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An artificial intelligence-based application

Abstract

Accurate cost estimation in the preliminary stages of project development is critical for making informed planning decisions. However, such early estimates are typically restricted by limited information. In this paper, the widely recognised intelligence of Feed-Forward Artificial Neural Networks (FFANNs) is used to process actual data from 68 concrete road bridges and provide a surrogate model for the accurate estimation of the Bill-of-Quantities (BoQ). Specifically, two FFANNs are trained to estimate the superstructure and piers concrete and steelbased on the construction method and the bridge dimensions. As the relevant metrics demonstrate, the FFANNs capture very well the complex interrelations in the dataset and produce highly accurate estimates. Furthermore, their generalization capability is superior to the capability ofrespectivelinear regression models. As the data used to train the FFANNs is normally available early in the project lifecycle, the proposed model enables early, yet accurate cost estimates to be obtained.

Keywords: Artificial Neural Network, Bill of Quantities, Bridge, Construction Cost estimate, Infrastructure Planning.

Introduction

Providing accurate forecasts of construction costs in the preplanning phases of construction projects is vital (Dursun & Stoy, 2016) as cost estimation accuracy has decisive impact on strategies for asset development, potential project screening, and resource commitment for further project development (Oberlender &Trost, 2001). Estimates prepared at the initial stages of a project can play several important roles: they can form the basis of cost-benefit analysis, for selection of potential delivery partners, to support a to-build-or-not-to-build decision, and very often as a benchmark for future performance measure (Ahiaga-Dagbui &Smith, 2014). They are also typically used for the estimation of preconstruction costs as a fixed or sliding percentage (Hollar & Rasdorf, 2013).

The soaring urban and inter-urban traffic needs generate an ever-increasing pressure for allocation of funding towards the construction of motorway infrastructure. This is a critical issue which currently attracts significant debate and disagreement (Hollar et al., 2013). Gibson, Denison, Wallace and Kreis (2015) note that the fiscal developments of recent years make it difficult to plan appropriate policies and infrastructure projects that maintain transportation systems at current service levels as the available public funding does not necessarily meet the expanding transportation needs of citizens. In this context, as motorway projects require a substantial investment of funds, developing a reliable and accurate project cost estimate in the initial decision-making process is a task of critical importance to the sponsoring organisation and the project team.

Apparently, in times of resource scarcity, it is even more necessary for the decision makers to estimate the budget of high-cost, large-scale construction projects like road bridges with adequate accuracy, early in the planning process, in order for the national funds to be invested as efficiently as possible. However, the required accuracy is notoriously difficult to be achieved as the conceptual stage involves very limited project information. Yeung and Skitmore (2012) note that in the very early stages of construction projects, there are situations where only such basic information as project type, project size and preliminary project specification is known concerning a new project and the client-owners' consultant estimators have to resort to using either the price of a very similar project or the mean price of a (base) group of projects. Similarly, Hyari, Al-Daraiseh and El-Mashaleh (2016) highlight the fact that detailed estimates are usually possible not earlier than the stage of procurement, i.e. after completion of the detailed project design and therefore, earlier cost estimates can only be based on historical data and cost forecasting models. This unsurprisingly leads to early estimates being highly inaccurate with the final actual cost exceeding in the vast majority of cases the initial estimate.

As Rosenfeld (2014) notes, cost overruns in construction are a worldwide phenomenon with no geographical limits nor cultural associations. Flyvbjerg, Holm and Buhl (2003) highlight the correlation between cost overruns and project size arguing that larger projects present higher percentage cost escalations while other factors such as premature tender documents (Rosenfeld 2014) and procurement choices (Chen et al. 2016) have also been strongly associated with this global problem. Especially in the field of transportation projects, Flyvbjerg, Holm and Buhl (2003) note that the magnitude of cost overruns in highway projects and motorway bridges is substantially high. Specifically, nine out of ten transport infrastructure projects fall victim to cost escalation, which for fixed links (tunnels and bridges) and roads has an average value of 34% and 20% respectively. Furthermore, Lee's (2008) analysis of roads, rails, airports and ports projects found that road and rail projects had a maximum cost overrun of 50%. Vidalis and Najafi (2002) in their research on 708 highway projects for the Florida Department of Transportation found a combined cost overrun of $200 million.

This research paper introduces an Artificial Neural Network (ANN)-based model which, utilising actual Bill of Quantities (BoQ) data from 68 road bridge projects, enables thereliable estimation of the bridge superstructure and piers material quantities and by extension the more accurate estimation of the relevantcost. This 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 developing a model to directly predictthe cost, enhances the reliability of the estimation process. This results from the fact that the BoQ is based on final designs compliant to international standards with wide acceptance and use across countries (e.g. DIN, Eurocodes, AASHTO) while on the contrary, cost values are heavily influenced by country-specific actors (e.g. tendering system, inflation rate) which need to be adjusted for the model to be used more widely.

Literature Review

Research in road bridge cost analysis and management

The analysis of the construction cost of concrete bridges has been the aim for numerous past research efforts. Menn (1990) used a small sample of 19 motorway bridges built in Switzerland between 1958 and 1985 to investigate the cost of prestressed concrete bridges. He broke down the bridge structure into four components, i.e. mobilization, substructure, superstructure, and accessories and concluded that these factors' contribution to the total bridge construction cost is 8.00%, 23.50%, 54.50%, and 14.00%, respectively. Fragkakis and Lambropoulos (2004) collected actual cost information from a large sample of 119 concrete bridges and overpasses constructed between 1999 and 2003 as part of the Egnatia Motorway in

Greece. They divided the actual bridge construction cost into earthworks, foundation, substructure, superstructure and accessories and proposed the average cost values for four major deck construction methods. For example, concerning bridges consisting of precast prestressed beams and reinforced concrete slabs, the average cost percentages for the five elements above are 4.70, 26.70, 15.90, 34.40 and 18.30 % respectively.

The review of publications relating to cost estimation for road bridges reveals that very few studies use actual as-built design and structural data in order to produce cost estimate models. Fragkakis, Lambropoulos and Tsiambaos (2011) developed a bridge database with complete data from 157 pier foundations and developed a parametric model for conceptual cost estimation of concrete bridge foundations. A database with design and structural data for 322 bridge piers was used from Fragkakis, Lambropoulos and Pantouvakis (2014) in order to develop a cost estimate model for piers with regression analysis. Furthermore, Fragkakis, Lambropoulos and Pantouvakis (2010) applied regression analysis on a database consisting of 68 structures and derived material estimating models for three widely used deck construction methods (cantilever construction, precast pre-stressed beams, cast-in-situ box girders). Bridge cost estimation guidelines, mostly based on historical bid data, have also been developed by Departments of Transportation (DoT) in U.S. Such examples are California (2011), New York (2016) and Florida (2017). Moreover, in Dimitriou and Charmpis (2015) and Charmpis and Dimitriou (2015) alternative optimisation formulations and algorithmic configurations have been tested on a realistic large-scale sample of nearly 15,000 bridges from NY, USA, exposing the gains of optimal selection mechanisms on budget utilisation, while highlighting the importance of accuracy in bridges rehabilitation cost appraisal.

Most efforts on cost estimation of concrete bridges are constrained by design standards and codes and are based on a trial-and-error computer-aided process aiming to optimise the design from a technical or economical viewpoint.Sirca and Adeli (2005) addressed precast, prestressed concrete bridge systems consisting of type I beams and developed an optimization method for the superstructure cost. The general design process of the superstructure and the standard cross sections were based on the AASHTO specifications. The model addressed the superstructure as a single system and did not explore the superstructure components. Cohn and Lounis (1994) explored the optimal design of concrete motorway bridges through a three-level cost optimization approach. Their research concentrated only on the superstructure of prestressed bridges with span length between 10.00 and 15.00 m. and deck width between 8.00 and 16.00 m. They addressed superstructure systems with solid or voided slabs, single-cell box girders and precast prestressed beams with reinforced concrete composite slab. Lounis and Cohn (1993) proposed a method for bridges consisting of precast prestressed girders with reinforced concrete slab that enables the selection of the most economical girder type, optimal girder spacing, optimal prestressing force, and minimum superstructure cost per unit deck area. The specifications and constraints of the Ontario Bridge design standard were used. Aparicio, Casas and Ramos(1996) proposed a computer-aided design and cost estimating system addressing all elements of concrete highway bridges. The software package represents an expert system that uses specific design constraints to perform the complete bridge design. It produces the geometry and cost of all bridge elements and extracts design drawings. A thorough 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). The aforementioned studies address only the bridge superstructure and use standard beam shapes and cross sections dictated by the American or Canadian design standards and specifications. The research is characterized by the computer-intensive theoretical resolutions that result in the optimization of the final design from both technical and economic viewpoints. Although cost estimates based on computer-aided resolutions provide helpful insights, they fail to address the designers' attitude and experience that influence the as-built structural quantities for each project, as well as the structural changes that take place during the project's construction and were not predicted during the design phases.

Cost prediction at early design stages: challenges and methodological approaches

According to Burke (1999) and Flyvbjerg, Holm and Buhl (2002), at each phase in the project implementation (conception, tendering, design, construction) different levels of cost-estimating accuracy can be achieved from the detail of information available. Specifically the early cost estimates made at the conception phase are based on designs which only correspond to a general idea about what the project will entail, at a completion level of about 30%. As a result, many of the costs must be inferred from costs associated with past projects (Asmar, Hanna, &Whited, 2011). Nicholas (2004) also refers to the lack of realistic and accurate estimates as a result of inadequate information and highlights the fact that estimators have to rely largely on their own experience and historical cost information when preparing initial estimates.Ahiaga-Dagbui and Smith (2013) observe that an estimate can only be as good as the information it is based on so that, ceteris paribus, the level of accuracy of the estimates produced also increases as more information becomes available**.** However, despite their low level of accuracy, early cost estimates are used as the basis for the comparative evaluation of different investments decisions, design alternatives and eventually the selection of the most efficient technical solution. Odeck (2004) discusses the risk of inefficient investment decisions resulting from unreliable early cost estimations. He particularly highlights the fact that underestimated costs may be deceptive aswhen the viability of the project is being evaluated, the decision maker probably makes decisions based on larger values of Net Present Value than the actual ones. The end result may be that non-viable projects are being implemented and resources are inefficiently allocated due to inaccurate estimates.

In this context, the uncertainty which is inherent in the pre-construction phase of projects has repeatedly been connected by the literature with the occurrence of cost overruns. Flyvbjerg, Holm and Buhl (2002) note that the likelihood of actual costs being larger than estimated at a randomly selected project reaches the impressive percentage of 86%. Durdyev, Ismail and Bakar (2012) in their research for residential projects identified improper planning and inaccurate project cost estimation among the factors affecting cost overruns. Similarly, in their analysis for infrastructure projects, Lee (2008) examined 161 roads, rails, airports, and ports projects and concluded changes in the scope and unreasonable cost estimation have substantial impact on cost overruns. Similar conclusions for the impact of inaccurate cost estimates were also presented by Le-Hoai, Lee and Lee (2008). Cantarelli, vanWee, Molin and Flyvbjerg (2012) also note that road projects are particularly vulnerable to exceeding the estimated costs in the pre-construction phase and argue that although this phase is significantly shorter than the construction phase, it has the highest influence on cost overruns. Bridge construction in particular also presents substantial budget overruns (Odeck, 2004; Flyvbjerg, Skamris, & Buhl 2004, 2007; Azhar, Farooqui, & Ahmed,2008).

Numerous models have been developed to support decision makers in the challenging task of estimating construction project cost. Among the most popular and well-established modelling techniques for this purpose are the ANNs. An ANN is an information-processing system that has been developed asgeneralization of mathematical models ofhuman cognition or neural biology and exhibits the ability to capture the nonlinear relationships between variables. ANNs are made of simple processing units, called neurons, capable of storing experimental knowledge as a natural propensity. The elementary backpropagation artificial neuron forms the base component of the ANN. Typically the neuron is configured with a number of inputs, with each input having an associated weightwhich multiplies the signal transmitted. An activation/transfer, often sigmoid function is applied to convert the input of each neuron to output. The ANN type most suited for developing predictive models is the Feed-Forward ANN (FFANN) trained using a back-propagation algorithm that uses a gradient-descent approach for adjusting the ANN weights (Attalla & Hegazy, 2003). Back-propagation ANNs consist of an input layer, an output layer, and one or more hidden layers. The number of layers and the numbers of neurons in each layer determine the capability of the network to figure out the relationship between the independent variables and the dependent one. A single hidden layer is sufficient for almost any problem (Setyawati, Sahirman, & Creese, 2002). An ANN is feedforward if there exists a method which numbers all the nodes in the network such that there is no connection from a node with a large number to a node with a smaller number. All the connections are from nodes with small numbers to nodes with larger numbers (Yao, 1999).

The ANN gains its problem-solving capabilities through generalization of the knowledge gained during its training. According to Zhang, Patuwo and Hu (1998) the training process is usually as follows. First, examples of the training set are entered into the input nodes. The activation values of the input nodes are weighted and accumulated at each node in the first hidden layer. The total is then transformed by an activation function into the node's activation value. It in turn becomes an input into the nodes in the next layer, until eventually the output activation values are found. The training algorithm is used to find the weights that minimize some overall error measure such as the sum of squared errors (SSE) or mean squared errors (MSE). Hence the network training is actually an unconstrained nonlinear minimization problem. When supervised training is applied, input and output parameters of training data are randomly presented to the network thousands of times, called cycles or epochs. In each epoch, the network applies its training algorithm and calculates its predicted output. The errors between the predicted and the actual outputs are propagated backward to adjust the network's weighted connections so that the predicted output matches or becomes as close as possible to the actual output. This process is mathematically guaranteed to converge (Rumelhort, Hinton, & Williams, 1986). The distinct advantage of ANNs over the nonlinear regression is that no exact knowledge of the nonlinear relationship between the input and output variables is required as these relationships are determined implicitly by the ANN and therefore do not need to be specified by the user. The error of the trained model is used as a metric of its generalization capability. As Svozil, Kvasnicka, & Pospichal (1997) explain, a network generalises well when the input-output relationship computed by network is correct (or nearly correct) for input/output patterns never used in training the network. When the learning process is repeated too many times, then, overfitting may occur due to the network memorising the training data instead of capturing the underlying correlations among variables. In such case, the network performs satisfactorily during the training process but fails with data from the test set. Thus, the network has reduced generalization capability. The most commonly used method for avoiding overfitting is early stopping. This involves dividing data into two sets, one for training and one for validation, and computing the validation error periodically during training. Training stops when the validation error rate starts to increase. However, the validation error is not a good estimate of the generalization error, and thus, a third set of data, not used during the training process, is necessary to check the generalization performance of the ANN. This third set is called test set.

ANNs' powerful capabilities for capturing and modelling complex interrelations in real-world datasets have been widely identified in the literature (e.g. Marinelli, Lambropoulos, &Petroutsatou,2014; Dimitriou & Hassan, 2013; Karlaftis & Vlahogianni, 2011; Moselhi, Hegazy, & Fazio, 1992) and their suitability for cost estimation of different kinds of construction projects like buildings (Gunaydin & Dogan, 2004; Kim, An, & Kang, 2004), tunnels (Petroutsatou, Georgopoulos, Lambropoulos, & Pantouvakis, 2012), highway projects (Hegazy & Ayed, 1998; Al-Tabtabai, Alex, &Tantash, 1999; Xin-Zheng, Xiao-Chen, & Jing-Yan, 2010), drainage projects (Alex, Al Hussein, Bouferguene, & Fernando, 2010), water projects (Shehab, Farooq, Sandhu, Nguyen, &Nasr 2010, Chau & Sethi, 2012), hydroelectric power plant projects (Gunduz & Sahin, 2015) has also been highlighted. Other applications of ANNs include financial tools, electric load consumption prediction and intelligent manufacturing systems (Huang & Zhang 1994, Zhang, Patuwo & Hu (1998). Frazer (1995) also investigates the use of computer based techniques and models in the field of architecture.

In the area of bridges, Creese and Li (1995) used data from 12 timber bridges to develop an ANN capable for the estimation of the bridge cost from the volume of webs, the volume of the bridge decks and the weight of steel. Similarly, Ugwu and Kumaraswamy (2004) used data of location, pavement material and project configuration from 74 highway bridges in Hong Kong to train an ANN to predict their construction cost. Furthermore, Morcous, Bakhoum, Taha, & El-Said (2001) used data from 22 pre-stressed concrete bridges constructed in Egypt to develop a ANN capable of estimating the concrete volume and pre-stressed steel weight of bridge superstructures.The input attributes selected for the training ofthe ANN modelwere: the maximum span length, the superstructure type, the structure system, the construction method, the contract type, and the design type. Testing results with cross-validation experiments resulted in average network errors smaller than 11.50% in both output variables.

The literature survey indicates that ANNs have been used efficiently for the preliminary quantity estimate of highway bridges despite the difficulties emerging from the use of different design codes as well as the reluctance of public clients to supply financial information regarding constructed projects. Other methods frequently employed for project cost estimation include regression analysis (e.g. Trost & Oberlender, 2003; Lowe, Emsley, & Harding, 2006; Wang & Horner, 2007; Fragkakis, Lambropoulos, & Pantouvakis, 2010; Jafarzadeh, Wilkinson, González, Ingham, & Ghodrati Amiri 2014) and case-based reasoning (e.g. Karshenas & Tse, 2002; Kim & Kang, 2004; Doğan, Arditi, & Gunaydin, 2008; Koo, Hong, Hyun, & Koo, 2010). Kim, An, & Kang (2004) provide comparison of all the 3 methods performance and advantages / disadvantages. Their research based on the analysis of actual construction costs of 530 projects of residential buildings, concluded that the best ANN model performed more effectively than the other two approaches in estimating construction costs. Quite a number of other researchers have also verified the performance superiority of ANNs over regression. For instance, Attalla and Hegazy (2003) compared the two methods' performance in reconstruction cost prediction and concluded that the ANN-based model was able to include a much greater number of variables. Similarly, Shehab, Farooq, Sandhu, Nguyen and Nasr (2010) concluded that the ANN developed for water projects cost prediction produced much more accurate results compared to the regression one and thus demonstrated superior capabilities in mapping relationships between inputs and outputs in limited data environments. Gunduz and Sahin (2015) also confirmed in their research that the ANN that was trained on cost data from forty one hydroelectric power plant projects had substantially higher prediction accuracy than the respective regression model developed. 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.

Development of FFANN-based model for Road Bridge BoQ estimation

Data collection

The data used for the development of the model were collected from the final BoQs of 68 bridges of Egnatia Motorway, a 680-km-long motorway constructed in northern Greece between 1996 and 2008 as part of the trans-European Transport Network. The whole project includes 646 concrete bridges which account for the20% of the total construction cost. The greatest overall bridge length exceeds 1,000 m, and the longest single span reaches at 235 m. The designs were carried out by Greek and international structural design firms following international competitions. A thorough three-stage review process was applied to all designs before construction.

For the collection of the characteristics of each construction project, a list of questionswas distributed to the construction managers/supervisors responsible for each project and the contractor's civil engineers. These questions concerned 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, height of piers) and the quantities of concrete and reinforcing steel for each span and pier. After scrutinising the replies, on-site visits were held to check and confirm the validity and accuracy of the data provided.

The final datasetincludes three different types of bridges, distinguished by the use of different construction methodsas dictated by the varying landscape (mountainous, flat terrains, significant slopes, etc).Apart from the construction method, the dataset for each bridge also includes the superstructure material quantities i.e. concrete (V_c), reinforcing steel (B_s) andpre-stressed steel (B_p), as well as basic design parameters i.e. the length of the span or cantilever (l) and the deck width (b). Details of the bridge superstructure dataset are presented in Table 1.

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 (l_{adj}) as a function of the median value of the deck width for each construction method in the sample (b_{med}) as per equation 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.

$$l_{adj} = l * \frac{b}{b_{med}} \tag{1}$$

Similarly, the collected dataset for 321 piers included the height of each pier, H, the corresponding concrete volume, V_c', and the reinforced steel weight, B_s' (relevant ranges included in Table 2). Additionally, the length of the deck supported by each pier, l', was calculated as the average length of the spans situated on both sides of the pier and this value was adjusted as previously (equation 2) to give l'_{adj}. In the following section, a thorough investigation of the datasets' characteristics is presented.

$$l'_{adj} = l' * \frac{b}{b_{med}} \tag{2}$$

Multivariate data analysis

Multivariate analysis was undertaken to enable deeper understanding of the complexity of the interrelations between the variables of the datasets, i.e. the bridge type, b, l, V_c, B_s, B_p, l_{adj} for bridge superstructure and H, V_c',B_s' and l'_{adj} for bridge piers. Initially, the correlation matrices provided in Figure 1 and Figure 2 provide a better picture of how the variables co-relate. In particular, Figure 1 demonstrates the correlations between the superstructure variables while similarly Figure 2 concerns the variables of the piers. From Figure 1, it can be observed that there are pairs with strong, mainly nonlinear correlations. In Figure 2, the most apparent correlation lies unsurprisingly between the concrete volume V_c' and the reinforcement steel B_s', while other correlations (e.g. between piers height, H and concrete volume V_c') are much more stochastic.

For further investigation of the correlations in the available dataset, the multivariate datasets were analysed based on Andrews plots (Andrews, 1972) (Figure 3). Andrews plots depict multivariate datasets to enable insights on the existence of possible correlations but with no indication of their exact nature. 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]. The Function f(t) is defined for the i-th observation in the dataset X as per equation 3.

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

In varying the value of t in equation 3, data points which are similar will behave similarly in that the locus of their movement will be similarfacilitatingthus the identification of patternsas well as outliers in the dataset.Figure 3 shows thatat least four distinct clusterscan be identifiedin the superstructure's dataset.

On the other hand, no particular clusters can beexposed in the Andrews plot for the piers' dataset (Figure 4), revealing the stochastic nature of the interrelations among the selected variables and validating the initial evidence provided earlier by the correlation analysis. Concentrating on the piers' dataset and aiming to gain some insight into the type of the interrelations, the normality of each variable as well as their possible fitting to the Weibull and Lognormal distribution was checked. The relevant tests showed that none of the variables seem to follow any of the theoretical distributions.

These findings suggest that standard regression analysis may not be a suitable analytical framework, since the datasets do not fit to a theoretical distribution and thus this fundamental assumption of regression analysis cannot be fulfilled. Moreover, the underlying relation between the dataset variables possibly is of non-linear nature and of complex structure. Given the above, the BoQ estimation problem requires a modelling approach based on ANNs, known for their ability to handle complex 'mappings' from inputs to outputs. The experimental setup of the ANNs used is presented in the following section.

Application of the Feed-Forward Artificial Neural Network on the BoQ estimation

The estimation of a total BoQ for the superstructure and the piers of bridges is addressed by combining the results of two suitably selected, trained and tested FFANNs. This combination is able to adapt to the particularities of the two datasets, since the quality of ANN performance is dependent on the quantity of training data and on how the data are presented to the network. Therefore, several data-representation experiments with various network architectures, different number of hidden layers, hidden nodes and transfer functions were conducted, resulting to the structure presented in Figure 5.

It should be noted here that the current paper addresses the particularities of bridge cost estimation through the following two methodological features:

i. The use of binary/class/integer variables in the model building which enable the introduction of bridge class features like the type of a bridge, and ii.The training of a different ANN for each main component (superstructure, piers) and subsequent combination of the results.

These two elements ensure that the estimated models are accurate, robust and reliable, take into consideration realistic features in estimating bridges' cost and are also useful in project feasibility phase.

Starting from the configuration of the ANN corresponding to the superstructure, the deck width in meters (b), the adjusted length of span or cantilever in meters (l_{adj}) and the categorical variable representing the bridge type (Type) are the 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 m^3 (V_c), the weight of reinforcing steel in kg (B_s) and the weight of pre-stressed steel in kg (B_p) form the output layer of the ANN. Additionally, for the piers, the height (H) and the adjusted length of the span supported by each pier (l'_{adj}) are input into a hidden layer with 20 nonlinear neurons while the output layer estimates the volume of concrete in m^3 (V'_c) and the weight of reinforcing steel in kg (B'_s).

The respective datasets were for both cases 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 Levenberg-Marquardt 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. The validation set was used to monitor the performance of the network during training against over-fitting /memorisation, while test set was used for unbiased evaluation of the model's predictive capabilities after the training process was completed. This type of FFANN has several advantages including being straightforward, powerful in mapping nonlinear and stochastic interrelations within datasets, able to treat both continuous and categorical (integer) data and easy for coding and testing (Karlaftis and Vlahogianni, 2011).

The convergence diagrams for the training, validating and testing process of the complementary FFANNs (Figures 6 and 7) demonstrate the capability of the trained FFANNs to model the interrelations among the dataset variables (starting from a random state) with a substantially improved error component (reduced to 10^8 from 10^{12}), as the relevant MSE metric denotes. The magnitude of performance of the gradient and the number of validation checks are used to terminate the training. The gradient becomes very small as the training reaches a minimum of the performance. Training stops after a number of successive epochs where the validation performance fails to decrease (epoch 17 and onwards in Figure 6). As it can be observed from Figure 7, the training process for the piers' FFANN requires 28 iterations, an element possibly indicative of the complexity of the relevant dataset.

The performance of the proposed FFANNs can be further exposed by the regression plots for the three datasets (training, validating and testing). As can be observed in Figure 8, the superstructure FFANN is capable of notably accurate BoQ estimations, since the correlation of predictions and observations is very high for all sets (R~0.99) and the linear regression function almost coincides with the ideal line. This is a clear indication of the model's value for practical purposes.

Similarly, the regression analysis of the correlation between the observations and predictions made by the piers' FFANN is also very high (Figure 9) reaching an R value of R=0.99 for training (Figure 9a). However, it can also be observed that the correlation diagram is more scattered around the ideal correlation line for all sets (training, validation and testing), while the correlation coefficient for the validation and especially for the testing set lies at 0.90 (Figure

9b) and 0.96 (Figure 9c) respectively. Although the results can be regarded as satisfactory, this is an additional indication of the complexity of the interrelations between the variables of the piers.

An additional indication for the FFANNs' performance can be obtained by checking the distribution of errors; unbiased models are ideally expected to have normally distributed errors with mean equal to zero. The close-to-normal distribution of the errors for the three sets (training, validation and test sets) for both FFANNs as depicted in Figures 10 and 11, further verifies the reliability of the training process and suggests unbiased estimation capabilities for both models.

The above thorough evaluation of the developed FFANNs' capability to estimate the BoQ for both the superstructure and piers of road bridges offers encouraging evidence on the applicability and performance of such data-driven models in real-world problems. The final step of the proposed methodological framework involves its comparison against parametric estimation models. Such comparative analysis is provided in the next section.

FFANNs' performance comparison to regression models

In order to check the performance of the developed FFANNs, apart from the tests already presented, comparative statistics with standard regression models were also performed. Specifically, the performance of the developed FFANNs was compared against the performance of parametric linear regression models developed for the same data. The same test subset i.e. the 15% of the complete dataset was used in both cases.Two metrics of goodness-of-fit were used to provide a clear picture of the accuracy of the alternative models: the coefficient of determination (R^2), which is a measure of the variability explained by the models and the Mean Absolute Percentage Error (MAPE) which is an error metric. As presented in Table 3, the FFANN trained to estimate the superstructure BoQ outperforms the respective linear regression model in all the three construction methods and in both metrics.

The comparative results for the piers' FFANN constitute an even stronger indication of the model's strengths and robustness. As indicated in Table 4, the FFANN demonstrates superior performance compared to the statistical models both in terms of the R^2 and the MAPE. This is particularly evident for the estimation of the steel weight and can be attributed to the lack of data normality, which is a prerequisite for the development of reliable linear regression models. The difference observed in the MAPE value between the FFANN for the superstructure and the one for the piers is also worth noting; in the case of piers the MAPE is significantly higher compared to the equivalent values for the superstructure, an additional evidence of the prediction difficulty for the piers' dataset.

The above presented results provide strong evidence on the FFANNs' potential on predicting bridges' BoQ when used as surrogate mechanisms early in the design stage. Given the complex interrelationships among the variables for BoQ estimation and taking into account the overall very satisfactory computational performance of the developed models, it can be concluded that in the context of road bridge projects, the developed FFANNs are capable to provide reliable estimates of the material quantities required which in turn, can be used to yield cost estimates of improved accuracy.

Conclusions

Developing a reliable cost estimate forlarge-scale road transport projectsis a challenge for any authority or organisation, especially at the preliminary design phase, where only a general idea exists about what the project will entail. Aiming to enhance the accuracy of such preliminary cost estimates, two FFANNs were trained and tested on actual data from 68 concrete road bridges with the aim to reliably predict the BoQ of bridge superstructure and piers (concrete, pre-stressed steel and reinforcing steel) based on variables normally known even in the early implementation stages. Specifically, the variables used as input to the superstructure's FFANN were 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). Similarly, for the piers' FFANN, the input variables were the height of the pier and the adjusted length of span supported.As the relevant performance analysis demonstrates, the developed FFANN model captures very well the complex interrelations in the dataset and as a result of its strong generalization capability, it provides reliable estimations of the final material quantities. An accuratecost estimation can be then achieved by multiplying the properly selected material unit prices with the predicted material quantities. Furthermore, following comparison of the FFANNs' performance against the performance of the respective linear regression models, it became apparent that the use of artificial intelligence resulted in animproved level of accuracy. Therefore, the proposed cost estimation model represents a useful and reliable tool for the construction industry as it enables planners to reach informed, despite early, decisions for technical and economic planning of concrete bridge projects. Furthermore, the proposed surrogate model provides evidence of the potential usefulness of ANNs in civil infrastructure planning and design. Similar extended databases could be developed to include the remaining bridge elements (e.g. foundations and abutments), other road infrastructure elements (culverts, underpasses and overpasses) as well as motorway bridges constructed with different materials (e.g. steel girders and reinforced-concrete slabs) or construction methods (e.g. incremental launching)and lead to additional cost estimation models utilizing FFANNs.This research also highlights potential future directions for the field of construction software, as the artificial intelligence of this computational paradigm is also suitable for integration in the currently available software for infrastructure design and management.

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Figure 1. Correlation matrix for the variables of the superstructure dataset.

Figure 2. Correlation matrix for the variables of the pier dataset.

Figure 3. Andrews plot for the variables of the superstructure dataset.

Figure 4. Andrews plot for the variable of the pier dataset.

Figure 5. The selected FFANNs' structure.

Figure 6. Convergence diagram for the FFANN estimating the BoQ of superstructure.

Figure 7. Convergence diagram for the FFANN estimating the BoQ of piers.

Figure 8. Performance of the FFANN estimating the BoQ of superstructure.

Figure 9. Performance of the FFANN estimating the BoQ of piers.

Figure 10. Distribution of estimation errors from the FFANN estimating the BoQ of superstructure.

Figure 11. Distribution of estimation errors from the FFANN estimating the BoQ of piers.

Table 1.

Bridge superstructure dataset.

Table 2.

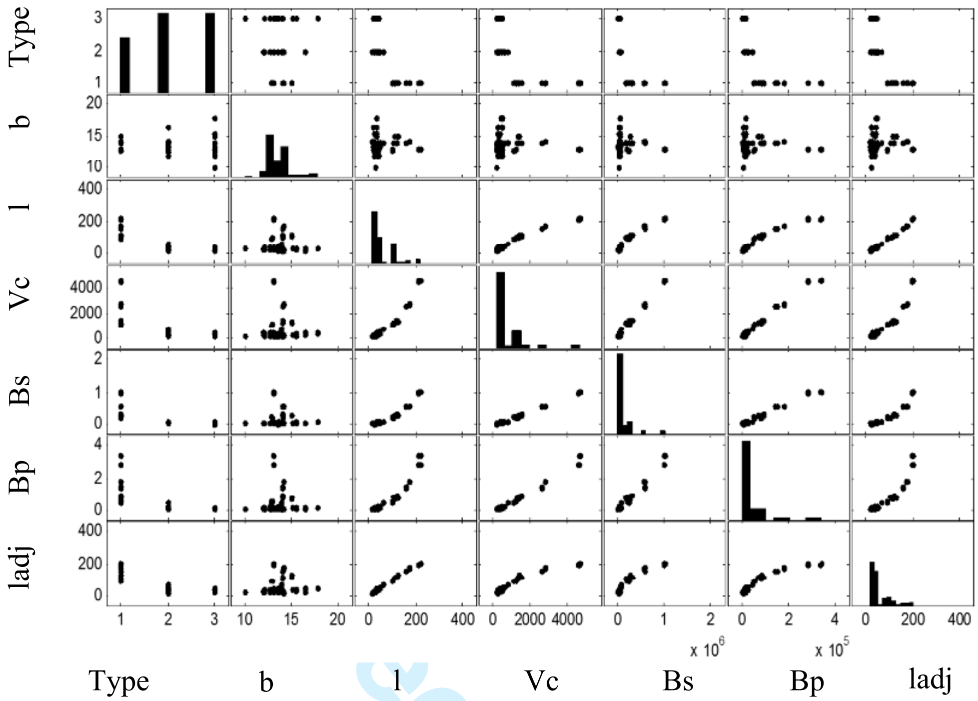
Ranges of height and material quantities in the bridge pier dataset.

Table 3.

Comparative statistics for the superstructure regression model and FFANN.

Table 4.

Comparative statistics for the pier regression model and FFANN .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b
l
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Bs
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ladj
x 10^6
x 10^5
Type
b
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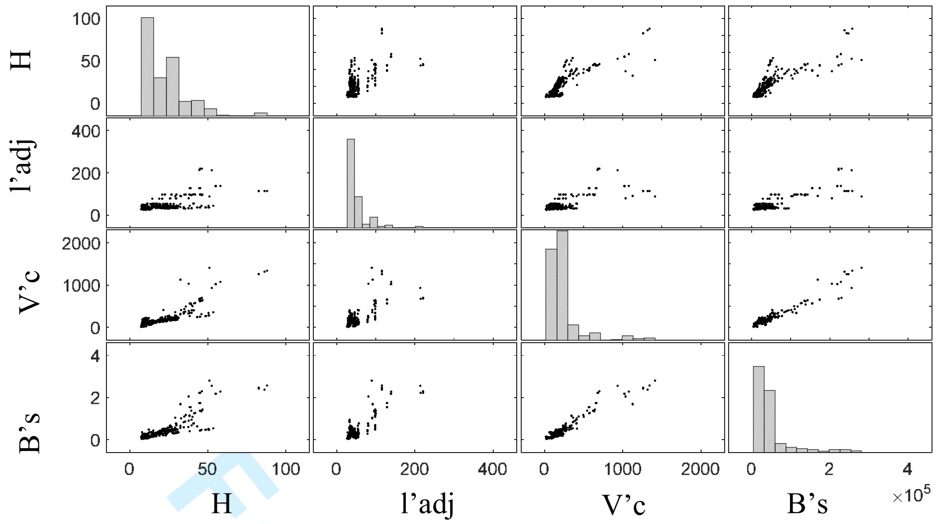
H
l'adj
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100
50
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2000
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H
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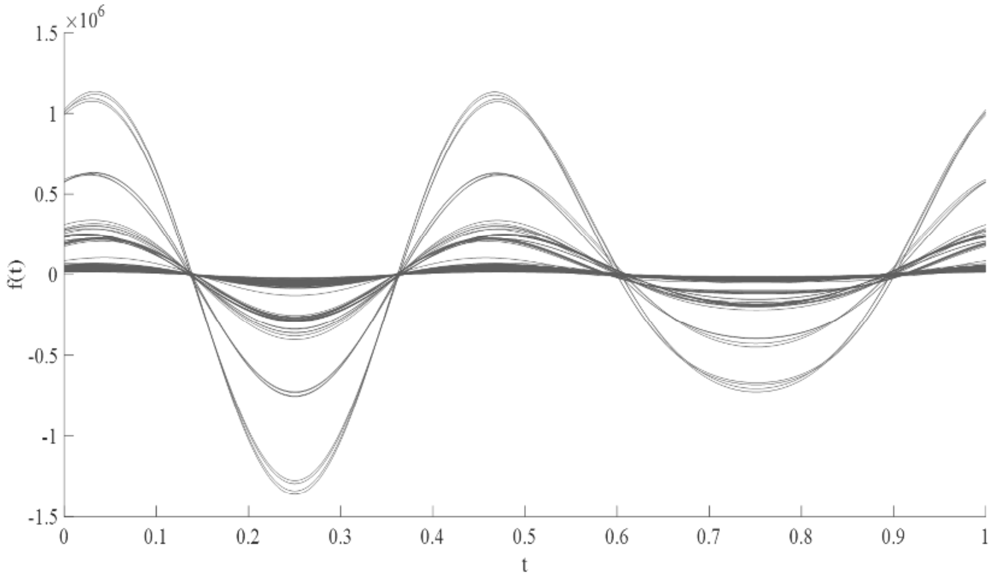

×10^6
1.5
1
0.5
0
-0.5
-1
-1.5
f(t)
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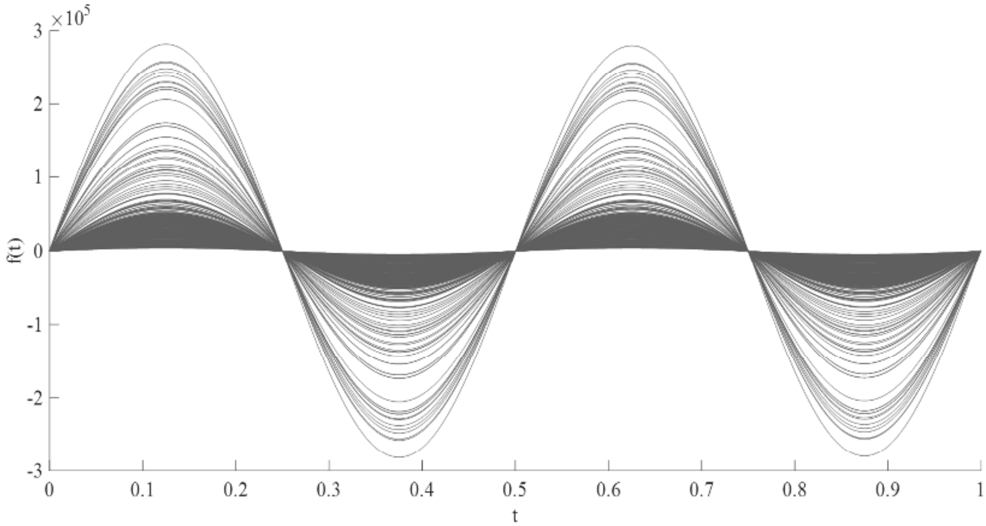
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
t


×10^5
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2
1
0
-1
-2
-3
f(t)
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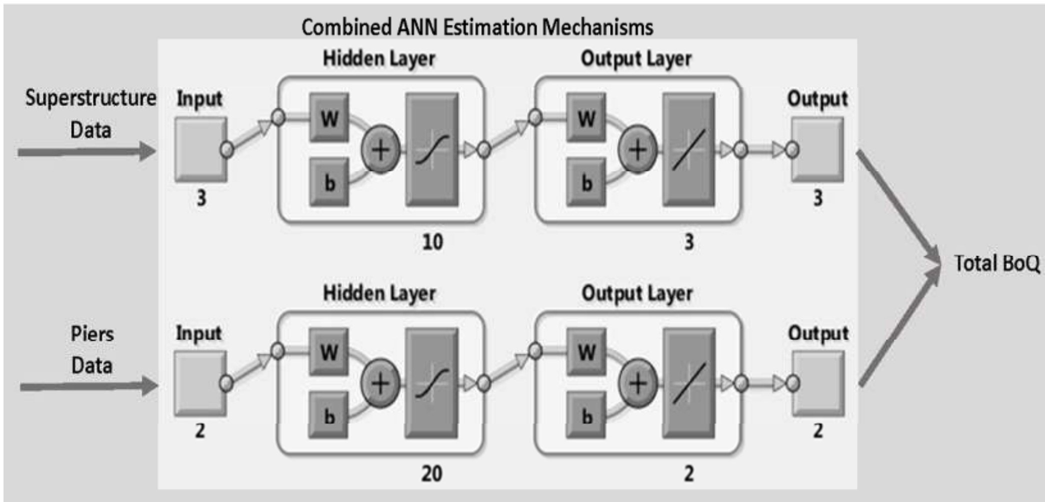
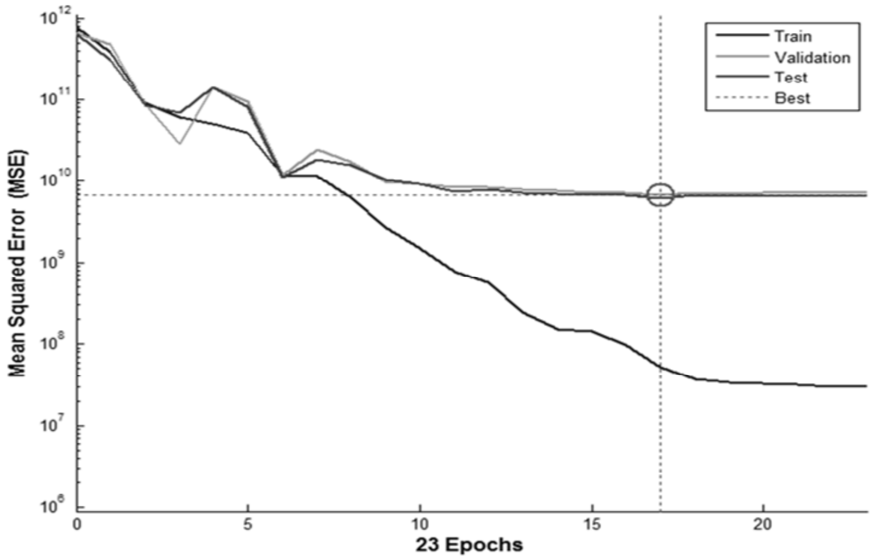
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
t


Combined ANN Estimation Mechanisms
Superstructure Data
Input
3
Hidden Layer
W
b
10
Output Layer
W
b
3
Output
3
Total BoQ
Piers Data
Input
2
Hidden Layer
W
b
20
Output Layer
W
b
2
Output
2


Train
Validation
Test
Best
Mean Squared Error (MSE)
10^{12}
10^{11}
10^{10}
10^{9}
10^{8}
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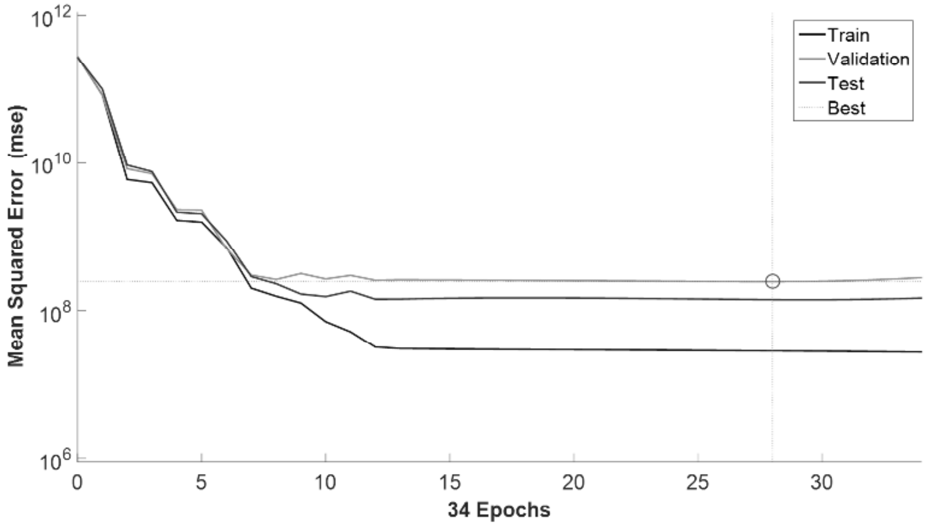
10^{6}
0
5
10
15
20
23 Epochs


Train
Validation
Test
Best
Mean Squared Error (mse)
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10^{6}
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5
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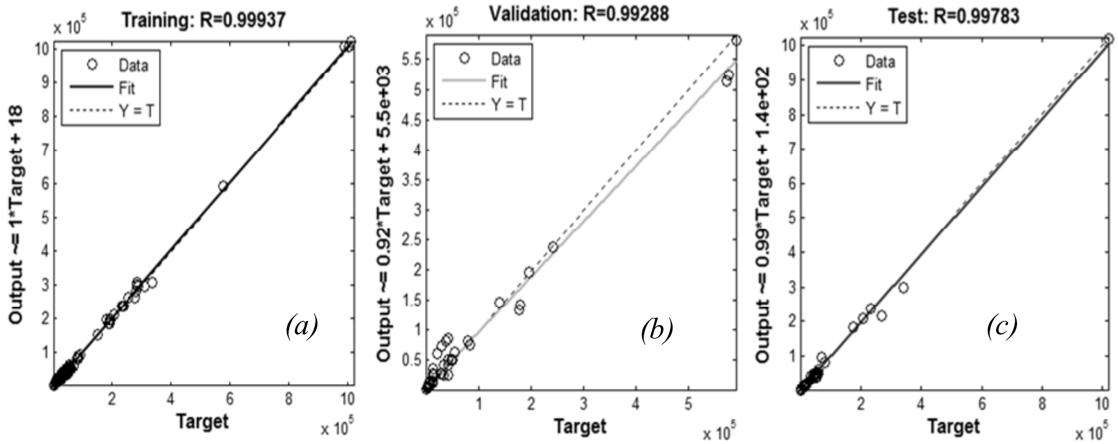
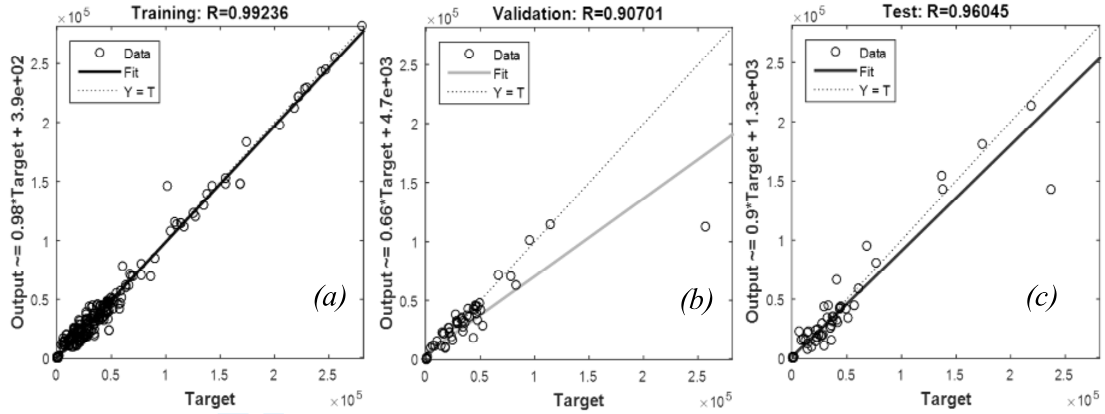
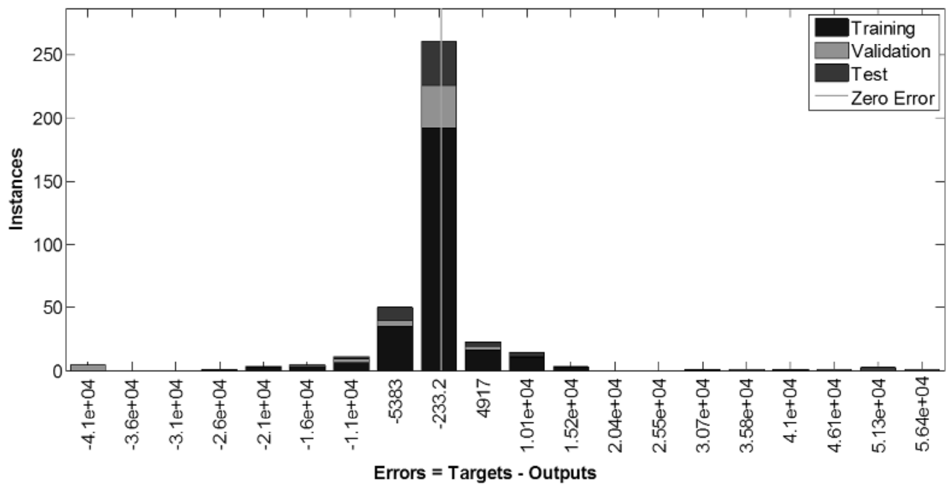
15
20
25
30
34 Epochs



Training: R=0.99937
Output ~= 1*Target + 18
Target
Data
Fit
Y = T
(a)
Validation: R=0.99288
Output ~= 0.92*Target + 5.5e+03
(b)
Test: R=0.99783
Output ~= 0.99*Target + 1.4e+02
(c)


Training: R=0.99236
Output ~= 0.98*Target + 3.9e+02
Data
Fit
Y = T
(a)
Target
Validation: R=0.90701
Output ~= 0.66*Target + 4.7e+03
(b)
Test: R=0.96045
Output ~= 0.9*Target + 1.3e+03
(c)


Training
Validation
Test
Zero Error
Instances
Errors = Targets - Outputs
0
50
100
150
200
250
-4.1e+04
-3.6e+04
-3.1e+04
-2.6e+04
-2.1e+04
-1.6e+04
-1.1e+04
-5383
-233.2
4917
1.01e+04
1.52e+04
2.04e+04
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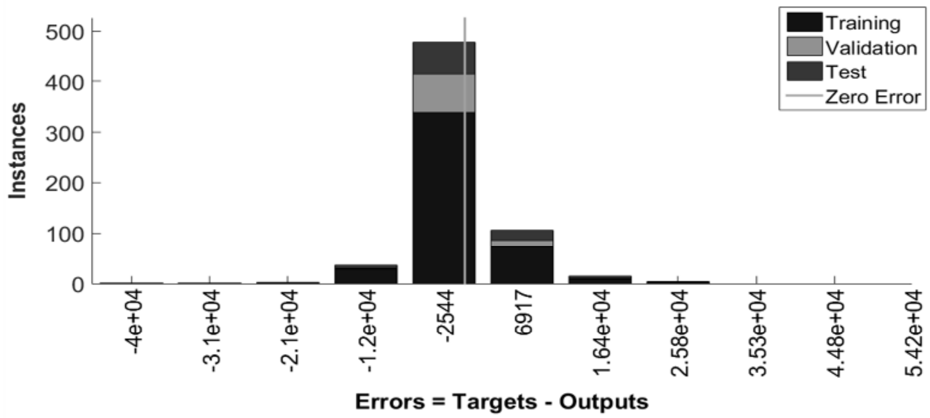
5.13e+04
5.64e+04


Instances
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400
300
200
100
0
Training
Validation
Test
Zero Error
-4e+04
-3.1e+04
-2.1e+04
-1.2e+04
-2544
6917
1.64e+04
2.58e+04
3.53e+04
4.48e+04
5.42e+04
Errors = Targets - Outputs

Construction Method	Number of bridges	Number of spans	Width, b (m)	Length, l (m)	Deck concrete volume, V_c (m^3)	Deck steel weight, B_s (kg)	Deck prestressed steel weight, B_p (kg)
Precast pre-stressed beams and slab	31	47	10.00 – 17.75	19.92 – 43.50	154 - 466	14,716 - 57,851	3,174 – 16,255
Cast-in-situ deck	22	47	11.95 – 16.50	17.0 – 65.0	184 - 801	22,717 – 85,146	4,234 – 42,627
Cantilever construction	15	33	12.78 – 14.20	100.0 – 220.4	1,102 - 4,609	173,396 – 1,021,463	49,131 – 339,493

Pier height H (m)	Pier concrete volume V_c’ (m^3)	Pier steel weight B_s’ (kg)
7.31 – 87.83	16.21 -1,411	4,169 – 280,720

	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
FFANN	0.979	11.48	0.995	13.94	0.981	16.12

	Pier Concrete Volume		Pier Steel weight		Overall	
	R2	MAPE (%)	R2	MAPE (%)	R2	MAPE (%)
Linear Regression	0.724	38	0.849	42	0.895	40
FFANN	0.962	37	0.974	31	0.982	34