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Neural Networks Model for Predicting Corrosion Depth in Steels

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ABSTRACT

The US Federal Highway administration released a study that the cost of corrosion and its preventive strategies for 1998 in the U.S. was approximately $276 billion approximately 3.2% of the US gross domestic product. Corrosion is an important and costly phenomenon and many models were developed to predict corrosion behavior. This paper presents an artificial neural networks (ANN) model to simulate the complex and nonlinear atmospheric corrosion process from observed experimental data. The input parameters to the model consists of temperature, time of wetness (TOW), sulfur dioxide concentration, chloride concentration, exposure time and the model output is corrosion depth. Good performance of ANN model was achieved. The interactions between the inputs were estimated by performing sensitivity analysis based on the developed model. The results showed good agreement with experimental knowledge. SO_2 *and* Cl^- *environments are more influential than other elements*

Keywords: *Corrosion, Steels, Neural networks, Prediction.*

1. INTRODUCTION

Corrosion is the disintegration of an engineered material into its constituent atoms due to chemical reactions with its surroundings. In the most common use of the word, this means electrochemical oxidation of metals in reaction with an oxidant such as oxygen. Formation of an oxide of iron due to oxidation of the iron atoms in solid solution is a well-known example of electrochemical corrosion, commonly known as rusting. This type of damage typically produces oxide(s) and/or salt(s) of the original metal. The atmospheric corrosion of materials is very important for the durability of structures and causes large economic costs [1-5]. Many investigations have been performed in the current century in order to clarify the role of environmental and climatic factors in the atmospheric corrosion of commonly used building and construction metals as well as to simulate their corrosion behavior. Unfortunately, it is difficult to model atmospheric corrosion because of the complex interactions between affecting factors [2-9]. Most of the corrosion models existing today are based on the semi-empirical or mechanistically based models. As these models use different approach in calculation of corrosion rate, these can give different output for same data. In contrast, the artificial neural network (ANN) method is excellent for modeling non-linear and complex systems and can interpolate from past experience. So, artificial neural network may model atmospheric corrosion processes well and a few researchers were used to predict corrosions behaviour [2, 4, 5, 7, 10, 11]. So the main aim of this paper is to apply this technic to describe and analyses the corrosion depth in steels as a function of temperature, Time of Wetness, Sulfur and chloride concentration and Exposure time.

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2. MATERIALS

The experimental data used to develop the model here came from the literature of long term exposure tests of steel and compiled from 42 references and reported by Cai. *et al*[2]. Although the amount of data available in the database looks at first glance to be quite generous, on more detailed examination, it is clear that the amount of data in the conditions of importance, i.e. at the boundaries between low and high corrosion rates, is quite sparse and most of the corresponds to the corrosion depth of 19 to 200 μm. Hence the very high and low values of corrosion depth data were removed.

A total of 313 data sets were available and 215 datasets were used for model development. Remaining 98 data sets were kept aside to evaluate the performance of developed model. The statistics of the data used in model development was shown in Table 1. General architecture of feed forward back propagation network is shown in Fig.1. It is simple architecture, because the network has four layers, which are called as input, two hidden and output layers. In input layer, there are five neurons which indicate temperature, time of wetness, SO_2, Cl^-, and exposure time. While the output node represents corrosion depth of mild steel.

Table 1. Statistical analysis of the input and output variables used in the model development.

Variables	Minimum	Maximum	Mean
Temperature °C	0.31	27.88	11.94
Time of Wetness (%)	0.15	0.95	0.43
SO_2(microgm/m^3)	2	171	29.11
Cl^-(mg/m^2/day)	8	641	50.44
Exposure Time(Years)	1	12	3.06
Corrosion of steel (mm)	9.9	254.4	75.1

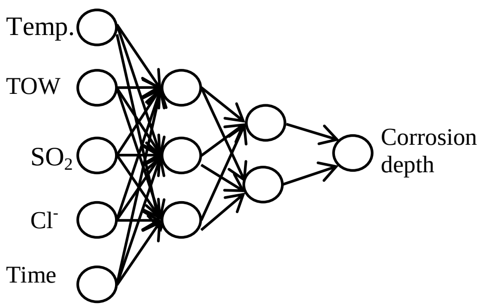

Figure 1: Schematic representation of artificial Neural Networks model representing inputs and output.

2.1. MODEL DEVELOPMENT

The main aim of the present work is to estimate the corrosion depth in steels as a function of temperature, time of wetness, sulfur and chloride concentration and exposure time. Both the input and output variables were first normalized within the range of 0.1 to 0.9. The process of fitting the model to experimental data is called training. It consists of adjusting the weights associated with each connection between the neurons. The model training was started with, two hidden layers with 2-15 hidden neurons in each layer. The minimum Mean Sum Squared Error (MSE) set as 0.00001 and the number of iterations to be executed was set as 120000. Initially the learning rate and the momentum rate were taken as 0.3 and 0.6, respectively for training. The numbers of hidden neurons are fixed for each model based on MSE and the mean error in prediction of training data (E_{tr}). For all patterns, *p*, the global error function, MSE is given by [12, 13]:

$$MSE = \sum_p E_p = \frac{1}{p}\sum_p \sum_i (T_{ip} - O_{ip})^2 \quad (1)$$

where, T_{ip} is the target output and P_{ip} is the predicted output for the ith input neuron for the pth pattern.

$$E_{tr}(x) = \frac{1}{N}\sum_{i=1}^{N} |(T_i(x) - P_i(x))| \quad (2)$$

The Mean error in output prediction

Where, $E_{tr}(x)$ = Mean error in prediction of training data set for output parameter *x*

N= Number of data sets

$T_i(x)$= Targeted output

$P_i(x)$= predicted output

Single hidden layer and two hidden layers were tried out for getting minimum MSE. Varying learning rates from 0.1 to 0.9 with the 0.05 step started the training. Based on MSE and E_{tr} of the training the learning rate was selected model. The number of hidden neurons in the layer and the learning rate for each model was fixed and it was tried with varying momentum from 0.1 to 0.9 with the 0.05 steps. Based on MSE and E_{tr} the momentum was selected. Finally, the optimum architecture for the model achieved through the above procedure was chosen for analysis of corrosion depth in steels. Sigmoid function had been used activation function for neurons. Back propagation algorithm used for training the network and the complete description can be found elsewhere.

3. RESULTS AND DISCUSSSION:

The performance of the developed model was evaluated by predicting corrosion depth from 98 new unseen experimental data resulted R value of 0.91. The comparison between the predicted and experimental values and the respective percentage errors for randomly selected 18 datasets were shown in Fig. 2. The average error is 3.914% in prediction is better than earlier report with the same data [2].

The effectiveness of the developed model does not end with the predictions of the corrosion depth with test data, but it can be used for the examination of the data and to construct the relationships between the inputs and output. The relationships are very difficult to correlate due to nature of variable meteorological (temperature, time of wetness, and exposure time) and pollution conditions (SO_2 and Cl^-). For example, the determination of time of wetness is often leading to its indirect estimate from RH to rainy days data. Considering and not considering the pollution parameters makes the model complex. The interaction between these variables with time of wetness and temperature are multiplicative of unknown magnification which is difficult to accept as a rule. However, neural networks are known for mapping complex systems. Hence, the predicted relationships will be presented

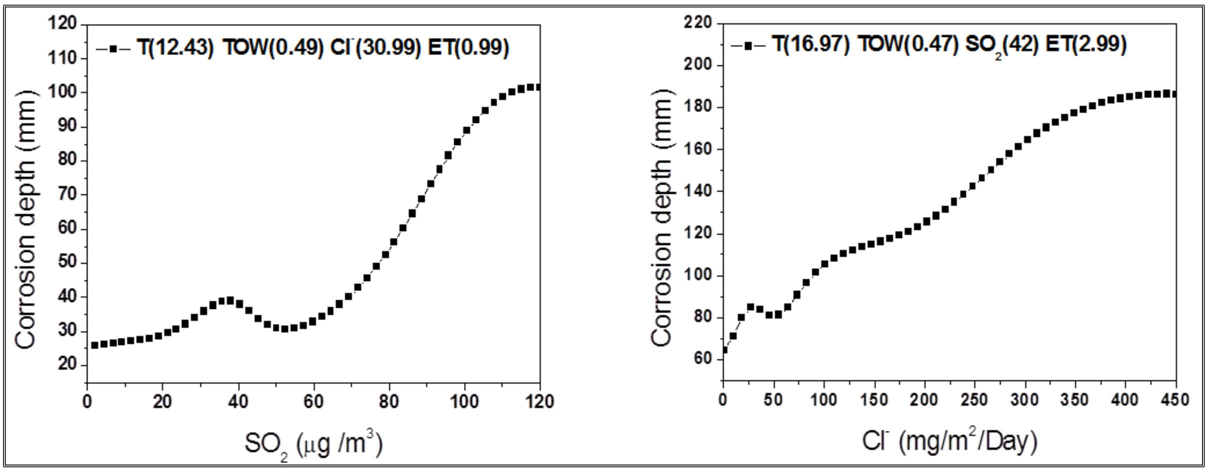

Figure 2: Predicted effect of SO_2 and Cl^- on corrosion depth.

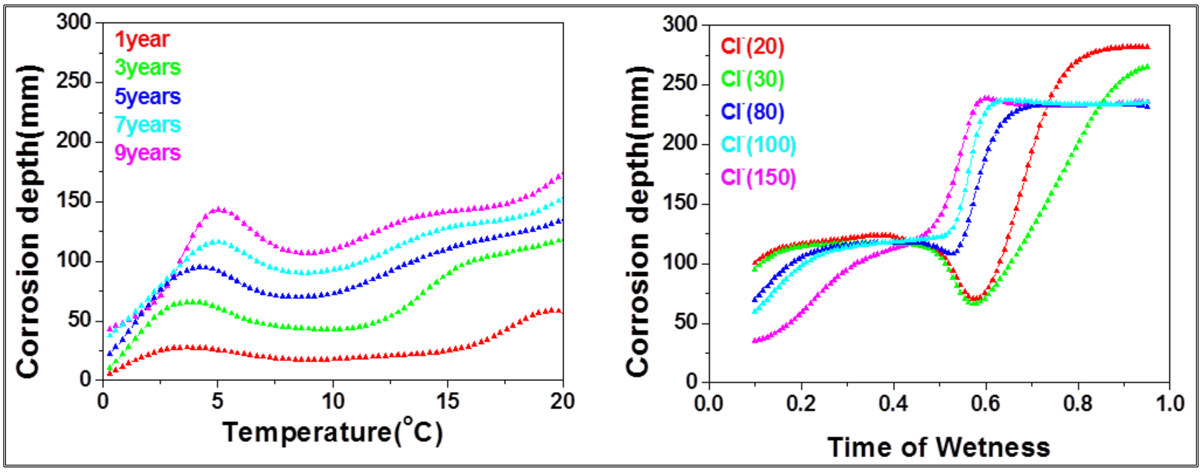

Figure 3: Predicted effect of Temperature and Time of wetness varying time and Cl^- respectively on corrosion depth. (TOW : 0.45, SO_2 : 7, Cl^- : 7).

here. The complete predictions of the model are huge, therefore representative predictions were shown. The neural networks models are created on numbers and equations. Hence, the reason behind the calculations will be tried to explain. In industrial environments, the effects of SO_2, TOW, Cl, temperature, and exposure time have significant effects on corrosion depth and the effects have been quantified performing sensitivity analysis on trained model.

Fig.2. shows the predicted corrosion depth as a function of isolated SO_2 (a) and Cl^- (b) and keeping other elements constant. These two pollution elements are known for increasing tendency of corrosion. In the case of SO_2 the increase from 0 to 120 increases the corrosion depth to a value of maximum 100. Especially, the SO_2 additional level from 60 to 120 is significant. When chloride percentage increases from 0 to 450 the corrosion rate increased to the maximum. This is due to chloride as well as the presence of significant amount of SO_2. Fig. 3 represents model predictions as a function of temperature and time of wetness with varying time and chloride. The increase in temperature from 0 to 20°C resulted the corrosion depth of 160µm and importantly linear relations with all the time. Whereas the relationship between time of wetness and chloride are nonlinear, time of wetness is a very complex variable and its influence is significant. In the presence of chloride it will be more prominent.

Fig. 3. Shows Change in temperatures and time of wetness changes the corrosion depth. These changes and the interactions between these elements are unknown, nonlinear, very complex. Creating these systems in real life and conducting experiments with these variations are expensive and time consuming. The predicted understandable contour plots allow the range of conditions for the optimization of the corrosion depth by visual inspection. The various color bands indicate the range of corrosion depth as a function of Temperature and time of wetness. From figure 4, it is quite clear that higher temperature as well as time of wetness gives the maximum corrosion depth and vice versa. The optimum operating

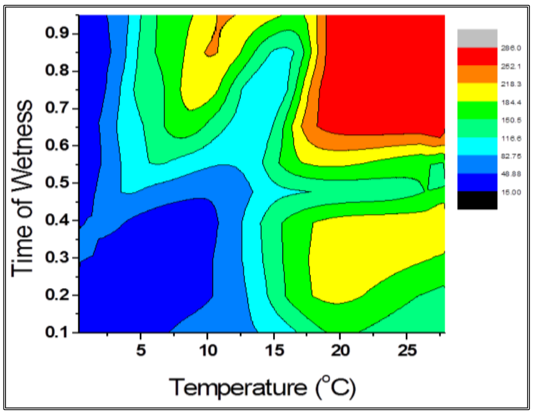

Figure 4: The Combined effect of temperature and time of wetness on Corrosion depth at SO_2: 2, Cl^-: 14.99, ET : **4.**0.45, SO2 : 7, Cl^- : 7).

conditions for less corrosion depth will occur below 10^oC and moisture below 0.4. This picture represents the complexity in the system.

4. CONCLUSIONS

The predictions with unseen experimental data show that the model was useful for complicated and non-linear corrosion behaviour. Adequate consistent data is essential for an actual and capable prediction. The sensitivity analysis helps to construct the real systems and to identify the effect of input variables. The two pollution parameters and time of wetness were identified as most influential parameters. The predictions by the model provide useful information from relatively small experimental databases (313 data sets). The recognized interactions would be very beneficial to industries for planning their experiments.

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