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Time series prediction with a hybrid system formed by artificial neural network and cognitive development optimization algorithm

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Abstract. Time series prediction is a remarkable research interest that is widely followed by scientists and researchers. Because many fields include processes of such time series analyses, different kinds of approaches, methods, and techniques are employed often in order to achieve alternative ways of prediction. It appears that artificial-intelligence-based solutions have strong potential for providing effective and accurate prediction approaches in even most complicated time series structures. For further details and explanation, this study aims to introduce an alternative artificial-intelligence-based approach to artificial neural networks and cognitive development optimization algorithm, as a recent intelligent optimization technique introduced by the authors. This study aims to predict different kinds of time series by using the introduced system/approach. In this way, it is possible to discuss application potential of the hybrid system and report findings related to its success of prediction. The authors believe that the study provides a good chance to support the literature with an alternative solution approach and see the potential of a newly developed, artificial-intelligence-based optimization algorithm for different applications.

1. Introduction

Artificial intelligence is an important research field applied to problems of almost all real-life fields. Nowadays, it has become apparent that the need for intelligent solution approaches is a vital factor in overcoming real-world problems effectively. Because of their high potential for success, artificial intelligence has outstanding popularity, leading to intense design and development of new approaches, methods, or techniques. Furthermore, it has also been a traditional way to apply each newly introduced artificial-intelligence-based solution approach to problems of different fields.

Considering the fields of mathematics and statistics, there are many different types of problems in which artificial intelligence is often employed. At this point, it appears that data series preformed with time factor is among attractive research interests. According to the literature, the term time series is defined as flow of data saved over time: weekly, monthly, or even yearly [1-4]. It has been realized that time series may enable us to understand many aspects of the subject or event from which time series data are obtained. Accordingly, time series analysis has become a remarkable application; hence, the growing

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popularity of such applications is in 'predicting the future flow of time series. To predict the future flow of time series is to analyze previous states of time series to find more information about the flow in the future. The background of this approach benefits from the idea of the past patterns of time series that will be observed in the future [1].

The approach of time series prediction corresponds to events or problems from almost all fields of our life. Thus, future conditions related to changes in financial values, sales, productions or even behaviors of natural dynamics can be predicted by means of the time series prediction. Thus, it is possible for scientists, researchers, or experts within a field to imagine future status and, finally, reach decisions about new applications or problem solutions. Eventually, time series prediction has become an important application as a result of unstoppable, chaotic changes in the real life and the nature of 'uncertainty' because of this situation.

Based on the literature of time series prediction, traditional approaches or methods have failed to adapt to a complicated and new form of time series [5]. Hence, remarkable efforts have been made to introduce and employ alternative solutions to overcome prediction problems of difficult and challenging time series. Thus, it was noticed that the usage of artificial intelligence could overcome the related issues and, furthermore, offer many advantages of 'intelligent mechanisms' to solve real-world problems. This field has become a popular application interest when time series prediction gained importance in the context of an encountered problem. Today, development of artificial-intelligence-based hybrid systems is one of the most attractive applications; hence, there are many examples of time series prediction applications conducted via hybrid systems structured with more than one method or technique.

The purpose of this study is to employ an alternative, artificial-intelligence-based approach to time series prediction. The study equipped with artificial neural networks and cognitive development optimization algorithm, which is a recently introduced optimization technique, focuses on a hybrid system. As a supportive factor for the training process of the artificial neural network model, cognitive development optimization algorithm is a single-objective optimization algorithm drawing inspiration from ideas regarding cognitive development by Piaget [6-9]. This study aimed to predict different kinds of time series by using the introduced system/approach. In this way, it was possible to discuss application potential of the hybrid system and report findings related to its success on prediction. In addition, the authors believed that this study could be a good chance to support the literature with an alternative solution approach and see the potential of a newly developed, artificial-intelligence-based optimization algorithm with different applications.

Motivation and the main contributions here can be expressed briefly as follows:

- The study deals with a remarkable research interest as 'time series prediction';
- The study tries to employ an alternative approach to the literature of time series prediction;
- The study employs a novel prediction approach by using cognitive development optimization algorithm for the first time for training model(s) of artificial neural network to perform time series prediction;
- The study aims to deal with predicting advanced time series through showing its chaotic characteristics;
- The study generally proves that hybrid artificial intelligence techniques are effective enough in predicting time series, even though they are chaotic. In this way, more practical and effective aspects of artificial intelligence techniques can be understood according to traditional approaches.

This study is structured as follows. The second section concerns the background for application of artificial-intelligence-based techniques in time series prediction. Afterwards, the third section explains materials and methods used within the study. In this way, readers are provided with enough information about artificial neural networks, cognitive development optimization algorithm, and the designed prediction system/approach. The third section is followed by some information on the applications aimed at predicting some time series (the fourth section). Next, the fifth section reports the results obtained with the (chosen) ANN-CoDOA system. Then, a comparison-based evaluation process with the system and some other alternative ones are done and explained in the sixth section. The seventh section is devoted to a brief discussion. Finally, the paper ends with conclusions and suggestions for some future studies.

2. Background

When we focus on the associated literature, it is possible to see many alternative studies on time series prediction. Because there has been a remarkable interest in such scientific studies, newly introduced approaches, methods, and techniques have been employed in time series prediction studies in order to evaluate the success of these 'new comers'. It is also important that artificial intelligence appears as a strong factor to perform successful studies on time series prediction. Because this study also focuses on the employment of an artificial intelligence technique, it is better to take a brief look into the recent literature on the intersection of artificial intelligence and time series prediction. As extending the previous background review done by the authors in [10], some remarkable research studies from the literature are as follows:

- Gan et al. and Wong et al. performed some prediction-based research studies using Artificial Neural Networks (ANN) technique [11,12];
- In a research, Gentili et al. employed fuzzy logic, feed forward neural network, and a nonlinear local predictor to perform prediction operations on a periodic hydrodynamic oscillatory time series [13];
- Chen and Han performed a study on predicting multivariate chaotic time series. They used a Radial Basis Function (RBF) for prediction processes [14];
- In their study, Wu et al. developed a prediction approach to chaotic time series [15]. Briefly, they predicted time series of Mackey-Glass, gas furnace (Box-Jenkins), and EEG. At this point, the prediction processes were done by iterated extended Kalman filter supported by single multiplicative neuron model;
- Yadav et al. published a study in 2007 [16] concerning Single Multiplicative Neuron (SMN) for time series prediction purposes. On the other hand, Zhao and Yang performed a study similar to [14]; however, they used PSO-SMN to predict time series of Mackey-Glass, gas furnace (Box-Jenkins), and EEG [17];
- Yao and Liu ran a Fuzzy Logic (FL) prediction process to overcome prediction problem(s) about atmospheric visibility in Shanghai [18];
- Particle Swarm Optimization (PSO) was used by Unler to perform optimization-based time series prediction operations [19]. Similarly, Zhao and Yang used particle swarm optimization for prediction purposes [20];
- The literature contains many different studies based on the employment of Ant Colony Optimization (ACO) to predict systems with chaotic flows [5,21-24];
- Yeh introduced a model that provides a parameter-free simplified swarm optimization for training Artificial Neural Network (ANN) [25]. In this study, the model was run over different time series (including EEG time series);
- In their study, Nourani and Andalib employed a Wavelet Least Square Support Vector Machine system (WLSSVM) to predict hydrological time series [26]. Aiming to predict Suspended Sediment Load (SSL) on a monthly basis for the Aji-Chay River, the authors performed a comparison-based approach by including some other approaches, such as ad-hoc Least Square Support Vector Machine (LSSVM) and even models of Artificial Neural Network (ANN), to obtain prediction results;
- Regarding the sub-field of machine learning, Bontempi et al. produced a book chapter to provide reviews of recent approaches for predicting the time series via specific machine learning techniques [27]. By providing a research study aimed at predicting general time series, this study is different from the alternatives aiming to handle chaotic time series only. It is an important background study with its timeline of wide scope;
- The literature also comes with some studies in which the authors employ some hybrid systems structured via optimization algorithms and SVM to overcome time series prediction problem. For example, Hu and Zhang employed Support Vector Machines (SVM) and Chaotic Simulated Annealing Algorithm (CSAA) to predict time series [28]. On the other hand, Liu and Yao employed a hybrid system, including PSO and least square SVM, to perform prediction processes [29]. Readers are referred to [30-36] for more details about SVM on prediction problems;
- Ren et al. studied predicting short-term traffic flow via an artificial-intelligence-based approach. In this context, they used a prediction approach including BP Neural Network-Niche Genetic Algorithm (NGA) [37]. In another study on predicting traffic-flow, Ding et al. predicted 'lane-change trajectory by drivers' in urban traffic flow [38]. In the context of predicting urban traffic flow, Yin et al. developed an alternative approach and introduced the Fuzzy-Neural Model (FNM) for predict traffic flow observed in urban street network [39];
- Dunne and Ghosh applied an alternative approach to predict traffic flow (hourly) by considering rainfall effects [40]. In detail, they employed a neuro-wavelet model including Stationary Wavelet Transform (SWT);
- As a three-technique hybrid system formation, Pulido et al. employed Ensemble Neural Networks (ENN)-fuzzy logic (as Type-1-Type-2) and Particle Swarm Optimization (PSO) to perform predictions over Mexican stock exchange [41];
- Huang et al. used Chaos over BP Artificial Neural Networks (CBPANNs) system supported by Genetic Algorithm to perform time series predictions [42]. Briefly, they employed their system to predict wind power. In another study on predicting power and speed of wind, Jiang et al. used a hybrid system based on Support Vector Regression (SVR) model and Cross Correlation (CC) analysis. They

supported their system with the algorithms of Cuckoo Search (CS) and Brainstorm Optimization (BSO) [43] and applied the research to wind turbines running on a wind farm (China);

- Doucoure et al. used multi-resolution analysis along with artificial wavelet neural network model to predict wind speed [44]. Briefly, the authors developed a prediction system that could be used in the context of renewable energy sources. In general, the main purpose of the study was to apply intelligent, alternative management approach to a micro grid system by achieving renewable energy within isolated and grid-connected power systems [44];
- Chandra used a recurrent neural networks system trained by means of the technique of Cooperative Coevolution (CC) to predict chaotic time series [45];
- In their study, Chai and Lim used artificial neural networks and weighted fuzzy membership functions (NEWFM) to perform business cycle predictions [46]. In detail, the authors used some chaotic time series [adjusted leading composite index time series with coordinate embedding (time-delay)] for the NEWFM and predicted the flow of business in this way [46];
- Seo et al. employed artificial neural networks and adaptive neuro-fuzzy inference system to perform prediction operations on water levels tracked daily [47]. The theory of wavelet decomposition theory was also used within this research study;
- Marzban et al. conducted a research for predicting some chaotic time series [48]. In detail, they benefited from differently structured Dynamic Neural Networks (DNN) to predict chaotic systems such as Mackey-Glass and Henon Map;
- Okkan employed a Wavelet Neural Network-based (WNN) approach to perform reservoir in-flow predictions monthly (as the data obtained from the basin of Kemer Dam in Turkey) [49]. In detail, the system used here includes Discrete Wavelet Transform (DWT)-Feed Forward Neural Networks (FFNN), which is supported by the Levenberg-Marquardt optimization algorithm;
- Zhou et al. developed a dendritic neuron model (with dendritic functions and phase space reconstruction) to predict financial time series of Shanghai Stock Exchange Composite Index, Deutscher Aktienindex, DJI Average, and N225 [50];
- In a research study, Wang et al. used Differential Evolution (DE) supported by Teaching-Learning Based Optimization (TLBO) to predict chaotic time series [51];
- Regarding the prediction of time series with chaotic flow, Heydari et al. employed a Takagi Sugeno Kang (TSK) second-order fuzzy system supported by ANFIS (Artificial Neural Fuzzy Inference System) [52];
- Wang et al. studied time series prediction by means of a back propagation-based neural network model trained by Adaptive Differential Evaluation (ADE) [53]. The authors obtained positive, improved results within their study;
- Catalao et al. used a hybrid system in their study to predict short-term electricity prices [54]. In detail, they employed Particle Swarm Optimization (PSO), Wavelet Transform (WT), and ANFIS for their research purposes;
- Kose and Arslan (the authors) used an ANFIS-Vortex Optimization Algorithm (VOA) system to achieve time series prediction [10]. In the study, they focused on chaotic time series and predicted time series of electroencephalogram (EEG) successfully [10];
- Patra et al. employed an adaptive Local Linear (optimized) Radial-Basis Functional Neural Network (LLRBFNN) model to predict financial time series [55]. The system was successful enough in predictions and showed better performances than some other alternative systems reported in the study;
- In another recent study on financial time series prediction, Ravi et al. built a hybrid model including three different solution elements [56]. They designed some three-stage hybrid models by employing chaos for constructing the phase space in Stage 1, Multi-Layer Perceptron (MLP) network model in Stage 2, and particle swarm optimization with multi-objective mechanism (MOPSO) and elitist Non-Dominated Sorting Genetic Algorithm (NDSGA) in Stage 3;
- Méndez et al. used a different approach to predict both short-term and long-term time series [57]. In detail, they built a Modular (structured) Neural Network (MNN) model with two methods of competitive clustering and winner-takes-it-all.

By following the rapid look into the associated literature, it is now more meaningful to focus on the time series prediction approach, built with Artificial Neural Networks and the intelligent optimization technique of cognitive development optimization algorithm in this study. Fundamentals of the techniques and the hybrid system of these techniques will be explained respectively in the next section.

3. Materials and methods

Essential features/functions of the techniques, i.e., artificial neural networks and cognitive development optimization algorithm, and also details regarding the predicting approach, as materials and methods of this study, are as follows.

3.1. *Artificial neural networks*

Since the first introduction of artificial intelligence field, popularity of some general techniques has rapidly increased because they are capable of solving most of problems accurately. Artificial Neural Network (ANN) is one of these techniques, still applied to different kinds of problems related to different fields. ANN is a general model of data processing system, which is inspired from the human brain structure. Generally, a typical ANN model includes some artificial neurons, which are some kind of distributed, parallel calculation elements. By taking some sets of artificial neurons, it is possible to form different ANN models. A typical ANN model can deal with many tasks such as classification, prediction, intelligent optimization, control, pattern recognition, etc. [58-69]. The general structure of a multi-layer ANN is provided in Figure 1 [68].

The first structure of artificial neuron was introduced by McCulloch and Pitts [70]. Besides, there were a remarkable increase in research studies and introduction of different ANN models (i.e., Multi-layer or single perceptron, self-organizing map, ADALINE, adaptive neuro-fuzzy inference system, and probabilistic network) [56-58,60,62,69,71-73].

Simply, the intelligent mechanism of an ANN works as follows. It learns from the environment and responds appropriately to newly encountered situations by means of the learned experiences or information, which is similar to the mechanism of humans' (and even some other living organisms) behavior towards learning new things from experiences and using them for solving new problems (or solving already known problems better) [60-62,69,71-73]. Learning an ANN can be done by three different learning strategies: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning deals with inputs and desired outputs to train ANN, while unsupervised learning uses only inputs, and the reinforcement learning focuses on feedback value(s) received [60-62,69,71-73].

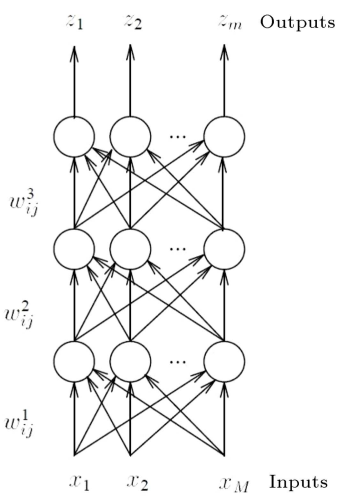

Figure 1. Structure of a multi-layer ANN [68].

Common ANN is structured as follows. The network includes artificial neurons connected to each other over weights. In general, an artificial neuron employs input(s) with weight(s), a function of summation, and an output. Herein, inputs are multiplied by weight values, and the sum of them is used by a transfer function. The output by the transfer function is that of the neuron [69,71-73]. Larger models of ANN can be obtained by using such connections more and more along artificial neurons [69,73].

Nowadays, ANN is still popular in the sense of artificial-intelligence-based applications, as indicated before. At this point, the hybrid system formation is common usage of ANN.

3.2. *Cognitive development optimization algorithm*

Cognitive Development Optimization Algorithm (CoDOA) is one of the recent intelligent optimization algorithms, introduced by Kose and Arslan with simple equations and inspiration from ideas by Piaget for the subject of cognitive development [6,7-9,74]. Cognitive development is known as every person's improvement in terms of knowledge, and Jean Piaget explained that concept. In detail, Piaget indicates that a person's cognitive development is completed through different stages of development: social interaction, maturation, balancing over new concepts, and improvement of cognitive background [7-9,74]. CoDOA is currently used in many studies and run widely in interdisciplinary applications.

Typically, the CoDOA employs the running process of the following stages [6,74]:

- Stage of initialization;
- Stage of socialization;
- Stage of maturation;
- Stage of rationalizing;
- Stage of balancing.

The listed stages are algorithmic ones designed through inspiration from the stages run within cognitive development period. In the CoDOA, designed stages (so, steps) are repeated in a loop until the stopping criteria are met [6,74].

CoDOA with its algorithmic steps is as follows (in the most recent form) [6,74-75]:

- **Step 1 (stage of initialization)**: Define the algorithm parameters (N for particle number, ex for experience of a particle, ir for interactivity rate, *max ir* for max. *ir* (*min ir* is 0.0), r for the rationality rate, and *ml* for maturity limit. Adjust necessary values/parameters for the objective problem.

- **Step 2:** Randomly locate the particles over solution space. Calculate fitness. Upgrade *ir* of the particle with the best fitness so far by a random value:

$$\begin{aligned}&\text{best\_}p\text{\_}ir\text{\_(new)}\\&\quad=\text{best\_}p\text{\_}ir\text{\_(current)}\\&\qquad+(\text{ran.}^{*}\text{best\_}p\text{\_}ir\text{\_(current)}),\end{aligned}\tag{1}$$

also, add 1 to *ex* of that particle.

- **Step 3:** Loop steps.

Step-3.1 (stage of socialization): Subtract 1 from *ex* of the particles with the least mean fitness among all particles (if the aim is minimization). Add 1 to *ex* of the particles with fitness under mean fitness among all particles (if the aim is minimization). Upgrade *ir* of these particles by a random value:

$$\begin{aligned}&p_j\text{\_}ir\text{\_(new)}=p_j\text{\_}ir\text{\_(current)}\\&\quad+(\text{ran.}^{*}p_j\text{\_}ir\text{\_(current)}).\end{aligned}\tag{2}$$

Step 3.2: Upgrade *ir* of all particles by a random value:

$$p_i\text{\_}ir\text{\_(new)}=\text{ran.}^{*}p_i\text{\_}ir\text{\_(current)}.\tag{3}$$

Step 3.3: Refresh positions of the particles (except from the best one so far) by the following equation:

$$\begin{aligned}&p_i\text{\_pos.\_(new)}=p_i\text{\_pos.\_(current)}\\&\quad+(\text{ran.}^{*}(p_i\text{\_}ir\text{\_(current)}^{*}\text{(global}\\&\quad\text{\_best\_pos.}-p_i\text{\_pos.\_(current)}))).\end{aligned}\tag{4}$$

Step 3.4: Calculate fitness. Apply Eq. (1) for the best particle and add 1 to its *ex*.

Step 3.5. (stage of maturation): Upgrade *ir* of all particles having *ex* better than *ml* (less if the aim is minimization, and more if the aim is maximization) by the following equation:

$$\begin{aligned}&p_j\text{\_}ir\text{\_(new)}=p_j\text{\_}ir\text{\_(current)}\\&\qquad+(\text{ran.}^{*}p_j\text{\_}ir\text{\_(current)}).\end{aligned}\tag{5}$$

Apply Eq. (1) for the best particle and add 1 to *ex* of that particle.

Step 3.6 (stage of rationalizing): Upgrade *ir* and positions of the particle with *ex* less than 0 by the following equations:

$$\begin{aligned}&p_j\text{\_}ir\text{\_(new)}=p_j\text{\_}ir\text{\_(current)}\\&\quad+(\text{ran.}^{*}(\text{best\_}p-ir\text{\_(current)}/p_j\\&\quad\text{\_}ir\text{\_(current)})),\end{aligned}\tag{6}$$

$$\begin{aligned}&p_i\text{\_pos.\_(new)}=p_i\text{\_pos.\_(current)}\\&\quad+(\text{ran.}^{*}(p_i\text{\_}ir\text{\_(current)}^{*}\text{(global}\\&\quad\text{\_best\_pos.\_}p_i\text{\_pos.\_(current)}))).\end{aligned}\tag{7}$$

By using Eq. (8), upgrade r times *ir* of the particles with *ex* being at least 0:

$$\begin{aligned}&p_j\text{\_}ir\text{\_(new)}=p_j\text{\_}ir\text{\_(current)}+(\text{ran.}^{*}\text{(best}\\&\quad\text{\_}p\text{\_}ir\text{\_(current)}/p_j\text{\_}ir\text{\_(current)})).\end{aligned}\tag{8}$$

Step 3.7 (stage of balancing): Upgrade *ir* of all particles by Eq. (9):

$$p_i\text{\_}ir\text{\_(new)}=\text{ran.}^{*}p_i\text{\_}ir\text{\_(current)}.\tag{9}$$

Step 3.8: Calculate fitness. Apply Eq. (1) for the best particle and add 1 to its *ex*.

Step 3.9: For big problems, check stability and run in-system optimization if necessary. Turn back to the start of the loop if the stopping criteria have not been met, yet.

- **Step 4:** Find optimum value(s) mean solution-optimum solution.

CoDOA employs simple equations for making it easier to design and apply. Hence, it has been used for the ANN model in this study in order to have an alternative approach to time series prediction and realize the potential of the CoDOA in such problem solutions.

CoDOA is an algorithm/technique that is the subject of a sub-field called swarm intelligence. Included under artificial intelligence, swarm intelligence deals with particle-based systems derived from the idea of behaviors seen among social swarms (i.e., birds, fishes, bees, ants, and even humans) observed in collectivity [69,76]. In association with this sub-field, many different intelligent algorithms/techniques structured especially for optimization problems have been developed in the literature so far. For example, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Cuckoo Search (CS), and Artificial Bee Colony (ABC) are some of today's popular swarm intelligence

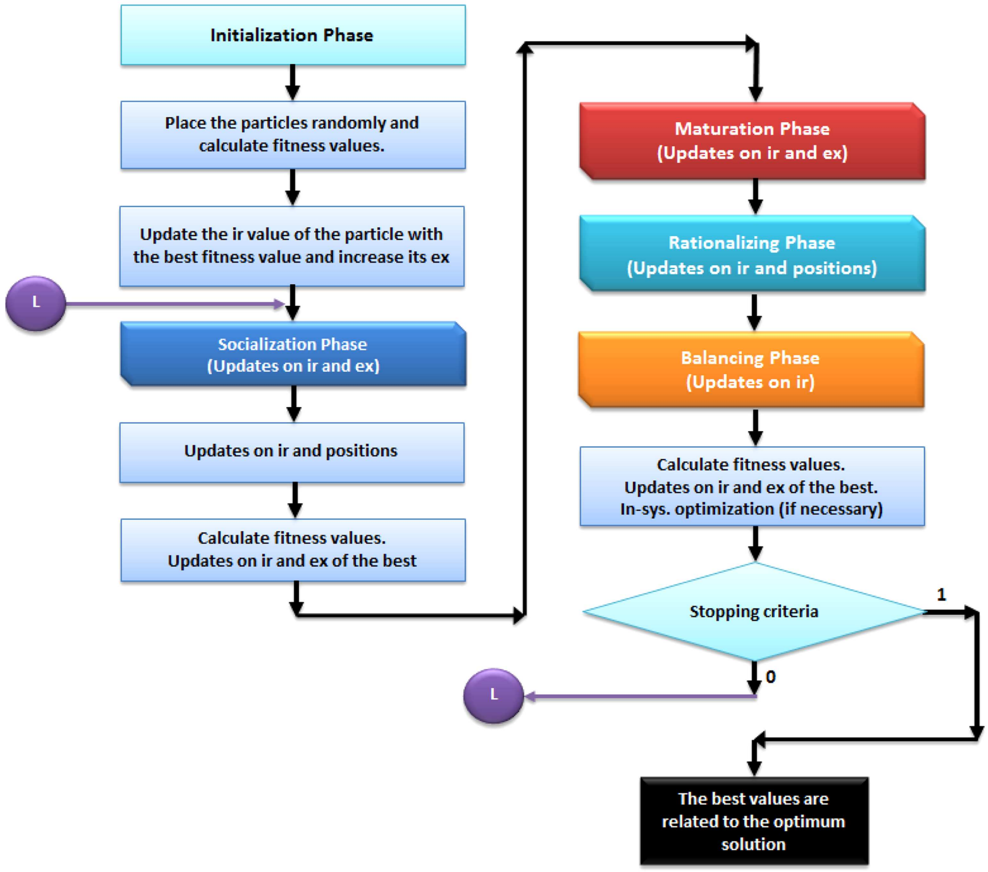

Figure 2. Flow chart of CoDOA.

algorithms/techniques. Readers are referred to [77-84] to get detailed information regarding swarm intelligence and the known algorithms/techniques.

Considering the algorithmic steps, a concise flow chart of the CoDOA appears in Figure 2.

3.3. *Time series prediction approach of ANN supported by CoDOA*

Time series prediction approach designed here is based on two Artificial Intelligence techniques: ANN and CoDOA. The system structured over these techniques is some kind of hybrid one aiming to predict future states of time series. ANN-CoDOA system briefly employs an ANN model trained by the CoDOA. Due to its simplicity, CoDOA has been employed to train the ANN model instead of traditional training approaches, i.e., back-propagation algorithm.

The approach considered here appears not very innovative; however, CoDOA has been employed for the first time to train ANN to predict time series. The novelty/innovation here may deal with the prediction success according to alternative approaches and as a first-time alternative in the associated literature. The followed prediction approach is as follows:

- For training, particles of the CoDOA are associated with weight and bias of the ANN (CoDOA was employed to optimize the weight and bias);
- ANN is trained according to the Mean Square Error criteria by considering differences between obtained output values and desired output values;
- ANN model is Multi-Layer Perceptron (MLP) employing four inputs and one output;
- ANN model briefly tries to predict $x(t+3)$ by using $x(t)$, $x(t-3)$, $x(t-6)$, and $x(t-9)$. It is important to mention here that there are many different combinations of lags used for the prediction approach. However, performed past studies have shown that these lags have been the most appropriate ones. Of course, further investigations are always open for alternative choice of lags.

Figure 3 shows a brief view of the ANN-CoDOA prediction system.

4. Applications of time series prediction

It is an important point to understand the effectiveness level of the designed system in order to understand if it can overcome the problem of prediction and become an alternative in the associated literature. Therefore,

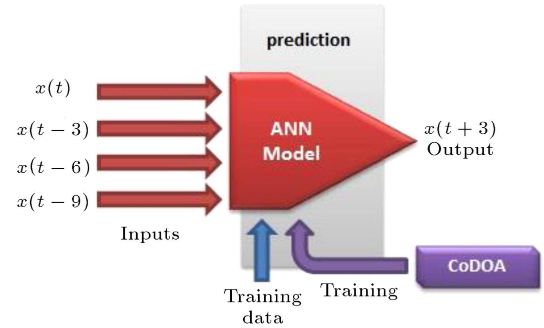

Figure 3. ANN-CoDOA prediction system.

it has been applied to different time series data in order to test its accuracy in prediction. Here, four different CoDOA settings (in the context of parameters) have been used for a single ANN model structure, as explained in the next paragraphs.

4.1. Considered time series

This study obtained time series from the 'DataMarket', which is a Web source for enabling users to reach different kinds of data taken from the real life and visualized over a platform for general use [85]. On choosing time series, greater degree of focus was given to the data of natural dynamics. It is important that all the chosen time series be drawn according to the saved/provided data points for each of them. Considered time series are briefly as follows [85]:

- ANN-CoDOA system has been used firstly to predict the dataset of 'daily maximum temperatures measured in Australia, Melbourne between 1981 and 1990' [85]. From 3650 data rows, a sample of 1106 data rows has been chosen for the prediction. This time series is called as 'Application 1';
- Following the first prediction, the system has been applied to the dataset of 'Application 2' relating to 'winter negative temperature sum (in °C) between 1781 and 1988' [85]. A total of 208 data rows have been chosen for the prediction;
- The third prediction (Application 3) has been done on a dataset for the 'mean annual Nile flow between 1871 and 1970' [85]. A total of 208 data rows have been chosen for the prediction;
- The fourth prediction operation (Application 4) has been performed by using the dataset for the 'Mackey Glass time series corrupted with the noise levels at 20 dB' [85]. Mackey Glass time series is actually a time series showing chaotic flows based on Eq. (10) [86]. For this time series, a total of 700 data rows have been chosen for the prediction.

$$\frac{dx}{dt} = \beta \frac{x_\tau}{1 + x_\tau^n} - \gamma\, x, \qquad \gamma,\, \beta,\, n > 0. \tag{10}$$

4.2. Settings of ANN and CoDOA

As mentioned before, four different CoDOA settings (in the context of parameters) have been used for a single ANN model structure along with prediction applications in this study. By performing prediction applications to each hybrid system designed, the system with the best results has been chosen to take part in the comparison-based evaluation.

Table 1 provides information about essential settings of the ANN model structure used in the prediction applications. On the other hand, different parameter values used for getting four different CoDOA settings are presented in Table 2.

Hybrid systems employing the same ANN and four different CoDOA settings have been applied to the related time series. At this point, 65% of data (rows) for each time series have been used for the 'training' processes; generally, predictions have been observed over the whole time periods by including all the points whether they are associated with the training (65% of the data) or not (remaining/35% of the data). Results obtained with the applications are reported under the next section.

5. Application findings-results

To make sure which ANN-CoDOA solution is more successful in predicting the used time series, prediction errors obtained with four different applications have been compared. In order to make comparisons, errors in prediction performances have been calculated with the Mean Absolute Error (MAE). MAE is presented briefly as follows [87].

Table 1. Settings of ANN used in the prediction applications.

Number of inputs (input layer)	4
ANN input(s)	$x(t)$, $x(t-3)$, $x(t-6)$, and $x(t-9)$ regarding the time series
Number of outputs (output layer)	1
ANN output(s)	$x(t+3)$ regarding the time series
Number of hidden layer(s)	2
Number of neurons at each hidden layer	8 neurons in each hidden layer
Used activation function	Sigmoidal

Table 2. Four different CoDOA settings.

Parameters	Setting 1	Setting 2	Setting 3	Setting 4
Number of particles (N)	50	75	100	150
Iteration (stopping criterion)	1500	3000	6000	7500
Initial interactivity rate (ir)	0.15	0.25	0.50	0.75
Max. interactivity rate (ir)	5.0	5.0	10.0	10.0
Maturity limit (ml)	2	2	3	5
Rationality rate (r)	2	5	2	4

Table 3. MAE obtained with four different ANN-CoDOA systems.

Application (time series)	ANN-CoDOA system including CoDOA with the			
	Setting 1	Setting 2	Setting 3	Setting 4
Application 1	15.5930	14.2297	**11.6652**	13.6155
Application 2	17.2641	16.8513	13.8674	**13.3127**
Application 3	13.2280	12.9501	**11.0182**	12.4883
Application 4	19.6382	18.9203	**18.1366**	20.0841

Let y_i be the observation i and $\hat{y}_i$ be the prediction regarding y_i,

$$\text{MAE} = \text{mean of } \ |e_i|\,, \tag{11}$$

$$\text{where } \ e_i = y_i \ - \ \hat{y}_i. \tag{12}$$

Table 3 presents MAE obtained with four different ANN-CoDOA systems.

Based on Table 3, the ANN-CoDOA system run according to Setting 3 (Table 2) has shown the best performance in three of the four prediction applications. In addition, the result of one remaining application (Application 2) is close enough to the best result obtained. In this context, Figures 4 to 7 show the visual summaries for the prediction applications done for Application 1 to Application 4 by the ANN-CoDOA system including CoDOA with Setting 3. By means of the figures, readers can understand the prediction processes better by comparing both original times series (at the top with blue color) with the predicted time series (at the bottom with red color).

The results obtained here show that the ANN-CoDOA system with Settings 3 of CoDOA is successful enough in predicting the related time series accurately. In addition to the evaluation work, it is also important to compare successful ANN-CoDOA with some alternative systems, including the ANN and other techniques/algorithms of swarm intelligence. In addition, some recent alternative prediction approaches can be compared with the ANN-CoDOA. Details of these evaluation processes are provided under the sixth section.

6. Comparison-based evaluation

In addition to the evaluation of predictions done by ANN-CoDOA, a comparison-based evaluation was performed to realize the effectiveness of the ANN-CoDOA. At this point, the chosen (best) ANN-CoDOA system of former prediction results was compared with alternative hybrid systems, in which the same ANN model structure (Table 1) with changing optimization algorithms as trainers was used. The evaluation was done according to the same criteria under Eqs. (11) and (12).

As for the trainers, Particle Swarm Optimization (PSO) [82,88,89], Cuckoo Search (CS) [90,91], Firefly Algorithm (FA) [92,93], and Bat Algorithm (BA) [94,95] were used for the ANN, and each different system was employed over the same time series considered in this study (the ANN-CoDOA system has been run again during this evaluation in order to check its harmony with the results previously obtained by applications/evaluation).

Table 4 reports MAE obtained over the time series by different ANN-based systems.

Results provided in Table 4 show that ANN-CoDOA is better than other systems for three of four applications. In addition, the result of Application 3 is close to the best value obtained by ANN-CS system. Thus, we can say with confidence that the ANN-CoDOA approach/system is successful and effective enough in predicting time series according to alternative hybrid, ANN-based systems.

Out of the comparison of different ANN-based systems, the approach of ANN-CoDOA was compared

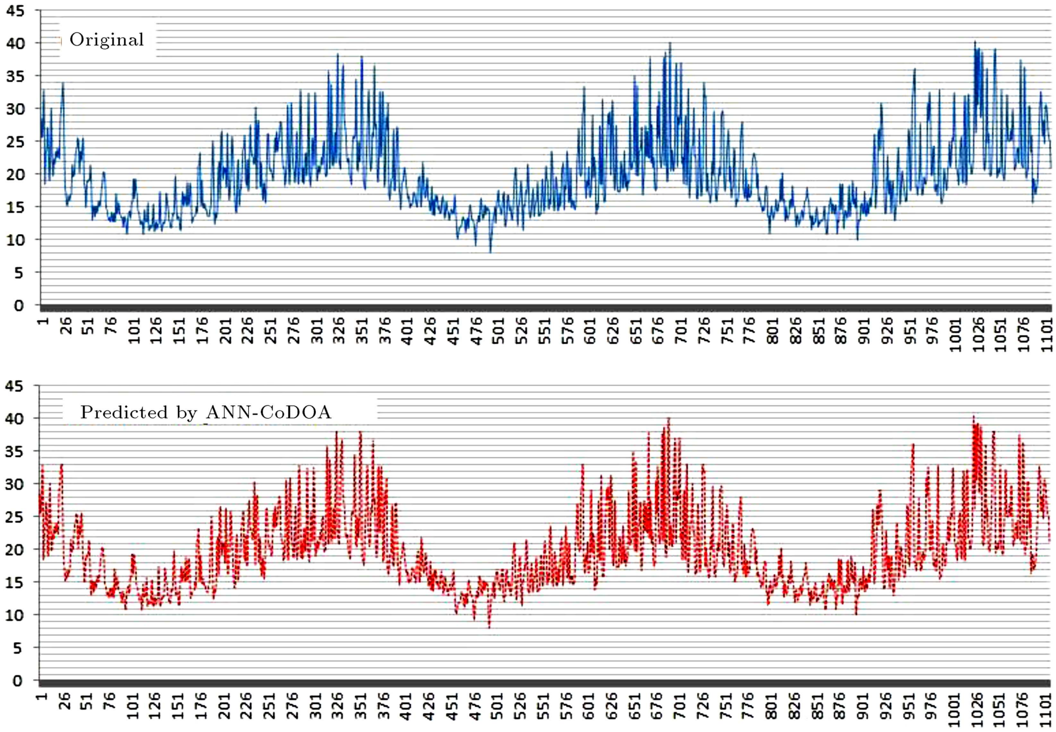

Figure 4. Prediction for Application 1: 'daily maximum temperatures in Australia (Melbourne) between 1981 and 1990'.

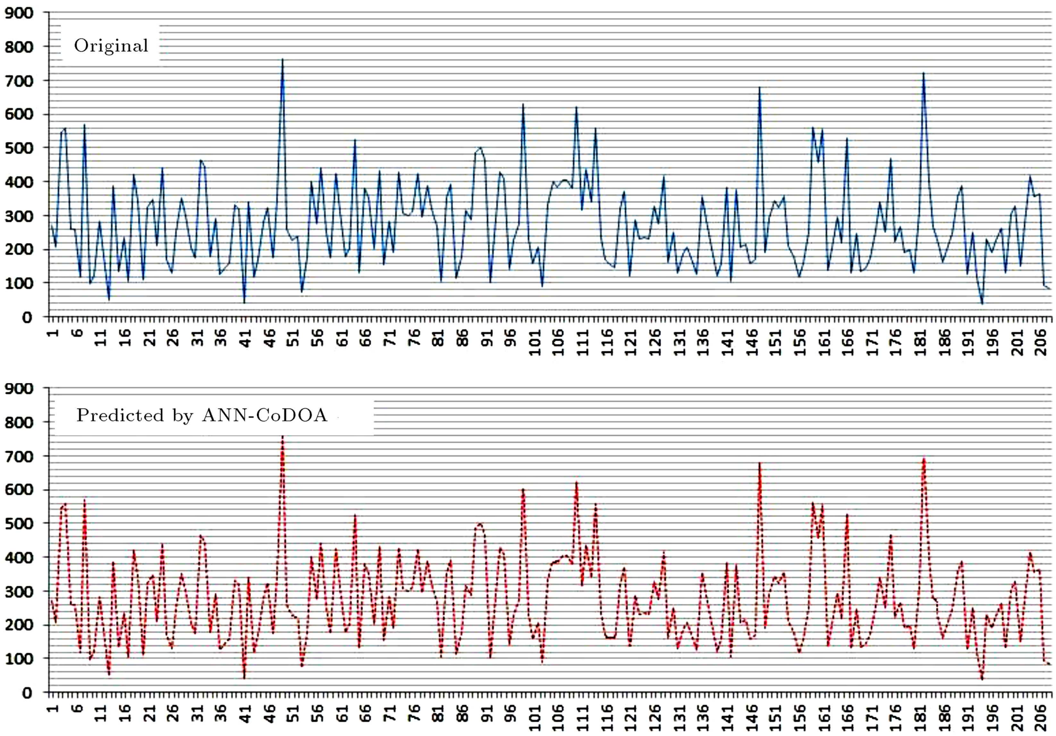

Figure 5. Prediction for Application 2: 'winter negative temperature sum (in deg. °C), between 1781 and 1988'.

with some alternative time series prediction approaches over the four applications. In detail, alternative time series prediction approaches include Dynamic Boltzmann Machine (DyBM) [96], Support Vector Machine (SVM) [97], Hidden Markov Model (HMM) [98], and Bayesian learning on Gaussian process model (BG) [99]. The authors of this study have developed the related approaches again by considering their essential features and functions introduced in the associated studies.

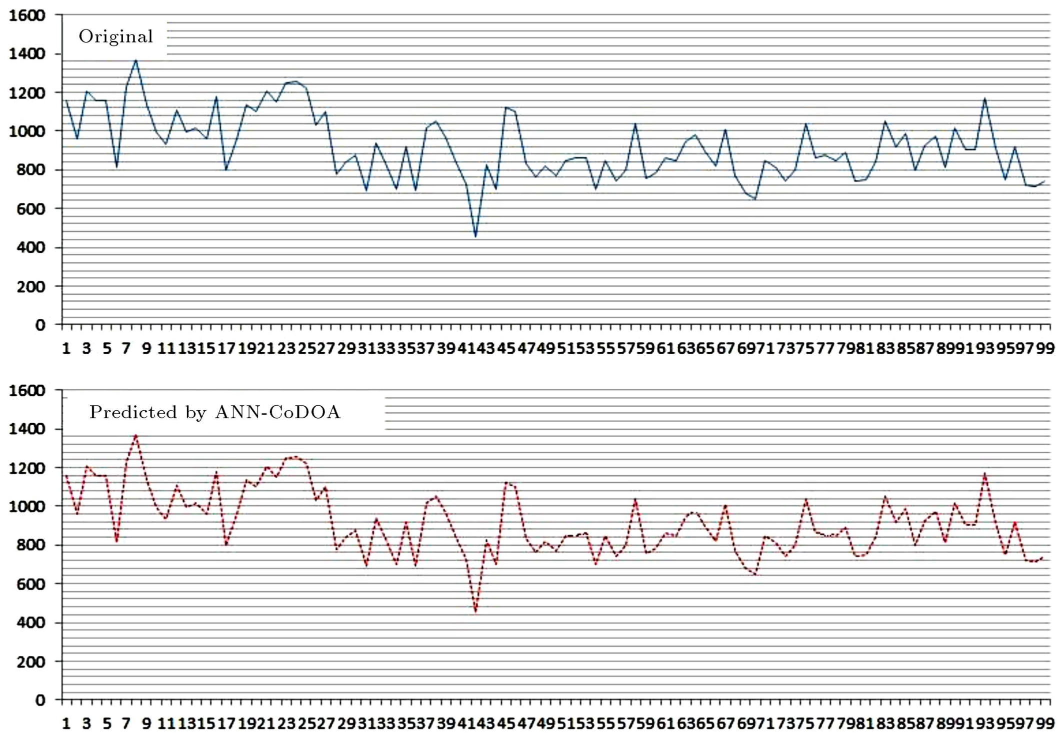

Figure 6. Prediction for Application 3: 'mean annual Nile flow between 1871 and 1970'.

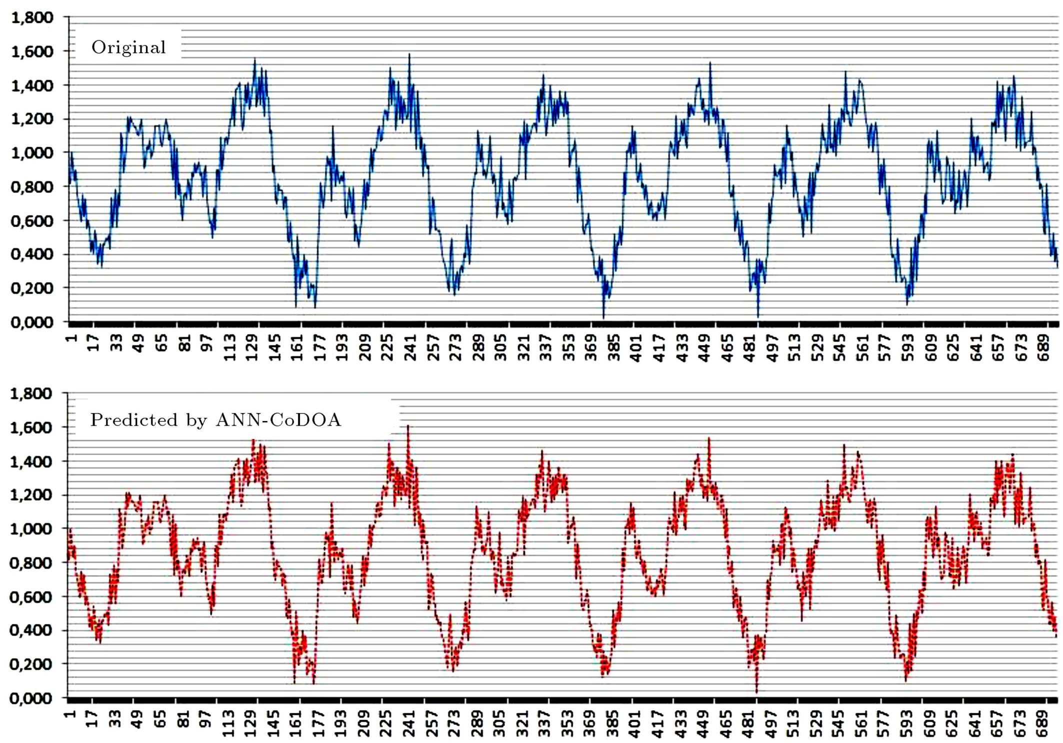

Figure 7. Prediction for Application 4: 'Mackey glass time series corrupted with the noise levels at 20 dB'.

Table 5 presents the MAE obtained for the time series via ANN-CoDOA and some other alternative approaches.

According to Table 5, the ANN-CoDOA is good for two of the performed four applications when it is compared with alternative prediction approaches out of ANN-based models. Considering all applications, it is possible to express that ANN-CoDOA generally performs well and has MAE values close to the better ones, even though it is not the best system to predict

Table 4. MAE obtained over the time series via five different ANN based systems.

Application (time series)	ANN-CoDOA	ANN-PSO	ANN-CS	ANN-FA	ANN-BA
Application 1	**11.5899**	22.1116	12.7588	18.5277	19.0280
Application 2	**14.1811**	26.7781	14.5231	16.8091	14.1159
Application 3	11.8569	21.6025	**11.5894**	19.8201	19.3862
Application 4	**18.0513**	32.0989	19.1633	27.3165	22.6091

Table 5. MAE obtained for the time series via ANN-CoDOA and some other alternative approaches.

Application (time series)	ANN-CoDOA	DyBM [96]	SVM [97]	HMM [98]	BG [99]
Application 1	**11.7218**	13.0855	12.8777	12.0317	14.5901
Application 2	15.2146	20.7098	**13.4511**	15.1708	17.3047
Application 3	**11.8719**	18.6231	11.9972	12.0350	20.1790
Application 4	18.2398	28.5105	19.8071	**17.6208**	22.6311

the objective time series.

7. Derived ideas from the study

Considering the works done here, it is possible to mention some remarkable points briefly that are important for the characteristics of this study and its effects on the associated literature(s):

- Predicting time series is a remarkable issue, especially in Informatics era that requires rapidity in forming information/data, manipulating it, sharing it, and obtaining alternative information/data (i.e., future states, explanations for problems/solutions), which is greatly usable. Hence, the research study done here is an important alternative to similar studies done in the associated literature(s);
- Results obtained here show importance of artificial intelligence and its role in solving real-world problems. It is also important that artificial intelligence is a science building the future because of its interdisciplinary scope;
- Dealing with chaotic time series is an important research way in time series prediction. This study briefly shows the effectiveness of the introduced ANN-CoDOA system/approach (and the role of artificial intelligence and the related techniques) in predicting chaotic time series successfully enough;
- According to the comparison done, the ANN system supported by CoDOA appears with better results than some other alternative systems. Therefore, results obtained here can be accepted as a good contribution to the alternative research studies done so far about time series prediction;
- Because the literature is a dynamic environment, which will always have better candidates, there is an open opportunity for author(s) to continue future studies;
- Predicting natural dynamics is an important point for dealing with real-world problems. Research study done here has been a good solution in this manner;
- Swarm intelligence is an important sub-field of artificial intelligence and employs the potential for the future. Use of CoDOA here and its effective role in shaping the solution are remarkable points for supporting the ideas about swarm intelligence;
- The author(s) think that the future of artificial intelligence is always based on designing appropriate hybrid systems by using the most recent approaches, methods, and techniques. This study is a remarkable example of developing a hybrid artificial intelligence system to solve real-world problems;
- By improving the scope of this research and adding some modular components to the structure of the system, which is able to derive some feedback for people/users (according to meaning of future states of time series), thus forming general artificial intelligence systems, such as Expert Systems [100-102]. Furthermore, the designed hybrid system here may be a small part of bigger, adaptive control systems, which continuously support some real-time processes.

8. Conclusions and future studies

A hybrid time series prediction approach of Artificial Neural Network (ANN) and Cognitive Development Optimization Algorithm (CoDOA) techniques were introduced. As a new single-objective optimization algorithm, CoDOA is an algorithmic inspiration from the ideas by Piaget expressed for cognitive development. The technique of CoDOA was used within ANN model to perform the learning process. Eventually, the usage of both these techniques enabled the authors to obtain an additional solution approach to time series prediction.

ANN-CoDOA system was applied to some time series data for testing its success and effectiveness in time series prediction. At this point, the obtained results showed that the ANN-CoDOA system was able enough to predict time series effectively enough. Additionally, the ANN-CoDOA system was better than some other alternative prediction systems built with ANN and different swarm intelligence techniques/algorithms. Research study done here has also many outputs as briefly expressed under the section devoted to general discussion.

The authors were encouraged by the obtained positive results to continue future developments of the approach and the hybrid system. In the context of future studies, it was planned to apply the system to more difficult, alternative time series data in order to investigate its success in time series prediction. Another planned future study is related to evaluating the prediction performance of the approach/system by changing parameters of both ANN and CoDOA techniques and considering alternative lags chosen from time series as inputs to the ANN and not investigated before. Finally, there will be also some studies on using CoDOA and alternative artificial intelligence techniques (as different from ANN) to investigate performances of different hybrid systems in predicting times series.

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