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A Hybrid Optimization Algorithm for Enhanced Web services with QoS measures in Cloud Computing

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Abstract. In the environment of Big Data analytics worldwide, cloud web services were deployed across Internet and Intranet domains. Moreover, cloud computing, while possessing significant advantages and experiencing rapid development, faces trust complexities, privacy concerns, and security issues. These challenges necessitate the implementation of Quality of Service (QoS) measures in optimisation techniques for web service selection. This study focuses on the selection of component services and the use of an efficient algorithm with end-to-end quality measures. However, data diversification and service characteristics may reduce the accuracy of these measures. To address this, a novel QoS-based web service selection algorithm was developed, incorporating both weighted and subjective attributes. The proposed methodology employs a hybrid optimisation algorithm that integrates randomised attribute searches with the Invasive Weed Optimisation (IWO) algorithm. Furthermore, it calculates QoS measures based on the weighted attributes of web services. Many researchers have applied nature-inspired concepts to deal with optimisation complexities in Big Data, including the Eagle Perching Algorithm to improve the efficiency of cloud web services. In addition, the evolution of the Bald Eagle Search (BES) algorithm has been utilised as a nature-inspired approach, providing an efficient technique for optimisation problems by imitating the behaviour of bald eagles. The results demonstrate that the proposed methodology achieves improved performance metrics when compared with existing approaches, confirming its effectiveness in the evaluation of web service optimisation.
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1 Introduction

The Significance of Cloud computing has been the predominant paradigm to assist IT service and product applications and medium to small-scale businesses. The privileges of cloud computing are multi-fold such as indulging the share and the optimized usage of Unrestricted flexibility and Scalability, IT cum resources, greater automation level, services access range, and decrement in the software cost and computer costs. Moreover, this cloud computing possesses the privileges and has rapid development, the part also faces the trust complexities, privacy concepts, and Security issues which allows for implementing the Qos measures in the optimization techniques.(Pan, Ding, Fan, Li, & Yang, 2015) Generally, the Cloud computing paradigm involves various kinds of services such as PAAS-Platform As A Service, IAAS-Infrastructure As A Service, and SAAS–Software As A Service. The Third-Party cloud computing providers are involved in the maintenance of the services and the computation of the services infrastructure rather than the organization's full-fledged participation in the investment of a large amount of money for this purpose. Hence due to the privilege of the Organisations, in carrying out the cloud computing technology, cloud services attain the proliferation level in the market in the recent decade.

There is an utmost complexity in the selection of the optimal services in cloud computing which convinces the necessities of the users. The consistency of the composite service is defined by the services repository wherein each separate cloud service is fetched based on the distinct metrics values. The objective of cloud service composition is to satisfy the functional requirements of the business logic. This composition of Composite cloud service has been specialized by the non-functional components referred to as Quality of Service parameters.(Jain, Khandelwal, Katkar, & Nygate, 2016) This QoS Parameter would aid the users to evaluate the Composition in the Quality of service. In this survey, the novel approach for optimizing the cloud service selection by the implementation of the Eagle Search algorithm and Invasive Weed optimization algorithm ensured Quality of measures. (Zhou, Chen, & Zhou, 2014)The study focuses on the selection of component services and employing the efficient algorithm with end-to-end Quality of measure, The Qos measures have been presented in the dynamic web services composition and the Qos Optimization in composite service. These approaches are too sensitive to the set parameters and easily placed in premature convergence. On the Other side, the Meta-heuristic algorithms would be the proficient approach for non-linear optimization complexities.

In recent decades, among researchers, the computation based on nature-inspired ones has been a significant and attentive concept for the modelling of the artificial-computation system.(Chen et al., 2016) Nature is driven as the significant source of innovative ideas, concepts, and thoughtful mechanisms in the cloud computing technologies and also in resolving the mathematical conflicts. The evolution of BES- Bald Eagle-Search was utilized as the nature-inspired approach would drive as the efficient technique for optimization issues which imitates the bald-eagles behavior while in the search of prey.(Alsattar, Zaidan, & Zaidan, 2020) The study on the proficient Quality of Service data would have a place in SOC-Service Oriented Computing. The measure on Quality of measure ought to be the co-activity of the preferences, services, and users set.(Xin, Fan, & Lai, 2012) The Data diversification and the service characteristics would decline the accuracy level of the measures. In this Survey a novel QoS measure web-services algorithm implemented the weight attributes and the subjective attributes.(Ma, Wang, Sun, Zou, & Yang, 2013).

The major contribution involved in the study were:

- Implementation of the optimization techniques for cloud web services in Big Data in an efficient way.
- Evolution and implementation of global Hybrid Invasive weed algorithm for the input of pre-processed dataset and performing the optimized system of web services.
- Calculation of Quality-of-service measures on the weights of the web-services attributes.
- Implementation of nature-inspired concept for the optimization complexities in Big Data and thus employing Eagle-Perching Algorithm in the efficiency enhancement of cloud web-services.
- Comparison of the performance metrics results with the existing approaches to evaluate the proposed methodology.

2 Related Works

A The following section deals with the literature review of the optimization in big data, invasive weed algorithm research, and eagle perching algorithm.

2.1. **Big Data optimization**

This study explored several ways the integration in the analytics of Big Data along with the optimization approach of big data Networks this paper explores various means of integrating Big Data analytics with network optimization. This optimization would have the goal of the enhancement of the quality of the user. For this study, BDD- Big Data-Driven optimization framework prevailing in the mobile networks has been implemented in the study. This research (Slavakis, Giannakis, & Mateos, 2014) presented the current cross-disciplinary attempts in the Big-Data science. This article also encompasses the design models from the varied Signal processing related tasks of data analytics which include DL-dictionary-learning, subspace- clustering, CS-compressive-sampling, and PCA-principal component-analysis.

This article (Ning & You, 2019) demonstrates the present enhancements in the optimization field of modernized data lenses. This article also outlines the vital challenges and the characterization of the optimization in a Big Data-driven platform. This approach also incorporates mathematical programming and ML-machine learning processes for the benefit of decision-making phenomena. It also highlights the capable research choices. This article (Z. Yang, Jia, Ioannidis, Mi, & Sheng, 2018) proposed the algorithm for multi-stage processing techniques prevailing in Big Data analytics. This would cache the interface data sets and determine the data sets which can be re-utilized.

Likewise, (Arslan, Pehlivan, & Kosar, 2018) demonstrated the 3 algorithms for the process of parameter-tuning and transmitting the scheduling to the transfer throughput level at the maximum range. These resultant inferences would in turn enhance the transfer throughput level to ten times as such. This study is prevalent in broader area networks. In this article, (Antonova & Aksyonov, 2018) addressed the methodologies of the decision-making process which permits the non-programmers to assess and in the generation of the system-operation substitutes and in selecting the one based on given criteria. This study would be applicable to rectify the optimization problem.

Similarly, this article (Bhattacharya, Islam, & Abawajy, 2016) determined the evolving algorithm and the improvisation techniques to handle the sparseness conflicts and the higher-dimensionality complexities in Big-Data optimization. This study utilizes the genetic operators to extend the range of search processes and to present the diversification in Big Data. This study (Facchinei, Scutari, & Sagratella, 2015) illustrated the decomposition framework in optimization techniques parallel. The optimization process is carried out for the summation of an individual non-smooth convex function and the differentiable function as well. The framework was found to be strongly flexible and it constitutes the Gauss-Seidel scheme and Jacobi Scheme also.

This article (Hong, Razaviyayn, Luo, & Pang, 2015) establishes the BSUM- Block Successive Upper-Bound Minimization which is founded to be the strong algorithm for the optimization of Big Data. The major advantage of the algorithmic framework is that it possesses flexibility of framework and the convergence guarantee of the algorithm. This study (Yi, Deb, Dong, Alavi, & Wang, 2018) implemented the adaptive-mutation operators which aim to improvise the standardized-NSGA third algorithm performance. This mutation-operators approach has been analyzed upon 2 cross-over NSGA Third algorithmic operators which cover the SI-single-point cross-over, SBX-simulated-binary cross-over, and the UC-Uniform cross-over.

2.2 Invasive Weed algorithm

This research paper (Bouzary, Chen, & Krishnaiyer, 2018) illustrates the SCOS – optimal selection problem and Quality of service-aware service composition problem. These problems have been outlined as the optimization problem. Hence the modified approach discrete IWA-invasive-weed algorithm was implemented and considered as the new methodology for the rectification of the optimal selection problem NP-based issue in the cloud manufacturing frame. The functionality of the optimization approach is analyzed by various multi-dimensional benchmark functions. The resultant information which is implemented by the proposed approach exhibits a high level of performance in comparison with the all-other conventional approaches. The paper majorly focuses on the address of the IWO algorithm which dwells as the robust and effective algorithm for optimization.

The objective of the paper of (Qasim & Mitras) stated the new approach known as the Hybrid-Algorithm where the algorithm would yield the positive attributes and reduces the negative attributes of the other two algorithms. The other two algorithms include the grey-wolves algorithmic approach and the next one is IWO – Invasive weed algorithm. The resultant algorithm which is referred to as the hybrid algorithm is the Invasive-weed optimization grey-wolves optimization algorithm –IWOGWO. The complication of the paper is relied on in obtaining the optimal predominant solutions for the complexities of higher measurement and complexities of non-restricted ones for the prevention of other local issues.

This paper (Jatoth, Gangadharan, & Fiore, 2019) illustrated the novelty methodology Optimal-Fitness Aware Cloud-service Composition approach which utilizes the modified IWO algorithm – Invasive weed algorithm. This optimization algorithm deals with the multiple-Quality of Service parameters. This also further balances the connectivity restrictions and the Parameters of Quality of service. Here in this paper, the performance of the methodology was assessed upon real-world cloud services Information set. Hence the focus of the paper relied on determining the better most optimal-fitness aware composition of the same cloud service. This research (Malmir, Farokhi, & Sabbaghi-Nadooshan, 2014) presents the fast relevant classification optimization approaches. Since the significance of Data mining is found to be vital, the study suggests the four-fast growing algorithms which are classified and compared with the other algorithms. This includes the following comparisons as the MLP – Multi-Layer Perceptron-networks implemented with IWO-Invasive weed algorithm, ICA- Imperialist Competitive algorithm, DE-Differential Evolution, and PSO- Particle swarm optimization algorithm. These phenomenal classifications were performed on the database of WBS- Wisconsin Breast Cancer. On the inferences, the algorithm is further categorized with another kind of GA – Genetic algorithm classifiers, which exhibited the accuracy of the classifiers and the speed level of the categorized classifiers.

The research (Ahmadi & Mojallali, 2012) presents the novelty optimization approach as the hybrid algorithm which retrieves the random properties of the IWO-Invasive weed optimization methodology and the chaotic search. The Proposed functionality of the optimization method was determined by the benchmark functions of multi-dimensional type. The resultant data proposed would expose a higher level of performance in comparison with the other conventional approaches. This paper (Zhou et al., 2014) illustrated the new scheduling invasive-weed optimization algorithm for the phenomena of optimization of NFSP-new idle flow-shop-scheduling problem. This proposed methodology possesses the criteria for decreasing the complete time at its maximum level. The resultant outcomes from the study infer that the new idle flow-shop scheduling complexity can be rectified by the implementation of the IWO-invasive weed algorithm and it qualifies with high robustness.

This algorithm in this paper (Sharma, Nayak, Rout, & Krishnanand, 2013) demonstrates the implementation of the radical dual-mutation approach capable of rectifying the higher dimensional complexities. These higher dimensional issues would possess the non-homogeneous spaces of search in consideration of the decision variables individually. The implementation of the study on the 5 unit-system and two other various 10 unit-system exhibited the feasibility validation and efficiency validation.

The study (Su, Ma, Guo, & Sun, 2014) defines the service-selection complexity. This problem has been designed as the non-linear optimization methodology with the restriction constraints which led to the novelty of the IWO-invasive weed algorithm has been considered for the study. This research (Velmurugan, Khara, Nandakumar, & Saravanan, 2016) provides a novel approach to the Invasive weed algorithm in Vertical Handoff for decision-making. Hence the study of the Vertical Handoff algorithm has been equated with the other existing approaches of OPTG and SSF methodologies for the benefits of decision-making.

This paper (Pahlavani, Delavar, & Frank, 2012) defines that the methodology of the Invasive weed algorithm was evaluated, launched in comparison with the GA –other genetic algorithms, modelled, and implemented in the studies. The comparison with the genetic algorithm-GA would be utilized to rectify personalized-urban multi-criteria-quasi optimum-path problems. The inferences also illustrated the proposed study to attain the best result outcomes in terms of running time, fitness functionality, and in the metrics of quality.

2.3 Eagle perching algorithm

This research (Habachi, Touil, Charkaoui, & Echchatbi, 2018) incorporates the CSA- Crow-search algorithm considered as the locally involved optimizer which is of Eagle strategy to resolve the UC problem (Unit commitment) in the smart grid technology systems. This paper (Alsattar et al., 2020) determines the nature-inspired and novel BES-Bald Eagles-search algorithm. This BES algorithm is the optimization algorithm and also the metaheuristic type. This algorithm would exhibit the intelligent-social strategy of the bald eagles which they the tendency in searching the prey (fish) for them.

The research (Chen et al., 2016) was implemented based on the novel fresh approach eagle strategy which is an enhanced NMS-Nelder Mead simplex methodology and it is crossed with the ABC meta-heuristic approach (Artificial bee colony). This novel proposal would require improvising the identification of the parameter of the photovoltaic models. (Gavvala, Jatoth, Gangadharan, & Buyya, 2019) utilized the approach of Eagle strategy for the design-model creation of Qos-aware service composition of cloud computing. Achieving this, there established the equalization between the exploitation and the exploration of service composition. This is involved to recover the complexities of premature convergence to that of relevant proficient points.

Likewise (Angayarkanni, Sivakumar, & Rao, 2020) illustrated the optimization of the Support-vector regressions parameters through evolving the BES- Bald-Eagle search algorithm with the GWO optimization algorithm (Grey-wolf optimization). The purpose of the paper is to estimate the approximation of the flow of the data traffic. This article (Mythili & Manavalan) implemented the EO approach (Eagle optimization methodology) to eliminate the Gaussian-Noise. Elimination of the noise is from the Image-data and the approach has been implemented for selecting the proper structuring-element size as well. Similarly (Kesavaraja & Shenbagavalli, 2018) employed the Virtual Machine-VM allocation policy utilizing the Eagle searching strategy involved in KH optimization methodology- Hybrid Krill-Herd technique. This optimization method would improvise the cloud service computing technique for all the users of the Internet. This cloud-service computing also yields the connectivity of all the data centres for resource-sharing by this Virtual-machine.

This article (X.-S. Yang & Deb, 2010) focuses the randomized optimization by evolving the novel two-way stage hybrid methodology referred to as the Eagle strategy. This study would reveal the combination of Firefly and the randomized search algorithm. This algorithm utilizes the Levy walk approached iteratively. The study (Talatahari, Gandomi, Yang, & Deb, 2015) incorporates the present enhanced ES algorithm- Eagle search optimization approach) with the various distinct evolutions. This algorithm would be referred to as the ES-DE algorithm. This method is employed by the strategy of interfacing the MATLAB software and the structural-analysis coding (SAP2000 code). The Eagle Search-Differential evolution performance was assessed by resolving the 4 benchmark complexities. The focus of the paper also relied on steel-frame weight minimization. This study (Yapıcı & Çetinkaya, 2017) implemented the ESPSO approach for rectifying the conflicts of reactive Power-optimization and also in the power-loss elimination. The ESPSO is the enhanced particle-swarm optimization algorithm utilizing the Eagle-strategy method. The inferences of the results implied the proposed method to be a more efficient and high-level approach to the conventional approaches.

3 Proposed Methodology

The primary objective of the study is obtaining the optimized selection of cloud services based on implementing the Hybrid Invasive Weed algorithm and Eagle Search optimization algorithm along with Quality of Measure factors. The optimization of the cloud computing web services would be performed by the selection of a Sequence set of the dataset and the assessment of the Quality of measures. The data is then subjected to the optimization algorithms such as the Invasive weed algorithm and the Eagle search algorithm. Various web service links had been optimized. The comparison of the performance metrics of the proposed model with the conventional existing methods is performed.

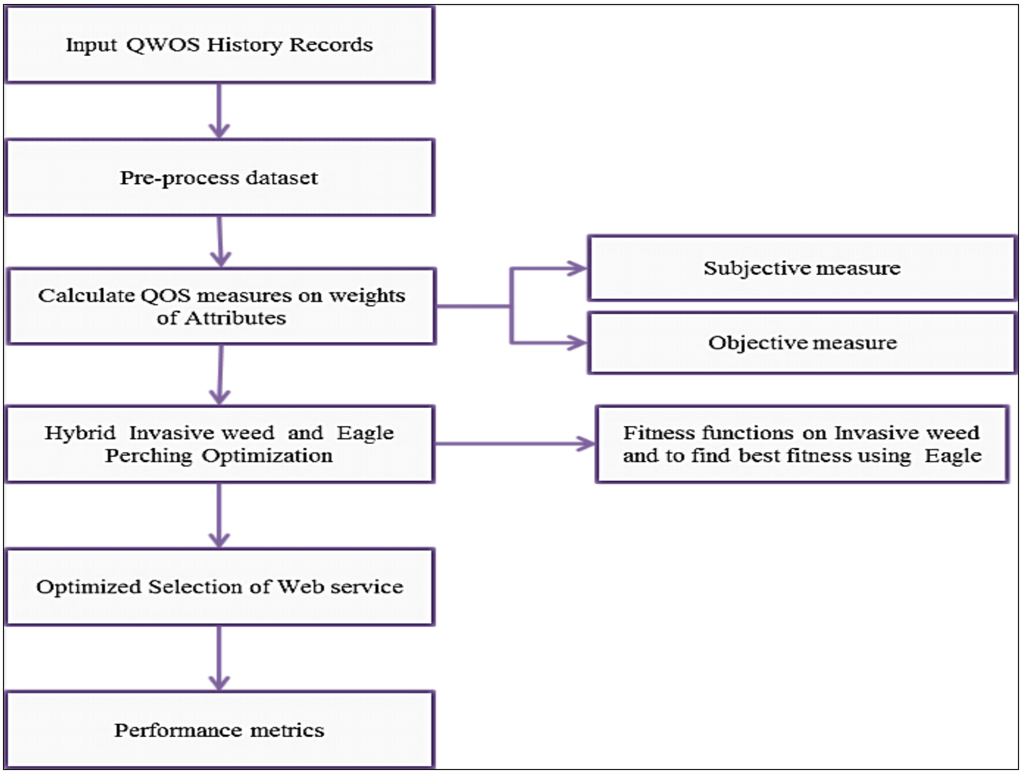

Fig: 1 Proposed Overall flow

3.1 Pre-Processing of Dataset

The Historical records would be fetched from the data set. This dataset describes real-world Quality of service evaluation data set results from 339 users on the count of 5,825 Web services. Has been conducted various classified larger-scale Quality of service assessments of real-world web services. This would have been implemented for gaining the Quality-of-service datasets of the user's web services.

3.2 QoS Measures calculation

The data set has been subjected to the QoS calculation in terms of assessing the Throughput value and the Response time value of the selected specified web services. This Response Time of the Web-service would be determined as the time-line period between the users who transmits the request to the timeline the service-user receives the related response to the request. The Through-put is defined as the average percentage rate of the size of the message in terms of bit value which is delivered in the communication channel each second. To calculate the brief demonstration of the throughput data and the response time of the selected web services by the various users, it has been chosen the 339 users from the count of 5,825 Web services. The comparison of the response time and the throughput evaluation on the distinct web services have been performed. The Prep-processed Data set would include the Quality of services measures for the five thousand and eight hundred and twenty-five web services. These Web services would be recommended for the experimental analysis of the web-service selection.

3.3 IWO-Invasive Weed algorithm

This algorithm is the metaheuristic optimization algorithm which imitates the colonization-behavior approach of the weeds. This Algorithm is the population-based dependent algorithm. (Basak, Maity, & Das, 2013) In this algorithm generally, the general characteristic attribute of the weed is that it increases the population as a whole or in the Particularized region which may be small or large. Here in the proposal, the web services count has been considered.

The 4 stepwise procedures to be followed are:

3.3.1 Initialization Step

The specific number of weeds were randomly selected and scattered over the whole D dimensional-search region space. The population at the initial stage per generation will be defined as X= $\{\vec{X_1}, \vec{X_2} \ldots\ldots\ldots \vec{X_m}\}$

3.3.2 Reproduction Step

The number of seeds produced by the population $\vec{X_i}$ where i belongs to {1, 2, 3,…m} will have the dependency on the fitness function by worst fitness and best fitness. The population member of each was permitted for seed production within the particularized area.

3.3.3 Spatial Distribution Step

The Seeds which are generated were scattered randomly upon the D dimensional space of the search region. This is performed by the general random distribution of the numbers with the Variance σ^2 and Zero mean numbers.

$$\sigma_u = \sigma_{minm} + \left(\frac{t_{maxm} - t}{t_{maxm}}\right)^{m\_n\_u} . (\sigma_{maximum} - \sigma_{minimum})$$

Where the m_n_u denotes the modulation index of non-linear form t, max m is the maximum count of iterations involved, and t represents the iteration count.

3.3.4 Competitive exclusion step

This drives the selection procedure of the Invasive weed algorithm. If there is no offspring in the growth of plants, then either it may have the chance to go extinct or would place in the world. There is a required factor for competition type in the plants to restrict the maximum range of plant count prevailing in population. Here in this scenario, the fittest plants which include the reproduced ones and the existing plants have been considered in the colony. The step procedure of the IWO algorithm was repeated unless the maximum count of the iteration numbers or the function evaluations is attained. Hence in each generation, the size of the population ought to be lesser than or equalized to the variable $pop\ ma\,xm$. This phenomenon is referred to as the competitive-exclusion.

3.3.5 Invasive Weed Algorithm based selection of solution

The algorithm will forward the selection process in accordance to keep the constant value to the population size in the consecutive generations. The operation defines the survival rate of the target matrix and the trial matrix to the next generation. i.e., at n = n + 1. This operation of selection may be outlined as:

$$\begin{cases} \vec{Y}_{i,n+1} = \vec{U}_{i,n}, & if\ f(\vec{V}_{i,n}) \le f(\vec{Y}_{i,n}) \\ \qquad\quad = \vec{Y}_{i,n}, & if\ f(\vec{V}_{i,n}) > f(\vec{Y}_{i,n}) \end{cases}$$

U, V is two matrices, randomly chosen index, which ensures that $\vec{U}_{i,n},$ gets at least one component from $\vec{V}_{i,n}$.
Le′vy $\sim v = n^{-\alpha}, (1 < \alpha \le 3)$ here α is the eagle motion is essentially a random walk process with a power-law step length distribution with a heavy tail.

3.4 Eagle Search Optimization algorithm

The two side stage strategies of the behavior of Eagles are considered in the approach. At first, the Eagle would be assumed that it will exhibit the Levy-walk method in the entire domain. Once the Eagle finds out the prey, The Eagle would alter itself to the chasing strategy. On the second side, the Chasing strategy could be presented as the intensive-local search method mechanism utilizing the optimization approaches such as the Nelder Mead methodology. The PSO-Particle Swarm optimization algorithm has also been utilized as the effective meta-heuristic optimization algorithm; The Eagle strategy has been outlined in the pseudo code section. In this Data flow, The Fire-fly algorithm has been used as the local-search algorithm and modelled to resolve the optimization complexities globally.

3.4.1 Weight calculation

The Weight attribute relevant feature is denoted by w_i.

Web services W={w_1,w_2,w_3....w_i}

Qos attributes Q={a_1,a_2,a_3,....a_j}

While each column single QoS Parameter Q_j denoted by E has two QoS parameters namely Throughput Tp and response time Rt

$q_{i,j} = Tp_{i,j}. Rt_{i,j}$

For multiply the QoS matrix here we are using strassen multiplication

$$E=\begin{bmatrix} q_{1,1} & q_{1,2} & \cdots & q_{i,j} \\ q_{2,1} & q_{2,2} & \cdots & q_{2,j} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ q_{i,1} & q_{i,2} & \cdots & q_{i,j} \end{bmatrix} \quad (1)$$

To calculate web service relevant feature need the maximum normalized value of Q_j column Let L be the array where L={$l_1, l_2, l_3, \ldots, l_m$ with 1 $\leq m \leq$ i

$$L(j) = \sum_{m}^{i} q_{m,j} \quad (2)$$

$$M_{i,j} = \frac{q_{i,j}}{\max(L(j))} \quad (3)$$

$M_{i,j}$ *measures the difference from the maximum normalized value*

Different Weight contribution denoted by {e1,e2, e3,....,e_j}

$$x_{i,j} = e_j\left[\frac{q_{i,j}}{\max(L(j))}\right] \quad (4)$$

Weighted matrix denoted by E'

$$E'=\begin{bmatrix} e_{1,1} & e_{1,2} & \cdots & e_{i,j} \\ e_{2,1} & e_{2,2} & \cdots & e_{2,j} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ e_{i,1} & e_{i,2} & \cdots & e_{i,j} \end{bmatrix} \quad (5)$$

Relevant feature ($w)_i = \sum_{i=1}^{L} x_{i,j}$ (6)

Hybrid Eagle Strategy with Invasive weed optimization-based optimization with parallel map and reduce:

Invasive weed Algorithm

Objective functions $f_1(x), \ldots, f_t(x)$
Initial guess $x^{n=0}$
While(||$x^{n+1} - x^n$||>tolerance)
Map and reduce initial values
Random search by performing Le'vy walk
Evaluate the objective functions
Invasive Weed Algorithm based selection of solution
If(a better solution is found)
Update the current best
End if
Update n=n+1
Calculate means and standard deviations
End while

The random-step length factor has been taken from the distribution of Levy. The Levy-walk possesses a randomized step length.
Levy ~ v = $n^{-\alpha}$ where the value is ($1 < \alpha <= 3$),

This has the infinite mean and infinite variance. The Eagle strategy motion is necessary as the random-walk process with step length-distribution of the power law. In this special case, the notation $\alpha = 3$ which is correspondent to Brownian motion, and the notation α equals 1 and it has the stochastic tunneling characteristics.

3.5 Map and reduce Method

The part illustrates the iteration sequence of Map-reduce jobs. In this Map Reduce jobs count of fifty Map-reduce jobs would be presented for a single iteration in Map Reduce -Eagle search or Invasive-weed algorithm. The resultant inference of the Map Reduces jobs relies on the population which is of the updated form. This population which is of the updated one has been fetched as the input variables for the consecutive next phase of the Map-Reduce methodology. Master will scatter the data into ten splits of the n value. ('n' equalized to 10 equivalent splits). These splits have been backed up in the distributed-file system. The number count of the Map and Reduce method for three hundred and thirty-eight is one. The swarm has been spitted into the q count of populations and also the map-task of each one is overlapped with the sub-population. Such sub-population has been backed up and stored as h-key values and I pair values. The value denotes the candidate service along with the Quality-of-service characteristics and the key value denotes the abstract service.

The various task outcomes of the method would be transmitted as the inputs to the required Reduce functions. By the utilization of parallel-batch processing, the reducer fetches all the data of each abstract service. The reducer would merge all the data of iterative-sub-populations. It has been stored on the list. This whole list is then forwarded to the Map-Reduce –MR- Eagle search /Invasive weed algorithm. This optimization algorithm would produce the output for 338 web services individually (in terms of dominant population and the out-key). This exhibited as the perfect optimized service-composition method with robustness factor and the scalability factor.

4 Performance Evaluation

comparison of the performance metrics with the existing approaches to evaluate the proposed methodology is stated in the following section. The Experimental analysis on the larger set of Dataset is implemented for the comparison of the present proposal performance. The resultant outcome of the experiment will illustrate the efficiency of the current approach. Here in this approach, the Web service is associated with the non-functionality QoS–Quality of service parameter-set such as the throughput, reliability factor, and the response time of the web service. This would determine the service's overall performance efficiently.

4.1 Evaluation results

The algorithm has been applied to the relevant benchmark of the web-services challenge –WSC-2009. This Dataset would efficiently give the test sets. The resultant graphical representation Consists of web services of the above range. The Test data set constitutes the 4 files which include WSDL-File which describes the registry services in the outputs and inputs. The file WSLA stores the Quality of services such as the throughput and the response time and the service criteria values, the XML file which stores the output and inputs of the query related to the service registry, and the organized file in a hierarchical way utilizing the ontology in OWL-file(Z. Wang, Cheng, Zhang, & Chen, 2020).

4.1.1 Comparative analysis I

The comparative analysis of the proposed and existing in terms of latency, response time, execution time and price, availability, and success rate are depicted in this section.

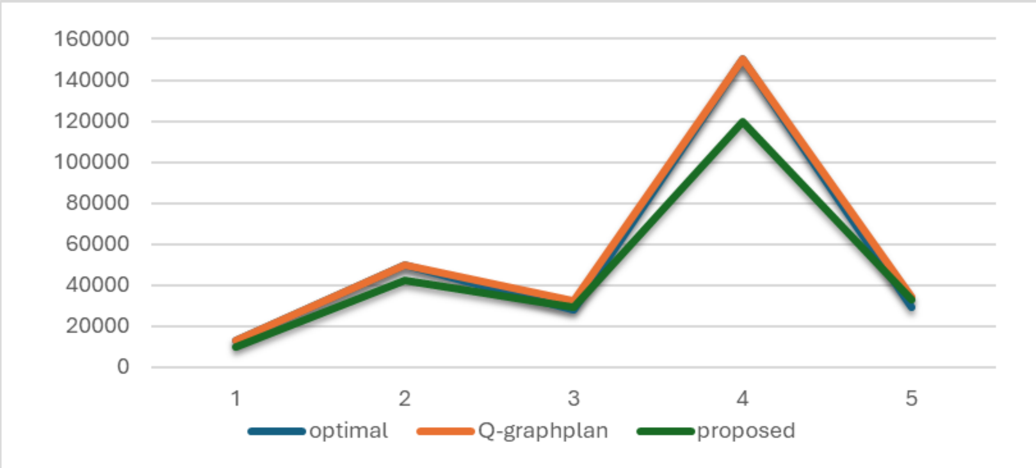

Fig.2. Latency of Optimal, Q-Graph plan and proposed result(Z. Wang et al., 2020)

Figure 2 demonstrates the optimality concept, Q-Graph-plan's solution, and proposed solution which are illustrated above. Here in this graph, the latency factor is considered. The latency factor is reduced compared to the existing solutions and it shows better-proposed results since the latency is referred to as the total amount of time taken for sending the information. And it reduced for the proposed method.

Table 1: Optimality concept of Q-Graph plan and proposed result(Z. Wang et al., 2020)

Latency(ms)					
Optimal	13000	49500	28000	150000	29000
Q-graph plan	13000	50000	32000	150000	34000
proposed	10000	42000	29000	120000	33000

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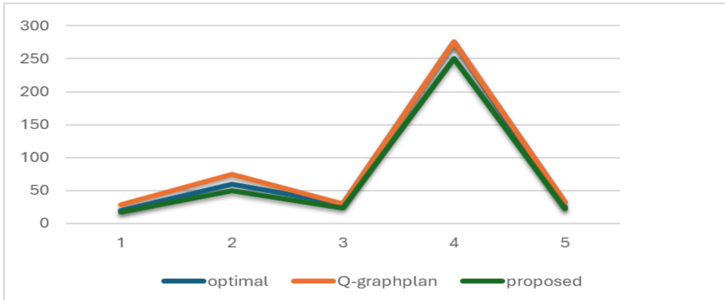

Fig 3: Execution price of Optimal, Q-graph plan, and proposed result(Z. Wang et al., 2020)

Fig.3 illustrated the execution price of the various approaches. The execution price of the proposed method and the existing optimal and Q-graph plan are illustrated in fig.3 and table 2. It shows the proposed method occupies a lesser price compares with the existing methods.

Table 2: Execution time of Optimal, Q-graph plan, and proposed result(Z. Wang et al., 2020)

Execution Price(ms)					
Optimal	20	60	30	275	25
Q-graphplan	28	75	30	275	32
proposed	17	50	23	250	22

Here the comparison of the proposed data set of WSC 2009performance with the existing ones includes the Quality-of-service parameters such as execution price, the response time of the web service, latency of the data, successful-rate, reliability, and availability factor. This has been fetched from the genuine website information in the experimental.

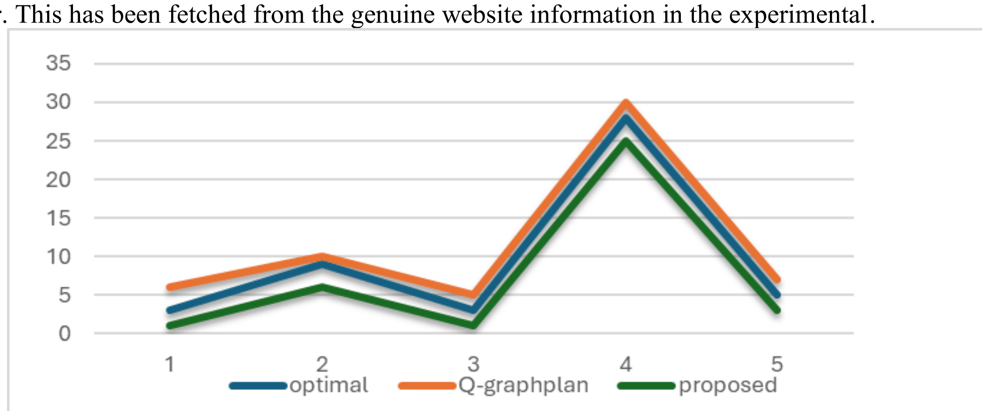

Fig. 4. Reliability comparison(Z. Wang et al., 2020)

Figure 4 and Table 3 define the reliability of the proposed and existing approaches. It shows reduced factors in reliability measurement for the proposed method compared with existing approaches depicted the better performance of the proposed method.

Table 3: Comparison of reliability(Z. Wang et al., 2020)

Reliability					
Optimal	3	9	3	28	5
Q-graph-plan	6	10	5	30	7
proposed	1	6	1	25	3

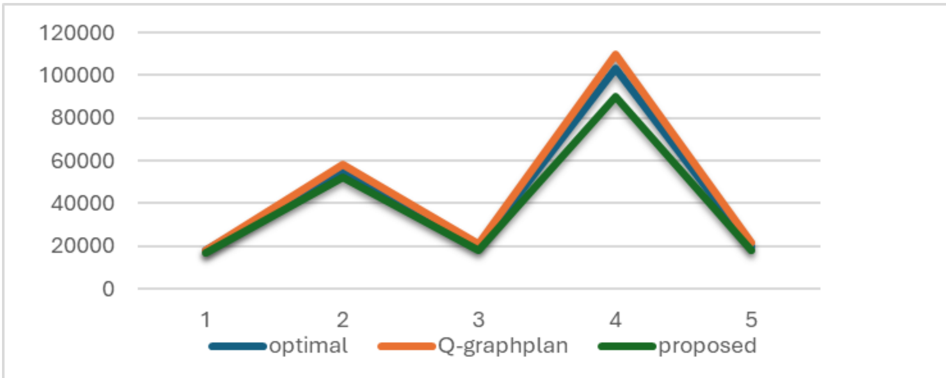

Fig. 5. Response time comparison(Z. Wang et al., 2020)

Figure 5 illustrated the various response time variations in approaches. Table 4 and fig.5 depicted the proposed and existing response time comparison. His proposed method takes lesser time in execution compared with the existing method.

Table 4: Response time comparison(Z. Wang et al., 2020)

Response Time(ms)					
optimal	18000	55000	20000	103000	20000
Q-graphplan	18000	58000	21000	110000	21500
proposed	17000	52000	18000	90000	18000

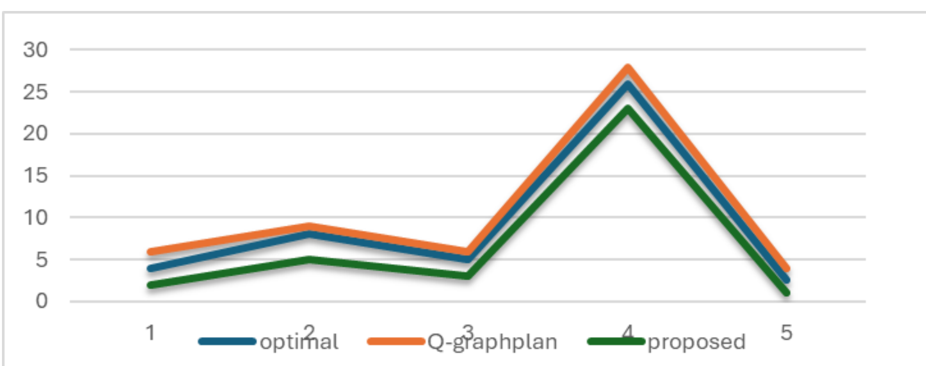

Fig.6. Availability comparison(Z. Wang et al., 2020)

Figure 6 and Table 5 present the availability differences between the proposed and existing optimal approaches. The availability is lesser compared with existing approaches.

Table 5: Availability comparison(Z. Wang et al., 2020)

Availability					
optimal	4	8	5	26	2.5
Q-graphplan	6	9	6	28	4
proposed	2	5	3	23	1

In the first stage, the optimality solution has been calculated. These optimal data values of the test data set have been determined. The Quality of service parameters was set to detect the test data set solutions and to the same weight measure in Q-Graph-plan.(Z. Wang et al., 2020) The Quality of service values of the Q-Graph-plan solution has been compared with the optimized values per criteria. In this graph, the red line graph denotes the Q-Graph-plan composition Quality of service values, and the blue representation of the graph denotes the optimal data values by the utilization of the single-objective techniques of optimization. The inferences of the result would be implied that the representation of the Q-Graph-plan would find the solution inference where Quality of service criteria have the optimal approximation value.

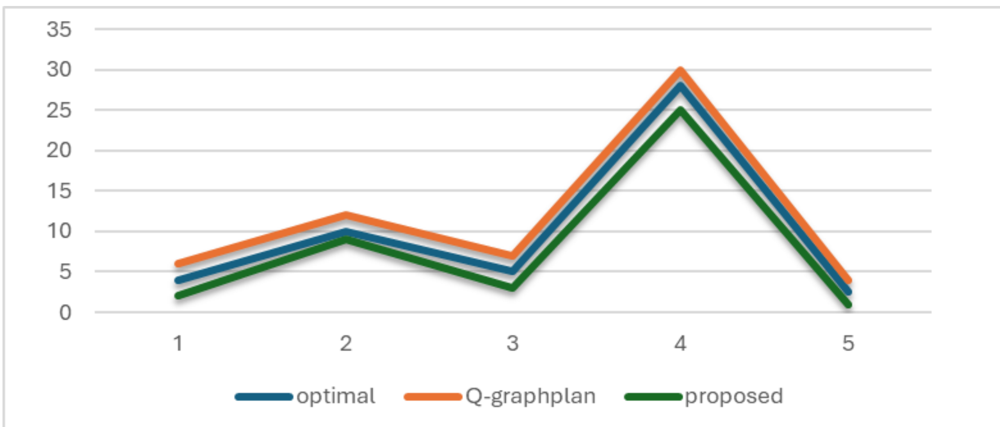

Figure 7. Success-Rate Comparisons

Figure 7 and Table 6 illustrated the variations in entire success rate calculations to the existing approaches.

Table 6: Success rate comparisons

Success Rate					
optimal	4	10	5	28	2.5
Q-Graph plan	2	9	3	25	1
Proposed	6	12	7	30	4

4.1.2 Comparative analysis II

In the second stage, the effectiveness of the algorithm is illustrated in the planning graph. The approach has evaluated the search response time on every test case several times by utilizing the mentioned two algorithms. The average response time was also calculated in the approach. The precision methodologies of the current proposal have been compared with the service-selection methods of the existing approaches. The service selection of the web service was artificially presented and the resultant data of service selection per randomized picked user requirements. The Baseline has been obtained in synthetic-dataset and Quality of service-selection of the web services individually. In this approach, the Top-1 percentage, 3%, 5 %, and 1% were selected individually for each of the service-selection needs. The comparison of the top mentioned percentages is illustrated in table 7.

Table 7**:** Comparison of Top percentages (Precision)

Top-1%			
Method	Top-1%	Top-3%	Top-5%
PC&Q	68	75	82
PC&T	48	53	66
I-QP	86	87	93
Integrated	92	94	98
Proposed	93	95	99

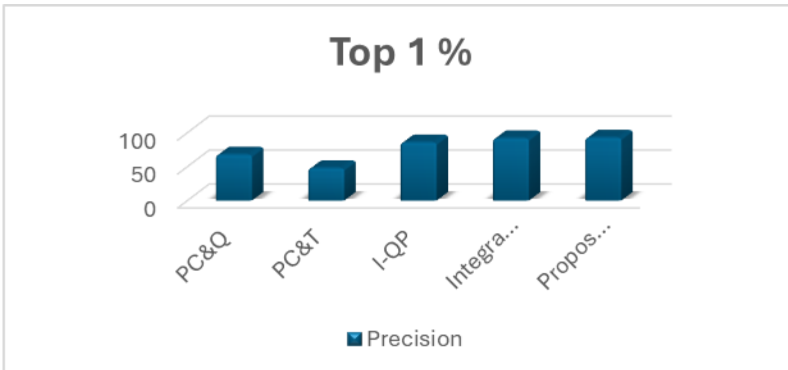

Figure 7. Precision Comparison (top 1%)(H. Wang, Yu, Wang, & Yu, 2015)

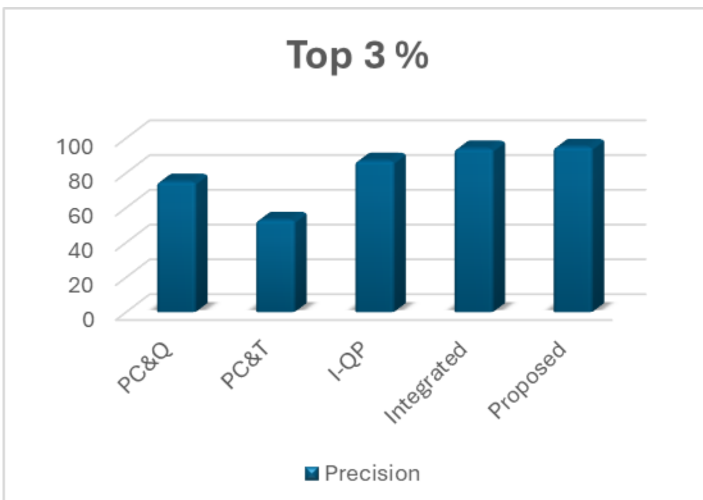

Fig. 8: Precision comparison (top 3) (H. Wang et al., 2015)

The service-selection mechanism per quantity of hundred requirements was conducted through PC and T, PC and Q methods, integrated methodologies in the absence of I-QP Qualitative preference, and the proposed methodology in a separate way.(H. Wang et al., 2015) The results of the service selection obtained by the various approaches would be placed in comparison with the Baseline. Hence the precision factor would be the decision parameter to assess the satisfaction level of the users of several approaches.

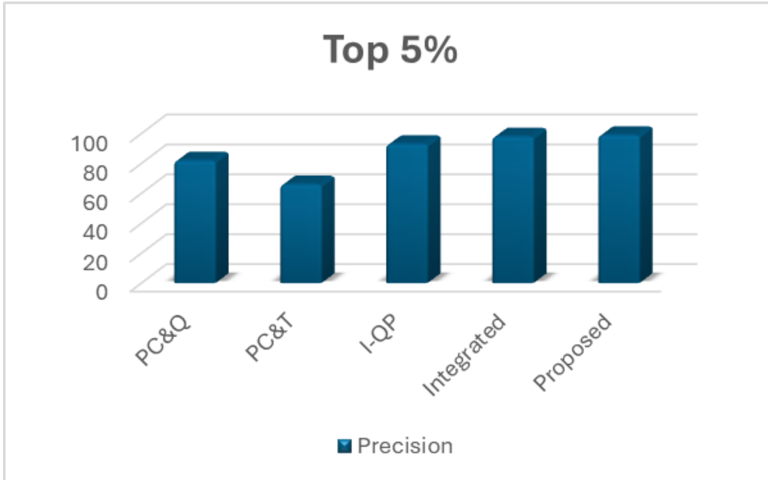

Fig. 9. Precision comparison (Top 5%)(H. Wang et al., 2015)

This methodology could thrive as the evidenced solution in the cloud computing application sectors of service selection of the Big Data Era. The precision factor compared for the proposed and existing approaches for top 1 to 5 % percentages depicted as higher values from fig.7 to fig.9.

4.1.3 Comparative analysis III

This section deals with the Reduction in Computational Complexity: The Diagrammatic observation has proven that the complexity of the computation level of Integrated-methodology is considerably low than the other previous techniques.

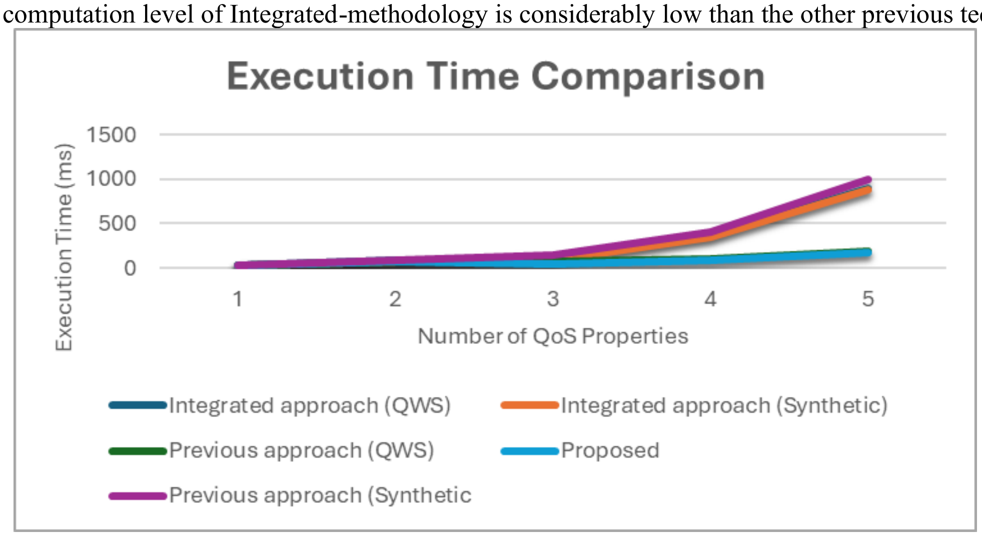

Fig. 10. Execution time comparison(H. Wang et al., 2015)

Fig.10, shows the execution time of various approaches illustrated above. This is because the quality-of-service quantitative attributes was transmitted into the qualitative attribute approach through the other previous methods. The proposed method withstands the quantitative attributes of Quality-of-service and majorly decreases the complexities of the computation.

Hence in the summarization, the integration approach implements as the method to hold the challenge in handling the larger service data volume. This approach fits more capable for the service-selective application prevailing in the Big Data domain.

5 Conclusion

In this Decade, the optimization technique and Quality of service-aware of the cloud web service selection play a significant conflict in the method of service composition. In this focus of the paper, the issue has been designed as the non-linear optimization complexity underneath the end-to-end quality of service constraints. Hence it has been formulated and implemented the new Meta-heuristic search strategic approach known as Eagle Strategy (Eagle search algorithm) and effective discrete IWO-Invasive-weed algorithm to rectify this problem of computation conflicts and to encompass the optimization with the Quality-Of-service measures. The Experimental analysis and Theoretical assessments would present the inferences on feasibility factor, robustness measure, and the efficiency of the methodology.

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