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IJIE

Journal homepage: http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

A Comparative Study of Deep Learning Model and Simple Prediction Charts in Construction Noise Prediction

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DOI: https://doi.org/10.30880/ijie.2022.14.04.030
Received 28 April 2021; Accepted 27 December 2021; Available online 20 June 2022

Abstract: Construction noise monitoring is crucial to assess the impacts of construction noise on the workers and surroundings. However, the existing noise prediction methods are time-consuming in which required laborious work for the computation of the noise levels. This study aims to assess the accuracy and reliability of the deep learning model (DL) that adopted the stochastic modelling and artificial neural network (ANN) in construction noise prediction. The artificial neural network was trained with the output of stochastic modelling. The outcome of noise level prediction using simple prediction chart (SPC) and DL model was discussed and compared to 3 case studies. The case studies were conducted at construction sites located in Semenyih, Selangor, Malaysia. The results of DL model showed high accuracy of predicted noise levels along with an absolute difference of less than 2.3 dBA. Besides, the predicted noise levels are reliable as the R-squared value was high. On that account, DL model is proved to be reliable and accurate in noise level prediction and it has the potential to be utilized as a managerial tool to monitor construction noise more effectively.

Keywords: Artificial neural network, construction noise, deep learning, noise pollution, noise prediction, stochastic modelling

1. Introduction

Occupational noise exposure among construction workers has been increasing significantly over the years; the construction industry was found to be the second most impactful source that caused noise pollution to the environment [1], [2]. In recent years, the increase of environmental issues consciousness and escalation in growth of "mega projects" resulting in the negative impacts from construction noise are no longer acceptable [3]. The construction site is one of the common areas that emit disruptive noise that may negatively affect the construction workers and residents [4].

Hence, noise prediction is crucial in the planning stage to prevent potential noise hazards. In recent years, the probabilistic approach, stochastic Monte Carlo approach, simple prediction chart (SPC) technique and artificial neural network (ANN) had been applied to noise prediction method and produced reliable outcomes [5]-[9]. Noise monitoring is usually conducted to assess the severity of negative impacts on employees and the environment. The outcome of the studies proved that noise prediction models are reliable and accurate as compared to the deterministic approach. Hence, these noise prediction models can be utilized as a supervisory and planning tool in construction activities.

However, the techniques mentioned above are time-consuming as they required laborious work to perform a complex calculation. Thereby, to solve this problem, the application of a multilayer perceptron (MLP) neural network is introduced in this study. Among the various types of ANN, MLP has been commonly applied in traffic and urban noise forecasting and predictive research [9]-[13]. However, research related to construction noise prediction using MLP is relatively diminutive. Several previous works have adopted the concept of deep learning not only in acoustic noise prediction but

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also in other sectors [9], [14]-[18]. A researcher developed a model with the concept of ANN and advanced fuzzy techniques to predict the excessive noise in industrial embroidery, and the results were confirmed to be reliable [14].

2. Methods

2.1 Stochastic Modelling Configuration

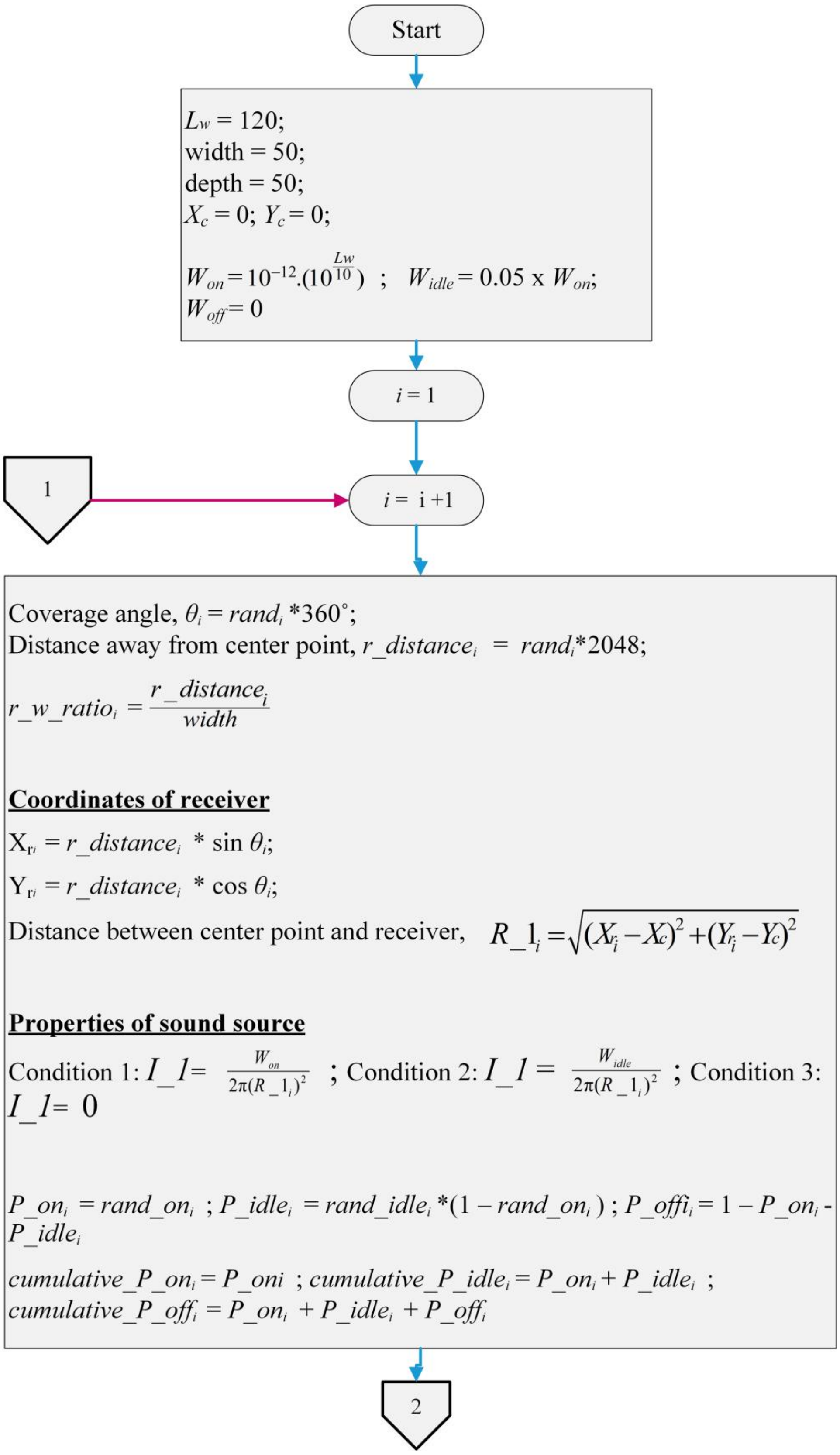
A stochastic model is applied to predict a set of possible results based on the possible randomness or likelihood within a specific period [19]. Stochastic modelling is found to be feasible, especially in construction noise prediction based on previous studies [5], [8], [20]. The application of stochastic modelling is to simulate the activities of the actual scenario at construction sites as a means to predict the sound pressure levels at different locations based on the predetermined randomized parameters. Hence, the concept is adopted in this study to generate the input data for ANN. MATLAB software is utilized to execute the simulation with the consideration of these several important parameters such as (1) sound properties of dynamic machinery; (2) random movement and position of dynamic machinery; (3) different sizes of working sub-area; (4) distance away from the sound level receiver; (5) coverage angle from the site centre; (6) operational duty cycles of dynamic machinery. The stochastic modelling generated 100, 000 data with different mean level deviation and standard deviation due to the randomized parameters during the simulation. A study proved that it is necessary to have large samples of up to 20, 000 to generate a smooth probability distribution curve [6]. As a result, the number of iteration for both the nested loops were determined as 20, 000 steps. The total execution time for the simulation was 19 hours with the hardware specifications of Central Processing Unit (CPU) Ryzen 3 3100 @ 3.9 GHz and Random Access Memory (RAM) 16 GB @ 2666 MHz. Lastly, the output of the stochastic modelling comprised the coverage angle, r/w ratio, fully operating, idling and off-duty modes, mean level deviation and standard deviation. The framework of stochastic modelling is demonstrated in Fig.1.

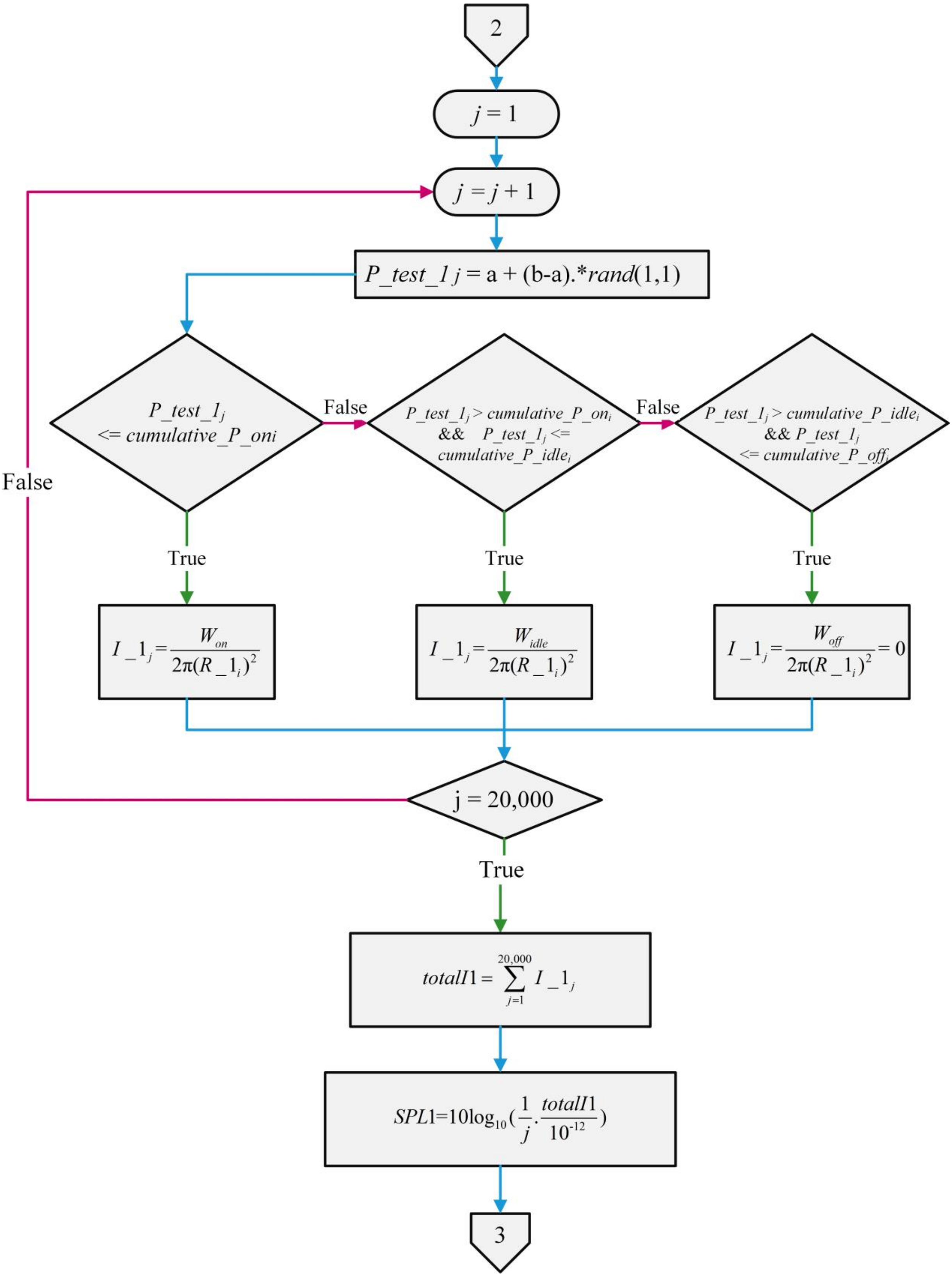
2.2 Artificial Neural Network Configuration

The idea of a neural network originated from a perceptron model developed in the 1950s [21]. An artificial neural network (ANN) is an imitation of the human brain [22]. ANN is commonly named multilayer perceptron, and it is a feed-forward ANN that consists of an input layer, hidden layer and output layer. A multilayer perceptron with a single layer of the hidden layer is usually called the shallow neural network and if there is more than one hidden layer, then it would be called a deep neural network [22]. Each node represents a neuron, and a nonlinear activation function is involved in each hidden layer [23]. The mechanisms of a shallow neural network are based on a simple feed-forward propagation algorithm. For the ANN model of this study, the ReLU function is selected as the activation function because it has been proven to be the optimum activation function and it helps the training process of the model by reducing vanishing gradient problems when it is used in hidden layers; moreover, the model with ReLU function asymptotes faster during the training than other activation functions [23-26]. Adam optimizer was selected in this study because it is favourable and commonly used and has been recognized as the best optimizer among other optimization techniques [27], [28]. The configuration of the parameter for the neural network is presented in Table 1. The flowchart of the ANN configuration is illustrated in Fig. 2. As mentioned in section 2.1, the mean level deviation and standard deviation were determined as the dependent variable whereas the remaining output will be taken as the independent variables for the training of the artificial neural network.

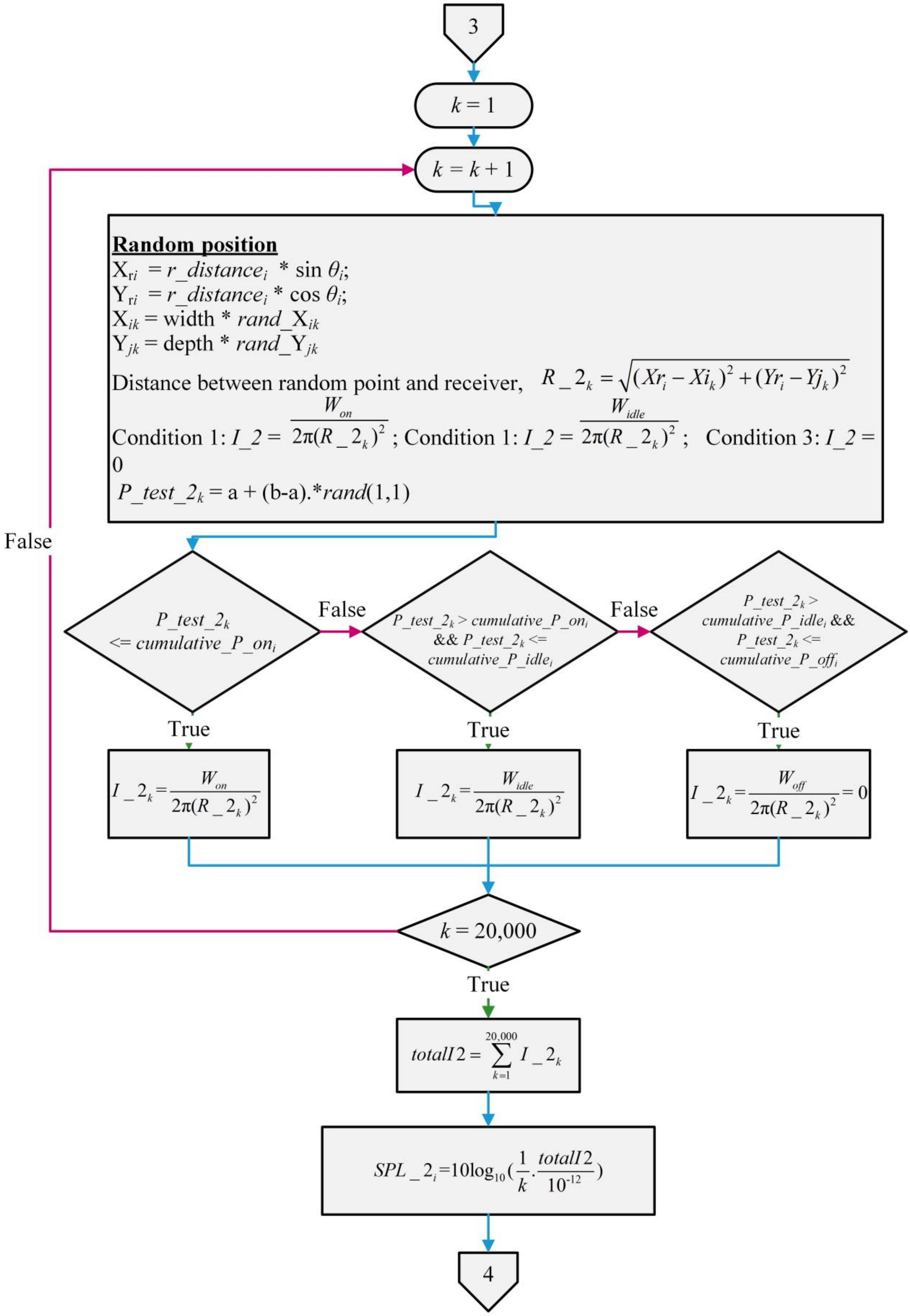
Table 1 - Configuration of hyperparameter for the neural network

Training, Test, Validation Split	60 %, 20 %, 20 %
Number of epochs to train	200
Number of hidden layers	10
Number of hidden neurons	475
Activation function	ReLU
Optimizer	Adam
Learning rate	10^{-4}
Batch size	32

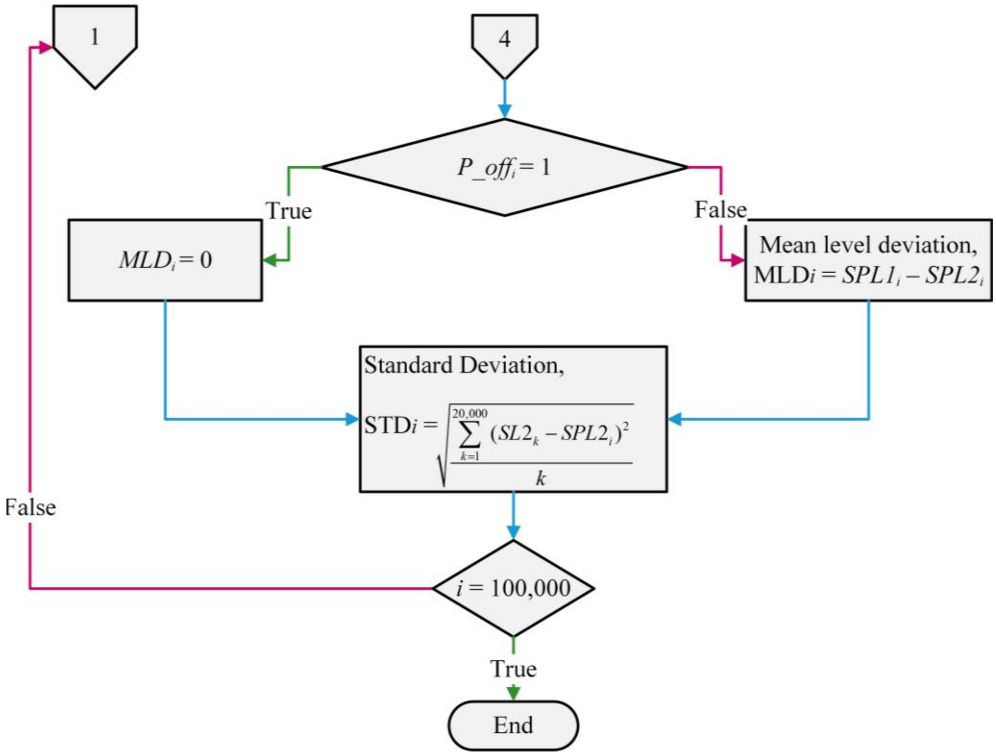

Start
L_w = 120;
width = 50;
depth = 50;
$X_c = 0$; $Y_c = 0$;
$W_{on} = 10^{-12}.(10^{\frac{Lw}{10}})$; $W_{idle} = 0.05$ x W_{on};
$W_{off} = 0$
$i = 1$
1
$i =$ i +1
Coverage angle, $\theta_i = rand_i$ *360°;
Distance away from center point, $r\_distance_i$ = $rand_i$*2048;
$r\_w\_ratio_i = \frac{r\_distance_i}{width}$
Coordinates of receiver
$X_{ri} = r\_distance_i$ * sin θ_i;
$Y_{ri} = r\_distance_i$ * cos θ_i;
Distance between center point and receiver, $R\_1_i = \sqrt{(X_{r_i} - X_c)^2 + (Y_{r_i} - Y_c)^2}$
Properties of sound source
Condition 1: $I\_1 = \frac{W_{on}}{2\pi(R\_1_i)^2}$; Condition 2: $I\_1 = \frac{W_{idle}}{2\pi(R\_1_i)^2}$; Condition 3: $I\_1 = 0$
$P\_on_i = rand\_on_i$; $P\_idle_i = rand\_idle_i*(1 - rand\_on_i)$; $P\_offi_i = 1 - P\_on_i - P\_idle_i$
$cumulative\_P\_on_i = P\_oni$; $cumulative\_P\_idle_i = P\_on_i + P\_idle_i$; $cumulative\_P\_off_i = P\_on_i + P\_idle_i + P\_off_i$
2
(a)


2
j = 1
j = j + 1
P_test_1j = a + (b-a).*rand(1,1)
P_test_1j <= cumulative_P_oni
False
P_test_1j > cumulative_P_oni && P_test_1j <= cumulative_P_idlei
False
P_test_1j > cumulative_P_idlei && P_test_1j <= cumulative_P_offi
False
True
True
True
$I\_1_j = \frac{W_{on}}{2\pi(R\_1_i)^2}$
$I\_1_j = \frac{W_{idle}}{2\pi(R\_1_i)^2}$
$I\_1_j = \frac{W_{off}}{2\pi(R\_1_i)^2} = 0$
j = 20,000
True
$totalI1 = \sum_{j=1}^{20,000} I\_1_j$
$SPL1 = 10\log_{10}(\frac{1}{j}.\frac{totalI1}{10^{-12}})$
3

(b)


3
k = 1
k = k + 1
Random position
$X_{ri} = r\_distance_i * \sin \theta_i$;
$Y_{ri} = r\_distance_i * \cos \theta_i$;
X_{ik} = width * $rand\_X_{ik}$
Y_{jk} = depth * $rand\_Y_{jk}$
Distance between random point and receiver, $R\_2_k = \sqrt{(Xr_i - Xi_k)^2 + (Yr_i - Yj_k)^2}$
Condition 1: $I\_2 = \frac{W_{on}}{2\pi(R\_2_k)^2}$; Condition 1: $I\_2 = \frac{W_{idle}}{2\pi(R\_2_k)^2}$; Condition 3: I_2 = 0
$P\_test\_2_k$ = a + (b-a).*$rand$(1,1)
False
$P\_test\_2_k$ <= $cumulative\_P\_on_i$
False
$P\_test\_2_k$ > $cumulative\_P\_on_i$ && $P\_test\_2_k$ <= $cumulative\_P\_idle_i$
False
$P\_test\_2_k$ > $cumulative\_P\_idle_i$ && $P\_test\_2_k$ <= $cumulative\_P\_off_i$
True
True
True
$I\_2_k = \frac{W_{on}}{2\pi(R\_2_k)^2}$
$I\_2_k = \frac{W_{idle}}{2\pi(R\_2_k)^2}$
$I\_2_k = \frac{W_{off}}{2\pi(R\_2_k)^2} = 0$
k = 20,000
True
$totalI2 = \sum_{k=1}^{20,000} I\_2_k$
$SPL\_2_i = 10\log_{10}(\frac{1}{k}.\frac{totalI2}{10^{-12}})$
4

(c)



(d)

Fig. 1 – Framework of stochastic modelling (a) part 1; (b) part 2; (c) part 3; (d) part 4

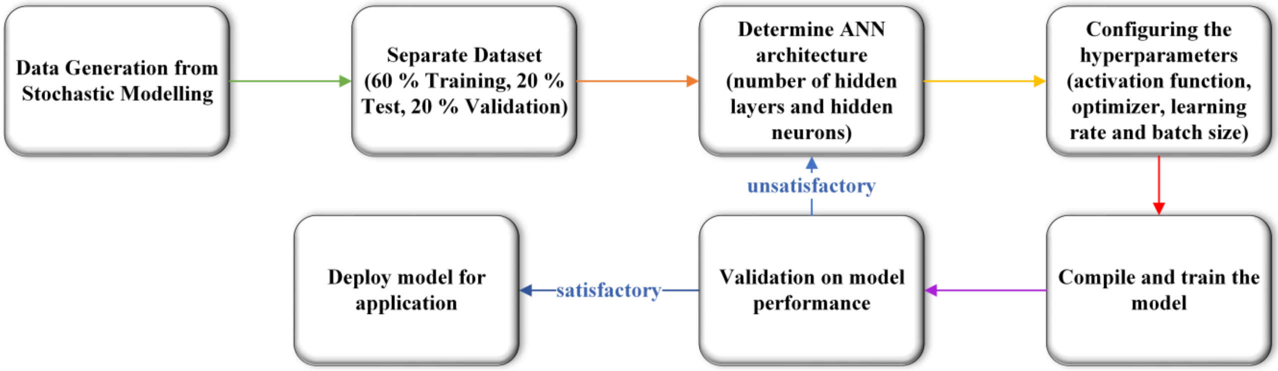


Fig. 2 - Framework of Artificial Neural Network

2.3 Application of Simple Prediction Charts

The most crucial factor when applying the simple prediction chart method is to identify the overall size of the construction site and divide the site into various sub-areas, then the noise levels of the respective areas will be predicted and combined to obtain the overall noise levels. Besides, multiple machines that are being operated for different activities can be clustered within a sub-area. The noise level at a receiver can be obtained by using the following seven steps:

(a) Select the sound power level of a machine.
(b) Determine the width and depth of the sub-area.
(c) Identify the angle away from the sub-area centre.
(d) Compute the distance between the plant and receiver, and the r/w ratio.
(e) Determine the standard deviation by referring to simple prediction charts [7].
(f) Determine the mean level deviation by referring to the simple prediction charts [7].
(g) Calculate the mean noise level by using Eq. (1).

Lastly, combine the mean noise levels from each sub-area by applying Eq. (2) to obtain the equivalent mean noise levels and Eq. (3) is used to compute the combined standard deviation.

$$L = L_w - 20\log_{10} r - 8 + \Delta L \qquad (1)$$

where L = mean level, sound pressure level corresponds to the source at centre of site (dBA), L_w = sound power level (dBA), r = distance between receiver and center of sub-area (m), ΔL = mean level deviation (dBA).

$$L_{Aeqn} = 10.\log_{10}(10^{\frac{Lp_1}{10}} + 10^{\frac{Lp_2}{10}} + ... + 10^{\frac{Lp_n}{10}}) \qquad (2)$$

where Lp_1, Lp_2,…, Lp_n is the mean noise level of each machine calculated by using Eq. (1).

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2 + ... + \sigma_n^2} \qquad (3)$$

where σ_1, σ_2,…, σ_n, is the standard deviation of the mean noise level for each machine.

2.4 Data Collection From Field Works

This research mainly focused on the construction activities related to infrastructure works such as drainage systems and sewerage systems. A total number of three case studies with different parameters such as the site aspect ratio, the coverage angle, the distance between the noise receiver and the site centre, and the earth-moving machine duty cycles were carried out at residential projects in Semenyih, Selangor, Malaysia. The procedures for the noise level measurement were in accordance with BS ISO 6395:2008, BS 5228-1:2009, and BS ISO 3744:2010 [29]-[31]. Noise level measurement was conducted according to the procedures as illustrated in Fig. 3. Moreover, site properties (size of sub-area within the construction site) were measured using a measuring tape and the height of the tripod; whereas the sound level meter (SLM) was measured by using a distometer. A Type 1 sound level meter SoundTrack LxT of Larson Davis calibrated with the reference sound of 94 dBA at 1 kHz with the tolerance of 1 dBA, were used to conduct all the noise level measurement. The sound level meter was set at 1.2 m - 1.5 m away from the ground level and 3.5 m away from the reflective structure as stated in Guidelines for Environmental Noise Limits and Control [32]. The readings of background noise and equivalent continuous A-weighted sound pressure level, L_{AFeq} of each control point were measured for 30 minutes. To conduct the measurement of the sound power level of the machine, the basic length, l of the machine will be measured and the radius, r will be determined according to BS ISO 6395:2008 Annex A [29]-[31]. The sound power level was obtained at 6 different locations that were calculated by using a set of the coordinate system surrounding the machine, and the measurement duration at each point was 30 seconds. A demonstration of sound level measurement of the control point for case study 2 is shown in Fig. 4.

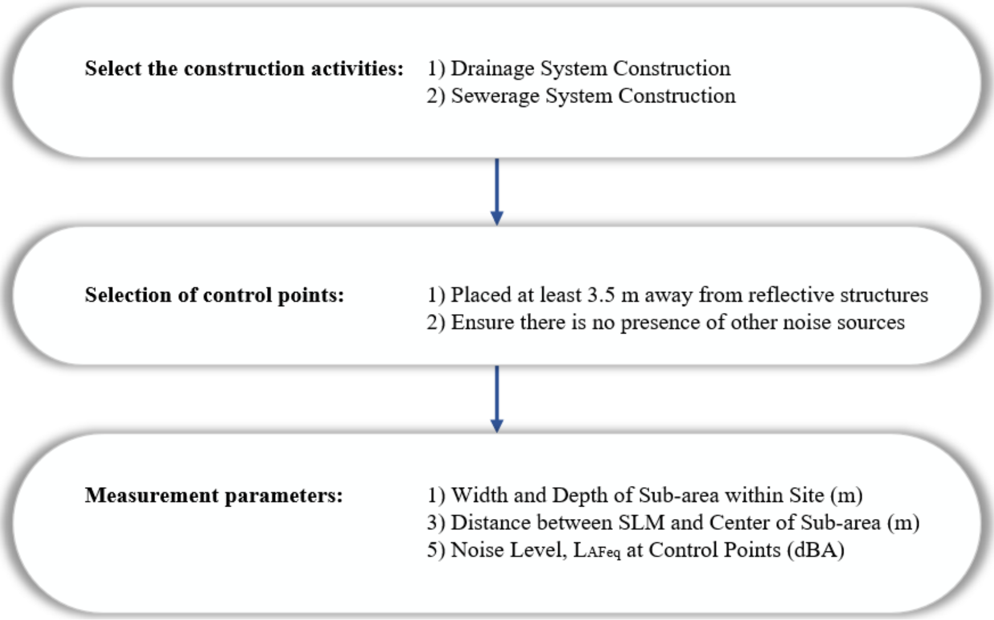


Fig. 3 - Procedures of field works

Fig. 4 - Example of the measurement of control point 2 for case study 2

3. Results and Discussion

This section discusses the background noise level, predicted noise levels and actual noise levels of different case studies. Case study 1 had a background noise of 54.0 dBA because it resulted from the traffic noise as the sub-area was located 20 m away from the entrance of the construction site. Case studies 2 and 3 had the lowest background noise of 47.0 dBA because the sub-area was an isolated area located 50 m away from other construction activities. The disparities between the predicted and actual results will be assessed by using absolute difference for the accuracy and R-squared value for the reliability. The lower the value of absolute difference indicates high accuracy; where the closer the R-squared value to 1, specifies the higher the reliability of the prediction. Moreover, the variation of standard deviation for the prediction from both SPC and DL is discussed as well. The result shows the feasibility, accuracy, and reliability of the construction noise prediction with the application of the deep learning (DL) model. The construction activity for case study 1 was the drainage system whereas the activities for case studies 2 and 3 were the construction of the sewerage system. Case studies 1, 2 and 3 were configured with the aspect ratio of 1:1, 2:1 and 1:2 correspondingly. The sound power level of two crawler excavators (107.9 dBA and 105.2 dBA) (CE 1 and CE 2) were involved in this study for the SPC and DL noise prediction.

3.1 Comparison between Simple Prediction Chart and Deep Learning Model

For case studies 1, 2 and 3, the absolute difference between the SPC and DL for each control point was not more than 0.2 dBA. Although the idling time of the machine during measurement was 10 % of the total activity time, this did not affect much on the equivalent continuous sound pressure level during the prediction. Based on the data from Table 2, the average predicted standard deviations from both SPC and DL had an insignificant difference of 0.2 dBA as well. The disparities resulted from the inclusion of duty cycles in DL whilst the SPC considered the machine operates at all times [6], [7]. However, overall DL outperformed the SPC technique with the introduction of different duty cycles in the stochastic model. The relationship between the prediction and actual value is presented in Fig. 5.

3.2 Comparison between Deep Learning Model and Actual Measurement

By interpreting the data, the absolute difference between the DL prediction and actual values ranged from 0.9 dBA to 2.3 dBA as demonstrated in Fig. 5. This is because the simulation of stochastic modelling covered the sub-area entirely whereas, in the actual scenario, the machines only cover specific areas within the sub-area. Hence, this may give rise to the disparities between the DL and actual measurement. Case study 1 had a slightly lower absolute difference because the machine travelled more frequently to transfer the excessive soil to a different location each time after excavating the trench due to space limitations. Contrarily, for case studies 2 and 3, the machine only travelled in a straight line during the sewerage system construction activities even though there were excavation works as well. This is due to the fact that the machine only placed the subsoil along the trench after excavation. Therefore, the movement of the machine within the sub-area for case studies 2 and 3 was much lesser than in case study 1. Besides, the variation of predicted standard deviation using DL was ranging from 1.8 dBA to 5.1 dBA. The standard deviation explains the noise level distribution within the sub-area in which a higher variation of duty cycles will result in a higher standard deviation. This explains the accuracy of the prediction highly relies on the operational duty cycle and the coverage area [5]-[8]. Despite this, the R-squared value of the case studies was above 0.992 which represents high strength of association between the prediction and actual value; the closer the value to 1.0, the higher the strength of association [8], [20], [33]. Fig. 6 presents the results of the accuracy and reliability test.

Table 2 - The results of noise prediction using SPC and DL based on the given parameters

Case Study	Machine	Control Points	L_w (dBA)	*w:d* ratio	*r* (m)	*r/w* Ratio	*SPC* L_{AFeq} (dBA)	σ_{SPC}	*DL* L_{AFeq} (dBA)	σ_{DL}
1	CE 1	CP 1	107.9	1:1	13.87	0.694	77.1	3.5	77.0	3.7
		CP 2		1:1	23.25	1.163	72.6	2.3	72.6	3.7
		CP 3		1:1	27.61	1.381	71.1	2.0	71.1	1.8
2	CE 2	CP 1	105.2	2:1	8.00	0.400	77.7	4.0	77.7	4.2
		CP 2		2:1	9.32	0.466	77.1	4.0	77.2	4.6
		CP 3		2:1	19.87	0.994	71.1	4.0	71.3	3.7
3	CE 2	CP 1	105.2	1:2	9.58	0.958	77.6	2.0	77.5	3.9
		CP 2		1:2	12.85	1.285	75.8	5.0	75.6	3.4
		CP 3		1:2	22.46	2.246	70.3	3.8	70.2	3.4
							Average STD = 3.4		Average STD = 3.6	

L_w = Sound power level, r = Distance, SPC L_{AFeq} = SPC predicted noise level, σ_{SPC} = SPC standard deviation, DL L_{AFeq} = DL predicted noise level, σ_{DL} = DL standard deviation.

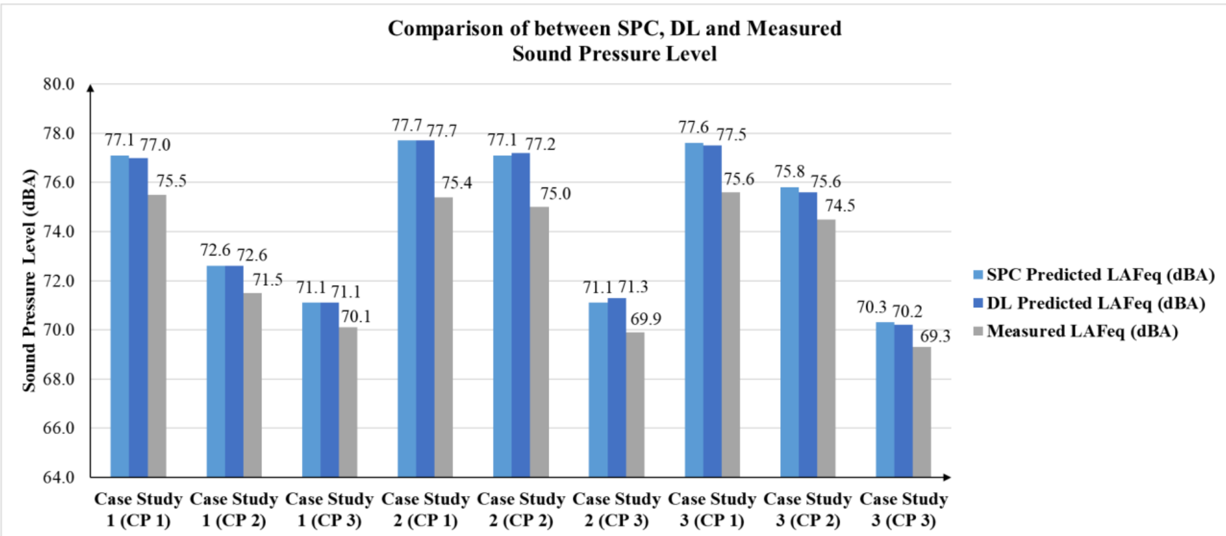
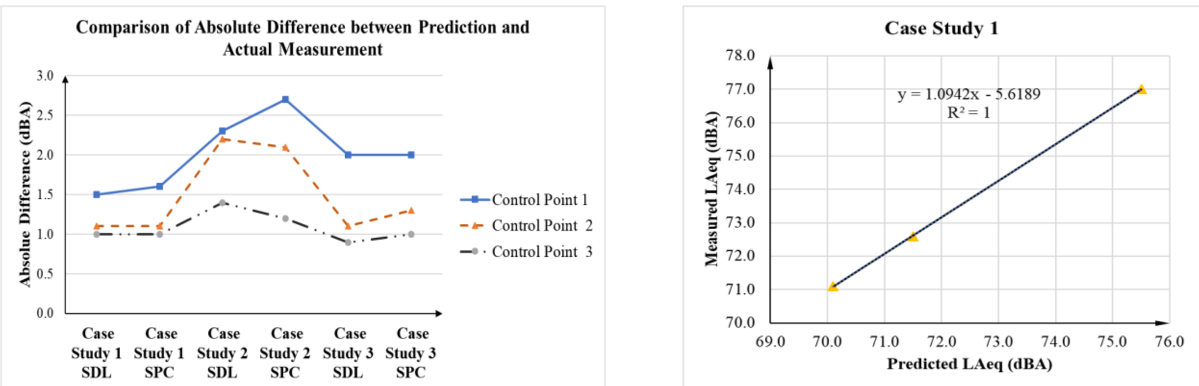
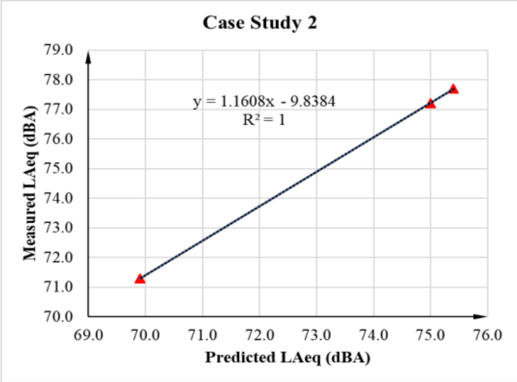


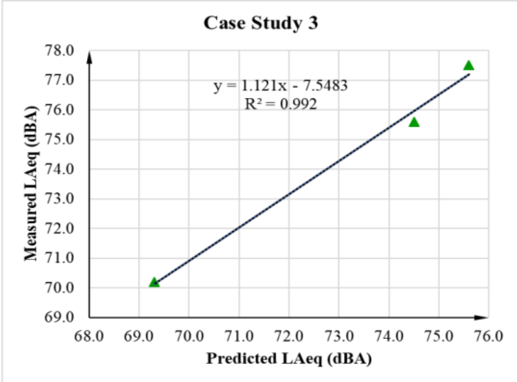
Fig. 5 - Comparison between prediction and measure sound pressure level



(a) (b)



(c)



(d)

Fig. 6 - (a) Absolute difference between predictions and actual value; (b) reliability for case study 1; (c) reliability for case study 2; (d) reliability for case study 3.

4. Conclusion

The outcome of this study presents the association between stochastic modelling and artificial neural network can predict sound pressure level at a construction site with satisfactory performance. To support this statement, the highest absolute difference between DL prediction and actual value was 2.3 dBA. The highest standard deviation value was 4.6 dBA due to the variation in duty cycle and coverage area of the machine. However, the lowest R-squared value was 0.992 among the case studies which indicates strong strength of association between the prediction and actual measurement. Hence, the deep learning model has the potential to be further developed in predicting construction noise with more parameters included that may enhance the predictive performance.

Acknowledgement

The author would like to express his sincere gratitude to Lee Kong Chian Faculty of Engineering and Science (LKC FES), University Tunku Abdul Rahman, Sg Long Campus, Malaysia for providing Research Scholarship Scheme (Vote Number 6220/O15) to fund this research.

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