



On the modeling of the annual corrosion rate in main cables of suspension bridges using combined soft computing model and a novel nature-inspired algorithm

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Received: 21 February 2021 / Accepted: 2 June 2021

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Abstract

Suspension bridges are critical components of transport infrastructure around the world. Therefore, their operating conditions should be effectively monitored to ensure their safety and reliability. However, the main cables of suspension bridges inevitably deteriorate over time due to corrosion, as a result of their operational and environmental conditions. Thus, accurate annual corrosion rate predictions are crucial for maintaining reliable structures and optimal maintenance operations. However, the corrosion rate is a chaotic and complex phenomenon with highly nonlinear behavior. This paper proposes a novel predictive model for the estimation of the annual corrosion rate in the main cables of suspension bridges. This is a hybrid model based on the multilayer perceptron (MLP) technique optimized using marine predators algorithm (MPA). In addition, well-known metaheuristic approaches such as the genetic algorithm (GA) and particle swarm algorithm (PSO) are employed to optimize the MLP. In order to implement the proposed model, a comprehensive database composed of 309 sample tests on the annual corrosion rate from all around the world, including various factors related to the surrounding environmental properties, is utilized. In addition, several input combinations are proposed for investigating the trigger factors in modeling the annual corrosion rate. The performance of the proposed models is evaluated using various statistical and graphical criteria. The results of this study demonstrate that the proposed hybrid MLP-MPA model provides stable and accurate predictions, while it transcends the previously developed approaches for solving this problem. The effectiveness of the MLP-MPA model shows that it can be used for further studies on the reliability analysis of the main cables of suspension bridges.

Keywords Suspension bridges · Main cables · Annual corrosion rate · Artificial intelligence · Multilayer perceptron · Marine predators algorithm

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1 Introduction

Main cables of suspension bridges are important components in these structures, which carry the traffic loads. These cables are composed of several wires that usually made of high-strength carbon steel and protected against corrosion with a protection layer of zinc [1]. They maintain the stability conditions of the bridge. Therefore, the safety and reliability of suspension bridges are directly related to the accurate evaluation of the current state of their main cables. However, these components are subjected to deterioration with time due to the corrosion after the consumption of the protecting zinc layer. The corrosion rate of the wires' surface highly depends on the chemical proprieties during the cable manufacturing and the surrounding

environmental conditions in which the bridge is located [2]. Inspection plans are currently the only possible way to get limited information on the wires' condition. In this method, the condition of the internal wires is evaluated by removing the external cover and wedging the wire perimeter at specific locations, which is normally carried out by an expert operator [3]. Therefore, only limited information can be obtained regarding the corrosion development on the main cables due to the physical and operational obstacles in the inspection process and the provided low maintenance and inspection budget. However, accurate prediction of the annual corrosion rate in the main cables of suspension bridges based on the available information not only determines the safety state of the wires, but also can be used for determining the remaining useful life of the cables, optimizing the inspection plans and maintenance or replacement actions under the minimum expenditure costs.

Corrosion growth on the surface of steel structures has been proven to be one of the most complex issues, which creates several challenges for these structures with high expenditure costs [4, 5]. Regarding the bridge cables, this structural components are exposed to highly variable temperature ranges and different weather conditions during their service life [6]. To this end, several researchers have investigated the most influencing environmental parameters of the metal response for the bridge cables due to corrosion degradation, in which they have concluded that the main factors are: the temperature values (T), the surrounding acidity (pH), humidity tenure, concentration of the contaminant and ions, and the wetness extended period [7, 8]. Bettie et al. [9, 10] studied the suspension bridges in New York City, which indicated that pH values below 4 will lead to the water penetration to the internal cables, while Eiselstein and Caligiuri [11] found that the collected concentrations of water contaminants from the cable interior were significant. Stahl [12] mentioned that the causes could be related to the imperfections in the protective cover layers or the cables manufacturing. Others studied such as the works of Suzumura and Nakamura [13] and Sloane et al. [14] evaluated the inside conditions of the main cables under the ambient condition and revealed that the effects of the change in humidity and temperature during the day play a critical role in the rate of corrosion rate. It can be concluded that the surrounding environmental parameters have a significant negative impact on the corrosion rate in the bridge cables. Therefore, it is important to model the corrosion rate in the bridge cables by the use of the available environment variables from the inspection reports.

There are several studies in the literature for developing corrosion rate models in metals using different environmental variables, specifically in bridge cables. However, this phenomena is found to be highly chaotic, complex and

nonlinear, while the models used are hardly able to capture the variability of the corrosion rate accurately [15–17]. The power law [18] is the most common model to predict the corrosion rate in structures made of steels, including carbon steel wires. It models the corrosion growth as a function of time and constant variables extracted using simple fitting approaches based on experimental tests. However, the abilities of this model have been proved to be restricted regarding the range and the use, while the obtained results found to be inaccurate and incapable to estimate the corrosion rate process accurately in many applications [19]. More recently, the use of machine learning techniques has gained more attentions by the researchers as they have a great potential to accurately describe the complex relationship of high-dimensional chaotic databases [20, 21]. Artificial neural networks (ANNs), support vector machine/regression (SVR/SVM), adaptive neurofuzzy inference system (ANFIS) and gene expression programming (GEP) are the most relevant for solving a variety of engineering problems [22–25]. However, the main drawback of the AI-based techniques is that the selection of their hyperparameters to train the models is normally carried out manually (trial and error), which does not guarantee optimum results. Thus, a new trend that consists of using metaheuristic algorithms is adopted in this field, which provide powerful solutions for capturing the global optimum results for the AI-based techniques [26–28]. As a result, hybrid AI techniques would offer more robust and faster computational models compared to the empirical correlations. Therefore, they could be an important decision tool for modeling the annual corrosion rate in the main cables of suspension bridges.

These smart computational techniques have been progressively used for estimating the corrosion process in many steel structures. For example, the support vector regression (SVR) model has been used to model the corrosion rate in different seawater environments using 3C steels by Wen et al. [29]. Chou et al. [30] used the same databases with different standalone and hybrid AI models using metaheuristic algorithms, where the authors concluded the outperformance of the hybrid AI models in terms of accuracy, efficiency and computational time costs. Mohamed El Amine et al. [31] also used hybrid SVR with three metaheuristic models, namely genetic algorithm (GA), particle swarm optimization (PSO) and firefly algorithm (FA) to predict the maximum corrosion depth in oil and gas pipelines, where the results proved that the power law and the other empirical correlations provide poor accuracy compared to the intelligent approaches. The same authors recently implemented various AI techniques such as ANN, M5 Tree (M5Tree), multivariate adaptive regression splines (MARS), locally weighted polynomials (LWPs), kriging (KR), and extreme learning machines

(ELM), for better understanding of the relationship between the corrosion phenomena and the related environmental variables [32]. Ya-jun et al. [33] establish several hybrid models for characterizing the corrosion morphology in rusted steel bars, where the SVR was combined with particle swarm optimization (PSO) and grid search (GS) algorithm to estimate the corrosion rate using seven cross-sectional parameters. The proposed hybrid techniques proved to be accurate and efficient. However, there are a limited number of studies in the literature around using the hybrid models, especially for modeling the annual corrosion rate in main the main cables of suspension bridges. Karanci and Betti [34] are the first who implemented the AI models for bridge cables, where the authors compared the linear regression, ANN and SVR to solve the problem. However, the approaches they implemented in their work statistically did provide acceptable results due to the complexity of the database and the low generalization of the AI models used in the work. This shows that there is a need for more advanced AI models to enhance the prediction results of such complex problem.

The main purpose of this study is to develop high-efficient and accurate hybrid soft computing approaches for modeling the annual corrosion rate in the main cables of suspension bridges. A novel predictive model is proposed for the estimation of the annual corrosion rate as a function of the surrounding environmental properties based on a worldwide database. A computationally powerful technique called multilayer perceptron (MLP) is coupled with a novel metaheuristic algorithm called marine predators algorithm (MPA), which is utilized as a novel framework to solve the current problem. Besides, two powerful algorithms called particle swarm (PSO) and genetic algorithm (GA) are also implemented to represent the abilities of the proposed framework. Different assessment criteria are used to evaluate the performance of the developed framework. In addition, the performance of the proposed framework is compared to the available prior machine learning models. The rest of the paper is structured as follows: Section 2 describes the worldwide corrosion rate database, where a statistical analysis is reported. Section 3 gives the details of the implemented framework using the proposed AI techniques. The implementation, results and discussion are presented in Sect. 4. Section 5 summarizes the main findings of this study.

2 Real-field database

2.1 Atmospheric annual corrosion rate database

To study and model the nonlinear corrosion rate behavior in the main cables of suspension bridges as a function of

the surrounding environmental properties, a previously collected database by Karanci and Betti is investigated in this paper [34, 35]. This worldwide database includes more than 250 test sites of atmospheric corrosion rate gathered from around 33 countries, in which it covers 309 measurements of the annual corrosion rate (C_{rate}) for carbon steel specimens under various atmospheric conditions in a one-year period of time.

It is well understood that a wide range of factors can potentially affect the annual corrosion rate (C_{rate}) in the main cables of suspension bridges. However, as the corrosion growth process is considered as stochastic, chaotic and highly nonlinear, it is difficult to select the main trigger affecting parameter. In this study, the influence of six environmental factors are taken into account by having their relative values as input variables. More specifically, the temperature, T ($^{\circ}\text{C}$), relative humidity, RH (%), wetness time of the moisture surface layer on the metal, TOW (%), precipitation of the annual rain, P (mm), rainwater pH, pH and the chloride ion concentration, Cl^{-} (mg/L) are used as the input variables as the surrounding environmental properties. The annual corrosion rate, C_{rate} (mm /year), observed in the wires of the main cables is considered as the main target parameter (output variable).

It should be noted that several other factors can also potentially affect the annual rate of corrosion, including the exposure time of the main cables and other weather conditions, and however, it is quite difficult to obtain such information. The data used in this study only include the parameters are indicated in the database collected from various cyclic tests of corrosion at different environmental conditions by Karanci and Betti [34]. The worldwide corrosion database is used in this work to develop a robust predictive model based on a novel hybrid AI technique for the annual corrosion rate (C_{rate}) in the main cables of suspension bridges. Moreover, an investigation of the most affecting parameters during the modeling process of the annual corrosion rate (C_{rate}) is carried out. Table 1 reports the descriptive statistics of the input and output variables of the atmospheric corrosion worldwide database.

2.2 Statistical analysis of the database

According to Table 1, the mean, maximum, minimum, median, standard deviation (SD) and the range are reported for each input variable, $X = \{T, RH, TOW, P, pH, Cl^{-}\}$, and the output variable $Y = \{C_{\text{rate}}\}$. It is obvious that the input variables have different ranges and scales. For example, the ranges of T , RH , P and C_{rate} are 32.92 $^{\circ}\text{C}$, 0.98%, 3664 mm and 373.4 $\mu\text{m}/\text{year}$, respectively. Therefore, there is a need to normalize the data before using them in the modeling process in order to arrange all the input/output in the same scale. Figure 1 plots the

histograms of the input and output variables, which shows that each variable has a variety of different values indicating the complexity of the problem. Figure 2 presents the scatter plots between the annual corrosion rate (C_{rate}) and the input variables. It can be seen from these figures that only Cl^- shows a slight correlation to C_{rate} with $R^2 = 0.5251$. The values reported in Table 1 also confirm this, where the correlation coefficient has a value of 0.725. It can be concluded that statistically, this parameter has a high influence on C_{rate} compared to the other parameters. In addition, the statistical analysis of the database shows a chaotic pattern and a complex form of the database, which could create challenges the proposed AI models to accurately predict the annual corrosion rate (C_{rate}) of the main cables for suspension bridges.

3 Proposed modeling framework

3.1 Multilayer perceptron (MLP)

Artificial neural networks (ANNs) are one type of the artificial intelligence models inspired by the biological nervous system. In the last decades, ANNs have been widely used and applied to modeling complex engineering problems [36–39]. Multilayer perceptron (MLP) is the most common type of ANNs that consists of an input layer and an output layer. The connection between those two layers is constructed through hidden layers. A general MLP framework with a hidden layer is shown in Fig. 3.

In MLP, the computational process to calculate the points of the output layer are performed by using three steps as follows [40]:

1. First, Eq. 1 is calculated based on the connecting weight values between the input and hidden layers.

$$S_j = \sum_{i=1}^n w_{ij} I_i + \beta_j \quad (1)$$

where I_i and w_{ij} denote the i -th input value and the weight of the connection branch between I_i and the j -th hidden neuron, respectively.

2. Second, an activation function is utilized to calculate the output of each neuron in the hidden layer. The activation function used in this work is the sigmoid function and expressed as follows:

Note that there are several types of activation functions, which can be used in step 2.

$$f_i(x) = \frac{1}{1 + e^{-S_j}} \quad (2)$$

3. After completing the two above steps, the result of the output layer is calculated as follows:

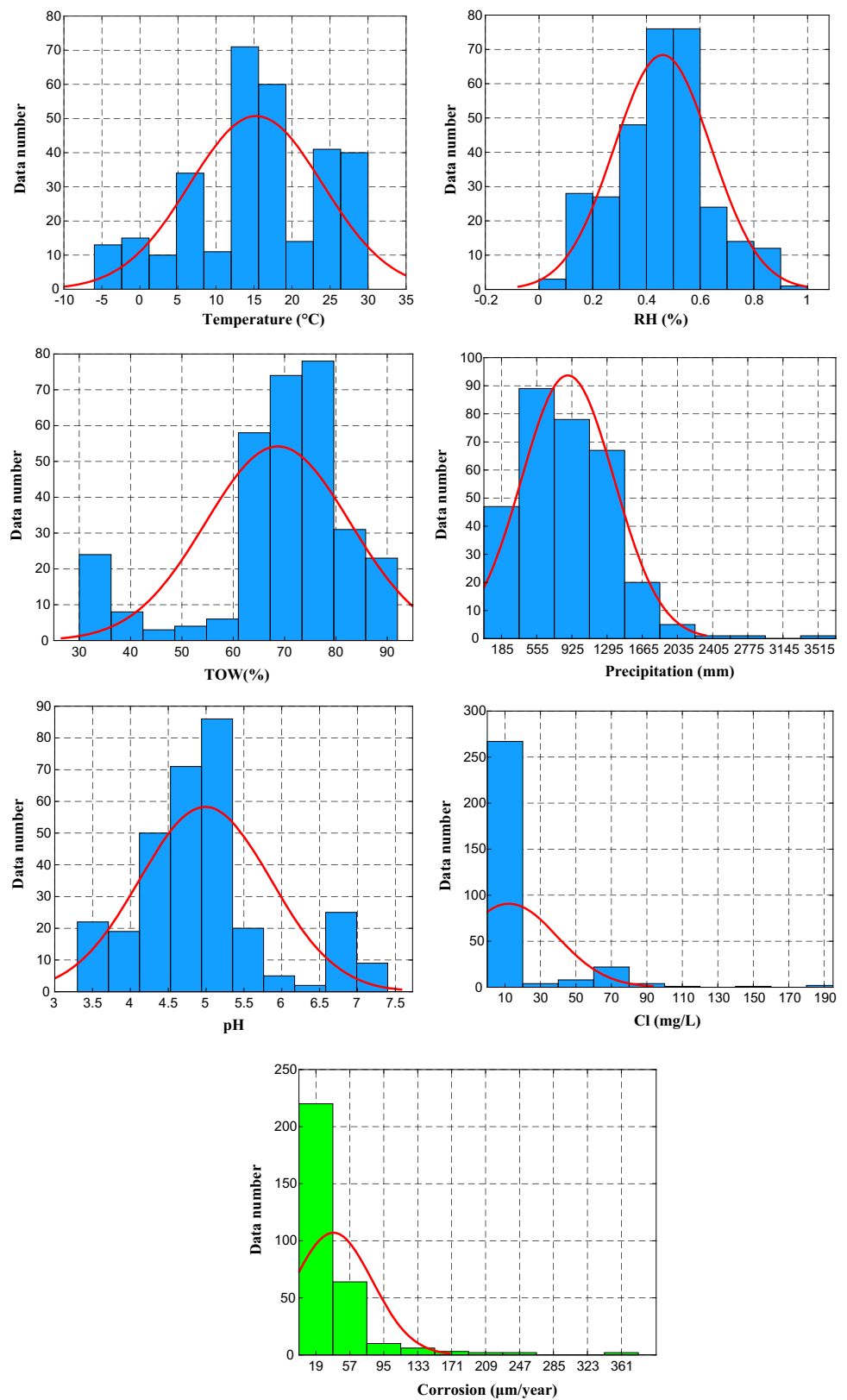
$$\hat{y}_k = \sum_{i=1}^m w_{ki} f_i + \beta_k \quad (3)$$

The efficiency of the MLP is strongly affected by its learning procedure. Generally, some types of the back-propagation algorithms are used for training the MLPs. Those methods have several disadvantages including the tendency to be snared in local minima, slow convergence, and high dependency on the initial parameters [41]. As a reliable alternative solution to the above-mentioned weaknesses of the back-propagation algorithms, metaheuristic algorithms (ME) have been applied in the literature for training the MLPs [42, 43]. These studies show that the metaheuristic algorithms have higher efficiency in optimizing the MLP networks. Therefore, this study evaluates a novel metaheuristic algorithm, namely marine predators algorithm (MPA), to train the MLP for accurate

Table 1 Descriptive statistics of the atmospheric corrosion worldwide database

	Variables	Input variables						Output variable
	Unites	T (°C)	RH (%)	TOW (%)	P (mm)	pH	Cl^- (mg/L)	C_{rate} ($\mu\text{m}/\text{year}$)
Statistics	Maximum	29.82	0.98	91.1	3677	7.37	192.73	376.7
	Minimum	− 3.1	0	33.3	13	3.448	0.01	3.3
	Mean	15.296	0.460	68.700	882.427	4.989	12.351	38.530
	SD	8.750	0.180	14.104	486.834	0.868	27.172	43.762
	Median	15.7	0.47	69.2	792	4.905	2.4	28.1
	range	32.92	0.98	57.8	3664	3.922	192.72	373.4
	Correlation with C_{rate}	0.262	0.325	0.293	0.058	−0.012	0.725	1

Fig. 1 Histograms of the input (in blue) and output (in green) variables used to develop the predictive AI models (color figure online)



and robust predictions of the annual corrosion rate of the main cables of suspension bridges. Besides, the

effectiveness of the proposed MLP-MPA model is compared to other metaheuristic algorithms such as genetic

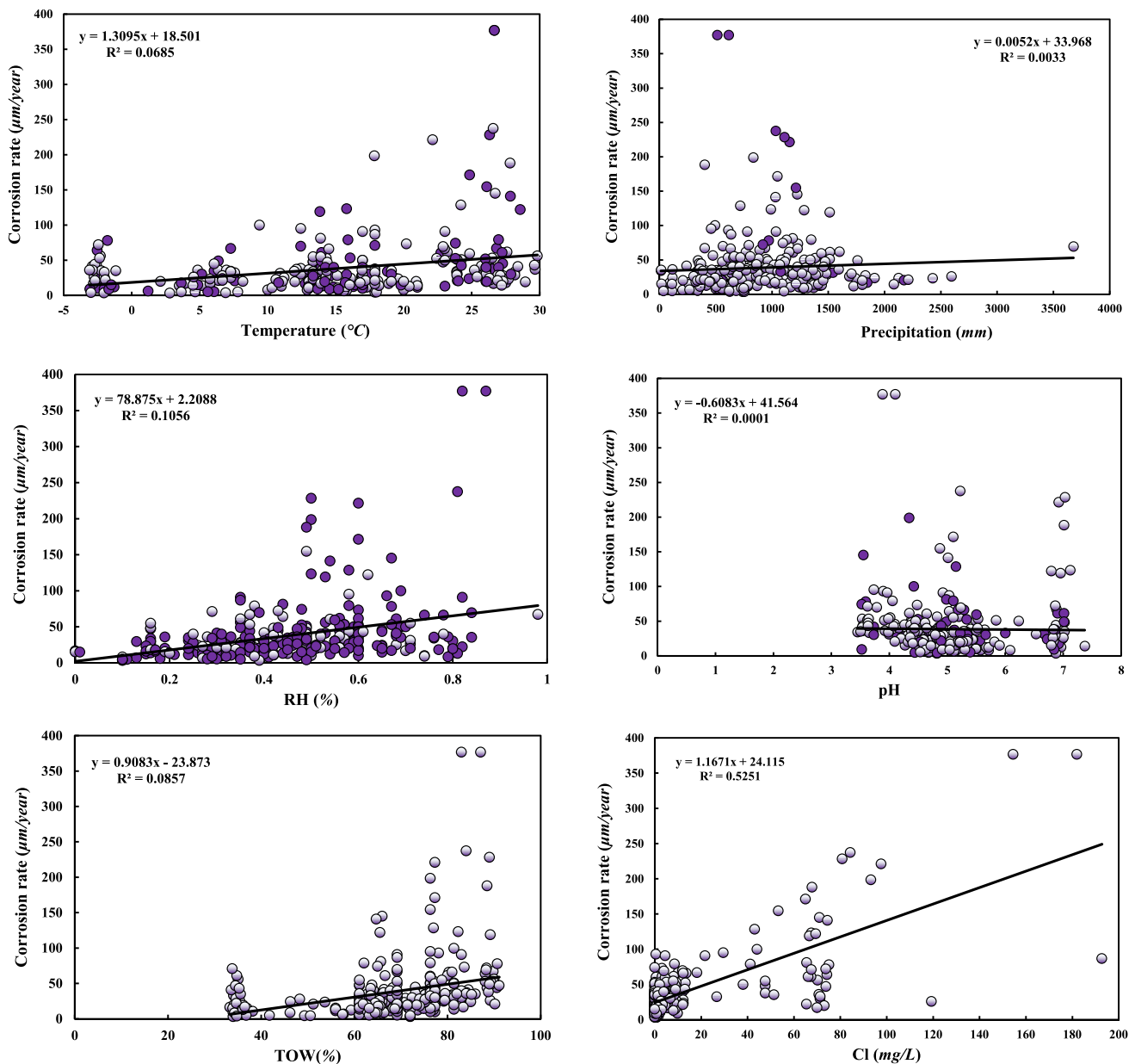


Fig. 2 Scatter plots of the input variables (i.e., T , P , RH , pH , TOW , CL^-) versus the output variable (i.e., annual corrosion rate, C_{rate})

algorithm (GA) and particle swarm optimization (PSO) and the MLP standalone for solving this complex problem. The details of the proposed ME algorithms to auto-optimize the MLP training are described in the following sections.

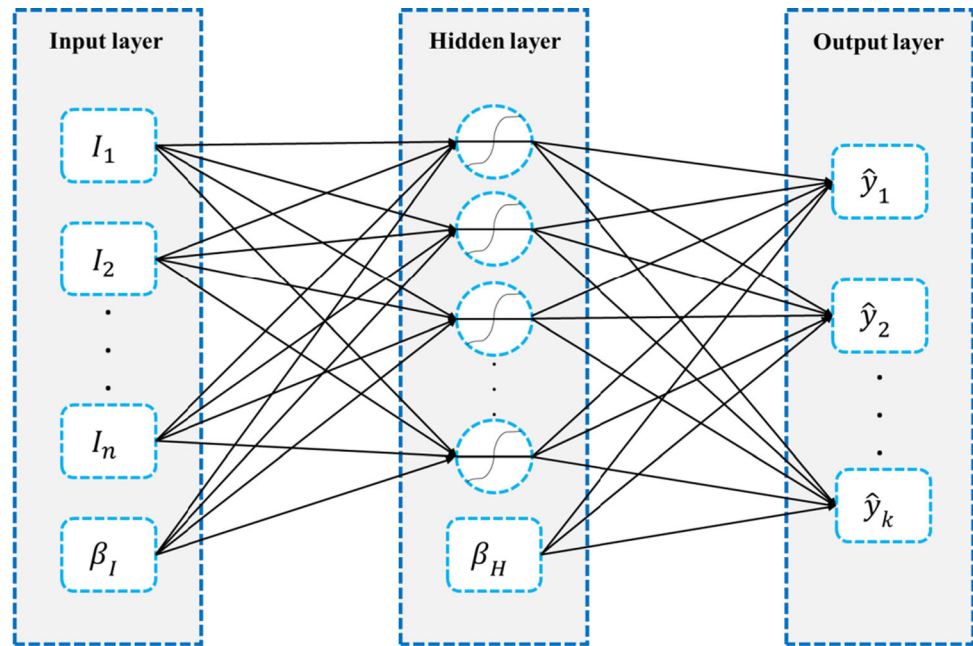
3.2 Marine predators algorithm (MPA)

Marine predators algorithm (MPA) is a newly meta-heuristic algorithm developed by Faramarzi et al. [44]. This algorithm was inspired to explore the prey behavior of the marine predators in the oceans. The recent literature shows that the MPA is an efficient and robust technique to solve various complex engineering optimization problems

[45, 46]. In this work, a novel application of the MPA is used for auto-training the MLP model. The initial solution in the MPA is created randomly as follows:

$$X_i = X_i^{\min} + (X_i^{\max} - X_i^{\min}) \times \text{rand} \quad (4)$$

where $X_i^{\max}$ and $X_i^{\min}$ explain the upper and lower boundaries of the decision variables, while rand is to generate a uniform random number in the range of 0 to 1. Then, the initial solutions are arranged as a matrix as follows:

Fig. 3 Multilayer perceptron neural network

$$X = \begin{bmatrix} X_{1,1}^1 & \cdots & X_{1,d}^1 \\ \vdots & \ddots & \vdots \\ X_{n,1}^1 & \cdots & X_{n,d}^1 \end{bmatrix}_{n \times d} \quad (5)$$

where n and d are the number of predators and the number of decision variables, respectively. The Elite matrix is constructed by sorting the solutions based on the fitness values of the objective function (Eq. 6).

$$E = \begin{bmatrix} E_{1,1}^1 & \cdots & E_{1,d}^1 \\ \vdots & \ddots & \vdots \\ E_{n,1}^1 & \cdots & E_{n,d}^1 \end{bmatrix}_{n \times d} \quad (6)$$

where $\bar{E}$ represents the top predator vector.

The MPA optimization procedure consists of three main stages based on the velocity ratio between the predator and prey, which can be detailed as follows:

3.2.1 Exploration stage

In the first stage, if the predator velocity is higher than the prey velocity, their positions are updated using the Brownian movement. The mathematical formulation of this stage can be expressed as:

$$\begin{aligned} & \text{While } \text{Iter} < \frac{1}{3} \text{Max_Iter} \\ \overline{\text{stepsize}}_i &= \overline{R_{Br}} \oplus (\overline{E_i} - \overline{R_{Br}} \oplus \overline{X_i}) \quad i = 1, \dots, n \\ \overline{X_i} &= \overline{X_i} + P \cdot \overline{R} \oplus \overline{\text{stepsize}}_i \end{aligned} \quad (7)$$

where $\overline{R_{Br}}$ is a vector of random numbers with a normal distribution, the notation $\oplus$ represents the entry-wise

multiplication, and P is a constant number equal to 0.5. In addition, Iter denotes the current iteration number, while Max_Iter explains the maximum number of iterations.

3.2.2 Intermittent stage

The second stage is between the exploration and the exploitation phases. If the velocity of the prey is equal to the velocity of the predator, this stage is applied. First, the predators are divided into two groups that one of those groups is applied to the exploitation and the other group is employed for the exploration, which can be expressed as follows: The exploitation group:

$$\begin{aligned} & \text{While } \frac{1}{3} \text{Max_Iter} < \text{Iter} < \frac{2}{3} \text{Max_Iter} \\ \overline{\text{stepsize}}_i &= \overline{R_L} \oplus (\overline{E_i} - \overline{R_L} \oplus \overline{X_i}) \quad i = 1, \dots, \frac{n}{2} \\ \overline{X_i} &= \overline{X_i} + P \cdot \overline{R} \oplus \overline{\text{stepsize}}_i \end{aligned} \quad (8)$$

The exploration group:

$$\begin{aligned} \overline{\text{stepsize}}_i &= \overline{R_{Br}} \oplus (\overline{E_i} - \overline{R_{Br}} \oplus \overline{X_i}) \quad i = \frac{n}{2}, \dots, n \\ \overline{X_i} &= \overline{X_i} + P \cdot CF \oplus \overline{\text{stepsize}}_i \end{aligned} \quad (9)$$

where $\overline{R_L}$ is a vector of random number based on the Lévy distribution. CF represents an adaptive parameter to control the step size for the predator movement.

3.2.3 Exploitation stage

The final—third—stage of the MPA algorithm is the case where the predator velocity is more than the prey velocity. Thus, this stage is applied by using Eq. 10.

$$\begin{aligned} & \text{While Iter} > \frac{2}{3} \text{Max_Iter} \\ \overline{\text{stepsize}}_i &= \overline{R}_L \oplus (\overline{E}_i - \overline{R}_L \oplus \overline{X}_i) i = 1, \dots, n \\ \overline{X}_i &= \overline{X}_i + P \cdot \overline{R} \oplus \overline{\text{stepsize}}_i \end{aligned} \quad (10)$$

In this algorithm, the search agents escape the possibility of trapping in local minima by using the eddy formation and FADs' effect to update their positions. This process is expressed as follows:

$$\overline{X}_i = \begin{cases} \overline{X}_i + \text{CF}[X_i^{\min} + R(X_i^{\max} - X_i^{\min})] \oplus \overline{U} & \text{if } r \leq \text{FADs} \\ \overline{X}_i + [\text{FADs}(1 - r) + r](\overline{X}_{r1} - \overline{X}_{r2}) & \text{if } r > \text{FADs} \end{cases} \quad (11)$$

where FADs is the probability of FADs' effect that is equal to 0.2, $\overline{U}$ is a binary vector, r is a random number within the range 0 to 1, $r1$ and $r2$ subscripts are random indexes of prey matrix.

3.3 Genetic algorithm (GA)

The genetic algorithm (GA) is a famous evolutionary algorithm and one of the most powerful methods in numerical/engineering optimization, which is based on Darwin's theory of "evolutionary biology." This algorithm was first developed by Holland [47]. Training the MLP using the GA can briefly stated with the following steps. Firstly, a set of an initial population is generated randomly, and their related fitness function values are evaluated. Then, two parents from the first population are chosen based on their fitness function values and the evolutionary operations are used as the crossover and mutation to create a new population. At the end of each generation, the new best populations are replacing the old ones. The generation process continues until the stopping criterion is satisfied. More explanation of the GA can be found in [48].

3.4 Particle swarm optimization (PSO)

The particle swarm optimization (PSO) was first proposed by Eberhart-Phillips and Kennedy [49]. This algorithm is inspired from the social behavior of birds or fishes. In auto-optimizing of the MLP parameters using the PSO, the optimum values of the decision variables are modeled by the particle's position, which exchanges depending on the fitness value of the objective function that is calculated in the solution space. In each iteration of the PSO algorithm, the particles search to find the best position [50, 51]. In this

regard, the position of each particle is updated by using Eq. 12 as follows:

$$X_{\text{new}} = X + V_{\text{new}} \quad (12)$$

where X and X_{new} are the current position and the new position of each particle, respectively. V_{new} is the new velocity of each particle, which is calculated as given by Eq. 13.

$$V_{\text{new}} = w \times V + C_1 \times r_1(p_{\text{best}} - X) + C_2 \times r_2(g_{\text{best}} - X) \quad (13)$$

where V is the current velocity of each particle, w is the inertial weight coefficient, r_1 and r_2 are random numbers that fall in the interval [0, 1]. p_{best} and g_{best} are the personal best position of each particle and the global best position of all the particles, respectively. C_1 and C_2 denote the positive acceleration constants.

Figure 4 shows the proposed framework structure for the modeling process for the estimation of the annual corrosion rate (C_{rate}) in the main cables of suspension bridges using the auto-optimized MLP with the ME algorithms (i.e., MPA, GA and PSO).

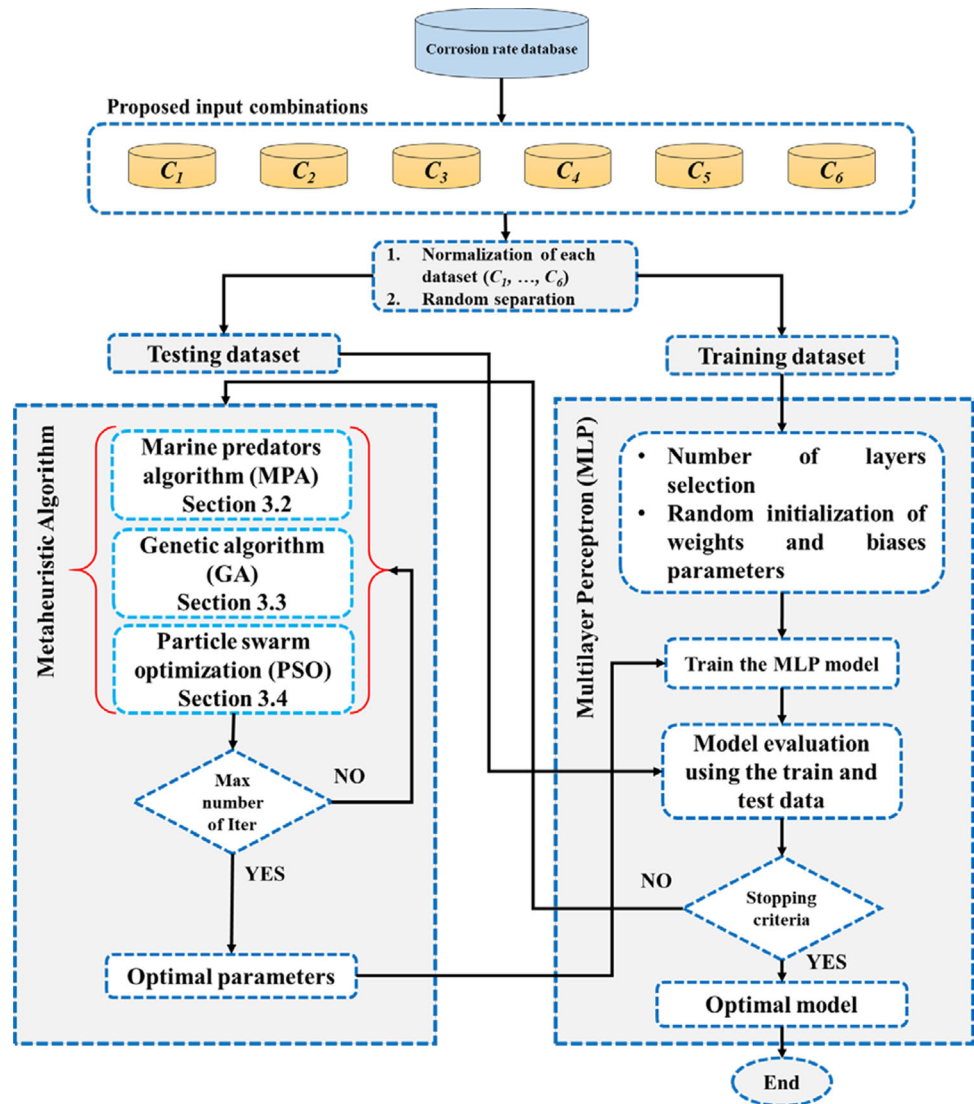
4 Implementation, results and discussion

In this section, the performance of the proposed AI models based on the hybrid MLP techniques is evaluated to find the best metaheuristic algorithm that could enhance the MLP prediction ability and accuracy. This section discusses the prediction implementation, results' performance and modeling accuracy of the four MLP models (i.e., MLP-MPA, MLP-PSO, MLP-GA and MLP). Moreover, several scenarios using different combinations of the input variables are covered. In addition, testing the hypothesis, the effectiveness of the prediction, the AI models' evaluation framework and the metaheuristic performance are discussed comparing the obtained results.

4.1 Implementation strategy

As stated before, the annual corrosion rate (C_{rate}) is significantly affected by several parameters. Thus, the selection of the input variables based on the database described in Sect. 2.1, would have a significant influence on the output variable in order to better describe the C_{rate} . To do so, six different combinations ($C_1, \dots, C_6$) are proposed for modeling C_{rate} using the six input variables as C_1 : CL^- , C_2 : CL^-, RH , C_3 : CL^-, RH, TOW , C_4 : CL^-, RH, TOW, T , C_5 : CL^-, RH, TOW, T, P and C_6 : CL^-, RH, TOW, T, P, pH . To explain the choice of the selection, it should be mentioned that this order is suggested based on the values of the correlation coefficient and R^2 of the database as analyzed in

Fig. 4 Auto-optimized MLP model using metaheuristic algorithms



Sect. 2.2. The parameters with the highest values are considered with the strongest relationship to the output variable (C_{rate}). Table 2 describes the proposed input combinations for modeling C_{rate} in the main cables of suspension bridges.

Each database related to a specific combination among the six is randomly divided into 80% to train and develop the AI models and 20% to test the outcome of the AI models. Besides, it should be noted that the selection of the setting parameters of the metaheuristic algorithms is an important task for the optimum generalization of the MLP parameters. Thus, the utilized setting parameters for the three proposed algorithms in this study are reported in Table 3.

Several error metrics are employed to compare the real-field values of the annual corrosion rate (C_{rate}) with the predicted ones using the proposed AI models. These indicators are used as powerful tools to illustrate the models

and combinations' performances compared to each other's on the one hand and for the evaluation of the global accuracy, reliability and efficiency of the AI models on the other hand. Table 4 summarizes the error metrics used, including each indicator and the corresponding formula [52, 53].

4.2 Results

Following the modeling process using the four proposed predictive AI models (i.e., MLP-MPA, MLP-PSO, MLP-GA and MLP) and the six suggested combinations ($C_1, \dots, C_6$), the performance results obtained using the error metrics are presented in Table 5. Moreover, the results between the predicted and real-field values using the prediction error variance ($PEVar$) and bias are compared and summarized in Table 6. Higher values of CI indicate the model/combination with the higher performance, whereas

Table 2 Input variable combinations for modeling the corrosion rate (C_{rate})

Combination	Input variables for the models' development	Output variables
C_1	CL^-	C_{rate}
C_2	CL^- , RH	C_{rate}
C_3	CL^- , RH , ToW	C_{rate}
C_4	CL^- , RH , ToW , T	C_{rate}
C_5	CL^- , RH , ToW , T , P	C_{rate}
C_6	CL^- , RH , ToW , T , P , pH	C_{rate}

Table 3 Utilized setting parameters for the metaheuristic algorithms

Algorithm	Setting parameters	Values
GA	Population size	30
	Crossover's probability	80%
	Mutation's probability	70%
	Type of replacement	Elitism (10% of the population)
	Type of selection	Linear ranking
	Maximum number of generation	100
PSO	Number of particles	30
	Maximum number of iteration	100
	C_1 , C_2	2
	w	0.9
MPA	Number of search agents	30
	Maximum number of iteration	100
	P	0.5
	$FADs$	0.2

the lower values of the $RMSE$, MAE and $MAPE$ indicate the accurate model/combination among the others. In addition, the model/combination with the smallest value of $PEVar$ and bias is considered as the most stable and accurate. Both tables are quite revealing several information that can be pointed as follows:

- The obtained results using the four error metrics clearly show that the performance of the AI models for modeling of the annual corrosion rate (C_{rate}) in the main cable of suspension bridges highly depends on the input combinations. Despite the suggested order of the input combinations based on the correlation coefficient values, the resulted corresponding prediction output is not found to be in the same order. This can be due to the complexity of the phenomena where some inputs have a large influence, while others are less affecting. Another reason can be pointed out that some features can be attributed as noise data, in which including such datasets will disturb the results. In Karanci and Bettifrom study [34], the TOW and P datasets were eliminated. Projecting on the obtained results, we can observe that using MLP-MPA, C_5 (with P) gives lower values than C_4 (without P) in terms of RMSE.
- In terms of the performance of the proposed predictive AI models, results of Table 5 and Table 6 indicate that the novel hybrid MLP-MPA outperformed the other AI models for all the suggested combinations. However, the performance order of the MLP-GA, MLP-PSO and MLP is not obvious as the outcome results are different with each combination and from the training to testing phases.
- According to Table 5, among the suggested six combinations ($C_1, \dots, C_6$), C_6 that includes all the input variables shows the best performance based on the error metrics, while the novel proposed hybrid model using MLP-MPA provides the highest and most accurate results among the other AI models. Thus, using MLP-MPA and C_6 datasets, the RMSE, MAE, MPAAE and CI values yielded during the training phase are $13.4745 \mu\text{m/year}$, $9.9589 \mu\text{m/year}$, 43.6469% and 0.6643 , respectively. In the same respect, these values are $12.0204 \mu\text{m/year}$, $8.61 \mu\text{m/year}$, 42.6877% , and 0.6544 in the testing phase.
- Results in Table 6 also confirm the chaotic pattern of the obtained results, where no specific order can be made depending on the number and order of the input combinations. However, the sixth combination (C_6),

Table 4 Performance error metrics description

Metric	Definition	Equation
RMSE	Root-mean-squared error	$\sqrt{\frac{1}{n} \sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate,i}^{Pre})^2}$
MAPE	Mean absolute percentage error	$\frac{1}{n} \sum_{i=1}^n \left \frac{(C_{rate,i}^{obs} - C_{rate,i}^{Pre})}{C_{rate,i}^{obs}} \right \times 100\%$
MAE	Mean absolute error	$\frac{1}{n} \sum_{i=1}^n C_{rate,i}^{obs} - C_{rate,i}^{Pre} $
CI	Confidence index	WI $\times$ NSE where :
		$NSE = 1 - \frac{\sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate,i}^{Pre})^2}{\sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate}^{avg})^2} \quad -\infty \leq NSE \leq 1$
		$1 - \frac{\sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate,i}^{Pre})^2}{\sum_{i=1}^n (C_{rate,i}^{Pre} - C_{rate}^{avg} + C_{rate,i}^{obs} - C_{rate}^{avg})^2} \quad 0 \leq d \leq 1$
Bias	Bias variance	$\frac{1}{n} \sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate,i}^{Pre})$
R^2	Correlation coefficient	$1 - \frac{\sum_{i=1}^n (C_{rate,i}^{obs} - C_{rate,i}^{Pre})^2}{\sum_{i=1}^n (C_{rate,i}^{avg} - C_{rate,i}^{Pre})^2}$
DR	Discrepancy ratio	$\text{Log} \frac{C_{rate,i}^{obs}}{C_{rate,i}^{Pre}}$

$C_{rate,i}^{obs}$: Observed value of the i -th annual corrosion rate from the test result measurements

$C_{rate,i}^{Pre}$: Predicted value of the i -th annual corrosion rate measurement

C_{rate}^{avg} : Average value of the annual corrosion rate from the test result measurements

which includes all the input variables, yields the best results using the four AI models in the training and testing phases. On the other side, the best AI model cannot be decided based on the results in this table. Accordingly, the MLP standalone yields the lowest *Bias* value in the training phase ($Bias = 0.0002$), while the MLP-MPA has the lowest values of the *PEVar* and bias in the testing phase ($PEVar = 0.442$, $Bias = -0.8558$).

4.3 Discussions

From the results reported in Tables 5 and 6, it can be concluded that the developed MLP models using all the input variables are suitable for predicting the annual corrosion rate (C_{rate}) of the main cables of suspension bridges. However, it is crucial to evaluate the performance of these predictive AI models in terms of stability and accuracy. Thus, a more detailed investigation is required to illustrate the performance of the proposed MLP models based on the metaheuristic algorithms. Therefore, in this section the performance of the four MLP models is studied, noting that only the sixth combination, C_6 (i.e., all input variables), is considered due to its outperforming results comparing to the other input combinations.

4.3.1 Comparison with previous studies

The scatter plots are excellent illustrations to show the agreement of the predicted values of C_{rate} against the real measurements. Figure 5 shows the scatter plots of the C_{rate}^{Obs} versus the C_{rate}^{Pre} using the MLP, MLP-GA, MLP-PSO and MLP-MPA models. These figures include the training and testing phases, whereas the regression fitting lines (i.e., dashes blue line is for the training data sets, while the dashes red-line is for the testing data sets) and the coefficient of determination R^2 are illustrated for each phase. According to Fig. 5, the novel developed MLP-MPA model yields the best-recorded R^2 in both training (0.9562) and testing (0.9411) phases, respectively. Following that, MLP-PSO also presents accurate results with values equal to $R_{Train}^2 = 0.9236$ and $R_{Test}^2 = 0.8736$. The MLP-GA yields the lowest R^2 in the test phase ($R_{Test}^2 = 0.6365$), while the MLP standalone results are considered as average ($R_{Train}^2 = 0.8616$ and $R_{Test}^2 = 0.8818$).

In order to show the abilities of the proposed AI models, the values of R^2 are compared with the ones obtained using the models previously developed by other researchers. Table 7 presents a comparative study based on the R^2 values between this work results and other AI models, including the linear regression (LR), artificial neural

Table 5 Performance error metrics of the modeling process using the proposed models and combinations

	Training phase				Testing phase			
	RMSE ($\mu\text{m}/\text{year}$)	MAE ($\mu\text{m}/\text{year}$)	MAPE %	CI	RMSE ($\mu\text{m}/\text{year}$)	MAE ($\mu\text{m}/\text{year}$)	MAPE %	CI
C_1								
MLP	31.1176	18.9423	77.5333	0.3434	27.7295	16.7494	64.9906	0.2455
MLP-GA	34.4738	21.3998	105.5901	0.1968	32.6901	23.3825	118.6569	0.0904
MLP-PSO	31.1008	18.7714	79.1001	0.3747	29.0985	17.8530	72.8694	-0.8500
MLP-MPA	24.2056	16.0509	73.2267	0.2279	60.3015	26.3542	60.6356	0.1233
C_2								
MLP	35.0178	20.6638	75.7523	0.1737	43.1315	23.9696	88.2120	0.1024
MLP-GA	35.3294	19.0223	71.9685	0.1812	29.2608	16.7688	57.1086	0.1403
MLP-PSO	32.6280	19.3955	65.3278	0.3201	26.7192	17.7306	87.8409	-0.2603
MLP-MPA	26.0647	16.6574	66.2009	0.4045	30.9318	16.6031	61.6858	0.3788
C_3								
MLP	35.1927	24.7033	96.3425	0.3006	27.0579	20.5780	101.9476	-0.0745
MLP-GA	33.6496	21.4254	85.1693	0.2652	23.9242	18.0244	94.9903	0.0708
MLP-PSO	38.3031	22.6651	81.2874	0.2041	24.1642	18.7748	67.8307	-0.2559
MLP-MPA	21.7851	14.3454	59.6663	0.4967	17.5748	12.3495	44.7278	0.5801
C_4								
MLP	49.1373	37.0685	158.8209	-0.1006	42.5889	34.0582	174.8653	-0.2740
MLP-GA	26.7857	18.1418	81.8253	0.4163	24.1529	16.4559	65.4705	0.2087
MLP-PSO	29.1807	18.4618	67.6261	0.3382	27.8634	18.0828	57.9780	0.3316
MLP-MPA	15.8693	11.4990	46.1926	0.5593	30.8678	16.4212	69.0966	0.4872
C_5								
MLP	35.3258	25.6370	101.4415	0.2086	41.8857	29.0552	115.5841	0.1949
MLP-GA	24.6063	16.9211	69.6357	0.4467	23.9638	18.3980	76.6142	0.4169
MLP-PSO	30.9615	21.3593	65.5132	0.3877	24.9740	15.8902	62.2350	-1.0644
MLP-MPA	18.8609	12.5029	47.1132	0.5937	14.2149	9.6493	48.4684	0.2067
C_6								
MLP	20.9673	14.5010	63.0906	0.5170	25.7190	15.9245	58.9132	0.5622
MLP-GA	17.1451	13.0843	56.2457	0.6045	32.3140	16.7193	66.7041	-0.3203
MLP-PSO	14.3200	10.7704	49.7421	0.6162	36.0695	15.2528	44.5830	0.5192
MLP-MPA	13.4745	9.9589	43.6469	0.6643	12.0204	8.6100	42.6877	0.6544

*The best outcome results among the others are indicated in bold numbers

network (ANN) and support vector regression (SVR) based on four different kernel functions as linear, radial basis function (RBF), sigmoid and polynomial. Moreover, the input variables are also reported, while the same C_{rate} database is employed. It should also be noted that in Table 7, the ANN and SVR-sigmoid models do not include the annual precipitation (P) as an input variable, while the SVR-RBF and SVR-polynomial use only four input variables among the six (i.e., T , RH , pH , Cl^-).

It can be concluded from Table 7 that the four proposed models using the MLP technique and the metaheuristic approaches manage to accurately predict the C_{rate} in the main cables of suspension bridges despite their complexity by using all the input variables of the database. By comparing the best previous model, SVR-RBF that yields an R^2

value equal to 0.836, with the four proposed AI models, an improvement is captured in terms of R^2 using the MLP, MLP-GA, MLP-PSO and MLP-MPA that equal to 3.54%, 4.86%, 9.59% and 14.02%, respectively.

4.3.2 Modeling uncertainties

The effectiveness of the proposed models can be estimated by evaluating the uncertainties provided by the modeling process. One way is to compare the ratio $C_{\text{rate}}^{\text{Pre}}/C_{\text{rate}}^{\text{Obs}}$ with the unit line as plotted in Fig. 6 using the training and testing phases. More the ratio values are close to the unit, more the model is effective and the related uncertainties are low. It can be seen that the novel hybrid model, MLP-MPA, has the closest values to the unit, indicating the

Table 6 Comparative results of the prediction error variance and bias of the proposed models and combinations

		Training phase				Testing phase			
		MLP	MLP-GA	MLP-PSO	MLP-MPA	MLP	MLP-GA	MLP-PSO	MLP-MPA
C_1	PEVar	1.6926	2.9174	1.7854	1.4162	1.1498	2.6316	1.2352	1.0198
	Bias	0.0765	-4.2750	0.2529	-0.0027	2.4741	-8.1555	-7.5167	13.1476
C_2	PEVar	1.5205	1.2936	1.1410	1.0819	1.5204	0.8691	1.8404	1.3605
	Bias	1.3521	4.9604	0.3595	0.1806	-1.3450	5.0860	-7.6710	-1.4651
C_3	PEVar	2.6286	1.2945	1.6036	0.8247	3.5463	1.9926	0.8815	0.5703
	Bias	2.4917	-3.5195	9.9669	0.3356	-3.4754	-10.4679	4.1736	1.2477
C_4	PEVar	6.7245	1.7553	0.9346	0.4474	6.8233	0.9384	0.5947	1.3662
	Bias	-14.2582	-1.3414	4.0256	0.0921	-16.7803	-3.9060	1.5056	2.0642
C_5	PEVar	2.6936	0.8827	0.7811	0.5243	2.8844	1.5666	0.7147	0.5916
	Bias	0.1654	-1.8232	0.7650	0.3439	-1.5621	1.4740	-8.5868	-1.5811
C_6	PEVar	0.9047	0.6560	0.7039	0.4334	0.7114	0.7517	0.4479	0.4442
	Bias	0.0002	-1.8164	0.5644	-0.2412	-1.0666	-5.0871	-3.4214	-0.8558

*The best outcome results among the others are indicated in bold numbers

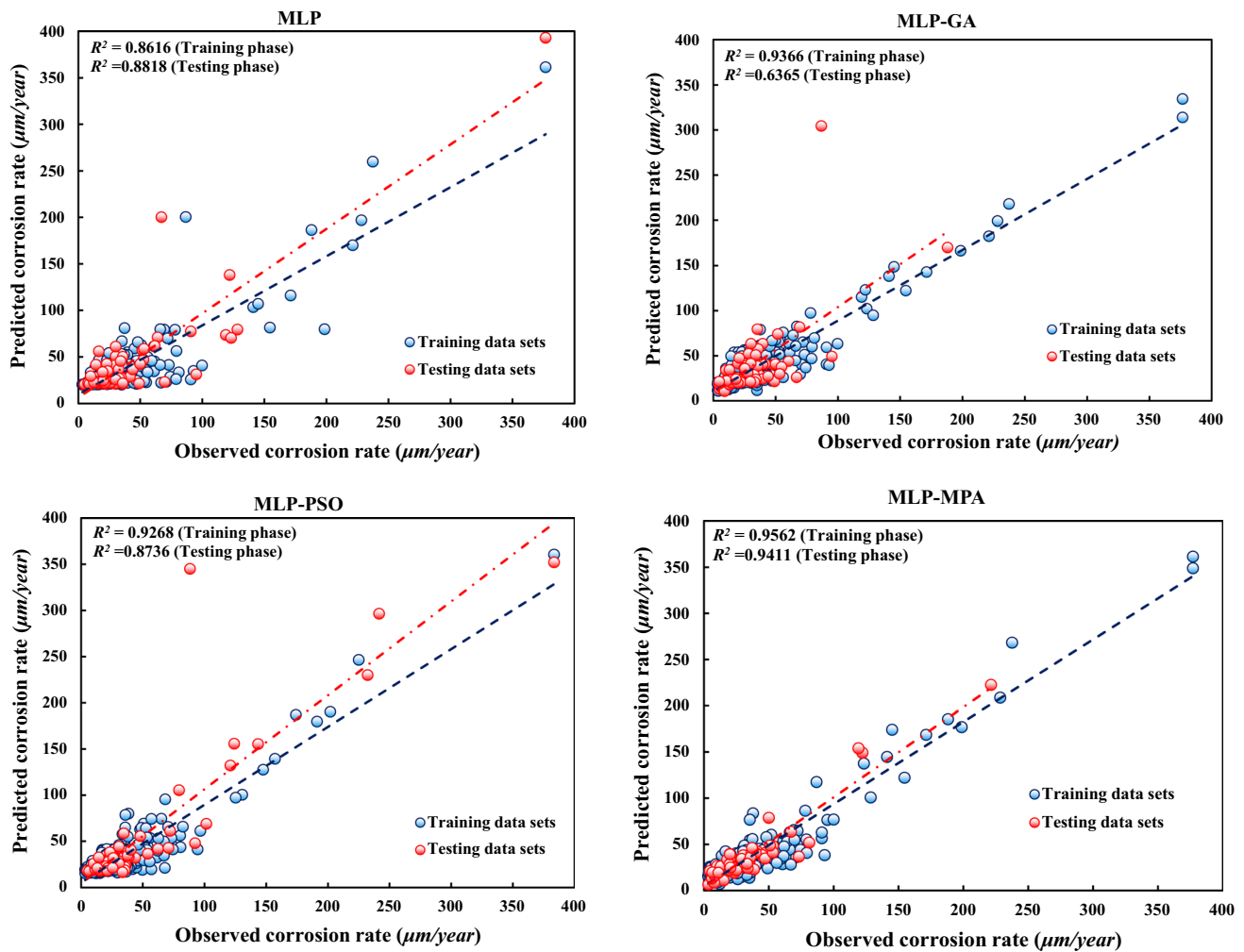
**Fig. 5** Scatter plots of the $C_{\text{rate}}^{\text{Obs}}$ versus the $C_{\text{rate}}^{\text{Pre}}$ using the four predictive AI models

Table 7 Comparative R^2 results with the previous developed AI models

Model	Selected input variables	Overall R^2 value
Linear regression	T, RH, TOW, P, pH, Cl^-	0.526
ANN	T, RH, TOW, pH, Cl^-	0.721
SVR-linear	T, RH, TOW, P, pH, Cl^-	0.513
SVR-RBF	T, RH, pH, Cl^-	0.836
SVR-sigmoid	T, RH, TOW, pH, Cl^-	0.543
SVR-polynomial	T, RH, pH, Cl^-	0.82
MLP—proposed	T, RH, TOW, P, pH, Cl^-	0.8656
MLP-GA—proposed	T, RH, TOW, P, pH, Cl^-	0.8766
MLP-PSO—proposed	T, RH, TOW, P, pH, Cl^-	0.9162
MLP-MPA—proposed	T, RH, TOW, P, pH, Cl^-	0.9532

*Models in bold have the best R^2 values compared to the others

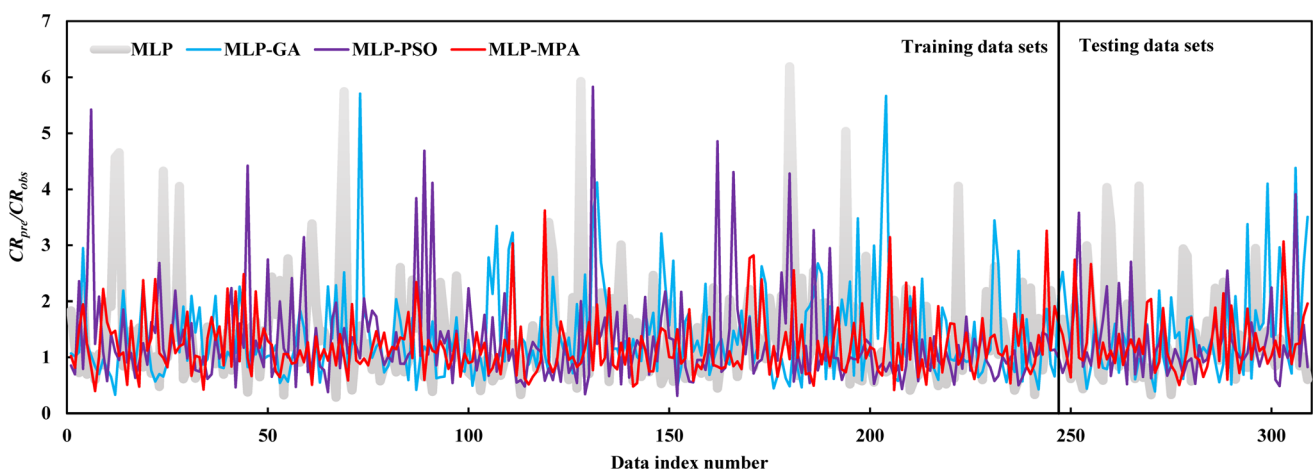
highest effectiveness among others. Furthermore, the figure shows that the MLP-GA and MLP-PSO provide approximately the same error ranges, while the MLP standalone model clearly has the highest rate of uncertainties. The discrepancy ratio (DR) is another method for illustration of the uncertainties related to the modeling process, which investigates the models' performance by considering the $C_{\text{rate}}^{\text{Pre}}/C_{\text{rate}}^{\text{Obs}}$ ratio. The formula of the DR criterion is mentioned in Table 2, while zero values indicate an equal values of the $C_{\text{rate}}^{\text{Pre}}$ and $C_{\text{rate}}^{\text{Obs}}$. Moreover, the model provides an overestimation or underestimation results in case the average results are positive or negative, respectively.

The DR values of the MLP, MLP-GA, MLP-PSO and MLP-MPA predictive models are shown in Fig. 7. As it can be seen, the DR values of the MLP-MPA are nearest to zero, while the MLP model shows a dispersed results compared to other AI models. More specifically, the DR results are in the range of $[-0.4, 0.55]$, $[-0.48, 0.75]$,

$[-0.5, 0.75]$ and $[-0.54, 0.79]$ for the MLP-MPA, MLP-GA, MLP-PSO and MLP, respectively. The above results confirm that the trial-and-error approach (i.e., MLP standalone) is an ineffective method to achieve the optimum prediction results with low modeling uncertainty for the problem of annual corrosion rate (C_{rate}) estimation in the main cables of suspension bridges.

4.3.3 Taylor diagram

The Taylor diagram is employed as the final criterion to show the robustness and accuracy of the best and the worst models among the developed ones. This type of diagram combines several indexes in order to present how the predicted values are matched to the real measurements. Thus, utilizing three error metrics as the standard deviation, correlation coefficient and RMSE, the Taylor diagram plots during the training and testing phases are obtained as illustrated in Fig. 8. Looking at the training phase, it can be seen that the MLP-MPA model is the closest to the

**Fig. 6** Time series of the $C_{\text{rate}}^{\text{Pre}}/C_{\text{rate}}^{\text{Obs}}$ ratio using the four developed AI models in the training and testing phases

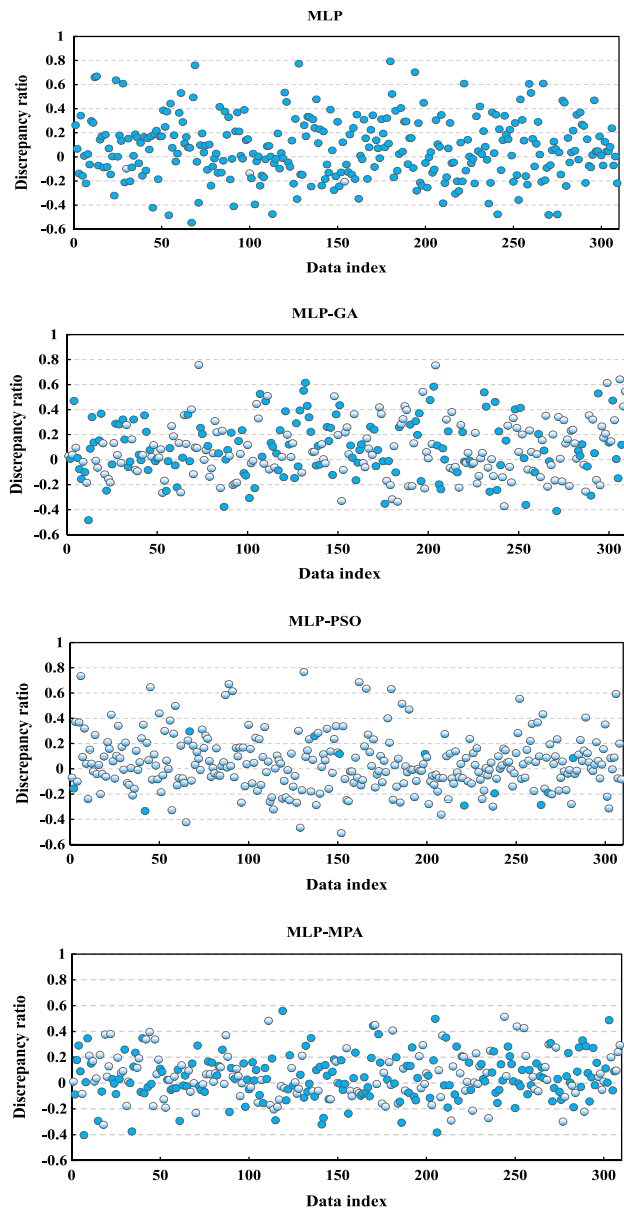


Fig. 7 Time series of the discrepancy ratio (DR) using the four developed AI models

observed result circle, followed by the MLP-GA and MLP-PSO. The MLP model has the minimum standard deviation value among all the models. However, using the testing datasets, the performance of the predictive AI models is captured in a different way. Only the MLP optimized by the novel metaheuristic algorithm, MPA, shows an accurate result, in which the statistical significance of the obtained results clearly proves the capability of this algorithm for auto-optimum selection of the MLP parameters to solve the present problem. The abilities of the other models as illustrated in Fig. 8 using the testing phase datasets are not as accurate as the MLP-MPA model. Therefore, among

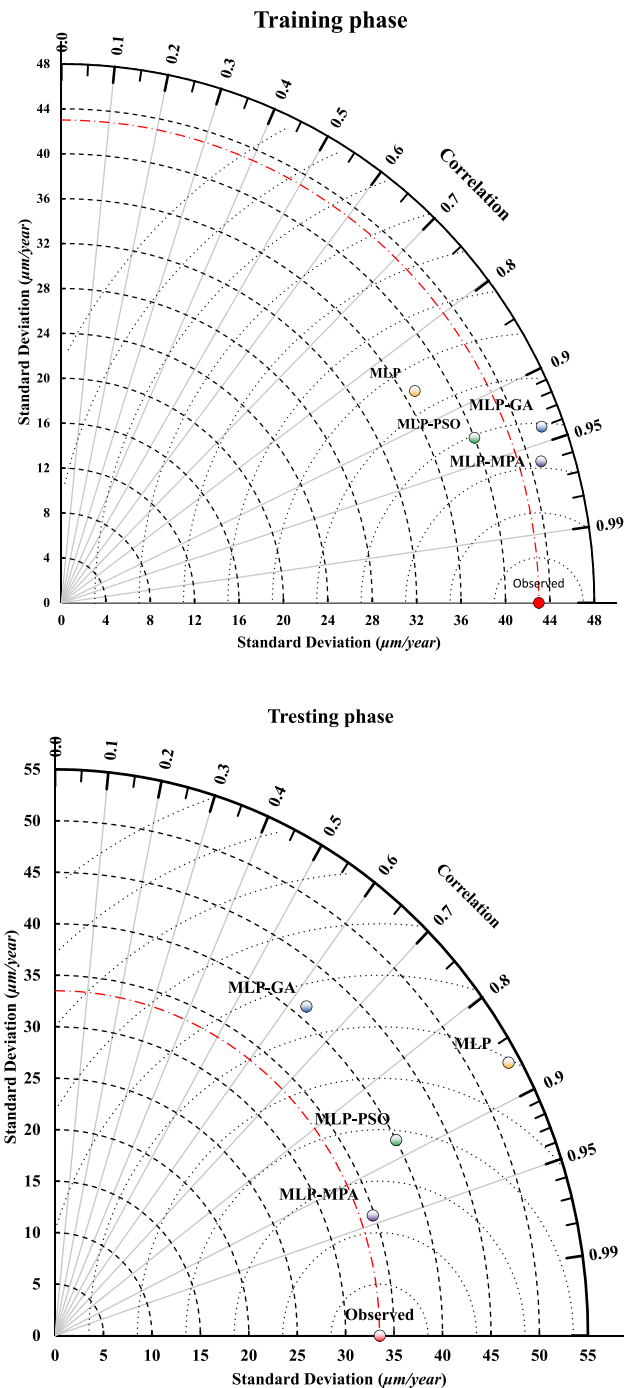


Fig. 8 Taylor diagram plots of the proposed predictive AI models during training and testing phases

the developed predictive models using the MLP technique coupled with the metaheuristic algorithms, the MLP-MPA is a stable, accurate and effective new approach form modeling the annual corrosion rate (C_{rate}) of the main cable of suspension bridges using the complex database in this work.

5 Conclusion

The annual corrosion rate (C_{rate}) in the main cables of suspension bridges is a nonlinear complex problem with chaotic pattern and stochastic behavior. On this occasion, to provide an accurate and stable framework for C_{rate} prediction in the main cables of suspension bridges, a novel hybrid model based on the multilayer perceptron (MLP) and new metaheuristic algorithms (ME), namely marine predator algorithm (MPA), is proposed in this paper. To compare the efficiency of the achieved results and full abilities of the MLP-MPA model, two other ME algorithms are used, including genetic algorithms (GA) and partial swarm algorithm for an auto-optimum selection of the MPL parameters. Moreover, C_{rate} data gathered from more than 255 different places around the world are employed in terms of six input combinations in order to investigate the influence of the input parameters on modeling the output (C_{rate}) variable. The evaluation of the results includes various criteria as several error metrics, graphical visualizations and Taylor diagrams, while the performance of the best predictive model is compared to the previous AI models in the literature. The findings from this research can be summarized as:

1. Proposing different input combinations for modeling of C_{rate} indicates the complexity of the modeling problem, where no pattern is found according to the obtained results from each combination. However, all the proposed models yield the best results using all the input variables. Thus, keeping all the original data information is important for accurate C_{rate} modeling. Besides, this study reveals that the previous studies have removed some information regarding the input variables, which could affect the original features of the annual corrosion rate predictions.
2. By comparing the results obtained using all the input variables with the previously developed models, the effectiveness of the proposed hybrid AI models is found to be superior. The improvement values using the R^2 compared to the best previous model (SVR-RBF) are 3.54%, 4.86%, 9.59% and 14.02% using the proposed MLP, MLP-GA, MLP-PSO and the novel MLP-MPA, respectively.
3. Furthermore, the novel hybrid model using the MLP optimized by the MPA shows an excellent performance in the prediction of C_{rate} using all the suggested comparative criteria. The MLP-MPA outperforms all the other AI models in this research, while its excellent prediction ability can be illustrated with the highest yielded R^2 (0.9532) and the lowest RMSE (13.183 $\mu\text{m}/\text{year}$) values in overall.

However, more detailed studies are required for modeling the annual corrosion rate in suspension bridges using deep

learning in overall. The use of data mining and feature selection based on advanced hybrid deep learning and metaheuristic models can be recommended for future works, for optimum understanding and modeling of this complex problem.

Declarations

Conflict of interest The authors of the manuscript confirm that there are no conflicts of interest regarding its publication.

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