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Gray Wolf Optimisation Based Energy Efficient Green Cloud Computing

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Abstract

Scheduling workflows on the cloud is recognised to be an NP-complete problem. But metaheuristic algorithms have been successfully tweaked to deal with this issue in a more efficient manner. Grey wolf optimization (GWO) is a fascinating new metaheuristic approach proposed recently for dealing with continuous optimization issues. Here, we propose the IGWO algorithm as a chaotic-theory-enhanced replacement for the GWO method. The proposed strategy has the potential to prevent the system from settling into a local optimum and speed up the rate at which the GWO converges. Using the CloudSim simulator, we simulate the proposed workflow scheduling system, and the results show that our solution is superior to the alternatives in terms of energy efficiency, cost, and maketime.

Keywords

Grey Wolf Optimization, Chaos Theory, Workflow Scheduling, Makespan

1. Introduction

Researchers have shown that reducing the amount of energy used in cloud computing and minimising its impact on the environment is a difficult problem to address [1, 2]. Data centres utilise a significant amount of power so that cloud users can access the services they require via the cloud. There is the potential for millions of servers to be utilised in a cloud computing environment, each of which will require a substantial amount of power. As a direct and immediate result of this phenomenon, vast volumes of carbon dioxide are released into the atmosphere [3]. By the year 2025, it is anticipated that cloud data centres will be responsible for one-fifth of the total electricity consumption (EC) across the globe [4, 5]. It is possible that it will account for 14% of all carbon emissions by the year 2040 [4]. Cloud data centres have become the front line in the fight against climate change as a direct consequence of this.

It is required to implement a strategy that is both effective and efficient in order to achieve maximum utilisation of available resources while simultaneously minimising energy consumption (EC) in cloud data centres. This is necessary in order to achieve maximum utilisation of available resources. Over the course of time, the impact on the environment may grow more extensive and important. The rise in population all over the world has resulted in a corresponding expansion of the size and scope of the world megacities. It is possible that the strategic application of a wide range of different technical and computational techniques has the ability to considerably improve the quality of life in these megacities. It is possible to develop smart cities when the aforementioned technologies are connected together in a Cloud of Things (CoT) [5]. CoT enables the interconnection of various components of these cities with the Internet of Things (IoT), such as hospitals, houses, stores, automobiles, and so on [6], as well as the integration of cloud computing platforms. This helps to improve the quality of services that are offered and the long-term viability of smart cities. It is possible that the management of the consumption of energy in CoT might be improved, which would result in large savings in carbon emissions.

Consolidating virtual machines is one method that can help cloud data centres reach their full potential in terms of both efficiency and cost savings (VMs). There are four separate steps that can be broken down into when consolidating virtual machines. As a first step, we have compiled a list of all of the overworked physical machines (PMs), as these machines have the potential to slow down and deliver poor quality of service (QoS) [7] to cloud clients. We have done this because these machines have the ability to slow down and deliver poor quality of service to cloud clients. We took this action in order to address the problem as quickly as was humanly practicable. It is feasible to improve quality of service (QoS) by moving some virtual machines from physical machines (PMs) that are excessively crowded to PMs that have less activity [8]. In the second stage, you will seek for any PMs that aren't being completely utilised so that the virtual machines that they host can be moved to other PMs and the PMs that aren't being used can be put to sleep. If you find any PMs that fit this description, then you will move on to the third step. It is possible to prevent the loss of energy that would otherwise be spent in dormant PMs, which is something that would normally happen. The very last thing that you need to do is locate sufficient physical machines (PMs) to transfer all of the virtual machines away from the physical machines that are stressed or idle. The final step is to figure out which of the potential VMs ought to take the place of the PM due to the PM poor performance.

A Service Level Agreement, more commonly referred to as a SLA, is a legal document that specifies the minimum acceptable level of service that a cloud service provider is obligated to give to its customers. This level of service must be acceptable to the customer. A cloud user and a cloud service provider have come to terms on the terms of this agreement (SLA). However, there is a chance that PM performance could be significantly affected if virtual machines are merged on the fly [9], and service level agreements (SLAs) would not be met. Therefore, it is of the utmost importance to find a balance between energy efficiency and performance, ideally with the lowest possible EC and the maximum degree of SLA satisfaction that is achievable. It is feasible to put both EC and SLAV to a halt by employing a technique known as live VM migration [10,11]. It is extremely necessary to have an accurate prediction of the future circumstances around the PM in order to achieve these goals. There is a direct correlation between the quantity of CPU that a PM requires and its effective cost. The purpose of this article is to report on the findings of an unique prediction model that can determine whether PM is overloaded or underloaded. The model will be introduced in this article. It is possible to use the Linear Regression prediction model that has been proposed in order to produce forecasts regarding the utilisation of CPUs in the future.

2. Related works

It is generally agreed that the problem of scheduling several work processes is NP-complete. The challenges that are connected with workflow scheduling have inspired the development of a number of heuristic and meta-heuristic algorithms that have been proposed as possible solutions. The remaining time will be spent discussing both heuristic and meta-heuristic ways of addressing the current topic of discussion.

The authors in [2] introduced a new scheduling method that was based on the ant colony algorithm in order to reduce the amount of time required for the workflow and the makespan. This was done in order to save time. These are extremely important obligations that have been disregarded up until this moment. A approach that is based on costs is presented in [3] with the intention of optimally assigning workloads to the resources that are available through the use of cloud computing. The goal of this scheduling method is to achieve the highest possible levels of production while simultaneously minimising costs as much as possible. The scheduler assigns one of three separate priority levels—high, medium, or low—to each and every individual job that it processes.

A bi-objective hybrid genetic scheduling technique was presented in [4] for the purpose of coordinating the execution of parallel programmes in heterogeneous distributed environments, such as cloud computing infrastructure. These applications have a low priority. The genetic programming approach is utilised in this method in order to generate a hybrid population of scheduling agents. Utilizing this method has many benefits, one of which is that it reduces the amount of time needed to complete a task and the amount of money spent on communication.

The transformation of a problem with several goals into a weighted version of a problem with a single purpose is one method that can be utilised in the process of finding a solution to the issue. With the assistance of the heuristic approach,

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the authors in [5] are able to transform the multi-objective problem into a problem with a single objective. Making massive-scale graph computing projects more accessible has been the primary emphasis of the group activities recently. To this end, they have been concentrating their efforts on making advantage of the capabilities offered by cloud computing. Using this approach, a list of activities is compiled, the tasks are ranked according to their level of significance, and finally, the method chooses the undertaking that has the highest priority in order to delegate it to the cloud computing environment virtual machine that operates most effectively.

The authors in [6] suggested a scheduling solution that was founded on the idea of reducing a multi-objective problem to a single-objective problem. This approach was the foundation of their proposed solution. This strategy was devised with the intention of boosting both productivity and reliability. They published their findings and devised an algorithm for dependable dynamic level scheduling (RDLS), which was based on DLS. Instead of presenting the user with a single response that cannot be altered, as was the case with the method that came before this one, this approach gives them a variety of reasonable possibilities that are based on the algorithm output. These options are derived from the algorithm predictions.

The authors in [8] were successful in finding a solution to the issue of workflow scheduling because they made use of the multi-objective evolutionary technique (MOEA). This strategy is utilised with the intention of accomplishing the twin aims of reducing costs and improving levels of performance. In addition to taking into account these two criteria, the algorithm also takes into account any limitations imposed by time or money. In order to handle workflow scheduling problems that involve many conflicting goals and a diverse set of constraints, population-based algorithms like SPEA2 and NSGA-II and local search algorithms like MOEA and PAES have been put to use. R-NSGA-II is an additional multi-objective technique that identifies Pareto optimal solutions. It does this by establishing a balance between runtime, overall cost, and reliability [9]-[12].

The majority of multi-objective heuristic algorithms are able to operate magnificently in a grid architecture, according to the findings of research. On the other hand, there have only been a limited number of tests conducted in a cloud setting. On the other hand, the issue with the amount of energy that is being consumed has, for the most part, been neglected in favour of a shorter makespan and reduced prices. The authors in [13] present an approach that, in addition to the criteria described above, also takes into account the amount of work that can be done in a given amount of time. Our proposed solution takes into account not only the lifespan and the cost of implementation, but also the energy consumption and the throughput of the system. This study proposes a multi-objective optimization method as a means to attain the goal of effectively creating Pareto answers for workflows that take place within a green cloud environment. This research was carried out by the authors of this study.

3. Proposed Method

The amount of energy that is spent by a machine when it is in a stationary position is referred to as the machine static power, while the amount of energy that is consumed by the equipment while it is being utilised is referred to as the machine dynamic power. The difference between dynamic power consumption and static power consumption is that dynamic power consumption refers to the amount of power that is drawn when the machine is ON but also performing some tasks, and this power consumption always varies depending on the workloads that are being assigned to the machine. Static power consumption, on the other hand, refers to the amount of power that is drawn when the machine is OFF but not performing any tasks. The term static power consumption refers to the quantity of electricity that any machine will always use if it is turned on but not actively doing anything with it. As a direct result of this, the following equation can be utilised to represent either the system net energy consumption or its overall energy consumption:

$$\text{Net energy } (E) = \text{Static energy} + \text{Dynamic energy}$$

Because there are so many different aspects to consider, it is difficult to make an exact prediction regarding the changing energy consumption of a machine. The amount of labour that needs to be done, the order in which activities need to be completed, the number of instructions needed to carry out a certain action, and so on are all examples of these elements.

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Let say we had a cutoff point of 100 watts; we would consider a piece of equipment to be energy efficient if its net power usage fell within a range that included that figure. For example, if the range included 100 watts, the machine would be considered energy efficient. The modelling work that will be given in the subsequent chapters will throw light on the thinking that was behind the selection of this particular power as the cutoff. In the event that the net power is more than this figure, the source virtual machine will be live migrated to a different virtual machine (VM). This will result in the virtual machine dynamic power consumption being switched off, which will lead to a significant reduction in the amount of power that the VM consumes overall.

Because of this, certain pieces of data need to be preprocessed in order to identify servers with workloads that are lower than a given threshold value. The servers are either put into a sleep mode or turned off completely in order to achieve this goal of reducing the amount of energy consumed by the system. Assume for the moment that each of these locations possesses its very own data centre and that it is stocked with servers.

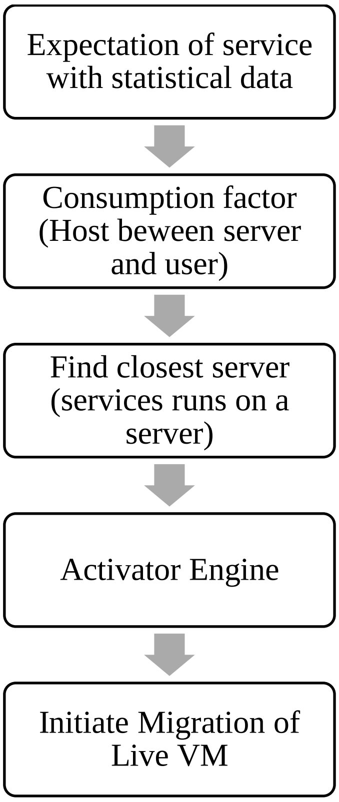

Figure 1. Working Mechanism of a single VM

It will be possible to move the VMs that are situated on that server to another server once the process of the activator engine has been completed. This will result in increased server utilisation and lower transfer costs for such machines.

Proposed algorithm for VM Task optimisation

The reactions of all of the wolves in the population, including the alpha, beta, and delta wolves, move closer and closer to being ideal as the GWO algorithm progresses. The fitness function is what is used to decide which particles are the best at each iteration, and the particle that is regarded to be the best is called alpha. The fitness function is what is used to decide which particles are the best at each iteration. The values that are discovered in the new position in each dimension are equal to the values that are discovered on average among the superior particles in that dimension. These discoveries have been made. At each stage of the process, there is a movement of particles that is carried out non-greedily, meaning that it does not take into consideration the relative fitness of the particles being moved.

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The proposed algorithm includes customizable particle trajectories with regard to the number of steps that are taken; nevertheless, this does not have any bearing on the fitness levels of the system. When evaluating how well the new location fits the requirements, it is customary to compare it to the previous location, which was regarded as the perfect location in the past. When there are no obvious paths moving forward, the particle will revert to the action that was best for it in the past. This happens when there are no evident paths leading forward. As can be seen in the picture on the right, as soon as it has discovered the global optimum, it then continues its search for a solution that is even better than the global optimum. On the other hand, if it is unable to find a solution of this kind, it will reset itself to its original condition.

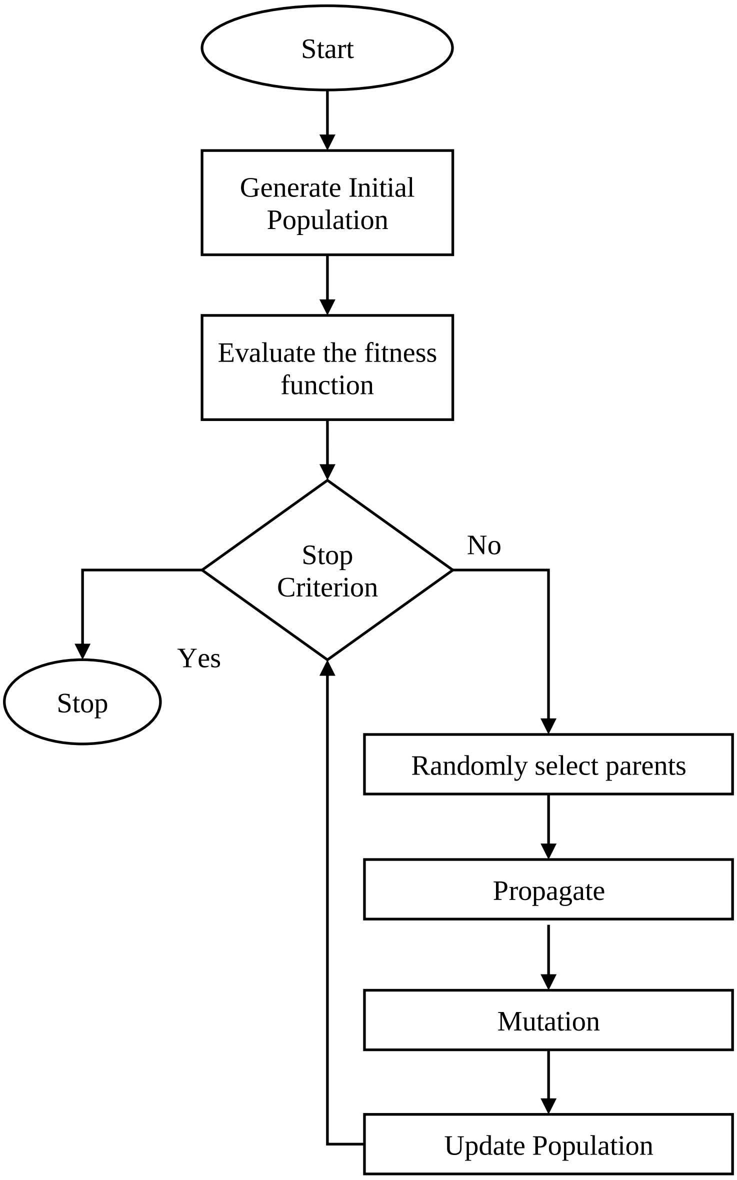

Figure 2: Modified GWO Flowchart

In this paper, we present GWO, a novel metaheuristic optimization approach that was conceived as a response to the odd courtship rituals of black widow spiders. This method was conceived as a response to the distinctive courtship rituals of black widow spiders. When compared to competing approaches, GWO stands out for a number of reasons, including the speed with which it reaches convergences and its capacity to avoid difficulties connected with reaching a local optimal solution when exploring or exploiting feature spaces. Because it can keep a healthy balance between its exploitations and discoveries — that is, it can search wider areas in search of the best possible global solutions — GWO is an appropriate strategy for optimizations to use when there are a large number of potential local optimums. This is because GWO is able

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to search wider areas in search of the best possible global solutions. A Flowchart Illustrating the Different Workflow Processes in a Commercial Setting is given in Figure 2.

4. Results and Discussions

We achieved this by comparing the GWO approach with the methodology that was advised by making use of the 23 mathematical optimization functions that are regarded as industry standards and that were presented at CEC 2005. In doing so, we were able to determine which way was superior. We came to the conclusion that using functions with varying degrees of complexity, such as single exponential, multi-exponential, and finite-dimensional varieties, would be the best way to measure our progress. Beginning with the simulation and continuing all the way through to the final numerical results, cloudsim is used throughout this entire procedure. In order to run the simulator, you will need a desktop computer that has a Core i7 processor that is running at 2 GHz and 4 GB of main memory.

Tables 1, 2 successively exhibit the results that were achieved by applying the suggested technique to the relevant functions ten times. These results were then averaged to determine the mean value. Every conclusion that has been shown as a result of this effort is in accordance with the standard that was established by the IEEE CEC in 2005. One thousand separate searches are performed in total whenever the algorithm is executed in its entirety. This brings the overall number of searches to one thousand.

Provided that the size of the population is also thirty, the projected response size for this survey is a group of thirty persons, which is reasonable given that the size of the population is also thirty. In order to give a comparison that is both accurate and fair, it is assumed that the population sizes of the algorithms that are being analysed are the same, as are their processing capabilities (Figure 3 – 5).

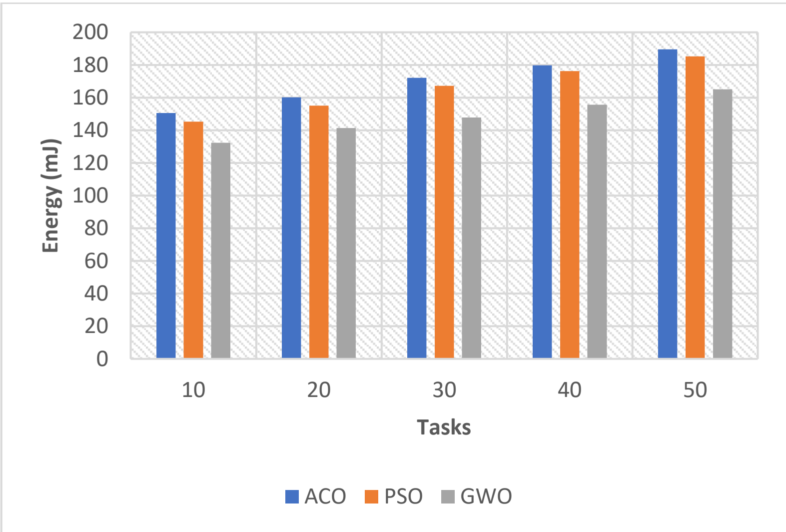

Figure 3: Energy Consumption

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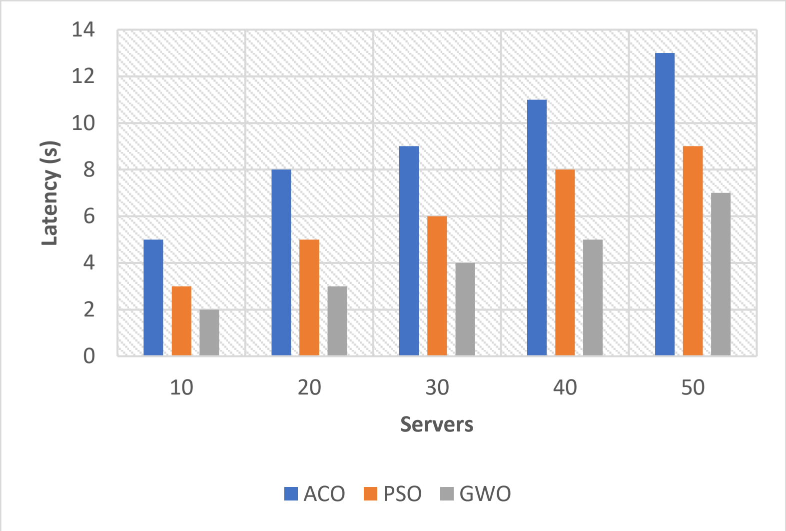

Figure 4: Latency

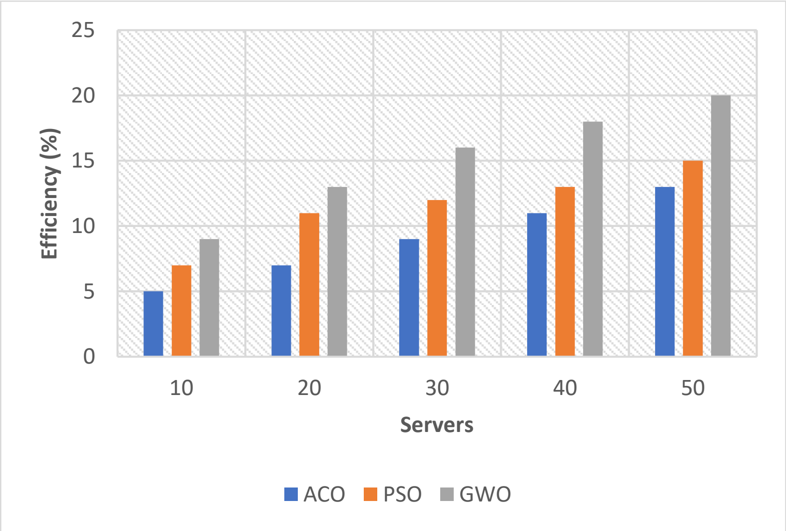

Figure 5: Energy Efficiency

Table 1: Computational Time (ms)

Servers	ACO	PSO	GWO
10	3.21	3.10	2.25
20	7.96	7.34	6.35
30	19.84	18.27	16.58
40	31.75	29.18	26.95
50	35.77	34.07	47.44

Table 2: Communication Time (ms)

Servers	ACO	PSO	GWO
10	3.01	2.91	2.86
20	7.46	6.88	6.70
30	18.61	17.14	15.55
40	29.70	29.53	28.94
50	44.76	44.67	44.50

It is possible that the criteria of cloud clients will be satisfied because tasks are currently being distributed across multiple machines. We are going to study green computing, which is a subclass of cloud settings, within the constraints of this section. A growing number of people are becoming familiar with the concept of green computing, which describes the implementation of information technology that has a smaller impact on the natural world. That is, figuring out how to develop systems and subsystems, as well as how to use and dispose of them, in a manner that requires as little support and as few resources as possible from the world that is surrounding you. This includes figuring out how to develop systems and subsystems in a way that allows for maximum autonomy. The development of more effective algorithms is essential to the achievement of one of the primary objectives of green computing: a reduction in the amount of energy that is consumed. One of the key goals of environmentally friendly computing is to achieve this. In the following paragraphs, we will conduct an analysis of the amount of time, money, and energy that will be necessary to carry out the duties, as well as an investigation into the amount of energy that will be consumed by the algorithm that has been suggested.

When applied to workflows of a medium scale, it has been established that the suggested strategy performs superiorly to the alternatives that were investigated in terms of its efficiency. The method that was suggested to be utilised for the Montage workflow is effective across a number of dimensions, which was one of the reasons why it was suggested. When applied to scheduling issues, reverting to optimal states in the event of failure to identify the appropriate replies has a significant impact on the length of time required to complete the task, the amount of money spent, and the amount of energy used.

It was occasionally required to include a small bit of chaos when doing fine-tuning on the parameters of metaheuristic algorithms. As part of our inquiry, we came up with a chaotic variant of the regular GWO by introducing a little bit of randomness into the equations. This was done so that the results would be more unpredictable. Ten different kinds of chaotic maps were employed in order to evaluate how reliable the method is. This was done so that the amount of dependability could be assessed. According to the findings, a considerable improvement in the performance of the new algorithms can be accomplished by utilising deterministic chaotic signals in place of constant and/or random value inputs. This change can result in a large improvement. The statistical evidence and the performance rates of the GWO indicate that the adjusted algorithms will significantly enhance the dependability of the global optimality and will also boost the consistency of the outputs. This will be the case because the adjusted algorithms will boost the performance rates of the GWO. This goal will be reached by increasing the reliability of the GWO outputs while simultaneously increasing its pace of performance. Any advancement made in such an evaluation can provide insight into the method by which chaotic metaheuristic algorithms function, in addition to providing insight into the junction of metaheuristic algorithms and chaos. This understanding can be garnered from the results of the evaluation.

5. Conclusions

It was demonstrated that the proposed algorithm possessed a greater level of efficiency than the baseline approach as well as other algorithms. It was suggested that we apply numerous chaotic functions in our approach, which is based on random number generation. In the event that a better response cannot be found, it will remember the best response from the previous iteration for a certain number of iterations before falling back on the best response from the previous iteration. As a result of this enhancement, the rate of convergence increased, and there was no longer any risk of becoming mired in a situation where a local optimal solution was the only viable option. In addition, the performance of the binary version of the suggested method was analysed to demonstrate its applicability to the task scheduling problem, and a practical task scheduling challenge was proposed for scientific workflows of varying sizes. Both of these things were done to demonstrate the applicability of the suggested method to the problem. Simulations using the proposed algorithm revealed that it has a faster running time, lower costs, and uses less energy than other algorithms.

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