

## Sparrow Search Algorithm-based Resource Management in Internet of Things (IoT)

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### Abstract

**INTRODUCTION:** The principle of Internet of Things (IoT) completely concentrates on integrating heterogeneous entities for establishing seamless cooperation among virtual and physical entities. IoT has facilitated a paradigm shift of the Internet from collaborating networks to physical world interaction. The IoT devices are potent in sensing, processing, communicating and data storing that are derived from the physical world. The majority of the IoT applications are considered to be pervasive in characteristics and face huge challenges due to unattended IoT devices and constrained resources.

**OBJECTIVES:** The proposed Sparrow Search Algorithm-based Resource Management (SSARM) targets on the potential assignment of resources to gateways in an IoT environment with better establishment in maintaining the tradeoff between intensification and diversification. It concentrates on the reduction of total data transmission cost in the IoT environment.

**METHODS:** In this paper, Sparrow Search Algorithm-based Resource Management (SSARM) is proposed based on the inspired by the foraging, group wisdom and anti-predation characteristics of sparrow for potential assignment of multiple resources to gateways in IoT. This SSARM balances the degree of exploitation and exploration in the optimization search space to an acceptable level.

**RESULTS:** The simulation results of this proposed SSARM confirmed better throughput of 23.82%, reduced delay of 18.21% and minimized energy consumption of 20.28% when compared to the existing schemes.

**CONCLUSION:** This SSARM offers better accuracy in stability, convergence rate, precision in searching and preventing the value of local point of optimality.

**Keywords:** Internet-of-Things (IoT), Resource Allocation, Sparrow Search Algorithm, Gateways, Optimization search space

Received on 22 January 2021, accepted on 28 April 2021, published on 13 May 2021

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doi: 10.4108/eai.13-5-2021.169915

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### 1. Introduction

The rapid proliferation emerging in the domain of Internet of Thing (IoT) and its associated application has introduced a challenge to its users with respect to the scalable number of devices deployed in the environment [1]. The management of physical sensing resources, data formats and a large variety of protocols need to be handled with the objective to derive maximum merits

from the deployed equipments [2]. However, the process of provisioning and efficiently managing the IoT devices is cumbersome in most of the situations [3]. This management also in turn depends on the concept of resource sharing, resource pooling, elasticity characteristics and on-demand provisioning [4]. The IoT device resources are generally linked statically to particular applications and users as they necessitate huge efforts during their management, configuration and deployment [5]. Moreover, low utilization and high costs incurred during the management of resources also pose

another challenge that needs to be handled in a predominant manner [6]. For instance, a medical equipment is useful only to a smaller degree of measurements in a day that could serve as a vital information among the users [7]. In this situation, organizing the device resources into pools and providing their service based on the business model of Pay-As-You-Go is considered to be essential [8]. Moreover, the challenge in IoT resource management completely focuses on applying the paradigms of cloud computing to the domain of IoT that aids the users in allocating the interested device resources to the virtual pool of IoT devices [9].

At this juncture, the process of assigning the resources to the required gateway is considered to a NP-Hard problem [10]. Hence, intelligent metaheuristic approaches are considered to be ideal candidates that could be used for better allocation process when compared to the traditional Hungarian method of assignment [11-12]. Further, the contributed Sparrow Search Algorithm offers better stability, convergence rate, precision in searching and preventing the value of local point of optimality which motivates its use in the assignment problem of resources to gateways in IoT [13].

In this paper, Sparrow Search Algorithm-based Resource Management (SSARM) is contributed for assigning suitable resources to gateways in the IoT environment based on the characteristic group wisdom and foraging properties of sparrows. This proposed SSARM classifies the entire sparrow search agents into producers and scroungers sparrow search agents in order to balance the deviation between the intensification and diversification process. It is proposed with the objective of improving the performance in terms of searching precision, rate of convergence, stability and escaping from the local point of optimality. The simulation experiments of the proposed SSARM are conducted in terms of mean throughput, mean delay and energy consumptions for different service arrival rates and epochs of simulation.

The major contributions of the proposed SSARM are listed as follows.

- i) It is proposed for efficient mapping of optimal resources to gateways in the IoT environment.
- ii) It is proposed with the capability of balancing the degree of exploitation and exploration during the process of resource assignment.
- iii) It is proposed with the potential of improving stability and preventing the possibility of being trapped into a local point of optimality.

## 2. Related Work

Kim (2016) has proposed a mechanism for resource allocation based on Asymptotic Shapley value for dealing with the challenges faced in resource allocation in an IoT based network [14]. This scheme considers the merits of compliant game values to facilitate the reduction of the communication cost and delay involved. This model

utilises shape value for real-world application of the proposed bandwidth apportionment scheme for appropriate mapping at the gateway. The whole set of system resources are efficiently utilised and multimedia traffic services in a reactive IoT network are also enabled. It is seen that the model involves more energy and delay. Tsai et al (2018) have proposed a scheme that facilitates resource allocation in IoT based networks. The proposed Search Economics based Resource Allocation (SERA) focuses on the communication cost during the assignment of multiple resources to gateways [15]. SERA is based on the concepts of meta-heuristics and clustering for achieving a mapping between the gateways and resources. SEA and kNN algorithms are used for creating a potential assignment. It is found that the scheme offers better response time and consumes less energy in contrast to the prevailing resource allocation schemes. Nevertheless, this scheme does not offer better response time and throughput for varying service rates.

Gai & Qui (2018) have propounded Reinforcement Learning-based resource allocation scheme that supports efficient allocation of resources to existing gateways [16]. This scheme approves the merits of dynamic programming for probable distribution of resources in an IoT based network. It is combined with QoE for building the pre-determined and table that contains cost mapping to provision optimum resource allocation. It offers the benefits of content centric framework for refining resource distribution with reduced response time and delay. Nevertheless, the resources' accessibility rate can be improved. Chowdhury et al.(2019) have designed a scheme for efficient allocation of resources based on Deep reinforcement learning for dealing with the issues of resource scheduling and allocation for reactive user requests in the network with varying demands [17]. This model focuses on improving the efficacy in resource management so as to improve the throughput and response time. It is based on the learning approach that chooses the strategy of ideal resource provision for improving the network performance. It produces an optimal strategy that focusses on the decrease of energy consumption along with acceptable level of user satisfaction. It also handles the rapid drift in user demands. It supports the concept of adaptive learning for efficient utilization of resources. The proposed model involves reduced response time and energy in contrast to baseline schemes.

Sangaiah et al. (2020) have come up with a Heuristic Optimization Algorithm inspired based WOA (WOARM) for effective resource allocation that aids in attaining effective load balancing and reduced communication cost [18]. HOA includes Whale Optimization Algorithm (WOA) that focuses on the maximum limitations found in mapping resources into the gateway. It deals with finding an optimal solution that assists in launching effective mapping during resource allocation. WOA includes a joint hunting approach that is used by humpback whales. Karthick & Gomathi (2020) have propounded a resource allocation scheme that is based on Gray Wolf

Optimization (GWORM) [19]. It is flexible and scalable capable of allocating resources on a huge scale. It is proficient in dealing with the limits that represent increased overhead, analytical complication and slow conjunction of numerous IoT inputs. It is seen that the proposed GWO based scheme offers better results in contrast to the benchmarked schemes taken for investigation.

### Extract of the literature

The existing works of the literature is determined to possess the following shortcomings.

- i) Most of the existing works are either significant in exploitation or exploration, but not both during the process of assigning resources to gateways in IoT.
- ii) Majority of the existing approaches fail in establishing a balance between the local and global search during the resource allocation process.
- iii) The stability and precision involved during the process of resource allocation in the existing schemes still possess a room for improvement.

## 3. Proposed Sparrow Search Algorithm-based Resource Management (SSARM)

The proposed SSARM is an attempt to facilitate better assignment of resources to gateways with the objective to reduce the total data transmission cost. This resource allocation of IoT can be represented as an undirected graph  $G = (V_r, E_r)$  with ' $V_r$ ' and ' $E_r$ ' representing the gateway nodes and the IoT resource nodes and its possible assignment in a specific time. This problem of resource allocation can be expressed as shown in Equation (1).

$$RAP_{\text{Gateway\_Resource}} = \text{Minimize } T_{\text{DTC}} \quad (1)$$

Where, ' $T_{\text{DTC}}$ ' is the total cost of data transmission under the assignment of resources to the gateways in a specific time period.

### The assumptions considered in the proposed SSARM approach

The assumptions considered in the implementation of the proposed SSARM approach are listed as follows.

1. The producer sparrow search agent typically possesses high levels of energy efficient resources and facilitate foraging regions for the second level scroungers sparrow search agents. The assignment of each resource to a gateway completely depends on the fitness values possessed by them.
2. Once the sparrow search agent detects the change in the assignment of resources to gateways, they start exploring the complete search space for potential reassignment through a threshold termed alarm limit.
3. The number of producer sparrow search agent and scrounger search agent is considered to be constant

in the entire population. Moreover, the producer sparrow search agent can exploit the entire search space until it has a scope of improvement.

4. The solution (assignment of resources) will be explored by the producer sparrow search agent until the fitness value possessed by them cannot be improved.
5. The scrounger search agent follows the strategy of producer search agent during exploration and are completely responsible for facilitating optimal resource assignment process.
6. The sparrow search agent that is closer to the expected solution, adopt a rapid movement approach and in contrast, the sparrow search agents that are far away from the expected solutions utilize a group random walk strategy.

In the proposed SSARM, the agents that allocate resource (food) to gateways of an IoT environment are considered as the sparrows. The agents' (sparrows) position are represented as a matrix presented in Equation (2).

$$SP_{\text{Pos}(i,d)} = \begin{bmatrix} SP_{\text{Pos}(1,1)} & SP_{\text{Pos}(1,2)} & \dots & SP_{\text{Pos}(1,d)} \\ SP_{\text{Pos}(2,1)} & SP_{\text{Pos}(2,2)} & \dots & SP_{\text{Pos}(2,d)} \\ \dots & \dots & \dots & \dots \\ SP_{\text{Pos}(m,1)} & SP_{\text{Pos}(m,2)} & \dots & SP_{\text{Pos}(m,d)} \end{bmatrix} \quad (2)$$

Where, ' $m$ ' is the number of sparrow agents and ' $d$ ' represents the dimensions through which the variables considered for optimization during the assignment of resources to gateways are attained. Moreover, the value of fitness associated with the complete set of sparrow agents is expressed based on the vector depicted in Equation (3).

$$SP_{\text{Fit\_Pos}(i,d)} = \begin{bmatrix} f(SP_{\text{Pos}(1,1)}, SP_{\text{Pos}(1,2)}, \dots, SP_{\text{Pos}(1,d)}) \\ f(SP_{\text{Pos}(2,1)}, SP_{\text{Pos}(2,2)}, \dots, SP_{\text{Pos}(2,d)}) \\ \dots \\ f(SP_{\text{Pos}(m,1)}, SP_{\text{Pos}(m,2)}, \dots, SP_{\text{Pos}(m,d)}) \end{bmatrix} = \begin{bmatrix} f(SP_{\text{Pos}(1)}) \\ f(SP_{\text{Pos}(2)}) \\ \dots \\ f(SP_{\text{Pos}(m)}) \end{bmatrix} \quad (3)$$

Where, ' $m$ ' is the number of sparrow agents and each individual row value ' $f(SP_{\text{Pos}(i)})$ ' highlights the fitness value associated with the individual sparrow search agent.

In the proposed SSARM, the gateways that possess the superior fitness value always possess the maximized priority of obtaining the assignment of resources through the sparrow search agent processes. This possibility of assignment is rendered to the gateways with predominant fitness value as the sparrow search agents are responsible for searching of resources and guiding the complete movement of exploring the resources that could be possibly assigned to a specific gateway in the complete search space.

At this juncture, the search agents are classified into producers and scroungers search agent. The producer sparrow search agents are capable of exploiting the complete search space. On the other hand, the scroungers'

search agent is responsible for exploring the population search space during the assignment of resources to gateways of IoT. In this context, the location related to the producer search agent is updated during every iteration based on Equation (4).

$$SP_{Pos(i,j)}^{t+1} = \begin{cases} SP_{Pos(i,j)}^t * \exp\left(\frac{1}{\alpha * MaxIter}\right), & \text{if } A_{Val} < TS \\ SP_{Pos(i,j)}^t + Q_{RND} * U_{DM}, & \text{if } A_{Val} \geq TS \end{cases} \quad (4)$$

Where, 'MaxIter' and 't' represent the maximum number of iterations and the current iteration, respectively. 'Q<sub>RND</sub>' is the random number which follows the properties of normal distribution. 'A<sub>Val</sub>' and 'TS' represent the alarm value and threshold of safety, respectively.

Further, the scrounger sparrow search agent behaves according to the assumptions in equations (4) and (5), respectively. As mentioned previously, the producer search agents are frequently monitored by some scrounger sparrow search agents. The scrounger sparrow search agents immediately transit from their existing position and competes with the producer sparrow search agents when the producer sparrow search agent is capable of determining the optimal assignment of resources to gateways in IoT environment. If the assignment of resources to gateways determined by scrounger sparrow search agents are better attained when compared to the producer sparrow search agent, they start exploiting the search space with maximized speed and better rate of convergence. The formula used for updating the position of scrounger sparrow search agent is depicted in Equation (5).

$$SP_{(i,j)}^{t+1} = \begin{cases} Q_{RND} * \exp\left(\frac{SR_{Worst}^t - SR_{(i,j)}^t}{i^2}\right), & \text{if } i > \frac{n}{2} \\ SR_{Pos(i,j)}^t + |SR_{(i,j)}^t - SR_p^{t+1}| + A^+ * L_s, & \text{if Otherwise} \end{cases} \quad (5)$$

Where, 'SR<sub>Worst</sub><sup>t</sup>' and 'SR<sub>p</sub><sup>t+1</sup>' represent the global worst location and producers' sparrow search agent position in the current iteration. The matrix 'A<sup>+</sup>' is determined based on  $A^+ = A^T(AA^T)^{-1}$ . This matrix 'A<sup>+</sup>' is a single dimensional matrix in which every element is randomly assigned a value of -1 and +1. Moreover, it is identified that each 'i<sup>th</sup>' scrounger sparrow search agent has the probability of starving under the condition ' $i > \frac{n}{2}$ '.

In the implementation process, it is assumed that the sparrow search agents which are aware about the trapping to the local point of optimality account to about 10-20% of the total population considered in the search space. The positions of the sparrow search agents are initialized randomly in the complete population search space. Based on the assumption (6), the mathematical model used for assignment of the resources based on the sparrow search agent is depicted in Equation (6).

$$SP_{(i,j)}^{t+1} = \begin{cases} SP_{Best}^t + \beta |SP_{Pos(i,j)}^t - SP_{Best}^t|, & \text{if } f_{p(i)} > f_{Gl\_Best} \\ SP_{Pos(i,j)}^t + \delta \left( \frac{SP_{Pos(i,j)}^t - SP_{Worst}^t}{(f_{p(i)} - f_{Gl\_Worst}) + \epsilon_{ZDE}} \right), & \text{if } f_{p(i)} = f_{Gl\_Best} \end{cases} \quad (6)$$

Where, 'SP<sub>Worst</sub><sup>t</sup>' and 'SP<sub>Best</sub><sup>t</sup>' represent the current global worst solution and the current global best solution, respectively. Further, 'β' and 'δ' correspond to the control parameter step size (it is a normally distributed random number with the mean and variance value of '0' and '1', respectively) and random number ( $\delta \in [-1, +1]$ ). Furthermore, 'f<sub>Gl\_Worst</sub>' and 'f<sub>Gl\_Best</sub>' depict the fitness values of the current global worst solution and the current global best solution, respectively. In addition, a small constant termed 'ε<sub>ZDE</sub>' is used for preventing the issue of zero-division-error.

In this implementation process, the sparrow search agents are considered to exploit the search space in a predominant manner under the condition  $f_{p(i)} > f_{Gl\_Best}$ . In contrast, the sparrow search agents are determined to explore well under the condition  $f_{p(i)} = f_{Gl\_Best}$ . Thus, the tradeoff between the rate of exploitation and exploration can be well balanced based on the parameters of 'δ' that range between -1 and +1. The scope of the algorithm targets on mapping appropriate resources to gateways of IoT in a more optimal manner. In addition, the primitive steps of the proposed SSARM are summarized as the pseudocode depicted in Algorithm 1.

#### Algorithm 1: The primitive steps of the proposed SSARM

Iter<sub>Max</sub>: Maximum number of iterations  
 N<sub>PS</sub>: Number of producer sparrow search agents  
 SP<sub>PD</sub>: Number of sparrow search agents that balance the degree of exploitation and exploration  
 A<sub>Val</sub>: Value of the alarm  
 N<sub>TPS</sub>: The total number of sparrow search agents

Initialize a population of 'n' sparrows and define its relevant parameters

**Output:** SP<sub>Best</sub><sup>t</sup> and f<sub>Gl\_Best</sub>

1. While (t<sub>sp</sub> < Iter<sub>Max</sub>)
2. Determine the current best and worst individual global solution (assignment of resources to gateways in IoT) and grade them based on the fitness values.
3. A<sub>Val</sub> = rand(1)
4. For i=1:N<sub>PS</sub>
5. Update the location of the producer sparrow search agent based on Equation (2)
6. End for
7. For i=N<sub>PS</sub> + 1: N<sub>TPS</sub>
8. Update the location of the scrounger sparrow search agent based on Equation (4)
9. End for
10. For i=1: SP<sub>PD</sub>

11. Update the location of the sparrow search agent that balances exploitation and exploration well based on Equation (5)
12. End for
13. Estimate the new location of the sparrow search agent in the current iteration
14. Update the position of sparrow search agent, when the fitness value of search agents towards assignment is improving in subsequent iterations
15.  $t_{sp} = t_{sp} + 1$
16. End While
17. Return 'SP<sub>Best</sub>' and 'f<sub>Gl\_Best</sub>'

#### 4. Results and Discussions

In the first part of the analysis, the proposed SSARM and the benchmarked GWORM, WOARM and SERA approaches are investigated based on different service arrival rates [20-24]. The simulation environment comprises of gateways and resources that could be possibly allocated to suitable gateways. The time incurred in executing a specific task is 5 milliseconds. The diversity

factor considered in the implementation of the proposed work is 0.78.

From Figure 1, the response time of the proposed SSARM approach is determined to be decreased with a corresponding increase in the rate of services. This respective increase in the response time is mainly due to the tradeoff during the resource allocation process by the producer and scrounger sparrow search agents. From Figure 2, it is seen that the execution time of the proposed SSARM and the benchmarked GWORM, WOARM and SERA approaches are considered to be minimized independent of the arrival rates of service, since it incorporates a better coefficient of adjustment and random parameters that precisely aid in better allocation of resources to the gateways of IoT. The response time of proposed SSARM scheme with different service arrival rates is considered to get minimized by 10.21%, 12.28% and 13.94% when compared to the baseline GWORM, WOARM and SERA approaches. The execution time of the proposed SSARM scheme with different service arrival rates is also determined to get reduced by 8.26%, 9.84% and 11.64% in contrast to the baseline GWORM, WOARM and SERA approaches.

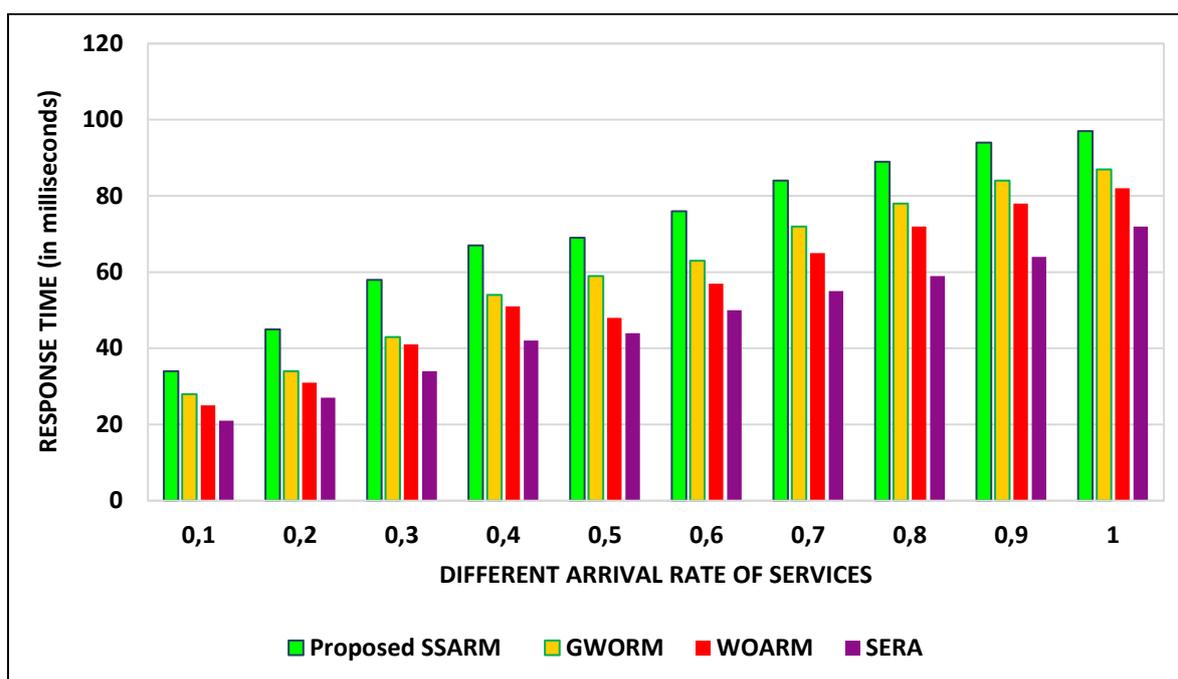


Figure 1. Proposed SSARM: Response Time with Different Service Arrival Rates

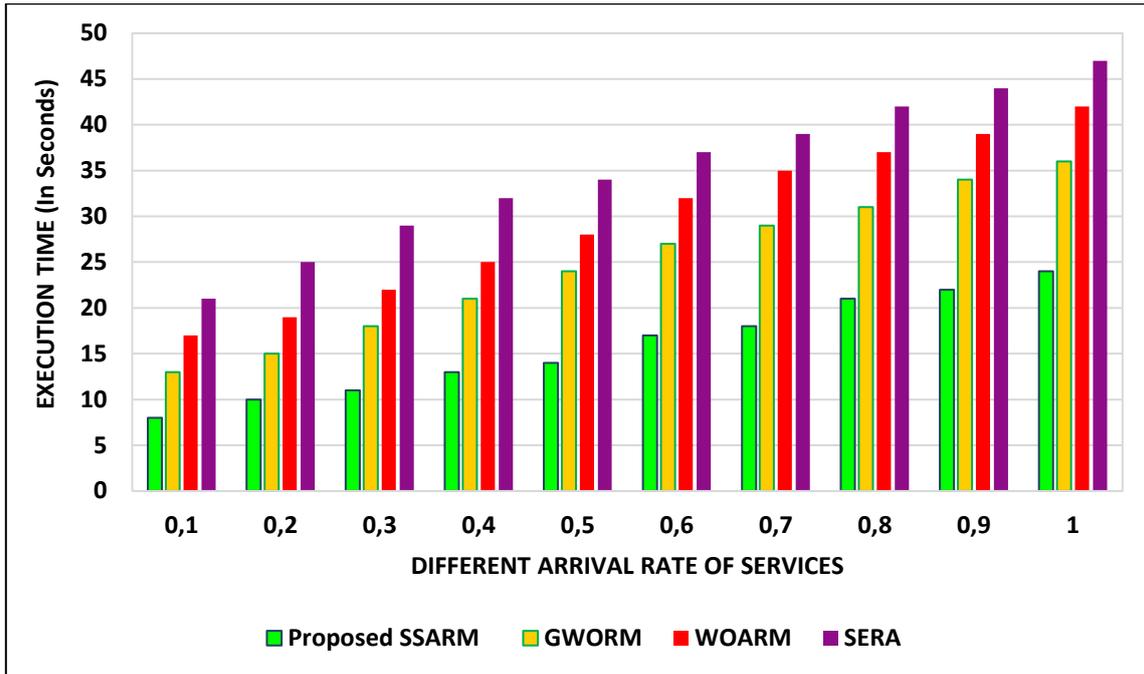


Figure 2. Proposed SSARM: Execution Time with Different Service Arrival Rates

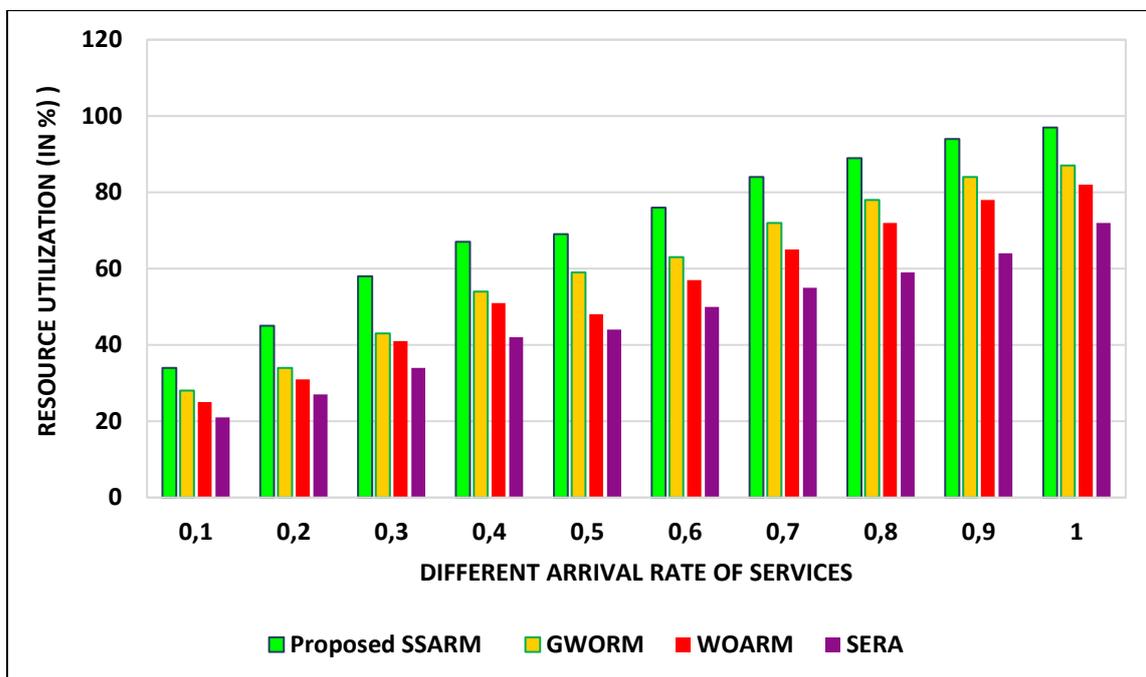
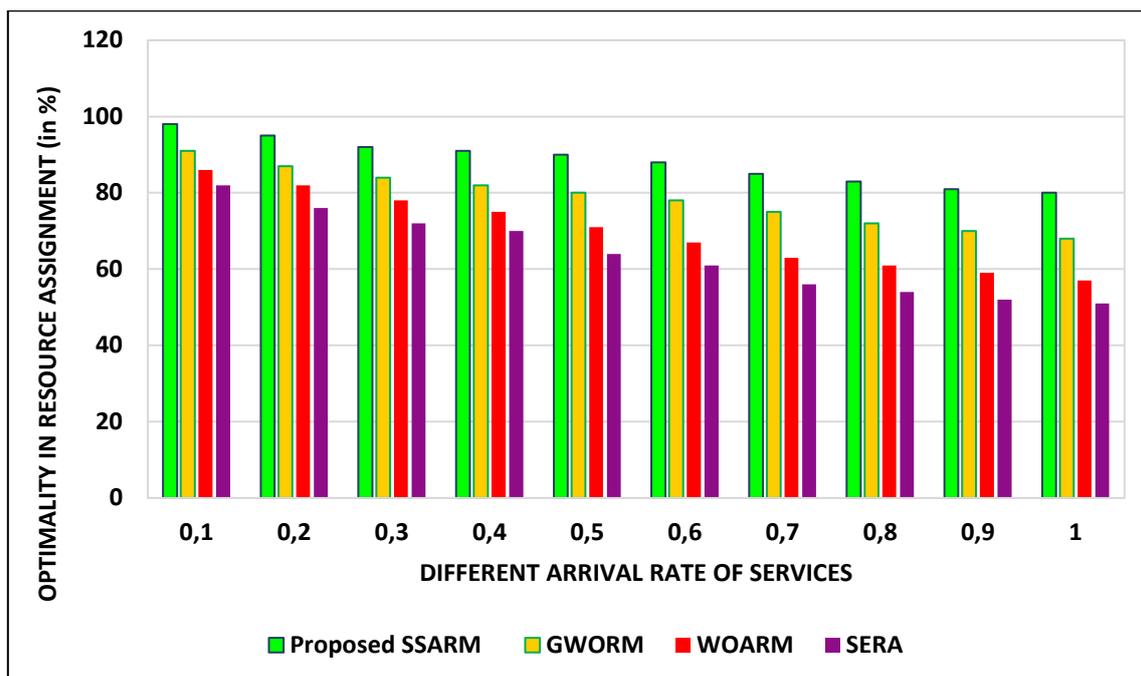


Figure 3. Proposed SSARM: Resource Utilization with Different Service Arrival Rates



**Figure 4.** Proposed SSARM-Optimality in Resource Assignment with Different Service Arrival Rates

Figure 3 and 4 demonstrate the resource utilization and optimality in resource assignment with different service arrival rates. The resource utilization and optimality in resource assignment facilitated by the proposed SSARM is considered to be considerably higher than the baseline approaches since the rate of exploitation and exploration maintained is phenomenal during the assignment process. The resource utilization of the proposed SSARM scheme with different service arrival rates is proved to be reduced 8.94%, 10.39% and 12.16% when compared to the baseline GWORM, WOARM and SERA approaches. The optimality in resource assignment attained by the proposed SSARM scheme with different service arrival rates is also confirmed to get improved by 9.18%, 10.84% and 12.28% in contrast to the baseline GWORM, WOARM and SERA approaches.

In the second part of investigations, the proposed SSARM and the benchmarked GWORM, WOARM and SERA approaches are evaluated based on decrease in total data transmission cost and increase in mean throughput

with different epochs of simulation. Figure 5 and 6 highlight the decrease in total data transmission cost and increase in mean throughput facilitated by the proposed SSARM and the benchmarked GWORM, WOARM and SERA approaches with different episodes of simulation. The results prove that the total data transmission cost get decreased and at the same time, the mean throughput increase with different epochs of simulation, since the inclusion of two classes of sparrow search agents aid in better exploration and exploitation of the search space. The decrease in the total data transmission cost of the proposed SSARM scheme with different epochs of simulation is determined to be reduced 10.74%, 11.85% and 13.28% when compared to the baseline GWORM, WOARM and SERA approaches. The increase in mean throughput achieved by the proposed SSARM scheme with different epochs of simulation is also confirmed to get improved by 11.21%, 12.98% and 13.48% when compared to the baseline GWORM, WOARM and SERA approaches.

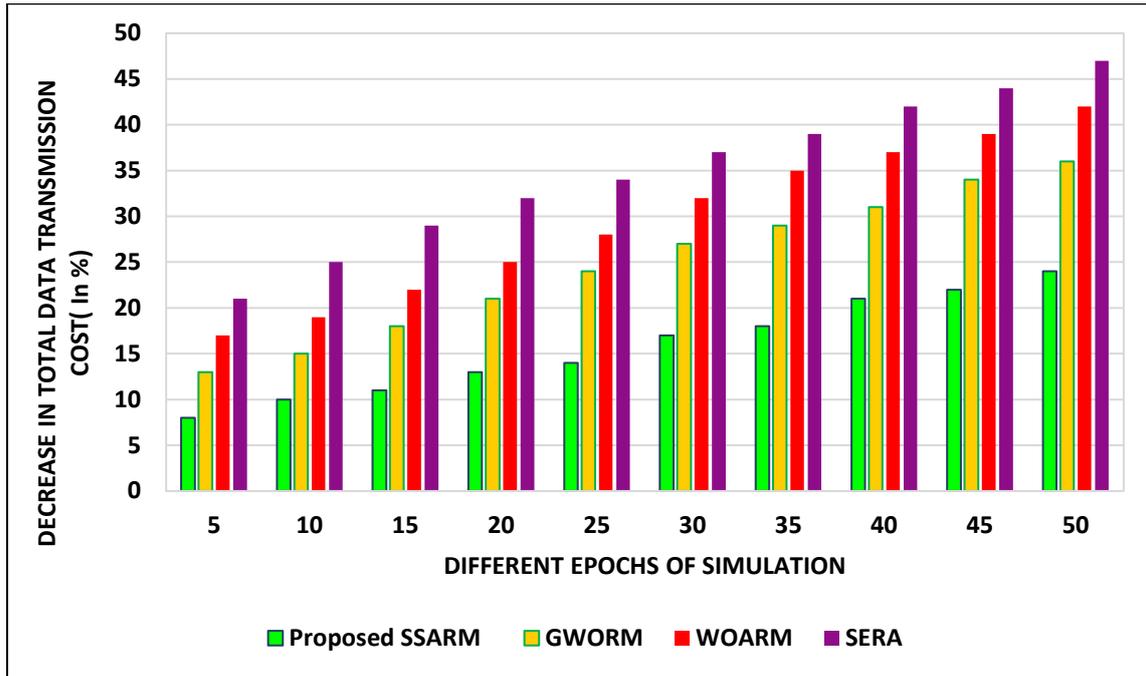


Figure 5. Proposed SSARM-Optimality in Resource Assignment with Different Epochs of Simulation

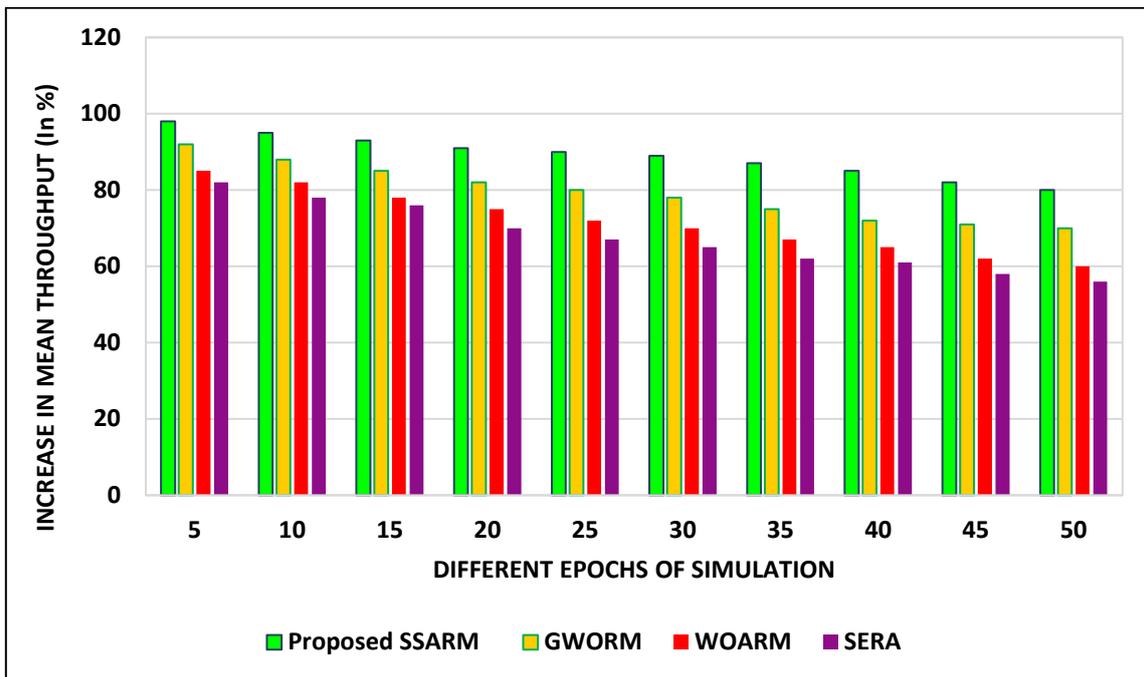


Figure 6. Proposed SSARM-Optimality in Resource Assignment with Different Epochs of Simulation

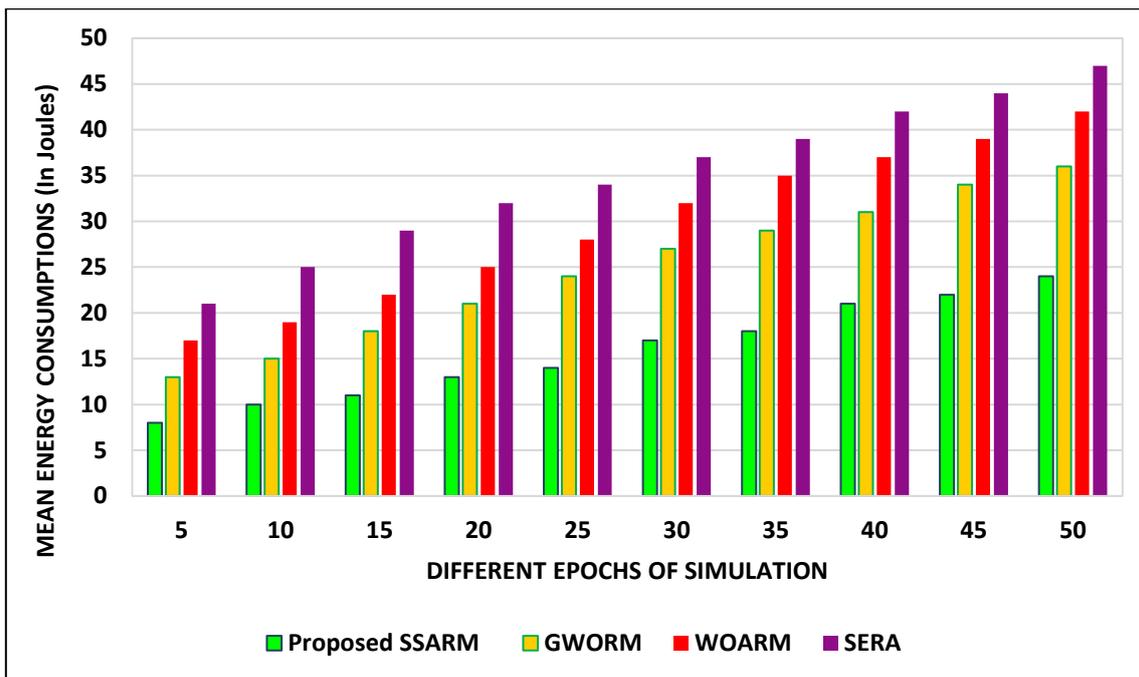


Figure 7. Proposed SSARM-Mean Energy Consumptions with Different Epochs of Simulation

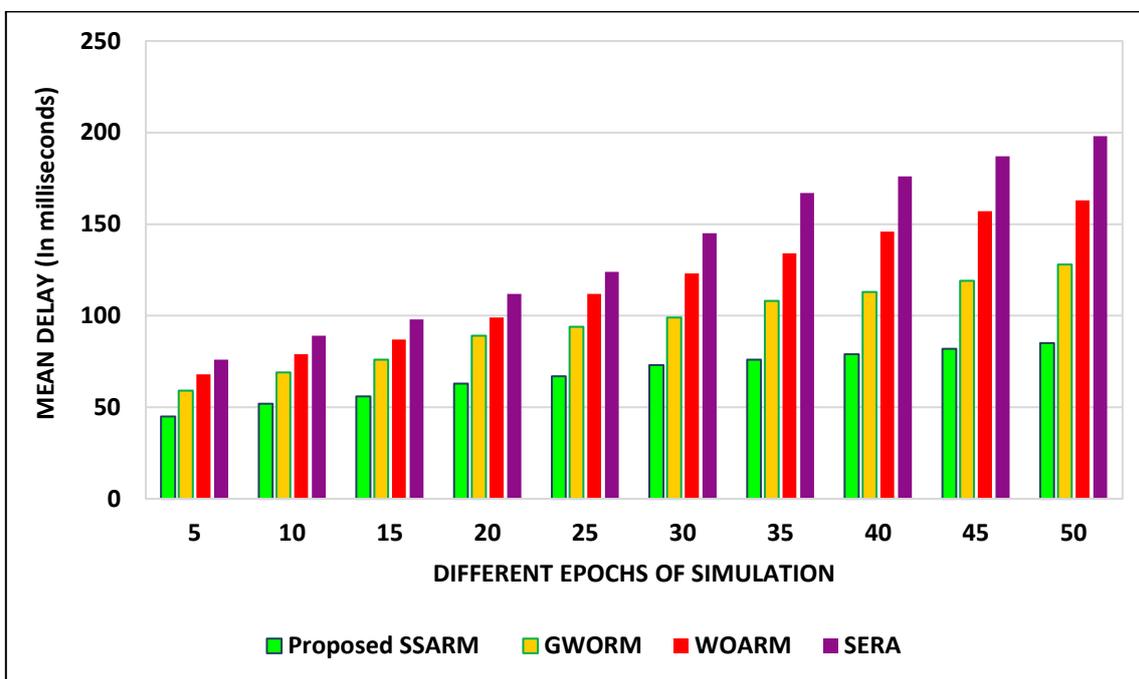


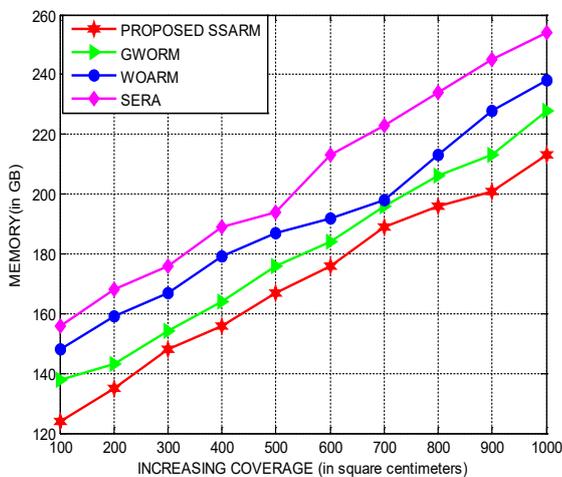
Figure 8. Proposed SSARM-Mean Delay with Different Epochs of Simulation

In addition, Figure 7 and 8 demonstrate the mean energy consumptions and the mean delay attained by the

proposed SSARM and the benchmarked GWORM, WOARM and SERA approaches with different epochs of

simulation. In the proposed SSARM, the energy consumption and mean delay are visualized to decrease with respective increase in the epochs of simulation. This is mainly due to the number of services potentially handled by the proposed scheme in the assignment of resources to gateways in a more potential way. The mean energy consumption of the proposed SSARM scheme with different epochs of simulation is determined to be reduced 7.12%, 9.56% and 11.84% when compared to the baseline GWORM, WOARM and SERA approaches. The mean delay achieved by the proposed SSARM scheme with different epochs of simulation is also confirmed to get reduced by 8.24%, 9.86% and 11.62% when compared to the baseline GWORM, WOARM and SERA approaches.

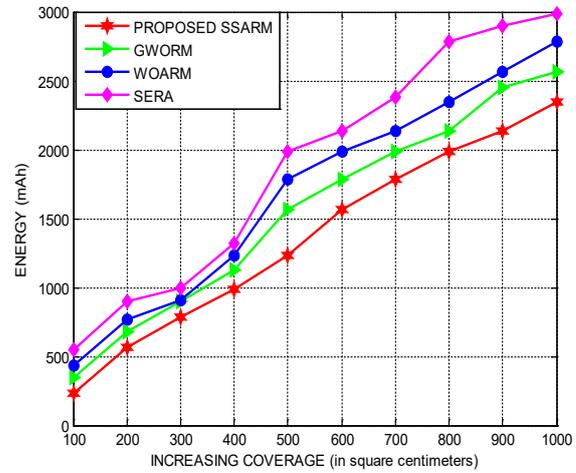
In addition, Figure 9 and 10 highlight the performance of the proposed SSARM and GWORM, WOARM and SERA approaches with respect to memory and energy under increasing coverage area. The memory and energy consumed by the proposed SSARM is determined to be comparatively lower than the baseline schemes since the exploitation and exploration rate are effectively balanced independent of coverage. The memory utilized by the proposed SSARM is considerably minimized by 7.12%, 8.94%, 9.49% and 10.76% when compared to the baseline schemes. Moreover, the energy consumed by the proposed SSARM is also minimized by 7.12%, 8.94%, 9.49 and 10.76% in contrast to the baseline schemes.



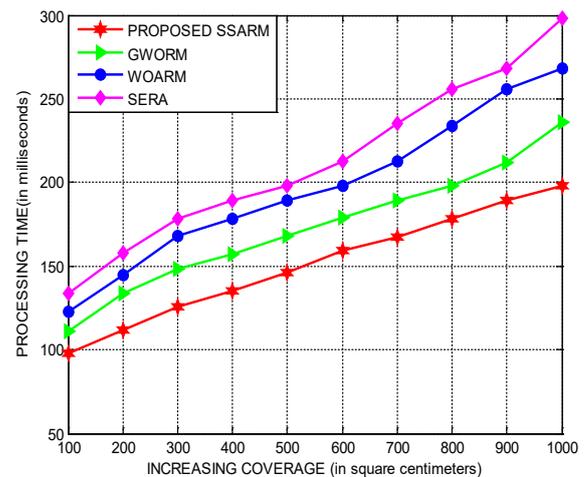
**Figure 9.** Proposed SSARM-Memory Utilized with Increasing Coverage

Figure 11 presents the processing time of the proposed SSARM and GWORM, WOARM and SERA approaches with increasing coverage area. The processing time of the proposed SSARM is minimized substantially when compared to the baseline schemes since the adoption of potential search equation aids in better exploitation of the population search space. The processing time incurred by the proposed SSARM is identified to be minimized by

8.94%, 9.76%, 10.56% and 11.42% when compared to the baseline schemes.



**Figure 10.** Proposed SSARM-Energy Utilized with Increasing Coverage



**Figure 11.** Proposed SSARM-Processing Time incurred with Increasing Coverage

## 5. Conclusion

In this paper, Sparrow Search Algorithm-based Resource Management (SSARM) is proposed as an attempt to facilitate better assignment of resources to gateways with the objective to reduce the total data transmission cost. It is formulated based on the exploitation and exploration potentiality of producers and scrounger sparrow search agents towards the objective of optimal assignment of resources to gateways. It is proposed for sustaining the degree of exploitation and exploration in the optimization

search space to an acceptable level. This SSARM is proposed with the merits of better stability, convergence rate, precision in searching and preventing the value of local point of optimality. The results confirm that the resource utilization and the optimality in resource assignment of the proposed SSARM scheme with different service arrival rates are proving to be reduced on an average by 10.49 % and 10.77% in contrast to the baseline GWORM, WOARM and SERA approaches. The total data transmission cost and throughput of the proposed SSARM are also minimized by 18.21% and 15.62% respectively when compared to the benchmarked approaches. Moreover, the energy consumptions and mean delay of the proposed SSARM scheme are also confirmed to be minimized by 15.18% and 14.48% when compared to the baseline approaches considered for investigation. As a part of the future plan, it is decided to formulate a rider optimization algorithm-based resource allocation approach and compare it with the proposed SSARM scheme. The proposed SSARM scheme can also be explored with multiple constraints that could be possibly impacted during the process of allocating resource to gateways in IoT.

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