2024, 21(5 Special Issue): 1811-1826
https://doi.org/10.21123/bsj.2024.10551
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Hybrid optimized data aggregation for fog computing devices in internet of things

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ICCDA2023: International Conference on Computing and Data Analytics 2023.

Received 28/12/2023, Revised 22/04/2024, Accepted 24/04/2024, Published 25/05/2024

Abstract

In the recent few years, the applications using Internet of Things (IoT) are becoming extremely important as they facilitate continuous and seamless interactions among humans and devices in order to improve the quality of life. With the increase in the devices used in an application for smooth and efficient operations, the amount of data generated is high. Today, fog computing has been emerging as an extended version of the cloud infrastructure that provides highly scalable services that are latency-aware to the end devices that are geographically distributed. By adding the fog layer to the cloud computing paradigm, Quality of Service (QoS) can be improved in delay-sensitive and in time-critical applications. Owing to the increase in deploying fog networks on a large scale, the efficiency of energy can become a very important issue in the paradigm of fog computing. This can bring down service costs and further protect the environment. There has been plenty of research that was conducted for reducing consumption of energy in Wireless Sensor Network (WSN) and fog computing, primarily focusing on the optimization techniques. This was to enhance energy conservation. In this work, a new and novel hybrid optimization technique based on TABU Search (TS), Particle Swarm Optimization (PSO), and River Formation Dynamics (RFD) algorithms were proposed. The Hybrid RFD-TS, along with a hybrid RFD-PSO technique, was in the solution space search used for the local optimum, which is avoided. The experimental results demonstrated the efficacy of the proposed met.

Keywords: Cloud Computing, Clustering, Energy Efficient Heterogeneous Clustering Algorithm (EEHCA), Fog Computing, Security, Internet of Things (IoT), Metaheuristic Algorithms, Wireless Sensor Network (WSN).

Introduction

Internet of Things (IoT) is a data network made up of the objects like actuators, sensors, and radio-frequency identifiers linked by the Internet. Over a period of time, the IoT has been receiving plenty of attention owing to its capacity of being able to interact and also execute certain tasks either

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together or even react to the events. The key traits driving the IoT are Security, Heterogeneity, Sensing, Enormous Nature, Dynamic Scale, Connectivity, and Intelligence. The features mentioned above have been contributing to the effective implementation and the use of IoT in all applications and information systems. All collected work has demonstrated that the IoT that was implemented in different fields resulting in the development of intelligent health, infrastructure, smart buildings, intelligent homes, intelligent energy, and smart cities [1] .

Owing to the limited number of constraints of the IoT, there are several real-time applications like healthcare that need higher bandwidth and power of processing. Maintaining storage and processing the large amount of data locally may not be viable. Thus, there is a need for external storage space and processing units to extract the required information from the data. Thus, the cloud has been linked to the IoT devices to store and perform analysis of data in an efficient manner. Processed data are then acknowledged according to the user requirements. With the increase in the number of requests of the cloud, there is congestion that has been created to the network owing to resources and their centralization. Owing to such reasons, the cloud network may not always be a suitable candidate for applications that are time-critical. To manage the issues mentioned, researchers can propose a new paradigm known as fog computing [2].

Fog computing has been built in the form of an extended version of cloud computing that meets the requirements of IoT. Generally, these fog nodes will be distributed inside the vicinity of the user, and this will reduce the latency by establishing adjacent and localized connections. Therefore, fog devices can have many advantages in comparison to cloud computing, like resources of computation, power supply, and communication resources. Furthermore, these fog devices can create challenges to designing that can achieve response requirements. Fog computing has been implemented in the form of a distributed computing infrastructure to provide elastic resources by means of bringing the services to devices that are located close to the end-user. Computing has been directly permitted at the edge of the network and is then transmitted to the infrastructure of the core data centre. All raw data are processed with intermediate results being transmitted to achieve the needs of the bandwidth and completion time [3,4].

Wireless Sensor Networks (WSN) is largely used as the acquistion network for the IoT application. It contains task-specific sensors for measuring various aspects of the environment, such as temperature, motion, humidity or medical sensors for measuring pulse, blood pressure and so on. Further, it can provide some solutions to various challenging problems like safety monitoring of health, buildings, wildfire, battlefield, and wildlife. A primary component of the WSN can be the sensor mote that consists of microprocessor, sensors, and wireless transceivers and is powered by batteries [5]. Security has become a vital aspect in the applications of the WSN. Implementing various security policies can be a challenging and complex issue owing to the constraints on the resources of the nodes. There are some short-distance transmissions capable of reducing certain threats to security, and at the same time, there can be some risks that are faced, especially in aspects like wormhole attacks, flooding, replaying message altering, and spoofing. Thus, it becomes important to ensure confidentiality, integrity, protection, freshness, and authenticity of data.

To ensure secure communication in the WSNs environment [6], there are some efficient cryptographic algorithms that are needed. It may be ideal to select an efficient and suitable cryptographic algorithm that has ideal power consumption, storage, and speed of operation. But as each of these algorithms that are applied to the WSNs has specific advantages, it may be crucial to ensure the cryptographic algorithm is well-suited for all types of environments of the WSN. Advanced Encryption Standard (AES) is one type of cryptographic algorithm that has been defined by the National Institute of Standards and Technology (NIST) in the year 2001 as the Federal Information Processing Standard (FIPS) 197. This was employed by the federal government agencies in the US. It refers to a symmetric block cipher algorithm that was developed using the Rijndael method for encrypting and decrypting information with the same key. Unlike the Rijndael, which can handle larger block sizes or key lengths, the AES is capable of encrypting or decrypting about 128-bit blocks with 128, 192, or 256-bit keys [7].

Optimization techniques can work in various fields like WSN, Neural Network, Artificial Intelligence, and data mining. The TS algorithm is one type of meta-heuristic algorithm that is loosely connected to the concept of evolutionary computing. It is capable of tackling problems that are NP-hard such as combinatorial optimization problems. The TS algorithm can bring down the criticality of certain regions within the search space by using this approach. Different intensification and diversification methods have been applied. It is based on a certain specific type of problem that the solution can be determined as some may provide better results within the same set. The TS makes use of both short-term and long-term memory that can result in intensification and diversification. Also, aspiration criteria may be employed in the process of optimization [8]. The TS algorithm had been initiated to overcome both local minima and maxima and was called the local optima. There have been various methods that were employed to overcome this problem of local optima. During the time of the search, there was a drastic change that was provided to reduce this problem. For the purpose of this work, the TS, RFD-TS, and RFD-PSO that were used for WSNs and IoT-based fog computing were used. The remainder of the investigation has been organized in the manner mentioned below. All related work and methods used were discussed in Sections 2 and 3. The simulation results were presented in Section 4. Section 5 concluded the work.

Related works

The further work models IoT service requests and their scheduling which was a problem of optimization with integer programming that minimizes the latency of service requests. The problem of scheduling by nature is NP-hard, and therefore, they may be inadequate for problems of a larger size. Aburukba et al.,[9] had introduced a new and customized implementation of the Genetic Algorithm (GA) for the IoT requests. The GA has been tested within a simulation environment that is further evaluated and compared with other techniques like Waited-Fair Queuing (WFQ), Round Robin (RR), and Priority-Strict Queuing (PSQ). The experiments have shown that there was an overall latency of the approach, which was 21.9% to 46.6% compared to the other algorithms. Dar et al.,[10] attempted to reduce the time taken for investigating the problem of multi-node, multi-user, and multi-task offloading. The process of task offloading for both task and fog nodes had been modelled. The time for total task completion was built, and the optimization with the constraints was generated. This could be NP-hard and challenging to solve using traditional methods. Lastly, an Improved Differential Evolution (IDE) algorithm was employed to resolve the problem of offloading. The simulation proved that the performance was good and could shorten the time taken for completion of tasks when compared to the other algorithms.

Tellez et al.,[11] had proposed a simple TS method that was employed for optimal load balancing to be made between the fog and cloud nodes for resource constraints. The primary goal in using the TS was that in the case of online computations, the layers and tasks received had to be processed. The work also took into consideration the bi-objective cost function, in which the first one was the cost of computation processing fog nodes and the other for the cloud nodes. At the time of optimization, the convex combinations for the objective functions were employed to reduce the problem of optimization to cases that were mono objective. The experimental tests were performed

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using synthetic scenarios of the tasks that had to be executed. The experiments demonstrated that using the proposed techinque with memory usage, the cost of computation and load balancing can be minimized. Ghobaei-Arani et al.,[12] had proposed a new task scheduling appraoch that was based on the moth-flame optimization that assigned a set of tasks that were optimal to the fog nodes. This was done in order to meet the quality of service of the Cyber-Physical System (CPS) applications to ensure the total time taken for task execution is reduced. The reduction of transfer time and task execution will be the objective functions. Experiments demonstrated that the proposed method ensured a lower time of execution in comparison with the other algorithms.

Kumar J, & Saxena V., [13] had presented the quality-of-service composition method that was based on Multi-Population GA (MPGA), IoT-Cloud architecture, and Fog-IoT computing. This resulted in the use of a 5-layered architecture that was implemented using a Fog computing system which was the transport layer. This work focused on the transport layer that was further divided into four different sub-layers, which are storage, security, pre-processing, and monitoring. Next, the work further implemented a new MGPA that was based on the QoS model in which the authors also considered seven different dimensions of the QoS such as location, availability, security, reputation, reliability, response time, and cost. The results of the experiment proved that there had been excelled results for the MPGA based on execution time and fitness that could handle an ambulance emergency study case. The problem of resource management was NP-hard, and therefore, Ren et al.,[14] had proposed a new powerful hybrid algorithm to manage resources in fog computing that was with the GA and the Ant Colony Optimization (ACO). The GAs has been found to be computationally expensive as they tend to have some problems, such as not being able to obtain optimal solutions. For this, the speed of convergence and precision may be optimized using the ACO algorithm. Therefore, there can be some powerful feedback pros to the ACO on the rate of convergence. This algorithm employed the universal investigation power of the GA and was further transformed into the ACO primary pheromone. The algorithm also outperformed the GA and the ACO.

Methodology

Energy efficiency can be viewed as the most crucial issue in the WSN as it has a limited range of transmission, the ability to process, energy storage, and communication bandwidth. A sensor network that is homogeneous consists of resource-constrained devices that are tiny with similar hardware capabilities [15]. Its functionality helps in gathering sensed data and forwarding the same to a central location. Research focuses on increasing the lifetime of the network by means of designing energy-efficient protocols distributed evenly among the sensor nodes. There is also a heterogeneous sensor network that employs a varied range of devices that can help in achieving global goals. Clustering includes grouping of sensor nodes and selecting of Cluster Heads (CH) [16]. During the time of transmitting data, the CH gathers all the data from the nodes in the cluster, performs data aggregation before they are sent to the sink. Here, an Energy Efficient Heterogeneous Clustering Algorithm (EEHCA) has been presented. In this section, the methods such as TS, RFD, RFD-TS, PSO, and RFD-PSO have been discussed.

Tabu Search (TS) Algorithm

The TS refers to a meta-heuristic guiding local heuristic search processes in order to explore the entire solution space outside their local optimal area. In TS, the local search employs a strategy that can modify S (x) with the progress in search by replacing it with any other neighborhood S*(x). This can further guide any local neighborhood search process that can reach a solution which can be x’ $\in$ S(x) from a solution x $\in$ X in an iterative manner by means of an operation wherein certain stopping criteria are met. In this, X can be the set of feasible

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solutions where $S(x) \subset X$ can be the related neighborhood for a solution x. The TS moves to the acceptable neighbour with every iteration, which will be the case even if it results in an objective function deteriorating. This is unlike the case of the hill-climbing method in which the neighbour solutions are improved with functional values that are given [17].

The primary aspect of the TS approach was to make use of special memory structures that help in determining S*(x), and therefore, will organize a way that helps in exploring space. To avoid getting stuck in a space, the TS will further forbid some moves from them being re-initiated for a certain period using the short-term memory structure. This is further taken advantage of by designating the selected attributes that appear in the recently visited solutions as TABU-active. The TABU tenure is the number of iterations during which the attribute has been preserved. Additionally, the ambition criteria are used by the TS as a tool that overrides the TABU's status, allowing for flexible performance.

River Formation Dynamics (RFD) Algorithm

An RFD algorithm and its overview will be given below. There is an amount of soil that has been assigned to every node, and this will drop with movement eroding paths (by taking sediment from their nodes). This may also include depositing the carried sediment (thereby increasing node altitude). The likelihood of choosing the next node depends on the gradient's reduction, which is correlated with the real elevation difference between the node and its neighbor. Initially, a flat environment is produced, with node elevations being identical unless when the procedure keeps the height constant at zero. Since these drops will be placed on the first node, further site research may be possible in order to identify the best path. For each step, there may be groups of drops that traverse sequentially and perform an erosion of the nodes visited [18].

In the RFD, the first step is initializing the nodes, that can define a new set of solutions. On initialization of drops, a suitable number of drops are positioned on the initial nodes. The algorithm will be executed until such time the final condition is met. This will mean all drops continue in the same path. Also, to lessen the actual time taken to compute this, there can be a top limit on the various iterations that have been introduced with the condition that verifies the solution, which is not improved by the last set of *n* iteration. The drops move slowly toward their objective until they can vanish and begin a new in the subsequent iteration. The likelihood that the drop k will stay in node i and that node j will be chosen as the next is Eq. 1

$$P_k(i,j)=\begin{cases}\dfrac{\text{gradient}(i,j)}{\text{sum.}(d_j)^{\propto}}, & for\ j\in V_k(i)\\ \dfrac{\omega/|\text{gradient}(i,j)|}{\text{sum.}(d_j)^{\propto}}, & for\ j\in U_k(i)\\ \dfrac{\delta}{\text{sum.}(d_j)^{\propto}}, & for\ j\in F_k(i)\end{cases} \qquad 1$$

Wherein, $V_k(i)$, U_k *(i)* and $F_k(i)$ refers to the set of neighbors that have higher, lower and flat altitude, respectively. Neighbors have been chosen from the surrounding nodes of (up to 8), and this excludes the ones in the cells that with an obstacle. A gradient is the difference in altitude between two consecutive nodes, where ω and δ are specific coefficients with small, fixed values.

If it turns out to be ineffectual, the drop will evaporate carrying the same amount of silt as a drop that was lowered by a parameter. The path analysis (analyzePaths()) will determine an appropriate solution by evaluating how well it can carry out more erosion. This is carried out on the paths that are traversed by employing a subsequent node to lower each node's altitude to a gradient. The reduction is the best drop multiplied by the parameter for increasing convergence. The equation is given Eq. 2

$$\text{erosion}(i,j)=\begin{cases}\dfrac{\varepsilon V.gradient(i,j)}{(N-1).M.pathLength_k}, & for\ j\in V_k(i)\\ \dfrac{\varepsilon U}{|gradient(i,j)|.(N-1).M.pathLength_k}, & for\ j\in U_k(i)\\ \dfrac{\varepsilon F}{(N-1).M.pathLength_k}, & for\ j\in F_k(i)\end{cases} \qquad 2$$

Wherein, εV, εU, and εF refer to the parameters that are connected to certain groups of neighbours: they may have either a positive, negative

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or a flat gradient. $PathLength_k$ refers to the length of the path that is traversed by a drop. N and M refer to the number of nodes and the number of drops.

Particle Swarm Optimization (PSO) Algorithm

PSO based on social or cognitive aspects of nature useful in solving issues in engineering and computer science. They have entities called particles within a multi-dimensional search space where a particle indicates a feasible determination to the issue of multi-dimensional optimization. The fitness of each solution is dependent on the performance function when optimization is resolved [19].

A particle motion can be manipulated by using two different aspects through information obtained from iteration-to-iteration that accumulates within memory an optimal solution called the pbest, and from particle-to-particle. It then searches for better solution and negotiates using the area of search. The particle also accumulates an optimal solution that is attained using the particle, and this further finds an attraction which is called the gbest. In each iteration, the pbest and the gbest will be updated when they are improved. The process will persist and iterate in anticipation of the consequence that has been congregated. If not, a suitable solution may not be found under such limitations. It is possible to find optimal solutions using iteration once the PSO is set. By means of the fitness function decision, the particles will all have to be optimized, and their speed has to be determined by means of their flight direction and their distance. After this, for every iteration, two extremes are tracked, and the best particles will update themselves. The first will be the particle itself that finds an optimum solution which is P_{id}; another end will be the optimum result P_{gd}. And is in Eq. 3

$$v_{id}(t+1) = wv_{id} - c_1 r_1\left(p_{id} - x_{id}(t)\right) - c_2 r_2\left(p_{gd} - x_{id}(t)\right)$$

$$x_{id}(t+1) = x_{id}(t) - v_{id}(t+1) \qquad 3$$

The real number of iterations (t), the particle's speed (vid), the actual position of particle i (xid), the random numbers (r1 and r2) between 0 and 1, the acceleration factors (c1 and c2), and the weighting coefficient (w) are all expressed in Eq. 2.

Proposed Hybrid RFD-TS Algorithm

There are certain flaws in the real RFD algorithm that prevent it from working correctly in the given path generation problem. A lot of these coefficients make it difficult to tune an algorithm for a particular scenario. Nevertheless, for such complex environments, the rate of convergence is found to be small. Certain non-improving solutions that are approved for escaping from a local optimum are also allowed by the TS. A TABU list, which can be used in both continuous and discrete spaces, is used to accomplish this. When dealing with more difficult problems like scheduling, quadratic assignment, and vehicle routing, TABU search can yield routing solutions that, for the most part, outperform the previous best solutions.

The primary goal of hybridization was to advance the effectiveness of the basic individual algorithm that can expand search space, convergence, and local exploration. For improving the quality and convergence of the river drops in RFD, the hybrid RFD-TS approach is proposed. In this algorithm, the solutions for each drop will be part of the evolution. By using the TABU list, the TS algorithm can also enhance its ability of both local and global search. Employing the TS into the RFD for global information exchange or local deep search enhances the rate of convergence, accuracy, and local/global exploration [20].

The pseudo-code for the RFD-TS algorithm:

Start
Step 1: Initialization of the parameters
RFD algorithm
Step 2: Construction of a drop ***():***
Repeat
Move the drops
Erode the paths
Deposit the sediments
Until such time a complete assignment has been constructed

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TS algorithm:
While (termination criterion has not been met)
S: = best solution within the neighbourhood of S;*
If (Cost (S) < Cost (Best))
Best: = S;
EndIf
Update the TABU list;
EndWhile
Step 3: Analyse the paths and record the identified best solution
Step 4: Terminate if maximum number of iterations reached, else, go to Step 2
End

Fig.1 shows the flowchart for the hybrid RFD-TS algorithm

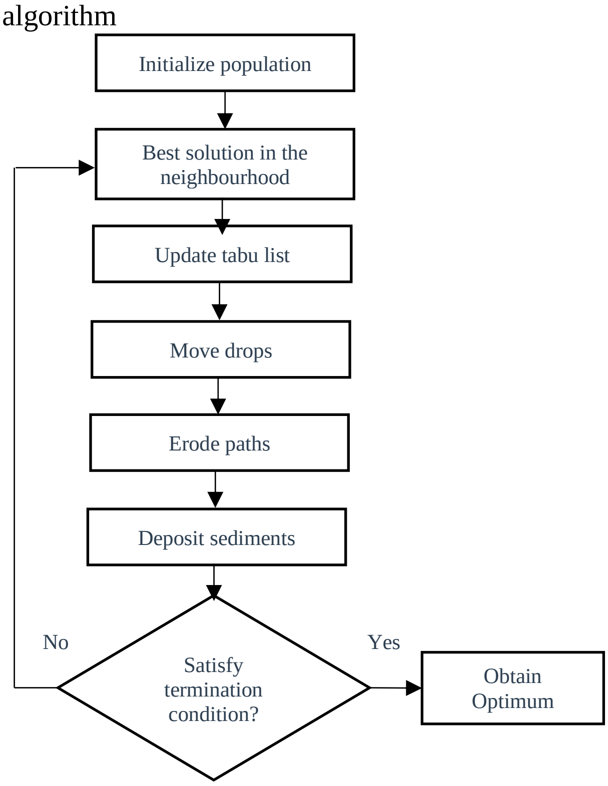

Figure 1. Flowchart for Hybrid RFD-TS Algorithm

Proposed Hybrid RFD-PSO Algorithm

The hybrid RFD-PSO algorithm is further introduced in this work. This algorithm has been changed so that exponential functions must be used to determine the formula for the next node's probability of transition. For a given problem, the efficiency of the algorithm can be influenced by a number of additional RFD coefficients. Tuning these values can be difficult at times [21]. You can get rid of this by altering the formula. It is also possible to include the distance from an objective node heuristic (as demonstrated by the A* algorithm). Based on two distinct coefficients, this was done: The exponent's base, or pBase, is also the coefficient of convergence tuning. dj is the Cartesian distance between node j and its destination.

$$P_k(i,j) = \frac{pBase^{gradient(i,j)}}{(d_j)^{\propto}} \Big/ total' \qquad 4$$

$$total = \sum_{l \in V_k(i) \cup U_k(i) \cup F_k(i)} \frac{pBase^{gradient(i,j)}}{(d_j)^{\propto}}$$

The probability values exhibit a uniform distribution, ranging from extremely low values for negative gradients to rapidly increasing values for positive gradients. Certain flat gradients have a fixed value assigned to them; in this case, it is 1. Making sure the exponent base value is adjusted for a particular scenario based on the rate of increase—which is the maximum gradient value and can be applied to erosion values—might be more logical.

Pseudo-code for the RFD-PSO algorithm:

Start

Step 1: Initialization of the parameters

RFD algorithm

*Step 2: Construction of a drop **()**:*

Repeat

Move the drops

Erode the paths

Deposit the sediments

PSO algorithm:

For every particle

Compute the fitness value

In case the fitness value > pBest

Set the current value to be the new pBest

End

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P-ISSN: 2078-8665 - E-ISSN: 2411-7986
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Select the particle having the best fitness value for all particles as the gBest

For every particle

Compute the particle velocity according to Eq.3

Update the particle position in accordance with Eq.3

Step 3: Analyse the paths and record the identified best solution

Step 4: Terminate if maximum number of iterations reached, else, go to Step 2

End

Fig. 2 depicts the flowchart for a hybrid RFD-PSO algorithm.

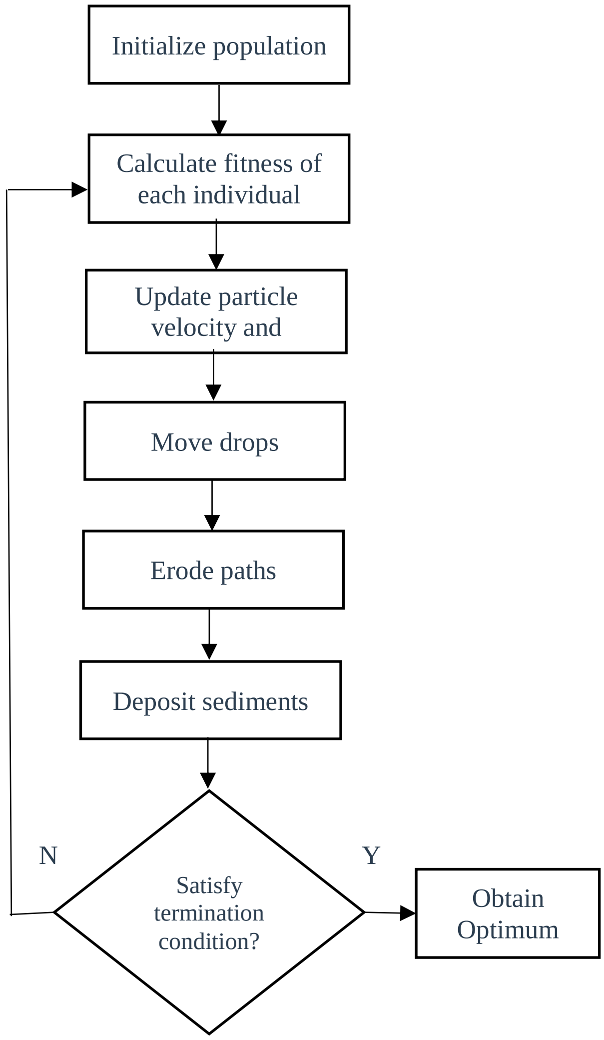

Figure 2. Flowchart for Hybrid RFD-PSO Algorithm

Results and Discussion

The MATLAB and Optimized Network Engineering Tool (OPNET) simulation tool is used for evaluating the algorithms. In this section, the 1000 sq. meter, BS location - Outside the network based on nearest FOG to the cluster and 3000 & 6000 nodes are used. The performance of EEHCA, TS, RFD-TS and RFD-PSO methods are evaluated. The round of nodes, residual energy (low, medium & high energy nodes), Packet Delivery Ratio (PDR), and the end-to-end delay are shown in Fig. 3 to Fig. 13.

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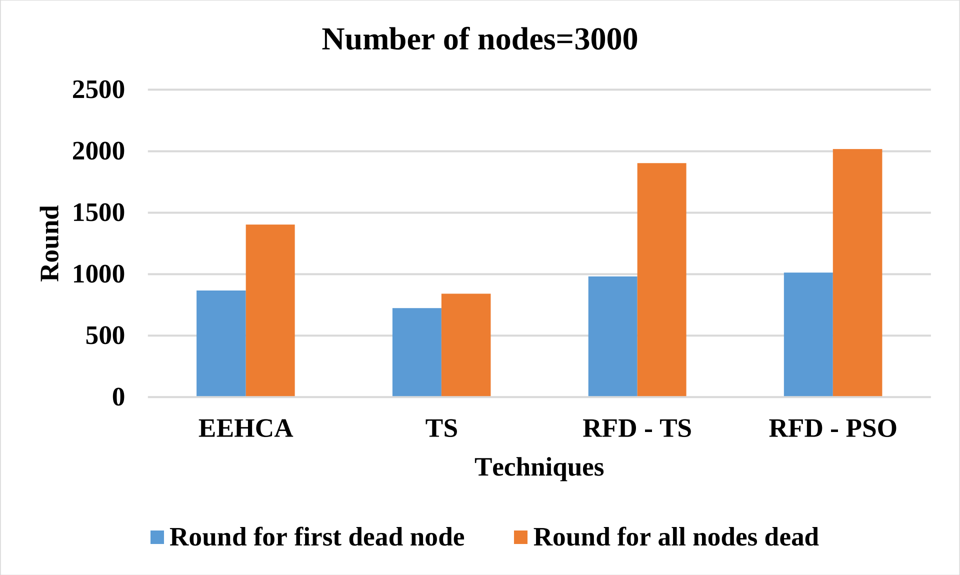

Figure 3. Round of nodes for RFD-PSO

From Fig. 3, it can be observed that the RFD-PSO has a higher round for the first dead node by 15.54% for EEHCA, by 33.31% for TS, and by 3.11% for RFD-TS, respectively. The RFD-PSO has a higher round for the all dead node by 35.95% for EEHCA, by 82.23% for TS and by 5.91% for RFD-TS, respectively.

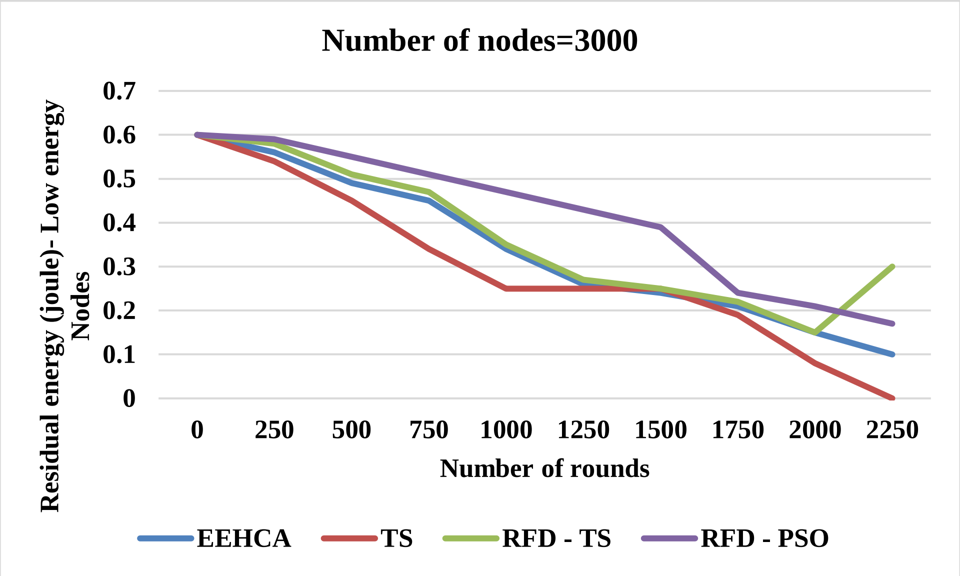

Figure 4. Residual Energy-Low Energy Nodes for RFD-PSO

From Fig. 4, it can be observed that the RFD-PSO has a higher average residual energy (low energy nodes-3000) by 20.1% for EEHCA, by 34.03% for TS and by 11.7% for RFD-TS, respectively.

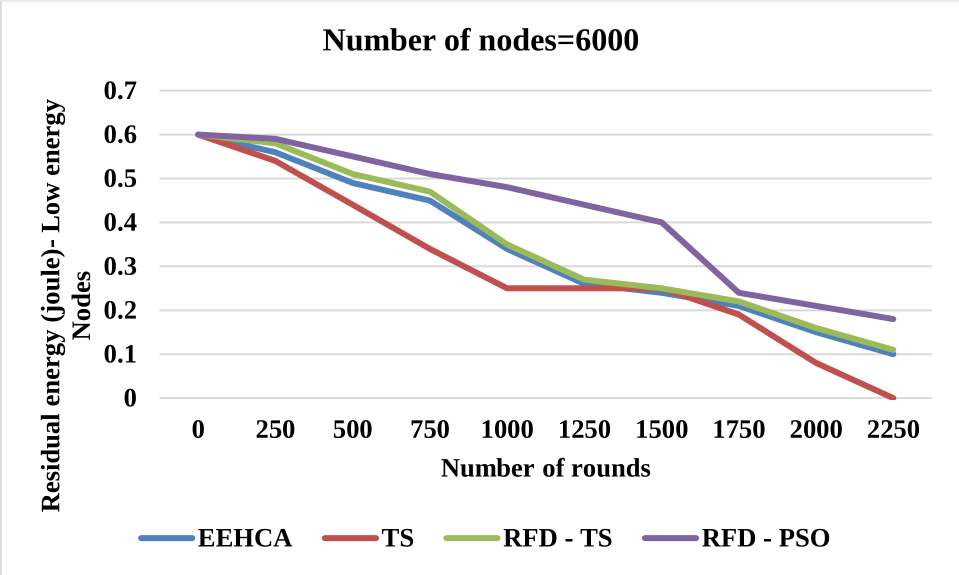

Figure 5. Residual Energy-Low Energy Nodes for RFD-PSO

From Fig. 5, it can be observed that the RFD-PSO has a higher average residual energy (low energy nodes-6000) by 21.05% for EEHCA, by 35.29% for TS and by 17.61% for RFD-TS, respectively.

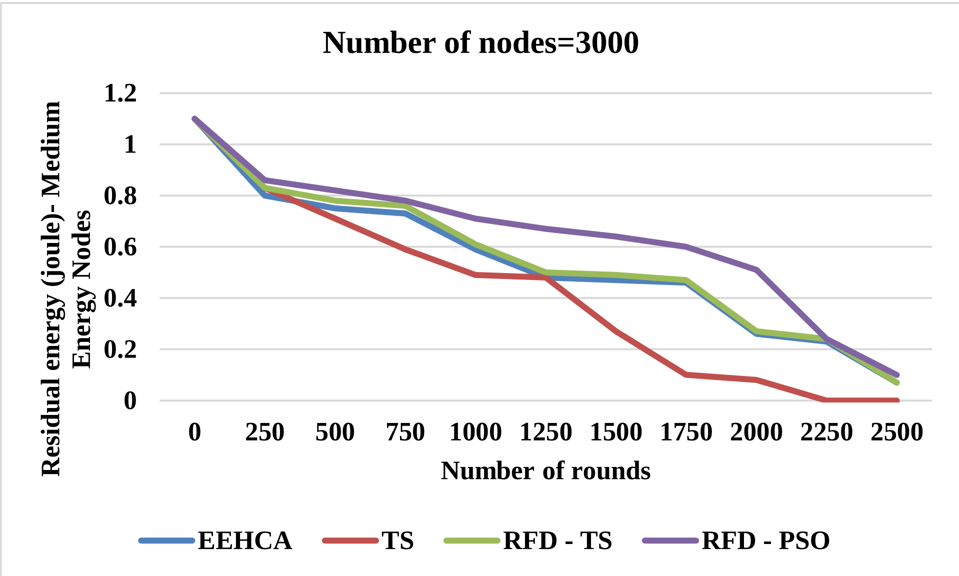

Figure 6. Residual Energy-Medium Energy Nodes for RFD-PSO

From Fig. 6, it can be observed that the RFD-PSO has a higher average residual energy (medium energy nodes-3000) by 16.81% for EEHCA, by 40.75% for TS and by 13.84% for RFD-TS, respectively.

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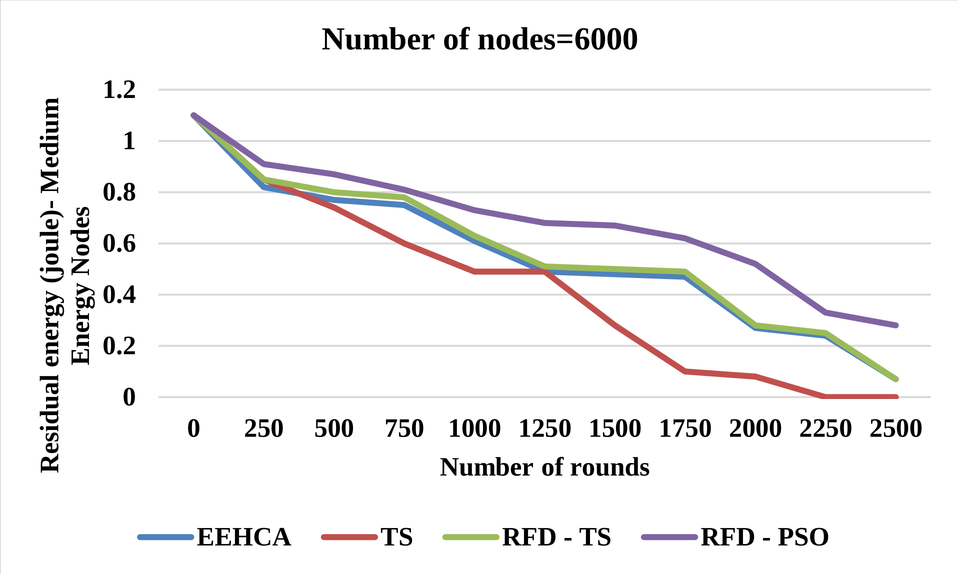

Figure 7. Residual Energy-Medium Energy Nodes for RFD-PSO

From Fig. 7, it can be observed that the RFD-PSO has a higher average residual energy (medium energy nodes-6000) by 21.33% for EEHCA, by 45.55% for TS and by 18.28% for RFD-TS, respectively.

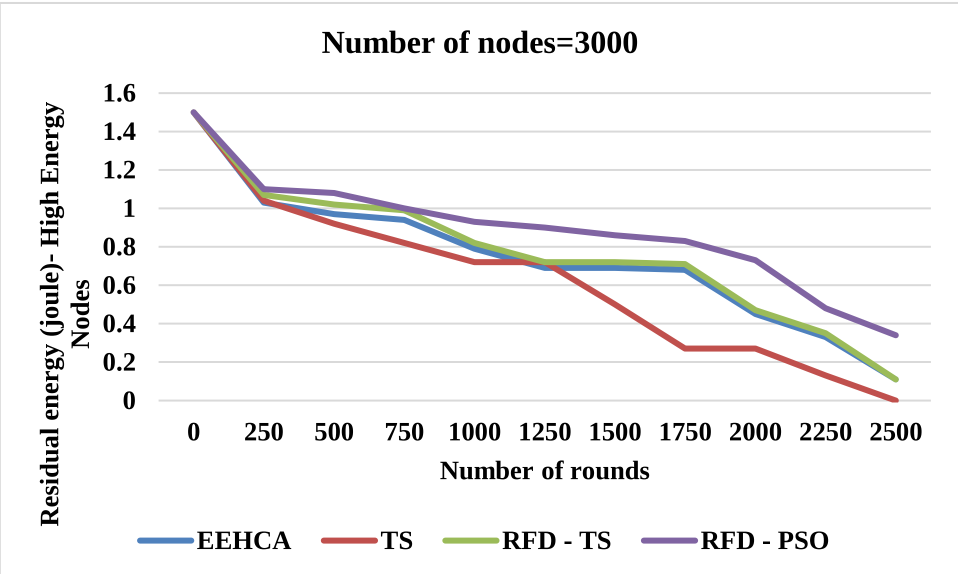

Figure 8. Residual Energy-High Energy Nodes for RFD-PSO

From Fig. 8, it can be observed that the RFD-PSO has a higher average residual energy (high energy nodes-3000) by 17.51% for EEHCA, by 34.37% for TS and by 13.93% for RFD-TS, respectively.

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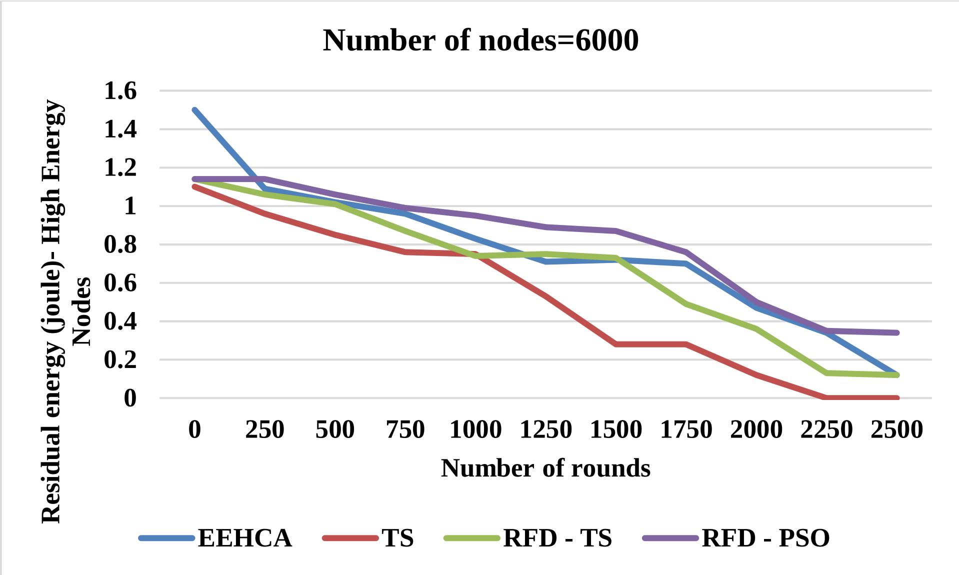

Figure 9. Residual Energy-High Energy Nodes for RFD-PSO

From Fig. 9, it can be observed that the RFD-PSO has a higher average residual energy (high energy nodes-6000) by 6.07% for EEHCA, by 45.96% for TS and by 19.4% for RFD-TS, respectively.

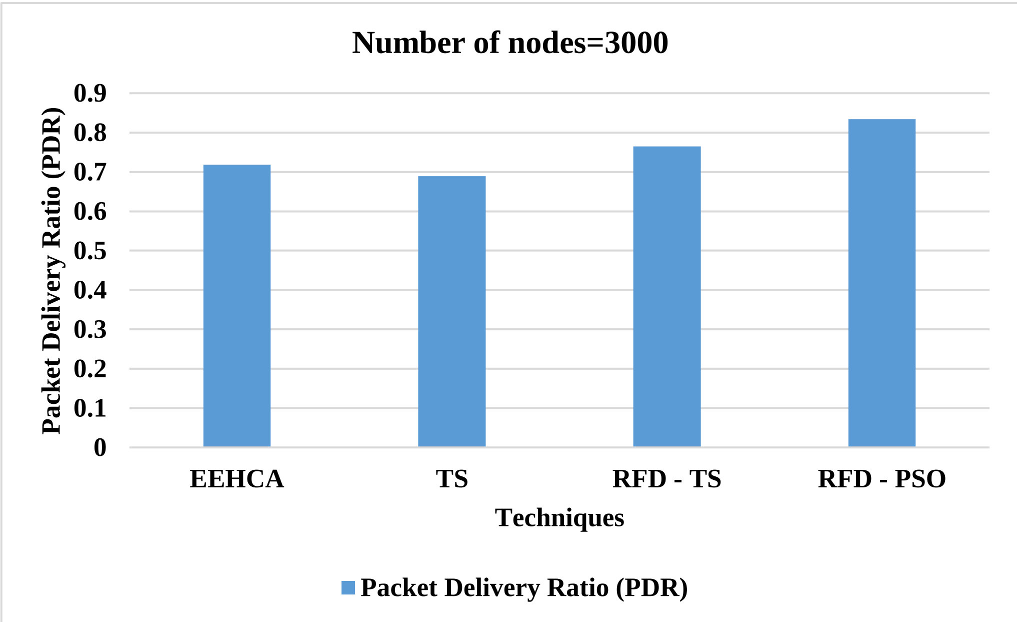

Figure 10. Packet Delivery Ratio (PDR) for RFD-PSO

From Fig. 10, it can be observed that the RFD-PSO has a higher PDR by 14.94% for EEHCA, by 19.03% for TS and by 8.71% for RFD-TS, respectively.

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https://doi.org/10.21123/bsj.2024.10551
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
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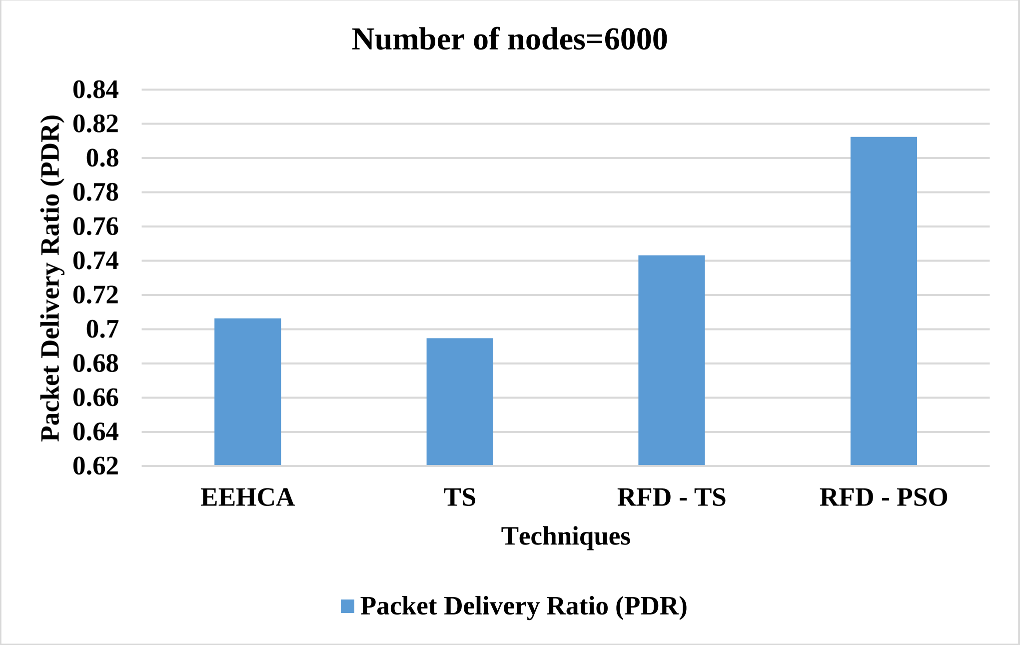

Figure 11. Packet Delivery Ratio (PDR) for RFD-PSO

From Fig. 11, it can be observed that the RFD-PSO has a higher PDR by 13.95% for EEHCA, by 15.61% for TS and by 8.89% for RFD-TS, respectively.

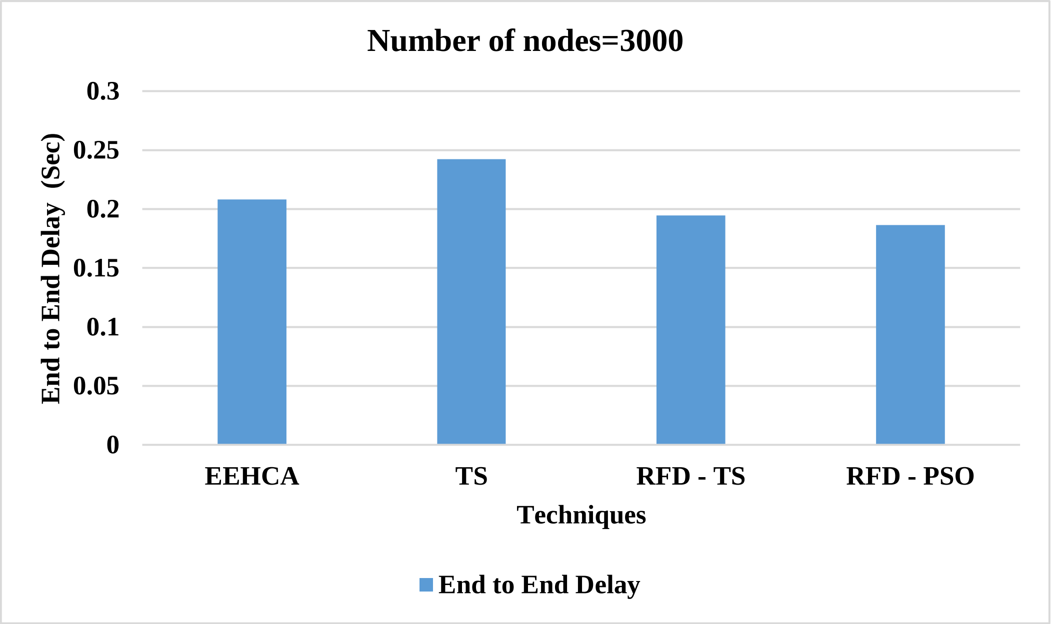

Figure 12. End to End Delay for RFD-PSO

From Fig. 12, it can be seen that the RFD-PSO has a lower end-to-end delay by 10.95% for EEHCA, by 26.03% for TS and by 4.25% for RFD-TS, respectively.

2024, 21(5 Special Issue): 1811-1826
https://doi.org/10.21123/bsj.2024.10551
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

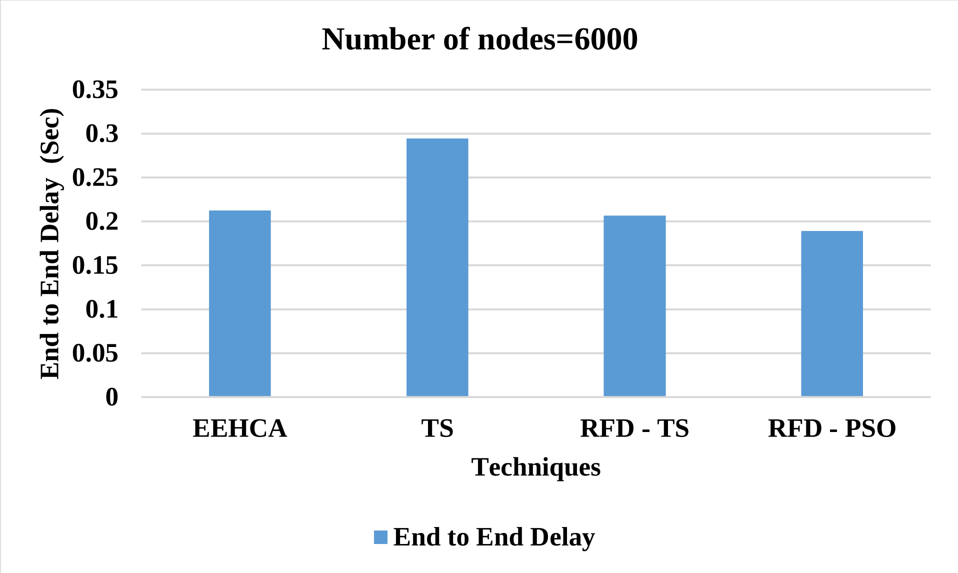

Figure 13. End to End Delay for RFD-PSO

From Fig. 13, it can be seen that the RFD-PSO has a lower end-to-end delay by 11.55% for EEHCA, by 43.5% for TS and by 8.88% for RFD-TS, respectively.

Conclusion

Large data is served by fog computing, which is thought of as an expanded form of cloud computing in the Internet of Things. Furthermore, fog computing can enhance computation, communication, and storage services to the network's edge. For the purpose of this work, the PSO, TS, RFD-PSO, and the RFD-TS were suggested. The TS algorithm was employed in order to reduce the problem of local optima during the time the other techniques of local search had been facing a similar problem. The RFD optimization algorithm was used to compute an optimal path within a certain specified time duration. The PSO is a technique of swarm intelligence that is based on a population performing the process of optimization aiming to obtain a fitness function. These hybrid algorithms (RFD-TS and RFD-PSO) were introduced by a small updating strategy to enhance velocity, factors of acceleration, and obtaining optimal individual locations. Here the PSO strategies were employed to optimize both the position and the velocity of the RFD along with the TAB list (or the neighborhood solution) that was used for optimizing the RFD. Results had proved that the RFD-PSO had a higher PDR (of 3000 nodes) by about 14.94% for the EEHCA, by 19.03% for the TS, and by 8.71% for the RFD-TS, respectively. Furthermore, the RFD-PSO had a higher PDR (of 6000 nodes) by about 13.95% for the EEHCA, by 15.61% for the TS, and finally, by 8.89% for the RFD-TS, respectively.

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Technology and Applied Sciences, Oman.

Authors' Contribution Statement

Conception, design & revision M.J. , Acquisition of data, proofreading S.M. , Analysis A. D. , Interpretation S.G.; Drafting the N.S. R.

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تجميع البيانات الهجين الأمثل لأجهزة الحوسبة الضبابية في إنترنت الأشياء

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الخلاصة

في السنوات القليلة الأخيرة، أصبحت التطبيقات التي تستخدم إنترنت الأشياء ((IoTفي غاية الأهمية لأنها تسهل التفاعلات المستمرة والسلسة بين البشر والأجهزة من أجل تحسين نوعية الحياة. مع زيادة الأجهزة المستخدمة في التطبيق لإجراء عمليات سلسة وفعالة، أصبحت كمية البيانات التي يتم إنشاؤها عالية. اليوم، ظهرت حوسبة الضباب كنسخة موسعة من البنية التحتية السحابية التي توفر خدمات قابلة للتطوير بدرجة كبيرة وتدرك زمن الاستجابة للأجهزة النهائية الموزعة جغرافيًا. ومن خلال إضافة طبقة الضباب إلى نموذج الحوسبة السحابية، يمكن تحسين جودة الخدمة ((QoSفي التطبيقات الحساسة للتأخير وفي التطبيقات الحرجة للوقت. ونظرًا لزيادة نشر شبكات الضباب على نطاق واسع، يمكن أن تصبح كفاءة الطاقة قضية مهمة جدًا في نموذج حوسبة الضباب. وهذا يمكن أن يخفض تكاليف الخدمة ويحمي البيئة بشكل أكبر. لقد تم إجراء الكثير من الأبحاث لتقليل استهلاك الطاقة في شبكة الاستشعار اللاسلكية ((WSNوحوسبة الضباب، مع التركيز في المقام الأول على تقنيات التحسين. وكان هذا لتعزيز الحفاظ على الطاقة. في هذا العمل، تم اقتراح تقنية تحسين هجينة جديدة ومبتكرة تعتمد على خوارزميات بحث TABU (TS)، وتحسين سرب الجسيمات ((PSO، وديناميكيات تكوين النهر (.(RFDكان Hybrid RFD-TS، جنبًا إلى جنب مع تقنية RFD-PSO الهجينة، في حل البحث الفضائي المستخدم للحل الأمثل المحلي، وهو ما تم تجنبه. وأظهرت النتائج التجريبية فعالية اللقاء المقترح

الكلمات المفتاحية: الحوسبة السحابية، التجميع، خوارزمية التجميع غير المتجانسة الموفرة للطاقة (EEHCA)، حوسبة الضباب، الأمن، إنترنت الأشياء (IoT)، خوارزميات ميتاهيرستية، شبكة الاستشعار اللاسلكية (WSN).