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PREDICTING FIRE RESISTANCE RATINGS OF TIMBER STRUCTURES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

This paper describes a method to predict the fire resistance ratings of the wooden floor assemblies using Artificial Neural Networks. Experimental data collected from the previously published reports were used to train, validate, and test the proposed ANN model. A series of model configurations were examined using different popular training algorithms to obtain the optimal structure for the model. It is shown that the proposed ANN model can successfully predict the fire resistance ratings of the wooden floor assemblies from the input variables with an average absolute error of four percent. Besides, the sensitivity analysis was conducted to explore the effects of the separate input parameter on the output. Results from analysis revealed that the fire resistance ratings are sensitive to the change of Applied Load (ALD) and the number of the Ceiling Finish Layer (CFL) input variables. On the other hand, the outputs are less sensitive to a variation of the Joist Type (JTY) parameter.

Keywords: artificial neural networks; fire resistance; wooden floor assembly; sensitivity analysis.

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1. Introduction

The ability to maintain the structural integrity of wood structures under fire exposure has been well established. Modern buildings with exposed wood structural members are popular since they have a pleasing appearance, easy to use, and offer necessary fire resistance [1]. Historically, the height of the conventional wood buildings in the United States was restricted under four stories due to structural barriers and fire concern [2]. Thanks to many advanced mechanical properties, the engineered timber products such as Cross-Laminated Timber and Structural Composite Lumber can be used as primary structural materials for the construction of medium-height tall buildings [3]. Intensive research has been conducted to enable engineered wood for high-rise buildings in both structural aspects [4–9], as well as fire characteristics [1, 2, 10, 11].

Recent research revealed that the fire resistance capacity of the engineered timber, including Glued Laminated Timber and Cross-Laminated Timber, have been proven to outperform that of the lightwood frames and even steel and concrete components [2]. Fire performance tests for mass timber had been carried out in Europe [12–15] and recently, in North America [16–18]. The tests provided a reliable source to obtain the required minimum fire resistance ratings for structural members. ASTM

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E119 Standard Test Methods for Fire Tests of Building Construction and Materials [19] or 2015 International Building Code [20] provides the minimum fire resistance requirements for building systems using prescriptive and performance-related provisions.

Both tested assemblies and methods for calculating fire resistance are provided in the 2015 International Building Codes. A Component Additive Method is applied to the building codes to determine the fire resistance ratings of assemblies. The method was developed by the National Research Council of Canada in the 1960s. It was a result of reviewing the Ten Rules of Fire Endurance Rating [21] for the multiple standard fire test reports. A set of rules in the document offers a method to account for the contributions of individual layers to the fire resistance ratings of the assembly. Detailed information of these rules is listed in Appendix A.

The fire endurance ratings of a floor can be estimated either by summing the performance time contribution of (i) the fire-exposed membrane, (ii) framing members, (iii) and any additional protection parts, or performing the standard fire tests. For the first method, as stated in the 2015 International Building Code [20] "The fire resistance rating of a wood frame assembly is equal to the sum of the time assigned to the membrane on the fire-exposed side, the time assigned to the framing members and the time assigned for additional contribution by other protective measures such as insulation. The membrane on the unexposed side shall not be included in determining the fire resistance of the assembly."

Performance time was assigned for each component of the floor assemblies. Table 722.6.2(1) and Table 722.6.2(2) in the 2015 International Building Code presents the time assigned for wallboard membranes and framing members. Table 1 shows the time assigned for some popular types of finish materials. The time assigned for other members such as wood studs and joists were calculated from ASTM E119 fire resistance tests. It worth noting that the fire testing for floor assemblies is normally performed with fire exposure from below, thus the protective membranes on the exposure side would require floor assemblies. In addition, the assigned time obtains from membranes for unexposed sides should stand at least 15 minutes.

Table 1. Time assigned to wall board membranes [20], 1 inch = 2.54 cm

Description of finish	Time (minutes)
3/8-inch wood structural panel bonded with exterior glue	5
15/32-inch wood structural panel bonded with exterior glue	10
19/32-inch wood structural panel bonded with exterior glue	15
3/8-inch gypsum wallboard	10
1/2-inch gypsum wallboard	15
5/8-inch gypsum wallboard	30
1/2-inch Type X gypsum wallboard	25
5/8-inch Type X gypsum wallboard	40
Double 3/8-inch gypsum wallboard	25
1/2-inch + 3/8-inch gypsum wallboard	35
Double 1/2-inch gypsum wallboard	40

An alternative method to estimate the fire resistance ratings of the floor assemblies is to apply Artificial Neural Networks (ANN). The ANN technique can take advantage of the available experimental data and analytical ability of the Artificial Intelligence. To perform the ANN method, numerical or experimental data collected from the previous publications are used to develop, train, validate, and test ANN models. During these processes, the ANN models establish the non-linear relationship between the inputs and the outputs; as a result, the successful ANN models are able to predict the outputs from the unseen input data. The ANN method is presented in detail in section 3 of this study.

Regarding the application of ANN model, a number of research related fire issues are available in the literature. For example, Cachim [22] applied the ANN model for calculation of temperatures in timber under fire loading. A multilayer feed forward network with three input variables, namely the density of timber, the time of fire exposure, and the distance from the exposed side, were used. The output of the model was the temperature in timber. The model was trained validated and tested with the numerical data created by numerical simulations. Results from the study revealed that the ANN model could accurately calculate the temperature in timber members subjected to fire.

The application of the ANN model was also found in the research of Tasdemir et al. [23]. An ANN with four input parameters was used to evaluate the final cross sections of the wooden samples remaining from the fire. The experimental tests were also conducted to validate the model. A total of 150 experimental test results were used for training and validation of the proposed ANN model, and 30 test results were used for testing. The conclusion of the study suggested that the ANN model can be safely used to predict the cross sections of wooden materials remaining from the fire. Recently, Naser [24] used ANN models to estimate the thermal and structural properties of timbers at the material and elemental level. The study concluded that the method using artificial intelligence could improve the current state of fire resistance evaluation.

Besides the application for fire-related in wood structures, the ANN model has become a popular technique in many engineering fields. For instance, Nguyen and Dinh [25] utilized an ANN model to predict the bridge deck ratings and develop decay curve for the bridge deck. In that study, data of 2572 bridges from the National Bridge Inventory were used to develop, train, and test the ANN model. The conclusion from the study indicated that the accuracy of bridge rating prediction was 98.5 percent within the margin error of ±1, and the ANN model can effectively be used to develop the bridge deck deterioration curve. The ANN model was also used by other investigators for estimating ultimate load carrying of nonlinear inelastic steel truss [26] or predicting the concrete compressive strength [27]. The aim of this research is to develop a supervised learning ANN model for predicting the fire resistance ratings of the wooden floor assemblies. The proposed ANN model had 11 input variables with one output. A number of ANN models with different learning algorithms were developed and evaluated. The performance of each model in training, testing, and validation process were compared to acquire the best ANN model. Additionally, the selected ANN model was applied to conduct the sensitivity analysis to examine the influence of the input parameters to the output. Details of the research are presented in the following sections.

2. Data preparation

Data used in this research were collected from the previous published technical reports [17, 18], implemented by the National Research Council of Canada. The original document contained fire resistance tests results on full-scale floor assemblies of total 85 experimental records. Since the experimental tests were conducted on many floor assemblies with various configurations; as a result, some specific parameters in the final reports only contained a limited number of data points. In order to obtain the consistent data set, only samples included full records of all parameters were selected. In addition, this study focused on wood structures. Thus, the floor assemblies with steel joists were removed from the database.

Table 2. Conversion information

Type	Original values	Values in Table 3
Joist	Wood Joist (WJ)	1
	Wood-I-Joist (WIJ)	2
	Wood Truss (WT)	3
	Wood I-Joist flange (WIJ*)	4
Sub-floor	Ply	1
	Oriented Strand board (OSB)	0
Cavity Insulation	Rock Fiber Insulation Batts (R1)	1
	Glass Fiber Insulation Batts (G1)	2
	Cellulosic Fiber Insulation (C1)	3

Table 3. Fire resistance test results

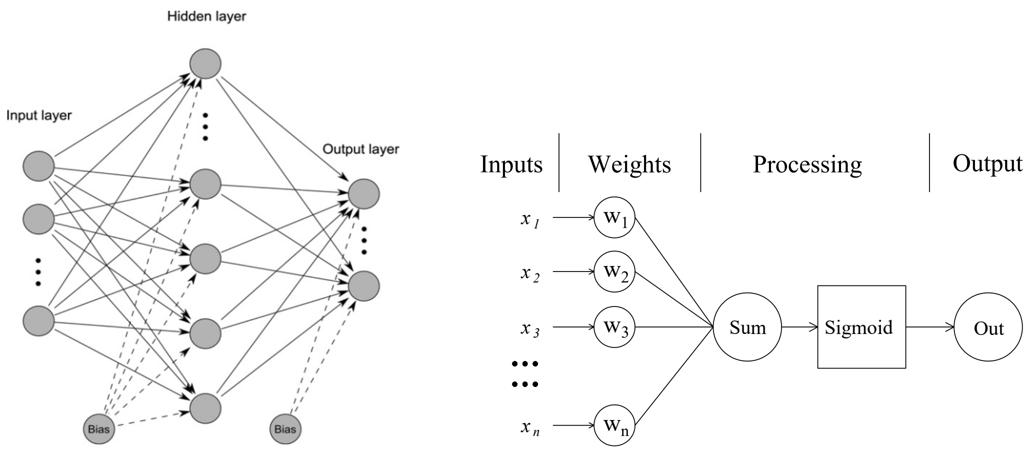
Joist			Ceiling Finish		Sub-Floor		Cavity Insulation			Applied load (N/m^2)	Fire Resistance Ratings (minutes)
Type	Depth (mm)	Spacing (mm)	Thickness (mm)	Layer	Type	Thickness (mm)	Type	Thickness (mm)	Spacing (mm)		
JTY	JDE	JSP	CFT	CFL	SFTY	SFTH	CITY	CITH	CISP	ALD	FRR
1	235	406	12.7	2	1	15.9	1	90	406	3830	72
1	235	406	12.7	2	1	15.9	2	90	406	3830	67
1	235	406	12.7	1	1	15.9	2	90	406	3830	36
1	235	406	12.7	1	1	15.9	1	90	406	3830	60
2	240	406	12.7	2	1	15.9	2	90	406	3950	64
2	240	406	12.7	1	1	15.9	1	90	406	4644	46
2	240	406	12.7	2	1	15.9	1	90	406	3950	77
2	240	610	12.7	2	1	19	2	90	406	2969	75
2	240	610	12.7	2	1	19	2	90	406	2490	74
2	240	610	12.7	2	1	19	2	90	610	3112	65
1	235	406	12.7	2	1	15.9	2	90	406	5075	65
1	184	406	12.7	2	1	15.5	2	89	406	3304	67
1	235	406	15.9	1	1	15.5	1	89	203	5075	54
1	235	406	15.9	1	1	15.5	1	178	406	4980	59
3	305	406	12.7	2	1	15.5	2	89	406	5602	66
4	241	406	15.9	1	0	15.5	1	178	406	5315	39
3	305	406	12.7	2	1	15.5	2	89	406	4213	68
3	305	610	12.7	2	1	15.5	2	89	406	3783	68
4	241	610	12.7	2	0	19	2	89	406	3447	61
4	241	610	15.9	1	0	15.5	1	89	305	4118	50
3	330	406	12.7	2	1	15.5	2	89	406	6847	63
3	305	610	12.7	2	1	19	2	89	610	3783	55
3	286	406	12.7	2	1	15.5	2	89	406	3543	64
1	235	406	15.9	1	1	15.5	1	89	406	5219	50
1	235	610	12.7	2	1	19	2	89	610	3256	57
1	235	406	12.7	2	1	15.5	2	89	610	5027	57
1	235	610	12.7	2	1	19	1	89	610	3256	63
1	235	406	12.7	2	1	15.5	3	235	610	4980	87
1	235	610	12.7	2	1	15.5	2	89	610	3783	59
4	241	406	15.9	1	1	15.5	3	241	305	5410	80
4	241	406	15.9	1	1	15.5	1	267	305	5458	60
3	305	610	12.7	2	1	19	2	89	610	3735	56
3	305	610	12.7	2	1	19	1	89	610	3735	60
4	241	406	15.9	2	1	15.5	1	267	305	5363	90
3	305	406	15.9	2	1	15.5	3	305	406	5793	99

It is worth noting that the original values data in the columns of Joist Type, Sub-floor Type, and Cavity Insulation Type were not a number. To make a readable input for the ANN model, the values in these columns were converted into the number. The conversion is listed in detail in Table 2. Data after refinements and conversions are presented in Table 3. The final data consisted of 36 test samples; each of them included 12 properties. The contents from column 1 to column 11 in Table 3 were used as the input data for the ANN model, and data in column 12 were the output.

3. Artificial Neural Network

3.1. Network structure

An Artificial Neural Network is a collection of processing neurons grouped in layers, as depicted in Fig. 1(a). The function of each neuron is to receive input data from connected neurons of the previous layer, analysis the data through the weights adjusting procedure, process data (using summation and sigmoid functions in this case), and transmits output data to the neuron of the subsequent layer. The analyzing scheme of an individual processing neuron is illustrated in Fig. 1(b). The neurons in each layer are only connected with neurons from other layers. No link exists between neurons in the same layer. The ANN is classified as a shallow network; thus, only three layers of neurons are presented in the ANN structure, namely (i) an input layer, (ii) a hidden layer, and (ii) an output layer. The number of neurons in each layer is selected depending on the certain requirements of the problems.



(a) Feed-forward network

(b) Individual neuron

Figure 1. The scheme of an ANN structure

3.2. Performance assessment

Performance of the ANN model was evaluated through two factors: coefficient of determination (R^2) and Mean Squared Error (*MSE*). The coefficient of determination measures the correlation between input and output variables using Eq. (1)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{1}$$

where y_i is the i^{th} actual output; $\bar{y}$ is the mean of the actual outputs; $\hat{y}_i$ is the i^{th} predicted outputs; and n is the total number of samples. *MSE* is the mean squared difference between predicted outputs and actual outputs. *MSE* can be calculated using Eq. (2)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

3.3. Choice of networks

Eleven properties of the floor assembly, namely Joist Type (JTY), Joist Depth (JDE), Joist Spacing (JSP), Ceiling Finish Thickness (CFT), Ceiling Finish Layer (CFL), Sub-Floor Type (SFTY), Sub-Floor Thickness (SFTH), Cavity Insulation Type (CITY), Cavity Insulation Thickness (CITH), Cavity Insulation Spacing (CISP), and Applied Load (ALD), were selected as the input parameters of the ANN model, and the Fire Resistance Ratings (FRR) of the floor assembly was assigned as the output. The dataset was divided randomly into three subsets in which 80%, i.e., 26 test samples, of the entire dataset was employed for training model, 10%, i.e., 5 test samples, for validation and the remaining 10%, i.e., 5 test samples, was utilized for testing the prediction accuracy of the ANN model.

A sigmoid function was selected as an activation function, and the feed-forward back-propagation learning method was assigned for the proposed ANN model. The feed-forward back-propagation technique works by using the errors presented in the network output to adjust the weights in each layer in two different processes called feed-forward process and back-propagation process. In the feed-forward process the inputs are used to obtain the outputs with some network errors. The errors are then passed backwards to the input layers through the back-propagation process, the weights are adjusted during this process to minimize the network errors to an acceptable level.

To find an optimal training algorithm that works for the available data, eight ANN models were developed and tested with eight popular training algorithms [28]. The performances of the models were assessed through MSE values of the four parameters, namely training performance (Train_Perf), testing performance (Test_Perf), validation performance (Validation_Perf), and the number of epochs (Num_Epochs). For each model, the performance result of 10 trials were compared. The best performance results from those models are listed in Table 4. It can be seen, the Levenberg-Marquardt algorithm (trainlm) produces the best performance on training, testing, and validation with a low number of epochs. For this reason, the Levenberg-Marquardt algorithm was selected for the proposed ANN model.

Table 4. Performance of the ANN model with different learning algorithms

#	Algorithm	Details	Train_Perf	Test_Perf	Validation_Perf	Num_Epochs
1	trainrp	Resilient Backpropagation	27.10	22.20	11.00	6
2	trainlm	Levenberg-Marquardt	0.88	1.41	2.46	6
3	traincgp	Polak-Ribiére Conjugate Gradient	5.98	6.01	0.54	6
4	traincgb	Conjugate Gradient with Beale Restarts	5.58	3.04	3.18	6
5	trainbfg	BFGS Quasi-Newton	16.50	6.21	7.89	6
6	trainoss	One Step Secant	14.30	2.04	5.54	6
7	traincgf	Fletcher-Powell Conjugate Gradient	26.90	6.83	12.49	6
8	traingdx	Variable Learning Rate Gradient Descent	25.50	9.80	6.24	10

To determine the necessary number of nodes in the hidden layer of the proposed ANN model, 20 different ANN models were developed by changing the number of nodes in the hidden layer from one node to 20 nodes. Each model was performed ten trials to obtain the average performance results. The performance of the ANN models was evaluated through the MSE value of the training, testing, and validation stage with the same dataset. Fig. 2 presents the performance results from these ANN models. The ANN model containing six neurons in the hidden layer generated the best results. Consequently, that ANN model was chosen. Table 5 presents a brief information of the selected ANN model.

Table 5. Detailed information of the selected ANN model

Parameter	Information
# neurons in the input layer	11
# neurons in the hidden layer	6
# neurons in the output layer	1
Training method	Feed-forward back-propagation
Training algorithm	Levenberg-Marquardt (trainlm)
Activation function	Sigmoid

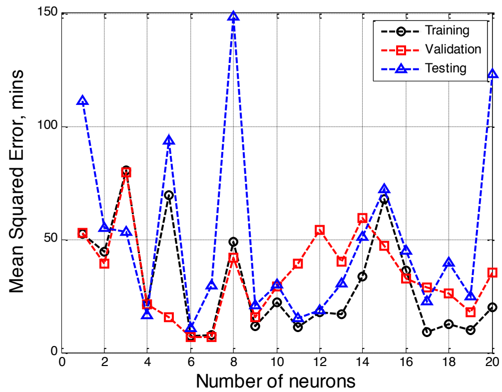


Figure 2. Model performance of 20 ANN models

4. Prediction of fire resistance ratings

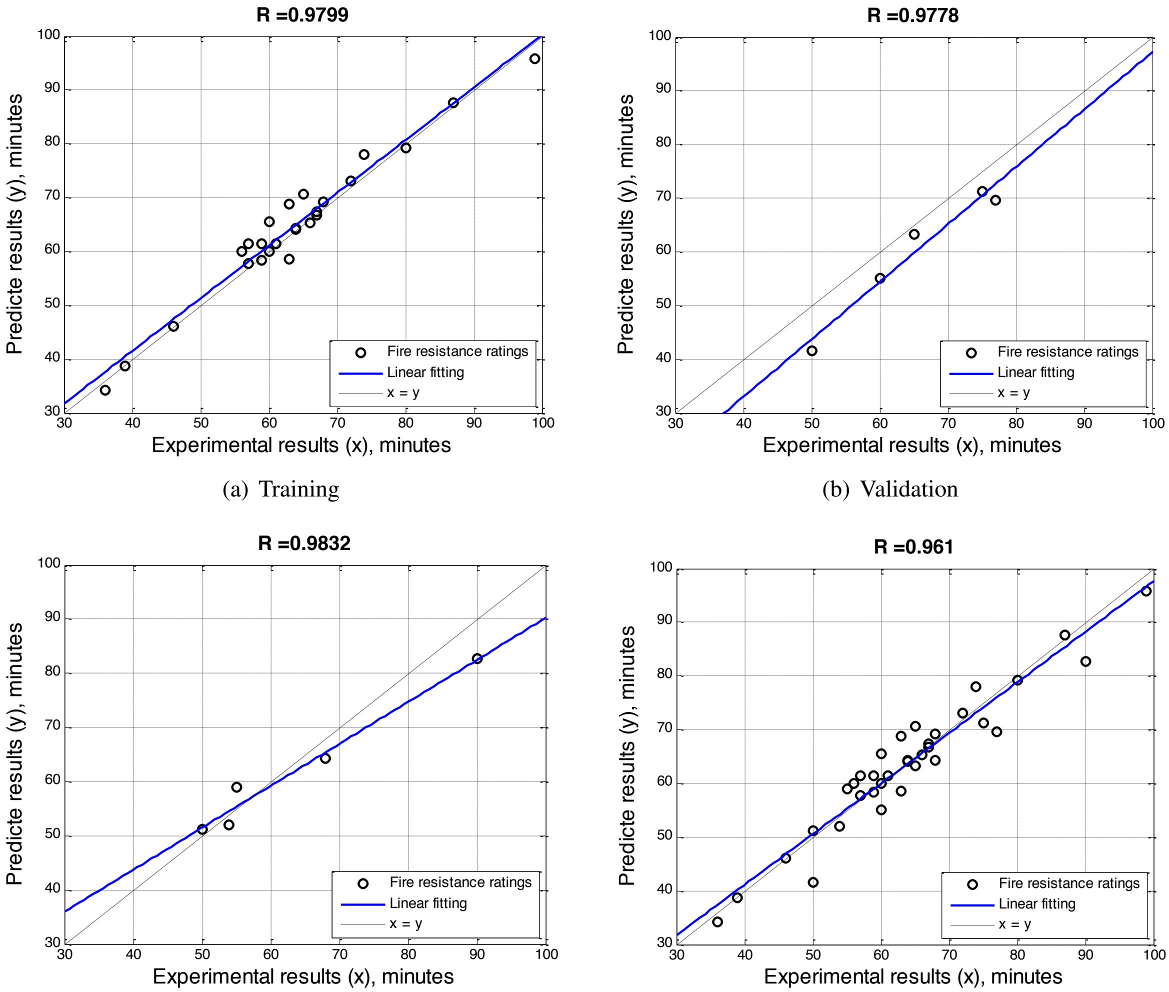
4.1. Applicability of ANN to fire resistance ratings prediction

Performance results of the proposed ANN model are presented in Table 6. It is worth noting that the overall performance was calculated for the entire data including training dataset, validation dataset and testing dataset. As can be seen, the ANN model performed well in all stages with the values of R^2 were 0.9799, 0.9832, and 0.9778, for training, validation, and testing, respectively. Ideally, if a model perfectly predicts the output, the value of R^2 will be equal to 1. The R^2 for the overall was 0.9610 indicated a good prediction ability of the proposed ANN model. Besides R^2, MSE is an alternative indicator that can be used for evaluating the performance of the ANN model. The smaller the MSE value is, the stronger the relationship between experimental and predicted data. For the training data set, the value of MSE was 7.69. The MSE values were found higher for unseen data sets, which were 17.7 and 33.1, for testing and validation, respectively.

Table 6. Performance results of ANN model

	Training	Validation	Testing	Overall
R^2	0.9799	0.9832	0.9778	0.9610
MSE	7.69	33.1	17.7	12.7

The linear regression plot was used in this study to present the results from the proposed ANN model. The plots for the performance of the proposed ANN model at different stages are shown in Fig. 3. In these figures, the linear fitting line presents the relationship between the experimental results and the predicted values produced from the model. In addition, the "$x = y$" line shows a perfect correlation between inputs and outputs.



(a) Training (b) Validation

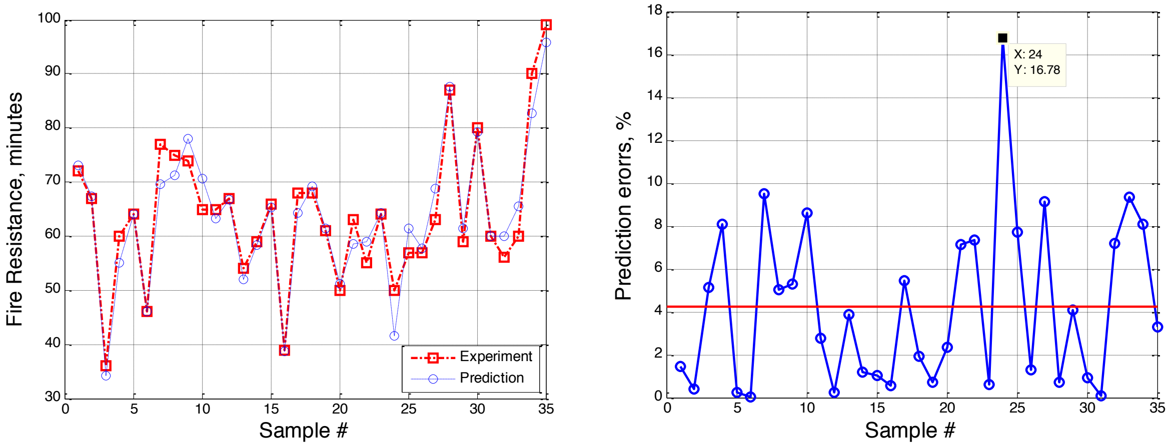
(c) Testing (d) Overall

Figure 3. Linear regression plot of ANN performance

The experimental data and the predicted values obtained from the ANN model were plotted in Fig. 4(a). The absolute prediction errors for each sample were also presented in Fig. 4(b). It is clear that the proposed ANN model can accurately predict the fire resistance ratings of the wooden floor assemblies from the inputs. The mean absolute prediction error was about four percent. The highest error of about 17 percent was found in test sample number 24, as shown in Fig. 4(b). This can be considered as an outliner, and the issue could address if this data point is excluded from the database.

4.2. *Sensitivity Analysis*

A sensitivity analysis was performed for the selected ANN model to evaluate the effects of the input parameters on the fire resistance ratings. In order to conduct the sensitivity analysis, each in-



(a) Experimental vs prediction values

(b) Absolute prediction errors

Figure 4. Performance of ANN model

put parameter was divided into five groups, namely Lowest (Low), Middle Low (Mid-Low), Middle (Mid), Middle High (Mid-High), and Highest (High) [29]. The Middle is the mean value of the Lowest and Highest. The Middle Low and Middle High represent halfway from the Lowest to the Middle, and from the Middle to the Highest, respectively. Detailed values of these input parameters are listed in Table 7.

Table 7. Input data for sensitivity analysis

Input parameters	Low	Mid-Low	Mid	Mid-High	High
JTY	1	1.75	2.50	3.25	4
JDE	184	221	257	294	330
JSP	406	457	508	559	610
CFT	12.7	13.5	14.3	15.1	15.9
CFL	1	1.25	1.50	1.75	2
SFTY	0	0.25	0.50	0.75	1
SFTH	15.5	16.4	17.3	18.1	19
CITY	1	1.50	2	2.50	3
CITH	89	143	197	251	305
CISP	203	305	407	508	610
ALD	2490	3579	4668	5757	6847
FRR	36	52	68	83	99

The sensitivity analysis was conducted for each input parameter by changing its value from Low to High while keeping the other inputs constant at the average values. The results of the sensitivity analysis for different input parameters are presented in Fig. 5. In this figure, the horizontal axis represents the five levels of input variables, while the vertical axis represents the fire resistance ratings of the wooden floor assemblies.

It can be seen clearly that the fire resistance ratings of the wooden floor assemblies were most

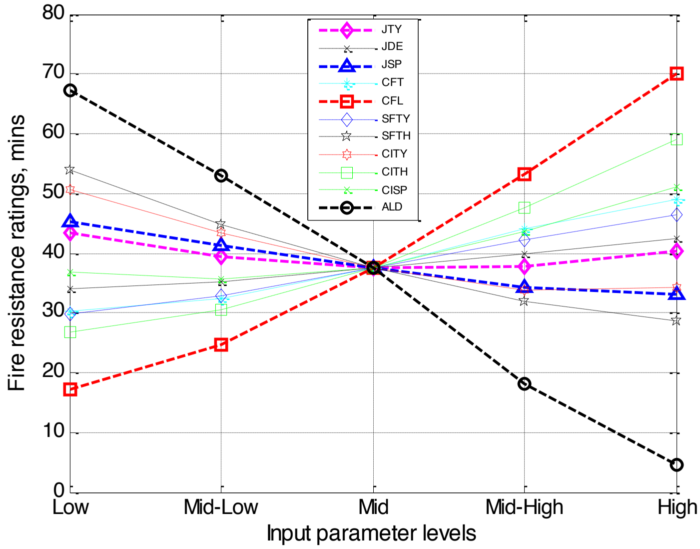


Figure 5. Fire resistance ratings vs inputs

sensitive to the Applied Load (ALD) and the number of the Ceiling Finish Layer (CFL). To be specific, for the ALD factor, the fire resistance rating is high when the applied load on the floor is low, and vice versa. In the case of CFL, an increase in the number of ceiling finish layer would result in an increase of the floor fire resistance capacity. By contrast, the Joist Type (JTY) was found to have a minimal effect on the fire resistance ratings of the wooden floors. In other words, within this study context, a change in the types of joists yielded a limited influence on the fire resistance ratings of the wooden floor assemblies.

5. Conclusions

In this paper, a method to estimate the fire resistance ratings of the wooden floor assemblies using Artificial Neural Networks was presented. A number of ANN models were developed and tested with the experimental data collecting from previous published. The selected ANN model performed well in predicting the fire resistance ratings with an average absolute prediction error of about four percent. Regarding the sensitivity analysis results, the Applied Load (ALD) and the number of the Ceiling Finish Layer (CFL) input variables were found to have significant effects on the outcome of the ANN model. The Joist Type (JTY) parameter, on the other hand, produced an insignificant influence on predicting the output of the proposed ANN model.

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Appendix A.

Harmathy's Ten Rules of Fire Endurance (Resistance) Rating [21]

Rules	Contents	Explanations
1	The "thermal"fire endurance of a construction consisting of a number of parallel layers is greater than the sum of the "thermal"fire endurance characteristics of the individual layers when exposed separately to fire.	Where two layers of panel materials, such as gypsum wallboard or plywood, are fastened to studs or joists separately, their combined effect is greater than the sum of their individual contributions to the fire endurance rating of the assembly.
2	The fire endurance of a construction does not decrease with the addition of further layers.	This is a corollary to Rule 1. The fire resistance will not decrease with the addition of layers such as wallboard or other panel materials, regardless of how many layers are added or where they are located within the assembly.
3	The fire endurance of constructions containing continuous air gaps or cavities is greater than the fire endurance of similar constructions of the same weight but containing no air gaps or cavities.	Wall and ceiling cavities formed by studs and joists protected and encased by wall coverings adds to the fire resistance rating of these assemblies.
4	The farther an air gap or cavity is located from the exposed surface, the more beneficial its effect on the fire endurance.	In cases where cavities are formed by joists or studs and protected by 2-inch-thick panel materials against fire exposure, the beneficial effect of such air cavities is greater than if the protection is only 1/2 inch thick.
5	The fire endurance of an assembly cannot be increased by increasing the thickness of a completely enclosed air layer.	An increase in the gap distance between separated layers does not change the fire resistance of an assembly.
6	Layers of materials of low thermal conductivity are better utilized on the side of the construction on which fire is more likely to happen.	A building material having relatively low thermal conductivity, such as a wood-based material, is more beneficial to the fire resistance of the assembly if placed on the fire-exposed side of the framing than it would be on the opposite side.
7	The fire endurance of asymmetrical constructions depends on the direction of heat flow.	Walls which do not have the same panel materials on both faces will demonstrate different fire resistance ratings depending upon which side is exposed to fire. This rule results as a consequence of Rules 4 and 6, which point out the importance of location of air gaps or cavities and of the sequence of different layers of solids.
8	The presence of moisture, if it does not result in explosive spalling, increases fire resistance.	Materials having a 15 percent moisture content will have greater fire resistance than those having 4 percent moisture content at the time of fire exposure.
9	Load-supporting elements, such as beams, girders and joists, yield higher fire endurance when subject to fire endurance tests as parts of floor, roof, or ceiling assemblies than they would when tested separately.	A wood joist performs better when it is incorporated in a floor/ceiling assembly, than tested by itself under the same load.
10	The load-supporting elements (beams, girders, joists, etc.) of a floor, roof, or ceiling assembly can be replaced by such other load-supporting elements which, when tested separately, yielded fire endurance not less than that of the assembly.	A joist in a floor assembly may be replaced by another type of joist having a fire resistance rating not less than that of the assembly.