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# Estimation of fog utility pricing: a bio-inspired optimisation techniques' perspective

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**ABSTRACT**

Due to the limited data storage capacity available to Internet service providers and large-scale enterprises, the concept of resource sharing arises. The services can be given on lease to enterprises through Service Level Agreements. Being the extension of the cloud computing, fog computing architecture brings the resources near end users. In order to get the services on lease, the enterprises are supposed to pay for the resources or services which are being used by them. In this paper, four nature inspired algorithms are analysed in order to determine the efficient management of services or resources so that the cost of resources can be reduced and the billing can be attained through calculation of the utilised resources. Pigeon inspired optimization, enhanced differential evolution, binary bat algorithm and simple human learning optimization are used to evaluate the energy consumed by the edge nodes or cloudlets that in turn can be used for estimating the bill through the Time of Use pricing variable. We evaluate the aforementioned techniques to analyse their performance regarding the bill calculation on the basis of fog servers usage. Simulation results demonstrate that BAT algorithm gives significantly better results than other three algorithms in terms of resource utilisation and bill reduction.

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**KEYWORDS**
Cloud computing; fog computing; bio-inspired algorithms; optimisation techniques; utility; pricing

## 1. Introduction

In distributed systems, services or resources are shared among multiple systems which are kept in different locations but connected over a network to work on a single goal. Distributed computing maximises performance by connecting users and resources in a cost-effective and reliable manner. It also ensures fault tolerance and resource accessibility is enabled if one of the components fails. Cloud computing being considered as the type of distributed computing, involves the services which are available to users from remote locations. Cloud computing is an emanating computing architecture that depends on shared computing resources to manage applications in spite of having local servers. Cloud computing enables the end users to utilise several resources and services, such as storage and processing through the Internet. The on-demand delivery of the IT resources is assured by accenting the services via pay as you go model. The service providers are paid by the cloud customers for providing the services to the end users.

A user can utilise many services when they are required immediately just by billing for the ones they are consuming. Moreover, cloud computing can be viewed for eradicating the charges of developing

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and maintaining the IT structure for small-scale and medium-scale firms. Because of a few deep-rooted issues various softwares cannot seem to operate efficiently in the cloud system. Like; the information and data cannot be transmitted to a cloud at the same rate which was at production simultaneously because of low bandwidth. Hence, notable delays are experienced which cannot be borne in some cases. The idea of fog computing was launched, in order to minimise the antecedent delays and to make sure about the efficient allocation of resources. Due to fog computing it has been witnessed that several issues related to distributed computing had been overcome. These issues include ineffective resources management, quality of service (QoS) and security problems. Fog computing's data is managed restrictively in an implicit environment at a faster momentum than in the integrated unified cloud server.

Fog computing idea was put forward by Cisco Systems, which smooths out the process of wireless transfer of data in the Internet of Things model by pulling the computing potential closer to the fringe of a network to make vigorous access for machines. The primary aim of fog computing can be to increase the efficacy and eradicate major data transference to the cloud for examining, storage and for different operational motives. The major advantage can be the lower inertness for machines and lower network charge on the foundation of the internet. There can be multiple app arenas of the fog computing which include, smart grid, smart buildings, software-defined networks and smart buildings [1]. The extended empirical operations happen in the cloud system, though temporary data processing that is held at the edge nodes/fog servers. It would be wrong to assume that fog computing is an alternative of the cloud. However, it accompanies cloud by minimising the sent data to the cloud through the internet foundation.

Aforementioned, fog computing minimises the load of sent data and it conserves the network bandwidth accordingly. With this, it also revamps the response time of the system by placing the data closer to the verge of the matrix and formulating the immediate availability of data. Fog computing also reduces latency.

The firms outsource the facilities through the fog facilitators for their services. However, it is essential to effectively and efficiently allocate the resources to minimise the rates and costs. One of the ways of cutting these costs can be done through consuming the resources optimistically via Terms of Use (ToU) paradigm which is already applied affluently. We can take a usual exemplar to demonstrate the case of smart homes where bill is calculated for the energy consumption by smart metres [2,3]. Figure 1 illustrates the basic 3-tier architecture of cloudlets. The server is situated in the top tier. The middle layer represents the application tier which consists of cloudlets. Lastly, the final tier shows the clients. The cost and the optimal scheduling energy can be controlled the clients. A required estimate of the rates of expended resources has been increased because of the rise in demand of cloud services. Now, we can hire Pigeon inspired optimization (PIO), enhanced differential evolution (EDE), binary bat algorithm (BBA) and simple human learning optimization (SHLO) to keep an estimate of the accounts on the point of the power used by cloudlets. Because of this resource utilisation or consumption can be altered through the pricing signals.

We have employed four optimisation methods which are bio-inspired known as PIO, EDE, BBA and SHLO in this paper. This is to know the best solution for the billing estimates based upon the consumption of cloudlets. Besides this, ToU pricing indication has also been executed which examines the utilisation of the system efficiently and reduces the overall rates which will be beneficial for service providers as well as the clients. ToU rate plan lets the user determine how much and when the energy was consumed and likewise consumers can save their operational costs. EDE uses trial vector strategy [4,5] while PIO uses the homing behaviour of pigeons [4–6] in order to acquire the optimal solutions. The echo-locative behaviour of bats is used in the BBA [7–9] while human learning mechanisms are used is SHLO [10] to obtain the optimal solution. The reason of selection of these techniques is that they perform better than many other techniques. BBA performed better than Particle Swarm Optimization (PSO), GA and PIO [4,5,11] and PIO outpaced EDE in [12,13]. These optimisation algorithms perform better than other algorithms in terms of approximating the cost and resource which are being utilised.

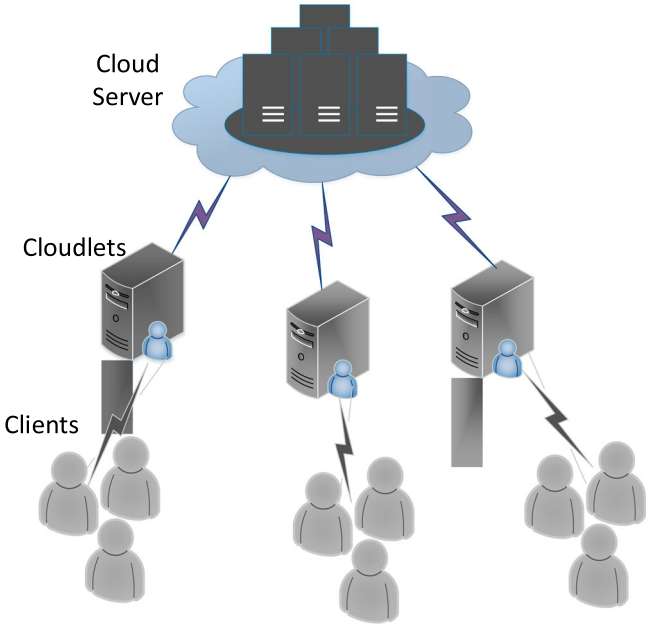


**Figure 1.** General 3-tier architecture.

The remaining article is compiled accordingly. Related work is presented in Section 2, the proposed system is presented in Section 3, Section 4 represents the results of the proposed model and lastly, Section 5 gives a conclusion and future limitations.

## 2. Related work

Fog computing is a formative computing mechanisation because of which many researchers are exploring it and the cloudlet resource management. Paper's literature review consists of the cost estimation methods for estimating the consumption of cloudlet accumulation bills.

The researchers in [12] presented a cost planning algorithm. Its aim was to maintain a balance between the execution of application and the cost of utilising the cloud resources. This proposal can also be used for the massive scale applications for energy efficiency. The authors in [13], presented greedy algorithm for Basic Service Placement Problem and Cost Aware Service Placement Problem. The major objective of the proposal was to aid service facilitators in minimising the access latency and lower the cost of consumption of resources and placement costs on cloudlets for service providers. One issue with this is that the privacy of the users' adaptability is neglected. In [14], the authors have presented a Cost Deadline Based model to ensure that the tasks are scheduled with CloudSim. Its main aim is to minimise the ratio of overlooked deadlines and help in defining the costs of users and service providers. Resources are not efficiently allocated in this model.

In [15], the authors have presented a heuristic model based on the cloud pricing model. This work lowers the amount of required VM instances and acquires a cost discount along with ensuring the users of SLA. Relatively, 30% of the cost has been reduced. However, this work does not consider the operational and communication costs of the task. In [16], the researchers have proposed priority based load balancing perspective which aligns the VM to the averages allocated to every VM. The goal of the aforementioned work is to make the improved services readily available for the people who are letting the service providers earn more revenue. The disadvantage of this model is that threshold figures are used. Aslanpour et al. in [17] have proposed cost saving super professional executor (Suprex) with auto scaling processing. The aim of this model is to facilitate an implementer with an advantage to hide the

bonus VM until the calculated time is suspended to resolve the problem of terminated VM startup. This implementer decreases leasing costs of VM relatively by 7%. In few cases it may result in reduced consumption. In [18], a model for modified resource planning and forecasting with reference to characteristics and traits of a user is presented by a cloud broker in the virtual federation atmosphere. QoS is neglected in this model. In paper [19], authors have presented a Science Gateway Cloud platform and a cost adaptive resource management plan amidst by work-flow allocating plan with a division policy. However, cost performance is degraded when resources are inefficiently managed.

In [20], the aims of authors are to reduce the cost for every element and the overall calculation for the user and CSP both. Energy rate reduction algorithms are proposed in this work. Multiple CSPs can be used to improve the QoSs. The researchers in [21] have presented dual side dynamic control algorithms for cost and postpone trade-offs for users and CSP in MCC for which both non-cooperation and cooperation situations are made under consideration. QoS and the deadlines are neglected in this work.

In [22], Cheng et al. has proposed a deep reinforcement learning model which does resource allocation and chore plans to reduce energy costs for CSPs with a massive number of customer demands and huge data centres. ToU and RTP can be the pricing indicators used in this work together with Pay-As-You-Go billing method. Energy cost effectiveness can be enhanced by 310% and 140% minimisation in runtime can be attained. While dealing with a huge number of user requests, many dependencies are included. The authors in [23], have presented a mathematical model for strong on-demand pricing framework using IaaS cloud service instances by keep the user's and provider's utility in mind. Genetic algorithms are used for optimal approximation and reduced execution cost. Strong behaviour of a network cannot be analysed by this model. In [24], authors have proposed the balanced load with optimised cost planning algorithm to reduce rates and operating strength. The requests that have been already accommodated are scheduled again to make room for the new requests at CSP. This aforementioned algorithm is unable to be compatible with the VMs when they are occupied in data centres and the latest demands are in queue.

Li et al. [25] Proposes a negotiation-based iterative approach for task scheduling that is used to reduce the billing strong energy costing. 51.8% enhancement in electric bill minimisation is achieved. [26] Is the extension of [25] since they both address the same issue. The authors in [26], have proposed a negotiation-based cost minimisation method to lower the user costs. The objective of this work is scheduling the electricity consumption so that the users electric bill can be reduced. The overall cost reduction achieved is of 64.22% in comparison to the other methods. Both have illustrated the dynamic energy costing which includes ToU and total power consumption dependent.

The researchers in [27], presented a framework to modify the resource consumption and price minimisation through strong VM allocation in cloud. 16% total is reduced through this model. Anyhow, further enhancements can be made. In [28], an admission cost framework is presented for showing various resource utilisations. The aim of this effort is to improve the model within cloudlet environment. The authors in [29], has proposed an extension in storage for the existing clouds to use simulations of storage as a service (STaas) components. For the reliability of this extension, resource allocation and costs are evaluated. However, this model has no process for working with complicated SLAs and definite value-models are not utilised. In paper [30], the authors have presented a VM placement plan that solve optimal price issue beside this the rescheduling of VM for utilisation-aware trends are also presented. The aim of such model is to reduce the operation cost to lower the degraded performance than required threshold. Cost oriented model (CoM) is presented in [31] to align cloud technology resources optimally for demand by the parted management. This is done to lower the rent cost of cloud resources. In [32] QoS metric based resource allocation techniques are proposed for the reduction of cost of cloud workloads and implementation time with QoS horizons. This consumption can be further improved. The researchers in [33] have presented a virtually effective algorithm for strong joint VM costing, planning of job and server allocation including geo distributed data centres to optimise the revenues of the owner of the cloud. However, these backup resources are costly.

In [34], the algorithm stabilises the load efficiency in VMs by allocating tasks with reference to the exploring attitude of honeybees. It also reduces the cost of using VM instances. However, loads of the dependent projects are neglected in this work. An effective dynamic scheduling and pricing (DynSP) algorithms for delays is proposed in [35] to increase the revenues of the service providers. This algorithm can only work with two service classes. The researchers in [36] have presented bi-level cost optimisation idea to plan the usage of the energy cost of customers in order to gain the optimum performance. This work has neglected the security. In [37], authors have presented the optimum cost algorithms, in order to examine that which resources are supposed to be leased from local clouds to follow the work-flow implementations with deadlines. The authors in [38] have proposed cost-based resource scheduling approach which will optimise the profit of providers and it will also use some techniques to balance the load. Its aim is to reduce the overall cycle time and enhance the profit of service facilitators and making the customers satisfied by giving first priority to those who have already paid the service providers for the consumed resources. The only disadvantage of this model is that the figures that are taken are from static threshold. Yang et al. have presented a dynamic resource scheduling model in [39] for NFV enabled MECs which include fast virtual heuristic based incremental scheduling processes and a better optimal way. The main objective of the article is to effectively schedule resources from NFV enabled MECs so that reduced latency and cost-efficiency is attained. Relatively, 33% cost can be reduced by this work presented but this cannot aid multiple services which require different performances. In [40], a numerical framework of cloud computing is presented with reference to the economic fractional dynamic function. This enables the broker to individually optimise the overall cost which involves the execution cost and the costs of efforts while incurring switches to cloud computing. We cannot deny the fact that economic systems are relied on other various factors too. The authors in [41], presented a cloud computing simulation framework of smart grid applications, which will examine the VM/cloudlet patterns, cost forecasting and the operating time of smart grid projects. In this work, security is ignored.

## 3. Proposed methodology

In the above proposed work, we will exercise the PIO and EDE as well as the ToU pricing model to make an estimate of cloudlet utilisation costs. This project can only be achieved when we examine the energy that is being used by smart homes, cloudlets or fog machines. Figure 2 illustrates the aforementioned planning of cloudlets. Top tier shows the placement of cloud server. Some cloudlets have been interconnected with a smart metre to look at energy utilisation for billing estimates later on. The bottom tier consists of smart homes that are inter-related to smart metre. All the information that is acquired via smart metre about the consumption of energy is transferred to the cloudlets. Later, the techniques for optimisation are used and optimal allocation of power usage from smart homes and cloudlets are examined. This information is transmitted via smart homes to cloudlets which calculate the overall energy usage cost. This cost can be determined by estimating the number of resources consumed by homes or clients. The Pay-As-You-Go pricing framework is executed in order to do the cost estimations of resources consumed. The optimal plan that is acquired in this work, estimates the lowest optimal cost of cloudlets. The users can keep a check and manage the cost and energy utilised by enhanced planning. Four techniques are used for optimal planning namely PIO, EDE, BBA and SHLO.

### *3.1. Working of optimisation techniques*

The functioning of algorithms used for bill estimation is explained in the following section. The algorithms will give the explanations for the usage of the four bio-inspired methods in our case.

#### *3.1.1. Pigeon inspired optimization*

This originated by the idea of homing attitude of pigeons and this was presented in 2014 by Duan and Qiao [6]. This model is used because of its good optimum performance a high merging speed

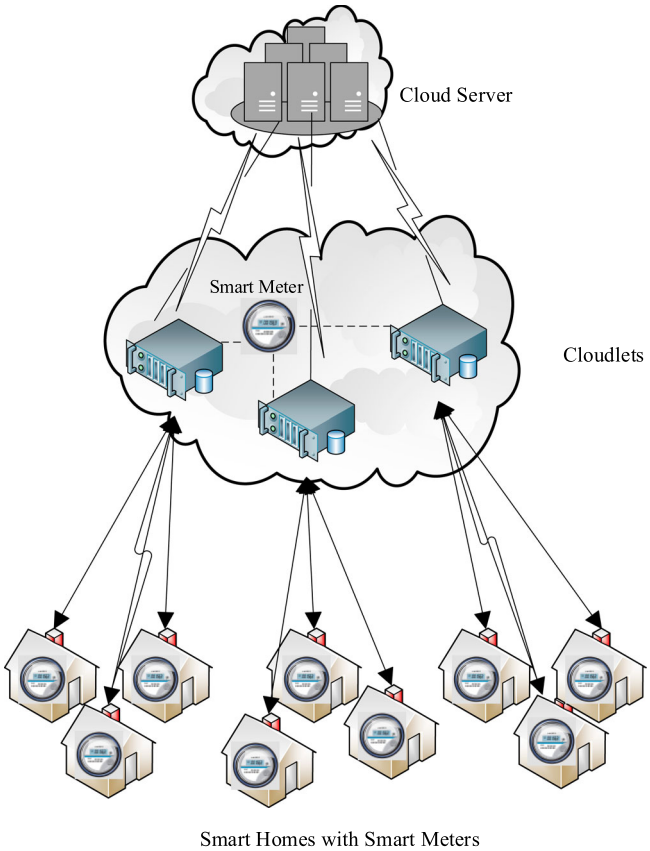


**Figure 2.** Proposed architecture of cloudlet.

that is the top advantage of PIO [42]. Map & Compass Operator and Landmark Operators are the two important operators that are used in this case.

*(a) Map and Compass Operator*

Firstly, each and every criterion is given a name and the sample is created randomly. The consolidation of the pigeons (cloudlets and homes) is measured. Magneto-receptors are used to examine the magnetic fields of earth which are plotted in the brains of pigeons. The scope of sun compasses to fix their directions. Pigeons are likely to be less dependent on sun and the magnetic elements as they proceed to their destinations.

*(b) Landmark Operator*

The Pigeons flutter to their destinations in this operator by depending upon the landmarks which are adjoining or neighbouring. The pigeons fly directly to their targets if they are well aware with their landmarks. Whereas, if the pigeons are not familiar with the landmarks then the ones who are familiar are tracked. The fitness function states that all of the population is arranged, even in that half of it cannot use the landmark operators. This is how we will look for the optimal solution i.e. bill estimation.

Algorithm 1 illustrates the PIO technique. Few of the operations are acquired from [6] where X denotes the position and Nj denotes the amount of pigeons. Xc denotes the global optimal output of fitness function.

### *3.1.2. Enhanced differential evolution*

Storn and Price presented this algorithm in 1997 for resolving the complicated optimisation issues [43]. However, in the improved version trial vector approach is used to improve the efficiency. To find ideal

**Algorithm 1:** Pigeon inspired optimisation

```
Initialize Parameters
Set initial path Xa for each cloudlet or fog device
Set Xb=Xa, Ni=1
Estimate fitness of cloudlets or fog devices
Find best solution
Map and compass operations
for Ni=1 to Ni1max do
    for a=1 to Nj do
        while Xa is beyond search range do
            Compute Xa and Va
        end
    end
    Calculate Xa, and update Xb and Xc
end
Landmark operations
for Ni= Ni1max+1 to Ni2max do
    while Xb is beyond search range do
        Sort all available fog devices according to fitness values
        Nk = Nk/2
        Retain half of fog devices with desired fitness values and discard other half
        Xd=average of rest of fog devices
        Compute Xa
    end
    Evaluate Xa, and update Xb and Xc
end
Xc is output of fitness function
```

**Algorithm 2:** Enhance Differential Evolution

```
Initialize parameters
Generate new population randomly
for x = 1:T do
    Estimate initial fitness (cost)
    Conduct mutation
    for y = 1:Max do
        Estimate fitness
        Conduct crossover
        Create five trial vectors using different crossover rates
        Find best trial vector l_new
    end
    Perform selection
    if (l_new) < (l_worst) then
        l_worst = l_new
    end
end
```

solution, mutations are done beside creation of mutant vector and target vector. Five test vectors are created with unique crossover rate values. By using three unique crossover rates, we get first three test vectors. Uniqueness of search space and convergence pace is improved by fourth and fifth test vectors, at the same time. Subsequently, selections start to take place. Test vector with lowest objective figure is to be determined from those five test vectors a final test vector is determined.

Algorithms 2 illustrate the working of EDE where fitness is said to be the cost and the optimal trial vector is going to be the one with the lowest cost.

### 3.1.3. Binary bat algorithm

This was presented by Xin She Yang in 2010 [7] for solving the complicated optimisation issues. Influenced from the echo-locative attitudes to bats, global optimisation is held. BBA which is the binary version of BA [8] uses simulated bat hunting and navigating in binary search spaces by shifting their places between 0 and 1 value. Bats use intuitive sonar to hunt and navigate. Bats lower their loudness and increase the emission rate of ultrasonic sound when they are about to chase the prey. BBA is manifested and renowned for producing competitive results in comparison with PSO and Genetic Algorithm (GA) with reference to confluence pace and enhanced local optimal avoidance [8,9]. Mirjalili et al. stated that BBA has high convergence speed with improved performance in determining global solutions.

**Algorithm 3:** Binary Bat Algorithm

```
Initialize Population
Initialize Pulse rate and loudness
while itr<maxitr do
    Adjust frequency and update velocities
    if Rand>pulse rate then
        Select Gbest randomly and change some of the dimensions of position vector with
        Gbest
    end
    Generate a new solution randomly
    if Rand<loudness & f(population)<f(Gbest) then
        Accept the new solutions and update pulse rate and loudness
    end

    Rank the bats and update Gbest
    Update position
end
Evaluate fitness
```

Algorithm 3 illustrates how a BBA works where fitness is said to be cost and Gbest is said to be the lowest cost.

### 3.1.4. Simple human learning optimization

This model stimulated through human assimilation mechanisms. Three learning operators are formed to bring solutions and determine the optima by emulating the assimilate attitudes of humans. The operations of SHLO are validated and findings are compared with Binary Particle Swarm Optimization (BPSO), Modified Binary Differential Evolution (MBDE), Adaptive Binary Harmony Search Algorithm (ABHS) and Binary Fruit fly Optimization Algorithm (BFOA). The results after the experiments shows that SHLO does significantly a better job than ABHS, MBDE, BPSO and BFOA [10]. Taking into account,

the simplicity of execution besides the importance of global search ability, SHLO proves to be a committed modifying technique.

**Algorithm 4:** Simple human learning optimization

```
Initialize Population randomly
Calculate the fitness of each individual
while itr terminated do
    Output result
end
 Generate a new generation
Calculate the fitness of new individuals
Update the population
```

Algorithm 4 demonstrates the working of SHLO algorithm where fitness is considered to be the cost and the output result gives the minimum cost.

## 4. Simulations and results

To evaluate the nature inspired algorithms for the purpose of bill estimation, MATLAB is used. A cloud computing environment is created in MATLAB, in which six fog nodes are used with round the clock operational time to acquire the simulation results. Simulations are conducted by considering different values of power consumption along with operational time (LOT) of the cloudlets in which resources are being consumed (Table 1).

Along with the nature inspired techniques including PIO, EDE, BAT and SHLO, ToU pricing signal is used to reduce the cost of the cloudlets. The cloudlets are scheduled in a way that resources are efficiently utilised which leads to the overall reduction in bills.

Figure 3, shows the resource consumption of the users. Higher the number of resources utilised, higher will be the cost. Results depict that EDE utilises the least amount of resources as compared to the other three algorithms. About 90% of the resources can be utilised by SHLO while 80% of the resources can be utilised by BAT algorithm. PIO can utilise 65% resources, however, EDE can utilise only 45% resources approximately. As SHLO can acquire more amount of resources, hence, this will lead to user satisfaction as more amount of resources can be acquired by the consumers.

In Figure 4, cost of the utilised resources is given. Consumers have to pay for the resources they utilise. This shows that SHLO has the highest cost. This is so because SHLO can utilise more amount of resources as compared to other three algorithms. Although EDE acquires least amount of resources inspite of that the cost of EDE is approximately the same as that of SHLO. BAT algorithm is the most cost-effective algorithm as it acquires more resources with the least cost.

Figure 5, represents the hourly cost of the resources utilised by the consumers. The highest peaks, round about 53 cents, are formed by EDE as shown in figure. The peaks formed by SHLO are 10% less

**Table 1.** Power consumption and operational time.

| Fog nodes | Power consumption (kWh) | LOT |
|---|---|---|
| Fog node1 | 0.2 | 19 |
| Fog node2 | 0.5 | 13 |
| Fog node3 | 0.7 | 5 |
| Fog node4 | 1.15 | 3 |
| Fog node5 | 1.2 | 7 |
| Fog node6 | 1.4 | 20 |

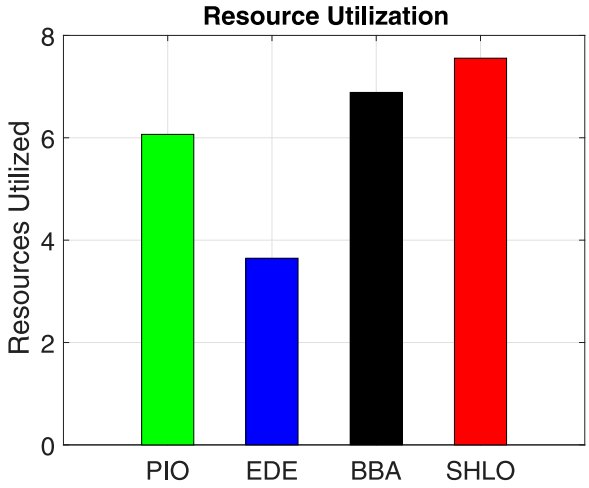


**Figure 3.** Comparison of resource utilisation for PIO, EDE, BAT and SHLO.

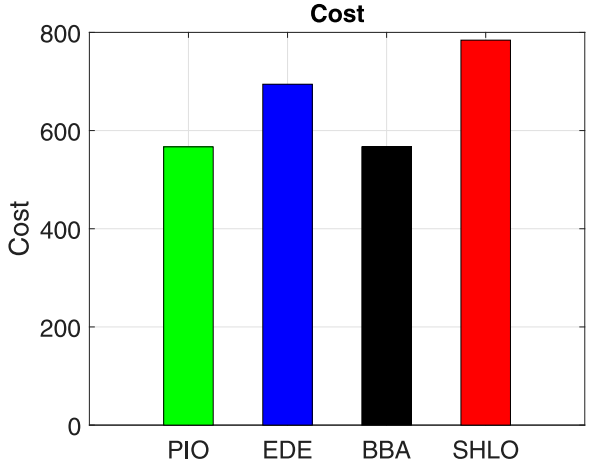


**Figure 4.** Comparison of utilisation cost for PIO, EDE, BAT and SHLO.

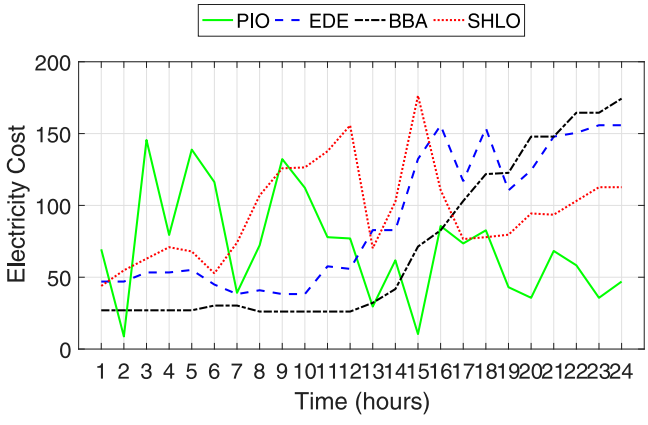


**Figure 5.** Hourly cost for the simulation.

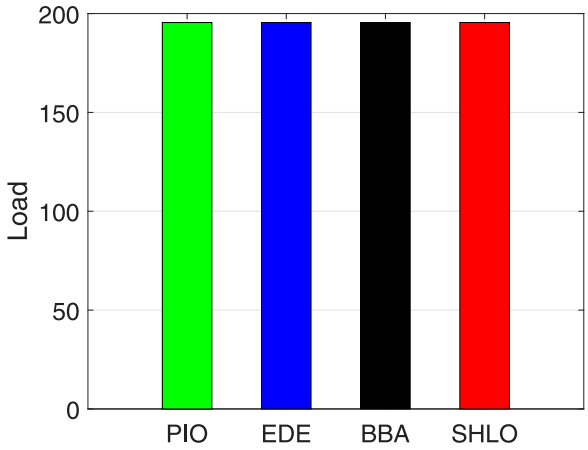


**Figure 6.** Total load for the simulation.

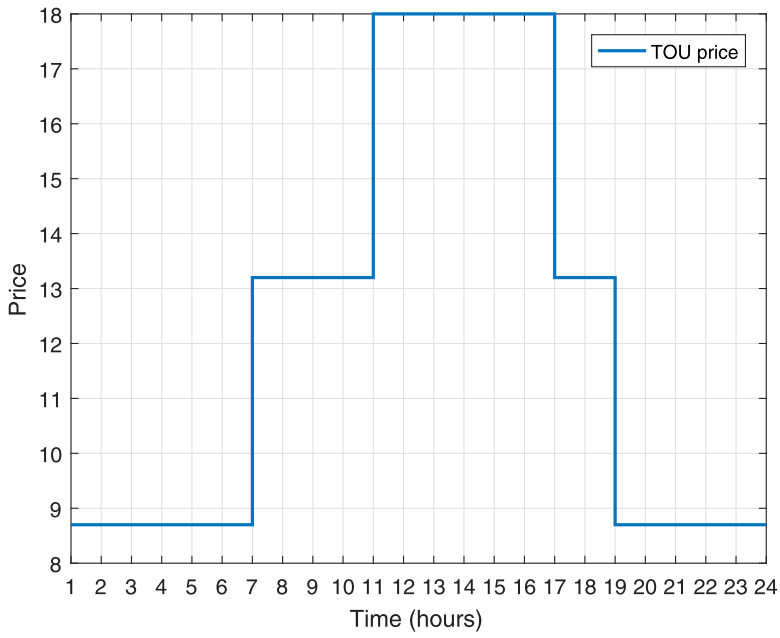


**Figure 7.** Time of use pricing signal.

than that of EDE. Likewise, the cost of PIO and BAT algorithms is less than the other two algorithms comparatively.

From 6 it is clear that all the four algorithms are bearing an equal amount of load. Under this even distribution of load, all these techniques are compared and evaluated.

Figure 7, shows the ToU pricing signal which is used for estimating the costs. By using this pricing signal, consumers can manage the overall consumption cost and consequently bills can be reduced.

## 5. Conclusions

In this paper, four nature inspired algorithms were evaluated and compared in terms of their performance regarding the estimation of utility charging on the basis of usage of cloudlets. The PIO, EDE,

BAT and SHLO along with the ToU pricing signal were employed for bill estimation. The evaluation is performed based on the resources utilised by the consumers and thus their hourly consumption cost. Simulation results show that the BAT algorithm can acquire more resources with the least cost. Large amount of resources can be utilised by SHLO, therefore, it has a higher cost as compared to the other three algorithms. EDE utilises the least amount of resources with much higher cost. From the simulation results, we also conclude that the BAT performs better than other three algorithms in terms of both resource utilisation and bill reduction. These approaches lead to bill estimation based upon the usage of cloudlets. In future, we intend to study and experiment with other significant Bio-Inspired optimisation algorithms, such as PSO, Bacteria Foraging Optimization Algorithm (BFO), and the Evolving Bat Algorithm for utility pricing where the simulations would be carried out in a controlled environment established in dedicated simulator such as the iFogsim.

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