approach using multiple regression analysis is valid for heavy construction projects.

In addition to researching the application of regression analysis to estimate the cost of construction projects, another direction of research has been focused on the application of neural networks to obtain expected project costs. Thus, Ahiaga-Dagbui and Smith [1] in their research on 98 water-related construction projects built in Scotland in the period 2007–2011 applied ANN to determine models for cost estimation. Impacts, such as construction site conditions, price changes, purchases, various possible risks, and contractual changes, were taken into account.

Separate cost models for normalized target cost and log of target costs were developed. Variable transformation and weight decay regularization were then explored to improve the final model's performance. As a prototype of a wider research, the final model's performance was very satisfactory, demonstrating ANN's ability to capture the interactions between the predictor variables and final cost. Ten input variables, all readily available or measurable at the planning stages for the project, were used within a Multilayer Perceptron Architecture and a quasi-Newton training algorithm [1].

El Sawy et al. [31] pointed out that cost prediction is one of the tasks of successful management of construction projects, that is, cost management. Cost prediction is a demanding task. Instead of the usual methods, one should turn to the more sophisticated ways of predicting. In the mentioned research [31], the researchers used the ANN approach to develop a parametric cost-estimating model for site overhead costs. The research was conducted on 52 real-life cases of building projects constructed in Egypt during the seven-year period from 2002 to 2009. N-Connection Professional Software version 2.0 was used for the development of neural network models. The neural network architecture is presented for the estimation of site overhead costs as a percentage of the total project price.

When it comes to the problem of construction site overhead costs, it is worth noting the quite new research from Poland from 2019 [16] for a few reasons. The authors claim that the "Construction site overhead costs are key components of cost estimation in construction projects. The estimates are expected to be accurate, but there is a growing demand to shorten the time necessary to deliver cost estimates." After considering and then combining several types of neural networks, in order to select the members of the ensemble, the authors developed three models intending to predict a construction site overhead cost index.

It was proved that proposed models offer better cost prediction than those based on single neural networks [16].

Neural networks are also applied by Petroutsatou, Georgopoulos, Lambropoulos, and Pantouvakis [7] for early cost estimation for 33 twin tunnels with a total length of 46 km in Greece. As first, the authors determined the parameters that affect the temporary/final support and the final cost of tunnel construction, such as geometrical, geological, and data related to quantities of works. After that, the data were analyzed using two neural network types: the first was multilayer feed-forward network (MLFN), and the second was a general regression neural network (GRNN). In the next step, model results have been compared with costs and quantities from the real projects. It was concluded that the usage of developed models leads to fairly accurate cost estimation and quantities of works for road tunnels. It was also concluded that the NNs usage for cost estimation is beneficial, due to NNs capability for modeling nonlinear data relationships.

A very interesting artificial neural network (ANN) approach to predicting index of indirect cost of construction projects in Poland was applied in research presented in [32]. Based on the quantitative study of 72 cases of building projects constructed in Poland, "the factors conditioning indirect costs and the actual costs incurred by enterprises during project implementation" have been determined [15].

Another relevant research was carried out by Juszczyk et al. [8] on a sample of 129 sports field construction projects that have been implemented in Poland in recent years. The possibility and justification of the application of the NN for the assessment of total construction costs for sports' fields were explored. As one of the research tasks was to establish a set of cost predictors, 7 predictors regarding the technical and functional characteristics were established. After that, the data were analyzed using two neural network types: multilayer perceptron networks (MLP) and radial base function networks (RBF). By applying Pearson's correlation coefficient between real and predicted values of construction costs and by using the root mean square error (RMSE) as the measure of prediction errors, satisfactory results were established for MLP networks. This proved the applicability of the cost estimation network. In the next step, the analysis for a group of 5 MLP networks was performed and the results were compared. As a comparison measure, Pearson's correlation coefficient was used between the actual and predicted construction cost and the root mean square error (RMSE) as the measure of the prediction errors. The accuracy of the estimation was tested using mean absolute percentage error (MAPE). The best results for all assessors were established for one network. In conclusion, this type of network can be recommended for estimating the sports field construction costs.

It was to be expected that the course of modeling development of these interdependencies would be redirected towards the comparison of the accuracy and applicability of the models obtained using various techniques. In this respect, comparative models obtained by applying different regression techniques without neural networks, as well as using neural networks, supporting vectors, case-based reasoning techniques, and others, have been developed.

Kim et al. [9] have been exploring the performance of three cost estimation models. A database of 530 implemented project costs of Korean residential buildings has been used. Three-type techniques have been applied for estimating construction costs and their results have been compared: multiple regression analysis (MRA), neural networks (NNs), and case-based reasoning (CBR). Model performance was measured by the Mean Absolute Error Rate (MAER) as the measure of the difference between estimated and actual construction costs. Comparing results from 40 test data, the best MAER of 2.97% with the 48% of the estimates within 0–2.5% of the actual error rate and 98% within 10% has been established. The CBR model gave MAER of 4.81% with 43% of the estimates within 2.5% and 83% within 10%. In spite of these results, the authors point to slowness in establishing a NN model because of the trial and error process. They point to the need to take into account the compromise between accuracy, speed, and clarity when explaining the cost and choosing an estimation model. In this sense, CBR is considered a better model. Future research is expected to create a hybrid model that would combine different techniques.

On the other hand, the research, which was carried by the authors [33], compared the accuracy of cost estimation using two types of models-linear based regression models and vector support vector machines (SVMs) models. The models were applied on a database of 75 buildings built on the territory of the Federation of Bosnia and Herzegovina. The usual estimators, the coefficient of determination R^2, and the mean absolute percentage error (MAPE) were used. MAPE is a measure of accuracy, so a better result was established for SVM which also has a better R^2. The weakness of the SVM model is the speed of convergence in relation to the LR model.

From all of the aforementioned, it can be concluded that neither one of the techniques nor one of the estimation models can be considered absolutely the best for all the conditions and circumstances of the construction of this type of structure. Olawe and Sun [34] and Ahsan and Gunawan [35] stated that, despite the availability of various control techniques and project control software, many construction projects still do not achieve their cost goals.

4. Cost Predicting System (CPS) as the Part of Building Management Information System (BMIS)

4.1. Basic Framework. Timely cost estimation of satisfying accuracy is one of the crucial factors that affect project performance and thus represent essential management information for the highest level of management in business systems. In this regard, a cost predicting system (CPS) is proposed as a possible integrative component of the system responsible for improving the effectiveness and effectivity of the construction through cost planning and predicting different levels of detail, phases, and project as a whole. All of these systems are integrated into the Building Management Information System (BMIS) as shown in Figure 1.

As the assessment procedures themselves are demanding in terms of required knowledge as well as time-consuming, it is necessary to integrate them into a single information management system that possesses the necessary historical and other data used in these models and forms part of the Decision Support System (DSS) in business construction and project systems. Ma et al. [36] point out a large amount of information that is collected on a daily basis, thanks to information systems in construction companies. Authors call them "reusable legacy information" and discuss two approaches to their possible use, using general or specialized software.

Reflecting on the future development of construction through the prism of past experience and knowledge as well as of new development trends, the integration of separate segments is a development challenge and therefore probably an imperative. The solutions it brings have a synergistic potential with the ability to improve significantly the operational, functional, economic, management, and quality dimensions of the construction. Watson [37] classifies the "fragmented structure" into one of the underlying, inherent construction industry problems. Egan [38], in his famous Rethinking Construction, advocates "... the use of computer modeling to predict the performance for the customer." The same author considers one of the goals to be "annual reductions of 10% in construction cost and construction time."

It can be argued that the strength and potential of computer modeling, as a technical platform, are unprecedented at the obtained development level. What needs to be reexamined is the utilization of such potential and of new possibilities. Again, utilization should be linked to a human factor, that is, lack of readiness, engagement, organizational, and managerial competencies, that is, attitude and commitment to integration. Egan [38] points out that "... the way forward for achieving the ambition of a modern construction industry lies in commitment." Recognizing the benefits that integration can bring and the commitment to integration is a longer-term process that will underpin the future development of construction industry.

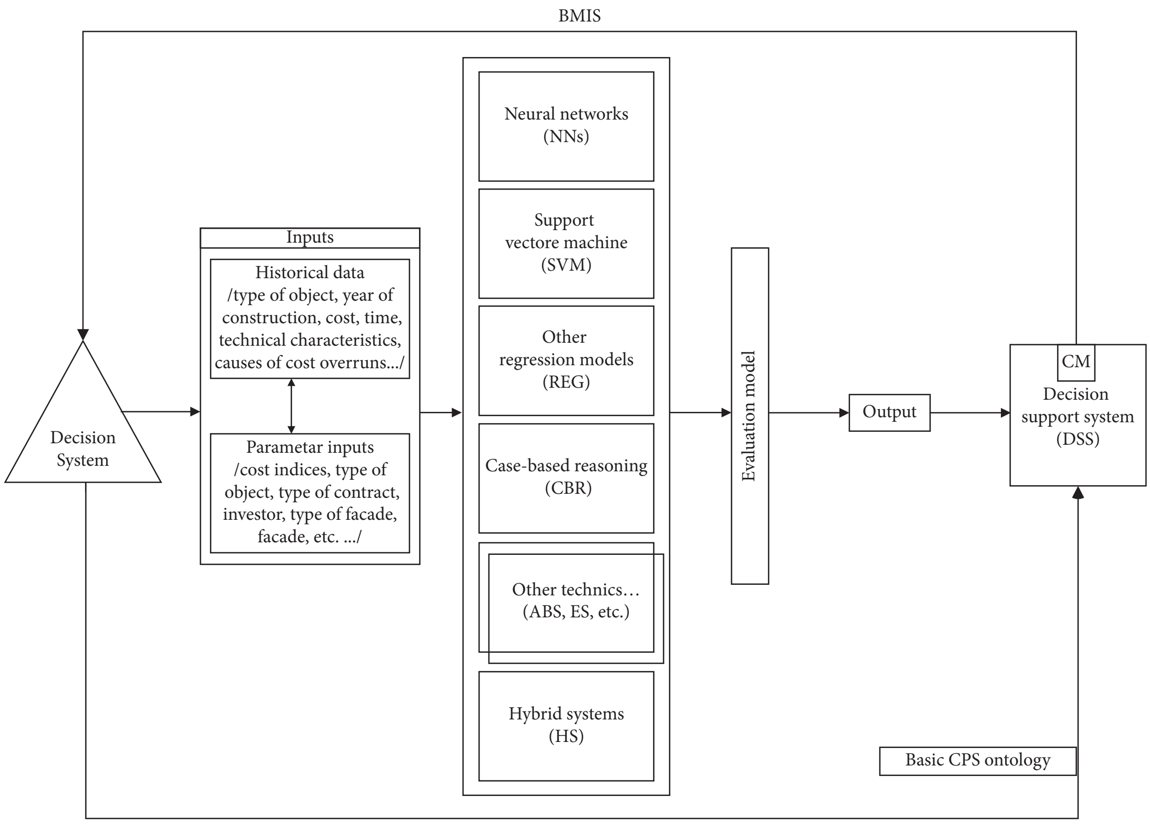

Figure 1: CPS ontology.

The development of a unique information management system is inevitable technical support for the operation of an integrated construction system. The authors of this paper advocate an open modular, upgradeable, flexible, and adaptable system that would in its generic form be widely applicable, with the possibility of incremental adaptation and upgrade depending on the local needs. In this regard, it is worth highlighting the developed multimodel-based Management Information System concept as one of the results of the "Mefisto" research project presented by Scherer and Schapke in their paper [39]. The conceptual multilevel model of the information system is presented in the paper, in which the third level is foreseen for construction economic (cost and time) and specification models.

4.2. CPS Ontology. When it comes to the starting points for creating the proposed CPS ontology, it is the result of previous and subsequent research of other authors and own research results [1, 8, 10, 18, 29, 30, 33, 40].

Its essential determinants are as follows:

(i) Integration of different models and cost prediction techniques.
(ii) Use of historical data for implemented projects.
(iii) Valorization of results obtained by applying two or more estimation models.
(iv) Foreseeing the application of hybrid models depending on the degree of their development.
(v) Integration of output into the Decision Support System (DSS).

Although the proposed CPS ontology integrates different models of cost predicting, this paper focuses on NNs due to their specific characteristics and capabilities identified by previous research [7, 8, 10–12, 33, 40, 41].

Based on the above, the following benefits of NNs should be highlighted:

(i) Self-learning ability in the training-process.
(ii) Knowledge-generalization ability.
(iii) Possible prediction on other data sets.
(iv) Processing rate.
(v) Rate of estimation of a large number of variants.
(vi) Applicability for problems in which it is difficult to determine the functional dependence between dependent and independent variables.
(vii) Good predictive ability in conditions of insecurity and incomplete data.
(viii) Prediction based on previous cases and so on.

Figure 1 shows the basic structure of CPS ontology as part of the comprehensive Building Management Information System (BMIS).

Although NN also has deficiencies ("black box" decisions), it can generally be said that they are more pronounced when it comes to other intelligent techniques applied to cost estimation. Significant contribution in terms of comparing "intelligent techniques in construction project cost estimation" was made by Elfaki et al. [10] The authors compared five categories of intelligent cost estimation techniques: Machine Learning Systems (ML) techniques-neural networks and the support vector machine (SVM), Knowledge-Based Systems (KBS) techniques, expert systems and case-based reasoning (CBR), evolutionary systems (ES) used as optimization tools, Agent-Based System (ABS) simulating actions, and interactions and evaluating the effects on the system. Hybrid Systems (HS) is the fifth and perhaps the most challenging category because it represents a set of different techniques. This enables overcoming the limitations of each individual technique.

Thus, for example, the authors list deficiencies of the KBS systems to be "difficulty of self-learning and time-consuming during the rule acquisition process," while for ES somewhat difficult generalization is listed.

Based on the above, the proposed CPS ontology was structured, consisting of the following components:

(i) Input-data component.

(ii) Central-processing component.

(iii) Output with the evaluation module.

The input part consists of a database of historical project data and an input parameter database. These bases are complex and structured according to certain predetermined criteria (e.g., by category and type of structures or by other defaults), so that data selection can be made according to a variety of criteria. This allows the creation of homogeneous databases that provide accurate time estimation data while processing. The historical database includes data on constructed structures, planned and incurred costs, and time of construction, as well as reasons for cost and deadline overruns (risks). It also includes categories and types of structures, their purpose, and their technical characteristics, for example, the number of floors, size, surface, type of facade, year of construction or reconstruction, type of client, and type of contract.

The input parameter database contains the appropriate parameters that are the inputs in the estimation models and defines the individual features from the historical database. There are, for example, price indices by months and years, currency rates, parameters that determine the technical characteristics of the structure (e.g., various types of facades can be encoded with certain numbers), parameters of the purpose of the structure, parameters related to the type of risk, and type of client and contract.

The process part integrates appropriate prognostic software systems that use these data, so that, through processing, the estimated costs for a particular structure based on its characteristics are obtained, and by data processing, a more similar and homogeneous group of previously constructed structures is determined. In the specific case, the processing can be done using one (which is not recommended), two, or more models within the system, and in the evaluation part, the accuracy of the results is compared using statistical indicators (most often it will be MAPE and R^2) as the usual measures of accuracy and suitability of the model. As can be seen from Figure 2, the NNs module itself integrates different types of networks (GRNN, MLP, Multilayer Perceptron, RBF NNs, Polynomial NNs, Cascade Correlation NN, Probabilistic NNs, etc.), which are suitable for different data types so that, by processing, the optimal type and network architecture for the structure in question are determined on the homogeneous database as possible. The homogeneity of the base is achieved by a series of parameters, not only by the type of structures but also by the financial value of the investment, similar technical characteristics, the type of client and contract, and so on. The homogeneity of the database positively influences the reliability of the estimation. If necessary, the normalization of the input data is performed. As the result of the processing of a particular database, the optimal network type with all the indicators that define it is obtained. The results are stored in the DSS system and used in cost estimation and future business decisions. In this paper, the GRNN network is presented as part of the NNs of the CPS module. Optimal data processing results would be integrated into the DSS system together with the parameters of the selected network and data processing architecture (the number of neurons per layer, the number of hidden layers, the activation function, the sigma parameter value, the number of iterations, the conjugate algorithm gradient, the validation method, and other).

One of the future development trends should certainly be sought in the development and application of hybrid models that carry significant synergistic potential in solving cost prediction problems, but also other complex problems.

The chosen most accurate result, together with all the relevant features of the processed model, becomes part of the Decision Support System (DSM), which has a complex structure, Cost System (CS) being an integral part of it, while both are part of the wider Building Management Information System (BMIS). Regardless of the choice of modules and techniques, it is clear that such an integrated cost prediction system provides a powerful tool for fast multivariate data processing and evaluation of results and saves time compared to conventional unintegrated partial and time-consuming processes. This is a strong argument for applying such a system as systematic support in making business decisions.

5. Predicting Construction Costs by Using Process-Based and Data-Driven Model

5.1. Methods. As the first phase of the investigation, a survey was conducted to collect data for estimated and real construction cost of the structures, construction time (predicted and real), year of the construction, structure type (purpose), construction site region, technical characteristics of the structure, and other data (e.g., about risk factors), but not relevant for this research. Data were collected by the questionnaires and, due to the sensitivity of some data, during face-to-face interviews with project participants (investors, contractors, designers, and construction surveyors). The survey covered one hundred and sixteen structures constructed in the Republic of North Macedonia

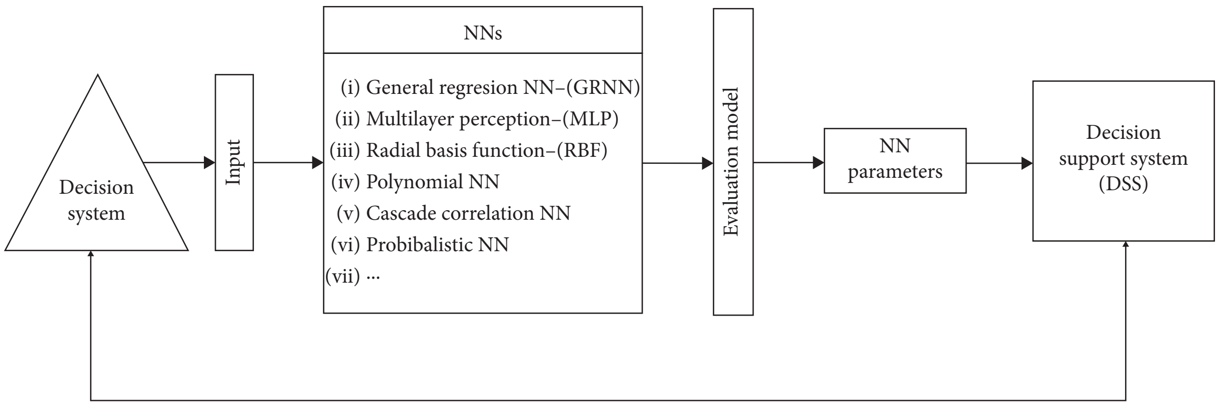

Figure 2: NNs as part of CPS.

and in the Republic of Croatia during the last two decades. The database will be described in more detail below. In the next phase of the investigation, the historical data for constructed structures were used in the process for developing the construction cost prediction model.

In order to predict the price of the construction accurately, the combination of two types of methods (models) is used: process-based method and data-driven method. The main difference between process-based models and data-driven (statistical) models is that the process-based models are based on the assumed knowledge of the actual process. Process-based models use the laws of the considered physical process, so that their results have broad applicability. To develop a process-based model, a very good understanding of the process is required, along with accurate and extensive data in order to obtain that analytical law (mathematical formulae) for the process [32].

The data-driven (statistical) models are based only on the observed relationships in the data and do not assume knowledge about the laws between the input and output variables in the actual process; they use only the actual values of the input and output variables and need only good selection of relevant independent variables and an appropriate output (dependent) variable which will describe the process well.

When the estimations of the parameters for the process-based models are difficult to be obtained, when they are not precise, or when the data for the development of the process-based models are not available, then the data-driven models can be used [32]. In civil engineering, data-driven models became popular because of the increasing availability of the data in the construction industry. They make maximal use of the available data, extracting useful relationships and conclusions from the existing data sets.

5.2. Process-Based Model. The process-based model used in this paper for predicting the construction cost is Bromilow's well-known "time-cost" model [28], which gives the relation between the construction time and construction price (equation (1)).

$$A = P \cdot B^{Q}, \tag{1}$$

where A is the contracted time, B is the contracted price, P is the model parameter showing the average time needed for construction of a monetary value, and Q is the parameter that shows time dependence of cost change [28].

Equation (1) is used in this paper for the relation of contracted time and contracted price and also for real time and real price, because these data are available in the input data:

$$A_1 = P_1 \cdot B_1^{Q_1}, \tag{2}$$

$$A_2 = P_2 \cdot B_2^{Q_2}, \tag{3}$$

where A_1 and B_1 are contracted time and contracted construction cost, respectively, and A_2 and B_2 are real time and real construction cost, respectively.

In order to obtain simpler equations for modeling, equations (2) and (3) will be logarithmized:

$$\ln(A_1) = \ln(P_1) + Q_1 \ln(B_1), \tag{4}$$

$$\ln(A_2) = \ln(P_2) + Q_2 \ln(B_2). \tag{5}$$

By summing up equations (4) and (5), (6) is obtained:

$$\ln A_1 + \ln A_2 = \ln(P_1) + \ln(P_2) + Q_1 \ln(B_1) + Q_2 \ln(B_2). \tag{6}$$

From equation (6), the dependence of B_2 (real cost) from A_1, A_2, and B_1 can be obtained:

$$\ln(B_2) = \frac{1}{Q_2}\left(\ln A_1 + \ln A_2 - \ln P_1 - Q_1 \ln B_1 - \ln P_2\right). \tag{7}$$

Because of equation (7), as input data for the artificial neural network used in this paper, the actual values for real price, real time, contracted price, and contracted time are not used, but logarithm of their values.

5.3. Data-Driven Model. The data-driven model used in this paper is artificial neural network (ANN), more specifically, general regression neural network (GRNN), which will be described below.

Over the last two decades, artificial neural networks (ANNs) were of great interest in civil engineering, because they have demonstrated very good and often very accurate solutions to the wide range of complex nonlinear computation problems from many branches of civil engineering [40, 42]. ANNs are empirically derived modeling methods and versatile predictors that are being trained using a comprehensive set of examples of the problem, which is being solved, and their target solutions. Inspired by biological neural systems, they learn from experience, that is, from many input patterns and their appropriate outputs. The success of ANN applications depends mostly on selecting appropriate type and structure of the NN for solving the problem and the quality of the data used for training of the ANN.

For different type of data, different type of ANN or modeling method will be suitable. Several types of modeling methods should be always tested in order to choose the one which will give the most accurate results. In this research, multilayer perceptron (MLP), radial basis function (RBF), and general regression neural network (GRNN) were tested and the most accurate predicting was obtained using GRNN.

5.4. General Regression Neural Network (GRNN). GRNN is a neural network with a highly parallel structure that provides estimation of numerical variables and converges to a linear or nonlinear regression surface. This NN can be used for any nonlinear regression problem, for prediction, mapping, and modeling, or as a controller [43].

GRNN needs only a few training samples in order to converge to the basic function of the data, which makes this NN be very useful tool for application in practice, particularly for sparse data.

GRNN is very similar to RBF (radial basis function NN) with many nodes and, in comparison with well-known MLP NN (multilayer perceptron NN), it is faster to train and in many cases more accurate, but it is slower than MLP at classification of new cases and needs more memory space for storing the model.

The basic regression equation, from the statistical theory, is

$$y(X) = E\left[\frac{y}{X}\right] = \frac{\int_{-\infty}^{\infty} y f(X, y)\mathrm{d}y}{\int_{-\infty}^{\infty} f(X, y)\mathrm{d}y}. \tag{8}$$

E[y/X] is the conditional expectation of y for given X and $f(X, y)$ is the joint probability density function (jpdf) of the vector X and scalar y. When the function $f(X, y)$ is not known, it is being estimated from any of the Parzen estimators [44] using a finite set of observations of X and y and Gaussian Kernel [43]:

$$f\left(\frac{X}{y}\right) = \frac{1}{(2\pi)^{((p+1)/2)}\sigma^{p+1}}\frac{1}{n}\sum_{i=1}^{n}\exp\left(-\frac{\left(X - X^i\right)^T\left(X - X^i\right)}{2\sigma^2}\right)\exp\left(-\frac{\left(y - Y^i\right)^2}{2\sigma^2}\right), \tag{9}$$

where p is the dimension of the input vector X, n is the number of training samples, σ is the smoothing parameter, X is the input vector for which y should be estimated, X^i is i-th training sample, and Y^i is the appropriate measured value of y.

The integration over y in equation (8) can be computed by substitution equation (9) in equation (8), and the obtained estimation for Y is given in equation (10) [45].

$$\widehat{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\left(\left(X - X^i\right)^T\left(X - X^i\right)/2\sigma^2\right)\right)}{\sum_{i=1}^{n} exp\left(-\left(\left(X - X^i\right)^T\left(X - X^i\right)/2\sigma^2\right)\right)}. \tag{10}$$

The architecture of GRNN is shown in Figure 3 [46]. There is the same number of neurons in the input layer as predictor variables and input neurons feed the values of input variables to the neurons in the hidden layer. Each neuron from the hidden layer contains the data for each row (case) from the training set, that is, the values of all predictors and target value for one case. The hidden layer computes the Euclidean distance of the test case from the neuron's center and applies kernel RBF function. The resulting value is fed to the next pattern layer. Pattern layer has only two neurons: numerator summation unit which for each hidden neuron adds up the weight values multiplied by the actual value of the target variable and denominator summation unit which adds up the weight values from the hidden neurons. The value from the numerator summation unit is divided by the value from the denominator summation unit in the decision layer.

In the next section, the results for the prediction is going to be presented.

5.5. Database. Database consists of 116 structures data, built on the territory of the Republic of North Macedonia, 75 in total, and 41 built on the territory of the Republic of Croatia during the last two decades. The database consists of 51 buildings data, 53 construction structures, and 12 others (e.g., gas stations, multilevel car parking, electrical substations, and storage buildings). For future research, homogenization of bases is recommended to obtain more accurate results. In this research, the focus was on the number of cases in the database and the analysis and comparison of multiple models with an emphasis on the evaluation of the hybrid model.

6. Results

For modeling the data and predicting the real construction price, general regression neural network (GRNN) from the

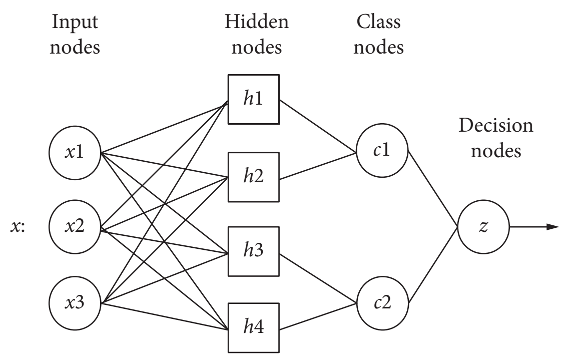

Figure 3: GRNN architecture [46].

predicting modeling software DTREG [46, 47] was used. The standard estimators of the model, the mean absolute percentage error (MAPE), and the coefficient of determination R^2 which reflects the overall fit of the model are MAPE = 0.73% and R^2 = 99.55%. The coefficient of correlation between actual and predicted values of the target variable is 0.998 (Table 1, Validation data).

The available data used for modeling were purpose of the facility, planned (contracted) price, real price which was achieved, and contracted and real construction time.

Bromilow time-cost model is used for choosing the input values for the target and predictors. According to the discussion in the previous section, ln (real price) is used as a target variable, and ln (real time), ln (contracted time), ln (contracted price), and purpose of the facility are used as predictors. Initial input knowledge that is available is the values of the target variable and predictors for 116 built structures.

For all numerical variables (predictors and target), DTREG obtains their minimal, maximal, mean value, and their standard deviation (Table 2).

For validation of the model, DTREG offers 4 choices:

(1) Random percent of the rows are held out when the model is being made and after the building of the model, that number of rows is run through the model and the error is evaluated.

(2) Control variable is used to select which rows will be selected to be held out for testing.

(3) Cross-validation with the chosen number of folds.

(4) Cross-validation with one row left out of each built model.

In Table 1, the results for the training and validation data are given using cross-validation method with 10-fold.

DTREG computes the relative importance of each predictor to the quality of the model, using sensitive analysis. Table 3 shows this importance with an accuracy of 3 decimal places. The displayed values are percentage values of the importance of every predictor in the model for predicting the target variable (real cost).

It can be seen that the most important predictor for predicting the real price is the planned (contracted) construction price.

Table 1: Results for the training and validation data (DTREG software).

Estimators of the model accuracy (DTREG)	Value
Training data	
Mean target value for input data	13.358369
Mean target value for predicted values	13.356284
Variance in input data	4.4677631
Residual variance after model fit	0.0024144
Proportion of variance explained by model R^2	0.99946 (99.946%)
Coefficient of variation (CV)	0.003678
Normalized mean square error (NMSE)	0.000540
Correlation between actual and predicted R	0.999731
Maximum error	0.3219897
RMSE (root mean squared error)	0.0491365
MSE (mean squared error)	0.0024144
MAE (mean absolute error)	0.0288461
MAPE (mean absolute percentage error)	0.2199448
Validation data	
Mean target value for input data	13.358369
Mean target value for predicted values	13.35876
Variance in input data	4.4677631
Residual variance after model fit	0.0199458
Proportion of variance explained by model R^2	0.99554 (99.554%)
Coefficient of variation (CV)	0.010572
Normalized mean square error (NMSE)	0.004464
Correlation between actual and predicted R	0.997882
Maximum error	0,5402981
RMSE (root mean square error)	0.1412296
MSE (mean square error)	0.0199458
MAE (mean absolute error)	0.0984472
MAPE (mean absolute percentage error)	0.7326534

Figure 4 shows the chart for the dependence of the predicted target values (ln (real cost, euro)) and the most important predictor (ln (planned costs, euro)).

Figure 5 shows the chart for the dependence of the actual and predicted values of the target variable.

Discussion with the Proposal of the Results Integration into Decision Support System.

Before choosing the GRNN model for predicting, other two predictive models were tested: multilayer perceptron (MLP) and radial basis function (RBF) neural network.

Because the relationship between target variable and predictors is not known in advance, several models must be tested in order to choose the best one for the actual data to provide the highest accuracy.

Table 4 presents the comparison of the accuracy among these three predictive models that were tested, using Bromilow "time-cost" model, the results for validation data for all 3 predictive models (GRNN, MLP NN, and RBF NN).

It is necessary to point out that using the Bromilow "time-cost" model drastically improved the accuracy of the prediction of these three models.

Without using the Bromilow model and by using only the actual values of numerical variables, the contracted time, and cost and the real time, as well as the target (real cost), the MAPE of the GRNN model was over 100% because of large

Table 2: Minimal, maximal, mean value and standard deviation for the numerical variables (predictors and target).

Continuous variables					
Variable	Rows	Minimum	Maximum	Mean	Std. dev.
ln (planned costs, €)	116	9.05358	18.36511	13.27770	2.06661
ln (real costs, €)	116	9.09459	18.51599	13.35837	2.11371
ln (planned time, days)	116	2.70805	6.81619	5.07076	1.04090
ln (real time, days)	116	2.70805	7.50934	5.14528	1.063

differences in values of the target variable. Figure 6 shows part of the input data, used for training of GRNN.

In practice, the hybrid models have demonstrated in many cases better results than when applying only one of them. Lee et al. [48] proposed a hybrid ANN (artificial neural network) called GRNNFA, which is a combination of fuzzy adaptive resonance theory model (FA) and the general regression neural network model (GRNN), developed for classification of noise data. The model removes the noise that is embedded in the training data and retains the best features of the two single models, fast training, good learning, and a network with an incremental growing structure. The performance of this hybrid model, when compared to the other published results, presented better results. The accuracy of predicting was around 96.11%.

To solve the issue of large-scale data, Wang et al. [49] proposed the TSE-GRNNs (tree-structure ensemble general regression neural networks) model. First, small-scale sample subsets are constructed using the regression tree algorithm. After that, GRNN submodels are constructed on these sample subsets, followed by the application of TSE-GRNNs method to establish the predictive model. Experiments show excellent predictive results.

Other authors also used ANN for predicting construction costs.

The authors in [50] used ANN to predict construction cost for apartment projects in Vietnam and obtained accuracy of the model with MAPE about 10%. They compared the ANN model with multiple linear regression (MLR) model and genetic algorithm model (GA), and the best accuracy was obtained with the ANN.

The author Juszczyk [13] uses several types of MLP to model the cost estimation of the construction works (residential buildings). The mean average percentage error (MAPE) for the validation data for the 5 MLP NN was from about 7% to 13%.

It is very important to mention that the accuracy of the model depends mostly on the selection of appropriate predictors for the chosen target variable and the selection of the appropriate ANN or some other regression models.

The authors in [14] have proposed data-driven methods for cost estimation of spherical storage tanks projects, based on the application of ANNs and hybridized regression models with genetic algorithm (GA), without using ANNs. The variables used in these models were thickness, tank diameter, and length of the weld. They have used two types of NNs (multilayer perceptrons): with Levenberg-Marquardt algorithm (LMNN) and Bayesian regulated (BRNN). The results have shown that both ANNs have performed

Table 3: Importance of the variables.

Overall importance of variables	
Variable	Importance
ln (planned costs, €)	100.000
Purpose of the facility	0.377
ln (planned time, days)	0.069
ln (real time, days)	0.042

Table 4: Comparison of the accuracy among GRNN, MLP NN, and RBF NN (results for validation data).

Predictive model	MAPE%	R^2	R
GRNN	0, 73	99, 55	0, 998
MLP NN	0, 97	98, 99	0, 995
RBF NN	0, 96	98, 97	0, 995

better than hybridized regression models without using ANNs. LMNN has shown better estimation than BRNN. The correlation between real data and predicted values was more than 90%, and the mean square error was around 0.4. Author's future work is focused on the comparison between this proposed model and another ANN hybridized with a metaheuristic such as GA, Bees algorithm, Ant Colony algorithm, or Artificial Bee Colony algorithm.

The author Badawy [51] has proposed hybrid model for estimation of the cost of residential buildings in Egypt. Real data were used from 174 real residential projects. The proposed model was composed of ANN model and multiple linear regression models. The MAPE of the hybrid model was 10.64% which was less than other hybrid models developed in the research. The analysis has shown that the most important factors in the cost prediction were the number of floors and the area of the floors.

In relation to DSS system, the parameters of the GRNN model can be stored in CPS: minimal and maximal sigma values, validation method (cross-validation with 10-fold), the type of kernel function, and then the parameters of the optimization algorithm of GRNN (number of iterations and absolute and relative convergence tolerance). Also, another recommendation before developing the model with some of the predictive models from the CPS system is to verify the data if the values of the input data have significant differences among them. If this is the case, then normalization of the data can be made before developing the predictive model. Also, the authors believe that in near future software can be developed which can select and try every predictive model from the CPS system and choose the most appropriate for the actual data.

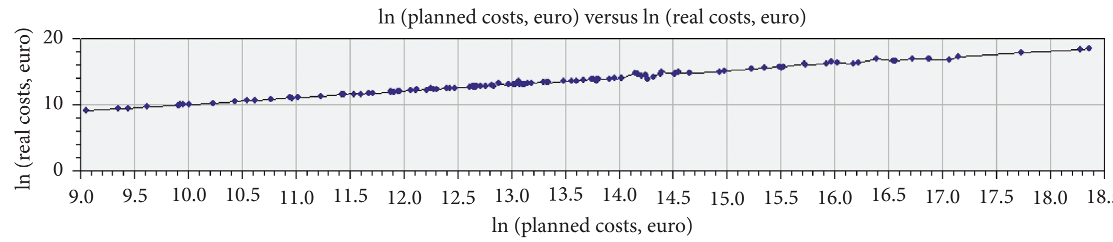

Figure 4: Dependence between the predicted target values (ln (real cost, euro)) and the values of the most important predictor (ln (planned costs, euro)).

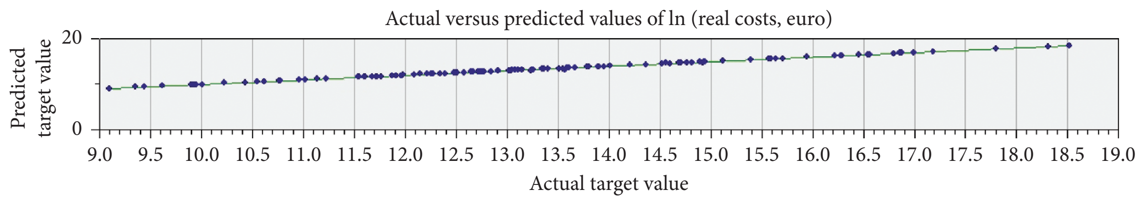

Figure 5: Dependence of the actual and predicted values of the target variable.

No.	Purpose of the facility	ln (planned cost, euro)	Planned costs (euro)	ln (real costs, euro)	Real cost (euro)	ln (planned time, days)	Planned time (days)	ln (real time, days)	Real time (days)
1	Sport	16.72373993	18324324.32	16.85098316	20810810.81	5.899897354	365	5.899897354	365
2	Sport	16.87218537	21256756.76	16.9907451	23932432.43	6.305362462	547.5	7.286191715	1460
3	Education	16.56156799	15581081.08	16.56156799	15581081.08	6.816188085	912.5	7.063048163	1168
4	Education	16.8772583	21364864.86	16.8772583	21364864.86	6.593044534	730	7.152660322	1277.5
5	Education	16.54318672	15297297.3	16.54318672	15297297.3	6.816188085	912.5	7.509335266	1825
6	Sport	17.14771507	28000000	17.19023446	29216216.22	6.08221891	438	6.08221891	438
7	Sport	18.27861886	86756756.76	18.3138176	89864864.86	6.23636959	511	6.23636959	511
8	Sport	17.72753356	50000000	17.8054951	54054054.05	6.162261618	474.5	6.162261618	474.5
9	Education	18.36511089	94594594.59	18.51599092	110000000	5.899897354	365	5.899897354	365
10	Education	14.52208076	2027027.027	14.56130147	2108108.108	5.499419787	244.55	5.499419787	244.55
11	Water tank LISEC	12.40181722	243243.2432	12.50717774	270270.2703	4.791234729	120.45	5.499419787	244.55
12	Water tank lokvarka	13.75994071	945945.9459	13.8934721	1081081.081	5.899897354	365	6.593044534	730
13	Water tank petehovac	13.60579003	810810.8108	13.60579003	810810.8108	5.899897354	365	5.899897354	365

Figure 6: Part of the input data (13 rows, from 116) used for training.

7. Conclusions

Due to the complex cost estimation problems in the field of building construction, lack of data, uncertainty, and risks, especially in the initial phases of the project, the model of the cost prediction system (CPS) as a part of the comprehensive Building Management Information System is proposed. On the one hand, the CPS uses historical data on implemented projects and a database of appropriate parameters, and on the other hand, several models of cost prediction are based on intelligent prediction techniques. These techniques have already been tested in solving various problems of the construction industry. The paper presents CPS ontology with the indicated basic components. The NNs are singled out as especially suitable. The reasons are explained in detail.

The paper analyzes the cost estimation with a concrete database using a hybrid model which is a combination of process-based Bromilow model and data-driven GRNN network using the DTREG software. Accuracy with MAPE of 0.73% was obtained, with coefficient of determination R^2 of 99.5% and correlation coefficient of 0.998. The results were compared with the results obtained using other prognostic models with ANNs, by applying the same software. The presented processing in the proposed model would be enabled through the CPS system components and the stored data would be used. Processing results are stored in the system and used in future processing. Processing results are stored in the Decision Support System and used in future cost estimates and decision-making. The analysis and comparison of partial use of software with those included in the cost prediction system indicate a significant time saving and an increase in the quality of the assessment in the latter case.

Therefore, the authors find the proposed model as a useful tool for all participants in the construction project for early cost prediction, when numerous factors, which determine cost, are unknown.

Finally, the authors believe that research results, particularly the experience of process-based and data-driven models combination, as well as the proposed CPS model as support for decision-making contribute to the body of knowledge in the field of cost prediction for construction projects.

The development of the proposed cost prediction system should be the subject of future research. A special emphasis in future research should be put on the development of hybrid models. This concept can be applied more widely and can also cover the problem of predicting the duration of construction projects in the early stages.

Data Availability

The authors declare that data supporting the results reported in this paper can be found in the authors' databases. The data are available upon request (contact person: Silvana Petruseva, e-mail: silvana@gf.ukim.edu.mk).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Proposition of a Model for Selection of the Hybrid Contract Implementation Strategy for a Pilot Project of Regular Road Maintenance in Montenegro

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Performance-based maintenance contracts (PBMCs) are modern contracts that should allow road maintenance entities to contract maintenance activities more successfully and generate money value. In the case of Montenegro, a gradual approach of PBMC introduction is recommended through a hybrid contract for routine road maintenance. Hybrid contract implementation will enable a lower level of client risk in the early stages of PBM contract. Game theory is used for selection of an adequate model for hybrid contract structure in terms of size and nature of the BoQ elements. In addition to the estimated or charged quantities of works from previous contracts, the model also includes parameters that to some extent take into account the experience and expertise of contractors and clients, but also the availability of road data. In order for model to be applied, historical data from traditional road maintenance contracts, which were implemented in the previous period in Montenegro, are used.

1. Introduction

The length of the Montenegrin road network is 6.848 km. It is made up of 884 km main roads, of 964 km regional roads, and of around 5000 km local roads. Out of 1.848 km main and regional roads which are classified as state roads by the current law, 92% are asphalt roads. According to the report [1], quality of roads, which are on the SEETO road network in Montenegro (length around 670 km), is very good 2.24%, good 37.39%, medium 51.55%, and poor 8.81%.

Traffic Authority is a state entity under which jurisdiction is, among other activities, the management, development, construction, reconstruction, maintenance, and protection of state roads. The main management difficulties arise from unfavourable topography and geological structure of the terrain, very uneven, seasonal use of road infrastructure during the year, budgetary limitations and accumulated maintenance problems, lack of road infrastructure database, lack of private initiative in road sector, and an insufficiently shaped model of road and road network maintenance.

State road maintenance encompasses regular and investment maintenance in accordance with the midterm programme and annual plans. Investment maintenance is conducted on basis of technical documentation and contains construction works within the existing road profile in order for the lower array of the road to be renewed or replaced, improvement of construction road elements, repair of road facilities, landslide remediation, etc. Regular maintenance contains review, determination, and assessment of the state of the road; cleaning, ordering, and fixing of the road, walls, and other elements of the road (slopes and drainage systems) in places; repair of road facilities; cleaning, repair, and renewal of signalization and equipment; ordering of green surfaces along the road; maintenance and remediation of electrotechnical and machine installations in tunnels; cleaning of snow and ice, and covering of the road in case of ice; and maintenance and remediation of electrotechnical and machine installations in tunnels.

In the transition period, in the 1990s, very little was invested into maintenance, including regular maintenance. The situation changed in the beginning of the twenty-first century when there was an investment of 2.5 million euro into regular maintenance in 2003. Today, the investment is around 10 million annually. Starting with 2005, in accordance with public procurement procedures, four-year contracts are concluded for regular maintenance with selected contractors. These are traditional contracts which entail contracting and payment by unit prices of contracted works: measurement/input/based maintenance.

The traditional system aims at executing planned quantity of activities and not the effect which planned activities within given scope could have on the final condition of the road. In the traditional system, duty of the client (road maintenance entity) is expert supervision of quality and quantity control of executed works (in house or through a consultant) and payment of approved works. Programs and plans of regular road maintenance, the adoption of which is within jurisdiction of the road maintenance entity, need to be based on available financial resources, realistic assessment of the state of the road, importance of the road, traffic load, etc. in order to have optimal activity plan as a result. Programs and plans need to ensure that necessary activities are conducted on the right location (part of the road network), at the right time and with the required quality. The task of the contractor is to execute planned activities in accordance with technical standards in order to be paid for the conducted works, and the quantity and quality of which are determined through measurement. Mistakes in preparation of programs and plans result in an increased scope of variations and claims during the contract and are not at all desirable for any of the participants. Moreover, inadequate programs and plans of maintenance could lead to insufficient maintenance and a lack of undertaking preventive measures which leads to poorer condition of the roads regardless of resources available for regular maintenance. Application of the traditional model is faced with difficulties in terms of control of quality, time, and expenses. Moreover, according to papers analysed, the traditional method is frequently connected with a high level of political influence and corruption [2].

The other method applied in the world is performance-based maintenance contracting (PBMC). PBMC is a "method under which the selected contractor has to plan, design, and implement maintenance activities in order to achieve short- and long-term road condition standards for a fixed price, subject to specified risk allocation" [3] (p. 118). This method belongs in the performance-based contracting (PBC) which is defined as a type of contract in which payment for the deliverable is explicitly linked to the contractor's successfully meeting or exceeding certain clearly defined performance indicators [4, 5].

PBMC entails multiannual, lump sum contract, where the emphasis is put on the payment for the final result, i.e., performance of the maintained road. Performance levels are minimum conditions of road, bridge, road side, and traffic assets that must be met by the contractor over the entire contract period and may cover other services such as winter services, the collection and management of asset inventory data, call-out and attendance to emergencies, and response to public requests, complaints, and feedback. To optimize total system cost, performance levels may differ from traffic levels on a road section [5]. In this type of contract, performance levels and indicators are defined for each road asset or service provided under the contract. Fixed payments are made if performance levels are met, or payments are reduced due to noncompliance.

These contracts should inspire the contractor to apply innovative methods and procedures connected to maintenance, among other things, and to augment internal works control, in order to increase income and, at the same time, decrease expenses during the lifecycle of the roads by improving the level of quality of service [5, 6]. Payment is done through a lump sum set on an annual or a monthly level after checking that the contractor is meeting the performance standards properly as defined in the contract. In that sense, it is important that performance levels should be easily understood, clearly defined, objectively and easily measurable, affordable, and consistent with relevant laws and regulations, and have low collection cost [3].

A large number of authors have analysed various aspects and models of PBMC application. In some works, the advantages of the PBMC method in compassion to the traditional method are emphases [2, 4, 5, 7] in following areas: cost savings, up to 40%, or setting costs at a fixed level; better risk allocation; assurance of quality; more consistent (and/or better) service level and road users satisfaction; availability of initial funding sources; achieving a sustainable road management system; increased flexibility; increased transparency; and reducing the resource consumption for road authority. Some of indirect benefits for road maintenance entity are savings on rehabilitation costs, since roads in good condition avoid rehabilitation, and safeguards against cost overrun from frequent claims and contract amendments to increase quantities of work.

However, challenging factors which significantly influence PMBC application should also be mentioned, especially when it comes to developing countries. These are lack of support from government; dependency on external funding; political influence and corruption; lack of experience in introducing PBMC; lack of proper planning; fear of losing job; loss of competition; loss of control of the network; the contractors' performance and attitude; inflexibility to change anything once the contract has been started; and challenges in estimating the cost of PBMC especially because of the not sufficient understanding relationship between the financial cost of maintaining KPIs (key performance indicators) at a particular level, and it is a very high-risk area if the modelling predictions are not right levels [3]. Besides that, it is difficult to formulate a specific maintenance standard to define the maintenance operations, for roads in poor condition [5].

Outside of these two opposing methods of contracting, there is the hybrid contracting which is present in practice and which is treated in various manners in the literature [4], In this work, under a hybrid contract, we will consider a contract within which a part is contracted through the traditional method of unit prices and quantity measurements, and a part of contracted in accordance with PMBC principles. Payment for most of the services is being linked to meeting performance indicators. Application of this model should enable the combination of the best characteristics of both models in order for contract implementation to be optimal for each participant. This method can be used by the client (road maintenance entity) to adjust the sharing of risk between the contractor and client, mostly in cases when neither the client nor the contractor has enough knowledge to implement PBMC. Application of a hybrid contract carries a higher level of risk for the contractor in comparison to the traditional system but a lower level of risk in comparison to the PBMC. In opposition to this, the risk for the client is the highest in the traditional system and the lowest in the PBMC, being of a medium level in the hybrid model.

The first steps to initiating PBMC systems should be confined to a relatively simple contract (s) for PBM covering the routine maintenance of a package of roads, mostly in a hybrid manner, to only a carefully selected part of the network. The first step to initiating PBMC systems is conduction of the pilot project, in which the purpose is to test the existing institutional framework for longer-term implementation of PBMC; induce changes in the road maintenance system; test market readiness; establish the right balance of risk allocation between participants; create critical mass of knowledge; and expertise in the road maintenance entity and the local contracting industry to implement new types of maintenance contracts [7].

Preparation and implementation of a pilot project requires preliminary considerations about the following: (1) legal, regulatory, and financial climate, (2) data, (3) long-term strategy, (4) selection of roads for pilot projects, (5) technical assistance (and fields of assistance), (6) pilot implementation, (7) the contract, (8) allocation of risk, and (9) the timeline for a pilot PBM contract [5].

After analysing the state of road maintenance in Western Balkan countries, the key recommendations are given to improve the situation in this area: establishing proper practice of road network data collection, and structure budget into categories (routine and winter maintenance, periodic maintenance, rehabilitation, structures' maintenance, and emergency works); establishing database and GIS systems; establishing regular maintenance analysis and studies on short- and medium-term basis, and regular budget allocations for update of data and general work on the asset inventory; making a strategic decision on how to collect data; establishing the basics of the system and implement asset management principles; and performing asset valuation at regular intervals (not to exceed 2 to 3 years) [1].

The implementation of some of the above recommendations in the road maintenance policy in Montenegro is ongoing.

2. Materials and Methods

Introduction of the PBMC methodology implies launching a small-scale pilot project that would allow both the road maintenance entity and the contractors to adopt a different approach. Successful implementation of the pilot project requires an adequate strategy that would enable road maintenance entities to contract maintenance activities more successfully and get value for money.

Assessment of impact of different factors on the PBCM project success, as well as the possibility of optimization and appropriate model selection, were the subject of interest of researchers, although only a few of them investigated the simultaneous effect of several factors [8–10].

Gericke et al. [4] assume that the procurement of PBC would deliver 20% greater VfM than a non-PBC contract. According to the results achieved on two pilot maintenance projects in Serbia (total length of 1,200 km, which were realized as hybrid contracts in the period from 2004 to 2007), the pilot project territories achieved routine maintenance cost savings in range from 31% to 55%, average 46% for 5 years compared with the central region of Serbia during the same period [11]. The main challenge in those projects was the lack of sufficient qualified staff with the road administration, consultants, and contractors [5].

Some of the analysed factors in the literature from the aspect of the PBMC impact and success are as follows:

Contract duration, activity type, and contract size–the large projects with strong competition, long duration and extension periods, long outsourced road sections that incorporate crack sealing, pothole repair, illumination repair/maintenance, and mowing activities, and favour PBMC [8]

Cumulative equivalent single axle load, speed of construction work, the traffic, and rainfall have been used in the game theory and the simulation for the optimization of benefit for the client and profit for the contractor [9]

Performance levels and contractual performance criteria [4], [12] and thresholds for applying penalties/incentives [13]–mathematical optimization models and a computational tool have been developed in order to meet contractual conditions: (1) types of performance indicators; (2) their threshold levels; and (3) the appropriate levels of penalties and incentives [10]

Risks allocation between the participants [2, 4, 14, 15]: if too much risk is allocated to the contractor, the price will be high, and if too little risk is transferred, then the goal of obtaining efficiency and effectiveness of the contract is not achieved [9]

The method of contractor selection-cost reductions was largest when contractors faced strong competition and have gained experiences with PBCs [5]

Based on the analysed literature, the factors influencing the pilot project implementation can be divided as follows:

(1) Factors that are variable during the project implementation and which cannot be controlled by the project participants (uncontrolled factors): political, legal and regulatory, monetary, macroeconomic, climate, force majeure, traffic volume, axle loads, etc.
(2) Factors that are a consequence of the initial state of the system in which the project is implemented: availability of necessary knowledge and training, competence and competition of contractors, scope and timeliness of available road data, assess of existing road, availability of resources for contract execution, etc.
(3) Factors that are initially determined by the client (road maintenance entity) with the purpose of achieving the greatest value of money through the project implementation, and on the basis of which, the tender documentation and selection of contractors are prepared. The most important factors are as follows: duration of contract, location, and road included, type of maintenance activity that will be included, size contract, risk allocation, performances levels, type of PBMC (pure or hybrid, and size and nature of the BoQ elements), penalties systems, efficient performance monitoring and inspection system, etc.

Although the interaction of these factors is significant, the third group of factors deserves special attention, because they enable the selection of the optimal strategy of the road maintenance entity.

There are general recommendations for each of these factors [1, 5, 7, 16] and specifically for Montenegro [17]:

Duration of contract: pilot contract duration of 5 years is recommended for Montenegro.

Road included and location: the actual choice should be made based on the study. Neighbouring roads should be selected, in a limited area, in order to facilitate the execution of works, but also the performance of supervision. The recommended road length for Montenegro pilot project would be of 180–300 km. It would be desirable to have a maintenance center location in the selected area.

Performances levels: it is necessary to set out appropriate level of service for different road types and traffic levels. Accordingly, the appropriate optimal number of maintenance performance indicators should be determined. These indicators should be clearly defined in the specifications (maintenance standards), easy to calculate and evaluate, realistic and achievable.

Type of maintenance activity that will be included is as follows: the contract should cover all routine maintenance (including winter maintenance). *Regular road maintenance in Montenegro, according to the Law on Roads, includes routine maintenance and elements of periodic maintenance for which it is not necessary to do technical documentation (periodic maintenance is not specifically defined by law). The law also defines investment maintenance for which it is necessary to prepare technical documentation*. The condition of the road depends on routine maintenance, but periodic maintenance (in the form of paving, surface treatment, or other bituminous treatments) has the greatest impact on preventing road deterioration, as it is necessary to include both components in terms of sustainability of the required performance level. A step-by-step approach is envisaged.

Size contract: it is recommended to allocate between 4,000 and 6,000 €/km/year for routine and winter maintenance for pilot project in Montenegro.

Type of PBMC (pure or hybrid): the implementation of hybrid contracts will enable a lower level of client risk in the early stages of PBM contract implementation. This is particularly desirable for application in case of insufficient client experience.

Risk allocation: in pilot projects, it is desirable for the client to fully take risk of emergency works, some other physical works, and legal and regulatory changes. On the other hand, the contractor should take the risk related to the physical works (cost amount and timing). Other risks should be shared between the client and the contractor, so that the client assumes most of the risks related to price escalation and site access and 3rd party activity, a contractor, a smaller part of these risks. Also, the contractor is expected to assume most of the risk related to asset management and traffic and axle load variation.

Penalties systems: penalties must be adequately defined. They are applied in cases when the contractor does not perform the maintenance standards, i.e., when maintenance functions are not performed properly on time. Reduction variants also depend on whether the job positions are paid in a lump sum or according to the BoQ system. In the case of positions that are paid as a lump sum, it is possible to reduce the fixed amount, or the percentage of the lump sum, or to award penalty points (demerit points) for each omission with the agreed value of penalty points. In the latter case, the total value of all penalties is also agreed. In the case of positions paid on the basis of BoQ, the reduction is made in the event that the execution is delayed or due to failure to achieve the defined quality of these positions. In pilot projects, it is recommended that in the contracts, first, until the contractor gains experience, a certain number of errors are allowed for which the payment is not reduced. In the following years, the number of allowed errors decreases.

Efficient performance monitoring and the inspection system: performance monitoring is a key to the success and manner and monitoring inspections' frequency. Monitoring methodology should be clearly defined and spelled out in the contract. It implies that experts who are specially trained in the PBMC application participate in this.

As noted, in the case of Montenegro, a gradual approach to the introduction of PBMC is recommended through a hybrid contract for routine road maintenance. The combination of BoQ and lump sum elements of works in hybrid contracts depends not only on the degree of risk that the client wants to transfer to the contractor, but also on the financial resources available formaintenance.

The risks associated with fixed-price contracts (such as "pure" PBMC) are the costs associated with project change. If a change occurs on the project that requires a change order from the contractor, the price of the change is typically very high. Even when the price for changes is included in the original contract, changes on a fixed-price contract will create higher total project costs than other forms of contracts because the majority of the cost risk is transferred to the contractor, and most contractors will add a contingency to the contract to cover their additional risk. In the other hand, the hybrid contract provides a calibrating risk allocation between the client and contractor, simply by adjusting the size and nature of the BoQ elements. In essence, the shorter the contract, the more risks it is appropriate for the client (road maintenance entity) to carry. In this regard, the issue of the size and nature of the BoQ elements in the hybrid contract is elevated.

Some of the recommendations for the contract structure are the follows:

Emergency maintenance, periodical maintenance works, minimal rehabilitation (if unavoidable), and some works of winter maintenance should be paid as BoQ elements [1, 16]

The payment for the more variable or contentious elements should be made on the basis of measured quantities and unit rates, BoQ [7]

Based on experiences in the region, only cyclical regular maintenance activities, which require a small amount of material, or material is not needed at all, should be included in the lump sum and paid based on satisfied performance levels, i.e., treated as performance-based items, and other works to be calculated and paid for as BoQ elements [16]

In the continuation, a model for choosing the structure of a hybrid contract in terms of size and nature of the BoQ elements will be proposed. In that sense, we will consider the possibility of game theory application.

Game theory is a complex scientific field that deals with strategic decision-making in different situations, in which several decision makers participate with different interests [18]. The essence of all game theory definitions is the existence of conflict (of different levels) between participants (players) who make decisions, with defined rules, in order to choose from all available strategies those that allow the best game outcomes. The process of rational decision-making in different conflict levels and players' interests, as well as in risk and uncertainty conditions, can be mathematically formalized and analysed by game theory application. Each game consists of three important components: (1) there are at least two individuals called players. (2) Each player has a set of actions which he/she may follow. These courses of actions are named strategies. (3) The outcome of each strategy is determined and associated with each outcome, and there is a value named payoff for each player [19].

Despite some limitations, game theory has found application in a variety of business areas. It is especially applicable in various areas of project management [20], selection of bidders in construction or in general [21–23]. In addition, some papers discuss the application of this theory from the aspect of defining an appropriate contract model [24, 25]. The interest of some authors was focused on public-private procurement [26, 27], on resolving disputes or cooperation in the PBMC project implementation [9, 28].

Special groups of games are games against nature. There is only one player who makes a rational choice and is interested in the outcome. The player (called "decision maker") only needs to list available options and then choose the optimal outcome. There does not exist a conscious opponent because nature is presumed to be completely indifferent to the player's decision. However, these games can also be treated and solved as two-person games. The basic assumption is that nothing is known about the probability distribution governing nature's "selection" of states [19]. Both players (player and nature) are assumed to have finitely many pure strategies and the m by n "payoff" matrix $A = [a_{ij}]$ is known. The a_{ij} is assumed to represent the gain obtained by decision maker if he applies his i-th strategy while nature is in state j.

3. Proposition of Model for Choosing the Structure of a Hybrid Contract in terms of Size and Nature of the BoQ

Defining the structure of a hybrid contract from the point of size and nature of the BoQ elements may be seen as a game against the nature. The player is an investor (road maintenance entity), while the nature represents the conditions that can have a crucial influence on the client's decisions. We start from the assumption that the client may have different benefits if they use a specific position of work (work item) from the contract (contracts per unit rate) in relation to the strategy that the same work item defined at the flat rate price (lump sum). The amount of its benefits in both cases depends on the conditions in which the client makes the decision and which also influence prices that are expected from the bidder. The whole situation should be seen in the context of uncertainty, i.e., limited knowledge of the conditions in which the client should make a decision.

The client has two strategies at disposal regarding each work item from the PBMC pilot project. Work item may be agreed in such a way that it is calculated and paid as follows:

Lump sum item: the payment is made based on the price from the contract, without the influence of the change of quantities to the contracted price, or

Unit rate item: the payment is made on the basis of measured quantities and unit rates, BoQ

In the first case the responsibility of the client lies only in establishing whether the works have been completed in accordance with the specifications and standards; they do not measure the quantities of the completed works for the needs of payment for the work. Defining the quantities that will be realized (and therefore paid) is the responsibility of the contractor.

In the second case, defining the quantities that will be realized (and therefore paid) is the responsibility of the client, because they order and approve their realization. The payment is made based on the measured quantity of work and the contracted unit rate. Of course, it is mandatory to achieve the performances defined by the contract as well as specification for that specific work item. It is assumed that in both cases, the risk allocation model of other uncontrolled factors is defined (political, legal and regulatory, monetary, macroeconomic, climate, force majeure, traffic volume, axle loads, etc.). These factors may have an impact on both prices and quantities.

The savings that the client may have if they make a contract in one or the other way will be the client's payoff. In order to calculate it, the prices for specific work item should be assumed. These prices are obtained in the tender procedure by selection of the contractor and the representation of the factor of uncertainty in this problem.

Depending on this, the contractor may use different approaches to defining their prices for the needs of the bid and contract. In both cases, the price depends on the price of necessary resources for the item realization, but also on the risks that may influence the change of prices of resources and they are a consequence of uncontrolled factors. In case of contracting the works as lump sum, the contractor will also calculate the risk that refers to the change of the quantity of works due to the impact of uncontrolled factors.

The contracted prices, paid by the client for a specific work item, for the two previous cases, may be presented:

$$C_{\mathrm{BoQ}} = q_m \cdot (c_r + r_r), \tag{1}$$

$$C_{\mathrm{LS}} = q_c \cdot \left(c_r + r_r + r_q\right), \tag{2}$$

where C_{BoQ} is the total price when it is contracted as BoQ, C_{LS} is the total price when it is contracted as LS, q_m is the measured quantity of works to be paid, q_c is the estimated quantity of works that the contractor calculated when preparing his bid, and it is unknown to the client, c_r is the price of resources expressed by the work item measurement units, based on the estimate of the contractor when preparing his bid, r_r is a part of the unit rate of the contractor which includes the risks that may influence the change of the price of resources, and r_q is a part of the unit rate of the contractor which included the risk that refers to wrongly estimated q_c, based on the estimate of the contractor when drafting the bid. It is assumed that this amount will always be ≥0.

The contractor shall always include the cost of risk in their tender price, so it is assumed that $r_r \geq 0$ and $r_q \geq 0$. They present the planned price reserve that the contractor defined at the moment of submitting the bid (price premium due to the fear of the unknown). If work items are not described in reasonable detail by the available data, the contractor will have to increase its offered prices [7].

In the context of the PBMC contract, it is also necessary to consider and incorporate into the problem and work item quantity that is necessary to do in order to achieve the required maintenance standards and keep the performance level. From the point of view of the client, multiplying this quantity and the contractor's prices could lead to the calculation of the necessary costs of items in both cases, as shown in the following equations:

$$\mathrm{NC}_{\mathrm{BoQ}} = q_n \cdot (c_r + r_r), \tag{3}$$

$$\mathrm{NC}_{\mathrm{LS}} = q_n \cdot \left(c_r + r_r + r_q\right), \tag{4}$$

where $\mathrm{NC}_{\mathrm{BoQ}}$ is the necessary costs for a specific work item, when it is contracted as BoQ, $\mathrm{NC}_{\mathrm{LS}}$ is the necessary costs for a specific work item when it is contracted as LS, and q_n is the quantity of works necessary to do in order to achieve the required maintenance standards.

There are opportunities for the contractor to increase profit margins when the work item is contracted according to LS. Rationalisations, improved efficiencies, and effectiveness of design, process, technology, or management can reduce the cost of achieving the specified service levels [5]. In that sense, the contractor will strive to achieve q_n.

The total benefit (cost savings) that the client may get is shown by

$$\mathrm{CS}_{\mathrm{Boq}} = \left(C_{\mathrm{LS}} - C_{\mathrm{BoQ}}\right) - \left(C_{\mathrm{BoQ}} - \mathrm{NC}_{\mathrm{BoQ}}\right), \tag{5}$$

$$\mathrm{CS}_{\mathrm{LS}} = \left(C_{\mathrm{Boq}} - C_{\mathrm{LS}}\right) - \left(C_{\mathrm{LS}} - \mathrm{NC}_{\mathrm{LS}}\right), \tag{6}$$

where $\mathrm{CS}_{\mathrm{BoQ}}$ is the total savings for a specific work item, when it is contracted as BoQ, and $\mathrm{CS}_{\mathrm{LS}}$ is the total savings for a specific work item when it is contracted as LS.

The first part of these equations expresses savings arising directly from the manner of contracting the price. That part is reduced by the costs that could be avoided if the quantity of the works done was equal to those that are necessary.

Let us assume the following, according to

$$u = q_n - q_m, \tag{7}$$

$$v = q_n - q_c. \tag{8}$$

where u is the difference of the quantity of work necessary to do and the quantity ordered/approved by the client in case of contracting BoQ. This value also depends on the responsibility and qualifications of the client, but also on the available date on the situation of the road. If $u < 0$, the client approved less than the necessary quantities, which will eventually mean increase of costs in the future maintenance because of the road deterioration. The case $u > 0$ means better maintenance level than the one contracted and reduction of costs in the future. The case $u = 0$ means that the quantity of realized, approved, and paid works represents the proper measure for adequate maintenance based on the contract. v is the difference of the quantity which is necessary to do and the quantity estimated by the contract when drafting the bid, in case of contracting LS. It should be repeated that in case of contracting the work item based on LS, the contractor is responsible for defining the quantity necessary to do in order to achieve the maintenance standard.

It has already been mentioned that in case of contracting the work item based on LS, the contractor estimates the quantity of work q_c. For the estimation of the total price C_{LS} for that specific work item, the contractor took into account the unit rate in which they included the reserve $r_q \geq 0$. A link may be established among this reserve r_q, the quantity of work q_c estimated by the contractor, the quantity of work necessary to achieve the standard q_n, the estimated price of resources c_r, and the estimated reserve r_r according to

$$r_q = \frac{(q_n - q_c)}{q_c}\left(c_r + r_r\right) = \frac{v}{q_c}\left(c_r + r_r\right). \tag{9}$$

Due to the conditions $r_q \geq 0$ and equation (9), the following may be concluded by

$$v > 0 \Longrightarrow r_q = \frac{v}{q_c}\left(c_r + r_r\right), \tag{10}$$

$$v = 0 \Longrightarrow r_q = \frac{v}{q_c}\left(c_r + r_r\right), \tag{11}$$

$$v < 0 \Longrightarrow r_q = 0. \tag{12}$$

Equation (10) refers to the case when the contractor underestimated the quantity of works to be done in order to meet the standards, and equation (12) refers to the case when the contractor, when drafting their bid, estimated the quantities to be realized. The case in which the contractor accurately estimated the quantities is expressed in equation (11). All the described situations may be a consequence of different experiences of contractors, but also of different levels of accuracy, as well as the availability of information on the existing state of the road.

Starting from equations (5) and (6), along with the application of the expressions provided in other equations, we get the expressions that can be used for calculation of the client's savings (payoff), depending on whether the contractor underestimated, overestimated, or accurately estimated the quantity of works when defining the C_{SL} price:

For the case $v \geq 0$, the client's savings (payoff) are

$$\mathrm{CS}_{\mathrm{BoQ}} = 2u\left(c_r + r_r\right), \tag{13}$$

$$\mathrm{CS}_{\mathrm{LS}} = \left[\left(\frac{v \cdot q_m}{q_m - v} - u\right)\right]\left(c_r + r_r\right), \tag{14}$$

For the case $v < 0$ the client's savings (payoff) are

$$\mathrm{CS}_{BoQ} = (2u - v)\left(c_r + r_r\right), \tag{15}$$

$$\mathrm{CS}_{LS} = (2v - u)\left(c_r + r_r\right). \tag{16}$$

where $\mathrm{CS}_{\mathrm{BoQ}}$ is the total savings for a specific work item, when it is contracted as BoQ, $\mathrm{CS}_{\mathrm{LS}}$ is the total savings for a specific work item, when it is contracted as LS, c_r is the price of resources expressed by the work item measurement units, based on the estimate of the contractor when preparing his bid, r_r is a part of the unit rate of the contractor which includes the risks that may influence a change of the price of resources, q_m is the ordered/applied quantity of works that would be paid in case of contracting as BoQ, u is the difference of the quantity of works necessary to do and the quantity that is ordered/approved by the client, in case of contracting as BoQ, and v is the difference of the quantity of works necessary to do and the quantity estimated by the contractor when drafting the bid, in case of contracting as LS.

It is assumed that all the maintenance standards will be met, so the model does not take into account the penalties for not achieving the maintenance standards. In addition, the incentive system is not included.

We must bear in mind that u and v are the indicators whose distribution is unknown in advance, so they should also be included in possible states of nature.

The problem is reduced to the game against nature with two possible strategies of the client and the states of nature that depend on the indicators u and v. In an extensive description, the game could be represented as in Figure 1(which was created using Gambit Software).

If we knew the probability of distribution governing the "selection" of the states of nature, the problem could be solved by the theory of statistical decisions [29].

We will simplify this model by introducing the assumption that $u = 0$; that is, the client is responsible and well trained and has valid information on the state of roads based on which it is possible to accurately estimate the values q_n.

With this simplification, the matrix of the game is provided in Table 1. It shows the client's payoff for two possible strategies: (1) contract the given work item as unite price item (BoQ), and (2) contract the item as a lump sum item (LS). Another participant is "nature" which has 2 states whose distribution of probabilities is not known in advance.

If the client's payoff is divided by $(c_r + r_r)$, i.e., if the expected savings of the client are expressed in relation to $(c_r + r_r)$, that will not influence the choice of optimal strategy. In this way, we can express the client's savings as a relative saving in relation to the work item unit rate. The value of such an organized game should be multiplied with $(c_r + r_r)$ in order to get the value of initial game (Table 2). An equivalent game would, in such a situation, depend on the indicators v and q_m.

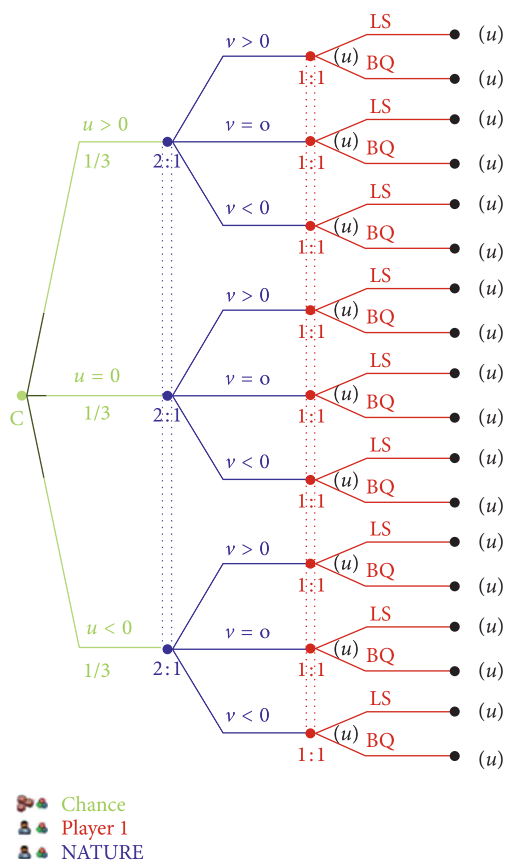

Figure 1: Extensive description of the game.

Table 1: The matrix of the simplified game.

		Nature		
		$v > 0$	$v = 0$	$v < 0$
Client	BoQ	$0 \cdot (c_r + r_r)$	$0 \cdot (c_r + r_r)$	$-v(c_r + r_r)$
	LS	$((v \cdot q_m)/(q_m - v)) \cdot (c_r + r_r)$	$((v \cdot q_m)/(q_m - z)) \cdot (c_r + r_r)$	$2v \cdot (c_r + r_r)$

Table 2: The matrix of the equivalent game.

		Nature		
		$v > 0$	$v = 0$	$v < 0$
Client	BoQ	0	0	$-v$
	LS	$(v \cdot q_m)/(q_m - v)$	$(v \cdot q_m)/(q_m - v)$	$2v$

4. Results

In this game against nature, the client makes decisions. According to the rules of game theory, they should behave rationally. The rationality of their choice depends on the criteria they apply, on his attitude towards risk, on their ideas about profit and loss, etc. [29]. On the other hand, nature is not considered a rational opponent. There are ways to choose optimal strategy for these types of games, and they include Laplace, Hurwitz, Wald, and Savage criteria [30]. “The mixed strategies in games against nature demand a high expertise and can only be found in situations where these strategies improve the effects of minimax-strategies that are used in cases of risk-aversion” [31] (p. 1).

4.1. Laplace Criterion. According to Laplace, all states of nature should be regarded as equally probable because nothing is known about the real probabilities [29]. According to this assumption, the choice of optimal strategy is reduced on the choice of the strategy that has the highest expected benefit for the participant. Practically, that means that payoff for each row of the matrix individually is added, and then the strategy that has the highest value of this sum is chosen. This criterion c may be expressed by

$$c = f(a_{ij}) = \max\left(\frac{1}{m}\sum_{j}^{m} a_{ij}, i = 1, \ldots, n\right). \quad (17)$$

4.2. Wald's (Maximin) Criterion. This criterion implies that the player (who is a pessimist) choses the most cautious position. The player supposes that the nature game is against him and that the most unfavourable situation for the player will occur. The player attempts to create the best outcome in this type of situation, which is known as the maximin principle. There are situations where using this criterion is justified: in cases when possible consequences of the decisions are unfavourable or when the possibility of predicting possible consequences is extremely low.

In this way, the player is choosing the saddle point strategy in a game if it contains a saddle point. In a game without a saddle point, that is a pure strategy, which is actually not the mixed strategy game solution [30]. This can be presented by

$$c = f(a_{ij}) = \max\left[\min(a_{ij}), i = 1, \ldots, n\right]. \quad (18)$$

4.3. Hurwicz's Criterion. This approach is a kind of combination of the previous criterion. Hurwicz defines α, as "the index of optimism" which is supposed to measure the attitude of the decision maker toward risk. The value α is between 0 and 1, and the closer it is to 1, the more the decision maker is considered a bigger optimist. When $\alpha = 1$, the decision maker is the most optimistic; if $\alpha = 0$, then he is the most pessimistic. This index is combined with Wald's criterion, which can be expressed by

$$c = f(a_{ij}) = \max\left\{\alpha\left[\max(a_{ij}), i = 1, \ldots, n\right] + (1-\alpha)\left[\min(a_{ij}), i = 1, \ldots, n\right]\right\}. \quad (19)$$

4.4. Savage's Criterion. This strategy is designed to minimize the maximum regret that a player may feel from a decision by creating a regret matrix $R = [r_{ij}]$. To create the regret matrix, a player will take each entry and subtract it from the highest entry in its column. If the entry is the highest entry in a column, then in the regret matrix, the corresponding value will be 0, as shown in equation (20). This strategy is attempting to make the player feel as good as possible no matter the circumstances of their game play [30]. Then, in the matrix game R, the decision makers should apply Wald's (minmax) criterion. This can be presented by

$$r_{ij} = \begin{cases} a_{ij} - \max(a_{ij}), & a_{ij} - \max(a_{ij}) > 0, j = 1, \ldots, m, \\ 0, & a_{ij} - \max(a_{ij}) \le 0, j = 1, \ldots, m, \end{cases} \quad (20)$$

$$c = f(a_{ij}) = c(r_{ij}) = \min\left[\max(r_{ij}), i = 1, \ldots, n\right]. \quad (21)$$

The optimal strategies of the client (decision makers) depend on the earlier-mentioned indicators v and q_m, and of course, on the criterion he applies. In the context of the described problem and the adopted assumptions, we consider the application of the Laplace criterion justified.

There is possibility to apply the model before publishing the tender for the pilot project of maintenance according to PBCM. To that end, these indicators would be calculated based on the collected data on the implementation of the previous contracts on maintenance, which were enforced as input-based contracts with unit rates of works. For the needs of payments, the realized quantities of work q_m were measured, and instead of the unknown value of the indicator v, we can anticipate the expected values of this indicator for each work item.

The contracted values of regular maintenance (with winter maintenance) in the previous period (from 2005 to the last contract from 2019) were between 8.5 million and 10 million euros per year. During the four-year contracts, there was a smaller deviation of realized value than the total agreed price (1–5%).

For the implementation of the model, performance data of the contract from 2015 to 2019 were available. Performance data of previous contracts were not available, while the contract from 2019 was not taken into account as it is a four-year contract currently still in progress. The last completed four-year contract (2015–2019) identified 111 detailed out-of-winter maintenance elements (work elements) and 6 elements belonging to winter maintenance. The following data on the elements were available to us, by road sections (5 sections in total): q_m is the quantity measured and approved for payment; q_e is the quantity of work estimated in the tender; c_c is the contracted unit prices.

Based on available data, we first selected the work elements for the model's application. We excluded winter maintenance works from consideration, because these works are variable and extremely dependent on climate conditions. In addition, for contracting these works as LS, special conditions must be met regarding the existence of climatological stations on the road network [28]. We selected other work elements according to the Pareto principle, by choosing from all elements those which, when added up, contribute to the final value of the contract (without the value of winter maintenance) around 85%. In doing so, we merged some of the detailed work elements into one work item (given the same type of work, the same measurement units, and a similar unit price). In this way, we identified 14 work items we applied the model. Table 3 shows selected works items for model implementation, values of paid works per road sections (S1 to S5), and percentage of their contribution in total value of contracts (without winter maintenance).

For the assessment v, we used the next assumption: since the contract was a contract with unit prices, the contractor was not particularly interested in assessing the amount of

Table 3: Overview of selected works for implementation of the model.

No.	Description of the item	Measurement units	Value of paid works per road section for period 2015–2019 (€)					Contribution in total value (%)
			S1	S2	S3	S4	S5	
1	Hot patch asphalt (repair of larger surfaces)	m^2	1, 101, 509	892, 105	858, 927	729, 203	591, 949	22.17
2	Protection of slopes with suspended steel wire meshes	m^2	696, 213	483, 358	633, 173	314, 801	601, 186	14.49
3	Marking horizontal signalization lines	km	536, 609	495, 607	312, 100	314, 797	401, 497	10.94
4	Installation and replacement of safety fence	m	199, 129	271, 258	303, 084	182, 555	229, 004	6.29
5	Hot patch asphalt (repair smaller surfaces and potholes)	t	12, 828	235, 571	322, 500	206, 951	128, 283	4.81
6	Inspection service	h	215, 461	183, 298	122, 467	140, 096	238, 960	4.78
7	Cleaning gutter	m	151, 941	128, 779	110, 145	207, 225	188, 878	4.18
8	Cleaning of landslide material	m^3	134, 357	146, 023	19, 813	228, 236	242, 095	4.09
9	Cutting shrubs, trees, and grass	m^2	56, 897	143, 633	112, 991	136, 544	148, 651	3.18
10	Laying of the levelling wearing course AB 11	t	147, 700	165, 845	97, 221	56, 319	119, 410	3.11
11	Forging slopes from unstable parts of rocks	m^3	53, 098	220, 281	14, 885	65, 372	117, 348	2.50
12	Repair of stone walls	m^3	2,241	29,997	352,254	0	10,755	2.10
13	Cleaning of drainage channels and ditches	M	22,037	79,487	91,205	98,386	42,086	1.77
14	Mechanical scraping-profiling of existing asphalt pavement	m^2	88,963	83,272	50,093	41,074	44,796	1.64
		Total						**86.06**

Table 4: Game matrix.

		Nature		
		$v > 0$	$v = 0$	$v < 0$
Client	BoQ	0	0	$-(q_m - q_e)$
	LS	$(q_m - q_e) \cdot q_m/q_e$	$(q_m - q_e) \cdot q_m/q_e$	$2(q_m - q_e)$

work that should be performed (q_c) during the realization of the contract, because under that contract, the risk of quantity change was not under the responsibility of the contractor. We can, therefore, assume that it is $q_c = q_e$.

The second assumption is the same as the assumption of simplifying the model: we believe that the client has a lot of experience, responsibility, and knowledge, so he ordered, controlled, and approved payment, only the amount that needed to be performed. That means $q_n = q_m$, because $u = 0$.

By respecting these two assumptions, based on equations (7) and (8), we get the difference of the quantity of works necessary to do and the quantity estimated by the contractor when drafting the bid, according to

$$v = q_n - q_c = q_m - q_e, \tag{22}$$

where q_n is the amount of work that is necessary to achieve the requirements, q_c is the valued amount of work valued by the contractor in the formation of the offer, unknown to the client, q_m is the measured amount of work to be paid for, $q_e$is the amount of work valued by the client in the tender.

Based on this, we may write an expression for the payoff client, in which instead of q_m and q_e, we will use the expected q_m and q_e values (Table 4).

Expected values q_m and q_e are reached on basis of values q_m and q_e per road sections and are shown in Table 5.

The game matrix for item 1 and "hot patch asphalt (repair of larger surfaces)" are given in Table 6.

If we assume equally probable state (1/3), then, by applying Laplace criterion, the following solution is reached:

$$\mathrm{OV}_{\mathrm{Boq}} = \frac{1}{3}(0 + 0 - 31966) = -21310.5, \tag{23}$$

$$\mathrm{OV}_{\mathrm{LS}} = \frac{1}{3}(70443 + 70443 + 63931) = 68272.4. \tag{24}$$

Based on equations (23) and (24), we can conclude that for this item, the optimal strategy is contracting by the LS method.

Similarly, we can resolve games for other items of works using the Laplace criterion. Optimal values and game strategies are given in Table 7. The same table (last column) provides recommendation regarding the manner of contracting of these items based on documents which refer to Serbia [16].

Discrepancies of the proposed strategies according to the model with recommendations from documents which refer to Serbia cannot be understood as incorrectness of the model. Opportunities and conditions in contract implementation regarding maintenance of roads are different from conditions in Montenegro; thus, in the case of the Serbian model, data from implementation of contracts should be applied in the model.

Table 5: Expected values of q_m and v for selected works.

No	Work item	Measurement units	Expected (qm)	Expected $v = qm - qe$
1	Hot patch asphalt (repair of larger surfaces)	m^2	**74,926**	**31,966**
2	Protection of slopes with suspended steel wire meshes	m^2	**59,773**	**18,005**
3	Marking horizontal signalization lines	km	**1,404**	**−335**
4	Installation and replacement of safety fence	m	**4,132**	**−5,068**
5	Hot patch asphalt (repair smaller surfaces and potholes)	t	**1,051**	**−429**
6	Inspection service	h	**9,484**	**−48**
7	Cleaning gutter	m	**720,151**	**2,991**
8	Cleaning of landslide material	m^3	**12,771**	**−257**
9	Cutting shrubs, trees, and grass	m^2	**1,649,486**	**62,286**
10	Laying of the levelling wearing course AB 11	t	**1,178**	**523**
11	Forging slopes from unstable parts of rocks	m^3	**5,497**	**2,812**
12	Repair of stone walls	m^3	**2,128**	**1,124**
13	Cleaning of drainage channels and ditches	m	**49,447**	**12,255**
14	Mechanical scraping-profiling of existing asphalt pavement	m^2	**58,259**	**10,939**

Table 6: Game matrix.

Pos. 1.		Nature		
		$v > 0$	$v = 0$	$v < 0$
Client	BoQ	0	0	−31,966
	LS	70,443	70,443	63,931

Table 7: Overview of optimal strategies using the Laplace criterion ($pi = 1/3$) for selected works.

No.	Work item	Unit measure	Laplace criterion for $pj = 1/3$	Optimal strategy	Recommendation for Serbian conditions
1	Hot patch asphalt (repair of larger surfaces)	m2	68272.4	LS	BoQ
2	Protection of slopes with suspended steel wire meshes	m2	33105.0	LS	BoQ
3	Marking horizontal signalization lines	km	111.6	BoQ	BoQ
4	Installation and replacement of safety fence	m1	1689.3	BoQ	BoQ
5	Hot patch asphalt (repair smaller surfaces and potholes)	t	142.8	BoQ	BoQ
6	Inspection service	h	16.1	BoQ	LS
7	Cleaning gutter	m1	4068.4	LS	LS
8	Cleaning of landslide material	m3	85.8	BoQ	BoQ
9	Cutting shrubs, trees, and grass	m2	82635.8	LS	LS
10	Laying of the levelling wearing course AB 11	t	919.1	LS	BoQ
11	Forging slopes from unstable parts of rocks	m3	5636.0	LS	LS
12	Repair of stone walls	m3	3939.4	LS	BoQ
13	Cleaning of drainage channels and ditches	m1	107183.2	LS	LS
14	Mechanical scraping-profiling of existing asphalt pavement	m2	19028.7	LS	BoQ

5. Conclusion and Recommendations

The proposed model can serve for the selection of work items which would be contracted based on the BoQ system in hybrid contract for the PBMC pilot project. In this manner, for the implementation of the PBMC pilot project, optimal saving for the client could be made, depending on the manner of contraction of specific work items. For the selection of items, historical data from previous contracts which are contracted by unit prices should be used.

In further research, additional expenses which the client would have in case of contracting certain work items in accordance with BoQ, i.e., the LS system, could be considered. These expenses would have an impact on the decrease of expected savings of the client, and in this manner, it would have an impact on optimal strategy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Study on Key Cost Drivers of Prefabricated Buildings Based on System Dynamics

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The prefabricated building as a major initiative has been put forward by China in recent years to promote the transformation and upgrading of the construction industry, but its rapid development also faces high cost constraints. Therefore, it is necessary and urgent to study the key cost drivers and cost control paths of prefabricated buildings. Most of the current research focuses on the construction cost of prefabricated building as a static object. This article, on the other hand, regards the construction cost of prefabricated building as a dynamic formation process and conducts systematic research from product systems, technical systems, construction processes, and management modes. The influence factors of prefabricated building cost are defined and screened with the help of HSM and previous research results. A cause-and-effect model and cost control model of prefabricated building cost driver are established. Based on the model test of the actual project, the cost generation of prefabricated buildings is simulated. Through sensitivity analysis, key cost drivers of prefabricated building are identified and ranked as degree of design standardization, unit price, prefabrication rate, information technology level, transportation mode, labor level, machinery level, transportation distance, etc. Accordingly, corresponding strategies are proposed for the cost control of prefabricated buildings.

1. Introduction

In recent years, the prefabricated buildings have become the main direction for the transformation and upgrading of China's construction industry and the innovation of construction methods. The Guidance on Vigorously Developing Prefabricated Buildings issued by the general office of the state council in 2016 and the 13th five-year plan of the Ministry of Housing and Urban-Rural Development both regarded the development of prefabricated buildings as an important direction for the future development of the construction industry. The State Council of China even proposed to make prefabricated buildings account for 30% of new buildings within about 10 years [1]. Hence, prefabricated buildings in China face unprecedented opportunities and challenges.

However, at the same time, the high construction cost has been a major factor restricting the development of prefabricated buildings [2]. In general, when the prefabrication rate is more than 60%, the unit cost can be increased by 25%~30% [3]. People often attribute the high prefabricated building cost to high component price, large component transportation loss, and high hoisting machinery requirements [4]. However, the factors influencing prefabricated building cost are more diverse and the cost relationship is more complex. Therefore, it is necessary to study the complex relationship in the formation of prefabricated building construction cost. Poorly planned and constructed projects are more likely to incur higher operating costs, leading to negative impacts [5]. In addition, high cost is mainly due to stakeholder goals, conflicts of interest [6, 7], and the problem of path planning caused by the conflict of goals [8, 9]. Moreover, it is necessary to systematically analyze the influence of various factors on the construction cost of prefabricated buildings and explore the prime path of cost control.

At present, the study of prefabricated construction costs mainly focuses on the cost comparative study with traditional cast-in-situ buildings [10, 11], the relationship between prefabricated rates and prefabricated construction cost [12, 13], the cost control methods of prefabricated buildings, etc. [14–16]. The above study has laid a certain foundation for the later research of the cost composition and control direction of prefabricated buildings. However, the present research mainly regards the cost of prefabricated buildings as a static research object and seldom considers the causes of the complicated relationship among cost drivers, the multiple feedback mechanism, and the influence of the external environmental changes. High cost is a common problem worldwide, with cost overruns occurring in about 90 percent of projects and 50 percent of construction projects in Asia [17], and cost overruns on prefabricated buildings remain unresolved [18]. Among them, poor planning tends to result in excessive cost [8]. Prefabricated construction is a construction method combining industrial production with on-site construction. It depends more on the maturity of the component processing industry, the standardization of design, and the efficient connection among component processing, transportation, storage, and installation. Therefore, it is necessary to carry out systematic research on product systems, technical systems, construction processes, management modes, and so on to comprehensively control the cost of fabricated buildings [19].

In view of the rational man hypothesis, prospect theory holds that subjective factors make judgment and reasoning different from person to person. The more complex the problem is, the less subjective decisions can be taken, and more standardized decisions are needed. Therefore, this paper uses system dynamics to carry out cost control and decision-making in a standardized way. System dynamics is a tool for the analysis of complex dynamic feedback systems. This method combines qualitative and quantitative methods and is very effective for the study of nonlinear and high-order complex time-varying systems. This study uses system dynamics to study the cost factors and cost control of prefabricated buildings. Although the maintenance cost is essential, the prefabricated buildings in China are in the promotion period, and it is difficult to measure the dynamic feedback relationship among various cost factors during the operation and maintenance period. Moreover, construction cost is the cost that builders pay most attention to [20, 21]. Performance feedback in the construction process can have a positive impact on the optimization of the construction process [22]. Therefore, this paper takes the construction cost as the research object by analyzing and screening the influence factors of prefabricated building construction cost. It establishes system dynamics model of cost control, simulates the formation process of prefab building construction cost, and then analyzes the sensitivity factors of construction cost, so as to put forward the corresponding strategies for the cost control of prefabricated building.

2. Literature Review

At present, the research on prefabricated building cost is mostly based on the cost composition. Li et al. [11], through a comparative analysis of the cost composition of prefabricated buildings and traditional cast-in-place buildings, concluded that the high cost of civil construction of prefabricated buildings, especially the high cost of materials, was the main reason for the high cost of prefabricated buildings. Hong et al. [23] further discussed the driving factors leading to the increase of prefabrication cost and found that the prefabrication rate was almost linearly correlated with the prefabricated construction cost. In terms of cost influencing factors, Liu and Chen [12] established the cost structure of prefabricated building, and Jin et al. [4] obtained six key cost-influencing factors such as construction level, construction maturity, standard, production level, capability, and management level of prefabricated components through questionnaire survey and factor analysis. In the above studies, the cost composition and main influencing factors of prefabricated buildings were well sorted out, but cost drivers and their influence on the cost formation process were not considered. In other words, the relationship between cost drivers and costs was not established to quantify the impact.

In terms of cost control, Anvari et al. [14] applied GA to optimize the process of production, transportation, and assembly of components to control costs. Chen et al. [24] optimized the production technology of prefabricated components through the process reengineering of prefabricated components. Wang and Wang [25] proposed the strategy of taking BIM as the center, promoting stakeholder communication, mitigating key schedule risks, and the interaction behind the risk network to reduce costs. Hammad et al. [16] applied BIM to establish a framework to analyze social, environmental, and economic factors of prefabricated buildings. Ham et al. [26] studied the performance potential of BIM-assisted identification of single design errors and proposed a proposal to reduce costs by controlling design errors based on BIM [27]. Li et al. [28] combined BIM and RFID technologies to achieve the goal of refined prefabricated building construction management. The above studies on cost control mainly put forward corresponding improvement strategies from different aspects such as design, production, transportation, installation, and application of information technology, but failed to systematically analyze or identify the most critical control path. Feedback path is an important aspect of cost analysis [22].

To sum up, the existing research is limited to the static cost analysis and cost control in the link of a certain research. However, the cost of prefabricated building is different from that of traditional manufacturing industry and construction industry. The cost influence factors are more diverse, and the cost relationship is more complex. The cost increase may be caused by different reasons, or a single reason may induce multiple cost increases. In short, the cost increment is the result of the dynamic interaction of cost drivers, and it is necessary to analyze the impact of a factor on the whole from a systematic perspective. System dynamics is a method to study the overall behavior of the whole system by analyzing the feedback structural relationship between variables in the social and economic system [29]. In the field of engineering construction, engineering cost analysis has been applied. For example, Lyneis et al. [30], Ning and Wang [31], and He and Cheng [32] all used system dynamics tools to analyze cost factors in engineering projects. Based on the system dynamics, this paper focuses on the relationship among the stages of prefabricated building design, production, transportation, and assembly and simulates the dynamics of prefabricated building cost system under time changes by combining the influence of policies and standards and other external links so as to find a more realistic cost control path.

3. Establishment of Cause-and-Effect Model of Prefabricated Buildings Cost

3.1. Analysis of Cost Influencing Factors

3.1.1. Definition of Cost Influencing Factors. Different from traditional buildings, prefabricated buildings maintain not only the characteristics of traditional site construction, but also have the characteristics of industrial production. Besides, the cost factors are more diversified. This paper only considers the incremental cost of prefabricated buildings, which is different from traditional cast-in-place buildings. Hall's three-dimensional structure model is a coordination tool consisting of logical, time, and knowledge dimensions and an analysis tool for the relationship between managers and programs [33]. In order to avoid the deviation of cost factor selection due to individual subjective decision, standardized means are adopted. Based on the three-dimensional model, a prefabricated building cost analysis model can be established as shown in Figure 1. Through the cross-exploration of the time dimension, the logic dimension, and the knowledge dimension, the corresponding cost influencing factors are defined.

From the perspective of time dimension, the construction of prefabricated buildings is mainly divided into design and construction stages. Among them, the construction stage includes component production, transportation, and assembly stages. In terms of logic dimension, the process of prefabricated building construction includes target determination, analysis, feedback optimization, decision-making, and implementation. From the perspective of knowledge dimension, it is necessary to include professional knowledge such as management and operation and information technology and emphasize the control of quality, schedule, and cost. According to the three-dimensional model, the cost influencing factors of prefabricated buildings are analyzed with time dimension as the main stage direction:

(1) *Research, Development, and Design Stage.* In the R&D and design stage of prefabricated buildings, technical planning, design, optimization, and decision-making should be carried out on the basis of design standards and specifications. Compared with traditional cast-in-place buildings, prefabricated buildings add technical planning, research and development of new components, standardized design, component separation design, mold design, assembly and construction design, etc. In addition, the design should be fully communicated with professional design teams and component manufacturers to ensure professional collaboration and component production quality. In order to achieve the effect of design-processing-assembly integration, the special requirements of production, transportation, and field installation should be taken into account. At the same time, it is also necessary to use information technology to further improve the standardization, accuracy, and management efficiency of the design. All of the above stages will affect the cost of prefabricated buildings to some extent.

(2) *Construction Stage.* In the process of component production, component production technology level, component standardization degree, component factory scale, component order quantity, and other factors will affect component production cost. In the transportation link, different transportation schemes bring different transportation costs, and there are inevitable losses in the transportation process. In the construction and assembly process, it will also involve the management of the site, the level of artificial machinery, the formulation and implementation of the construction plan, and other factors. In addition, in the whole construction stage, it is necessary to use information technology means to strengthen the component procurement, distribution, storage, and installation of fine, standardized management, to improve the construction quality.

3.1.2. Cost Influencing Factors Screening. There are many studies on the cost composition of prefabricated buildings in relevant literature. Through the analysis of the previous research results, the cost influencing factors of prefabricated buildings can be further studied/investigated. For example, decision-making cost and design cost will be generated in the design stage of prefabricated building, and prefabricated component cost, transportation cost, component prefabricated cost, and site construction cost will be generated in the construction stage [12]. In terms of cost composition, studies have shown that the cost of prefabricated components accounts for 26% to 60% of the total cost, followed by labor cost (17%–30%) and transportation cost (10%) [23]. In the design stage, the designer's experience level, design standardization, and the integrity of relevant design specifications will affect the design level, and the occurrence of design errors will lead to the rework and delay of the project [26]. The scale and location of the component plant are closely related to the cost of component production and transportation. Secondly, the influence of manual technology and specification [27] must be studied. In the final construction and assembly stage, the standardization and unified design of components in the early stage will facilitate the site management. The site work also needs to consider unloading, protection, and storage, supplemented by the assistance of construction technology and machinery [23]. In addition, the prefabrication rate, type of prefabricated components, and market maturity are the key factors influencing the cost-effectiveness of China's prefabricated construction market [23]. Building information modeling (BIM) is a technology that can be effectively applied to

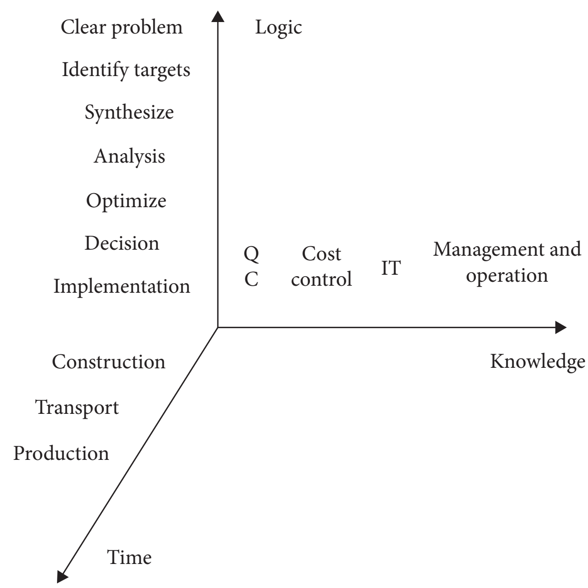

Figure 1: HSM of life cycle cost for prefabricated buildings.

different parts of the construction project [26]. Based on the above analysis, combined with the scope defined above and Jin et al. [4]'s research on cost-influencing factors, factors influencing the construction cost of prefabricated buildings are screened out in Table 1.

3.2. Establishing the Basic Model of Causality. The causal relationship between each selected factor is further analyzed and established, as shown in Figure 2. First of all, from design level, prefabrication rate to component production and manufacturing, transportation, storage, and assembly, every link will affect the construction cost, and policy orientation will also indirectly affect the construction cost by affecting the construction environment of prefabricated buildings. Secondly, the design and construction quality of the project are an indirect variable that affects the cost, and the management level, information technology application level, and so on will also affect the design and construction quality. Based on the analysis of cost influencing factors and impact paths, a causal diagram of prefabricated building cost factors can be established, as shown in Figure 2.

Around the center of construction cost, Vensim is applied to conduct modeling, and it is concluded that there are multiple feedback paths in causality, and multiple feedback paths reveal the complexity of the system. The main feedback loops in causality are as follows:

Construction cost ⟶ The quality of the project ⟶ Engineering change ⟶ Component order quantity ⟶ Component manufacturing ⟶ Construction cost

Construction cost ⟶ The quality of the project ⟶ Engineering change ⟶ Component order quantity ⟶ Transportation loss ⟶ Component transportation ⟶ Construction cost

Construction cost ⟶ The quality of the project ⟶ Engineering change ⟶ Component order quantity ⟶ Component manufacturing ⟶ Component quality ⟶ Component assembly ⟶ Construction cost

Component order quantity ⟶ Component manufacturing ⟶ Component quality ⟶ Engineering quality ⟶ Engineering change ⟶ Component order quantity

Among the loops, the construction cost will affect the project quality, and the reduction of project quality will lead to more engineering changes, which will bring about changes in the order quantity of engineering components, thus affecting the production cost of components and finally the construction cost. The number of components corresponds to the cost of component manufacturing and other factors and then to the engineering quality. The poor engineering quality leads to engineering changes, which ultimately affects the number of components.

4. Cost Control Model and Simulation Analysis of Prefabricated Building

4.1. Establishing the Basic Control Model

4.1.1. Stock Flow Diagram. In order to further clarify the feedback form and control law of the system, the variable properties are further distinguished on the basis of causal loop diagram, after which is drawn the system stock flow diagram. In order to simplify the analysis, the design level in Figure 2 can be replaced with design cost, equipment mechanization level with unit price of machinery, artificial technology level with artificial unit price, policy subsidies with subsidies, and component market maturity with component market unit price. Take transportation, production, and assembly process as the flow, take component

Table 1: Factors influencing the construction cost of prefabricated buildings.

Stage and link	Construction cost impact factor
Design	Designer experience Precast housing design specifications and standards Standardization of component design Prefabrication rate
Production	Component order quantity The size and capacity of the state of the system Technical level of production workers Production specifications and standards for components Member type Market maturity
Transportation	Distance Methods Transport losses
Storage	Storage time
Assembly	Managerial and worker experience Degree of construction mechanization
Other	Information technology level The management level Policy norm

inventory, component production, transportation and installation costs, and planned costs as the inventory, and take construction cost as the sum of the inventory. Based on the causal relationship, the stock flow diagram is established as shown in Figure 3.

4.1.2. Cost Control Model Establishment. By using Vensim, the cost control model is established, the relationship between factors in the model is defined, and the system operation results are simulated. In order to quantify the influence of factors, score and assign some variables, such as design level, standardization level, information level, transportation mode, and other factors. Here, the prefabrication rate and construction cost are treated in a linear relationship (see [23]), where the linear proportional coefficient is 0.56 [23]. According to the current prefabricated building incentive policy, when the prefabricated rate is more than 50%, the subsidy will be added. The assembly construction cost model finally established is as follows:

$$C = \begin{cases} f(i) \times \sum c - a, & i \geq 0.5, \\ f(i) \times \sum c, & i < 0.5, \end{cases} \tag{1}$$
$$f(i) = e \times i + f,$$

where C is construction costs, $\sum c$ is design stage cost, cost of production, transportation, and installation of components such as aggregation, $f(i)$ is the corresponding linear function related to the rate of prefabricated, i is precast rate, e and f are constant, a is the corresponding amount of subsidies.

(1) Main Models in the Design Stage. The design cost of cast-in-place buildings is generally 30 yuan/m^2, and the cost of prefabricated buildings is about 30% more than that of cast-in-place buildings [15]. According to the empirical data, the design defect rate is within 5%. The standardization degree, prefabrication rate, and information technology level of components will have a positive impact on the design level. According to the value method of Jia [34], the value range of standardization degree is [0, 1], and the value range of information technology level is [0, 1]. Then, the main models in the design stage are as follows:

$$\begin{aligned} D(x) &= AX + b, \\ \omega &= f(D) \times \alpha, \\ f(D) &= \varepsilon \times D, \end{aligned} \tag{2}$$

where $D(x)$ is the level of deepening design, A is the coefficient matrix, x is $\{x_1, x_2, \ldots, x_n\}$, including variables such as standardization degree and information level, and b is a constant. α is the maximum value of the design defect rate, $f(D)$ is the linear relation function related to the design level, ω is the design defect rate, and ε is the correlation coefficient that can be 1/3 and convert the deepened design into the radio.

(2) Main Models in the Component Production Stage. The main models of component production stage are as follows:

$$\begin{aligned} C_p &= Q \times P, \\ Q &= \sum_{i=1,2,\ldots,n} q_i \times \lambda, \\ q_1 &= Q \times \omega, \\ q_2 &= Q \times \delta, \end{aligned} \tag{3}$$

where C_p is the accumulation of component production cost, Q is the number of components, P is the unit price of components, q_i is the corresponding number of components, including component order quantity, transportation loss, and engineering change, λ is the capacity coefficient of the prefabricated component factory, q_1 is the engineering change, ω is the design defect rate, q_2 is the transportation loss, and δ is the transportation loss rate.

(3) Main Models in the Installation Stage. Installation costs include labor cost and machinery cost, in which the number of mechanical shifts and labors is related to the number of components installed, and the relationship coefficient is taken from the prefabricated building quota. The main models in the installation stage are as follows:

$$\begin{aligned} C_{\text{pre}} &= \sum p_{\text{pre}}, \\ p_{\text{pre}} &= p' q, \\ q &= Q \times \beta, \end{aligned} \tag{4}$$

where C_{pre} is installation costs of cumulants, $\sum p_{\text{pre}}$ is the sum of the components of cost, including labor, and machinery use fee, Q is the number of units of each item, p' is

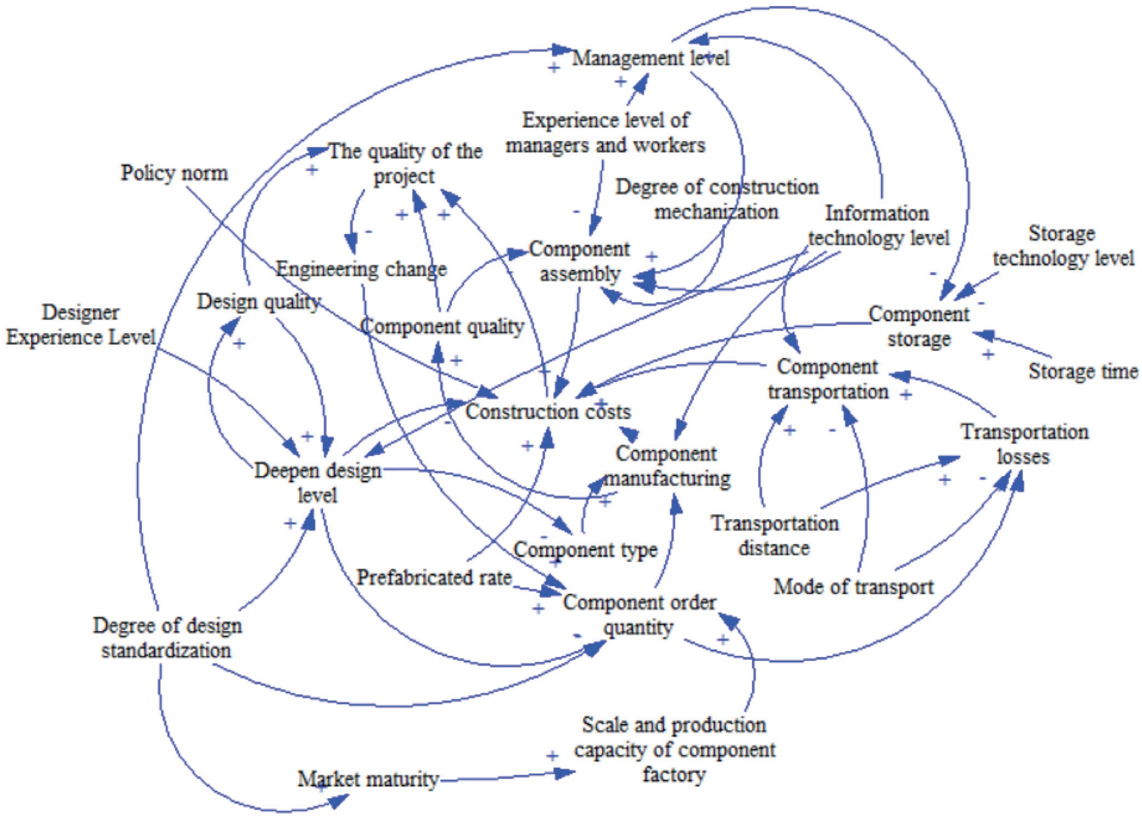

Figure 2: Cause-and-effect diagram of assembly construction cost.

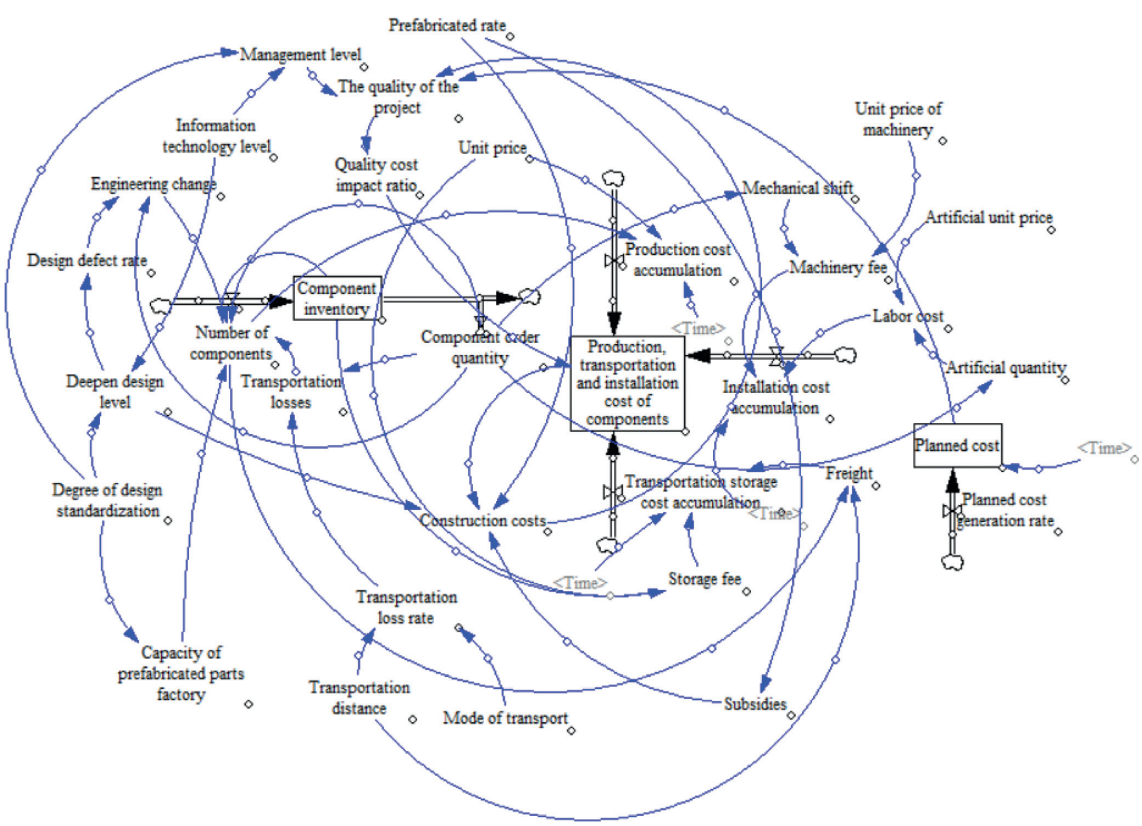

Figure 3: Flowchart of cost control stock of prefabricated building construction.

the unit price of each item, q is the number of components, and β is the relationship coefficient of the corresponding quota.

(4) Main Model of Transportation and Storage Cost. Transportation and storage costs include storage costs and transportation costs. According to the research results, the proportion of storage costs is 0.4 [15], and the transportation costs are calculated according to the national standard of vehicle transportation costs. The main models are established as follows:

$$\begin{aligned} C_{\mathrm{tr}} &= \sum p_{\mathrm{tr}}, \\ p_{\mathrm{tr1}} &= p'_{\mathrm{tr1}} \times q_{\mathrm{tr1}} \times \gamma_1, \\ p_{\mathrm{tr2}} &= Q \times L \times \gamma_2, \end{aligned} \tag{5}$$

where C_{tr} is transportation storage costs of cumulants, $\sum p_{\mathrm{tr}}$ is the sum of each item cost including transportation cost and storage cost, p'_{tr1} is price, q_{tr1} is storage quantity, λ, γ_1, and γ_2 are the corresponding cost coefficients of transport and storage, respectively, Q is the number of components, and L is transportation distance.

(5) Other Models. According to Taguchi quality theory and related studies [35], the relationship between quality and cost is parabolic, and quality is related to management level and information technology level. The relationship model obtained is as follows:

$$\begin{aligned} \theta &= gQ_u^2 + hQ_u + k, \\ Q_u &= f(M, I), \end{aligned} \tag{6}$$

where θ is the relation ratio between quality and cost, Q_u is the engineering quality level, g, h, and k are the coefficients of the quality equation, and $f(M, I)$ is the function of quality and management level (M) and information technology level (I).

Some parameters in the model are set as shown in Table 2.

4.2. Cost Control Model Test. Five practical assembly project cases have been selected to simulate the model. Among the five cases, case 1 is located in Jinan, Shandong; cases 2, 3, and 4 are located in Haidian, Tongzhou, and Changping, Beijing, and case 5 is located in Nanjing, Jiangsu. The basic data of the five cases are shown in Table 3.

The data of five cases have been substituted into the model. Then the model fitting results have been obtained through Vensim model simulation operation, and the fitting results have been compared with the actual engineering construction costs, as shown in Table 4. The data show that the fitting deviation is less than 10%, so the above control model is available.

4.3. Simulation and Analysis of Important Influencing Factors

4.3.1. Cost Control Simulation. Using this model and the data of a prefabricated building project in Beijing, we set the first month as the time for construction decision and design and the next 28 months as the construction period. After relevant data are input into the model, the curve of the whole project construction period is obtained as shown in Figure 4.

As can be seen from the graph, the project has a period of rising cost in the early stage of the construction phase, and the cost also keeps rising rapidly for a long time after the construction period. However, due to the combined effect of quality, transportation, and other factors, the increase is in a state of fluctuation.

4.3.2. Analysis of Simulation Results. Using Vensim composite simulation, we can find the uncertainties input into the system and measure the impact of uncertainties on the construction cost by changing the values of the uncertainties and observing the changes in the construction cost curve. The change rates were taken as ±5% and ±10%, respectively, and the final construction cost being the index to calculate the corresponding sensitivity coefficient. The calculation formula is as follows:

$$E = \left| \frac{C_i - C_0}{C_0} \div \beta \right|, \tag{7}$$

where E is the sensitivity coefficient, C_i is the corresponding project construction cost, C_0 is the original project construction cost, and β is the change rate.

In comprehensive comparison of sensitivity coefficients, the results are given in Table 5.

The simulation results finally confirm eight related factors, which correspond to the influencing factors. The unit price of labor and the unit price of machinery correspond to the level of labor and machinery and the corresponding policies and regulations of subsidy. The final results of influencing factors are as shown in Table 6.

According to the results, the degree of standardization has the most significant impact on the construction cost, with a wide range of impact, including market maturity, design, management, and other aspects. The research results of Hong et al. [23] and Jin et al. [4] show the great impact of market maturity, which proves the important role of large-scale and standardized construction in prefabricated building market from the side. Therefore, it is necessary to perfect the whole industrial chain, increase the number of component factories, improve production capacity, and form scale effect from a macro perspective.

Secondly, component unit price and prefabrication rate have a great impact on building cost. This paper calculates the incremental cost of prefabricated buildings compared with ordinary cast-in-place buildings. Since the component itself has the most direct impact on the construction cost, the unit price and prefabrication rate of the component reflect the incremental cost brought by the component itself. In the calculation of the prefabrication rate, when the prefabrication rate is too high, over 80%, its cost will suddenly rise. This might lead us to wonder, "Do we need to go for too high a prefabrication rate?." In order to control the cost in this aspect, it is necessary to reduce the loss from the perspective

Table 2: Basic equation parameters.

Parameter	Values or ranges of values
Linear correlation coefficient between prefabrication rate and construction cost	0.56
Subsidies	180 yuan/m^2
Design defect maximum	5%
Transportation loss rate	1%
Artificial rate	1.084
Mechanical rate	0.0439
Component storage cost coefficient	0.4
Component transportation cost coefficient	0.21 yuan/piece·km
Mass equation coefficients g, h, and k	0.4, 0.8, 1
Engineering quality level	[0, 1]
Degree of design standardization	[0, 1]
Capacity coefficient of the prefabricated component factory	[0, 1]
Information technology level	[0, 2]
Deepen design level	[0, 3]

Table 3: Basic information of prefabricated projects cases.

Project	Number of components (m^3)	Unit price (yuan)	Mechanical unit price (yuan/machine-team)	Artificial unit price (yuan/man-days)	The total cost (ten thousand yuan)	Construction period (month)	Construction area (m^2)	Prefabricated rate (%)
Case 1	18181	2988	2000	100	5794.82	28	156806	15
Case 2	1628	2996	1800	93	759.28	28	11180	58
Case 3	2697	2991	2200	95	1209.12	38	16401	45
Case 4	1940	3427	1121	97	800.88	15	8383	40
Case 5	1377	3722	51	100	742.71	25	3584	15

Table 4: Construction cost fitting results.

	Case 1	Case 2	Case 3	Case 4	Case 5
Fitting cost (ten thousand yuan)	5923.18	781.48	1125.35	730.20	789.21
Actual cost (ten thousand yuan)	5794.75	759.28	1209.11	800.88	740.11
Difference (ten thousand yuan)	128.42	22.20	83.76	70.68	49.10
Deviation (%)	2.22	2.92	6.93	8.83	6.63

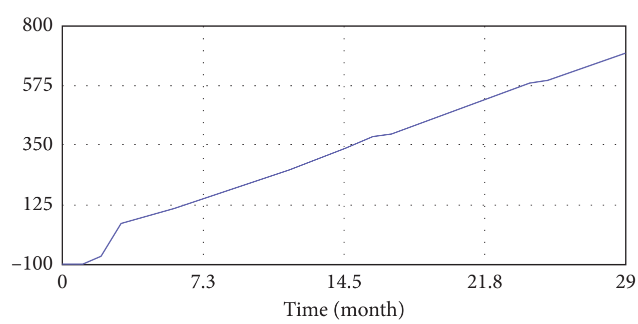

Figure 4: Project construction cost curve.

of components and reduce the unit price of components through scale effect.

Thirdly, the improvement of information technology level will bring significant impact on the reduction of costs. With BIM and the Internet of Things being the representative of the emerging information technologies and are widely used in the field of construction, they can greatly improve the precision and efficiency of design and construction. The semi-industrial production and construction method of prefabricated buildings is more conducive to the deep integration of industrialization and informatization, so that all parties involved in the project work together to

Table 5: Sensitivity analysis table.

Influencing factors	Rate of change (%)	Construction costs	Sensitivity coefficient	The sorting
Current	0	652.78		
Unit price	−10	601.26	0.79	2
	−5	627.23	0.78	
	5	677.93	0.77	
	10	702.71	0.76	
Prefabricated rate	−10	623.34	0.45	3
	−5	638.24	0.45	
	5	667.08	0.44	
	10	681.33	0.44	
Information technology level	−10	661.19	0.13	4
	−5	656.87	0.13	
	5	648.95	0.12	
	10	645.44	0.11	
Degree of design standardization	−10	649.02	0.06	1
	−5	650.90	0.06	
	5	654.66	0.06	
	10	656.55	0.06	
Mode of transport	−10	655.76	0.05	5
	−5	654.27	0.05	
	5	651.29	0.05	
	10	649.79	0.05	
Artificial unit price	−10	650.61	0.03	6
	−5	651.69	0.03	
	5	653.86	0.03	
	10	654.94	0.03	
Unit price of machinery	−10	651.08	0.03	7
	−5	651.93	0.03	
	5	653.63	0.03	
	10	654.48	0.03	
Transport distance	−10	652.31	0.01	8
	−5	652.54	0.01	
	5	653.01	0.01	
	10	653.25	0.01	

Table 6: Results of influencing factors.

The sorting	1	2	3	4	5	6	7	8
Influencing factors	Degree of design standardization	Unit price	Prefabricated rate	Information technology level	Mode of transport	Artificial level	Mechanical level	Transport distance

improve the efficiency and quality of construction and reduce costs.

In addition, transportation mode and transportation distance are the main factors affecting the cost of assembly construction. Due to the large volume of components and other reasons, logistics transportation will face great challenges, and it is necessary to make an appropriate plan for timely delivery and to carry out additional protection for loading and fixation of components during transportation [23], which will increase the construction cost. Transportation management mode needs to be further improved.

Finally, improvements in artificial machinery will contribute to cost savings in prefabricated buildings. Therefore, it is necessary to maintain the management control in the construction process to ensure the efficient operation of manual and mechanical work.

5. Conclusions and Recommendations

Prefabricated building construction cost is a dynamic complex system under the comprehensive influence of multiple factors. Based on the systematic analysis of the impact of prefabricated building cost, this paper establishes a model to simulate the impact of various factors on construction cost and draws the following conclusions:

(1) The cost influencing factors of prefabricated buildings can be roughly divided into design, production, transportation, storage, construction, and installation, as well as other factors including information technology and management level. There are many correlations in the complex system composed of the above factors, thus forming the following important influence paths on cost: the design level will affect the design cost, the application of information technology will affect the design and management level, the level of labor and machinery will affect the installation costs, the transportation distance and mode will affect the transportation cost, and the component quality will affect the production cost. These ultimately affect construction costs.

(2) The cost control model can be established by using Vensim system dynamics software, and the running result of the system can be simulated by defining the relationship between the factors in the model. The deviation between the fitting result of the model and the actual project construction cost is within a reasonable range, which proves that the system dynamics model can be used as a cost control model for prediction and analysis.

(3) Through the simulation of the cost control model, the construction cost of the prefabricated building has been rising dynamically, the cost rises rapidly during the early stage (especially the design stage) and increases slowly during the construction period, and it is affected by quality, transportation, and other factors; the cost growth is volatile and unstable.

(4) According to the results of system simulation, the main cost influencing factors of prefabricated building include eight factors: unit price of components, prefabrication rate, information technology level, degree of design standardization, transportation mode, labor level, mechanical level, and transportation distance. Among them, the degree of design standardization is the most influential factor, followed by the unit price of components, the prefabrication rate, information technology level, transportation mode, labor level, mechanical level, and transportation distance.

(5) Based on the main influencing factors, prefabricated construction cost control should start from the macro perspective, improve the industrial chain, and increase the degree of market standardization. Further strengthen the application of BIM and other information technology, and improve the level of construction management, improve transportation process, and speed up the efficiency of artificial and mechanical application.

Therefore, the cost of prefabricated buildings in China can be further controlled from the following aspects:

(1) Improve the industrial chain and stimulate the market mechanism based on competition with strong policy support. The macro policy has always been a strong favorable factor. Under the guidance of the policy, more component factories have been established to form a favorable situation of scale, further promote the improvement of the upstream and downstream industry chain, give full play to the synergies of the whole industry chain, and carry out industrialization thoroughly. Prefabricated buildings have been an important achievement of the industrialization of buildings. Improving the industrial chain of prefabricated buildings and dividing the construction market more directly simply play a leading role in encouraging the market-oriented development of buildings. Further stimulate the market mechanism based on competition and promote the process of construction marketization. Therefore, under the background of industrialization, prefabricated building construction path is clearer, construction efficiency is further improved, and prefabricated building market is more prosperous.

(2) Combine BIM technology to improve the level of information technology. BIM technology has always been a focus of attention and development in the construction industry. The application of BIM technology will bring the improvement of design level, management level, and other aspects. Integrated delivery mode and intelligent technology application are two major trends of the future information development of prefab building. The development of prefab building driven by information will drive the industrial transformation of the future construction industry. The great value of information technology in prefab building, which vigorously promotes the development of prefab building through deep integration of building industrialization and information, will certainly inject new vitality into the transformation of the construction industry. It enables all parties involved in the construction of the project to work together better, realize the integration of green, industrialization and informatization in the construction industry, and make a big push towards the direction of intelligence, modernization and standardization. Through the use of information means to strengthen the component procurement, distribution, storage, and installation of fine, standardized management, the construction quality, cost, and progress of dynamic management can improve the assembly efficiency, and the construction quality.

(3) Adopt fine management strategy to fully control the production, transportation, and construction process. Based on the technical means of information

technology, the process is effectively refined and decomposed by using the fine management concept. In view of the important influencing factors, such as unit price of components, transportation distance and mode of transportation, and the level of artificial machinery, strict control and continuous improvement measures are adopted to make cost control more detailed and standard. Under the background of the industrialization of prefabricated buildings, refined management will further bring the innovation of technical means, and the management efficiency is significantly improved.

There are still some deficiencies in this study. For example, the difficulty of cost control is not considered, and the cost control is not extended to the full life cycle. As the operation and maintenance period of China's prefabricated buildings continue, this will serve as the direction of in-depth study. Since prefabricated buildings are always been the focus of national promotion, corresponding proposals on the development of prefabricated buildings have been put forward on the national two sessions. Therefore, we should continue to pay attention to the problems of prefabricated buildings.

Data Availability

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request. The data, models, or codes are the data used to generate Figure 4 and Tables 4–6.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Research Article

Application of Artificial Intelligence for the Estimation of Concrete and Reinforcement Consumption in the Construction of Integral Bridges

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Estimation of basic material consumption in civil engineering is very important in the initial phases of project implementation. Its importance is reflected in the impact of material quantities on forming the prices of individual positions, hence on forming the total cost of construction. The construction companies use the estimate of material quantity, among other things, as a base to make a bid on the market. The precision of the offer, taking into account the overall conditions of the business realization, directly influences the profit that the company can make on a specific project. In the early stages of project implementation, there are not enough available data, especially when it comes to the data needed to estimate material consumption, and therefore, the accuracy of material consumption estimation in the early stages of project realization is smaller. The paper presents the research on the use of artificial intelligence for the estimation of concrete and reinforcement consumption and the selection of optimal models for estimation. The estimation model was developed by using artificial neural networks. The best artificial neural network model showed high accuracy in material consumption estimation expressed as the mean absolute percentage error, 8.56% for concrete consumption estimate and 17.31% for reinforcement consumption estimate.

1. Introduction

Cost estimation in construction represents a quantitative estimate of the probable resource expenses required for completing the activity [1]. A lot of factors affect the cost price. Each of these factors must be analysed, quantified, and estimated.

Estimating the final price requires a large number of elements to be synchronized. The process of defining the elements determining total costs includes the calculation of work quantities and then transferring them into expected costs. The basic elements or resources used and involved in the project during construction can be divided into several groups as follows:

(i) Work
(ii) Material
(iii) Equipment
(iv) Profit
(v) Time [2]

In order to carry out a project, it is necessary to organize teams with a large number of people. The initiative for entering the process of project implementation is started by the investor. The other participants in the project are a consultant, designer, expert supervision, contractor, and stakeholders.

In addition to the investor, the contractor has an important role on the project, since he represents a direct executor of the construction. An investor chooses a contractor based on certain criteria. Most commonly, these criteria require the construction of the highest quality structure with the minimum amount of money expended and in the shortest time possible. Clearly, these are the criteria that strive to idealize the entire course of the project and are therefore difficult to achieve.

The investor and contractor estimate costs for themselves, separately. Depending on the cost estimation results, the decisions are made about the further steps in the project. It is often the case that certain project implementation is withdrawn after the estimation, or the design is significantly modified.

A large number of factors, such as availability, quality, and the level of details in technical documentation, estimation method as well as the expertise of people performing the estimate, determine its quality and reliability from the aspect of satisfactory accuracy. The initial phases of project implementation are characterized by the insufficient data quantity. Each subsequent phase brings new data. The availability of the necessary data helps to increase the accuracy of the estimate. In 1974, Barnes presented the dependence of cost estimate accuracy and the phase of the project (see Figure 1).

The price offered by a contractor for project implementation is usually the main and quite often the only criteria based on which the investor chooses a contractor. Thus, the procedure for choosing a contractor according to this criterion is extremely simple, since the bidder with the lowest price will be chosen as the contractor. The problem with this method of contractor selection is the inability to see whether the project will be successfully completed, i.e., whether the contractor who offered the lowest price will be able to complete the project in the expected or at least satisfactory way (taking into account expenses, quality, and time).

A preliminary project cost estimate is the first serious estimate to be made on a project. During the initial phases of project implementation, it is not necessary to have a sufficiently accurate cost estimate. Since the material is one of the elements that affects the overall cost of the project, in order to reach its estimate, it is necessary, among other things, to determine the quantities of construction material required in the project. After determining the quantities, they are multiplied by the corresponding unit prices of these materials, and thus, we arrive at an estimate of the material costs which is one of the items in the sum of total expenses. The advantage of the cost estimation algorithm, in which there is a cost breakdown of items, is that it updates the cost separately, position by position, when new data become available. Also, the positive side of this approach is that positions can be monitored separately, allowing decision makers to make better decisions about the project during its initial phase.

In this study, the estimate of material consumption is performed for the materials which are most present in bridge construction, reinforcement, and concrete. The estimate is based on the values taken from the bills of quantities and cost estimates from the design documentation based on which the works were contracted.

2. Application of Artificial Neural Networks in Construction

Application of neural networks, one of the artificial intelligence techniques, in construction engineering, is quite widespread. They can be used in all the project implementation phases. The journal Microcomputers in Civil Engineering published a paper in 1989 which refers to the use of neural networks in this area. The authors of this paper are Adeli and Yeh [4]. The application of neural networks in construction is becoming more and more common because, in addition to the wide range of abilities they have, the rapid development of software packages has contributed to this.

Neural networks can be used for different types of estimates. One of them is the cost estimation of different types of construction and it has been processed by a large number of authors in their works [5–11]. In addition to cost estimation, neural networks can be used to estimate the duration of construction projects, which was also a topic dealt with by certain authors [8, 12]. Estimation of material consumption for the facility construction is another one of the estimates that is possible to be performed by applying neural networks. Despite this, there are only few papers in the literature that present the results of neural network applications for the purpose of estimating material consumption.

Fragkakis et al. represented the conceptual model for cost estimation of bridge foundations, which also gives the estimation of material consumption. Independent variables, which are relevant to the model, were identified by experts in the interviews. For defining this model, the authors used the stepwise regression methodology in order to determine whether the results were consistent with the expert opinion. The main assumptions underlying the correct application of the regression method were examined, and the necessary adjustments were made. The proposed method of conceptual cost estimation and material consumption estimation provides quick and reliable results that can be very useful in the early phases of a project [13].

An estimation of required material quantities, concrete, and reinforcement in multistorey buildings was performed by Mučenski et al. The forecasting model was defined using neural networks. Model analysis and definition data were taken from 115 major multistorey projects. The input variables of the model for forecasting the required amount of concrete and reinforcement are as follows: total gross area, average gross floor area, number of stiffening walls, longitudinal raster, transverse raster, and type of landing structure. The best results were shown by a network trained with the BFGS (Broyden–Fletcher–Goldfarb–Shanno) algorithm with an average error of 12.49% [14].

Garcia de Sotto et al. made an estimate of the materials and presented the methodology which was used to achieve estimate of satisfactory accuracy in the early phases of project implementation. They used neural networks, among other things, for modelling. Obtained results showed a significant improvement compared to the situation in practice [15].

The same authors, Garcia de Sotto et al., aimed to devise a process for developing a model which would be used for the preparation of preliminary estimates of construction material quantities taking into consideration data which are available during the early phases of the project and to assess the model by using the Akaike information criterion. The

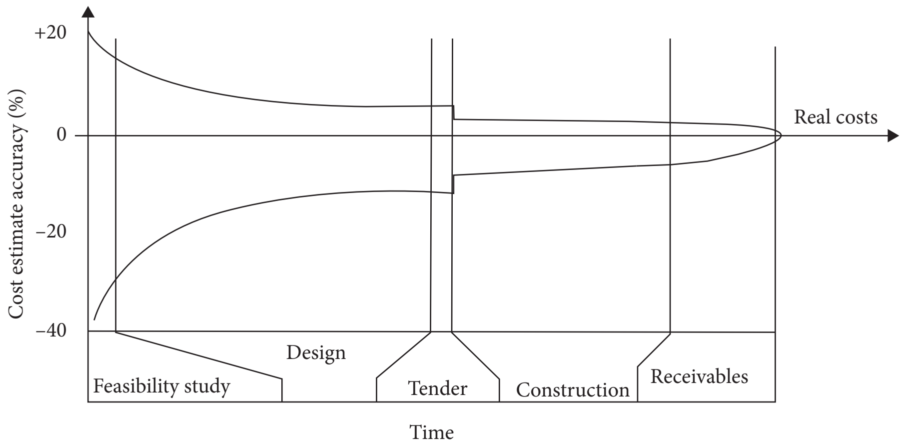

Figure 1: Cost estimate reliability [3].

proposed procedure is illustrated by an example in which data from 58 designs were used to define the model. These data were used for estimating used up concrete and reinforcement by using the neural network technique. For choosing the model with the highest accuracy, Akaike information criteria were used [16].

3. Materials and Methods

The first step undertaken for the purposes of this research is data collection and analysis. The data collected, after analysis, had to be prepared for model formation. In the end, two final models for the estimation of construction material consumption were defined, one for the concrete consumption and the other for reinforcement consumption.

The data were collected from the Main Designs of Integral Road Bridges, which were built on highways in the territories of Montenegro, Bosnia and Herzegovina, and Serbia. The term integral bridges is a modern term for concrete and composite frame structures of bridges without expansion joints and bearings [17]. There are several definitions of integral bridges. According to some, integral bridges are single-span frames with no expansion joints and bearings. In addition to this, we can find other definitions in the literature. They define this type of bridges as continuous frames without expansion joints and bearings just above the piers.

The research included 101 structures. Among them, there are 48 bridges from Montenegro, 29 bridges from Bosnia and Herzegovina, and 24 bridges from Serbia. The design documentation was prepared in three countries, so its form differs from one another. Therefore, the analysis and data preparation processes were complex. Only the same types of work were taken from all the bills of quantities and cost estimates in order to achieve data uniformity. In bills of quantities and cost estimates, the types of works are divided into preliminary, earthworks, concrete, reinforcement, tensioning works and prestressing, insulating, asphalt, and finishing works. Data on quantities of concrete and reinforcement were taken from concrete and reinforcement types of work.

An integral part of the technical documentation for the main design of bridges is the bill of quantities and cost estimate, and all the necessary data are obtained from them. The spans of these bridges range from 11.5 to 28 meters, the number of spans is from 1 to 18, the length of bridges without wing walls ranges from 11.5 to 784.4 meters, and the pier height is from 2.8 up to 65 meters. These projects were carried out in the period from 2010 until 2016.

After collecting the material quantity data, model input data were determined. Model inputs will represent certain design characteristics of bridges. The criteria for choosing such characteristics were their direct impact on material consumption. Based on this, the following characteristics were chosen: bridge length, bridge width, pier height, and bridge span. The data about bridge characteristics were taken from the main designs of these structures. Some of the data, such as pier height and bridge span, had to be corrected in such a way that a single value could be used as an input size. This is the reason why, when pier height is mentioned, as input data, it implies the mean height of middle piers. In case of a single-span structure, as a mean pier height, it is implied that the mean abutment height was used. Regarding the span of the bridge, this parameter had to be corrected for the fact that it is not the same if you have a larger number of smaller spans or a smaller number of larger spans in the identical length of the bridge. Due to this fact, the bridge span, as an input parameter, implies the mean of the span. The input data, prepared in the aforementioned manner, are presented with their limit and mean values in the table (see Table 1).

In order to improve the model for the material consumption estimate, as the input parameters, the data on construction technology and structure foundation are introduced.

For the span structure of analysed bridges, two types of formworks were used: formworks on a fixed scaffolding and formworks on mobile scaffolding. For that reason, the new input variable, named construction technology, has a value of 0 for formworks on a fixed scaffolding and the value is 1 when the formworks are on a mobile scaffolding.

The method of founding determines the amount of material used for founding. The bridges whose data were

Table 1: Input data.

Input data number	Input data description	Data type	Meas. unit	Min	Max	Mean value
Input 1	Bridge length	Numeric	m	11.5	784.4	153.25
Input 2	Bridge width	Numeric	m	6.5	30.55	11.52
Input 3	Pier height	Numeric	m	2.8	35.9	13.65
Input 4	Bridge span	Numeric	m	11.3	44.5	24.07
Input 5	Construction technology	Discrete	—	0	1	—
Input 6	Founding method	Discrete	—	0	2	—

used in this research were founded shallow, deep, or combined. The new input variable, named the founding method, depending on the method of founding, has the following values: 0 in case of shallow founding, 1 in case of deep founding, and 2 in case of combined founding.

The next step is defining the model output data. Based on the considered parts of the research, one output from each model was determined, which is the total amount of concrete and the total amount of reinforcement for the construction of integral road bridges (see Tables 2 and 3).

In the process of model formation using artificial neural networks, the available data should be divided into two sets. These two sets represent the training and test sets. The data of the training set are used for training and from the test set for checking the network.

Various recommendations can be found in the literature regarding the percentage ratio of these sets. A large number of authors select data in the ratio 90% to 10%, 80% to 20%, 85% to 15%, or 70% to 30% [18]. Of course, these are just recommendations, and the specificity of each of the problems being solved makes us decide on the appropriate ratio between the two sets. In this research, the training and test set will be divided in the ratio 80% to 20%. In 6 models, a direct division will be made into training and test sets, and in 2 models, a random selection of data will be done. The cross-validation procedure (*k*-fold cross-validation and leave-one-out cross-validation) shall be used to randomly select data.

Network training is preceded by a transformation, i.e., scaling data to fit everyone within a certain size range. The choice of ranges for scaling inputs and outputs depends on the activation function of the output quantities. Data can be scaled using standardization and normalization [19, 20]. The result of these methods is to reduce certain data to the same order of magnitude. Moreover, they enable the analysis of data of the same importance when forming the model, which means that it will also provide data analysis with a smaller size range. The data scaling methods used in the study are StandardScaler (*Z*-score normalization) and min-max normalization.

Network formation begins with determining the network architecture. This involves defining the number of layers and the number of neurons in each of the layers. Some authors recommend that it is not necessary to take more than two hidden layers when defining an artificial neural network [18, 21, 22]. The confirmation that the networks with two hidden layers gave reliable results is found in many theoretical results and numerous simulations in various engineering fields. In addition, there are theoretical results that indicate that a single hidden layer is sufficient for the network to approximate any complex nonlinear function with sufficient accuracy [23].

The number of neurons in the hidden layers is not uniquely determined. There are recommendations in the literature but not a precise and reliable way of determining them. A large number of neurons lead to the problem of overfitting, while the insufficient number of neurons leads to the problem of underfitting, i.e., poor approximation of the dependence between input and output quantities. The number of neurons should be such that it does not lead to any of these issues, but to enable data to exhibit its most useful characteristics. The recommendations made by some authors refer to the upper limit of the number of neurons in the hidden layer. Lippmann (1987), Nielsen (1987), and Hecht-Nielsen (1990) recommend determining the number of neurons following inequality (1), whereas Rogers and Dowla (1994) give recommendations for the maximum number of neurons, N_H, following inequality (2). It is advisable to accept a smaller number from the ones stated in the inequality, where N_i is the number of input parameters and N_S is the number of training samples:

$$N_H \leq 2 \times N_i + 1, \quad (1)$$

$$N_H \leq \frac{N_S}{N_i + 1}. \quad (2)$$

In the process of defining a model, one must strive to find a model with the best possible opportunity for generalization. Generalization is a process in which knowledge that is valid for a certain set of cases is transferred to some of its supersets [24], i.e., based on data which are not presented to the model during the training (the validation set), the model has the ability to result in satisfactory sizes even though based on data which are not presented during training. The validation set is introduced to avoid the problem of overfitting or determine stopping points of the training process [25]. Generalization in forecasting is further enhanced by the cross-validation process. This procedure is performed on the data from the test set.

Constant performance measurement is done during the model definition. Performance measurement, in fact, is an accuracy forecast. The difference between the actual (desired) and the forecast value is the forecasting error, and a measure of accuracy is defined. There are a number of accuracy measures for forecasting in the literature. The accuracy of the model in this study was determined using the mean absolute percentage error (MAPE). A satisfactory generalization probability in models is achieved if the

Table 2: Output data of the first model.

Output data number	Output data description	Data type	Meas. unit	Min	Max	Mean value
Output 1	Total quantity of concrete	Numeric	m^3/m^2	1.05	3.11	1.54

Table 3: Output data of the second model.

Output data number	Output data description	Data type	Meas. unit	Min	Max	Mean value
Output 1	Total quantity of reinforcement	Numeric	kg/m^2	117.26	415.58	250.8

Table 4: Activation functions of a multilayer perceptron model of the artificial neural network.

Function	Mark	Explanation	Range
Identity	x	Only in the output layer	$(-\infty, +\infty)$
Rectified linear unit function	$\text{Max}(0, x)$	Neuron activation is forwarded directly as an output if positive, and if negative, it is forwarded to 0. It has been shown to have 6 times better convergence than a hyperbolic tangent function	$(0, +\infty)$
A hyperbolic tangent	$[2/(1+e^{-2x})]-1$	Neuron activation is forwarded directly as an output if positive, and if negative, it is forwarded to 0. It has been shown to have 6 times better convergence than a hyperbolic tangent function	$(-1, +1)$

deviation between the forecasted and expected results at the training and test set is small.

The forecasting model was formed in Python 3.7 software package. In order to solve the problem that is the subject of the research, models about estimating material consumption, a multilayer perceptron MLP is formed, which is one of the artificial neural network types.

The most commonly used neuron activation functions in the hidden layers are logistic sigmoid (logistic), a hyperbolic tangent (tanh), and the function of rectified linear unit (ReLu). The activation function of output neurons is mostly linear. Bearing in mind, the number and other data characteristics, following the aforementioned recommendations, during the model formation, for hidden neurons, the function of rectified linear unit (ReLu), and a hyperbolic tangent (tanh) were used, whereas for the output neurons, the identity function was used (see Table 4).

4. Results

Artificial neural network models, multilayer perceptron (MLP), are formed based on defined input and output sizes and other required parameters. The number of layers as well as the number of neurons in hidden layers is determined based on recommendations, and the number of neurons in the input and output layer is determined based on the number of input and output sizes. The largest number of hidden neurons which was taken in the models is 13 based on expressions (1) and (2). 8 artificial neural network models were formed. In one half of these models, the data were used which were scaled by using the StandardScaler procedure, whereas for the other the min-max procedure was used.

All neural networks in both models, NMB1, NMB2, NMB3, NMB4, NMB5, NMB6, NMB7, and NMB8 for the model forecasting concrete consumption and NMA1, NMA2, NMA3, NMA4, NMA5, NMA6, NMA7, and NMA8 for the model forecasting reinforcement consumption, have 6 input and 1 output size. Neural network models with StandardScaler standardization for forecasting concrete consumption and reinforcement consumption are presented in tables (see Tables 5 and 6). They also list the characteristics of each model with a measure of accuracy given by the mean absolute percentage error (MAPE).

The following three neural network models are formed using the data which were scaled by applying the principle of min-max normalization. Data about model characteristics as well as the estimation accuracy which is determined by the mean absolute percentage error (MAPE) are presented in tables (see Tables 7 and 8).

Random data selection was done with two models using k-fold cross-validation for $k = 10$ and leave-one-out cross-validation (LOOCV). Estimation accuracy in these models is determined through mean absolute percentage error (MAPE) (see Tables 9–12). In those models where data division was done in accordance with k-fold cross-validation, the data were scaled by using a Standard Scaler, and in those models where the division was done with LOOCV, the data were scaled with min-max function. Two of each model that gave the best results are presented here.

By comparing presented models, it can clearly be seen that models NMB1 and NMA8 have the highest estimation accuracy. For model NMB1, StandardScaler was used for scaling the data. It defines 3 layers of neurons, one of which is input and one output layer. In the hidden layer, there are 12 neurons. The activation function of a hidden layer is the function of rectified linear unit (ReLu). The measure of the accuracy assessment model is expressed through mean absolute percentage error and is 8.56%.

Model NMA8 processed data which were scaled by using min-max normalization. The network architecture of this model is represented by 3 layers of neurons. There are 6 neurons in the input layer, 1 in the output, and 9 neurons in a hidden layer. The activation function of a hidden layer is

Table 5: Artificial neural network models for estimating concrete consumption (StandardScaler).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB1	MLP 6-12-1	ReLu	Identity	7.68	8.56
NMB2	MLP 6-4-1	Tanh	Identity	10.7	11.51
NMB5	MLP 6-7-1	ReLu	Identity	8.01	9.95

Table 6: Artificial neural network models for estimating reinforcement consumption (StandardScaler).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA1	MLP 6-7-1	Tanh	Identity	18.85	20.74
NMA2	MLP 6-13-1	ReLu	Identity	10.83	18.51
NMA5	MLP 6-8-1	ReLu	Identity	16.74	19.33

Table 7: Artificial neural network models for estimating concrete consumption (min-max normalization).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB3	MLP 6-11-1	ReLu	Identity	9.97	10.5
NMB4	MLP 6-12-1	Tanh	Identity	10.78	10.81
NMB6	MLP 6-7-1	ReLu	Identity	8.78	10.73

Table 8: Artificial neural network models for estimating reinforcement consumption (min-max normalization).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA3	MLP 6-7-1	ReLu	Identity	18.28	19.03
NMA4	MLP 6-3-1	Tanh	Identity	19.15	19.41
NMA6	MLP 6-9-1	ReLu	Identity	18.26	18.78

Table 9: Artificial neural network models with random data choice for estimating concrete consumption (k-fold cross-validation, $k = 10$).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE (%)	σ (%)
NMB7	StandardScaler	MLP 6-4-1	ReLu	Identity	12.69	3.64

Table 10: Artificial neural network models with random data choice for estimating concrete consumption (LOOCV).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB8	Min-max	MLP 6-11-1	ReLu	Identity	10.69	11.06

Table 11: Artificial neural network models with random data choice for estimating reinforcement consumption (k-fold cross-validation, $k = 10$).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE (%)	σ (%)
NMA7	StandardScaler	MLP 6-4-1	ReLu	Identity	22.91	2.5

Table 12: Artificial neural network models with random data choice for estimating reinforcement consumption (LOOCV).

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA8	Min-max	MLP 6-9-1	ReLu	Identity	14.12	17.31

the function of a rectified linear unit (ReLu). Mean absolute percentage error is 17.31%.

The two models with the highest accuracy were selected as the final models for the estimation of concrete and reinforcement consumption, and based on them, the forecasting models were defined.

5. Conclusion

Based on the results presented in the study, it is concluded that the models with the highest accuracy of concrete consumption and reinforcement for the construction of integral road bridges are artificial neural network models whose architecture is represented by three layers of neurons, six of which are in the first layer, and one in the last output layer. In the hidden layer, there are 12 neurons in the concrete consumption estimation model, while 9 neurons are in the reinforcement consumption estimation model. The activation function of the hidden layers of neurons is the function of a rectified linear unit (ReLu), while the activation function of the output layers is linear (Identity). The accuracy measure is represented in both models by mean absolute percentage error (MAPE). In the model for concrete consumption, MAPE = 8.56%, whereas MAPE for the estimate of reinforcement consumption is 17.31%.

It is possible to improve the accuracy of a forecasting model by increasing the number of data in the data base. Additionally, the forecasting model would have the potential to be more widely applied if the database was expanded with certain features of the structures such as the type of cross section, height of the cross section, number of spans, number of piers, and structural system. The database could be improved by entering data on the category of the road (type and significance of the road) on which the bridges are located. The justification for the existence of this type of data in the database lies in the fact that the category of the road directly affects the load of bridges, which affects main characteristics of bridges and thus the amount of concrete and reinforcement. The potential parameters by which the database could be expanded would, in fact, be the input parameters of the forecasting model.

The use of a forecasting model would be particularly beneficial to the contractor when he is also the designer (for the contract-type design-build). With the help of a forecast model, without having to develop the preliminary design and only on the basis of sketches, the contractor could estimate the amount of material. The estimated amount of material is significant to him in the competitive bidding phase in order to submit as precise a bid as possible.

In the early phases, the amount of data available on future structures is insufficient for forming the accurate estimate. This means that the error in estimating material consumption is also greater than the estimates made in the subsequent phases of implementation. Quantity, type, and quality of data, which are available at the time of evaluation, condition the application of a model. This is the reason why it is necessary to adjust the input parameters to the data we have. The estimation importance in the early phases lies in the fact that the results of this early estimate directly affect assessing a total cost which in the further process determines/recommends us, or not for entering into the project implementation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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