TIME SERIES PREDICTION WITH A HYBRID SYSTEM FORMED BY ARTIFICIAL NEURAL NETWORK AND COGNITIVE DEVELOPMENT OPTIMIZATION ALGORITHM

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Utku Kose¹ (Corresponding and Lead Author)
Usak University - Computer Sciences Application and Research Center, Usak / Turkey

Academic Affiliation : PhD. Assist. Prof.
Postal Address : Usak University - Computer Sciences Application and Research Center, Karahalli Vocational School, Yeni Mahalle Ali Ihsan Canli Street, No:172, 64700, Karahalli / Usak / Turkey

Phone (GSM) : +90532 590 83 26
Fax : +90276 221 21 53
Academic E-Mail : utku.kose@usak.edu.tr

Ahmet Arslan
Konya Food and Agriculture University - Dept. of Computer Engineering, Konya / Turkey

Academic Affiliation : PhD., Prof. Dr.
Postal Address : Konya Food and Agriculture University - Dept. of Computer Engineering, Dede Korkut Dist. Beysehir Street, No: 9, 42080, Meram / Konya / Turkey

Phone (GSM) : +90535 344 40 99
Fax : +90332 223 54 90
Academic E-Mail : ahmet.arslan@gidatarim.edu.tr

Abstract
Time series prediction is a remarkable research interest, which is widely followed by scientists / researchers. Because many fields include analyzing processes over such time series, different kinds of approaches, methods, and techniques are often employed in order to achieve alternative prediction ways. It seems that Artificial Intelligence oriented solutions have strong potential on providing effective and accurate prediction approaches in even most complicated time series structures. In the sense of the explanations, this study aims to

¹ Utku Kose’s Present Address: Suleyman Demirel University, Dept. of Computer Engineering, Faculty of Engineering, E9 Block, Z-23, West Campus, 32260, Isparta / Turkey (utkukose@sdu.edu.tr)
introduce an alternative, Artificial Intelligence based approach of Artificial Neural Networks, and Cognitive Development Optimization Algorithm, a recent intelligent optimization technique introduced by the authors. Here, it has been aimed to predict different kinds of time series, by using the introduced system / approach. In this way it has been possible to discuss about application potential of the hybrid system and report findings related to its success on prediction. The authors believe that the study has been a good chance to support the literature with an alternative solution approach and see potential of a newly developed, Artificial Intelligence oriented optimization algorithm on different applications.

**Keywords: time series prediction; time series analysis; artificial neural networks; cognitive development optimization algorithm (CoDOA); artificial intelligence**

1. INTRODUCTION

Artificial intelligence is an important research field, which has been applied in problems of almost all fields of the real-life. Nowadays, it can be seen that need for intelligent solution approaches have been a vital factor to overcome real-world based problems effectively. Because of its high success potential, Artificial Intelligence has an outstanding popularity leading to intensely 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 on 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 seems that data series taken along a time is among attractive research interests. According to the literature, the term time series is defined as a flow of data saved over a time past, which can be along a week, monthly, and even yearly [1-4]. It has been figured out that time series may enable us to understand many aspects on the subject or event from which a time series data is obtained. Because of this, time series analysis has become a remarkable application way and finally, popularity of applications on ‘predicting the future flow of time series’ has increased in time. Prediction of the future flow of time series is the analysis of previous states of a time series for obtaining ideas about the flow in the future. Background of this approach benefits from the idea of that the past patterns of a time series will be observed in the future [1].
The approach of time series prediction has relations with events or problems from almost all fields of our life. Here it is good to express that future states related to changes in financial values, sales, productions or even behaviors of natural dynamics can be predicted, thanks to the time series prediction. Thus, it is possible for scientist, researchers, or experts within a field to have idea about future states and finally reach to decisions for new applications or problem solutions. Eventually, predicting the time series 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.

If the background of time series prediction is examined, it can be seen that previously introduced, traditional approaches or methods had failures for more complicated, new form of time series [5]. Because of this issue, there have been remarkable efforts to introduce and employ alternative solutions to overcome prediction problem on difficult - challenging time series. In this way, it was noticed that the usage of Artificial Intelligence can overcome the related issues and furthermore, give many advantages of ‘intelligent mechanisms’ to solve real-world based problems. In time, this field has become a popular application interest when time series prediction is important in the context of an encountered problem. Today, development of Artificial Intelligence based hybrid systems is one of the most attractive application ways and because of this we can see many examples of time series prediction applications done via hybrid systems structured with more than one method, or technique.

Purpose of this study is to employ an alternative, Artificial Intelligence oriented approach for time series prediction. The study focuses on a hybrid system by Artificial Neural Networks, and Cognitive Development Optimization Algorithm, which is a technique of optimization introduced recently. 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 as by Piaget [6-9]. Within this study, it was aimed to predict different kinds of time series, by using the introduced system / approach. In this way it has been possible to discuss about application potential of the hybrid system and report findings related to its success on prediction. Also, the authors believe that this study is a good chance to support the literature with an alternative solution approach and see potential of a newly developed, Artificial Intelligence oriented optimization algorithm on different applications.
Motivation and the main contributions here can be expressed briefly as:

- The study deals with a remarkable research interest as ‘time series prediction’.
- The study tries to employ an alternative approach for the literature of time series prediction.
- The study employs a novel prediction approach by using Cognitive Development Optimization Algorithm as the first time for training model(s) of Artificial Neural Network to perform prediction of time series.
- The study aims to deal with predicting advanced time series showing chaotic characteristics.
- The study generally proves that hybrid Artificial Intelligence techniques are effective enough on predicting time series, even they are chaotic. In this way, more practical and effective sides of Artificial Intelligence techniques according to traditional approaches are understood by readers.

Regarding the study subject, following content is structured as: The second section is about the background for application of Artificial Intelligence oriented techniques in time series prediction. After that, the third section explains materials and methods used within the study. In this way, readers are enabled to have 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 done for predicting some time series (the fourth section). Next, the fifth section reports the results obtained with the (chosen) ANN-CoDOA system. After the fifth section, a comparison based evaluation process done with the system and some other alternative ones is explained under the sixth section. After the seventh section devoted to a brief discussion, the paper finally ends by focusing on conclusions and discussing 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 on such scientific studies, especially newly introduced approaches, methods, and techniques are immediately employed in time series prediction studies, in order test success of these ‘new comers’. It is also important that Artificial Intelligence seems a strong factor in providing successful studies on time series prediction. Because this study also focuses on employment of an Artificial Intelligence technique, it will be better to take a brief look at to the recent literature in the
intersection of Artificial Intelligence and time series prediction. By also considering and extending the previous background review done by the authors in [10]:

- Gan et al., and also Wong et al., have performed some prediction oriented research studies by using widely used Artificial Neural Networks (ANN) technique [11, 12].
- In a research, Gentili et al. have 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 have used a Radial Basis Function (RBF) for prediction processes [14].
- In their study, Wu et al. developed a prediction approach especially for chaotic time series [15]. Briefly, they have predicted time series of Mackey-Glass, gas furnace (Box-Jenkins), and EEG. At this point, the prediction processes have been done thanks to Iterated Extended Kalman Filter supported by Single Multiplicative Neuron Model.
- About using Single Multiplicative Neuron (SMN) for time series prediction purposes, Yadav et al. has a study published in 2007 [16]. On the other hand, Zhao and Yang have performed a study similar to [14], but they have used PSO – SMN to predict time series of Mackey-Glass, gas furnace (Box-Jenkins), and EEG [17].
- Yao and Liu run 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]. As similar, Zhao and Yang are other researchers to use Particle Swarm Optimization for prediction purposes [20].
- The literature contains also many different studies that are based on employment of Ant Colony Optimization (ACO) to predict systems with chaotic flows [5, 21-24].
- Yeh has introduced a model, which provides a parameter-free simplified swarm optimization for training of Artificial Neural Network (ANN)[25]. In the study, the model was run over different time series (including also EEG time series).
- In their study, Nourani and Andalib have employed a Wavelet Least Square Support Vector Machine system (WLSSVM) to predict hydrological time series [26]. As aiming to predict Suspended Sediment Load (SSL) as monthly for the Aji-Chay River, the authors have performed a comparison based approach by including also some other approaches like 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 review about recent approaches for predicting the time series via specific Machine Learning techniques [27]. By providing a research study aimed to predict general time series, this study is different from the alternatives aiming to chaotic time series only. It is an important background study with its time-year and 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 have employed a hybrid system including PSO and Least Square SVM to perform prediction processes [29]. Readers are referred to also [30-36] to have more idea about using SVM on prediction problems.

- Ren et al. achieved a study on predicting short-term traffic-flow via an Artificial Intelligence-based approach. In this context, they have used a prediction approach including BP Neural Network – Niche Genetic Algorithm (NGA) [37]. In another study on predicting traffic-flow, Ding et al. have predicted ‘lane-change trajectory by drivers’ in urban traffic flow [38]. In the context of predicting urban traffic-flow, also Yin et al. have developed an alternative approach and introduced the Fuzzy-Neural Model (FNM) for prediction purposes on traffic-flow observed in urban street network [39].

- Dunne and Ghosh have performed an alternative approach to predict traffic-flow (hourly) by taking effects by rainfall into consideration [40]. In detail, they have 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 predictions on time series [42]. Briefly, they have employed their system to predict wind power. In another study on predicting wind power – speed, Jiang et al. have used a hybrid system based on Support Vector Regression (SVR) model, and Cross Correlation (CC) analysis. They have supported their system with the algorithms of Cuckoo Search (CS), and Brainstorm Optimization (BSO) [43] and applied the research to wind turbines running at a wind farm (China).
In a study by Doucoure et al. multi-resolution analysis along with Artificial Wavelet Neural Network model were used to predict wind speed [44]. Briefly, the authors have developed a prediction system that can be used in the context of renewable energy sources. As general, main purpose of the study was stated as getting intelligent, alternative management approach for a micro grid system achieving use of renewable energy within isolated and grid-connected power systems [44].

Chandra has used a Recurrent Neural Networks system trained thanks to the technique of Cooperative Coevolution (CC) to predict chaotic time series [45].

In their study, Chai and Lim have used Artificial Neural Networks and weighted fuzzy membership functions (NEWFM) to perform some predictions on business cycle [46]. In detail, the authors have used some chaotic time series [adjusted leading composite index time series with of 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 also Adaptive Neuro-Fuzzy Inference System to perform prediction operations on water levels tracked daily [47]. The theory of Wavelet Decomposition theory has also been used within this research study.

Marzban et al. have provided a research for predicting some chaotic time series [48]. In detail, they benefited from differently structured Dynamic Neural Networks (DNN) to predict chaotic systems like Mackey-Glass and Henon Map.

Okkan has employed a Wavelet Neural Network (WNN) based approach to perform predictions for monthly reservoir in-flow (as the data obtained from the basin of Kemer Dam in Turkey) [49]. In detail, the system used here included Discrete Wavelet Transform (DWT) – Feed Forward Neural Networks (FFNN), which is supported by the Levenberg-Marquardt optimization algorithm.

Zhou et al. have developed a Dendritic Neuron Model (with dendritic functions and phase space reconstruction) for predictions over 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 perform some prediction operations on chaotic time series [51].
Regarding predicting 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. provided a study on predicting time series thanks to a Back Propagation oriented Neural Network model trained by Adaptive Differential Evaluation (ADE) [53]. The authors have obtained positive, improved results within their study.

Catalao et al. have used a hybrid system in their study to predict short term electricity prices [54]. In detail, they have 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 applications [10]. In the study, they have focused 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 perform some prediction studies over financial time series [55]. The system has been successful enough on predictions and shown 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 have designed some three-stage hybrid models 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 for both short-term and long-term time series prediction [57]. In detail, they have built a Modular (structured) Neural Network (MNN) model with two methods of competitive clustering and winner-takes-all.

Following the rapid look at to 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 within the next section.
3. MATERIALS AND METHODS

As materials and methods of this study, essential features / functions of the techniques: Artificial Neural Networks and Cognitive Development Optimization Algorithm, and also details regarding the predicting approach within 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 have been capable of solving most of problems accurately. Artificial Neural Network (ANN) is one of these techniques, which are still applied in 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 like classification, predicting, intelligent optimization, control, pattern recognition…etc [58-69]. General structure of a multi-layer ANN is provided in Figure 1 [68].

First structure of artificial neuron has introduced by McCulloch and Pitts [70]. Next to that, there were a remarkable increase in research studies and introduce of different ANN models (i.e. Multi-layer, Single Perceptron, Self-Organize Map, ADALINE, Adaptive Neuro-Fuzzy, Probabilistic Network) [56-58, 60, 62, 69, 71-73].

Simply, intelligent working mechanism of an ANN is as follows: It learns from the environments and gives appropriate responses to newly encountered situations, thanks to the learned experiences – information, which is like the mechanism seen as humans’ (and even some other living organisms’) behavior on learning new things from experiences and using them on solving new problems (or solving better already known ones) [60-62, 69, 71-73]. Learning of an ANN can be oriented on three different learning strategies as: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning deals with using 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].
Common ANN is structured as follows: The network includes artificial neurons connected to each other over weights. As general, an artificial neuron employs input(s) having weight(s), a function of summation and finally an output. Here, inputs are multiplied with the weight values, and sum of them is used by a transfer function. The output by the transfer function is output of the neuron [69, 71-73]. Thanks to such connections more and more along artificial neurons, bigger models of ANN can be obtained [69, 73].

Nowadays, ANN is still popular in the sense of Artificial Intelligence based applications, as it was indicated before. At this point, hybrid system formation is a common usage of ANN.

3.2. Cognitive Development Optimization Algorithm

Cognitive Development Optimization Algorithm (CoDOA) is one of recent intelligent optimization algorithms, as introduced by Kose and Arslan with simple equations and an inspiration from the ideas by Piaget for the subject of cognitive development [6, 7-9, 74]. Cognitive development is known as a process in which each person comes through and this concept was explained by Jean Piaget. In detail, Piaget indicates that a person’s cognitive development is completed through different stages of development called as like social interaction, maturation, balancing over new concepts and improving cognitive background [7-9, 74]. CoDOA is currently in also additional improvement studies and run widely within multidisciplinary applications.

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

- Stage of Initialization,
- Stage of Socialization,
- Stage of Maturation,
- Stage of Rationalizing,
- Stage of Balancing.

The listed stages are algorithmic steps designed by inspiring from the stages thought within cognitive development period. In the CoDOA, designed stages (so, steps) are repeated in a loop until the stopping criteria is 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, $maxir$ for max. $ir$ ($minir$ is 0.0), $r$ for the rationality rate, $ml$ 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 via a random value:
  \[ best_p\_ir\_\_{\text{new}} = best_p\_ir\_\_{\text{current}} + (\text{ran.} \times best_p\_ir\_\_{\text{current}}) \]  
  Also, add 1 to the $ex$ of that particle.

- **Step-3:** Loop steps:
  - **Step-3.1. (Stage of Socialization):** Subtract 1 from $ex$ of the particles having fitness at least (if the aim is minimization) mean fitness among all particles. Add 1 to $ex$ of the particles having fitness under (if the aim is minimization) mean fitness among all particles. Upgrade $ir$ of these particles via a random value:
    \[ p\_j\_ir\_\_{\text{new}} = p\_j\_ir\_\_{\text{current}} + (\text{ran.} \times p\_j\_ir\_\_{\text{current}}) \]  
  - **Step-3.2:** Upgrade $ir$ of all particles via a random value:
    \[ p\_i\_ir\_\_{\text{new}} = \text{ran.} \times p\_i\_ir\_\_{\text{current}} \]  
  - **Step-3.3:** Refresh positions of the particles (except from the best one so far) by following equation:
    \[ p\_i\_pos.\_\_{\text{new}} = p\_i\_pos.\_\_{\text{current}} + (\text{ran.} \times (p\_i\_ir\_\_{\text{current}} \times (\text{global\_best\_pos.} - p\_i\_pos.\_\_{\text{current}}))) \]  
  - **Step-3.4:** Calculate fitness. Apply Equation 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, more if the aim is maximization), via following equation:
    \[ p\_j\_ir\_\_{\text{new}} = p\_j\_ir\_\_{\text{current}} + (\text{ran.} \times (p\_j\_ir\_\_{\text{current}} / \text{best}_p\_ir\_\_{\text{current}}))) \]  
    Apply Equation 1 for the best particle and add 1 to the $ex$ of that particle.
  - **Step-3.6. (Stage of Rationalizing):** Upgrade $ir$ and positions of the particle with $ex$ less than 0, via following equations:
    \[ p\_j\_ir\_\_{\text{new}} = p\_j\_ir\_\_{\text{current}} + (\text{ran.} \times (\text{best}_p\_ir\_\_{\text{current}} / p\_j\_ir\_\_{\text{current}}))) \]  
    \[ p\_i\_pos.\_\_{\text{new}} = p\_i\_pos.\_\_{\text{current}} + (\text{ran.} \times (p\_i\_ir\_\_{\text{current}} \times (\text{global\_best\_pos.} - p\_i\_pos.\_\_{\text{current}})))) \]  
    By using the Equation 8, upgrade $r$ times the $ir$ of the particles with $ex$ at least 0:
    \[ p\_j\_ir\_\_{\text{new}} = p\_j\_ir\_\_{\text{current}} + (\text{ran.} \times (\text{best}_p\_ir\_\_{\text{current}} / p\_j\_ir\_\_{\text{current}}))) \]  
  - **Step-3.7. (Stage of Balancing):** Upgrade $ir$ of all particles via Equation 9:
\[ p_{ir\_new} = \text{ran.} \times p_{ir\_current} \] (9)

- **Step-3.8.** Calculate fitness. Apply Equation 1 for the best particle and add 1 to its \( ex \).
- **Step-3.9.** For especially big problems, check stability and run in-system optimization if necessary. Turn back to the start of the loop if the stopping criteria is not met, yet.
- **Step-4:** Optimum value(s) mean solution – optimum solution.

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

CoDOA is an algorithm – technique, which is the subject of a sub-field called as Swarm Intelligence. Included under Artificial Intelligence, Swarm Intelligence deals with particle based systems coming from the idea of behaviors seen among social swarms (i.e. birds, fishes, bees, ants, and even humans) observed as collectively occurring [69, 76]. As associated with this sub-field, many different intelligent algorithms – techniques structured for especially 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 algorithms – techniques. Readers are referred to [77-84] to get detailed information regarding Swarm Intelligence and the known algorithms – techniques.

Considering the algorithmic steps, brief flow chart of the CoDOA is as like 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, which is trained by the CoDOA. Because of its simplicity, CoDOA has been employed to train the ANN model rather than using traditional training approaches i.e. Back-Propagation Algorithm.

The approach considered here seems not very innovative but it is first time to employ CoDOA for training ANN for time series prediction. The novelty / innovation here may deal with the
prediction success according to alternative approaches and as a first-time alternative for the associated literature. The prediction approach followed is as:

- For training, particles of the CoDOA are associated with weight and bias of the ANN (CoDOA was employed for the optimizing the weight and the 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 \( x(t - 9) \) respectively. It is important to mention here that there are many different combinations of lags used for the prediction approach. But performed past studies have shown that these lags have been the most appropriate ones. Of course, further investigations are always open for alternative choose of lags.

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

4. APPLICATIONS ON TIME SERIES PREDICTION

It is an important point to understand effectiveness level of the designed system in order to have idea about if it can overcome the problem of prediction and become an alternative for the associated literature. So, it has been applied on different time series data, in order to test its accurateness on 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

Time series considered in this study are 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, more focus was given for data from natural dynamics. It is important that all the chosen time series are 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 firstly used for performing prediction on the data set related to ‘daily maximum temperatures measured in Australia, Melbourne between
1981 and 1990’ [85]. From 3650 data row, sample of 1106 data row has been chosen for the prediction. This time series is called as ‘Application – 1’.

- Following to the first prediction, the system has been applied on the data set of ‘Application – 2’ as related to ‘winter negative temperature sum (in deg. C), between 1781 and 1988’ [85]. A total of 208 data row has been for the prediction.

- The third prediction (‘Application – 3’) has been done on a data set for the ‘mean annual Nile flow, between 1871 and 1970’ [85]. A total of 208 data row has been for the prediction.

- The fourth prediction operation (‘Application – 4’) has been performed by using the data set for the ‘Mackey Glass time series corrupted with the noise levels at 20dB’ [85]. Mackey Glass time series is actually a time series showing chaotic flows as based on the Equation 10 [86]. For this time series, a total of 700 data row has been for the prediction.

\[
\frac{dx}{dt} = \beta \frac{x_t - \gamma x}{1 + x_t^n}, \quad \gamma, \beta, n > 0, \quad (10)
\]

4.2. Settings of ANN and CoDOA

As it was expressed before, four different CoDOA settings (in the context of parameters) have been used for a single ANN model structure along prediction applications in this study. After performing prediction applications with each hybrid system designed, the system with the best results has been chosen to be taken 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 were applied to the related time series. At this point, 65% of data (rows) for each time series have been used for the ‘training’ processes and generally, predictions were observed over the whole time periods by including all the points even they are associated (65% of the data) or not associated.
(remaining / 35% of the data) with the training. Results obtained with the applications are reported under the next section.

5. APPLICATION FINDINGS – RESULTS

For being sure about which ANN-CoDOA solution is more successful at predicting the used time series, prediction errors obtained with four different applications were compared. In order to make comparisons, errors in prediction performances were calculated with the Mean Absolute Error (MAE). MAE is briefly as [87]:

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

$$MAE = \text{mean of } |e_i|$$

where $e_i = y_i - \hat{y}_i$  

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

Table 3 figures out that the ANN-CoDOA system run according to the Setting – 3 (Table 2) has shown the best performance along three of four prediction applications. Also result in one remaining application (Application – 2) is close enough to the best result obtained. In this context, Figure 4 to 7 show the visual summaries for the prediction applications done for the Application – 1 to the Application – 4 by the ANN-CoDOA system including CoDOA with the Setting – 3. Over the figures, readers can have idea about the prediction processes by comparing both original times series (on top with blue color) and the predicted time series (on bottom with red color).

The results obtained here show that the ANN-CoDOA system with the Settings – 3 of CoDOA is successful enough at predicting the related time series accurately. In addition to that 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. Also, some recent, alternative prediction approaches can be compared with the ANN-CoDOA. Details on these evaluation processes are provided under the sixth section.

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6. COMPARISON BASED EVALUATION

In addition to the evaluation of predictions done by ANN-CoDOA, a comparison based evaluation has been performed to have more idea about 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 same ANN model structure (Table 1) with changing optimization algorithms as trainers was used. The evaluation was done according to the same criteria under Equation 11 and 12.

As 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 has been employed over the same time series considered in this study (The ANN-CoDOA system has been run again during this evaluation in order to see its harmony with the results previously done applications / evaluation).

MAE obtained over the time series via different ANN based systems are reported in Table 4.

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

Out of the comparison of different ANN based system, the approach of ANN-CoDOA has been compared with also some alternative time series prediction approaches, over the four applications. In detail, alternative time series prediction approaches were 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 related approaches have been developed again by the authors of this study by considering their essential features and functions introduced in the associated studies.

Table 5 presents the MAE obtained for the time series via ANN-CoDOA and some other alternative approaches.
According to the Table 5, we can indicate that the ANN-CoDOA is good at 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-enough performances and has MAE values near to the better ones even it is not the best system predicted the objective time series.

7. DERIVED IDEAS FROM THE STUDY

In the light of the works done here, it is possible to briefly talk about some remarkable points, which are important for the characteristic of this study and its effects on the associated literature(s):

- Predicting time series is a remarkable issue for especially in Informatics Era, which requires rapidness 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. Because of that, research done here is an important alternative for similar studies done in the associated literature(s).

- Results obtained here show importance of Artificial Intelligence and its role on solving real-world based problems. It is also important that Artificial Intelligence is a science building the future because of its multidisciplinary 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 so 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 seems having better results than some other alternative systems. So, 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 the author(s) to continue future studies.

- Predicting especially natural dynamics is an important point for dealing with real-world based problems. Research study done here has been a good solution in this manner.

- Swarm Intelligence is an important sub-field of Artificial Intelligence and it employs a potential for the future. Use of CoDOA here and its effective role on shaping the solution are remarkable point for supporting the ideas about Swarm Intelligence.
The author(s) think that the future of Artificial Intelligence will be always based on designing appropriate hybrid systems by using most recent approaches, methods, and techniques. This study is a remarkable example of developing a hybrid Artificial Intelligence system to solve real-world based problems.

Next things on improving scope of this research and so structure of the system may be adding some modular components, which are able to derive some feedback for people / users (according to meaning of future states of time series) and forming general Artificial Intelligence systems like 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

With this study, a hybrid time series prediction approach of Artificial Neural Network (ANN) and Cognitive Development Optimization Algorithm (CoDOA) techniques has been 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, usage of both these techniques has enabled the authors to obtain an additional solution approach regarding time series prediction.

ANN-CoDOA system has been applied in some time series data for testing its success and effectiveness on time series prediction. At this point, obtained results figure out that the ANN-CoDOA system is able enough to predict time series effectively enough. Additionally, the ANN-CoDOA system is 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.

It is important that the authors have been encouraged by the obtained positive results to continue to future developments on the approach and the hybrid system. In the context of future studies, it is planned to apply the system on more difficult, alternative time series data in order to see more about its success on time series prediction. Another future study planned is related to evaluating the prediction performance of the approach / system by changing parameters of both ANN and CoDOA techniques more and also 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 on alternative Artificial Intelligence techniques (as different from ANN), to see performances of different hybrid systems on predicting times series.

REFERENCES


Utku KOSE: Utku KOSE is a Lecturer in Usak University, Turkey and also the Director of the Computer Sciences Application and Research Center at the same university. He received the B.S. degree in 2008 from computer education of Gazi University, Turkey as a faculty valedictorian and next, he had the M.S. degree in 2010 from Afyon Kocatepe University,
Turkey. Now, he continues D.S. / Ph. D. at Selcuk University, Turkey in the field of computer engineering. Between 2009 and 2011, he has worked as a Research Assistant in Afyon Kocatepe University. Following, he has also worked as a Lecturer and Vocational School - Vice Director in Afyon Kocatepe University between 2011 and 2012. Currently, he His research interest includes artificial intelligence, the chaos theory, distance education, e-learning, computer education, and computer science.

Ahmet ARSLAN: Ahmet ARSLAN is a Professor in Department of Computer Engineering at Selcuk University, Turkey. He received the B.S. degree in 1984 from electrical – electronic engineering of Firat University, Turkey. After that, he received M.S. degree in 1987 from the same field of the Firat University, Turkey and completed D.S. / Ph. D. at Bilkent University, Turkey in the field of computer engineering. Between 1992 and 1999, he has worked as an Assistant Professor in Firat University. Following, he has also worked as Associated Professor at the Firat University, until 2005. He served as Head of Department of Computer Engineering (2004-2012), Director of Computer Research and Application Center (2002-2012), and Dean of Faculty of Technology (2011-2013) in Selcuk University, Turkey. His research interest includes data mining, machine learning, computer learning, and computer assisted designing.

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**Figure 5.** Prediction for the Application – 2: ‘winter negative temperature sum (in deg. C), between 1781 and 1988’. ([color figure](#))

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# Tables

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

<table>
<thead>
<tr>
<th>Number of inputs (input layer)</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN input(s)</td>
<td><em>x(t), x(t - 3), x(t - 6), and x(t - 9) regarding the time series</em></td>
</tr>
<tr>
<td>Number of outputs (output layer)</td>
<td>1</td>
</tr>
<tr>
<td>ANN output(s)</td>
<td><em>x(t + 3) regarding the time series</em></td>
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<td>Number of hidden layer(s)</td>
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<tr>
<td>Number of neurons at each hidden layer</td>
<td>8 neurons at each hidden layer</td>
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<tr>
<td>Used activation function</td>
<td>Sigmoidal</td>
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**Table 2.** Four different CoDOA settings.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Setting – 1</th>
<th>Setting – 2</th>
<th>Setting – 3</th>
<th>Setting – 4</th>
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</thead>
<tbody>
<tr>
<td>Number of particles (<em>N</em>)</td>
<td>50</td>
<td>75</td>
<td>100</td>
<td>150</td>
</tr>
<tr>
<td>Iteration (stopping criteria)</td>
<td>1500</td>
<td>3000</td>
<td>6000</td>
<td>7500</td>
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<tr>
<td>Initial interactivity rate (<em>ir</em>)</td>
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<td>0.25</td>
<td>0.50</td>
<td>0.75</td>
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<td>Max. interactivity rate (<em>ir</em>)</td>
<td>5.0</td>
<td>5.0</td>
<td>10.0</td>
<td>10.0</td>
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<tr>
<td>Maturity limit (<em>ml</em>)</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Rationality rate (<em>r</em>)</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>4</td>
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</table>

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

<table>
<thead>
<tr>
<th>Application (Time Series)</th>
<th>ANN-CoDOA system including CoDOA with the;</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Setting – 1</td>
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<tr>
<td>Application – 1</td>
<td>15.5930</td>
</tr>
<tr>
<td>Application – 2</td>
<td>17.2641</td>
</tr>
<tr>
<td>Application – 3</td>
<td>13.2280</td>
</tr>
<tr>
<td>Application – 4</td>
<td>19.6382</td>
</tr>
</tbody>
</table>
Table 4. MAE obtained over the time series via five different ANN based systems.

<table>
<thead>
<tr>
<th>Application (Time Series)</th>
<th>ANN-CoDOA</th>
<th>ANN-PSO</th>
<th>ANN-CS</th>
<th>ANN-FA</th>
<th>ANN-BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Application – 1</td>
<td>11.5899</td>
<td>22.1116</td>
<td>12.7588</td>
<td>18.5277</td>
<td>19.0280</td>
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<tr>
<td>Application – 4</td>
<td>18.0513</td>
<td>32.0989</td>
<td>19.1633</td>
<td>27.3165</td>
<td>22.6091</td>
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</table>

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

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Application – 2</td>
<td>15.2146</td>
<td>20.7098</td>
<td>13.4511</td>
<td>15.1708</td>
<td>17.3047</td>
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<tr>
<td>Application – 3</td>
<td>11.8719</td>
<td>18.6231</td>
<td>11.9972</td>
<td>12.0350</td>
<td>20.1790</td>
</tr>
<tr>
<td>Application – 4</td>
<td>18.2398</td>
<td>28.5105</td>
<td>19.8071</td>
<td>17.6208</td>
<td>22.6311</td>
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