Artificial Intelligence Applied in the Concrete Durability Study

E. F. Felix, E. Possan, and R. Carrazedo

Abstract Interest in artificial intelligence (AI) in engineering research and practice has increased in recent years, especially the use of artificial neural network (ANN). The ANN has similar characteristics to biological neural networks, efficiently recognizing patterns and behaviors, suited to provide an accurate tool to map and understand the concrete degradation. This chapter presents the positive aspects of artificial neural network to model different concrete degradation mechanisms and provides a detailed procedure for ANN design. As example, the concrete carbonation depth is modeled by an ANN and the results show the its ability to map the carbonation phenomenon.

Keywords Concrete structures · Computer science · Machine learning · Complex systems modeling

1 Introduction

In computer science, Artificial Intelligence (AI) or Machine Intelligence is a branch of computational systems based on human behavior, with the ability to learn and solve problems (Aggarwal et al. 2018). Learning is the link of human behavior and computational tools from AI, for it is this capability that make mankind what it is.

Hertzmann and Fleet (2012) define machine learning as a set of computational tools that provides a way to instruct computer to perform task through examples.

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J. M. P. Q. Delgado (ed.), *Hygrothermal Behaviour and Building Pathologies*, Building Pathology and Rehabilitation 14,
https://doi.org/10.1007/978-3-030-50998-9_5

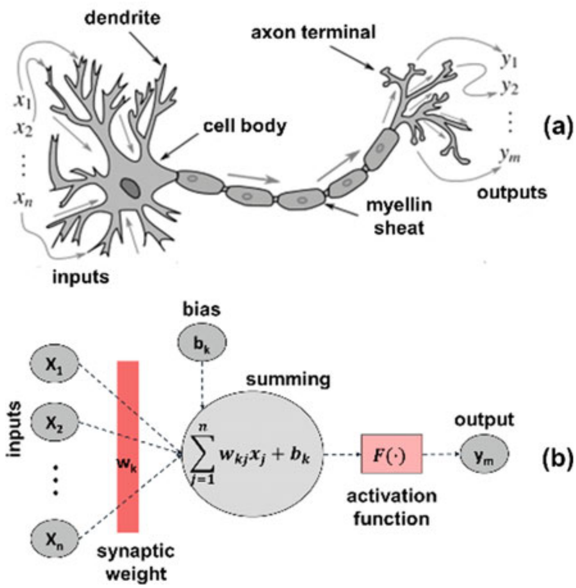


Fig. 1 Representation of **a** biological and **b** artificial neural network

Thus, allowing machines to learn through experience, to adjust to new situations and to perform tasks like human beings.

Over the past few years, the evolution of AI led to the development of several machine learning techniques and methods. We highlight the artificial neural networks (ANN), which have relatively low computational cost and provide simple and efficient solutions.

ANN are systems composed by processing units, called neurons, whose function is based on the human nervous system (Fig. 1) and have the property of mapping complex functions with high generality (Haykin 2008).

Furthermore, ANN go beyond mapping inputs and outputs, and it is able to pick out correlations that are not easily found (Braga et al. 2000), which is the main reason for its increasing exploit in engineering.

1.1 Application of ANN in Civil Engineering

An ANN is a numerical model based on connected units inspired by neural networks, which can transmit information and process it, simulate learning, pattern classification and data processing.

One of the reasons that ANN widely spread is the backpropagation training algorithm (Rumelhart et al. 1986). This technique is easily implemented based on downward Gradient Descent optimization algorithm, and most of the works developed with ANN in civil engineering uses the backpropagation algorithm to train its network (Adeli 2001; Lazarevska et al. 2014; Shafabakhsh et al. 2015; Abambres and Lantsoght 2019).

The first publication about machine learning in civil engineering was made by Adeli and Yeh (1989). They presented a perceptron ANN to design steel beams. After that, some research using machine learning in civil engineering were developed and, most of them, focused in pattern recognition and data mapping and classification.

As example, Moselhi et al. (1991) applied an ANN to evaluate different scenarios of sale and purchase for real estate market. In the same trend, Chao and Skibniewski (1994), Sonmez and Rowings (1998), Li et al. (1999), Muqeem et al. (2011), Dayanand and Shanmugapriya (2016) published papers that show ANN capable to estimate construction workforce productivity.

Artificial neural networks have also been applied in geotechnics. Williams and Gucunski (1995) used backpropagation neural networks to uncover the average soil thickness and elastic properties, while Goh (1995) shown that an ANN is able to associate soil parameters obtained from laboratory. Other studies proved that ANN are capable to define soil constitutive models and the mechanical behavior of geomaterials (Basheer 2000; Javadi et al. 2003, 2005; Nassr and Javadi 2018).

Nevertheless, ever since the publication of Adeli and Yeh (1989), ANN have been mostly applied to structures and materials studies in civil engineering. In the area of structures, ANN were used for the design and analysis of structural components (Kang and Yoon 1994; Kushida et al. 1997; Gu et al. 2010), structural optimization (Hajela and Berke 1991; Rogers 1994, Jenkins 1999; Babiker et al. 2012), structural dynamics, impact and earthquakes (Adeli 1994; Chen et al. 1995; Stavroulakis and Antes 1998; Vafaei et al. 2013; Al-Suhaili et al. 2014) and also damage assessment and risk management (Wu et al. 1992; Papadrakakis et al. 1996; Masri et al. 2000; Abbas and Khan 2016).

In the area of materials, ANN were used to estimate mechanical properties for concrete, such as compressive strength (Ni and Wang 2000; Kim 2009; Oztas et al. 2006; Alshihri et al. 2009; Diab et al. 2014) and Young modulus (Topçu and Saridemir 2007; Gholampour et al. 2017; Duan et al. 2013, 2017). ANN were also able to evaluate the workability of concrete (Jain 2006; Deepak et al. 2019), consistency of fresh concrete mixture (Poon et al. 2007) and even concrete mix constituents and proportions (Ji et al. 2006).

Works that relate in a multidisciplinary way the areas of materials and structures, such as the durability study, have been developed over the last years (Smets and Bogaerts 1992; Trasatti and Mazza 1996; Cai et al. 1999; Topçu et al. 2009; Karakoç et al. 2011; Felix et al. 2019). Parthiban et al. (2005) verified the efficiency of the ANN applying to create a predictive model for the corrosion potential of steel bars in reinforced concrete structures. It was found that the model was able to estimate the potential under 5% of error. Ukrainczyk and Ukrainczyk (2008) demonstrated the possibility use of ANN to analyze the sensitivity and influence of various parameters related to corrosion (environmental conditions, structure geometry and boundary conditions or material properties) to determine the damage in concrete bridges.

1.2 Predicting Concrete Durability

The concrete structure's durability depends on several parameters such as the characteristics of building construction stages (concept design, construction plans and materials specifications, construction and operation and maintenance), aggressiveness of the environment, use in service life and expected service life of structures (Mehta and Monteiro 2013).

Possan and Andrade (2014) highlight that the degradation of concrete is related to the building's exposure environment (marine, urban, industrial) and its aggressiveness, which is expressed by the aggressive agents present in the atmosphere (CO_2, chloride ions, sulfates, alkalis, among others).

The exposure environment influences the speed and intensity of a structure degradation, and the aggressive agents enables both a durability analysis and evaluation of useful life (Dal Molin et al. 2016).

Considering users safety, the service life of a reinforced concrete structure is about 120 years, if repair and regular maintenance is carried out (ISO 2004). The decrease of the expected service life and the demand for repairs and maintenance follows from design and execution errors as well as pathological manifestations.

Corrosion of reinforcing steel is the leading cause of deterioration in concrete and the most important pathological manifestation of reinforced concrete structures (Taffese and Sistonen 2013; Possan and Andrade 2014).

In concrete structures by the shore, rebar corrosion is mainly function of the chloride ions due to the sea salt spray. In urban regions, corrosion is mainly induced by the ingress of atmospheric carbon dioxide into concrete, commonly referred to as 'carbonation induced corrosion' (Mehta and Monteiro 2013).

Until the mid-1980s, CO_2 or Cl- diffusion models were obtained by linear and non-linear regression, considering, for example, the water/cement ratio (w/c), type of binder and exposure conditions (Kobayashi and Uno 1990). In the following years, physical-chemical mechanisms involved in the hydration reactions of the cement paste and dissolution of CO_2 in the concrete pore fluid were included, providing accuracy to evaluate the carbonation front (Papadakis et al. 1991; Ishida and Maekawa 2001; Maekawa et al. 2003). However, these models are awfully complex, requiring parameters that are not easily measured, such as diffusion coefficient of carbon dioxide in concrete, and laborious equations to be solved.

With the advance of software and hardware, and development of machine learning technique, new formulations were proposed, reducing inherent uncertainties of the prediction models. The use of ANN stood out, especially in modeling concrete carbonation. Depending on the training algorithm, the number of iterations for training could be reduced, also reducing the time spent for the simulation when compared to other techniques (Lu and Liu 2009; Know and Song 2010; Hamzehie et al. 2014; Akpinar and Uwanuakwa 2016).

Thus, in the next chapter we show general aspects regarding the characteristics and functionalities of an ANN employed to model a deterioration mechanism of concrete. It is also introduced an application example of the prediction of the concrete carbonation depth of structures by the shore, using a Multilayer Perceptron Neural Network.

2 Artificial Neural Network: Basic Concepts

McCulloch and Pitts (1943) is the first work to introduce a mathematical model for the representation of an artificial neural system. Fifteen years later, Rosenblatt (1958) brought in the concepts of the perceptron network, which is a network with only one processing layers. This network stood out because it could perform pattern recognition using a supervised learning method.

Although ANN were introduced in the 60 s, they only spread out in the 80 s, after the work of Hopfield (1982). He shown that ANN could solve many different problems in many subjects and was able to publish several works sequentially. Different models and training techniques were proposed, that could fit in each area of knowledge.

2.1 Neuron Model

Neural networks are models based on connected units called "artificial neurons" that resemble neuron in a human brain. These neurons are disposed in layers, interconnected though connections associated with synaptic weights. These weights are adjusted as learning proceeds, resembling the property of storing knowledge.

Haykin (2008) states that an ANN have five basic elements:

(a) A set of input x_k carrying its own synaptic weight w_k;
(b) An adder to the input, weighted by the respective neuron weights;
(c) An activation function $F(\cdot)$, restricting the output range;
(d) A bias b_k, responsible to increase or decrease net input of the activation function;
(e) An output y_k, as indicated in Fig. 1b.

Thereby, the output of neuron k of a Perceptron network is given by:

$$y_k = F(z_k) = F\left(\sum_{j=1}^{n} w_{kj} x_j + b_k\right) \tag{1}$$

Each entry $x_k \in \mathbb{R}$ is weighted by a $w_{kj} \in \mathbb{R}$, which forms the current neuron weight vector $w_k = (w_{k1}, w_{k2}, \ldots, w_{kn})^T$. Each neuron has a bias $b_k \in \mathbb{R}$ which is a fixed addition, evolving into the parameter z_k. $F: \mathbb{R} \rightarrow \mathbb{R}$ is an activation function that process the net input parameter z_k and yields the neuron output $y_k \in \mathbb{R}$.

2.2 Activation Function

The activation function converts the net input parameter into the net output, and evaluate the neural decision considering the neuron internal state (Haykin 2008).

ANNs have processing units (neurons) that are associated with an activation state. This state is characterized by the activation functions, which can be discrete or continuous, chosen according to the problem to be modeled. Activation functions are also known to be logical thresholds.

In general, there are several activation functions that can be used. Silva et al. (2004) states that the linear, stepped, logistical sigmoid and hyperbolic tangent are the most used functions to solve problems associated to mapping and pattern recognition (Fig. 2).

According to Haykin (2008) the sigmoid functions are the most frequently used function in the construction of an ANN, as these increasing functions are homogeneous and asymptotic. Besides, these functions are continuous, symmetric, monotonic increasing, limited and with derivatives that can easily be obtained.

2.3 Topology of an Artificial Neural Network

The topology of an ANN limits the type of problem that can be solved by the neural system. Networks with only one processing layer can solve only linearly separable problems, and recurring networks can solve even dynamics (Braga et al. 2000).

The topology is distinguished by the number of processing layers and how one layer interacts with each other. There are several studies that describes how neurons should be arranged according to the type of problem to be modeled (Berthold et al. 2010; Zhang 2017; Felix et al. 2019). However, there is no specific rule to stablish the best structure for each problem.

Some rules from practice may serve as guideline, but no predetermined rule exist for stablishing the training algorithm, the number of processing layers, the number of hidden layers and the type of connection. Thus, the topology must be adjusted to each problem (Fausett 1993).

Pruning a network is made by successive refinements, reducing the size of the neural network, checking the importance of each connection, until the number of neurons be within an acceptable range. Overfitting is expected when the number of neurons is in excess, and the networks might lose its ability to recognize patterns or even memorizing data (Haykin 2008).

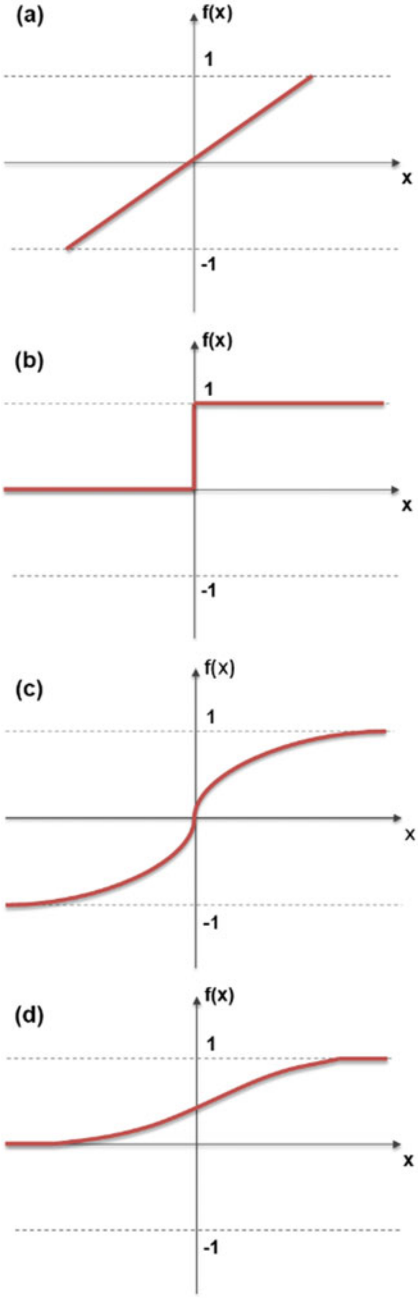


Fig. 2 Representation of a function: **a** linear; **b** Heaviside; **c** hyperbolic tangent; and **d** sigmoid

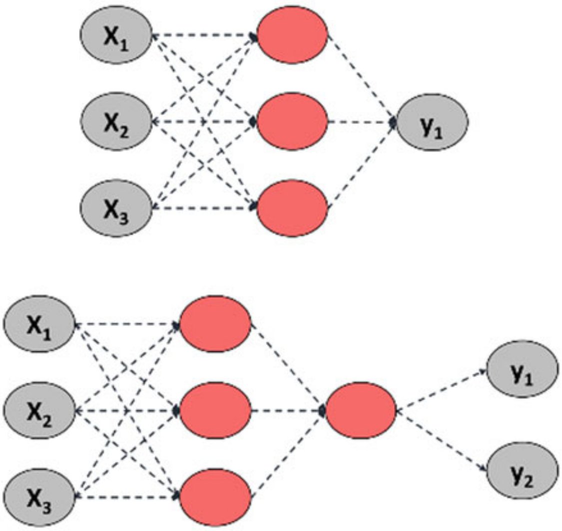


Fig. 3 Representation of different architectures

Figure 3 presents two topologies, where variables x_1, x_2, …, x_n are the inputs, and y_1, y_2, …, y_n, are the outputs. Dotted lines are links between neurons, from one layer to another, and it is through these connections that information is processed.

There are several ways to link neurons, such as feedforward and feedback. In the former, connections are sequential, that is, the output of a neuron in a layer is the input of a neuron in the next one, as seen in Fig. 4a. In the latter, connections can be made in either way (Fig. 4b).

2.4 Learning Method

One of the most important characteristics of an ANN is the ability to learn. Learning is associated to adapting the weights of the network, following a pre-stablished rule, improving the results. Learning is defined as the process that changes the free parameters by a stimulation from the environment which the network is inserted (Fausett 1993). Thus, the objective of a network is stablishing an implicit model by adjusting its parameters.

The method responsible for adjusting the network parameters and consequently how the synaptic weights are adjusted defines the type of learning. According to Martins et al. (2001), the supervised learning is the most used training method, in which the network is initially controlled by a supervisor that provides both input and output as pairs with the objective to map a relationship between them (see Fig. 5). Once such map is found, new outputs are provided and compared with the expected target values. If output and target values diverge, the connection weights are adjusted.

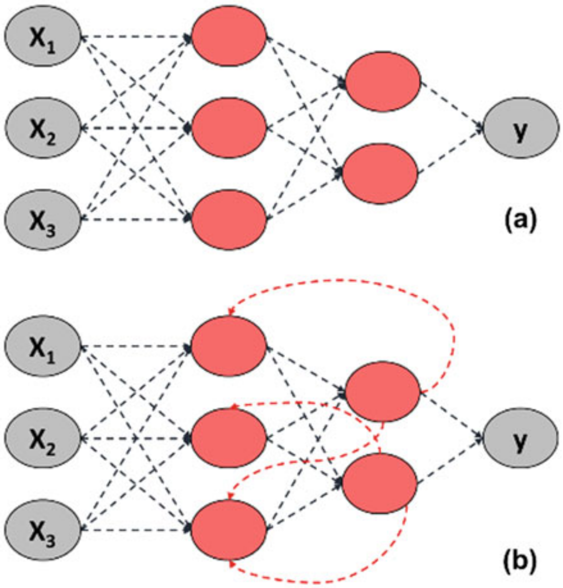


Fig. 4 Representation of **a** feedforward ANN and **b** feedback ANN

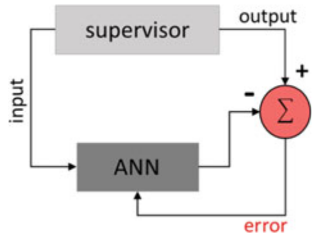


Fig. 5 Representation of supervised learning

Error minimization is incremental, since small adjustments are made at each stage of the training process. Training process is concluded when a tolerance for the error is reached, or a threshold is achieved, such as a certain number of iterations. Synaptic weights are no longer modified.

2.5 Training Algorithm

Perceptron is the simplest form of an ANN and is used for binary classification separated by hyperplanes (Haykin 2008). Thus, perceptron networks can only solve linearly separable problems, and is able to solve logical problems with binary response.

Rosenblatt (1958) proposed the perceptron network, using only a single neuron, being able to pattern recognition and classification in two classes. The number of

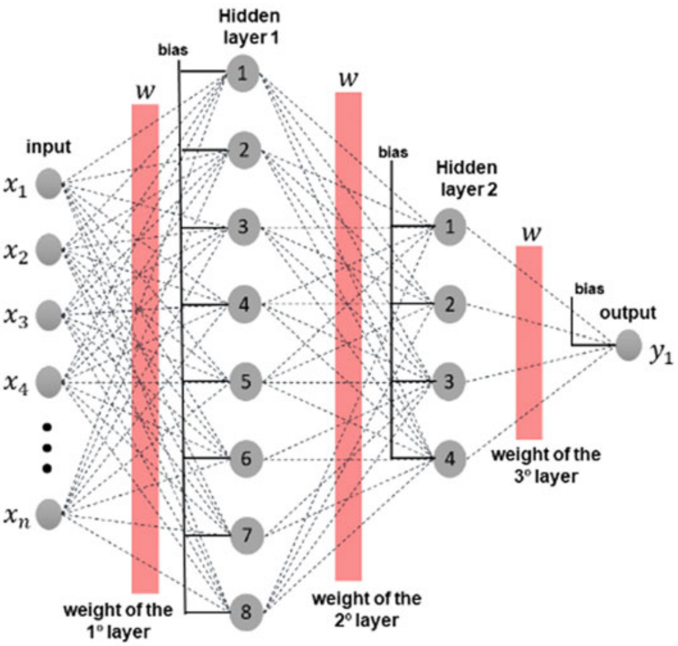


Fig. 6 Representation of a multilayer perceptron ANN

neurons must be increased in order to classify multi-pattern classes. The training algorithm used in the perceptron network is known as backpropagation algorithm or only backpropagation.

The multilayer perceptron (MLP) is a class of feedforward network composed of more than one processing layer (Fig. 6). This enables the network to solve non-linear problems.

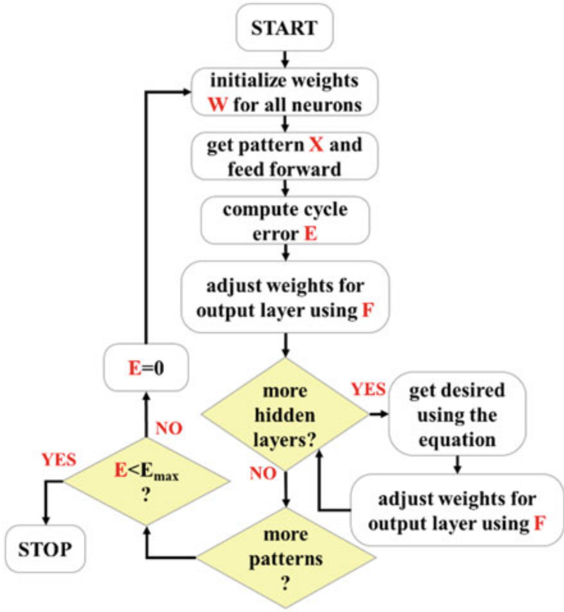
According to Fausett (1993), MLPs have three fundamental layers: input; hidden layer; and output. The first and the last layer do not have computational potential, they only store values and build patterns. The hidden layers, on the other hand, are the computational layers, since process takes places in these layers to generate the implicit model.

The same training algorithm of perceptron is used on MLP networks, the backpropagation. This algorithm was developed based on learning by error correction. In Fig. 7, a simplified representation of the backpropagation process is presented.

3 Application of ANN to Model the Concrete Carbonation

Carbonation study and their influence factors have been reported for over half of a century and a large theoretical background on the topic is available (Meira et al. 2003;

Fig. 7 Flowchart of backpropagation algorithm



Kwon and Song 2010; Izumi et al. 1986; Kari et al. 2014; Felix and Possan 2018). Interest in the area has led several researchers to develop models of concrete carbonation evolution and/or prediction over time.

Until the mid-1980s, models for carbonation depth prediction were obtained through linear and non-linear regression, considering different factors, such as the water/cement ratio, the binder type and the exposure conditions (Izumi et al. 1986).

Because of increasing computing technologies and improvement of machine learning techniques, new formulations for carbonation depth prediction were developed aiming to reduce uncertainties associated to modeling. Among these techniques, ANN has been becoming commonplace regarding the carbonation phenomenon modeling. Whereas 492 articles were published in Science Direct database related to concrete carbonation modeling in the last decade reached, 27.6% employed a machine learning technique (Support Vector Machine, ANN, generic algorithms and others).

Within the 492 articles related to concrete carbonation modeling, only 8.2% are related to structures by the shore, due to difficulties to associate the carbonation depth with both CO_2 content and Cl^- concentration because most models are either deterministic or based on nonlinear regressions that involve only one of the agents (Liu et al. 2016; Zhu et al. 2016).

Thus, there are only a few models capable to estimate the concrete carbonation depth with the combined effect of chloride ions and CO_2. In this sense, authors present a Multilayer Perceptron ANN to predict the concrete carbonation depth in structures by shore. The following parameters are considered: water/cement ratio, exposure time, and distance of the structure to the shore, the latter being the representative parameter of the combined action of CO_2 and Cl^-.

3.1 General Aspects of the ANN Modeling Process

Figure 8 shows the steps to obtain a prediction model of carbonation depth by an MLP neural network, using backpropagation training algorithm, with the following requirements: minimum error, the average error, the correlation coefficient, among others.

The first step is to define a database, divided in three sets: training, validation and performance. After some topologies are defined, a convergence analysis is performed to determine the best learning rate of the training algorithm and the activation function that better fits the problem. The third step is the networks training and validation, reducing chances of over-training the networks (overfitting). At last, at the fourth step, a performance analysis is carried out, selecting the network that better fits the problem.

These steps were applied to model the concrete carbonation depth, and all procedures and results are presented in sequence.

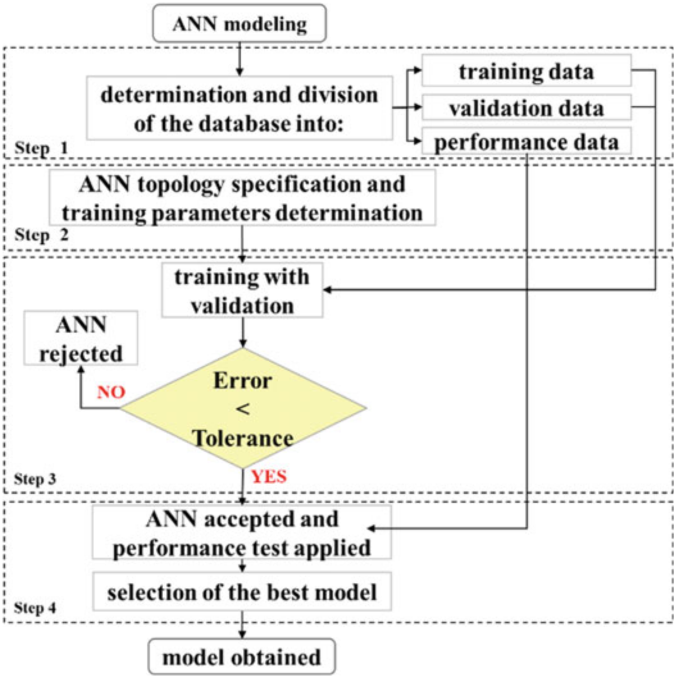


Fig. 8 ANN modeling process

3.2 Database Assembly

The database is provided by Meira et al. (2006), which presents the carbonation depth of concrete structures located close to marine environment, in João Pessoa, Brazil. They provided the carbonation depth of specimens of 15 × 15 × 140 cm made of CP-II E Portland cement (equivalent to the ASTM C 595/IP and/or CEM II/B-S), with cement/water ratio of 0.5, 0.57 and 0.60, with distances of 10, 100, 200 and 500 m from the sea, and carbonation depths collected at 6, 10, 14, 18 and 46 months after exposure.

The database was divided into three sets, one for training, other for validation and the last for the testing. Figure 9 shows how data was distributed in each set, as follows: 60% for the training, 20% for the validation and 20% for the performance analysis.

Selecting the input variables may hinder mapping between input and output. In this sense, the following input variables were employed: w/c ratio, exposure tine to the aggressive atmosphere, distance from the shore. The w/c ration is related to the compressive strength and concrete compactness, as wells to the void ratio of the cement matrix. The distance from the shore is related to the exposure to the aggressive

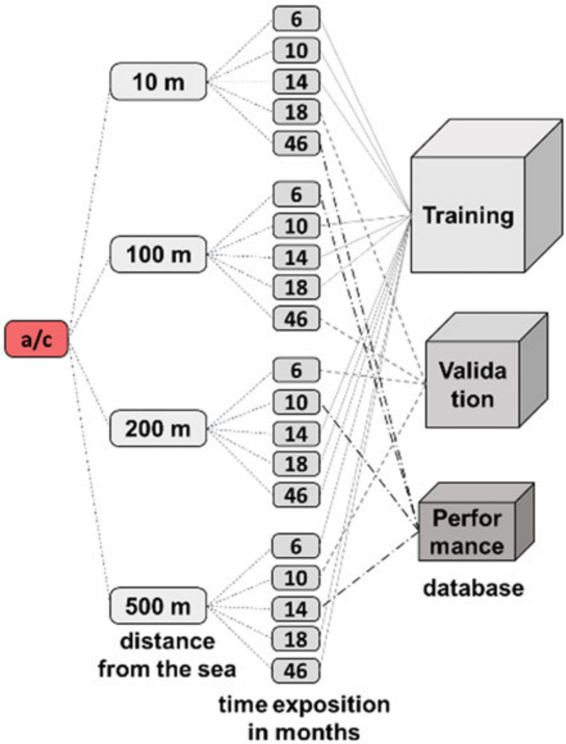


Fig. 9 Database division

agents – the combined diffusion of CO_2 and Cl^-. Meira et al. (2003) describe that low carbonation depth is found closer to the coast, as diffusion of chlorides increases.

3.3 Training Parameters and ANN Topology

The topology of an ANN is defined by the number of input and output neurons, by the number of hidden layers and the number of neurons in each hidden layer. In this work, 90 topologies were created, employing one or two hidden layers, with one to nine neurons (see Fig. 10).

As the network learning is supervised through backpropagation training algorithm, it must be stablished the value of the learning rate, which is related to the network convergence. Therefore, twelve networks were simulated varying the learning rate from 0.05 to 0.6 (increments of 0.05). A network with topology [3-4-1] was adopted, which represents a network with "3" neurons in the input layer, "4" neurons in the processing layer and "1" neuron in the output layer. The former are the selected input variables and the latter is the concrete carbonation depth.

Figure 11 presents the required number of iterations to train the selected topology network, as well the root mean squared error (RMSE) for training and validation. It

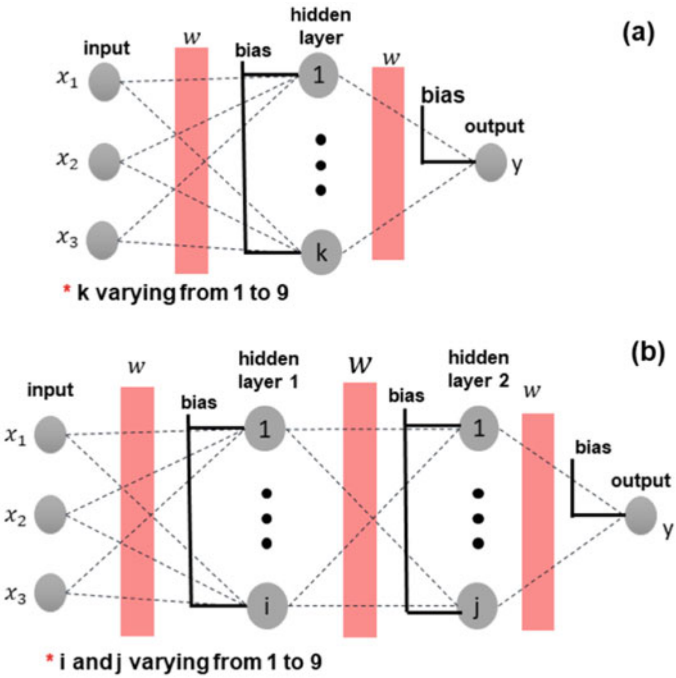


Fig. 10 The basic topology selected to train with **a** one hidden layer and **b** two hidden layers

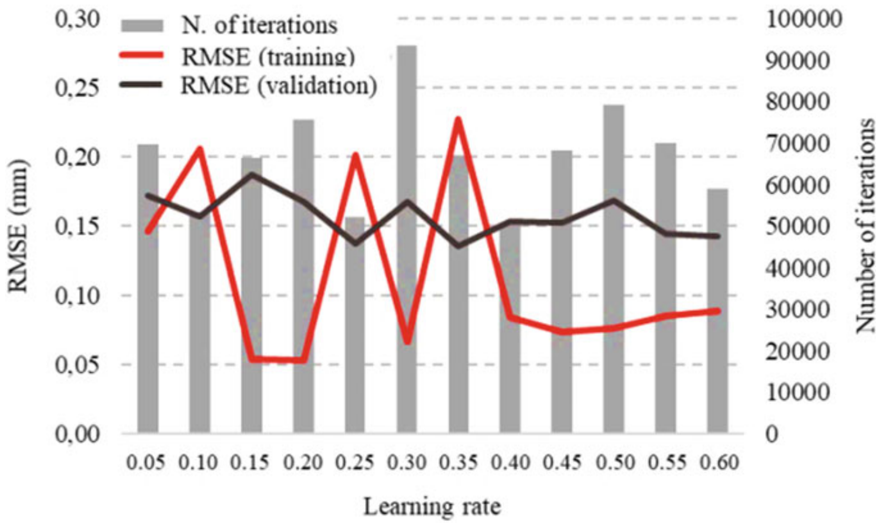


Fig. 11 Influence of the learning rate on training and validation

can be observed that the learning rate $\alpha = 0.4$ resulted in the best mapping for the concrete carbonation phenomenon, considering RMSE (of training and validation) and number of required iterations for network learning.

Figure 11 express the importance of choosing a learning rate that provides efficient and optimized training. Adoption of inadequate rate could result in slow (in terms of processing) and inefficient (in terms of accuracy) training.

3.4 ANN Training and Validation

After choosing an adequate learning rate, ANN training was initiated. The maximum number of interactions (10E + 5) and the root mean squared error (RMSE), according to Eq. (2), were used as convergence criteria.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})} \tag{2}$$

where RMSE is the root mean squared error of the network, n is the output number, y_i is the output of the network and $\bar{y}$ is the average of the outputs.

The ANN were created with a computational package called project-yapy, proposed by Konzen and Felix (2011) in C++ object-oriented language. The code was employed and validated in Felix et al. (2018) and Felix et al. (2019). Nevertheless, there are several software's that provide packages and libraries with ANN,

Table 1 ANN with the best RMSE

Topology	Training		Validation	
	RMSE	R[b]	RMSE	R[b]
[3-7-1][a]	0.2852	0.9882	0.1963	0.9619
[3-1-3-1][b]	0.4124	0.9794	0.2423	0.9650
[3-1-7-1][b]	0.2294	0.9947	0.2307	0.9748
[3-2-3-1][b]	0.2593	0.9931	0.2692	0.9294
[3-2-7-1][b]	0.1790	0.9957	0.2995	0.9138
[3-4-5-1][b]	0.0885	0.9990	0.2836	0.9593
[3-5-1-1][b]	0.4399	0.9723	0.2658	0.9492
[3-6-3-1][b]	0.2229	0.9936	0.2765	0.9660
[3-7-8-1][b]	0.2994	0.9883	0.2632	0.9758
[3-8-5-1][b]	0.4506	0.9708	0.2705	0.9603
[3-9-5-1][b]	0.1036	0.9990	0.2312	0.9676
[3-9-8-1][b]	0.2677	0.9912	0.3627	0.9443
[3-9-9-1][b]	0.0565	0.9996	0.2969	0.9798

[a][x-y-z] topology, where x indicates the input number, y the neuron number in the hidden layer and z the output number
[b][x-y-w-z] topology, where x indicates the input number, y the neuron number in the first hidden layer, w the neuron number in the second hidden layer, and z the output number

where users can assemble the network architecture, calibrate the training parameters, and more, making modeling quite simple.

Table 1 presents the ANN results for network with RMSE below 0.3. The following three ANN were selected, considering both coefficient of determination (R^2) and the root mean squared error (RMSE): [3-7-1], [3-1-7-1] e [3-9-5-1]. Figures 12, 13 and 14 present comparative graphs between carbonation depth provided by reference and calculated by the selected networks, as well their respective coefficient of determination.

Table 2 presents the overall performance of the selected networks.

The RMSE from training and validation data observed in Table 1 and the performance analysis from Table 2 show that the network [3-9-5-1] is the network that best describes the carbonation evolution in reinforced concrete structures by the shore. This network presented a coefficient of determination of 0.974 and a maximum error of only 0.54 mm for the carbonation depth. This difference is twice smaller than the accuracy of the equipment used to examine the carbonation depth in concrete structures.

After selecting the network, the network was once again required to calculate the carbonation depths for all initial database, and results are compared with the observed in situ depths. Residues are presented in Fig. 15.

The difference between measured and calculated results muster around zero, which indicates that the network adequately describes the carbonation phenomenon.

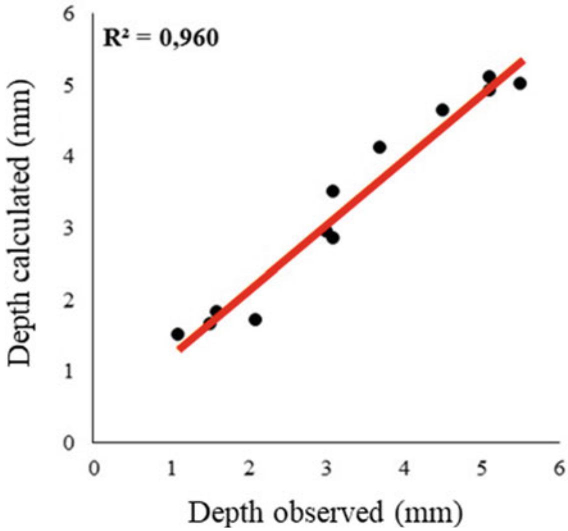


Fig. 12 Coefficient of determination obtained in the performance analysis with the ANN [3-7-1]

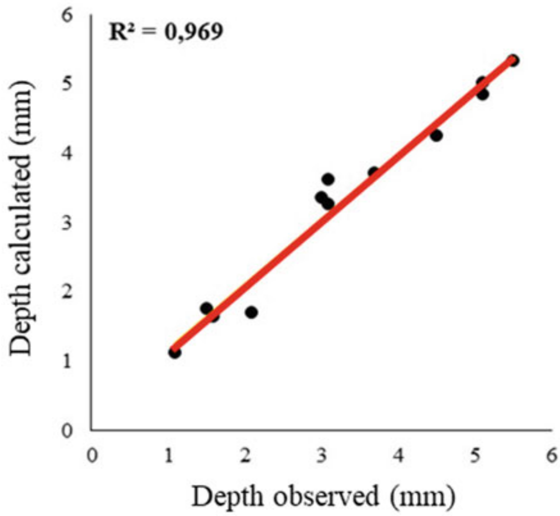


Fig. 13 Coefficient of determination obtained in the performance analysis with the ANN [3-1-7-1]

Figure 16 maps the carbonation depth of a concrete structure with w/c ratio of 0.5 yet varying distance from the shore and exposure time to atmosphere. As expected, the carbonation depth decreases as the structure is closer to the shore.

At last, the use of an ANN for modeling engineering problems may be summarized as follows:

1. Implement a training program of neural networks with supervised learning, or define a commercial software that provides libraries with ANN;

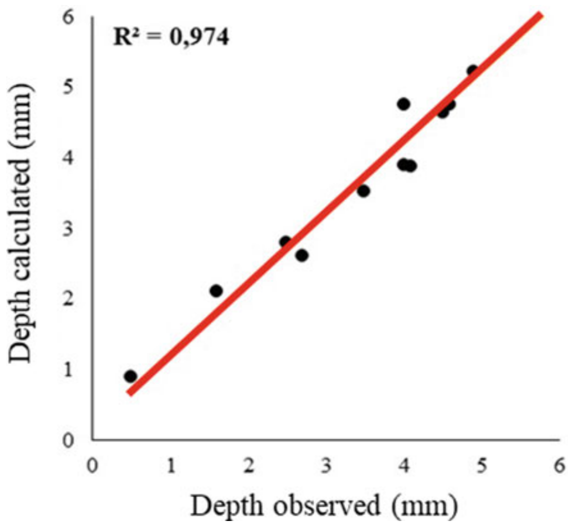


Fig. 14 Coefficient of determination obtained in the performance analysis with the ANN [3-9-5-1]

Table 2 Performance Analysis of the 3 best ANN

Topology	RMSE	R^2	E_{max}
[3-7-1]	0.181	0.942	0.613
$[3\text{-}1\text{-}7\text{-}1]^2$	0.500	0.951	0.597
$[3\text{-}9\text{-}5\text{-}1]^2$	0.130	0.974	0.542

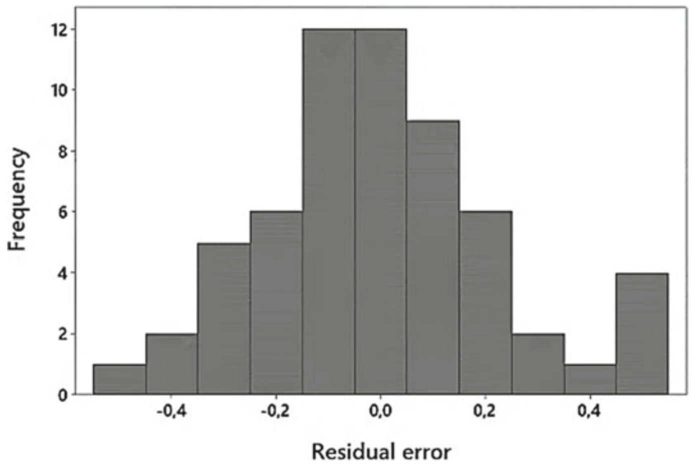


Fig. 15 Histogram of the obtained residues with the compared carbonation depths

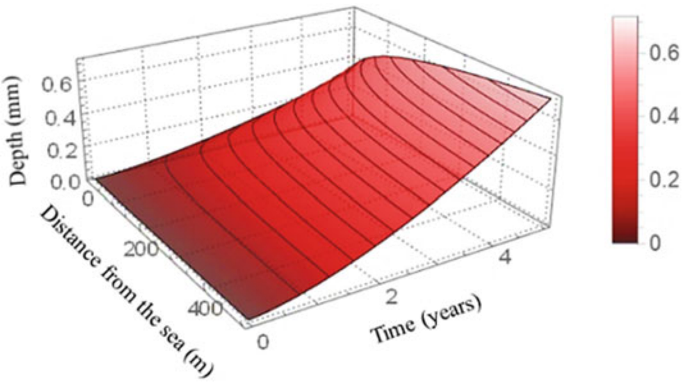


Fig. 16 Carbonation depth in function of the exposure time and distance from the shore

2. Define the database;
3. Split the database in three set: training, validation and network testing;
4. Select input variables and network topologies for training;
5. Specify training parameters, such as activation function, training algorithm, algorithm learning rate, stop conditions of training;
6. Train with simultaneous validation;
7. Select some networks with best fitting;
8. Select of best model through performance tests.

4 Final Remarks and Conclusions

Neural networks are under development ever since 1940, however only recently it evolved for most diverse areas. Nowadays the numbers of studies and development of new technologies and tools associated to Artificial Intelligence is expanding, mainly within engineering.

In this work, we presented a Multilayer Perceptron Neural Network capable to predict the carbonation depth of concrete structures located by shore. The model adequately represented the influence of CO_2 in concrete structures, considering the distance of concrete element from shore. It was able to represent the inverse effect of the combined action of CO_2 and Cl^-, where chloride ions ingress is preponderant comparing to CO_2 action.

The developed model supports the concept that artificial intelligence can be applied to solve several problems related to civil and materials engineering. ANN may improve researches regarding life cycle, sustainability and durability of concrete structures. Yet we miss one thing for the dissemination in technical environment, a software with a friendly interface.

Acknowledgments The financial support by the Coordination for the Improvement of Higher Education Personnel (CAPES) and the Brazilian National Council for Scientific and Technological Development (CNPq) is gratefully acknowledged.

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