Load Balancing in Cloud Computing using Nature-Inspired Algorithms: A Systematic Literature Review

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Abstract

Cloud computing is a well-known phenomenon in the current era. As the demand for cloud computing is increasing, the need for resource optimization and efficient task scheduling is also arising. In recent studies, researchers are using improved and hybrid versions of nature-inspired algorithms to address the above-mentioned problems. This study aims to systematically review the optimization challenges in cloud computing and to identify the most commonly used nature-inspired algorithm based on the above problems. We conducted a systematic literature review by following the Kitchen-ham guidelines and Prisma format. Through careful review, we identified 52 studies that were extracted from 396 initial studies to address four research questions. After Abstract and title-based screening, four Quality criteria and a set of inclusion and exclusion criteria were carefully applied. We have found four major optimization challenges in cloud computing that were targeted by the researchers. These challenges are Task Scheduling, Load Balancing, Resource Allocation, and Resource Scheduling. Our findings show that Task Scheduling was the most discussed challenge (53.85%) followed by Load Balancing (36.54%) while Resource Scheduling was the least dis-cussed challenge (3.85%). The findings also revealed that Particle Swarm Optimization (PSO) was the most commonly used nature-inspired algorithm (20.63%) followed by the Genetic Algorithm (14.29%), while Pigeon Inspired Algorithm was the least used algorithm. The research trends are shifting towards improved versions of nature-inspired algorithms. Re-searchers are using mathematical approaches to improve the efficiency of current nature-inspired algorithms. Recent studies also show that we can improve the performance efficiency of nature-inspired algorithms by in-creasing the number of considered factors or by combining two nature-inspired algorithms.

Keywords [1]

Cloud Computing, Load Balancing, Nature-inspired Algorithms, Resource Optimization.

1. Introduction

Cloud computing is one of the most important and major advancements in the IT industry. As soon as cloud computing entered the IT market it revolutionized the way of computing. The IT industry is a very saturated market and it is very difficult for a new person or company to enter the market because of its high demand for computing resources and infrastructure costs. Cloud computing is a dream coming true for be-ginners, as it is based on pay per use model [1].

In cloud computing, there are four major deployment models as follows:

Public Cloud:

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The public cloud is a model based on the type of cloud services that are available for public use and it is owned by large organizations selling its services.

Private Cloud:

The private cloud is a model based on the type of cloud services that are available only for exclusive use for a close number of people and it is managed by a single organization or a third party.

Hybrid Cloud:

A hybrid cloud is a combination of different clouds like public, private, and community clouds.

Community cloud:

A community cloud is made for a common purpose or functionally for a specific community. It is owned by a group of organizations for a third party. By using cloud computing a user can access a nearly infinite number of computing resources just by connecting to the internet. Cloud computing is based on two major components Abstraction and the other is Virtualization.

Abstraction:

Cloud computing is abstract, a user or a developer using cloud services doesn't know the physical location of the machine that an application or service used is running or the location where our data is stored.

Virtualization:

Cloud computing virtualizes different computing resources by resource pooling and sharing storage on demand by the user.

As cloud computing is growing and becoming more and more common day by day, cloud task scheduling and resource optimization are becoming more and more challenging. Cloud Data Centers are located in different regions across the globe. Almost every region has its power and network prices on top of that they have their policy regarding data privacy. This raises the problem of resource optimization and task scheduling. Multiple virtual machines are running at the same time in a single machine and recourse demand from a user is not an easy task to predict.

For the last five years, researchers are using nature-inspired algorithms for solving the problem of task scheduling and resource optimization. Nature-inspired or metaheuristic algorithms are the type of algorithms that are inspired or based on the phenomena of nature.

These types of algorithms are immensely used in the latest research for solving these two problems. Some commonly known nature-inspired algorithms are Genetic Algorithms, Ant colony optimization, Particle Swam optimization, Differential Evolution.

This SLR is organized as follows: Section II describes the Related Work for this SLR, section III describes the Research Methodology used in this paper, section IV describes the Results of the SLR and a Discussion of those results, and section V concludes the SLR.

2. Related Work

Technology is becoming more and more advanced, so the demand for computing resources is increasing exponentially. This resulted in an immense increase in demand for cloud bases systems. This result in the problem of efficient task scheduling and resource allocation. In recent studies, nature-inspired algorithms are mostly used to address optimization challenges. In recent studies, researchers are not only using this nature inspired algorithm but also improving these nature-inspired algorithms by creating a hybrid approach by merging two algorithms like a new algorithm using New Caledonian Crow Learning Algorithm, reinforcement learning, and parallel strategy [2]. Along with nature-inspired algorithms, mathematical techniques are playing a vital role in improving the performance of available nature-inspired algorithms. Cock-roach swam optimization was used along with a hybrid mathematical model[3].

This SLR was performed to explore different optimization challenges and which types of new approaches are used along with nature-inspired algorithms in recent studies.

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3. Research Methodology.

Systematic Literate review (SLR) is a term that is highly used in research that is being done in the domain of software engineering [4]. The objective of performing an SLR is to identify all available research in the targeted area, along with evaluating and interoperation of available research. There is no room for a biased SLR, which makes an SLR a very credible approach for finding research gaps and provides a summary of the studies on a topic under consideration. To the best of our knowledge, there is no SLR from 2017 till March 2022 that provides an analysis of emerging optimization challenges in cloud computing and the use of nature-inspired algorithms to solve those challenges. To fulfil this research gap, we are performing an SLR using the guidelines proposed by Kitchenham[4].

3.1. Research Goals, Objectives, and Questions

The major Research Goal of our SLR is:

RG: To see the various optimization challenges and their solutions using nature-inspired algorithms in cloud computing.

This research goal is divided into research objectives which are further divided into various research questions.

The research objectives of this SLR are:

OB1: To identify various optimization challenges in cloud computing.

OB2: To explore various nature-inspired Algorithms from the literature that are used to address the above challenges.

These research objectives are further mapped to the research questions. Hence, the research questions of our SLR are:

RQ1: What are the optimization challenges in cloud computing?

RQ2: Which is the most discussed optimization challenge in cloud computing?

RQ3: What is the most commonly used nature-inspired Algorithm in the literature based on the above optimization challenges?

The mapping of Research Goals to Research Objectives and Research Objectives to Research Questions is shown in TABLE 1.

Table 1

MAPPING OF RESEARCH GOAL TO RESEARCH OBJECTIVES (ROS) AND RESEARCH OBJECTIVES TO RESEARCH QUESTIONS (RQS).

Research Goal	Research Objectives	Research Questions
RG	OB1	RQ1, RQ2
	OB2	RQ3

3.2. Search Query

For designing the search query, we first identified the key terms. The key terms were identified using previous knowledge, by getting opinions from the experts, and by studying the literature. Identifying a single search term for all electronic libraries is a tricky process because every electronic library has its own rules and procedure for implementing the search query for this purpose, we have used Population, Intervention, and Outcome (PICO) format to design our search query as it is a credible way of designing a query and reveals maximum results[5]. All the identified keywords are put in the PICO format to design the query. The search query after applying the PICO format is shown in TABLE 2.

Table 2

SEARCH QUERY

Population	"Cloud Computing" OR "Cloud Services" OR "Virtual Machine".
Intervention	“Nature Inspired" OR “Evolutionary" OR "Metaheuristic".
Outcome	“Load Balancing" OR "Load Optimization" OR "Resource Balancing “OR "Resource Optimization”.
Query	(“Cloud Computing" OR "Cloud Services" OR "Virtual Machine") AND ("Nature Inspired" OR “Evolutionary". OR "Metaheuristic") AND ("Load Balancing" OR "Load Optimization" OR "Resource Balancing “OR "Resource Optimization").

3.3. Electronic Databases

Five electronic databases were considered for conducting this SLR. The databases are IEEE Xplore, Science Direct, ACM, Wiley, and Springer Link. These libraries are considered as the papers here are mostly open access and they have quality papers covering the whole domain [6]. The electronic libraries that were considered for re-search are machined in TABLE 3.

Table 3

ELECTRONIC LIBRARIES

ID	Library	URL
LB1	IEEE Xplore	https://ieeexplore.ieee.org/
LB2	Science Direct	https://www.sciencedirect.com/
LB3	ACM	https://dl.acm.org/
LB4	Wiley	https://onlinelibrary.wiley.com/

LB5	Springer Link	https://link.springer.com/

3.4. Study Selection procedure

One of the key steps of an SLR is the Study Selection procedure. We have followed the Prisma procedure to conduct the SLR [7]. This procedure is mentioned in Figure 1 and it is very similar to pipe and filter architected as we are feeding data to a pipe and after applying a certain filter it gives some output which is then fed as input to the next pipe and the same process is repeated till the last pipe. This procedure is based on four phases that are Identification, Screening., Eligibility, Included.

Identification

After executing the above-mentioned query on the five selected databases, a total of 396 studies were found. No additional studies were found using any other (forward/backward snowballing) technique. No duplicates were found in these studies. Hence, at the end of the identification phase, we had a set of 396 studies.

Screening

In this phase, we applied title and abstract-based careening on the set of 396 studies coming from the Identification phase. After applying, title-based screening, 266 studies were removed as either they were not targeting optimization or nature inspired algorithms to solve the discussed challenge. Now, after the title-based screening, a set of 130 studies were found. Now, after applying abstract-based screening, 74 studies were discarded and we were left with 56 studies. This means that at the end of the screening phase, 56 studies were left in the pool.

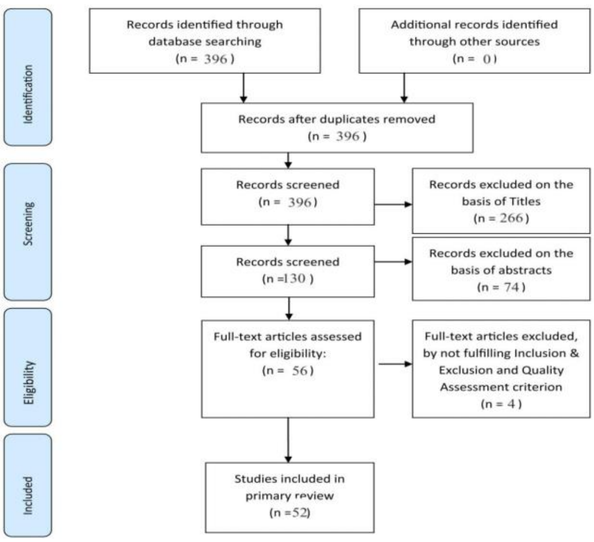

Figure. 1. Study Selection Procedure

The inclusion/exclusion and quality assessment criteria that were used in filling data extraction forms are shown in Table 4.

Table 4

INCLUSION/EXCLUSION AND QUALITY CRITERIA.

Criteria Type	**Description**
Inclusion Criteria	The studies were published between January 2017 and March 2022. The studies were only published in journals and conferences The studies were published only in the English language Only peer-reviewed articles will be considered.
Exclusion Criteria	Articles that do not meet the above inclusion criteria. Articles do not explicitly use the nature-inspired algorithm for load balancing but discuss nature-inspired algorithms generally or only cite nature-inspired algorithms. Articles that do not explicitly state the findings. Articles that do not evaluate the results of the algorithm used.
QAC	Are the research objectives and Questions clearly defined? Is the context of research well addressed? The full text of the articles should be accessible. Context and environments are specific and clearly stated

While fulfilling the data extraction forms, we found that two of the studies were not fulfilling the quality assessment criterion of “Full text of articles should be accessible”, hence, these two studies were discarded. Therefore, at the end of the eligibility phase, a set of 52 studies was left in the pool.

The 52 studies that were the output of the Eligibility phase were considered for this Systematic Literature Review.

A comparison of the proportion of studies from each library before and after applying the study selection procedure is shown in Figure 2.

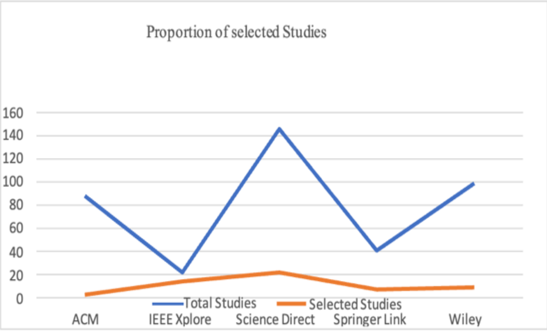

Figure. 2. Proportion of Selected Studies from Digital Libraries

Before reporting the results from the analysis and synthesis of data from the selected studies, the demographic information and an overview of these studies are initially reported.

4. Results and Discussion

This section describes in detail the results of the research questions described above.

After reading the studies, we found that mainly there are four types of optimization challenges discussed in the literature which are mostly related to resource allocation, load balancing, resource scheduling, and task scheduling.

We found that Task scheduling was the most discussed optimization challenge, it was discussed in 28 studies. The second most discussed study in literature is load balancing which was referred to in 19 studies. Resource allocation and resource scheduling were least referred to in the literature only 5 and 2 studies targeted these challenges. These results are presented in TABLE 5.

Table 5

PROBLEMS DISCUSSED IN THE LITERATURE.

Problem	**Count**	**Reference**
Task Scheduling	28	[8][9][10][11][12][13][14][15][2][16][17][18][19][20][21][22][23][24][25][26][27][28][29][30][31][32][33]
Load Balancing	19	[34][35][36][37][3][38][39][40][41][42][43][44][45][46][25][47][48][49][50]
Resource Allocation	5	[51][52][53][54] [55]
Resource Scheduling	2	[56][57]

After reading the studies we came to know that Particle Swarm Optimization (PSO) was the most used nature-inspired algorithm. The proportion of various studies in the literature is shown in Figure 3. Many studies have used this While using this algorithm, researchers have proposed improvements in the algorithm to gain better accuracy for the discussed optimization challenge, whereas some researchers have also used this algorithm in combination with other nature-inspired algorithms or some search-based algorithms like hill-climbing search. This algorithm is still in demand as many researchers are still using it in recent years.

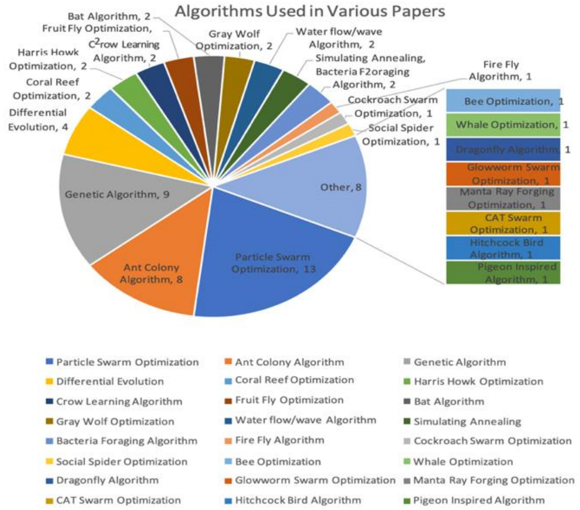

Figure. 3. Various Nature-Inspired Algorithms Discussed in the Literature.

5. Conclusion

In this SLR, we targeted the most commonly occurring challenges in cloud computing that are targeted by the researchers in the most recent papers (from January 2017 to March 2022). We discovered that Task Scheduling, Load Balancing, Resource Allocation, and Resource Scheduling are the main optimization challenges occurring in cloud computing. To address these challenges, the results show that many na-ture0inspired algorithms have been proposed or used in the literature. Particle Swam Optimization (PSO) is the most commonly used nature-inspired algorithm in recent studies. Now research trends are shifting towards improved and hybrid approaches of nature-inspired algorithms. Plenty of researchers are also using mathematical approaches to improve the efficiency of current existing algorithms along with the hybrid approach.

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