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Research Article

Predictive modelling of acoustic emission signal data for corrosion assessment: A modified dimensional analysis based approach

Shilpa Vishal Patil [a,*]

[a] *Department of Civil Engineering, Vishwakarma Institute of Technology, Pune, 411037 Maharashtra, India*

ABSTRACT

Acoustic emission (AE) technique has been proved as a powerful technique for structural health monitoring. AE technique can also be efficiently used for evaluation of corrosion activity in concrete. Despite its advantages, an effective analysis of data recorded by AE technique still founds to be a challenging task demanding an appropriate damage assessment methodology. For quantification of damages, various methods for analysis of AE data have been proposed but not a single method has found to be standardized for specific application. In this paper, a procedure for analysis of AE signals is proposed using modified dimensional analysis method. Many times, it becomes difficult to choose the appropriate AE parameter which can be effectively co-related to the physical feature for development of accurate prediction model. Hence, in the present research work an attempt has been made to develop a model by incorporating primary characteristic AE waveform parameters. A corrosion rate prediction model using modified dimensional analysis of AE signals is developed and compared with the model developed using non-linear regression analysis. The performance of two models is further assessed using different statistical parameters. The study demonstrated that the methodology of modified dimensional analysis indicated improvement in the corrosion rate predictions. Thus, modified dimensional analysis can be implemented as a promising method for analysis of complex AE signal data as well as for development of statistical modelling of corrosion phenomenon in reinforced concrete based on recorded AE parameters.

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1. Introduction

Cracking of concrete due to corrosion of steel embedded in concrete is a major cause for deterioration of reinforced concrete (RC) structures. The risk of corrosion increases with the increase in age of the structure. Deterioration of the structure due to corrosion is of a great concern in the maintenance and repair of many civil structures in the coastal regions. Hence, for safety of RC structures, early detection of damages and appropriate prediction of corrosion status is the need of the day. For such damage detection, use of non-destructive techniques is on the rise as it is non-invasive in nature. The non-destructive techniques like half-cell potential, linear polarization resistance method, Tafel extrapolation technique and infrared thermograph are some of the practically adopted techniques for corrosion monitoring of RC structures (Song and Saraswathy 2007). Acoustic emission (AE) technique is one of the non-invasive techniques used for detection of corrosion and subsequent cracking of concrete. AE technique detects corrosion by capturing energy released by micro-cracks generated in concrete due to corrosion reaction (Ing et al. 2005; Idrissi and Limam 2003; Patil et al. 2014). The past studies by Ohtsu and Tomoda (2008), Kawasaki et al. (2010, 2013) and Di Benedetti et al. (2013) have revealed that

* *Corresponding author.* E-mail address: shilpa.patil@vit.edu (S. V. Patil)
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AE technique can indicate an early warning of corrosion as compared to well-established electrochemical techniques. Idrissi and Limam (2003) showed a good correlation between the acoustic emission activity and corrosion current density. It is also reported in the literature that AE is a very powerful technique used for structural health monitoring which provides adequate information about the condition of structures for executing maintenance work in RC structures (Fricker and Vogel 2007; Di Benedetti and Nanni 2014; Patil et al. 2017; Nair and Cai 2010; Verstrynge et al. 2022).

Different methods are being used for analysis of data collected using AE technique. Usually, two main approaches namely parameter-based analysis and signal-based analysis of AE data are used in practice to characterize the damage due to corrosion. The parameter-based analysis includes study of variation of different AE parameters like cumulative signal strength, RA value & average frequency, b-value or Ib-value as well as intensity analysis based on historic index and severity index. The second approach of signal-based analysis mainly includes evaluation of the entire waveform recorded in AE system on the basis of three-dimensional localization of the AE source. One of the effective signal-based AE techniques is SiGMA analysis which identifies 3D AE source location based on moment tensor analysis (Zaki et al. 2015). Another method of a cluster analysis of AE data is also being used to correlate with the failure mechanisms of the material under study (Yu et al. 2023). Various machine learning tools are also being used now a days for corrosion rate prediction in cementitious mortars (Ji and Ye 2023; Thirumalaiselvi and Sasmal 2024). Thus, various researchers have proposed various methods in AE technique for quantification of damage and not a single method yet has found to be universally approved or standardized for specific application.

Although, AE technique is known as a qualitative technique, Ing et al. (2005) had tried to correlate absolute energy parameter of AE data with gravimetrical mass loss; but they could not establish any confirm relationship. On the other hand, Patil et al. (2015) have demonstrated the implementation of AE technique for quantification of corrosion in RC elements by establishing a nonlinear relationship between AE parameter and loss in mass of steel rebars. This relationship was obtained by performing non-linear regression analysis on the data collected through laboratory-based experimentation under accelerated corrosion condition. The mathematical expression formulated by Patil et al. (2015) is based on only one AE parameter namely "cumulative signal strength" (CSS). Even though analysis based on one AE parameter is easy and practicable, the evaluation of the entire AE waveform may provide wider perception to understand the failure mechanism. Many times, it also becomes difficult to choose the appropriate AE parameter which can be effectively co-related to the physical feature for development of accurate prediction model. Hence, in the present research work an attempt has been made to develop a model by incorporating five primary characteristic AE waveform parameters namely - amplitude, AE counts, rise time, duration and signal strength for prediction of corrosion rate of reinforcing steel in concrete. A comprehensive approach of modified dimensional analysis is used here to develop the model based on AE parameters. Although the method of dimensional analysis is a well-established mathematical method, its application for the analysis of AE signal data has not been explored yet.

2. Modified Dimensional Analysis

Dimensional Analysis is a mathematical technique which has been used in varied engineering and non-engineering applications. The technique is based on Buckingham Pi theorem but, it involves certain limitations such as need of accurate selection of number of parameters for the analysis, accurate selection of dimensionless groups and accurate elimination of redundant variables. To overcome these limitations, Butterfield (1999) had suggested modification in the method which is less complex and comprehensive. The major advantage of this modified Buckingham Pi theorem suggested by Butterfield (1999) is that it helps to maintain the dimensional homogeneity and mathematical stability of the final formulation. Thus, due to less complexity involved, this modified method has been applied to predict various engineering properties such as: to predict load settlement characteristic of large spread footings in sand (Phatak and Dhonde 2000), to predict ultimate torsional strength of RC beams (Phatak and Dhonde 2003), to predict 28-days compressive strength of cement (Phatak and Deshpande 2005; Pawar et al. 2024), to predict mechanical behaviour of plastic hinges developed in RC beams at ultimate loading conditions (Corrado and Carpinteri 2009) and to determine ultimate load capacity of shell foundations (Esmaili and Hataf 2013). The method of modified dimensional analysis has been also used for corrosion rate prediction of various grades of stainless steel in marine oil environment (Akpa 2013) as well as magnesium and related alloys in sodium chloride environment (Jayabharathy et al. 2017).

Despite of application of modified dimensional analysis in the fields of metal corrosion, its application for prediction of corrosion of steel embedded in concrete identified using AE parameters has not been investigated yet. Hence, the current research paper proposes a unique procedure of application of modified dimensional analysis (MDA) using AE signal parameters to predict the corrosion of steel embedded in concrete. The efficacy of the model developed using MDA is compared with the earlier model developed by author using non-linear regression analysis as explained in Patil et al. (2015). The performance of both the models is evaluated further based on statistical measures.

3. Data Used for Modified Dimensional Analysis

The data utilised in the current study is obtained from the earlier experimental work performed by Patil et al. (2014, 2015) for assessment of corrosion in RC elements using AE technique. As reported in earlier publications (Patil et al. 2014, 2015), the researchers performed an experimental study by subjecting the cylindrically shaped RC specimens having diameter of 6 cm and height of 10 cm to accelerated corrosion. The experimental programme consisted of testing specimens made of different cement type (OPC and PPC), steel type (TMT and CRS) and rebar diameter (12 mm, 16 mm, and 20 mm). An impressed current technique with constant voltage of 3V was used for achieving accelerated corrosion of specimens as explained in Patil et al. (2014). The accelerated corrosion process was carried out till the specimen develops visible crack on the concrete surface due to corrosion. During the entire testing process, the corrosion activity in specimen was continuously monitored using AE technique. All the measurements were recorded at room temperature and with 100% humidity level under chloride induced accelerated corrosion conditions. A schematic diagram of the AE measurement system followed in earlier experimental work is presented in Fig. 1.

After completion of the test, the loss in mass of steel rebars removed from concrete specimens were recorded. A statistical tool - Analysis of Variance was used further to understand the significance of all material variables on recorded AE signal parameters and inferred that the influence of material variation on AE parameters is insignificant. Further the non-linear regression analysis (NLRA) was executed to establish the mathematical relation in between maximum CSS parameter recorded by AE and measured mass loss of steel rebars (Patil et al. 2015). In the current study, the AE data recorded during this laboratory based experimental work is used for performing MDA. The AE parameters used for MDA includes maximum cumulative duration, maximum cumulative count, maximum cumulative rise time, maximum cumulative signal strength and maximum cumulative amplitude along-with the other parameters like initial and final weight of rebar. These specific AE parameters are selected for analysis as these are primary characteristic AE parameters and can be easily obtained from AE waveform. Table 1 presents the data used for MDA.

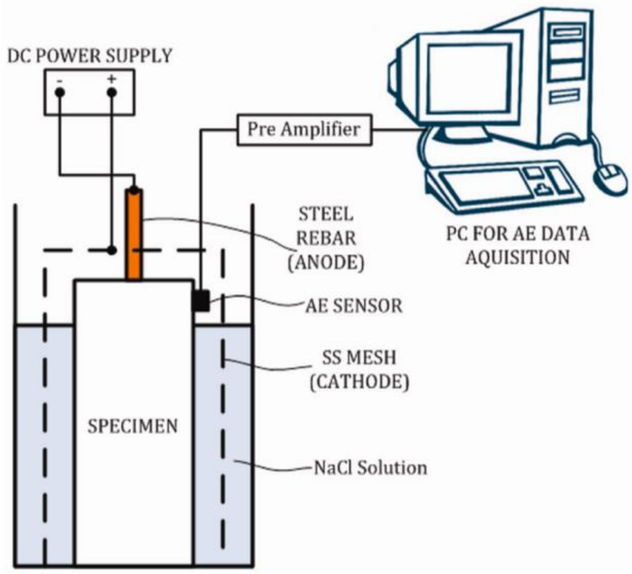

Fig. 1. Acoustic emission measurement system – schematic diagram (Patil et al. 2015).

Table 1. Data used for MDA.

Sr. No.	Initial weight of rebar before corrosion (*g*) (W_i)	Maximum cumulative amplitude values (pico-volt) (A_f)	Maximum cumulative signal strength values (picovolt-second) (S_f)	Maximum cumulative rise time values (second) (R_f)	Maximum cumulative count values (nos.) (C_f)	Maximum cumulative duration values (second) (D_f)	Final weight of rebar after corrosion (*g*) (W_f)
1	91.47	5.25E+10	8.04E+06	2.80E+04	2.19E+03	7.59E+04	88.86
2	91.50	6.61E+11	7.49E+07	3.20E+05	2.46E+04	8.23E+05	87.97
3	94.31	3.26E+11	3.48E+07	1.16E+05	1.58E+04	3.69E+05	88.63
4	164.01	4.05E+10	5.38E+06	1.99E+04	1.57E+03	5.61E+04	160.83
5	169.36	1.02E+11	1.39E+07	5.33E+04	4.06E+03	1.47E+05	165.75
6	261.60	6.38E+13	1.18E+10	6.26E+07	3.92E+06	1.28E+08	249.23
7	268.14	8.12E+13	1.37E+10	1.10E+08	3.93E+06	1.55E+08	256.36
8	248.60	2.55E+13	3.90E+09	1.55E+07	9.54E+05	3.69E+07	233.62
9	269.24	1.89E+11	2.64E+07	4.64E+04	6.12E+03	1.89E+05	263.72
10	266.83	1.79E+11	2.70E+07	4.58E+04	7.10E+03	1.76E+05	260.92
11	268.07	5.42E+10	6.00E+06	2.04E+04	3.33E+03	7.51E+04	263.78
12	269.12	1.93E+11	1.29E+07	3.59E+04	5.96E+03	1.30E+05	264.34
13	265.33	2.86E+11	2.73E+07	1.45E+05	1.12E+04	3.24E+05	256.70
14	266.93	9.31E+11	1.19E+08	6.49E+05	3.72E+04	1.43E+06	259.34

4. Modelling Technique Adopted Using MDA

Butterfield (1999) states that a specific system consisting of n parameters can be described by set (K) = (K_1 , K_2 , K_3 , ..., K_n), consisting of total m primary dimensions as (D) = (D_1, D_2, D_3, D_4, ..., D_m). This system always has a minimum set - $D_{\min}$ which can dimensionally define all the parameters in the set K. Next, the number of dimensionless groups can be considered as difference between number of parameters in K and number of parameters in $D_{\min}$. The dimensionless groups (π_1, π_2, π_3, π_4, ... π_N) can be further assembled to determine the dependent parameter of interest. Thus, by applying this methodology, the set K for corrosion prediction of steel embedded in concrete using AE parameters is given as follows:
K = (final weight of rebar (W_f), initial weight of rebar (W_i), maximum cumulative duration (D_f), maximum cumulative count (C_f), maximum cumulative rise time (R_f), maximum cumulative signal strength (S_f), maximum cumulative amplitude (A_f)).

The units for all these parameters considered are: weight of rebar in gram; maximum cumulative duration in second; maximum cumulative rise time in second; maximum cumulative signal strength in volt-second; maximum cumulative amplitude in volt, whereas maximum cumulative count is unitless term.

Thus, the set defined in terms of their respective dimensions is, K=(M^1, M^1, T^1, 0, T^1, $M^1L^2T^{-3}A^{-1}T^1$, $M^1L^2T^{-3}A^{-1}$). Here, n = 7 and m = 3 which is also set D. Hence, the number of isolated variables as well as dimensionless Pi-groups are obtained as, $N = n - m = 4$. In the current study $D_{\min} = D$. Now, the set R is selected such that all the variables of set R have distinct dimensions. Therefore, selecting $R = (Wi, Sf, Rf)$. Subsequently, Q is selected from R following the modified Buckingham Pi theorem protocol. Therefore:

$$\mathrm{Q} = (Wi, Sf, Rf) \tag{1}$$

$$\mathrm{NOTQ} = (Wf, Df, Cf, Af) \tag{2}$$

Now, the dimensionless Pi-groups are generated by considering combinations of variables from Q and NOTQ sets. Hence, the dimensionless Pi-groups are:

$$\pi_1 = (Wi, Sf, Rf, Wf)$$

$$\pi_2 = (Wi, Sf, Rf, Cf)$$

$$\pi_3 = (Wi, Sf, Rf, Af)$$

$$\pi_4 = (Wi, Sf, Rf, Df) \tag{3}$$

Now solving for π_1,

$$\pi_1 = (W_i^a, S_f^b, R_f^c, D_f^1) \tag{4}$$

Eq. (4) can be presented in dimensional form as below:

$$[M^0 L^0 A^0] = [[M^1]^a, [M^1 L^2 T^{-3} A^{-1} T^1]^b, [T^1]^c, [M]^1 \tag{5}$$

Now, by comparing the indices of both sides of equation we get:
M: $0 = a + b + 1$
L: $0 = 2b$
T: $0 = b + c$
A: $0 = -b$
Hence, $a = -1$, $b = 0$, $c = 0$. By replacing these values of a, b and c in Eq. (4) we get:

$$\pi_1 = \left(\frac{W_\mathrm{f}}{W_\mathrm{i}}\right) \tag{6}$$

Similarly solving for the remaining Pi-terms we get:

$$\pi_2 = C_f \tag{7}$$

$$\pi_3 = \left(\frac{R_f \cdot A_f}{S_f}\right) \tag{8}$$

$$\pi_4 = \left(\frac{D_\mathrm{f}}{R_\mathrm{f}}\right) \tag{9}$$

Now to find final weight of rebar, articulating $\pi_1$as a function of (π_2,π_3, π_4), such that π_1 = $\psi(\pi_2, \pi_3, \pi_4)$ where ψ is an undetermined function. From Eqs. (6), (7), (8) and (9), substituting the Pi-terms in above equation we get:

$$\left(\frac{W_f}{W_i}\right) = \psi\left(C_f, \left(\frac{R_f \cdot A_f}{S_f}\right), \left(\frac{D_f}{R_f}\right) \tag{10}$$

To determine the precise nature of (ψ), the power-product relationship of the dimensionless group is exercised as follows:

$$\pi_1 = \beta_1 \, {\pi_2}^{\beta_2} \, {\pi_3}^{\beta_3} \, {\pi_4}^{\beta_4} \tag{11}$$

or

$$\left(\frac{W_f}{W_i}\right) = \beta_1 \left(C_f\right)^{\beta_2} \left(\frac{R_f \cdot A_f}{S_f}\right)^{\beta_3} \left(\frac{D_f}{R_f}\right)^{\beta_4} \tag{12}$$

$$W_f = W_i \, \beta_1 \left(C_f\right)^{\beta_2} \left(\frac{R_f \cdot A_f}{S_f}\right)^{\beta_3} \left(\frac{D_f}{R_f}\right)^{\beta_4} \tag{13}$$

The values of constants (β_1, β_2, β_3, β_4) are further calculated by performing non-linear analysis using SOLVER function of MS Excel. The final equation obtained is as shown in Eq. (12).

$$W_f = W_i \cdot 1.143\left(C_f\right)^{0.00379} \left(\frac{R_f \cdot A_f}{S_f}\right)^{-0.009} \left(\frac{D_f}{R_f}\right)^{-0.001249} \tag{14}$$

Thus, Eq. (14) represents the model developed for prediction of final weight of rebars using MDA.

5. Results and Discussion

Using the model developed based on dimensional analysis as presented in Eq. (14), the final weight of steel rebars, mass loss and corrosion rate values are calculated. The details of calculations and comparative assessment with the results of NLRA model are discussed in detail in following sections.

5.1. Prediction of the final weight of steel rebar

Based on the developed model using MDA, the final weights of rebar are calculated. The final weights of rebar are also calculated using the NLRA model presented by Patil et al. (2015) which is as shown in Eq. (15).

$$y = 1.05 \cdot 10^6 \cdot e^{0.711x} \tag{15}$$

In Eq. (15), y indicates maximum CSS value whereas x represents mass loss of steel rebar calculated by gravimetric method. The values so calculated are compared with actual final weight of the rebar measured after completion of the experimental work as mentioned in earlier work of Patil et al. (2015). Fig. 2 presents the comparative graph for final weights of rebar measured and calculated using NLRA as well as MDA model.

From Fig. 2 it can be clearly noticed that the final weights of rebar calculated using MDA model are perfectly in agreement with that of values calculated using earlier developed NLRA model as well as with measured values. These predicted final weight values of steel bars are further used to compute the mass loss and then the corrosion rate as described in ASTM G1-03 (2017).

5.2. Prediction of corrosion rate

Figs. 3 and 4 represents the scatter plot between actual corrosion rate and predicted corrosion rate using MDA and NLRA models respectively.

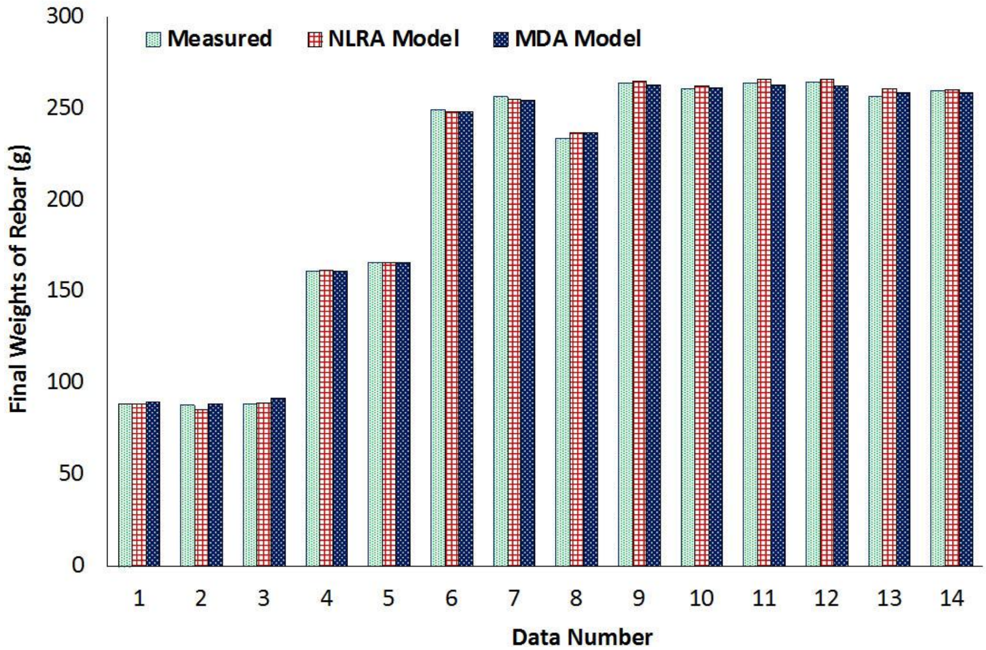

Fig. 2. Final weights of rebars using MDA model and earlier NLRA model.

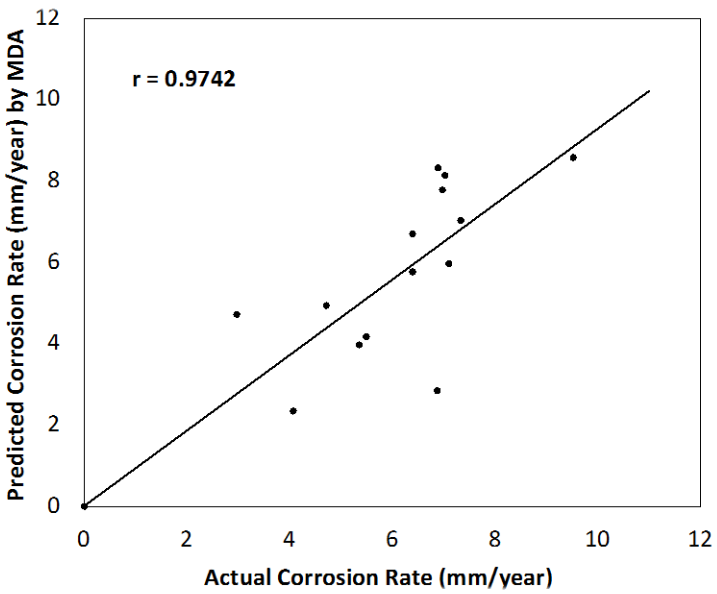

Fig. 3. Predicted values vs. actual values of corrosion rate using MDA model.

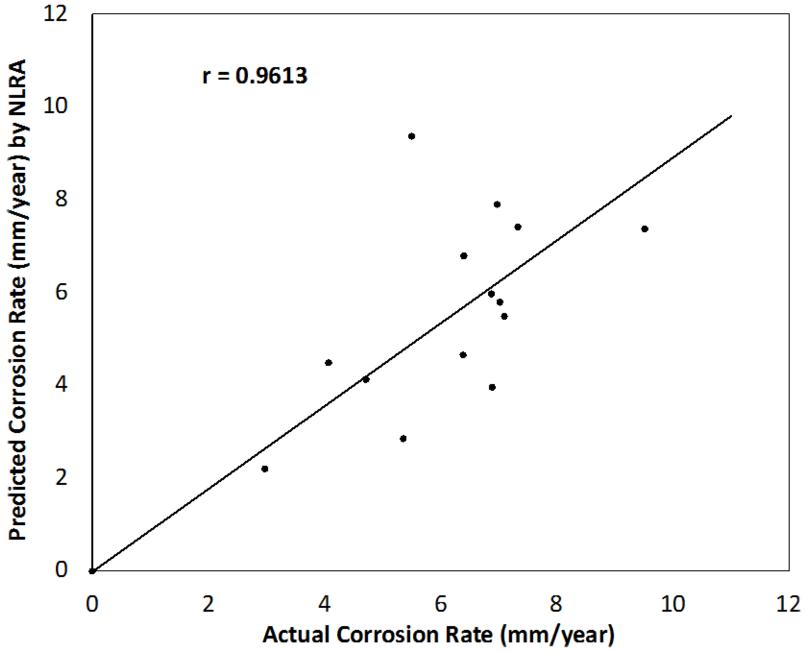

Fig. 4. Predicted values vs. actual values of corrosion rate using NLRA model.

From Fig. 3, it can be observed that for MDA model, the scatter of points is less from the equality line between predicted and actual corrosion rate values with a high correlation coefficient value (r=0.97) as compared to NLRA model shown in Fig. 4. To understand the performances of both the developed models, various statistical measures are calculated as presented in Table 2. The commonly adopted statistical measure is the correlation coefficient (r) which computes the degree of relatedness of the variables. The value of r nearer to 1.0 denotes a linear relationship between the two variables. The square of correlation coefficient is termed as coefficient of determination (R^2). The value of R^2 varies from zero to one and the higher value represents better concurrence between predicted and observed values. However, R^2 value remains unaffected to proportional/additive differences between the predicted and observed data. This may result in obtaining higher value of R^2 even if predicted values fluctuate considerably in magnitude, exhibiting major flaws in the model. Another most commonly adopted measure for evaluating the quality of predictions is Root Mean Square Error (RMSE). It specifies how far model simulations fall from observed true values with lower value indicating good predictions. But similar to R^2, this parameter is also influenced by the higher error values. A statistical measure - Mean Absolute Error (MAE) explains the difference between the modelled and observed values. It has been observed that the extent by which RMSE surpasses the MAE implies the range of outliers in the data. Another statistical measure – coefficient of efficiency or Nash-Sutcliffe Efficiency (E) is also broadly used to estimate the performance of models. It is expressed as the ratio between mean square error and the variance in the observed data, deducted from one. Its value varies between -infinity to one and values closer to 1.0 denotes better agreement in observed data and model. The negative value of E implies that the observed mean is a better predictor than the model (Legates and McCabe 1999). Based on the above definitions, the values of all above mentioned statistical measures for both the models are calculated to evaluate the performance of MDA and NLRA model as presented in Table 2.

Table 2. Performance of models.

Model	MDA Model	NLRA Model
Correlation Coefficient - r	0.9742	0.9613
Coefficient of Determination - R^2	0.9491	0.9241
Root Mean Square Error - RMSE	2.0993	4.2051
Mean Absolute Error - MAE	1.1615	1.4339
Nash-Sutcliffe Efficiency - E	0.1302	- 0.3161

From Table 2 it can be observed that there is a marginal difference in r as well as R^2 values of the two models. Thus, correlation coefficient and coefficient of determination value implies that both the models are relatively good with no prominent differences. On the other hand, RMSE value for the NLRA model is nearly twice that of the MDA model indicating better prediction by MDA model. Moreover, the extent by which RMSE exceeds MAE is approximately three times greater for the NLRA model than that of the model developed using MDA signifying existence of greater outlier in NLRA model. The Nash-Sutcliffe Efficiency – E value for the NLRA model is negative implying that the observed mean is a better predictor than the model, whereas for the MDA model, E value being positive and close to zero, infers that the observed mean is as good a predictor as the model. Thus, the statistical measures calculated for both these models indicate lesser extent of outliers in the data predicted by MDA model than that of the model based on NLRA implying better performance of MDA model as compared to NLRA model.

6. Conclusions

The study presented in this paper is the first approach towards modelling the rate of corrosion of steel rebar in concrete using a comprehensive method of MDA implemented for AE parameters. A model is developed using MDA for AE parameters collected for quantification of corrosion and the performance of developed model is compared with the model based on NLRA. The performance of both the models is evaluated further using statistical measures like r, R^2, RMSE, MAE and Nash-Sutcliffe Efficiency – E. The outcomes of the study can be summarized as below.

- Based on the selected data for performing MDA, the developed model is presented as:

$$W_f = W_i \cdot 1.143\left(C_f\right)^{0.00379}\left(\frac{R_f \cdot A_f}{S_f}\right)^{-0.009}\left(\frac{D_f}{R_f}\right)^{-0.001249}$$

  This equation predicts the weight of steel rebar after corrosion based on weight of rebar before corrosion and the primary characteristic AE parameters recorded during the active corrosion process. Using these predicted values of weight of steel rebars after corrosion, corrosion rate can be calculated using procedure described in ASTM G1-03 (2017).
- The model developed using MDA exhibited higher values of r, R^2 as well as E and lower values of MAE and RMSE, demonstrating better performance than the NLRA model.
- Instead of using few energy-based AE parameters for analysis, primary characteristic AE waveform parameters namely - amplitude, counts, rise time, duration and signal strength can be efficiently used combinedly for successful formulation of corrosion prediction models using MDA.
- MDA is a promising tool for analysis of AE parameters which can be successfully used to formulate predictive model using few datasets unlike other machine learning based approaches which demands large datasets for training and testing of models.

Thus, the current study reveals that the presented methodology for application of MDA using AE signal parameters can be promisingly used to formulate the corrosion prediction model for RC elements by ensuring mathematical stability. With the help of MDA, it is also demonstrated that, the dimensional homogeneity helps to check the accuracy of the relationship between different variables and improves the predictions of physical phenomena. The procedure for analysis of AE signal data using MDA is a simplified process as compared to other AE data analysis methods as it uses simple tools like spreadsheets. The dataset used in the current study is limited to laboratory-based experiments in accelerated condition. However, it is necessary to extend the study further to check the applicability of developed model to variable field data considering real world environment conditions.

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Conflict of Interest
The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Author Contributions
The author confirms sole responsibility for all aspects of the study including conception and design, acquisition of data, analysis and interpretation of data, drafting the manuscript, revising it critically for important intellectual content; and gave final approval of the version to be published.

Data Availability
The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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