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Fog Enabled Cloud based Intelligent Resource Management Approach using Improved Dynamical Particle Swarm Optimization model for Smart Home IoT Devices

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ABSTRACT: In recent days, resource management is a significant design issue in Fog computing based smart home environment. This paper introduces an efficient fog computing based resource allocation technique named Improved Dynamical Particle Swarm Optimization (ID-PSO) algorithm to optimize the allocation of resources. This paper enhances the traditional PSO algorithm by including the auto-adaptive strategies in a dynamic way for improving the exploration/exploitation trade off and diversity of the presented model. It eliminates the PSO algorithm from trapping into local minima. An extensive experimental analysis takes place to verify the effective performance of the IDPSO algorithm. The experimental outcome stated the superior results of the presented IDPSO algorithm over the compared models. The presented ID-IPSO model shows minimum latency of 38s, minimum bandwidth requirement of 2250B/s, and minimum response time of 1s and minimum energy consumption of 115 kWh under the presence of 95 operations.

Keywords: PSO algorithm, Fog computing, Smart home, Resource management.

Abbreviations: ID-PSO,Improved Dynamical Particle Swarm Optimization; IoT, Internet of Things; Qos, Quality of Service; GFC, Gateway-based Fog Computing; VRP, Virtualization based Resource Provisioning; MOP, Multi-objective problem.

I. INTRODUCTION

In recent times, major developments have been evolved in Big Data and Internet of Things (IoT) applications [1]. Consequently, these applications need an extensive data with processing ability for provisioning services and it is possible by deploying Cloud data-centres [2]. When these applications are applied inside the Cloud data-centres, it identifies the maximum delay as well as response duration because of massive geographical distance and requirements of data bandwidth among clients and data-centre [3]. In order to resolve these complexities, new technique has been introduced which is named as Fog computing. It mainly aims to minimize the delay by expanding the integration of cloud data-centres along with boundary of network. Hence, IoT environments have the ability of reducing fog assisted Cloud computation which results in the implementation of latency sensitive applications.

Resource management is development of assigning a resource for a specific application inside the distributed system that leads to observe a definite Quality of Service (QoS) limitation and reduce the overheads involved in the process and unwanted energy consumption. There is a common plethora of previous scheduling technique that has been allocated to distributed systems namely, MESOS, YARN and BORG in cloud that has been generated to function in centralized computing infrastructure. Hence, the scheduling tool is not applied to perform inside a definite platform along with maximum mobile edge device, delay sensitive applications rather it could not be applied to wider geographical areas which is essential in performing operations in Fog computing platforms [4]. The Resource organization in Fog computing mainly concentrates in managing computation as well as memory storage among edge devices and Cloud data-centres in order to precede a task with lower delay with reply time [5].

In last decades, some of the IoT and Fog computing methods are often attentive on singular or particular sub-set of parameters along with the domains of response time, delay, network bandwidth, and power Capturing every attributes in the Fog computing resource organizations are mostly essential in the method of smart equipments that has been connected to IoT system and assure maximum QoS [6].

Because of difficulty in optimizing multi-objective attributes to trade-off decision making in resource organization, the researching nature or bio-inspired technique are challenging task to report the issues of resource organization [7]. This paper presents an effective fog computing based resource allocation model utilizing Improved Dynamical Particle Swarm Optimization (ID-PSO) technique for optimizing the resource allocation. The proposed model is an enhancement of classical PSO algorithm through the inclusion of auto-adaptive strategies in an active way to improve the exploration/exploitation exchange and variability of the presented model. It removes the PSO algorithm from trapping into local minima. A widespread experimental analysis is carried out for verifying the betterment of the proposed model. The experimental outcome stated the superior results of the presented IDPSO algorithm over the compared models.

II. RELATED WORK

Singh & Chana [8] exploring IoT applications in Fog computing is developed by several unsolved challenging studies. The upcoming portion presents a study on resource organization in Fog computing. Tuli *et al.,* [9] prepared a workload distribution problem to study the tradeoffs among energy consumption with delay in a Cloud-Fog computing method. Additionally, the initial problems are decayed into 3 sub problems for solving separately, which explains that Fog computing is competent in decreasing transmission latency with message bandwidth, but do not regard as system network bandwidth as well as energy consumption. Deng *et al.,* [10] presented a proximal technique to combined store distribution in the geo-dispersed platform with decreasing carbon footprint. Furthermore, the generated outcome shows decreased carbon footprints while streaming a video as cloud facility. Do *et al.*, [11] presented a cost efficient resource organization method included in the medical Cyber-physical System that virtual machine placement, role allocation with base station organization is examined. The simulation outcome reveals that the presented technique is far better when compared to greedy technique with respect to energy conservation.

Gu *et al.*, [12] introduced a Gateway-based Fog Computing (GFC) design to wireless sensors as well as actuator networks that has a master with slave nodes, flows, control virtual gateway operations, and resources. Testing outcomes reveal that GFC executes a maximum outcome with respect to response time. Yu *et al.*, [13] presented a Virtualization based Resource Provisioning (VRP) technique to Fog computing with a design utilizing the model of parallel as well as allocated load balancing. Additionally, the techniques are estimated in Cloud-Analyst which discovers the presented result to reduce the system energy cost. Stojkoska & Trivodaliev [14] presented the conceptual method to smart homes utilizing IoT to Fog-computing that implies energy consumption could be decreased using integration of geographically allocated renewable energy sources. Wang *et al.*, [15] presented the 3-layer hierarchical game structure to resource management in Fog computing for solving the challenges concern for quicker data procedure with lowest response time. These explore work details that Fog device is further able to decrease latency as related to the cloud with practicing a minor enhance in energy consumption. Consequently, the trade-off among latency and power consumption helps to generate distinct efficiency. Annicchiarico & Cerrolaza [16] proposed a method for solving an effective coupling resource management problem, a fog computing model has been developed and extend the Hungarian algorithm for managing the coupling resource which can get minimum delay for realizing effectual and sustainable services .

The above study describes about under-provisioning as well as over-provisioning of resources in previous Fog computing with IoT resource organization methods. Here, Fog gadget consist of excessive performance measure calculate and storage space, but it is not possible to provide the same ability of resources as Cloud data-centers conserves. Hence, effective resource management is essential to process the user request in a definite interval of time. In order to resolve these issues, the amount of resources applied to implement the client must be detected appropriately, so that given resources can be applied in an effective manner.

III. PROPOSED MODEL

Because of the benefits of dominance schemes to manage multi-objective problem (MOP), i.e., there is no requirement to convert MOP to single objective problem with their ability of constructing various group of Pareto-optimal solutions in a single run, a NSGA-II stimulated schemes are utilized to modify the Dynamically Improved Particle Swarm Optimization (DI-PSO) methodology presented. The usual point of the MOP problem is established under and Pareto dominance condition with the elitist non-dominated sorting method utilized in DI-PSO. In common, MOOPs consists to concurrently optimization the group of objective operations that is to be diminished or exploited. The problems are controlled with number of equality as well as inequality operations that should satisfy with some possible outcome. The problem formula is written as

$$\frac{\text{Mini}}{\text{Maxi}} f_y(u) = |f(u)_1, f(u)_2, \cdots, f(u)_Y| \tag{1}$$

$$\text{Subjected to}\begin{cases} g_x(u) \leq 0, & x = 1,2,\cdots,X \\ h_k(u) = 0, & k = 1,2,\cdots,K \\ u_q^{(X)} \leq u_q \leq u_q^{(l)} & q = 1,2,\cdots,Q \end{cases}$$

The plan is to discover a design vector of variables, such that

$$f_p(U^*) = mn\, f_p(U), p = 1,2,\cdots,Y \tag{2}$$

But, this is not a general condition with objective operations that is performed between them in a reverse manner. One method for resolving these problems are to discover the larger number of outcomes that satisfies the criteria of Pareto optimization to multi-objective issues. In Pareto optimize, an outcome vector is said to control the resultant vector, if the subsequent situation is concurrently satisfied :

(1) Estimation outcome $U^{(1)}$ is no worse than estimate outcome $U^{(2)}$ in every objective:

$$f_p\left(U^{(1)}\right) \leq f_p\left(U^{(2)}\right), p = 1,2,\cdots,Y \tag{3}$$

(2) Estimation outcome $U^{(1)}$ is strictly optimal than outcome $U^{(2)}$ in any case of objective operation:

$$\exists \overline{y} \epsilon \{1,2,\cdots,Y\}: f_{\overline{y}}\left(U^{(1)}\right) < f_{\overline{y}}\left(U^{(2)}\right) \tag{4}$$

Executing the Pareto criterion to group of outcomes P, it is probable for detecting the non-dominated group of outcomes P' that is not controlled with some member of set P. If the set P denotes the whole possibility of search space, the outcome non-dominated set P' is known as Pareto Frontier (PF). Usually, in MOP there is not a smaller objective operation. Thus, the role of designer is to recognize the larger number of probable Pareto smallest with respect to them choose the most fitting outcome that in a cooperation method permits solving the group of objective operations.

Elitist non-dominated sorting schemes within the design of DI-PSO to manage multi-objective problems as the method for detecting the non dominated group of outcomes. These schemes were stimulated on NSGA-II technique formulated. It is selected because of its effectiveness with quicker speed to manage multi-objective problems together with including elitism through transmission features dependent on models of control as well as thickness. Elitism is probable in the technique because of the group of frontiers of non-dominated outcomes removed from 2 successive iterations of the technique, parent, with children populations in the case of the GA. The alteration procedures are initially estimated with utilizing a Pareto non-domination classifier method of the total population generated with the group of parent as well as children, pursued with process that measures the density of results neighbouring an exacting outcome in the population. The initial phase goes to the non-domination classifier method primarily suggested with Goldberg the final one have the allocation of a density index dependent on the Manhattan distance among close to nearby exact outcome of similar rank.

Non-dominated Sorting scheme

The arranging scheme and how to achieve the Pareto frontiers that are stored in exterior file are explained in a step-by-step system. Primarily, an arbitrary N-sized swarm population (Sw_P_z) is generated. An N-sized children population (Sw_Q_z) is achieved from the preceding one with executing swarm intelligence operatives. This population is arranged into non-domination levels. Every result is allocated with a fitness equivalent to its non-domination level. So minimized of the fitness is supposed.

Phase 1. Merge swarm populations (Sw_P_z) and (Sw_Q_z) and form aSw_R_z ($Sw\_R_z = Sw\_P_z \cup Sw\_Q_z$) notation. Execute a non-dominated sequence to z and recognize various fronts: $F_p, p = 1,2,\ldots,$ and so on.

Phase 2. Set novel swarm Sw_P_{z+1} = 0. Set counter . Till $\left|Sw_{P_{z+1}}\right| + \left|F_p\right| < N,$ execute $Sw_P_{z+1} = Sw_P_{z+1} \cup F_p$with $p = p + 1$.

Phase 3. Execute the Crowding-sort process on the final frontier that could be totally allocated in the residual slots stay in Sw_P_{z+1} including the most extensively spread ($N-|Sw\_P_{z+1}|$) outcomes by utilizing the crowding distance values in the arranged F_p to Sw_P_{z+1}. Such processes are dependent on the crowding distance metric (Crowd_d_p), which is described in the following sections.

Phase 4 .Generate a new children swarm population (Sw_Q_{z+1}) obtained from swarm population Sw_P_{z+1} by utilizing position as well as velocity swarm equations.

From above technique, it is noted that each outcome have 2 parameters: a non-dominated rank (r_p) which are non-dominated anywhere the outcome is present, with local (Crowd_d_p) that are measure of the search space surrounding the result and are not taken with some other population result.

Estimate of Crowding Distance Metric (Crowd_ $\boldsymbol{d_p}$).

Crowd_ d_p is estimation of the density of outcomes around the exact solution that goes to a frontier (F) of the swarm population arranged in non-domination levels. To obtain these metric, the average distance of 2 outcomes on each side of result is occupied. The distance allocated processes are explained under step by step procedure.

Step Crw_1. Identify the number of results in F as x = |F|. To every p -outcome set, initially allocate Crowd_$d_p = 0$.

Step Crw_2. To every objective operation $y = 1,2,\cdots,Y$, arrange the set of worse direct their objective operation values (f_y).

Step Crw_3. For $y = 1,2,\cdots,Y$, allocate a huge distance to edge results: $Crow\_d_{x_1^y} = Crow\_d_{x_X^y} = \infty$, with to every other solutions $q = 2$ to ($x - 1$), allocate

$$Crow_{d_{x_q^y}} = Crow_{d_{x_q^y}} + \frac{f_y^{\left(x_{q+1}^y\right)} - f_y^{\left(x_{q-1}^y\right)}}{f_y^{mx} - f_y^{mn}} \quad (5)$$

The index x_q indicates the outcome index of -th member as arranged record. Accordingly, to some objective, the indexes x_1 as well as x_X indicate a smallest and maximum objective operation values, correspondingly. The attributes f_y^{mx} and f_y^{mn} could be set as highest as well as lowest population values of -th objective operation. To show the above mentioned process, Fig. 1 shows the schematic analysis of the elitist non-dominated arranging mechanism with crowding distance arranging method to work growth.

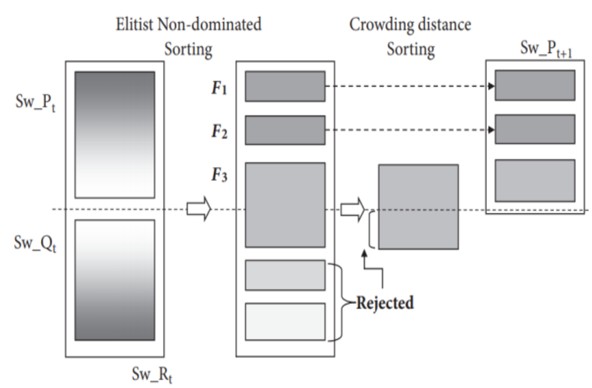

Fig. 1. Elitist non-dominated and crowding distance sorting process.

The basic DI-PSO Pseudo code is written as pursues:

Start

Initialize swarms

Assess fitness and set leaders$\left(\mathrm{P}_{\mathrm{p_GenBest,q}}^{\mathrm{n}}\right)$

Keeps in a leader pool

Recognize the top best leader over Crowd_d_p .quality measure

$\mathrm{K} = 0$

While(Kmx)

For each particle in$\left(\mathrm{Sw_P}_{p,q}^{z}\right)$ do (to obtain$\mathrm{Sw_Q}_{p,q}^{z}$)

Choose leader in the leader pool ($\mathrm{P}_{\mathrm{p\_GenBest,q}}$)

Update velocity and its position

Adopt auto-adaptive mechanisms and operators

Assess fitness

Update $P_{p\_\mathrm{best,q}}$

End For

With ($\mathrm{Sw\_P}_{p,q}^{z}$ and $\mathrm{Sw\_Q}_{p,q}^{z}$) do

Elitist Non-dominated Sorting
Crowding distance Sorting
Obtain Sw_P^{z+1}
End with
If Inactive then do
Adopt exploration dynamic operator
Elitist Crossover Operator
End do
Update the top best into the external archive $K = K + 1$.
End While
Return Results
End

It could be examined that the initial phase are the swarm initialized. Next, the group of leaders are also initialization through the non-dominated swarm particles. These set of leaders are stored in exterior file known as leader pool. Afterwards, the parameters are computed to every particle with leads to choose the optimal solution. In every creation of particle, a leader is chosen with fight are executed. Then the auto-adaptive mechanisms discussed over are executed. Next, the particle is estimated and its equivalent $P_{p\_best,q}$ is informed. A novel particle returns $P_{p_{best},q}$ its particle generally if the particles are dominated or if both are incomparable. Behind every particle has been informed, the group of leaders are informed, moreover. At last, the quality measures of the group of leaders are recomputed. These methods are frequent to particular fixed number of iterations.

IV. PERFORMANCE VALIDATION

The performance of the proposed model has been investigated in terms of network bandwidth, latency, response time and energy consumption. The performance of the proposed technique has been evaluated in Fog computing environment using iFogSim toolkit. Fig. 2 explains the components involved in the automation of smart homes in a simulation platform by the use of iFogSim toolkit. A variety of sensing devices are employed for controlling diverse actions like light, voltage, motor speed, room temperature and security of smart home.

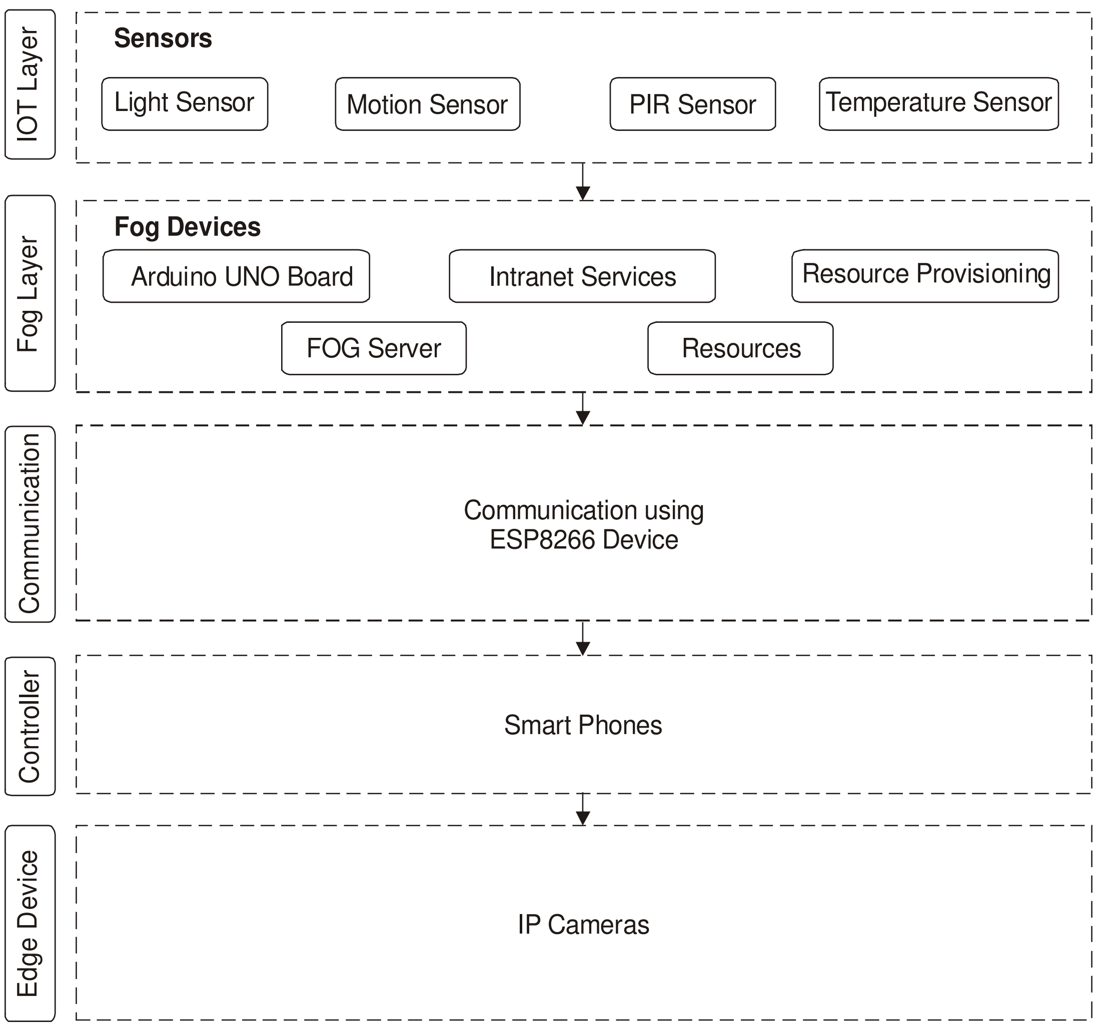

Fig. 2. Interlink of Components in Smart Home Automation with iFogSim Toolkit.

Fig. 3 depicts the network bandwidth analysis of several techniques under changing number of operations. The figure clearly stated that the VRP model offered ineffective resource allocation and exhibits maximum network bandwidth requirement.

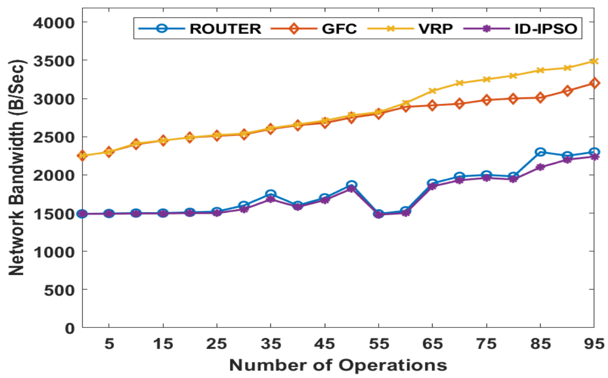

Fig. 3. Network Bandwidth analysis.

Then, the GFC model showed slightly better resource allocation and exhibits slightly lower network bandwidth requirement. Next to that, the ROUTER model [3] offers better resource allocation and minimum network bandwidth requirement over the compared methods. But, the ID-IPSO model offered effective resource utilization and better network bandwidth requirement over the related techniques is important manner. For instance, under the maximum operation of 95, the VRP method requires a maximum network bandwidth of 3400B/s. Next, the GFC model offered slightly lower network bandwidth of around 3200B/s. Then, the ROUTER model offered near optimal results with the minimum network bandwidth of 2350B/s whereas the presented ID-IPSO model shows minimum bandwidth requirement of 2250B/s respectively. This value ensured the betterment of the ID-PSO model in terms of network bandwidth utilization.

Fig. 4 shows the latency analysis of several techniques under changing number of operations. The figure clearly stated that the VRP model offered ineffective resource allocation and exhibits maximum network latency.

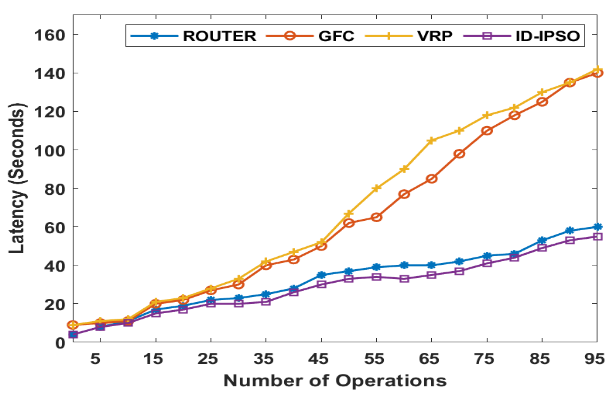

Fig. 4. Latency analysis.

Then, the GFC model showed slightly better resource allocation and exhibits slightly lower network latency. Next to that, the ROUTER model offers better resource allocation and minimum network latency over the compared methods. But, the ID-IPSO model offered effective resource utilization and better network latency over the related techniques is important manner. For instance, under the maximum operation of 95, the VRP method requires a maximum latency of 142s. Next, the GFC model offered slightly lower latency of around 140s. Then, the ROUTER model offered near optimal results with the minimum latency of 60s whereas the presented ID-IPSO model shows minimum latency of 38s respectively. This value ensured the betterment of the ID-PSO model in terms of network latency.

Fig. 5 depicts the response time analysis of several techniques under changing number of operations. The figure clearly stated that the VRP model offered ineffective resource allocation and exhibits maximum response time. Then, the GFC model showed slightly better resource allocation and exhibits slightly lower response time. Next to that, the ROUTER model offers better resource allocation and minimum response time over the compared methods. But, the ID-IPSO model offered effective resource utilization and better response time t over the related techniques is important manner. For instance, under the maximum operation of 95, the VRP method requires a response time of 24s. Next, the GFC model offered slightly lower response time of around 19s. Then, the ROUTER model offered near optimal results with the minimum response time of 2s whereas the presented ID-IPSO model shows minimum response time of 1s respectively. This value ensured the betterment of the ID-PSO model in terms of network response time.

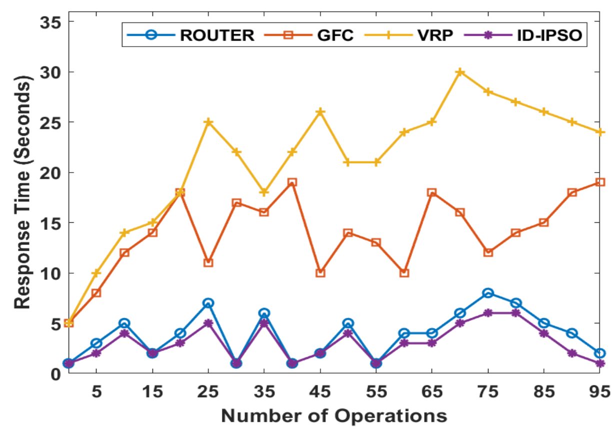

Fig. 5. Response time analysis.

Fig. 6 depicts the energy consumption analysis of various methods under varying number of operations. The figure clearly stated that the VRP model offered ineffective resource allocation and exhibits maximum energy consumption. Then, the GFC model showed slightly better resource allocation and exhibits slightly lower energy consumption. Next to that, the ROUTER model offers better resource allocation and minimum energy consumption over the compared methods. But, the ID-IPSO model offered effective resource utilization and better energy consumption over the related techniques is important manner. For instance, under the maximum operation of 95, the VRP method requires a maximum energy consumption of 175kWh. Next, the GFC model offered slightly lower energy consumption of around 174kWh. Then, the ROUTER model offered near optimal results with the minimum energy consumption of 120kWh whereas the presented ID-IPSO model shows minimum energy consumption of 115kWh respectively. This value ensured the betterment of the ID-PSO model in terms of energy consumption.

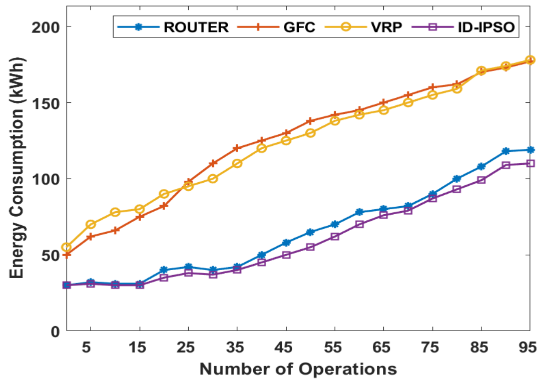

Fig. 6. Energy Consumption analysis.

V. CONCLUSION

This paper has devised an efficient fog computing based resource allocation technique using ID-PSO algorithm to optimize the allocation of resources. This paper enhances the traditional PSO algorithm by including the auto-adaptive strategies in a dynamic way for improving the exploration/exploitation exchange as well as variety of presented model. It eliminates the PSO algorithm from trapping into local minima. The simulation takes place in the automation of smart homes in a simulation platform by the use of iFogSim toolkit. The presented ID-IPSO model shows minimum latency of 38s, minimum bandwidth requirement of 2250B/s, and minimum response time of 1s and minimum energy consumption of 115 kWh under the presence of 95 operations.

VI. FUTURE SCOPE

In future, the ID-IPSO model can be deployed in real time platform.

Conflict of Interest. The author does not have any conflict of interest.

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