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Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities

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ABSTRACT

Typically, there are a lot of challenges to be faced with providing better performance and energy optimization in the Internet of Things (IoT) in a smart city. In IoT and wireless sensor networks (WSNs), the nodes are generally grouped as clusters, which lead to forming Cluster Head (CH) that collects data from all other nodes and explicitly communicates with Base Station. In this paper, numerous objectives like delay minimization, energy sustainability could be accomplished through implementing a clustering algorithm on the intra-distance inter-distance between the CH and nodes. The optimization variables such as distance, delay, and energy used in IoT devices are taken into account to achieve the desired CH selection. In order to develop an enhanced IoT-Wireless Sensor Network (WSN) model, this paper introduces an advanced approach for CH selection using a modified Rider Optimization Algorithm (ROA). In the proposed algorithm, the solutions are sorted into two sets based on the best fitness value. The first set is updated using the averaged value of bypass and follower riders while the second set is updated through the averaged value of attacker and overtaker riders, which is called as Fitness Averaged-ROA (FA-ROA). The performance of the proposed FA-ROA is verified through a comparative analysis using various state-of-the-arts optimization models by concerning the number of alive nodes and normalized energy.

Introduction

Smart city is a concept where sensors in IoT networks are extensively used to administer several services like smart transport, traffic control, smart power dissipation, etc in urban areas [1,2]. With the ever-growing demand of IoT over a couple of decades, the software and hardware for sensor nodes are developed to screen and collect several varieties of information [3–6]. Generally, IoT is the interconnection between computing devices having Internet with the capacity of transmitting and receiving data. Moreover, the configuration of heterogeneous sensors having the ability to sense the data from surrounding environment permits the view of complicated nodes where the parameters are proficiently handled [7–9]. Typically, WSN is a set of spatially distributed sensors to monitor and store the activities of surroundings and configure the gathered information in a centralized position [10]. Recently, researchers and scholars concentrate on the improvement of energy efficiency problems. One of the best solutions to solve energy efficiency in IoT is clustering of sensor nodes, which can achieve the performance in a better manner. In order to improve the efficiency in WSN topological limitations, QoS, and battery are the major constraints [11].

WSNs obtain wide recognition after the emergence of IoT owing to the needs to screen the nodes in the surroundings [12–14]. Moreover, optimizing the resources in complicated systems is plays vital importance towards the optimization of energy resource. In this scenario also clustering is considered as the best solution. For this reason, a lot of researchers focused on the progression of optimizing energy using smart clustering models. In general, when the nodes are classified as clusters, then the clusters formulates CHs. Then, the CH gathers data from non-CHs i.e. other nodes in the cluster are considered as cluster members. The gathered information is then analyzed and transmitted to the BS. In IoT-WSN, the CHs transmit information explicitly to the BS to reduce the distance which proportionally reduces the energy consumption.

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Distributed clusters were introduced in earlier models where all the sensor nodes determine transmissions, security and functions [15–17]. The varied cluster in these models significantly reduces performance, as some nodes experience a dramatic variation in BS and CH, and although safety is a major concern [18–20]. Moreover, dynamic clustering is proposed, but it has high computational time, which in turn lead to more delay and load. High energy consumption causes long-term models to fail. Several optimization algorithms and evolutionary models have been used to improve energy efficiency. However, IoT-WSN consumes more energy due to factors such as temperature, load and data traffic. An energy-efficient IoT-WSN framework that consumes minimal energy and improves stability is therefore needed. The main contributions of this paper are as follows.

1. An optimal CH selection process is proposed using the metaheuristic algorithms. For this reason, the WSN-IoT characteristics like energy, distance and delay, load and temperature are utilized to enhance the performance CH selection.
2. In order to attain enhanced performance, optimization variables like load, delay, temperature, distance should be minimized and energy consumption must be minimized using the proposed FA-ROA model.
3. Eventually, the proposed model is compared with the state-of-the-arts models to verify the performance in terms of normalized energy and alive nodes.

The organization of this paper is based on the following order: Section "Literature review" presents the literature regarding CH selection models. Section "Motivation" presents the motivation and novelty of work. The objective model considered for CH selection in IoT-linked WSN is illustrated in Section "Objective model for selection of the optimal cluster head in IoT". The contribution of improved ROA for optimal CH selection is demonstrated in Section "Optimized cluster head selection using improved rider optimization algorithm". Section "Results and discussions" deliberates the attained results, and Section "Conclusion" concludes the paper.

Literature review

Related works

In [21],the authors have presented a multi-criteria-based CH selection model named Improved Grid-Based Hybrid Network Deployment (IGHND) in IoT-based WSN using various parameters such as level, energy, and distance which influencing network lifetime and node energy. Moreover, the relative effect for all parameters in CH was determined by Analytical Network Process (ANP). The experimental outcome outperformed the efficiency of the proposed CH selection model over existing models in terms of network lifetime and stability.

In [22], the authors have introduced an Energy-efficiency Hierarchical Clustering index tree (ECH-tree) to arrange the sensor nodes which are separated with regions in a grid cell. In order to answer for continuous queries, a time-correlated region query was employed. Moreover, these queries answer through grouping the values of the respective sensors connected to the BS. The simulation outcome confirmed energy efficiency through the conventional models.

In [23], the authors have developed a solution using fuzzy clustering pre-processing by employing Particle Swarm Optimization (PSO) for CH selection. Here, the fuzzy clustering model was utilized for clustering the sensor nodes with respect to its positions. Moreover, the fitness was evaluated using energy and distance parameters. At last, PSO was used to choose the CH in a hierarchical topology. The simulation outcome proved that the proposed model obtained the minimized mortality rate and increased network lifetime.

In [24], the authors have presented a novel Firefly-based Clustering Approach (FiCA) in IoT. This clustering model includes micro-clustering stage where Real-World Things (RWTs) were grouped as clusters and macro-clustering stage where the nodes were combined with small neighbouring clusters. Moreover, the IoT clusters were permitted to join or remove RWTs based on their influence, region, and current events. The experimental results proved that performance has improved the stability of the clusters.

In [25], the authors have presented an Improved Energy Efficient Cluster Head Selection protocol-WSN (IEECHS-WSN) to transmit the received data. Generally, 2 CHs were chosen for different clusters and their corresponding functionalities to enhance the life-cycle of the network and also minimize energy consumption. Data entropy was used to cluster the dual CHs, and to fuse and classify the nodes. The experimental results showed the enhanced life cycle, throughput and minimized energy consumption over conventional models.

In [26], the authors proposed an energy aware, reliable link optimization model for IoT devices. In addition, the packet error rate is reduced by maintaining optimal distances between nodes. The experimental results show that the link life is increased to 180% by selecting the appropriate parameters. In [27], the authors proposed a cloud-fog based scheduling algorithm to maximize energy for IoT applications. The authors intend to reduce the delay in transferring packets from source to destination. The experimental results show that the energy is optimized by 22% and the delay is reduced to 12.5%.

In [28], the authors have developed a Variable-Categorized Clustering Algorithm (VCCA) based on fuzzy logic. In fact, VCCA chooses the CH, which has high network capacity through a classification procedure with the cluster parameters to organize a cluster network. Moreover, Fuzzy Inference System (FIS) was employed to determine the results using rule-based variable mapping and maximum scalability. The experimental analysis verified the performance by comparing with traditional schemes in terms of life cycle, energy, throughput, and latency.

Review

Table 1 summarizes the features and challenges of conventional cluster head selection models. The IGHND [21] achieved extended network lifetime and stability and enhanced performance, but it failed to concentrate on the mobility of the nodes and needs to involve various scenarios. The ECH-tree [22] attained minimized energy consumption and efficiency, however, increasing number of sensor node increase load and delay and has poor network lifetime. The PSO [23] reduced computation time and mortality rate, yet it has poor region specification and reduced network life cycle. The FiCA [24] achieved stability and prolonged life cycle however, it has low Quality-of-Service (QoS) and high energy consumption. The IEECHS-WSN in [25] obtained enhanced throughput and lifetime and reduced energy consumption, but, it has high computational time and low reliability. In [26,27] achieved normalized energy and enhanced lifetime, but it has high network complexity and complex clustering among networks. The VCCA [28] attained enhanced throughput, latency, and lifetime, yet it has slowed processing and highly expensive. Thus, there is a need to develop an enhanced and proficient IoT-WSN model with the potential to accomplish optimal CH selection with respect to energy saving mode.

Motivation

Cluster formation is a very challenging task and it has many issues. In Optimizing the energy consumption, the selection of CH plays a vital role. For resolving shortcomings in reducing energy consumption and increasing network lifetime, FA-ROA is proposed. The proposed approach contributes following primary features:

1. We suggest Fitness Averaged-ROA (FA-ROA), a multi-objective cluster head selection optimization model in IoT. This approach takes into account the CHs candidate nodes, residual energy ratio, and energy balance degree to ensure energy efficiency.

Table 1
Literature Survey.

Author [Citation]	Method	Features	Challenges
Farman et al. [21]	IGHND	1. Achieves extended network lifetime, stability 2. Attains enhanced performance	1. Only few parameters considered 2. Needs to involve various scenarios
Tang et al. [22]	ECH-tree	1. Accomplishes minimized energy consumption 2. Achieves efficiency	1. More No of sensor node increase load and delay 2. Poor network lifetime
Ni et al. [23]	PSO	1. Reduced computation time 2. Reduced mortality rate	1. Poor region specification 2. Reduced network life cycle
Jabeur et al. [24]	FiCA	1. Achieves stability 2. Attains prolonged life cycle	1. Low QOS 2. High energy consumption
Jesudurai and kumar [25]	IEECHS-WSN	1. Obtains enhanced throughput and lifetime 2. Reduced energy consumption	1. High computational time 2. Low reliability
Reddy and Babu [37]	ALO and MFO	1. Accomplishes balanced temperature & load 2. Attains sustainability and lifetime	1. Energy storage can be extended 2. Allocation of the region is difficult
Reddy and Babu [38]	SAWOA	1. Achieves normalized energy 2. Enhanced lifetime	1. High network complexity 2. Complex clustering among networks
Kwon et al. [28]	VCCA	1. Attains enhanced throughput and latency 2. Obtains lifetime	1. Slow processing 2. Highly expensive

2. The suggested model achieves a large coverage ratio and less redundancy ratio.
3. To select a CH, we use parameters such as energy residue of the sensor, delay. This, along with Euclidean distance, is employed at FA-ROA so that CHs deliver aggregate data to the Base Station (BS) in a successful manner. Our present approach yields residual energy's threshold value being estimated.

Objective model for selection of the optimal cluster head in IoT

Objective model

CH selection for WSN-IoT utilizes temperature, load distance, delay, and energy for deriving a multi-objective function. The main objective of this proposal is to optimize the load, temperature, delay, and distance between all available nodes, and maximize the normalized energy left in a node which is shown in Eqs. 1 to (3). Here, ρ and ω implies constants as 0.9 and 0.3.

$$O_1 = \frac{O^{energy}}{O^{load}} + \frac{O^{energy}}{O^{temp}}. \tag{1}$$

In Eq. (1) O^{energy} is objective function for energy, O^{load} is objective function for load and O^{temp} is objective function for temperature. $\frac{O^{energy}}{O^{load}}$ makes sure that energy is more and load is less, also $\frac{O^{energy}}{O^{temp}}$ will make sure that energy is more and temperature is less.

$$O_2 = \frac{\rho}{O^{dis}} + (1-\rho)O_1. \tag{2}$$

$$O_3 = \omega O_2 + \frac{(1-\omega)}{O^{delay}}. \tag{3}$$

The following section describe the mathematical model of the five-performance metrics.

Energy: Eqs. (4) to (7) exhibits energy consumption where, E(Sie) represents energy of ie^{th} node and E(ch_{je}) represents the energy of je^{th} CH.

$$O_{energy} = \frac{O^{energy}(u)}{O^{energy}(v)}. \tag{4}$$

$O^{energy}(v)$ represents node with maximum energy and $O^{energy}(u)$ represents energy of every other node in the cluster.

$$O^{energy}(u) = \sum_{je=1}^{U} nE(je). \tag{5}$$

In Eq. (5) U is number of nodes in cluster, n is constant between $[0,1]$

$$nE(je) = \sum_{ie=1;ie\in je}^{U} (1 - E(S_{ie}) * E(ch_{je})); 1 \leqslant je \leqslant U. \tag{6}$$

In Eq. (6) ie iterates through all the normal nodes (except cluster head); it ranges from 1 to U

$$O^{energy}(v) = U * \max_{ie=1}^{U}(E(S_{ie}) * \max_{je=1}^{U} E(ch_{je})). \tag{7}$$

In Eq. (7) when ie varies from 1 to U the energy obtained is maximum, it is taken as energy of ie^{th} node.

Distance: Eq. (8) states the mathematical form of distance model, in which, the value of O^{dis}(u) lies in the interval $[0,1]$. In Eq. (9), O^{dis}(u) represents the distance among normal node to the CH and the distance among CH to the BS of the network. Moreover, Eq. (10) refers the distance among 2 normal nodes.

$$O^{dis}(u) = \frac{O^{dis}(u)}{O^{dis}(v)}. \tag{8}$$

$$O^{dis}(u) = \sum_{ie=1}^{V}\sum_{je=1}^{U} ||S_{ie} - Ch_{je}|| + ||ch_{je} - BS||. \tag{9}$$

$$O^{dis}(u) = \sum_{ie=1}^{V}\sum_{je=1}^{U} ||S_{ie} - S_{je}||. \tag{10}$$

Delay: Eq. (11) explains the computational form of node delay, which is a ratio of CH in WSN and number of nodes, O^{delay} ranges with in the interval $[0, 1]$. Reducing the total number of nodes in the cluster typically minimizes latency.

$$O^{delay} = \frac{\max_{je=1}^{U}(ch_{je})}{V}. \tag{11}$$

Load and Temperature: The load and temperature of the nodes are fed to the Xively-IoT network (http://www.xively.com/xively-iotplatform). Nodes maintaining low temperature and lower load are considered for optimal CH choice.

System model

Normally, there exists ample of issues to be solved to facilitate improved performance and energy optimization in IoT [42]. WSN's CH is typically chosen using parameters like delay, distance and energy. With the integration of WSN to the IoT devices, temperature, and load parameters are considered as well. The primary objective of this efficient selection of CH using FA-ROA is to reduce distance, delay, load and temperature and increase the residual energy of the nodes. Fig. 1 shows the geometrical representation of proposed CH Selection Model. Typically, number of clusters in a WSN may change and CHs are chosen from the overall nodes associated in WSN. As stated earlier, performance metrics such as nodes distance, delay, and residual energy are considered for the selection of CH in WSN. Thus, only CHs can explicitly communicate with the BS and all the other nodes have not permitted to

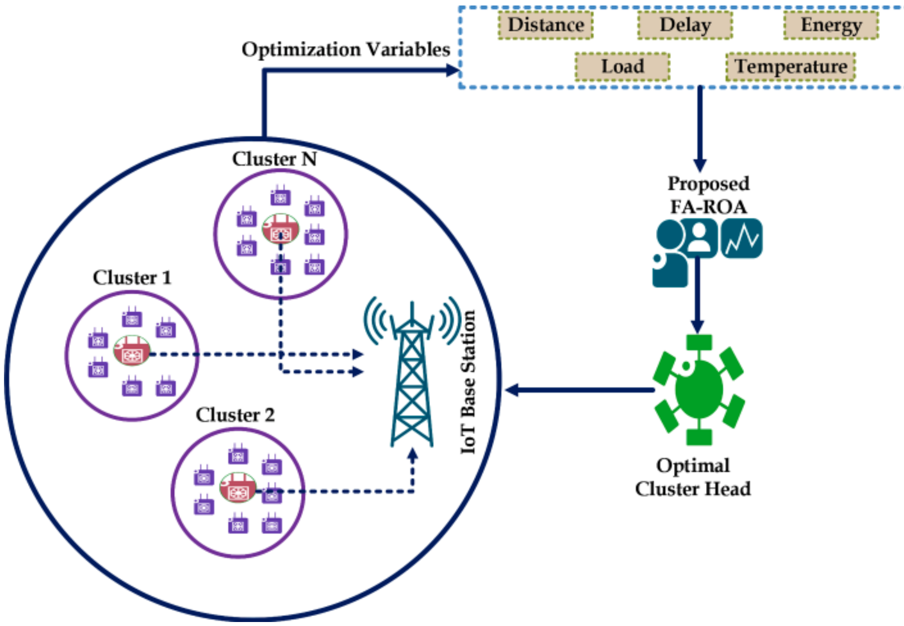

Fig. 1. Geometrical Representation of proposed CH Selection Model.

communicate with the BS. In WSN-IoT systems, the CH selection becomes more complicated as the parameters from both WSN and IoT networks. Hence, a multi-objective function is derived using certain parameters like temperature, load, energy, distance and delay of nodes. This multi-objective problem will be solved by using our proposed FA-ROA.

Optimized cluster head selection using improved rider optimization algorithm

Conventional ROA

Generally, ROA [29] is developed based on the idea of a set of riders riding to reach the goal/a target position. Besides, this algorithm is composed of bypass, follower, overtaker, and attacker riders with each group having individual working methodology. The mathematical model of ROA is presented as follows.

Initialization: Firstly, the group is initialized as referred in Eq. (12), in which indicates the number of riders equivalent to which refers group, specifies the number of coordinates or dimension and M^{ti} (a,b) represents location of a^{th} rider on time T. Moreover, the team of riders is determined using the sum of bypass, follower, overtaker, and attacker which are considered as B_i, F_i ,O_i and A_i respectively.

$$M^{ti} = \{M^{ti}(a,b)\}; 1 \leqslant a \leqslant C; \quad 1 \leqslant b \leqslant D. \tag{12}$$

Consider the angles corresponding to the location, steering, and vehicle coordinate for a^{th} rider as θ_a, $(T_i)^{t_i+1}_{(a,b)}$ and τ. Moreover, the major parameters of the vehicle for a^{th} the rider are accelerator ei_a, brake br_a and gear Ei_a. The brake and accelerator values range between 0 and 1 while the gear value lies among 0–4.

Determining success rate: After initializing rider sets and specifications, the performance level for all riders is assessed. Then the success rate for all riders is updated to determine the leader i.e. optimal rider who has the maximum value over all riders. Moreover, local convergence is the attacker's influence and, instead, global convergence is overtaker's liability. Generally, an arbitrary search is performed by the riders to proficiently attain the target. The followers use the leader's multi-directional search space. The overtaker uses the success rate and selects the optimal-dimensional space using a directional indicator when in the last convergence step.

Leader rider location update: The rider who is having a high success rate and almost near to the target is considered to be the leader rider. Moreover, the leader rider may change according to the success rate over time. Usually, all riders' performance rate is measured and the leader is decided based on the last iteration.

Model of riders' location: Generally the standard ROA has four riders: bypass rider who is riding the primary path to attain the goal location, follower tries to follow the leader rider, overtaker concentrates on their particular path to attain the target, and attacker attains the goal by occupying the rider's location. Furthermore, all riders have predefined rules to attain the target using exact exploitation of gear, accelerator, steering, and brake. The riders' location alters by tuning the parameters using predefined rules and updated continuously until the riders attain the maximum time i.e., off-time ti_{off}.

When the bypass rider riding in the normal path by ignoring the leader's path, then the location update for this group is arbitrary as defined in Eq. (13), where, γ indicates an arbitrary number in 0 and 1, τ specifies an arbitrary number in 1 and C, ν refer to a value ranging 1 and [1], μ denotes an arbitrary value lies in 0 and 1 of size $1 \times$ D.

$$X^{Bi}_{ti+1}(a,b) = \gamma[M^{ti}(t,b) * \mu(b) + M^{ti}(\nu,b) * [1-\mu(b)]]. \tag{13}$$

Hence, the location of all bypass riders is updated to attain the target. The follower updates their location based on the location of the leading rider in order to attain the target using coordinate selector as expressed in Eq. (14), where, refers to coordinate selector, X^{Li} specifies the leaders' location, L_i represents the index of leader, $Ti^{ti+1}_{a,b}$ points to steering angle of a^{th} rider in c^{th} coordinate, and d^{ti}_a denotes the distance needs to be covered by a^{th} rider which is calculated using the multiplication value of velocity and rate of off-time of the rider.

$$X^{Fi}_{ti+1}(a,c) = X^{Li}(Li,c) + \left[\cos(Ti^{ti+1}_{a,b}) * X^{Li}(Li,c) * di^{ti}_a\right]. \tag{14}$$

Overtaker riders change their position utilizing 3 criteria such as coordinate selector, relative success rate and direction indicator as indicated in Eq. (15), where, X_{ti}(a,c) specifies the location of a^{th} rider in c^{th} coordinate, and $Di^{ili}_{ti}(a)$ indicates direction indicator of rider on.

$$X^{Oi}_{ti+1}(a,c) = X_{ti}(a,c) + \left[Di^{ili}_{ti}(a) * X^{Li}(Li,c)\right]. \tag{15}$$

To determine the coordinate selector, the generalized distance vector is calculated by subtracting the location of a^{th} rider to the leader.

Similarly, the attacker rider tries to capture the leader's position by using the same update procedure of follower. In addition, all the co-ordinates are updated by attacker instead of specific co-ordinates as stated in Eq. (16).

$$Xi_{ti+1}^{Ai}(a,b) = X^{Li}(Li,b) + \left[\cos(Ti_{a,b}^{ti+1}) * X^{Li}(Li,b)\right] + di_a^{ti}. \tag{16}$$

Activity Counter: When the success rate of rider on goes beyond the rate determined on, then the activity counter uses 1, otherwise 0 for lagging as given in Eq. (17).

$$Ai_m^{ti+1}(a) = \begin{cases} 1; & if \quad r_{TI+1}(a) > r_{ti}(a), \\ 0; & \quad otherwise. \end{cases} \tag{17}$$

Steering Angle: Activity counter is used to update the steering angle as defined in Eq. (18).

$$Ti_{a,b}^{ti+1} = \begin{cases} Ti_{a+1,b}^{ti} & if \ Ai_m^{ti+1}(a) = 1, \\ Ti_{a-1,b}^{ti} & if \ Ai_m^{ti+1}(a) = 0. \end{cases} \tag{18}$$

Gear: It is updated using activity counter on and the greater value for the gear is stated in Eq. (19).

$$Ei_a^{ti+1} = \begin{cases} E_a^{ti} + 1 & if \ Ai_m^{ti+1}(a) = 1, E_a^{ti} \neq |Ei| \\ E_a^{ti} - 1 & if \ Ai_m^{ti+1}(a) = 0, E_a^{ti} \neq 0 \\ Ei_a^{ti}, & otherwise \end{cases}. \tag{19}$$

Success Rate Re-Determination: The performance rating of the rider is re-assessed to determine the optimal leader.

Parameters update at the end of location update: At the end of the iteration, the rider parameters are modified to assess the optimum solution. The criteria required to be changed at the end of the iteration are gear, brake, off-time run, accelerator, and steering angle along with performance rate-based operation counter as 0–1.

Termination: The optimization process continues until the end. Finally, the best solution is obtained using optimization of specific parameters. Algorithm 1 represents traditional ROA model pseudo-code.

Algorithm 1: Conventional ROA Model [29]

```
Data: Arbitrary Location of riders,
Result: Leading rider,
Allocate the population
Allocate the rider parameters
Evaluate the success rate
while While condition do
    for a = 1 to C do
        Upgrade bypass rider location using Eq. 13
        Upgrade follower location using Eq. 14
        Upgrade overtaker location using Eq. 15)
        Upgrade attacker location using Eq. 16
        Rate riders using their rate of success
        Select a rider with a better success rate as leader.
        Upgrade the rider parameters
        Return
    end
end
```

Proposed model

In general, WSN is composed of groups of clusters in which all clusters comprised with the corresponding CHs that act as a coordinators to collect data from sensor nodes and transmit to the BS. For this reason, there is a necessity to select the appropriate CH which has the influence on determining the overall performance of the network. In order to choose the optimal CH among cluster of nodes, modified ROA is implemented. Although ROA has many advantages to solve complex problems, it requires further improvements to achieve the enhanced performance. In fact, the improvement is made in the processing of group update. The proposed ROA algorithm is as follows:

Algorithm 2: Proposed FA-ROA Model

```
Data: Arbitrary Location of riders,
Result: Leading rider,
Allocate the population
Allocate the rider parameters
Evaluate the success rate
while While condition do
    Evaluate Fitness
    Sort
    for 1 to 5 do
        Update the solution as per Eq. 20
    end
    for remaining fitness do
        Update the solution as per Eq. 21
    end
    Rate riders using their rate of success
    Select a rider with a better success rate as leader rider.
    Upgrade the rider parameters
    Return
end
```

Once the fitness evaluation is completed, they are sorted based on the best fitness. As here have 10 solutions, 10 fitness values might be obtained. Further, the corresponding solutions of 1st five fitness values are updated as per Eq. (20), which is the average of bypass rider and follower rider update given in Eqs. (13) and (14), respectively. Conversely, the solutions of remaining five fitness values are updated by averaging the overtaker rider and attacker rider update as well (based on Eqs. (15) and (16)), which is given in Eq. (21).

$$X_{ti+1} = \frac{X_{ti+1}^{Bi} + X_{ti+1}^{Fi}}{2}. \tag{20}$$

$$X_{ti+1} = \frac{X_{ti+1}^{Oi} + X_{ti+1}^{Ai}}{2}. \tag{21}$$

Algorithm 2 represents the pseudo-code of proposed FA-ROA model. Fig. 2 shows the flow chart of the proposed model.

1. Start the process.
2. Initialize the initial population (Riders), upper and lower bound, and other initial parameters. When iteration is equal to the maximum number of iteration, the process ends, otherwise the following steps 3 to 8 occur.
3. Evaluating the fitness value of each riders using Eqs. (13)–(16)
4. Sort the fitness values in the ascending order.

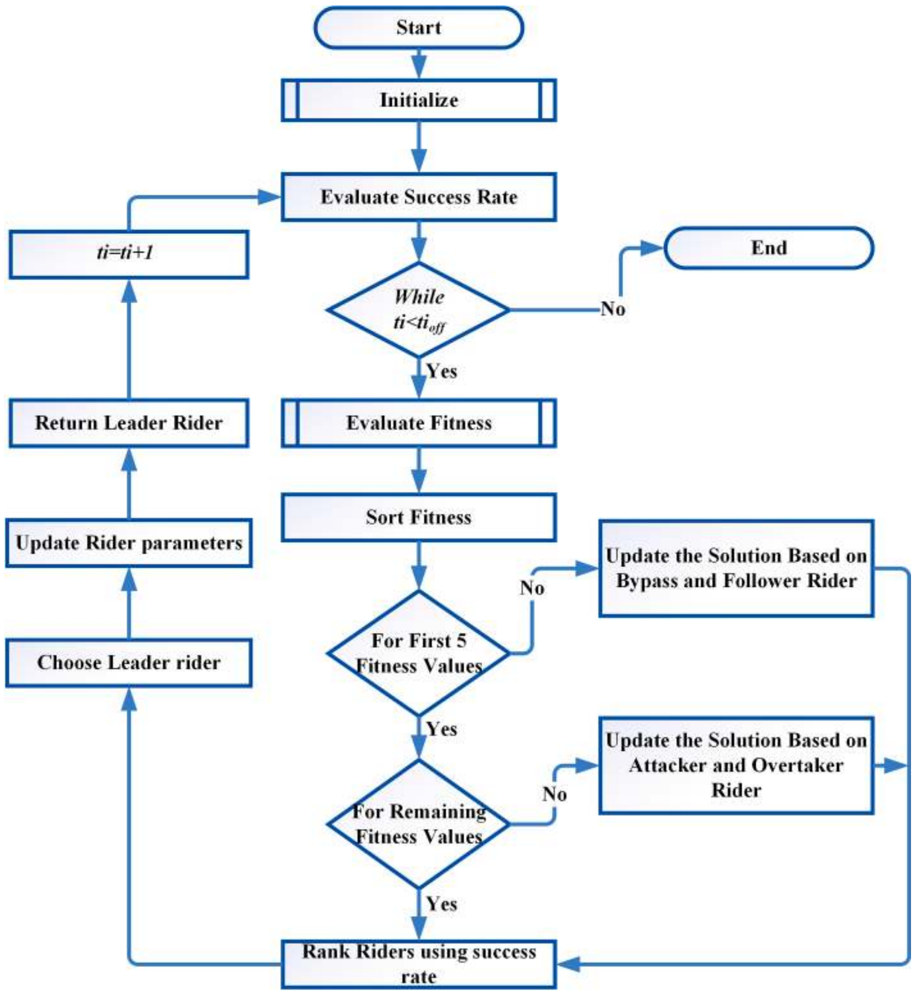

Fig. 2. Flowchart Representation of proposed FA-ROA Model.

5. Set the top five fitness values as Bypass and Follower riders and the remaining fitness values as Attacker and Overtaker riders.
6. Rank the rider by using the success rank.
7. Choose leader rider, update rider parameters, and return leader rider.
8. Loop to step 2 for next iteration.

Results and discussions

Experimental setup

The experimentation of proposed CH selection for WSN-IoT network was implemented in MATLAB 2018a. The experimental analysis was performed with the following optimization variables such as delay, distance, energy along with load, and temperature of WSN and IoT networks [39–41]. The simulation was carried out with 2000 iterations using the capability of proposed FA-ROA for CH selection process. In this process, the sensor nodes and IoT devices, were dispersed inside the IoT-linked WSN network with the size of 100 × 100 m^2. The BS is located at the center of the network. The variable E_{Ie} specifies the network's initial energy as 0.5, E_{fs} indicates free space energy with the value of 10 pJ/bit/m^2, E_{PA} denotes power amplifier energy with 0.0013 pJ/bit/m^2 value and E_{DA} represents the energy of data aggregation as 5 nJ/bit/signal. Moreover, the performance of the proposed FA-ROA was verified through a comparative analysis using the state-of-the-arts models such as Artificial Bee Colony (ABC) [30], Genetic Algorithm (GA) [31], Particle Swarm Optimization (PSO) [32], Gravitational Search Algorithm (GSA) [33], ABC-GSA [34], Moth Flame Optimization (MFO) [35], MFO-Ant Lion Optimization (ALO) [26], Whale Optimization Algorithm (WOA) [36], Self Adaptive WOA (SAWOA) [27], and ROA [29].

Performance analysis

Here, a cluster of nodes is utilized to verify the performance of the

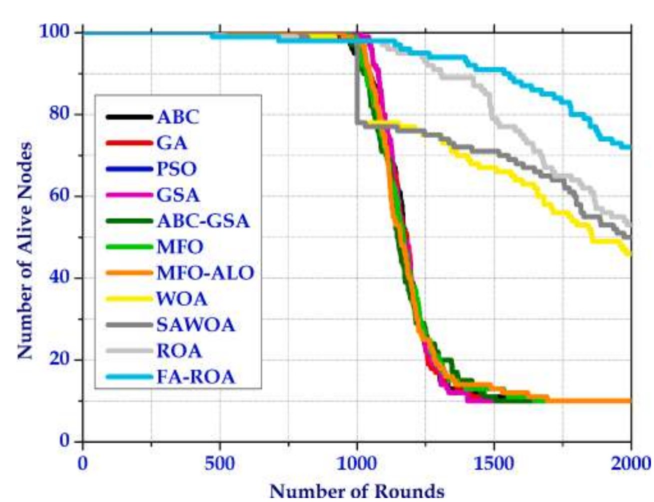

Fig. 3. Number of alive nodes Vs Rounds.

proposed model in a WSN-IoT network. In Fig. 3, it verifies the number of alive nodes at the time of 1500th iteration as 89.82% better than ABC, 88.88% better than GA, 85.88% superior to PSO, 87.82% improved than GSA, 86.75% better than ABC-GSA, 88.88% better than MFO, 86.88% superior to MFO-ALO, 38.46% superior to WOA, 28.57% improved than SAWOA, and 12.5% better than ROA.Fig. 4 shows normalized energy metric efficiency compared with conventional approaches. At first, the network 's initial energy is .55 *joule* as the number of rounds increases; residual energy tends to decrease, lowering live nodes. Fig. 6 shows the proposed system maintains relatively high energy rates compared to traditional models. Even at 2000 iterations, the proposed model retains energy at higher levels as cluster heads are distributed productively across the network and ensure appropriate temperature, optimum load, resulting in optimum residual energy than other existing systems. From Fig. 4, it is clear that the proposed model is 50%, 49.52%, 48.23%, 47.65%, 47.88%, and 80% superior to ABC, GA, PSO, GSA, ABC-GSA, and MFO in order, in terms of normalized energy for 90 nodes. Fig. 5 shows the load performance with 2000 nodes as 12.5% better than GA, 12.5% superior to PSO, 12.5% better than GSA, and 12.5% superior to SAWOA. Fig. 6 reveals the normalized network energy performance at 500th iteration as 66.66% superior to ABC, 66.66% better than GA, 66.66% improved than PSO, 66.66% better than GSA, 66.66% superior to ABC-GSA, and 1.02% better than ROA, respectively. The temperature performance at 1500th iteration is 11.11%, 11.11%, 8.69%, 8.02%, 1.01%, 0.89%, and 0.89% better than ABC, GA, PSO, GSA, WOA, SAWOA, and ROA, respectively as shown in Fig. 7. Fig. 8 portrays the stochastic representation of load and temperature performance with 100 nodes which shows when the load increases in a network, it proportionality increases the temperature of the network. Thus, the proposed model validated the performance and proved its enhanced efficiency. In Table 2 provides the notations used in the current research work.

Statistical analysis

Table 3 tabulates the statistical analysis of best, worst, mean, median, and standard deviation of the proposed model and the conventional models in terms of alive nodes. In a cluster of nodes, for all iterations, the distance among the nodes should be kept as minimum in order to maximize the number of alive nodes till the final iteration. The overall mean performance of number of alive nodes is 68.88%, 68.88%, 68.88%, 68.88%, 68.88%, 68.88%, 68.88%, 48.14%, 44%, and 40.42% better than ABC, GA, PSO, GSA, ABC-GSA, MFO, MFO-ALO, WOA, SAWOA, and ROA, respectively. The standard deviation analysis is 47.72%, 46.76%, 46.26%, 50.32%, 46.76%, 48.1%, 47.13%, 73.52%, 73.35%, and 21.1% superior to ABC, GA, PSO, GSA, ABC-GSA, MFO, MFO-ALO, WOA, SAWOA, and ROA, respectively. On the other hand, Table 4 represents the overall statistical analysis by means of normalized energy. Similarly, for energy consumption analysis, the distance between the nodes must be minimized for all iteration. The mean

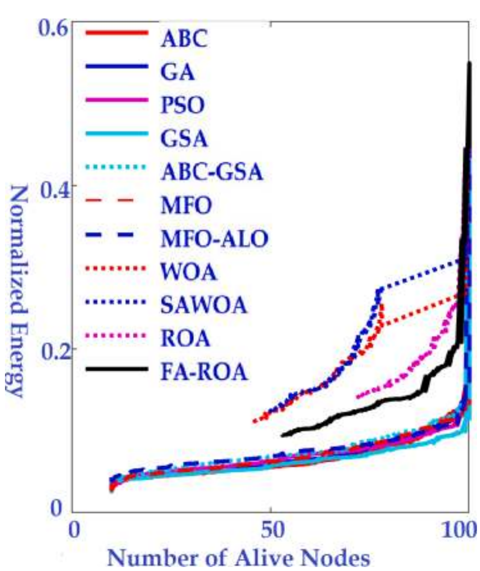

Fig. 4. Normalized Energy Vs Number of live nodes.

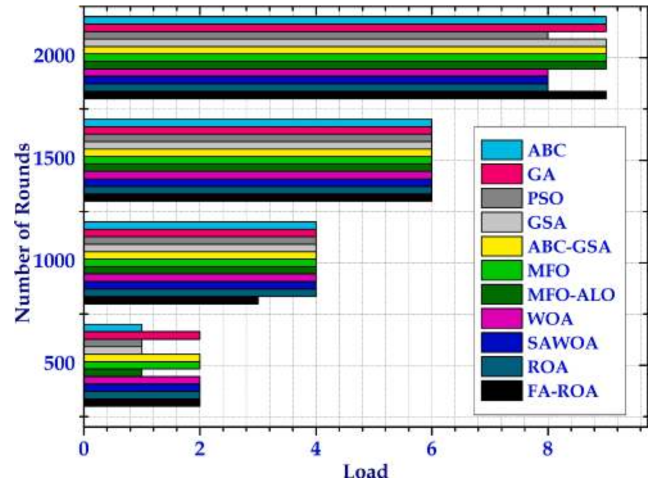

Fig. 5. Load Vs Round.

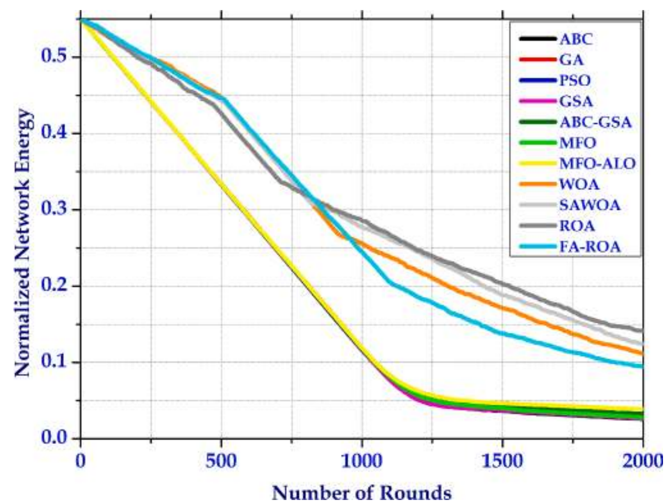

Fig. 6. Normalized network energy.

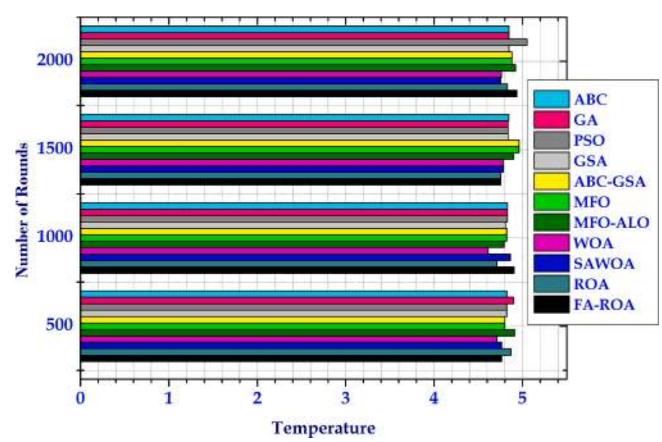

Fig. 7. Temperature Vs Rounds.

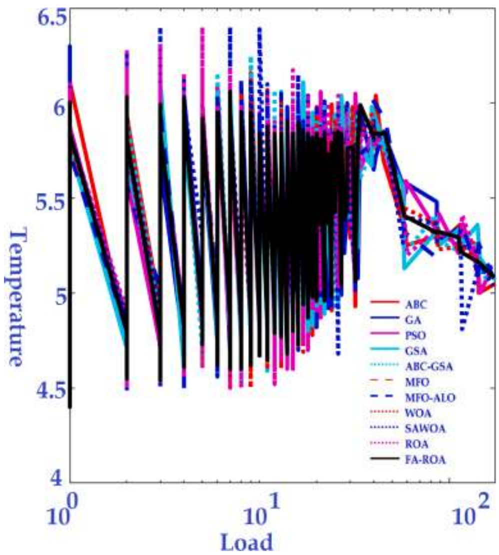

Fig. 8. Temperature Vs Load.

Table 2
Table of Notations.

CH	≜	Cluster Head i
BS	≜	Base Station
O	≜	Objective Function
ρ and ω	≜	Constant (0.9) and Constant (0.3) respectively
S_{ie}, S_{je}	≜	Normal nodes
$E(S_{ie})$	≜	Energy of ie^{th} the normal node
$E(ch_{je})$	≜	Energy of je^{th} CH
$o^{dis}(u)$	≜	Distance among normal node and the CH
C and H	≜	Number of Riders and Group of Riders respectively
D	≜	Number of coordinates
$M^T(a,b)$	≜	Location of a^{th} the rider on time T.
B_i	≜	Bypasser
F_i	≜	Follower
O_i	≜	Overtaker
A_i	≜	Attacker
θ_a	≜	Location of a^{th} rider
$Ti^{T+1}_{a,b}$	≜	Steering angle
ei_a	≜	Accelerator
br_a	≜	Brake
Ei_a	≜	Gear
T_{off}	≜	Off-time
γ	≜	Arbitrary number between 0 and 1
τ, ∂	≜	Arbitrary number between 0 and number of riders
μ	≜	Arbitrary value lies among 0 and 1 of size 1 × D.
X^{Li}	≜	Location of the leader
di^T_a	≜	Distance needs to be covered by a^{th} rider
Di^{ili}_T(a)	≜	Direction indicator
Si^C_T(a)	≜	Relative success rate
Ai^T_m(a)	≜	Activity counter
O^{energy}	≜	Ojective Function for Energy
O^{load}	≜	Ojective Function for Load
O^{temp}	≜	Ojective Function for Temperature
O^{delay}	≜	Ojective Function for Delay
n	≜	Constant between 0 & 1
U	≜	Number of nodes in the cluster

Table 3
Overall comparative analysis on the number of Alive nodes of the proposed model Vs conventional models.

Methods	Best	Worst	Mean	Median	Std-Dev
ABC [30]	0	2	0.045	0	0.23665
GA [31]	0	2	0.045	0	0.23238
PSO [32]	0	3	0.045	0	0.23022
GSA [33]	0	3	0.045	0	0.24901
ABC-GSA [34]	0	2	0.045	0	0.23238
MFO [35]	0	2	0.045	0	0.23453
MFO-ALO [37]	0	3	0.045	0	0.23022
WOA [36]	0	20	0.027	0	0.46731
SAWOA [38]	0	20	0.025	0	0.4642
ROA [29]	0	2	0.0235	0	0.15799
FA-ROA	0	2	0.014	0	0.1217

Table 4
Overall comparative analysis on normalized energy of the proposed model Vs conventional models.

Methods	Best	Worst	Mean	Median	Std-Dev
ABC [30]	0	2	0.045	0	0.23665
GA [31]	0	2	0.045	0	0.23238
PSO [32]	0	3	0.045	0	0.23022
GSA [33]	0	3	0.045	0	0.24901
ABC-GSA [34]	0	2	0.045	0	0.23238
MFO [35]	0	2	0.045	0	0.23453
MFO-ALO [37]	0	3	0.045	0	0.23022
WOA [36]	0	20	0.027	0	0.46731
SAWOA [38]	0	20	0.025	0	0.4642
ROA [29]	0	2	0.0235	0	0.15799
FA-ROA	0	2	0.014	0	0.1217

performance of proposed FA-ROA is 22.13% better than ABC, 21.83% better than GA, 21.83% superior to PSO, 22.13% better than GSA, 21.23% better than ABC-GSA, 21.68% better than MFO, 20.01% superior to MFO-ALO, 6.84% superior to WOA, 4.25% improved than SAWOA, and 10.54% improved than ROA. Thence, the proposed model is verified and validated in terms of energy consumption, and number of alive node at final iteration.

Conclusion

In this paper, an advanced model for the CH selection was proposed with the WSN network parameters like distance, delay, and energy with IoT network parameters such as temperature, and load. The main objective of this CH selection model was to minimize the distance, delay, load, and temperature of the devices and maximize the normalized energy. For this purpose, the CH selection process was achieved through the proposed FA-ROA model. To the next of the implementation, the performance was validated by comparing the proposed FA-ROA over the standard conventional models ABC, GA, PSO, GSA, ABC-GSA, MFO, MFO-ALO, WOA, SAWOA, as well as ROA in terms of delay, normalized energy, alive nodes, but also cost-function metrics resulting in a larger convergence ratio. Thence, the proposed CH selection model confirmed its efficiency is superior over the traditional algorithms. Examining additional performance measures such as network traffic rate, network density, Quality of Service (QoS) can expand the proposed methodology.

CRediT authorship contribution statement

Mamoun Alazab: Conceptualization, Methodology, Software. **Kuruva Lakshmanna:** Data curation, Writing - original draft. **Thippa Reddy G:** Visualization, Investigation. **Quoc-Viet Pham:** Software, Validation. **Praveen Kumar Reddy Maddikunta:** Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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