Evaluating Bio-Inspired Optimization Techniques for Utility Price Estimation in Fog Computing

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***Abstract*—With continuous advancements in the domain of information and communication technologies, large-scale enterprises and the Internet service providers have realized about the limited capacity of data storage available to them. This leads to the concept of sharing of resources among the enterprises by renting these services through the Service Level Agreements (SLAs). Fog Computing is proposed to be an extension of cloud computing architecture where the resources are brought near the end users. Fog computing, in contrast to cloud computing provides services along with the computing resources. To borrow the services, the enterprises have to pay according to their usage of the services or resources. In this paper, two nature inspired algorithms are compared to determine the efficient management of resources so that the cost of resources can be minimized and the billing can be achieved through calculation of the utilized resources. Pigeon Inspired Optimization (PIO) and Enhanced Differential Evolution (EDE) are used to determine the energy consumed by the cloudlets or edge nodes that in turn can be used for estimating the bill through the Time of Use pricing variable. We evaluate both of the aforementioned technique to determine their performance regarding the bill calculation on the basis of usage of fog servers. Simulation results demonstrate that PIO gives significantly better results than EDE in terms of resource utilization whereas for bill reduction EDE outperforms PIO based technique.**

***Keywords* - Cloud computing; Fog computing; Bio-inspired Algorithms; Utility; Pricing;**

I. INTRODUCTION

In distributed computing, components of a software system are distributed or shared among multiple systems to improve the efficiency and performance. Cloud computing is considered as the type of distributed computing that involves the services available to users from remote locations. Cloud computing is an emerging computing architecture that relies on shared computing resources to handle applications rather than having local servers. Cloud computing enables the users to utilize various services and resources, such as processing and storage through the Internet. The on-demand delivery of the Information Technology (IT) resources is ensured by metering the services through the pay as you go model. The cloud customers pay to the service providers for providing the services to the end users. One can acquire as many resources as are needed instantly by only paying for what they are using. In fact, the cloud computing has eliminated the costs of development and maintenance of the IT infrastructure for small and medium organizations. Due to some inherent problems several applications cannot work effectively in the cloud environment. For example, due to the low bandwidth the data cannot be transmitted to the cloud at the same rate at which it is generated. Therefore, significant delays are encountered that cannot be tolerated in certain cases. To avoid the aforementioned delays and to ensure the efficient delivery of resources the idea of fog computing was introduced. Fog computing has demonstrated its effectiveness to overcome various issues of distributed computing, such as: (i)inefficient resource management, (ii) Quality-of-Service (QoS), (iii) security, and (iv) privacy issues. The data in the fog environment is processed locally in a virtual platform at a much faster pace than in a consolidated centralized cloud server.

The term Fog computing was coined by Cisco Systems also known as edge computing, it facilitates in wireless data transfer in the Internet of Things (IoT) paradigm by taking the computing power near to Edge of network so that devices have easy and robust access. The key objective of fog computing is to enhance effectiveness and minimize data transmissions in bulk to cloud for analysis, storage, and processing purposes. One of the key benefits is the lesser latency for devices and lesser network load on the internet backbone. There are several application domains of fog computing, such as smart buildings, smart cities, smart grid, vehicular networks, and software-defined networks [1]. The long-term analytic processing takes place in the cloud environment whereas short term data analysis are carried out at the fog servers or edge nodes. It is also important to mention that the fog computing cannot be a replacement of the cloud but actually complements cloud computing by reducing the data sent to the cloud for processing through the backbone Internet. As stated earlier, the fog computing reduces the bulk of data sent to the cloud and consequently conserving network bandwidth. Moreover, it also improves the system response time by keeping the data close to the edge of the network and making the data available instantly. Furthermore, the fog computing not only supports

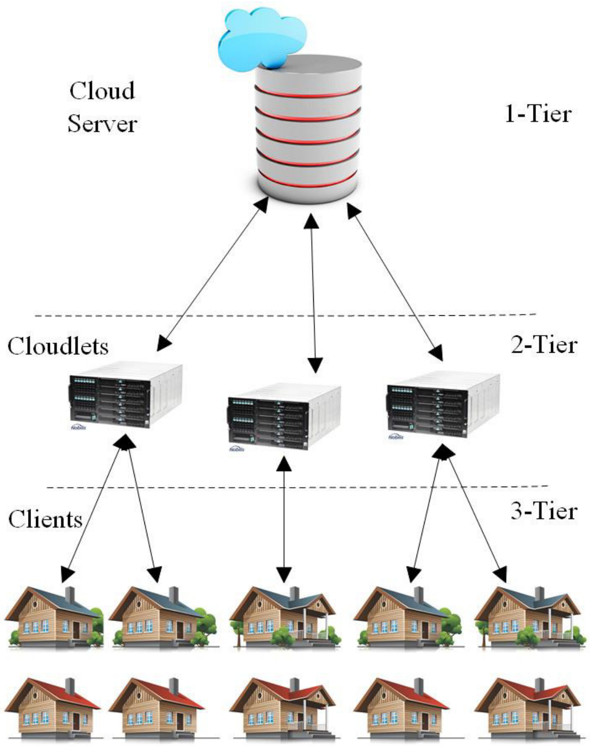

Figure 1. General 3-Tier Architecture

mobility but also minimizes the latency.

The enterprises rent the resources from the fog service providers for the utilized services. However, it is important to efficiently manage and utilize the resources to reduce the prices. One way to cut the costs is to optimally utilize the resources through the Time of Use (ToU) model that has already been successfully applied. A common example to illustrate the scenario is of smart homes where smart meters are placed for measuring the energy consumed that is subsequently used for bill calculation [2], [3]. Figure 1 shows general 3-tier architecture of edge nodes or cloudlets. The cloud server is placed in the first tier which is also the top-most layer. The second (middle) tier is the application tier that comprises of cloudlets whereas the bottom layer which in fact is the third tier contains the clients. The consumers or clients can control or manage the cost and energy consumed by optimal scheduling. Due to the increased demand of cloud services, the need to estimate the cost of the consumed resources has significantly increase. To that end, our objective is to estimate the bills on the basis of the energy consumed by the cloudlets by employing the Pigeon Inspired Optimization (PIO) and the Enhanced Differential Evolution (EDE). As a result, the resource usage or utilization can be adjusted in response to the pricing signals.

In this paper, we employ two bio-inspired optimization techniques namely, the PIO and the EDE to determine the optimal solution for estimating the bill based on the usage of the cloudlets. Along with bio-inspired techniques, ToU pricing signal is used that actually advocates the efficient utilization of the system along with the reduction in the overall costs that eventually will benefit both the customers as well as service providers. Through ToU rate plan, one can determine when and how much energy is being consumed and likewise consumers can save their operational costs. The trial vector strategy is used in the EDE [4], [5] while homing behaviour of pigeons is considered in the PIO [4]–[6] to obtain the optimal solution. These algorithms perform better than other algorithms in terms of estimating the cost and load of resources which are being used.

The rest of the paper is organized as follows. Section II presents the related work whereas the proposed model is described in Section III. In Section IV, results and simulations of the proposed system are explained whereas Section V concludes the paper and highlights the directions for future work.

II. Related Work

As fog computing is a nascent computing technology, hence with its emergence many researchers are scrutinizing fog computing and cloudlet resource management. This literature review is based on cost estimation techniques which are used for estimating the bills based on the usage of cloudlet resources.

The authors in [7], proposed a cost makespan aware scheduling heuristic which is a cost scheduling algorithm. The objective of this work is to acquire the balance between the cost for the utilization of cloud resources and the performance of application execution. However, this proposed scheduling can be extended for large scale applications by keeping energy efficiency in mind. Cost saving super professional executor (Suprex) with auto-scaling mechanism is proposed by Aslanpour *et al.* in [8]. The aim of this work is to provide an executor with the capability to isolate the surplus VM till the billed hour is terminated in order to overcome the challenge of postponed VM startup (Suprex). Suprex executor, reduces the renting cost of VM by 7%. However, in some situations, this executor results in lower utilization. The aim of [9], is to lessen the cost for each queue and the sum cost for both mobile user and the CSP. Algorithms for energy cost minimization, while verifying finite processing delay are proposed in this work. Since, single CSP is used in this work hence, quality of offloading service is sacrificed which can further be enhanced by using multiple CSP's.

Cheng *et al.* in [10], have proposed a deep reinforcement learning (DRL) based system with resource provisioning and task scheduling to minimize the energy cost for CSPs with huge amount of user requests and large-scale data centers. ToU and RTP are the pricing signals applied in this work along with Pay-As-You-Go billing contract or agreement. However, dependencies are involved while dealing with large amount of user requests. In [11], the authors have proposed a mathematical framework for dynamic on-demand pricing model using IaaS cloud service instances by considering user's and provider's utility. Genetic algorithm is used for optimized estimation and minimized execution cost. However, dynamic behaviour of network is not analyzed. The authors in

In [12], a negotiation-based iterative approach for task scheduling (NBTS) is proposed to minimize the bill under dynamic energy pricing. The proposed algorithm ends when total energy cost is not diminished. Up to 51.8% improvement is achieved in electric bill reduction. The paper [13] is the extension of [12] as they both are addressing the same problem. The authors in [13], have proposed a negotiation-based cost minimization (NBCM) algorithm in order to minimize the energy cost of users. Along with that task scheduling (NBTS) and energy storage control (NBSC) systems are also proposed. The main aim of this work is to schedule electricity consumption in a way that the electric bill of the users can be minimized. The total energy cost reduction of 64.22% is achieved as compared to the baseline methods. Both [12] and [13] have used dynamic energy pricing including ToU and total power consumption-dependent.

The authors in [14], have proposed a VM placement scheme to resolve the cost optimization problem along with that VM reallocation grounded on resource utilization-aware activities is also proposed. The objective of this work is to lower the operating cost so that the performance degradation is lessened than the threshold. However, it does not reflect overall trends i.e., temporary resource utilization is done. In [15], Cost-oriented model (CoM) is proposed to optimally allocate cloud computing resources for demand side management. The aim of this model is to reduce the rental cost of cloud resources. Amazon cloud computing service-based pricing scheme along with ToU and RTP for demand side management is used in this paper.

The algorithm proposed in [16], balances the load effectively among VMs by mapping tasks on the basis of foraging behaviour of honey bees. It also minimizes the cost of consuming virtual machine instances. Although, the load of independent tasks is considered for balancing, yet the load of dependent tasks is not considered in this work. In [17], dynamic energy aware cloudlet based mobile cloud computing model is proposed which focuses on solving the energy consumption in wireless communications. The authors in [18], have presented a survey on FinTech with five technical aspect. Fundamentals of fabricating active FinTech solutions is the main contribution of this work. Keke Gai in [19], have proposed a dynamic content oriented privacy protection model which is used to increase the privacy protection level on the basis of dynamic programming. For the evaluation of the model, an android app is also developed.

III. Proposed Methodology

In the proposed system, we employ the PIO and the EDE along with the ToU pricing signal to estimate the cost of the cloudlet utilization. The task is accomplished by determining the energy consumed by the smart homes and cloudlets or fog devices. Figure 2 shows the proposed architecture of the cloudlets. In the top-most layer, cloud server is placed. The cloudlets are connected with the smart meter to determine the energy consumed which is further used for bill estimation. The bottom-most layer contains the smart homes that are incorporated with the smart meters. The information about the energy consumption of all of the smart homes that is gathered through the smart meter is transmitted to the cloudlets. Subsequently, the optimization technique is applied and optimal schedule of power consumption of all of the smart homes and cloudlets is analyzed. Energy consumption information is sent from smart homes to the cloudlets which leads to the total energy consumption cost calculation. The cost is determined from the estimation of the amount of resources utilized by the clients or homes. The pay as you go pricing model is applied for cost estimation of the resources utilized by the consumers. The optimal schedule obtained in this case, leads to the estimation of the lowest possible cost of the cloudlets. The consumers can control or manage the cost and the energy consumed by optimal scheduling. For optimal scheduling, two bio-inspired optimization techniques namely the PIO and the EDE are used. The problem of bill estimation on the basis of usage of cloudlets is solved using these two optimization techniques.

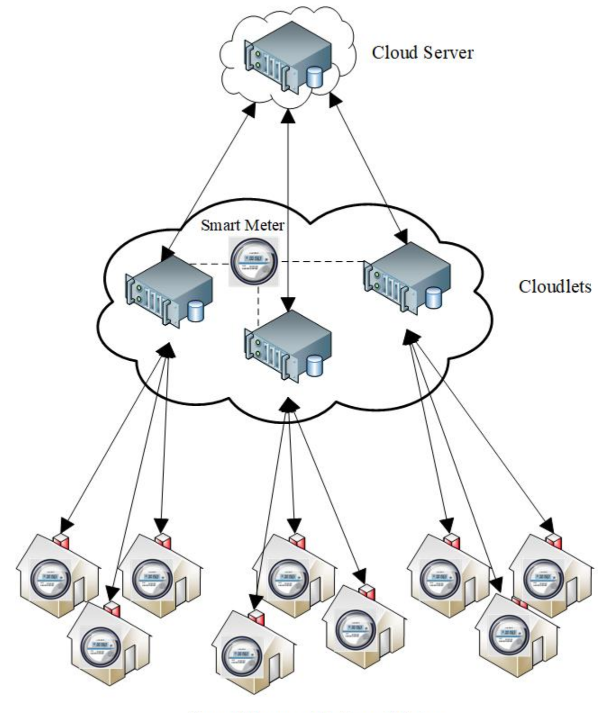

Figure 2. Proposed Architecture of Cloudlet

A. Working of optimization techniques

The working of the two bio-inspired algorithms used for the estimation of the bills is described in this section. The algorithms below provide the details about the utilization of the two techniques in our scenario.

1) Pigeon Inspired Optimization (PIO): Inspired from the homing behaviour of pigeons, the PIO was proposed by Duan

Algorithm 1: Pigeon Inspired Optimization

```
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
```

and Qiao in 2014 [6]. The PIO is used due to its better optimization performance and a high convergence speed that in fact are the most remarkable advantages of the PIO [20]. Two major operators used in this technique are: (i) Map and Compass Operator and (ii) Landmark Operator.

a) Map and Compass Operator

Initially, all of the parameters are initialized and population is generated randomly. The fitness of all the pigeons, in our case cloudlets and homes, is calculated. To build the map or plot in their brains, pigeons use magneto-reception to judge the earth's magnetic field. The latitudes of the sun are regarded as the compass to adjust their direction. The pigeons depend little on sun and magnetic particles as they move towards their destination.

b) Landmark Operator

In landmark operator, the pigeons fly near to their target by leaning on the neighbouring or adjacent landmarks. They will fly straight to their goal if the landmarks are familiar to them. On the other hand, if they are unfamiliar to the landmarks and also far from the destination then the pigeons who are familiar with the landmarks will be tracked. According to the fitness function, all the population is sorted and among them half of the population is abandoned using the landmark operator. This is how pigeons search for food and in our case, we will search for an optimal solution i.e., the bill estimation.

Algorithm 1 shows the working of the PIO technique. Some of the algorithmic operations are taken from [6] where X is the position, V is the velocity and Nj is the number of pigeons. Xc is the global optima 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 I_new
    end
    Perform selection
    if (I_new) < (I_worst) then
        I_worst = I_new
    end
end
```

2) Enhanced Differential Evolution (EDE): Differential Evolution (DE) was proposed by storn and price in 1997 [21] for solving the complex optimization problems while in the Enhanced version, trial vector strategy is used to enhance the accuracy and efficiency. To determine the optimal solution, crossover and mutation are performed along with the formation of mutant vector and target vector. Five trial vectors are formed with distinct crossover rate values. By taking three distinct crossover rates, we obtain first three trial vectors. Convergence speed and diversity of search space are enhanced by fourth and fifth trial vectors, simultaneously. After crossover and mutation, selection takes place. The trial vector with minimum objective value is selected among those five trial vectors as the final trial vector.

The working of the EDE is given in Algorithm 2 where fitness is considered as the cost and the best trial vector is the one with the minimum cost.

IV. 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 as shown in table I .

Along with the PIO and the EDE, ToU pricing signal is used to minimize the cost of the cloudlets. The cloudlets are scheduled in a way that resources are efficiently utilized

Table I
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

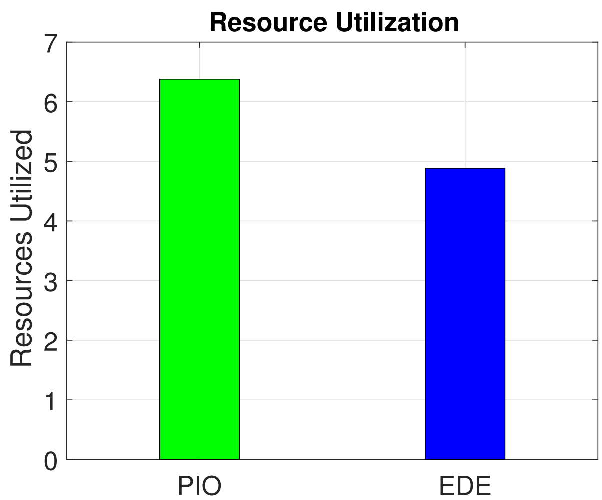

Figure 3. Comparison of Resource Utilization for PIO and EDE

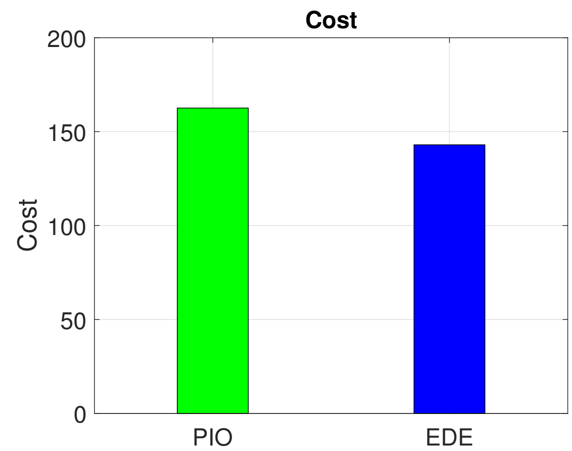

Figure 4. Comparison of utilization Cost for PIO and EDE

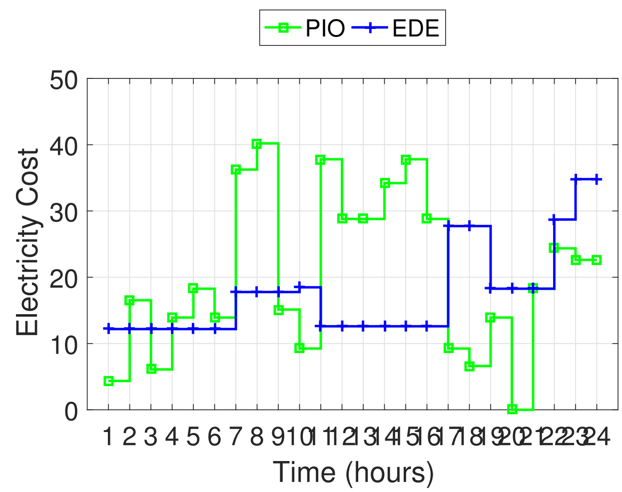

Figure 5. Hourly Cost for the simulation

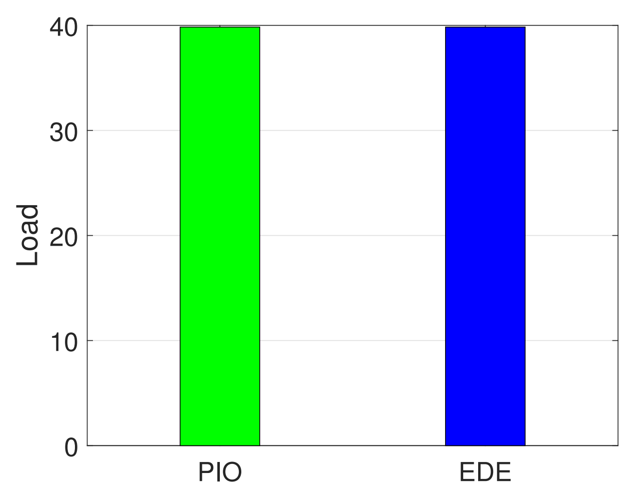

Figure 6. Hourly Cost for the simulation

which leads to the overall reduction in bills. Figure 3, shows the resource consumption of the users. Higher the number of resources utilized, higher will be the cost. Results clearly depict that by using the PIO algorithm, more resources can be acquired as compared to the EDE. Around 15% more resources can be used in PIO in comparison to the EDE. This will lead to user satisfaction as more number of resources can be utilized by the consumers. In Figure 4, cost of the utilized resources is given. This shows that the cost of PIO is approximately 25% more than that of the EDE. This is because through PIO more resources can be utilized as compared to EDE. Therefore, consumers have to pay for the resources which are utilized by them.

Figure 5, represents the hourly cost of the resources utilized by the consumers. From figure, it can be seen that highest peaks are formed by the PIO from 8 to 16 and the maximum cost is increased till 40 cents while maximum cost required by EDE is 35, i.e., 5% less than EDE. From 6 it is clear that both the PIO and the EDE are bearing equal amount of load. Under this even distribution of load, these two 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.

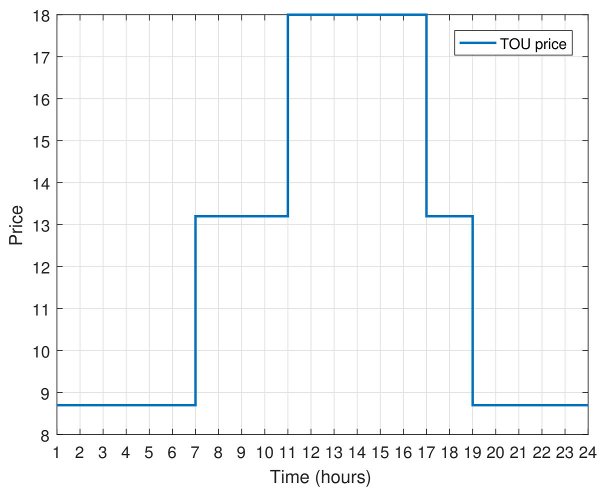

Figure 7. Time of Use Pricing Signal

V. Conclusions

In this paper, two nature inspired algorithms were evaluated and compared in terms of their performance regarding estimation of utility charging on the basis of usage of cloudlets. The EDE and the PIO along with the ToU pricing signal were employed for bill estimation. The evaluation is performed based on the resources utilized by the consumers and thus their hourly consumption cost. Simulation results show that the PIO requires more resources, therefore, it has a higher cost as compared to the EDE. The cost of EDE is approximately 12% less than that of the PIO. From the simulation results, we also conclude that the PIO performs better than the EDE in terms of resource utilization while the EDE outperforms the PIO concerning the 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 optimization algorithms, such as Particle Swarm Optimization (PSO), Bacteria Foraging Optimization Algorithm (BFOA), and the Evolving Bat Algorithm (EBA) 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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