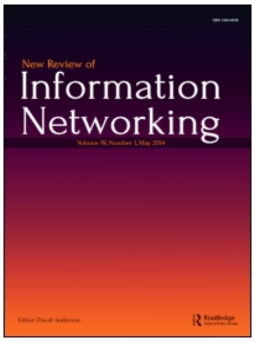

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Energy Efficient Cluster Head Selection for Internet of Things

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ABSTRACT

Recently, Internet of Things (IoT) devices are highly utilized in diverse fields such as environmental monitoring, industries, and smart home, among others. Under such instances, a cluster head is selected among the diverse IoT devices of wireless sensor network (WSN) based IoT network to maintain a reliable network with efficient data transmission. This article proposed a novel method with the combination of Gravitational Search Algorithm (GSA) and Artificial Bee Colony (ABC) algorithm to accomplish the efficient cluster head selection. This method considers the distance, energy, delay, load, and temperature of the IoT devices during the operation of the cluster head selection process. Furthermore, the performance of the proposed method is analyzed by comparing with conventional methods such as Artificial Bee Colony (ABC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and GSO algorithms. The analysis related to the existence of the number of alive nodes, convergence estimation, and performance in terms of normalized energy, load, and temperature of the IoT devices are determined. Thus the analysis of our implementation reveals the superior performance of the proposed method.

KEYWORDS

WSN; IoT; cluster head selection; GSA

Introduction

Growth of the sensing devices has increased with the rapid development of technology (Kawamoto et al. 2013; Z. Li et al. 2016). Generally, wireless sensor network (WSN) is considered of principle importance in the field of network technology (Duan et al. 2014). WSN is used to provide quick operation with sufficient self-organization throughout the world at any location. In addition, through continuous improvement, WSN has been utilized in numerous applications (Dai and Xu 2010; Agarwal et al. 2015). The system interconnected with computing device, digital and mechanical instruments, animals, people, or other objects is called IoT (Kougianos et al. 2016; Liu et al. 2016; Park et al. 2016; Misra et al. 2016). These IoT are supplied with unique identifiers. Additionally, in absence of user-to-user or user-to-computer influence, the IoT system has the capability to convey data over the network. Thus, people

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have close interaction with the physical world based on the real time activity of the sensor nodes (Ashraf and Habaebi 2015; Perera and Vasilakos 2016). Rather than customize data from the surrounding environment, the users can observe, sense, and regulate the objects placed in the corresponding environment (C. Li et al. 2016; F. Li et al. 2016; Zhang et al. 2016).

The resource of the nodes in WSN based IoT have limited capability in terms of processing, bandwidth, volume of storage, and power of battery, which differentiate WSN from other networks (Yachir et al. 2016; Wu et al. 2013). Basically, the WSN are provided with battery power that is to be recharged. Under such instances, proper scheduling of energy utilization is required, especially when the sensors are distantly connected (Abusalah et al. 2008; Zhong and Wu 2010). Numerous nodes transfer multiple data from node to the base station about the same event, which leads to transfer of redundant data (Moosavi et al. 2016; Marco et al. 2016). Thus, the consumption of energy associated with the network became high. Since there are three main processes for the nodes such as information sensing, processing, and transmitting, complexity of the network increased. Therefore, the transfer of redundant data should be reduced and a large amount of energy should be saved in order to enhance the life expectancy of the network (Cavalcante et al. 2016; Hsu and Lin 2016; Raza et al. 2016).

However, some challenges have arisen from these developments and triggered research attention in recent years that are unsolved by other researchers. Among the challenges, energy awareness is considered the foremost challenge under IoT (Luo and Ren 2016; Sivieri et al. 2016; Karkouch et al. 2016; Zhu et al. 2016). Energy awareness is used in IoT to provide an energy saving mechanism to the appliances connected to the network. Subsequently, the truthful operating environment is achieved by some primary protocols such as routing protocols and Medium Access Control (MAC). However, these protocols may fail to operate in some cases. Additionally, node clustering is an improved method under WSN to improve the network scalability and life time, but unsolved under IoT. Furthermore, hierarchical protocols, location-based protocol, and data-centric protocols, among others, for clustering the nodes in WSN have been used to save energy by withstanding the network lifetime using multiple operating conditions.

Literature review

Related works

In 2014, Junqi Duan et al. proposed the energy aware trust derivation approach using a game theoretic method to provide security in IoT. Initially, the assistance of the nodes in WSN was attained by the risk strategy model. Furthermore, the overhead of the trust derivation methodology was reduced by the game theoretic approach. The simulations associated with the trust derivation approach were performed and have provided superiority with high security and efficiency in the network of IoT.

In 2016, Zhou et al. have adopted the Enhanced-Channel-Aware Routing Protocol (E-CARP) to create the deployment of Internet of Underwater Things. The principle objective considered in this experimentation was the achievement of an inexpensive data forwarding and less energy consumption system. Additionally, the proposed method addressed the basic problems from the conventional CARP method that does not follow the reusability property and Ping-Pong method that selects the relay node when the network is in steady state. The simulation results were observed, which provided the network with the least communication cost and high capability.

In 2016, Tie Qiu et al. have suggested the routing protocol called Global Information Decision (ERGID) for the purpose of emergency response IoT, which was considered as the challenging point. The delay estimation process called Delay Iterative Method (DIM) deals with the issue related to the removal of valid paths. Furthermore, the Residual Energy Probability Choice was utilized to balance the load of the network. The simulation result associated with the delay, packet loss, and consumption of energy was taken into account in this method. Moreover, some critical experiments were related to STM32W108 sensor nodes. Thus, the response ability of the network at real time was proven through the entire experimentation.

In 2016, Il-Gu Lee and Myungchul Kim developed interference-aware self-optimizing (IASO) to reduce the occurrence of adjacent channel interference (ACI). Through this method, multichannel with multilevel carrier sense was adopted along with process to adapt to gain control. The dynamic range of the amplifier was increased in this experimentation with the sufficient reduction of false carrier sensing and saturation. Ultimately, the network emulation was carried out and has improved the overall throughput, energy efficiency, and latency, which have maximally improved the quality of the IoT network.

In 2016, Tie Qiu et al. introduced a Greedy Model with Small World (GMSW) in order to maintain the robustness of the IoT structure with increased performance. At first, the local importance of the nodes was determined by the greedy criteria. Here, they considered that the feasibility of the optimization algorithm was obtained by the small world model. Subsequently, the proposed algorithm was used to provide the network with minimal world properties by adding together the shortcuts among the nodes based on the local importance. The speed of the GMSW algorithm to access the network with a small number of shortcuts can be achieved through the performance evaluation of the proposed with the existing methods.

Review

The literature has stated the diverse energy awareness protocols used in IoT of the network. Different protocols using Game theoretic approach (Duan et al. 2014), Iterative method (Qiu et al. 2016), IASO (Lee and Kim 2016), Greedy model (Qiu et al. 2016) for energy awareness in IoT have been explained in the literature. However, it requires additional improvements to handle the challenges still present. The corresponding challenges such as complication in solving mixed strategies (Duan et al. 2014), expensive system architecture (Qiu et al. 2016), requirement of precise channel estimation (Lee and Kim 2016), and complication in solving competitive problems (Duan et al. 2014), among others. The aforesaid challenges against the energy awareness objective under IoT are not yet dealt with by any researchers. Furthermore, the cluster head selection in WSN is one of the best methods to save additional energy among the nodes, which were implemented by several researchers, but has not yet been applied in IoT operation. Therefore, it is necessary to implement the cluster head selection process using suitable meta- heuristic algorithm with high convergence speed for developing energy awareness in IoT.

Framework of cluster head selection on IoT

Architecture of network

The architecture of the IoT network is shown in Figure 1. Here each sensor node is connected with separate IoT devices. Since the WSN consists of numerous nodes, the IoT network is supposed to consist of Nnumber of IoT devices. The role of the sensor node is to observe and transmit the information to the concerned IoT device, which then conveys it to the IoT base station. The required dimension range that the device can transform the information is within L_m and L_n in meters. In this network, a cluster head should be selected among three clusters that contain several IoT devices. Accordingly, the three selected devices are represented as A, B, and C, which collects information from the other devices and transfer the information to the IoT base station I_B. On the whole, in this article, the clusters of the network are represented as C_{In} and the cluster head is represented as H_{In}. More to the point, D_{mn} refers to the distance between the m^{th} devices to the n^{th} device and D_{HI_B} refers to the distance between the cluster head and the base station.

Cluster head selection

In general, the cluster head of the WSN is selected based on the parameters such as distance, delay, and energy. Rather than in IoT network, it is necessary to consider the parameter of the IoT devices. Since, the WSN is connected with the IoT devices; it is needed to consider both the load and temperature of the

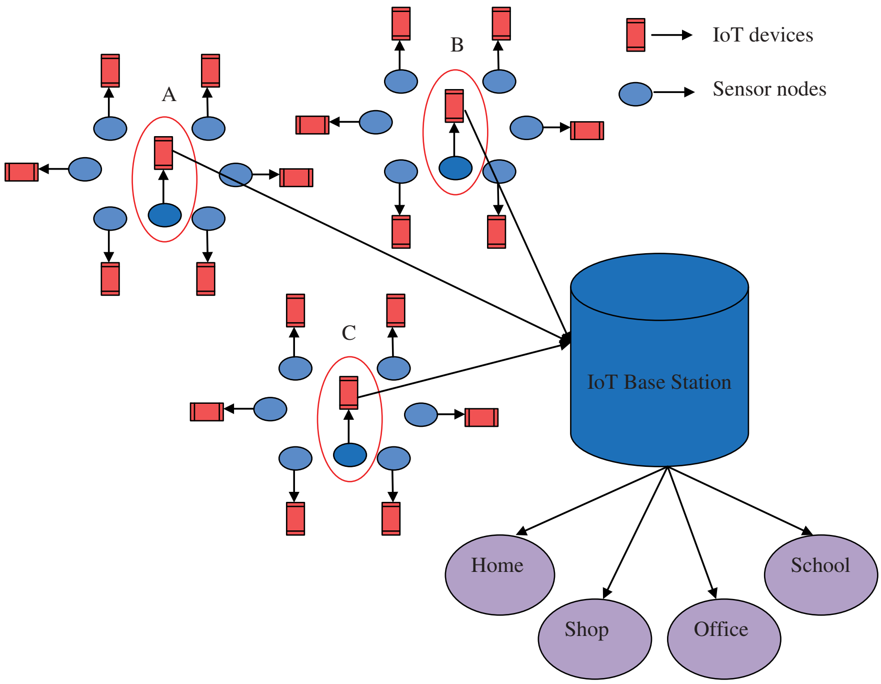

Figure 1. Architecture of IoT network.

devices. Collectively, cluster head selection process depends on the parameters such as distance, delay, energy, load, and temperature of the IoT devices. In fact, the distance, delay, load, and temperature of the devices should be less and the energy should be higher. The objective function of the experiment is based on the maximization function that is shown in Eq. (1), Eq. (2), and Eq. (3), where (β, γ) is the constant that assigns the fixed value (0.9, 0.3).

$$OF_1 = O_f^{energy}\ {}^1\!/\!O_f^{load} + O_f^{energy}\ {}^1\!/\!O_f^{temperature} \tag{1}$$

$$OF_2 = \beta\ {}^1\!/\!O_f^{dis\tan ce} + (1-\beta)OF_1 \tag{2}$$

$$OF_3 = \gamma OF_2 + (1-\gamma){}^1\!/\!O_f^{delay} \tag{3}$$

Distance computation

The distance between the IoT devices as well the base station is computed using Eq. (4), where $O_f^{dis\tan ce}(m)$ computes the distance between the normal node and the cluster head and between the cluster head and the base station of the IoT network, which is expressed in Eq. (5). On the other hand, $O_f^{dis\tan ce}(n)$ computes the distance between two normal nodes, which is expressed in Eq. (6). The value of $O_f^{dis\tan ce}(m)$ should be within the range 0 and 1.

$$O_f^{dis\tan ce} = \frac{O_f^{dis\tan ce}(m)}{O_f^{dis\tan ce}(n)} \tag{4}$$

$$O_f^{dis\tan ce}(m) = \sum_{p=1}^{N}\sum_{q=1}^{H}\left\|I_{norm}^{p} - H_{In}^{q}\right\| + \left\|H_{In}^{q} - I_B\right\| \tag{5}$$

$$O_f^{dis\tan ce}(n) = \sum_{p=1}^{N}\sum_{q=1}^{H}\left\|I_{norm}^{p} - I_{norm}^{q}\right\| \tag{6}$$

Energy computation

The energy utilized by the IoT devices is measured using Eq. (7). The value of energy should be higher than one. In Eq. (10), $E(I_{norm}^{p})$ refers the energy of the p^{th} normal node and $E(I_{norm}^{q})$ refers to the energy of the q^{th} normal node.

$$O_f^{energy} = \frac{O_f^{energy}(m)}{O_f^{energy}(n)} \tag{7}$$

$$O_f^{energy}(m) = \sum_{q=1}^{H_{In}} nE(q) \tag{8}$$

$$nE(q) = \sum_{\substack{p=1 \\ p \in q}}^{M} (1 - E(I_{norm}) * E(H_I)) \; ; \quad 1 \le q < H_{In} \tag{9}$$

$$O_f^{energy}(n) = H_{In} * \underset{p=1}{\overset{H_{In}}{Max}}\left(E(I_{norm}^{p})\right) * \underset{q=1}{\overset{H_{In}}{Max}}\left(E(I_{norm}^{q})\right) \tag{10}$$

Delay computation

The delay suffered by the IoT devices during the transmission of information to the station is computed using Eq. (11) which obtains a value between 0 and 1. The number of members under each cluster should be less to compensate the delay. In Eq. (11), the numerator value represents the number of cluster heads in a particular network and the denominator denotes the total number of IoT devices.

$$f_{delay} = \frac{\underset{q=1}{\overset{H_{In}}{Max}}\left(H_I^{q}\right)}{N} \tag{11}$$

Load and temperature Computation

The load and temperature of the IoT devices are measured using the appropriate devices promoted by Xively (https://www.xively.com/xively-iot-platform).

Proposed gsa based cluster head selection

Conventional GSA algorithm

In 2009, Rashedi et al. invented a population search algorithm called GSA. The GSA algorithm is based purely on the law of gravity. Here, the agents are considered as the objects. Accordingly, the operation of the algorithm is based on the movement of the objects. The objects are attracted to each other by the force of gravity. Each object may contain the heavier or lighter mass. However, the objects with heavier mass are only attracted to other objects. Let us consider Nnumber of agents, where the position of the m^{th} agent is shown in Eq. (12). The variable z_m^d in Eq. (12) represents the position of the m^{th} agent in dimension$d$.

$$Z_m = (z_m^1, \ldots\ldots., z_m^d, \ldots\ldots..z_m^n) \quad for \quad m = 1, 2....N \tag{12}$$

The force performing on the corresponding mass m from mass n of the objects is represented in Eq. (13), where $M_m^P(t)$ represents the passive gravitational mass of m^{th} agent at time t and $M_n^A(t)$ represents the active gravitational mass of n^{th} agent, $r_{mn}(t)$ represents the Euclidean distance of m^{th} and n^{th} agents shown in Eq. (14) and $g(t)$ represents the gravitational constant that is a function of the initial value g_0 and time t as given in Eq. (15) and ε represents a constant.

$$F_{mn}^d(t) = g(t)\frac{M_m^P(t) \times M_n^A(t)}{r_{mn}(t) + \varepsilon}(z_n^d(t) - z_m^d(t)) \tag{13}$$

$$r_{mn}(t) = \|Z_m(t), Z_n(t)\|_2 \tag{14}$$

$$g(t) = g(g_0, t) \tag{15}$$

It is supposed to be calculating the overall force to demonstrate the stochastic behavior of the algorithm. Thus, the overall force that acting on m^{th} in dimension d weighted sum of the forces from other agents with dimension d is expressed in Eq. (16) where $rand_n$ represents the random number [0, 1].

$$F_m^d(t) = \sum_{n=1, n\neq m}^{N} rand_n F_{mn}^d(t) \tag{16}$$

Furthermore, the acceleration A_m^d of m^{th} agent in dimension d is measured by the law of motion that is given in Eq. (17) where $M_{mm}(t)$ represents the mass of inertia of m^{th} agent.

$$A_m^d = \frac{F_m^d(t)}{M_{mm}(t)} \tag{17}$$

The position and velocity of the m^{th} agent is represented in Eq. (18) and Eq. (19). Subsequently, the update of the gravitational mass and inertia mass is calculated based on Eq. (20), Eq. (21), and Eq. (22) where the fitness function of m^{th} is referred as $f_m(t)$, best agent is denoted as $B(t)$, and worst agent is denoted as $W(t)$.

$$V_m^d(t+1) = rand_m \times V_m^d(t) + A_m^d \tag{18}$$

$$Z_m^d(t+1) = Z_m^d(t) + V_m^d(t+1) \tag{19}$$

$$M_m^P(t) = M_n^A(t) = M_{mm}(t) = M_m(t), \quad m = 1, 2....N \tag{20}$$

$$m_m(t) = \frac{f_m(t) - W(t)}{B(t) - W(t)} \tag{21}$$

$$M_m(t) = \frac{m_m(t)}{\sum\limits_{n=1}^{N} m_n(t)} \tag{22}$$

The best and the worst agents through the minimization function of n^{th} agent are represented in Eq. (23) and Eq. (24). Similarly, the best and the worst agent through the minimization function are represented in Eq. (25) and Eq. (26).

$$B(t) = \min_{n \in 1,...N} f_n(t) \tag{23}$$

$$W(t) = \max_{n \in 1,...N} f_n(t) \tag{24}$$

$$B(t) = \max_{n \in 1,...N} f_n(t) \tag{25}$$

$$B(t) = \min_{n \in 1,...N} f_n(t) \tag{26}$$

According to this algorithm, the number of agents should be less to have better performance. Hence, the agents with heavier mass are selected. However, the exploration power and the exploitation ability of the search algorithm are improved by selecting the *Kbest* agents, which are the agents with best fitness value and heavier mass. Therefore, the total force in Eq. (16) can be modified as in Eq. (27).

$$F_m^d(t) = \sum_{n \in Kbest, n \neq m} rand_n F_{mn}^d(t) \tag{27}$$

The pseudo code of the conventional GSA algorithm (Algorithm 1) is illustrated as follows.

ALGORITHM 1 Pseudocode of conventional GSA algorithm.

Generate the population of the agents $m = 1, 2....N$

For all m

Calculate mass M,$g(t)$, $B(t)$and $W(t)$

Compute the initial position $Z_m^d(t)$and velocity $V_m^d(t)$of all agents

Compute the fitness function of all agents

Identify the $Kbest$agents

Compute the force on each agent using eq. (27)

Compute the acceleration of all agents using eq. (17)

Update the velocity and position of the agents using eq. (18) and eq. (19)

Continue till the stopping condition

Proposed GSA algorithm

The proposed algorithm (Algorithm 2) used in cluster head selection procedures of the IoT network is a combination of GSA and ABC algorithms. The standard GSA algorithm updates the position and velocity of the agents until it reaches the stopping condition. Alternately, the proposed GSA algorithm applies the concept of update procedure of employed bee phase of ABC algorithm. The velocity updated using the concept of ABC algorithm is expressed in Eq. (27), where $V_m^d(t)$ represents the current velocity of the particular agent, $V_n^d(t)$ represents the velocity of the neighborhood agent, and φ_m represents a random number between [-1, 1].

$$V_m^d(t+1) = V_m^d(t) + \varphi_m(V_m^d(t) - V_n^d(t)) + A_m^d \tag{28}$$

ALGORITHM 2 Pseudocode of proposed GSA algorithm.

Generate the population of the agents $m = 1, 2....N$

For all m

Calculate mass M,$g(t)$, $B(t)$and $W(t)$

Compute the initial position $Z_m^d(t)$and velocity $V_m^d(t)$of all agents

Compute the fitness function of all agents

Identify the $Kbest$ agents

Compute the force on each agent using eq. (27)

Compute the acceleration of all agents using eq. (17)

Update the velocity of the agents by applying the update of employed bee phase of ABC algorithm as in eq. (28)

Update the position of agents using eq. (19)

Continue till the stopping condition

The flowchart of the proposed GSA algorithm for cluster head selection is shown in Figure 2.

The description of the aforementioned pseudo code and flowchart is depicted as follows.

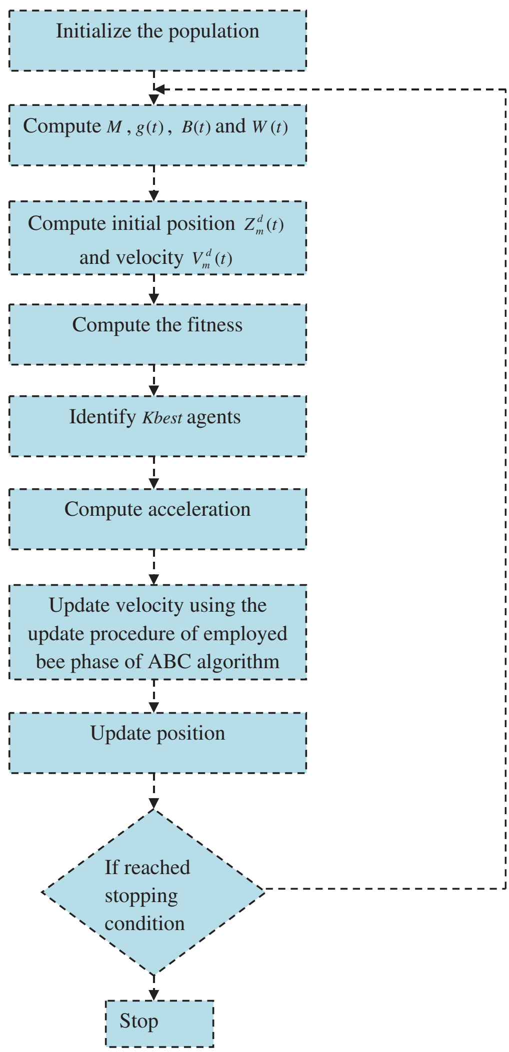

Figure 2. Flowchart of proposed GSA algorithm.

(1) The population of the agents required for the operation of the GSA algorithm is taken as$m = 1, 2....N$.
(2) Among the group of agents, the mass of the agents are calculated from which the best and worst agent is identified based on the mass of the agents.
(3) The initial velocity and the position of the agent are determined.
(4) The fitness of the agents is calculated.
(5) The agent with best fitness value and heavier mass is taken as$Kbest$.
(6) The total force of the agents is calculated using Eq. (27).
(7) The acceleration of the agents is calculated using Eq. (17).
(8) The velocity of the agents is updated using the concept of the employed bee phase under the ABC algorithm using Eq. (28).
(9) With the computed velocity, the position of the agents is calculated using Eq. (19).
(10) The procedure is repeated until the algorithm reached its stopping condition.

Results and discussions

Simulation procedure

The simulation of the cluster head selection of IoT devices under the WSN based IoT network was implemented in MATLAB R2015a. The real time data acquisition was performed by the Xively IOT platform from which the data were read through Xively IOT API (downloaded from http://in.mathworks.com/matlab central/fileexchange/46986-xivelyread). The experimentation was performed by considering the distance, energy, delay, load, and temperature of the IoT devices. The simulation procedure was accomplished based on the fixed values of the following parameters. At the beginning of the experimentation, the base station of the IoT network was localized in the center followed by localizing the IoT devices in the area of $100m \times 100m$. Accordingly, the initial energy of the network $I_E$was assigned to be 0.5, the required energy of the free space model I_F was assigned to be $10pJ/bit/m^2$. Furthermore, the power amplifier energy I_P was assigned to be $0.0013pJ/bit/m^2$, where the essential energy of the transmitter was assigned to be I_T and was assigned to be $50nJ/bit/m^2$. Ultimately, the data aggregation energy I_D was assigned to be $5nJ/bit/signal$. The corresponding experimentation was accomplished until the completion of 2,000 rounds.

Sustainability of network

The sustainability of the WSN based IoT network is graphically represented in Figure 3. The sustainability of the network is determined by

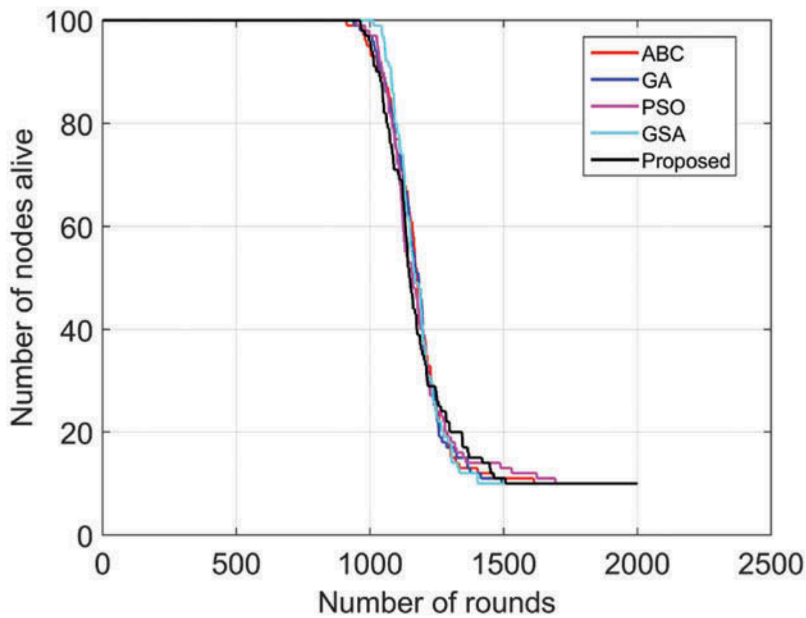

Figure 3. Graphical representation of network sustainability Vs number of rounds.

estimating the total number of alive nodes existing until 2,000 rounds. For instance, the general fact is that the life of the network enhances with the number of alive IOT devices existing in the network. Figure 3 compares the network sustainability of the proposed method with conventional methods such as ABC, GA, PSO, and GSO. Here, the proposed methods holds 100 alive nodes until completion of 1,000 rounds; after which the number of alive nodes decreases as the rounds increase. On the other hand, there are 20 alive nodes present until the completion of 1,300 nodes, whereas more than 10 nodes exist until the completion of 2,000 rounds. This achievement of the proposed method is definitely better than the conventional methods.

Analysis of convergence

The line chart representation of convergence of the proposed method with the convergence algorithms is shown in Figure 4. In general, the convergence of the algorithm should be enhanced with the increment of the iteration. Here, the convergence method until the end of 10 iterations is 74% better than PSO algorithm, 95% better than GSA algorithm, 84% better than GA algorithm, and 17% better than GA algorithm. Thus, the convergence of the proposed method has improved for the cluster head selection of the WSN based IoT network.

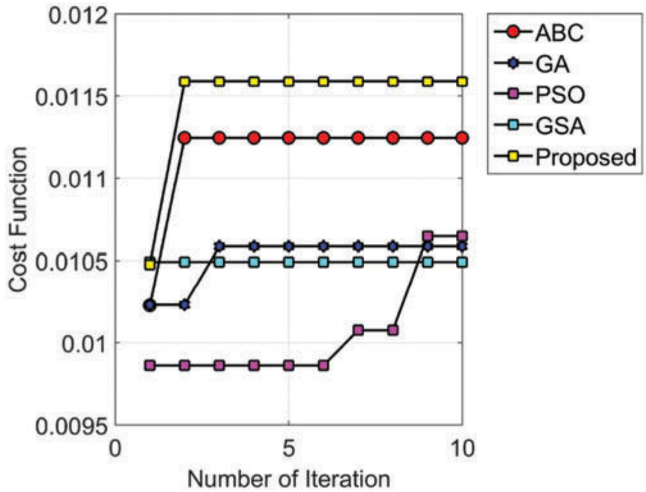

Figure 4. Line chart of convergence analysis.

Performance analysis interms of normalized energy, load, and temperature

The performance analysis of the cluster head selection on WSN base IoT network in terms of normalized energy of the IoT devices until the final round is shown in Figure 5. The energy of the IoT devices should be increased until the last round of the cluster head selection operation. Initially, the energy is high and it reduces as the number of rounds increases for both the proposed as well as for the conventional methods. The normalized energy of the proposed method is 0.55 at the beginning round and 0.055 at the final round. Subsequently, the normalization of the proposed method

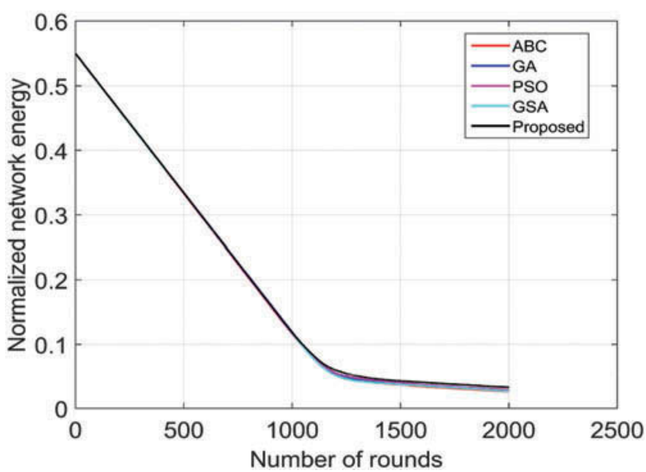

Figure 5. Analysis of normalized network energy of IoT device Vs number of rounds.

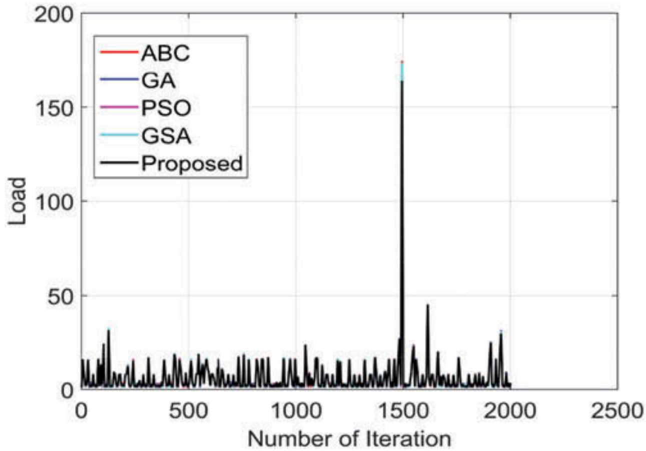

Figure 6. Analysis of IoT device load Vs number of rounds.

is better than the conventional methods until 2,000 rounds, which thus provides superiority to the proposed algorithm.

The performance analysis of the load of IoT devices in correspondence with the number of rounds is shown in Figure 6. Here, the calculated load is the average load of the 10 cluster head selected for each instance. This average load of the IoT devices should be decreased to maintain the reliable network. In Figure 6, the load of the proposed method is low near to 1,500 rounds. However, in 1500^{th} round, there is a sudden increase in load. Then, it again comes to the previous level. The peak of the proposed method obtained in the 1500^{th} round is less than the ABC and GSA algorithms. Collectively, in all rounds, the load of the proposed method is less than the conventional methods, which therefore maintains the consistency of IoT based WSN network.

The analysis of the proposed with the conventional methods in terms of existing temperature of the IoT devices for cluster head section in related numbers of rounds is shown in Figure 7. Basically, the stability of the network is maintained if the average temperature of IoT devices in each instant is reduced. Initially, the average temperature is highly reduced and subsequently the average temperature increases until 2,000 rounds. On comparing the proposed and the existing methods, the temperature of the proposed method is less than the existing methods.

Conclusion

Since a WSN based IoT network is highly used in a variety of applications, a cluster head is necessary to select among numerous IoT devices to make proficient data transmission. In this article, a novel method with the linkage of GSA and ABC algorithms was proposed to satisfy the adept cluster head

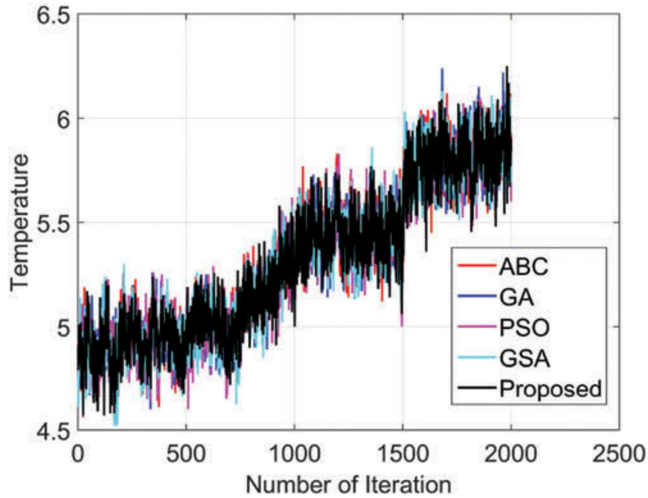

Figure 7. Analysis of IoT device temperature Vs number of rounds.

selection. Distance, energy, delay, load, and temperature of the IoT devices were considered in the proposed cluster head selection process. The performance analysis in terms of network sustainability, convergence evaluation, and performance in terms of normalized energy, load, and temperature has determined by comparing the proposed method with existing methods such as ABC, GA, PSO, and GSA algorithms. Taking into account the overall analysis, the performance of the proposed method is a better fit than conventional methods for the cluster head selection of IoT devices.

References

Agarwal, A., G. Misra, and K. Agarwal. "The 5th Generation Mobile Wireless Networks- Key Concepts, Network Architecture and Challenges." *American Journal of Electrical and Electronic Engineering* 3.2 (2015): 22–28. Print.

Abusalah, L., A. Khokhar, and M. Guizani. "A Survey of Secure Mobile Ad Hoc Routing Protocols." *IEEE Communications Surveys & Tutorials* 10.4 (2008): 78–93. Print.

Ashraf, Q. M., and M. H. Habaebi. "Autonomic Schemes for Threat Mitigation in Internet of Things." *Journal of Network and Computer Applications* 49 (2015): 112–27. Print.

Cavalcante, E., J. Pereira, M. P. Alves, P. Maia, R. Moura, T. Batista, F. C. Delicato, and Paulo F. Pires. "The Interplay of Internet of Things and Cloud Computing: A Systematic Mapping Study." *Computer Communications* 89-90 (2016): 17–33. Print.

Dai, H., and H. Xu. "Key Predistribution Approach in Wireless Sensor Networks Using LU Matrix." *IEEE Sensors Journal* 10.8 (2010): 1399–409. Print.

Duan, J., D. Gao, D. Yang, C. H. Foh, and H. H. Chen. "An Energy-Aware Trust Derivation Scheme With Game Theoretic Approach in Wireless Sensor Networks for IoT Applications." *IEEE Internet of Things Journal* 1.1 (2014): 58–69. Print.

Hsu, C. L., and J. C. C. Lin. "An Empirical Examination of Consumer Adoption of Internet of Things Services: Network Externalities and Concern for Information Privacy Perspectives." *Computers in Human Behavior* 62 (2016): 516–27. Print.

Karkouch, A., H. Mousannif, H. A. Moatassime, and T. Noel. “Data Quality in Internet of Things: A State-of-the-art Survey.” *Journal of Network and Computer Applications* 73 (2016): 57–81. Print.

Kawamoto, Y., H. Nishiyama, Z. M. Fadlullah, and N. Kato. “Effective Data Collection Via Satellite-Routed Sensor System (SRSS) to Realize Global-Scaled Internet of Things.” *IEEE Sensors Journal* 13.10 (2013): 3645–54. Print.

Kougianos, E., S. P. Mohanty, G. Coelho, U. Albalawi, and P. Sundaravadivel. “Design of a High-Performance System for Secure Image Communication in the Internet of Things.” *IEEE Access* 4 (2016): 1222–42. Print.

Lee, I. G., and M. Kim. “Interference-aware Self-optimizing Wi-Fi for High Efficiency Internet of Things in Dense Networks.” *Computer Communications* 89-90.1 (2016): 60–74. Print.

Li, C. Z., J. Hong, F. Xue, G. Q. Shen, X. Xu, and L. Luo. “SWOT Analysis and Internet of Things-enabled Platform for Prefabrication Housing Production in Hong Kong.” *Information Systems* 62 (2016): 29–41. Print.

Li, F., Y. Han, and C. Jin. “Practical Access Control for Sensor Networks in the Context of the Internet of Things.” *Computer Communications* 89-90 (2016): 154–64. Print.

Li, Z., R. Chen, L. Liu, and G. Min. “Dynamic Resource Discovery Based on Preference and Movement Pattern Similarity for Large-Scale Social Internet of Things.” *IEEE Internet of Things Journal* 3.4 (2016): 581–89. Print.

Liu, Y., W. Han, Y. Zhang, L. Li, J. Wang, and L. Zheng. “An Internet-of-Things Solution for Food Safety and Quality Control: A Pilot Project in China.” *Journal of Industrial Information Integration* 3 (2016): 1–7. Print.

Luo, S., and B. Ren. “The Monitoring and Managing Application of Cloud Computing Based on Internet of Things.” *Computer Methods and Programs in Biomedicine* 130 (2016): 154–61. Print.

Marco, P. D., G. Athanasiou, P. V. Mekikis, and C. Fischione. “MAC-aware Routing Metrics for the Internet of Things.” *Computer Communications* 74.15 (2016): 77–86. Print.

Misra, G., V. Kumar, A. Agarwal, and K. Agarwal. “Internet of Things (IoT) – A Technological Analysis and Survey on Vision, Concepts, Challenges, Innovation Directions, Technologies, and Applications (An Upcoming or Future Generation Computer Communication System Technology).” *American Journal of Electrical and Electronic Engineering* 4.1 (2016): 23–32. Print.

Moosavi, S. R., T. N. Gia, E. Nigussie, A. M. Rahmani, S. Virtanen, H. Tenhunen, and J. Isoaho. “End-to-end Security Scheme for Mobility Enabled Healthcare Internet of Things.” *Future Generation Computer Systems* 64 (2016): 108–24. Print.

Park, H., H. Kim, H. Joo, and J. S. Song. “Recent Advancements in the Internet-of-Things Related Standards: A OneM2M Perspective.” *ICT Express* 2 (2016): 126–129. Print.

Perera, C., and A. V. Vasilakos. “A Knowledge-based Resource Discovery for Internet of Things.” *Knowledge-Based Systems* 109 (2016): 122–36. Print.

Qiu, T., D. Luo, F. Xia, N. Deonauth, W. Si, and A. Tolba. “A Greedy Model with Small World for Improving the Robustness of Heterogeneous Internet of Things.” *Computer Networks* 101 (2016): 127–43. Print.

Qiu, T., Y. Lv, F. Xia, N. Chen, J. Wan, and A. Tolba. “ERGID: An Efficient Routing Protocol for Emergency Response Internet of Things.” *Journal of Network and Computer Applications* 72 (2016): 104–12. Print.

Rashedi, E., H. N. Pour, and S. Saryazdi. “GSA: A Gravitational Search Algorithm.” *Information Sciences* 179 (2009): 2232–48. Print.

Raza, S., P. Misra, Z. He, and T. Voigt. “Building the Internet of Things with Bluetooth Smart.” *Ad Hoc Networks* 57 (2016): 19–31. Print.

Sivieri, A., L. Mottolaa, and G. Cugola. "Building Internet of Things Software with ELIoT." *Computer Communications* 89-90 (2016): 141–53. Print.

Wu, D., L. Bao, and C. H. Liu. "Scalable Channel Allocation and Access Scheduling for Wireless Internet-of-Things." *IEEE Sensors Journal* 13.10 (2013): 3596–604. Print.

Yachir, A., Y. Amirat, A. Chibani, and N. Badache. "Event-Aware Framework for Dynamic Services Discovery and Selection in the Context of Ambient Intelligence and Internet of Things." *IEEE Transactions on Automation Science and Engineering* 13.1 (2016): 85–102. Print.

Zhang, D., L. T. Yang, M. Chen, S. Zhao, M. Guo, and Y. Zhang. "Real-Time Locating Systems Using Active RFID for Internet of Things." *IEEE Systems Journal* 10.3 (2016): 1226–35. Print.

Zhong, S., and F. Wu. "A Collusion-Resistant Routing Scheme for Noncooperative Wireless Ad Hoc Networks." *IEEE/ACM Transactions on Networking* 18.2 (2010): 582–95. Print.

Zhou, Z., B. Yao, R. Xing, L. Shu, and S. Bu. "E-CARP: An Energy Efficient Routing Protocol for UWSNs in the Internet of Underwater Things." *IEEE Sensors Journal* 16.11 (2016): 4072–82. Print.

Zhu, T., S. Dhelim, Z. Zhou, S. Yang, and H. Ning. "An Architecture for Aggregating Information from Distributed Data Nodes for Industrial Internet of Things." *Computers & Electrical Engineering* (2016). http://dx.doi.org/10.1016/j.compeleceng.2016.08.018