ANALYSIS OF HEAVY METAL CONCENTRATION IN SOILS OF A WASTE DISPOSAL SITE IN KHULNA USING ARTIFICIAL INTELLIGENCE TECHNIQUE

Shyamol Kumar Sarkar*[1] and Islam M. Rafizul[2]

[1]Post-graduate student, Department of Civil Engineering, Khulna University of Engineering & Technology, Bangladesh, E-mail: shyamolsarkar12@gmail.com
[2]Professor, Department of Civil Engineering, Khulna University of Engineering & Technology, Bangladesh, E-mail: imrafizul@yahoo.com

***Corresponding Author**

ABSTRACT

Analysis of heavy metal concentration in soils is very essential for their unfavourable environmental and wellbeing impacts due to have a moderately high density and toxic behavior. The assortment of soil samples is labored and time consuming as well as the finding of heavy metal concentrations in the laboratory was costly. In these endeavours, artificial intelligence techniques (AI) such as adaptive Neuro-fuzzy inference system (ANFIS), support vector machine (SVM) and artificial neural networks (ANN) were executed for the analysis of heavy metal concentrations in soils of a certain waste disposal site at old Rajbandh, Khulna. The point of this investigation was to fix the functions, algorithms, optimization methods, for AI techniques based on their best performance and then select a good technique for the analysis of heavy metal concentrations in soils. In this investigation, soil samples were gathered from eighty-five areas at a profundity 0-30 cm from the existing ground surface of the selected disposal site. In the laboratory, the concentrations of heavy metals of Pb, Cu, Ni, Zn, Co, Cd, As, Sc, Hg, Mn, Cr, Ti, Sb, Sr, V and Ba in soils were measured.

The result reveals the model with SCP, gaussmf, linear and hybrid was the best-fitted model of ANFIS for the prediction of heavy metal concentrations in soils. In addition, in SVM analysis, the model SVM-RBF with 15 folds was selected for the prediction of heavy metal concentrations in soils. In ANN, the model LT (Levenberg-Marquardt and Tansig functions) with neuron structure 2-10-1 was selected. The accuracy of the predicted results was checked based on the acceptable limits of prediction parameters like R value, RMSE, MAPE, GRI and percentage recovery. Among all heavy metals analysis in ANFIS, the maximum R-value 0.999 was found with the minimum RMSE 0.12 for Sc indicating the best correlation in prediction of Sc in soils. The others value of prediction parameters (MAPE= 36.00, GRI=1.50, percentage recovery=123.43%) for Sc were found within the acceptable limits. In addition, in SVM analysis, maximum R-value 0.73 with RMSE 2.03 was found for Cu; while, maximum R-value 0.88 with the minimum RMSE 1.01 for As was found in ANN. The outcomes showed that ANFIS model was a solid procedure than that of other counterparts of SVM and ANN to analyse the heavy metal concentrations in soils with the acceptable degree of robustness and accuracy. Therefore, the performance of AI techniques may be stated by the sequence of ANFIS > SVM > ANN. Here it can be noted that one can easily be computed the concentration of a particular heavy metal in soils by inserting GPS values (latitude and longitude) only in the developed rule viewer of ANFIS. Therefore, this newly developed model will further be helpful for other researchers in this line to analysis heavy metal concentration in soils of selected waste disposal sites.

Keywords: *Waste disposal site, Soil, Heavy metals, Soft computing systems, Khulna*.

1. INTRODUCTION

Heavy metals are metallic components that have moderately high density and poisonous behavior even at low concentration (Alloway et al., 1990). In waste disposal site, municipal solid waste (MSW) decays and creates three components of solid (degraded waste); liquid (leachate that is penetrating into the fundamental layer) and landfill gas (Sanjida and Rafizul, 2018). Open dumping discharge enormous amount of destructive as well as toxic synthetic compounds like heavy metals to the neighbouring water bodies as well as basic soil layer, and so on. The greater part of the environmental and human health issues originate from the emanation of heavy metals from the proliferated leachate, contaminated soil, landfill gas (LFG), non-methanic volatile organic compounds as well as menacing air contaminants in waste disposal site (Talib et al., 2008). In Khulna city, the greater part of the MSWs were gathered from door to door without any sorting and dumped in an open disposal site at Rajbandh. The emanations of poisonous heavy metal element from MSW, leachate and soil will be vulnerable to the environmental constituents and the nearby inhabitants. The assessment of heavy metal distribution in soils is significant to save the environment. Moreover, for various soil assessment techniques, heavy metal concentrations are needed. However, the collection of soil samples is labored, time consuming and determination of heavy metal concentration in soils from laboratory is expensive. The prediction of heavy metal concentration using artificial intelligence techniques (AI) may be the answer for take care of this issue. In the literature, the AI techniques such as adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), artificial neural networks (ANN), fuzzy logic (FL), knowledge-based systems (KBSs), genetic algorithms (GAs), biogeography-based optimization (BBO) etc. are available. These AI techniques have many functions, algorithms, optimization methods, which can be used. The aim of this study is to fix functions, algorithms and optimization methods for all AI techniques based on their best performance and select a best AI technique for the analysis of heavy metal concentrations in soils. In this study, for the analysis of heavy metal concentrations in soils, the AI techniques such as ANFIS, SVM and ANN was performed.

A study stated that over the last few years or so, various AI techniques for analysis of heavy metals concentrations in soils and other quality parameters; environmental modelling; water quality monitoring and assessment; estimation as well as forecasting in climatic sciences (Soyupak et al., 2003). In this study, AI techniques such as ANFIS, SVM and ANN were implemented to analysis heavy metal concentrations in soils of a selected waste disposal site at old Rajbandh, Khulna. In ANFIS, the validation of models was performed by interchanging different input and output membership functions as well as optimization methods to select the best model of ANFIS. In addition, for SVM analysis various models with different kernel functions were formed to select best-fitted model of SVM. The cross-validation with different folds was also performed to control overfitting of the data. Furthermore, for selecting the best-fitted model of ANN; different neuron structures, different training functions as well as various transfer functions was implemented. The results of ANFIS, SVM and ANN model were also compared with the satisfactory values of correlation coefficient (R), root mean square error (RMSE), mean absolute percentage error (MAPE), geometric reliability index (GRI) and percent recovery. Therefore, the newly developed model of AI techniques will further be helpful for other researchers in this line to analysis heavy metal concentration in soils of selected waste disposal sites.

2. METHODOLOGY

The concentrations of relevant heavy metal in soils were measured and monitored through standard test methods and the AI techniques such as ANFIS, SVM and ANN were performed to predict the heavy metal concentrations, which were highlighted in the following articles.

2.1 Soil Sampling

In this investigation of model fixation, overall sixty soil samples were gathered from the separate locations of a selected open disposal site at old Rajbandh, Khulna, Bangladesh. Every one of the samples were gathered at a profundity of 30 cm from the existing ground surface. The latitude and longitude of all the soil-sampling positions was recorded using GPS apparatus, which were later brought into a geographic information system (ArcGIS 10.1) shown in Figure 1.

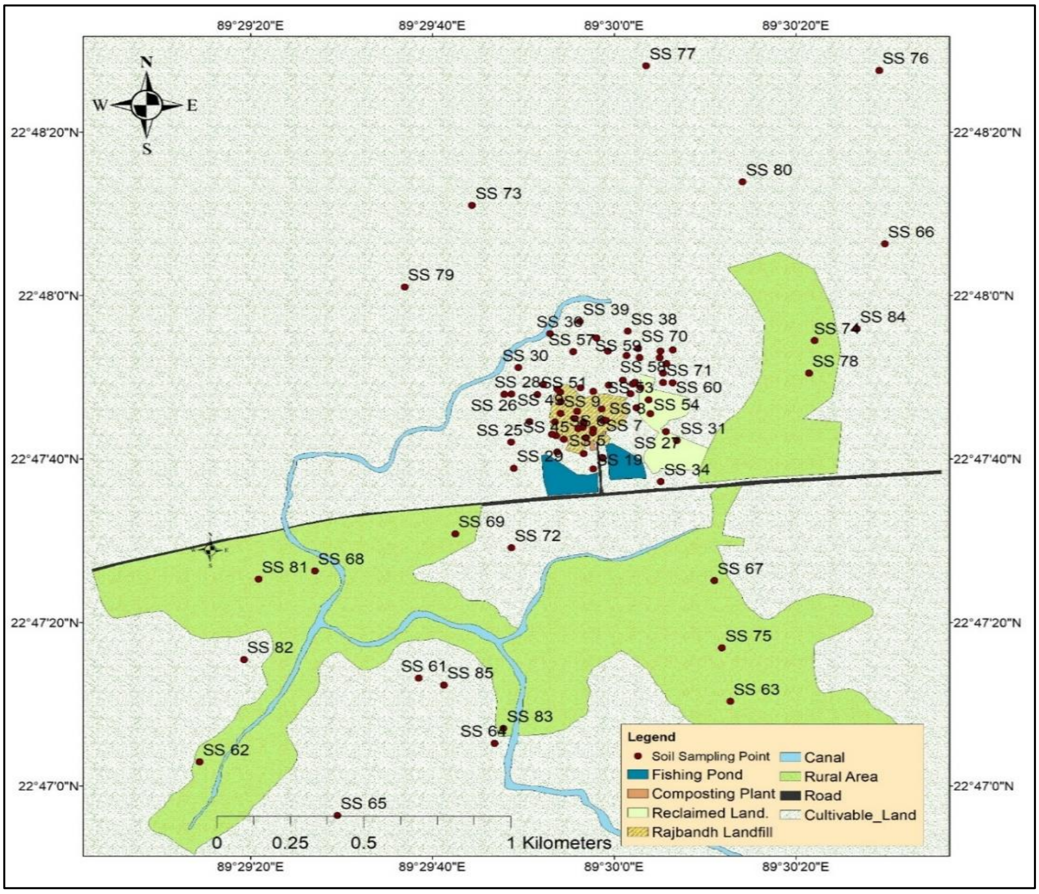

Figure 1: Location map showing soil sampling points of the selected waste disposal site at old Rajbandh, Khulna

2.2 Laboratory Investigations

In laboratory investigation, at first 10 gm of every soil pattern was taken into a 100 ml conical flask. The flask had already been washed with deionized water organized by adding 6 ml HNO3/HClO4 acid in ratio 2:1 and left overnight. Subsequently, HCl solution changed into brought in ratio 1:1 to the digested sample and re-digested once more for another 30 minutes. The digested sample washed into one hundred ml volumetric flask and obtained mixture changed into cooled right down to room temperature. After acting the digestion, the concentration of the heavy metals of Pb, Cu, Ni, Zn, Co, Cd, As, Sc, Hg, Mn, Cr, Ti, Sb, Sr, V and Ba in mg/kg were determined by the use of atomic absorption spectrophotometer (AAS) method and the quantity of each heavy metal deduced from the calibration graph.

2.3 Modelling of AI Techniques

In this study, artificial intelligence (AI) techniques such as adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM) and artificial neural network (ANN) were performed through MATLAB to analysis heavy metal concentrations in soils of waste disposal site. The latitude and longitude of soil sampling points of the selected waste disposal site were used as inputs, while, heavy metal concentrations were considered as outputs in AI techniques. In this study, total 85 sampling point's data were considered among which training data 83% (70) and testing data 17% (15) were assigned in AI techniques. The adopted AI techniques are hence discussed in the following articles.

2.3.1 Adaptive Neuro-Fuzzy Inference System

In ANFIS, the steps for the prediction heavy metal concentrations reveals as:

- ✓ First open Neuro-Fuzzy Designer app and load the training data from workspace.

- ✓ Generate the FIS to train the model of different selected functions and algorithms.
- ✓ Get the FIS output for training with training error.
- ✓ Load the data of testing and get the FIS output of testing.
- ✓ Export ANFIS model structure, rules viewer and surface viewer.
- ✓ Predict the concentration of heavy metals in soils.

2.3.2 Support Vector Machine

In SVM, the steps for the prediction heavy metal concentrations reveals as:

- ✓ First open regression learner app and import the data.
- ✓ Select particular kernel functions and validation methods.
- ✓ Train the model and export the results.
- ✓ Predict the concentration of heavy metals in soils.
- ✓ Use personal coding for representing the outcomes.

2.3.3 Artificial Neural Network

In ANN, the steps for the prediction heavy metal concentrations reveals as:

- ✓ First, open neural network or data manager window and import the data.
- ✓ Create neural network model by selecting various training and transfer functions.
- ✓ Train ANN model and simulate the test data.
- ✓ Export of All Outputs
- ✓ Predict the concentration of heavy metals in soils.

2.4 Assessment of Model Performance

The predicted concentration of heavy metals were determined from ANFIS, SVM and ANN. Getting predicted results, the predicted concentrations were assessed with the following prediction parameters.

2.4.1 Correlation Coefficient

A correlation coefficient (R) is the statistical measure of the linear relationship between a dependent variable and an independent variable. In completely related variables, the worth will increase or decreases in cycle. In negatively related variables, the worth of 1 will increase and therefore the value of the opposite decreases. The "R" represents it that displays within the following Equation (1).

$$R = \frac{n(\sum y.y_p)\ (\sum y)(\sum y_p)}{\sqrt{[n\sum y^2\ (\sum y)^2][n\sum y_p^2\ (\sum y_p)^2]}} \tag{1}$$

Where y = observed value, y_p = predicted value, n = number of observations.

A research conducted by Smith (1986) advised that the worth of R lies between zero to one. It's additionally advised some pointers for deciding the performance of the model. If $|R| \geq 0.8$: a strong correlation exists, $0.2 < |R| < 0.8$: correlation exists and $|R| \leq 0.2$: a weak correlation exists. as soon as the worth of |R| is larger than 0.9, then a very strong correlation exists between the variables.

2.4.2 Root Mean Square Error

The root mean square error (RMSE) is one in every of the foremost oftentimes used measures of the goodness of fit of generalized regression models. It's drawn by the following Equation (2).

$$RMSE = \sqrt{\frac{\sum_1^n (y - y_p)^2}{n}} \tag{2}$$

According to Schweizer (2010), lower values of RMSE indicate a higher match with the expected results and zero suggests that no error. RMSE may be a workable factor of however accurately the model predicts the response, and it's the foremost necessary criterion for appropriate match of results if the main purpose of the model is predicting any value.

2.4.3 Mean Absolute Percentage Error

The mean absolute percent error (MAPE) measures the scale of the error in percentage terms. it's calculated as the average of the unsigned proportion errors, as shown in the following Equation (3).

$$MAPE = \frac{1}{n}\sum \frac{\left|y - y_p\right|}{|y|} \times 100\,\% \tag{3}$$

In a comprehensive analysis of county-level projections, the MAPE was on the average higher by regarding 30–40% than strong measures of central tendency for many strategies and projection horizons (Rayer, 2007).

2.4.4 Geometric Reliability Index

A version of the geometric reliability index (GRI) was outlined by way of the inverse of the coefficient of variation. The reliability index is that the shortest distance from the origin of reduced variables. Using geometry, the reliability index will be dignified by the subsequent Equation (4).

$$GRI = \frac{1 + \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\frac{\hat{y}_t - y_t}{\hat{y}_t + y_t})^2}}{1 - \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\frac{\hat{y}_t - y_t}{\hat{y}_t + y_t})^2}} \tag{4}$$

Where $\boldsymbol{y_t}$ = observed value, $\boldsymbol{\hat{y}_t}$ = predicted value, n = number of observations.

According to Leggett and Williams (1981), GRI could be a statistical procedure to work out the reliability of a model. The index could be a range GRI ≥ 1 represents the perfectness and dependability of model.

2.4.5 Percent Recovery

The percent recovery suggests that what percentage of measured worth is recovered by the expected value. It's depicted by the subsequent Equation (5).

$$Persent\ Recovery = \frac{y_p}{y} \times 100 \tag{5}$$

According to Walfish (2006), recoveries within the ranges of 20-200% for internal standard are thought as 'acceptable'. Food and Drug Administration (FDA), Investopedia declares that recovery shouldn't have to be compelled to be 100% however ought to be consistent. FDA approved variability limit for Lower Limit of Qualification (LLOQ) is +/- 20%. Therefore, the best frame of recovery is 80-120% that represents the robustness of the model.

3. RESULTS AND DISCUSSION

3.1 Validation of Models in ANFIS

In this study, to validate the models of ANFIS, twenty models symbolized A to T were formed considering sub-clustering partitioning (SCP); different input membership function (MF) like gaussmf, trimf, trapmf, psigmf, gbellmf; output MF like linear and constant; optimization method such as hybrid or back-propagation (BP) as well as number of epochs. A developed ANFIS rules viewer determined the predicted concentration of particular heavy metal in soils. The performance of different models (A to T) of ANFIS were examined based on the satisfactory limits of the prediction parameters such as R and RMSE. The results of twenty models (A to T) in ANFIS at different functions for Co with the values of R and RMSE provided in Table 1. For model A (SCP, gaussmf, linear and hybrid) the value of |R| was found to be 0.80 indicating the strong correlation between input and output variables in ANFIS analysis. In this study, the models B, E, F, G, I, J, K, M, N, Q, R, and S provided the R-value within a range of 0.2 < |R| < 0.8 indicating correlations between input and output variables. However, R-values for rest models (C, D, H, L, O, P and T) were found below 0.2 with weak correlations. The model H (SCP, trimf, constant and BP) shows comparatively the lower R-value (0.03) with higher RMSE value (6.71) than that of other models. In addition, two models such as C and D shows R and RMSE values of -0.28 and -0.13 as well as 2.53 and 4.98, respectively, these two models indicated the performance of weak downhill correlations between input and output variables. Besides, the model A shows the maximum value of R 0.80 and minimum value of RMSE 1.52. Based on results of R and RMSE, model A with SCP, gaussmf, linear and hybrid can be considered as fitted model of ANFIS for the prediction of all studied heavy metal concentrations in soils of waste disposal site.

Table 1: Validation of different models in ANFIS for Co

Model name	**GENFIS**	**Input membership function**	**Output membership function**	**Optimization method**	**Epochs**	**Co**	
						R	**RMSE**
A	Sub Clustering	gaussmf	linear	Hybrid	100	**0.80**	**1.52**
B	Sub Clustering	gaussmf	Constant	Hybrid	100	0.64	1.92
C	Sub Clustering	gaussmf	linear	Back Propagation	100	-0.28	2.53
D	Sub Clustering	gaussmf	Constant	Back Propagation	100	-0.13	4.98
E	Sub Clustering	trimf	linear	Hybrid	100	0.79	1.53
F	Sub Clustering	trimf	Constant	Hybrid	100	0.62	1.97
G	Sub Clustering	trimf	linear	Back Propagation	100	0.39	2.66
H	Sub Clustering	trimf	Constant	Back Propagation	100	0.03	6.71
I	Sub Clustering	trapmf	linear	Hybrid	100	0.67	1.87
J	Sub Clustering	trapmf	Constant	Hybrid	100	0.50	2.16
K	Sub Clustering	trapmf	linear	Back Propagation	100	0.32	2.40
L	Sub Clustering	trapmf	Constant	Back Propagation	100	0.04	5.30
M	Sub Clustering	psigmf	linear	Hybrid	100	0.62	1.96
N	Sub Clustering	psigmf	Constant	Hybrid	100	0.61	1.98
O	Sub Clustering	psigmf	linear	Back Propagation	100	0.17	2.45
P	Sub Clustering	psigmf	Constant	Back Propagation	100	0.19	4.98
Q	Sub Clustering	gbellmf	linear	Hybrid	100	0.66	1.88
R	Sub Clustering	gbellmf	Constant	Hybrid	100	0.53	2.13
S	Sub Clustering	gbellmf	linear	Back Propagation	100	0.47	2.35
T	Sub Clustering	gbellmf	Constant	Back Propagation	100	0.13	4.98

3.2 Validation of Models in SVM

In this study, total sixteen models (A to D with 5, 10, 15 and 20 fold numbers) for SVM analysis were formed with different kernel functions like linear-SVM (SVM-L), quadratic-SVM (SVM-Q), cubic-SVM (SVM-C) and gaussian or radial basis function-SVM (SVM-RBF) for fold numbers 5, 10, 15 and 20. The selected model was then compared in terms of the best values of R and RMSE to assess the performance of each model. In this analysis, Arsenic (As) was considered in compare to the results of heavy metals for selecting the best model of SVM.

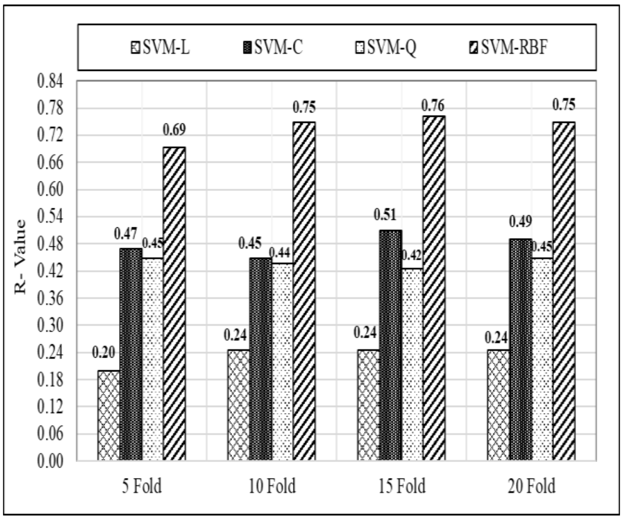

Figure 2: Variation of R with different fold numbers and kernel functions of SVM for As

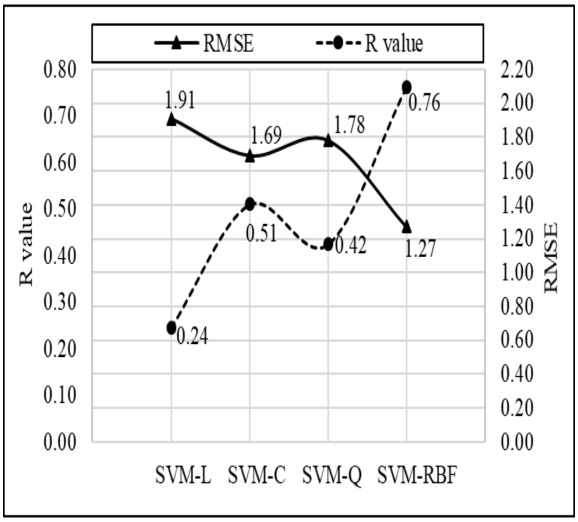

Figure 3: Variation of R and RMSE with kernel functions of SVM of As in soil

The variation of R for As were clearly expressed in Figure 2 for different kernel function and fold number. The SVM-RBF shows the higher value of R than that of other kernel functions of SVM-L, SVM-Q and SVM-C in SVM for fold numbers 5, 10, 15 and 20 (Figure 2). Among the entire folds considered in this analysis, the fold number 15 shows the maximum R-value (0.76) with minimum RMSE (1.27). Figure 3 entirely shows that fold number 15 provides the maximum R-value (0.76) with minimum RMSE (1.27) for model D-15 (SVM-RBF with 15 folds). Based on aforementioned R and RMSE, model D-15 (SVM-RBF with 15 folds) in SVM was selected for the modelling of heavy metal in soils of selected waste disposal site.

3.3 Validation of Models in ANN

In this study, different models of ANN were performed by changing the number of neurons as well as various training and transfer functions of ANN through MATLAB. In ANN analysis, four neuron structures were formed with different neuron numbers of 5, 10, 15 and 20 successively. In this analysis, the selection of neuron structure was performed based on the best values of R and RMSE. The neuron structure 2-10-1 shows the best performance for As with maximum R value (0.88) and minimum RMSE (1.01) than that for the other neuron structures (like 2-5-1, 2-15-1 and 2-20-1). After fixing the neuron structure (2-10-1), different models were formed by interchanging different training functions like levenberg-marquardt (TRAINLM), one-step secant (TRAINOSS) and scaled conjugate gradient (TRAINSCG) as well as transfer functions like tangent sigmoid transfer function (TANSIG), linear transfer function (PURELIN) and log-sigmoid transfer function (LOGSIG). Among all model, LT shows the higher value of R (0.88) than that of other models with minimum RMSE (1.01). On the contrary, model SP shows the lower value of R (0.31) than the other models with maximum RMSE (1.87). Therefore, the model LT (levenberg-marquardt and TANSIG) with neuron structure 2-10-1 was selected for the prediction of heavy metal concentrations in soils of waste disposal site.

3.4 Performance of AI Techniques

The predicted concentration of heavy metal in soils of unknown soil sampling points were determined with various AI techniques such as ANFIS, SVM and ANN. The variation of measured and predicted value of Hg and Sc in soil were depicted in Table 2. From Table 2, it was observed that predicted concentrations are very closer to the measured concentration of Hg and Sc for ANFIS than that of SVM and ANN. The acceptance of predicted results was assessed by some prediction parameters like R, RMSE, MAPE, GRI and recovery percentage. Figures 4 to 8 describe the variation of prediction parameters for all studied heavy metal with acceptable ranges stimulate in literatures. In Figure 4, ANFIS model shows the higher value of R (training) for all studied heavy metals than other models of

AI techniques. The values of R for most of the heavy metals were found in the ranges of 0.81 to 0.999. According to Smith (1986), it indicated the robustness of ANFIS model. Moreover, ANN shows comparatively the better performance than that of SVM.

Table 2: Predicted results of Hg and Sc for various AI techniques

Soils sampling points	Measured	Predicted Hg from AI techniques			Measured	Predicted Sc from AI techniques		
		ANFIS	SVM	ANN		ANFIS	SVM	ANN
5	7.22	6.56	8.58	7.91	16.83	16.99	10.43	15.55
10	4.76	5.49	4.80	5.07	14.76	16.16	10.64	15.01
20	5.03	4.88	1.08	0.80	11.77	10.83	9.86	5.93
25	3.77	3.16	3.64	4.27	10.77	10.73	11.57	12.02
30	1.98	1.58	1.97	0.92	9.58	10.96	9.71	5.33
35	3.45	1.74	3.19	4.81	8.65	8.88	8.12	6.46
45	1.92	2.56	5.22	5.44	9.94	12.39	10.96	13.54
50	1.11	2.38	3.72	4.32	8.07	10.27	9.20	9.94
55	1.26	2.02	3.15	4.00	5.72	8.07	8.04	5.83
60	0.77	1.43	3.08	2.00	3.02	4.85	8.52	7.69
65	2.12	3.43	4.07	3.52	10.02	9.71	11.72	11.13
70	1.07	2.76	3.46	3.85	8.41	5.98	11.85	10.72
75	1.68	2.86	3.13	3.49	6.14	7.23	11.93	10.68
80	0.77	1.75	3.13	3.49	3.39	5.16	11.93	10.68
85	2.95	3.70	2.16	0.78	10.19	9.71	9.69	9.64

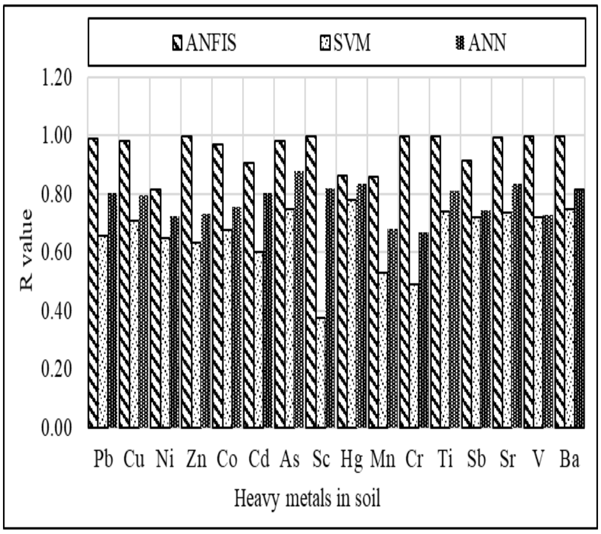

Figure 4: Variation of R with AI techniques

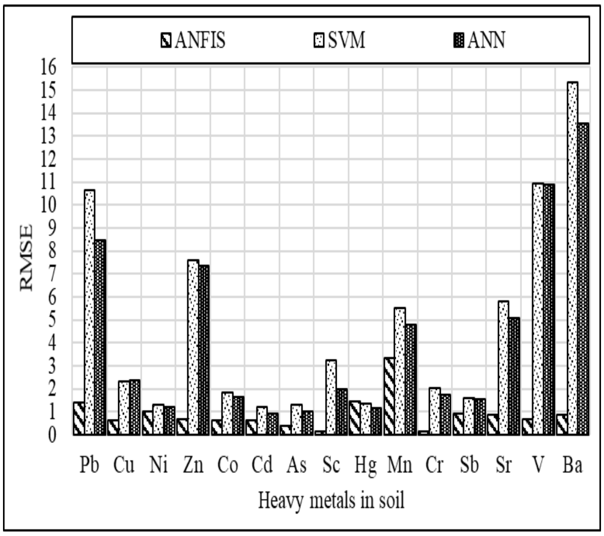

Figure 5: Variation of RMSE with AI techniques

In addition, ANFIS model shows the minimum value of RMSE in training for all studied heavy metals than that of other models of AI techniques (Figure 5). On the other hand, SVM shows the maximum RMSE indicating worse performance than ANN does. Therefore, the performance of R and RMSE in training can be expressed as ANFIS > ANN > SVM

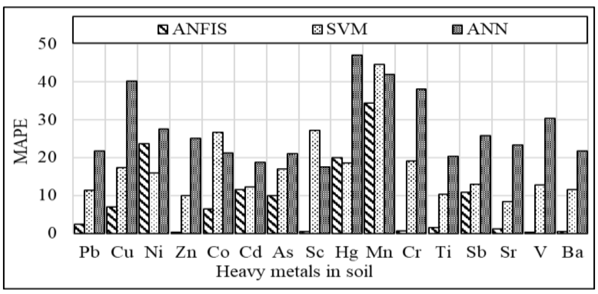

Figure 6: Variation of MAPE with AI techniques

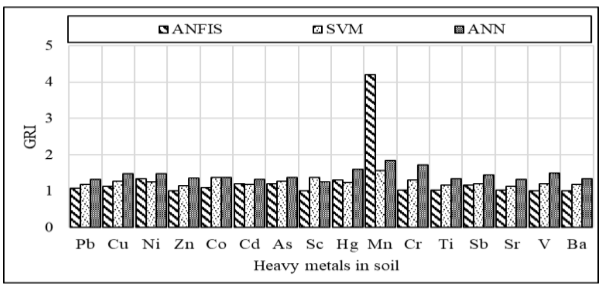

Figure 7: Variation of GRI with AI techniques

In Figure 6, most of all heavy metals show MAPE value in the ranges of 30-40% in ANFIS model for training than other models of AI techniques. On the other hand, ANN shows the maximum MAPE, which indicating worse performance than SVM. In addition, the GRI value for most of all heavy metals were found very close to 1 in ANFIS model than that of other models of AI techniques for training (Figure 7). On the contrary, ANN shows more scattered values of GRI than that of SVM model. Therefore, the performance of MAPE and GRI in training can be expressed as ANFIS > SVM > ANN.

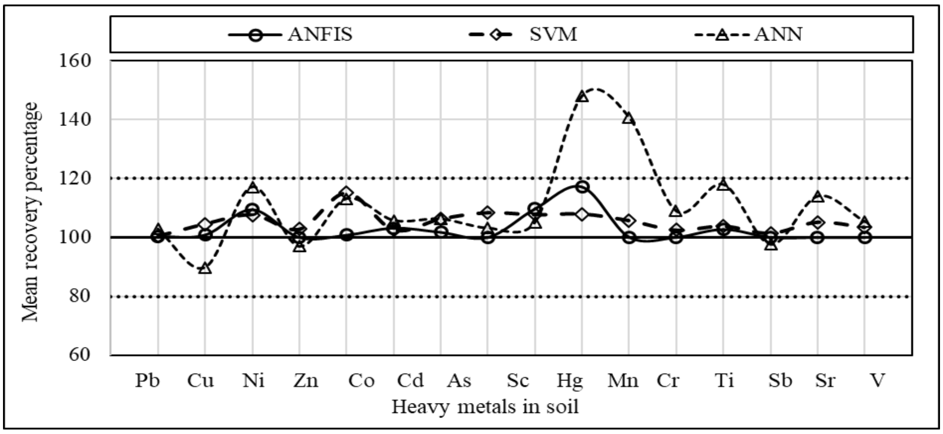

Figure 8: Variation of level for recovery percentage with various AI techniques

In Figure 8, the mean percentage recovery for most of all heavy metals were found very closer to the fit level (100%) in ANFIS model than that of other models of AI techniques for training. In SVM, percentage recovery were found in the ranges of 80-120% and most of them were near to fit level (100%). On the contrary, ANN shows more scattered values of percentage recovery from fit level than SVM. Therefore, the performance in training can be expressed as ANFIS > SVM > ANN.

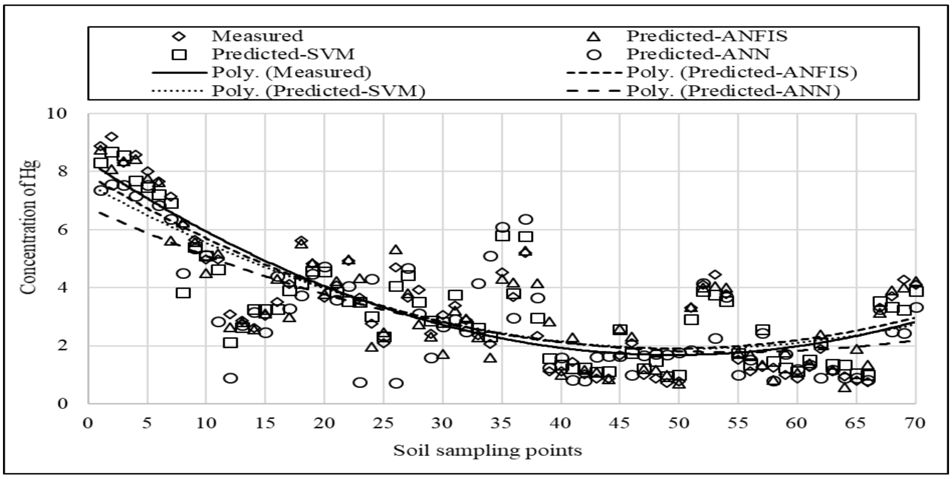

Figure 9: Variation of predicted results of Hg for different AI techniques in training

The predicted concentration of Pb (Figure 9) in ANFIS model was very closed to the measured concentration than other AI techniques, whereas, ANN shown less close measured concentration than that of other AI techniques. The results of various AI techniques from present study and literature were summarised in Table 3. In the present study, ANFIS shows the best performance for all criteria of goodness like R, RMSE, MAPE, GRI and percentage recovery. In addition, SVM shows comparatively the better results for most of the prediction parameters than ANN. Based on results published by Emamgholizadeh et al. (2014), the order of AI techniques was found as ANFIS > ANN. In addition, the results also stated by Rooki et al. (2011) and proved SVM > ANN. Therefore, finally the sequence of ANFIS > SVM > ANN was selected for best prediction of heavy metal concentrations in soils.

4. CONCLUSIONS

ANFIS model was a reliable technique than that of other counterparts of SVM and ANN to analyse the heavy metal concentrations in soil with the acceptable degree of robustness and accuracy. The combinations of best functions and algorithms were chosen for ANFIS with GENFIS: SCP, Input MF: Gaussmf, Output MF: Linear, Optimization Method: Hybrid and no. of epoch: 100; for SVM with kernel function: SVM-RBF and fold number: 15 and for ANN with training function (Levenberg-Marquardt), transfer function (Tansig) and no. of neurons 10. These selected AI techniques with fixed functions and algorithms may be used of other researchers without further analysis of AI techniques to predict heavy metal concentrations in soils of a selected waste disposal site.

Table 3: Summary of results of various AI techniques

Prediction parameters		**Present study**	**Literature**	**Final remarks**
R value	Training	ANFIS > ANN > SVM	ANFIS > ANN	ANFIS > SVM > ANN
			SVM > ANN	
	Testing	ANFIS > SVM ≥ ANN	ANFIS > ANN	
			SVM > ANN	
RMSE	Training	ANFIS > ANN > SVM	ANFIS > ANN SVM > ANN	
	Testing	ANFIS > SVM > ANN	ANFIS > ANN SVM > ANN	
MAPE	Training	ANFIS > SVM > ANN	-----	
	Testing	ANFIS > ANN > SVM	-----	
Mean percentage recovery	Training	ANFIS > SVM > ANN	-----	
	Testing	ANFIS > ANN > SVM	-----	
GRI	Training	ANFIS > SVM > ANN	-----	
	Testing	ANFIS > SVM > ANN	-----	
Performance of predicted results in training		ANFIS > SVM > ANN	-----	
Performance of predicted results in testing		ANFIS > SVM > ANN	-----	

REFERENCES

Alloway, B. J., Jackson, A. P., and Morgan, H. 1990, "The accumulation of cadmium by vegetables grown on soils contaminated from a variety of sources". Sci. of the total Env. Vol. 91, pp. 223-236.

Leggett, R. W., and Williams, L. R. 1981, "A reliability index for models". Ecological Modelling, Vol. 13(4), pp. 303-312.

Rayer, S. 2007, "Population forecast accuracy: does the choice of summary measure of error matter?" Population Research and Policy Review, Vol. 26(2), pp. 163.

Rooki, R., Ardejani, F. D., Aryafar, A., and Asadi, A. B. 2011, "Prediction of heavy metals in acid mine drainage using artificial neural network from the Shur River of the Sarcheshmeh porphyry copper mine, Southeast Iran". Environmental earth sciences, Vol. 64(5), pp. 1303-1316.

Sanjida, K., and Rafizul, I. M. 2018, "Multivariate statistics and spatial distribution of heavy metals in soils of waste disposal site in south western region of Bangladesh". Paper presented at the 33rd Int. Conference on Solid Waste Technology and Management, Annapolis, USA, (ISSN: 1091-8043)

Schweizer, K. 2010, "Some guidelines concerning the modelling of traits and abilities in test construction".

Soyupak, S., Karaer, F., Gürbüz, H., Kivrak, E., Sentürk, E., and Yazici, A. 2003, "A neural network-based approach for calculating dissolved oxygen profiles in reservoirs". Neural Computing and Applications, Vol. 12(3-4), pp. 166-172.

Walfish, S. 2006, "Analytical methods: a statistical perspective on the ICH Q2A and Q2B guidelines for validation of analytical methods". Bio Pharm International, Vol. 19(12), pp. 1-6.