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Cost premium prediction of certified green buildings: A neural network approach

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ABSTRACT

Built environment has a substantial impact on the economy, society, and the environment. Along with the increasing environmental consideration of the building impacts, the environmental assessment of buildings has gained substantial importance in the construction industry. In this study, an artificial neural network model is built to predict cost premium of LEED certified green buildings based on LEED categories. To verify the viability of the model, multiple regression analysis is used as a benchmarking model. After validating the prediction power of the neural network model, a global sensitivity analysis is utilized to provide a better understanding of possible relationships between input and output variables of the prediction model. Sustainable Sites and Energy & Atmosphere LEED categories were found to have the highest sensitivity in cost premium prediction. In this study, our goal was to reveal the significant relationships between LEED categories and the cost premium, and offer a decision model that can guide owners to estimate cost premiums based on sought LEED credits.

1. Introduction

The construction industry has a significant impact on the environment, economy, and society. Buildings are one of the biggest contributors to greenhouse gas emissions; for which they are responsible for 38% of all CO_2 emissions [1]. Increased awareness of the enormous ecological footprint of the build environment has substantially increased the importance and popularity of various green building initiatives as a possible solution to remediate the damages incurred on the planet. Many of these initiatives focus on enhancing biodiversity, improving air and water quality, reducing solid waste generation, and conserving natural resources of buildings. These initiatives are changing the construction industry and increasing the share of the green building market significantly [2]. The value the overall green building market is estimated to be $36 billion to $49 billion with an anticipated market value of $96 billion to $140 billion by 2013 [3]. As of September 2009, commercial buildings certified with *The Leadership in Energy and Environmental Design* (LEED) green building rating system in USA reached to the number of 3855 and accounted for 613 million square foot in total [4].

Along with these market values and increasing trend of the green construction practices, the green market has been promoted to bring major improvements through employing green building practices. Primary drivers cited in the literature for green building adoption include minimizing operating and maintenance costs, increasing employee health, productivity, and satisfaction, and improved indoor environment quality [2,5]. For instance, some green buildings were reported to consume 26% less energy and have demonstrated 13% lower maintenance cost when compared to average commercial buildings [6]. These benefits come with a cost, and with lower first-costs that are competitive with conventional buildings, the attractiveness of green buildings will significantly improve [7]. This is especially true, since the construction firms still perceive that green buildings cost significantly more than their conventional counterparts [2]. But, even if the project is finished with a budget comparable to its conventional alternative, certain project costs would still be correlated with specific green strategies. In this paper, we are concerned with identifying the relationship between the cost premium of green buildings and LEED credits utilizing artificial intelligence techniques to aid decision makers in selecting their green strategies.

Few decision models are found in the literature that specifically target green buildings. Castro-Lacouture et al. [8] proposed a mixed integer optimization model that maximizes LEED credits attained while considering design and budget constraints. Wang et al. [9] developed an object-oriented framework that tackles specific problem areas related to green building design optimization. Through their framework, they utilized multi-objective genetic algorithms to explore the trade-off between life-cycle cost and life-cycle environmental impacts in green building design. In another study, Wang et al. [10] developed a methodology to optimize the

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building shapes using genetic algorithms by using life-cycle cost and life-cycle environmental impact as two objective functions for green performance evaluation.

Although no studies have used Artificial Neural Network (ANN) for cost prediction of green buildings, many studies have utilized ANN to predict building costs during pre-design phase of conventional buildings. ANN models were adapted for many reasons; such as learning by example, parallel processing and fast response, tolerance for fault and noisy data, and better classification and prediction capability than traditional statistical methods [11,12]. For instance, Gunaydin and Dogan [13] developed a neural network model for 30 residential building projects to estimate cost per square meters. Kim et al. [14] used three different prediction models; neural network, regression analysis, and case-based reasoning, to predict the cost of 530 buildings in Korea. In another study, Kim et al. [15] provided hybrid models of neural networks and genetic algorithms for preliminary costs estimation of 498 residential buildings. Emsley et al. [16] developed an ANN model to predict building cost by utilizing project strategic variables, site related variables, and design related variables. Attalla and Hegazy [17] used ANN modeling and statistical analysis for determining the cost deviation of the reconstruction project. Apart from ANN, some studies have utilized multiple regression analysis for cost prediction. For instance, Stoy et al. [18] used regression analysis for determination of the cost drivers of the 70 residential building properties. Although there have been many studies predicting building costs by using ANN modeling, none have utilized green building ratings in cost prediction; a research gap that is aimed to be filled by this study.

The purpose of this study is to predict the cost premium of green buildings based on LEED categories. To reach this goal, a relationship between LEED categories and cost premium is investigated. This is accomplished by ANN modeling and verified by traditional statistical approaches. Sensitivity analysis is then carried on to identify critical LEED categories and offer an intelligent tool for decision makers to aid their decisions during the pre-design stage. The rest of the paper is organized as follows. First, a review of green building systems is conducted. Next, green building associated cost studies are reviewed. Next, the ANN design, data collection and preparation, and ANN results are presented. Subsequently, a regression model is conducted and the ANN results are compared with the regression results. Next, sensitivity analysis of the ANN model is provided to assess the effect of input variables on the output variable. Finally, findings are summarized and future work is pointed out.

2. Green building rating systems and cost premiums

Building assessment tools have emerged as an important strategy to mitigate the potential negative impacts of the built environment [19]. The primary purpose of these building assessment tools is to evaluate the environmental characteristics of the buildings by using a set of standards that aim to achieve more environmentally friendly building performance [19]. Many of these building environmental assessments tools have emerged throughout of the world [20,21]. For instance, *BRE Environmental Assessment Method* (BREEM) has been recognized widely in the United Kingdom building industry. *Building Environment Performance Assessment Criteria* (BEPAC) assessment tool has emerged as a voluntary and comprehensive building assessment tool in Canada. Also, through an international collaborative, *The Green Building Challenge* developed a comprehensive method for environmental performance assessment of the buildings. Resource consumption, environmental loading, indoor environmental quality, and service quality are included as major assessment criteria in their assessment tool; GB-Tool software.

In addition to earlier mentioned building rating systems, LEED and Green Globes are considered as the most important assessment tools in the United States [22]. Green Globes, developed by Green Building Initiative, assesses the performance of the buildings with respect to energy, water, resources, emissions, and environmental management. The tool is used widely for new constructions, major renovations, multi-residential structures, and institutional buildings. Yet, the most widely used assessment tool is the LEED rating system that has been developed by the U.S. Green Building Council. LEED includes five major areas of sustainability; sustainable sites (SS), water efficiency (WE), energy and atmosphere (EA), materials and resources (MR), and indoor environmental quality (IEQ). Apart from these categories, it also includes two other categories; innovations in design (ID) and regional priority (RP). LEED can be applied to new constructions and major renovations, existing buildings, commercial interiors, core and shell, schools, retails, healthcare, homes, and neighborhood development.

Several studies have been conducted regarding the cost premium of green buildings. In 2007, Davis Langdon analyzed the Australian Green Star rating system by comparing the cost of the green and non-green buildings to estimate the cost premium of the green rating system on construction costs [23]. The study concluded that a 5-Star green building had a 3–5% premium with respect to a conventional counterpart. In another study, one office building has been assessed for the cost premium study of the BREAM rating and the study revealed that a 6% premium was explained by the sustainable design features for the building [24]. Fowler and Rauch [6] assessed the cost premium of LEED certified buildings and concluded that the cost premiums of the building projects ranged from 1% to 8% with respect to the level of LEED certification desired. Kats [25] conducted a study on 30 green school projects that were built in 10 different states between 2001 and 2006. On the basis of the study results, it was found that green school design provided 1–2% additional cost when compared with a conventional design [25]. In another study, an in-depth analysis of LEED-NC certified buildings revealed that high performance sustainable building projects required higher capital investment and the required capital was proportional to the intended building overall LEED-NC rating [26]. According to this report, the cost premium of the green project is likely to follow the increasing cost trend with respect to the higher levels of LEED certification. On the other hand, Nilson [27] estimated LEED Gold certification to be 0.82% of total construction costs for a New York office building. Also, Stegall [28] estimated a premium of 1–2.8% of the total project cost for a new house that aims to achieve LEED Silver certification. In a study conducted by Packard Foundation [29], they estimated that a premium of 0.9%, 1.3%, 1.5%, or 2.1% of total hard costs is required to achieve LEED Certified, Silver, Gold, or Platinum for an office building, respectively. As can be seen, although the estimated cost premium percentages were different, many studies have concluded that green certification is likely to result in a premium. Also, green building certification related premium costs were expected to change according to the type of green certification, the desired level of green rating, and the nature of the buildings, and would likely increase with higher levels of certification.

3. Data collection

74 LEED-NC version 2.2 certified building cases were used for ANN development. The data were gathered from previous case studies published online (see Table 1). Data extracted for each building consisted of construction year, building type, city, and actual construction cost. Additionally, scores achieved from LEED categories; SS, WE, EA, MR, IEQ, and ID were collected. RP was not available in LEED version 2.2, and was not included. Also, buildings

Table 1
The data description of the 74 LEED-NC certified buildings in USA.

Description	Mean	Minimum	Maximum	Std. deviation	Output/input
SS point	8.12	3	12	2.25	Input
WE point	3.21	1	5	1.21	Input
EA point	6.82	1	17	4.37	Input
MR point	5.47	1	11	1.58	Input
EQ point	9.08	4	14	2.44	Input
ID point	4.12	1	5	1.09	Input
Building grade	2.37	1	5	1.00	Input
Year built	–	2000	2008	–	–
Premium cost ($/sf)	4.98	0.31	18.33	4.06	Output

were graded from 1− 5 to account for elements related to the economic scale of the buildings. All costs were normalized according to year and location by using the spatial and temporal cost indexes suggested by RS Means [30]. The normalization was accomplished using the following equations:

$$C_x = \frac{I_x}{I_a} * C_a \tag{1}$$

$$C_{2009} = \frac{I_{2009}}{I_a} * C_y \tag{2}$$

where C_x is the building cost in Columbus, OH, C_a is the cost in other cities, I_x is the city index for Columbus, OH, and I_a is the city index of city a. C_{2009} is the cost equivalent in year 2009, C_y is the cost in year y, I_{2009} is the time index based on January 1, 2009, and I_y is the time index for year y. After obtaining the normalized cost values for each building, actual building costs were used to calculate cost premiums of green buildings. The cost premium assumptions were based on the study that was conducted by Kats [26]. This study was selected for cost premium calculation because of the larger number of cases that it included as compared to other similar studies. In his study, Kats determined the premium cost to achieve different levels of LEED certification; such as platinum, gold, silver, and certified (see Table 2). Linear interpolation was used to calculate LEED Gold certification cost premium, since Kats study had limited cases to correctly predict its premium cost. The result of the linear interpolation predicted at 4.41% cost premium for LEED Gold certification. This strategy was chosen to provide consistency between more rigorous certification level and cost premium.

4. ANN model development and results

A total of seven variables were used as inputs in the modeling process as shown in Table 1. Premium cost was entered as an output variable for the ANN model. 80% of the building cases were used for training and 20% were used for testing the neural network. The training cases were randomly selected and were used to train the network and compute the weights of the inputs. The test cases were used to measure the performance of the selected ANN model. Several network structures with different number of nodes in the hidden layer were trained and tested. This strategy was chosen to find the best performing network architecture among different models. Utilizing STATISTICA®, 1000 ANN models were developed using feed-forward back-propagation multilayer perceptron and radial basis function architectures. Logistic sigmoid, hyperbolic tangent, negative exponential, and identity activation functions were used for both hidden and output neurons. Based on running several neural network models, the best performing neural network model was chosen (see Table 3). The chosen neural network model is developed using feed-forward back-propagation multilayer perceptron architecture, and consists of an input layer with seven input variables, one hidden layer with five neurons, and an output layer with one output variable (see Fig. 1). Hyperbolic tangent activation function was used for the neurons in the hidden layer and logistic sigmoid function was used for the output neuron. Accordingly, each neuron's output was calculated using Eq. (3) while the output of the output neuron was calculated using Eq. (4).

Table 2
Cost premiums for LEED certification levels.

Certification level	Certified	Silver	Gold	Platinum
Cost premium (%)	0.66	2.11	4.41[a]	6.5

[a] Gold certification had a 1.82% cost premium in Kats [26].

Table 3
The properties of the best performing ANN architecture.

Model architecture	Hidden activation	Output activation	Training MSE	Testing MSE	R^2-train	R^2-test
MLP 7-5-1	tan *h*	Logistic	0.073	0.156	0.98	0.96

$$f(X_j) = \tan h\left(\sum_{i=1}^{n} X_i w_{i,j} + \theta_{i,j}\right) \tag{3}$$

$$f(X_k) = \frac{1}{1 + e^{\sum_{j=1}^{n} X_j w_{j,k} - \theta_{j,k}}} \tag{4}$$

where X_i is the input variable value, $w_{i,j}$ is the connection weight between the input neuron i and hidden neuron j, $w_{j,k}$ is the connection weight between the hidden neuron j and output neuron k, $\theta_{i,j}$ and $\theta_{j,k}$ are the bias terms for the respective neurons, and i, j, and k are the number of neurons for the input, hidden, and output layers, respectively. Once the network is built, the ANN model is trained by exemplars that include individual set of input/output data. As ANN models are a set of processing elements and connections with adjustable strengths, the learning is accomplished by adjusting the connection weights between neurons iteratively. Current neural network model utilized supervised learning that compared the ANN output with target output, which was an actual value. On the basis of this supervised learning algorithm, the mean square error between the target output and the model output is minimized overall the training data by adjusting the connection weights within the model according to the equation:

$$\text{MSE} = \frac{\sum\left(Y_i - \widehat{Y}_i\right)^2}{n} \tag{5}$$

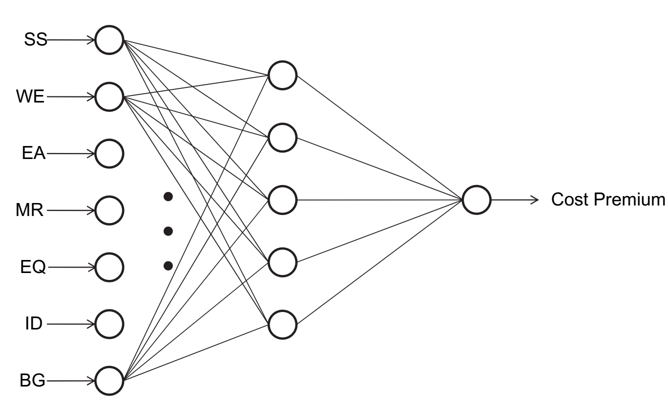

Fig 1. Architecture for the best performing ANN model.

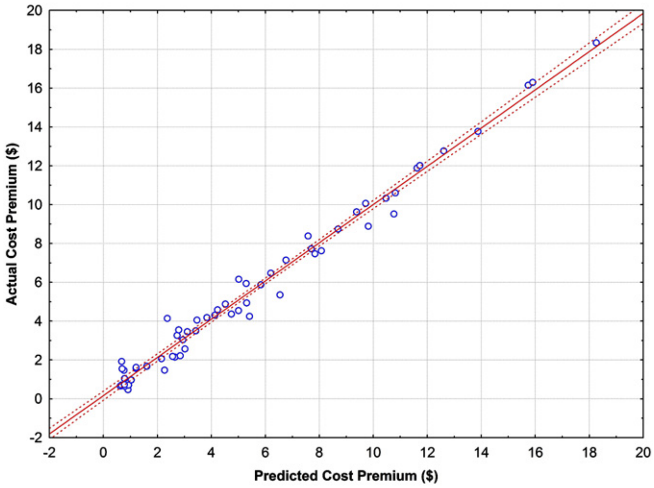

Fig. 2. Predicted versus actual cost premiums for training data.

where Y_i is the observed value, $\widehat{Y}_i$ is predicted value, $\overline{Y}_i$ is mean value, and i an integer from 1 to n. The selected feed-forward multilayer perceptron model used back-propagation as a learning rule and the training stopped when the error reached the minimum value it can attain. The final weights are stored in the weight matrix. The network with the final weights is then tested by the data set which was not used in the training process to validate the prediction power of the network model.

Once the network has been trained and tested, statistical tools were used to describe the prediction power of the developed model. Fig. 2 depicts actual vs. predicted cost premiums for the training data. According the neural network model, correlation coefficient, r, was 0.992 for training data, the corresponding coefficient of determination, R^2, was 0.983. The coefficient of determination is much higher than 0.7, a generally accepted R^2 value, and shows that the prediction rate is significantly high for the developed ANN model. Fig. 3 shows the actual vs. prediction of the testing data set. According the neural network model, correlation coefficient, r, was 0.981 for test data and the corresponding coefficient of determination, R^2, was 0.962. Again, the coefficient of determination shows that the prediction rate is significantly high for testing data. Although the data set was relatively small, the figures show a very close approximation between the actual cost premium values and the neural network output.

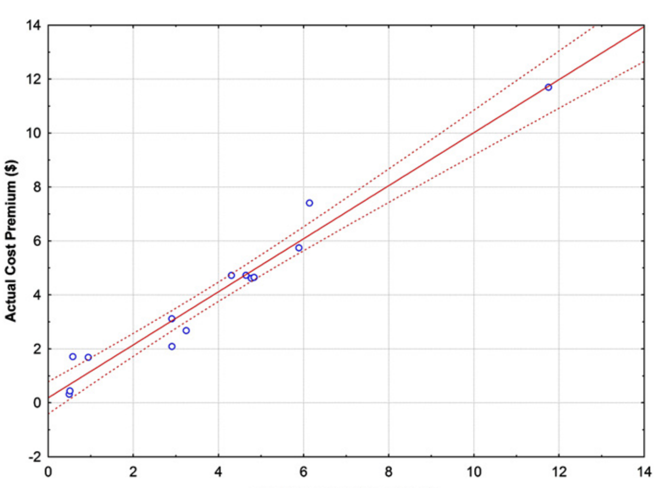

Fig. 3. Predicted versus actual cost premiums for testing data.

Table 4
Regression model results for training data.

Input variables	B	SE coeff	T value	Significance
Constant	−16.67	1.6741	−9.9617	0.000
SS	0.6561	0.1260	5.2058	0.000
WE	0.5351	0.2307	2.3190	0.024
EA	0.3226	0.0668	4.8291	0.000
MR	0.3714	0.1804	2.0581	0.045
IEQ	0.2404	0.1195	2.0121	0.049
ID	0.5452	0.2356	2.3141	0.025
BG	2.5380	0.2637	9.6244	0.000

5. Benchmarking of the best ANN model with traditional statistical approach

After obtaining the prediction results of the neural network model for both training and testing data, these results were compared with regression model for validation of the findings. This step was conducted to compare the neural network model results with the linear regression model and to assess whether the neural network model provided more accurate prediction result for the LEED cost premium. With this approach, the predictive power of the neural network was compared to a well-established prediction technique; multiple regression analysis [31].

First, multiple regression analysis was conducted on the training data set of the neural network model to test the effect of input variables on the dependent variable; LEED cost premium. Multiple regression is used to derive a linear equation that would best describe the relationship between several independent variables and a dependent scale variable [32]. Although some LEED categories include related components, the categories were assumed to be independent statistically according to correlation analysis results. The properties of the regression model for LEED cost premium prediction are summarized in Table 4. The linear regression model was significant as a prediction model ($p < 0.05$). Coefficient of determination, R^2, was found to be 0.815. The coefficient of correlation, r, was calculated as 0.901 and showed that there was a moderate linear relationship between dependent and independent variables in the regression model. All input variables, building grade (BG), SS, WE, EA, MR, IEQ, and ID points, were found to contribute significantly to the prediction of LEED cost premium ($p < 0.05$). Figs. 4 and 5 depict actual vs. predicted cost premiums for the training and testing data, respectively. According

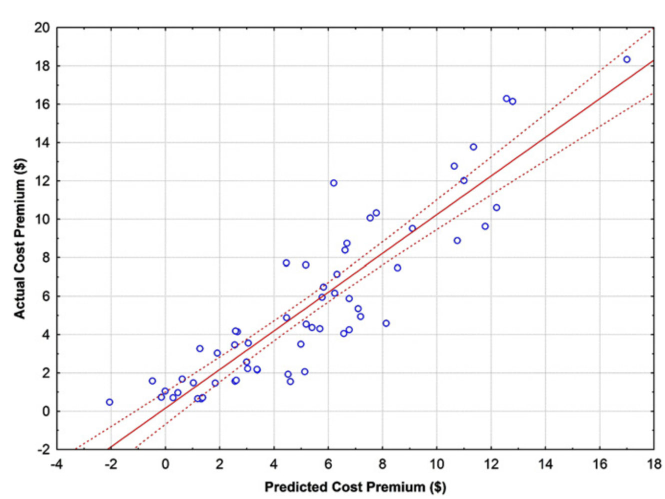

Fig. 4. Regression model-based predicted versus actual cost premiums for training data.

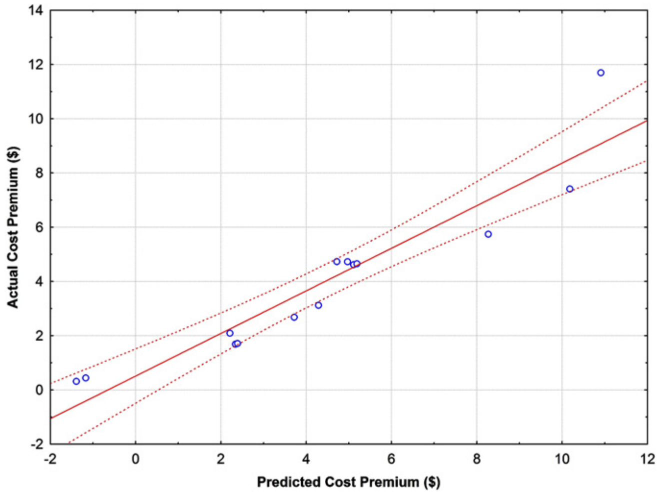

Fig. 5. Regression model-based predicted versus actual cost premiums for testing.

to the multiple regression model, correlation coefficient, r, was 0.941 for testing data. Coefficients of determination (R^2) for training and testing data were 0.811 and 0.885, respectively.

Comparison between the two estimation models, ANN and multiple regression, was based on three factors: coefficient of correlation, r, coefficient of determination, R^2, and the value of standard error of estimates, $S(y,x)$. The correlation coefficient expressed the strength of the linear relationship between predicted and actual LEED cost premiums. The coefficient of determination expressed the proportion of the total variation in predicted value explained by the regression line. Estimation model with lower variation between actual and predicted values would have a higher value of coefficient of determination. The coefficient of determination is calculated using the following equation:

$$R^2 = 1 - \frac{\sum\left(Y_i - \widehat{Y}_i\right)^2}{\sum\left(Y_i - \overline{Y}_i\right)^2} \tag{6}$$

where Y_i is the observed value, $\widehat{Y}_i$ is predicted value, $\overline{Y}_i$ is mean value, and i an integer from 1 to n. In the current study, ANN model has provided higher r and R^2 values for both training and testing data when compared with the regression model. These values indicated that ANN prediction results showed higher correlation with actual values when compared with regression model.

In addition, the standard error of estimate was used as another comparison factor for both prediction models to evaluate both neural network and regression model in respect of their prediction values. It was used to measure the variability in the estimated regression line. The standard error of estimate was calculated by the following equation:

$$S_{y,x} = \sqrt{\frac{\sum\left(Y_i - \widehat{Y}_i\right)^2}{n-2}} \tag{7}$$

where Y_i is the observed value, $\widehat{Y}_i$ is predicted value, n is the number of the data set, and i is an integer from 1 to n. For both training and testing data set, the neural network model has provided significantly lower standard error of estimate values, 0.574 and 0.614, for training and testing results, respectively. These results indicate that ANN model had less deviation between the predicted and the actual values. Moreover, Figs. 4 and 5 indicated that the regression model showed wider confidence interval in the scatter plots when compared to the ANN model. This result

Table 5
Comparison between ANN and regression estimation models.

Comparison factor	ANN-training	ANN-testing	Regression-training	Regression-testing
r	0.9917	0.9807	0.9014	0.9418
R^2	0.9835	0.9617	0.8125	0.8869
$S_{y,x}$	0.5743	0.6139	1.7242	1.2763

was due to the high $S_{y,x}$ that caused a wider confidence interval because of the higher variability between the actual and predicted values. On the other hand, the data clustered more tightly around the line in ANN prediction due to the high correlation between actual and predicted LEED cost premiums and less variation on the estimated regression line. Table 5 summarizes the comparisons that were made between ANN and multiple regression. Based on these results, it was validated that neural network model had higher prediction rates and fitted better for both training and testing data set.

6. Sensitivity analysis and knowledge extraction from ANN

Once the ANN model was built, tested, and verified, sensitivity analysis was conducted to evaluate the influence of each independent variable to LEED cost premium. Sensitivity analysis provides vital insights to the usefulness of individual input variables. Through sensitivity analysis, variables that do not have significant effect could be taken out of the neural network model and key variables could be identified. In this study, global sensitivity analysis of the ANN model was conducted to provide useful explanatory insights regarding the relative contribution of the input parameters on the prediction model. Sensitivity analysis was conducted by estimating the relative contribution of each variable. This analysis is accomplished by measuring the deterioration in network error when each variable is removed [33]. The root mean squared error produced by the network without the variable is divided by the root mean squared error of the original network to produce a ratio that indicates the importance of the variable removed to the network. Consequently, the sensitivity ratio would be greater as the importance of the variable to the network increases. Based on the sensitivity analysis results which are presented in Fig. 6, SS, EA, and BG have shown the highest sensitivity among the independent input variables. SS, EA, and BG were also found to be the most significant input variables in the regression model.

When looked more closely to the efforts required to achieve SS points, high sensitivity of SS was expected. For instance, to achieve points in SS category, minimizing pollution from construction

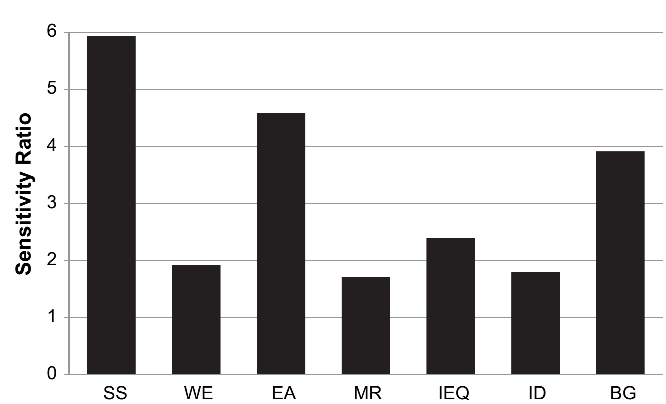

Fig. 6. Sensitivity analysis results of input variables for the best ANN model.

activities by soil erosion or water sedimentation is required. This requirement might create more mobilization work than conventional buildings. Secondly, high community connectivity which gives priority to urban areas for site selection may result in higher construction costs when compared to projects in less dense areas. Furthermore, proximity to public transportation credit may require acquiring land closer to mass transit, which in turn might increase the cost of the project. Other SS possible credits, such as high-albedo roof coverings or vegetated roofs for preventing heat island effect need innovative design and materials that may add cost to the project.

In addition to SS category, high sensitivity magnitude of EA points was not surprising, as well. Required commissioning of energy systems, credits related to implementing new technologies for heating, ventilating, air conditioning, refrigeration systems, lighting, and day lighting controls, domestic hot water systems, and renewable energy systems can all be considered as potential reasons of high sensitivity magnitude of EA points for the LEED cost premium.

Additionally, current study has graded the buildings with respect of their function and nature. The high sensitivity magnitude of the building grade indicates that LEED cost premiums are significantly affected by the type and nature of buildings. Every building is considered unique and large variations in the unit area cost of the green design can be explained by the differences between the features of the buildings [34,35]. As a result, high significance level of BG variable was consistent with the outcome of the earlier studies. Consequently, the sensitivity analysis results were vital for illuminating the block-box structure of the neural network. The sensitivity results can also be used by practitioners to guide them through the possible higher cost impacts of SS and EA LEED categories with respect to other categories.

7. Conclusion and further study

In the current study, LEED cost premium prediction models were built based on ANN and regression analysis. ANN and multiple regression models were compared to each other with respect to their predictive power, utilizing statistical comparison factors liker, R^2, and standard error of estimate. On the basis of comparison factors, ANN model provided more accurate prediction results with higher r and R^2 values, and lower standard error of estimate for fittings of the actual versus predicted values. After validating the predictive power of the neural networks, global sensitivity analysis was accomplished to provide a clear understanding of the possible relationships between input and output variables of the prediction model. According to the knowledge extraction method of sensitivity analysis, the independent input variables SS, EA, and BG showed highest sensitivity for the prediction model.

Although the limited amount of cases used for developing the ANN model was limited, the results are encouraging for further research of expanded data sets. Also, the unavailability of construction duration of some of the projects and soft costs such LEED registration, commissioning, or consulting may have affected the accuracy of model predictions. With increased depth and breadth of information, the accuracy of the prediction model may improve significantly and trigger the up-coming cost studies related to green certification. Another limitation is related to the unavailability of a comprehensive database that analyzes cost premiums of buildings. In the absence of this database, albeit limited, Kats' study was used. By utilizing studies that have more comprehensive database, it might possible to have more accurate predictions for other buildings. Planned future work includes utilization of expanded data sets and a closer study of the interdependence of LEED points and its effect in prediction.

References

[1] Retrieved from: EIA, Energy Information Administration. Annual energy outlook. US Department of Energy http://www.eia.doe.gov/oiaf/aeo/index.html; 2008 [accessed 1.10.10].
[2] Ahn Y, Pearce A. Green construction: contractor experiences, expectations, and perceptions. Journal of Green Building 2007;2:106–22.
[3] McGraw Hill Construction. Green outlook 2009: trends driving change; 2009.
[4] USGBC. US Green Building Council; 2010.
[5] Lapinski A, Horman M, Riley D. Lean processes for sustainable project delivery. Journal of Construction Engineering and Management 2006;132:1083.
[6] Fowler KM, Rauch EM. Assessing green building performance: a post occupancy evaluation of 12 GSA buildings. Pacific Northwest National Laboratory Report number PNNL-17393; 2008.
[7] Horman M, Riley D, Lapinski A, Korkmaz S, Pulaski M, Magent C, et al. Delivering green buildings: process improvements for sustainable construction. Journal of Green Building 2006;1:123–40.
[8] Castro-Lacouture D, Sefair J, Flórez L, Medaglia A. Optimization model for the selection of materials using a LEED-based green building rating system in Colombia. Building and Environment 2009;44:1162–70.
[9] Wang W, Zmeureanu R, Rivard H. Applying multi-objective genetic algorithms in green building design optimization. Building and Environment 2005;40: 1512–25.
[10] Wang W, Rivard H, Zmeureanu R. Floor shape optimization for green building design. Advanced Engineering Informatics 2006;20:363–78.
[11] Moselhi O, Hegazy T, Fazio P. Neural networks as tools in construction. Journal of Construction Engineering and Management 1991;117:606–25.
[12] Boussabaine A. The use of artificial neural networks in construction management: a review. Construction Management and Economics 1996;14: 427–36.
[13] Gunaydin HM, Dogan SZ. A neural network approach for early cost estimation of structural systems of buildings. International Journal of Project Management 2004;22:595–602.
[14] Kim GH, An SH, Kang KI. Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning. Building and Environment 2004;39:1235–42.
[15] Kim GH, Yoon HE, An SH, Cho HH, Kang KI. Neural network model incorporating a genetic algorithm in estimating construction costs. Building and Environment 2004;39:1333–40.
[16] Emsley M, Lowe D, Duff A, Harding A, Hickson A. Data modelling and the application of a neural network approach to the prediction of total construction costs. Construction Management and Economics 2002;20: 465–72.
[17] Attalla M, Hegazy T. Predicting cost deviation in reconstruction projects: artificial neural networks versus regression. Journal of Construction Engineering and Management 2003;129:405–11.
[18] Stoy C, Pollalis S, Schalcher HR. Drivers for cost estimating in early design: case study of residential construction. Journal of Construction Engineering and Management 2008;134:32–9.
[19] Cole RJ. Emerging trends in building environmental assessment methods. Building Research and Information 1998;26:3–16.
[20] Seo S, Tucker S, Ambrose M, Mitchell P, Wang CH. Technical evaluation of environmental assessment rating tools: research and development corporation. Project no. PN05.1019; 2006.
[21] Larsson NK. Development of a building performance rating and labeling system in Canada. Building Research and Information 1999;27:332–41.
[22] Haselbach L. The engineering guide to LEED – new construction: sustainable construction for engineers. McGraw-Hill Professional; 2008.
[23] Davis Langdon. The cost and benefit of achieving green buildings. Davis Langdon; 2007.
[24] Rawlinson S. Sustainability offices. Building Magazine. Davis Langdon; 2007.
[25] Kats G. Greening America's schools: costs and benefits. Capital E Research Report; 2006.
[26] Kats G. The costs and financial benefits of green buildings. A Report to California's Sustainable Building Task Force; 2003.
[27] Nilson ML. Quantifying the cost impacts of LEED-NC Gold construction in New York city. Senior Honors Thesis, Lafayette College, Easton, PA; 2005.
[28] Stegall N. Cost implications of LEED Silver certification for new house residence hall at Carnegie Mellon University: Senior Honors Research Project. Pittsburgh, PA: Carnegie Mellon University; 2004.
[29] Packard Foundation. Building for sustainability report: six scenarios for the David and Lucile Packard foundation Los Altos project. Los Altos, CA: The David and Lucile Packard Foundation; 2002.
[30] RS Means. Building construction cost data. 62nd ed. ed: RS Means Company; 2009.
[31] Adya M, Collopy F. How effective are neural networks at forecasting and prediction? A review and evaluation. Journal of Forecasting 1998;17:481–95.
[32] Sheskin D. Handbook of parametric and nonparametric statistical procedures. CRC Press; 2007.
[33] StatSoft I. Electronic statistics textbook. Tulsa, OK: StatSoft; 2010.
[34] GSA. GSA LEED cost study: final report. Rep. no GS-11P-99-MAD-0565. Washington, D.C: U.S. General Services Administration; 2004.
[35] Matthiessen L, Morris P. Costing green: a comprehensive cost database and budgeting methodology. Davis Langdon; July, 2004.