NON-PARAMETRIC BILL-OF-QUANTITIES ESTIMATION OF CONCRETE ROAD BRIDGES' SUPERSTRUCTURE: AN ARTIFICIAL NEURAL NETWORKS APPROACH

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Bridge construction responds to the need for environmentally friendly design of motorways and facilitates the passage through sensitive natural areas and the bypassing of urban areas. However, according to numerous research studies, bridge construction presents substantial budget overruns. Therefore, it is necessary early in the planning process for the decision makers to have reliable estimates of the final cost based on previously constructed projects. At the same time, the current European financial crisis reduces the available capital for investments and financial institutions are even less willing to finance transportation infrastructure. Consequently, it is even more necessary today to estimate the budget of high-cost construction projects -such as road bridges- with reasonable accuracy, in order for the state funds to be invested with lower risk and the projects to be designed with the highest possible efficiency. In this paper, a Bill-of-Quantities (BoQ) estimation tool for road bridges is developed in order to support the decisions made at the preliminary planning and design stages of highways. Specifically, a Feed-Forward Artificial Neural Network (ANN) with a hidden layer of 10 neurons is trained to predict the superstructure material quantities (concrete, pre-stressed steel and reinforcing steel) using the width of the deck, the adjusted length of span or cantilever and the type of the bridge as input variables. The training dataset includes actual data from 68 recently constructed concrete motorway bridges in Greece. According to the relevant metrics, the developed model captures very well the complex interrelations in the dataset and demonstrates strong generalisation capability. Furthermore, it outperforms the linear regression models developed for the same dataset. Therefore, the proposed cost estimation model stands as a useful and reliable tool for the construction industry as it enables planners to reach informed decisions for technical and economic planning of concrete bridge projects from their early implementation stages.

Keywords: artificial neural networks, bill of quantities, concrete bridge, cost.

INTRODUCTION

Bridge construction increases through time as a response to the soaring urban and inter-urban traffic needs; in addition, developing social concern for traffic impact on the environment further contributes to the construction of new bridges. However,

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according to research studies such as Flyvbjerg *et al*. (2004), Odeck (2004), Flyvbjerg (2007) and Azhar *et al*. (2008), bridge construction presents substantial budget overruns. In this context and given the significant cost of a bridge, the decision makers need to have reliable estimates of the final cost, early in the planning process. This need is rendered even more imperative as due to the contemporary financial crisis, the available public funds for construction projects are decreasing. Furthermore, financial institutions are less willing to finance transportation infrastructure, due to their decreased liquidity in conjunction with the increased traffic risk (e.g. rise of oil price, reduction of users' available budget for tolls). Consequently, in these times, it is even more necessary to estimate the budget of high-cost construction projects -such as road bridges- with adequate accuracy in order for the State funds to be invested with lower risk and the projects to be designed with the highest possible efficiency.

Attending to the above need, this research paper introduces an ANN-based model which, utilising actual project data, achieves reliable estimation of the bridge superstructure material quantities and thus renders possible more accurate estimation of the bridge superstructure cost. The latter is achieved by multiplying the quantities predicted by the model with the unit prices specified by the user. The use of material quantities as a means to extract the cost instead of directly predicting the cost enhances the applicability of the estimation as material quantities are mostly based on the applied design codes representing international standards with wide acceptance and use across countries (e.g. DIN, Eurocodes, AASHTO). On the contrary, cost values are heavily influenced by country-dependent factors (e.g. tendering system, inflation rate) and require proper adjustment to be suitable for use outside a national context.

LITERATURE REVIEW

The management of the construction cost of concrete bridges has been the aim for numerous previous research. A review of publications on cost optimisation of concrete bridge components and systems has been presented by Sarma and Adeli (1998) and Hassanain and Loov (2003). Cost optimization models for bridges have also been developed by Lounis and Cohn (1993), Cohn and Lounis, (1994), Sirca and Adeli (2005). Furthermore, Aparicio *et al*. (1996) proposed a computer-aided design and cost estimating system addressing all elements of concrete highway bridges. Geographically limited bridge cost estimation guidelines have also been developed by the Departments of Transportation (DoT) of California (2011) and New York (2012).

Regarding the cost of different bridge sections, Menn (1990) highlighted the significant impact of the superstructure concluding that it contributes on average 54% of the total bridge cost while Fragkakis and Lambropoulos (2004) found that the superstructure accounts for 34 to 50% of the total bridge construction cost, depending on the design system and construction method used.

As far as the ANNs are concerned, their powerful capabilities for capturing and modelling complex interrelations in real-world datasets have been widely identified in the literature (Marinelli *et al*. 2014, Dimitriou and Hassan 2013, Karlaftis and Vlahogianni 2010, Lee *et al*. 2008, Moselhi *et al*. 1992) and their suitability for cost estimation of various construction projects like buildings (Kim *et al*. 2004), tunnels (Petroutsatou *et al*. 2012), highway projects (Hegazy and Ayed 1998) and drainage projects (Alex *et al*. 2010) has also been highlighted. In the area of bridges, Creese and Li (1995) applied ANNs to estimate the cost of timber bridges based on data collected from 12 projects. The volume of webs, the volume of the bridge decks and

the weight of steel were used as input variables for the prediction of the output variable namely the actual bridge cost. Similarly, Ugwu and Kumaraswamy (2004) developed an ANNs model trained with data from 74 highway bridges in Hong Kong with the aim to predict their construction cost. The input variables were the structure's location, the pavement material and the project configuration. Furthermore, Morcous *et al*. (2001) developed an ANNs model with a back-propagation algorithm to estimate the concrete volume and pre-stressed steel weight of bridge superstructures. A set of 22 pre-stressed concrete bridges constructed in Egypt was used in training and testing the network. The fairly limited literature on the use of ANNs for bridge cost estimation can be attributed to the lack of suitable data i.e. large, reliable and homogeneous databases with actual data from constructed road bridges; the availability of such data is drastically restrained by the use of different design codes as well as the reluctance of public clients to supply financial information regarding constructed projects.

ANNS MODEL FOR BRIDGE BOQS ESTIMATION

Data collection

The data used for the development of the model were collected from the final BoQs of 68 bridges of a major motorway project constructed in northern Greece between 1996 and 2008. The designs were all carried out by Greek and international structural design firms following international competitions and were in compliance with the German DIN standards and Greek regulations for earthquake loading. A thorough three-stage review process was applied to all designs before construction.

In order to collect and record the characteristics of each construction project, a list of questions was prepared requesting general information (e.g. location, highway section and design office), the bridge's fundamental design parameters (e.g. number of spans, construction method used, length of each span, width) and the quantities of concrete, reinforcing steel and pre-stressed steel for each span. The questions were initially answered by the construction managers/supervisors responsible for each project and the contractor's civil engineers. After scrutinising the replies, the authors visited several construction sites, in order to check and confirm the validity and accuracy of the data provided.

The final database covers a wide range of bridge characteristics including various landscape profiles (mountainous, flat terrains, significant slopes, etc) and different construction methods. Specifically, three different construction methods leading to a different type of bridge are represented in the sample as per Table 1.

Table 1. Characteristics of the structures included in the database

Construction Method	Type of Bridge	Number of bridges	Number of spans
1	precast pre-stressed beams with composite slab	31	47
2	cast-in-situ deck	22	47
3	cantilever construction	15	33

Apart from the construction method/type of the bridge, the database also includes the material quantities of concrete (Vc), reinforcing steel (Bs), pre-stressed steel (Bp) as well as basic design parameters such as the length of the span or cantilever (l) and the

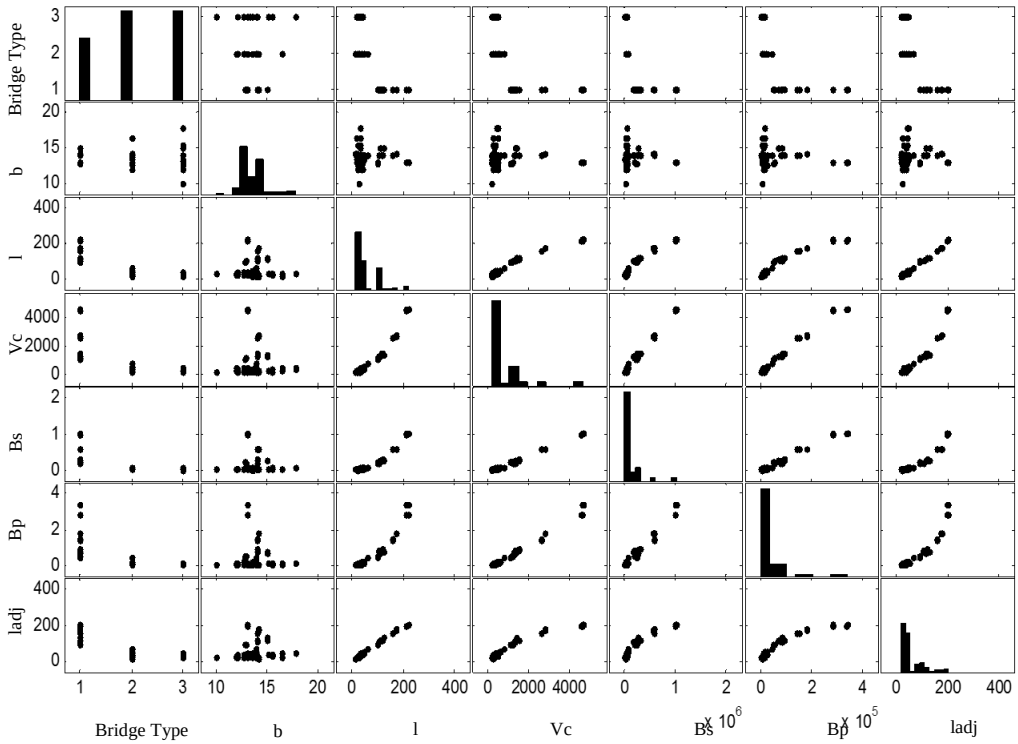
deck width (b). In order to take into account the difference of deck width among the bridges of the data sample, an adjusted length of the span or cantilever was also defined (ladj) as a function of the median value of the deck width for each construction method in the sample (bmed) as per eq.1. This value equals 13.10 m for superstructures with precast beams, 13.50 m for superstructure with cast-in-situ box girders and 14.00 m for cantilever construction.

$$l_{adj} = l * \frac{b}{b_{med}} \qquad (1)$$

Data multivariate analysis

A multivariate analysis was undertaken to offer a better understanding of the complexity of the interrelations between the aforementioned variables of the dataset bridge type, b, l, Vc, Bs, Bp, ladj. The matrix of the correlation diagrams provided in Fig. 1 provides a better picture of how the variables co-relate e.g. the plot of the down left corner shows how the variable ladj varies within each one of the three bridge types available. The various correlations presented in Fig. 1 reveal that there are pairs with an obvious (mostly nonlinear) trend and others with no obvious correlation, though an underlying pattern in the dataset can be initially assumed.

Fig 1. Correlation diagram matrix of the sample bridge variables.



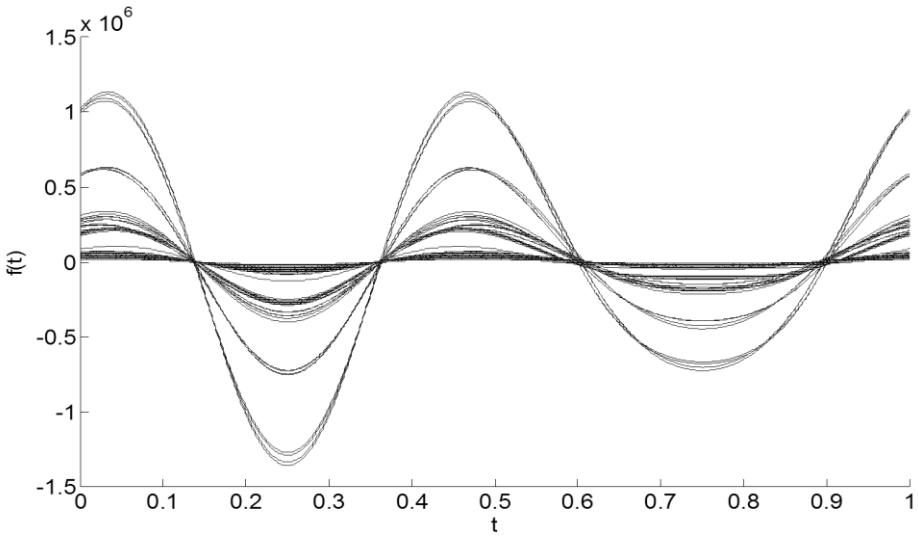
For further investigation of the correlations in the available dataset, the multivariate analysis based on Andrews plots (Andrews 1972) was conducted (Fig. 2). Andrews plots provide a statistically sound way to depict multivariate datasets and get insights on possible correlations (Khattree and Naik 2002) but does not provide the exact nature of these correlations. Further information about Andrews plot can be found in Garcia-Osorio and Fyfe (2006). In the specific form of the Andrews plot used in the present study, each observation i, is represented by a function f(t) of a continuous

dummy variable t over the interval [0,1]. Function f(t) is defined for the i-th observation in the dataset X as follows:

$$f(t) = X(i,1)/\sqrt{2} + X(i,2)/\sin(2\pi t) + X(i,3)\cos(2\pi t) + ... \quad (2)$$

The projection of all observations in a comprehensive way facilitates the identification of patterns (similarities among multivariate data) as well as outliers in the dataset. Specifically, in varying the value of t in eq.2, we are moving along the curve; data points which are similar will behave similarly in that the locus of their movement will be similar. As depicted in Fig. 2, the Andrews plot analysis, identifies at least four clusters in the dataset, offering evidence on correlations which could be further investigated by means of non-linear regression models. Therefore, the above presented identification of some pattern among the data provides incentives for developing a nonlinear model for bridge BoQ estimation and testing its performance on real-world dataset. As already mentioned, the modelling approach will be based on ANNs and is presented in the following section.

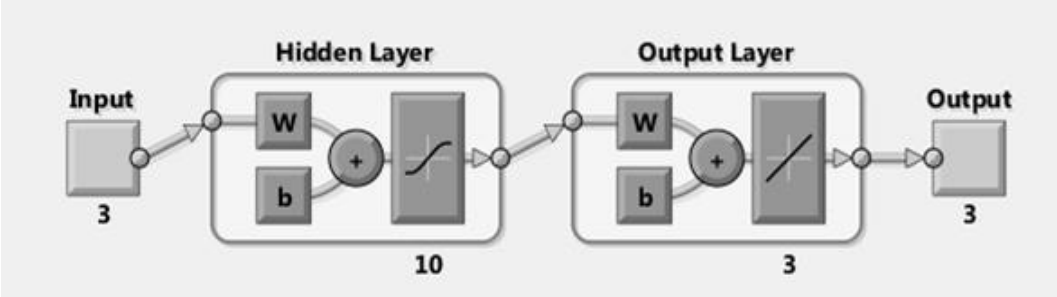
Fig 2. Andrews plot for the complete bridges dataset.



Application of the Feed-Forward Artificial Neural Network on the Dataset

The available dataset was used for the training of an ANN based on a Feed-Forward setup (FFANN). The structure of the FFANN is presented in Fig. 3, where the deck width in meters (b), the adjusted length of span or cantilever in meters (ladj) and the categorical variable representing the bridge type (Type) are fed as inputs to a hidden layer of 10 nonlinear neurons each of which has a log-sigmoid transfer function. Three linear functions for estimating the volume of concrete in m3 (Vc), the weight of reinforcing steel in kg (Bs) and the weight of pre-stressed steel in kg (Bp) form the output layer of the ANN.

Fig. 3. A standard depiction of the selected ANNs structure.



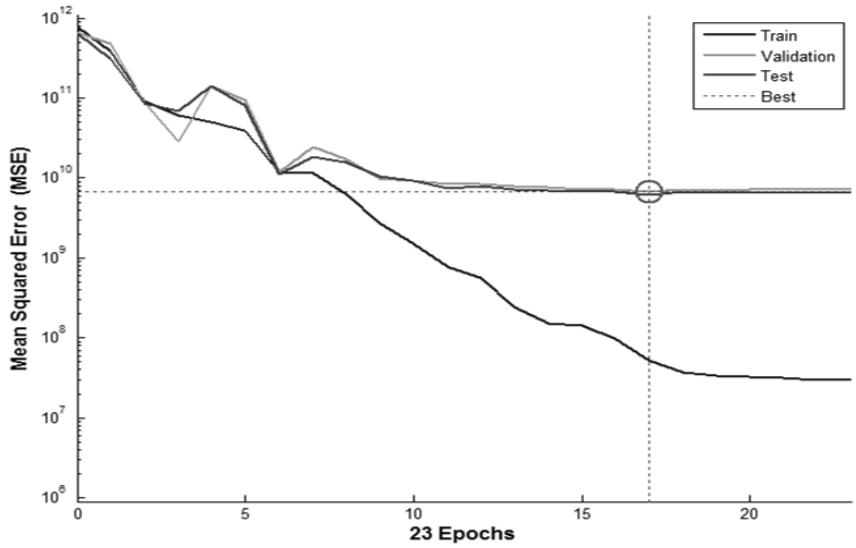
Several FFANN structures with differing size and transfer functions were tested, but the one selected exhibited better characteristics concerning the over-fitting and generalisation abilities trade-off. This type of FFANN has several advantages including being straightforward, powerful in mapping nonlinear interrelations within datasets, able to treat both continuous and categorical (integer) data and easy for coding and testing.

The training process of the selected FFANN was based on the Levenberg-Marquardt routine of nonlinear optimisation. In particular, the dataset was divided in three parts, namely, for training, validating and testing into typical proportions of 70%, 15% and 15% respectively. The training set was used by the optimisation routine to update the weights of the connections between the layers with the aim to minimise the Mean Squared Error (MSE) between observations and predictions.

Then, the validation set was used to test the trained model against over-fitting /memorisation. Specifically, if a model performs satisfactorily during the training process but the error increases in validation, this indicates that the model 'memorises' instead of capturing the underlying correlations among variables.

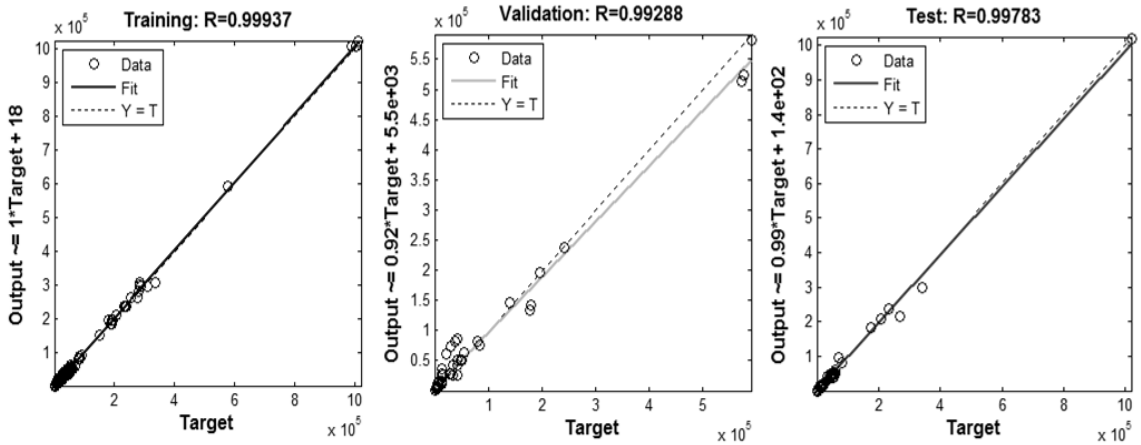
Finally, the test set was used for unbiased evaluation of the model's performance. In Fig. 4, the convergence diagram of the calibration process for the complete dataset is presented, exhibiting the capability of the calibrated (starting from a random state) FFANN to model the interrelations among the dataset variables with a small error component (<10^8), as measured by the MSE metric.

Fig 4. Convergence diagrams of the selected ANNs training process.



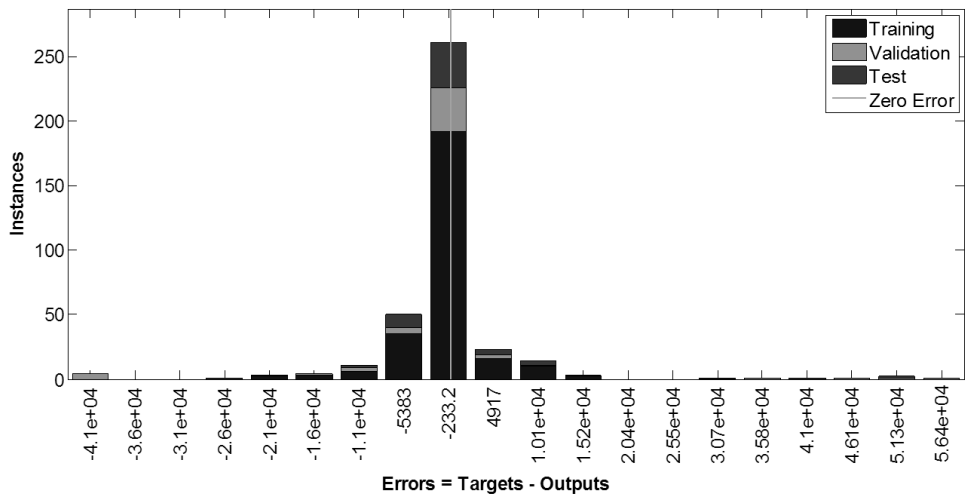
The performance of the proposed FFANN can be further exposed by the correlation diagrams for the three sets (training, validating and testing), presented in Fig 5. It can be observed that the selected model setup and its calibration are liable to estimate bridge superstructure BoQ with notable accuracy, since the correlation of predictions and observations is very high (R~0.99) for all sets. This is a clear indication of the model's value for practical purposes.

Fig 5. Performance analysis of the selected ANNs.



Moreover, the almost normal distribution of the errors for the three sets (training, validation and test sets) presented in Fig. 6, further supports the reliability of the calibration process as this type of error distribution suggests unbiased estimation capabilities of the model.

Fig 6. Distribution of errors for the database used (distinguished in training, validation and test sets).



Comparative statistics

In order to check the performance of the proposed model, apart from the goodness-of - fit tests already presented, comparative statistics with standard regression models were also performed. In particular, the proposed ANN model was compared against the parametric linear regression models developed in Fragkakis *et al*. (2010) for the same dataset and for each construction method. The comparison process concerned the same test subset i.e. the 15% of bridges from each of the three construction methods.

Two metrics of goodness-of-fit were used, the adjusted coefficient of determination (R2), which typically provides a measure of the variability explained by the models, and an error metric, the Mean Absolute Percentage Error (MAPE). This combination of metrics provides a clear picture of the accuracy of the alternative tests. As observed in Table 2, the ANNs model outperforms all the three linear regression models in both metrics. Similar performance superiority of the ANNs over linear regression has also been reported by Creese and Li (1995) for their timber bridge cost prediction model.

Table 2. Comparative statistics for the alternative regression methods for each construction method.

	Precast Beams		Cast-in-Situ		Cantilever	
	R2	MAPE (%)	R2	MAPE (%)	R2	MAPE (%)
Linear Regression	0.967	12.29	0.952	16.82	0.956	16.36
ANNs	0.979	11.48	0.995	13.94	0.981	16.12

CONCLUSIONS

The development of large-scale road transport projects in the current financial circumstances requires reliable cost estimates in the preliminary design phases where the most influential cost-wise decisions are taken. Aiming to support these preliminary decisions, the current paper presented a contemporary, robust and reliable model for bridges superstructure cost estimation. The estimation is achieved by multiplying the properly selected unit prices per material with the superstructure material quantities (concrete, pre-stressed steel and reinforcing steel) which the ANN predicts following proper calibration with data from 68 recently constructed concrete bridges. Input variables for the ANNs model are the deck width, the adjusted length of span or cantilever and the type of the bridge (with precast beams, with cast in situ deck or cantilever construction). As demonstrated, the developed model captures very well the complex interrelations in the dataset providing reliable estimations of the final quantities for bridges and demonstrating strong generalisation capability. The performance of the proposed ANNs model was further compared against the performance of linear regression and it was clear that the ANNs led to improved results in terms of accuracy. Therefore, the proposed cost estimation model stands for a useful and reliable tool for the construction industry as it enables planners to reach informed decisions for technical and economic planning of concrete bridge projects from their early implementation stages. Furthermore, the proposed model provides evidence of the potential usefulness of ANNs in cases of civil infrastructure planning and design as similar databases and cost estimation models could be developed for the remaining bridge sections (piers and foundations) and other road infrastructure elements (e.g. culverts). Moreover, this particular artificial intelligence computational paradigm is suitable for integration in the currently available design and management infrastructure software and thus, this research also makes a valuable contribution to the construction software industry.

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