An Adaptive Neural Fuzzy Inference System for the Estimation of the Atmospheric Corrosion Rate of Steel

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ABSTRACT

This paper aims to develop a practical Adaptive Neural Fuzzy Inference System (ANFIS) for estimating carbon steel's Atmospheric Corrosion Rate (ACR). The ANFIS model is developed using 125 datasets. The input variables of the ANFIS model include average Temperature (T), average Relative Humidity (RH), total Rainfall (Rf), Time of Wetness (TOW), and average Chloride Ion (Cl^-). The output variable of the Machine Learning (ML) model is the ACR value. The results of the proposed model are compared to those of the literature. The comparisons reveal that the ANFIS model established in this study outperforms the existing equations in predicting ACR. Furthermore, a Graphical User Interface (GUI) is developed for practical use in predicting the ACR of carbon steel.

Keywords-steel corrosion rate; adaptive neural fuzzy inference system; GUI; machine learning

I. INTRODUCTION

The estimation of atmospheric corrosion has been the subject of many studies worldwide. Authors in [1] presented a deterioration model and assessed metallic bridges that have been corroded by the atmosphere. Authors in [2, 3] addressed the atmospheric corrosion process of metals in the context of different environmental conditions. Authors in [4-7] considered the impact of relative humidity on atmospheric corrosion. Authors in [8] established the effects of temperature on atmosphere corrosion. Authors in [9] calculated the atmosphere corrosion rate as a function of the time of wetness. The impact of rainfall on the rate of atmospheric corrosion was investigated in [10, 11]. It has been found that the most prevalent and important atmospheric corrosive agents are Cl^- from the sea and Sulphur Dioxide (SO_2) [12-15]. Authors in [16] proposed a model for predicting atmospheric corrosion that considered exposure time, temperature, humidity, wetness time, and pollutant concentration. The ACR model can be a basic linear [17, 18], a basic log-linear [18-21], or a dose-response function [22-24], demonstrating quantitative correlations of the environmental influences on the corrosion process. Empirical equations to calculate the ACR were also proposed in [19, 21, 25]. However, these equations only considered a few input parameters, which are Cl^-, SO_2, and TOW. It should be noted that the atmospheric corrosion process is influenced by many external factors of corrosion such as humidity and temperature and pollutant factors.

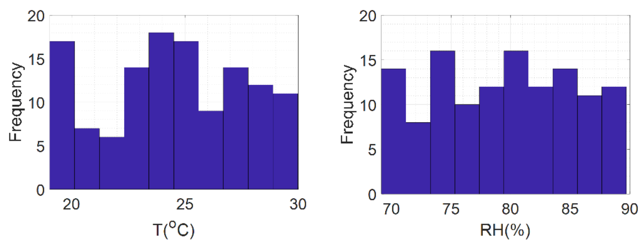
The ANFIS has been recently employed as the primary way to increase the volume and diversity of datasets [26-30]. ANFIS is a hybrid of Artificial Neural Networks (ANNs) and fuzzy inference that is commonly used to handle complicated, nonlinear problems in various engineering fields. The Sugeno fuzzy model, first proposed in [31], served as the foundation for this tool. Modeling nonlinear functions, predicting chaotic time series, and identifying nonlinear modules in the online control system are all done with the ANFIS architecture in simulations [32]. Authors in [33] used ANFIS to predict the axial compression capacity of steel columns with oval hollow sections. However, the application of ANFIS to predict the ACR of steel has not been considered so far. The purpose of this study is to develop a practical ANFIS model for predicting the ACR of carbon steel. The ANFIS models were trained using a total of 125 test datasets from the literature. It should be noted that the datasets employed in this study focus on the pre-engineering steel structures in the industrial zones. Correspondingly, the input variables of the ANFIS model include average T, average RH, total Rf, TOW, and Cl^{-}. The ACR of carbon steel is the ANFIS model's output variable. The model's proposed results are compared with the literature. The comparisons showed that the ANFIS model established in this study is more accurate than the existing equations in predicting the ACR of carbon steel. Furthermore, a GUI is developed to compute the ACR of carbon steel.

II. DATA COLLECTION

A total of 125 experimental ACR datasets were collected from [34-36], and from our own estimated or converted values. It should be noted that 79 datasets were adopted from [34], while 30 and 16 data samples were used from [35] and [36], respectively. Experimental tests were performed in various locations from North to South Vietnam. Five different environmental properties that can potentially affect the value of the ACR are the input parameters of the ANFIS model, including T, RH, Rf, TOW, and Cl^{-}. The ACR of carbon steel is the ANFIS model's output variable. The range and statistical features of the test data are summarized in Table I, and the distribution of the parameters considered is shown in Figure 1. The distributions of the input parameters of the dataset are displayed in Figure 1. The statistical properties of the experimental results are described in Table I, where five input variables, numbered from X1 to X5, are considered for ANFIS model performance.

TABLE I. DESCRIPTIVESCRIPTIVE STATISTICS FOR THE DATA

Input variable	T (X1)	RH (X2)	TOW (X3)	Cl^{-} (X4)	Rf (X5)	K (output)
	(°C)	(%)	(hrs)	(mg/m^2.day)	(mm)	(g/m^2)
Min	19.03	69.15	3006.0	0.41	999.5	89.8
Mean	24.55	79.45	4699.3	7.99	1533	228.7
Max	29.98	89.71	6359.0	30.50	3007	355.9
SD	3.11	5.83	875.6	5.15	337.5	61.9
COV	0.13	0.07	0.19	0.64	0.22	0.27



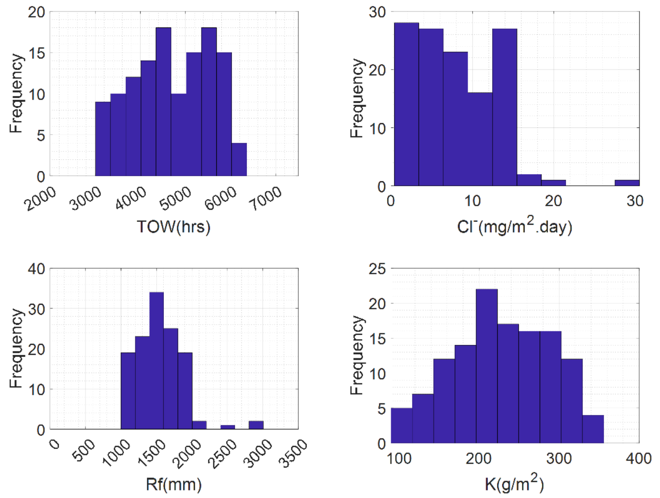


Fig. 1. Histograms of the consideted datasets.

III. EMPIRICAL FORMULAS FOR CALCULATING THE ACR OF CARBON STEEL

The current study presents the existing corrosion rate calculation formulas. The ACR of carbon steel was calculated using three common formulas, proposed in [19, 21, 25], which are listed in Table II.

TABLE II. EMPIRICAL EQUATIONS FOR CORROSION RATE OF STEEL

No.	Ref.	Formulas	Eq.
1	[19]	$K = a + b.\ln(SO_2) + c.\ln(Cl^{-}) + d.\ln(TOW)$	(1)
2	[25]	$K = 0.31(SO_2) + 0.57(Cl^{-}) + 0.31(TOW)$	(2)
3	[25]	$K = 0.30(SO_2) + 0.69(Cl^{-})$	(3)

TOW is the time of wetness (hrs), SO_2 is the average sulfur dioxide deposition rate (mg/m^2.day), Cl^{-} is the average chloride ion (mg/m^2.day)

IV. MACHINE LEARNING MODEL

In the ANFIS models, the standard input and output variables for training and testing were normalized in a range of 0 to 1, according to (4):

$$X^N = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (4)$$

where X is the data test sample, X^N is the normalized data sample, and X_{min} and X_{max} are the minimum and maximum values of the parameters under consideration. The coefficient of determination (R^2) and Root Mean Square Error (RMSE) are utilized to evaluate the performance of the ANFIS models. The definitions of these indicators are expressed by:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(t_i - \bar{o})^2}\right) \quad (5)$$

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(t_i - o_i)^2} \quad (6)$$

where t_i and o_i represent the target and output of the i^{th} data point, respectively, $\bar{o}$ is the mean of the output data samples, and N is the total number of datasets. The distribution of data, such as the training and testing datasets, as well as their structure and clusters have a significant impact on the ANFIS model precision. Therefore, a reliable technique is proposed for the appropriate data to be obtained. Six training-test ratios were tested against 54 ANFIS models. R^2 and RMSE values were used to find the best model. The proper structure is chosen based on the input data, input and output membership functions, fuzzy rules, and the number of membership functions. The ANFIS design is made up of five main levels [31], as shown in Figure 2.

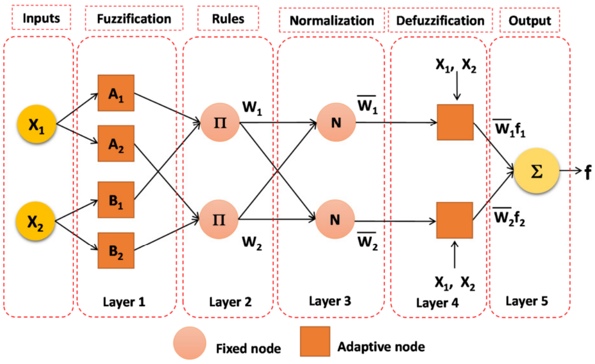


Fig. 2. The ANFIS structure for two input variables.

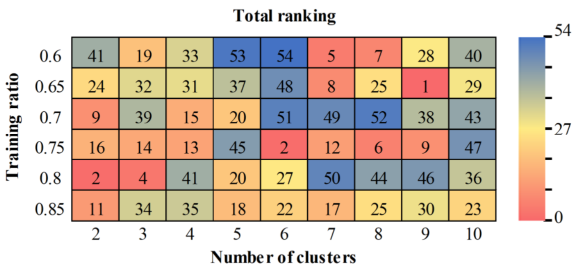


Fig. 3. Ranking of 54 ANFIS models.

TABLE III. ANN PERFORMANCE AND STATISTICAL PROPERTIES

MFs	Parameters	Inputs				
		X_1^N	X_2^N	X_3^N	X_4^N	X_5^N
MF1	σ	0.0975	0.0826	0.1673	0.0818	0.0286
	c	0.2241	0.5595	0.8719	0.5137	0.0292
MF2	σ	0.0277	0.0844	0.0974	0.1687	0.0229
	c	0.7979	0.6466	0.3976	0.5346	0.1355
MF3	σ	0.1322	0.1940	0.1748	0.0806	0.1284
	c	0.4857	0.0487	0.1858	0.1319	0.9159
MF4	σ	0.1651	0.1128	0.0202	0.0248	0.0724
	c	0.7054	0.2776	0.5584	0.8567	0.8273
MF5	σ	0.0720	0.0729	0.0865	0.0699	0.1088
	c	0.7651	0.4714	0.2925	0.4629	0.2597
MF6	σ	0.1207	0.0168	0.0429	0.1875	0.1007
	c	0.1797	0.0917	0.3170	0.6144	0.7090

The six training ratios include 0.60/0.40 (ANFIS-01), 0.65/0.35 (ANFIS-02), 0.70/0.30 (ANFIS-03), 0.75/0.25 (ANFIS-04), 0.80/0.20 (ANFIS-05), and 0.85/0.15 (ANFIS-06). The number of clusters ranged from 2 to 10. The ranking of the tested ANFIS models is summarized in Figure 3. The Gaussian membership function parameters and shapes of the corresponding ANFIS models are depicted in Table III and Figure 4, respectively.

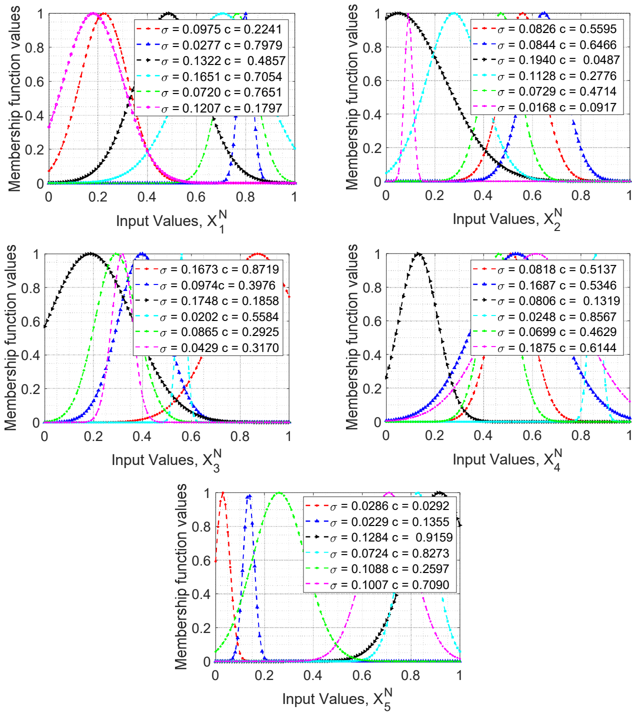


Fig. 4. Membership functions for input variables.

V. RESULTS AND DISCUSSION

Figures 5-7 illustrate the comparison of the ANFIS model results with those from the literature. The comparison shows that the inaccuracies are minor, with most of them being less than 0.25. These results also emphasize that ML models, such as ANNs or ANFIS, are superior in predicting engineering problems [37-39].

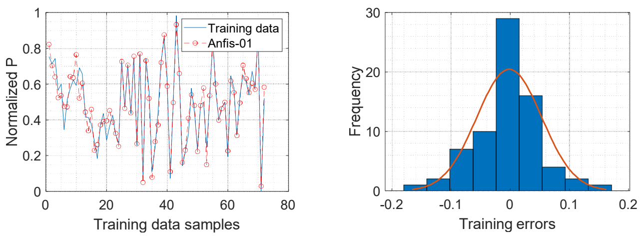


Fig. 5. Training data performance of ANFIS-01 model.

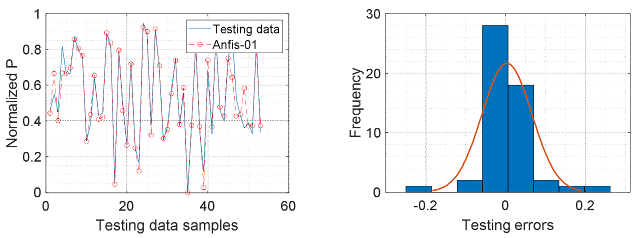


Fig. 6. Testing data performance of ANFIS-01 model.

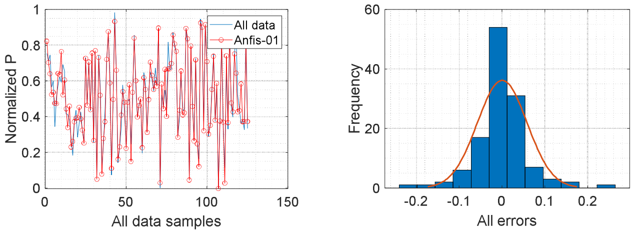


Fig. 7. All data performance of ANFIS-01 model.

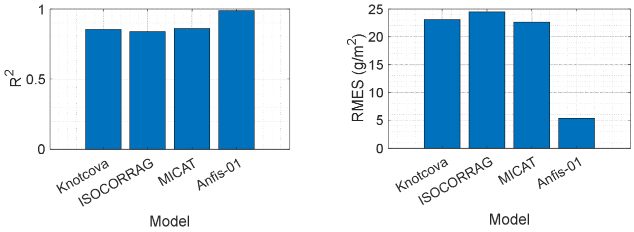


Fig. 8. Comparison of statistical parameters (R^2 and RMSE) between ANFIS and empirical models.

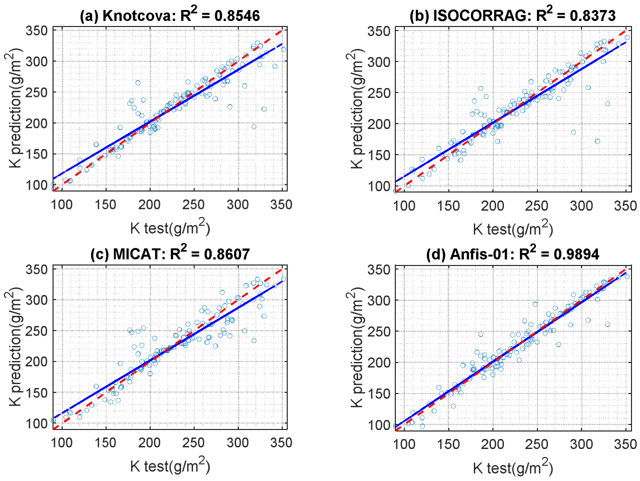


Fig. 9. Comparison of regressions between ANFIS and empirical models.

Figures 8 and 9 display the ACR comparisons between the ANFIS model and existing methods, and it can be observed that the ANFIS model has the highest R^2 value. Additionally, the RMSE of the ANFIS model was shown to be the smallest among all models considered in this study. These results highlight that the developed ANFIS model is reliable and accurate for calculating the ACR of carbon steel.

VI. GRAPHICAL USER INTERFACE

This study also developed a GUI tool, based on the ANFIS model, for easily calculating the ACR of carbon steel in practice utilizing the proposed method. An instance of the GUI can be seen in Figure 10.

VII. CONCLUSIONS

This study developed a practical Adaptive Neural Fuzzy Inference System (ANFIS) for predicting the Atmospheric Corrosion Rate (ACR) of carbon steel. The ANFIS model was trained in 125 datasets.

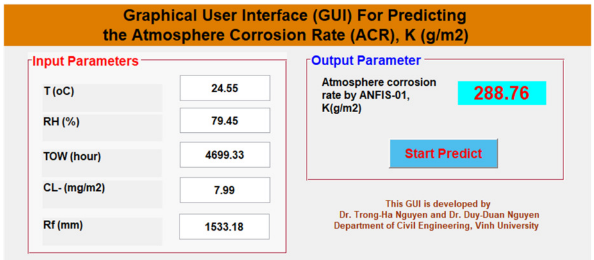


Fig. 10. GUI for calculating the ACR of carbon steel.

The input variables of the ANFIS model include the average Temperature (T), average Relative Humidity (RH), total Rainfall (Rf), Time of Wetness (TOW), and average Chloride Ion (Cl^-). The output variable of the Machine Learning (ML) model is the ACR value. The proposed model's results were compared the ones from the literature and a Graphical User Interface (GUI) tool was developed to quickly calculate the carbon steel ACR.

The ANFIS model predicted the ACR with higher accuracy compared to the equations proposed in [18, 19] ISOCORRAG, and MICAT. The coefficient of determination (R^2) value of ANFIS was significantly higher than those of other empirical formulas. Meanwhile, the Root Mean Square Error (RMSE) obtained from ANFIS was smaller than those attained from other models.

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