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Intelligent Service Selection in a Multi-Dimensional Environment of Cloud Providers for Internet of Things Stream Data through Cloudlets

Omid Halimi Milani ¹, Seyyed Ahmad Motamedi ², Saeed Sharifian ² and Morteza Nazari-Heris ^{3,*} 

¹ Department of Electrical and Computer Engineering, University of Illinois at Chicago, Chicago, IL 60607, USA; ohalim2@uic.edu

² Department of Electrical Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran 159163-4311, Iran; motamedi@aut.ac.ir (S.A.M.); sharifian_s@aut.ac.ir (S.S.)

³ Department of Architectural Engineering, 104 Engineering Unit A, Pennsylvania State University, University Park, PA 16802, USA

* Correspondence: mun369@psu.edu; Tel.: +1-8137350493

Abstract: The expansion of Internet of Things (IoT) services and the huge amount of data generated by different sensors signify the importance of cloud computing services such as Storage as a Service more than ever. IoT traffic imposes such extra constraints on the cloud storage service as sensor data preprocessing capability and load-balancing between data centers and servers in each data center. Furthermore, service allocation should be allegiant to the quality of service (QoS). In the current work, an algorithm is proposed that addresses the QoS in storage service allocation. The proposed hybrid multi-objective water cycle and grey wolf optimizer (MWG) considers different QoS objectives (e.g., energy, processing time, transmission time, and load balancing) in both the fog and cloud Layers, which were not addressed altogether. The MATLAB script is used to simulate and implement our algorithms, and services of different servers, e.g., Amazon, Dropbox, Google Drive, etc., are considered. The MWG has 7%, 13%, and 25% improvement, respectively, in comparison with multi-objective water cycle algorithm (MOWCA), k-means based GA (KGA), and non-dominated sorting genetic algorithm (NSGAI) in metric of spacing. Moreover, the MWG has 4%, 4.7%, and 7.3% optimization in metric of quality in comparison to MOWCA, KGA, and NSGAI, respectively. The new hybrid algorithm, MWG, not only yielded to the consideration of three objectives in service selection but also improved the performance compared to the works that considered one or two objective(s). The overall optimization shows that the MWG algorithm has 7.8%, 17%, and 21.6% better performance than MOWCA, KGA, and NSGAI in the obtained best result by considering different objectives, respectively.

Keywords: energy consumption; load balancing; makespan; storage allocation; edge computing; Internet of Things



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1. Introduction

Cloud computing is a new Internet-based technology that stores data on servers and makes it available to clients on demand. Two of the most important drivers in its increased utilization are cost reductions and the streamlining of technological infrastructure [1]. In recent years, cloud computing has gotten a lot of press in both the corporate and academic worlds. This is a service- and application-related technology that runs on a distributed network, employs virtual resources, and may be accessed via networking and Internet standards [2,3]. The Internet of Things (IoT) and its potential needs have enhanced the importance of cloud computing. The number of cloud-based servers that provide the proper structure for IoT manifestation has expanded. Plus, there are a large number of users and sensors that produce a high volume of data [4]. The proper usage of cloud

services based on QoS criteria is essential. Furthermore, sensors have a limited battery and should work for a long time without a need to recharge. Distributed clouds can be helpful in processing IoT sensors' data [5].

One of the issues that must be considered in modern systems is energy consumption, which should be considered on both sides, users and servers. Furthermore, optimal energy consumption can have a significant impact on reducing air pollution. According to data released in 2014, the American data centers consumed 70 billion KW/h of Electrical energy. Therefore, there is a lot of research focusing on energy consumption [6–8]. On the other side, building energy efficiency and estimating building occupancy information effectively in real time as well as reducing the energy consumption in non-residential buildings are studied widely in the literature [9,10]. Large companies such as Amazon, Google, Salesforce, Microsoft, and IBM have begun to set up a new data center to host Internet applications and data processing centers. The current service providers give users the option of using services based on their demands and paying according to their usage (pay as you go) [11]. The necessity of maintaining data drives the usage of storage services [12]. To address overload in one service, load balancing among different services was proposed in the literature [13,14].

IoT devices include many examples of sensors that have different applications in smart homes, healthcare, transportation, building, and cities. Storing data in cloud services is cost effective, which is practical in addressing the high demand for IoT devices. However, cloud storage services face challenges such as energy consumption and load balancing among services [14,15]. The existence of different service providers makes it difficult to choose the proper service. Furthermore, the network has an arbitrary topology, and selecting an appropriate service among the available services of different service providers becomes another issue that should be considered. Another commonly discussed issue in cloud computing is the processing time. The needed time to process various data is based on data type, size, and rates [16,17]. There are several works around service allocation.

To the best of our knowledge, there is no work with capabilities of minimizing energy consumption and reducing service completion time, in addition to addressing load balancing among services, and the short comparison is available in the table. Considering different services from a variety of service providers is also addressed in the present work. A hybrid modified MOWCA and GWO algorithm have been proposed in the present study. The modified algorithm can explore better; as a result, a better solution set can be proposed. Two layers, fog and cloud, will be managed simultaneously to have a comprehensive solution. Finally, a structured technique for analyzing complex decisions in addition to different methods is used to evaluate the proposed algorithm.

The remainder of this paper is organized as follows: In Section 2, a brief discussion about recent articles in this area is presented. Architecture, algorithms, and mathematical models are presented in Section 3. In Section 4, the proposed method is evaluated and compared to other works. In Section 5, the paper is concluded.

2. Related Work

Cloud computing and IoT are used in a variety of fields, including medical engineering and social media [18]. A variety of architectures and algorithms are proposed in this area to fulfill users' demands efficiently.

2.1. Architectures in Service Allocation

Some cloud-based architecture is centralized, and the centralized architecture creates a latency in the processing and storing of data. The latency is because of the great distance between IoT devices and cloud providers. Therefore, the fog architecture can reduce latency. Managing energy consumption is presented in edge computing for IoT (ECIoT) architecture and leads to an optimal solution [19]. Fog computing was introduced in 2012 by researchers of the Cisco company with a new view to the set of all networks (including 3 G/4 G/LTE/5 G) and everything (all smart objects, Internet of Everything) with a hierarchical structure. Using the architecture expressed in fog–cloud, the energy

optimization of both cloud and fog layers can be managed simultaneously to contribute to the IoT development goal [20]. Fog computing architecture involves three main layers: IoT devices as the first layer, the fog layer as the second layer, and finally, the cloud layer [8,15].

Cloudlet is a project presented by a group of researchers from Mellon University [21]. The goal of using cloudlets is to have available resources near the IoT devices. Data compromise risk is reduced by having edge computing. Cloudlets have more capacity for processing and battery power in comparison to other fog nodes.

2.2. Algorithms in Service Allocation

Researchers have indicated that service allocation is an NP-hard problem. There are no polynomial-time algorithms for NP-hard problems. Some research focused on designing a deep neural network, the hybrid usage of deep neural networks, and metaheuristic algorithms, which all can be considered as alternative solutions. In the current study, there are different services available to be selected; however, considering the proper service is challenging. Moreover, there are different objectives considered in this work that boost the probability of trapping at a local minimum. To escape from the local minimum, bio-inspired algorithms are considered as they have shown a good capability for handling this issue [22]. A bunch of studies is concentrated on load balancing. Researchers are using definitive and innovative methods in a fair distribution of loads among services. The primary objective of load balancing is preventing overload in services. In [23], a random algorithm is used for outsourcing data to different services in which the physical distance is a criterion for selecting a service. In some cases, service failure occurs due to a lack of attention to the load balancing between services [24]. In [25], using the honeybee algorithm and introducing a new algorithm named honey bee behavior-inspired load balancing (HBB-LB) address equitable load distribution between virtual machines and maximizes processing speed. Round robin is also used for equitable load distribution. Broberg et al. [26] chose low-cost cloud storage services with the meta content delivery network (CDN) method. They found and optimized service selection based on its cost; the process did not encompass an equitable load distribution between storage services [27,28]. In [29,30], a kind of NSGAI is used to address load balancing as the main criteria.

Some studies are performed to reduce completion time. Services have different processing speeds [31]. In [32], a model for load balancing on the Internet is presented, aiming to reduce the overall processing time for different tasks. In the other work, both the firefly algorithm and particle swarm optimization are made to balance the load of the entire system and reduce the makespan as well [33]. In [34], the MOGWO method, which is one of the multi-objective algorithms, is used to distribute data equitably among virtual machines and to reduce the working time. In [35], by using the GWO algorithm, the time of the makespan is diminished, and other determinants of QoS are not considered. In another research, the combined GWO and cuckoo search algorithm is used to minimize the makespan and to reduce the needed services [36]; however, other aspects of service allocation are not considered. In [37], the integer programming method is used to reduce the cost of storing data and data retrieval time in a multi-cloud provider environment. In [38], particle swarm optimization (PSO) is used to minimize the cost of the sending and processing of different tasks. The game theory is used for task scheduling in [39] for designing the mathematical model. The algorithm is proposed to deal with big data and to consider energy consumption. However, the available bandwidth as one of the factors in transmitting data and energy consumption is not considered. In [40], an adaptive mode for assigning different services for tasks by considering the time is used. In [41], the proposed algorithm is used to achieve the minimum energy and running time in which load balancing is not considered. In [42], in addition to minimizing energy consumption, the GWO and BAT algorithms are used to distribute the work equitably among services. In another research, energy and cost are optimized in service allocation [43]. In [44], the NSGAI algorithm is used to achieve the minimum energy and makespan for service allocation in which load balancing is not considered. The Pareto's results as one of the important factors in multi-objective problems are

improved. Both energy consumption and load balancing between solutions are considered while satisfying the spacing metric [45]. Table 1 summarizes and compares the proposed model in this study with those introduced in the literature.

Table 1. Comparison of the proposed algorithms in this study.

References	Processing Time	Transmission Time	Load Balancing	Energy
[25,29]	✓		✓	
[32]			✓	✓
[34,35]	✓		✓	
[40]				✓
[41]	✓			✓
[43]			✓	
[44,45]			✓	✓
The current study	✓	✓	✓	✓

3. Proposed Algorithm for Fog–Cloud Architecture

The system model consists of different parts, as illustrated in Figure 1. Storing data as fast as possible by consuming less energy is critical. The first cloudlets are assumed as the first sub-layer in the presented model. Neighbor cloudlets are considered as a second sub-layer in the model. To accomplish the processing of data as quickly as possible, the distribution of data among different cloudlets is adopted to avoid overload. Using the distributed model is not only limited to failure in service allocation but also reduces energy consumption. The reliability of the system is reduced by rejecting a request from different users. Furthermore, rejecting requests destroys the service level agreement. The distribution of data among various services increases the availability of services due to more available free space. The availability of different services is one of the QoS factors. Therefore, the distribution of data among different services satisfies the QoS. By distributing data among services, failure in one service does not lead to loss of all data [8].

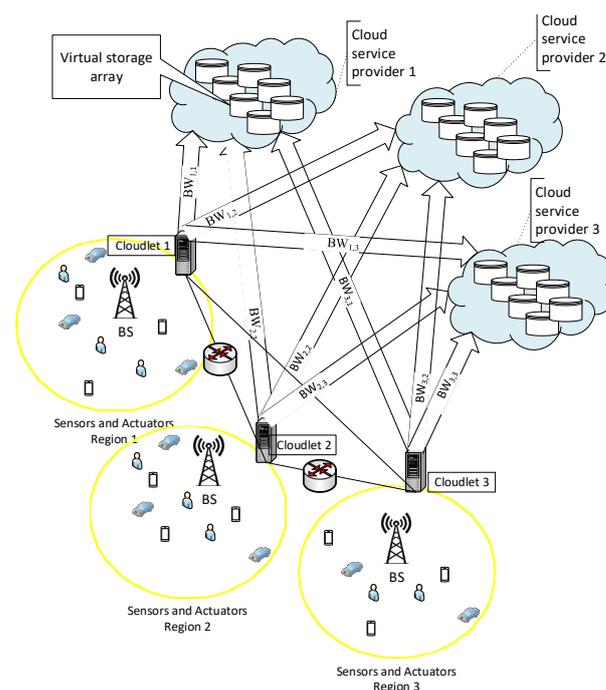


Figure 1. Proposed architecture from sensors through cloudlet to cloud providers for storing IoT data.

Each cloudlet manages a batch of data to be processed in or out of that cloudlet. The proposed algorithm runs in cloudlet to find appropriate services in and out of cloudlet in both layers. The storage capacity and CPU are both considered in service allocation.

3.1. Mathematics and Cost Functions

In this section, the mathematical model is introduced. In Table 2, the description of parameters is listed.

Table 2. Symbols and notations of objects' functions.

Symbol	Description
E^{idle}	Energy consumption in an idle mode
E^{busy}	Energy consumption in a busy mode
D	Data volume
m	Number of available services in fog layer
n	Number of data
f_j	An active indicator of cloudlet _j
f_{ij}	Allocate indicator of <i>i</i> th data to cloudlet _j
E_{tot}	Total energy consumption in each solution
Cn_j	Number of CPUs
T_c	Time criterion for processing in the fog layer
$\frac{capT_i}{capC_i}$	The used percentage of cloudlets.
$\frac{capT}{capC}$	The average usage ratio of cloudlets
LB_c	Load-balancing criterion among services in fog layer
T_s	Consumed time criterion in transmitting to cloud layer
k	Number of storage services
BW_{jz}	Bandwidth between <i>j</i> th cloudlet and <i>z</i> th cloud
LB_s	Load-balancing criterion among services in cloud layer
P	Total number of populations in multi-objective algorithms
p_i	The <i>i</i> th solution in P
D_i	The <i>i</i> th data's volume
C_a	The <i>a</i> th cloudlet's service
cp_j	The capacity of the <i>j</i> th cloudlet's service
S_a	The <i>a</i> th cloud storage's service

3.1.1. Mathematical Model for Energy Consumption

Servers consume energy in both idle and busy modes. According to [46], the energy consumption of servers can be represented by a linear relationship between energy consumption and CPU utilization. Energy consumption can be calculated according to the proportion of service usages [47]. The total energy consumption in allocating services to a batch of data is E_{tot} .

$$E_{tot} = \sum_{j=1}^m [f_j \times ((E_j^{busy} - E_j^{idle}) \times \frac{\sum_{i=1}^n (f_{ij} \times D_i)}{cp_j} + E_j^{idle})] \text{ s.t. } \sum_{i=1}^n f_{ij} \times D_i \leq cp_j, j = 1, \dots, m \quad (1)$$

f_j has two values: 1 when the service is utilized and 0 when the service is not used. f_{ij} has two values and it can be either zero or one, it is 1 when data "*i*" is outsourced to service "*j*".

3.1.2. Mathematical Model for Processing Time

Processing time has a direct relation to the size of data and a reverse relation to the number of CPUs in one service according to (2).

$$T_c = \max_j \left\{ \frac{\sum_{i=1}^n f_{ij} \times D_i}{Cn_j} \right\}; j = 1, 2, \dots, m \quad (2)$$

3.1.3. Mathematical Model for Load Balancing in the Fog Layer

As mentioned, load balancing will increase the availability of services. The load balancing in the fog layer is addressed in (3) [29].

$$LB_c = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{capT_i}{capC_i} - \frac{capT}{capC} \right)^2} \quad (3)$$

3.1.4. Mathematical Model for Transmission Time

The data are outsourced to the appropriate storage service after being pre-processed. The total transmission time for a batch of data is shown in (4).

$$T_s = \max_j \left\{ \sum_{i=1}^n \sum_{z=1}^k \frac{x_{iz} \times D_i}{BW_{jz}} \right\}; j = 1, 2, \dots, m \quad (4)$$

x_{iz} can be either zero or one, it is one when the storage services are selected, and it is 0 when the storage service is not selected.

3.1.5. Mathematical Model for Load Balancing in the Cloud Layer

There are different services that are suggested by a variety of service providers. The minimum value for (5) satisfies the reliability of the system.

$$LB_s = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{capT_{si}}{capS_i} - \frac{capT_s}{capS} \right)^2} \quad (5)$$

Different equations are addressed in this work, all of which are important for service selection to be considered all together, as a result, the multi-objective algorithms are proposed.

3.2. Proposed Hybrid Algorithm

The block diagram of the proposed algorithm is shown in Figure 2. Monitoring services and making the decision based on the gathered information are done in the first cloudlet in which the data are received.

The water cycle algorithm is adopted from nature. It is a population-based algorithm like a genetic algorithm [47]. Each member of the population is represented by $3 \times n$ matrix (6).

$$Lp_i = \begin{Bmatrix} D_1 & D_2 & \dots & D_n \\ C_a & C_b & \dots & C_c \\ S_a & S_b & \dots & S_e \end{Bmatrix} \quad (6)$$

The costs of different layers are shown in (7).

$$Cost_{Fog_layer} \propto E_{tot}, T_c, LB_c, Cost_{storage} \propto E_{tot}, T_s, LB_s \quad (7)$$

The goal is to minimize all five objects in the problem (8). No other solution cannot dominate a solution in the Pareto. In mathematical terms, $p_1 \in P$ dominates $p_2 \in P$ if two conditions are satisfied [48].

$$\begin{aligned}
 &Cost_i(p_1) \leq Cost_i(p_2) \quad \forall i \in \{E_{tot}, T_c, LB_c, T_s, LB_s\} \\
 &\text{and} \\
 &Cost_j(p_1) < Cost_j(p_2) \quad \exists j \in \{E_{tot}, T_c, LB_c, T_s, LB_s\}
 \end{aligned}
 \tag{8}$$

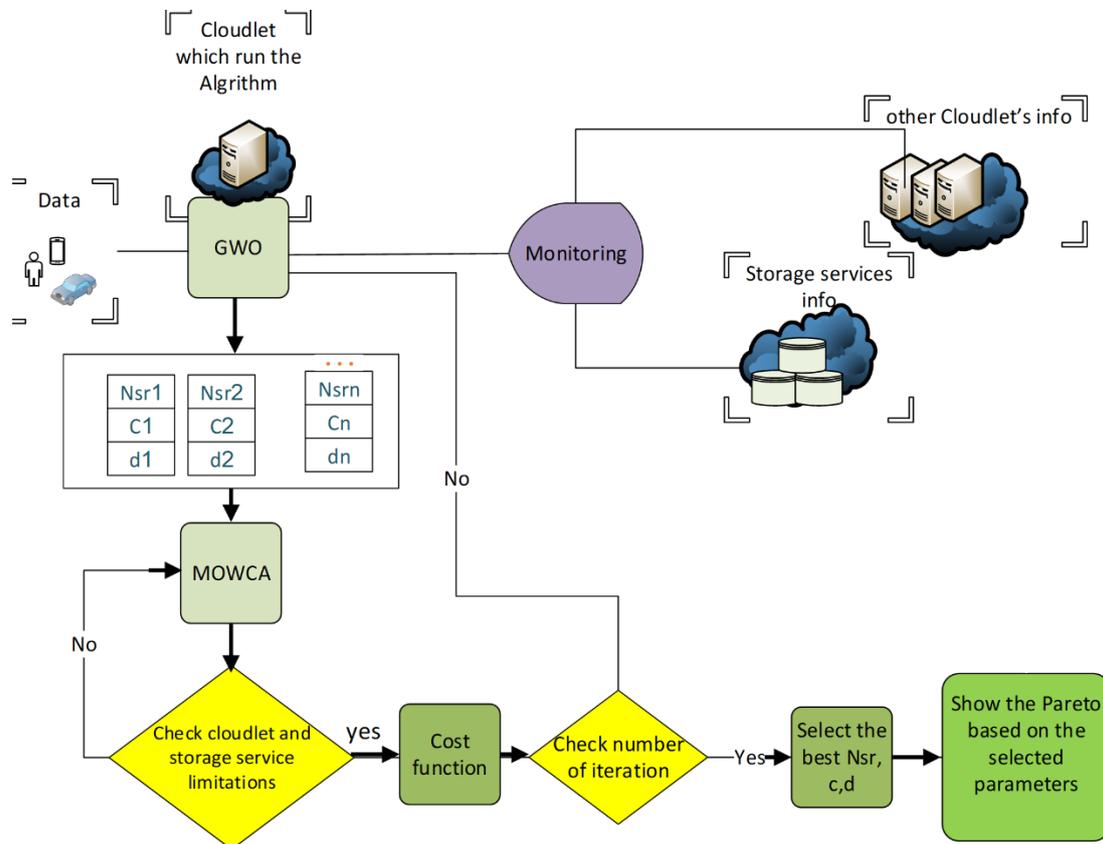


Figure 2. Decision-making block diagram.

The number of solutions in the first iteration of the algorithm in the resultant Pareto is low, but gradually, the number of non-dominated solutions is increased by moving the answers to the global minimum in the proposed algorithm. In the MOWCA, the solutions are governed by the sea and the rivers. The answers go toward Pareto, and Pareto is going to be updated. Finally, the answers in Pareto are categorized as a sea and rivers based on crowding distance [49].

Hybrid Multi-Objective Water Cycle and Grey Wolf Optimizer (MWG)

Escaping from the local minimum is important and, for this reason, determining appropriate d_{max} is essential. Furthermore, G as a coefficient is used in the process of generating new solutions, and it is crucial for a better exploration of the solution space.

The GWO algorithm is one of the fastest optimization methods [50]. The MWG algorithm is the modified combined algorithm, which optimizes the hyperparameter of the multi-objective algorithm and provides better exploration in the solution space in comparison to the naïve ones. In the beginning, a population with 10 members is randomly generated. Each member of this population has three features based on three hyperparameters of multi-objective algorithm. MWG optimizes the objects based on the initialized values. Then, the MWG determines the crowding distance and dominant solutions. Crowding distance is calculated for all non-dominant solutions. The main objective of using crowding distance is to increase the diversity of solutions. In the rest of the paper, the mathematics of the algorithm is given and Table 3 includes the mathematical symbols.

Table 3. Mathematical symbols of a proposed algorithm.

Symbol	Description
p_{Stream}^j	Solution j , which is considered as a stream in the algorithm
p_{Sea}^j	Solution j that is considered as a sea in the algorithm
p_{River}^j	The solution that is considered as a river in the algorithm
G	The coefficient for generating new solutions
d_{max}^i	The maximum acceptable distance between solutions and the sea in the algorithm
\vec{X}	The position of a solution as a hunt in the algorithm
\vec{X}_α	The first-best solution in the algorithm
\vec{X}_β	The second-best solution in the algorithm
\vec{X}_δ	The third-best solution in the algorithm
$\vec{X}(t + 1)$	The new result, which is calculated for Nsr , C , and d_{max}
$rand$	A number between 0 and 1
itr	The current iteration in the algorithm
r_1	A random vector in the range (0,1]
r_2	A random vector in the range (0,1]
n_{pf}	The number of solutions in the Pareto
d_i^p	Shows the distance between every two answer choices in the Pareto
\bar{d}^p	Shows the average distance between every two answer choices in the Pareto

In the exploration phase of the algorithm, new positions for rivers and streams are achieved based on Equations (9)–(11).

$$p_{Stream}^{j+1} = p_{Stream}^j + rand \times G \times (p_{Sea}^j - p_{Stream}^j) \tag{9}$$

$$p_{Stream}^{j+1} = p_{Stream}^j + rand \times G \times (p_{River}^j - p_{Stream}^j) \tag{10}$$

$$p_{River}^{j+1} = p_{River}^j + rand \times G \times (p_{Sea}^j - p_{River}^j) \tag{11}$$

A large value for d_{max} prevents convergence, and a smaller value of d_{max} tends to trap in the vicinity of the sea and reduces the exploration. The value of d_{max} controls the position of different solutions around the sea, and it decreases gradually based on (12).

$$d_{max}^{i+1} = d_{max}^i - \frac{d_{max}^i}{itr} \tag{12}$$

Finally, the position of a hunt is calculated as (13)–(16):

$$\vec{D}_\alpha = \left| \vec{F} \vec{X}_\alpha - \vec{X} \right| \vec{D}_\beta = \left| \vec{F} \vec{X}_\beta - \vec{X} \right| \vec{D}_\delta = \left| \vec{F} \vec{X}_\delta - \vec{X} \right| \tag{13}$$

$$\vec{X}_1 = \left| \vec{X}_\alpha - \vec{A}(\vec{D}_\alpha) \right| \vec{X}_2 = \left| \vec{X}_\beta - \vec{A}(\vec{D}_\beta) \right| \vec{X}_3 = \left| \vec{X}_\delta - \vec{A}(\vec{D}_\delta) \right| \tag{14}$$

The vectors of A and F are calculated based on (15).

$$\vec{A} = 2 \vec{a} \vec{r}_1 - \vec{a} \quad \vec{F} = 2 \vec{r}_2 \tag{15}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3} \quad (16)$$

To get close to the prey, the amount of \vec{a} reduces from 2 to 0 gradually. All the values in the obtained Pareto are normalized based on their objectives. The cost is defined as the summation of all five objectives for each solution in the Pareto. The best answer choice is the one with the minimum cost.

In the next iteration, for normalizing the achieved Pareto, the previously selected best results are considered. Unlike single-objective problems, which are concluded in one cost at the end of each iteration, there is a Pareto in multi-objective algorithm, which involves different solutions at the end of each iteration.

4. Simulation

The number of CPUs in a service plays an important role in the processing speed. For example, t2.nano has one CPU, and t2.large has two CPUs, all of which are assumed in the simulation environment as a variety of available services [51]. The cloud services have different throughputs, which lead to different transmission times. Table 4 illustrates the different cloud service providers' throughput, which is adapted from [52]. Different data volume is considered according to real IoT sensors' data for storing in three batches. For different scenarios, different batch sizes are considered. Moreover, 80% of services are contemplated to be needed to fulfil the demand for a batch of size 400 to validate the reliability of service allocation. The data size has a uniform distribution between 20 and 500 for each batch of data [52,53].

Table 4. Different cloud service providers' throughput [52]. Reproduced from [52], the name of the publisher: Wiley Online Library.

Cloud Service Provider	Throughput (Mbps)
Amazon S3a	1.349
Box	2.128
Dropbox	2.314
OneDrive	2.233
Google Drive	4.465
SugarSync	2.171
Cloud Mine	1.474
Rackspace	1.704

There is a relationship between the number of CPUs and energy consumption in each service. According to the SPECpower benchmark, the maximum power consumption was assumed to be 250 W for each CPU. To consider energy, 200 W in the idle mode and 300 W in the busy mode were assumed for each CPU [54].

4.1. Simulation Setups

It is assumed that there are 32 storage services in the cloud layer and 32 processing services in the fog layer. There are multi-objective algorithms that addressed energy and load-balancing in service selection in recent years, such as NSGAI and the modified GA called KGA. In the KGA, k-means is used to have an elitist set of the population [29]. The average results of 10 separate runs for each algorithm are calculated. The Pareto's answers are sorted, and the mean of 10 separate Paretos is calculated for each objective. The results are reported in the BOX diagram, which has a quartet and means. The box diagram gives a better visual distribution of solutions for each objective in the resultant Pareto. Numerical experiments are conducted using MATLAB on a Laptop with a Core i7 2.59–2.60 GHz

CPU. The number of populations for the first part of the MWG algorithm is 10, and for the second part of the MWG algorithm it is 50.

The setting parameters of other algorithms in the simulation are listed in Table 5.

Table 5. Different algorithms and the setting parameters.

Algorithms	Parameters	Settings
NSGAII [44]	Population size (pop), crossover probability, mutation probability	50, 0.8, 1
KGA [29]	Population size (pop), crossover probability, mutation probability, number of centroids	50, 0.8, 0.1, 4
MOWCA [50]	Population size (pop), number of streams, the distance of sea (dmax)	50, 4, 1

4.2. Evaluation

In Figure 3, the distribution of different solutions' energy consumption in the Pareto of various algorithms is shown. Based on Figure 3, the percentage of the resultant solutions, which have a minimum energy consumption from MWG, is more in comparison to the other algorithms' result. Thus, it gives us more options in selecting the best solution that satisfies other objectives (e.g., processing time, load balancing). Meanwhile, the resultant solution from MWG has a minimum energy consumption in comparison to the other algorithms' result.

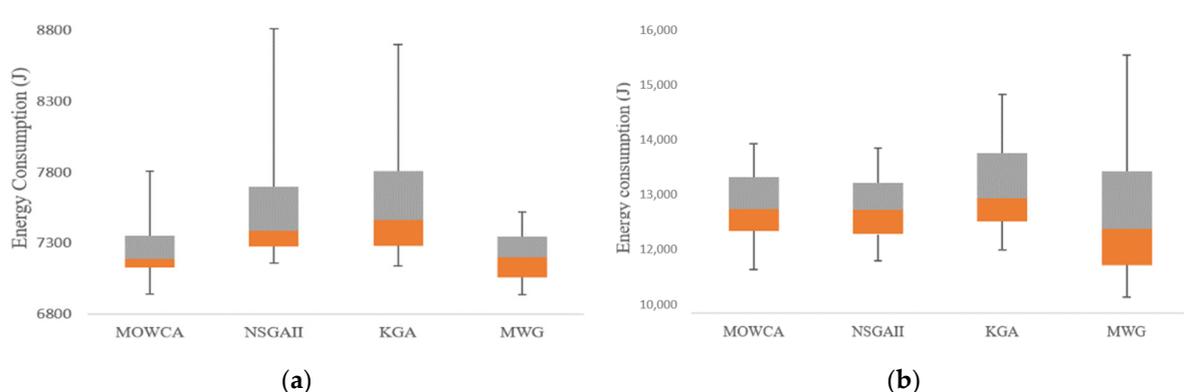


Figure 3. Comparison between algorithms due to the distribution of different solutions' energy consumption in the resulted Pareto after 100 iterations for (a) 100 data items and (b) 400 data items.

In the MWG, rivers and seas lead other answers toward the optimum solution. The number of solutions in Pareto for MWG is more than that in the other two KGA and NSGAII algorithms based on energy consumption criteria. Figure 4 shows the distribution of different solutions' processing time in the Pareto for different algorithms. If time plays a critical role, the MWG recommends some solutions that have less processing time in comparison to other algorithms, even for a specific case, such as the maximum demand scenario.

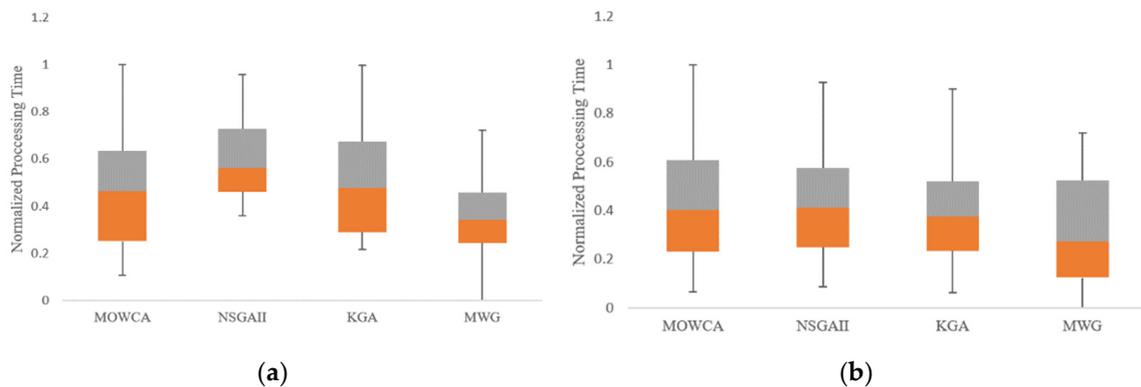


Figure 4. Comparison between algorithms due to the distribution of different solutions' processing time in the resulted Pareto after 100 iterations for (a) 100 data items and (b) 400 data items.

Another factor that should be considered for the service allocation is the load balancing between the VMs in the cloudlet as well as services from different cloudlets.

Figure 5 shows the distribution of different solutions' load balancing in the Pareto of various algorithms. Service may fail because of the overload. Thus, having a fair distribution of data among services increases reliability as one of the critical factors in QoS. NSGAI and KGA use the method of mutation and crossover. These methods are good in escaping from a local minimum; they are random-based methods in which the global minimum may be ignored as well. Based on Figure 5, the resultant solution from MWG has a minimum energy consumption in comparison to the other algorithms' result.

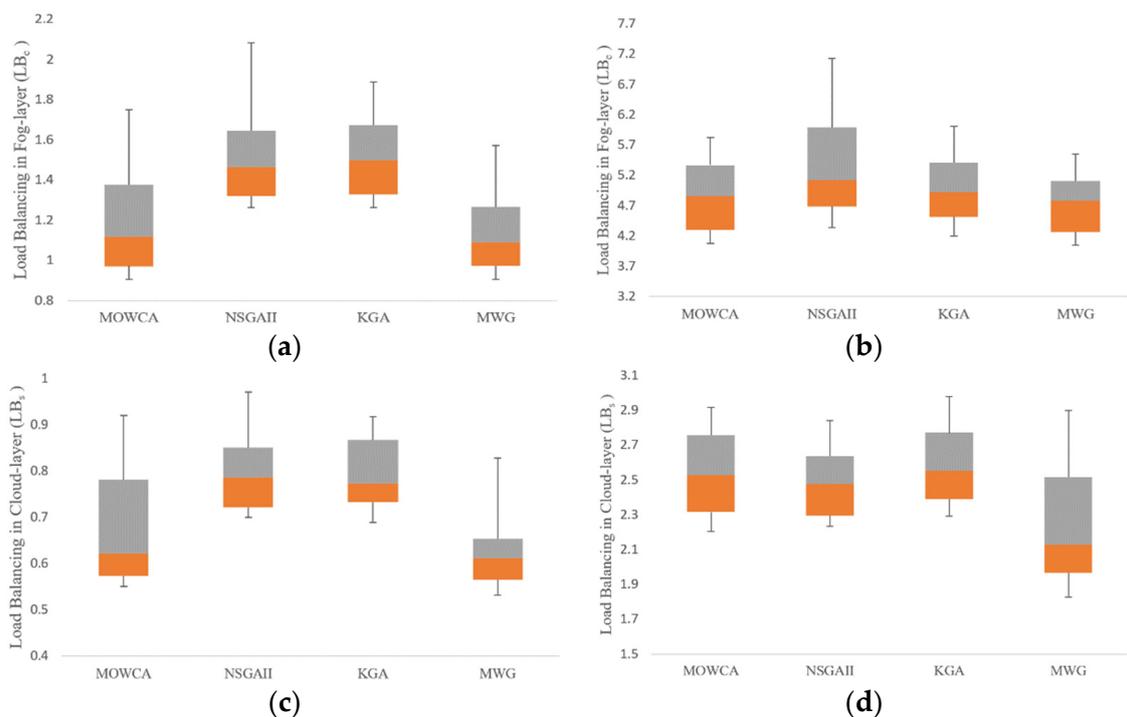


Figure 5. Comparison between algorithms due to the distribution of different solutions' load balancing in the resulted Pareto after 100 iterations for (a) 100 data items in the fog layer, (b) 400 data items in the fog layer, (c) 100 data items in the cloud layer, and (d) 400 data items in the cloud layer.

On the other hand, many services such as Dropbox, after processing data, outsource data to cloud storage services for storing. Service providers around the world provide a variety of services for users. The throughput of different service providers varies. Therefore, the

needed time to outsource data to cloud services varies based on available bandwidth. Figure 6 shows the distribution of different solutions' transmission time in the Pareto of various algorithms. Based on Figure 6, the percentage of the resultant solutions that have a minimum transmission time from MWG are more in comparison to the other algorithms' result. Therefore, it gives us more options in selecting the best solution that satisfies other objectives (e.g., processing time, load balancing). Meanwhile, the resultant solution from MWG has a minimum transmission time in comparison to the other algorithms' result.

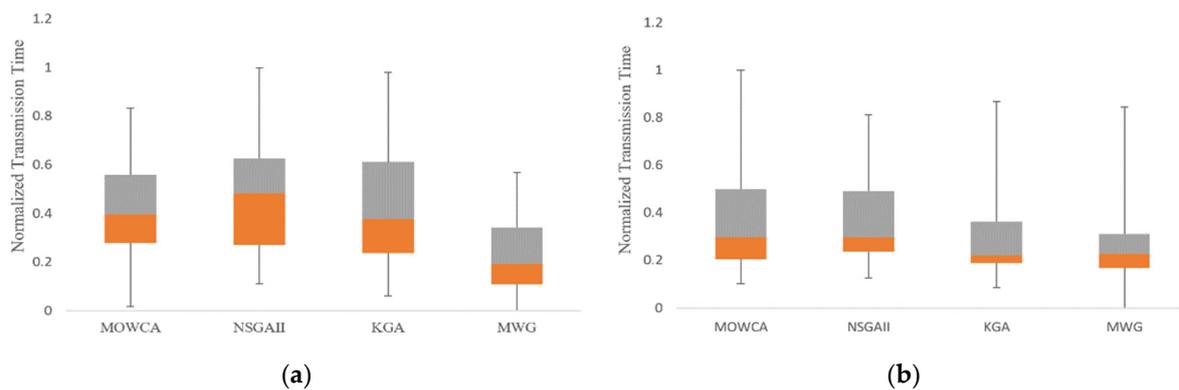


Figure 6. Comparison between algorithms due to the distribution of different solutions' transmission time in the resulted Pareto after 100 iterations for (a) 100 data items and (b) 400 data items.

4.3. Metric of Spacing

The statistic factor for comparing two different multi-objective algorithms is the regularity of answers in the Pareto. This factor is demonstrated with a metric of spacing. Regularity in different algorithm's Pareto is calculated based on (17).

$$SP = \sqrt{\frac{1}{n_{pf} - 1} \sum_{i=1}^{n_{pf}} (d_i^o - \bar{d}^o)^2} \quad (17)$$

The other important factor in the multi-objective algorithms is to have a comprehensive solution. Solutions should consider all objectives and have a better distribution. The smaller value for SP based on (17) shows that the solutions in the Pareto are distributed better than in the one with a larger value for SP. The average metric of spacing for MWG is improved 7%, 13%, and 25% in comparison to that for MOWCA, KGA, and NSGAI, respectively. Detailed results are listed in Table 6.

Table 6. Metric of spacing for different algorithms.

Data Number	Iteration	KGA [24]		NSGAI [41]		MOWCA [45]		MWG	
		Min S	Max S	Min S	Max S	Min S	Max S	Min S	Max S
100	100	130	134	165	189	102	112	114	139
200		237	244	257	259	232	248	210	215
400		311	325	352	389	304	314	267	269

4.4. Metric of Quality

The quality of the Pareto shows the difference between the optimum and obtained results. Since the optimum solutions are not defined in NP-HARD problems, the new

method is suggested in which the quality of Pareto among different algorithms can be compared.

In Algorithm 1, all solutions are gathered from different algorithms' Pareto. Solutions are sorted based on the non-dominated solution. Then, solutions are sorted based on crowding distance. Finally, an aggregated Pareto is achieved. The number of solutions from each algorithm's Pareto in the Aggregated Pareto shows the quality of different algorithms in comparison to each other. By considering all workloads, the MWG algorithm has 4%, 4.7%, and 7.3% advantages in metric of quality in comparison to MOWCA, KGA, and NSGAI, respectively.

Algorithm 1 Pareto Quality Function (Metric of Quality)

Inputs: Different Algorithms' solutions in their Pareto

Output: The percentage of each Algorithms' solutions in the new optimum Pareto

1: Insert Pareto of the AlgorithmsTT

2: pop \leftarrow Nondominated Sorted population

3: CD \leftarrow Crowding Distance (pop)

4: Aggregated Pareto \leftarrow Sort pop based on CD

5: $N_a \leftarrow$ Number of Algorithms

6: for k = 1 to N_a do

7: for j = 1 to Number of Solutions in K^{th} Algorithm's Pareto do

8: if Solutions_j \in Aggregated Pareto Set then

9: end if

10: end for

11: Metric of Quality(k) = $\frac{N(k)}{N_{sp}}$

12: end for

4.5. Evaluation of the Optimum Result

The answer choice with the minimum cost is considered as the best in each Pareto based on the analytic hierarchy process (AHP) [55]. The alternatives are solutions in the Pareto, and the criteria are the mentioned five objectives. All objectives are considered to have the same importance. The best solution among the Pareto's solutions of each algorithm is determined based on AHP. Table 7 shows a comparison between different algorithms in each objective (e.g., the MWG has a 32.15% improvement in processing time for 200 data items).

Table 7. Comparison of algorithms' best solution based on AHP.

Main Algorithm	Objectives	100 Data			200 Data			400 Data		
		MOWCA	KGA	NSGAI	MOWCA	KGA	NSGAI	MOWCA	KGA	NSGAI
MWG	Energy	1.37	4.11	5.48	1.79	3.06	5.1	1.6	3.2	4
	Load balancing, fog	4.95	30.69	33.66	6.57	14.14	15.15	5.13	15.38	20.51
	Load balancing, cloud	6.12	30.01	33.71	10.08	24.11	26.28	16.68	26.05	30.23
	Processing time	4.31	15.47	34.72	20.93	32.15	37.8	19.33	29.52	32.69
	Transmission time	5.64	11.54	17.69	6.63	8.63	13.95	6.11	9.8	14.17

The overall optimization results show that MWG algorithm has 7.8%, 17%, and 21.6% better performance in comparison with MOWCA, KGA, and NSGAI based on the obtained result from Pareto.

5. Conclusions

This paper presented a new hybrid multi-objective algorithm for storage service selection in a collaborative and heterogeneous cloud and fog environment. Five objectives are considered altogether in the proposed work. The mathematical models for energy, load-balancing, and time are proposed in this study. Numerical experiments are conducted to compare the performances of the proposed MWG, MOWCA, KGA, and NSGAI. Testing results in a case study demonstrate the better performances of MWG in metric of spacing and metric of quality in comparison to MOWCA, KGA, and NSGAI. In comparison to MOWCA, KGA, and NSGAI, the average metric of spacing for MWG improved by 7%, 13%, and 25%, respectively. On the other hand, the total optimization findings reveal that the MWG algorithm outperforms MOWCA, KGA, and NSGAI by 7.8%, 17%, and 21.6%, respectively, based on the Pareto result. The analysis of the obtained results show that the energy consumption is reduced, fair load distribution among services is achieved, and the time for processing and transmitting is optimized. The Pareto and the optimum result show the superiority of the proposed hybrid MWG algorithm in comparison to other algorithms in service selection. In future works, the influence of other parameters, such as the node price will be added as an object to the mathematical model, which will be analyzed in more detail. Additionally, other practical applications will be considered, such as latency and user's demands and constraints. Furthermore, the algorithm with better performance in terms of quality of service can be proposed.

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