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# Prediction of Atmospheric Corrosion of Ancient Door Knockers via Neural Networks

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**ABSTRACT**

The importance of door knockers persuades us to anticipate the atmospheric corrosion through Neural Network (NN) which is validated by data originated from literature. NNs are used in order to anticipate the effective parameter on bronze atmospheric corrosion including the ambient temperature, exposition time, relative humidity, PH, $SO_2$ concentration as an air pollutant and also metal's precipitations. As these factors are extremely complicated, exact mathematical language of the diverse metals corrosion are not comprehended. The results of this study showed that $SO_2$ concentration as an air pollutant and time of exposition are the fundamental effects on corrosion weight loss of bronze.

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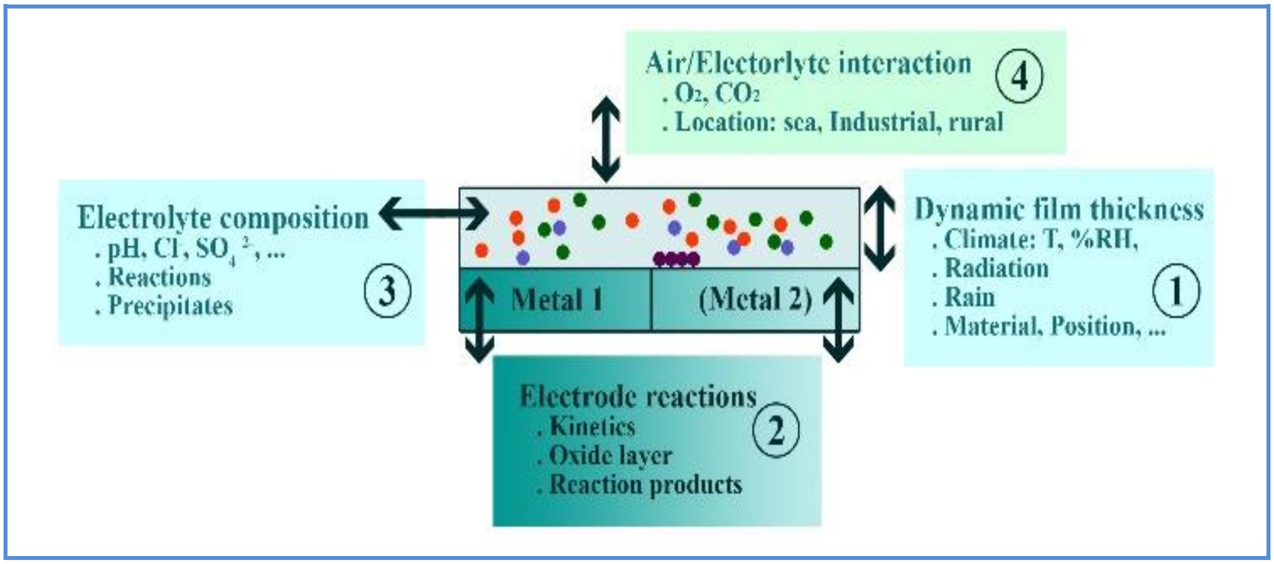
### Graphical Abstract




### Introduction

A door knocker is part of a door rig which allows people outside a house to attract the attention of the people inside. As shown in Figure 1 the door knockers are often ornate, a simple fitting with a metal ring or bob. The importance of door knockers has led to anticipate the atmospheric corrosion via Neural Network (NN). As proved, the atmospheric corrosion is controlled via a complicated interaction as visually depicted in Figure 2. Various metals can be in contact with each other and an electrolyte film. The film thickness changes (1) in space and time owing to climate changes such as: relative humidity (%RH), radiation, rain and temperature (T) low [1] and high [2]. Also, dust and hygroscopic species play a critical role in film formation. Electrode reactions (2) of metal electrolyte interfaces occur involving eventually formation of oxide and reaction products precipitation. Major electrochemical reactions include metal dissolution and oxygen reduction. These reactions and precipitations can be referred to the local composition of electrolyte layer (3). The second one (precipitations) can be referred to the location showing the availability of sulphate, chlorides, and other potential species. It should be highlighted that all species effect the film conductivity. Consequently, layer interaction of the environment (4) makes sure the $O_2$ and $CO_2$ access. Nowadays, merely the effective interactions which are investigated can distinguish current models according to executed simplification. In case of changing environment and type of metal, there can be expected no anticipative power. Furthermore, it should be noticed that atmospheric corrosion is known as the main parameter toward reducing the loss of bronze materials. The caused losses factors include the humidity, solar radiation, temperature and chemicals. Atmospheric corrosion motivates the cathode and anodic electrochemical reactions to occur in a thin electrolyte film. Corrosion of atmospheric has been known as an electrochemical process and extremely complicated one due to having the non-linear behaviour and depending on different pollution and climatic parameters and related to material. In other word, various parameters are involved in the corrosion of atmospheric. Therefore, it is not easy to determine the affective factors on the degradation's process of materials exposed under "outdoor" conditions [3].

Quantification and evaluation of corrosion processes need time and classic mathematical functions toward anticipating the non-linear processes [4]. Therefore, there is certain opportunity to anticipate the corrosion loss of materials by artificial neural network tools. The anticipation of strong non-linear and time-dependent events refers to neural network's pros.

NNs are known as suitable tools in order to approximate the relations of the data to the rest of the tools, in terms of being non-structured data, with a high nonlinearity degree, incomplete data and inaccurate. This kind of information often takes place in the atmospheric corrosion process. NN can simulate the relations which can be rigidly evaluated and predicted by classical procedure (e.g. analysis of regression) as they can model more complicated relations in comparison to the classical procedure (e.g. analysis of regression). NNs are suitable toward modelling of complicated case study especially due to their typical property which can be trained in terms of measured data and generalization's capability [5]. The current study covers the concept of neural networks toward anticipating the atmospheric corrosion of ancient door knockers as case study.

**Figure 1.** various type of door knockers

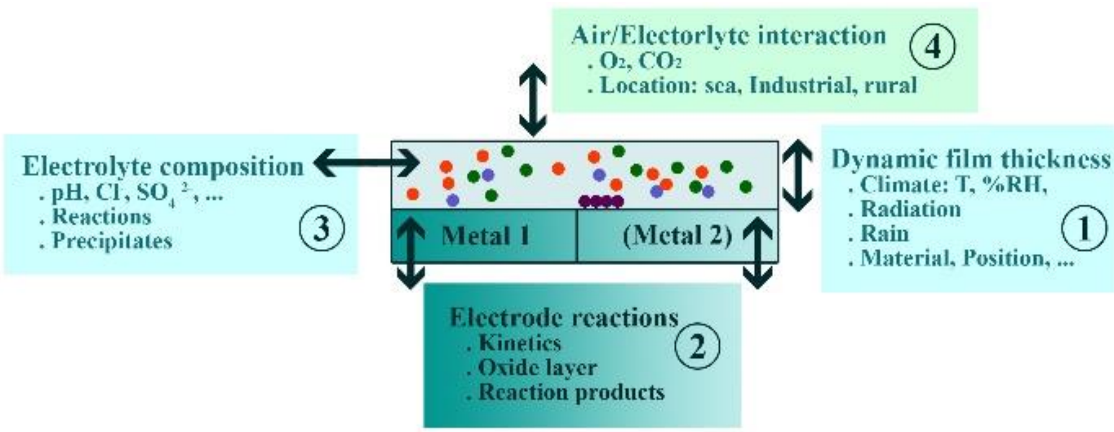



**Figure 2.** Effective parameters on atmospheric corrosions

## Neural Networks (NNs)

NNs are appointed as suitable tools in order to distribute the collateral processing of information during the calculations execution meaning that the information recording, processing and transferring are performed by means of the whole NN [6] and, then, by means of particular memory places [7] (Figure 3). A neuron included a body, called a soma, which the input transmission channel in the form of dendrites [8].

$$z = \sum_{i=1}^{n} w_i x_i - h \qquad (1)$$

where *y* is the neuron's output modelling the electric impulse of the axon is $\sigma$ stated by a transfer function of non-linear, the argument of which is the inner potential of [3]. Moreover, Creation of a user program of algorithms should be considered due to transmogrifying the data base of input to the data base of output. However, NNs would not be faced with any strict step. Therefore, the creation of algorithm would not be required during the learning [5].

$$y = \sigma(z) \tag{2}$$

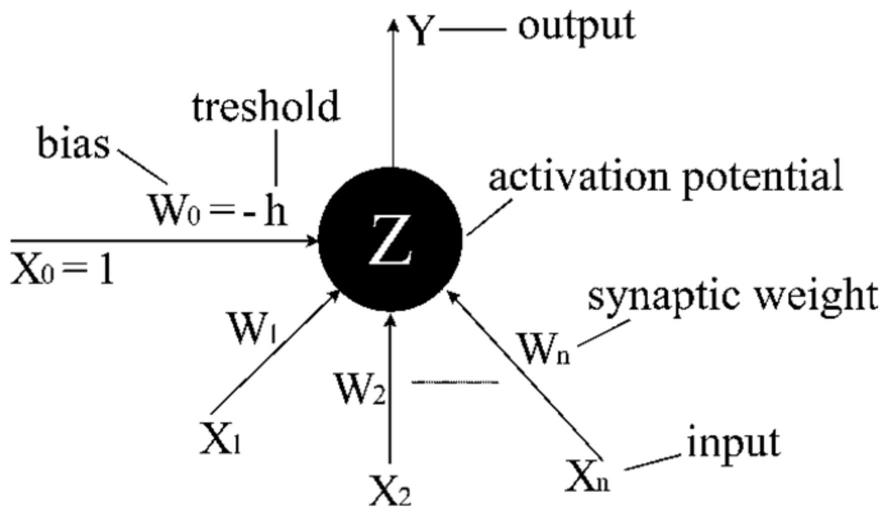



**Figure 3.** Mathematical model of neuron

**Anticipation of Corrosion Loss**

The data conditioning for network training should be performed before the creation and design of NN. It should be highlighted that the data is adapted from the National museum of Iran. The whole dataset were divided to two parts such as data for network training and testing. Input data were included the ambient temperature, relative humidity, precipitation amount, PH, $SO_2$ concentration as a pollutant and exposition time. Also, the output data was included corrosion weight loss of bronze illustrated in Figure 4 [3].

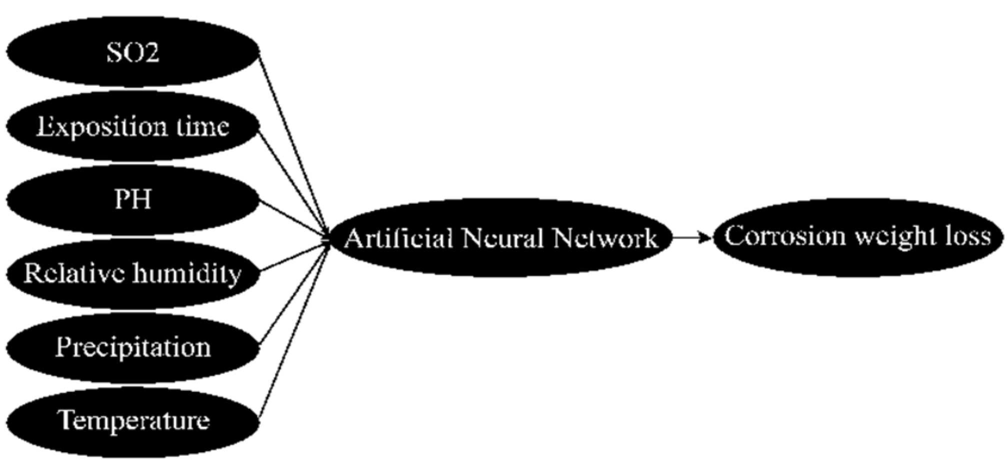



**Figure 4.** Scheme of input and output data

NN were combined with the STATISTICA software which is called STATISTICA–NN. It should be noticed that hybrid of STATISTICA–NN enables the selected data among others with the best performance and most suitability, it contains analytic techniques, efficient investigative and enables obtaining of the summary descriptive statistics in order to perform the analysis of sensitivity toward creating the response plots [3]. It should be highlighted that, according to the literature, the multilayer feed-forward NN topology 6-7-1 can be demonstrated as the perfect outcome of anticipating corrosion weight loss (Figure 5) [3].

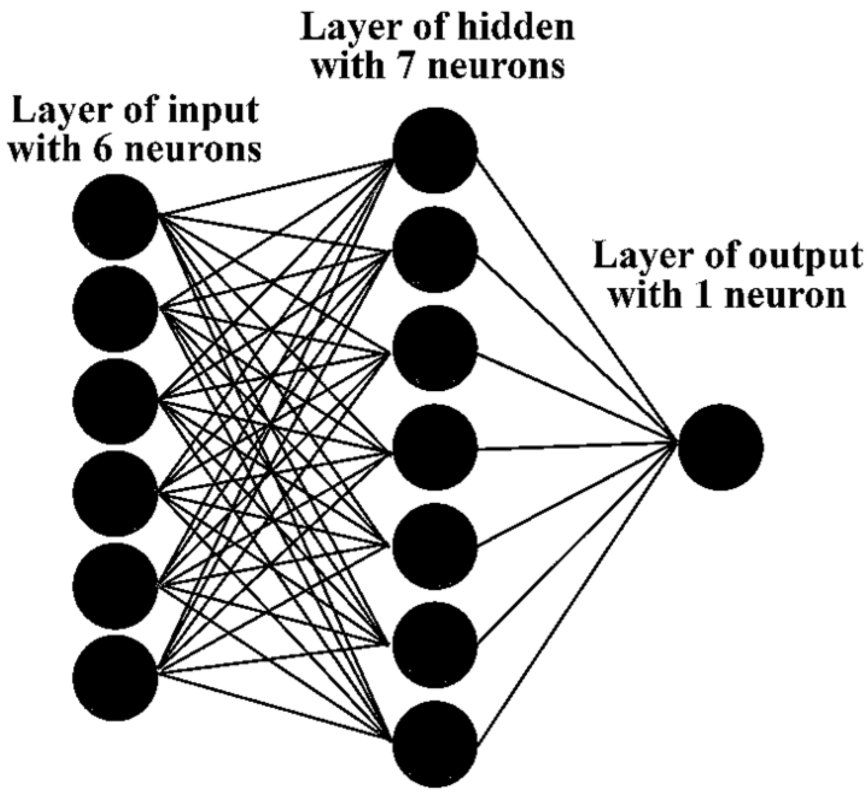



**Figure 5.** Neural network's structure with topology 6-7-1

An NN was obtained from the selected NN parameters and $C^{++}$ was performed to be an independent program on software of STATISTICA. This program provides the basis of input data setting to anticipate the corrosion weight loss of bronze which is related to the various climatic and pollution parameters.

The inaccurate rate between anticipated and actual output represents an anticipation error. Indeed, from the technical perspective the error is mainly shown as follows:

The below equation RMS would be referred to the Root Mean Squared which would not offset the employed units.

$$RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1}(y_i - O_i)^2}{n-1}} \qquad (3)$$

The relation of EXP_RMS would be referred to the error calculation which would compensate for the employed units.

$$EXP - RMS = \sqrt{\frac{\sum_{i=0}^{i=n-1}(y_i - O_i)^2}{\sum_{i=0}^{i=n-1}(y_i)^2}} \qquad (4)$$

where: $n$ - patterns number a test set, $y_i$ – anticipated outputs, $O$i - Outputs of experimentalas shown in Eq.(3).

Anticipation errors of the selected NN model was calculated according to Equations (3) and (4) which are RMS=39.105 [g.m$^{-2}$] and EXP_RMS=6.895%. Comparison of experimental and anticipated information is depicted in Figure 6. The model provides the anticipating corrosion loss of bronze with an admissible error [3].

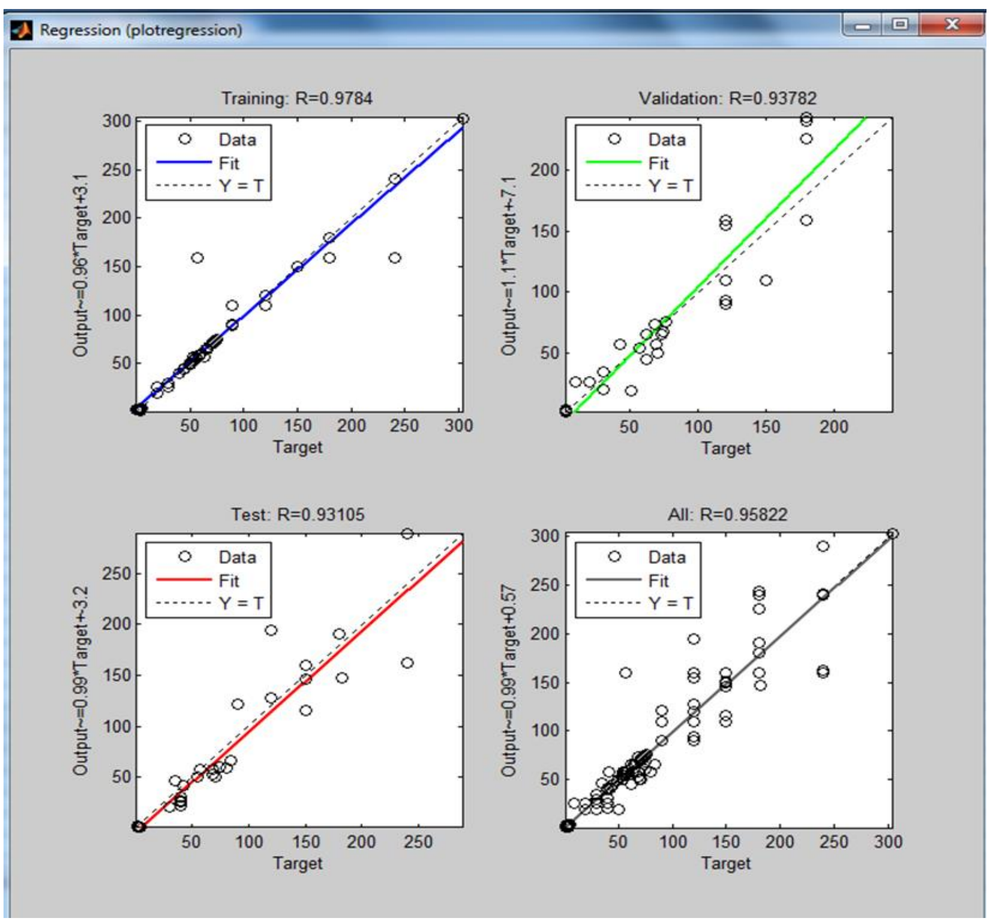



**Figure 6.** Comparison of anticipated and measured data

For the current NN model the analysis of sensitive information was performed. Therefore, the analysis of sensitive information illustrates the value influences of each input to the output value. The analysis of sensitive information ispresented in Table 1. It should be highlighted that $SO_2$ concentration as an air pollutant and time of exposition have the superlative effect on corrosion weight loss of structural metals[3].

**Table 1.** Analysis of sensitive information

| Parameters | Relative significance of the Parameters | Order |
|---|---|---|
| $SO_2$ | 47.343 | A |
| Exposition time | 41.068 | B |
| PH | 12.389 | C |
| RH | 2.104 | D |
| Precipitations | 2.289 | E |
| T | 1.117 | F |

**Conclusion**

A neural network was designed in order to anticipate the corrosion loss of bronze according to the input effective factors on metals corrosion. This provides the anticipating bronze corrosion loss with an admissible relative error around (~7%). It can be concluded that exploitation of NN is useful. It is obligatory to present complicated mutual relations among parameters especially toward anticipation of metal's corrosion loss. In this regard, researchers paid special attention to the determination of metal corrosion loss. Therefore, the metal corrosion loss has been designed toward anticipating and visualizing the output parameters. The results of current research showed that $SO_2$ concentration as an air pollutant and time of exposition are the most effect on corrosion weight loss of bronze.

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## References

[1] Saeidi S., Khoshtinat Nikoo M., Mirvakili A., Bahrani S., Amin N.A.S., Rahimpour M.R. *Rev. Chem. Eng.,* 2015, **31**:209

[2] Saeidi S., Talebi Amiri M., Amin N.A.S., Rahimpour M.R. Int. J. Chem. Reactor Eng., 2014, **12**:639

[3] Jančíková Z., Zimný O., Koštial P. *Metalurgija*., 2013, **52**:379

[4] Lenort R., Klepek R., Samolejová A. *Metalurgija*., 2012, **51**:225

[5] Jančíková Z., Roubíček V., Juchelková D. *Metalurgija*., 2008, **47**:339

[6] Shahpar M., Esmaeilpoor S. *Chem. Method*., 2017, **2**:98

[7] Saeidi S., Jouybanpour P., Mirvakilli A., Iranshahi D., Klemeš J.J. *J. Clean. Produc*., 2016, **136**:23

[8] Spicka I., Heger M., Franz J. *Archiv. Metal. Mater.* 2010, **55**:921

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