International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I7P244

Volume 70 Issue 7, 422-437, July 2022

Original Article

Hybrid Optimized Fuzzy Based Cluster Head Selection for WSN Data Communication in IoT Environment

Kanakaraju R [1], Arun Vikas Singh[2]

[1](Under Visvesvaraya Technological University, Belagavi, 590018), Department of Electronics and Communication Engineering, T John Institute of Technology, Bengaluru, Karnataka 560083, India
[2] Department of Computer Science and Engineering, PES University, Bengaluru, Karnataka 560085, India

[1]mrkanakaraju@gmail.com

Received: 17 May 2022 Revised: 15 July 2022 Accepted: 18 July 2022 Published: 27 July 2022

Abstract *- Wireless Sensor Network (WSN) is resource-constrained and is applied in different applications, namely health care observation, home monitoring, military systems, etc. Moreover, these applications are interconnected with various devices, which are proficiently interrelating with each other with the Internet, and it is called the Internet of Things (IoT). Usually, WSN is a most significant role over IoT structure. The sensors are arbitrarily located in harsh environments where communication networks experience various privacy problems in WSN, which is critical for data transmission. This paper's Political Caviar Social Optimization Algorithm (PCSOA) is developed for Cluster Head Selection (CHS) for WSN data communication in IoT structure. The Deep Residual Network (DRN) is applied for predicting energy and is trained by the developed Political Caviar Social Optimization Algorithm (PCSOA). Moreover, an Adaptive Genetic Fuzzy System (AGFS) with various objectives, like residual energy, predicted energy, distance, trust factors, Link Life Time (LLT), and delay, is utilized for selecting CHs. In addition, PCSOA is employed for effective routing considering fitness parameters as different objectives. The proposed DRN+PCSOA outperformed other methods delay, distance, residual energy, and trust by 0.1941sec, 55.63m, 0.1991J, and 0.6109, respectively.*

Keywords *- Routing, Adaptive Genetic Fuzzy System, Political Optimizer, Link Life Time model, Wireless Sensor Network.*

1. Introduction

The WSN is a most vital section of IoT architecture. Generally, it is the collection of different nodes, named sensors, which can be positioned globally for monitoring, computing, sensing, and communicating with other networks as well as various physical features of environmental circumstances, like temperature, humidity, sound, and so on. The data gathered by the sensor node is transmitted to Base Station (BS) or sink node for additional processes. Moreover, WSN is executed in hostile situations where human access is troublesome. The common WSN applications are landslide, military applications, weather observation, forest fire identification, healthcare observation, and so on. However, energy utilization is individual of the most important shortcomings in WSN owing to restricted battery limitations [10]. WSN includes two kinds, namely heterogeneous and homogeneous [9]. Besides, IoT is a more developing system, which is an extension of internet access by the interconnection of various devices, like sensors, vehicles, and mobile phones. The quantity of devices interconnected to the internet and digital identity is gradually increasing. Moreover, IoT has become the most significant element in human life during the development of technologies. IoT refers to a developing network covering objects, including several physical entities, like wearable devices, watches, and smart objects. IoT is considered an interconnection of sensors and actuators or networks with a unique structure to share information [9]. Besides, the sensors that exist in WSNs are inadequate in storage memory, radio communication capacities, battery, and processing capacity. In addition, the energy required for data communication is a hundred periods greater than the energy required for data processing [11] [12].

WSN is a fast-emerging information attainment model that integrates the current technologies with the network, communication, and microelectronics. Hence, WSN is essential in numerous domains, like industry management, urban transport system, environment observation, and military [13]. Although, the most important problem of WSN is how to collect the node energy while preserving indispensable network behavior. Several sensor network platforms are battery-functioned models. Thus, it is essential in extreme energy constraints [14] [15]. The energy exploitation must be controlled to increase the system lifespan. The sensor node in Wireless Sensor Network has two functions: gathering information as of physical structure then information routing since BS and data collection from WSN for further processing. Other ways to increase the network lifetime include essential constraint selection, routing models for increasing energy efficiency, and clustering to ensure appropriate network function. The routing approach of WSN has two major groups, including flat and hierarchical routing methods. In addition, protocol operation and network structure are two major routing techniques. The routing process is applied to increase the scalability and robustness and decrease data retransmission. Besides, the hierarchical routing model effectively increases the system lifetime and network scalability and decreases the delay [3]. The multihop routing process is another common technique used in huge-scale networks to transmit data to BS [17] [16]. Furthermore, network lifespan is implanted in sensor grouping to save energy and reduce long-distance communication. Consequently, long-distance communication is evaded to improve the node lifetime [18] [19].

The routing approach is considered the most vital process of WSN since it affects the energy consumption among nodes. The secure trust-interested routing technique also recognizes the routing assaults and provides important network operation [1]. The hybrid reserved dependent clustering model was introduced, including comparative distance to BS and remaining energy by CHS [13]. Additionally, fuzzy security protocol and trust management schemes are mostly ensured for IoT-enabled clusters to design the secure technique for exchanging the data amongst nodes in the Internet of Things architecture. The scalability is highly decreased by routing schemes through managing overhead packets. However, the energy use is improved if the network dimension is high.

Moreover, an energy effectual cluster-based routing approach constructed on multihop routing and fuzzy logic was introduced in [20] [16]. This approach devised the fuzzy logic approach and cluster size formation for the execution process. The Two Tier Distributed Fuzzy Logic based Protocol (TTDFP) was designed in [21] [16] for increasing WSN lifetime through computing the routing effectiveness. Besides, the adaptive distribution model efficiently functions in sensor network applications, and a fuzzy clustering process was done to optimize WSN performance. The hierarchical routing approach includes improved scalability and flexibility by comparing flat and hierarchical routing methods. The research mostly focused on hierarchical routing schemes in modern days [22] [3]. The novel cluster-based approaches are introduced for controlling network lifetime and energy consumption [23] [24] [25].

This investigation's major determination is to devise a CHS model for WSN data communication in IoT based on a hybrid optimized fuzzy system. Here, the IoT-WSN simulation is performed, where CHs and nodes are moving nodes. Moreover, trust, LLT, mobility, and energy models are also considered. After that, the DRN model [26] is utilized for predicting energy, and DRN is trained by devised PCSOA. Accordingly, the devised PCSOA is newly introduced by combining Autoregressive Conditional Value at Risk by Regression quantiles (CAViaR) [27] and Social Optimization Algorithm (SOA) [28] along with Political Optimizer (PO) [29]. Furthermore, CHS is performed through AGFS [30] with PCSOA based on various measures, such as trust factors, residual energy, distance, predicted energy, LLT, and delay. The routing process is based on developed PCSOA and various measures such as fitness function.

The chief influences of this paper are clarified through obeying,

1.1. Developed PCSOA for energy prediction and routing:

The energy prediction, CHS selection, and the routing procedure are supported using devised PCSOA. The DRN is utilized for predicting energy, and a designed PCSOA trains the DRN. In addition, the AGFS model is applied for an effective CHS selection process, which is trained by devised PCSOA. The PCSOA is newly introduced by integrating CAViaR and SOA with PO. Moreover, various fitness measures, like distance energy, delay, distance trust factors, and LLT, are considered.

The outstanding subdivisions of the paper are listed in this way: Subdivision 2 specifies traditional CHS and routing techniques. Subdivision 3 denotes the approaching model of IoT WSN. Subdivision 4 elucidates the developed model for optimum CH selection and routing. Subdivision 5 discusses the efficiency of the proposed model by relating it with standard methods. Subdivision 6 presents the conclusion.

2. Motivation

The network lifespan and energy effectiveness are the most important concerns in the WSN routing process. These issues and challenges faced by prevailing routing approaches are measured as a major inspiration to devise innovative CHS methods for routing in IoT-WSN.

2.1. Literature survey

This unit explains the literature survey of current WSN routing approaches through its advantages and restrictions. Mohd Adnan *et al.* [1] developed a fuzzy logic-driven clustering model for WSN. The unequally sized clusters were considered in this approach, and the distributed fuzzy logic system identified the cluster radius. Moreover, the multihop transmission was done to reduce energy consumption.

This approach effectively increases the network lifetime, although it failed to include a lightweight, secure system for better performance. To increase the system performance, Susan Augustine and J. P. Ananth [2] designed Taylor kernel fuzzy C-means (Taylor KFCM) for CHS in WSN. Accordingly, the Taylor KFCM was developed by incorporating the Taylor series and KFCM. Moreover, several factors, namely trust, distance, and energy, were considered for the effectual CHS process. This approach has less delay, even though it failed to simulate this technique in real-time. To perform the simulation in real-time, Alghamdi, T.A [3] presented Firefly position update Dragonfly Algorithm (FPU-DA) for CHS in WSN. In addition, several measures, such as security, distance, energy, and delay, were considered for effectual CHS. This method's computational time was highly reduced but did not improve the connectivity and coverage performance. To increase coverage and connectivity performance, Qian Ren and Guangshun Yao [4] introduced Energy Efficient Cluster Head Selection (EECHS) in WSN. This model employed a scheduling node to monitor and accumulate the data. The energy consumption was highly decreased in this technique. However, this method failed to balance the consumed and harvested energy.

R. Kowsalya and B. Rosiline Jeetha [5] modelled a Hybrid Decision-Making system with Firefly Routing Algorithm (HDMFRA) to balance harvester and consumed energy WSN-based IoT system. Here, data storage and transmission of data were performed based on FA. Even though this method did not maintain energy consumption, the network lifetime increased. To decrease energy consumption, Dipali K. Shende and S. S. Sonavane [6] presented Crow Whale Optimization Algorithm (CWOA) for multicast routing in WSN. The CWOA was designed by integrating Crow Search Algorithm (CSA) and Whale Optimization Algorithm (WOA). This method's revealing rate was highly increased, but the routing performance was still ineffective. For executing an effective routing process, Jenn-Wei Lin *et al.* [7] devised a Bipartite Flow Graph model used for routing in IoT-based WSN. The virtual CH generation was done to maintain the failures of CH. The flow graph technique obtained fault tolerance with less energy consumption. This approach highly increased the network lifetime, although it did not reduce the computational complexity. To reduce the computational complexity, Biswa Mohan Sahoo *et al.* [8] designed a hybrid optimization method for cluster constructed routing in WSN. This scheme integrated Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for effective routing. The network's lifetime remained highly increased in this method, although it did not solve time complexity.

2.2. Challenges

The most significant encounters experienced by prevailing CHS and routing approach in WSN are described as follows,

- Usually, the data transmission is more challenging between nodes in a network since the utilized system should have highly reduced energy consumption, increased speed, and minimal delay.
- For considering energy consumption and delay, a fuzzy logic-enabled clustering algorithm [1] was devised for WSN, although this approach failed to reduce the computation cost.
- To reduce the computational cost, Taylor KFCM was designed in [2] for CHS in WSN, even though this approach did not conduct real-time experiments to validate.
- To execute real-time tests, FPU-DA was introduced in [3] for CHS in WSN. This method failed to make an effective balance through obtaining the objectives at serviceable computation cost.
- For controlling the cost consumption, in [4], EECHS was developed for WSN. However, this approach failed to include other efficient mobile devices for better system performance.

3. System model

The IoT-assisted WSN model with various nodes contained in the network is advertised for sending information packets to sink nodes considering effectual routes. The IoT-assisted WSN encompasses several devices connected wireless by the internet. The IoT-based WSN contains Base Station (BS), Cluster Heads (CHs), and cluster nodes. The wireless connections among IoT nodes indicate absolute announcement in radio choice, which is dispersed between uniform mode dimensions. Moreover, each node includes separate ID and collection nodes to formulate clusters in the network. The BS is accountable for receiving information between IoT nodes.

Furthermore, IoT nodes send information to BS depending on CH’s. The IoT system is now separated into dissimilar clusters, where normal nodes are similar cluster nodes. After grouping clusters, data packets are transmitted from the normal node to CH. Thus, CH stores all information and broadcasts to BS. Thus, complete nodes are positioned in a definite location in the network among CH toward BS.

3.1. Energy model

The energy model [31] in WSN is demonstrated with data transmission and different nodes. Usually, WSN includes various dispersed sensors, which is functioned with batteries in such a way that increasing rounds can drain energy, thus increasing the network lifespan. Assume the starting node's energy by way of H_0Which represents batteries are non-rechargeable. The minimal amount of energy vanishes and mainly depends on communication distance, while data is received through the transmitter. Moreover, network transmission is carried out through energy dissipation, power amplifier, and radio electronics. Therefore, it is denoted that huge energy is detached when data transmission is done with distance. The energy model of WSN, while the sensor node transmits r bits data, is expressed as,

$$H_j(r) = H_i(r) + H_l(r, x) \quad (1)$$

where,$H_j(r)$ represents transmitted energy, $H_l(r, x)$ Implies energy consumed during node conveys 1-bit information, $H_i(r)$ Signifies energy utilized during node collects and transmits 1-bit information, x specifies transfer distance, and r specifies information bits.

$$H_j(r) = \begin{cases} r \times H_i + r \times H_n \times x^2\,; & if x \leq x_0 \\ r \times H_i + r \times H_g \times x^4\,; & if x > x_0 \end{cases} \quad (2)$$

where, H_i is expended energy, as soon as the node sends 1-bit information in the free area, H_n Denotes energy consumed, while node directs 1-bit information in multipath fading.

$$x_0 = \sqrt{\frac{H_n}{H_g}} \quad (3)$$

The energy used in sensor nodes helps to collect r bits of information which is specified as,

$$H_y(r) = r \times H_i \quad (4)$$

where, $H_y(r)$ Represents received energy.

$$\gamma = H_j + H_y \quad (5)$$

3.2. Mobility model

The mobility model [32] is afforded for specifying the sensor node's movement and estimating variation in node location. Here, the mobility model is applied to find the nodes' motion.

Let us contemplate nodes f_x and f_a positioned at $(m, p)$and(m^*, p^*) In the period $b = 0$. The nodes f_x and f_a leads to a new location with various velocities built on two angles $\phi_{f,x}$ and $\phi_{f,a}$. Moreover, node f_x changes the distance $E_{f,x}$and node f_a directs distance $E_{f,a}$ At period $b = 0$. Consider (m_x, p_x) and (m_a, p_a), which symbolizes reorganized positions employed by nodes f_x and f_a at period $b = 1$.

The Euclidean distance among nodes f_x and f_a at period $b = 0$ is specified by,

$$E(f_x, f_a, 0) = \sqrt{|m - m^*|^2 + |p - p^*|^2} \quad (6)$$

where, $(m, p)$and(m^*, p^*) refers to the new node's location f_x At $b = 0$. Let us consider node f_x and f_a are transmits in a velocity $a_{f,x}$ and$a_{f,a}$ by making angle $\phi_{f,x}$ and $\phi_{f,a}$ By x-axis. Therefore, distance consumed in the node by explicit period d is expressed as,

$$E_{f,x} = a_{f,x} \times d \quad (7)$$

$$E_{f,a} = a_{f,a} \times d \quad (8)$$

At the time $d = 1$, when the node f_x directs at distance $E_{f,x}$ and angle $\phi_{f,x}$, later new location of a node f_x at period d is denoted as,

$$m_x = m + a_{f,x} \times d \times Cos(\phi_{f,x}) \quad (9)$$

$$p_x = p + a_{f,x} \times d \times Cos(\phi_{f,x}) \quad (10)$$

where, $\phi_{f,x}$ is an angle where node f_xSends to a novel position. Moreover, when the node$f_a$sends in distance $E_{f,a}$ at angle $\phi_{f,a}$, then new node location b_l at time d is given by,

$$m_a = m^* + a_{f,a} \times d \times Cos(\phi_{f,a}) \quad (11)$$

$$p_a = p^* + a_{f,a} \times d \times Cos(\phi_{f,a}) \quad (12)$$

The distance between nodes at f_x positioned at location (m_x, p_x) and (m_a, p_a) at time d is denoted as,

$$E(f_x, f_a, d) = \sqrt{|m_x - m_a|^2 + |p_x - p_a|^2} \quad (13)$$

where, (m_x, p_x) and $(m_a, p_a)a$ represented the new location of nodes f_x and f_a.

3.3 Link lifetime model

The LLT [34] is estimated at each hop through route request packet transmission. Moreover, each sensor node computed the path lifetime between previous and current hops. The LLT is estimated by,

$$X = \frac{-(vw+me)+\sqrt{(v^2+w^2)y^2-(ve-wm)^2}}{(v^2+m^2)} \quad (14)$$

where,

$$v = s_p\, cos\gamma_p - s_m\, cos\gamma_m \quad (15)$$

$$w = Z_p - Z_m \quad (16)$$

$$m = s_p \, sin\gamma_p - s_m \, sin\gamma_m \quad (17)$$

$$e = \Upsilon_p - \Upsilon_m \quad (18)$$

where, (Z_p, Υ_p) denotes points of mobile node p and (Z_m, Υ_m) signifies mobile node points at m, whereas s_p and s_m Represents speediness of mobile node p and m. The direction of node movement p and m is referred as γ_p and γ_m.

3.4. Trust model

The trust model is applied for secure communication in WSN to evade the miscommunication produced in suspicious nodes in a network. Generally, every node is constructed on the trust factors, for instance, indirect, direct, and overall trust.

3.4.1. Direct trust

This trust [33] is computed depending on four major elements: routing behavior, energy, unselfishness, and rank threshold. The direct trust is estimated by,

$$D_{t,r} = \frac{(E_{t,r} + A_{t,r} + J_{t,r} + I_{t,r})}{4} \quad (19)$$

where, $D_{t,r}$ signified direct trust, $E_{t,r}$ implies routing behaviour, $A_{t,r}$ represents energy, $J_{t,r}$ is unselfishness, and $I_{t,r}$ denotes rank threshold.

3.4.2. Indirect Trust

Indirect trust [33] estimation of the nearby node utilizes indirect information concerning other nearby nodes. This trust is employed when the transaction count between two nodes is minimal. Thereby nearby general nodes among nodes are used to find the nearby trust. Consider that nodes a and c have less transaction count and common nearby nodes between a and c are M. The indirect trust is calculated by,

$$I_{t,r} = \frac{\sum_{M=1}^{M=4}(D_{t,M} \times DT_{M,r})}{\sum_{M=1}^{M=4}(D_{t,M})} \quad (20)$$

Where M indicates the neighboring node among a and c.

3.4.3. Overall Trust

Overall trust [33] of every node is estimated by the weighted accumulation of indirect and direct trust. This trust is estimated by,

$$O_{t,r} = (\varpi_1 \times D_{t,r}) + (\varpi_2 \times I_{t,r}) \quad (21)$$

where, ϖ_1 implies weight associated with direct trust, and ϖ_2 denotes the weight of indirect trust here, $\varpi_1 + \varpi_2 = 1$.

4. Developed CHS model using Hybrid an Optimization-based Deep Learning Approach

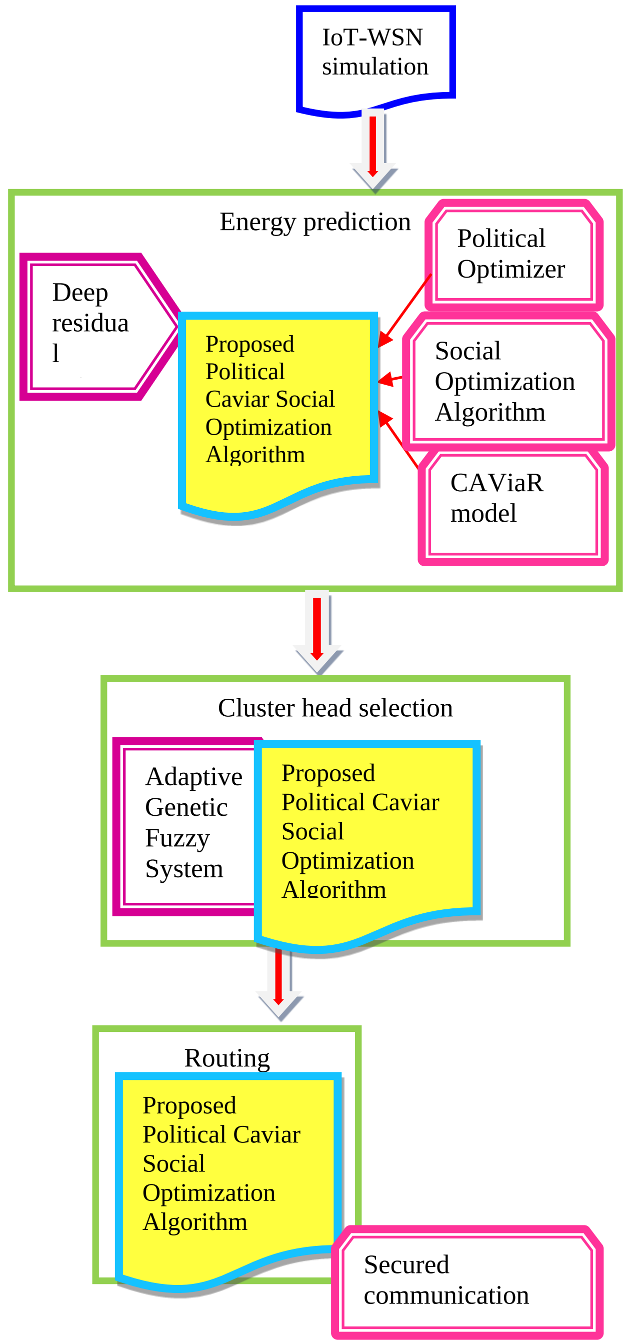

Fig. 1 Block diagram of introduced CHS selection model for secure communication using the optimization algorithm

This section illustrates the energy prediction and routing process using a developed optimization algorithm. Here, PCSOA is introduced for effective CHS and energy prediction process. Originally, IoT-WSN simulation was performed in which nodes and CHs are considered moving nodes. Furthermore, energy, mobility, LLT, and trust models are also considered. The energy prediction is carried out using DRN [26] and is trained by a designed PCSOA. After that, CHS is done based on AGFS [30] and PCSOA. Besides, various objectives include residual energy, predicted energy, distance, trust factors, LLT, and delay. Once CHS is done, routing is carried out using designed PCSOA by considering the above objectives as fitness parameters. The block diagram of the introduced CHS selection model for secure communication using an optimization algorithm is shown in figure 1.

4.1. Energy prediction using Political Caviar Social Optimization Algorithm-based Deep residual network

The energy prediction process predicts future energy needs to obtain energy supply and demands. Here, the energy prediction is carried out using DRN, which is trained by developed PCSOA.

4.1.1. Proposed Deep residual network

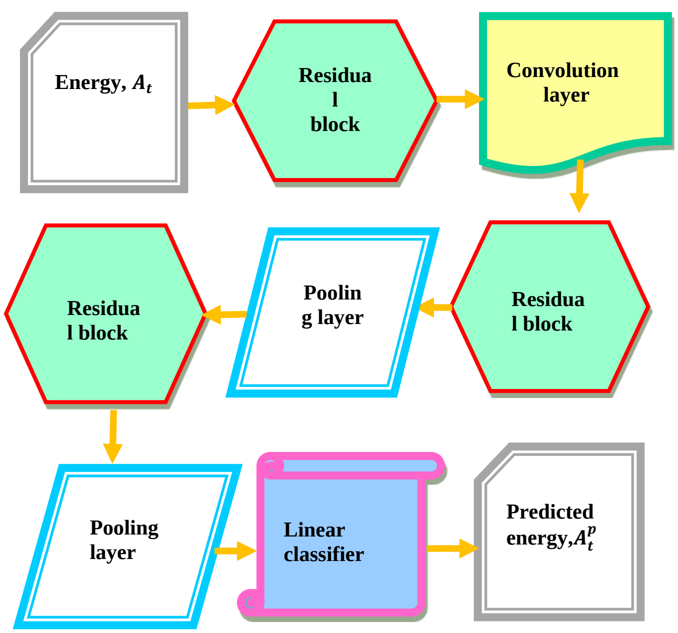

Fig. 2 Structural representation of DRN

DRN model [26] encompasses numerous layers, namely residual blocks, linear classifier, pooling, and convolutional layer. The energy A_t It is considered as input for the DRM structure. The DRN achieved better training and learning execution even in restricted training data. So, the DRN structure is used for the energy prediction method, and the DRN structure is exposed in figure 2.

Convolutional layer

The 2D convolution layer is applied to reduce unlimited boundaries in the training procedure. This layer represents proficient local receptive fields as well as weight-sharing performance. The input of the convolutional layer is managed by filters, which are named utilizing kernels. This layer employs mathematical functions used for reducing the filter matrix input to facilitate the dot product of the kernel is computed. The convolutional layer expression is given by,

$$D2c(A_t) = \sum_{m=0}^{a-1} \sum_{w=0}^{a-1} D_{m,w} \bullet A_t(q+m)(s+w) \quad (22)$$

$$D1c(A_t) = \sum_{y=0}^{cin-1} D_y * A_t \quad (23)$$

where, A_t Is Two Dimensional (2D) outcome attained from the previous layer, q and $s$are employed for recording the coordinates in input, D implies $\eta \times \eta$ kernel matrix, which is learnable constraints in training, m and w specified position index in 2D kernel matrix, D_y indicates kernel size of y^{th} input neuron, and $*$ symbolizes cross-correlation operator without zero padding.

Pooling layer

The pooling layer is connected with a sequential convolutional layer, which is applied to reduce the spatial dimension of the feature map, effectively controlling the overfitting problems.

$$m_{out} = \frac{m_{in} - \rho_m}{z} + 1 \quad (24)$$

$$w_{out} = \frac{w_{in} - \rho_w}{z} + 1 \quad (25)$$

where, m_{in} and w_{in} symbolizes width and height of input 2D matrix, ρ_m indicates kernel size height, ρ_w represents width for kernel size, m_{out} and w_{out} are width and height of 2D matrix output.

Activation function

The non-linear activation function is measured in DRN to learn the composite and non-linear features, which is executed to improve the nonlinearity of extracted features. Moreover, Rectified Linear unit (ReLU) is also used to increase the operation, and it is labelled as a non-linear activation function. The ReLU is detailed as follows,

$$Re\,L\,U(A_t) = \begin{cases} 0, A_t < 0 \\ A_t, A_t \geq 0 \end{cases} \quad (26)$$

where, A_t Symbolizes input energy.

Batch normalization

Here, the training set is alienated into numerous small sets, termed mini-batches in batch normalization and mini-batches employed for training. Moreover, it qualifies a discussion among convergence and computational complications. Here, input layers are normalized by scaling and altering activation factors acceptable to progress the reliability and speed of training.

Residual Blocks

Residual blocks elucidate substitute correlation amongst convolutional layers. Moreover, this block contains shortcut construction from input to output when associated with CNN. The input is straightly connected to the output layer, which is detailed as follows,

$$A_t^p = J(A_t) + A_t \tag{27}$$

Furthermore, element matching element is applied for identical input and output when the dimension is different, which is represented as,

$$A_t^p = J(A_t) + P_a A_t \tag{28}$$

where, A_t and A_t^p are input and outcome of residual blocks, J refers to mapping connection from output and input, and P_a is the same dimension element.

Linear classifier

A linear classifier combines a softmax function and a Fully Connected (FC) layer. FC layer associations every neuron from one layer to another, embracing correlated perception of a multi-layer perceptron.

$$A_t^p = R_{Y\times Z} a_{Z\times O} + Q_{Y\times O} \tag{29}$$

where, $R_{Y\times Z}$ denotes weight matrix $Y \times Z$, $a_{Z\times O}$ Denotes input feature, Q symbolizes bias. The Softmax function is employed to normalize the input vector into a vector of possibility fit into each class. The class with extreme probability is selected as the last energy predicted outcome. The final output of predicted energy from DRN is indicated as A_t^p.

4.1.2. Developed Political Caviar Social Optimization Algorithm

The devised PCSOA is applied to train the DRN for effectual energy prediction. CAViaR [27] specifies the evolution of quantile in distinction to time based on the autoregressive procedure and estimates feature using regression quantiles. This model is a statistical approach, and it is applied to estimate the amount of potential loss that could occur over a definite period with records. Instead, PO [29] is developed by stimulating the multi-phased process in politics. This prototype comprises five phases: party creation and constituency distribution, party switching, election operation, parliamentary activities, and inter-party selection. This optimization approach effectively promotes the exploitation and exploration phase. In addition, SOA [28] is a population-based method, and it is designed depending on the social features of human beings. This method comprises two dissimilar justice principles: equality of opportunity and community. SOA effectively solves economic dispatch problems and executes well on unrestrained and constrained functions. Incorporating CAViaR, SOA and PO achieve effective performance by resolving optimization problems. The steps of developed PCSOA are expressed as follows,

Initialization

At first, solution initialization is performed, where S with total v solution is initialized.

$$S = \{S_1, S_2, \dots, S_v, \dots, S_z\};\ 1 \le v \le z \tag{30}$$

Where v denotes a total number of solutions, S_v specifies v^{th} the solution, as well as $S \in P_{Y\times Z}, U$.

Fitness measure estimation

The optimum solution is calculated based on the error function, and it is considered a minimization issue, which is given by,

$$\xi_{fit} = \frac{1}{b}\sum_{i=1}^{b}\left[A_i - A_t^p\right]^2 \tag{31}$$

where, ξ_{fit} refers to fitness measures, A_i indicates expected output, A_t^p Implies predicted output from DRN, and b is the total number amount of data.

Equality of opportunity

The equality of opportunity in SOA denotes that the succeeding location of every entity is formulated as,

$$S_q^{new} = S_q^{old} + rand\left(WN - NZ \times S_q^{old}\right) \tag{32}$$

Where $rand$ signifies a random number, WN refers to the best position, NZ signifies coefficient of personal choice, S_q^{old} refers old position of an entity. Here, the best position is given as,

$$WN = rand\{WB, PN\} \tag{33}$$

Where WB refers to the best solution, and PN signifies density point. The standard updated expression of CSOA is specified as,

$$S_q^{w+1} = \delta_0 + \delta_1\left(S_q^{w-1} + e\left(S_q^{w-1}\right)\right) + \delta_2\left(S_q^{w-2} + e\left(S_q^{w-2}\right)\right)(1 - randNZ) + randWN \tag{34}$$

To solve engineering problems, the PO approach is included. From PO,

$$V_{qt}^{h}(w+1) = V_{qt}^{h}(w+1) + k\left(V_{qt}^{h}(w) - V_{qt}^{h}(w-1)\right)$$
$$if\ V_{qt}^{h}(w-1) \leq g^{*} \leq V_{qt}^{h}(w)$$
or
$$if\ \ V_{qt}^{h}(w-1) \geq g^{*} \geq V_{qt}^{h}(w) \tag{35}$$

The above expression is rewritten in terms of CSOA, thus,

$$S_q^{w+1} = S_q^{w-1} + k\left(S_q^{w} - S_q^{w-1}\right) \tag{36}$$

$$S_q^{w+1} = S_q^{w-1} + kS_q^{w} - kS_q^{w-1} \tag{37}$$

$$S_q^{w-1} = \frac{S_q^{w+1} - kS_q^{w}}{(1-k)} \tag{38}$$

Substitute equation (38) in (34),

$$S_q^{w+1} = \delta_0 + \delta_1\left[\frac{S_q^{w+1}}{(1-k)} - \frac{kS_q^{w}}{(1-k)} + e\left(S_q^{w-1}\right)\right] + \delta_2\left(S_q^{w-2} + e(S_q^{w-2}\right) \\ (1 - randNZ) + randWN \tag{39}$$

$$S_q^{w+1} - \frac{\delta_1 S_q^{w+1}}{(1-k)} = [\delta_0 - \frac{k\delta_1 S_q^{w}}{(1-k)} + \delta_1 e\left(S_q^{w-1}\right) + \delta_2\left(S_q^{w-2} + e(S_q^{w-2})\right)] \\ (1 - randNZ) + randWN \tag{40}$$

$$\frac{S_q^{w+1}}{(1-k)}\left((1-k) - \delta_1\right) = \delta_0 - \frac{k\delta_1 S_q^{w}}{(1-k)} + \delta_1 e\left(S_q^{w-1}\right) + \delta_2\left(S_q^{w-2} + e(S_q^{w-2})\right)) \\ (1 - randNZ) + randWN \tag{41}$$

$$S_q^{w+1} = \frac{(1-k)}{\left((1-k) - \delta_1\right)}\left[\delta_0 - \frac{k\delta_1 S_q^{w}}{(1-k)} + \delta_1 e\left(S_q^{w-1}\right) + \delta_2\left(S_q^{w-2} + e(S_q^{w-2}\right)\right] \\ (1 - randNZ) + randWN \tag{42}$$

where, δ_0 denotes position vector of unknown parameters, $e(.)$ implies fitness, S_q^{w-1} represents the social location of q^{th} individual at $(w-1)^{th}$ iteration, S_q^{w-2} is the social location of q^{th} individual at $(w-2)^{th}$ iteration and $rand$ symbolizes random integer ranges from $[0,1]$.

From CSOA,

$$S_q^{w+1} = \delta_0 + \delta_1\left(S_q^{w-1} + e\left(S_q^{w-1}\right)\right) + \delta_2\left(S_q^{w-2} + e\left(S_q^{w-2}\right)\right) + rand(WT - CO) \tag{44}$$

Substitute equation (38) in equation (43) thus,

$$S_q^{w+1} - \frac{\delta_1 S_q^{w+1}}{(1-k)} = \delta_0 - \delta_1\frac{kS_q^{w}}{(1-k)} + \delta_1 e\left(S_q^{w-1}\right) + \delta_2\left(S_q^{w-2} + e\left(S_q^{w-2}\right)\right) + rand(WT - CO) \tag{45}$$

$$S_q^{w+1} = \frac{(1-k)}{(1-k-\delta)}\ (\ \delta_0 - \frac{\delta_1 kS_q^{w}}{(1-k)} + \delta_1 e\left(S_q^{w-1}\right) + \delta_2\left(S_q^{w-2} + e\left(S_q^{w-2}\right)\right) + rand(WT - CO)) \tag{46}$$

where CO represents an empty point, and it is computed in the below section.

Principle of community

Society seems to be bigger and collective association should be high. Therefore the empty point is enhanced. Therefore, the principle of community is specified as,

$$S_q^{new} = S_q^{old} + rand(WB - CO) \tag{47}$$

where CO indicates an empty point, and WB represents the best solution. Here, the empty point is estimated by,

$$CO = \frac{S_1\frac{1}{d_1} + S_2\frac{1}{d_2} + \cdots + S_O\frac{1}{d_O}}{\frac{1}{d_1} + \frac{1}{d_2} + \cdots + \frac{1}{d_O}} \tag{48}$$

where d implies results formulated by a society member.

Estimation of density and empty point

The density point is specified as,

$$PN = \sum_{q=1}^{N}\frac{d_q}{\sum_{x=1}^{N} d_x}S_q \tag{49}$$

where, d_q are results formulated by q^{th} society member, d_x represents results generated by x^{th} society member, and S_q indicates the old location of an entity.

The empty point is formulated by,

$$\mathrm{CO} = \sum_{\mathrm{q}=1}^{\mathrm{N}}\frac{\frac{1}{\mathrm{d_q}}}{\sum_{\mathrm{x}=1}^{\mathrm{N}}\frac{1}{\mathrm{d_x}}}\mathrm{S_q} \tag{50}$$

Where, $\frac{d_q}{\sum_{x=1}^{N} d_x}$ symbolizes relative fitness. The density point is expressed as,

$$PN = \sum_{q=1}^{N}\hat{d}_q S_q \tag{51}$$

Moreover, an empty point is represented as,

$$CO = \sum_{q=1}^{N}\check{d}_q S_q \tag{52}$$

Additionally, $\hat{d}_q$ is denoted as

$$\hat{d}_q = \frac{e^{\frac{d_q}{d_{max}}}}{\sum_{x=1}^{N} e^{\frac{d_x}{d_{max}}}} \tag{53}$$

where, d_{max} refers to maximal results attained by society. In addition, $\breve{d}_q$ is denoted as

$$\breve{d}_q = \frac{e^{-\frac{d_q}{d_{max}}}}{\sum_{x=1}^{N} e^{-\frac{d_x}{d_{max}}}} \tag{54}$$

Evaluate the feasibility of the solution

The best solution is obtained by fitness measure, where the least value is considered optimal, and the fitness function is estimated using equation (31).

Terminate

The above processes are repetitive till the best solution is attained for energy prediction. The pseudo-code of the developed PCSOA is organized in table 1.

Table 1. Pseudo code of devised PCSOA

S.NO.	Pseudo code for introduced PCSOA
1	Input: S, w and w_{max}
2	Output: Optimum solution S_q^{w+1}
3	Start
4	Initialize arbitrary population S
5	Evaluate population
6	WB ←Best solution
7	**For** $w = 1$ to w_{max} do
8	CO ←Calculate empty point
9	**For** $l = 1$ to I do
10	$WN = rand(WT, CO)$;
11	$NZ = rand\{0,1,2\}$;
12	Compute S_q^{new} using expressions (42) and (46)
13	**end**
14	**If** S_q^{new} better than S_q^{old} then
15	$S_q \leftarrow S_q^{new}$
16	**end**
17	Compute new population
18	WT ←Best solution;
19	PN ←Estimate density point
20	**For** $q = 1$ to N do
21	Evaluate S_q^{new} using equation (47)
22	**end**
23	**If** S_q^{new} better than S_q^{old} Then
24	$S_q \leftarrow S_q^{new}$
25	**end**
26	Estimate new population
27	WT ←Optimal solution;
28	**end**
29	Optimal solution

4.2. CHS using Adaptive Genetic Fuzzy System

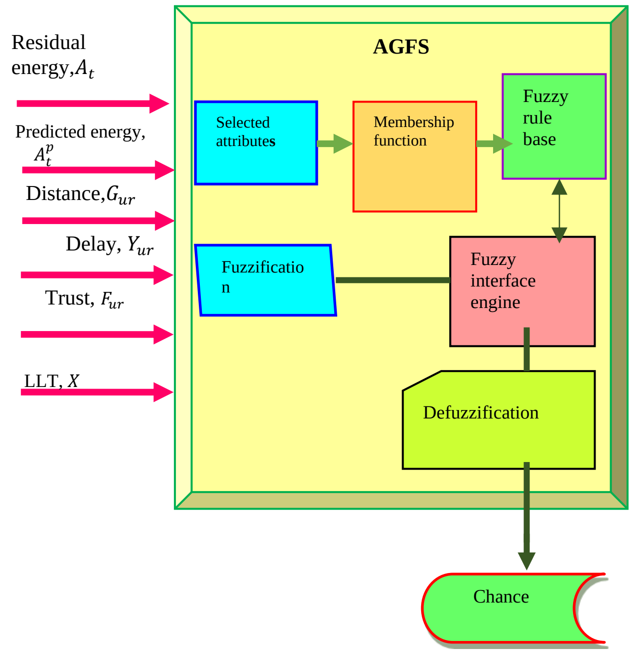

Fig. 3 Architecture of AGFS

The CHS process is performed using AGFS [30], where every node's chances are computed. The AGFS model obtains a better accuracy rate even in high-dimensional data. Thus, it is used for CHS. The five input elements for AGFS are residual energy, predicted energy, delay, distance, trust, and LLT. The rule set $B_R = (B_R\,; 1 \le g \le k - F)$ is formulated and ordered in fuzzy rule base using developed PCSOA, which is already illustrated in section 4.1.2. The chances are low, medium, very low, and low, although the nodes have hwitha higher medium chance iare Figure 3 displays the AGFS model.

4.3. Routing based on Political Caviar Social Optimization Algorithm

After CHS is completed, the routing process is carried out for secure communication, which is explained in this section. The devised PCSOA is applied for routing, and it is newly developed by combining CAViaR [27] and SOA [28] with PO [29]. Moreover, this section comprises solution encoding and fitness function of developed PCSOA.

4.3.1. Solution encoding

Solution encoding is an illustration of a solution vector employing an optimization algorithm. The solution encoding model effectively detects the best possible route for transmitting data to a destination from the source. Here, the CHS path is obtained from source 2 to destination 10. The solution encoding of developed PCSOA is displayed in figure 4. Moreover, the dimension of solution encoding is indicated as $1 \times m$, which $m$represents the number of CH needed.

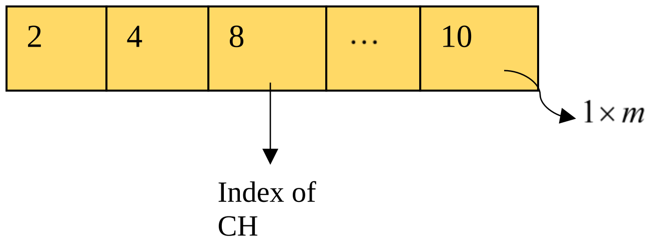

Fig. 4 Solution representation for routing

4.3.2. Fitness function

The fitness value is estimated to find the best path, so it is evaluated using several elements, namely trust, residual energy, predicted energy, distance, LLT, and delay. Accordingly, a fitness function is computed by the below expression,

$$\rho_f = \frac{1}{z^2}\left[\sum_{a=1}^{z}\sum_{b=l+1}^{z} A_t + A_t^p + (1 - G_{ur}) + (1 - Y_{ur}) + F_{ur} + X\right] \quad (55)$$

where, $A_t$implies energy, A_t^p represents predicted energy, G_{ur}indicates distance, Y_{ur} is delay, F_{ur}signifies trust, and it is the combination of direct, indirect, and overall trust, as well as X symbolizes LLT. The fitness measures are explained as follows:

Delay

Delay is defined as the proportion of nodes in the path with regards to whole nodes, and it is denoted as,

$$Y_{ur} = \frac{1}{T}\sum_{k=1}^{c} j_k \quad (56)$$

where T indicate the total number of nodes, and c specifies the number of nodes in the route.

Distance

The distance is referred to as the distance between two nodes with a normalization factor, and it is estimated by,

$$G_{ur} = \|V_r - V_y\|_{GN} \quad (57)$$

where GN represents the normalizing factor.

Trust

The trust factor includes three direct, indirect, and overall trusts, which are already explained in section 3.4.

LLT

The LLT term is already deliberated in section 3.3.

4.3.3. Political Caviar Social Optimization Algorithm for routing

The designed optimization algorithm, CSOA, is used for productive routing to perform secure communication. The developed CSPOA is already explained in section 4.1.2. Based on the optimal routing process, the nodes gather the data and transmit it to CH, which communicates to BS. Once the sink gathers the data, it is forwarded to the cloud server, which third parties service provider then uses.

5. Results and Discussion

The results and discussion of devised CHS approach for WSN communication in IoT networks are clarified in this section.

5.1. Experimental setup

The accomplishment of devised DRN+PCSOA is executed in MATLAB with Windows 10OS, 8GB RAM, and an Intel i3 processor. The simulation parameters employed in this approach are specified in table 1.

Table 1. Simulation parameters

Simulation parameters	**Value**
X and Y axis (in meters)	X-axis=100 Y-axis=100
Sink Coordinates	Sink.x=0.5*100 Sink.y=0.5*100
Optimal Election Probability node to become cluster head	0.1
Initial Energy	0.5
Receiver Energy	50*0.000000001
Transmitter Energy	150*0.000000001
Free space energy	10*0.000000000001
Amplifier energy	0.0013*0.000000000001
Data Aggregation Energy	5*0.000000001

5.2. Performance metrics

The evaluation metrics, including residual energy, delay distance, and trust, are measured for computing the performance of the developed technique. Moreover, these metrics are already clarified in section 3.

5.3. Comparative techniques

The developed DRN+PCSOA is compared with existing routing techniques, like FPU-DA [1], EA-DBCRP [2], Taylor KFCM [3], EECHS [4], and CSOA-based DMN to reveal the performance improvement of devised technique.

5.4. Comparative analysis

The analysis of developed DRN+PCSOA with 100, 150, and 200 nodes by altering the number of rounds based on trust, delay, residual energy, and distance.

5.4.1. Analysis with 100 nodes

The analysis of devised DRN+PCSOA for various performance metrics with the various number of rounds is shown in figure 5. Figure 5a) plotted the investigation of developed DRN+PCSOA for the delay. The delay of FPU-DA, EA-DBCRP, Taylor KFCM, EECHS, CSOA-based DMN and designed DRN+PCSOA is 0.3154sec, 0.3006sec, 0.2309sec, 0.2912sec, 0.1944sec, and 0.1803sec in 500 number of rounds. The distance analysis for the introduced routing technique is specified 5b). The distance of the designed DRN+PCSOA is 33.11m, and the existing approaches are 40.23m, 43.67m, 41.55m, 42.19m, and 34.86m, while the number of rounds is 500. Figure 5 c) depicts the analysis of residual energy for devised DRN+PCSOA. The residual energy of existing approaches and DRN+PCSOA is 0.1313J, 0.1980J, 0.2053J, 0.2315J, 0.2373J, and 0.2626J in 500 rounds. The comparative study of trust for DRN+PCSOA is represented in figure 5 d). When the number of rounds is 500, the trust of DRN+PCSOA is 0.5203, whereas existing methods are 0.5083, 0.5173, 0.5163, 0.5165, and 0.5212.

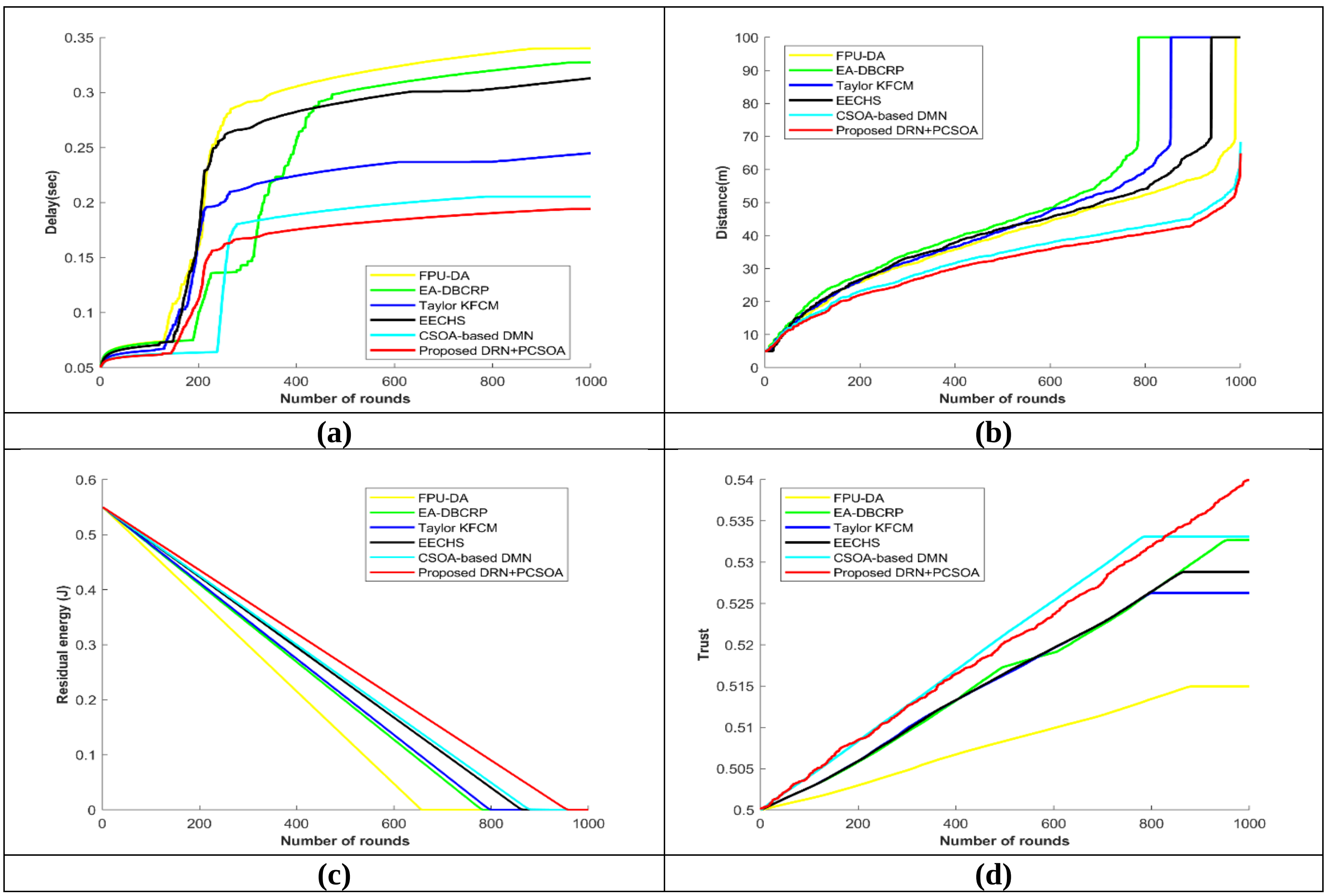

Fig. 5 Comparative analysis of developed PCSOA with 100 nodes a) Delay b) Distance c) Residual energy, and d) Trust

5.4.2. Analysis with 150 nodes

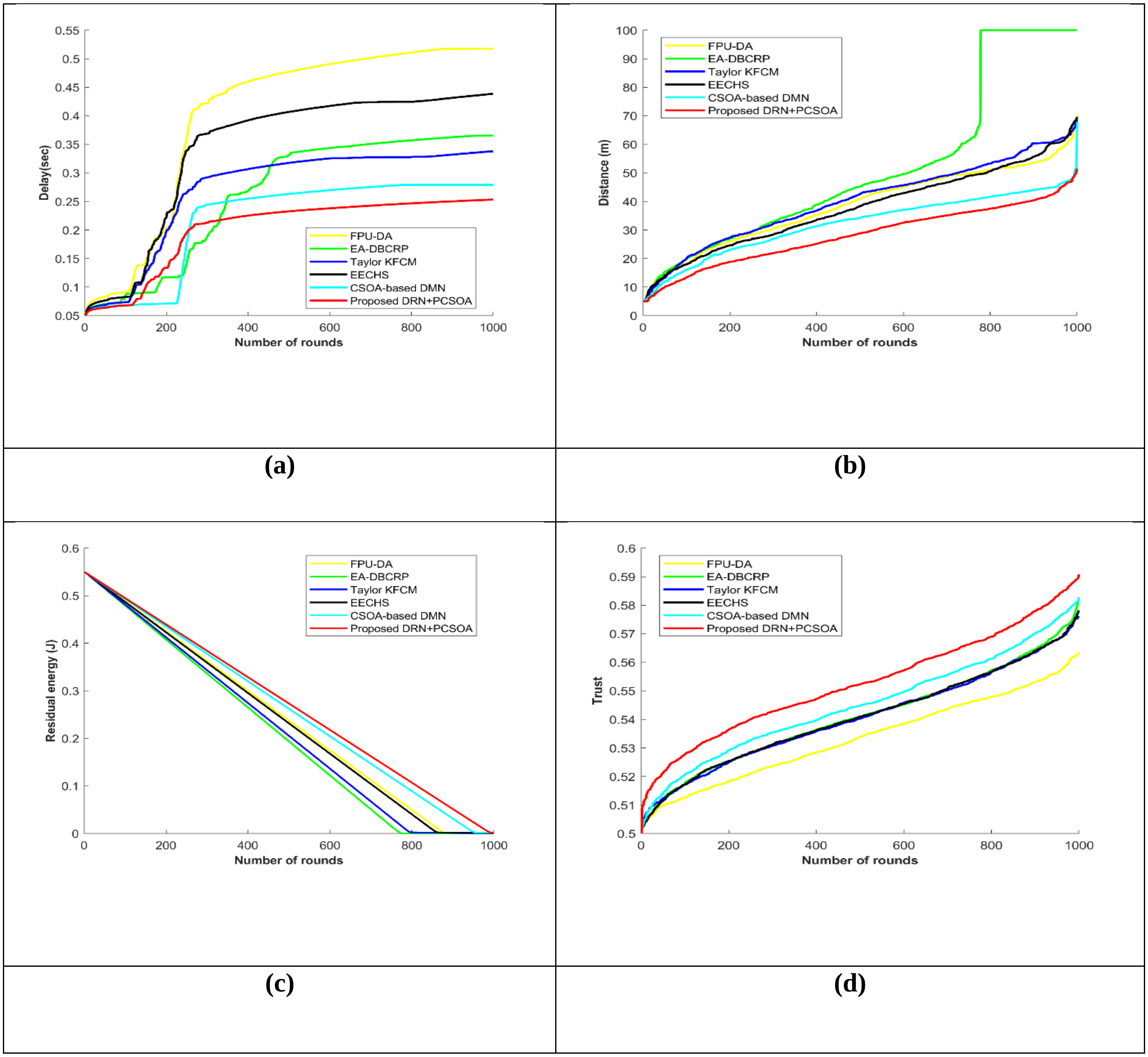

Fig. 6 Comparative analysis of developed PCSOA with 150 nodes a) Delay b) Distance c) Residual energy, and d) Trust

Figure 6 indicates the analysis of devised DRN+PCSOA for various performance metrics by altering the number of rounds. Figure 6 a) depicts an examination of delay for devised DRN+PCSOA. The delay of existing approaches and devised DRN+PCSOA is 0.4772sec, 0.3317sec, 0.3176sec, 0.4069sec, 0.4053sec, and 0.2631sec in 500 number of rounds. Figure 6b) plotted the analysis of developed DRN+PCSOA for distance. FPU-DA, EA-DBCRP, Taylor KFCM, EECHS, and CSOA-based DMN distances 38.41m, 42.0m, and 34.30m in 500 rounds. The A comparative study of residual energy for DRN+PCSOA is represented in figure 6 c). When the number of rounds is 500, the residual energy of DRN+PCSOA is 0.2620J, whereas existing methods are 0.2373J, 0.1935J, 0.2053J, 0.2316J, and 0.1312J. The analysis of trust for the introduced routing technique is specified 6d). The trust of designed DRN+PCSOA is 0.5448, and the existing approaches are 0.5339, 0.5409, 0.5402, 0.5410, and 0.5377, while the number of rounds is 500.

5.4.3. Analysis with 200 nodes

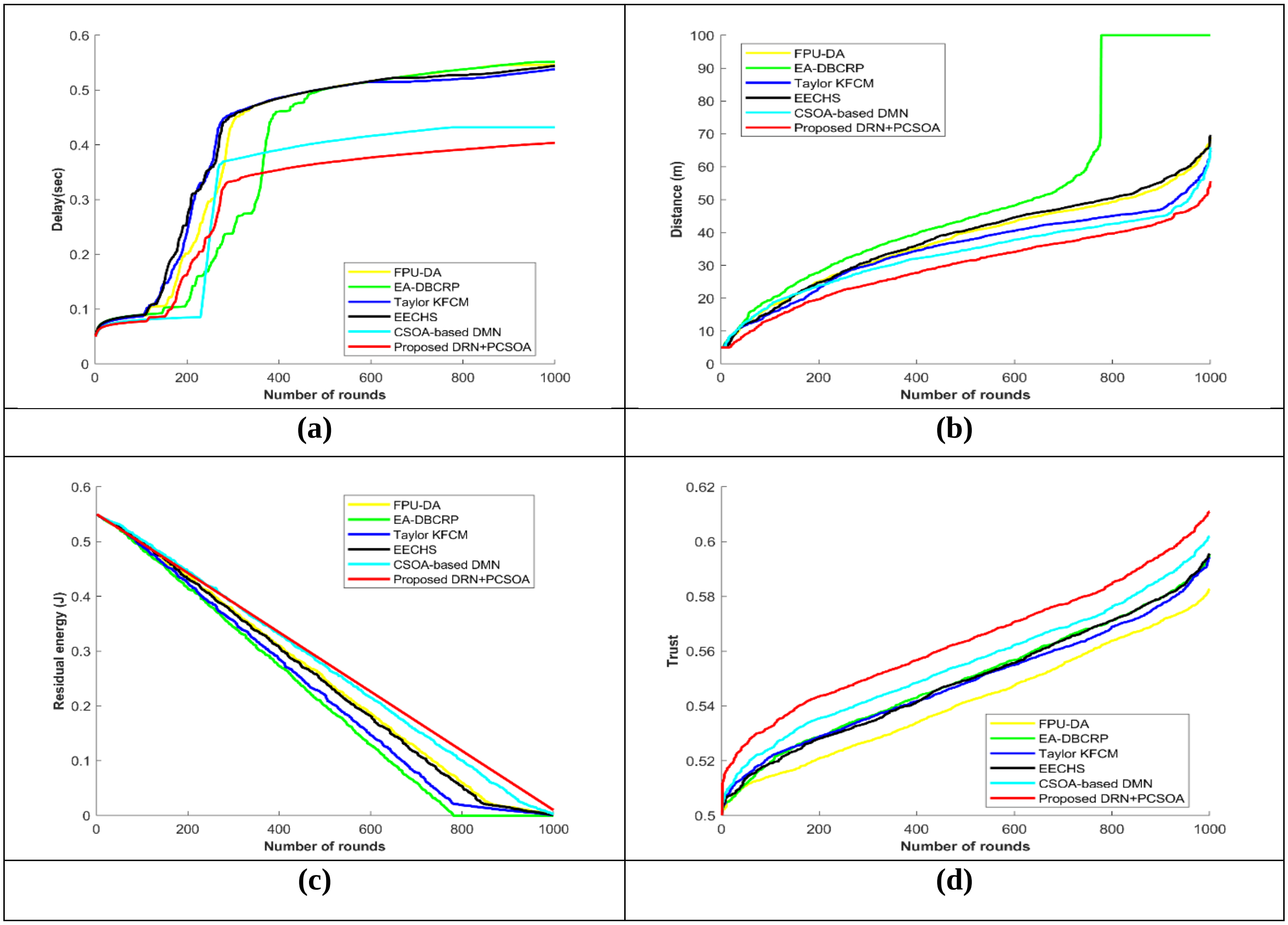

Fig. 7 Comparative analysis of developed PCSOA with 200 nodes a) Delay b) Distance c) Residual energy, and d) Trust

The analysis of devised DRN+PCSOA for various performance metrics with the various number of rounds is exposed in figure 7. Figure 7 a) exploits the analysis of developed DRN+PCSOA for the delay. The delay of FPU-DA is 0.5028sec, EA-DBCRP is 0.5017sec, Taylor KFCM is 0.5025sec, EECHS is 0.5026sec, CSOA-based DMN is 0.4054sec and designed DRN+PCSOA is 0.3671sec in 500 the number of rounds. The distance analysis for the introduced routing technique is specified 7 b). The distance of designed DRN+PCSOA is 31.25m, and the existing approaches are 39.95m, 44.10m, 37.54m, 40.65m, and 34.63m, while the number of rounds is 500. Figure 7 c) specifies the analysis of residual energy for devised DRN+PCSOA. The residual energy of existing approaches and devised DRN+PCSOA is 0.2485J, 0.2001J, 0.2202J, 0.2438J, 0.2745J, and 0.2802J in 500 number of rounds. The comparative study of trust for DRN+PCSOA is represented in figure 7 d). When the number of rounds is 500, the trust of DRN+PCSOA is 0.5636, whereas existing methods are 0.5414, 0.5501, 0.5484, 0.5492, and 0.5553.

5.5. Comparative discussion

Table 2 specifies a comparative discussion of advanced DRN+PCSOA with existing routing approaches with 100, 150, and 200 nodes by considering different performance metrics. The delay of existing approaches and devised DRN+PCSOA is 0.5461sec, 0.5513sec, 0.5378sec, 0.5441sec, 0.4318sec, and 0.4037sec in 1000 number of rounds. The AGFS is utilized for CHS. Thereby, the devised optimization algorithm obtained minimal delay. The distance of FPU-DA is 69.004m, EA-DBCRP is 100m, Taylor KFCM is 64.86m, EECHS is 69.72m, CSOA-based DMN is 65.94m, and designed DRN+PCSOA is 55.63m. The devised hybrid optimization algorithm effectively reduces the distance. When the number of rounds is 650, the residual energy of DRN + PCSOA is 0.1991J, whereas existing methods are 0.1535J, 0.0933J, 0.1135J, 0.1466J and 0.1870J. The employed DRN model significantly increases the residual energy. The trust of designed DRN+PCSOA is 0.6109, and FPU-DA, EA-DBCRP, Taylor KFCM, EECHS, CSOA-based DMN are 0.5826, 0.5954, 0.5943, 0.5956, and 0.6019, while number of rounds is 1000. The trust factors, like direct, indirect, and overall, are included. Thus, the trust measure is highly increased in devised PCSOA. Hence, from the below table, it is well known that the established DRN+PCSOA attained better performance with a delay of 0.1941sec for 100 nodes as well as distance, residual energy, and trust of 55.63m, 0.1991J, and 0.6109 in 200 nodes.

Table 2. Comparative discussion

Nodes	Metrics	FPU-DA	EA-DBCRP	Taylor KFCM	EECHS	CSOA-based DMN	Proposed DRN + PCSOA
100 nodes	Delay (sec)	0.3400	0.3272	0.2448	0.3128	0.2053	**0.1941**
	Distance (m)	100	100	100	100	68.33	**64.91**
	Residual energy (J)	0.0055	0.0923	0.1017	0.1358	0.1434	**0.1762**
	Trust	0.5149	0.5326	0.5262	0.5288	0.5330	**0.5399**
150 nodes	Delay (sec)	0.5178	0.3653	0.3380	0.4385	0.4223	**0.2789**
	Distance (m)	70.11	100	68.71	69.64	100	**67.80**
	Residual energy (J)	0.1433	0.0864	0.1018	0.1360	0.0059	**0.1754**
	Trust	0.5635	0.5817	0.5761	0.5781	0.5700	**0.5828**
200 nodes	Delay (sec)	0.5461	0.5513	0.5378	0.5441	0.4318	**0.4037**
	Distance (m)	69.004	100	64.86	69.72	65.94	**55.63**
	Residual energy (J)	0.1535	0.0933	0.1135	0.1466	0.1870	**0.1991**
	Trust	0.5826	0.5954	0.5943	0.5956	0.6019	**0.6109**

6. Conclusion

This paper deliberates an optimized fuzzy system for effective CHS in the IoT-WSN system. The optimization approach is mainly devised by combining SOA and CAViaR methods with PO. The DRN is utilized for the energy prediction process, and the DRN is trained by devised PCSOA to obtain improved prediction performance. The fuzzy system, AGFS, is applied to select the best cluster Head. Thus the data broadcast is done between the source node and to destination. In addition, several multiobjective factors, for instance, energy, delay, distance, LLT, and trust factors, including indirect, direct, and overall trust, are also included. The routing process is also carried out using devised PCSOA; secure communication is performed. The CHS method obtained a high network lifetime and minimal delay and distance. Moreover, the performance of the developed CHS approach is evaluated using four metrics, namely distance, trust, delay, and residual energy. Thus, the devised DRN+PCSOA obtained better performance regarding delay of 0.1941sec, the distance of 55.63m, residual energy of 0.1991, and trust of 0.6109. Furthermore, other optimization algorithms and the fuzzy system can be included for an effective CHS process.

References

[1] Adnan, M., Yang, L., Ahmad, T. and Tao, Y., “An Unequally Clustered Multi-Hop Routing Protocol Based on Fuzzy Logic for Wireless Sensor Networks,” *IEEE Access*, vol.9, pp.38531-38545, 2021.

[2] Augustine, S. and Ananth, J.P., “Taylor Kernel Fuzzy C-Means Clustering Algorithm for Trust and Energy-Aware Cluster Head Selection in Wireless Sensor Networks,” *Wireless Networks*, vol.26, pp.5113-5132, 2020.

[3] Alghamdi, T.A., "Energy Efficient Protocol in Wireless Sensor Network: Optimized Cluster Head Selection Model," *Telecommunication Systems*, vol.74, no.3, pp.331-345, 2020.

[4] Ren, Q. and Yao, G., "An Energy-Efficient Cluster Head Selection Scheme for Energy-Harvesting Wireless Sensor Networks," *Sensors*, vol.20, no.1, pp.187, 2020.

[5] Kowsalya, R. and Jeetha, B.R., "Secure and Efficient Fire-Fly Data Routing Algorithm for Wireless Sensor Networks in Iot Monitoring Systems," *in Journal of Physics: Conference Series*, vol.1917, no.1, pp.012007, 2021.

[6] Shende, D.K. and Sonavane, S.S., "Crowwhale-ETR: Crowwhale Optimization Algorithm for Energy and Trust Aware Multicast Routing in WSN for Iot Applications," *Wireless Networks*, vol.26, no.6, pp.4011-4029, 2020.

[7] Lin, J.W., Chelliah, P.R., Hsu, M.C. and Hou, J.X., "Efficient Fault-Tolerant Routing in Iot Wireless Sensor Networks Based on Bipartite-Flow Graph Modeling," *IEEE Access*, vol.7, pp.14022-14034, 2019.

[8] Sahoo, B.M., Pandey, H.M. and Amgoth, T., "GAPSO-H: A Hybrid Approach Towards Optimizing the Cluster-Based Routing in Wireless Sensor Network," *Swarm and Evolutionary Computation*, vol.60, pp.100772, 2021.

[9] Kavitha, V., "Privacy Preserving Using Multihop Dynamic Clustering Routing Protocol and Elliptic Curve Cryptosystem for WSN in Iot Environment," *Peer-to-Peer Networking and Applications*, vol.14, no.2, pp.821-836, 2021.

[10] Patil, B. and Kadam, R., "A Novel Approach to Secure Routing Protocols in WSN," *in Proceedings of 2018 2nd International Conference on Inventive Systems and Control (ICISC)*, pp.1094-1097, January 2018.

[11] Wang J, Gao Y, Liu W, Sangaiah AK, Kim HJ, "An Intelligent Data Gathering Schema with Data Fusion Supported for Mobile Sink in Wireless Sensor Networks," *in Proceedings of International Journal of Distributed Sensor Networks*, vol.15, no.3, pp. 1550147719839581, 2019.

[12] S. M. Mahdi H. Daneshvar, Pardis Alikhah Ahari Mohajer, Sayyed Majid Mazinani, "Energy-Efficient Routing in WSN: A Centralized Cluster-Based Approach Via Grey Wolf Optimizer," *IEEE Access*, vol.7, pp.170019-170031, 2019.

[13] K. Vijayalakshmi and P Anandan, "A Multi Objective Tabu Particle Swarm Optimization for Effective Cluster Head Selection in WSN," *Cluster Computing*, vol.22, no.5, pp.12275-12282, 2019.

[14] Yadav, A.K. and Tripathi, S., "QMRPRNS: Design of Qos Multicast Routing Protocol Using Reliable Node Selection Scheme for Manets*," Peer-to-Peer Networking and Applications*, vol.10, no.4, pp.897-909, 2017.

[15] Satyajit Pattnaik and Pradip Kumar Sahu, "Assimilation of Fuzzy Clustering Approach and EHO-Greedy Algorithm for Efficient Routing in WSN," *International Journal of Communication Systems*, vol.33, no.8, pp.E4354, 2020.

[16] Vinitha A and Rukmini MS, "Secure and Energy-Aware Multihop Routing Protocol in WSN Using Taylor-Based Hybrid Optimization Algorithm," *Journal of King Saud University-Computer and Information Sciences*, 2019.

[17] Jakobsen MK, Madsen J, Hansen MR, "DEHAR: A Distributed Energy Harvesting Aware Routing Algorithm for Ad-Hoc Multihop Wireless Sensor Networks," *in Proceedings of 2010 IEEE International Symposium on A World of Wireless, Mobile and Multimedia Networks (Wowmom)*, pp.1-9, June 2010.

[18] Amit Kelotra and Prateek Pandey, "Energy-Aware Cluster Head Selection in WSN Using HPSOCS Algorithm," *Journal of Networking and Communication Systems*, vol.2, no.1, pp.24-33, 2019.

[19] Jacob John, Paul Rodrigues, "Multi-Objective HSDE Algorithm for Energy-Aware Cluster Head Selection in WSN," *Journal of Networking and Communication Systems*, vol.2, no.3, pp.20-29, 2019.

[20] Purkait R, Tripathi S, "Energy-Aware Fuzzy Based Multihop Routing Protocol Using Unequal Clustering," Wireless Personal Communications, vol.94, no.3, pp.809-33, 2017.

[21] Sert SA, Alchihabi A, Yazici A, "A Two-Tier Distributed Fuzzy Logic Based Protocol for Efficient Data Aggregation in Multihop Wireless Sensor Networks," *IEEE Transactions on Fuzzy Systems*, vol.26, no.6, pp.3615-29, 2018.

[22] Behera, T.M., Mohapatra, S.K., Samal, U.C. and Khan, M.S., "Hybrid Heterogeneous Routing Scheme for Improved Network Performance in Wsns for Animal Tracking," *Internet of Things*, vol.6, pp.100047, 2019.

[23] Sert, S.A., Bagci, H. and Yazici, A., "MOFCA: Multi-Objective Fuzzy Clustering Algorithm for Wireless Sensor Networks," *Applied Soft Computing*, vol.30, pp.151-165, 2015.

[24] Darabkh, K.A., Odetallah, S.M., Al-Qudah, Z., Ala'F, K. and Shurman, M.M., "Energy-Aware and Density-Based Clustering and Relaying Protocol (EA-DB-CRP) for Gathering Data in Wireless Sensor Networks," *Applied Soft Computing*, vol.80, pp.154-166, 2019.

[25] P.Suma,Dr.O.Nagaraju and Dr.Md.Ali Hussain, "LA Based Optimal Path Selection for Mobile Adhoc Network," *Journal of Networking and Communication Systems*, vol.2,no.1, pp.43-50,2019.

[26] Chen, Z., Chen, Y., Wu, L., Cheng, S. and Lin, P., "Deep Residual Network Based Fault Detection and Diagnosis of Photovoltaic Arrays Using Current-Voltage Curves and Ambient Conditions," *Energy Conversion and Management*, vol.198, pp.111793, 2019.

[27] Engle, R.F. and Manganelli, S., "Caviar: Conditional Autoregressive Value at Risk By Regression Quantiles," *Journal of Business & Economic Statistics*, vol.22, no.4, pp.367-381, 2004.

[28] Karimi, N. and Khandani, K., "Social Optimization Algorithm with Application to Economic Dispatch Problem," *International Transactions on Electrical Energy Systems*, vol.30, no.11, pp.E12593, November 2020.

[29] Askari, Q., Younas, I. and Saeed, M., "Political Optimizer: A Novel Socio-Inspired Meta-Heuristic for Global Optimization," *Knowledge-Based Systems*, vol.195, pp.105709, 2020.

[30] Dennis, B. and Muthukrishnan, S., "AGFS: Adaptive Genetic Fuzzy System for Medical Data Classification," *Applied Soft Computing*, vol.25, pp.242-252, 2014.

[31] Chen, Z., He, M., Liang, W. and Chen, K., "Trust-Aware and Low Energy Consumption Security Topology Protocol of Wireless Sensor Network," *Journal of Sensors*, 2015.

[32] Ahmed, G., Zou, J., Fareed, M.M.S. and Zeeshan, M., "Sleep-Wake Energy Efficient Distributed Clustering Algorithm for Wireless Sensor Networks," *Computers & Electrical Engineering*, vol.56, pp.385-398, 2016.

[33] Tandon, A. and Srivastava, P, "Trust-Based Enhanced Secure Routing Against Rank and Sybil Attacks in Iot," *in Proceedings of Twelfth International Conference on Contemporary Computing (IC3)*, pp. 1-7, 2019.

[34] Balachandra, M., Prema, K.V. and Makkithaya, K., "Multiconstrained and Multipath Qos Aware Routing Protocol for Manets," *Wireless Networks*, vol.20, no.8, pp.2395-2408, 2014.