Correlating Discriminative Quality Factors (CDQF) for Optimal Resource Scheduling in Cloud Networks

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Abstract*—The Correlating Discriminative Quality Factors (CDQF) for Optimal Resource Scheduling in cloud networks has been addressed in this manuscript. It is since the resources under the cloud platform are loosely coupled according to the SLA between the cloud platform and the resource partakers. This enables the possibility of multiple resources from diversified partakers, those intended to accomplish similar services. The resource scheduling intends to select one resource among available resources to accomplish the scheduled task(s). The contemporary contributions related to resource scheduling are specific to traditional QoS factors, including cost, deadline constraints, and power consumption. However, the quality of service is often influenced by the contextual factors of the IAAS. Hence, this manuscript portrayed a novel resource scheduling strategy that orders the resources under the degree of optimality proposed in this manuscript. Unlike traditional resource scheduling methods, this manuscript portrayed a set of context-related factors that are further used to define the heuristic measure called "Degree of Optimality." The experimental study on the simulated environment elevates the proposal performance advantage as opposed to other existing methods.

Keywords*—Resource management (RM); resource scheduling (RS); resource provisioning (RP); QoS; infrastructure-as-a-service (IAAS)

I. INTRODUCTION

With the increased number of digital resources deployment on the networked cloud systems, the corresponding resource optimization scheduling mechanisms with higher levels of quality factors have a significant impact on the consumers' community and the providers' community of Cloud platforms. Nowadays, almost all organizations are leveraging Cloud computing capabilities to minimize their ownership cost and improve the productivity of their employees. Optimal resource scheduling quality factors are vital to improving end-user satisfaction, so this study focused on correlated discriminative quality factors for optimal resource scheduling in cloud networks.

Resource management (RM) is signified as a protection activity containing diverse workloads and resources from the submission to the workload's execution. The RM in the cloud contains 2 phases: a) resource scheduling (RS) and b) resource provisioning (RP). The RP is determined to detect sufficient resources for the specified workload based on QoS pre-requisites described by the cloud's consumers. At the same time, RS is mapping and performing cloud consumers' workloads based on RP's chosen resources.

Based on QoS pre-requisites, resource scheduling for sufficient workloads could be a challenging task. For effective resource scheduling, it is required to deliberate the requirements of QoS [1]. Hence, there is a requirement for uncovering RS's research tasks to perform the workloads deprived of impacting other QoS pre-requisites.

RS is an evolving research domain in the cloud because of the huge resource cost and execution time. Diverse RS factors and criteria are directed towards divergent classifications of RSAs (Resource Scheduling Algorithms). The effective RS lessens the cost of execution, energy consumption, performance time, and deliberating other QoS essentials such as availability, reliability, scalability, and security.

This paper is structured as follows. Section 2 discusses the various existing solutions that are closer to optimal cloud resource scheduling and its quality factors, while Section 3 presents correlating discriminative quality Factors for Optimal Resource Scheduling. Section 4 presents the experimental setup and empirical setup. The conclusion of Section 5 includes the future scope of the work.

II. RELATED WORK

The researchers have contributed "Multi-objective optimization scheduling" based on considerations such as economic costs, system execution, confines, and consumption of energy. By deliberating computational resources, the scheduling model is suggested, which segregates the budget costs and resources for lessening the task length, hence reducing the completion time of the task and enhancing the resource utilization of the system [2]. The work [3] presents fast completion time replication algorithms for "task-based replication." Initially, the algorithm adapts fuzzy clustering for preliminary resource pre-processing and later implements task duplication and acyclic graph scheduling. By deliberating the execution times of task, utilization rate, and resource costs are considered in the cloud environment utilizing multi-output, multi-input feedback "control dynamic resource scheduling algorithm" for assuring application under time confines for the optimal implementation execution [4]. For indefinite parameters in a hybrid environment, two "dynamic resource allocation" algorithms utilizing the Pareto optimization model have been suggested based on deadline and cost restraints [5].

Nevertheless, two of the algorithms' time intricacies are maximum, and both are higher than or equivalent to O (n2). The "adaptive workflow scheduling heuristic" model, which considers the confines of time and cost, has been proposed, even though the method schedules only data workflow analysis in the hybrid environment of the cloud [6]. The work [7] presents that the "Multi-objective scheduling" model is proposed based on cost & time optimization objectives with storage & bandwidth confines.

The model concentrated on enhancing the usage of "private cloud resources" for attaining the balance between costs and performance. The work [8], [9], [10] presents the scheduling issue in the way the same to concentrate on current research. For addressing the optimization and IaaS provider benefits, here, an "adaptive hybrid cloud particle swarm optimization scheduling algorithm" has been proposed. Nevertheless, this model only deliberated the cloud provider's benefits without any cost from the users' perception. The work [9] presents further; the researchers have suggested that the concentration needs to enhance the overall system's performance despite whether exploring private or public resources of the cloud.

Lastly, the task outsourcing towards the public cloud method is suggested for lessening the outsourcing cost while simultaneously increasing the rate of using the internal cloud data center [10]. Consequently, the research assumed mathematical programming for optimized scheduling. Nevertheless, this method cannot solve scheduling issues containing a huge amount of data, and its "optimization objectives" are costly. The work [11] presents the cloud RM program's proposal based on identical objectives of increasing the utilization of resources and lessening the costs. Nonetheless, the method is mostly utilized for migrating on and off the virtual machine and is not implemented for the real instance of optimizing the task scheduling.

Researchers in [12] analyzed different job types along with the availability of resources and developed a scheduling strategy that performs at a resource broker. However, the model was deported due to its computational cost and scheduling overhead. The contemporary contribution [13] portrayed a resource scheduling strategy for IAAS, using multiple Quality factors to schedule the resources. However, the contribution estimating optimality of resources has been limited to quality factors such as make-span, price, and availability. The quality factors linked to the context of the target IAAS are not in the scope of this contemporary model, and load is the other crucial factor, which is not in the scope of this contemporary scheduling strategy. Jiang et al. [15] investigated the scheduling of concurrent workflows in high-performance computing resources (HPC clouds). They describe a scheduling strategy that tries to reduce the total cost of computation, communication, and the earliest possible start time. In the last decade, a dynamic algorithm [16] for load balancing had been proposed. The static algorithm requires extensive knowledge of the forthcoming quantity of requests (tasks) and the availability of cloud-based virtual machines (cloud resources). When the number of clients grows, a long auction deadline interval will have a detrimental effect on the cloud service provider's earnings. Proposed a Cloud Resource Broker (CRB) by Somasundaram et al. [17] that has been assisted by an adaptive load balancing (ALB) and elastic resource provisioning and de-provisioning and (ERPD) mechanism. Yang et al. [18] proposed the bat algorithm (BA) as a unique heuristic optimization method in 2010, and a number of enhanced variants have been developed to deal with cloud computing resource scheduling. In [19], used stochastic integer programming to solve problems involving resource provision optimization. In a cloud computing context, the technique reduces the total cost of resource provisioning. The optimal solution is derived using a two-stage approach for formulating and solving stochastic integer programming. [20] In this research, the BAT method is utilized to address the multi-objective workflow scheduling problem in the Cloud, with the goal of optimizing execution time and reliability. Comparative simulations using the Basic Randomized Evolutionary Approach (BREA) were conducted, and it was observed that the BAT algorithm outperforms the other algorithm. In [21], an Opposition Learning-based Grey World Optimizer Algorithm is presented as a hybrid strategy for reducing the duration and expense of Cloud jobs. The evolutionary algorithm for cloud-based e-learning workload scheduling was introduced to optimize the scheduling of e-learning workloads subject to a predetermined set of conditions [22]. The two-tier VM architecture includes a front and background VM that dynamically share the VM's processing speed [23]. The issues of load balancing include scalability, availability, and load migration. To solve these obstacles, the hotspot mitigation algorithm [24] was created. [25] offered a detailed comparison of resource scheduling methods and resource allocation policies. This survey focused on resource scheduling and left other aspects of distributed computing out. It is based on the Imperfect Information StackelBerg Game (IISG) with a hidden markov model [26]. (HMM). Due to the cloud's heterogeneous and dynamic character, it's vital to deploy models that benefit both parties. It includes execution time, communication delay, reaction time, migration time, etc. Scheduling reduces completion time [27] and maximizes resource usage [28, 29]. Cloud scheduling is difficult due to the uncertainty of arriving jobs [30]. A Profit Maximization Algorithm (PMA) can address the profit maximization problem by dynamically arranging all arriving workloads in private or public clouds [31].

With these common constraints observed in these contemporary models, this manuscript aimed to derive a novel resource scheduling strategy intended to estimate the degree of optimality of the corresponding resource through contextual quality factors defined.

III. Correlating Discriminative Quality Factors (CDQF) for Optimal Resource Scheduling

This manuscript's contribution portrayed a novel method that schedules the resources in IAAS of cloud computing under a heuristic measure called the degree of resource optimality (dro) that has been estimated by using diversified quality of service factors related to the context of the service called IAAS. The adopted qualities of service factors related to the resources of the IAAS are (i) Degree of Response Time (ii) Degree of Service Denial, (iii) Degree of Realization, (iv) Degree of Load Adoption, and (v) Degree of Cost Feasibility.

The information about the task(s) initiated at the SAAS includes the roundtrip time that indicates the arrival and expiration time of the corresponding task, the required service, and the resource's acceptable budget. Based on the corresponding task(s) information header, the resource broker performs the resource scheduling under the proposed scheduling strategy.

A. QoS Factors of the Resources

The proposed method of resource scheduling in IAAS of cloud computing estimates the optimum scope of pairing the task(s) initiated at SAAS and the available resources at IAAS under the diversified quality of service factors. Unlike the traditional scheduling strategies, the proposal derived quality of service factors in the context of Infrastructure-As-A-Service (IAAS), which are used further to estimate the optimality of a resource to be scheduled.

Primarily, the above-stated approach has evaluated the projected quality metrics of resource transmission for overall resources available. Later, these resources are ordered as per quality metrics, and these are deliberated to be the prominent pre-requisite for optimal utilization of the resource. Moreover, this model has been utilized to evaluate every optimal metric of resource utilization, which has been exhibited regarding the available resources and has been discussed in the below sections.

By receiving the task's headers, the scheduler has scheduled the corresponding tasks towards optimum resources, which attain the task. Moreover, this article's intent is optimal resource scheduling for attaining high optimality towards completing tasks and utilizing resources. Here, the resources set, which were available towards schedule were $R = \{r_1, r_2, r_3, ...r_x\}$.

Resource scheduling towards tasks has been required as the utilization of resources and completion of the task. Moreover, the resource selection by the degree of resource optimality is scheduled for the respective task proposed in the manuscript. Here, aspects for optimal utilization of resources have been explored as follows:

- Often, the resource reflects the divergent scope and diversified QoS factors.
- The primary concern of metrics associated with the quality of resource utilization is divergent from one another.

Thus, it is evident that resource, which has scored better under QoS is not optimal, often under manifold objective quality parameters. Further, in terms of this limitation, this contribution's projection deliberates manifold objective quality parameters for scheduling resources for a respective task.

The depicted diversified quality factors of the resources recommended towards resource scheduling in IAAS are,

1) Degree of response time (drt)*:* This metric term the maximum time required for the corresponding resource to respond to the resource broker, which is the aggregate of mean value and mean deviation observed from the past anomalies of the response time of the corresponding resource observed by the resource broker. This metric was critical during resource allocation (s) to the deadline constrained task(s) (Eq. 1).

$$art(r) = \frac{1}{n}\sum_{i=1}^{n} rt(t_i, r)$$

$$mdrt(r) = \frac{1}{n}\left(\sum_{i=1}^{n}\sqrt{\left(art(r) - rt(t_i, r)\right)^2}\right) \tag{1}$$

$$drt(r) = art(r) + mdrt(r)$$

2) Degree of service denial (dsd)*:* The Degree of service denial is another crucial factor of quality of service that indicates the scope of unresponsiveness of the scheduled resource, which is the aggregate of mean and mean deviation of unresponsive schedules against the total number of schedules of the corresponding resource (Eq. 2):

$$rsr(r_i) = \frac{\sum_{j=1}^{ruc(r_i)}\begin{Bmatrix} 1 \exists reschedule\, is\, true \\ 0 \end{Bmatrix}}{ruc(r_i)} \tag{2}$$

From the above-stated equation, the notation $rsr(r_i)$ signifies the resource r_i rescheduling rate representing the schedules ratio perceived in averse to the number of times the r_i has been scheduled. Furthermore, the representation $ruc(r_i)$ indicates the actual amount of times r_i has been scheduled.

3) Degree of realization (dr)*:* The other quality factor of resource scheduling adopted is Degree of Realization, which is the absolute difference between the mean count of successful task realizations and the corresponding mean deviations.

$$\boldsymbol{ar(r) = \frac{1}{n}\left(\sum_{i=1}^{n} 1 \exists task\, t_i\, realized\right)}$$ // average of realization.

$$mdr(r) = \frac{1}{n}\left(\sum_{i=1}^{n}\left(ar - \begin{Bmatrix} 1 \exists if\ task\, t_i\ realized \\ 0 \end{Bmatrix}\right)\right)$$ // mean distance of the realization.

$dr = r - mdr$ // degree of realization.

4) Degree of load adoption (dla)*:* The expected load on the resource during the stipulated schedule expected by the task(s) is another quality factor of the resources labeled as Degree of Load Adoption. The estimation of load adaption carried as follows:

Find the time interval of the resource in use, which is the average time of the corresponding resource against the total number of times that resource is scheduled.

Find the number of time intervals of the resource, which is the ratio of the total time that resource in service and the time interval.

Then find the mean load and mean deviation of the load observed in all of these time intervals. The aggregate of these mean load and mean deviation of the load can denote the Degree of Load Adoption.

$$tin(r) = \frac{1}{n}\sum_{i=1}^{n} et(t_i, r)$$ // time interval

$$al(r) = \frac{1}{n}\sum_{i=1}^{n} l(tin_i, r)$$ // mean load

$$mdl(r) = \frac{1}{n}\left(\sum_{i=1}^{n}\sqrt{\left(al(r) - l(tin_i, r)\right)^2}\right)$$ // mean load deviation

$$dla = al(r) + mdl(r)$$ //degree of load adoption

5) Degree of cost viability (dcv) *:* The resource cost is crucial; resource scheduling is carried under the Service Level Agreement. The client who initiated the task accepts the pay per resource, which is certainly lesser than the upper limit concluded in SLA. Hence, the resource with minimal cost would be most viable. However, it is not at the loss of other quality factors. In this context, rather than opting for a resource with minimal cost, the proposed scheduling strategy adopts a resource that is qualified under other quality factors and has a cost of pay per use as lesser than the agreed budget level. The selected resource's coast viability can derive as the difference between the max level of the agreed cost and the estimated cost of the resource against pay for one use (Eq. 3):

$$ac = \frac{\sum_{i=1}^{n}\left(ecr(r_i) - mac(t)\right)}{n}$$

$$mdc = \frac{\sum_{i=1}^{n}\left(\sqrt{\left(ac - \left(ecr(r_i) - mac(t)\right)\right)^2}\right)}{n} \tag{3}$$

$$dcv = ac - mdc$$

B. The Heuristic Measure (Degree of Resource Optimality (dro))

Let Degree of Response Time (drt), Degree of Service Denial (dsd), Degree of Realization (dr), Degree of Load Adoption (dla), and Degree of Cost Viability (dcv) as a set of QoS metrics denoted for each resource r_i as $M_{(r_i)} = \{drt, dsd, dr, dla, dcv\}$.

To explore the proposed model, let $dcv(r_i), dla(r_i)$ be QoS factors that have been utilized for identifying every resource scope. These key metrics have been utilized for sequencing the resources, as described in the following algorithm.

The initial process normalizes the feasibility of cost and degree of load adoption (dla) as follows and as shown in Fig. 1:

step 1. $foreach\{r_i \exists r_i \in R \wedge i = 1,2,3,\ldots,|R|\}$ // Begin.

step 2. $ndcv(r_i) = dcv(r_i)^{-1}$ //degree of cost viability in normal form $ndcv$, which lies among 0 & 1.

step 3. $ndcv_{abs} \leftarrow abs(ndcv(r_i))$ //The set $ndcv_{abs}$ comprises absolute values of the corresponding degree of cost viability in normal form perceived for every resource.

step 4. End // of step 1.

step 5. $foreach\{r_i \exists r_i \in R \wedge i = 1,2,3,\ldots,|R|\}$ // Begin.

step 6. $ndla(r_i) = dla(r_i)^{-1}$ // the degree of load adoption in a normal form $ndla$ which is in the range of 0 to 1.

step 7. $diff_{abs} \leftarrow abs(ndla(r_i))$ //The set $diff_{abs}$ comprises absolute values of entries in $diff$.

step 8. End // of step 5.

step 9. $foreach\{r_i \exists r_i \in R \wedge i = 1,2,3,\ldots,|R|\}$ // Begin.

step 10. $km(r_i) = 1 - \left(ndcv(r_i) \times ndla(r_i)\right) \exists \left(ndcv(r_i) < 1 \,\|\, ndla(r_i) < 1\right)$ //the outcomes have been subtracted from one that is to attain maximum value since the product of 2 decimal fractions provides another decimal fraction, which is lower than fractions of decimal incorporated in multiplication.

step 11. End // of step 9.

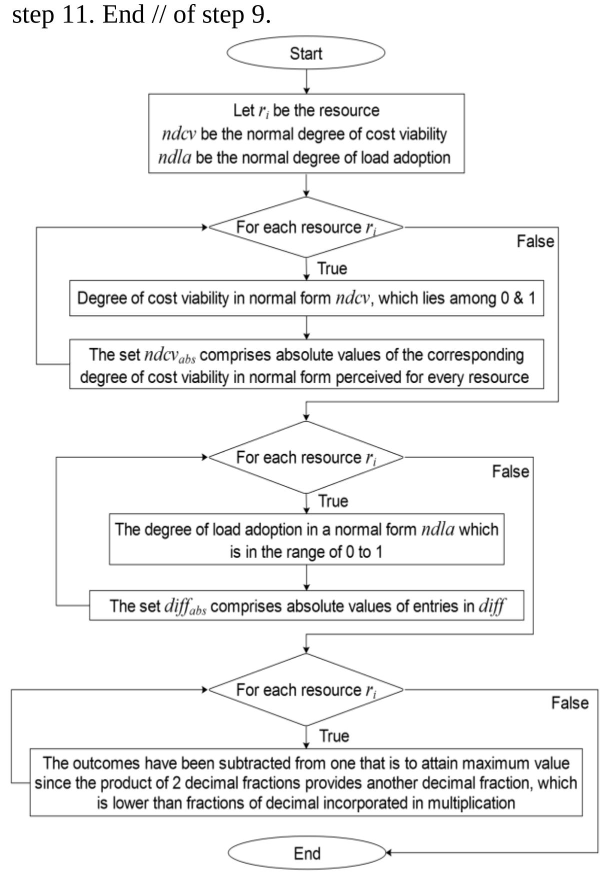

Fig. 1. Flowchart Representation of the Heuristic Measure.

Later, the resources available have been rated about every metric so that every resource would have a unique rating for a metric. Moreover, resources would be rated in an increasing sequence of resulting metric values. When maximum values are optimal, then such a resource possessing minimum value over the resulting metric would be rated as one. Besides, resources possessing maximum value for the respective metric would be rated in the form of $\{n \exists n \leq x\}$. The representation x depicts the number of resources. When minimum values are said to be optimal, then resources would be rated in a decreasing sequence of resultant metric values so that the resource possessing maximum value for the resulting metric has been rated as one. In contrast, the resource possessing minimum value for the resulting metric has been rated to be $\{n \exists n \leq x\}$.

With the process completion, every resource reflects manifold ratings about specific quality parameters. Moreover, these ratings would be utilized as input for assessing the Degree of Resource Optimality $dro(r_i)$ as follows (Eq. 4):

For each resource $\{r_i \exists i = 1, 2, ..., x\}$ // Begin.

$$\mu(r_i) = \frac{km(r_i) + drt(r_i) + dsd(r_i) + dr(r_i)}{4} \quad (4)$$

//The above-stated equation portrays average ratings attained for divergent resource r_i metrics.

$$dro(r_i) = \left[\frac{\left\{ \sqrt{(\mu(r_i) - km(r_i))^2} + \sqrt{(\mu(r_i) - drt(r_i))^2} + \sqrt{(\mu(r_i) - dsd(r_i))^2} + \sqrt{(\mu(r_i) - dr(r_i))^2} \right\}}{4} \right]^{-1} \quad (5)$$

Eq 5 Degree of Resource Optimality $dro(r_i)$ is the inverse of root mean square distance of ratings allocated to a resource r_i as the lowest distance is said to be optimum.

With the completion of evaluating the degree of resource optimality for specified resources, then resources would be organized in decreasing sequence of their rating attained for prominent metrics.

Further, choose a set of resources possessing an optimal rating about key metrics under the given threshold.

The chosen resources have been organized in decreasing the sequence of their Degree of Resource Optimality $dro(r_i)$ that assists in projecting the optimal resource in the primary place of its sequenced list. Here, a similar order would be considered the preferred order to select resources regarding the task schedule.

IV. Experimental Setup and Empirical Analysis

The empirical study compares of projected CDQF model and other existing "job scheduling with efficient resource monitoring (JS-ERM) approach [12]" & "multi-objective scheduling method based on ant colony optimization (MOSACO) [13]" that is simulated utilizing Cloudsim [14]. Here it allows for simulating high dimensional CC network synthesizing input jobs so that there could be no priority sequence applicable to corresponding jobs. The confines are executed for performing simulation from 1 processor towards another, and pre-emption is not enabled. They are scheduling the resources utilizing the QoS factors considered by proposed & other existing methods to analyze the performance. Moreover, we noticed the metrics of performance discussed in the next segment at distinct intervals of time.

The proposed CDQF has been assessed by comparing it with another JS-ERM [12] and MOSACO [13] contemporary approaches. Here, performance would be measured under several QoS metrics such as completion rate of the task, resource utilization rate, and rescheduling rate.

The rate of resource utilization perceived for CDQF would be high and maximum when compared with other contemporary MOSACO and JS-ERM approaches. Here, the rescheduling rate perceived for the CDQF model would be linear and minimal compared to other approaches. The rate of resource scheduling has been perceived as low in CDQF, which delivers an optimal job completion rate. Here, process complexity would be minimal for CDQF, which is minimum because of the scalable method modified for the degree of resource optimization assessment.

Here, Table I and Fig. 2 depict the rescheduling rate noticed at diverse intervals of time. The perceived rate of rescheduling is averse to the load of the task. This figure signifies that the projected model of this contribution CDQF has been prominently the best for lessening the rescheduling rate compared to other approaches. Further, Table II and Fig. 3 portrays that the rate of job completion perceived for the proposed model CDQF would be recommendable and prominent compared to MOSACO and JS-ERM contemporary approaches. Table III and Fig. 4 portray that CDQF added an advantage over the other two existing models for resource utilization rate that is considered a significant objective of resource scheduling techniques.

TABLE I. RESOURCE RESCHEDULING RATE STATISTICS

JS-ERM	0.05	0.052	0.07	0.09	0.12	0.135	0.14
MOSACO	0.04	0.06	0.065	0.08	0.095	0.1	0.12
CDQF	0.02	0.025	0.03	0.035	0.04	0.07	0.085

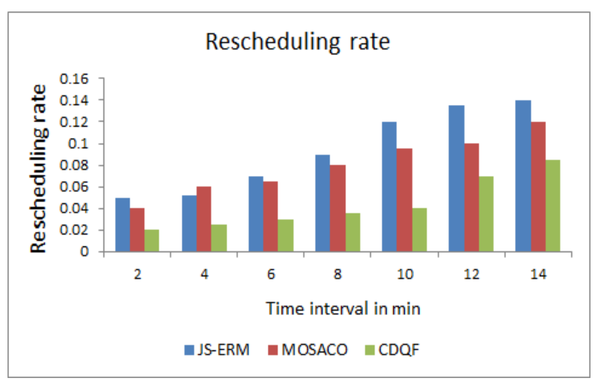

Fig. 2. Resource Rescheduling Rate Perceived.

TABLE II. JOB COMPLETION RATE STATISTICS

JS-ERM	0.96	0.92	0.92	0.91	0.9	0.895	0.89
MOSACO	0.965	0.94	0.93	0.93	0.925	0.922	0.922
CDQF	0.975	0.97	0.97	0.965	0.95	0.95	0.95

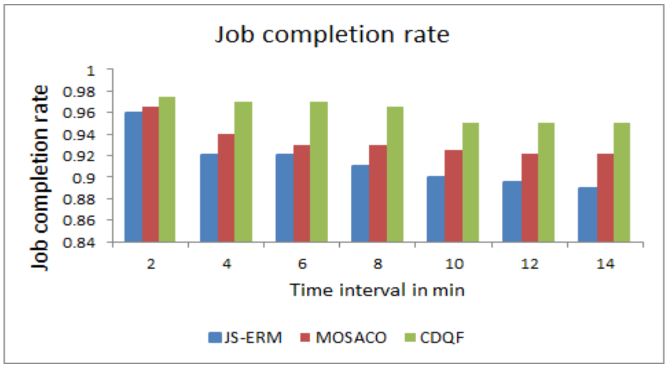

Fig. 3. Job Completion Rate Perceived.

TABLE III. RESOURCE UTILIZATION RATE STATISTICS

JS-ERM	0.59	0.6	0.7	0.72	0.8	0.82	0.89
MOSACO	0.8	0.82	0.88	0.9	0.9	0.87	0.92
CDQF	0.88	0.9	0.91	0.91	0.93	0.93	0.94

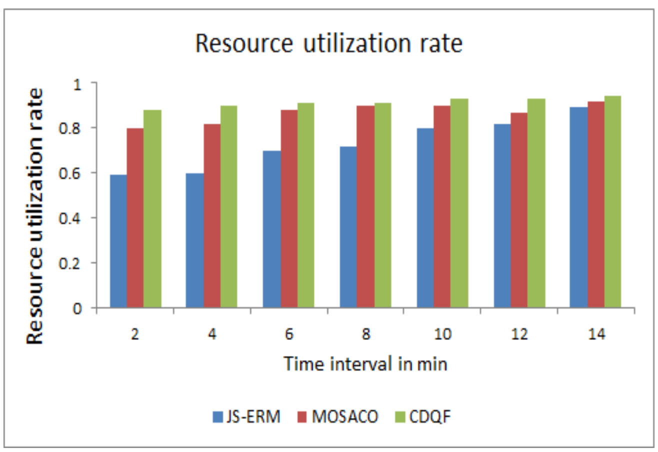

Fig. 4. Resource Utilization Rate Observed.

V. CONCLUSION

In this manuscript, a quality-aware scheduling algorithm optimizes the completion of tasks and resources scheduling cloud computing. Moreover, this article projected a novel scale known as Degree of Resource Optimality that signifies resources fitness under diversified QoS proposed metrics. The outcomes attained from this contribution's projected model have been compared to the other two existing methods, JS-ERM & MOSACO. The performance analysis is exhibiting that the projected method has been surpassed compared with the other two existing methods for divergent quality metrics. Here, empirical analysis of the proposed method of this contribution might impact further research for development. The load balancing and scheduling technique for attaining optimum VM scheduling (virtual machines) as resources in CC.

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