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Multi-Step Mobile Location Estimation using RF-Signal Cell-Phone Detector

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ABSTRACT: Many studies adopted extreme learning machine (ELM), support vector regression (SVR) among others in the quests for accurate prediction of sensors' location distance. Researchers have neglected the use of traditional statistical regression techniques. Traditional regression techniques, apart from easy usage, are very cheap for system analysis. Economic analysis calls for alternative only when the statistical techniques werefound deficient. This study applied statistical multivariate regression (MR) technique to predict location distance of mobile phone from the RF-signal detector with respect to the base-station location in consideration of two signal attributes; signal strength (SS) and signal quality (SQ) for data collected under line of sight (LoS) condition. The outcomes were compared with ELM techniquewhere the trained data were partitioned into two namely: training dataset - 70%; and testing data -30% respectivelyusing stratify sampling approach in MATLAB environment.Results emanatingfrom the prediction analysis showed that ELM achieves an accuracy of 100% and 99.72% for the training and testing set respectively. Under full line of sight, multivariate regression outcomes in SPSS environment were 0.966, 0.992, 0.974 and 0.5692 respectively for correlation, determination, accuracy and error coefficients. No significant difference was noticed in accuracy under partial or full barrier conditions. The outcomes indicated excellent prediction of mobile phone location distance. Based on the outcomes of this work, it could be confidently stated that mobile phone location distance can be efficiently and accurately predicted using ELM- and MR-based models. The field data can be managed with adoption of MR-based prediction model.

Keywords: MultivariateRegression,Extreme learning machine,support vector regression,signal strength, signal quality, detector.

I. INTRODUCTION

The challenge of providing reliable and accurate position location of mobile signals in wireless communication systems have attracted many attentions in recent years. The main factor behind the recent interest in position location has been the limitations on previously used methods of preventing unauthorized users.Robust cell phone signal detection is important in the emerging cost of detection failure [1]-[3]. The achievement of accurate detection will attract high cost but low cost of risk. In literature, the optimal (robust) detection system was based on the tradeoff between cost of accurate detection (hits) and false detection (false alarm, F_A) under known noise. This study proposed an improved system device for enhancing better location accuracy. The device (detector) will detect mobile phone position using predetermined signal attributes such as signal strength (SS) and signal quality (SQ) [1]- [5].

Many studies have been carried out on phone usage monitoring using phone detectors with acceptable level of accuracy [1]–[3]. However, there is a need to improve the accuracy of detection to further minimize error. Artificial intelligence is found to be versatile tool in this regard [6]-[8].In recent time, the use of computational intelligence and machine learning techniqueshave beendemonstrated in several field often with huge promising outcomes.ELM has been successfully utilized in fields of sciences and engineering with excellent results. Some of the unique work where it has been successfully deployed include but not

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limited to [9]–[14]. Therefore, this work is set to make use of Extreme learning machine (ELM) and statistical multivariate regression (MR) techniquein the estimation of mobile location distance.

The balance of the paper is organized as follows: review of the tools utilized in the study are presented in section 2; empirical studies that include description of the data set, experimental set-up adopted and the statistical SPSS software utilized are presented in section 3;section 4 gives detailed results and discussions based on artificial intelligence and SPSS software outcomes; while conclusions and recommendations for possible further studies are presented in section 5.

II. PROPOSED ARTIFICIAL INTELLIGENCE TOOLS

Extreme learning machine (ELM) is a branch of artificial intelligence (AI) utilized in this study. ELM comprises of single hidden layer feed-forward neural networks ($SLFN_S$) which has ability to randomlychoose hidden nodes in an attempt to determining the output weight. The challenge of slow nature of neural network (NN) has been resolved through the proposed ELM algorithm by [4],[15], [16] of the single hidden layer feed-forward neural networks ($SLFN_S$). To overcome these problems, [4], [15], [16]proposed a learning algorithm called extreme learning machine (ELM) for single hidden layer feed-forward neural networks (SLFNs). This prompts adoption of $SLFN_S$ algorithm in this study.

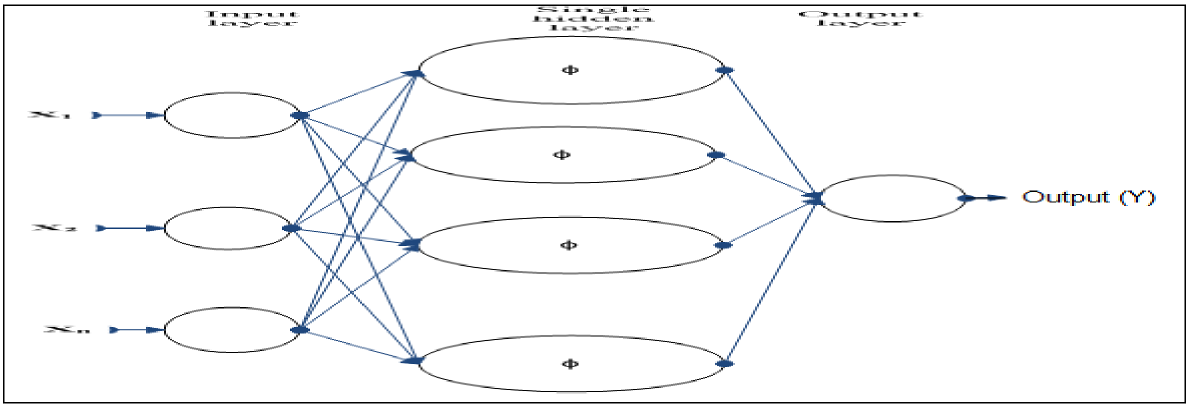

Fig.1: Proposed ELM schematic diagram for cell phonemobile location positiondistance prediction, where $x_1 \ldots x_n$ are the input values, ϕ is the activation function, and Y is the predicted distance value.

2.1 The Standard Process for ELM Algorithm

The standard $SLFN_S$ algorithm is as presented thus: Let there be available Nsamples(x_i, t_i), with $x_i = [x_{i1}, x_{i2}, ..., x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, ..., t_{im}]^T \in R^n$ then arises the standard SLFN with $\tilde{N}$ hidden neurons and activation function g(x) which is defined as:

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i . x_j + b_i) = o_j, \; j = 1, ..., N \quad \text{1a}$$

where w_i is the weight vector that connects the i^{th} hidden neuron and the input neurons, and β_i is the weight vector that connects the i^{th} neuron and the output neurons, and b_i represent the threshold of the i^{th} hidden neuron. The "." in $w_i . x_j$ is the inner product in equations 1a,1b and 1c respectively.

$$w_i = [w_{i1}, w_{i2}, ..., w_{in}]^T \quad \text{1b}$$

$$\beta_i = [\beta_{i1}, \beta_{i2}, ..., \beta_{im}]^T \quad \text{1c}$$

It must be noted that in the case of cell phonemobile position distance $y_{p_{ij}}$ estimation for instance, x_i will be the Signal Strength and Signal quality and they are independent variables. That is, there are inputs $x_{ij}, i = 1, ..., N; \; j = 1, ..., M$ and target t_i, which is the mobile phone location/ position distance $(y_{p_{ij}})$ values, where N is the number of data points and M, the number of independent variables x_{ij} (called predictors). Details about the dataset are presented later in section 3.

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Minimization model using SLFNbetween ranges o_j and t_j is expressed asequation 2:

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = t_j,\ j = 1, \ldots, N \qquad 2$$

In matrix format as equation:

$$\mathrm{H}\beta = \mathrm{T} \qquad 3$$

This can be transformed as equation 4a

$$\mathbf{H}(w_1,\ldots,w_{\tilde{N}},b_1,\ldots,b_{\tilde{N}},x_1,\ldots,x_N) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \ldots & g(w_{\tilde{N}} \cdot x_{\tilde{N}} + b_{\tilde{N}}) \\ . & & . \\ . & \ldots & . \\ . & & . \\ g(w_1 \cdot x_N + b_1) & \ldots & g(w_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \end{bmatrix}_{N\times\tilde{N}}$$

4

$$\beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ . \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N}\times m} \quad \text{and T} = \begin{bmatrix} T_1^T \\ . \\ . \\ . \\ T_{\tilde{N}}^T \end{bmatrix}_{N\times m}$$

The matrix in equation 4 is termed as neural network output matrix [17],[18]. The stated specifications utilized in SLFN in achieving the procedurethe for the proposed ELM frame work based on the previous studies[15],[16],[19].

The system input comprises independent variables (input $x_i \in R^n$) and target variable ($t_i \in R^m$), activation functiong(x), and the number of hidden neuron, $\tilde{N}$ while the target values and the weights of the layers are the output.

The relationship between input and output variables can be expressed as equation 5:

$$N = \{(x_i, t_i) | x_i \in \mathbf{R}^n, t_i \in \mathbf{R}^m, i = 1, \ldots, N\}, \qquad 5$$

The training procedure comprises three steps as stated as follows:

Step 0: Initialization: random numbers assigned to the input weight w_j and the bias b_j where j = 1, …, $\tilde{N}$

Step 1: Determines the hidden layer output matrix H.

Step 2: Determinesthe output weight β using:

$\beta = \mathrm{H}^{\dagger}\mathrm{T}$

$\mathrm{H}^{\dagger}$ stands for inverse of H.

Parametersβ, H and T are as defined in equations 1, 2 and 3.

2.2Performance Measure

Performance measure of the proposed models was evaluated using coefficient of correlation (CC)and root means errors (RMSE). Similar evaluation criteria was adopted using the multivariate regression analysis (MR), the analyses extended to coefficient of determination R^2 as shown in equations 6a, 6b and 7 respectively.

CC is used in studing the ralationship between the response variable y_p and preditor variable y_a , it measures the strength and direction of the relationship that exist between two variables[20].The CC formular can either be simply interpreted as the covariance between the standardized variables or it may mean the ratio of the covariance to the standard deviations of the two variables. The closer CC to 1 (-1) the stronger the relationship between the two variables.

The square of CC (R^2) which is also known as the coefficient of determination indicates how well predictor variable determines the response variable. It can be used that in determining the variability in the response variable as accounted for by the predictor variable. When the value of R^2(coefficient of determination) is close or near to 1, then, it means that the predictor variable accounts for large part of the variation in response variable [18].Root Means Square Error(RMSE) is found useful in detrmining the level of residuals/noises(errors) in the models.The closer the valueof RMSE to zero (0) the better theimagine prediction models developed. Equations 6a, 6b, and 7 are used for determining CC (R), R^2 (Coefficient of determination) and RMSE respectively.

$$R = \frac{\sum (y_a - y_a')(y_p - y_p')}{\sqrt{\sum (y_a - y_a')^2 \sum (y_p - y_p')^2}} \qquad 6a$$

y_a and y_p represent the actual and predicted values respectively while y_a' and y_p' stand for the mean of the actual and predicted values.

$$R^2 = \left(\frac{\sum y_a - y_a' \quad y_p - y_p'}{\sqrt{\sum y_a - y_a'^{\ 2} \sum y_p - y_p'^{\ 2}}} \right)^2 \quad 6b$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \left(\frac{y_{pi} - y_{ai}}{n} \right)^2} \quad 7$$

Where y_{pi} represent thepredicted value, y_{ai} its corresponding actual value and n, the size of the dataset used.

III. EMPIRICAL METHOD

3.1 Description of the dataset

Dataset were collected using the designed RF detector[1]-[2] that was moved under full line of sight(LoS) along Y- axis (mobile phone distance to detector, n) in the range 0.5m to 12m in step of 0.5m while base station (mast) to mobile phone distance, m varied at 1m interval along X-axisin the step of 1m.Fig. 2 gives the proposed relationship between the base station (mast), detector and the mobile phone location distance. The objective is to predict location distance of the mobile phone from the detector with respect to the mobile phone signal base-station (mast).A mobile phone base station is a wireless system that uses microwave radio communication.Mobile phones and base stations behave as two –way radios that produce radio frequecy radiation (RF) for easy communication.The base station mostly consist of the tower, antennas,hardware(Base Tranceiver Station and the link. [19]Signal quality and signal strength were measured from mobile phone as its distance varies from base station. The corresponding detect-ability was recorded as mobile phone distance varies from detector in vice versa.

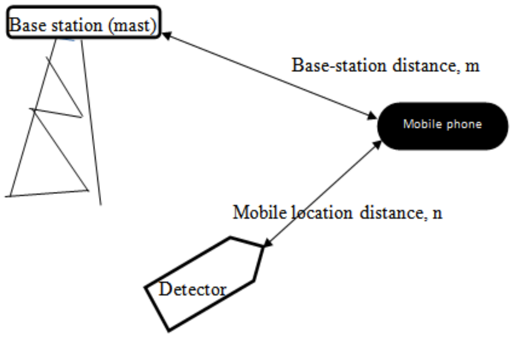

Fig.2: Relationship of mobile phone location, Base station and detector

3.1.1. Condition 1/scenario 1

(i) Detector was tested where no obstacle resides between the two antennas of the transmitting antenna of the mobile phone and the receiving antenna of the detector.
(ii) Distances were measured in metre using long tape rule, detector is being moved along Y- axis at 0.5m interval while mobile phone distances varied at 1m interval along X- axis and vice versa.
SS represents signal strength that is being measured by the detector when mobile phone is used within the environment.
SQ represents signal quality that is being measured by the detector when mobile phone is used within the environment.
The target here is mobile distance, that is, we want to actually predict the actual mobile distance of the mobile phone when it is being used within certain perimeter where the detector is being deployed.

Table1: Datasets **(**data on SS (dBm) and SQ (%) with full line of sight (LoS) for estimation/location**)**

Distance(m) y_{aij}	1m SS_1 x_{aij}	2m SS_2	3m SS_3	4m SS_4	5m SS_5	6m SS_6	7m SS_7	8m SS_8	SQ_1	SQ_2	SQ_3	SQ_4	SQ_5	SQ_6	SQ_6	SQ_8
0.5	-42	-40	-46	-49	-56	-59	-63	-63	84	83	74	70	68	63	53	51
1.0	-42	-40	-46	-44	-51	-56	-64	68	84	81	72	71	63	62	52	50
1.5	-40	-42	-48	-47	-54	-55	-61	-64	83	80	71	70	62	62	51	46
2.0	-40	-41	-47	-40	-59	-59	-68	-68	80	81	65	68	61	53	50	48
2.5	-43	-43	-48	-46	-61	-57	-65	-69	81	80	64	65	60	52	48	43
3.0	-45	-44	-52	-48	-62	-65	-66	-73	73	77	66	61	60	53	46	43
3.5	-45	-45	-52	-48	-63	-67	-64	-75	72	72	68	64	61	50	44	41
4.0	-47	-45	-55	-56	-60	-68	-67	-78	72	74	67	63	61	50	41	42
4.5	-48	-48	-56	-59	-68	-69	-69	-79	70	68	58	62	53	46	41	42
5.0	-47	-50	-59	-49	-68	-71	-72	-80	65	68	57	60	53	45	41	38
5.5	-49	-55	-60	-49	-67	-72	-74	-80	62	63	54	61	51	42	38	38
6.0	-49	-55	-62	-55	-69	-73	-77	-83	60	60	53	55	48	42	36	36
6.5	-53	-58	-64	-61	-72	-74	-78	-84	60	54	55	51	47	43	34	36
7.0	-52	-63	-66	-63	-74	-77	-79	-84	61	52	51	42	46	40	35	32

7.5	-52	-64	-85	-68	-78	-78	-83	-79	55	48	47	47	45	40	30	32
8.0	-51	-65	-85	-70	-77	-75	-83	-99	52	46	45	41	45	38	30	0
8.5	-56	-68	-78	-72	-72	-79	-99	-99	51	41	43	42	43	37	0	0
9.0	-57	-68	-76	-70	-79	-83	-99	-99	50	42	40	41	42	38	0	0
9.5	-57	-72	-77	-75	-82	-99	-99	-99	43	43	39	40	42	0	0	0
10.0	-60	-70	-78	-79	-82	-99	-99	-99	40	44	39	40	41	0	0	0
10.5	-70	-74	-74	-84	-99	-99	-99	-99	41	40	35	34	0	0	0	0
11.0	-99	-99	-78	-86	-99	-99	-99	-99	0	0	32	32	0	0	0	0
11.5	-99	-99	-84	-99	-99	-99	-99	-99	0	0	32	0	0	0	0	0
12.0	-99	-99	-99	-99	-99	-99	-99	-99	0	0	0	0	0	0	0	0

SS and SQ are the x_{aij} Signal Strength (dBm), SQ Signal quality and Distance y_{aij} measured in meter (m)

The results of statistical analyses on the data set are presented in tables 2a and 2b.The data scaling outcomes from table 2a show the level of suitability and applicability of the data set in terms of minimum, maximum, mean, median and standard deviation value. The coefficient of correlation (CC) (see table 2b) will reveal how far how each attribute will contribute to the accurate prediction of the target variable. High positive or negative correlation coefficients (close to 1 or -1)between experimental (actual)and predicted variables will be a pointer for proper selection and acceptability of the models.

Table 2a: Statistical Analysis of the Datasets

	mean value	Max. value	median	Stdev	min. value
DISTANCE(m)	6.25	12	6.25	3.535534	0.5
1m SS1	-55.9167	-40	-50	18.0167	-99
2m SS2	-60.2917	-40	-56.5	18.59986	-99
3m SS3	-65.625	-46	-63	15.288	-99
4m SS4	-63.1667	-40	-60	17.15826	-99
5m SS5	-72.9167	-51	-70.5	14.61362	-99
6m SS6	-76.2917	-55	-73.5	15.30126	-99
7m SS7	-80.2083	-61	-77.5	14.79712	-99
8m SS8	-78.4167	68	-81.5	33.63735	-99
SQ1	55.79167	84	60.5	25.37027	0
SQ2	54.04167	83	57	25.5334	0
SQ3	51.125	74	53.5	17.09643	0
SQ4	49.16667	71	53	19.48169	0
SQ5	43.83333	68	47.5	21.51171	0
SQ6	35.66667	63	42	22.28602	0
SQ6	27.91667	53	35.5	21.0897	0
SQ8	25.75	51	36	20.8957	0

Table 2b: Correlation between the target variable (Distance) and each of the attributes of the dataset

Attributes	Correlation
1m SS1	-0.82283
2m SS2	-0.93968
3m SS3	-0.9341
4m SS4	-0.93997
5m SS5	-0.95259
6m SS6	-0.96021
7m SS7	-0.95428
8m SS8	-0.63211
SQ1	-0.91503
SQ2	-0.93062

SQ3	-0.93347
SQ4	-0.90961
SQ5	-0.87236
SQ6	-0.91517
SQ6	-0.93938
SQ8	-0.92515

3.2 Computational Intelligence process

SLFN algorithm utilized in this study was implemented on MATLAB environment. In carrying the computation data set, table 1 was partitioned into 7:3 (70% to 30%) representing training and testing set respectively. Stratify sampling approach was adopted to ensure effective random partitioning.ELM model was trained and tested with 70% and 30% representing the training and the testing data setvia test –set-cross - validation methodwhich allows regression to be performed on the 70% dataset (training set)and estimatesfuture generalization accuracy on the remaining 30% of thedataset(testing set) Evaluation of the developed model was done using correlation coefficient (CC), coefficient of determination(R^2) and Root Mean Square error (RMSE) to determine model generalization accuracy.

3.3 Optimum parameters Search Strategy

ELM optimization parameters on the available data set were carried through a test-set-cross-validation technique. The optimization process can be analyzed thus: RMSE values and correlation coefficients were been monitored for each run of generated training data set and testing data set using group of parameters that includeactivation function (AF) and the number of hidden neurons (N). The identification of the optimal parameter performance measures and their corresponding values for the stated set of features were achieved by searching through all possible values of parameters in a given range.

In this study, the process was carried outwith an incremental step of parameters for the ELM activation functions. Thebest performance measures were identified through optimal values of the parameters and the activation function (AF) option associated with it.

The procedures presented in the previous works including [7], [12], [14], [21] were adopted in carrying out ELM analysis in MATLAB environment.

Mathematical form of the process is presented asfollows:

Assuming the set A that contains all the available activation functions options (AF), the representation of element A is of the form $A_i(j)$, where i, j, nf and nh are the activation function number, the selected number of hidden neuron, the available total number of activation functions, and the maximum assumed number of hidden neuron respectively. While the performance measure taken, index for best activation function and index for the best “number of hidden neuron”are represented by pm, ix and jx respectively.

The algorithm can be presented thus:

for initialization; let $jx = 0$, *then* $vx = 0$, *and* $ix = 0$

for the value $i = 1 \rightarrow nf$

for the value $j = 1 \rightarrow nh$

$pm = f(A_i(j))$ {Performance measure for the present parameters combination}

if pm *is better than* vx *then* $vx = pm$

$ix = i$; $jx = j$ {storing the index of the better parameter}

end

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As outcome of parameter search, it was discovered that sigmoid function archived acceptable result while the Sine function did not achieve acceptable results. In fact, sine function was producing negative correlation coefficient with huge errors as shown in the plot fig.5. As for the sigmoid function, their performances over ranges of number of hidden neurons are also plotted figs.3and4respectively. With these, it has become very clear that the sigmoid function shall be used for the proposed model development and implementation.

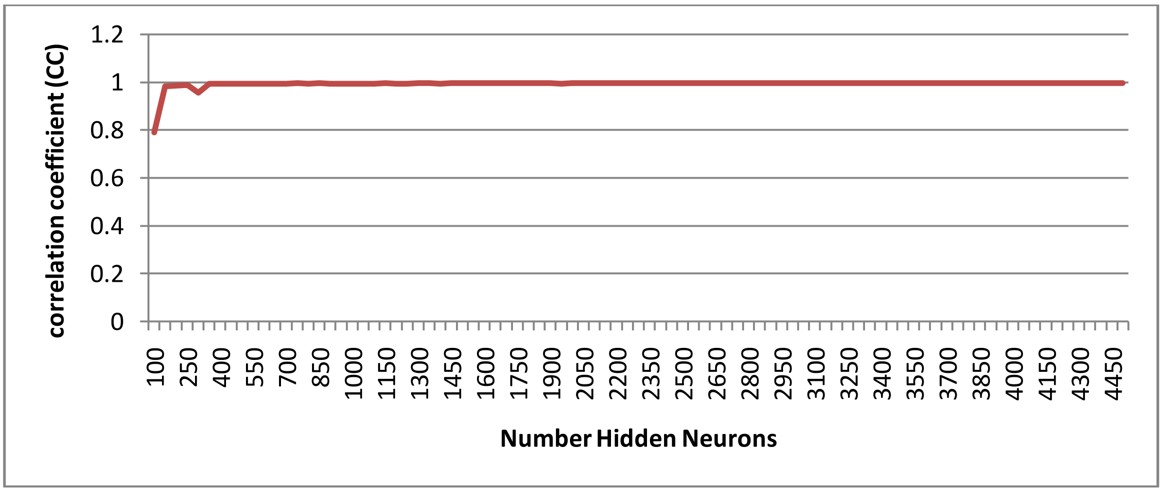

Fig. 3: Variation in the values of correlation coefficient as the number of hidden neuron changes for the sigmoid function

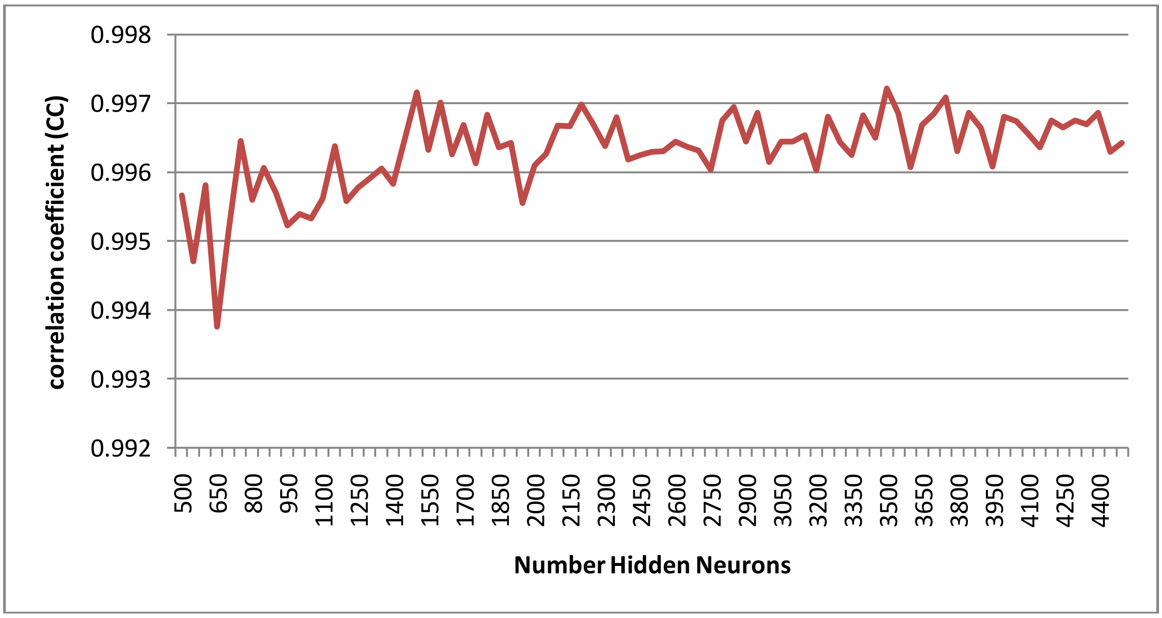

Fig. 4: Variation in the values of correlation coefficient as the number of hidden neuron changes for the sigmoid function (starting from 500 neurons for better visualization)

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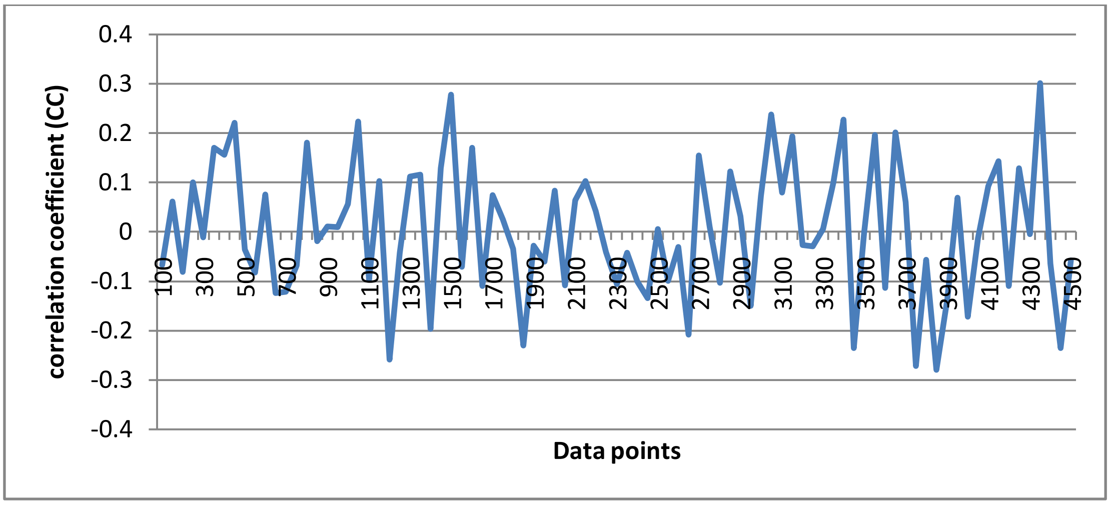

Fig. 5: Variation in the values of correlation coefficient as the number of hidden neuron changes for the Sine function

From the optimum parameter search and the plots visualizing the results, it is clear that the sigmoid function with 3400 hidden neurons archived the best possible performance, and these optimum parameters are then used to develop the final model. These optimum parameters are contained in the table 3. As for the sine function, the results are not acceptable as it reduced maximum of 30% correlation coefficient while sigmoid function archived upto 99.7% correlation coefficient. Therefore, it is clear that sigmoid function shall be employed in the proposed model. In other way, statistical bivariate regression analysis was carried out on model parameters to investigate the correlation of each of the parameters to the prediction mobile phone location distance. The result of bivariate analysis is shown in table 4. The bivariate analysis outcome shows that some parameters were corrected mobile distance while others were not. The outcome indicated the weakness in the use of bivariate analysis in accurate prediction of mobile phone location distance. Hence, the convergence to the use of multivariate analysis becomes expedient.SPSS for Window 17.0 computer package was used to carry out the analysis table 6.

Table 3: Optimum parameters for the proposed extreme learning machines model

ActivationFunction	sig
number of Hidden Neuron	3400

Table 4:The correlation exiting between pairs of variables using bivariate regression

	Distance (m)	1mSS1	2mSS2	3mSS3	4mSS4	5mSS5	6mSS6	7mSS7	8mSS8	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	SQ8
Distance	1	-0.82	-0.94	-.93	-.94	-.95	-.96	-.954	-.632	-.91	-.931	-.93	-.91	-.87	-0.91	-0.93	-0.92
1mSS1	-.823	1	.953	.747	.904	.902	.824	.756	.412	.972	.954	.855	.909	.948	.838	.771	.726
2mSS2	-.940	.953	1	.888	.958	.954	.912	.891	.524	.989	.996	.929	.953	.938	.896	.882	.862
3mSS3	-.934	.747	.888	1	.905	.866	.852	.884	.569	.853	.888	.925	.892	.772	.792	.848	.880
4mSS4	-.940	.904	.958	.905	1	.946	.927	.901	.536	.940	.951	.918	.957	.912	.904	.904	.888
5mS	-	.90	.95	.86	.946	1	.9	.888	.599	.942	.94	.9	.918	.95	.931	.87	.85

S5	.953	2	4	6			45				0	17		9		8	7
6mS S6	-.960	.824	.912	.852	.927	.945	1	.934	.586	.902	.889	.887	.867	.866	.976	.937	.890
7mS S7	-.954	.756	.891	.884	.901	.888	.934	1	.560	.850	.874	.887	.846	.811	.888	.986	.957
8mS S8	-.632	.412	.524	.569	.536	.599	.586	.560	1	.516	.515	.548	.517	.455	.539	.565	.579
SQ1	-.915	.972	.989	.853	.940	.942	.902	.850	.516	1	.988	.914	.940	.935	.897	.851	.825
SQ2	-.931	.954	.996	.888	.951	.940	.889	.874	.515	.988	1	.921	.950	.928	.865	.866	.848
SQ3	-.933	.855	.929	.925	.918	.917	.887	.887	.548	.914	.921	1	.929	.877	.869	.871	.856
SQ4	-.910	.909	.953	.892	.957	.918	.867	.846	.517	.940	.950	.929	1	.898	.849	.836	.830
SQ5	-.872	.948	.938	.772	.912	.959	.866	.811	.455	.935	.928	.877	.898	1	.878	.812	.778
SQ6	-.915	.838	.896	.792	.904	.931	.976	.888	.539	.897	.865	.869	.849	.878	1	.898	.858
SQ7	-.939	.771	.882	.848	.904	.878	.937	.986	.565	.851	.866	.871	.836	.812	.898	1	.956
SQ8	-.925	.726	.862	.880	.888	.857	.890	.957	.579	.825	.848	.856	.830	.778	.858	.956	1

IV. RESULTS AND DISCUSSION

4.1 ELM model for mobile phone location prediction

ELM model for mobile phone position distance has been developed through (training data sets and testing data sets using test – set- cross-validation approach. The predicted mobile phone position distance are positively and strongly correlated with the actual experimental data, this was clearly shown in the figure of the cross plots. The proposed model accuracy based on correlation coefficient(CC) was 100% for training data sets as clearly depicted in fig. 6. It could be seen from the cross plot that the predicted values were all on point with the actual mobile phone position distances. Since the performance level of any model is generally accessed by the testing outcome, the testing outcomes are presented as follows.

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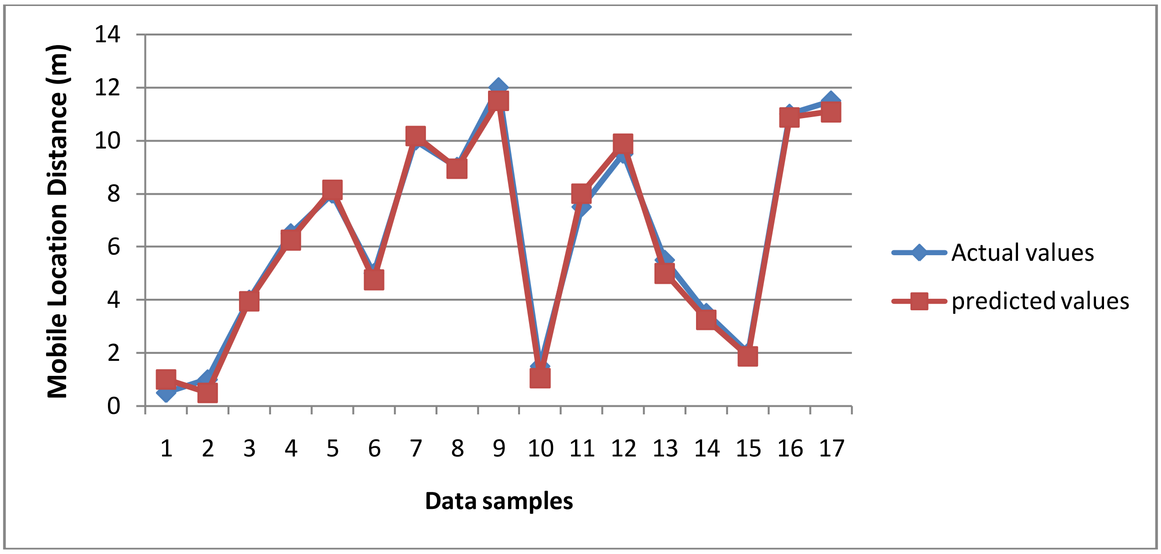

Fig. 6: Cross plots of training sets (actual values vs. predicted values)

30% of the data samples (i.e. the reserved 30%, the unseen data to model) were used to test the accuracy of the developed ELM model.It is highly interesting and fulfilling to note that, the model actually performed excellently during testing phase with an accuracy of 99.72% in terms of correlation coefficient. This show high correlation coefficient, which indicates that the estimated distance by the ELM model, is very close to the actual experimentally recorded distance for each data sample. Fig. 7 presents clearly the cross plot of actual values against predicted values.The obtained excellent accuracy in the testing phase of the model development indicates that the model is efficient, stable, and not over-fitted.

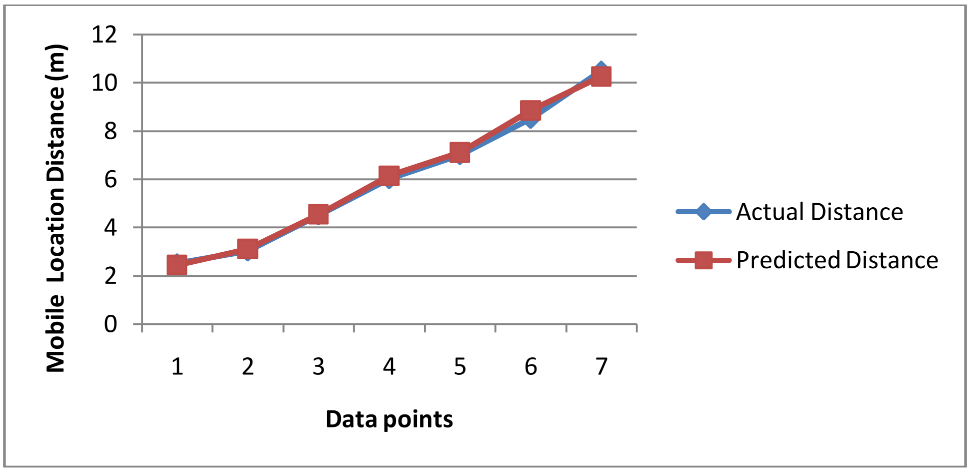

Fig. 7: Cross-plots of testing sets (actual values vs. predicted values)

These plots make it very easy to graphically observe the close relationship between the predicted distance by the proposed ELMmodel and the actual experimental values. The performance of the developed ELM based model is characterized with high CC, and low RMSE. Theperformancemeasures of the model are shown in table5.

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Table 5: The developed model quality performance determinants

	Training	Testing
CC	100%	99.72%
RMSE	0.0	0.219

4.2 Multivariate Regression (MR) model for mobile phone location prediction

The table 6 shows the estimated coefficients of the variables used for obtaining the predicted values for the distance. The generated multivariate regression model for mobile phone location distance prediction by the detector is expressed as

Predicted distance y_p = 31.243 + 0.163(1mSS1) + 0.102(2mSS2) - 0.003(3mSS3) + 0.010(4mSS4) - 0.027(5mSS5) - 0.086(6mSS6) + 0.035(7mSS7) - 0.003(8mSS8) - 0.038(SQ1) - 0.151(SQ2) - 0.019(SQ3) - 0.022(SQ4) - 0.043(SQ5) + 0.003(SQ6) - 0.041(SQ7) + 0.003(SQ8)

Model accuracy was tested using statistical Analysis of Variance (ANOVA) and correlation as shown in tables6 and 7, respectively.

The Hypothesis tested was:

H_0 : model is adequate

H_1 : model is not adequate

Decision rule utilized was to Reject H_0 (null hypothesis) if the p-value was less than α, otherwise accepted. Since the p-value (0.00) was less than α (0.05), there was no statistical reason to reject H_0 so therefore, it was concluded that the model was adequate.

The outcomes of the statistical analysis results presented in table 8 and interpreted as: R (0.996), which is the coefficient of correlation shows the level of correlation that exit within the model, it implies that there is a high correlation between variables of the model; R-squared (0.992), which is the coefficient of determination show that there is 99.2% assurance that the model is adequate and can be used for prediction; adjusted R-squared, since it is strong (0.974) and positive, it shows that the model is a very good for forecasting the future, decision making and prediction; and Standard Error of the Estimate (0.5692). With this low level of error, it shows that the error committed by predicting with this model is negligible (fig. 8). The summary of the accuracy results generated from other conditions of field data obtained from the detector inclusive of the one stated are presented in Table 8. This can be clearly seen from the outcomes that MR and ELM techniques performance are similar with difference less than 10% in term of prediction accuracy.

Table 6:Coefficients using multivariate regression under full line of sight

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	31.243	19.187		1.628	.147
	1mSS1	.163	.141	.832	1.161	.284
	2mSS2	.102	.153	.537	.666	.527
	3mSS3	-.003	.069	-.013	-.042	.968
	4mSS4	.010	.075	.051	.139	.893
	5mSS5	-.027	.093	-.111	-.289	.781
	6mSS6	-.086	.087	-.370	-.982	.359
	7mSS7	.035	.090	.147	.390	.708

	8mSS8	-.003	.008	-.026	-.353	.734
	SQ1	-.038	.122	-.273	-.311	.765
	SQ2	-.151	.121	-1.090	-1.244	.254
	SQ3	-.019	.037	-.092	-.513	.624
	SQ4	-.022	.030	-.119	-.722	.494
	SQ5	-.043	.041	-.261	-1.040	.333
	SQ6	.003	.047	.019	.063	.951
	SQ7	-.041	.069	-.243	-.590	.574
	SQ8	.003	.031	.019	.106	.919

a. Dependent Variable: Distances

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	285.232	16	17.827	55.027	.000[a]
Residual	2.268	7	.324		
Total	287.500	23			

a. Predictors: (Constant), SQ8, 8mSS8, 1mSS1, 3mSS3, SQ6, SQ5, SQ3, SQ4, SQ7, 4mSS4, 6mSS6, 7mSS7, 8mSS5, SQ2, 9mSS2, SQ1

Table 7:Model accuracy testing using correlation and standard error

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.996[a]	.992	.974	.56918	.992	55.027	16	7	.000

a. Predictors: (Constant), SQ8, 8mSS8, 1mSS1, 3mSS3, SQ6, SQ5, SQ3, SQ4, SQ7, 4mSS4, 6mSS6, 7mSS7, 8mSS5, SQ2, 9mSS2, SQ1

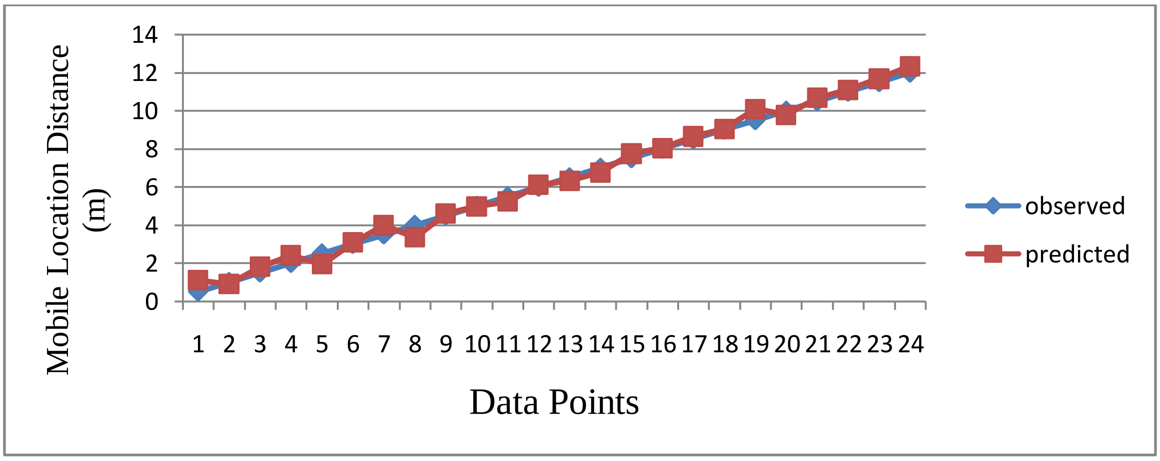

Fig. 8: Predicted and observed mobile phone location distance

Table 8 Summary of statistical accuracy measurements

Field data condition	R values	R-squared values	Adjusted R-squared values	Standard Error of Estimate values (SEE)	Judgment on prediction
Full line of sight	0.996	0.992	0.974	0.5692	Excellent
Partial line of sight	0.944	0.891	0.783	1.5812	Excellent
Barrier of 0.205m	0.981	0.962	0.890	1.1705	Excellent
Barrier of 0.308m	0.870	0.757	0.600	2.2361	Excellent
ELM (for all data conditions	0.9972	0.9944	-	0.219	Excellent

V. CONCLUSION AND RECOMMENDATION

Extreme learning machines (ELM) models have been an efficient artificial intelligent tool that have been successfully deployed in several prediction tasks often with promising outcomes and therefore it has been utilized in this study through integration of relevant parameters to predict mobile location distance.ELM model was developed through training and testing data sets using test-set-cross-validation approach. The computational techniques were carried out in MATLABenvironment, the result emanated from the predicted mobile phone location distance was closely, strongly and positively correlated with the actual values of the data set drawn from experimental data for the training sets. The reserved 30% (testing data) that has not been exposed to the model was later used to test the performance of the ELM model developed. The results emanated from the ELM developed model indicated accurate prediction of mobile phone location distance; this was characterized with high correlation coefficient (CC) and low RMSE of 100% and 99.2% 0.0 and 0.219 respectively for the training data sets and testing data sets. This high correlation and low errors indicated close and strong similarity between the estimated mobile location distance by the ELM model and the actual experimental data obtained for each sample.Similar results of deviation less than 10% were obtained using multivariate regression (MR) technique. The variation between the results obtained from ELM and MR techniques was not wide enough to warrant any significant change in prediction accuracy. It can be concluded from the excellent and accurate results emanating from both techniques that the methods can adequately predict mobile location distance. The excellent performance achieved in this study has indicated that the choice of prediction technique utilized depend large on the nature of field data, not necessary on the complexity of the technique.

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