scientific reports

OPEN

An energy aware cluster inspired routing protocol using multi strategy improved crayfish optimization algorithm for guaranteeing green communication in IoT

R. Chithra[1]✉, C. K. Sarumathiy[2], E. Padma[3] & R. Arulkumar[4]

Internet of things (IoT) has a significant impact on environmental and economic factors for interconnecting billions or trillions of devices that utilize various types of sensors during communications using Internet. Energy is identified as the heart of smart IoT applications since it permits the sensors to carry out their operations. Even though, sensors necessitate a small amount of energy for operations, rapid energy drain when billions and trillions of them interconnect is determined to crumble their performance by influencing energy stability. Clustering is the potential energy managing green communication mechanism which when implemented using metaheuristic techniques helps in achieving required quality of service by facilitating near-optimal solutions. In this paper, mult strategy-improved crayfish optimization algorithm-based intelligent clustering mechanism (MSCFOAICM) is proposed as a solution to the NP-hard problem of achieving green communication in IoT with maximized network lifetime. This MSCFOAICM scheme used a multi-objective fitness function that considered factors of delay, energy, distance, jitter and packet forwarding potential into account such that energy potent nodes are selected as cluster heads (CHs) during the clustering process. It uses multi-strategy-improved crayfish optimization algorithm for CH selection for establishing a better trade-off between exploration and exploitation. It then used a hybrid BWM-TOPSIS multicriteria decision making model for determining nodes' trust using direct and indirect interaction to prevent selection of malicious nodes as CHs. This protocol also prevented low energy nodes to be selected as CHs depending on residual energy estimation during the trust computation process. The number of clusters built during the implementation is determined to be optimal as it aids in sustaining maximized energy and extending network lifetime. The results of MSCFOAICM scheme confirm better throughput of 18.14%, operating IoT nodes of 19.42% and reduced mean transmission delay of 18.42%, compared to the baseline schemes.

Keywords Internet of things (IoT), Green communication, Multi-strategy improved crayfish optimization algorithm (MSICOA), Cluster head (CH) selection, Hybrid best worst method (BWM)-TOPSIS, Trust management model

Internet of Things (IoT) represents an ecosystem in which several physical devices are connected, for transmitting and receiving data through Internet. In IoT, term 'thing' represents any physical devices that include computing devices, wearable devices and sensors[1]. These physical devices inherit the capability of facilitating possible

[1]Department of Information Technology, K. S. Rangasamy College of Technology, Tiruchengode, Namakkal, Tamil Nadu 637 215, India. [2]Department of Computer Science and Engineering, Nitte Meenakshi Institute of Technology(NMIT), Nitte (Deemed to be University), Bengaluru 560064, India. [3]Department of Computer Science and Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS) Pallavaram, Chennai, Tamil Nadu 600117, India. [4]Department of Information Technology, Jeppiaar Institute of Technology, Sriperumpudur, Kanchipuram, Tamil Nadu 631604, India. ✉email: chithra@ksrct.ac.in

number of operations without human intervention. In specific, humans highly reliable upon the IoT system for the objective of achieving the day-to-day activities in the real-time[2]. This IoT ecosystem connected objects and facilitated communication for supporting wide range of IoT applications in different fields[3]. In specific, Clustering of IoT nodes into optimized clusters is identified as the predominant solution for managing energy in the network[4]. This clustering is responsible for clusters' formation with Cluster Heads (CHs) and cluster member nodes. Then the selected CHs takes the role of controlling each cluster in the network[5]. But this CHs selection process needs to be attained through the determination of influential factors such as delay, load, Residual Energy (RE), distance, node centrality, and so on[6]. Moreover, comprehensive number of factors need to be utilized for CHs selection such that frequent re-clustering process can be completely alleviated from the network. Once the CHs selection is obtained, the sensed data from the cluster member IoT nodes need to be forwarded to CHs in each cluster[7]. Then all the aggregated data at the CHs which is received from its individual cluster is transmitted to the sink for decision making about the actions to be taken in the target environment of monitoring[8]. Even though IoT has attracted a high degree of attention over the past decades, the remarkable potentiality of IoT network is hindered by the challenges of energy optimization, security, real time data analytics and data storage[2]. Hence these challenges need to be addressed in a more reliable manner such that the true potential of IoT is realized for it to be adopted in a diversified number of real time applications. Several researchers have handled the problem of trustworthy CHs selection since it plays an anchor role in data transmission and aggregation from lower to upper level in which sink node is present in the network[9].

The presence of malicious CHs node has the probability of increasing their reputation such that even the worst performing IoT nodes due to attack compromization have the possibility of being selected as CHs[10]. When these malicious nodes are selected as CHs, they intentionally or unintentionally waste the energy and drop packets. This intentional behavior eventually results in energy instability and reduced network lifetime[11,12]. Thus, trust management approaches are beneficial for computing trust value of selected CHs through direct and indirect interaction. This trust management approaches are identified to be better suitable and ideal solutions when the selected CHs are compromised by the malicious and selfish nodes[13]. Multicriteria-based decision-making approaches-based trust determination supports in identifying the actual trust of chosen CHs. It is capable of exploring the performance of each IoT node selected as CHs with possible number of factors used for evaluation[14]. The incorporation of fuzzy theory on the other hand enhances the process of handling the degree of vagueness and uncertainty realized during the process of trust estimation. Several innovative works have been contributed to the clustered IoT network[15]. These contributed mechanisms play an anchor role in enhancing security. But most of them were based on assumption that clustering architecture is constructed with the consideration of trustworthy CHs. The clustering and CHs mechanism without determining the trust of CHs IoT node is highly vulnerable. It directly influences the energy and network longevity of the network. Without the inclusion of trust management scheme into the process of CHs selection, there is a high possibility of realizing more amount of packet loss with high communication overhead and mean transmission delay in the network[16].

Research gaps identified

The existing works related to this research mainly concentrated on clustering and CHs selection. But majority of the existing methodologies ignored the process of determining the trust of selected CHs node with comprehensive number of factors to detect malicious behavior during data communication[17,18]. Most of the existing strategies pose the challenge of handling the heterogeneity and dynamic characteristic of the IoT data when applied in large scale network[19,20]. Majority of them mainly concentrated on the use of classical trust evaluation approaches. The classical trust computation strategies include Dempster Shafer Theory, Statistical Reliability coefficient, cipher block chaining-based parallel advanced encrypted standard, and so on[21]. However, these approaches failed in evaluating trust by considering comprehensive number of factors into account under vagueness and uncertainty.

Motivation

Green energy management is an important economic solution which introduces the wide option of facilitating superior energy utilization over the IoT networks. But green energy management methodologies which incorporate the benefits of edge intelligence over a controllable IoT network are identified to be very few in the available literature[22]. The integration of IoT networks with green energy-awareness is determined to be more ideal in a diversified number of real time applications that include smart industries, smart grids, smart homes, smart agriculture and smart cities[23,24]. At this juncture, the development and application of energy proficient solutions are highly important since the IoT nodes function with the help of an internal battery resource and possess high level of energy limitations during process of sensing, data processing, aggregating and forwarding data to the sink where reactive decision-making process is achieved in the real time implementation scenario[25]. In this context, it is also essential to determine the quantity of load or data which should be handled by IoT networks such that the overhead of the selected CHs can be potentially handled in real-time. To prevent the overhead of the CHs and ensure energy management[26]. The IoT nodes selected as CHs need to be explored and exploited with respect to different perspectives such as energy, distance, centrality and latency[27]. This process of optimizing the CHs selection can be effectively achieved through the inclusion of a nature-inspired methodology which could balance the tradeoff between the rate of exploration and exploitation in search space[28]. Keeping this in mind, a nature-inspired optimization algorithm with the added advantages of well-balanced stages of exploration and exploitation is investigated. From the investigation, a Multi-Strategy-Improved Crayfish Optimization Algorithm (MSICOA) proposed by Jia et al.[29] is identified to satisfy the requirements of being employed in process of CHs. The trustworthiness of chosen CHs needs to be identified in a more reactive manner such that worst IoT nodes are never selected as CHs in the networks, and frequent clustering and subsequent re-election process is significantly prevented in the network. In this clustering method, Fuzzy TOPSIS and BWM are integrated for the task of determining trust of IoT nodes such that frequent selection of CHs is completely prevented. This process of trust evaluation of CHs is mainly accomplished using BWM-Fuzzy TOPSIS since, (1) it is one of Multi-Criteria Decision-Making (MCDM) techniques which potentially minimizes the overhead of pairwise comparisons, (2) It facilitates an improved degree of consistency in terms of ranking IoT nodes with respect to different criteria of assessment compared to the classical BWM method, (3) It included merits of fuzzy theory to handle problems of uncertainty and vagueness while ranking nodes in the network.

Novelty

This proposed MSCFOAICM scheme is implemented as one of the few intelligent clustering approaches which completely concentrated on potential CHs selection that helped in sustaining energy during green communication. It is one among the few CHs selection algorithms which verifies the trust of selected CHs using multi-criteria decision-making strategy to preventing unnecessary packet drops and energy consumptions. The inclusion of BWM-fuzzy TOPSIS approach during trust evaluation of CHs node facilitated more reliability in determining the rank alternatives and criteria weights. This estimation of rank and criteria weights helps in handling the issue of uncertainty and subjective information. This BWM-fuzzy TOPSIS approach computationally requires a smaller number of pairwise comparisons on par with the Analytic Hierarchical Process. It is highly capable of handling the degree of precision and vagueness involved during the process of data exchanges under green communication.

Major contributions

The major contributions of the proposed energy-aware cluster-inspired routing protocol is summarized as follows:

(1) A Multi-Strategy Improved Crayfish Optimization Algorithm (MSICOA) is adopted for effectively exploring and exploiting the search space.
(2) It facilitates improved clustering, optimal selection of cluster heads (CHs), and formation of an optimized number of clusters to achieve energy balance and prolonged network lifetime.
(3) It is proposed as a green communication protocol which focuses on efficient management of the available energy resources within the network to promote sustainable IoT operation.
(4) It employed a BWM-fuzzy TOPSIS approach to evaluate the trustworthiness of the selected CHs.
(5) It ensured dynamic and frequent clustering and CH selection, which helps extend the operational lifespan of IoT nodes while minimizing energy consumption.
(6) It simultaneously addresses multiple trust dimensions—including communication, energy, and data to establish a comprehensive trust framework among IoT nodes.
(7) It enables accurate assessment of trust and reputation, facilitating reliable verification of CH trustworthiness.
(8) It incorporates a mechanism to detect misbehaving CHs, thereby safeguarding the network against potential attacks or compromises that could result in energy wastage and packet loss.

The ensuing sections are structured as follows. Section "Related work" gives a comprehensive review of existing green communication protocols contributed to literature for sustaining energy and network longevity in IoT networks with their merits as well as limitations. Section "Multi strategy-improved crayfish optimization algorithm -based intelligent clustering mechanism (MSCFOAICM)" gives a detailed view of proposed MSCFOAICM scheme with respect to the role of MFCOA and trust evaluating BWM-Fuzzy TOPSIS method used for clustering, CHs selection that confirmed the trust of CHs to sustain network energy and lifetime. Section "Results and discussion" shows the simulation results of the proposed MSCFOAICM and benchmarked approaches under the existence of static and mobile IoT nodes with the possible inferences and interpretation. Section "Conclusion" gives the conclusion with major contributions and future scope of improvement.

Related work

In this section, exhaustive review of existing green communication protocols contributed to literature for sustaining energy and network longevity in IoT networks is presented with their merits and limitations.

Kumar et al.[30] proposed a Hybrid Fuzzy Logic and Chicken Swarm Optimization Algorithm-based Clustering Mechanism (HFLCSOA) for establishing green communication which optimized energy utilization in sensor-supported IoT scenario. This HFLCSOA prevented uneven distribution of CHs which increased high energy consumption in IoT networks. It dealt with the challenges that arise when CHs is identified within range of communication of other CHs. It contextually used the advantages of GA, CSO and fuzzy logic for achieving optimized number of clusters' construction to minimize energy consumption in the network. It adopted the idea of constructing clusters by organizing IoT nodes depending on the chromosomes determined using GA through the estimation of minimized fitness fiction related to the network parameters. This fitness function computed by GA considered the factors of minimized energy consumption over each communication round, minimization in intra-cluster distance and reduction in inter-cluster distance during CH selection. It facilitated maximized degree of population diversity by utilizing the operations of crossover and mutation which eventually prevents the problem of uneven distribution of CHs nodes. Moreover, the results of the proposed approach confirmed improved results based on mean RE, node death percentage and alive operating nodes' percentage with increase in number of nodes. Geetha et al.[31] proposed a Deep Random Vector Functional Link Network (DRVLN) and Satin Bowerbird Optimizer (SBOA)-based Clustering Mechanism (DRVLN-SBOC) approach which satisfied the requirements of the expected load and helped in forecasting the degree of energy utilization in energy-aware

IoT networks. It was proposed as a potential green energy-aware cluster communication methodology which assisted in the determining effective set of CHs that attributed towards extended network lifetime. This green energy-aware clustering method was achieved using SBOA which clustered the IoT nodes into clusters, and DRVFLN used helped in better load prediction. It used the parameters of delay, distance and energy into account during the construction of fitness function that helped in choosing CHs in IoT network. It used Adam Optimizer which helped in optimizing the hyperparameters of the DRVFLN model such that better load forecasting can be achieved in the network. This capability of GA operators helped in attaining a balanced network load that eventually helped in prolonging network lifetime. The results of this DRVLN-SBOC approach under different scalable number of sensor nodes confirmed better results in terms of Mean Absolute Percent Error (MAPE) and Root Mean Square Error (RMSE). Moreover, this green communication strategy was identified to be extremely potent in regulating amount of renewable energy possessed in the network.

Then Dev et al.[32] have offered Harris Hawks Optimization algorithm (HHOA)-based Clustering Technique (HHOACT) for choosing optimal amount of CHs which assists in better energy optimization in IoT networks. This HHOACT approach is based on factors of temperature, RE, load, number of alive nodes and delay for facilitating the process of fitness function which helps in better clustering and subsequent CHs selection process. It incorporated the merits of exploration and exploitation inherent with the HHOA for the objective of sustaining energy in the IoT networks. The results confirmed improved results in based on even distribution of IoT nodes, number of operating nodes, energy utilization rate and end-to-end delay for varying number of IoT nodes during the process of clustering. Das et al.[33] proposed an Adaptive Spotted Hyena Tunicate Swarm Optimization Algorithm-based green communication mechanism for effective and efficient selection of CHs selection that prolonged the network longevity in IoT networks. This green communication strategy acts as an energy efficient clustering approach that selects CHs based on derivation of multi-objective function that includes factors of security, delay, distance, energy and QoS. It was proposed as one of the important approaches that facilitated better trustworthy CHs nodes that proportionally.

Singh et al.[34] proposed a greedy clustering Approach using Genetic Algorithm and mutation operator (GCAGAMO) for the objective of attaining required degree of QoS in heterogeneous IoT network. This GCAGAMO approach used a weighted fitness function which considered factors of distance, mean energy, RE and node density during clustering process. It was proposed with a three-tier heterogeneous architecture which addressed deployment problems associated with the IoT nodes such that functional duration is enhanced. Results of GCAGAMO approach with single and multiple sinks confirmed better energy balancing rate, throughput and data transmission delay independently to the operating nodes in the network. Sankar et al.[35] have proposed a Sand Piper CH Optimization Algorithm (SPCHOA) for selecting CHs which possesses high fitness value in the IoT network. This SPCHOA approach performed the process of clusters construction based on the computation of Euclidean distance. This Euclidean distance-based strategy was identified to decrease the energy consumptions, and at the same time increased the throughput and network lifetime on the other end.

Lei et al.[36] proposed a fuzzy clustering and PSO-based CH selection mechanism for improving the network operation rate to sustain energy stability and lifetime in IoT. This FCPSO approach organized IoT nodes into different clusters using fuzzy subsets to achieve necessitated degree of network functionality. It minimized time and computing overhead with respect to each IoT nodes such that current operations are performed between each of the determined sub-clusters. It included fuzzy clustering for handling the dynamically changing energy levels and node density to extend network lifetime. It combined merits of PSO and fuzzy clustering to attain a scalable solution to manage the distributed large network with less computational effort. It specifically used PSO for the optimization of the constructed clusters such that energy use and data transmission is optimally managed. Arivubrakan and Kanagachidambaresan[37] proposed a Woodpecker and Flamingo Search Optimization Algorithm (HWFSOA)-based multi-objective clustering and CHs selection mechanism which supported in determining number of CHs with energy efficiency. This HWFSOA scheme used factors of throughput, energy consumptions, distance and delay for assessing the value of the fitness function such that efficient IoT nodes are identified as CHs. This clustering approach managed the construction of optimal clusters which phenomenally balanced the network stability with extended network lifetime. The results confirmed better results in terms of network lifetime, energy consumption, throughput, delay and packet delivery rate independent of number of operational IoT nodes.

In addition, Kponhinto et al.[38] have proposed a Bacterial Foraging and Artificial Bee Colony Optimization Algorithm (BFABCOA) which focussed and achieved on the process of superior data gathering in IoT networks. This BFABCOA approach blended exploration phase of ABC algorithm with exploitation phase of BFOA algorithm such that suitable balance in the process of energy management can be achieved during clustering. This clustering was proposed as a multi-objective optimization protocol which employed the merits of ABC and BFOA towards determining the best solution that helps in balancing the rate of energy consumptions, link quality, cluster stability and velocity. The results of this BFABCOA scheme determined with different mobile IoT nodes confirmed better data packets received at the sink, network lifespan, energy consumption and throughput with different rounds and number of IoT nodes in the network. Lv et al.[39] have proposed an Evolutionary Rate Water Cycle Optimization Algorithm (ERWCOA) was proposed a green communication protocol which sustained more amount of energy in IoT networks. This ERWCOA approach addressed the problem associated with the challenges of data transmission efficiency, throughput, total number of rounds until its death, network longevity and energy consumptions per node. It used a local escaping operator which helped in preventing the algorithm from getting trapped into the local point of optimality. This prevention capability enhances potential of exploration, and at the same time used randomization-control operations which balanced the rate of exploration and exploitation in a more dynamic manner such that ideal CHs are identified. This clustering approach prevented redundant transmissions and minimized energy during the selection of CHs.

The results of ERWCOA approach confirm improved energy efficiency, packet delivery rate, mean transmission delay, throughput and network lifetime.

Table 1 gives a summary of existing green communication protocols proposed for IoT networks with their merits as well as limitations.

Extract of literature

The shortcomings identified from existing green communication protocols contributed for IoT networks is listed as follows.

(1) Quantifiable number of clustering schemes concentrated on the formation of rigid clusters, and many of them failed to organize the clusters optimally such that energy management can be achieved to the superior level in the network.
(2) Significant number of clustering and CHs selection approaches mainly targeted on potential selection of CHs, and most of them ignored to assess the trust of the selected CHs even though it is responsible for crumbing the energy and lifespan in the network[40–42].
(3) A number of clustering approaches were proposed for handling the impact of static IoT nodes rather than addressing the influence of mobile IoT nodes even though mobility has a potential impact during clustering and subsequent CH selection[43,44].

The above limitations are considered during formulation and implementation of proposed MSCFOAICM scheme which is detailed in the forthcoming sections.

Authors	Clustering and CHs selection method used	Merits	Limitations
Kumar et al.[31]	Hybrid Fuzzy Logic and Chicken Swarm Optimization Algorithm-based Clustering Mechanism (HFLCSOA)	This HFLCSOA approach was proposed for avoiding t uneven distribution of CHs in the entire network which increases the probability of resulting in high energy consumption in IoT networks	This clustering approach was complex in managing the available energy as it failed to adopt a weighted strategy of fitness evaluation
Geetha et al.[32]	Deep Random Vector Functional Link Network (DRVLN) and Satin Bowerbird Optimizer (SBOA)-Based Clustering Mechanism (DRVLN-SBOC) approach	It was proposed as one of the potential green energy-aware cluster communication methodology which assisted in the determination of effective set of CHs that attributed towards extended network lifetime in IoT networks	The inclusion of deep random vector functional link network increased the problem of computational overhead during the process of training the factors which helped in assessing the potential of the IoT nodes
Dev et al.[33]	Harris Hawks Optimization algorithm (HHOA)-based Clustering Technique (HHOACT)	This HHOACT approach used factors of temperature, RE, number of alive nodes, load and delay for facilitating the process of fitness function which helps in better clustering and subsequent CHs selection process	In spite of exhaustive use of factors during CHs selection, the challenges with respect to the trust assessment of chosen CHs proportionally increased in network
Das et al.[34]	Adaptive Spotted Hyena Tunicate Swarm Optimization Algorithm-based green communication mechanism	This green communication strategy was proposed as an energy efficient clustering approach that selected CHs depending on the derivation of multi-objective function that included the factors of security, delay, energy, distance and Quality of Service (QoS) into account	It only focussed on energy optimizing factors during the process of clustering, and meanwhile ignored the trust of selected CHs which introduces the problem of energy instability and shortened lifetime that occurs due to malicious CHs in the network
Singh et al.[35]	Greedy clustering Approach using Genetic Algorithm and mutation operator (GCAGAMO)	This GCAGAMO approach used a weighted fitness function which considered distance, mean energy, RE and node density during clustering and it was proposed as a three-tier heterogeneous architecture which addressed the deployment problems associated with the IoT nodes such that functional duration is achieved in the network	This adopted three-tier architecture even though assisted in the problem of node deployments, but still faced the challenge in the process of selecting optimal clusters which helps in managing the network energy to the significant level
Sankar et al.[36]	Sand Piper CH Optimization Algorithm (SPCHOA)	This SPCHOA approach performed the process of clusters construction based on the computation of Euclidean distance, and was identified to decrease the energy consumptions, and at the same time increased the throughput and network lifetime on the other end	The inclusion of SPOA could not handle the balance between exploration and exploitation to expected level, and thereby introduced energy holes in the network
Lei et al.[37]	A fuzzy clustering and PSO-based CH selection mechanism (FCPSOCHM)	This FCPSO approach organized the IoT nodes into different clusters which represents fuzzy subsets for achieving necessitated degree of network functionality and minimized time and computing overhead with respect to each IoT nodes such that current operations are performed between each of the determined sub-clusters	The process of fuzzy clustering utilized in this approach was rigid, and thereby introduced the challenge of categorizing the behaviour of IoT nodes in a more precise and reliable manner during the routing process
Arivubrakan and Kanagachidambaresan[38]	Woodpecker and Flamingo Search Optimization Algorithm (HWFSOA)-based multi-objective clustering and CHs selection mechanism	This HWFSOA scheme used throughput, energy consumptions, delay and distance for assessing the value of the fitness function such that efficient nodes are identified as CHs	This clustering approach suffered from the problem of nodes' scalability, and hence potential performance could not be realized with a greater number of IoT nodes
Kponhinto et al.[39]	Bacterial Foraging and Artificial Bee Colony Optimization Algorithm (BFABCOA)-based clustering	This BFABCOA approach blended exploration phase of ABC algorithm with exploitation phase of BFOA algorithm such that suitable balance in the process of energy management can be achieved during the process of clustering	This clustering approach was identified to be more suitable for mobile IoT nodes and exhibited moderate performance with static IoT nodes in the network
Lv et al.[17]	Evolutionary Rate Water Cycle Optimization Algorithm (ERWCOA)-based Clustering	This ERWCOA approach addressed the problem associated with the challenges of data transmission efficiency, throughput, total number of rounds until its death, network longevity and energy consumptions per node	This clustering scheme faced the challenge of hotspot and possessed only a minimal degree of tolerance to the IoT nodes that comprised of more amount of energy in the network

Table 1. Summary of existing green communication protocols used for clustering in IoT.

Multi strategy-improved crayfish optimization algorithm -based intelligent clustering mechanism (MSCFOAICM)

This Improved CFOA used for achieving an intelligent clustering mechanism during the process of green communication in IoT completely derives its inspiration from the behaviour of crayfish in the nature. The traditional CFOA was contributed by mimicking its foraging, competition and summer resort behaviour. These three different behaviours of crayfishes are modelled effectively and efficiently into three different phases of CFOA for the objective of balancing trade-off between degree of exploration and exploitation introduced by algorithm in search space. In specific, exploration stage of CFOA resembles summer resort behaviour, and the exploitation phase resembles the competition and foraging phase of the crayfishes. However, the regulation of the exploration and exploitation phases completely depends on the temperature. Hence, the crayfish either performs exploration or exploitation depending on the temperature which is analogical to the crayfish (search agents) which explores and exploits the search space depending on the satisfaction of factors (temperature) that are used for determining fitness value of nodes. When fitness value of candidate solution as identified by the crayfish (search agent) is more than or equal to normalized value of fitness function, then it employs the phase of exploration. On the other hand, it introduces the phase of exploitation when fitness value of candidate solution as identified by crayfish (search agent) is less than the normalized value of fitness function value. The classical CFOA possesses higher effect of global optimization and randomness. Before the start of CFOA, specific conditions (temperature) of the problem is specified in Eq. (1)

$$\mathrm{t_{mp}} = \mathrm{rand} \times \text{ Threshold } \mathrm{t_{mp(1)}} + \text{Threshold } \mathrm{t_{mp(2)}} \tag{1}$$

Population initialization

In this phase of population initialization, the candidate solution determined by the crayfish (search agent) is a $1 \times d$ dimensional matrix. This $1 \times d$ dimensional matrix is used for determining the finite amount of candidate solutions identified by the search agents in the search space. In this context, the collection of variables $\mathrm{CF_{(i,j)}} = \left(\mathrm{CF_{(1)}}, \mathrm{CF_{(2)}}, \mathrm{CF_{(3)}}, \ldots\ldots, \mathrm{CF_{(d)}}\right)$ signifies location of search agent which lies between lower and upper threshold of search space. During implementation of CFOA, the computation of ideal solution is achieved such solutions determined during each evaluation are compared, and potential solutions are identified as optimal from the entire problem. Then, positions of population of search agents' is determined based on Eq. (2)

$$\mathrm{CF_{(i,j)}} = \mathrm{LB_{(j)}} + \left(\mathrm{UB_{(j)}} - \mathrm{LB_{(j)}}\right) \times \mathrm{rand} \tag{2}$$

Where $\mathrm{CF_{(i,j)}}$represents position with respect to $\mathrm{i^{th}}$ search agent (crayfish) evaluated with respect to $\mathrm{j^{th}}$ dimension. Further $\mathrm{UB_{(j)}}$ and $\mathrm{LB_{(j)}}$ indicate lower and upper bound associated with $\mathrm{j^{th}}$ dimension used for evaluating candidate solutions in search space with rand, a random number that ranges between 0 and 1.

Exploration stage (summer escape stage)

This summer escape stage of exploration mimics the behavior of crayfish when the temperature of water is more than 30° Celsius. When temperature is more than 30° Celsius, the crayfish identifies it as a summer with high temperature and explores for a cool and moist cave. This behavior of crayfish is analogical to the process in which the search agents understand the condition prevailing in the problem domain of investigation and perform better exploration of candidate solutions such that feasible number of solutions is explored, and global optimization results are determined in search space. The candidate solutions are determined by the search agents (crayfish) based on Eq. (3).

$$\mathrm{CF_{CS}} = \frac{\mathrm{CF_{OP(IS)}} + \mathrm{CF_{OP(CP)}}}{2} \tag{3}$$

Where $\mathrm{CF_{OP(IS)}}$ and $\mathrm{CF_{OP(CP)}}$ represents the optimal position of the candidate solutions obtained by search agents (crayfish) until recent iteration, and optimal position of candidate solutions obtained by search agents (crayfish) from current population. However, the search agents may compete with one another during the process of exploring the candidate solutions. But this competition of search agents for exploring and identifying potential candidate solutions in a random event. This random event of search agents (crayfish) exploration is achieved based on a random number termed rand. In specific, when the value of $\mathrm{rand} < 0.5$, then the search agents do not compete with one another, and directly explore the available candidate solutions by updating its position based on Eq. (4)

$$\mathrm{CF_{CS\,(Explore)}}\,(\mathrm{New}) = \mathrm{CF_{CS(i,j)}} + \mathrm{C_D} \times \mathrm{rand} \times \left(\mathrm{CF_{CS}} - \mathrm{CF_{CS(i,j)}}\right) \tag{4}$$

Where $\mathrm{CF_{CS}}\,(\mathrm{New})$ represents the position update of the search agents (crayfish) with $\mathrm{C_D}$ as the curve of decrease as specified in Eq. (5)

$$\mathrm{C_D} = 2 - \left(\frac{\mathrm{N_E}}{\mathrm{N_{E(Total)}}}\right) \tag{5}$$

In this context, the parameter $\mathrm{C_D}$ depends on $\mathrm{N_E}$ and $\mathrm{N_{E(Total)}}$ which represents number of assessments and total amount of evaluations performed by search agents (crayfish) during phase of exploration.

Exploitation stage (competition stage)

This competition stage of exploitation mimics the behavior of crayfish when the temperature of the water is greater than 30 °C and the value of $\text{rand} \geq 0.5$. During this exploitation phase, the search agents (crayfish) compete with one another during the process of exploitation such that better results are identified through local optimization process. At this juncture, two or more search agents (crayfish) compete with one another to exploit he possible number of candidate solutions locally by adjusting their positions depending on Eq. (6)

$$\mathrm{CF}_{\mathrm{CS\ (Exploit)}}\ (\mathrm{New}) = \mathrm{CF}_{\mathrm{CS(i,j)}} - \mathrm{CF}_{\mathrm{CS}(z,\mathrm{j})} + \mathrm{CF}_{\mathrm{CS}} \tag{6}$$

Where $\mathrm{CF}_{\mathrm{CS}(z,\mathrm{j})}$ represents the random candidate solution identified by search agents (crayfish) during phase of exploitation in the search space.

This random candidate solution identification is achieved based on Eq. (7)

$$z = round\ (rand \times\ (\mathrm{Pop}_{\mathrm{Size}} - 1)) + 1 \tag{7}$$

Where $\mathrm{Pop}_{\mathrm{Size}}$ is the size of population (number of search agents used for exploitation objectives).

Exploitation stage (foraging stage)

This exploitation phase termed foraging stage mimics the behavior of crayfish in which they climb out the cave and identify the food when temperature is less than or equal to 30 °C. This is analogical to how the search agent (crayfish) exploits the search space when the condition needed for clustering and CHs selection is less than predefined threshold. In this phase the position of the candidate solution (food) as identified by search agent (crayfish) is determined based on Eq. (8).

$$\mathrm{F}_{\mathrm{P(CF)}} = \mathrm{F}_{\mathrm{P(G)}} \tag{8}$$

The degree to which exploitation needs to be employed in the search space depends on the constraints that decide on the process of exploitation. When the constraints which need to be employed in the problem domain are less than the degree of exploitation is proportionally minimized in search space. But the degree of exploitation introduced by search agent (crayfish) during this phase of exploitation is normally distributed as determined based on Eq. (9).

$$\mathrm{D}_{\mathrm{FI}} = \mathrm{C}_{\mathrm{DE}} \times \frac{1}{\sqrt{2 \times \pi \times \sigma}} \times \exp\left(\frac{-\left(\mathrm{t}_{\mathrm{mp}} - \mu\right)^2}{2\sigma^2}\right) \tag{9}$$

Where μ and σ represents mean and standard deviation of factors which is imposed during process of exploitation. In specific, C_{DE} indicates the control parameters considered for guiding the search agent (crayfish) during exploitation (local search). Further the degree of search agents (crayfish) exploitation depends on the factors that include the number of candidate solutions which need to be exploited in the search space, and the complexity of the factors considered during optimization. In this context, the number of candidate solutions which need to be exploited in the search space is determined using Eq. (10)

$$\mathrm{F}_{\mathrm{SIZE(CF)}} = \mathrm{C}_{\mathrm{DE(I)}} \times\ \mathrm{rand} \times \left(\frac{\mathrm{Fit}_{\mathrm{(i)}}}{\mathrm{Fit}_{\mathrm{(FS)}}}\right) \tag{10}$$

Where $\mathrm{C}_{\mathrm{DE(I)}}$ represents the factor of exploitation which aids in determining the number of candidate solutions which needs to be exploited in the search space. In specific, the value of $\mathrm{C}_{\mathrm{DE(I)}}$ considered during the exploitation phase is 3. Moreover, $\mathrm{Fit}_{\mathrm{(i)}}$ and $\mathrm{Fit}_{\mathrm{(FS)}}$ represents the fitness value associated with the individual search agent (crayfish) and the fitness value associated with candidate solutions' position in search space. In addition, this factor of $\mathrm{F}_{\mathrm{SIZE(CF)}}$ is mainly used for deciding upon the number of candidate solutions which need to be exploited in the search space such that what strategy can be adopted for exploiting the candidate solutions and identify the best local solution among them in search space is identified. Whenever value of $\mathrm{F}_{\mathrm{SIZE(CF)}} = \frac{(\mathrm{C}_{\mathrm{DE(I)}}+1)}{2}$, then the number of candidate solutions which need to be exploited in the search space is very high. Hence the number of candidate solutions which need to be exploited in the search space is partitioned for better exploitation using a food shredding factor ($\mathrm{F}_{\mathrm{P(CF)}}$) as specified in Eq. (11)

$$\mathrm{F}_{\mathrm{P(CF)}} = \exp\left(-\frac{1}{\mathrm{F}_{\mathrm{SIZE(CF)}}}\right) \times\ \mathrm{F}_{\mathrm{P(CF)}} \tag{11}$$

In this phase of exploitation, the total number of candidate solutions are partitioned proportionally with respect to the division of the total number of search agents into three new populations. The size of three new population complexity depends on the number of candidate solutions which need to be suitably exploited in the search space. This phase of exploitation pertains to the process of bipedal eating behavior of search agents (crayfish). Thus, the functions of sine and cosine are used for simulating this behavior of bipedal eating as specified in Eq. (12)

$$\mathrm{CF}_{\mathrm{CS}}\ (\mathrm{New}) = \mathrm{CF}_{\mathrm{CS\ (I,J)}} + \mathrm{F}_{\mathrm{P(CF)}} \times\ \mathrm{D}_{\mathrm{FI}} \times\ (Cos\,(2 \times\ \pi\ \times\ \mathrm{rand})) - sin\,((2 \times\ \pi\ \times\ \mathrm{rand}))) \tag{12}$$

On the other hand, when the value of $F_{SIZE(CF)} \leq \frac{(C_{DE(I)}+1)}{2}$, then the number of candidate solution which need to be locally optimized in the search space is nominal. Hence the search agent (crayfish) updates their positions in the search space as specified in Eq. (13)

$$CF_{CS}\ (New) = \left(CF_{CS\ (I,J)} - F_{P(CF)}\right) \times\ D_{FI} + D_{FI} \times\ rand \times\ CF_{CS\ (I,J)} \tag{13}$$

In addition, Algorithm 1 presents pseudocode of CFOA used for clustering and CH selection.

Input: Number of randomly deployed IoT nodes, number of iterations, size of the population (search agents), number of factors taken for evaluation (fitness evaluating parameters).
Output: Number of clusters and optimal number of CHs nodes

```
Generate initial population of search agents (crayfish) randomly
Compute fitness value related to every candidate solution CF_CS,G and CF_CS,L.
While Iter_Curr < Iter_Max
    Define the parameter of t_mp using Equation (1)
        If (t_mp > Threshold t_mp)
            Identify the global best candidate solution depending on Equation (3)
            If (rand < 0.5)
                Search agents (Crayfish) performs stage of summer resort based
                on Equation (4)
            Else
                Search agents (Crayfish) compete with one another based on
                Equation (6).
            End
        Else
                Food intake 'p' and food size 'Q' are determined using Eq. (9) and
                Eq. (10).
        If (F_SIZE(CF) > 2)
            Compute degree of exploitation (food shredding) F_P(CF) using Equation
            (11)
            Utilize the method of bipedal exploitation using Equation (12)
        Else
            Utilize the method of direct exploitation using Equation (13)
        End
End
Update the fitness value related to each of the candidate solution CF_CS,G and CF_CS,L.
Iter_Max = Iter_Max + 1
End
```

Algorithm 1. Pseudocode for CFOA-based clustering and CHs algorithm.

Reasons for modifying CFOA
Even though the classical CFOA possesses several merits, it overlooks some of the significant behavior of crayfish since it considered only the impact of temperature (threshold of conditions) into account rather than the other factors that contribute towards better global and local searching process in search space. The classical CFOA possesses a high challenge while determining optimal solution since search agents in latter stage of exploration cluster around local optimal positions limiting their movement. This restriction in in their movement slows down the speed of convergence and increases the probability of the solution from falling into local point of optimality during exploitation phases. To alleviate the challenges, Modified Crayfsh Optimization Algorithm (MCFOA) was propounded with the capacity to perform environmental update and Ghost Opposition-Based Learning (GOBL) for balancing the tradeoff between rate of exploration and exploitation in search space in the network.

Modification strategy 1: environment update mechanism
In this Environment update mechanism-based modification strategy, a water quality factor termed W_{QF} is included for assessing the fitness value of candidate solutions based not only on the current position but also on

different points in its neighborhood. This parameter of $\mathrm{W_{QF}}$ included in the MCFOA represents a hierarchical discretization which ranges between 0 and 5 for the objective of minimizing the computational complexity of adopted algorithm. This factor plays a significant role in deciding whether search agents' position need to be updated or can still get retained in the same position of the search space. The position update of search agents based on Environment update mechanism is determined using Eq. (14)

$$\mathrm{CF_{CS}\ (New) = CF_{CS\,(OC)} + \left(CF_{CS\,(RP)} - CF_{CS\,(i,j)}\right) \times Cos\,(\theta\,) \times A_{WF} \times W_{QF} \times Rand + CF_{CS\,(RP)} \times Sin\,(\theta\,) \times A_{WF} \times Rand} \tag{14}$$

But quality of candidate solutions as realized by search agents (crayfish) is different depending on the factors considered for exploration and exploitation, and this difference is represented by the term $\left(\mathrm{CF_{CS\,(RP)} - CF_{CS\,(i,j)}}\right)$.In this context, $\mathrm{CF_{CS\,(RP)}}$ and $\mathrm{CF_{CS\,(OC)}}$ denotes random location of population. Random position of candidate solutions identified between the current position and candidate optimal position as presented in Eqs. (15) and (16)

$$\mathrm{CF_{CS\,(OC)}} = \left(\mathrm{CF_{CS\,(Best)}} - \mathrm{CF_{CS\,(i,j)}}\right) \times r \tag{15}$$

Where r is random number in the range [0, 1] and it represents sensing force. Then the value of adaptive water flow factor ($\mathrm{A_{WF}}$) is determined based on Eq. (16)

$$\mathrm{A_{WF} = W_{FVF} \times Cos}\left(\frac{\pi}{2} \times \left(1 - \frac{\mathrm{Fit_{(i)}}}{\mathrm{Fit_{(FS)}}}\right)\right) \tag{16}$$

Where $\mathrm{W_{FVF}}$ is a constant which indicates the factor of water flow velocity which is set to the value of 2. When the value of $\mathrm{W_{FVF}} \leq 3$ then it means that the search agent (crayfish) identified that the current position is highly suitable for exploitation, and continuous exploitation can be employed for determining a greater number of better local solutions in the search space. Instead, when $\mathrm{W_{FVF}} > 3$, then search agent decides to move in the opposite direction depending on the water flow direction. This environment update mechanism considers the search agents behavior as a circle in which its position is at center of circle. Then, a random angle θ is considered for computing the direction in which the search agents need to move in search space. This determination of angle θ and direction of movement associated with search agents is achieved through the inclusion of roulette wheel selection algorithm. However, the search agents traversing or moving path is determined based on the current direction in which they are moving in search space. In entire circular movement of search agent, the angle θ can take any value between 0 and 360 degrees such that the magnitude of movement ranges between − 1 and + 1, respectively. When there is a deviation between the random angle θ then the search is identified to exhibit random movement which systematically widens up the search agents' search range. This inclusion of random angle θ improves the position of randomness and enhances the capability of the solutions from escaping from the local point of optimality and prevents local convergence to expected level. This Environment update mechanism-based modification strategy thereby enhanced the potentiality of the classical CFOA during exploration in search space.

Modification strategy 2: ghost opposition-based learning (GOBL) strategy

This GOBL strategy is implemented by considering the entire search space as a two-dimensional space. In this two-dimensional space, the x-axis has the upper and lower bound as $\mathrm{U_{BD}}$ and $\mathrm{L_{BD}}$, respectively. These lower and upper bounds represent search range of solution such that ghost generation can be significantly achieved in the search space. If $\mathrm{CF_{CS\,(OC)}\ (New)}$ is the location of new candidate solution and height of solution is $h_{(1,i)}$, then position of best candidate solution represents projected position of current candidate solution under exploration is determined as $\mathrm{CF_{CS\,(OC)}\ (GH)}$ with $h_{(2,i)}$as the height of best candidate solution. The position of ghost candidate solution ($\mathrm{cf_{CS\,(OC)}}$) determined in the search space is determined using Eq. (17)

$$\mathrm{cf_{CS\,(OC)} = CF_{CS\,(OC)}\ (New) - CF_{CS\,(OC)}}\ (i) + \mathrm{CF_{CS\,(OC)}\ (GH)} \tag{17}$$

Then the principle of lens imaging principle is adopted for computing the opposite learning value of the ghost candidate solution is computed. In this context, the GOBL strategy included into the MCFOA is achieved based on Eq. (18)

$$\mathrm{CF_{CS\,(OC)}\ (GH)} = \frac{(\mathrm{U_{BD} + L_{BD}})}{2} + \frac{(\mathrm{U_{BD} + L_{BD}})}{2k} - \frac{\mathrm{CF_{CS\,(OC)}}}{k} \tag{18}$$

Where the value of k is determined using Eq. (19) with $\mathrm{IIer_{Max}}$ and $\mathrm{IIer_{Curr}}$as the maximized number of iterations and the current iteration, respectively

$$\mathrm{k} = \left(1 + \left(\frac{\mathrm{IIer_{Curr}}}{\mathrm{IIer_{Max}}}\right)^{0.5}\right)^{10} \tag{19}$$

Further, Algorithm 2 presents pseudocode of CFOA used for clustering and CHs selection.

Input: Number of randomly deployed IoT nodes, number of iterations, size of population (search agents), number of factors used for evaluation (fitness evaluating parameters)
Output: Number of clusters and optimal number of CHs nodes
Generate the initial population of search agents (crayfish) randomly
Determine fitness value related to every candidate solution $CF_{CS,G}$ and $CF_{CS,L}$.
While ($Iter_{Curr} < Iter_{Max}$)
    If ($W_{FVF} > 3$) // The candidate solution is explored using environment update mechanism-based modification strategy//
        The best position of the candidate solution is determined based on Equation (14)
    Else
        If ($t_{mp} >$ Threshold t_{mp})
            If (rand < 0.5)
                Search agents (Crayfish) performs summer resort based on Equation (4)
            Else
                Search agents (Crayfish) compete with one another based on Equation (6).
            End If
        Else If
            If $F_{SIZE(CF)} \leq \frac{(C_{DE(I)}+1)}{2}$
                Utilize the method of bipedal exploitation using Equation (12)
            Else
                Utilize the method of direct exploitation using Equation (13)
            End If
        End If
    End If
  End For
 End For
 Compute value of k using Equation (20)
 End For
End While
Compute fitness value of solution in updated position to find the global best
End

Algorithm 2. Pseudocode for CFOA-based clustering and CHs algorithm.

Implementation of MCFOA

This MCFOA is started with the initialization of population size, number of factors used for evaluation and possible number of evaluations. This initial population is determined based on Eq. (2). Then the environment update strategy is adopted for checking the quality of the candidate solutions depending on the factor W_{FVF}, such that the solution needs to be updated, or the current position of the solution needs to be retained is decided. When $W_{FVF} \leq 3$, the search agents confirmed the quality of the candidate solutions as poor, and hence the position of the candidate solution needs to be changed based on the environment update strategy. Instead, when $W_{FVF} > 3$, search agents confirmed the quality of the candidate solutions as superior, and hence the position of the candidate solution is not changed. Furthermore, adaptive flow factor (A_{WF}) is used for deciding between bipedal feeding or direct feeding mechanism such that local optimization can be improved to anticipated level. Then the search agents decide the movement direction for find more number of potential candidate solutions in search position depending on Eq. (16). When the value of A_{WF} is lower, then search agent ignores search space as it cannot perform the summer vacation stage and hence updates the position in reverse direction opposite to current movement direction. Then the stage of exploitation is achieved when $t_{mp} >$ Threshold t_{mp} and $W_{FVF} > 3$. In this exploitation process, the better local optimization is achieved by search agents by determining fitness of candidate solutions in neighborhood of currently identified global optimal solution. In addition, the strategy of GOBL is employed for randomly generating the candidate solution by combining the fitness of current candidate solution and the global optimal solution in search space. The current candidate solution is compared with the randomly generated candidate solution depending on the fitness value, the solution between these which has more fitness value is retained in the search space. The integration of multiple positions of the candidate solutions exploited and explored by the search agents potentially prevented the algorithm from falling into local point of optimality. Finally, position of candidate solution is determined and updated by comparing value of fitness in its current iteration and the current global best solution in the search space as depicted in Fig. 1.

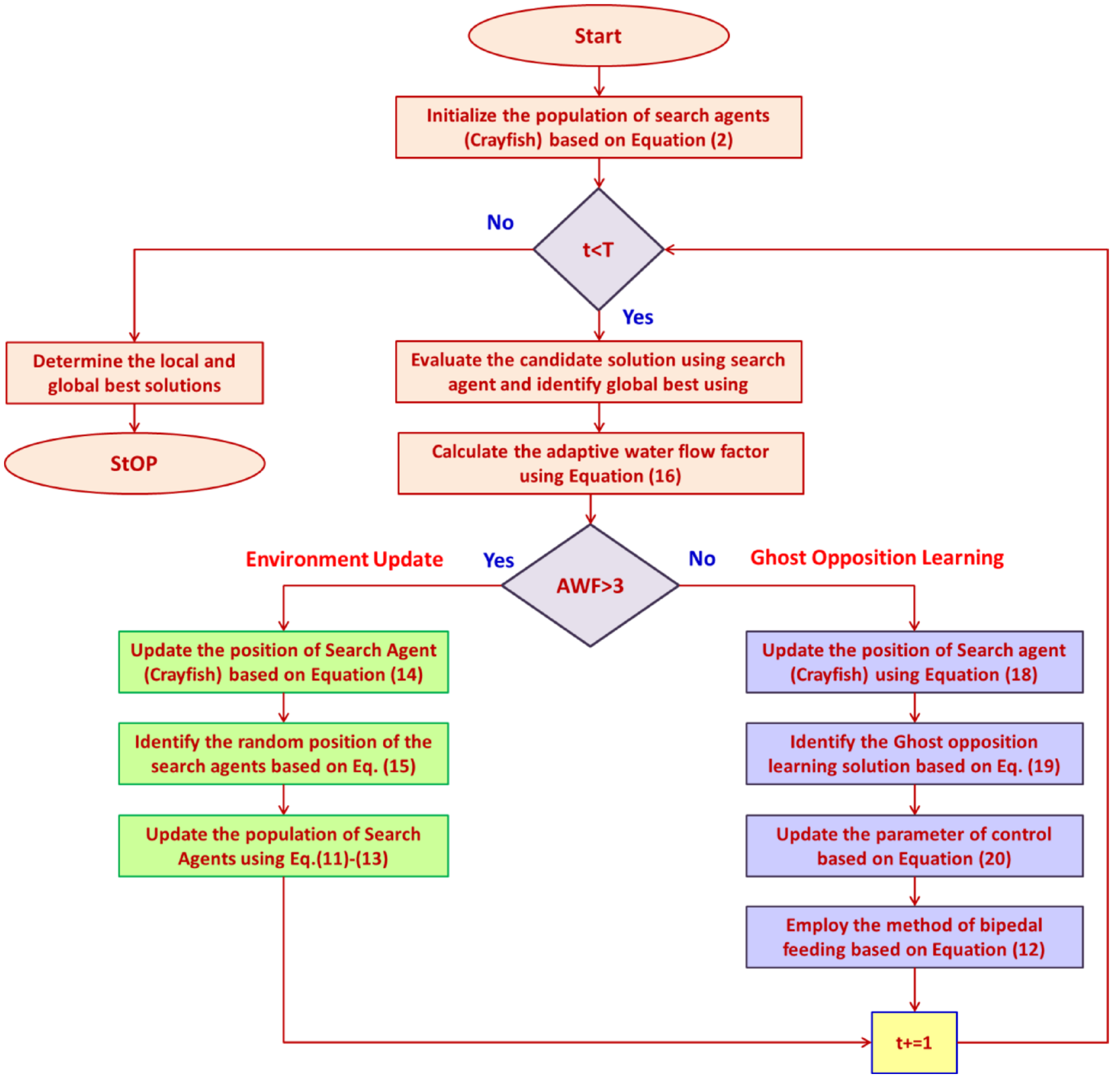

Fig. 1. Flowchart of MCFOA used for clustering and first level CHs selection.

Once the MCFOA is implemented for clustering and CHs selection in the network, the trust of the selected CHs is determined using BWM-Fuzzy TOPSIS-based Trust evaluation such that frequent selection of CHs and clustering process of completely prevented.

BWM-Fuzzy TOPSIS-based trust evaluation of CHs

In this section, the primitives of BWM and Fuzzy TOPSIS used for trust evaluation of the selected CHs are presented.

Best-worst method (BWM)

This BWM method partitioned the pairwise comparisons into two generic types that include reference comparisons and secondary comparisons. In case of reference comparison, the comparison a_{ij} is termed as reference when i represents best criterion and/ or j denotes worst criteria used for evaluation. On the other hand, a_{ij} is termed to be secondary comparison reference when neither i nor j is identified to be the best or worst criterion with the condition $a_{ij} \geq 1$. The detailed steps included onto the process of BWM are discussed as follows.

Step 1: Identification of the decision criteria set.

In this step, the factors that are used for determining the trust of selected CHs such that packet forwarding potential, energy utilization, packet dropping rate are identified in the network. This set of criteria considered for trust evaluation is defined as $\mathrm{C} = \{c_1, c_2, c_3, \ldots \ldots, c_n\}$, and these criteria are essential for deciding about the potential of the selected CHs during the process of data transmission.

Step 2: Determination of best and worst criteria.

This step is responsible for determining most desirable or most significant criteria at one end, and the least desirable and least significant criteria from the problem domain. However, no comparison is introduced at this step.

Step 3: Identify preference of best criterion over other criteria.

In this step, preference of best criterion is identified on par with the other comprehensive number of criteria used for evaluation using the number that ranges between 1 and 9 (These values are presented in Table 2). This vector associated with the best to the other criteria is specified using Eq. (20)

$$\mathrm{VA_{Best}} = (\mathrm{a_{B1}}, \mathrm{a_{B2}}\ , \mathrm{a_{B3}}, \ldots\ .., \mathrm{a_{Bn}}\ ) \tag{20}$$

Where $\mathrm{a_{Bj}}$ denotes preference of best criterion (B) over other criterion j such that $\mathrm{a_{BB}} = 1$.

Step 4: Identify preference of other criterion over worst criteria.

The preference of other criteria on par with worst criteria is determined through number which ranges between 1 and 9. (These values are presented in Table 2). This vector associated with other criteria over worst criteria is determined using Eq. (21)

$$\mathrm{VA_{Worst}} = (\mathrm{a_{1W}}, \mathrm{a_{2W}}\ , \mathrm{a_{3W}}, \ldots\ .., \mathrm{a_{nW}}\ ) \tag{21}$$

Where a_{jW} denotes the preference of criterion over worst criterion (W) such that $\mathrm{a_{WW}} = 1$.

Step 5: Estimation of the optimal weights.

Optimal weights related to every criterion used for assessing the best and worst criteria is identified based on the model specified in Eqs. (22–25)

$$\text{Minimize } \epsilon \tag{22}$$

Such that

$$\left|\frac{\mathrm{W_B}}{\mathrm{W_j}} - \mathrm{a_{Bj}}\right| \leq \epsilon \text{ for all } j \tag{23}$$

$$\left|\frac{\mathrm{W}_j}{\mathrm{W_W}} - a_{jW}\right| \leq\ \epsilon\ , \text{ for all } j \tag{24}$$

$$\sum_j w_j = 1 \tag{25}$$

$$w_j \geq\ 0 \text{ for all } j \tag{26}$$

In this BWM method, consistency ratio (ϵ^*) is used for highlighting the reliability of the comparisons with respect to the parameters or criteria of evaluation. When value of consistency ratio (ϵ^*) is high then the reliability of comparisons is higher. At the same, the reliability of the comparisons is lower when the value of consistency ratio is low. This consistency value is computed for different values of $\mathrm{a_{BW}}$, and determined values are presented in Table 2.

Then the consistency ratio (CR) based on Table 2 is computed using ϵ^* and the consistency value (CV) through Eq. (27)

$$CR = \frac{\epsilon^*}{\mathrm{CV}} \tag{27}$$

This consistency ratio helps in verifying the reliability of the final results. However, this BWM method as specified in[17] possesses a limitation in attaining full consistency and faces the challenges when the criteria is greater than 3. This challenge of BWM method has the possibility of yielding more than one single optimal solutions. To handle this limitation of BWM method, the objective function is fine-tuned based on the best-worst linear model described through Eqs. (28)–(32)

$$\text{Minimize } \epsilon^{\,l} \tag{28}$$

$\mathrm{a_{BW}}$	Consistency value (ϵ^*)
1	0.00
2	0.44
3	1.00
4	1.63
5	2.30
6	3.00
7	3.73
8	4.47
9	5.23

Table 2. Values of the consistency (ϵ^*) with scale 1 to 9.

Such that

$$\left|\frac{\mathrm{W_B}}{\mathrm{W_j}}-\mathrm{a_{Bj}}\right| \leq \epsilon^{l},\ \text{for all j} \tag{29}$$

$$\left|\frac{\mathrm{W}_j}{\mathrm{W_W}}-a_{jW}\right| \leq\ \epsilon^{\ l},\ \text{for all } j \tag{30}$$

$$\sum_j w_j = 1 \tag{31}$$

$$w_j \geq\ 0 \text{ for all } j \tag{32}$$

Fuzzy TOPSIS

This Fuzzy TOPSIS method is mainly adopted for ranking the alternatives based on the feasible number of criteria taken for evaluation such that the potent trust of CH nodes is identified in the network. This MCDM methodology used in implementation of incorporated Fuzzy TOPSIS model is accomplished by ensuing steps.

Step 1: Construction of decision-making matrix.

Decision matrix associated with the process of CHs (linguistic variables and its associated values are presented in Table 3) is determined based on Eq. (33)

$$A(DM_V) = \begin{bmatrix} ad_{11} & ad_{12} & \ldots & ad_{1q} \\ ad_{21} & ad_{22} & \ldots & ad_{2q} \\ \ldots & \ldots & \ldots & \ldots \\ ad_{s1} & ad_{s2} & \ldots & ad_{sq} \end{bmatrix} \tag{33}$$

Then the mean value of the direct interaction and neighboring nodes recommendation is computed for computing the new matrix based on Eq. (34)

$$\mathrm{R_{(i,j)}} = (\mathrm{a_{ij}}, \mathrm{b_{ij}}, \mathrm{c_{ij}}) = \frac{\sum_{\mathrm{r}} (\mathrm{a_{ij}}, \mathrm{b_{ij}}, \mathrm{c_{ij}})}{\mathrm{r}} \text{ for all i, j} \tag{34}$$

Step 2: Normalization of decision-making matrix.

In this step, the constructed decision-making matrix is normalized ($\mathrm{r_{(i,j)}}$) based on the relation specified in Eqs. (35)–(38)

$$\mathrm{r_{(i,j)}} = \left(\frac{\mathrm{a_{ij}}}{\mathrm{c_j^+}}, \frac{\mathrm{b_{ij}}}{\mathrm{c_j^+}}, \frac{\mathrm{c_{ij}}}{\mathrm{c_j^+}}\right),\ \mathrm{j} \in\ \mathrm{B} \tag{35}$$

$$\mathrm{c_j^+} = \mathrm{Max}\ \mathrm{c_{ij}},\ \mathrm{j} \in\ \mathrm{B} \tag{36}$$

$$\mathrm{r_{(i,j)}} = \left(\frac{\mathrm{c_j^-}}{\mathrm{c_{ij}}}, \frac{\mathrm{c_j^-}}{\mathrm{b_{ij}}}, \frac{\mathrm{c_j^-}}{\mathrm{a_{ij}}}\right),\mathrm{j} \in\ \mathrm{W} \tag{37}$$

$$\mathrm{c_j^+} = \mathrm{Min}\ \mathrm{a_{ij}},\ \mathrm{j} \in\ \mathrm{W} \tag{38}$$

Where B and W is the best and worst criteria used for evaluations.

Step 3: Construction of weighted normalized decision matrix.

The weighted normalized decision matrix is determined based on the obtained $\mathrm{r_{(i,j)}}$ such that weighted normalized decision matrix ($\mathrm{wr_{(i,j)}}$) is determined based on Eq. (39)

$$\mathrm{wr_{(i,j)}} = \mathrm{r_{(i,j)}} * W_j \tag{39}$$

Linguistic terms	Triangular fuzzy numbers
Very good (VG)	(9,9,10)
Good (G)	(7,9,10)
Moderately good (MG)	(5,7,9)
Fair (F)	(3,5,7)
Moderately poor (MP)	(1,3,5)
Poor (P)	(0,1,3)
Very poor (VP)	(0,0,1)

Table 3. Linguistic terms of triangular fuzzy numbers used in BWM-TOPSIS.

Where W_j which represents the weights of the different criteria used of evaluation is determined based on the BWM method explained in section "Best-worst method (BWM)".

Step 4: Identification of positive and negative ideal solutions.

The positive and negative solutions are identified based on Eqs. (40) and (41)

$$\mathrm{S}^{+} = \left(\mathrm{wr}_1^{+}, \mathrm{wr}_2^{+}, \ldots .., \mathrm{wr}_n^{+}\right) \tag{40}$$

$$\mathrm{S}^{-} = \left(\mathrm{wr}_1^{-}, \mathrm{wr}_2^{-}, \ldots .., \mathrm{wr}_n^{-}\right) \tag{41}$$

Such that

$$\mathrm{wr}_1^{+} = \mathrm{Max}\left\{\mathrm{wr}_{(\mathrm{i,j})}\right\} \text{ for every } i \text{ and } j \tag{42}$$

$$\mathrm{wr}_1^{-} = \mathrm{Min}\left\{\mathrm{wr}_{(\mathrm{i,j})}\right\} \text{ for every } i \text{ and } j \tag{43}$$

Step 5: Distance of solution from the positive and negative ideal solutions.

In this step, the distance between the identified solution from the estimated positive and negative ideal solutions are computed using Eqs. (44) and (45)

$$\mathrm{d}_{(\mathrm{i})}^{+} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{(\mathrm{i}),}\left(\mathrm{r}_{(\mathrm{i,j})}, \mathrm{wr}_1^{+}\right) \tag{44}$$

$$\mathrm{d}_{(\mathrm{i})}^{-} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{d}_{(\mathrm{i}),}\left(\mathrm{r}_{(\mathrm{i,j})}, \mathrm{wr}_1^{-}\right) \tag{45}$$

The above relations is used for computing distance of every solution from positive and negative ideal solutions as specified in Eq. (46)

$$d_c\left(\mathrm{r}_{(\mathrm{i,j})}, \mathrm{wr}_{\mathrm{j}}^{+}\right) = \sqrt{\frac{1}{2}\left(\left(a_j^{*} - a_{ij}\right)^2 + \left(b_j^{*} - b_{ij}\right)^2 + \left(c_j^{*} - c_{ij}\right)^2\right)} \tag{46}$$

Step 6: Computation of Closeness Coefficient.

In this step, closeness coefficient ($\mathrm{CC_R}$) associated with each of the ideal solutions is determined based on Eq. (47)

$$\mathrm{CC_R} = \frac{d_{(i)}^{-}}{d_{(i)}^{+} + d_{(i)}^{-}} \tag{47}$$

Step 7: Ranking of the selected CHs.

Finally, the IoT nodes selected as CHs are ranked based on descending order to determine the trust value associated with the identified CHs to confirm whether they continue to act as the CHs or the selection of CHs needs to be introduced.

In addition, Fig. 2 presents the comprehensive view of the adopted BWM-Fuzzy TOPSIS-based Trust evaluation method which is used for verifying the potentiality of the selected CHs in the IoT network.

Thus, the proposed MSCFOAICM scheme at the first level performed the process of clustering and CHs selection using MCFOA, and at the second level used the merits of BWM-Fuzzy TOPSIS method for evaluating the trust of selected CHs such that misbehaviour of selected IoT CHs is achieved for preventing the possibility of reclustering and frequent selection of CHs that managed network energy to maximized level and prolonged lifetime to the expected degree.

Results and discussion

The performance evaluation of proposed MSCFOAICM scheme and the benchmarked ERWCOA[39], BFABCOA[38], HWFSOA[37] and SPCHOA[35] approaches using the package INET and OMNeT + + network simulator. In specific, INET package is used as it facilitates disturbance and real radio signal propagation models with the realistic characteristics of IoT nodes. This experimentation is conducted with both static and mobile IoT networks.

Performance evaluation with static IoT network

In this section, the performance evaluation results of proposed MSCFOAICM and baseline approaches conducted by considering the evaluation parameters of network lifetime, energy consumptions, throughput and packets received at base station is presented. This performance evaluation is conducted for the objective of determining the efficiency of proposed MSCFOAICM scheme compared to benchmarked approaches used for comparison. Thie experimentation is conducted using the simulation environment of area 100 m × 100 m in which static IoT nodes are deployed randomly for the purpose of sensing and data aggregation. It comprises of a base station which is positioned at the coordinates of (50,0) with each of the IoT nodes possessing an initial energy of 0.5 Joules. This initial energy of 0.5 Joules is considered as $\mathrm{E_0}$ during the process of potential CHs selection in the network. In specific, 10% of all the active operating IoT nodes is considered as the maximized

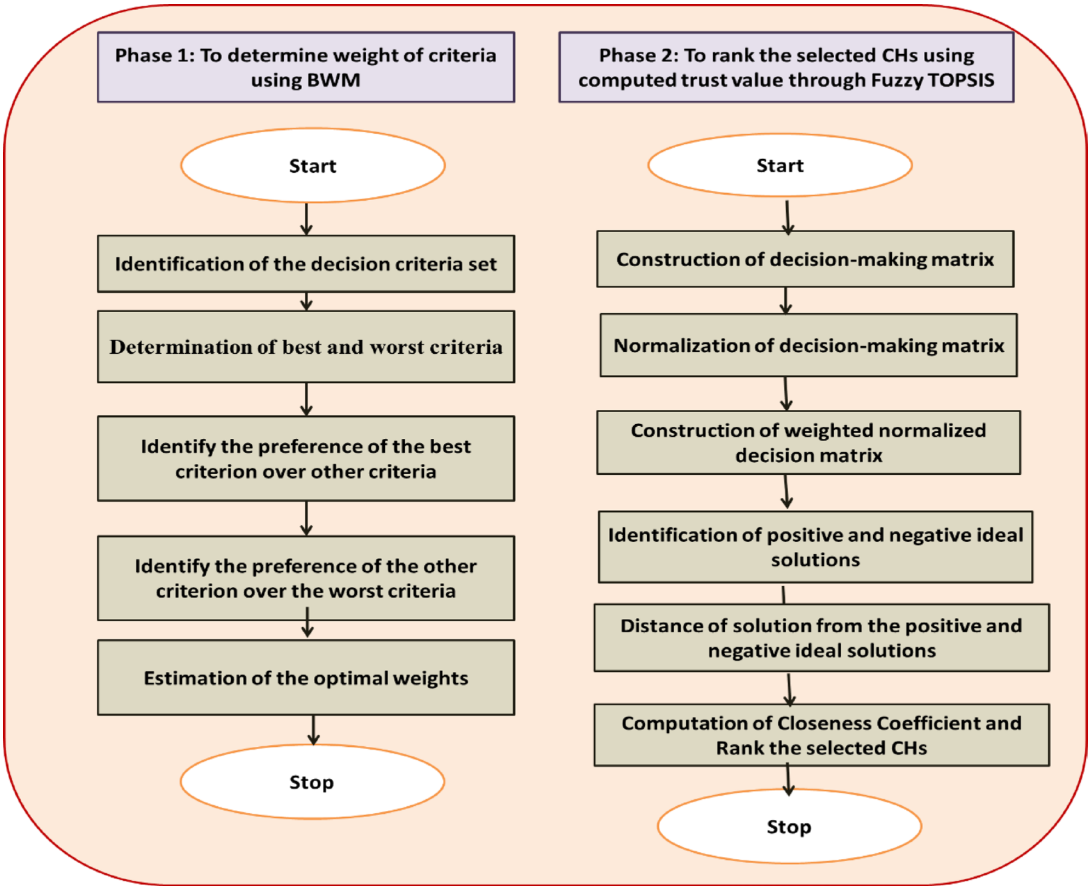

Fig. 2. BWM-Fuzzy TOPSIS-based trust evaluation method used for CHs selection.

number of CHs with the capability of the IoT nodes transmitting the data packets of size 4000 bits. Further, the experimental scenario is considered to comprise of 100 IoT nodes with the radio model parameters set to $\mathrm{E_{fs}} = 10\,\mathrm{pj/bit/m^2}$, $\mathrm{E_{elec}} = 10\,\mathrm{nj/bit}$, $\mathrm{E_{DA}} = 5\,\mathrm{nj/bit}$ and $\mathrm{E_{fs}} = 0.0013\,\mathrm{pj/bit/m^4}$, respectively. Moreover the value of the weights associated with fitness function evaluation actors are set to 0.25 equally for facilitating equal importance for all the four sub-objectives considered for evaluation. In this comparative analysis. The convergence rate of the proposed MSCFOAICM scheme and the baseline approaches are compared initially with respect to 500 number of iterations for the objective of assessing the validity of claimed propositions, and the results are presented in Fig. 3. It is identified that the proposed MSCFOAICM scheme exhibited high rate of rapid convergence which supported in higher achievement of the global minimum output compared to the baseline approaches such as benchmarked approaches used for comparison. In specific, the baseline ERWCOA and BFABCOA schemes possesses the weakness with respect to the process of local optima which made the candidate solution to get trap into local point of optimality. At the same time, HWFSOA and SPCHOA approaches used for comparison faces the challenge of energy management even though they possesses reactive methods of clustering and CHs selection. Further the proposed MSCFOAICM scheme handled the challenges of clustering which helped in sustaining the amount of energy utilization and network lifespan longevity to the expected level. Thus the proposed MSCFOAICM scheme confirmed better convergence rate and prevented the problem of local point of optimality during the optimization process.

Then Fig. 4 demonstrates the plots of network lifetime (rounds) attained by the proposed MSCFOAICM scheme and the benchmarked ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches with respect to FND, HND and LND with 200 IoT nodes and network are of 100×100 square meters. This plot evidently confirmed the potentiality of the proposed MSCFOAICM scheme in terms of network lifespan in which FND (First Node Death) represents the number of rounds in which one of all the IoT nodes becomes non-operational from the initialization of the networks' operation. Then HND (Half Node Death) and LND (Last Node Death) presents the number of rounds in which half of all the IoT nodes becomes non-operational from the initialization of the networks' operation, and number of rounds in which all the IoT nodes becomes non-operational from the initialization of the networks' operation. These three network lifetime of FND, HND and LND represents the network stability period. This result proved that the proposed MSCFOAICM scheme significantly extended the overall network lifetime since it introduced a greater energy efficiency during the process of data transmission. This proposed MSCFOAICM scheme confirmed a notable improvement with respect to network lifetime of about 10.21%, 11.76%, 12.98% and 13.28%, compared to the baseline ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches used for investigation. This improvement in the network lifetime is realized by observing

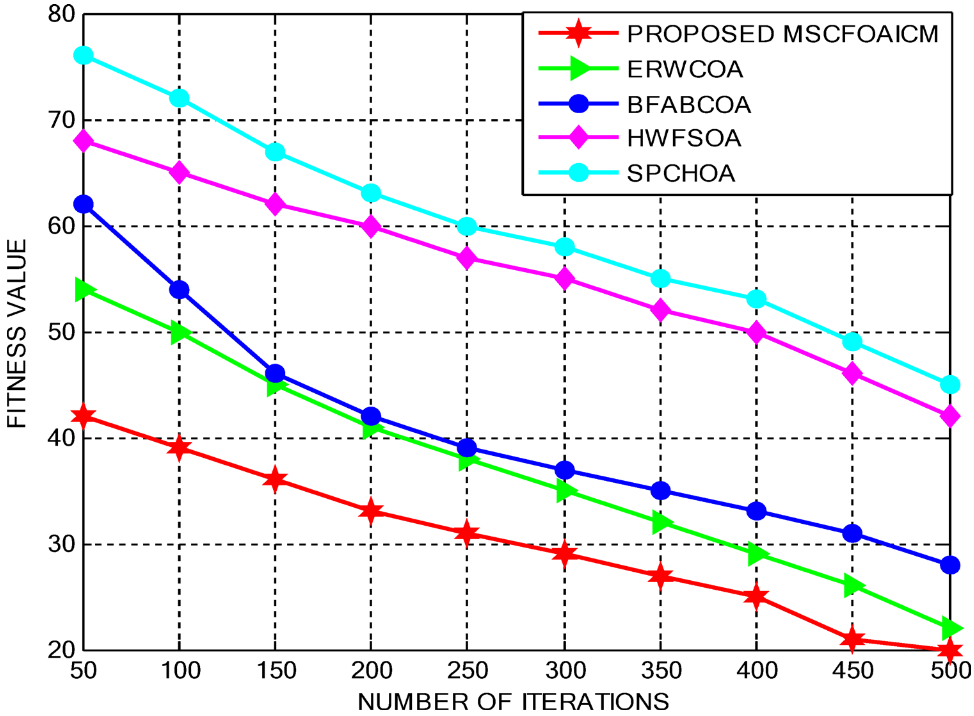

Fig. 3. MSCFOAICM-convergence analysis using fitness value with different iterations.

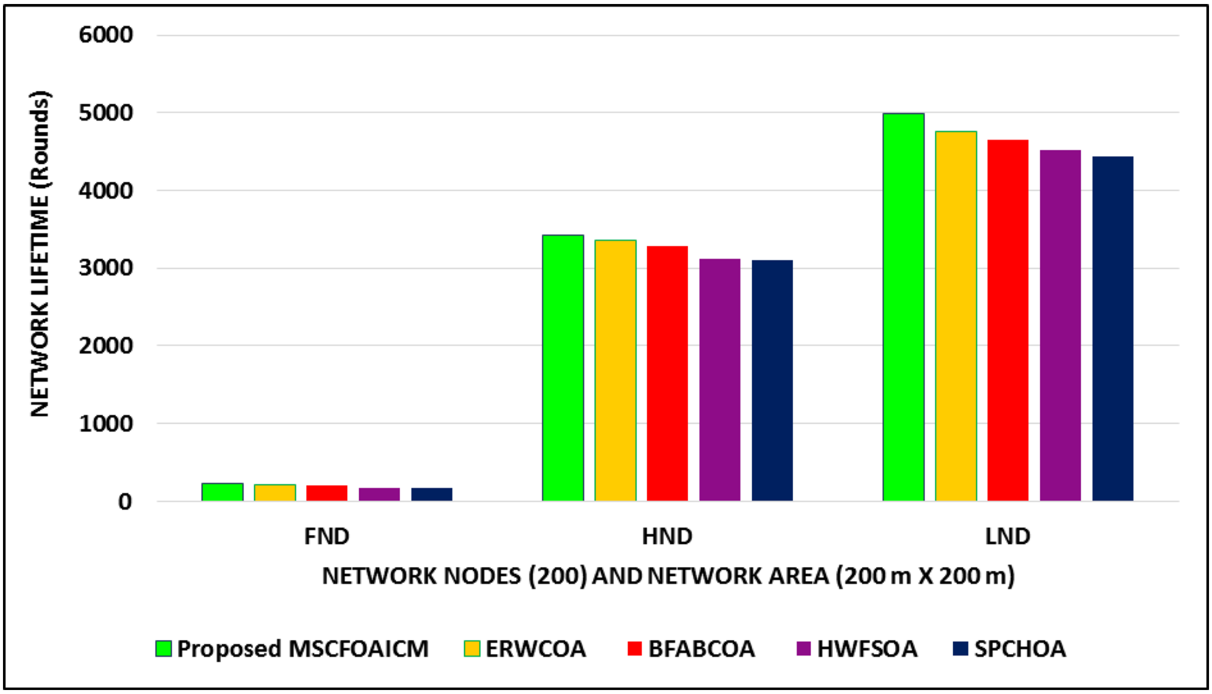

Fig. 4. MSCFOAICM-network lifetime (rounds) with different network area.

and exploring the number of operating IoT nodes in the network since its presence in the network displays a potential lifespan. In addition, the number of packets received by the sink is considered for evaluating the potential of the proposed MSCFOAICM scheme over the benchmarked approaches, and the results are presented in Fig. 5. This metric evaluation is necessary since it highlights how far the proposed MSCFOAICM scheme is capable in achieving the primary goal of data collection. The successful results of the proposed MSCFOAICM scheme is evident due to its capability of transmitting a comparatively greater number of data packets efficiently

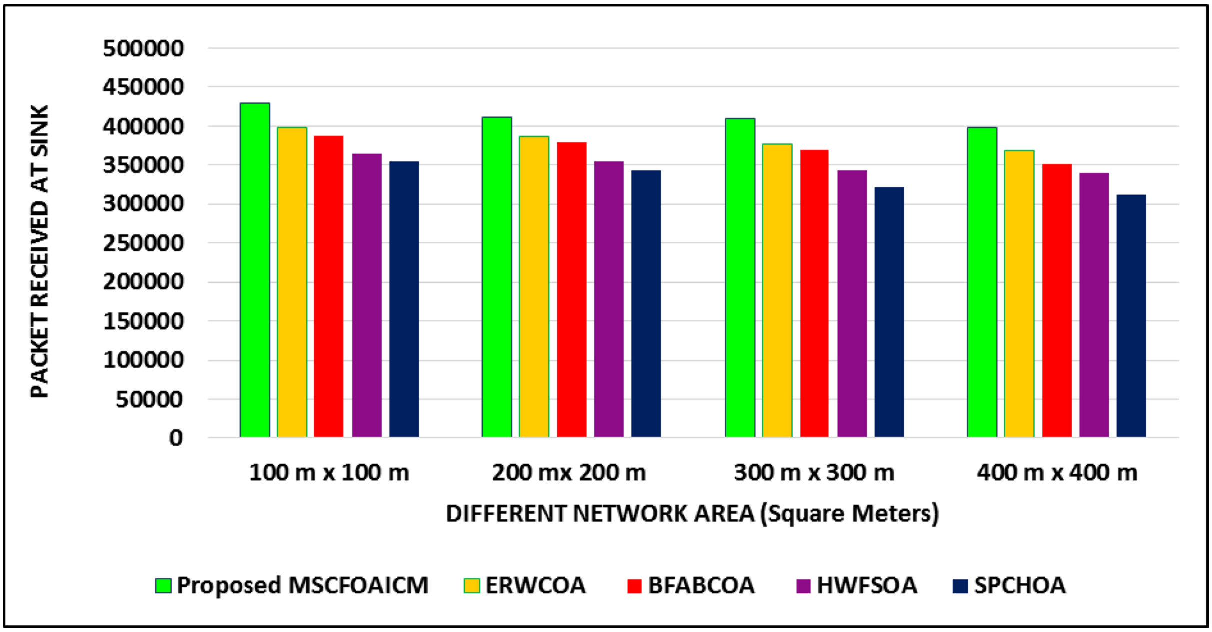

Fig. 5. MSCFOAICM-packets received at the sink with different network area.

to the sink. This success is mainly confirmed due to the inclusion of several factors which attribute towards better identification of optimal CHs with greater sustained RE in the network. At the same time, ERWCOA specifically possessed the limitations with respect to restricted exploration capability which hindered its performance. On the other hand, BFABCOA approach even in spite of potential clustering capability, it still suffered from the problem of selecting worst IoT nodes as CHs in the network. Moreover, HWFSOA and SPCHOA approaches performed marginally due to the limitations of limited factors and imbalanced exploration and exploitation trade-offs incorporated during the process of CHs selection. Thus the proposed MSCFOAICM scheme confirmed a maximized degree of packet received at the sink to about 8.95%, 10.65%, 11.64% and 12.76%, compared to the baseline ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches used for investigation.

Performance evaluation using different rounds in the mobile IoT network

In this section, the simulation experimental results of the proposed MSCFOAICM scheme and the benchmarked ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches obtained using the parameters of operating IoT nodes, throughput. mean transmission time and RE with varying rounds are presented. These evaluating factors are considered for assessing the potential of the proposed MSCFOAICM scheme and the benchmarked approaches since they help in quantifying the degree to which the adopted clustering and selected CHs is phenomenal in achieving the objective of data transmission with maximized degree of energy sustenance and minimized transmission delay in the network. Figures 6 and 7 highlights the performance results of the proposed MSCFOAICM scheme and the benchmarked ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches realized in the network with varying rounds. This exploration of the proposed MSCFOAICM scheme contextually addressed the problem of clustering to the expected level such that only reliable IoT nodes are selected as CHs in the network. This potential of the proposed clustering helped in attaining the required degree of QoS in the network. But the baseline ERWCOA and BFABCOA approaches even though confirmed better clustering but failed in verifying the trust of the IoT nodes. This ignorance resulted in energy wastage which shortened network lifetime of IoT nodes network with obvious packet drop during the process of data transmission. At the same time, the baseline HWFSOA and SPCHOA confirmed only a restricted exploitation in the search space which did not help in better determination of solutions. These results confirmed that the proposed MSCFOAICM scheme confirmed better sustenance of operating IoT nodes by 16.24%, 18.52%, 20.76% and 22.18%, better than the baseline approaches. Moreover, the throughput ensured by the proposed MSCFOAICM scheme is improved by 15.88%, 17.42%, 18.76% and 20.52%, better than the baseline approaches.

Further Figs. 8 and 9 depicted the results of mean transmission delay and RE incurred by the proposed MSCFOAICM scheme and the benchmarked ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches with varying rounds. This evaluation using mean transmission delay and RE is essential for identifying how far the proposed MSCFOAICM scheme and the benchmarked approaches are capable in minimizing the energy and time taken for transmitting the data from the IoT nodes to the selected CHs and forwarding the aggregated data to the base station for reactive decision-making process. This result revealed that the MSCFOAICM scheme is reliable in determining the optimal paths between the CHs and the base station and thereby minimized considerable amount of energy in the network. Thus the mean transmission time incurred by the proposed MSCFOAICM scheme is comparatively less to the expected level of 15.68%, 17.54%, 19.56% and 20.84%, better than the baseline approaches used for evaluation. In addition, the residual energy spent by the proposed MSCFOAICM scheme

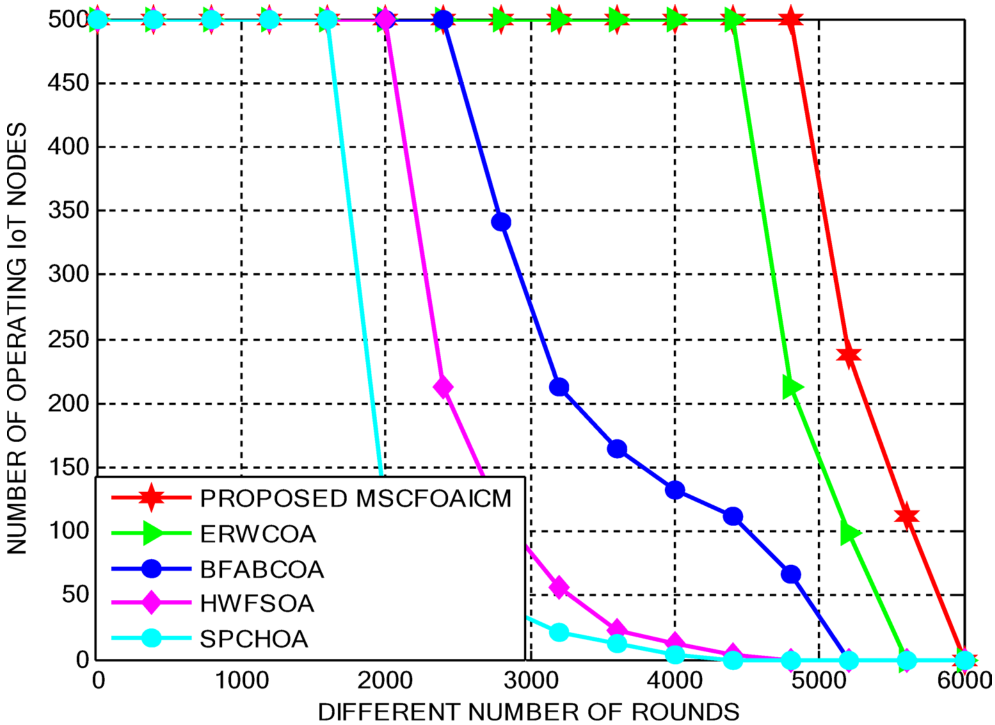

Fig. 6. MSCFOAICM-operating IoT nodes with different rounds.

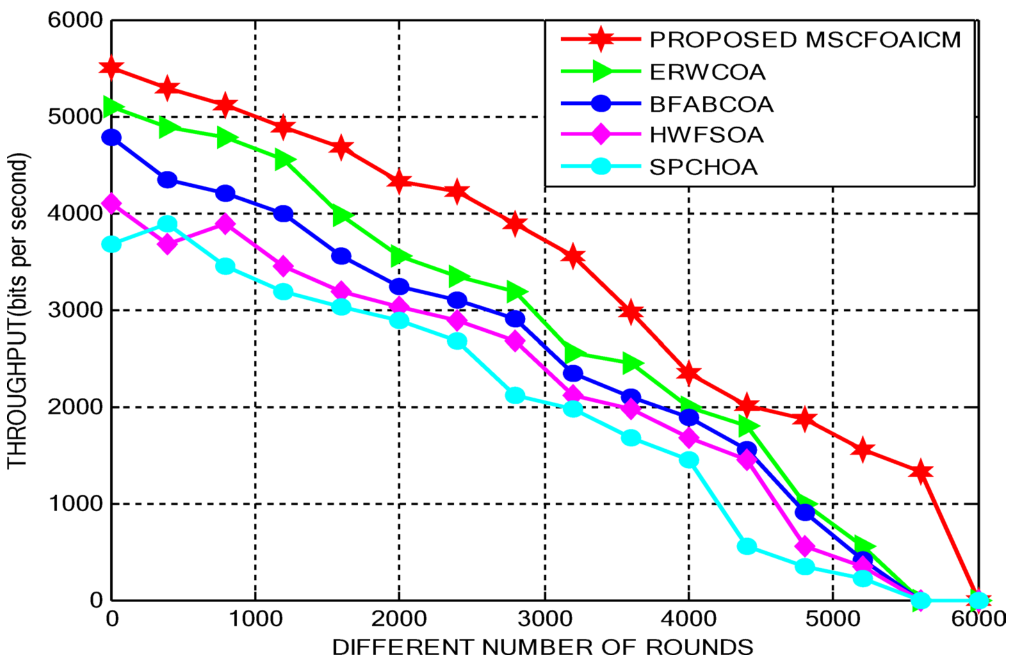

Fig. 7. MSCFOAICM-throughput realized under different rounds.

is significantly reduced by 14.76%. 16.42%, 17.98% and 18.96%, better than the benchmarked approaches used for comparison.

Performance evaluation using different IoT nodes in the mobile IoT network

In this section, the simulation experimental results of the proposed MSCFOAICM scheme with varying rounds are presented. Figures 10 and 11 demonstrates the results of the proposed MSCFOAICM scheme and the benchmarked approaches with varying number of operating IoT nodes in the network. This assessment with respect to operating IoT nodes is essential to determine how capable are the compared green IoT communication

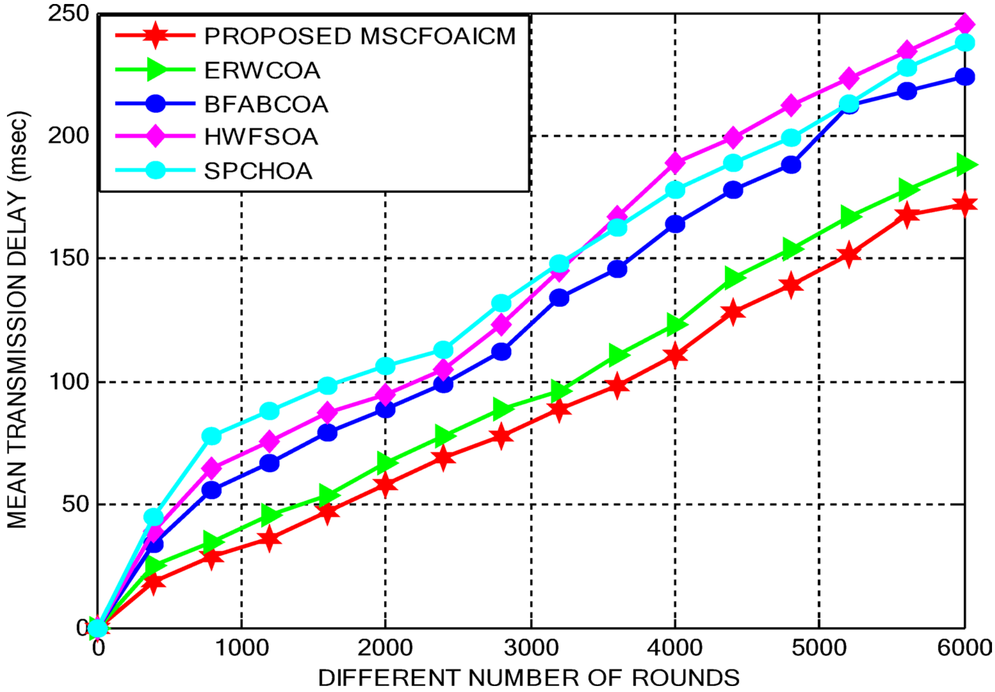

Fig. 8. MSCFOAICM-mean transmission delay under different rounds.

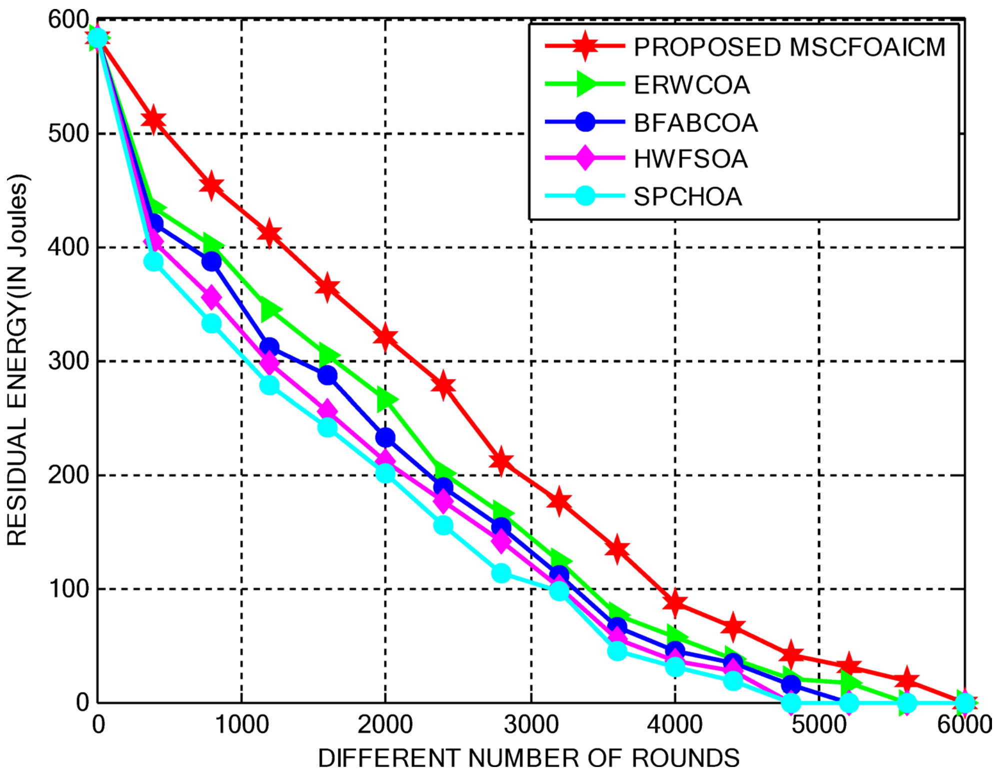

Fig. 9. MSCFOAICM-residual energy incurred under different rounds.

clustering protocols in performing the objective of maximizing the packet delivery rate, minimizing the energy utilization and mean transmission delay independent to the number of operating IoT nodes in the network. These results clearly proved that the proposed MSCFOAICM scheme employed a multi-objective function which helped in attaining better selection of CHs at one end, and at the other end facilitated the retention of these selected CHs by quantifying the trust value of them using the merits of BWM-Fuzzy TOPSIS method. The

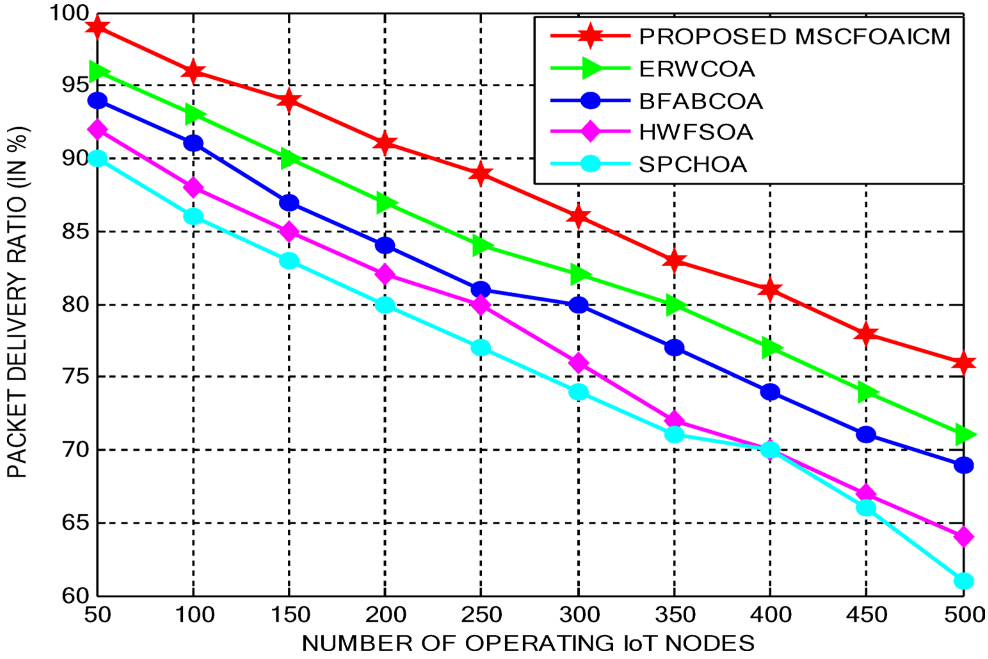

Fig. 10. MSCFOAICM-packet delivery achieved under different operating IoT nodes.

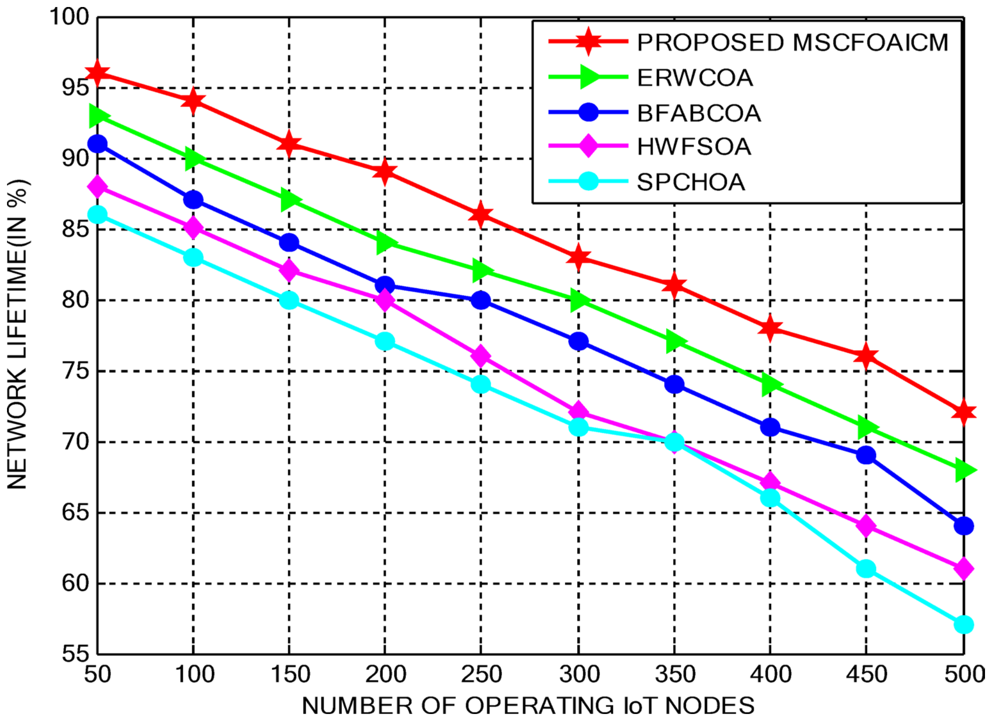

Fig. 11. MSCFOAICM-network lifetime sustained under different operating IoT nodes.

inclusion of BWM-Fuzzy TOPSIS handled the problem of decision-making bias and rank reversal such that frequent clustering and impotent IoT nodes being selected as CHs is completely prevented in the network. The benchmarked ERWCOA in spite of adopting a better clustering phenomenon, ignored to adopt a verification mechanism to check and confirm the trust level of the selected CHs which increased the probability of CHs during the process of data aggregation. Then BFABCOA facilitated better CHs selection but constructed a little a greater number of clusters during the process of data transmission. This addition of a greater number of clusters increased the probability of introducing an extra number of control and data packets into the network with additional communication overhead. Further HWFSOA confirmed a challenge in energy stability and network lifespan since the factors considered for attaining green IoT communication was highly limited. Moreover, the baseline SPCHOA approach performed comparatively lower in terms of delay since it failed in adopting a significant strategy that verified the reliability of the path established between the selected CHs and the sink node. Hence the proposed MSCFOAICM scheme confirmed maximized packet delivery rate of about 18.94%, 20.52%, 22.18% and 24.39%, better to the baseline approaches independent to the number of operating IoT nodes in the network. Further the proposed MSCFOAICM scheme confirmed maximized network lifetime of about 16.74%, 18.42%, 20.56% and 22.92%, better to the baseline approaches independent to the number of operating IoT nodes in the network.

In addition, Figs. 12 and 13 depicts the results of the proposed MSCFOAICM scheme and the benchmarked ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches with various operating IoT nodes. This exploration of the proposed MSCFOAICM scheme and the benchmarked approaches is conducted mainly to determine how far the incorporated CHs selection mechanisms are able to sustain energy and minimize the transmission delay which eventually targets on extending the network lifetime. These results conveyed that the proposed MSCFOAICM scheme reactively used the mechanism of environment update and GOBL to prevent the solution from being struck into the local point of optimality and identify better solutions at the global and local level. These results confirmed that the inclusion of balanced exploration and exploitation due to the merits of MCFOA supported in the process of maintaining high degree of RE in the network. It identified optimal number of clusters and minimized transmission delay to the necessitated level due to the incorporation of ghost opposition learning strategy, and trustworthiness identified through BWM-Fuzzy TOPSIS approach. On the other hand, the degree of energy sustained by the benchmarked ERWCOA and BFABCOA was identified to be relatively lower since it faced the challenge with respect to the optimal identification of clusters which introduced more degree of communication overhead in the network. At the same time, HWFSOA approach suffered from the problem of imbalanced exploration and exploitation during the process of clustering, and it was also identified to confirm only a marginal network stability due to the wastage of unnecessary energy that arise due to the construction of a greater number of clusters. Thus the proposed MSCFOAICM scheme with various operating IoT nodes at one end minimized the energy utilization to the minimized level of 14.98%, 16.84%, 18.42% and 20.18%, better than the baseline approaches used for comparison. The proposed MSCFOAICM scheme with various operating IoT nodes on the other end minimized the mean transmission delay of about 15.98%, 17.34%, 19.42% and 21.46%, better than the baseline approaches used for comparison.

Statistical validation of the proposed MSCFOAICM scheme

In this section, the statistical validation of the proposed MSCFOAICM scheme and the baseline ERWCOA, BFABCOA, HWFSOA and SPCHOA approaches with respect to the measures of minimum, maximum, mean, median and standard deviation determined based on residual energy. From Table 4, it is determined that all the proposed MSCFOAICM scheme and the baseline are stochastic and to present fair investigation process, each model is executed a comparative more number of times based on fitness function coined with respect to residual energy under the number of IoT nodes set to 100, 250 and 500 modes.

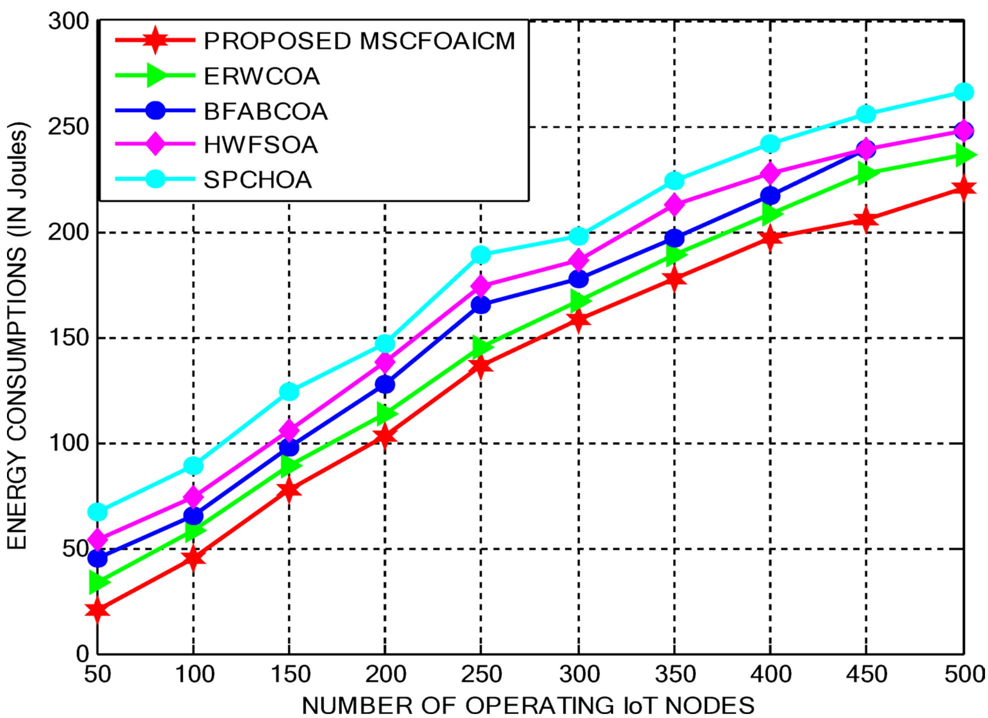

Fig. 12. MSCFOAICM-energy utilized under different operating IoT nodes.

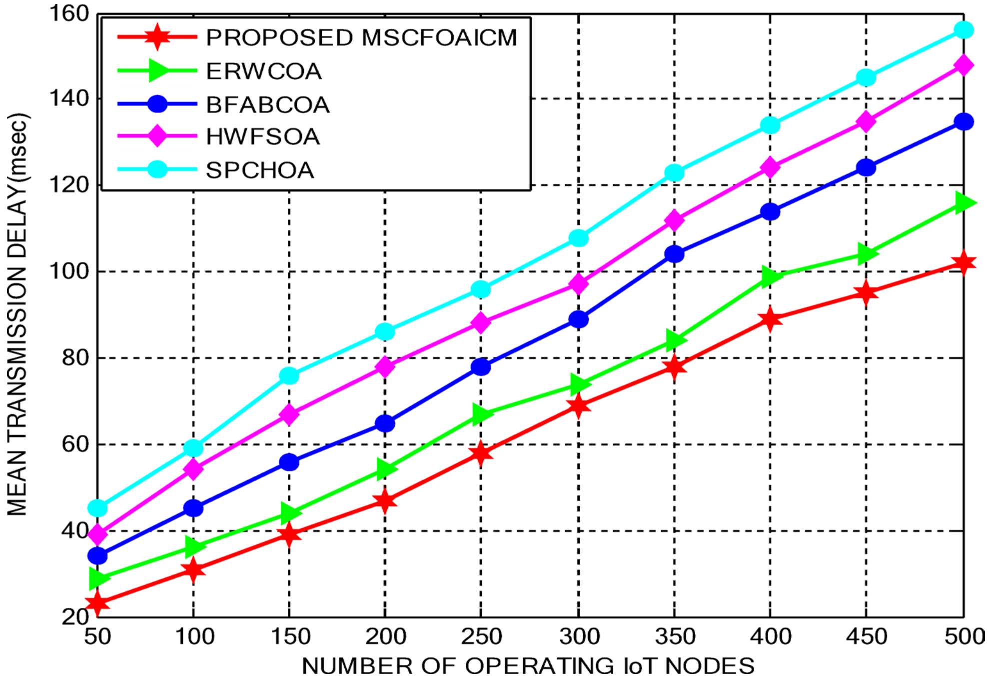

Fig. 13. MSCFOAICM-mean transmission delay under different operating IoT nodes.

Measures	MSCFOAICM	ERWCOA	BFABCOA	HWFSOA	SPCHOA
Number of IoT nodes-100					
Min	0.033126	0.007415	0.011111	0.007113	0.019284
Max	0.538471	0.438472	0.538462	0.538472	0.538462
Mean	0.252662	0.235468	0.228065	0.24146	0.237354
Median	0.251441	0.223642	0.203324	0.23176	0.226445
Standard deviation (SD)	0.15630	0.167086	0.165412	0.16042	0.167221
Number of IoT nodes-250					
Min	0.031324	0.002072	0.003106	0.003212	0.003456
Max	0.550785	0.536264	0.550276	0.543218	0.534218
Mean	0.280761	0.233045	0.271663	0.267854	0.265432
Median	0.395156	0.212268	0.284562	0.278652	0.267854
Standard deviation (SD)	0.172128	0.174221	0.173586	0.175641	0.174522
Number of IoT nodes-500					
Min	0.034328	0.002142	0.004562	0.003112	0.003231
Max	0.456321	0.523114	0.512432	0.528764	0.452321
Mean	0.265498	0.223218	0.248976	0.213986	0.227698
Median	0.354212	0.209864	0.267854	0.287652	0.298652
Standard deviation (SD)	0.170654	0.184632	0.198754	0.179842	0.189762

Table 4. Statistical analysis results for the proposed MSCFOAICM using residual energy.

It is also identified that the proposed MSCFOAICM scheme guaranteed better fault tolerance and mitigating energy hole which sustained maximized degree of energy during green communication in IoT.

Conclusion

This proposed MSCFOAICM achieved effective and efficient green communication in IoT with maximized energy management and network lifetime. It adopted a multi-objective fitness function that considered the factors of delay, energy, distance, jitter and packet forwarding potential into account and facilitated the selection of energy potent IoT nodes as the CHs in the network. It used MCFOA and guaranteed a better trade-off between the exploration and exploitation. It used a Hybrid BWM-TOPSIS Multicriteria decision making model for determining the trust of sensor nodes using direct and indirect trust to prevent the selection of malicious nodes as CHs. This protocol also prevented low energy nodes as the trustworthy node by determining

RE during the trust computation process. The simulation experiments conducted using INET package and OMNET + + simulator confirmed better packet delivery rate of 21.52%, network lifetime of 19.64% and reduced mean transmission delay OF 17.68% and minimized energy utilization rate of 18.52% under different operating IoT nodes in the network.

Data availability

All data generated or analysed during this study are included in this published article.

Received: 23 April 2025; Accepted: 3 September 2025
Published online: 06 October 2025

References

1. Abujassar, R. S. An innovative algorithm for multipath routing and energy efficiency in IoT across varied network topology densities. *Int. J. Netw. Distrib. Comput.* **13**(1), 14 (2025).
2. Pandiyan, P. et al. A comprehensive review of advancements in green IoT for smart grids: Paving the path to sustainability. *Energy Rep.* **11**, 5504–5531 (2024).
3. Rahmani, A. M. et al. A routing approach based on combination of Gray Wolf clustering and fuzzy clustering and using multi-criteria decision making approaches for WSN-IoT. *Comput. Electr. Eng.* **122**, 109946 (2025).
4. Sudhakar, T., Praveen, R. & Natarajan, V. An efficient ECC and fuzzy verifier based user authentication protocol for IoT enabled WSNs. *Sci. Rep.* **15**(1), 9974 (2025).
5. Ananthi, M., Valarmathi, K., Ramathilagam, A., Praveen, R. Hybrid lion and exponential PSO-based metaheuristic clustering approach for efficient dynamic data stream management Scientific Reports **15**(1) https://doi.org/10.1038/s41598-025-07404-9 (2025).
6. Siddique, A. A. et al. Sustainable collaboration: Federated learning for environmentally conscious forest fire classification in green internet of things (IoT). *Internet Things* **25**, 101013 (2024).
7. Krishna Meera, V., Balasubramanian, C., Praveen, R. Hybrid Hippopotamus Optimization Algorithm–Based Energy-Efficient Stable Cluster Construction Protocol for Data Routing in VANETs ABSTRACT International Journal of Communication Systems **38**(13) https://doi.org/10.1002/dac.v38.1310.1002/dac.70171 (2025).
8. Rup, C. & Bajic, E. Green and sustainable industrial internet of things systems leveraging wake-up radio to enable on-demand IoT communication. *Sustainability* **16**(3), 1160 (2024).
9. Poornima, I. G. A., Dontu, S., Maheswaran, M. & Vallabhaneni, R. Energy-effective optimal routing–driven hybrid optimizations–enabled iot-based wearable wireless body area network. *Int. J. Commun. Syst.*, **38**(6), e70037. (2025).
10. Qian, K. et al. Distributed detection of large-scale internet of things Botnets based on graph partitioning. *Appl. Sci.* **14**(4), 1615 (2024).
11. Balasubramanian, C., Sathya, G. & Praveen, R. Hybrid Mexican axolotl and bitterling fish optimization algorithm-based spectrum sensing multi-hop clustering routing protocol for cognitive sensor networks Scientific Reports **14**(1) https://doi.org/10.1038/s41598-024-82311-z (2024).
12. Nivitha, K., Pabitha, P., Praveen, R. CBBM-WARM: A workload-aware meta-heuristic for resource management in cloud computing China Communications **22**(6), 255–275 https://doi.org/10.23919/JCC.ja.2022-0665 (2025).
13. Sahu, R. & Tripathi, P. An intelligent forecasting system in internet of agriculture things sensor network. *Ad Hoc Netw.* **169**, 103752 (2025).
14. Jha, V. & Tripathi, P. Remediation of chaos in cognitive internet of things sensor network. *Ad Hoc Netw.*, 103830 (2025).
15. Yousefi, S., Derakhshan, F., Karimipour, H. & Aghdasi, H. S. An efficient route planning model for mobile agents on the internet of things using Markov decision process. *Ad Hoc Netw.* **98**, 102053 (2020).
16. Poluru, R. K., Kumar, R. & L An improved fruit fly optimization (IFFOA) based cluster head selection algorithm for internet of things. *Int. J. Comput. Appl.* **43**(7), 623–631 (2021).
17. Kannan, J., Kaliyamurthi, B., Kannan, V. & Chandrasekaran, S. Sine cosine–reptile search–based ch selection and optimized routing in WSN-assisted IoT to mitigate hotspot problem. *Int. J. Commun. Syst.* **38**(7), e70050 (2025).
18. Gao, C. & Mohammed, A. S. A new fuzzy-based nature-inspired routing method for mobile internet of things. *Int. J. Mobile Commun.* **25**(2), 208–228 (2025).
19. Kiani, F. & Rad, H. RG-ACA: Efficient and adaptive routing method for internet of things based on metaheuristic approach. *Int. J. Inform. Technol.* 1–8 (2025).
20. Babaker, S. et al. Improving reliability and data management in internet of things based wireless sensor networks. *Internet Technol. Letters*, e646. (2025).
21. Daniel, D. J. D. & Jagadeesh, S. A secure data storage architecture for internet of things using a hybrid Whale-Based Harris Hawk optimization algorithm and Fuzzy-Based secure clustering. *Secur. Priv.*, **8**(2), e70004. (2025).
22. Alazab, M., Lakshmanna, K., Reddy, T., Pham, Q. V. & Maddikunta, P. K. R. Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities. *Sustain. Energy Technol. Assess.* **43**, 100973 (2021).
23. Mohseni, M., Amirghafouri, F. & Pourghebleh, B. CEDAR: A cluster-based energy-aware data aggregation routing protocol in the internet of things using capuchin search algorithm and fuzzy logic. *Peer-to-Peer Netw. Appl.* **16**(1), 189–209 (2023).
24. Karthik, K., Balasubramanian, C. & Praveen, R. Hybrid golden Jackal and moth flame optimization algorithm based coverage path planning in heterogeneous UAV networks Scientific Reports **15**(1) https://doi.org/10.1038/s41598-025-15345-6 (2025).
25. Dogra, R. et al. A novel dynamic clustering approach for energy hole mitigation in internet of Things-based wireless sensor network. *Int. J. Commun. Syst.* **34**(9), e4806 (2021).
26. Jaiswal, K. & Anand, V. A Grey-Wolf based optimized clustering approach to improve QoS in wireless sensor networks for IoT applications. *Peer-to-Peer Netw. Appl.* **14**(4), 1943–1962 (2021).
27. Saidi, A., Benahmed, K. & Seddiki, N. Secure cluster head election algorithm and misbehavior detection approach based on trust management technique for clustered wireless sensor networks. *Ad Hoc Netw.* **106**, 102215 (2020).
28. Kumbhar, P. Y. & Naik, A. A. An energy-efficient Chebyshev fire Hawks optimization algorithm for energy balancing in sensor-enabled internet of things. *Int. J. Commun Syst*, **38**(2), e5976. (2025).
29. Jia, H. et al. Modified crayfish optimization algorithm for solving multiple engineering application problems. *Artif. Intell. Rev.* **57**(5), 127 (2024).
30. Kumar, M. et al. Green communication in internet of things: A hybrid bio-inspired intelligent approach. *Sensors* **22**(10), 3910 (2022).
31. Geetha, B. T. et al. Green energy aware and cluster-based communication for future load prediction in IoT. *Sustain. Energy Technol. Assess* **52**(3), 102244–102213 (2022).
32. Dev, K. et al. Energy optimization for green communication in IoT using Harris Hawks optimization. *IEEE Trans. Green. Commun. Netw.* **6**(2), 685–694 (2022).

33. Das, A. Designing green IoT communication by adaptive spotted hyena tunicate swarm optimization-based cluster head selection. *Trans. Emerg. Telecommun. Technol.* **33**(11) (2022).
34. Singh, S., Garg, D. & Malik, A. A novel cluster head selection algorithm based IoT enabled heterogeneous WSNs distributed architecture for smart City. *Microprocess. Microsyst.* **101**, 104892 (2023).
35. Sankar, S. et al. Cluster head selection for the internet of things using a sandpiper optimization algorithm (SOA). *J. Sens.* **2023(1)**, 3507600 (2023).
36. Lei, C. An energy-aware cluster-based routing in the internet of things using particle swarm optimization algorithm and fuzzy clustering. *J. Eng. Appl. Sci.* **71**(1), 135 (2024).
37. Arivubrakan, P. & Kanagachidambaresan, G. R. Multi-objective cluster head-based energy-aware routing protocol using hybrid woodpecker and Flamingo search optimization algorithm for internet of things environment. *Int. J. Inform. Technol. Decis. Mak.* **23**(02), 763–782 (2024).
38. Kponhinto, G. et al. A hybrid biologically-inspired optimization algorithm for data gathering in IoT sensor networks. *J. Netw. Syst. Manag.* **33**(2), 1–32 (2025).
39. Lv, C. & Long, G. Energy-efficient cluster head selection in internet of things networks using an optimized evaporation rate water-cycle algorithm. *J. Eng. Appl. Sci.* **72**(1), 34 (2025).
40. Balakrishnan, S. & Vinoth Kumar, K. Hybrid sine-cosine black widow spider optimization-based route selection protocol for multihop communication in IoT assisted WSN. *Tehnički Vjesn.* **30**(4), 1159–1165 (2023).
41. Lim, S. J. & Shin, B. M. A novel chain formation scheme for balanced energy consumption in WSN-based IoT network. *Tehnički Vjesn.* **31**(2), 525–533 (2024).
42. Khan, Z. A. & Abbasi, U. An energy efficient architecture for IoT based automated smart micro-grid. *Tehnički Vjesn.* **25**(5), 1472–1477 (2018).
43. Purushothaman, R. & Narmadha, R. *Enhancing Lifetime and Performance in Wireless Sensor Networks with Cooperative Stabilized Proactive Energy-Aware Cluster Routing Protocol*, Vol. 6, 311908–1914 (TEHNICKI VJESNIK-TECHNICAL GAZETTE, 2024).
44. Chandrasekaran, K. & Chinnasamy, K. Query based location aware energy efficient secure multicast routing for wireless sensor networks using fuzzy logic. *Tehnički Vjesn.* **30**(6), 1791–1798 (2023).

Author contributions
R.C.: Writing- Original Draft, Software, Methodology, Investigation, Experiments, Conceptualization, Data curation, Validation, Review & Editing. C.K.S: Conceptualization, Methodology, Data curation, Validation, Writing—Review & Editing. E.P.: Conceptualization, Methodology, Data curation, Validation, Writing—Review & Editing. R.A: Conceptualization, Methodology, Software, Data curation, Formal analysis, Investigation, Writing - Review & Editing.

Funding
Not Applicable.

Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
This article does not contain any studies with human participants or animals performed by any of the authors.

Additional information
Correspondence and requests for materials should be addressed to R.C.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.