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Original research article

Back Propagation Artificial Neural Networks and Regression Analysis Model for Predicting Pre-Evacuation Time in Plastic Industries in Thailand

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ABSTRACT

Required Safe Egress Time (RSET) consists of 4 elements, namely, fire detection time, alarm time, pre-evacuation time, and travel or movement time. Pre-evacuation time is currently regarded as the key critical evacuation process. If pre-evacuation time is not explicit, RSET timeline will not be reliable and effect on life of evacuees in the building. The purpose of this cross-sectional study was to develop the model for predicting pre-evacuation time in 10 plastic industries. Regression analysis was performed in order to find the factors significantly associated with pre-evacuation time. Only 4 influenced variables were tested by using regression analysis. Regression analysis and back propagation artificial neural networks model (BP-ANNs) were run to predict pre-evacuation time from 4 influential variables. BP-ANNs model was constructed as 4-10-1 by comprising of 4 input variables, 10 hidden nodes, 1 output variable, momentum was 0.05, learning rate was 0.08, and learning time was 100,000 epochs. The findings revealed BP-ANNs model showed the least error with the value of Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Root Mean Square Error (RMSE) were 2.04, 1.64, 1743.90 and 41.76 respectively when comparing with regression analysis model. BP-ANNs model can correctly predict pre-evacuation time with 75.15% accuracy. Therefore, BP-ANNs was an appropriate model for predicting pre-evacuation. This finding showed the advantage of BP-ANNs model which was more suitable to predict RSET and eliminated factors that could delay evacuation time in 10 plastic industries.

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Keywords: Pre-evacuation time; Regression analysis model; Back propagation artificial neural networks model; Plastic industries

1. Introduction

Fire can cause deaths, serious injuries, and significant damages to properties. Industrial plants are dangerous places for fire. In the past, industrial fires occurred quite often than they should. Many industries are at high risk of fire due to the nature of work, and unfortunately it only takes one mistake to cause a serious, life-threatening fire. The statistics showed the number of fire accidents during 2001 to 2015 account for 63.16, 73.91, 59.32, 64.15, 66.67, 58.82, 59.52, 26.09, 70.83, 52.17, 62.71, 65.22, 63.00, 63.00, and 77.00 percent respectively have a higher percentage of fire accidents compared with other types of accidents [1]. Fire accidents are shown in Fig. 1.

Fire risk assessment is a popular technique in industry, which consists of likelihood and consequence of event [2]. The results of fire risk assessment is accurate depending on deterministic data. In the contrast, the data from actual working conditions for assessing the risk, it is a stochastic data. Therefore, fire risk assessment is reliable by eliminating the variance of input variables. Fire risk assessment consists of two inputs stochastic data. Firstly, Available Safe Egress Time (ASET), the time at which tenability criteria are exceeding because of smoke, toxic effluents and heat in a specific space. Secondly, Required Safe Egress Time (RSET), it is the escape time. The universal criteria of safe fire evacuation timeline is shown in Fig. 2 [3]. The evaluation of RSET is an important step in performance based on fire safety engineering design. A key to guarantee the safety for occupants' safety in the building is RSET which must be less than ASET [4-5].

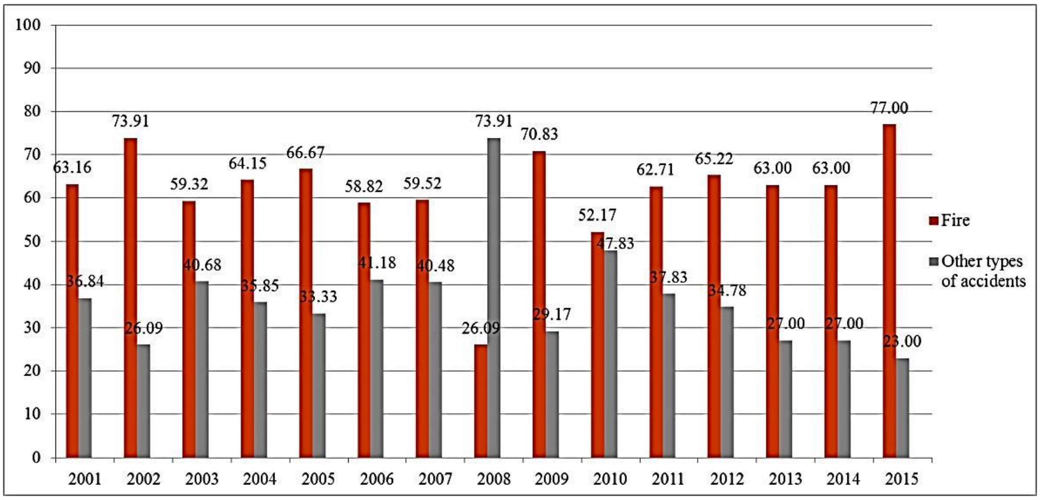

Fig. 1. Fire accidents.

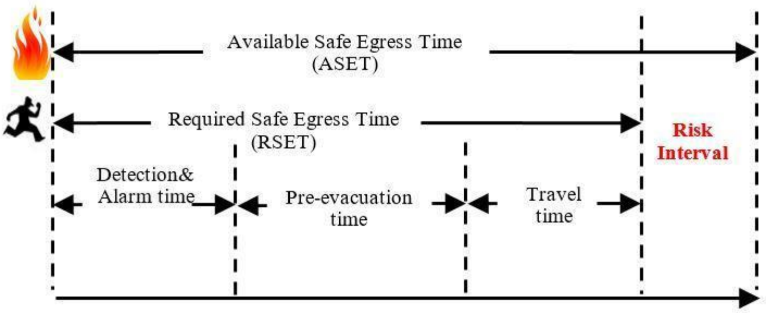

Fig. 2. Universal criterion of safe fire evacuation timeline.

RSET consists of four components are fire detection time, alarm time, pre-evacuation time, and travel or movement time respectively. From the literature review in assessing of RSET in the component of fire detection time, alarm time, and travel time found that many researchers published their findings. In terms of pre-evacuation time, many researchers attempted finding out the best solution. For instance, Guanquan and Jinhua [6] attempted calculating pre-evacuation time based on normal probability distribution. In some cases, pre-evacuation time, a random variable, is usually oversimplified to be defined as a fixed value for simplified calculation without consideration of its uncertainty such as Li-li et al. [7] defined pre-evacuation time was 120 seconds, Jian-ping et al. [8] stated that pre-evacuation time was a value in the range 2-5 minutes, and Chixiang et.al. [9] published that pre-evacuation time was 30-60 seconds. It is difficult to decide that how much pre-evacuation time in industry. The findings of research by Bryan and Proulx [10, 11] have discovered pre-evacuation time was more important than the time was needed for movement to a safe place. Consequently, pre-evacuation time is the key critical evacuation process. Therefore, this study attempted developing the model for predicting pre-evacuation time in plastic industries by using regression analysis and back propagation artificial neural networks.

2. Materials and Methods

2.1 Study Design and Setting

Ten plastic industries in central Thailand were purposively selected into this study as a type of industrial plant with a highest risk on fire [12]. Around 10-15 supervisors were selected in each industry observed and trained by researcher to correctly observe the time of target group during fire evacuation. The target group were workers in each department who engaged in fire evacuation after the alarm went off. They were unaware of being observed by the supervisors. 487 workers were observed during 3 months during period January – April 2015. 88.86 % (375) among them were recruited into the analysis. Multiple regression analysis and back propagation artificial neural networks model were performed to predict pre- evacuation time.

2.2 Instrument Development

A standardized form were used by the observer. This form consists of three parts: covering occupant characteristics questionnaire, building characteristics survey and pre-evacuation behavior observation. All collecting form was verified the Index of Consistency (IOC) by five fire specialist. There were three forms for collecting the data. Three forms of the study was described below.

2.2.1 Occupant characteristics

Questionnaire consists of three sections as below.

- Individual data of 375 workers were asked to do self-administered questionnaire. There were asked about sex, age, education level, marital status, income, work experience, section, position, physical condition, working building floor, fire experience, fire training participation, fire drill participation, using fire prevention and suppression devices, and fire prevention and suppression plan. All questions were multiple choice and filled in the blank.
- Knowledge about fire prevention and suppression questions consisted of 17 items. All items were binary choice (Yes or No). Cronbach's Alpha Coefficient was used for reliability analysis which was 0.611. If Cronbach's Alpha Coefficient greater than 0.6 is considered acceptable [13].
- Occupant attitude in fire questions consisted of 25 items. All items were Likert Scale [14]. Also, Cronbach's Alpha Coefficient was used for reliability analysis which was 0.880. If Cronbach's Alpha Coefficient greater than 0.8 is a good reliability [13].

2.2.2 Building characteristics survey

Building characteristics were surveyed by researcher which consisted of plant lay out, fire alarm type, number of building floor, building age, distance from work station to fire exit door, occupant density, width of corridor, number of exit access, width of exit access, height of exit access, number of window, width of window, height of window, number of fire exit door, width of fire exit door, height of fire exit door, fire exit door characteristics, fire resistance exit door, fire wall resistance, and fire prevention and suppression devices installation.

2.2.3 Pre-evacuation behavior observation form

Pre-evacuation behavior observation form consisted of two sections. The first section contained questions that identified pre-evacuation behaviors:

(1) notifying others
(2) fire investigation
(3) calling fire brigade
(4) ignore
(5) collect their belongings
(6) calling others
(7) close/open doors or windows
(8) shut down machine
(9) rescue others
(10) cover their nose with wet cloth
(11) ring an internal emergency response team (ERT)
(12) grasping fire extinguishers to put out fire
(13) fire hose to put out the fire
(14) repress the fire alarm bell
(15) call 191 or 199
(16) immediately fire evacuation to the fire exits
(17) seeing at the others
(18) asking the others
(19) Thought it was alarm test
(20) thought it was fault alarm

The second section of the observation form consists of the observation of pre-evacuation time which was transformed from pre-evacuation behaviors toward pre-evacuation time.

2.3 Model development and data analysis

Building characteristics and occupant characteristics were included into the model for their correlation with pre-evacuation time using Pearson's correlation coefficient and ANOVA at level of confidence 95% for quantitative and qualitative independent variables respectively. Stepwise multiple regression analysis covers eight affected variables from those analysis. Only four influenced variables were tested by using regression analysis and back propagation artificial neural networks. Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) will indicate the least error forecasting models.

3. Results

3.1 Regression analysis model

Building characteristics and occupant characteristics were included into the model for their correlation with pre-evacuation time was shown in Table 1. Stepwise multiple regression analysis covers eight affected variables from those analysis. Only four influenced variables were tested by using regression analysis as shown in Table 2. The stepwise multiple regression analysis model formula was shown in Equation (3.1).

$$Y = 693.846 - 6.620X_1 - 84.290X_2 + 112.992X_3 + 5.143X_4 \quad (3.1)$$

Where

Y = Pre-evacuation time (Second) X_1 = Occupant attitude in fire (total 125 marks)

X_2 = Number of fire exit door

X_3 = Fire training participation (fire training participation = 0, No fire training participation = 1)

X_4= Distance from work station to fire exit door (meter)

Table 1. Relationship between independent variables and pre-evacuation time (n=375).

Independent variables	Pearson's correlation	*p*-value*
Number of building floor	0.238	0.000
Building age (year)	-0.288	0.000
Number of window	-0.310	0.000
Number of fire exit door	-0.277	0.000
Distance from work station to fire exit door (m.)	0.160	0.002
Width of fire exit door (m.)	-0.165	0.002
Fire training participation	0.133	0.010
Occupant attitude in fire	-0.155	0.003

*p-value < 0.05

Table 2. Stepwise multiple regression analysis model of predicting pre-evacuation time (n=375)

Independent variables	Unstandardized Coefficients		t	*p*-value*
	B	Std. Error		
Constant	693.846	150.913	4.598	0.001
X_1	-6.620	2.036	-3.252	0.010
X_2	-84.290	20.383	-4.135	0.003
X_3	112.992	49.060	2.303	0.047
X_4	5.143	2.265	2.270	0.049
$R=0.934$ $R^2=0.871$ Std.Error = 59.866 F = 15.256 Sig=0.00				

*p-value < 0.05

The difference between the calculated output and actual output were then evaluated. The stepwise multiple regression analysis model develops the input to output mapping by minimizing a MAE, MSE, RMSE, and MAPE respectively. Which was expressed by the following Equation (3.2)-(3.5), shown in Table 3.

$$MAE = \frac{\sum_{i=1}^{n} |A_t - F_t|}{n} \quad (3.2)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (A_t - F_t)^2 \quad (3.3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (A_t - F_t)^2} \quad (3.4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| \times 100 \quad (3.5)$$

Where

A_t = Actual of pre-evacuation time (Second)

F_t = Forecasted of pre-evacuation time (Second)

i = Number of participants at consider n = Total number of participants

3.2 Back propagation artificial neural networks model

Artificial neural networks were a

simulation of the human brain working by computer programming [15]. WEKA was a software used to develop the multilayer perceptron (MLP) with the back propagation learning algorithm in this study, since it was the most widely used type of artificial neural networks in numerous pervious researchers [16], and it was also a universal function estimator [17]. The procedure of the back propagation neural networks were the error at the output layer that propagates backward to the input layer through the hidden layer in the network to obtain the final desired output. The gradient descent method was utilized to calculate the weight of interconnections to minimize the output error [18]. Before solving a problem, artificial neural networks must be trained continues until pre-defined number of 500, 5,000, 10,000, and 100,000 epochs respectively. In this research, the database was randomly divided into two sets: training and testing, in a 70/30 ratio [19]. Which were the training set containing 375 datasets

Table 3. Error comparison of stepwise multiple regression analysis model (MRA) (n=375).

No.	Independent variables				MRA model of forecasting (sec.)	Actual (sec.)	MAE	MAPE	MSE	RMSE
	X_1	X_2	X_3	X_4						
1	63	2	0	360.5	1962.26	364	4.70	1.29	7017.66	83.77
2	66	2	0	212	1178.66	695	0.86	0.12	336.59	18.35
3	69	2	1	212	1271.79	695	0.99	0.14	478.69	21.88
4	66	2	0	212	1178.66	695	0.86	0.12	336.59	18.35
5	63	2	0	212	1198.52	695	0.89	0.13	364.80	19.10
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
111	51	2	0	21.61	298.79	90	3.58	3.97	484.35	22.01
112	51	2	0	16.2	270.96	90	3.27	3.63	363.86	19.08
						Total	4.48	4.43	5557.45	74.55

Table 4. MAE calculated by BP-ANNs model (Momentum=0.05)

Hidden layer / Learning rate	H1				H2			
	Epoch				Epoch			
	500	5000	10000	100000	500	5000	10000	100000
0.05	131.78	130.98	130.98	130.98	119.46	109.98	108.98	103.55
0.06	130.99	130.19	130.19	130.19	119.03	109.33	108.45	103.67
0.07	130.00	129.20	129.20	129.20	118.74	109.03	106.26	103.96
0.08	128.95	128.21	128.21	128.21	118.51	108.51	108.51	103.44
0.09	127.99	127.43	127.43	127.43	118.08	109.18	108.89	106.98
0.1	127.27	126.87	126.87	126.87	117.82	109.89	109.49	107.77
0.2	123.17	123.06	123.06	123.06	119.29	117.17	117.10	114.78
0.3	122.63	122.61	122.61	122.61	129.81	128.18	128.25	125.51
0.4	124.44	124.44	124.44	124.44	149.60	148.42	148.13	145.49
0.5	131.90	131.90	131.90	131.90	172.04	171.07	170.88	168.72
Hidden layer / Learning rate	**H3**				**H4**			
	Epoch				**Epoch**			
	500	**5000**	**10000**	**100000**	**500**	**5000**	**10000**	**100000**
0.05	92.52	85.59	84.10	80.60	91.26	87.55	82.91	78.36
0.06	91.52	84.72	83.38	81.33	90.97	83.92	83.31	79.70
0.07	90.82	84.15	82.97	81.20	90.88	83.91	83.64	82.51
0.08	90.44	83.79	82.76	81.25	90.23	84.66	84.71	83.42
0.09	90.38	83.72	82.69	80.56	89.27	85.66	85.89	83.48
0.1	90.57	84.29	83.35	81.38	89.31	86.77	87.12	83.98
0.2	102.86	93.74	92.03	88.19	100.60	104.98	104.32	100.13
0.3	113.15	112.42	114.15	110.57	112.73	116.30	124.78	116.33
0.4	128.97	128.90	128.90	128.90	129.18	129.00	129.00	129.00
0.5	129.34	129.26	129.26	129.26	129.54	129.46	129.47	129.47

Table 4. MAE calculated by BP-ANNs model (Momentum=0.05) (Continued)

Hidden layer / Learning rate	H5				H6			
	Epoch				Epoch			
	500	**5000**	**10000**	**100000**	**500**	**5000**	**10000**	**100000**
0.05	91.00	83.49	81.58	76.55	90.84	83.85	81.75	76.78
0.06	90.65	83.29	81.74	76.58	90.82	76.58	99.78	81.60
0.07	90.47	83.34	82.25	76.85	90.74	82.41	81.33	77.35
0.08	89.22	85.07	84.90	83.44	89.99	83.01	82.48	79.14
0.09	88.87	85.94	86.08	83.27	89.70	83.67	76.27	71.64
0.1	89.57	87.12	87.38	83.95	90.16	86.70	77.75	74.64

Hidden layer / Learning rate	H5				H6			
	Epoch				Epoch			
	500	**5000**	**10000**	**100000**	**500**	**5000**	**10000**	**100000**
0.2	98.59	98.12	100.30	96.31	101.25	93.95	93.23	88.70
0.3	111.40	118.96	121.92	114.16	112.50	118.59	121.98	116.71
0.4	137.16	154.21	157.27	136.51	122.76	129.73	135.22	148.55
0.5	133.70	128.31	126.39	119.09	132.99	128.09	128.02	117.97

Hidden layer / Learning rate	H7				H8			
	Epoch				Epoch			
	500	**5000**	**10000**	**100000**	**500**	**5000**	**10000**	**100000**
0.05	89.32	80.76	78.39	78.39	81.24	89.41	80.29	74.39
0.06	88.43	80.81	78.88	75.80	88.54	81.33	78.66	73.74
0.07	87.85	80.92	79.61	76.65	87.92	81.26	79.45	75.43
0.08	88.13	81.73	80.71	77.62	88.07	81.38	80.46	76.18
0.09	88.73	83.65	82.99	77.19	88.55	83.13	81.49	81.49
0.1	89.63	84.91	84.30	82.66	89.28	84.09	82.55	76.78
0.2	101.78	96.97	96.31	90.70	100.85	96.80	94.74	85.21
0.3	112.96	121.32	120.61	118.31	115.67	112.53	110.79	107.06
0.4	131.91	149.06	162.76	164.54	132.56	147.72	157.21	167.23
0.5	132.59	128.37	128.00	117.35	136.84	132.52	129.52	108.84

Hidden layer / Learning rate	H9				H10			
	Epoch				Epoch			
	500	**5000**	**10000**	**100000**	**500**	**5000**	**10000**	**100000**
0.05	89.04	81.39	78.50	71.12	88.87	81.077	79.35	75.03
0.06	88.61	81.58	79.66	73.00	88.14	81.29	80.57	76.60
0.07	90.00	82.59	80.72	76.08	87.53	80.90	78.90	75.04
0.08	90.04	83.34	81.88	76.08	88.04	81.39	80.12	64.94
0.09	90.19	84.24	83.21	76.34	88.92	84.68	91.46	87.42
0.1	90.65.	85.39	83.74	78.44	90.72	86.30	82.09	76.20
0.2	101.34	105.55	105.03	93.38	99.86	100.17	99.47	91.00
0.3	114.86	113.63	113.44	109.13	115.03	147.62	152.72	116.74
0.4	122.12	119.54	118.22	111.13	127.33	121.17	121.58	92.08
0.5	136.61	134.43	130.45	129.95	136.70	134.69	130.38	129.57

Table 5. Error comparison of BP-ANNs model

No	Factors				BP-ANNs Model of forecasting 4-10-1 (Sec.)	Actual (Sec.)	MAE	MAPE	MSE	RMSE
	A_1	A_2	A_3	A_4						
1	0	63	360.5	2	150.50	364	0.59	0.16	125.22	11.19
2	0	66	212	2	1507.61	695	1.17	0.17	950.11	30.82
3	1	69	212	2	1498.87	695	1.16	0.17	929.79	30.49
4	0	66	212	2	1507.61	695	1.17	0.17	950.11	30.82
5	0	63	212	2	1481.96	695	1.13	0.16	891.08	29.85
.	.	.	.	.	.	.	.	.	.	.

Table 5. Error comparison of BP-ANNs model (Continued)

.	.	.	.	.	.		.	.	.	.	.
.	.	.	.	.	.		.	.	.	.	.
111	0	51	21.61	2	186.27		90	1.07	1.19	102.97	10.15
112	0	51	16.2	2	176.49		90	0.96	1.07	83.11	9.12
						Total	27029	2.04	1.64	1743.90	41.76

and the testing set containing 112 datasets. The infrastructure consists of 4 input variables, 1 output variable, 1 hidden layer, changing 1-10 hidden nodes, learning rate was during the 0.05-0.5, and momentum was during the 0.05-0.5. The results of BP-ANNs model forecasting were shown as MAE or RMSE in Table 4. The difference between the calculated output and actual output were then evaluated. The back propagation algorithm develops the input to output mapping by minimizing a MAE, MSE, RMSE, and MAPE respectively. Which was expressed by the following Equation (3.2) - (3.5), shown in Table 5.

(1) The forecast model efficiency compares the forecast errors by comparing MAE, MSE, RMSE, and MAPE resulting from forecast models, MAPE was given the least forecast errors, which according with the global performance of trained BP-ANNs by comparing with MAPE [20].

(2) The data was applied with BP-ANNs models. There were four input variables that affected pre-evacuation time were occupant attitude in fire, number of fire exit door, fire training participation, and distance from work station to fire exit door. The structure of BP-ANNs model used in this study was shown in Fig. 3.

(3) BP-ANNs model of forecasting were structured as 4-10-1 by comprising of 4 input variables, 10 hidden nodes, 1 output variable, momentum was 0.05, learning rate was 0.08, and learning time was 100,000 epochs were shown in Fig. 3. This BP-ANNs model can correctly predict pre-evacuation time was 75.15%. After creating the model, BP-ANNs model must be tested by considering MAE, MSE, RMSE and MAPE. These values will indicate the least error forecasting model when comparing with regression analysis model.

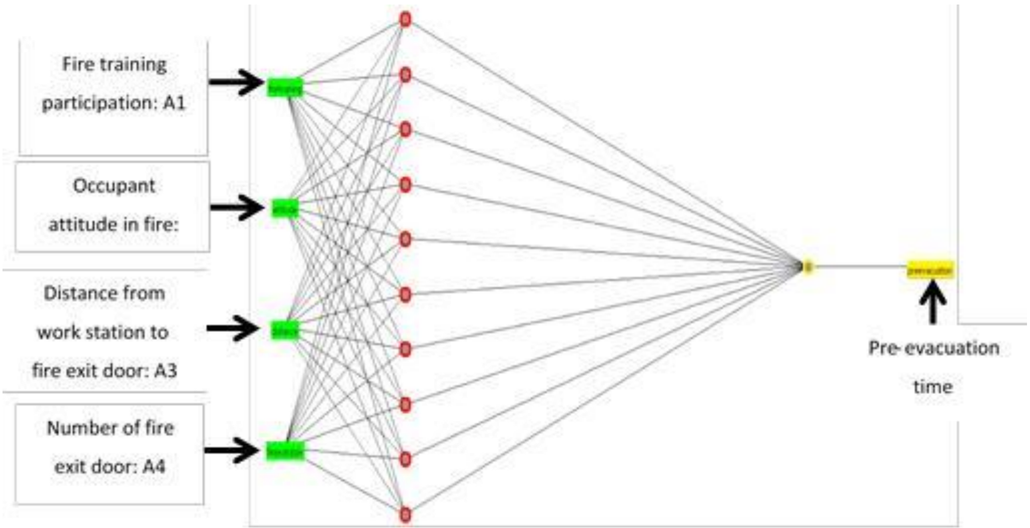

Fig. 3. Structure of BP-ANNs model.

(4) BP-ANNs model of forecasting can be calculated as follows:

- Computing the range, base, and normalize attribute of each input and output variable.

- Computing the attribute summation of each hidden node from Eq. (3.6), shown in Fig. 4 and Table 6.

$$X = (A_1W_{11}) + (A_2W_{21}) + (A_3W_{31}) + (A_4W_{41}) + \ldots + (A_nW_{n1}) + W_o \qquad (3.6)$$

Where

X = Summation of each hidden node

A_n = Attribute or input variable $(A_1, A_2, \ldots, A_n)$

W_{n1} = Attribute's weight of each hidden node $(W_{11}, W_{21}, \ldots, W_{n1})$

W_o = Threshold

- Computing the value of each hidden node with a sigmoid activate function from Equation (3.7).

$$f(x) = \frac{1}{1 + e^{-x}} \qquad (3.7)$$

- Computing the output node from Equation (6), shown in Table 7.

- Computing the BP-ANNs model of forecasting, shown in Table 8.

- Computing the MAE, MSE, RMSE, and MAPE.

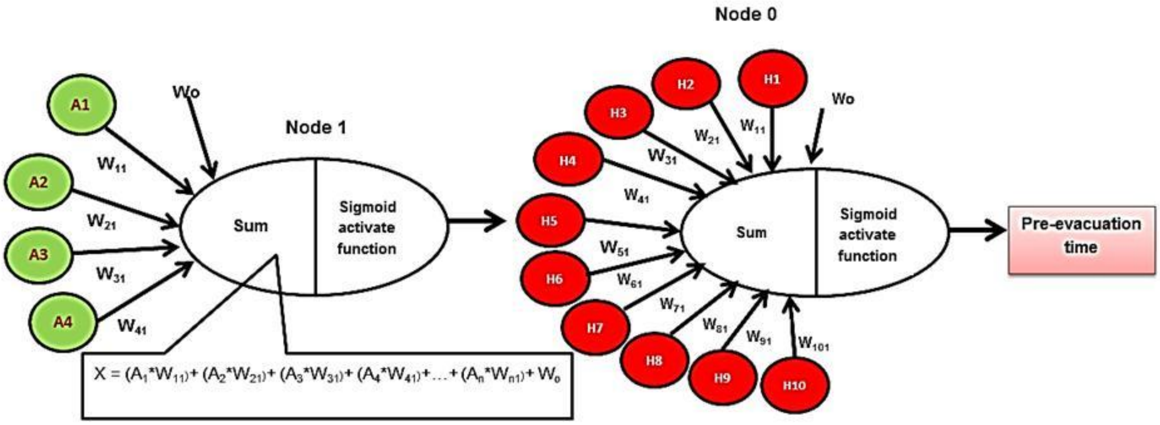

Fig. 4. BP-ANNs Model of hidden node 1

Table 6. Attribute's weight into the hidden node.

List of input node	Hidden Layer									
	Node 1	**Node 2**	**Node 3**	**Node 4**	**Node 5**	**Node 6**	**Node 7**	**Node 8**	**Node 9**	**Node 10**
A1	0.939	0.345	10.256	-2.080	-0.138	0.297	0.057	0.031	-19.251	-2.058
A2	5.249	1.413	-5.028	-6.773	-0.721	5.041	0.316	-5.425	-22.230	-6.586
A3	-31.495	-4.248	11.791	30.931	15.710	26.181	-83.503	0.873	4.370	15.300
A4	32.760	12.399	-33.459	32.382	-0.501	1.526	-3.409	3.119	-14.378	-2.848
Threshold	-22.631	-0.809	-19.125	-12.116	-1.567	-11.590	12.706	-7.158	-6.227	-12.753

Table 7. Hidden node's weight into the output node.

List of hidden node	Output : Pre-evacuation time
Node 1	-2.723
Node 2	2.663
Node 3	0.486
Node 4	2.778
Node 5	-4.436
Node 6	-4.153
Node 7	-8.251
Node 8	-12.974
Node 9	0.545
Node 10	-2.87
Threshold	7.478

Table 8. Output node calculation: Node 0 (Pre-evacuation time)

Sample No.	Sigmoid activate function f(H0) : Pre-evacuation time	BP-ANNs model for forecasting the pre-evacuation time (Seconds)	BP-ANNs model for forecasting the pre-evacuation time (Minutes)
1	-0.566893776	150.50	2.51
2	3.338434809	1507.61	25.13
3	3.313291715	1498.87	24.98
4	3.338434809	1507.61	25.13
5	3.264626337	1481.96	24.70
.	.	.	.
.	.	.	.
.	.	.	.
111	-0.463978926	186.27	3.10
112	-0.492121469	176.49	2.94

4. Discussion

There were eight items related to pre-evacuation time in plastic industries in Thailand ($p<0.05$). These were number of building floor, building age (year), number of window, number of fire exit door, distance from work station to fire exit door (m.), width of fire exit door (m.), fire training participation and occupant attitude in fire. Number of building floor, there was a positive relationship with pre-evacuation time because of the most of people had been working on the first floor (78.4%) when a fire occurred after fire alarm bell rings can move toward safe place easily that will be made decreasing pre-evacuation time which according with M. Kobes [21] has been found on the correlation between the possibility of a safe escape and the height of a building. Experience of fatal fires in buildings with more storeys has shown that there was a high probability of fire or smoke in their staircases. Building age (year), there was a negative relationship with pre-evacuation time which there was a possibility that the most people believe in fire prevention and suppression devices installation in a new building. No information was found in the literature about the influence of building age on pre-evacuation time. Number of window and number of fire exit, there was a negative relationship with pre-evacuation time as with building age. Distance from work station to fire exit door (m.), there was a positive relationship with pre-evacuation time. No information was found in the literature about the influence of distance from work station to fire exit door on pre-evacuation time. However, data has been found on a negative correlation between width of fire exit door and pre-evacuation time. Fire training participation, there was a positive relationship with pre-evacuation time that will be made increasing pre-evacuation time if they have attended in the fire training which according with LI Li-min and ZHU Guo-qing [22] has been found on the correlation between fire training with response time, The majority of them received fire drill or training has had the personal's response time within 1 minute. Finally, occupant attitude in fire had a negative correlation with pre-evacuation time as the result of the most people had not been concerned attitude in fire (77.4%) that will be made increasing pre-evacuation time.

Both regression analysis model and back propagation artificial neural networks model were run to predict pre-evacuation time from four influenced variables quite successfully. The comparison error of the forecasting pre-evacuation time between the regression analysis model and back propagation artificial neural networks model revealed that BP-ANNs model: 4-10-1 was less the error of the forecasting pre-evacuation time than regression analysis model. The error comparison of forecasting models were shown in Table 9 and Fig. 5. The forecast model efficiency compares the forecast errors by comparing MAE, MSE, RMSE, and MAPE resulting from forecast models, MAPE was given the least forecast errors, which according with the global performance of trained ANNs by comparing with MAPE. In general, the selected models were not very accurate in the most of the measuring dimensions. The classified forecasts with MAPE values are less than 10% as highly accurate forecasting, between 10% and 20% as good forecasting, between 20% and 50% as reasonable, and forecasting larger than 50% as inaccurate forecasting [23]. Both regression model and BP-ANNS were a good fit of the data which according with N. Udomsri [24] has been found that the multiple regression model can be used for predicting the demand of durian for domestic and export markets by comparing with Artificial Neural Networks (ANNs) model. The forecast data from two models have been compared and analyzed by Mean Absolute Percent Error: MAPE. The comparison error of two models forecasting demand of durian as highly accurate forecasting. The advantages and disadvantages of these models were shown in Table 10. BP-ANNs model can describe a non-linear relation between a predicted variable and its related independent variables. It is applicable to complex independent variables analysis and can yield a highly accurate forecasting data fit. Regression analysis model is readily applicable only to linear relation, but it is fast calculation time. For integrated pre-evacuation time evaluation, BP-ANNs model can be used as a helping tool to create an affected variables between pre-evacuation time and its related independent factors.

Table 9. The error comparison of forecasting models**.**

Forecasting model	**MAE**	**MSE**	**RMSE**	**MAPE**
MRA model	4.48	5557.45	74.55	4.43
BP-ANNs Model	2.04	1743.90	41.76	1.64

Table 10. Comparison of BP-ANNs and MRA model.

Method	Fitting formula	The error comparison of forecasting models by MAPE values	Calculation time on laptop computer ($CORE^{TM}$ i5)
MRA model	Linear relation (explicit)	4.43 (highly accurate forecasting)	≈1 second
BP-ANNs model	Non-linear and linear relation (implicit)	1.64 (highly accurate forecasting)	≈17 minutes (100,000 epochs)

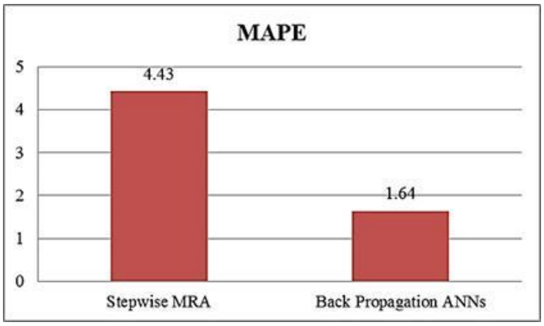

Fig. 5. The error comparison of forecasting models**.**

5. Conclusion

This research attempted to find out all of factors that affecting on pre-evacuation time and develop that model which can effectively forecast pre-evacuation time. Both MRA model and BP-ANNs were run to predict pre-evacuation time from four influential variables quite successfully. The comparison error of the forecasting pre-evacuation time between the regression analysis model and back propagation artificial neural networks model showed BP-ANNs model: 4-10-1 was less the error of the forecasting pre-evacuation time than regression analysis model. However, Both regression model and BP-ANNS are a good fit of the data because of having the MAPE values are less than 10% as highly accurate forecasting. The results of this calculation can be used as information to make a suitable fire evacuation plan and eliminate factors that make delay time in plastic industries in Thailand and foreign countries in the same aspect.

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