Intelligent Service Selection in a Multi-dimensional Environment of Cloud Providers for IoT stream Data through cloudlets

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Abstract

The expansion of the Internet of Things’ (IoT) services and a huge amount of data generated by different sensors, signify the importance of cloud computing services like 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. Also, it should be allegiant to the Quality of Service (QoS). The hybrid MWG algorithm has been proposed in this work, which considers different objectives such as energy, processing time, transmission time, and load balancing in both Fog and Cloud Layer. The MATLAB script is used to simulate and implement our algorithms, and services of different servers, e.g. Amazon, Dropbox, Google Drive, etc. have been considered. The MWG has 7%, 13%, and 25% improvement in comparison with MOWCA, KGA, and NSGAII in metric of spacing, respectively. Moreover, the MWG has 4%, 4.7%, and 7.3% optimization in metric of quality in comparison to MOWCA, KGA, and NSGAII, respectively. The overall optimization shows that the MWG algorithm has 7.8%, 17%, and 21.6% better performance in comparison with MOWCA, KGA, and NSGAII in the obtained best result by considering different objectives, respectively.

Keywords: Cloud Computing, Edge computing, Fog computing, Internet of Things, Multi-objective algorithms

1. Introduction

The Internet of Things (IoT) and their potential needs have enhanced the importance of cloud computing. The number of cloud-based servers that provide the proper structure for the manifestation of IoT is in an expanding manner. Plus, there are a large number of users and sensors that produce a high volume of data [1]. 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 switch or recharge. Distributed clouds can be useful for processing IoT sensors’ data [2].

One of the issues that must be considered in modern systems is energy consumption, which should be considered on both sides of energy consumption (i.e., user and server). Furthermore, optimal energy consumption can have a significant impact on reducing air pollution. According to data released in 2014, the Americans data centers had consumed 70 billion KW/h of Electrical energy. Therefore, there are a lot of researches focus on energy consumption [3, 4]. Large companies such as Amazon, Google, Salesforce, Microsoft, and IBM have begun to set up a new data center to host Internet applications and processes data. The current service providers give users the option of using resources based on their demands and pay due to their usage (Pay as you go) [5]. The necessity to maintain data highlighted the usage of storage services. The high number of data may cause overload in one service. To address overload in one service, load balancing among different services was proposed in the literature [6].

IoT devices include any examples of sensors and, such emerging technologies 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 [7]. Different service providers and services make it difficult to choose the proper service. The network has an arbitrary topology [8]. As a result, selecting an appropriate service among the services of different service providers is challenging. One of the most commonly discussed issues in cloud computing is the processing time. Needed time to process various data is based on data type, size and rates [9]. There have been several works in the area of resource allocation. The researchers have not found a polynomial equation with capabilities of achieving minimum energy consumption and time for service allocation in addition to addressing load balancing among services.

Different works have only optimized some metric of resource allocation with a narrow viewpoint. To the best of our knowledge, the time, load balancing and energy consumption are not all considered simultaneously in resource allocation. Considering different services from a variety of service providers are also addressed in the present work. A hybrid modified MOWCA and GWO algorithm have proposed in the present study. Cloudlets has been used in two sub-layers of Fog architecture. Two main layers of Fog and Cloud will be managed simultaneously to reduce the reluctant overload in Cloud services. Structured technique for organizing and
analyzing complex decisions in addition to different methods has been used to evaluate the proposed algorithm.

The remainder of this paper organized as follows: in Section 2, a brief discussion about recent articles has been presented in the area of resource allocation, architecture, and algorithms. Architecture, algorithm, 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 has been concluded.

2. Related Work
Most of the works are in different areas of SaaS, PaaS, and IaaS in Cloud computing [10]. Cloud computing and IoT are used in a variety of fields, including medical engineering, and social media [11]. Variety of architectures and algorithms were proposed in this area to fulfil users’ demands efficiently.

2.1. Architectures in Service Allocation
The Cloud based architecture was centralized and the centralized architecture makes a latency in the processing and storing data. The latency is because of the great distance between IoT devices and cloud providers. Therefore, the Fog architecture concept can reduce latency. Managing energy consumption is presented in ECloT architecture, which leads to an optimal time of processing [12]. The idea of Fog computing was introduced in 2012 by researchers of the Cisco company with a new view to the set of all networks (including 3G/4G/LTE/5G) and everything (all smart objects, Internet of Everything) with a hierarchical structure. By using the architecture expressed in Fog-cloud, the energy optimization of both cloud and Fog layers can be managed to contribute to the IoT development goal [13]. Fog computing is a claim for broad applications in IoT, wireless sensors, and wireless network. The architecture of Fog computing involves three main layers; the first layer is for IoT devices. Second, the fog layer and finally, the cloud layer [7].

Cloudlet is the project presented by a group of researchers from Mellon University. The goal of using cloudlet is to have processing of Data near to the IoT sensors. Also, data compromise risk will be reduced by having an edge computing, which is near to the IoT sensors. Cloudlets have more capacity for processing and battery power in comparison to other fog nodes.
2.2. Algorithms in Service Allocation

Researches have indicated that resource allocation is a kind of NP-Hard problem [14]. A bunch of studies have concentrated on load balancing. Researchers used definitive and innovative methods in a fair distribution of loads among services. The primary objective of load balancing is preventing overload in services. In [15], a random algorithm is used for outsourcing data to different services in which the physical distance is a criterion for selecting a service. Even though the distance between sensors and IoT devices had been considered in service selection, service failure resulted. The service failure occurred due to lack of attention to the load balancing between services. The error occurs due to overload and data loss in one specific service [16]. In [17], using the honey bee algorithm and introducing a new algorithm named honey bee behavior inspired load balancing (HBB-LB) addressed equitable load distribution between virtual machines and maximized processing speed. Round robin is also used for equitable load distribution. Broberg et al. [18] had chosen low-cost cloud storage resources with Meta CDN method. Although they find and optimized service selection based on its cost, the process does not encompass an equitable load distribution between storage resources [19]. In [20, 21], a kind of NSGAIi is used to address load balancing Criteria.

Some researches have been performed to reduce the time required to complete the users’ tasks. Different services have different processing speeds [22]. In [23], the author presented a model for load balancing on the Internet, which aims to reduce the overall processing time for different tasks. In the other work, both the firefly algorithm and particle swarm optimization has been made to balance the load of the entire system and reduce the makespan as well [24]. In [25], the MOGWO method, which is one of the Multi-objective Algorithms is used to distribute data equitably among virtual machines and also to reduce the working time. In [26], by using the GWO algorithm, the time of the makespan has been reduced, and other determinants of QoS have not been considered. In another research, the combined GWO and Cuckoo search algorithm was used to minimize the makespan and to reduce the needed resources [27]; however, the authors did not consider other aspects of resource allocation. In [28], the integer programming method is used to reduce the cost of storing data and data retrieval time in a multi cloud provider environment. In [29], the authors used the particle swarm optimization (PSO) to minimize the cost of sending and processing of different tasks. The game theory, which is used for task scheduling in [30] for the mathematical model, was proposed to deal with big data and to consider energy management. But, the available bandwidth as one of the factors in
transmitting data and also energy consumption was not considered. In [31], the author used an adaptive mode for assigning different services for tasks by considering the time.

In [32], the NSGAII algorithm was used to achieve the minimum energy and makespan for service allocation in which load balancing was not considered. In [33], in addition to minimizing Energy consumption, the GWO and BAT algorithms have been used to distribute the work equitably among services. In another research, energy and cost have been optimized in resource allocation [34]. In [35], the NSGAII algorithm was used to achieve the minimum energy and makespan for service allocation in which load balancing was not considered. The Pareto's results as one of important factors in Multi-objective problems improved. Both Energy consumption and Load Balancing between solutions considered while satisfying the spacing metric[36]

### 3. Proposed Algorithm for Fog-Cloud Architecture

The system model consists of different parts as illustrated in Fig. 1. The storing data as fast as possible by consuming less energy is critical. The first Cloudlet assumes as the first sub layer in the presented model. Neighbor Cloudlets assume as second sub layer in model. To accomplish the process of data as quickly as possible, the distribution of data among different Cloudlets has been adopted to avoid overload. Taking advantage of the distributed model is not only limited failure in service allocation, but also it has prevented from consuming energy in an idle mode. Rejecting request from different users reduces the reliability of the system. Furthermore, it destroyed the Service Level Agreement. Distribution of data among different services increases the availability of services due to their free space. The availability of different services is one of the QoS factors. So, the distribution of data among different services will satisfy the QoS. By distributing data among services, failure in one service will not lead to loss of all data.
Fig. 1. Proposed architecture from sensors through cloudlet to cloud providers for storing IoT data. Each Cloudlet will manage a batch of data to be processed in or out of that particular Cloudlet. Also, the Cloudlet should consider the storage services in Cloud providers. The proposed algorithm run in Cloudlet to find appropriate services in and out of Cloudlet in both Layers. The storage capacity and CPU considered in resource allocation.

The process of outsourcing data is depicted in Fig. 2. For instance, a batch of data is received by the cloudlet 1 from its proximity sensors. Then, data will be outsourced to proximity cloudlets based on the status of network and services. Finally, data will be transferred to the appropriate storage services based on the decision which have been concluded in the first Cloudlet.
3.1 Mathematics and cost functions

In this section, the mathematics of the model introduced. In Table 1, the description of parameters is listed.

**Table 1. Symbols and notations of objects’ functions**

| Symbol | Description |
|--------|-------------|
| $E^{idle}$ | Energy consumption in an idle state |
| $E^{busy}$ | Energy consumption in a busy state |
| $D$ | 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 $i$th data to cloudlet$_j$ |
| $E_{tot}$ | Total energy consumption in each solution |
| $Cn_j$ | Number of CPU |
| $T_c$ | Time criterion for processing in the Fog layer |
| $capT/capC_i$ | The used percentage of cloudlets. |
| $capT/capC$ | The average usage ratio of cloudlets. |
| $LB_c$ | Load-balancing criterion among services in Fog Layer. |
| Symbol  | Description                                                                 |
|---------|------------------------------------------------------------------------------|
| $T_i$   | Consumed time criterion in transmitting to Cloud layer.                      |
| $k$     | Number of storage services                                                   |
| $BW_{jz}$ | Bandwidth between $j$ th cloudlet and $z$ th cloud.                        |
| $LB_s$  | Load-balancing criterion among services in Cloud Layer.                     |
| $P$     | Total number of populations in Multi-objective algorithms                   |
| $p_i$   | The $i$ th solution in $P$.                                                 |
| $D_i$   | The $i$ th data’s volume                                                     |
| $C_a$   | The $a$ th cloudlet’s service                                               |
| $S_d$   | The $d$ th cloud storage’s service                                          |

### 3.1.1 Mathematical model for energy consumption

Servers consume energy in the idle and busy state. According to [37], the energy consumption of servers can be represented by a linear relationship within the energy consumption and CPU utilization. Energy consumption can be calculated according to the proportion of service usage [38]. The total energy consumption in allocating services to a batch of data is $E_{tot}$.

$$E_{tot} = \sum_{j=1}^{m} \left[ f_j \times \left( E_{j}^{busy} - E_{j}^{idle} \right) \times \frac{\sum_{i=1}^{n} (f_{ij} \times D_i)}{cp_j} + E_{j}^{idle} \right] \tag{1}$$

subject to:

$$\sum_{i=1}^{n} (f_{ij} \times D_i) \leq cp_j$$

The used energy in an idle and fully loaded states are $E_{idle}$ and $E_{busy}$, respectively. The indicator $D$ is used for demonstrating data size. In (1), $m$ shows the number of CPU and $n$ illustrate the number of data. $f_j$ 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 zero or one, it is 1 when data $i$ is outsourced to service $j$. $cp_j$ shows the capacity of the $j$’s service.
3.1.2 Mathematical model for processing time

Processing time has a direct relation to the size of data, and reverse relation to the number of CPU in one particular service according to (2). $T_c$ illustrates the total processing time for a batch of data

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

$Cn_j$ shows the speed of the processor $j$. $f_{ij}$ has two values and it can be zero or one, it is 1 when data $i$ is outsourced to service $j$.

3.1.3 Mathematical model for load balancing in the Fog layer

As mentioned, load balancing will increase the availability of services. The (3) address the load balancing in Fog-Layer [20].

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

In Eq. 3, $\frac{capT_i/capC_i}$ shows the usage ratio of ith cloudlet’s capacity. $\overline{capT}/\overline{capC}$ shows the average usage ratio of all cloudlets. $LB_c$ should be minimized to have a reliable system.

3.1.4 Mathematical model for transmission time

The data should outsource to the appropriate storage service after being pre-processed. The available bandwidth should be considered [47]. Eq. 6 shows the total transmission time for a batch of data.

$$T_s = \sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{z=1}^{k} x_{iz} \times \frac{D_i}{BW_{jz}} \quad (6)$$

$BW_{c,s}$ matrix shows the available bandwidth between cloudlets and service providers. The rows of the matrix represent different cloudlets, and the matrix’s columns represent different storage service providers. $Z$ represents different storage services. $x_{iz}$ can be either zero or one based on storage services selection.

3.1.5 Mathematical model for load balancing in the cloud layer

There are different services suggested from a variety of service providers. Eq. 7 perform balancing among various services.

$$LB_s = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \frac{capT_i/capS_i - \overline{capT}/\overline{capS}}{} \right)^2} \quad (7)$$
The closer result of $LB_z$ to zero shows the less inequality between the services. As a result, the overall system will be stable.

Minimizing each equation as the actual cost is the goal. Since different equations address different objectives and all of which are important in service selection, the Multi-objective algorithms will be used.

### 3.2. Proposed hybrid algorithm

Fig. 5 shows the block diagram of the proposed algorithm. Monitoring services, and making the decision based on the gathered information will be done in the first cloudlet in which the data has been received.

![Decision-Making block diagram](image)

**Fig. 5.** Decision-Making block diagram

The Water Cycle Algorithm is adopted from nature. It is a population-based algorithm like a genetic algorithm [38]. Each member of the population represents as a $3 \times n$ matrix, like (8).

$$p_i = \begin{bmatrix} D_1 & D_2 & \ldots & D_n \\ C_a & C_b & \ldots & C_c \\ S_d & S_e & \ldots & S_f \end{bmatrix}$$  \hspace{1cm} (8)
For example, \( D_1 \) uses services of \( C_a \) and \( S_d \) in Fog and Cloud layer respectively. The Multi-objective Water Cycle Algorithm has been modified to optimize different objectives. The costs of different layers are shown in Eq. 9 and Eq. 10.

\[
\text{Cost}_{\text{Fog-layer}} \propto E_{\text{tot}}, T_e, LC_B, LC_{BF} \\
\text{Cost}_{\text{storage}} \propto E_{\text{tot}}, T_s, LS_B, LS_{BF}
\]

The goal is to minimize all five objectives in the problem. 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 [39].

\[
\text{Cost}_i(p_1) \leq \text{Cost}_i(p_2) \quad \forall i \in \{E_{\text{tot}}, T_e, LC_B, T_s, LS_B\} \\
\text{Cost}_j(p_1) < \text{Cost}_j(p_2) \quad \exists i \in \{E_{\text{tot}}, T_e, LC_B, T_s, LS_B\}
\]

The number of solutions in the first iteration of the algorithm in resulted Pareto is low, but gradually, the number of non-dominated solutions increase by moving the answers to the global minimum in the MOWCA [40]. In the MOWCA, the solutions govern by the sea and the rivers. The answers go toward Pareto, and Pareto is going to be updated. Finally, the answers in Pareto will categorize as a sea and rivers based on crowding distance [41].

### 3.2.1 Combination of GWO and MOWCA algorithm (MWG)

The number of solutions in MOWCA algorithm which consider as a river is important in exploring the space of solutions. Escaping from the local minimum is important and for this reason, determining appropriate \( d_{\text{max}} \) is essential. Furthermore, \( G \) as a coefficient used in the process of generating new solutions is crucial for a better exploration of solution space.

The GWO algorithm is one of the fastest optimization methods [42]. The GWO algorithm is used to obtain proper values to initial parameters of MOWCA. The mathematical symbols which are used for GWO are shown in Table 2.

At the beginning, a population with 10 members will be randomly generated in GWO algorithm. Each member of this population has three features. The number of streams, initial distance from the sea in which evaporation taking part and new solution will be calculated (\( d_{\text{max}} \)), and \( G \) which enjoy in generating new solutions in different iteration for the same round of the algorithm. MOWCA will run and optimized the objects based on the initialized values. Determining crowding distance and dominate method are the main criterions for ordering solutions in Multi-objective algorithms [43]. Crowding-distance 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 these algorithms will be discussed.

| Symbol | Description |
|--------|-------------|
| $p^j_{Stream}$ | Solution $j$ which consider as a Stream in the algorithm. |
| $p^j_{Sea}$ | Solution $j$ which consider as a Sea in the algorithm. |
| $p^j_{River}$ | Solution $j$ which consider as a River in the algorithm. |
| $G$ | The coefficient for generating new solutions in MOWCA algorithm. |
| $d^j_{max}$ | The maximum acceptable distance between solutions and the Sea in MOWCA algorithm. |
| $\bar{X}$ | The position of a solution as a hunt in the GWO algorithm. |
| $\bar{X}_\alpha$ | The position of a solution as an $\alpha$ in the GWO algorithm. |
| $\bar{X}_\beta$ | The position of a solution as a $\beta$ in the GWO algorithm. |
| $\bar{X}_\delta$ | The position of a solution as a $\delta$ in the GWO algorithm. |
| $\bar{X}(t+1)$ | The new result which has been calculated through the GWO algorithm for Nsr, $d_{max}$, and $G$. |

In MOWCA, $p^j_{Stream}$ is one of the answers, which has been considered as a Stream due to crowding-distance and non-domination sorting. Rand is a number between 0 and 1. $G$ is determined with GWO algorithm. In the exploration phase of the algorithm new positions for rivers and streams have been proposed by Eq. 12 to 14.

$$p^{j+1}_{Stream} = p^j_{Stream} + \text{rand} \times G \times (p^j_{Sea} - p^j_{Stream}) \quad (12)$$

$$p^{j+1}_{Stream} = p^j_{Stream} + \text{rand} \times G \times (p^j_{River} - p^j_{Stream}) \quad (13)$$

$$p^{j+1}_{River} = p^j_{River} + \text{rand} \times G \times (p^j_{Sea} - p^j_{River}) \quad (14)$$

Large value for $d_{max}$ prevent from convergence, and a smaller value of $d_{max}$ tend to focus in the vicinity of the sea which reduces the exploration. The value of $d_{max}$ should be determined to control the position of different solutions around the sea, and it will decrease gradually due to Eq. 15.

$$d^{j+1}_{max} = d^j_{max} - \frac{d^j_{max}}{\text{Max(itr)}} \quad (15)$$

Nsr, $d_{max}$, and $G$ are optimized through the GWO algorithm based on the Pareto result of MOWCA algorithm. The GWO algorithm, the answers are directed with alpha, beta, and delta [42]. The best hunt agent ($\bar{X}_\alpha$), the second best hunt agent ($\bar{X}_\beta$) and the third best hunt agent
\( \tilde{X}_a \) are considered as alpha, beta, and delta using Equations 16 and 17. And, \( X \) represents the position of a hunt.

\[
\begin{align*}
\tilde{D}_a &= |\tilde{F}\tilde{X}_a - \tilde{X}| \\
\tilde{D}_\beta &= |\tilde{F}\tilde{X}_\beta - \tilde{X}| \\
\tilde{D}_\delta &= |\tilde{F}\tilde{X}_\delta - \tilde{X}|
\end{align*}
\tag{16}
\]

\[
\begin{align*}
\bar{X}_1 &= |X_a - \bar{A}(\tilde{D}_a)| \\
\bar{X}_2 &= |X_\beta - \bar{A}(\tilde{D}_\beta)| \\
\bar{X}_3 &= |X_\delta - \bar{A}(\tilde{D}_\delta)|
\end{align*}
\tag{17}
\]

The vectors of \( A \) and \( F \) are calculated due to Eq. 18.

\[
\begin{align*}
\bar{A} &= 2\bar{a}\tilde{r}_1 - \bar{a} \\
\bar{F} &= 2\tilde{r}_2
\end{align*}
\tag{18}
\]

The \( r_1 \) and \( r_2 \) are vectors in the range of \([0,1]\). Finally, the position of a hunt calculated due to Eq. 19.

\[
\bar{X}(t+1) = \frac{\bar{X}_1 + \bar{X}_2 + \bar{X}_3}{3}
\tag{19}
\]

To get close to the prey, the amount of \( \bar{a} \) reduced from 2 to 0 gradually. All the values in the obtained Pareto will be normalized based on their objectives. Then, the summation of all five objectives for each solution in the Pareto calculated due to Eq. 20. Then, the best answer choice’s cost will be considered as a GWO’s cost.

In the next iteration, for normalizing the achieved Pareto, the previous selected result as a best should be considered. Unlike, single objective problems which concluded in one cost at the end of each iteration, there is a Pareto in multi-objective algorithms which involves different solutions in each iteration. The reason for regarding the best answer choices from previous iterations in the subsequent iteration is for having a fair comparison among answer choices.

\[
Cost_{GWO} = \sum_{t=1}^{5} E_m + T_{cm} + B_{cm} + T_{sm} + B_{sm}
\tag{20}
\]

Finally, the optimized values for \( d_{max} \), Nsr, and \( G \) along with the Pareto will be achieved.

4. Simulation

A sample data sizes of different IoT sensors have been assumed for being stored. Network information, the available processing capacity in different services for both layers and the
available storage capacity in the cloud are all updated. Number of CPU in a service plays an important role in the processing speed. For example, t2.nano has a one CPU, and t2.large has two CPUs., all of which are assumed in the simulation environment as a variety of available services [44]. The Cloud services have different throughputs, which lead to different transmission time. Table 3 illustrates the different cloud service providers’ throughput.

Different size of data has been considered according to real IoT sensors’ data for storing in three batches. 100, 200, and 400 batch sizes of data considered to be stored as different scenarios. Also, 80% of services contemplated to be needed to fulfil the demand for 400 data to validate the reliability of resource allocation. The data size has a uniform distribution between 20 and 500 for each batch of data [45, 46].

| Table 3. Different Cloud Service Providers’ Throughput [50] |
|---------------------------------------------------------------|
| 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 CPU and also energy consumption in each service. According to the SPECpower benchmark, the maximum power consumption assumed 250 W for each CPU. To consider energy in both states, 200 W in the idle state and 300 W in the busy state assumed as consumed energy in each CPU [47].

4.1. Simulation Setups
It is assumed that there are 32 storage services in the Cloud layer and 32 processing services in Fog layer. There are Multi-objective algorithms which addressed energy and load-balancing in service selection in recent years such as NSGAII and the modified GA called KGA. In the KGA, k-means has been used to have an elitist set of the population [20]. The average results of 10 separate run for each algorithm has been calculated. The Pareto’s answer has been sorted and the mean of 10 separate Pareto will be calculated for each objective. The results are reported in BOX diagram, which has quartet and means. The box diagram is helpful in better understanding of the distribution of solutions for each objective in resulted Pareto in a statistic
way. Numerical experiments are conducted using MATLAB R2017b on a Laptop with a Core i7 2.59-2.60 GHz CPU.

The Number of the population in MWG is 50 for Multi-objective part, and 10 for GWO, and GWO algorithm has been used for prior values in MOWCA. The setting parameters of other algorithms in the simulation has been listed in Table 4.

| Algorithms | Parameters | Settings |
|------------|------------|----------|
| NSGAII     | Population size(pop), Crossover probability, Mutation probability | 50,0,8,1 |
| KGA        | Population size(pop), Crossover probability, Mutation probability, number of centroids | 50,0,8,0,1,4 |
| MOWCA      | Population size(pop), Number of streams, the distance of sea(dmax) | 50,4,1 |

**4.2. Evaluation**

The box diagram has been used for a better comparison between the resulted Pareto from different algorithms. Fig. 7 shows the distribution of different solutions’ energy consumption in Pareto of various algorithms.

![Comparison between algorithms due to the distribution of different solutions’ energy consumption in the resulted Pareto after 100 iterations for (a) 100 Data and (b) 400 Data](image)

In the MWG, rivers and sea lead other answers toward the optimum solution. The number of solutions is more in which energy consumption is less than the other two KGA, and NSGAII algorithms. Fig. 8 shows the distribution of different solutions’ processing time in the Pareto of various algorithms. If the time plays a critical role, the MWG recommends some solutions with less processing time in comparison to other algorithms even for a fully loaded state.
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.

Fig. 9 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 increase reliability as one of the critical factors in QoS. NSGAII and KGA use the method of mutation and crossover. Although these methods are good in escaping from Local minimum, they are random based methods in which the global minimum may be ignored as well.

Fig. 9. Comparison between algorithms due to the distribution of different solutions’ load balancing in the resulted Pareto after 100 iterations for (a) 100 Data in Fog Layer (b) 400 Data in Fog Layer (c) 100 Data in Cloud Layer, (d) 400 Data in Cloud Layer
On the other hand, many services like 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. Fig. 10 shows the distribution of different solutions’ Transmission time in the Pareto of various algorithms. The number of sea and rivers are determined by GWO algorithm in MWG. NSGA II and KGA have no leader in their pool of answer choices. The solutions in NSGA II are randomly generated based on crossover and mutation which may have a better or worse result.

Fig. 10. Comparison between algorithms due to the distribution of different solutions’ Transmission time in the resulted Pareto after 100 iterations for (a) 100 Data and (b) 400 Data

Table 5 shows the percentage of solutions in which the MWG algorithm has a better result in the Pareto in comparison to other algorithms. To have a comparison among other algorithms, colours are used. For instance, the green shows the second good algorithm, yellow shows the third-ranked among all algorithms, and the red is the fourth-ranked algorithm.

Table 5. Percentage of better results in the Pareto of MWG in comparison to other algorithms.

| Main Algorithm | Objectives       | 100 data   | 400 data   |
|----------------|-----------------|------------|------------|
|                |                 | KGA | MOWCA | NSGA II | KGA | MOWCA | NSGA II |
|----------------|-----------------|-----------------|------------|-----------------|------------|-----------------|
| Energy         |                 | 34% | 4%    | 40%     | 36% | 24%    | 26%     |
| Load Balancing Fog |                 | 72% | 6%    | 74%     | 22% | 8%     | 30%     |
| Load Balancing Cloud |                 | 80% | 18%   | 80%     | 64% | 54%    | 56%     |
| Processing Time |                 | 18% | 10%   | 56%     | 6%  | 8%     | 16%     |
| Transmission Time |                 | 14% | 38%   | 26%     | 14% | 4%     | 26%     |

4.3 Metric of Spacing

One of the critical factors in comparing two different multi-objective algorithms is the regularity of answers in the Pareto. This factor is demonstrated with a metric of spacing. The Eq. 21 has been used for determining regularity in different algorithm’s Pareto.

\[
SP = \sqrt{\frac{1}{n_{pf} - 1} \sum_{i=1}^{n_{pf}} (d_i - \bar{d})^2}
\] (21)
$n_{pf}$ shows the number of solutions in Pareto. $d_i$ shows the distance between every two answer choices in the Pareto. The average distance between every two answer choices in the Pareto is shown by $\bar{d}$. If $SP$ is smaller, the solutions in the Pareto are more regularly distributed. In Table 4, results for different algorithms have been shown which are Rounded to upper digits. According to Table 6, the average metric of spacing for MWG has 7%, 13%, and 25% optimization in comparison to the average metric of spacing for MOWCA, KGA, and NSGAII respectively.

| Data number | Iteration | KGA | NSGAII | MOWCA | MWG |
|-------------|-----------|-----|--------|-------|-----|
|             |           | Min | Max    | Min   | Max  |
| 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

Another factor should be considered is the quality of the Pareto which 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 the Algorithm 1, all solutions are gathered from different algorithms’ Pareto. Solutions have been sorted based on the non-dominated solution. Then, solutions have been sorted based on crowding-distance. Finally, an aggregated Pareto has been 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% optimization in metric of quality in comparison to MOWCA, KGA, and NSGAII respectively.

**Algorithm 1:** Pareto Quality Function (Metric of Quality)

**Input:** Different Algorithms’ solutions in their Pareto

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

**Begin**

1: Insert Pareto of algorithms
2: pop <= NonDominatedSorting(pop);[41]
3: CD <= CalcCrowdingDistance(pop);[41]
4: Aggregated Pareto = SortPopulation(pop) based on CD
5: $N_a$ = Number of Algorithms;
6: $N_{\Psi}$ = Number of Solutions in Aggregated Pareto;
The percentage of solutions from different algorithms’ Pareto which are involved in the Aggregated Pareto are demonstrated in Fig. 12.

**Fig. 12.** Different algorithms’ Pareto involvement in the Aggregated Pareto resulted in 100 iterations.

### 4.5 Evaluation of the optimum result

The answer choice with the minimum cost will be considered as the best in each Pareto based on Analytic hierarchy process (AHP) in which the alternatives are solutions in the Pareto and criteria are the mentioned five objectives [48]. All objectives are considered to have the same importance. The best solution among the Pareto’s solutions of each algorithm has been determined based on AHP. Each solution has different values for each objective. Table 7 shows a comparison between different algorithms in each objective. For instance, the MWG has 1.37 percent improvement in energy consumption for 100 data.

| Main Algorithm | Objectives       | 100 Data | 200 Data | 400 Data |
|----------------|------------------|----------|----------|----------|
|                |                  | MOWCA    | KGA      | NSGAII   | MOWCA    | KGA      | NSGAII   | MOWCA    | KGA      | NSGAII   |
|                | Energy           | 1.37     | 4.11     | 5.48     | 1.79     | 3.06     | 5.10     | 1.60     | 3.20     | 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    |
|                | Pros Time        | 4.31     | 15.47    | 34.72    | 20.93    | 32.15    | 37.80    | 19.33    | 29.52    | 32.69    |
|                | Transmission     | 5.64     | 11.54    | 17.69    | 6.63     | 8.63     | 13.95    | 6.11     | 9.80     | 14.17    |

**Table 7.** Comparison of algorithms’ best solution based on AHP
It can be concluded that the overall optimization results show that MWG algorithm has 7.8\%, 17\%, and 21.6\% better performance in comparison with MOWCA, KGA, and NSGAII in obtained best result from Pareto.

5. Conclusion

This paper presented a new hybrid Multi-objective algorithm for storage service selection in a collaborative and heterogeneous cloud and fog environment. Five objectives have been considered altogether in the proposed work. The Mathematical models for energy, load-balancing, and time has been proposed. Numerical experiments have also been conducted to compare the performances of the proposed MWG, MOWCA, KGA, and NSGAII. Testing results in a case study have demonstrated the good performances of MWG in metric of spacing and metric of quality in comparison to MOWCA, KGA, and NSGAII. Energy consumption has been reduced, the increment of fair load distribution among services has been achieved, and the time for processing and transmitting has been optimized as well. The Pareto and also 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 details. Besides, 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.
References

[1] S. P. Singh, A. Nayyar, R. Kumar, and A. Sharma, "Fog computing: from architecture to edge computing and big data processing." The Journal of Supercomputing, pp. 1-36, 2018.

[2] T. Baker, M. Asim, H. Tawfik, B. Aldawsari, and R. Buyya, "An energy-aware service composition algorithm for multiple cloud-based IoT applications," Journal of Network and Computer Applications, vol. 89, pp. 96-108, 2017.

[3] B. Varghese and R. Buyya, "Next generation cloud computing: New trends and research directions," Future Generation Computer Systems, vol. 79, pp. 849-861, 2018.

[4] S. Singh, I. Chana, M. Singh, and R. Buyya, "SOCCER: self-optimization of energy-efficient cloud resources," Cluster Computing, vol. 19, pp. 1787-1800, 2016.

[5] F. Durao, J. F. S. Carvalho, A. Fonseka, and V. C. Garcia, "A systematic review on cloud computing," The Journal of Supercomputing, vol. 68, pp. 1321-1346, 2014.

[6] A. Montazerolghaem, M. H. Yaghmaee, A. Leon-Garcia, M. Naghibzadeh, and F. Tashtarian, "A load-balanced call admission controller for ims cloud computing," IEEE Transactions on Network and Service Management, vol. 13, pp. 806-822, 2016.

[7] J. Pan and J. McElhannon, "Future edge cloud and edge computing for internet of things applications," IEEE Internet of Things Journal, vol. 5, pp. 439-449, 2018.

[8] R. Moreno-Vozmediano, R. S. Montero, E. Huedo, and I. M. Llorente, "Cross-site virtual network in cloud and fog computing," IEEE Cloud Computing, vol. 4, pp. 46-53, 2017.

[9] R. B. Halima, S. Kallel, K. Klai, W. Gaaloul, and M. Jmaiel, "Formal verification of time-aware cloud resource allocation in business process," in OTM Confederated International Conferences "On the Move to Meaningful Internet Systems", 2016, pp. 400-417.

[10] A. Celesti, F. Celesti, M. Fazio, P. Bramanti, and M. Villari, "Are next-generation sequencing tools ready for the cloud?", Trends in biotechnology, vol. 35, pp. 486-489, 2017.

[11] M. S. Hossain and G. Muhammad, "Cloud-assisted industrial internet of things (iiot)–enabled framework for health monitoring," Computer Networks, vol. 101, pp. 192-202, 2016.

[12] S. Li, N. Zhang, S. Lin, L. Kong, A. Katangur, M. K. Khan, et al., "Joint admission control and resource allocation in edge computing for internet of things," IEEE Network, vol. 32, pp. 72-79, 2018.

[13] L. Peng, A. R. Dhaini, and P.-H. Ho, "Toward integrated Cloud-Fog networks for efficient IoT provisioning: Key challenges and solutions," Future Generation Computer Systems, 2018.

[14] P. Krishnan, D. Raz, and Y. Shavitt, "The cache location problem," IEEE/ACM Transactions on Networking (TON), vol. 8, pp. 568-582, 2000.

[15] L. Liu and Q. Fan, "Resource Allocation Optimization Based on Mixed Integer Linear Programming in the Multi-Cloudlet Environment," IEEE Access, vol. 6, pp. 24533-24542, 2018.

[16] O. Osanaiye, S. Chen, Z. Yan, R. Lu, K.-K. R. Choo, and M. Dlodlo, "From cloud to fog computing: A review and a conceptual live VM migration framework," IEEE Access, vol. 5, pp. 8284-8300, 2017.

[17] P. V. Krishna, "Honey bee behavior inspired load balancing of tasks in cloud computing environments," Applied Soft Computing, vol. 13, pp. 2292-2303, 2013.

[18] J. Broberg, R. Buyya, and Z. Tari, "MetaCDN: Harnessing ‘Storage Clouds’ for high performance content delivery," Journal of Network and Computer Applications, vol. 32, pp. 1012-1022, 2009.

[19] Z. H. Lu, X. H. Gao, S. J. Huang, and Y. Huang, "Scalable and reliable live streaming service through coordinating CDN and P2P," in Parallel and Distributed Systems (ICPADS), 2011 IEEE 17th International Conference on, 2011, pp. 581-588.

[20] G. Peng, H. Wang, J. Dong, and H. Zhang, "Knowledge-based resource allocation for collaborative simulation development in a multi-tenant cloud computing environment," IEEE Transactions on Services Computing, vol. 11, pp. 306-317, 2018.

[21] M. Goudarzi, M. Zamani, and A. T. Haghighat, "A fast hybrid multi-site computation offloading for mobile cloud computing," Journal of Network and Computer Applications, vol. 80, pp. 219-231, 2017.

[22] T. Melodia, D. Pompili, V. C. Gungor, and I. F. Akyildiz, "Communication and coordination in wireless sensor and actor networks," IEEE transactions on mobile computing, vol. 6, 2007.
[23] T. Lv and Q. Ai, "Interactive energy management of networked microgrids-based active distribution system considering large-scale integration of renewable energy resources," Applied Energy, vol. 163, pp. 408-422, 2016.
[24] M. Aruna, D. Bhanu, and S. Karthik, "An improved load balanced metaheuristic scheduling in cloud," Cluster Computing, pp. 1-9, 2017.
[25] S. Ding, C. Chen, B. Xin, and P. M. Pardalos, "A bi-objective load balancing model in a distributed simulation system using NSGA-II and MOPSO approaches," Applied Soft Computing, vol. 63, pp. 242-267, 2018.
[26] K. Dasgupta, B. Mandal, P. Dutta, J. K. Mandal, and S. Dam, "A genetic algorithm (ga) based load balancing strategy for cloud computing," Procedia Technology, vol. 10, pp. 340-347, 2013.
[27] F. Ramezani, J. Lu, J. Taheri, and A. Y. Zomaya, "A Multi-Objective Load Balancing System for Cloud Environments," ed: British Computer Society, 2017.
[28] G. Liu and H. Shen, "Minimum-cost cloud storage service across multiple cloud providers," IEEE/ACM Transactions on Networking, vol. 25, pp. 2498-2513, 2017.
[29] S. Pandey, L. Wu, S. M. Guru, and R. Buyya, "A particle swarm optimization-based heuristic for scheduling workflow applications in cloud computing environments," in Advanced information networking and applications (AINA), 2010 24th IEEE international conference on, 2010, pp. 400-407.
[30] J. Yang, B. Jiang, Z. Lv, and K.-K. R. Choo, "A task scheduling algorithm considering game theory designed for energy management in cloud computing," Future Generation Computer Systems, 2017.
[31] S. K. Mishra, D. Puthal, B. Sahoo, S. K. Jena, and M. S. Obaidat, "An adaptive task allocation technique for green cloud computing," The Journal of Supercomputing, pp. 1-16, 2018.
[32] S. Bilgaiyan, S. Sagnika, and M. Das, "A multi-objective cat swarm optimization algorithm for workflow scheduling in cloud computing environment," in Intelligent Computing, Communication and Devices, ed: Springer, 2015, pp. 73-84.
[33] F. Ramezani, J. Lu, and F. K. Hussain, "Task-based system load balancing in cloud computing using particle swarm optimization," International journal of parallel programming, vol. 42, pp. 739-754, 2014.
[34] N. Akhter and M. Othman, "Energy aware resource allocation of cloud data center: review and open issues," Cluster Computing, vol. 19, pp. 1163-1182, 2016.
[35] A. S. Sofia and P. GaneshKumar, "Multi-objective Task Scheduling to Minimize Energy Consumption and Makespan of Cloud Computing Using NSGA-II," Journal of Network and Systems Management, vol. 26, pp. 463-485, 2018.
[36] O. H. Milani, S. A. Motamedi, and S. Sharifian, "Multiobjective Optimization in the Cloud Computing Environment for Storage Service Selection," in 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), 2018, pp. 65-69.
[37] X. Fan, W.-D. Weber, and L. A. Barroso, "Power provisioning for a warehouse-sized computer," in ACM SIGARCH computer architecture news, 2007, pp. 13-23.
[38] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems," Computers & Structures, vol. 110, pp. 151-166, 2012.
[39] L. Chunlin and L. LaYuan, "Cost and energy aware service provisioning for mobile client in cloud computing environment," The Journal of Supercomputing, vol. 71, pp. 1196-1223, 2015.
[40] R. Mahmud, R. Kotagiri, and R. Buyya, "Fog computing: A taxonomy, survey and future directions," in Internet of everything, ed: Springer, 2018, pp. 103-130.
[41] A. Sadollah, H. Eskandar, and J. H. Kim, "Water cycle algorithm for solving constrained multi-objective optimization problems," Applied Soft Computing, vol. 27, pp. 279-298, 2015.
[42] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," Advances in engineering software, vol. 69, pp. 46-61, 2014.
[43] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE transactions on evolutionary computation, vol. 6, pp. 182-197, 2002.
[44] Q. Zheng, R. Li, X. Li, N. Shah, J. Zhang, F. Tian, et al., "Virtual machine consolidated placement based on multi-objective biogeography-based optimization," Future Generation Computer Systems, vol. 54, pp. 95-122, 2016.

[45] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," IEEE Transactions on wireless communications, vol. 1, pp. 660-670, 2002.

[46] A. Ahrabian, S. Kolozali, S. Eshaeifar, C. Cheong-Took, and P. Barnaghi, "Data analysis as a web service: A case study using IoT sensor data," in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017, pp. 6000-6004.

[47] Y. Gao, H. Guan, Z. Qi, Y. Hou, and L. Liu, "A multi-objective ant colony system algorithm for virtual machine placement in cloud computing," Journal of Computer and System Sciences, vol. 79, pp. 1230-1242, 2013.

[48] T. L. Saaty, "What is the analytic hierarchy process?,” in Mathematical models for decision support, ed: Springer, 1988, pp. 109-121.