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# A Machine Learning–Driven Personalized Web Service Recommendation and Prediction System for Intelligent User-Centric Applications

Dr.S.Meenakshi[1], Shalini E[2], Dr.D.Sundaranarayana[3], Dhanalakshmi V[4], Repudi Pitchiah[5], Shanthi Vairavan[6], R. Naveenkumar[7]

[1]Assistant Professor, PG Department of Computer Applications (MCA), SRM Institute of Science and Technology, Ramapuram, Chennai. Email: meenaanandrk96@gmail.com

[2]Assistant Professor, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Chennai, tamilnadu, India. Email: shalini@maher.ac.in

[3]Associate Professor, Department of Computer Science & Engineering, VelTech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu. Email: d.sundaranarayana@gmail.com, Orcid: 0000-0001-6060-1420

[4]Assistant Professor of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Chennai, tamilnadu, India. Email: dhanalakshmiv@maher.ac.in

[5]Assistant professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, Email: repudipitchiah@kluniversity.in, https://orcid.org/0000-0002-3092-914X

[6]Professor & Principal, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Chennai, tamilnadu, India. Email: shanthiv@maher.ac.in, 0000-0002-6416-6291

[7]Dept of CSE, School of Engineering and Technology, CGC University Mohali-140307, Punjab India. Email: drnk1983@gmail.com, 0000-0001-9033-9400

**Abstract**

The dynamic and time-aware Quality of Service attributes are forecasted for the recommendation of efficient web services. The forecasting of QoS attributes are attained primarily by statistical techniques and optimization algorithms. These approaches lack in retrieving the optimized results and the absence of exploitation nature in optimization algorithms results in ineffective performance. To overcome the drawbacks, the optimization and machine learning technique is introduced in this research work. The genetic algorithm (GA) with high exploration ability and grey wolf optimization (GWO) algorithm with high exploitation ability is introduced to acquire the optimized QoS attributes. The performance of the GA-GWO is enriched by minimizing the over fitting issue. The machine learning based gradient boosting algorithm is incorporated for solving the over fitting problem.The proposed GA-GWO is highly efficient in acquiring the QoS attributes, which are prominent in managing and modelling the web services. The recommendation of personalized web services and attaining QoS is investigated by the performance of the proposed GA-GWO algorithm and it outperforms the other QoS attribute retrieving approaches.

*Keywords: Genetic algorithm, web service, grey wolf optimization, QoS attributes, gradient boosting and machine learning.*



## 1. Introduction

Cloud computing paradigm abstracts storage and computational resources as on-demand utility services, enabling dynamic provisioning and scalable resource allocation. This service-oriented architecture facilitates both individual users and enterprise systems to access infrastructure [1], platforms, and software without direct ownership or management of physical resources. Consequently, personal applications and business systems increasingly adopt cloud environments due to their flexibility, cost-efficiency, and scalability.

Web services play a pivotal role within this ecosystem by enabling interoperable communication between distributed software components. They support the development of complex software systems through integration and reuse of existing services, thereby reducing development time and enhancing modularity. Such service composition mechanisms rely heavily on standardized protocols, enabling seamless interaction across heterogeneous platforms.

The effectiveness of web service-based systems is critically dependent on the Quality of Service (QoS) attributes [2]. QoS encompasses multiple non-functional parameters such as response time, availability, reliability, throughput, and latency, which collectively determine the performance and user satisfaction of the service. As cloud environments are inherently dynamic and distributed, QoS attributes may fluctuate due to varying workloads, network conditions, and resource allocation policies.

Therefore, accurate prediction of QoS attributes has emerged as a significant research challenge in cloud computing. Predicting future QoS values enables proactive service selection, optimal resource allocation, and improved system performance. It also assists in maintaining service-level agreements (SLAs) and ensuring user requirements are consistently met. Advanced predictive models, often leveraging machine learning and statistical techniques, are employed to estimate QoS metrics based on historical data and contextual information.

The trustworthiness ofweb serviceis identified as a completeexcellencewith a measure of web services. It also imitates the user's perception of web service with reverence to numerousdependable attributes namely scalability, safety, reliability, security, and availability. For thesimilar reasons assessingand distinctive trustworthiness of software that are thoroughlyconnected to quality assurance, schemingoperativeapproaches or prototypes for trustworthiness of web serviceestimation has converted a stimulating and immediatelynecessitated research issue. Trustworthiness of web service isconsciousof service collection and estimation has increased hugedesirability in Cloud Computing and Service-Oriented Computing research communal over decades [3].

To offer the effective web service, certain approaches are introduced namely ranking based AHP, rating and selection system, selection of service based on trust-aware, estimation of trustworthiness based on SLA, prediction of ranking based on QoS, probabilistic framework based on trustworthiness, analysis of risk with the feedback, trust modelling and innovative feedback system. The service level agreement (SLA) is utilised to minimize and detect violations. The SLA violation makes the loss and the incidence of this can be as few as probable.

Two approaches reduce SLA violations: reactive substitution after failures and proactive prediction of future QoS violations to replace services in advance. Integrating time-aware QoS prediction enables early detection of SLA risks. QoS forecasting methods provide essential future performance insights, supporting service selection and improving reliability in QoS-aware cloud service management systems.The existing system faces the exploration and exploitation problem during the solution space identification. The training phase also faces the overfitting issues and it reflects in the solution identification. The drawbacks in the existing system is rectified by the introduction of gradient boosting for rectifying overfitting, the genetic and gray wolf optimization is initiated for the exploration and exploitation strategy.The GWO algorithm parodist's mechanism of the headship hierarchy and hunting of gray wolves. In addition, three core steps of hunting, prey searching, prey encircling, and prey attacking are instigated to accomplish the optimization problem.

The rest of the research article is structured as follows: the existing web service system and the QoS predicting systems are explained in section 2, the proposed Gradient Boosting using Genetic Algorithm based Grey Wolf Optimizer (GB-GA-GWO) algorithm for the QoS attribute prediction system is elaborated in Section 3, analysis of prediction result is showed in section 3 and the GB-GA-GWO is concluded with future scope in section 4.

## 2. Related Works

Gradient boosting is a variety of greedy algorithm and it can overfit a training dataset quickly whereas it benefit from the regularization approaches that modifies numerous portions of the algorithm. Generally, it enriches the performance of the algorithm by decreasing overfitting [4]. Genetic Algorithm (GA) is a variety of search-based optimization method that involves principles of Natural and Genetics Selection. It is recurrently utilised to discover the near-optimal or optimal solutions to tough complications, which is then would gross in a generation to resolve.Genetic Algorithm is a variant of evolutionary based computation technique and the best technique of solving research problem is identified via evolution [5].

Artificial Neural Network (ANN) is mainly utilized in learning based problem and the effective results are acquired. The Decision Trees provided necessary assistance in making decision making by utilising a guider called tree-structured and they were formerlyplanned to lever as well asproduce discrete forecasts and attributes. However, with asuitableextension, DTs can also be incorporated to progress and produce real-valued outputs and data. Support vector regressions (SVR) are a variant of SVMs, which are a popular ML technique for data classification. SVR was developed for the performance of data regressions, including TS-based regressions. Non-Linear Matrix Factorization (NLMF) and Deep forward Neural Network Collaborative Filtering (DNN-CF) used for filtering the significant features [6].

The support vector machine(SVMs) and support vector regression (SVRs)segment numerous communal perceptions; thus, SVMs and then SVRs are initiated. SVMs is mainly utilised for the classification of data that mainlycategorizethe administered data into multiple or single classes through the inventivemethod of representing the data into a higher-dimensional feature space by utilising a assumed kernel function and then splitting them based on a linear hyperplane in that given space.This mechanism is mainly utilised in the SVM and SVR.The autoregressive conditional heteroskedasticity (ARCH) portrayed the dynamic deviations in the time-varying inconsistency of a TS as a function of ancientfaults [7, 8].

ARFIMA models is comparable to that of ARIMA models, slight differencing is first pragmatic to preprocess the training data (TS) and this ARMA model is fitted efficiently. Self-exciting threshold autoregressive (SETAR) techniqueis aillustrative threshold approaches in TS research and a difference of AR models. The two-threshold, 3-regime of SETAR model is demonstrated for the attribute acquiring[9-11].

## 3. Gradient Boosting using Genetic Algorithm based Grey Wolf Optimizer (GB-GA-GWO)

The hybrid GB-GA-GWO is discussed in this section, the exploration and exploitation ability of genetic and grey wolf optimization has identified the QoS attributes effectively.

### *Generation of initial population based on learning strategy*

The effectiveness of the algorithm rely on the initial state population and the diversity of the population is minimized the processing duration that enriches the convergence of global value. The random initialization strategy is employed in the GWO algorithm and it has great impact on the algorithms search efficiency. Assume that the population individuals $A(a_1,a_2.....,a_{db})$ in the set of population PTwhere the opposite elements point is $a_i(i=1,2,3,....,db)$ with the upper bound ub and lower bound lb values in the $i^{th}$ dimension.The opposite points are calculated by the initialized random variables and the fitness value is estimated that are arranged in descending order. The wolf with high fitness value is considered as the initial population.

### *Parameter adjustment and gradient boosting strategy*

The exploration and exploitation of the optimization technique is balanced significantly and in the initial iteration of the algorithm, the robust exploration ability is benefit to magnify the range of search. In the subsequent iteration, the exploitation capability can fasten the process of optimization whereas the optimal solution is retrieved greater probability and the convergence of the approach is enriched. The coordinate among the global exploration and the local exploitation gives faster and robust convergence.The over fitting issue is rectified by the gradient boosting and the training set of data s_DB is utilized for the values $\{(\mathrm{ai},\mathrm{bi})\}_{\mathrm{i}=1}^{\mathrm{s\_DB}}$.

$$L\left(b,\widehat{f(a)}\right)=\sum_{i}^{s\_DB}\left[b_i-\widehat{f(a_i)}\right]^2$$

The exploration and the exploitation is adjusted dynamically by the adjustment strategy and it provide a way for the optimal solution search strategy. The parameter adjustment setting is equated as,

$$x = x_{max} + (x_{min} - x_{max}).\left(\frac{1}{1 + e^{t/max_{itera}}}\right)^k$$

where the initial and end values are signified as $x_{max}$ and $x_{min}$ for the parameters x respectively. The index of iteration is signified as t, the non-linear adjustment coefficient is signified by k and the maximum count of the iteration is signified by $max_{itera}$. The deviation in the convergence is denoted by the X for the parameter x. The search space is extended when the search space is |X|>1 and it is compressed when |X|<1. The entire process has high impact on balancing the local and global solutions.

### *Selection of population on optimized retention*

The evolution and the generation of population directly affects the optimization and the solution set. The superiors are inherited in the population in the paternal values to the subsequent generation without terminating the individuals that preserve the best values. Assume the process in the current generation PT($A_1$,$A_2$,……,$As\_{DB}$), the values with fitness is $A_i$ of $F_i$. The fitness value with highest value is copied to the subsequent generation of population and the whole fitness value TF as well as probability $p_i$ where the every individual is elected.

$$TF = \sum_{i=1}^{s_{DB}-1} F_i \qquad (i = 1,2,3, \dots \dots \dots, s_{DB} - 1)$$

$$PT_i = \frac{F_i}{\sum_{i=1}^{s_{DB}-1} F_i} \qquad (i = 1,2,3, \dots \dots \dots, s_{DB} - 1)$$

The fitness value of cumulative range for every individual is estimated and the selection of individual is executed by the bet roulette scheme until the count of the individuals in the population of children is reliable with the population of parent.

$$s_i = \frac{\sum_{i=1}^{i} TF_i}{TF} \qquad (i = 1,2,3, \dots \dots \dots, s_{DB} - 1)$$

The diversity in the generation of population is simple to drop into the optimum value at the local value for high dimensionality issue. To overcome the issues in the population generation by the high dimension that confirm the algorithms search spaces. In the GB-GA-GWO, the population value PT is segregated by $\vartheta \times \eta$subpopulation is given as $PT_{i,j}$(i=1,…. $\vartheta$;j=1,….. η). The optimized size of every subpopulation value $PT_{i,j}$ is investigated by 5×5 matrix. Every individual in the subpopulation in the cross is performed to escalate the variation of population. The exact division approach is equated below,

Population at the initial stage is given as PT

$$\begin{bmatrix} a_{1,1} & \cdots & a_{1,s\_DB} \\ \vdots & \ddots & \vdots \\ a_{PT,1} & \cdots & a_{PT,s\_DB} \end{bmatrix}$$

Subpopulation $PT_{i,j}$

$$\begin{bmatrix} a_{1,1} & \cdots & a_{1,5} \\ \vdots & \ddots & \vdots \\ a_{5,1} & \cdots & a_{5,5} \end{bmatrix} \cdots \begin{bmatrix} a_{1,(s_{DB}-4)} & \cdots & a_{1,s\_DB} \\ \vdots & \ddots & \vdots \\ a_{5,(s_{DB}-4)} & \cdots & a_{5,s\_DB} \end{bmatrix}$$

$$\vdots \qquad \cdots \qquad \vdots$$

$$\begin{bmatrix} a_{(PT-4),1} & \cdots & a_{(PT-4),5} \\ \vdots & \ddots & \vdots \\ a_{PT,1} & \cdots & a_{PT,5} \end{bmatrix} \cdots \begin{bmatrix} a_{(PT-4),(s_{DB}-4)} & \cdots & a_{(PT-4),s\_DB} \\ \vdots & \ddots & \vdots \\ a_{PT,(s_{DB}-4)} & \cdots & a_{PT,s\_DB} \end{bmatrix}$$

$$PT_{\gamma,1} \dots PT_{\gamma,v}$$

In genetic algorithm, the crossover operation has a prominent role and it is the main approach to generate the new population. The relevant random number $rnd_i$ belongs to 0 and 1 for every value in the population $a_i$. The value of the random number is less than the probability of crossover then the relevant individual is paired with the individual in the crossover ($PT_1$, $PT_2$). For the crossover operation ($PT_1$, $PT_2$) that generate random individuals λ belongs to 0 and 1 for the children $ch^1(ch_1^1 \ldots \ldots \ldots, ch_{s_{DB}}^1, ch^2), ch^2(ch_1^2 \ldots \ldots \ldots, ch_{s_{DB}}^2)$are generated by the parents is$PT^1(PT_1^1 \ldots \ldots \ldots, PT_{s_{DB}}^1, PT^2)PT^2(PT_1^2 \ldots \ldots \ldots, PT_{s_{DB}}^2)$ equated as,

$$ch_i^1 = \lambda PT_i^1 + (1-\lambda)PT_i^2, i = 1,2, \ldots \ldots, s\_DB)$$

$$ch_i^2 = \lambda PT_i^2 + (1-\lambda)PT_i^1, i = 1,2, \ldots \ldots, s\_DB)$$

### *Mutation of individuals*

The incidence of selection operation preserve the optimization strategy and the grey wolf are concentrated in a lesser optimal region that may cause the loss the diversity. To restrict this, mutation operation is performed. The mutation is performed in the rate of probability and the selected gene among the random upper and lower bound value that generate $a_i^{'} = (a_1^{'}, a_2^{'}, \ldots \ldots., a_{s\_SD}^{'})$.The operation is equated as,

$$a_i^{'} = \begin{cases} lb + \lambda * (ub - lb) & i = k \\ a_i & i = k \end{cases}$$

Where the random values are signified as λ, the lower and upper bound is signified as lb and ub respectively for the wolf $a_i$. The significant QoS attributes are retrieved and the personalized web services are recommended with the assistance of acquired attributes.

Algorithm 1. GB-GA-GWO

```
Initialize the parameters and population
t=0
while<Maxim_iter
Calculate the fitness values of all search agents
For i=1:N
        Update the search agents position
End for
        New_population←Exacepts the first best search agent
For i=1:N-1
        Generate subsequent population by Roulette Wheel Selection
End for
Population← new population and best search agent
Apply gradient filter
Generated sub population by generating the mechanism of partitioning
Selection of individuals with the probability of crossover
For i=1:N*population
End for
Generate the best positions on the mutation probability
t=t+1
end while
return best search agent
```

## 4. Result and Discussion

The accuracy of time series and machine learning approaches namely genetic algorithm (GA),Non-Linear Matrix Factorization (NLMF) and Deep forward Neural Network Collaborative Filtering (DNN-CF), support vector regressions (SVR), generalized autoregressive conditional heteroscedasticity (ARCH), autoregressive fractional moving average (AFMA) and self-exciting threshold autoregressive (SETAR) are compared with the proposed GB-GA-GWO. The existing and proposed approach utilised the QoS dataset and the forecasting model accuracy is evaluated. The performance of the proposed approach is investigated by the performance metrics namely mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE), and mean absolute scaled error (MASE).The outcomes are compared for diverse iteration and the prediction accuracy is estimated by the performance metrics. The numerical outcomes of the empirical experiment is elaborated in this section. The QoS dataset utilized in this approach is given in Table 1.

**Table 1. Description of Dataset**

| Statistics | Values |
|---|---|
| Invocation of Web service | 1,974,675 |
| Web service count | 5,825 |
| Countries utilizing the service | 30 |
| Service of the users | 339 |
| Response time mean values | 1.43 s |
| Throughput mean | 102.86 kbps |
| Response time in standard deviation | 31.9 s |
| Throughput in in standard deviation | 531.85 kbps |
| Count of the web service utilizing countries | 73 |

### Mean Absolute Error (MAE)

The measure of Mean Absolute Error (MAE) is the error among the corresponding observation articulates the similar phenomenon.It is also stated as an arithmetic average value of absolute errors.

$$MAE = \frac{1}{ft}\sum_{i=1}^{pt}|r_i - p_i|$$

where the forecasting duration of time is signified as ft, the rate of time is signified as i, predicted value is signified as $p_i$ and real observed value is signified as $r_i$. The MAE value rely on the measurements with error and the algorithm with minimum error is considered as better approach. The acquired values of MAE is given in Table 2.

**Table 2. Comparison of Mean Absolute Error (MAE)**

| | Existing | | | | | | | Proposed |
|---|---|---|---|---|---|---|---|---|
| Iteration | GA | NLMF | DNNCF | SVR | ARCH | ARFIMA | SETAR | GB-GA-GWO |
| 50 | 2.6 | 3.6 | 4.6 | 4.7 | 3.7 | 3.8 | 4.3 | 1.6 |
| 100 | 2.7 | 3.6 | 4.7 | 4.7 | 3.8 | 3.9 | 4.5 | 1.7 |
| 150 | 2.9 | 3.7 | 4.9 | 4.8 | 3.9 | 3.9 | 4.6 | 1.8 |
| 200 | 3.1 | 3.3 | 4.2 | 4.6 | 4.1 | 4.3 | 4.8 | 1.8 |
| 250 | 3.4 | 3.6 | 4.3 | 4.5 | 4.2 | 4.5 | 5.5 | 1.9 |

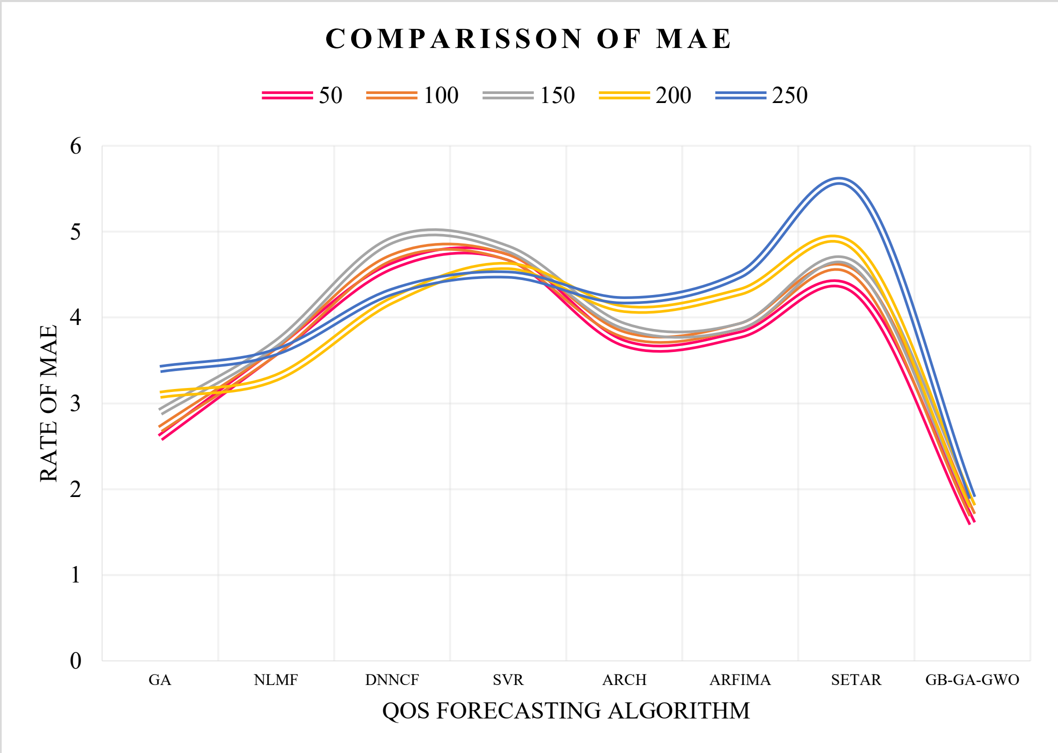


**Figure 1: Comparison of Mean Absolute Error (MAE)**

From the Figure 1, it is identified that the MAE error rate of GB-GA-GWO is minimum when compared with the other machine learning approaches. The error rate of GB-GA-GWO is an evident that the proposed approach is highly effective.

### *Mean Absolute Percentage Error (MAPE)*

The forecasting accuracy of the prediction algorithm is stated by MAPE and it is utilized for the identification of loss of function. The rate of prediction is MAPE and it is signified in percentage. The algorithm with minimum error denotes the effective prediction accuracy of the proposed algorithm.

$$MAPE = \frac{1}{ft}\sum_{i=1}^{pt}\frac{|r_i - p_i|}{r_i}$$

The values of MAPEs are considered as percentages, it is comparatively simple to comprehend the accuracy characterised by the MAPE delivered by a predictingscheme. The MAPE is also a measurement based on error.The acquired values of MAPE is given in Table 3.

**Table 3. Comparison of Mean Absolute Percentage Error (MAPE)**

| | Existing | | | | | | | Proposed |
|---|---|---|---|---|---|---|---|---|
| Iteration | GA | NLMF | DNN-CF | SVR | ARCH | ARFIMA | SETAR | GB-GA-GWO |
| 50 | 27 | 37 | 47 | 45 | 35 | 38 | 43 | 17 |
| 100 | 28 | 37 | 48 | 45 | 38 | 39 | 45 | 18 |
| 150 | 29 | 35 | 49 | 48 | 39 | 39 | 47 | 19 |
| 200 | 31 | 34 | 52 | 48 | 41 | 43 | 48 | 21 |
| 250 | 34 | 37 | 53 | 49 | 42 | 45 | 55 | 22 |

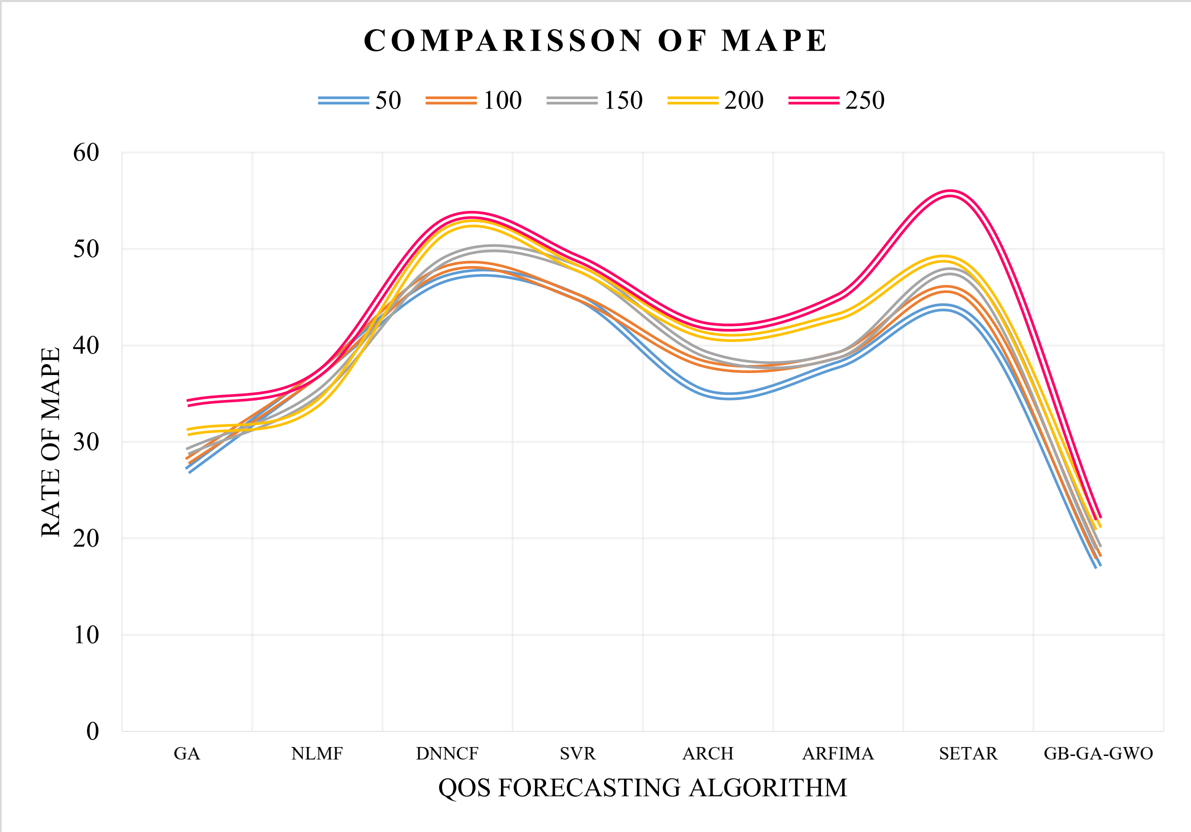


**Figure 2. Comparison of Mean Absolute Percentage Error (MAPE)**

From the Figure 2, it is identified that the MAPE error rate of GB-GA-GWO is minimum when compared with the other machine learning approaches. The error rate of GB-GA-GWO is an evident that the proposed approach is highly effective.

### *Root Mean Squared Error (RMSE)*

The variation among the values are measured by the Root Mean Squared Error (RMSE) and the incidence of error in the prediction model of the quantitative information is stated as RMSE. The rate of RMSE is generally considered as an exceptional error metric for the prediction of numerical information.

$$RMSE = \sqrt{\frac{1}{s\_DB}\sum_{i=1}^{s\_DB}(qe_i - \widehat{qe_\iota})^2}$$

where the index value of observation is signified as i and the dataset size is signified as s_DB (The observation set of values and the relevant forecasting values).The RMSE is a variety of MAE of squared original data that is $qe_i - \widehat{qe_\iota}$. This measure maximises the impact of outliers in the set of data (i.e., relevant value) via the square process to evaluate the capability of a method to state these outliers. The acquired values of RMSE is given in Table 4.

**Table 4. Comparison of Root Mean Squared Error (RMSE)**

| | Existing | | | | | | | Proposed |
|---|---|---|---|---|---|---|---|---|
| Iteration | GA | NLMF | DNN-CF | SVR | ARCH | ARFIMA | SETAR | GB-GA-GWO |
| 50 | 77 | 87 | 87 | 85 | 85 | 88 | 83 | 67 |
| 100 | 78 | 87 | 88 | 85 | 88 | 87 | 84 | 68 |
| 150 | 79 | 86 | 89 | 88 | 86 | 87 | 85 | 69 |
| 200 | 86 | 88 | 90 | 88 | 86 | 88 | 86 | 76 |
| 250 | 88 | 89 | 91 | 89 | 87 | 89 | 85 | 77 |

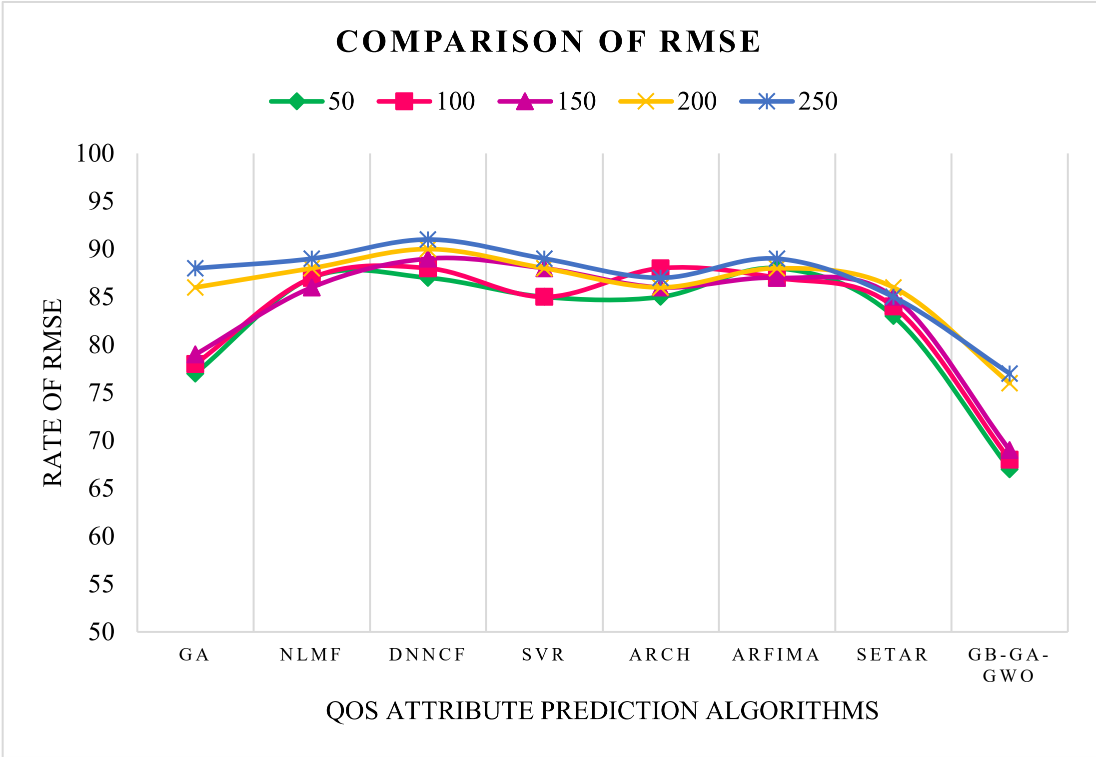


**Figure 3. Comparison of Root Mean Squared Error (RMSE)**

From the Figure 3, it is identified that the RMSE error rate of GB-GA-GWO is minimum when compared with the other machine learning approaches. The error rate of GB-GA-GWO is an evident that the proposed approach is highly effective.

### *Mean Absolute Scaled Error (MASE)*

The mean absolute scaled error (MASE) is the accuracy predicting measure. It is identified by the estimation of the mean absolute error of the prediction rates, which is divided by the mean absolute error of the values in-sample one-step simpleprediction. MASE is considered as a scale-free error metric that providesevery error as a ratio valueassociated to a baseline's average error.

$$\frac{1}{s\_DB}\sum_{i=1}^{s\_DB} = 1\left|\frac{(qe_i - \widehat{qe_i})}{\frac{1}{k}\sum_{j=1}^{k}\left|(qe_j - \widehat{qe_j})\right|}\right|$$

where the prediction and the forecast index is signified as j that is included in the training dataset and the size of the dataset is signified as s_DB. The value of MASE is identical to the value of MAPE whereby the major variation among them is that MASE and it utilises the training values of MAE. It is the denominator value in the above equation in the place oforiginal values in the observation utilised in the MAPE.The acquired values of MASE is given in Table 5.

**Table 5. Comparison of Mean Absolute Scaled Error (MASE)**

| | Existing | | | | | | | Proposed |
|---|---|---|---|---|---|---|---|---|
| Iteration | GA | NLMF | DNN-CF | SVR | ARCH | ARFIMA | SETAR | GB-GA-GWO |
| 50 | 88 | 98 | 97 | 95 | 95 | 97 | 93 | 68 |
| 100 | 89 | 98 | 97 | 95 | 96 | 98 | 94 | 69 |
| 150 | 89 | 96 | 98 | 99 | 96 | 98 | 95 | 69 |
| 200 | 96 | 99 | 99 | 99 | 96 | 99 | 96 | 76 |
| 250 | 99 | 99 | 99 | 99 | 98 | 99 | 96 | 78 |

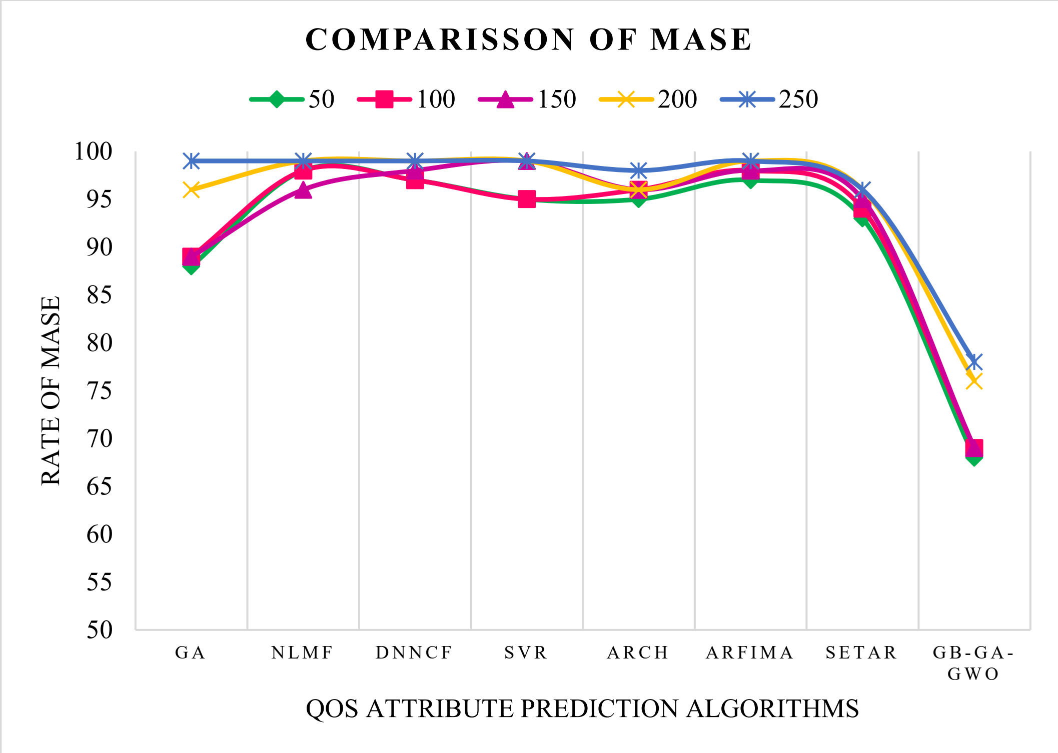


**Figure 4: Comparison of Mean Absolute Scaled Error (MASE)**

From the Figure 4, it is identified that the MAE error rate of GB-GA-GWO is minimum when compared with the other machine learning approaches. The error rate of GB-GA-GWO is an evident that the proposed approach is highly effective.

### *Time Consumption*

The time consumption is the time utilised to process the algorithm and the time consumption is represented in millisecond. The algorithm with minimum time consumption is considered as the efficient algorithm.

**Table 6: Time Consumption Comparison**

| | Existing | | | | | | | Proposed |
|---|---|---|---|---|---|---|---|---|
| Iteration | GA | NLMF | DNN-CF | SVR | ARCH | ARFIMA | SETAR | GB-GA-GWO |
| 50 | 9988 | 10098 | 10095 | 10195 | 10194 | 10297 | 10293 | 9968 |
| 100 | 9986 | 10097 | 10096 | 10195 | 10195 | 10297 | 10294 | 9969 |
| 150 | 9984 | 10096 | 10097 | 10199 | 10196 | 10298 | 10295 | 9969 |
| 200 | 9991 | 10099 | 10099 | 10199 | 10196 | 10299 | 10296 | 9976 |
| 250 | 10099 | 10099 | 10099 | 10199 | 10198 | 10299 | 10296 | 9978 |

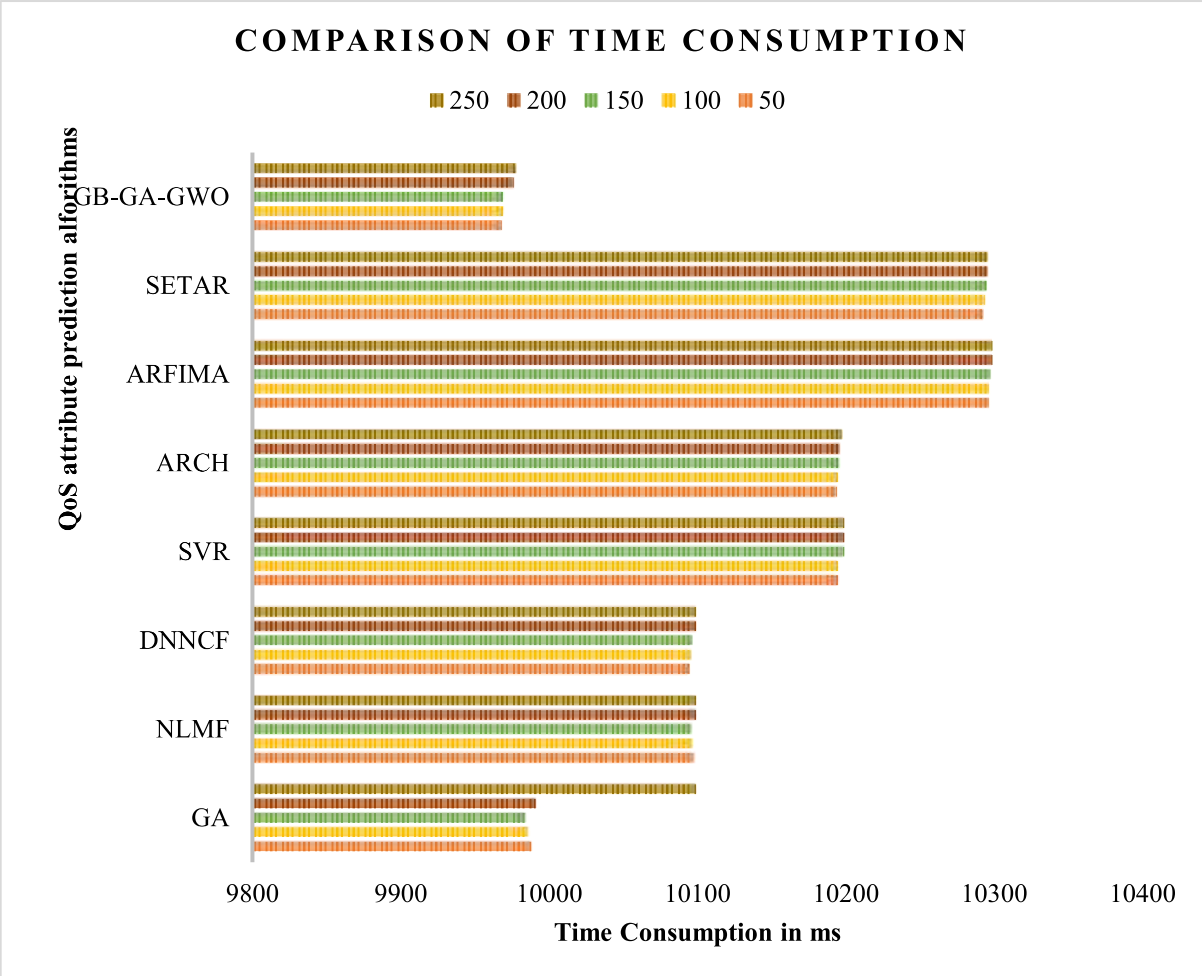


**Figure 5: Comparison of Time Consumption**

In Figure 5, the time consumption of GB-GA-GWO is minimum when compared with the other machine learning approaches. It is evident that the GB-GA-GWO is efficient.

## 5. Conclusion

In this research paper, the QoS attribute based web service recommendation issue is addressed and the forecasting of service for the user is described. The overfitting of testing data, exploration and exploitation issues are rectified with the hybridized gradient boosting with genetic algorithm based grey wolf optimization (GB-GA-GWO). The performance of the GB-GA-GWO is investigated in terms of forecasting accuracy with diversified parameters. The error rate of the proposed approach is minimum when compared to the existing machine learning techniques. The incidence of QoS attributes in the training phase has enriched the performance of the proposed approach and the shortcomings is rectified by the gradient boosting approach. The QoS attributes are forecasted effectively which in turn provide personalized assistance for the users of web service. In future, the approach can be extended for large-scale data that is with bigdata.

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