Performance Evaluation of Extreme Learning Machine Techniques for Prediction of Noise Pollution*

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Abstract

Urban planning, epidemiology research, and environmental management have significant challenges when predicting intraurban noise levels in communities, particularly in developing nations. To accurately predict changes in noise levels during intraurban development and the resulting noise pollution, the majority of existing noise-predicting models are limited. In this study, two noise prediction models namely, Classical Extreme Learning Machine (C-ELM) and Bi-directional Extreme Learning (B-ELM) were developed for Tarkwa Nsuaem Municipality, and their performances were evaluated using statistical indicators. Using statistical measures to compare the models' performances, the B-ELM outperformed the C-ELM. The indications show the difference, with the RMSE of B-ELM being 0.87 dB and that of C-ELM being 3.67 dB. Additionally, the B-Standard ELM's Deviation and Mean Square Error were 0.80 dB and 0.1399 dB, respectively, while for the C-ELM, they were 3.73 dB and 0.06 dB. The findings of the B-ELM were used to create a map that depicts the distribution of the expected noise levels. It was discovered that there is a hazard, meaning persons who live in that region are at a high risk of experiencing adverse health impacts from noise levels above 65 dB when comparing the expected noise levels to the EPA limits.

Keywords: Extreme learning, Noise, Noise pollution, Artificial neural networks

1 Introduction

In recent years, the escalation of ambient noise pollution in urban areas has emerged as a significant concern driven by diverse factors, including cultural diversity, social events, industrial growth, and infrastructural expansion. This surge poses grave health risks, as highlighted in literature citing cardiovascular issues, hearing impairments, sleep disturbances, and mental health disorders (Baffoe and Duker, 2019a; Passchier-Vermeer and Passchier, 2000). Despite regulatory efforts, such as mandates for hearing protection in developed nations, workplace-induced hearing loss remains prevalent (Golmohammadi *et al*., 2018; Jariwala *et al.*, 2017; Singh and Davar, 2004; Basner *et al.*, 2014).

With human activities and industrial operations continuing to expand, the trajectory of noise pollution is set for further increase, necessitating rigorous research to update noise pollution indices for informed urban planning and environmental conservation (Baffoe and Duker, 2019a). Efforts to mitigate noise exposure risks in workplaces safeguard workers and enhance operational efficiency (Golmohammadi *et al*., 2018).

In this context, this study aims to evaluate the effectiveness of extreme learning machine (ELM) strategies in predicting noise levels. ELM, a variant of single-hidden layer feedforward neural networks, offers rapid learning and commendable generalisation performance (Huang *et al*., 2006). The research will scrutinize four ELM methodologies, including bi-directional ELM, to assess their performance in noise prediction. Subsequent refinements to the ELM framework, such as optimally pruned ELM and fully complex ELM, have further improved learning speed and generalization capabilities (Huang *et al*., 2015; Huang *et al.*, Rong *et al*., 2008; Jordan and Mitchell, 2015; Parbat and Naganaik, 2007).

By comparing the performance of Classical Extreme Learning Machine (C-ELM) and Bi-directional Extreme Learning Machine (B-ELM) methods, this study seeks to provide insights into their efficacy in facilitating accurate environmental noise assessments, thus aiding in noise pollution mitigation and urban planning initiatives (Albadr *et al.*, 2018; Ding *et al.*, 2014;) This research contributes significantly to the field, providing a nuanced understanding of noise prediction methodologies and their implications for public health and urban development. The Ghanaian Environmental Protection Agency's mission is to manage, protect, and enhance the country's environment while also providing standard solutions to worldwide environmental issues. Therefore, it has set noise level standards for the communities in Ghana (Mensah, 2018).

Several studies emphasize the importance of comprehensive research on environmental pollution, notably noise pollution, to create a welcoming atmosphere and facilitate effective city planning and environmental management (Baffoe and Duker, 2019b). Various models have been developed to forecast noise levels accurately for these purposes. Notable models include the land-use regression model proposed by Morelli *et al*., (2015), the Multiple Linear Regression and Hybrid Approach by Baffoe and Duker (2019), and the

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Regression Equation for Modeling 10% Exceeded Sound Level (L10) as a Function of Traffic Density (L10) by Rao and Mitra (1971). Cho and Mun (2008) introduced a highway traffic noise prediction model that considered different road surfaces, while Parbat and Nagarnaik (2007) proposed assessment and modelling of noise levels using ANN (Ragettli *et al*.,2014).

Short-term traffic noise by Morelli *et al*., (2015), the Multiple Linear Regression and Hybrid Approach by Baffoe and Duker (2019), and the Regression Equation for Modeling 10% Exceeded Sound Level (L10) as a Function of Traffic Density (L10) by Rao and Mitra (1971). Cho and Mun (2008) introduced a highway traffic noise prediction model that considered different road surfaces, while Parbat and Nagarmaik (2007) proposed an artificial neural network model for predicting sound levels under traffic conditions.

Studies suggest that Artificial Neural Networks (ANN) outperform other approaches due to their ability to approximate complex nonlinear mappings efficiently. Feedforward neural networks, particularly single hidden layer feedforward networks (SLFNs), have been extensively studied for fault tolerance and learning capabilities. However, the iterative parameter adjustment process makes conventional learning methods for SLFNs prone to getting stuck in local minimums. To address these limitations, Extreme Learning Machines (ELM) have emerged as a hybrid system, (Bengio, 2009; Yang *et al*., 2012) combining the advantages of neural and artificial neural networks. ELM compensates for the deficiencies of traditional artificial neural networks by providing faster learning capabilities and efficient approximation of complex mappings (Baffoe and Duker, 2019b).

Therefore, this study on noise pollution modelling is crucial for creating a conducive environment and facilitating effective urban planning and environmental management. The development of advanced models such as ELM holds promise for more accurate and efficient forecasting of noise levels, aiding in sustainable development efforts

2 Resources and Methods Used

2.1 Study Area

The Tarkwa-Nsuaem Municipality (TNM) is situated between 5º 17' and 5º 19' north latitude and 1º 59' and 2º 00' west longitude. It is approximately 85 kilometres north of Takoradi, Ghana's Western Regional Capital. Tarkwa-Nsuaem Municipality was established in 2007 from the previous Wassa West District by Legislative Instrument (LI) 1886. To the north, south, east, and west, it is bordered by Prestea Huni-Valley, Ahanta West, Mpohor Wassa East, and Nzema East (Mensah, 2018). Fig. 1 shows the selected study area of TNM

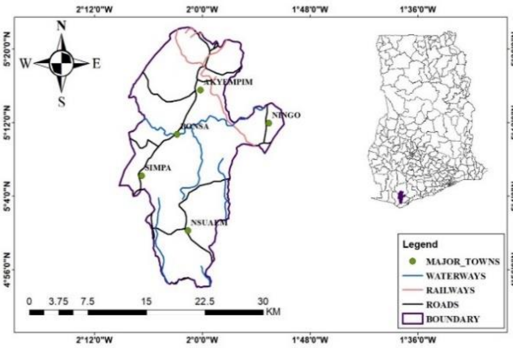

Fig. 1: Tarkwa Nsuaem Municipality

There are 90 477 people living in Tarkwa Nsuaem Municipality, according to the 2010 Population and Housing Census, with men outnumbering women (51.6% to 48.4%). The municipality's population is youthful, with 38.1% of people under the age of 15 and just 4.4% of people over the age of 60. As a result, the municipality's demographic pyramid has a wide base and a small proportion of elderly residents. The overall age dependence ratio for the municipality is 69.6, with females having a higher ratio (72.6%) than men (67.1). (Anon., 2014). The municipality is in a rainforest zone, with trees ranging from 15 to 40 meters.

2.2 Methods Used

2.2.1 Data Collection

The noise levels at certain places, such as monitoring stations, churches, workshops, and road networks, were measured using the sound level metre. The noise levels were also estimated using the area's digital city map. The microphone's diaphragm responded to the Variations in air pressure brought on by the sound waves when the sound level meter's microphone picked up those waves in the air. The device's screen displayed the sound pressure in decibels (dB) after the movement in the diaphragm

2.2.2 The B-ELM

Bi-directional Extreme Learning Machine (B-ELM) in a recently suggested learning approach for SLFNs called bi-directional ELM, specific hidden nodes are not picked at random. According to theory, this method tends to zero out the network output relatively early in the learning process. The recommended B-learning ELM's pace can be tens to hundreds of times quicker than existing incremental ELM techniques.

Additionally, the outcomes of the simulations show that the B-ELM, which has just two hidden nodes, can perform comparably to the I-ELM, which has hundreds of hidden nodes in terms of generalization. As a result, B-ELM may significantly reduce the number of concealed nodes compared to other I-ELM. The lianas can reach into the upper tree layer; therefore, the forest is dense with them. Mahogany, Wawa, Odum, and Sapele are examples of economically valuable trees. The Bonsa Reserve, Ekumfi Reserve, Neung South Reserve, and Neung North Reserve are among the main forest reserves in Tarkwa Nsuaem (Anon., 2014).

The terrain is undulating, with an average height of roughly 70 meters. The highest point is between 150 and 300 m above sea level. The Bonsa River and its tributaries, such as Buri, Anoni, Sumin, and Ayiasu, drain the area in a dendritic pattern (Anon., 2014).

Was transformed into electrical impulses, which were subsequently translated back to sound pressure. 20. The locations of the several spots where the sound levels were monitored were selected using the portable GPS. Ghana Meter Grid was used as the receiver's coordinate system.

The GPS receiver at each location took a long time to monitor more than four satellites before readings could be taken. This was done to ensure the obtained coordinates were within the allowable error margin. When calculating the horizontal coordinates of the various points, it was ensured that the GPS was unobstructed by any canopy.

Residual error function e and the network output weights B are related in the context of B-ELM, and this connection is known as the error-output weight ellipse relationship. Equation (1) gives an illustration of this:

$$\frac{\beta_{2n}^2}{\beta_{2n-1}^2} + \frac{\|e_{2n}\|^2}{\|e_{2n-1}\|^2} = 1 \quad (1)$$

$$\beta_2 n\ 2\ \beta_2 n-1\ 2 + \|e_2 n\|\ 2\ \|e_2 n-1\|2 = 1 \quad (2)$$

Where βi is the weight linking the ith hidden node to the output node, and ei stands for the residual error function for the present network with i hidden nodes. This phrase emphasizes that the success of learning only rests on Equation (3).

$$\frac{\beta_{2n}^2}{\beta_{2n-1}^2}\text{, if } |\ \beta_{2n}\ |/|\ \beta 2n-1| \rightarrow 1,\ \|e_2 n\| \ll \|e_2 n-1\|$$
(3)

Finding improved hidden node parameters (a, b) is the main goal of the approach to decrease the neural network's residual error as rapidly as feasible. The hidden node parameters (a, b) are produced randomly, much like I-ELM, where the number of

$$H^2{}_{ne} = e_{2n-1}.(\beta_2 n_{-1})^{-1} \quad (4)$$

$$\boldsymbol{\beta 2n} = \frac{(\mathbf{e2n-1}, \boldsymbol{H_{2n}^e})}{\|\boldsymbol{H_{2n}^e}\|^2} \quad (5)$$

$$= \frac{\beta 2n + 1 \quad (e2n-1, H_{2n}^r + 1)}{\|H_{2n}^e\|^2} \quad (6)$$

h: R → R is provided as the sigmoid or sine value activation. Given a succession of error feedback functions (x, a,b) based on Equation (7).

Hidden nodes L ∈ {2n+1, n ∈ Z}. However, the parameters of hidden nodes (a, b) are discovered when the number of hidden nodes L ∈ {2n, n ∈ Z}. For any continuous goal function f, given SLFNs with any bounded non-constant piecewise continuous function H: R → R for additive or sine nodes, a randomly generated function sequence $H_2 n+1\ r$ is produced. The error feed-back function sequence $H_2 n$,n ∈ Z, $lim n\rightarrow\infty \| f - (f_2 n-2 + H_2 n_{-1r} . \beta_2 n + H_2 n\ . \beta_2 n\| = 0$ holds with a 1 percent chance if the following Equations (4) to (6).

$$H_{2n}^e = e2n - 1 . (\beta_{2n-1})^{-1} \quad (7)$$

If SLFN is trained by B-ELM for any continuous target f and f = T, then we have \{($\tau_2 n_{-1}$,|$\beta_2 n$|/|$\beta_2 n_{-1}$|)|τ_{2n-1} ∈ {0, 1},|$\beta_2 n$|/|$\beta_2 n_{-1}$|∈{1, 0}.

Moreover, C-ELM exhibits excellent generalization capabilities and can approximate any function when utilizing typical activation functions like additive or Radial Basis Function (RBF). Its distinctiveness lies in the random feature mapping step, unlike Support Vector Machines (SVM) that rely on kernel functions or deep neural networks using techniques like Restricted Boltzmann Machines (RBM) or Auto-Encoders/Auto-Decoders for feature learning. ELM accommodates various nonlinear mapping functions, making it versatile for real-world applications, including classification and regression tasks. For ELM, Given N distinct training samples

$(x_i, t_i) \in R^n \times R(i = 1, 2, , \ldots . , N)$,

$$o_j = \sum_{i=1}^{K} \beta_i f_i(x_j) = \sum_{i=1}^{K} \beta_i f(x_j; a_i, b_i), \quad j = 1, \ldots, N$$
(8)

Oj is the output vector of the SLFN with respect to the input sample
xi.$ai = [ai1, \beta i2, \ldots . \beta i\ ]$ and bi learning parameters generated randomly of the jth hidden node, respectively.
$\beta i = [\beta i1, \beta i2, \ldots , \beta im]^T$ is the link connecting the jth hidden node and the output nodes.

$H\beta = 0$
(9)

where,

xi.a_i = [a_{i1}, β_{i2}, … . β_i] and b_i learning parameters generated randomly of the jth hidden node, respectively.
$\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T$ is the link connecting the jth hidden node and the output nodes.

Equation (8) may be used to express the output of an SLFN with $\tilde{N}$ hidden nodes, which can be additive or RBF:

(xj; ai, bi) is the major activation function of ELM. Set $ai.xj$ be the inner product of ai and xj. Equation (3.1) can be written compactly as Equation (9):

(x_j; a_i, b_i) is the major activation function of ELM. Set $a_i.x_j$ be the inner product of ai and xj. Equation (3.1) can be written compactly as Equation (10):

$H\beta = 0$
(10)

where,

$$H = \begin{bmatrix} f(ai.\,xi + b1) \cdots & (a\tilde{N}.\,x1 + b\tilde{N}) \\ \vdots \quad \ddots & \vdots \\ f(ai.\,xN + b1) \cdots & (a\tilde{N}.\,xN + b\tilde{N}) \end{bmatrix} \qquad (11)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{Mxn} \qquad (12)$$

and

$$O = \begin{bmatrix} O_1^T \\ \vdots \\ O_N^T \end{bmatrix}_{Mxn} \qquad (13)$$

H is referred to as the hidden layer's output matrix in this context to reduce the $\|O - T\|$ network cost function. According to ELM theories, the learning parameters a_i and b_i of the hidden nodes can be chosen at random without taking the input data into account. Once Equation (3.2) is transformed into a linear system, the output weights β may be calculated analytically by solving Equation (14) for the least squares as shown below:

$$\hat{\beta} = H^{\intercal} T \qquad (14)$$

Where H is $H^{\dagger}$ generalized Moore-Penrose inverse. Thus, the output weights are calculated using a mathematical transformation, and there are a number of effective ways to address the aforementioned issue, including the Gaussian elimination approach, the orthogonal projection method, the iterative method, and the single value decomposition (SVD) (Rao and Mitra, 1971). Any long training term where the network's parameters are iteratively modified with suitable learning parameters (such as learning rate and iterations). The three-step C-ELM method may thus be summed up as follows:

Input: a training set $(x_i, t_i) \in R^n \times R$($i = 1,2, \dots,$ N), the activation function f, and the hidden node number $\tilde{N}$.

Output: the output weights β.
Step 1: Set the concealed nodes' parameters at random (a_i, b_i) , i=1…,$\tilde{N}$.

Step 2: The hidden layer H's output matrix should be calculated.
Step 3: Identify the output weight β: $\beta = H^{\dagger}T$.

Analytically, the output weights may be calculated by discovering a least squares solution in the manner described as $\beta = H\dagger$T.

2.2.3 Statistical Indicators Model Performance Evaluation

Equations listed from Equation (15) to Equation (17) were used to compute statistical indicators in order to evaluate the accuracy of the proposed models utilized in this research (5.4). The Mean Square Error (MSE), Root Mean Square Error (RMSE), and Standard Deviation equations are indicators that aid in the objective evaluation of the models (SD).

The MSE is a single value that provide information about the goodness of fit of the regression line, and it is defined as:

MSE=∑〖(X-X̅)〗^2/N (15)

where, x is the measured value, $\bar{x}$ is the predicted value, and N is the number of observation points.

The RMSE presents the model's accuracy by comparing the deviation between predicted and measured noise levels. The value of RMSE is always positive and defined as.

RMSE=√(∑E^2/N) (16)

where N is the number of observation points, and E2 represents the error square.

SD=√(((∑〖(X-X̅)〗^2)/(N-1)) (17)

where N-1 is the degree of freedom, x is the measured value and $\bar{x}$ is the anticipated value. The

Standard Deviation (SD) quantifies how closely the data are grouped around the mean.

3. Results and Discussion

3.1 Results

Table 1 shows the errors propagated from the prediction of noise levels in Tarkwa Nsuaem Municipality (TNM) using C-ELM and that of the B-ELM, as compared with the observed. Fig. 2 shows the various predictions from the models applied.

Fig. 3 shows the trend of noise level as generated by C-ELM and B-ELM as compared to the observed (Target) using the testing data. The blue colour indicates the observed noise level, the orange colour represents the noise level predicted by C-ELM, and the ash colour shows the noise level predicted by B-ELM. The trend of errors produced by both prediction models using the testing data is shown in Fig. 3.

For the testing data, Table 2 presents the statistically based performance indicators of the C-ELM and B-ELM approaches.

The spatial distribution of the research area's noise levels was plotted using the outcomes of the generated model ELM method. Fig. 4 depicts the distribution of the expected noise in the research region. Comparison of the C-ELM and B-ELM was done using the statistical indicators mentioned earlier.

Table 2 Performance Indicators

ELM Technique	RMSE (dB)	MSE (dB)	Standard Deviation (dB)
B-ELM	0.8736	0.7632	0.8045
C-ELM	3.6751	13.506	3.7366

3.2 Discussion

The errors in predicting noise levels by the C-ELM and B-ELM models are analyzed in Section 2.1, revealing minor discrepancies between the projected outputs and testing data. Tables 1 and 2 and Figs. 3 and 4 demonstrate that the B-ELM model generally provides more accurate predictions than the C-ELM, aligning better with observed noise data. Specifically, the B-ELM exhibits less error inconsistency over the zero value, indicating its superior accuracy in predicting noise levels. This finding is reinforced by statistical measures such as the Root Mean Square Error (RMSE) and standard deviation, which illustrate the B-ELM's higher predictive power and precision compared to the C-ELM.

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The RMSE values further confirm the superior performance of the B-ELM, with a significantly lower RMSE of 0.8736 dB compared to the C-ELM's 3.6751 dB, as indicated in Table 2. Additionally, the standard deviation values highlight the B-ELM's better precision, with a deviation of 0.8045 dB for the B-ELM and 3.7366 dB for the C-ELM. Moreover, the Mean Square Error (MSE) values from Table 5.2 reinforce the effectiveness of both approaches, with the B-ELM providing an MSE of 0.7362 dB compared to the C-ELM's 13.506 dB, indicating the quality of fit of the regression line. These results underscore the utility of noise prediction models like the B-ELM in assessing noise exposure for urban planning and environmental management, particularly in areas lacking official noise maps or prediction models.

Table 1: A Sample of Errors Propagated During Predictions of Noise Levels for Testing Data

Observed	Predicted (C-ELM)	Residual (C-ELM)	Predicted (B-ELM)	Residual (B-ELM)
67	61.973	5.027	66.928	0.072
67	68.012	-1.012	66.918	0.082
66	68.192	-2.192	66.950	-0.950
65	74.011	-9.011	66.937	-1.937
65	65.970	-0.970	66.919	-1.919
63	61.845	1.155	64.900	-1.900
63	73.131	-10.131	63.877	-0.877
67	62.297	4.703	67.413	-0.413
67	66.188	0.812	67.403	-0.403
68	65.645	2.355	67.436	0.564
67	67.697	-0.697	67.429	-0.429

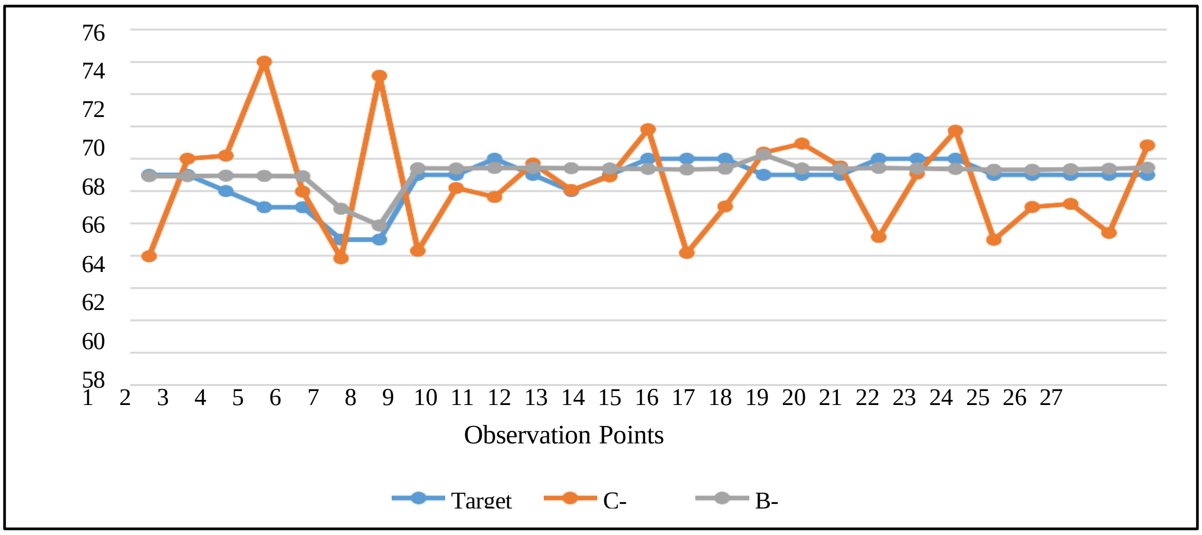

Fig. 2: Trend of Noise Level Yielded by Both Prediction Models for Testing Data

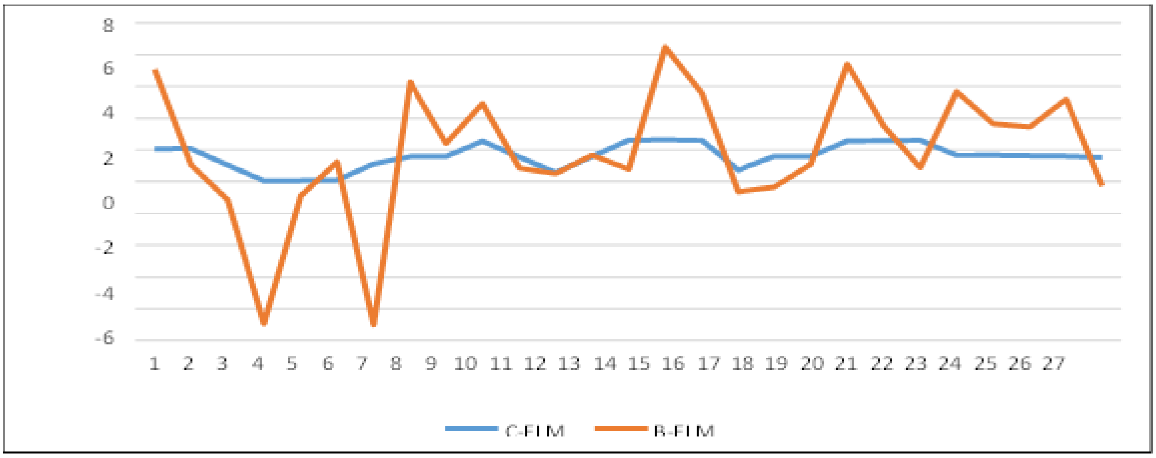

Fig. 3 Trend of Errors Generated from the Predictions Models for Testing Data

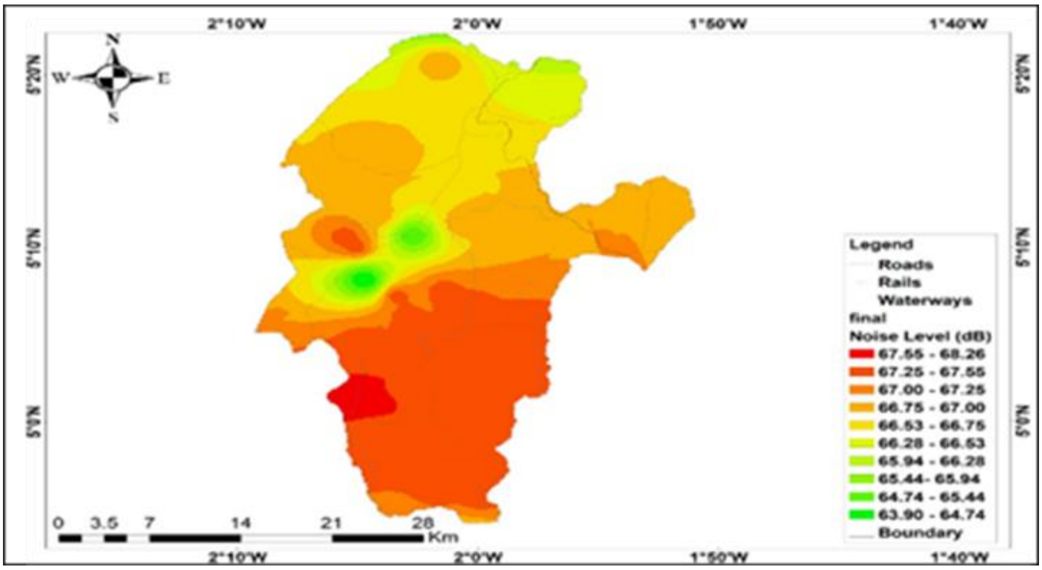

Fig. 4: Map of Study Area after Prediction

4 Conclusion

Two extreme learning machine algorithms have been used to forecast noise, and their effectiveness has been assessed using statistical measures. The models were created to complement the shortcomings of SLFNs and enhance them based on the strengths and capabilities of the Classical ELM and Bi-directional ELM. B-ELM outperformed C-ELM when comparing the performances of the ELM models using statistical measures. The indications show the discrepancy, with the RMSE of B-ELM being 0.8736 dB and that of C-ELM being, respectively, 3.6751 dB. Additionally, the B-ELM standard deviation and MSE are each 0.8045 dB and 0.7632 dB, respectively, while the C-ELM had 3.7366 dB and 13.506 dB.

A map showing the distribution of the predicted noise levels has been generated from the results of the B-ELM model. Comparing the predicted noise levels to the Environmental Protection Agency (EPA) standards of Ghana, it was observed that there is a threat, which means that people living in an area with noise level above 65 dB are at high risk of health effects of noise pollution including, psychological, sleep and behavioral disorder. The created models have demonstrated their capacity to map interurban noise concerning changing urban land use. Urban planning and noise management will benefit from this.

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