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RESEARCH ARTICLE

A Novel QoS Prediction Model for Web Services Based on an Adaptive Neuro-Fuzzy Inference System Using COOT Optimization

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ABSTRACT The adoption of adaptive neuro-fuzzy inference systems (ANFIS) and metaheuristic optimization approaches has been widely observed in recent research. Even so, integrating these methods improves the model's capability to solve complex problems. A novel enhanced prediction method based on COOT bird optimization was developed for selecting the optimal parameters of ANFIS in the current study. This method combines COOT optimization with ANFIS to model the quality of service (QoS) characteristics of web services by using the adaptive neuro-fuzzy inference system COOT (ANFIS-COOT). In this instance, the quality of the web service (QWS) dataset was obtained from the GitHub database, which consists of 120 web services data, and then evaluated using the presented model on the dataset for estimating response time and throughput of web services. As significant evidence of ANFIS-COOT's efficiency, the similar QWS data set is analyzed using four different prediction models: ANFIS, ANFIS-Beetle Antennae Search (ANFIS-BAS), ANFIS-Reptile Search Algorithm (ANFIS-RSA), and ANFIS-Snake Optimizer (ANFIS-SO). Moreover, the exploratory study used statistical benchmarks such as root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and determination coefficient (R^2) to emphasize the accuracy of the proposed model. Based on analysis results, the presented model achieved optimal values of RMSE (59.7473), MAE (15.8531), MAPE (0.0705), and R^2 of 96.32 %, as well as RMSE (1.335), MAE (1.1255), MAPE (0.1818), and R^2 of 97.12 % for modelling response time and throughput of web services, compared to other models. Eventually, this report demonstrates the viability of the ANFIS-COOT while tackling a complex problem and improving predictive performance.

INDEX TERMS Web service, QoS attributes, ANFIS, COOT optimization, prediction models.

I. INTRODUCTION

As time goes by, service-oriented architecture, called SOA, has been extensively embraced by organizations including academia, business, industries, the biomedical field, and many others. There have been several platforms that have assisted in making SOA easier to use, including SOAP (Southern object access protocol), WSDL (web services description language), and UDDI (universal description discovery and integration) [1]. Although it's not specific to one device or network, it's still a systematized resource for sharing information across large, disparate databases. As a result, shareholders have provided numerous web services (WSs) with equivalent functionality [2]. Web services are often part of a software system that uses the Internet to communicate from one electronic system to another [3].

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Because there are so many web-enabled devices in a network, web services offer phenomenal opportunities for users to retrieve and broadcast data via usual agreements [4]. Therefore, it is a dynamic web application that often provides a number of features that could be accessed using Extensible Markup Language (XML) communications over the internet [5]. The web services are designed to handle the issues with patented technology network device protocols while providing a limited degree of flexibility to various industry sectors, allowing a web service to respond to requests precisely and rapidly [6]. Web services can be further split into two categories: RESTful web services and SOAP web services. These are widely used in a variety of fields, primarily in digital academics, administration, government, electronic commerce, and the digital world [7]. As well, WSs are used in many real-world applications today, including films, publications, TV shows, novels, online ticket bookings, etc. It provides a variety of commended services and features in addition to filling the gap between individuals and the internet [8].

There are now multiple functionally identical web services available in many sectors due to the proliferation of web services [9]. The quality of service, accessibility, cost, and frequency of use seem to be specific requirements for every user. The web service that one user finds effective over a long period of time may not be as useful to another user [10]. Accordingly, a response concerning a web service from a frequent user is more precise than feedback from a user who employs a web server a few times or infrequently [11]. Additionally, the ubiquity of web services across several domains and the difficulty in resolving data imbalances have made examining the quality of web services an important factor in service selection [12]. This leads to programmers and users assessing the quality of service (QoS) features and examining their correlations with their metrics to assess service quality [13]. The main goal of QoS, which has emerged as one of the most significant ways to differentiate web services, is to discover their non-functional characteristics [13]. There are two major categories of QoS characteristics for online services: user-independent and user-dependent. These attributes have a wide range of values for different people because of unpredictable web access and different user situations [12]. The QoS requirements for non-functional web service characteristics, such as throughput and response time, are regarded as important determinants of the standard for online services with equivalent functionality [14].

Over the years in the computing world, myriad QoS-oriented techniques have been developed to address a wide range of problems such as choosing a cloud service selection [15], improved service setup [16], service identification [17], ensuring the reliability of services [18], and other difficulties. There have been multiple techniques employed to forecast QoS attributes using different techniques. In early research, L. Shao et al. [19] implemented a collaborative filtering method for the prediction of QoS attributes of web services. According to Chen *et al.'s* [20] analysis of several collaborative filtering QoS models, the latent factor predictor is frequently used due to its great adaptability and precision. Additionally, data characteristic awareness enhances the latent factor approach for extremely precise QoS attribute estimations presented in D. Wu et al. [21]. To model web services' QoS volatility, A. Amin et al. [22] developed forecasting models autoregressive integrated moving average (ARIMA) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH). For web services, Q. Tao et al. [4] built a trustworthy QoS prediction model by improving the traditional Universal Description, Discovery, and Integration (UDDI) first before introducing a new online service registration and identification system. In the prior work, probabilistic models were presented by S. Hwang et al. [23] for determining the QoS attributes of atomic and composite web services. Another work by H. Muslim et al. [24] offered a web service strategy for simulating QoS features called Service Relevance Aware Prediction, or S-RAP. In particular, cloud computing, web services, and healthcare can all benefit from the methods provided. For a sophisticated forecast, the decision-maker must emphasize a specific combination of data in a service-oriented environment where QoS variables are extensively disseminated over the distributed network [25]. Prior studies on machine learning (ML) methods have proved that ML-designed predictive models can describe a sophisticated relationship between input and output variables [26]. In general, many derivative-based optimization techniques, such as the gradient descent method, root mean squared propagation (RMSProp), steepest gradient descent, and Adam, are extensively employed to address sophisticated problems [27]. Existing studies evidence that machine learning algorithms have a concern with convergence to the global solution. Any non-linear complicated problem is frequently identified, categorized, and ordered into a polynomial, non-deterministic polynomial, non-deterministic polynomial problem complete, and non-deterministic polynomial hard problems based on space and time [28]. Numerous metaheuristic optimizations have been introduced that draw inspiration from nature and work quickly to find the optimal solution for complex problems. Earlier, a range of nature-inspired optimization techniques, such as genetic algorithms [29], particle swarm optimization [30], ant colony optimization [31], cat swarm optimization [32], beetle antennae search [33], and many others, have been exploited to overcome computational complexity problems.

According to the evidence in the scientific literature, integrating machine learning approaches with metaheuristic optimization delivers the optimum modeling and accuracy rate in the fastest way possible. Many techniques have been proposed for addressing a wide range of problems, including An article by R. Boutaba et al. [34] that addressed the application of machine learning techniques for QoS prediction in automatic networking. For the objective of assessing the medical quality of ultrasound video streaming, I. Rehman et al. [35] constructed a multi-layer perceptron neural network. The QoS constraints were simulated using a variety of soft computing techniques by W. Hussain et al. [36] to produce a feasible SLA. The two-phase neural network developed by W. Wang et al. [37] is comprised of a feed-forward neural network and a probabilistic neural network to recognize untrustworthy web services based on QoS attributes. Applying a variety of Artificial Neural Network (ANN) learning techniques by S. Kumar et al. [41] to assess the missing QoS values in light of past data, it was discovered that an ANN model with Bayesian-Regularization generated the most accurate predictions. In Internet of Things (IoT) systems, G. White et al. [42] devised a Long Short Term Memory (LSTM) based QoS prediction model. To identify the QoS characteristics of web services, D. Chen et al. [43] built recurrent-based neural networks that include an LSTM network layer. The study reported by N. Anithadevi and M. Sundarambal [3] illustrated that neuro-fuzzy logic is implemented to categorize and recognize unreliable web services. The ideal channels for video streaming in mobile Adhoc networks were determined by K. Venkatesh et al. [44] using an ANFIS-based forecasting model based on QoS parameters. W. Hussain et al. [45] introduced a QoS prediction model by integrating ANFIS with the ordering weighted average technique in SLA. Moreover, Ghafouri et al. [49] conducted a thorough review of QoS prediction models classified as memory-based methods, model-based methods, and Collaborative Filtering (CF) approaches paired with different approaches. Zheng et al. [50] performed an analysis on simulating the QoS of web services using the collaborative filtering technique.

A. INNOVATIONS

In an examination of existing techniques, the techniques presented in the literature failed to estimate the QoS parameters for web services and deliver user-reliable predictions. So the study employed metaheuristic optimizations in an adaptive neuro-fuzzy inference system to select the optimal parameters and to address the limitations of previously discussed approaches. The distinctive innovations of the paper are as follows:

- The article presents a novel hybrid forecasting system that makes use of the COOT (Coot bird) optimizer and the ANFIS approach for the best QoS prediction.
- In contrast to previous research, the current study utilized COOT optimization to determine the most effective ANFIS parameters to enhance ANFIS's performance.
- Conventional QoS modeling techniques such as ANN, ANFIS, LSTM, and CF are difficult to forecast when there are significant fluctuations in the data set.
- The presented methodology emphasizes addressing this problem by identifying the best ANFIS-COOT model parameters.
- By contrast, ANFIS-COOT can produce the requisite QoS values very quickly and accurately.

To meet the stated objectives, the article integrates the COOT optimization algorithm into an adaptive neuro-fuzzy inference system (ANFIS) to build an ANFIS-COOT predictor for modeling QoS values for web services. A comparison of the proposed model with existing approaches is undertaken as a means to emphasize how accurate the model is at predicting QoS values for the QWS dataset collected from 365 web services and the dataset collected from GitHub. Error analysis is conducted using a benchmark of RMSE, MAE, MAPE, and determination coefficient (R^2).The developed model delivered ideal values of RMSE (59.7473), MAE (15.8531), MAPE (0.0705), and R^2 (0.9632), as well as RMSE (1.335), MAE (1.1255), MAPE (0.1818), and R^2 (0.9712) for estimating response time and throughput, respectively. Eventually, it was discovered to employ a novel prediction system named ANFIS-COOT to simulate QoS features and estimate accurate and reliable QoS attributes for web services.

The rest of this article is arranged as follows. Section II addressed the quality of service data collection, the adaptive neuro-fuzzy inference system, and COOT optimization. The improved prediction model ANFIS-COOT for modelling QoS features is presented in Section III. Section IV provides the results of the proposed model. The conclusion of the intended work is provided in Section V.

II. MATERIALS AND METHODS

A. QUALITY OF WEB SERVICES (QWS) DATA

The study made use of QoS data from 365 distinct web services that were gathered from famous publicly available datasets known as the GitHub databases platform (https://qwsdata.github.io) [46]. In this study, 120 web services and their QoS data are taken into account for evaluating QoS features. The QWS dataset for analyzing web services includes inputs such as accessibility, reliability, compliance, best practices, and latency, and outputs such as response time and throughput. The following points highlight the significance of these qualities: First, accessibility refers to a web service's reachability or availability. In general, users are dissuaded from using online services with accessibility issues because these services may put off service requests, resulting in users getting chaotic as it relates to the work that the web service is supposed to do. Also, the chance that a service will respond to a query with an adequate answer within the specified response time is known as reliability. Similarly, compliance is the result of collaboration between the web service and the customer. The included best practices should not be interpreted as rigid rules but rather as ideas for how to create and enhance such services. Latency refers to the time span between getting the service request and responding to it. Eventually, response time is the span of time from submitting the inquiry to getting a response, and throughput is the number of web service requests processed in a certain period of time. Furthermore, the ANFIS system exploited 70 % of the data for developing the training model, with the remaining 30 % being used to evaluate the trained model's performance.

B. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The architecture of the adaptive neuro-fuzzy inference system (ANFIS) demonstrates that it comprises neural networks and fuzzy logic across five layers. L. Zadeh conceptualized fuzzy logic and fuzzy inference systems in 1965. Their purpose is to address difficulties that arise when dealing with decision-making processes that involve data that is ambiguous, unreliable, or inconsistent. Warren McCulloch and Walter Pitts devised neural networks in 1943, drawing inspiration from the operation of brain neurons. This concept, often referred to as "connectionism," involves the use of interconnected neurons to simulate intelligence. Then, ANFIS has been widely used in research to emulate a variety of global issues and has grown tremendously due to its potential to combine fuzzy logic features with artificial neural networks [55], [56], [57], [58]. In 1993, Jang et al. [54] developed the hybrid neural network named ANFIS by combining fuzzy logic and neural networks. Since it was an advanced and powerful artificial neural network that combined fuzzy logic and IF-THEN rule implementation to create connections between inputs and outputs as well as learning capabilities. Fig. 1 shows the schematic representation of ANFIS, which has two inputs and an output with five layers. The following is a summary of the descriptions of the layers. The first

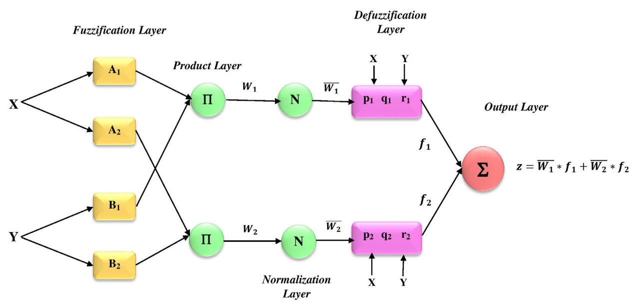


FIGURE 1. Architecture of ANFIS.

layer nodes are adaptable with an activation function known as the membership function. Utilizing input values and the membership function, fuzzy clusters [38], [39], [40] are created. With the use of sigmoid membership functions, the inputs in this layer were modified into fuzzy inputs. The following is the mathematical expression for generating fuzzy inputs in layer 1:

$$O_j^{l_1} = \mu_{A_j}(y_1), \quad j = 1, 2 \tag{1}$$

Here,

$$Sigmoid(y_j, a, c) = \mu(y_j) = \frac{1}{1 + e^{-a(y_j - c)}} \quad j = 1, 2, 3, \ldots \tag{2}$$

In layer 2, the output is computed by multiplying the incoming signals. Usually, the imprecise AND operation is used to calculate the firing strengths of nodes based on the membership values of the previous layer. The values of w_j are the product of the membership values, as indicated through equation (3).

$$O_j^{l_2} = w_j = \mu_{A_j}(y_1) \times \mu_{B_{j-2}}(y_2) \tag{3}$$

In layer 3, each node is static and employs the output of layer 2's firing strengths to determine the normalized firing strengths for each rule. The normalized output for the rule is obtained using equation (4) as the ratio of the current firing strength to the total firing strength.

$$O_j^{l_3} = \overline{w_j} = \frac{w_j}{\sum_{j=1}^{2} w_j} \tag{4}$$

In general, layer 4 is referred to as the defuzzification layer with adaptive nodes. A linear equation is used to compute the output of this layer by multiplying the output of the preceding layer by the following:

$$O_j^{l_4} = \overline{w_j} f_j = \overline{w_j}(p_j y_1 + q_j y_2 + r_j) \tag{5}$$

where f_j denotes the linear equation comprised of parameters p_j, q_j and r_j.

The final step is to determine the ANFIS output, which is expressed as the sum of all previous node outputs in equation (6).

$$O^{l_5} = \sum_j \overline{w_j} f_j = \frac{\sum_j w_j f_j}{\sum_j w_j} \tag{6}$$

C. COOT ALGORITHM

One of the most widely recognized metaheuristic optimization algorithms is named the COOT algorithm [47], which emulates the behavior and movement of coot birds on the surface of the water as they search for food or a particular location. Coots move at an inclination towards the direction of movement and emerge with ease from what is, mainly surf scoters, a region of resistance. The coot swarm activity on water comprises three movements: a random movement of activity, a synchronized (combined) movement, and a chain movement. The entire flock of coot birds is focused on the objective (food), while a few coots are functioning as leaders by moving in front of the group. The four distinct aquatic behaviors of coots on the water are listed below.

- Random movement.
- Chain movement.
- Changing the position following the group leaders.
- The leaders should direct the group to the perfect location.

Usually, in all metaheuristic optimization algorithms, the process commences with the stochastic population. As illustrated below, equation (7) is used to generate an initial random population.

$$CootPos(j) = r(1, d).*(X_{max} - X_{min}) + X_{min} \tag{7}$$

where $CootPos(j)$ represents the position of the coot, d refers to the dimension, X_{max} is the maximum and X_{min} is the minimum of search space.

$$\begin{aligned} X_{\max} &= [x_{\max_1}, x_{\max_2}, x_{\max_3}, \ldots, x_{\max_d}] \\ X_{\min} &= [x_{\min_1}, x_{\min_2}, x_{\min_3}, \ldots, x_{\min_d}] \end{aligned} \tag{8}$$

Following the development of the initial solutions, the fitness value of each coot is determined, and the NLC number of group leaders is then selected at random. The following is a description of the mathematical model of the four movements of coots on the surface of the water.

1) RANDOM MOVEMENT

The random movement is initiated using equation (9) in the search domain and carrying out the movement randomly.

$$Q = r(1, d).*(X_{\max} - X_{\min}) + X_{\min} \tag{9}$$

The search domain is probed by coot movements in various locations. Such movement will allow the optimization technique to avoid the local minima when it gets trapped in the local minima. Following that, equation (10) is used to determine the coot's new position.

$$CootPos(j) = CootPos(j) + A_1 \times R_2 \times (Q - CootPos(j)) \tag{10}$$

where R_2 belongs to [0, 1], A_1 is estimated by equation (11).

$$A_1 = 1 - t \times \left(\frac{1}{T}\right) \tag{11}$$

Here, t and T represent the current and total number of iterations.

2) CHAIN MOVEMENT

According to the existing research [48], the average location of two coots is determined via chain movement. The average locations of two coots were utilized to update the coot's position during chain movement, and this was done using equation (12).

$$CootPos(j) = \frac{1}{2}(CootPos(j-1) + CootPos(j)) \tag{12}$$

where $CootPos(j)$ is j^{th} the coot position and $CootPos(j-1)$ is the preceding coot of $CootPos(j)$.

3) CHANGING THE POSITION FOLLOWING THE GROUP LEADERS

Coots form groups, with a few of them leading the way. The remaining coots may move closer or adjust their position following the leaders of the group. The average position of coot leaders, which leads to rapid convergence, should be taken into account while updating the coots' position. Equation (13) is used to update the movement of coots during this phase.

$$K = 1 + (j * MOD\ NLC) \tag{13}$$

where j is known as the index number of the current coot, NLC is the number of leader coots, and K represents the index number of the leader coot.

During this step, the i^{th} coot should update its position depending on the leading coots K. The updated version is written as follows:

$$\begin{aligned} CootPos(j) = {} & LCP(k) + (2 \times R_1 \times \cos(2R\pi)) \\ & \times (LCP(k) - CootPos(j)) \end{aligned} \tag{14}$$

where $CootPos(j)$ denotes the current position of the coot, $LCP(k)$ is the elected leader, $R_1 \in [0, 1]$, $\pi = 3.14$, and $R \in [-1, 1]$.

4) THE LEADERS SHOULD DIRECT THE GROUP TO THE PERFECT LOCATION

To make the coot group move towards the optimal position, the leader coots should update their position towards the objective. In this sense, equation (15) is developed to achieve the final goal by updating the leader-coot positions.

$$LCP(j) = \begin{cases} B_1 \times R_3 \times \cos(2R\pi) \times (Gbest - LCP(j)) & \\ \quad + Gbest & R_4 < 0.5 \\ B_1 \times R_3 \times \cos(2R\pi) \times (Gbest - LCP(j)) & \\ \quad - Gbest & R_4 \geq 0.5 \end{cases} \tag{15}$$

where $Gbest$ represents the best position of the coot, R_3 and R_4 is between [0, 1], $\pi = 3.14$, R is in the domain $[-1, 1]$ and B_1 is determined by using equation (16).

$$B_1 = 2 - t \times \left(\frac{1}{T}\right) \tag{16}$$

where t and T denote the current and total number of iterations.

The pseudo-code of the COOT optimization algorithm is illustrated as follows:

III. ANFIS-COOT QOS PREDICTION MODEL

The proposed method aims to make web service access more efficient by choosing the best QoS constraints. This method identified the best ANFIS parameter values to improve ANFIS' ability to forecast quality of service aspects like response time and throughput. The COOT method, a novel evolutionary optimization that has a substantial influence on the initial problem convergence, is incorporated into ANFIS to generate the global optimum. So, the improvement of the ANFIS framework and its parametric settings for any given problem is commonly referred to as training. Similar to the existing ANFIS, which is recognized as an enhanced predictor for simulating QoS parameters by examining the input variables such as accessibility, reliability, compliance,

Algorithm 1 Pseudo Code of COOT Optimization Algorithm

Create the random coot population by using equations (7) and (8).
Set up the parameters $P = 0.5$, NLC (number of leader coots), $Ncoot$ (number of coots), $Ncoot = Npop - NLC$.
Pick the leader coots at random from the group of coots.
Compute the fitness values of coots and leader coots.
Identify the optimal coot or leader as the global minimum.
while $t \leq T$ **do**
  Apply equations (11) and (16) to estimate A_1 and B_1 parameters.
  if $rand < P$ **then**
    R, R_1 and R_3 are arbitrary vectors along the problem's dimension.
  else
    R, R_1 and R_3 are random numbers.
  end if
  for $i = 1 : number\ of\ coots$ **do**
    Obtain the value by using equation (13).
    if $r > 0.5$ **then**
      Find out the new position of the coot by equation (14).
    else
      if $r \leq 0.5$ **then**
        Find out the new position of the coot by equation (12).
      else
        Find out the new position of the coot by equation (10).
      end if
    end if
    Determine the fitness value of the coot.
    if $(fitness\ of\ coot < fitness\ of\ leader\ (k))$ **then**
      $Temp = leader(k)$; $leader(k) = coot$; $coot = Temp$
    end if
  end for
  for number of leaders **do**
    if $R_4 < 0.5$ **then**
      Find out the new position of leader coot by rule 1 of equation (15).
    else
      Find out the new position of leader coot by rule 2 of equation (15).
    end if
    if $(fitness\ of\ the\ leader\ coot < Gbest)$ **then**
      $Temp = Gbest$; $Gbest = leader$; $leader = Temp$; (Update the global optimum)
    end if
  end for
  $t = t + 1$
end while

best practices and latency to derive the QoS output values such as response time and throughput for selecting the best online services. Fig. 2 shows the evolution of the optimized design. The developed model, which comprised five layers and is shown in Figure 1, was built on the conventional ANFIS. Moreover, the Web service QoS data is frequently split into two sets, with the first set, which makes up about 70% of the dataset, being used to train the ANFIS to determine the optimum parameters. The second set, which accounts for 30% of the dataset, is used to ascertain the most effective pattern using ANFIS-COOT. The input parameters are presented by layer 1 and predicted results are produced by layer 5. The combination of premise and consequent parameters is estimated by the COOT algorithm in the ANFIS training. Following that, the ANFIS parameters are trained using the COOT method. Also, the COOT algorithm's best solution is then delivered back to the ANFIS, where it is used for the test phase. It is the sum of the antecedent and conclusion parameters that determines the length of a solution. In the ensuing step, the model is trained by passing through the training input data and its performance is checked using the mean square error (MSE), which is a widely used effectiveness metric and is described in equation (17). A COOT algorithm has been implemented to identify the appropriate parameters because the effectiveness of ANFIS relies on the initial parameters. The reported configurations for the combined model ANFIS-COOT are listed in Table 1. By doing so, prediction accuracy will increase. In the training phase, the network that equates to the minimum error is produced. The performance is then verified by the testing dataset.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(O_j - E_j\right)^2 \tag{17}$$

where O_j and E_j represent the observed and estimated values.

TABLE 1. Parameters used in ANFIS-COOT model.

Parameters	Values
X_{max}	100
X_{min}	-100
Population size	32
Minimum error	10^{-5}
Total number of iterations	200

IV. RESULTS

The objective of this study is to develop an augmented machine learning model for simulating the time series data of QoS features of web services to select the most optimal service. In this sense, the article attempts to construct an augmented prediction model by combining an adaptive neuro-fuzzy inference system with metaheuristic optimizations. The best prediction model will be developed based on its parameters. As a consequence, ANFIS encrypts

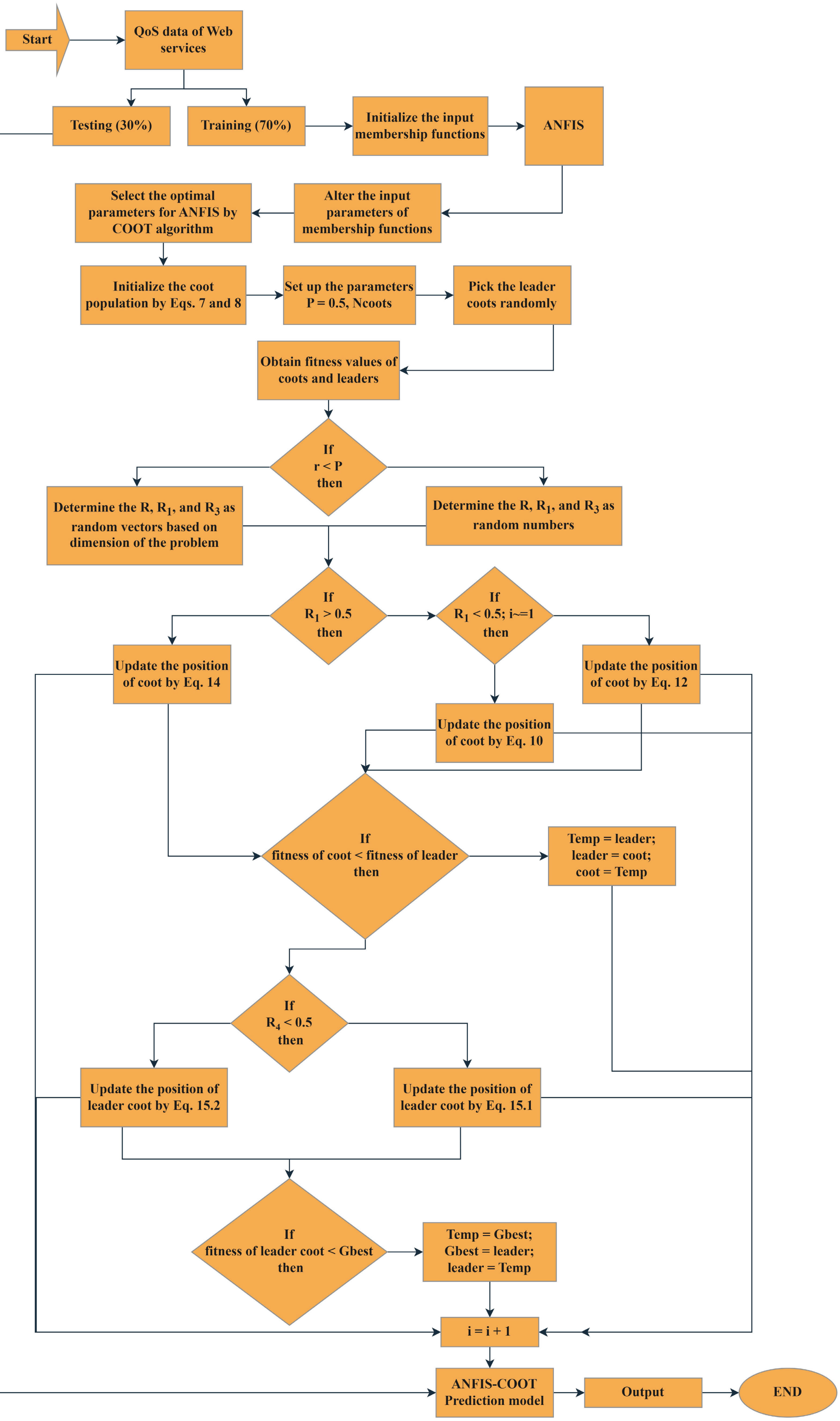


FIGURE 2. A framework of ANFIS-COOT.

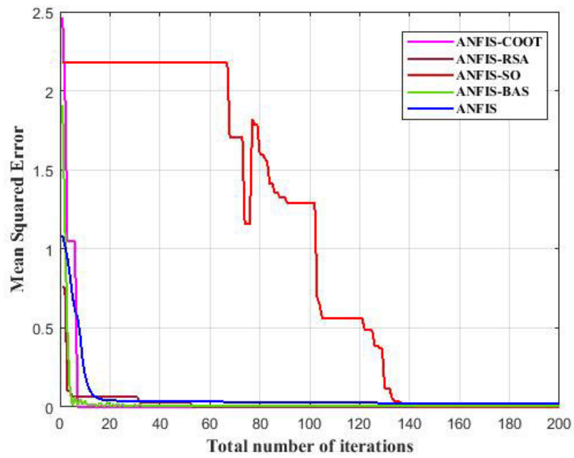


FIGURE 3. Convergence rate of different models for response time parameter.

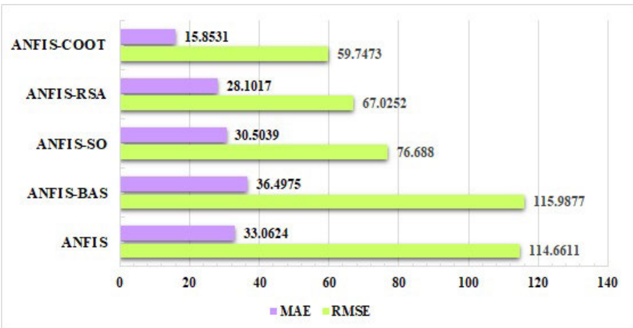


FIGURE 4. Comparative analysis of RMSE and MAE for response time parameter.

the well-known COOT algorithm optimizer to choose the system's ideal parameters. Based on the database of GitHub, an augmented model named ANFIS-COOT was evaluated over 200 iterations on the QWS dataset. To assess the reliability and effectiveness of the presented ANFIS-COOT model, the following statistical benchmarks have been investigated, which include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Determination Coefficient (R^2). The following is a mathematical description of statistical benchmarks:

RMSE

RMSE, a measurement of the difference between actual and estimated values, is perhaps the most commonly used statistic for measuring prediction dependability, which is represented in equation 18.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N} \left(O_j - E_j\right)^2}{N}} \tag{18}$$

MAE

The mean absolute error, or MAE, is the relative difference between actual and predicted outcomes. This strategy is

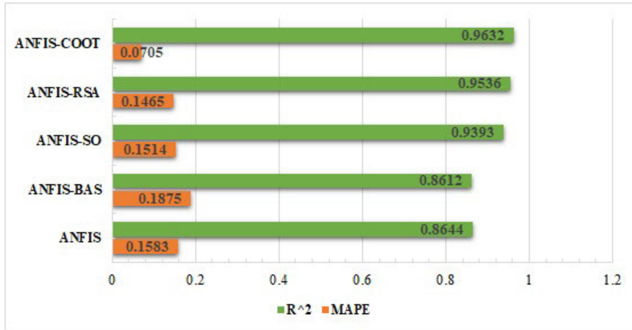


FIGURE 5. Comparative analysis of MAPE and R^2 for response time parameter.

illustrated in equation 19.

$$MAE = \frac{1}{N} \sum_{j=1}^{N} \left|O_j - E_j\right| \tag{19}$$

MAPE

In time series predictions, MAPE is frequently used to measure predicting accuracy. Equation 20 shows the formula for calculating MAPE.

$$MAPE = \frac{1}{N} \sum_{j=1}^{N} \frac{\left|O_j - E_j\right|}{E_j} \tag{20}$$

R^2

The reliability of predictions is assessed using the determination coefficient (R^2). If R^2, which usually ranges between 0 and 1, is extremely close to 1, it will produce estimates that are more precise. The equation to calculate R^2 is found in equation 21.

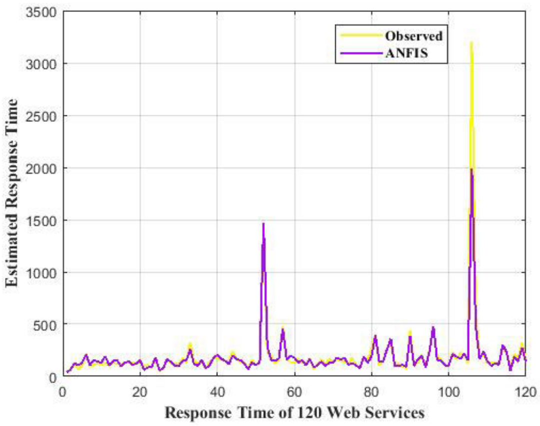
$$R^2 = 1 - \frac{\sum_{j=1}^{N} \left(O_j - E_j\right)^2}{\sum_{j=1}^{N} \left(O_j - \overline{O_j}\right)^2} \tag{21}$$

where O_j and E_j represent the observed and estimated values. $\overline{O_j}$indicates the mean of observed values.

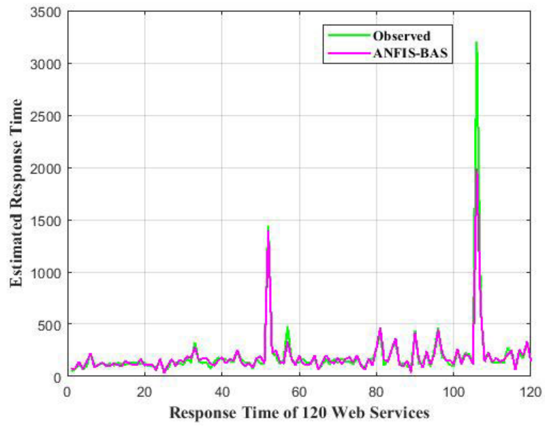
N is the total number of iterations.

A. ESTIMATING RESPONSE TIME USING ANFIS-COOT

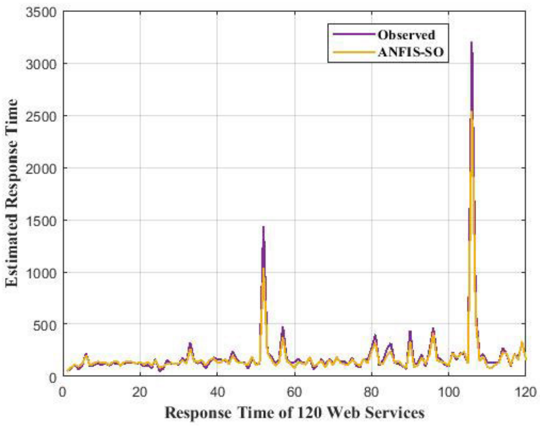
The developed model ANFIS-COOT is performed in this analysis to assess web service response times. The model was evaluated on QWS data across 200 iterations and demonstrated significant convergence. Moreover, the same QWS dataset was taken into account and modeled using alternative methodologies, namely ANFIS coupled with snake optimizer, beetle antennae search, and reptile search algorithms, in an attempt to demonstrate how well the ANFIS-COOT model works. The comparative analysis of convergence speed towards the optimal is depicted in Fig. 3. As a point of clarification, the ANFIS-COOT model performed admirably at the appropriate time. Initially, each of the



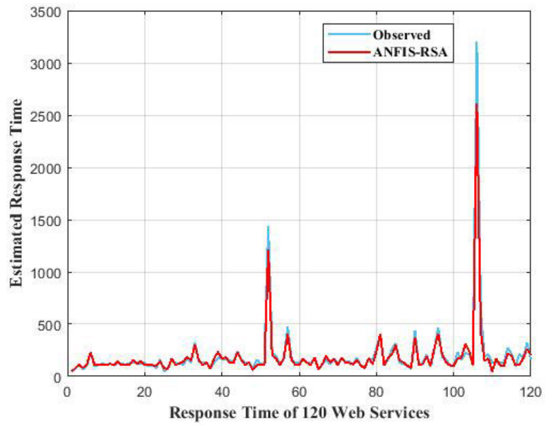
(a) ANFIS



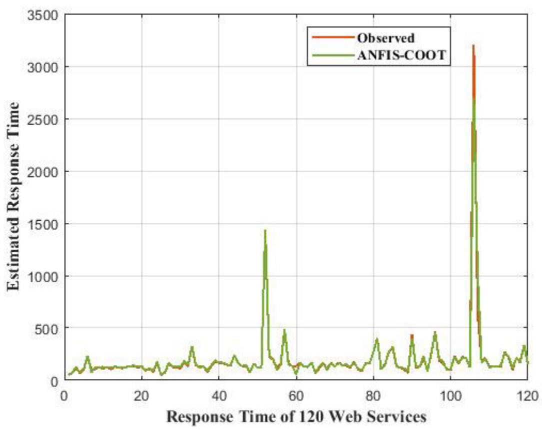
(b) ANFIS-BAS



(c) ANFIS-SO



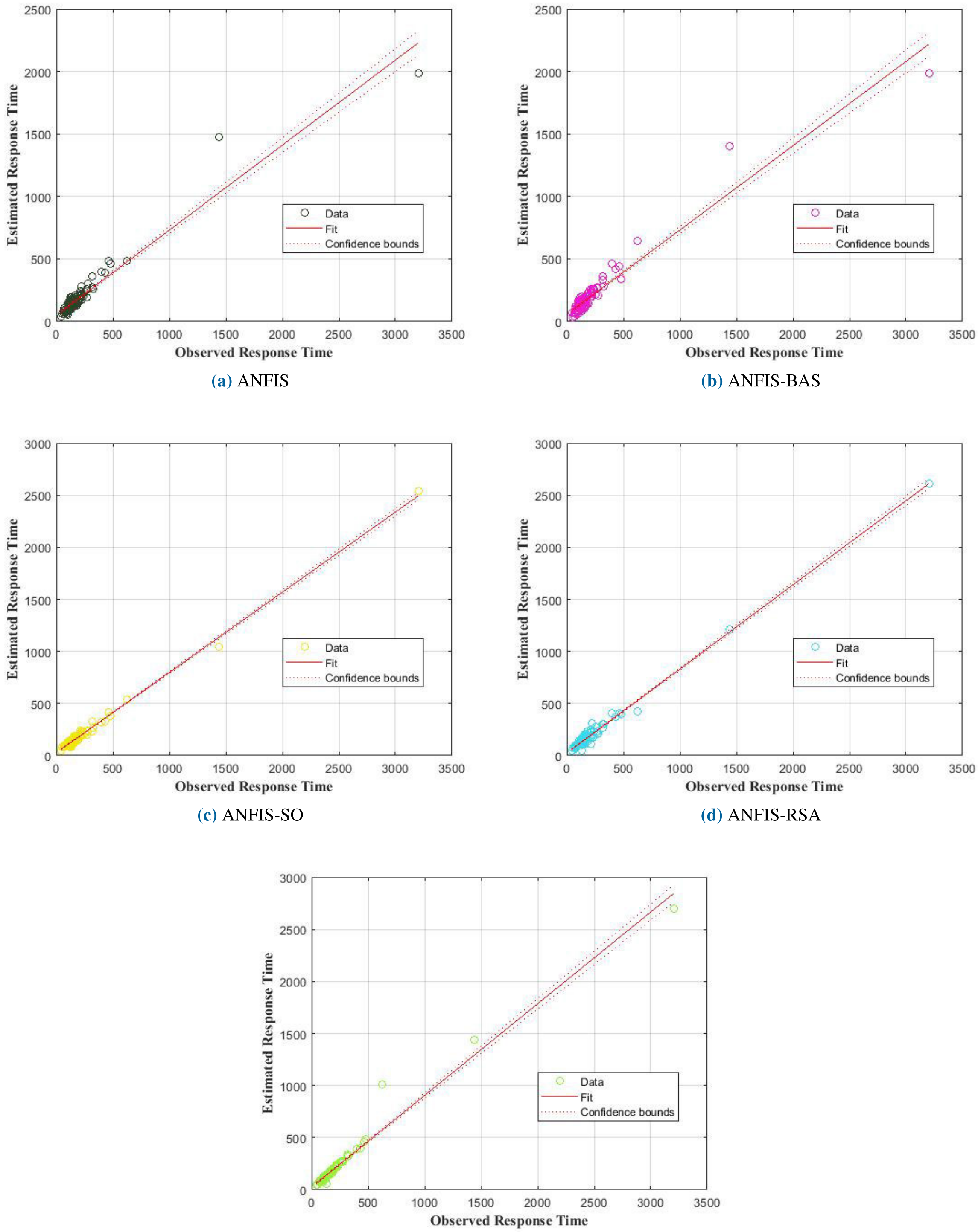
(d) ANFIS-RSA



(e) ANFIS-COOT

FIGURE 6. **Observed vs. estimated response time using different prediction models.**

four ANFIS models delivered acceptable results. However, as time progressed, their performance rapidly deteriorated. The statistical benchmarks achieved by ANFIS-COOT are compared to those achieved by existing models in Table 2. From Table 2, it is evident that the proposed model predicted the data even in the presence of high fluctuations, and it achieved the best metric values. Additionally, the graphical depiction of statistical measures is portrayed in Figs. 4, 5, and Fig. 6 illustrate the observed and anticipated response times using the provided models, and it is discovered that



(a) ANFIS

(b) ANFIS-BAS

(c) ANFIS-SO

(d) ANFIS-RSA

(e) ANFIS-COOT

FIGURE 7. Scatter plots for observed vs. estimated response time parameter.

the ANFIS-COOT method performed effectively. Fig. 7 shows the scatterplots comparing estimated and observed data. The scatter plot indicates the level of relationship between the estimated output and the observed output. Every point illustrates how much of the estimated output correlates to its associated value in the observed.

TABLE 2. Analysis of evaluation indicators for estimating response time.

Prediction Model	RMSE	MAE	MAPE	R^2
ANFIS	114.6611	33.0624	0.1583	0.8644
ANFIS-BAS	115.9877	36.4975	0.1875	0.8612
ANFIS-SO	76.6880	30.5039	0.1514	0.9393
ANFIS-RSA	67.0252	28.1017	0.1465	0.9536
ANFIS-COOT	**59.7473**	**15.8531**	**0.0705**	**0.9632**

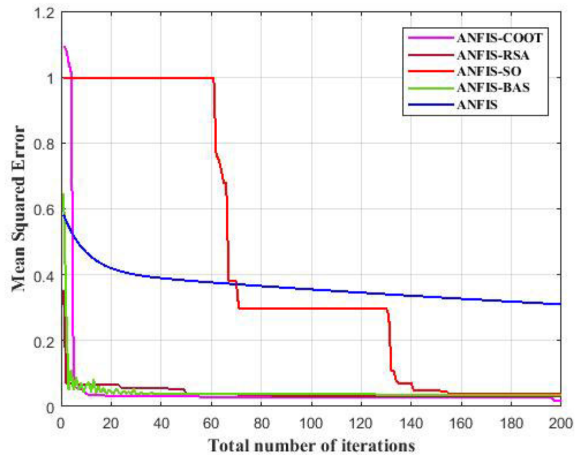


FIGURE 8. Convergence rate of different models for throughput parameter.

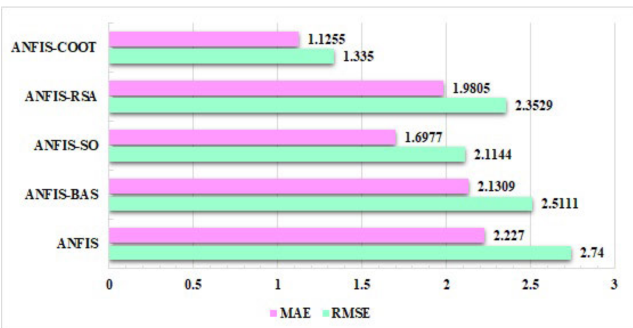


FIGURE 9. Comparative analysis of RMSE and MAE for throughput parameter.

B. ESTIMATING THROUGHPUT USING ANFIS-COOT

To develop the quality of service prediction models, the article integrates the ANFIS with metaheuristic optimization techniques, such as the ANFIS-COOT, ANFIS-RSA, ANFIS-SO and the traditional ANFIS. The devised prediction simulations were conducted against the QWS dataset over 200 iterations, and the acquired convergence of ANFIS-COOT was presented in comparison to four distinct models in Fig. 8. Table 3 displays the statistical measurements for web service QoS data that have been acquired after performing different forecasting approaches. The comparison of the techniques is shown in Fig. 9 along with the RMSE and MAE values. Fig. 10 shows how MAPE is portrayed in relation to the R^2 values of different techniques. In assertion, there is evidence that the ANFIS-COOT technique performs more accurately than others and in comparison to all other optimization methods combined, ANFIS-COOT has an RMSE, MAE, MAPE, and R^2. As shown in Fig. 11, ANFIS-COOT, ANFIS-RSA, ANFIS-SO, ANFIS-BAS, and ANFIS models are used to estimate throughput and visualize the observed against estimated values. An optimal result can be achieved with the ANFIS model using the COOT algorithm. The scatter plots in Fig. 12 provide a visual representation of how the predictions of all approaches compare with the observed results.

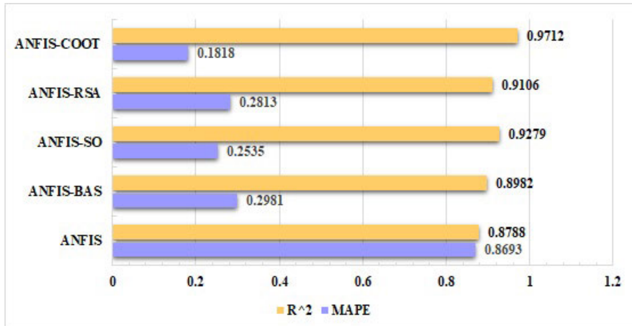


FIGURE 10. Comparative analysis of MAPE and R^2 for throughput parameter.

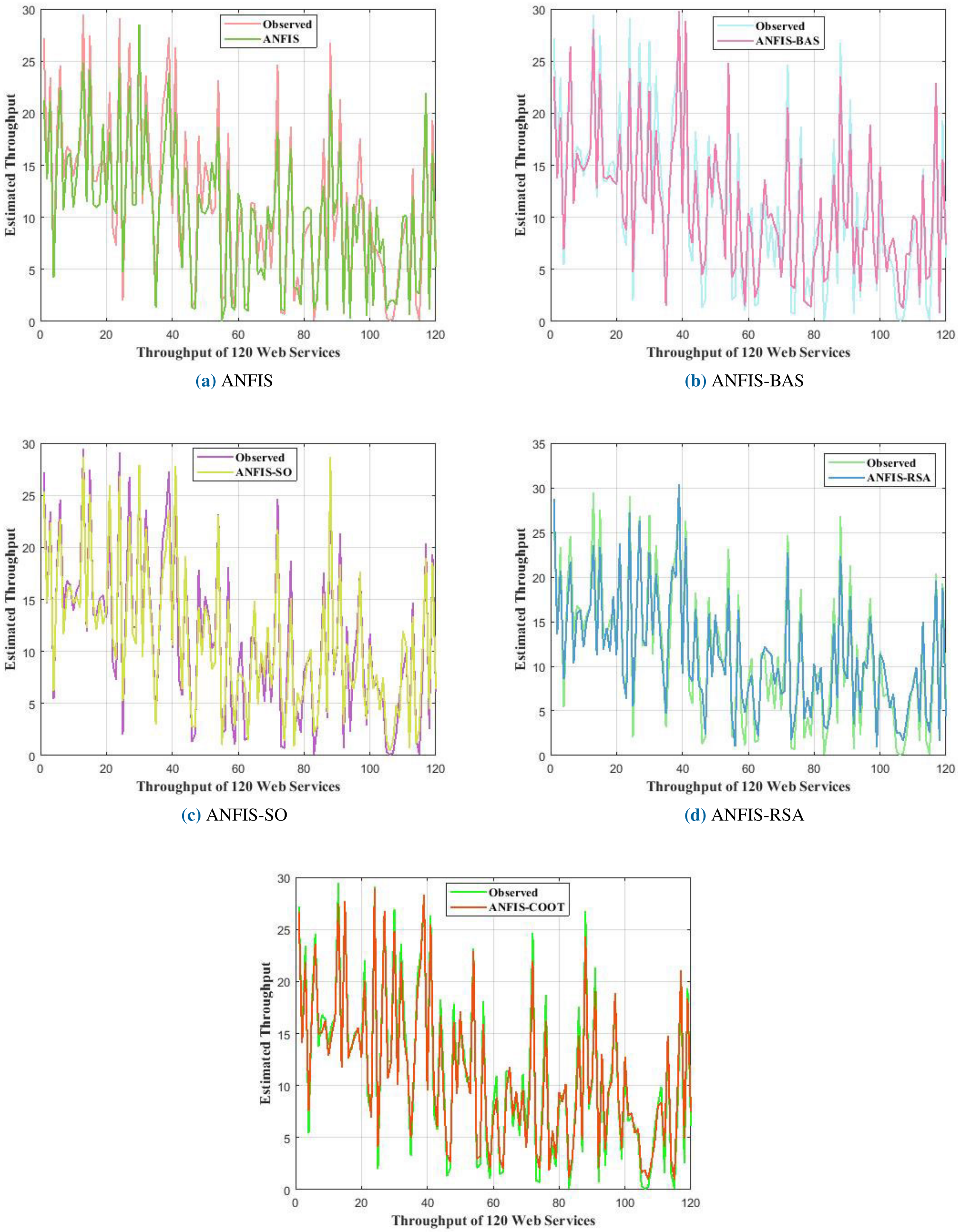
TABLE 3. Analysis of evaluation indicators for estimating throughput.

Prediction Model	RMSE	MAE	MAPE	R^2
ANFIS	2.7400	2.2270	0.8693	0.8788
ANFIS-BAS	2.5111	2.1309	0.2981	0.8982
ANFIS-SO	2.1144	1.6977	0.2535	0.9279
ANFIS-RSA	2.3529	1.9805	0.2813	0.9106
ANFIS-COOT	**1.3350**	**1.1255**	**0.1818**	**0.9712**

The computation result reveals that the presented ANFIS-COOT approach works more effectively than current techniques. The augmented approach ANFIS-COOT has the optimal results with an RMSE value of 59.7473, an MAE value of 15.8531, a MAPE value of 0.0705, and an R^2 value of 0.9632 for estimating response time, an RMSE value of 1.335, an MAE value of 1.1255, a MAPE value of 0.1818, and an R^2 value of 0.9712 for estimating throughput, which is superior compared to all other methods, according to the evidence of statistical measures and visual analytics.

C. COMPARATIVE ANALYSIS

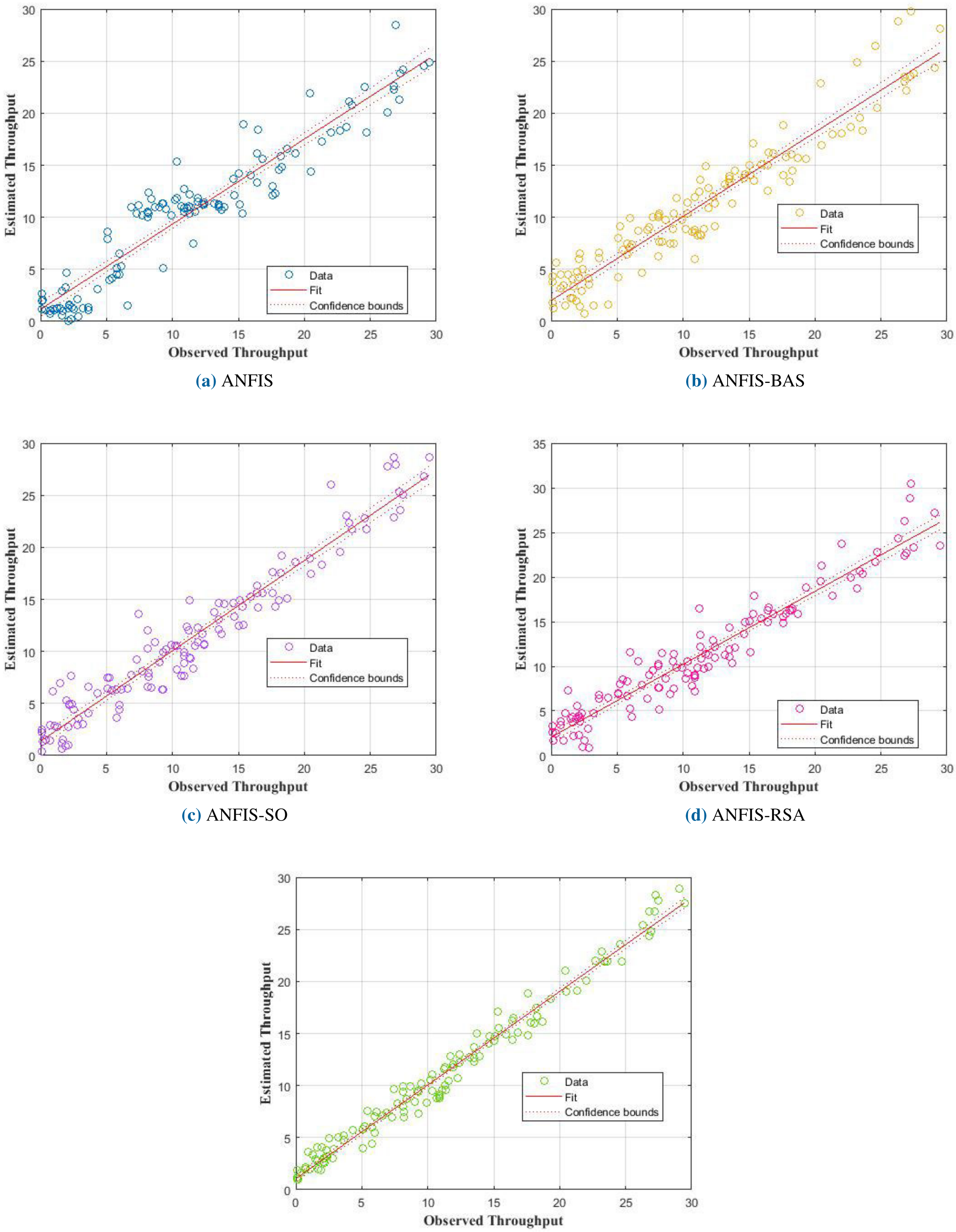
This section emphasizes the efficacy of the ANFIS-COOT prediction model by comparing it to previous studies. To accomplish this, it is necessary to compare the precision of the proposed technique to that of currently developed prediction models. For instance, Xiong et al. [51] integrated fuzzy neural networks and adaptive dynamic programming for modeling QoS characteristics for cloud-based services and discovered that the integration of these two techniques



(a) ANFIS
(b) ANFIS-BAS
(c) ANFIS-SO
(d) ANFIS-RSA
(e) ANFIS-COOT

FIGURE 11. Observed vs. estimated throughput using different prediction models.

delivers high accuracy in predictions. Chen et al. [52] explored missing QoS values for cloud-based web services using particle swarm optimization. Ding et al. [53] implemented deep integration of features by taking environmental data into account in QoS to accomplish joint QoS prediction. Zhang et al. [59] came up with the Levenberg Marquardt and Random Service System to assess predictions of trust and quality of service for the social Internet of Things and discovered that the resulting model demonstrates excellent reliability and quality. This study devised a prediction



(a) ANFIS (b) ANFIS-BAS (c) ANFIS-SO (d) ANFIS-RSA (e) ANFIS-COOT

FIGURE 12. Scatter plots for observed vs. estimated throughput parameter.

model using the ANFIS and COOT algorithms. Typically, the efficacy of ANFIS depends heavily on its parameters. Therefore, the COOT algorithm is used to select the optimal parameters of the ANFIS. As a consequence, for the purpose of comparing the proposed method, the recently developed hybrid methods ANFIS-BAS, ANFIS-SO, and ANFIS-RSA were identified and compared with traditional ANFIS. To demonstrate that the performance of ANFIS-COOT is feasible by evaluating statistical benchmarks against datasets. The error analysis is performed for prediction response time and throughput, which are depicted in Tables 2 and 3. According to Tables 2 and 3, ANFIS-COOT delivers the optimal statistical metrics RMSE (59.7473), MAE (15.8531), MAPE (0.0705), and R^2 (0.9632) for estimating response time and RMSE (1.335), MAE (1.1255), MAPE (0.1818), and R^2 (0.9712) for estimating throughput. Moreover, the study of experimental data reveals that latency affects response time, and reliability has a significant influence on throughput. Eventually, there will be an excess of web services with comparable features. Consequently, it is tricky to determine the most effective web service from an assortment of web services with identical functionality. To address this issue, the present research devised an ANFIS-COOT prediction model for selecting the best optimal web service based on response time and throughput values. As well, the proposed framework is not only confined to QoS predictions and the current dataset, which might be useful for analyzing different QoS datasets.

V. CONCLUSION

This study presents a machine learning approach for modelling the QoS attributes of web services. The approach initially integrated the COOT metaheuristic optimization with the adaptive neuro-fuzzy inference system to develop the augmented prediction model. Second, to demonstrate that the performance of the ANFIS-COOT model is exploited to analyze the QWS data which comprises inputs accessibility, reliability, compliance, best practices, and latency for modelling two vital attributes of web services namely response time and throughput. To emphasize the performance of the ANFIS-COOT prediction model, their accuracies are compared with statistical benchmarks: RMSE, MAE, MAPE, and R^2. It is also compared to existing models such as ANFIS, ANFIS-RSA, ANFIS-BAS, and ANFIS-SO. The ANFIS-COOT was able to predict both response time and throughput with significant accuracy. In the case of estimating response time, the error indicators were obtained as RMSE (59.7473), MAE (15.8531), MAPE (0.0705), and R^2 (0.9632). In the case of estimating throughput, the proposed model obtained RMSE (1.335), MAE (1.1255), MAPE (0.1818), and R^2 (0.9712). Based on the experimental results, it was evident the approach was capable of tackling complicated and complex predictions by selecting optimal parameters. The analysis found that the ANFIS with COOT optimization yielded the best results after performing several experiments. Moreover, the comparative analysis proves that the adoption of ANFIS-COOT can potentially improve the effectiveness of QoS parameter prediction. Importantly, these findings also indicate that ANFIS-COOT may be an effective technique for time series and non-linear complex problems.

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