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Prediction of Environmental Conditions of the Greenhouse Using Neural Networks Optimized with the Grasshopper Optimization Algorithm (GOA)

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Abstract— Automatic control of the greenhouse environmental conditions is among the most important necessities of modern agriculture. In order to better control and manage the conditions, some variables inside the greenhouse should be predicted such as temperature, humidity and CO2 values. The prediction of these variables in the greenhouse is usually depend on some external conditions as well as the past values of the same variables. In more recent years, several methods have been presented to predict the variables of the greenhouse based on artificial intelligence. In this paper, a prediction model is proposed for three variables of the greenhouse, these parameters include: temperature, humidity and CO2 values. The proposed model is based on machine learning and meta-heuristic algorithms. For this purpose, a feedforward neural network is used in the study. In this way, the weights and coefficients of the neural network are optimized by the grasshopper Optimization Algorithm (GOA) to reduce the prediction error. According to the simulation results of the proposed method, the RMSE value for temperature variable prediction is 0.15 and for humidity variable prediction is 1.06 and finally for CO2 variable prediction is 8.04. In order to evaluate the proposed model, the

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results have been compared with other state of the art methods. Based on the findings, the proposed method is superior to other methods in this field.

Keywords— Grasshopper Optimization Algorithm (GOA), greenhouse control, neural network, prediction.

I. INTRODUCTION

Greenhouses are a widely used system for artificially creating a suitable environment for agricultural products. Maintaining proper conditions such as temperature, humidity and carbon dioxide values is a major concern in

greenhouse environmental control, since these factors affect the development, quality and quantity of the production. Plants that are exposed to unusually high or low temperatures or humidity may be damaged, which result in significant financial losses to farmers [1]. Greenhouse climate control should consider common and non-linearity systems where variables are strongly dependent on external conditions and greenhouse design, although the former condition cannot be controlled independently. Climate management is considered as a fundamental concern to economic consumption of greenhouse energy, where increasing profit does not always mean improving overall efficiency. Therefore, developing a precise model of greenhouse climate is an important way to manage these dynamic changes and achieve efficient climate management [2-3]. Temperature, relative humidity and carbon dioxide are among the key inputs for the development of agricultural products. Bacteria, fungi and diseases are caused by poor or excessive air circulation. Deviation from any of these adjustments will prevent the production and development of agricultural products. Different equipment is designed for this purpose, but the climate conditions should be controlled to improve the greenhouse environment and reduce the energy consumption. Predictions are made using mathematical techniques as well as mechanical controls for the environment [4].

The initial cost of the greenhouses is increased by using more sensors, which ultimately increases the cost of the harvested product. The main factors used to imitate greenhouse conditions include environmental factors as temperature, humidity, wind speed, radiation intensity [5-6]. Initial modeling is one of the basic requirements to use other advanced technologies as well as renewable energy in the greenhouse, in addition to improving management conditions. Since 1990, artificial neural networks have been proposed to use in the internal forecasts of greenhouses, and numerous researches has been conducted in this area. Many studies focused on using neural networks and its performance [7-9]. However, numerous studies have been carried out, including studies that controlled greenhouse environmental conditions [10], physical modeling of the greenhouse, and predicted a small number of interior spaces [11-12]. Artificial neural networks have been used to replace different types of sensors in greenhouses in studies [13]. The results of other studies in this field demonstrate the superiority of neural networks over other state of the art methods in this field [14].

This paper presents an effective way to predict greenhouse environmental conditions based on neural network and machine learning methods. So, an improved neural network is employed to predict the greenhouse environmental conditions with high accuracy. In this study, the

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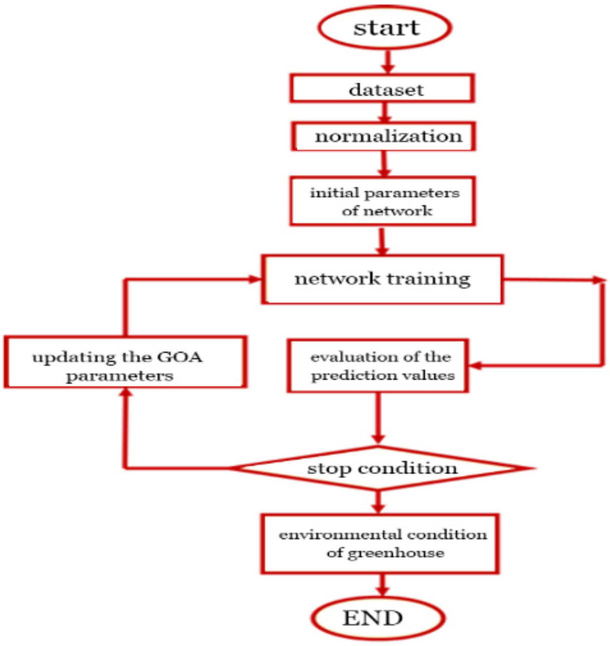
grasshopper optimization algorithm (GOA) is used to optimize multilayer perceptron (MLP) neural network parameters. The structure of this paper is that the suggested method is presented in the second part, the simulation and analysis of the simulation results are detailed in the third part, finally, the conclusion is presented in the fourth section.

II. PROPOSED METHOD

This paper aims to select an effective way to predict greenhouse environmental conditions. For this reason, an improved neural network is employed to predict the greenhouse environmental conditions with high accuracy. In this study, (GOA) is used to optimize MLP neural network parameters. The proposed method diagram is presented in Figure 1.



III. Figure 1: Diagram of the proposed method

Data preprocessing

Predicting one or more parameters is usually based on several past features or values of those parameters. As a result, the first step in predicting future values is reading data and normalizing the input values to the network. The input values are a series of features, or the past values of the parameters or a combination of these two. Data normalization, which is the most important part of the data pre-processing, also means mapping the input values to the network into a specific range such as [0,1]. This makes all the input data to be effective in the process. More

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normalization is obtained by dividing all values of one parameter by the maximum value of that parameter, based on the following equation:

$$\mathrm{x_N} = \frac{\mathrm{x_i}}{\mathrm{x_{max}}} \quad (1)$$

Grasshopper optimization algorithm (GOA)

The goal of the GOA, an inventive optimizer, is to simulate the social behavior of grasshopper insects in nature [19]. The developers of the GOA optimizer verified that it can beat a variety of popular optimizers, such as the GSA, BA, FA, GA, and PSO algorithms, when it comes to handling realistic and simulated optimization tasks [19]. The main behaviors of grasshoppers during either the nymph or adult phases include foraging, target pursuit, and team activities. As larvae, they typically make quick, slow-motion leaps. As adults, they move quickly and widely to reach agricultural regions in search of food supplies. These facts were represented by a model as [19]:

$$\mathrm{X_i} = \mathrm{S_i} + \mathrm{G_i} + \mathrm{A_i} \quad (2)$$

where $\mathrm{X_i}$ represents of ith insect, $\mathrm{S_i}$ depicts social interactions, $\mathrm{G_i}$ represents of ith insect gravity, and $\mathrm{A_i}$ represents wind advection. Noting that $\mathrm{X_i} = \mathrm{r_1 S_i} + \mathrm{r_2 G_i} + \mathrm{r_3 A_i}$, where $\mathrm{r_1}$, $\mathrm{r_2}$, $\mathrm{r_3}$ are random variables, may be used to express Eq.
inside [0, 1]. The components of Eq. (2) can be attainedas:

$$S_i = \sum_{j=1, j\neq i}^{N} s\left(d_{i\,j}\right) d_{i\,j}, d_{i\,j} = \left|x_{j\_} x_i\right|, d_{i\,j} = (x_{j\_} x_i)/d_{i\,j} \quad (3)$$

$$G_i = -g\hat{e}_g \quad (4)$$

$$A_i = -u\hat{e}_\omega \quad (5)$$

where g stands for the gravitational constant, $\hat{e}_g$ is the unity vector of gravity, u is a constant drift, and $\hat{e}_\omega$ is the unity vector of wind. where $d_{i\,j}$is the distance between two grasshoppers. The following steps may be used to get the s function in Eq. (3), which estimates the social attraction or repulsion forces:

$$s(r) = f\, e^{-r/l} - e^{-r} \quad (6)$$

where l displays the length scale and f the attraction's amplitude. The comfort zone refers to a situation in which the trend of the $s(r)$ function is neither alluring nor alluring. As a result, f and r factors not only have a substantial impact on the comfort zone but also the zones of attraction and repulsion. The s-function's behavior has an impact on how grasshoppers communicate with one another. The values of the f and l parameters may be adjusted to 0.5 and 1.5, respectively, in accordance with [19]. Additionally, the interval [1, 4] contains a map of insect distances.
According to Eqs. (3) – (5), the main rule in Eq. (2) can be reformulated as:

$$X_i = \sum_{j=1 j\neq i}^{N} s(|x_j - x_i|)\frac{(x_j - x_i)}{d_{i\,j}} - \; g\,\hat{e}_g\, u\,\hat{e}_\omega \quad (7)$$

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where N is the size of swarm. According to Eq. (7), the population cannot be converged to the specific target, because the insects will rapidly reach to the comfort region [19]. Therefore, a modified rule can be utilized as:

$$x_i^d = c\left(\sum_{j=1 j\neq i}^{N} c\frac{UB_d - LB_d}{2} s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j^d - x_i^d}{d_{ij}}\right) + T_d \qquad (8)$$

where d shows dimension, T_d is the best solution (goal) thus far achieved, UB_d and LB_d are the upper and lower bounds, and c is a decreasing factor. It should be noted that the external c minimizes the search tendency at the optimal site by more iterations, but the internal c aids GOA in diminishing grasshopper repulsion/attraction powers. As seen below, the c factor is obtained.

$$c = c_{max} - l\,\frac{c_{max} - c_{min}}{L} \qquad (9)$$

where c_{max} and c_{min} are, respectively, the maximum and minimum values, l is the in progress iteration, and L denotes the upper bound of iterations. The values of c_{max} and c_{min} are set to 1 and 10−5, respectively.
According to its current location, the location of the specified objective, and the circumstances of the entire population, a grasshopper in GOA achieves its new place. In GOA, the optimum solution should be viewed as the target that grasshoppers will discover and enrich. The comfort zone is gradually reduced by GOA thanks to the declining c factor. As a result, it can carry out a seamless shift from exploring to using the fitness landscape. While attraction forces can encourage grasshoppers to take advantage of the favorable environs of higher quality solutions, repulsion forces can help the population explore the fitness topography broadly.
Understand the following reasons why the innovative GOA can produce very promising solutions for a range of optimization cases:
In the early stages of the search, grasshoppers are able to make a number of abrupt, large-step jumps, allowing them to thoroughly search the uncharted territory.
In the last stages of optimization, grasshoppers frequently do local searches, which improves their exploitation capabilities.
As the comfort zone shrinks, grasshoppers are forced to gradually strike a balance between their propensities for exploration and exploitation, helping GOA to avoid premature convergence and find a promising global peak.
The GOA can increase the overall fitness of all grasshoppers, which helps it effectively improve the initial solutions that were generated at random.
As the search progresses, the fitness of the target site can be increased, indicating that more iterations can improve the approximation of the global best.

The Proposed Method GOA-ANN

Artificial neural networks are highly effective in predicting time series. Although selecting the right weights and coefficients has an important role in neural network training and can increase the accuracy of process. For this purpose, we take advantage of combining artificial neural network and grasshopper optimization algorithm to select the best weights and coefficients and improve the prediction accuracy. The optimization algorithm is a type of population-based optimization algorithm inspired by the swarm behavior of grasshoppers in nature. As a result,

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by modeling the optimization behaviors, this metaheuristic algorithm has a high search capability for optimization of complex problems. Figure 2 shows the structure of a neural network unit.

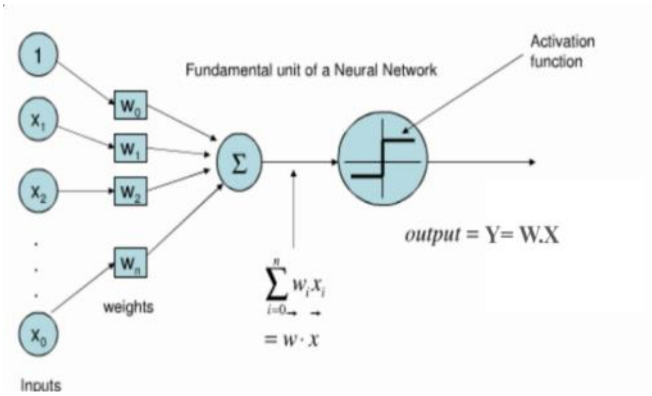

Figure 2: the structure of a neural network unit

In this network the weights are updated according to the following equation:

$$w_i(new) = w_i(old) + x_i y \qquad (2)$$

In Eq.2, x_i represents the network inputs, w_i represents coefficients and y is the network output. The neural network works in a way so that the inputs (x) are multiplied by coefficients (w) to obtain y. The goal is to achieve the Y or the predicted value with the least error. Optimized Ws must be determined for this purpose. The network needs to be trained to determine Ws. The network training process is performed using (GOA) to adjust W. In each step w is changed to minimize the prediction error. The grasshopper algorithm changes W each time and for that Ws calculates the error. This process is repeated so that the best w is found, the error is reduced and the prediction is done more accurately.

An illustration of a grasshopper's encoding approach in GOA-ANN is shown in Figure 3. The three main components of the planned encoding vector include two sets of connection weights between the layers and a number of bias terms. With relation to the total number of weights and biases in the target network, the length of these vectors may be determined. For GOA-ANN, a similar encoding technique is used. The choice of fitness function is another aspect of this that needs to be taken into account. They ought to be sent to the ANN network as the connection weights in order to reach grasshopper fitness. These vectors can be evaluated by the ANN network using training data. The network will then determine the fitness values of the appropriate solutions. In this article, the GOA-ANN trainer's fitness function for determining the fineness of the ANNs is the mean-squared error (MSE). The variance between the actual and projected solutions by the created Grasshoppers (ANNs) can be used to calculate the MSE measure for the training data. The goal is to as much as possible reduce the MSE's value.
Eq. (11) can be used to reach MSE:

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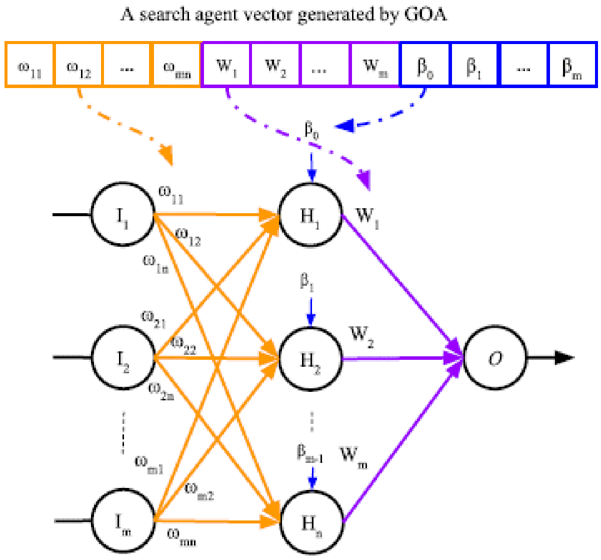

Figure 3 . Solution representation

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (11)$$

where y indicates the actual value, $\hat{y}$ shows the predicted one, and n denotes the total number of instances. The algorithm of GOA-ANN trainer can be described by the following steps:
1. Establishment Initially, the GOA-ANN generates a random assortment of grasshoppers.
2. Grasshopper mapping: The weights and biases of a possible ANN network are applied to the components of the grasshoppers.
3. Fitness evaluation The MSE function is used to assess the performance of the generated ANNs over all training dataset samples.
4. The ANN with the lowest MSE value should be found by the GOA-ANN. It is better to use ANNs with lower MSEs than those with higher MSEs.
5. Adjust the grasshoppers' postures as necessary.
6. Continue to the last cycle by repeating steps 2-4.
7. Termination and evaluation The process is eventually finished, and the ANN should be tested on the test/validation instances with the lowest MSE.

IV. EXPERIMENTAL RESULTS

In this section, the evaluation criteria of the proposed technique are presented along with the description of the database used, as well as the analysis of the results obtained from the simulation.

Database

In this study, a public greenhouse database available on the KAGGLE website is used for the process [15]. This database includes features as indoor temperature, indoor moisture, light intensity, greenhouse temperature, moisture outside greenhouse, volatile organic compound,

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CO2 and temperature time delays, humidity and CO2. The data is recorded by the sensors in the greenhouse over 10 minute's periods. In this study, temperature, humidity and CO2 levels are predicted within the greenhouse according to the features mentioned.

Evaluation Criteria

In order to evaluate the proposed method results, AE, RMSE, MAPE parameters are used for this purpose. The equations are presented in the following.
The average error of N forecasting results

$$AE = \frac{1}{N}\sum_{i=1}^{N}(A_i - F_i) \quad (3)$$

The square root of the mean square error

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N}(A_i - F_i)^2} \quad (4)$$

Mean absolute percentage error

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right| \times 100\% \quad (5)$$

In the above equations, N is the number of samples, F is the predicted value and A is the actual value. i is the sample number.

Evaluation of the results

In this section, first the proposed model and its parameters are explained and then the results are evaluated for predicting three parameters of temperature, humidity and CO2 level.
As mentioned, the proposed model is a feedforward neural network with three layers, the number of input layer neurons is 19 based on the number of database features, the number of hidden layer neurons and output layer are 7 and 1, respectively. Figure (5-1) is an example of the proposed network.

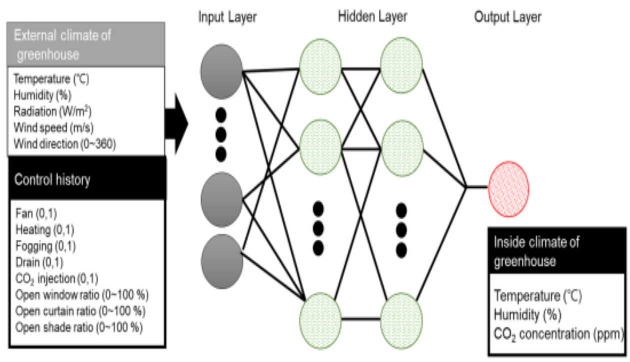

Figure 3 the proposed model network

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Table 1 also provides the grasshopper optimization algorithm parameters to optimize the coefficients and weights of the neural network.

TABLE 1 GRASSHOPPER OPTIMIZATION ALGORITHM PARAMETERS

Value	Parameter
10	Population size
20	Number of iterations
4	Minimum permissible value (for hidden layer size)
40	Maximum permissible value (for hidden layer size)
Error	Objective function

Prediction Results of the Proposed Model

In this section, the simulation results are presented to predict three parameters of temperature, humidity and CO2 in the form of the actual and predicted values diagram. In the diagram of the actual and predicted values, the horizontal axis is time and the vertical axis is the range values of the parameter. The actual and predicted values for temperature, humidity and CO2 level variables are drawn in Figures 4, 5 and 6, respectively. In these figures, the actual values is shown with a blue line and the predicted values with red dots. As can be seen in the figures, the prediction results are very consistent with the actual values, which indicates the high accuracy of the prediction.

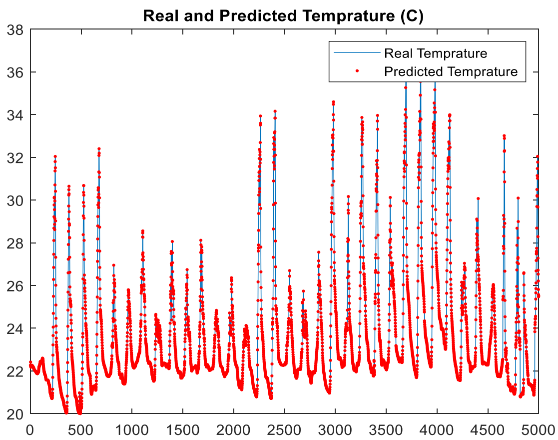

Figure 4 real and predicted temperature values

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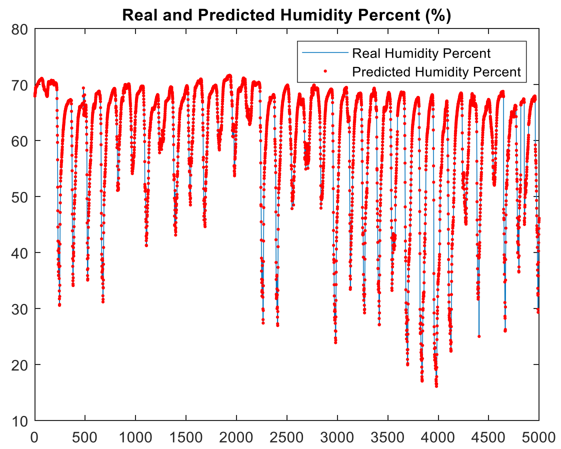

Figure 5 real and predicted humidity values

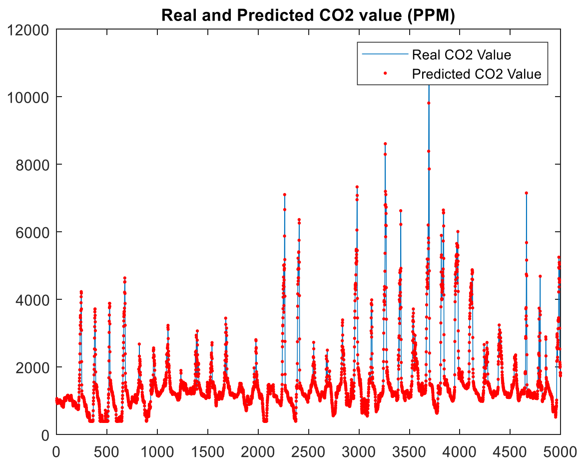

Figure 6 real and predicted CO2

Regression curve

In this section, the simulation results are presented to predict three parameters of temperature, humidity and CO2 in the form of regression diagram. In the regression chart, the predicted data should be around the FIT line. In fact, the more predicted data is on the Fit line, the less the prediction error. The regression curve for predicting the three variables of temperature, humidity and CO2 level is shown in Figures 7, 8 and 9, respectively. As can be seen, the predicted data almost coincides with the FIT line, which indicates the high efficiency of the proposed method in the field of predicting greenhouse environmental conditions

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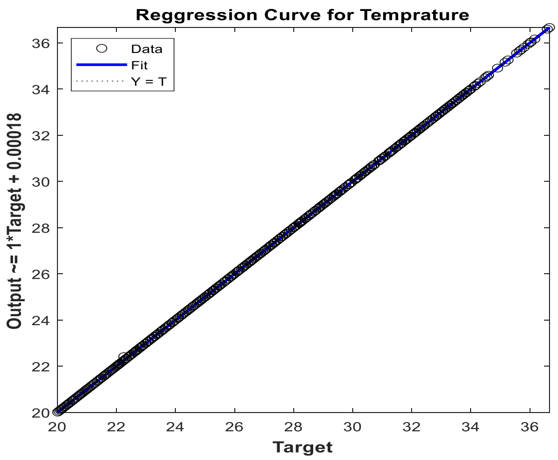

Figure 7 regression curve for temperature prediction

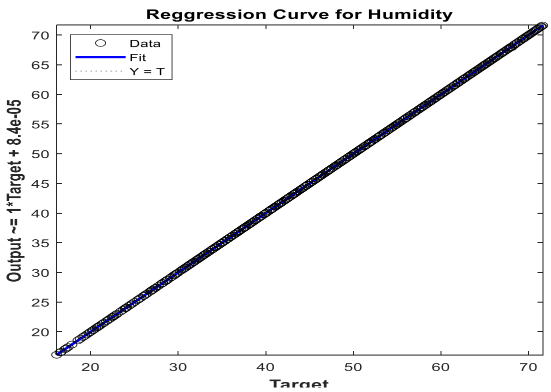

Figure 8 regression curve for humidity

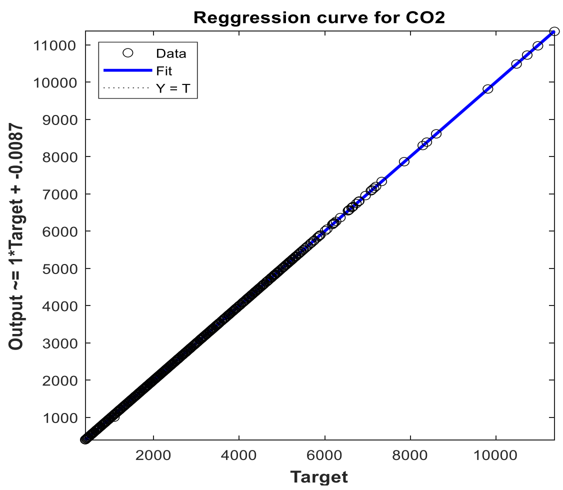

Figure 9 regression curve for CO_2

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Comparison of results

In this section, for further examination as well as comparing the performance of the proposed method, the values of the RMSE for predicting three parameters of temperature, humidity and CO2 are presented in Table 2. It should be noted that these error values have been obtained as a result of the average of 20 simulation performances, which increased the validity of the proposed method. The results of the proposed method are also compared with other methods. According to Table 2, the proposed method outperforms other methods in predicting all three variables of temperature, humidity and CO2.

TABLE 2: RESULT COMPARISON

Rmse	Method	
0.52	Temperature	
3.01	Humidity	NARX
19.24	CO2	
0.45	Temperature	
3.02	Humidity	RNN-LSTM
17.42	CO2	
0.89	Temperature	
5.67	Humidity	ANN
31.23	CO2	
0.15	Temperature	The proposed
1.06	Humidity	method
8.04	CO2	(NN-GOA)

V. CONCLUSION

In this study, a prediction model is proposed for three variables of the greenhouse as temperature, humidity and CO2. The proposed model is based on machine learning and meta-heuristic algorithms. So, a feedforward neural network is used in where the weights and coefficients of the neural network are optimized by the grasshopper Optimization Algorithm (GOA) to reduce the prediction error. According to the simulation results of the proposed method, the RMSE value for temperature variable prediction is 0.15 and for humidity variable prediction is 1.06 and finally for CO2 variable prediction is 8.04. In order to evaluate the proposed model, the results have been compared with other state of the art methods. Based on the findings, the proposed method is superior to other methods in this field.

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