Journal of Theoretical and Applied Information Technology
15th December 2023. Vol.101. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

THE IMPACT OF OBJECTIVE FUNCTIONS ON TASK SCHEDULING IN CLOUD COMPUTING ENVIRONMENT

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ABSTRACT

Cloud computing, which has grown in popularity in recent years, allows users to use computational resources remotely over the Internet. Cloud computing must be able to meet all user demands for high performance and efficient service quality (QoS). As a result, in order to meet these requests in a timely manner, an effective task scheduling mechanism must be created. The aim of this study is to explore the current landscape of task scheduling problems, laying out the challenges of task scheduling where objective functions issues are involved. We used a systematic literature review strategy to locate and review many significant journal and conference papers on four major online electronic databases (ScienceDirect, IEEE Explore, Springer, Wiley online library) that addressed our three predefined study questions. The first stage was to define inclusion and exclusion criteria before extracting data from the selected publications and deriving replies to our inquiries. Finally, (75) publications were chosen. We identified (70) publications on task scheduling describing (58) investigations on objective functions published between 2018 and mid-2022. Findings show a trend across work scheduling algorithms to choose diverse objective functions. These algorithms often optimize for time efficiency, cost-effectiveness, and resource use. In contrast, some algorithms specialize in a single objective function. This difference in methodology suggests that task scheduling performance depends on the objective function. The algorithm's effectiveness and adaptability in cloud-based job scheduling depend on these objectives' careful selection.

Keywords: *Cloud Scheduling, Multi-Objective Functions, Single-Objective Function, Task Scheduling, Cloud Computing.*

1. INTRODUCTION

As a result of the widespread use of the Internet in recent years, technology is seeing tremendous advancements in data processing and storage. The concept of cloud computing was suggested as a result of this technological shift. It moves computing and data from laptops and desktop computers to huge data centers. It is a cutting-edge technology platform that enables individuals all over the world to utilize computing and access data on the Internet at any time.

One of the most difficult elements of cloud computing is figuring out how to efficiently map jobs, also known as tasks or applications, to resources in a reliable, secure, and efficient manner. Task scheduling is the term for this mapping, and it is an NP-hard problem. It is more problematic due to its complex, dynamic character, high degree of employment and resource variability, problem scale, and other factors such as existing local schedulers and policies. [1, 2]

Cloud computing must be able to handle a high number of users at the same time. It must be able to meet all user requests in terms of high performance and efficient service quality (QoS). As a result, an effective job scheduling mechanism must be implemented to meet these requests in a timely way. There are many ways to categorize scheduling difficulties in heterogeneous environments. The

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

problem can be characterized as single or multi-objective depending on the number of objectives to be optimized. [3]

Furthermore, work interrelationships can be utilized to categorize scheduling issues as independent or dependent. Jobs in the first type are unrelated one to another, hence there are no inter-job relationships. Jobs in the latter category cannot be divided since they must be handled in a predetermined order, which means that the relationships at inter-job must be taken into account. The properties of distributed heterogeneous settings, such as cloud computing systems, are well-suited to autonomous work scheduling. This is primarily owing to the nature of their users, as these environments process jobs and applications submitted by several independent users Moreover, the value of independent task scheduling is highlighted in a variety of real-world scenarios. SPMD (Single Program, Multiple Data) approaches are used in data mining and the application of image processing, for example. [4]

Scheduling issues in cloud computing can also be classified by the environment in which they occur, which might be static or dynamic. First type, all relevant job and resource information is provided ahead of time. During the mapping process, this information will not be modified. Furthermore, when the allocation is completed, there is no expectations for new task coming at the system. Predictive studies, distributed computing system requirements assessments, and studying dynamic scheduler's behavior in terms of resource allocation are all applications and domains where this sort of scheduling is valuable.

Tasks removed or added to the system at runtime in the second type. This gives you a quick way to deal with unanticipated occurrences like resource failure. This sort of scheduler assigns workloads to resources based on actual data rather than estimates. [5, 6, 7]

The process of choosing the research problem is a crucial factor that influences the direction and development of this study. To ascertain the focal point of our inquiry into cloud-based task scheduling, an extensive analysis of key job scheduling methodologies was undertaken. Our major objective beyond mere research, as it delves into the subtle interplay between objective functions and the dynamics of task scheduling.

The major aim of this comprehensive review goes beyond a simple examination of primary work scheduling strategies. The examination of how different objective functions exert a significant impact on the landscape of task scheduling is intimately intertwined. Objective functions, which serve as crucial criteria for decision-making, have a significant impact on the allocation and implementation of tasks in cloud computing systems. The efficiency, adaptability, and overall performance of work scheduling algorithms are greatly influenced by the careful selection of a suitable objective function.

This paper seeks to explore the complex relationship between objective functions and task scheduling in order to analyze the subtle dynamics that govern optimal decision-making across cloud computing ecosystems. Objective functions play a crucial role in scheduling algorithms by serving as guiding principles that direct the algorithms towards attaining specific goals. These goals can include minimizing makespan, optimizing resource utilization, or balancing conflicting objectives. It is important to note that objective functions are not just evaluative metrics, but rather they provide a sense of direction and purpose to the scheduling algorithms. Gaining a comprehensive understanding of the difficulties associated with these functions is crucial for effectively navigating cloud-based task scheduling scenarios.

Furthermore, as we delve into the intricate aspects of task scheduling approaches, our analysis aims to discover and illuminate new research issues and obstacles. Continuous innovation and improvement of task scheduling algorithms is necessary in response to the dynamic nature of cloud computing. Through a comprehensive analysis of the existing body of literature, this review aims to establish a solid basis for future research efforts. By examining the significance of objective functions, this study seeks to uncover untapped areas of investigation and stimulate progress that will have a profound impact on the future development of cloud-based task scheduling.

This work's primary contributions are summarized as follows: which, how, and what:

• **Which** to increase system performance, which type of objective function is employed to improve task scheduling?

• **How** to boost system performance, how do we improve scheduling methods in the cloud?

• **What** are the limitations and problems of current cloud computing scheduling methods?

2. BACKGROUND

2.1 Task Scheduling

Described as the ability to properly distribute and assign many distinct jobs to multiple VMs, as well as complete all tasks in a timely manner. Scheduling's main goal is to assign tasks to

Journal of Theoretical and Applied Information Technology
15th December 2023. Vol.101. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

appropriate resources to meet one or more optimization criteria. About the procedure of scheduling process, tasks are sent to the cloud scheduler by users, and the cloud scheduler then investigates the state of the resources using cloud information service. After that, based on their requirements, map the tasks to various resources. The efficient scheduler allocates the required resources (such as VMs) to the tasks in the most efficient way possible. The job of the broker is vital. The list of virtual machines (VMs) and their quality of service (QoS) is available to brokers. A Vm with a high QoS and high performance. The broker receives the user's requests and forwards them to the Vm that best satisfies the user's needs and adheres to the SLA (service level agreement). The services quality for the request or task should not degrade when it is assigned to a specific Vm. A good QoS task is occasionally assigned to a low QoS Vm, resulting in poor resource utilization and a violation of the SLA. For that, the broker should use an efficient work scheduling mechanism [73].

2.2 Definition Of Objective Functions (Criteria)

The optimization problem can be classified as single criterion or multi-criteria depending on the number of criteria involved. The goal of single-criterion optimization is to discover the best solution based on just one criterion. When there are many criteria functions in an optimization issue, the goal is to identify one or more optimal solutions for each of them. In this case, a good solution for one criterion may be unsatisfactory for another, and vice versa. As a result, the purpose of multi-criteria optimization is to develop a group of solutions that satisfy all of the other criteria [6].

The following is a definition of the general single objective problem:

Minimize or Maximize F(x).

x is a vector expressing a solution. Whereas the following is a definition of the general multi-objective problem:

Minimize or Maximize F(x) = [F1 (x), F2 (x) , . . . , Fk (x)]

F1 and Fk are conflicting targets, while x is a vector expressing a solution [72].

3. RELATED WORK

In order to achieve a thorough and targeted assessment, our criteria for screening the literature were rigorously established. The establishment of inclusion and exclusion criteria aimed to find pertinent research that make a substantial contribution to the comprehension of the influence of objective functions on task scheduling in cloud computing systems. The criteria considered in this study include the alignment of the research with our major theme, the time frame of publication (from 2018 to mid-2022), and the methodology utilized. Our objective is to enhance transparency in our research focus and the systematic technique used to assess existing literature by explicitly outlining our problem selection process and criteria for screening relevant studies.

Related works on task scheduling in cloud computing using different algorithms with both type of objective functions are discussed in this section. As demonstrated in Tables (1, 2, and 3) a large amount of research has been conducted on task scheduling.

3.1 Objective Functions With Hybrid Meta-Heuristic Algorithms

Task scheduling based on differential evolution has been studied in [8,9]. Abualigah & Diabat use hybrid Deferential (DE) with Antlion algorithm to solve scheduling tasks in cloud computing, elite-based differential algorithm consider as a local search approach for developing exploitation and avoiding local optima, they used this technique to enhance **response time and makespan** [8]. Elaziz et al. use DE with Moth Search Algorithm to minimize **makespan**, DE can be used to conduct local searches so they used this algorithm to enhance **makespan** objective function [9]. Task scheduling based on Particle Swarm Optimization (PSO) studied In [10,11,12,13,14] enhance PSO is presented, the common goal in these papers is to reduce **makespane**. In another study, PSO presented to minimize **response time and energy consumption** [15]. Improved Harries Hawks (HHO) proposed in [16,17]. Annie & Radhamani proposed HHO to allocates tasks by identifying the overload and under load situation of VMs and improving **response time** using a PIO-based technique [16].

Attiya et al. they used Simulated Annealing (SA) as a local search to increase the rate of convergence and quality of solution obtained by the standard HHO algorithm which is **makespan**[17]. In most situation hybrid GA [18,19,20,11,21,22,15] outperforms Electro Search (ES), whale algorithm (WOA), Genetic Algorithm (GA), Ant Colony Optimization (ACO), PSO. These algorithms mainly focused on improving the **makespan and resource utilization**. Furthermore, most of these algorithms focus on

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

energy consumption metric and the improved algorithms enhanced the related objective functions.

Table 1: Hybrid Two Metaheuristic Algorithms for Cloud Computing Task Scheduling

No	*Merits*	*Demerits*	*Single /multi*
24	Enhanced: Makespan Resources utilization.	Other QOS parameters not considered Exploitation need more improvements	Multi
25	Enhanced: Makespan Energy consumption .	Cost not covered	Multi
33	Enhanced : Makespan Response time. Convergence rate.	It still gets stuck in local optima.	Multi
31	Enhanced: Makespan Resource utilization	Did not improve QoS parameters	Multi
27	Minimize both the makespan and the cost of using virtual machines . Fault tolerance and energy usage are both affected.	Need to better methods for job selection and virtual machine tweaking.	Multi
28	Improve both load and resource utilization cost. Better convergence speed.	Other QOS parameters not considered	Multi
34	Significantly enhanced optimal trade-offs between execution time (makespan) and financial cost (cost). A higher level of convergence.	Reliability and Security	Multi
26	Enhanced: Makespan Energy consumption	Did not improve other QoS parameters COST	Multi
23	Enhanced: Transfer time Overall cost	Total cost need more improvement. Other parameters not considered	Multi

3.2 Objective Functions with Single Meta-heuristic Algorithms

Cloudy-GSA was used in [23] to improve transfer time and overall cost by increasing VM exploitation. [24] Proposes an improved Multi-Verse Optimizer as a scheduler by adding a step to the original algorithm. The simulation results show that the time span and resource utilization are improved. To improve both makespan and energy consumption, improved rock hyrax algorithm [25] and Mean Grey Wolf optimization algorithm [26] are proposed. The cost of tasks is the focus of the Spacing Multi-Objective Antlion [27] and the Improved WOA algorithm [28]. The proposed algorithm outperformed the standard Antlion and WOA algorithms in simulation results using the Cloud analyst simulator. The simulation results showed that the proposed algorithms had a good performance in minimizing the execution time in [29] Bat optimization algorithm and [30] Modified Flower Pollination optimization algorithm for task scheduling. [31] Investigates task scheduling based on the particle swarm optimization (PSO) algorithm for task scheduling with the goal of minimizing the makespan and maximizing resource utilization. The proposed algorithm outperformed the basic PSO algorithms in simulation results. A similar study [32] used PSO to minimize energy consumption and task execution costs, and the simulation results showed that the new PSO algorithm outperformed basic PSO. A modified version of Discrete Symbiotic Organism Search (DSOS) is used on CloudSim in [33] and [34] to schedule tasks in the cloud. The results demonstrated that the proposed algorithms could reduce the task's makespan and response time. Table 2 shows the advantages and disadvantages of these algorithms.

Table 2: Hybrid Two Metaheuristic Algorithms for Cloud Computing Task Scheduling

No	*Merits*	*Demerits*	*Single / multi*
8	Enhanced: Response time Degree of imbalance Makespan.	Complexity time need improvement	Multi
10	Reduces overall completion time also having higher convergence accuracy.	Other QOS parameters not covered.	Single
18	Enhanced: Makespan Load balancing	Other QOS parameters not covered.	Multi

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

	Resource consumption		
19	Decreasing : Execution cost. Makespan. Degree of imbalance. Maximizing PH resource use.	Security and Reliability Not covered.	Multi
16	Enhanced : Makespans. Response time. Load.	Complexity time need more improvement	Multi
20	Enhanced: Time	Other parameters did not considered	Single
11	Makespan Resource utilization	Energy consumption not considered	Multi
12	Limited time, low cost, increased resource use and Balance load.	less security.	Multi
9	Makespan High throughput.	High time complexity	Multi
21	Enhance response time, completion time, and throughput	Load balancing Security related not covered	Multi
13	Minimize Makespan, cost and deadline violation rate	Optimizes the other QoS parameters are not covered.	Multi
14	As the workload grows, the processing speed of submitted applications slows.	For independent task only	Single
22	Enhanced: Makespan Energy consumption.	This procedure necessitates additional period for crossover and mutation, as well as chemotaxis and reproduction.	Multi
15	The convergence rate has improved, the response time has improved, and the energy consumption has decreased.	The security and privacy not addressed.	Multi

3.3 Objective Functions with Hybrid Meta-Heuristic and Heuristic Algorithms

Heuristic Task Scheduling with Artificial Bee Colony (HABC) algorithm presented in [35] to reduce **Makespan** and **balance the loads**. Task scheduling in view of both the **makespan** and **the cost** based on hybrid metaheuristic with heuristic algorithms is proposed in [36,37]. Task scheduling based on GA has been studied widely in [38, 39]. Pirozmand et al. use hybrid GA algorithm with Energy-Conscious Scheduling to solve task scheduling by **enhanced energy** and **time consumption** [38] while Zhou et al use GA with greedy strategy to solve scheduling tasks in cloud computing by enhanced **average response time** and **total completion time** [39]. In [40], a hybrid of PSO and both Longest job to fastest processor (LJFP) and minimum completion time (MCT) heuristic algorithms are implemented on CloudSim to schedule tasks in the cloud. The results showed that the proposed algorithms could enhance the **makespan, total execution time, balance degree and total energy consumption. Table 3** demonstrate the merits and demerits of each algorithm

Table 3: Hybrid Two Metaheuristic Algorithms for Cloud Computing Task Scheduling

No	*Merits*	*Demerits*	*Single/multi*
36	Enhanced: Makespan Cost with satisfied budget and deadline	The encoding approach only includes task-to-resource mapping and ignores task order, which can be crucial for workflow scheduling issues.	Multi
38	Enhance energy and time consumption	Higher computation time	Multi
40	Enhanced : Makespan Balance. Total energy usage.	Other parameters not considered	Multi
35	Minimize makespan and balance the loads	Energy consumption or cost not covered	Multi
39	Enhanced: Total completion time	Resource utilization or cost not covered	Single
37	Enhanced: Makespan Cost	Less reliability	Multi

4. METHOD

The primary process for our systematic review is depicted in Fig. 1. For our research, we followed the usual principles established by Kitchenham [57] and used a study procedure. We

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

picked a Systematic Literature Review approach to address our specific research objectives and conduct a full comparison study of the approaches that were reveal.

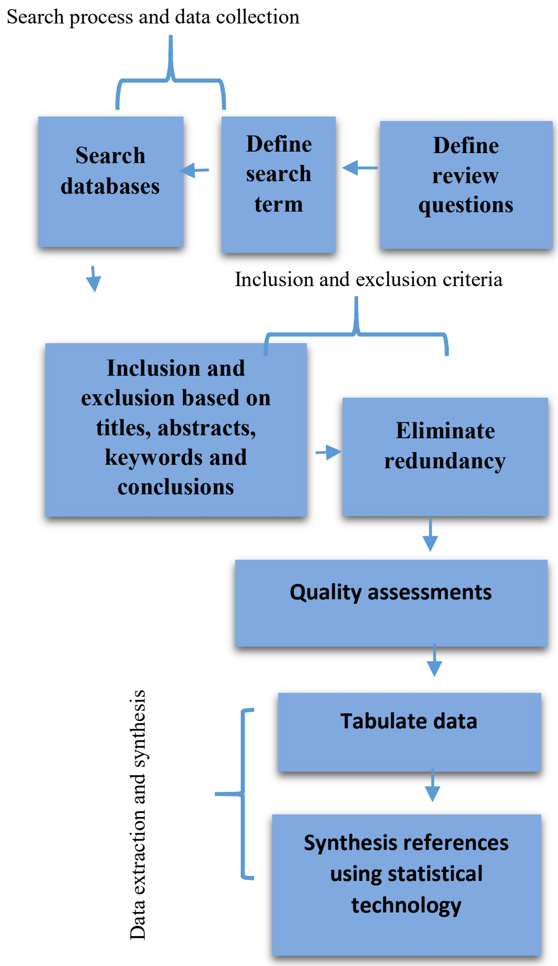


Figure 1: Procedure of the Systematic Review

4.1 Research Questions

A comprehensive review necessitates the development of a foundational group of research questions that guide the research technique. To explore the methods used for scheduling procedures on cloud platforms, we defined three main research questions. We adopt a standard approach to frame systematic review questions: Petticrew et al, PICOC.'s criteria [58]. We generate review questions using this method, based on five criteria: population, intervention, comparison, outcome, and context. As a result, in our systematic review, we developed our study questions based on these five features, as shown in Table.4.

RQ1. Between 2018 and 2022, what articles report on experiences with various objective functions?
RQ2. What issues have researchers noticed when performing a single objective function?
RQ3. How do single objective and multi-objective functions work?

Table 4: Picoc Criteria

Population	Objective functions for task scheduling in cloud
Intervention	Methodology for scheduling in clouds
Comparison	Differences in cloud scheduling objective functions
Outcome	The efficacy of objective functions and how they are implemented in clouds
Context	the domain of objective functions in task scheduling research, particularly studies that include experimental data

4.2 Search Strategy and Process

The manual search was conducted to look for specific papers published up to 2018 (we choose the articles that published in the last five years). The primary data is acquired by scanning well-known and widely used online electronic digital libraries for published papers (archival journals and conference proceedings). We chose these four digital libraries because they provide a primary source for publications, contain all high-profile venues for Computer Science papers or papers relevant to our research, and have search engines that are practical and accurate for our search strings. We looked through the references of all of the papers we chose to see if there were any possibly relevant research that we missed during our search and analysis.

4.3 Inclusion and Exclusion Criteria

The main criterion for including journal and conference proceeding papers in our evaluation is that they address issues that are relevant to our review questions. In our initial selection, we looked at articles that clearly addressed our review questions based on their titles, abstracts, keywords within the papers, and conclusions. In the interim, any publications that were no longer needed were eliminated. However, titles, abstracts, and conclusions are not always enough to determine whether or not a work will be accepted. As a result, in order to make a final choice on their selection, we retrieved the full context of those publications that were determined to be relevant in the initial phase in the final selection step.

4.4 Quality Assessment

The SLR's goal is to make an evaluation of the quality of existing work. This is based on each paper's quality score, and it uses brief quality assessment questionnaires to be completed following data extraction. The purpose of quality assessment is to provide extra information about the primary work that may be used to determine which elements should be given more weight when forming conclusions. [57] This is referred to quality questionnaire in Appendix A. Each question uses three-level response scale, with "Yes" worth one point, "Partially" worth 0.5, and "No" worth 0. Summing the quality scores of checklist questions yields the total quality of each publication. As a paper's score rises, it will be better able to handle the review questions in a more complicated and in-depth manner. The total quality rating of relevant papers was distributed in Table.5

Table 5: Total Quality Rating Of Relevant Papers

Scores	*No. of papers*	*Percent %*
5	8	13.8
5.5	21	36.2
6	10	17.2
6.5	17	29.3
7	2	3.4
Total	58	100%

4.5 Data Extraction and Synthesis

The data retrieved from the selected research publications provides a broad overview of alternative cloud scheduling methodologies. We tabulate the data and analyze it using a meta-analysis method [58] in order to answer the review questions posed in Section 4.1. We summarize the quantitative data to end the data collecting and review question analysis process, and then proceed to generalize and synthesize correlative answers addressing these review questions.

4.6 Articles Classification Scheme

Our classification method allows us to organize the literature in our work so that we can map it in general and answer our review questions in particular [59]. Several different approaches were used to classify the publications listed. Classification can help to simplify and minimize the complexity of a systematic review while also improving the study's accuracy. One of our unique contributions is the classification scheme we devised, which provides a framework for categorizing and defining objective functions type on task scheduling on clouds. The classification based on the common objective functions (Obj) used in scheduling, Fig 2 shows the common objective function from literature

4.6.1 Makespan (MS): the time it takes to finish the last task before leaving cloud system.

4.6.2 Cost (C): the total amount paid to a service provider by a user depending on resource usage.

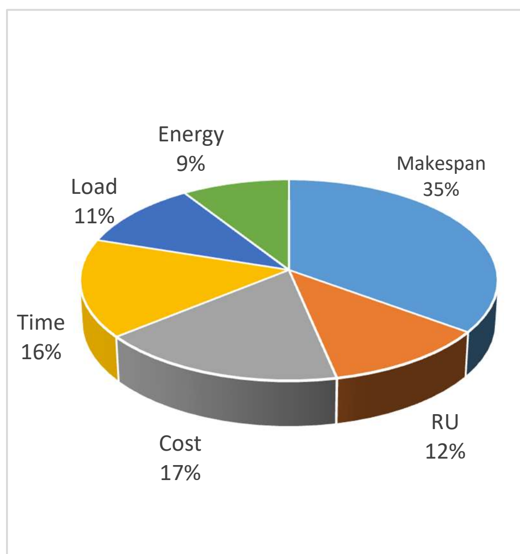
4.6.3 Resource utilization (**RU**): making the most of available resources by keeping them engaged as much as possible. Profiting from leasing restricted resources to cloud users on an as-needed basis is lucrative for service providers.

4.6.4 Load balance (L): the uniform distribution of loads across physical resources in cloud computing.

4.6.5 Energy efficiency (En): A reduction in the amount of energy utilized by a task is known as energy efficiency.

4.6.6 **Time (T):** is a broad concept that encompasses a range of measures associated with time. These metrics include task execution time, waiting time, start time, finish time, and overall turnaround time. Table 6 show the distribution of our literature based on objective functions.

Figure 2: The Distribution Based On Objective Functions



ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 6: The Distribution Based On Objective Functions

Obj	*MS*	*RU*	*C*	*T*	*En*	*L*
Ref	8 9 10 11 13 16 17 18 19 21 22 24 25 26 27 31 33 34 35 36 37 39 40 41 42 46 47 48 49 51 53 54 55 56 62 63 64 66 67 69 70 72	3 11 12 18 19 24 48 50 52 53 54 55 56 72	13 19 23 27 28 34 36 37 45 46 47 48 49 53 54 64 65 67 68 69 72	8 12 14 16 20 21 23 29 30 33 38 43 44 45 50 52 55 65 68	22 25 26 27 38 40 47 65 66 67 70	8 12 16 18 19 28 35 40 51 52 53 54 69

5. RESULTS

We used multiple search terms to find relevant papers in the scientific digital libraries provided in Section 4.2. Using our search keywords, we found 1,653, 1,566, 4,176, and 34 results from SpringerLink, IEEE Xplore, ScienceDirect, and Wiley library online, respectively. After an initial selection based on title, abstracts, keywords, and conclusion, 730 relevant papers were reviewed, including (73) IEEE articles, (391) ScienceDirect articles, (245) Springer articles, and (21) Wiley articles. In our second selection procedure, we reviewed the whole context of the relevant papers identified in the previous phase using the inclusion and exclusion criteria from Section 4.3. After deleting redundant papers from various digital collections, a total of (58) papers were chosen. These papers were included, and the key contributions of each are summarized online. Table.7 shows the distribution of peer-reviewed papers from various databases. The (58) papers included in the study were published In: IEEE published (8), ScienceDirect published (26), SpringerLink published (13), Wiley online library published (4) and (7) in other databases. Journal papers, conference papers are the two types of papers contained in this collection. Figure 3 depicts the distribution of various categories. The distribution of publications by year of publication is depicted in Figure 4. According to the trend in this graph, task scheduling on cloud platforms has gotten greater

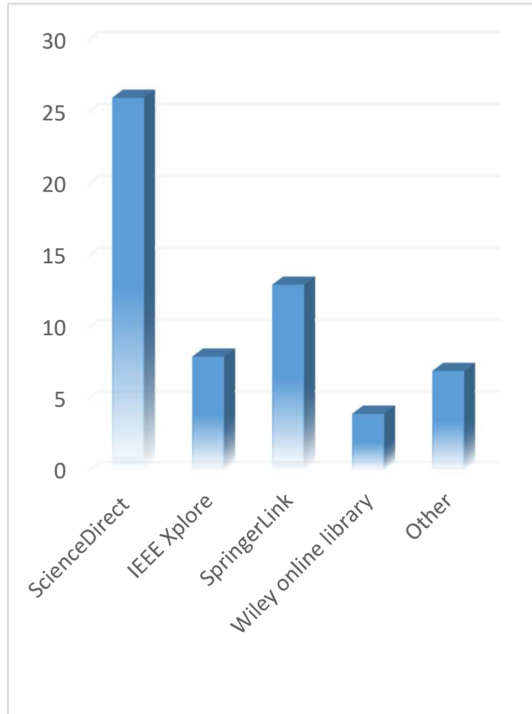


Figure 3: Papers Are Distributed According To The Type Of Publishing.

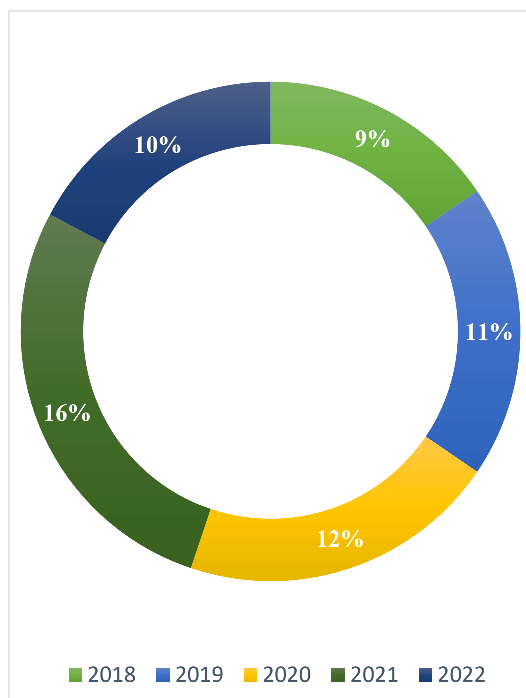


Figure 4: Papers Are Organized By Year of Public

attention in recent years. The most papers included were those published in 2020; the second most papers included were those published in 2021. Appendix A shows a summary of the distribution of the overall results of our publication quality assessment.

Table 7: Distribution of Related Work Papers In Databases

Electronic database	*No. retrieved articles*	*No. initial selected articles*	*No. final included articles*	*% final articles*
Science Direct	1,576	391	26	44.8
IEEE Xplore	1,066	73	8	13.7
Springer Link	1,253	245	13	22.4
Wiley online library	34	21	4	6.8
Other	--	--	7	12
Total	5496	730	58	100%

6. DETAILED RESULTS ANALYSIS

Based on our collected data, we address our three research questions (RQs) in this section

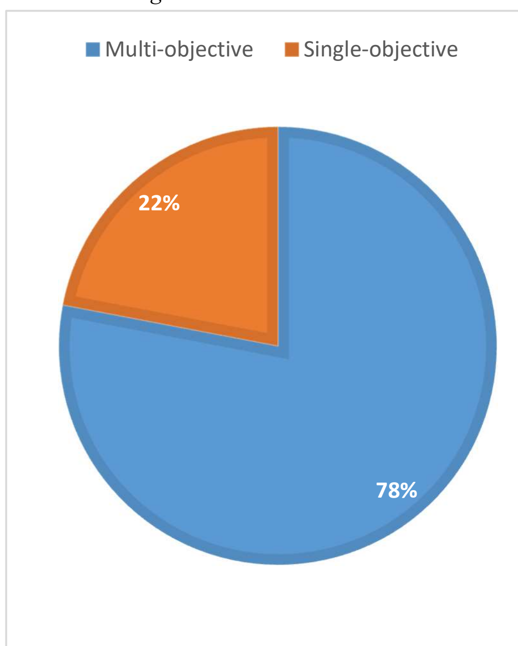
Rq1. Between 2018 And 2022, What Articles Report On Experiences With Various Objective Functions?

An optimization model that achieves the objectives by discovering the best optimal solution must be constructed. Because there is usually some sort of trade-off between optimization goals. Using single objective optimization, it is possible to assess the optimality of a specific solution in relation to another existing one. In Multi-Objective Optimization Problems, it is not possible to accomplish it directly (MOPs). Furthermore, while single objective optimization problems select a single optimal solution for predefined objectives, MOPs typically use a Pareto dominance relation technique to create a comparison model that replaces a single optimal solution with a range of alternatives, allowing for a variety of trade-offs between the objectives. For performance evaluation, just one of the several Pareto optimal solutions offered in MOPs must be chosen. The rest of this part provides a summary of the mechanisms in some of the selected research, based on single and multi-objective optimization approaches. Table. 8 shows the articles based on single and multi-objective functions, as well as the Fig 5 show the ratio of the distribution based on this classification. [3]

Table 8: Type of Objective Functions Used In the Articles

Single/ Multi	*Single objective function*	*Multi-objective functions*
References	10,14,17,20,29,30,39,41,42,43,44,62,63	8,9,11,12,13,15,16,18,19,21,22,23,24,25,26,27,28,31,33,34,3,36,37,38,40,45,46,47,48,49,50,51,52,53,54,55,56,64,64,66,67,68,69,70,72

Figure 5: Distribution of Objective Functions Type in Task Scheduling



Single objective: In [17] Attiya et al., proposed simulating annulling algorithm as a local search to increase the rate of convergence and quality of solution obtained by the standard HHO algorithm which is **makespan** however they ignored the other objective functions**.** With the same single objective function of minimizing the **makespan**, Fanian et al., in [41] proposed Simulated Annealing (SA) and firefly algorithm (FA) as hybrid algorithms. The advantages of both the firefly and simulated annealing processes are combined in this algorithm. Furthermore, efforts have been made to alter the firefly algorithm's principal population or primary solutions. The approach given here employs a superior main solution. Another feature of the new

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

algorithm that was taken into consideration was local search. whereas the other objective functions are ignored. Adhikari et al in [29] presented Bat optimization algorithm for task scheduling, the simulation results showed that the proposed algorithm had a good performance in minimizing the **execution time**. Miglani & Sharma in [42] produced a meta-heuristic algorithm a Modified PSO to reduce **makespan. [**30] Khurana & Singh, also produced a single meta-heuristic algorithm a Modified Flower Pollination optimization algorithm to reduce the **time** whereas other objective function not considered. In [44] Wu, produced Improved particle swarm optimization algorithm to reduce single objective function which is **time**. The same as with Arora et al., they work to reduced the **time** objective function [43]. As well as Dinani et al used meta-heuristic algorithm and result is the highest degree of **time** consumption for task execution was reduced [62]. Furthermore, Attiya et al work to enhance **makespan**[63].**Table 9** shows the articles with single objective fnctions.

Table 9: Single Objective Function References

No.	*Authors*	*Objective function*	*Type*
17	(Attiya et al., 2020)	Makespan	Single
41	(Fanian et al., 2018)	Makespan	Single
29	Adhikari et al. 2019	Time	Single
30	(Khurana & Singh, 2019)	Time	Single
42	(Miglani & Sharma, 2019)	Makespan	Single
44	(Wu, 2018)	Time	Single
43	(Arora et al., 2020)	Time	Single
62	(Dinani et al., 2022)	Makespan	Single
63	(Attiya et al., 2022)	Makespan	Single

Multi-objective: in[45] Gabi et al., proposed Multi-Objective Cat Swarm Optimization based on Simulated Annealing (CSM-CSOSA) to enhance **execution time** and **execution cost**. The same as with Muthsamy & Ravi Chandran, in [49] they proposed their algorithm to enhanced **makespan** and **cost**. In addition to Belgacem & Beghdad-Bey in [46] proposed the heterogeneous earliest end time (HEFT) and the ant colony algorithm (ACO) to enhance the same objective functions which are **makespan** and **cost.** In addition, Li, Wang, et al in [65] offers a Multi-swarm Co-evolution-based Hybrid Intelligent Optimization algorithm for scheduling numerous workflows that minimizes **total time and cost** while meeting each workflow's deadline restriction**.** While Hu et al., propose an energy-efficient scheduling system for processing a real-time-demanding user application to enhance both **energy usage and job execution time [66]**. **In** [47] Dubey & Sharma, introduce Chemical Reaction Partial Swarm Optimization algorithm to enhance **cost, energy,** and **makespan.** As the same Li, Xu, et al in [64] proposed Chaotic-nondominated-sorting Owl Search Algorithm to enhance **cost, energy,** and **makespan.** The simulation results showed that the proposed algorithms had a good performance in the considered objective functions. In addition, in [48] Konjaang & Xu, proposed Multi-Objective Workflow Optimization Strategy (MOWOS) algorithm by used MaxVM and MinVM selection algorithms techniques to reduced execution cost, **makespan** and **resource utilization** while other objective functions not considered such as **energy consumption** and **load balancing**. The simulation results showed that the proposed algorithms improved the considered objective functions. In [53, 54] Ben Alla et al. and Singh et al., work to enhanced multi-objective function (**makespan, resources utilization, cost, load balancing**). Loheswaran in [50] focus on **time** and **resurce utilization** while Gao et al., in [51] work on makespan and load balance onjective functions. Furthermore Golchi et al., in [52] ehnanced three objective functions (**load balance, resource utilization , response time**). Both Devaraj et al and Rani & Suri in [55, 56] focuse on **makespan** , **resource utilization** and **throughput** in their algorithms. Chandrashekar & Krishnadoss [67]and sellami et al., [72] propose an optimization algorithm to improved **makespan, and reduced energy and cost consumption.** Manikandan et al. [68] presented a novel hybrid Whale optimization algorithm-based MBA method (mutation-based Bees) to enhance the makespan and cost. Moreover **the execution time, cost, and load rate** which are the objectives that improved by Liu [69] by using the ant colony method. The multi-objective genetic algorithm used by Xia et al.,[70] to enhance **makespan** and **the energy consumption.** The simulation results showed that the proposed algorithms had a good performance in the considered objective functions. **Table 10** shows the articles with multi_objective functions.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 10: Multi- Objective Functions References

No.	*Authors*	*Objective Functions*	*Type*
45	(Gabi et al., 2018)	Time, Cost	Multi
47	(Dubey & Sharma, 2021)	Cost, Energy, Makespan	Multi
46	(Belgacem & Beghdad-Bey, 2021)	Makespan, Cost	Multi
48	(Konjaang & Xu, 2021)	Cost Makespan. Resource utilization	Multi
49	(Muthsamy & Ravi Chandran, 2020)	Makespan , Cost	Multi
50	(Loheswaran, 2021)	Time , Resource utilization	Multi
51	(Gao et al., 2020)	Makespan , Load balancing	Multi
52	(Golchi et al., 2019)	Load balance. Resource utilization. Response time	Multi
53	(Ben Alla et al., 2018)	Makespan, Resources utilization, Cost Load balancing	Multi
54	(Singh et al., 2020)	Makespan, Resource Utilization, Cost Load balance	Multi
55	Devaraj et al. 2020	Execution time. Makespan. Resource utilization. Throughput	Multi
56	(Rani & Suri, 2020)	Makespan, Throughput Resource utilization	Multi
64	(Li, Xu, et al., 2022)	Makespan, Cost, Energy consumption	Multi
65	(Li, Wang, et al., 2022)	Time, Cost.	Multi
66	(Hu et al., 2022)	Energy use, Makespan	Multi
67	(Chandrashekar & Krishnadoss, 2022)	Cost, Energy, Makespan	Multi
68	(Manikandan et al., 2022)	Time , Cost	Multi
69	(Liu, 2022)	Execution time, cost, and load balance.	Multi
70	(Xia et al., 2022)	Energy use, Makespan	Multi
72	(Sellami et al., 2020)	Cost, Energy, Makespan	Multi

Rq2. What Issues Have Researchers Noticed When Performing A Single Objective Function?

Several task scheduling strategies focus on certain objectives such as minimizing makespan, optimizing resource use, or reducing task waiting time. Nevertheless, the exclusive focus on a solitary objective function may not inevitably result in adverse effects, but rather may have a restricted influence on the performance of other vital metrics, thereby mildly impacting the overall efficacy of the task scheduling algorithm. Improving the utilization of Cloud resources and ensuring timely completion of tasks can have a modest impact on metrics such as makespan and task response time. The conventional approach to cloud scheduling, which focuses on single-objective optimization with an emphasis on factors like cost and time, has demonstrated limited effectiveness in addressing the changing requirements of consumers. These increasing expectations include the need for decreased execution time and costs. Therefore, it is imperative to employ algorithms that take into account a wider range of evaluation goal functions in order to improve the overall performance of the Cloud. The growing recognition of the significance of multi-objective optimization in cloud scheduling has been substantiated by recent scholarly investigations [57, 75].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Rq3. How Do Single Objective and Multi-Objective Functions Work?

Multi-objective searching is based on the same fundamental ideas as single-objective searching. However, there is a significant difference between the two in the manner they assess a solution's fitness. Unlike single-objective optimization, where fitness evaluation is simple and done by evaluating a single objective function. Concerning the single objective, consider the following scenario: we have a search space that covers the continuous interval D = [-100, 100]. If we want to maximize some continuous function f(x), we're dealing with a single-objective search problem with a simple solution concept: any value of $x \in D$ that maximizes f(x) is a solution. If there are multiple solutions, we are unsure which one to choose; if we have a preference for one solution over another, we must refine our solution notion. On the other hand, multi-objective functions, we can add a second continuous function, h(x), to create a two-objective search problem in which we want to maximize f(x) while minimizing h(x). It's possible that the value of x that maximizes f(x) isn't the same as the value that minimizes h(x); in this case, we'll need to investigate a trade-off curve. Pareto optimality would be a good solution notion for this problem; the solution would be the set of nondominated x values. If there is no alternative value x', a value x is nondominated for our problem. Such that $f(x') > f(x)$ and $h(x') \leq h(x)$, or $f(x') \geq f(x)$ and $h(x') < h(x)$. [71]

Multi-objective optimization, also known as multi-criteria optimization or vector optimization, is a type of mathematical optimization problem that involves determining a set of decision variables that satisfy constraints and provide acceptable values for all objective functions. Multiple objectives (a vector of objectives) must be optimized (minimized or maximized) simultaneously in these cases. These goals are frequently at odds with one another, so achieving one will impact negatively on the other. As a result, no one optimal solution exists for all of the goal functions. Instead, a group of optimal solutions known as Pareto optimal solutions or Pareto front solutions exists [74]. Multi-objective optimization is more complicated. Multi-objective optimization necessitates a more complex "fitness assignment" system that brings the several objective functions together and unifies them. Fitness assignment is a key component of multi-objective search. It is the process of converting a vector of objective function values into a scalar fitness value that may be used to rank and pick higher-quality solutions during the search. [58]

7. THREATS TO VALIDITY

We aimed to be as thorough as possible when doing this systematic review. However, it is possible that it has withstood multiple challenges to its validity. As a result, any efforts to understand or directly use the reviewed or conclusions in this systematic review should keep these limitations in mind:

7.1 Research Scope: Academic articles, technical reports, and web pages, among other sources, have discussed the use of objective functions in task scheduling in cloud systems. We have specifically excluded articles from national journals and conferences. Also removed are articles that focused on specific task scheduling themes but were more likely to address other difficulties than the objective functions in task scheduling problem. As a result, it is necessary to note that this systematic review included articles published in prominent international cloud computing publications in its qualifying.

7.2 Research Questions: The defined questions may not have covered the entire objective functions in task scheduling field, implying the possibility of defining further pertinent questions.

7.3 Study and Publication Bias: Based on past review experiences, five of the most dependable electronic databases were chosen. Indeed, statistics show that this five-electronic database would have to provide the most relevant and trustworthy studies. However, it is impossible to guarantee that all relevant primary research will be chosen. It's possible that any relevant studies were overlooked through the processes described in Section 4.5 There could be a number of causes for this, ranging from the search string to the data extraction process. We sought to avoid this as accurately as possible by following the references in source papers.

8. SELF-REFLECTION AND CRITICAL EVALUATION

Prior to examining the findings derived from this study, it is essential to participate in a rigorous self-evaluation of our own research. The conducted systematic literature review, which encompassed 75 papers and extensively examined the complexities of work scheduling in cloud computing, instigates a reflective analysis.

To ensure comprehensiveness, our selection criteria and methodological approach were designed to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

encompass a wide range of studies on objective functions in task scheduling. Nevertheless, it is imperative to recognize the potential biases and limitations that are inherent in doing a systematic review. The selection of databases, the predetermined research inquiries, and the temporal constraints may have impacted the extent of our discoveries.

The act of self-examination encompasses an evaluation of the clarity and logical consistency of our writing. The findings reported in this study highlight the importance of multi-objective functions. However, it is important to acknowledge the necessity for more in-depth investigation and contextual analysis of these findings. The current focus on adopting a comprehensive approach to improving Cloud performance necessitates a more intricate examination of the compromises and interconnections among different objective functions.

9. CONCLUSION

This work represents the culmination of a comprehensive analysis of task scheduling strategies in cloud computing, derived from a systematic examination of 75 scholarly papers. The focus of this analysis is to critically evaluate the prevailing approaches in task scheduling within the context of cloud computing. An analysis of 70 scholarly articles dedicated to the topic of task scheduling, spanning from 2018 to mid-2022, reveals that 58 of these studies specifically investigate objective functions. This examination sheds light on a landscape in which 22% of the strategies employed in these studies rely solely on single objective functions, while a substantial majority of 78% accept the utilization of multi-objective functions.

The results highlight the crucial significance of objective functions in determining the effectiveness of task scheduling strategies. Task scheduling algorithms commonly prioritize specific objective functions, such as makespan, resource usage, or task waiting time, as their major optimization targets. Nevertheless, it is important to note that a narrow concentration on a single objective function may unintentionally hinder the optimization of other functions, leading to a decrease in the overall effectiveness of scheduling algorithms. This highlights the need of algorithms that prioritize a comprehensive improvement of Cloud performance, taking into account several examination objective functions.

The presented analysis suggests that algorithms that employ multi-objective functions exhibit superior performance compared to algorithms that focus just on a single objective. The use of this sophisticated approach demonstrates the advanced optimization capabilities of cloud systems, resulting in a more comprehensive improvement in performance. In order to broaden the scope of this research, future endeavors will involve doing an extensive automated search spanning the past decade. This search will aim to evaluate the changes in researchers' inclinations towards different types of objective functions and their subsequent effects on the performance of cloud systems. Moreover, conducting a more comprehensive analysis of objective functions such as throughput, availability, and reliability, in conjunction with an examination of scheduling constraints including budget, deadline, priority, and fault tolerance, will enhance our comprehension of the complex dynamics that govern the scheduling of tasks in cloud-based environments.

Appendix A: Quality Questionnaire

No.	*Question*	*Score*
1	Is the research goal stated properly in the paper?	Y/p/N
2	Is the research question addressed in the paper?	Y/P/N
3	Is there a comparison?	Y/p/N
4	Is the study methodology adequately described in the paper?	Y/P/N
5	Is the scheduling method well-defined?	Y/P/N
6	Does the paper include defined data collection measures	Y/P/N
7	Does the paper defined the data collection procedures?	Y/P/N
8	Is there a discussion of the research's limitations in the paper?	Y/P/N

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