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An energy efficient chaotic sparrow search algorithm based clustering protocol for wireless sensor network communications

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***Abstract*---**Wireless sensor networks (WSN) include a collection of autonomous sensor nodes, which are generally deployed in a harsh or hostile environment to sense the physical parameters involved in the target region. It is highly utilized for target tracking, surveillance, and data gathering applications. Since the sensors in WSN operates on limited inbuilt batteries, it is needed to design energy efficient approaches to preserve energy and extend lifetime of the network. Earlier studies have reported that clustering is an effectual manner used for accomplishing energy efficiency and it is addressed with use of metaheuristic optimization algorithms. In this view, this paper present an energy efficient chaotic sparrow search algorithm based clustering (EE-CSSAC) technique for WSN. The proposed EE-CCSAC technique is dependent upon the integration of chaotic maps into the traditional sparrow search algorithm (SSA). In addition, the EE-CCSAC technique develops a fitness function with four variables to properly select the CHs and then organize clusters, thereby achieving energy efficiency. The experimental validation of the EE-CCSAC system takes place and the outcomes are related to recent clustering approaches. The simulation outcomes exhbited the effective outcome of the EE-CCSAC method on the other ones with respec to distinct estimation parameters.

***Keywords*---**WSN, Energy efficiency, Clustering, Metaheuristics, Sparrow Search Algorithm, Chaotic maps.

1. Introduction

Wireless Sensor Networks (WSNs) find extensive applications in military and civilian sectors. It has been widely employed in surveillance, target tracking, biomedical applications, monitoring natural disasters, building management systems, and habitat monitoring [1]. Sensors in natural disasters detect or sense

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an environment for predicting the disasters. In bio-medical application, sensor surgical implant monitoring patients' health. In seismic sensing, sensor adhoc deployment in a volcanic region detects eruptions or earthquakes [2]. WSN node uses non-rechargeable storage devices with limited energy and overall replacing batteries isn't feasible. Therefore, energy competence is a major problem, and developing power-effective protocol is crucial to extend lifetime of the sensor [3]. In WSN, energy utilization is a serious problem as sensors, and Cluster heads (CH) have a shorter life because of the requirements in energy utilization [4]. Fig. 1 illustrates the structure of WSN.

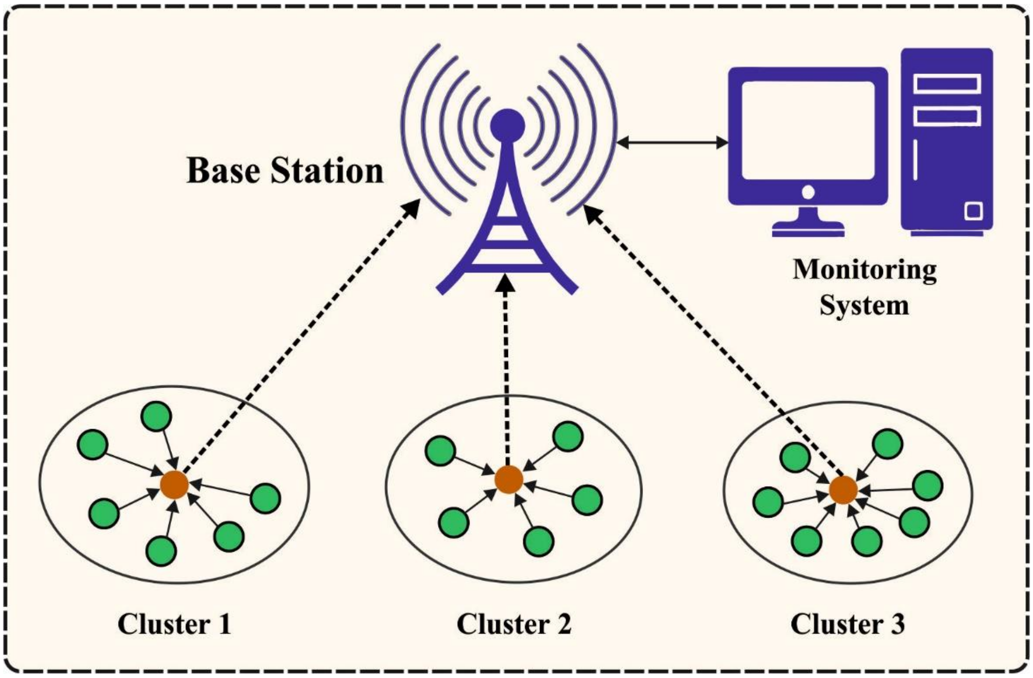

Fig. 1. Structure of WSN

Recently, various studies have been interested in offering a powerful WSN for energy utilization, and different methods have been presented for minimizing GPS for sensor location detection [5]. It consists of range free and range-based methods for estimating distance employed and angles of connectivity for the data to travel among the known nodes and unknown sensor node position [6]. WSN is proposed to be economical solution in home security, monitoring, military surveillance, and evaluating of energy utilization within a time frame. Thus, it is indispensable for the energy utilization to be efficiently utilized thus the lifetime of the network could be significantly extended [7]. The WSN has a large amount of sensing devices that are generally known as sensors combined with their battery life and range for sensor nodes which is utilized in collecting information to the base station for coverage when the structured networks need to establish for possibility in the coverage regions like factories, streets, building, and highways [8]. These sensors are interrelated, having their individual CHs to pass transmission via information that can be transmitted to the BS for the data to be processed and analyzed within the heterogeneous networks [9].

Sekaran et al. [10] present a new CH election method with GWO such as GWO-CH that considers the intra-cluster, sink distance, and residual energy (RE). Besides, they formulated weight parameters and objective functions for an effective cluster formation and CH election. In Mittal et al. [11], trust management, effective CH election, and enhanced routing protocol are needed for designing an efficient WSN solution. In this work, a CSO method with a fuzzy type-2 logic-based clustering method is recommended for extending the network lifespan and level of confidence. In intracluster transmission, a threshold-based data transmission method is utilized and a multihop routing system for intercluster transmission is applied for decreasing the dissipated energy from CH distant from BS.

In Maheshwari et al. [12], the BOA method is applied for choosing the best CH from a collection of nodes. The CH election is enhanced by distance to the node degree, remaining energy of the node, node centrality base station, and the distance to the neighbours. The routes among the CH and BS recognized through ACO method, select the best route depending on the node degree, residual, and distance energy. Masdari and Barshandeh [13], presented a new discrete version of the TLBO method which applies the swap and mutation operator for handling discrete solutions. Next, a new method has been employed for designing a hierarchical energy-aware clustering system for the WSN to diminish the energy utilization of the sensors. Trinh et al. [14] introduce a distributed fuzzy clustering system which employs 2 FLC methods for organizing WSN to different clusters. In addition to the system, they considered numerous mobile sink node and offer other FLCs for fuzzy sink election utilized by CH. In our system, CH cooperates in multihop routing of data packets to minimalize the energy utilization of WSN.

This paper presents an energy efficient chaotic sparrow search algorithm based clustering (EE-CSSAC) technique for WSN. The proposed EE-CCSAC technique is dependent upon the integration of chaotic maps into the traditional sparrow search algorithm (SSA). In addition, the EE-CCSAC technique develops the fitness function (FF) with four variables to properly select the CHs and then organize clusters, thereby achieving energy efficiency. The experimental validation of the EE-CCSAC approach occues and outcomes are compared with recent clustering approaches.

2. Design of Proposed EE-CCSAC Technique

In this study, a novel EE-CCSAC technique has been presented to accomplish energy efficiency in WSN. SSA is a novel kind of SI optimization method stimulated by observing the anti-predation and foraging behaviors of the sparrow. There are 2 behavior schemes in the foraging method of sparrow, one is discoverer and another is joiner. Simultaneously, to rise their predative rate, few joiners would monitor the discoverer for competing with them for food or forage near them. In SSA, the discoverer would focus attention on food and attain a large foraging range when compared to the discoverer. Generally, the discoverer account for 10% to 20% of the population, and the position upgrade equation can be given in the following:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot iter_{max_2}}\right) & if\ R_2 < ST \\ X_{i,j}^{t} + Q \cdot L & if\ R_2 \geq ST \end{cases} \tag{1}$$

In which: t implies the present iteration count; T stands for the maximal iteration count; $X_{i,j}$ signifies the position data of the ith sparrow in the jth parameter. $\alpha \in (0,1]$ denotes an arbitrary value; Q indicates a haphazard value that follows a standard distribution; L characterizes a matrix with each 1 element, as well as the size is $1 \times d$; $R2 \in [0,1]$ and $ST \in [\,0.5,1]$ correspondingly represents the earlier warning value and the safety value [15].

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right) & if\ i > n/2 \\ X_P^{t+1} + \left|X_{i,j}^{t} - X_P^{t+1}\right| \cdot A^{+} \cdot L & Otherwise \end{cases} \tag{2}$$

In which X_{worst} denotes the present worst location in the world; X_p characterizes the optimal location of discoverer in the present state. If $i > n/2$, it implies that because of lower fitness, the ith joiner is very hungry and has no food, hence he should fly to another position for finding food to attain high energy. Once a threat is found, the sparrow groups would carry out anti-predation behavior and its location can be upgraded by:

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left|X_{i,j}^{t} - X_{best}^{t}\right| & if\ f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{X_{i,j}^{t} - X_{worst}^{t}}{(f_i - f_w) + e}\right) & if\ f_i = f_g \end{cases} \tag{3}$$

Where: β signifies the step length control variable, i.e., a standard distribution arbitrary value with mean value of zero and variance of one; $K \in [-1,1]$ denotes an arbitrary value which means the direction where the sparrow moves, as well as a step length control variable; e implies set to a minimal constant to avoid the denominator in being 0; fi characterizes the fitness value of ith sparrow, f_w & f_g shows the worst fitness and optimum values of the existing population, correspondingly.

The chaos phenomenon has been unique occurrence in deterministic non-linear models that are created without adding some arbitrary issues. As chaotic variables are its individual arbitrariness, it is constantly searching as well as traversing the whole space and depicts follows capable law under the procedure. According to these features, the chaos has been frequently utilized for optimizing search issues for avoiding falls as to local optimum. The logistic mapping has a standard chaotic technique. As the technique was comparatively easy, the traversal randomly under the initialize procedure decreases the optimize result. [16] demonstrated that Tent map traverse further uniformly and the search speed was greater than the Logistic map.

$$y_{i+1} = \begin{cases} 2y_i, 0 \leq y \leq \frac{1}{2} \\ 2(1 - y_i)_f \frac{1}{2} < y \leq 1 \end{cases} \tag{4}$$

Tent chaotic map has been signified as follows after Bernoulli shift transformations:

$$y_{i+1} = (2y_i) mod\ 1 \tag{5}$$

Afterward investigation, it can be initiated that lesser periods under the Tent chaotic order, and it can be observed unstable periodic point. For prevent it from falling as to lesser or unstable period points. [17] established the arbitrary variable $rand(0,1) \times \frac{1}{NA}$ as to the novel Tent mapping formula, and the enhanced model as:

$$y_{i+1} = \begin{cases} 2y_i + rand(O,1)x\frac{1}{NA}, 0 \leq y \leq \frac{1}{2} \\ (6) \\ 1\ 1 \\ 2(1 - y_i) + rand(0_l 1)x_{\overline{NA'2}} < y \leq 1 \end{cases} \tag{6}$$

The formula later Bernoulli transformation as:

$$y_{i+1} = (2y_i) mod\ 1 + rand(0_l 1) \times \frac{1}{NA} \tag{7}$$

Where NA implies the amount of sparrows from the chaotic order, $rand$ (0,1) refers the arbitrary number chosen from the range of 0 and 1. Based on the features of Tent chaotic map, the steps of implementing the enhanced chaotic map formula for generating a chaotic order from the possible area as:

Step 1 Arbitrarily make the primary value y_0 from the range of 0 and 1, mark $i = 0$.

Step 2 Utilize Eq. (7) for starting the iterative computation for generating Y order, and every time i increment by one.

Step 3 End of the number of iterations obtains the maximal and store the created Y order.

The EE-CCSAC based clustering technique has resultant at, under the occurrence of 4 fitness parameters such as RE, node density, distance to neighbors, and distance in CH to BS. The fitness parameters have been provided thereby.

Residual energy (RE): CH performs several processes like sensing, gathering, aggregation, and data transmission. So, the CH employs the maximal energy to another node. Then, it can be essential for determining FF that share the load among each other sensors from the networks. The fitness parameter to effective usage of network energy is provided thereby.

$$R_e = e(n_i)$$

$$Avg_e = \frac{1}{n}\sum_{i=0}^{n} e\,(n_i)$$

$$f_1 = CH_{opt} * \frac{R_e}{Avg_e} = \frac{CH_{opt} * e(n_i)}{\frac{1}{n}\Sigma_{i=0}^{n} e(n_i)} \forall CH_{opt} = 5\%\ of\ n, e(n_i)$$

$$= 0.5J \; or \; 1.25J \; or \; 1.75J \tag{8}$$

where, R_e, Avg_e, and n_i represents the node RE, network average energy, and the entire count amount of SNs under the network. CH_{opt} signifies the optimum percentage of CHs. The main function f_1 illustrates the ratio of all nodes RE and network average energy. Node density: In intra cluster communication, cost is an essential parameter for improving the energy efficiency of networks [18]. The maximal node degree of CHs outcomes from efficient network performance and could be defined as:

$$f_2 = \max\left(n(CH_1), n(CH_2), n(CH_3) n\left(CH_j\right)\right) \forall n = 2 \; To \; 95, j = 1 \; to \; 15 \tag{9}$$

where $n(CH_j)$ refers the amount of sensors from the range of j^{th} CH (CH_j). The value of main function f_2 has superior to correct choice of CHs and it can be employed dependent upon decreasing energy utilization.
Distance to neighbors: In intracluster communication, the sensor broadcasts the data to CH. When the CH is reserved from CM, afterward the sensor decrease the energy when CH is nearby the member in which the adjacent SN utilizes lesser energy.

$$f_3 = \frac{1}{n_{s\tau}} \sum_{i=0}^{n_{sr}} d\, isT(CH, i) \; \forall dist(CH, i) = 1 \; to \; 35 \; m, n_{sr} = 1 \; to \; 100 \tag{10}$$

where, n_{sr} and $dist(CH, i)$ stands for the amount of sensors in sensing orders and Euclidean distance amongst the modes as well as CHs. Distance from CH to BS: In order to be efficient CH selective, the distance amongst CHs as well as BS converts a vital purpose. This follows mainly against the chosen CH is far away from the BS and it employs the energy quickly. This condition has been evaluated in the function provided under.

$$f_4 = \frac{1}{CH} \sum_{\mathrm{i=0}}^{\mathrm{CH}} d\, ist(BS, CH_i) \; \forall dist(BS, CH_i) = 1 \; to \; 70m, CH = 1 \; to \; 15 \tag{11}$$

where, $dist(BS, CH_i)$ refers the Euclidean distance amongst BS and i^{th} CH (CH_i). The f_4 main function condition is minimized and so chosen CH isn't far away from BS.
Once f_1, f_2, f_3, and f_4 function parameters have been evaluated, the main function called FF is determined as:

$$F = Maximize\ Fitness \; = \alpha * f_1 + \beta * f_2 + \gamma * \frac{1}{f_3} + \delta * \frac{1}{f_4} \tag{12}$$

where, α, β, γ, and δ defines the weighted coefficients for f_1, f_2, f_3, and f_4 FF parameters, correspondingly. The range of weighted coefficients differs from the interval of 0 and 1.

3. Experimental Validation

In this section, we have made a comprehensive comparative results analysis of the proposed model with existing techniques under varying node counts. Table 1 offers a brief comparative study of the proposed model with recent techniques interms of different measures. Fig. 2 inspects the ECM analysis of the proposed manner with other techniques under distinct nodes. The figure reported that the proposed technique has accomplished improved outcomes with minimal ECM. For sample, with 100 nodes, the proposed model has attained a least ECM of 30mJ while the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA algorithms have obtained increased ECM of 34mJ, 35mJ, 37mJ, 40mJ, and 47mJ respectively. Eventually, with 500 nodes, the proposed system has reached a minimal ECM of 94mJ but the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA methods have reached superior ECM of 106mJ, 107mJ, 126mJ, 132mJ, and 145mJ correspondingly.

Table 1 Result Analysis of Existing with Proposed Method in terms of Various QoS Parameters

No. of Nodes	**Energy Consumption (mJ)**					
	Proposed Method	TTMEAC	T2FLCSA	CSA	GWOCA	FFCA
100	30	34	35	37	40	47
200	51	55	58	64	66	72
300	63	71	75	83	93	97
400	71	82	85	98	104	112
500	94	106	107	126	132	145
No. of Nodes	**Network Lifetime (Rounds)**					
	Proposed Method	TTMEAC	T2FLCSA	CSA	GWOCA	FFCA
100	6000	5900	5800	5600	5500	5100
200	6100	5900	5700	5400	5300	4900
300	5800	5600	5500	5400	5200	4700
400	5700	5500	5300	5200	5000	4500
500	5500	5300	5100	4900	4800	4300
No. of Nodes	**Packet Delivery Ratio (%)**					
	Proposed Method	TTMEAC	T2FLCSA	CSA	GWOCA	FFCA
100	99.79	99.71	99.56	99.54	99.52	98.54
200	99.80	99.73	99.70	99.49	98.41	97.43
300	99.67	99.55	98.37	97.37	97.21	96.73
400	99.91	99.82	98.77	97.82	96.18	95.85
500	99.85	98.72	97.64	96.22	95.76	94.78
No. of Nodes	**End to End Delay (sec)**					
	Proposed Method	TTMEAC	T2FLCSA	CSA	GWOCA	FFCA
100	2.04	2.17	2.26	2.30	2.34	2.79
200	2.16	2.34	2.67	2.83	3.86	4.84
300	2.46	2.85	3.41	3.52	4.84	6.24
400	3.37	3.94	4.22	4.70	5.72	7.98
500	4.85	5.16	5.98	6.04	6.15	8.97
No. of Nodes	**Throughput (Mbps)**					
	Proposed Method	TTMEAC	T2FLCSA	CSA	GWOCA	FFCA
100	0.992	0.988	0.977	0.965	0.952	0.917

200	0.972	0.958	0.918	0.855	0.826	0.782
300	0.916	0.893	0.844	0.766	0.724	0.696
400	0.885	0.814	0.765	0.704	0.653	0.588
500	0.836	0.786	0.724	0.654	0.616	0.533

Next, the NWLT analysis of the proposed model with existing approaches under several node counts is made in Fig. 3. The outcomes exhbited that the proposed system has gained maximal NWLT. For instance, under 100 nodes, the proposed model has gained an increased NWLT of 6000 rounds but the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA techniques have accomplished reduced NWLT of 5900, 5800, 5600, 5500, and 5100 rounds correspondingly. Followed by, under 500 nodes, the proposed manner has reached an increased NWLT of 5500 rounds while the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA sytems have accomplished reduced NWLT of 5300, 5100, 4900, 4800, and 4300 rounds correspondingly.

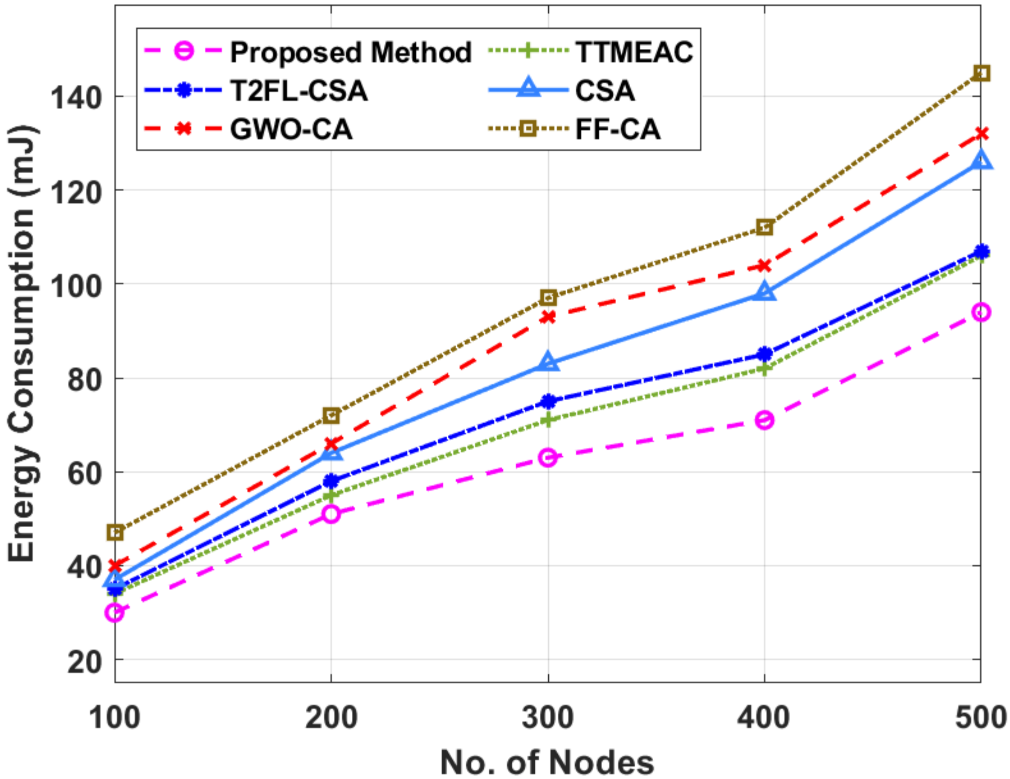

Fig. 2. Energy consumption analysis of proposed method

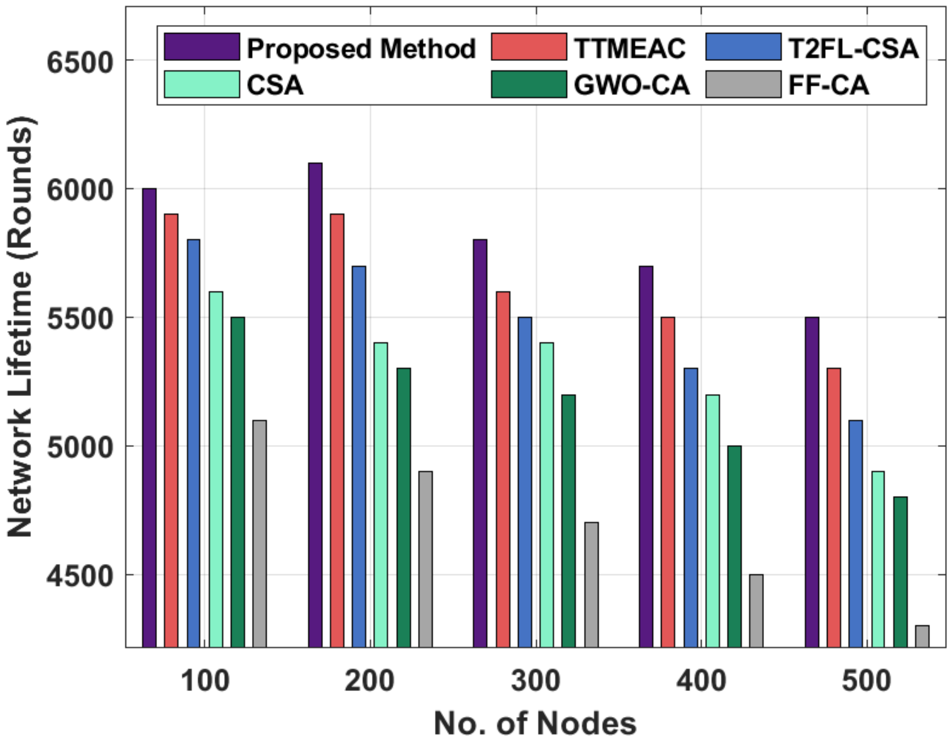

Fig. 3. Network lifetime analysis of proposed method

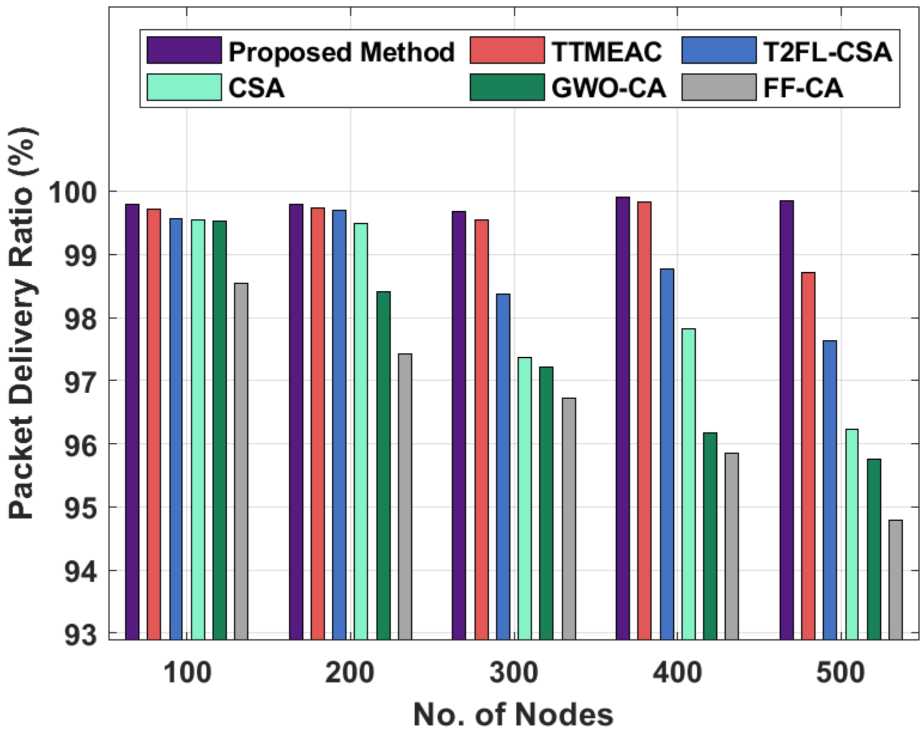

Fig. 4. Packet delivery ratio analysis of proposed method

Afterward, the PDR analysis of the proposed approach with existing manners under various node counts is made in Fig. 4. The results demonstrated that the proposed model has reached maximum PDR. For samples, under 100 nodes, the proposed model has attained an increased PDR of 99.79% though the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA systems have accomplished lower PDR of 99.71%, 99.56%, 99.54%, 99.52%, and 98.54% correspondingly. Furthermore, under 500 nodes, the proposed model has attained an improved PDR of 99.85% however the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA manners have accomplished reduced PDR of 98.72%, 97.64%, 96.22%, 95.76%, and 94.78% correspondingly.

Fig. 5 examines the ETED analysis of the proposed algorithm with other approaches under distinct nodes. The figure stated that the proposed manner has accomplished higher outcomes with the lower ETED. For sample, with 100 nodes, the proposed model has achieved a minimal ETED of 2.04s but the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA manners have obtained higher ETED of 2.17s, 2.26s, 2.30s, 2.34s, and 2.79s correspondingly. Eventually, with 500 nodes, the proposed system has attained a lower ETED of 4.85s while the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA algorithms have reached superior ETED of 5.16s, 5.98s, 6.04s, 6.15s, and 8.97s correspondingly.

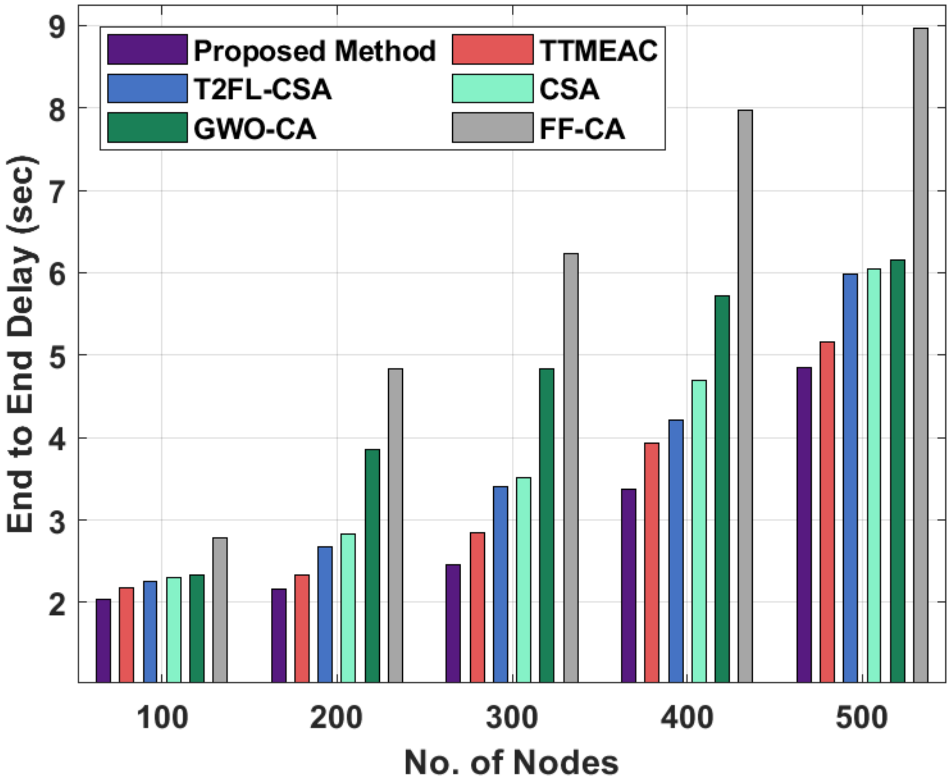

Fig. 5. End-to-end delay analysis of proposed method

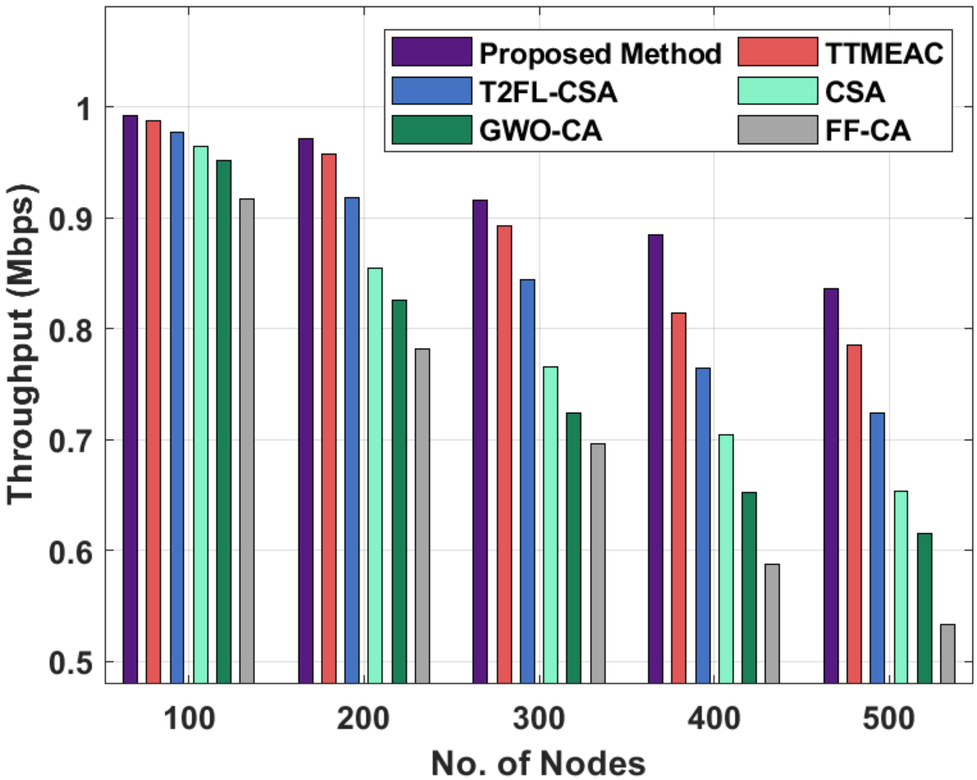

Fig. 6. Throughput analysis of proposed method

Then, the throughput analysis of the proposed technique with existing approaches under different node counts is made in Fig. 6. The results demonstrated that the proposed system has obtained maximal throughput. For instance, under 100 nodes, the proposed model has attained an increased throughput of 0.992Mbps although the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA systems have accomplished minimal throughput of 0.988Mbps, 0.977Mbps, 0.965Mbps, 0.952Mbps, and 0.917Mbps correspondingly. Eventually, under 500 nodes, the proposed manner has obtianed a higher throughput of 0.836Mbps however the TTMEAC, T2FLCSA, CSO-GWOCA, and FFCA schemes have accomplished lower throughput of 0.786Mbps, 0.724Mbps, 0.654Mbps, 0.616Mpbs, and 0.533Mbps correspondingly.

4. Conclusion

In this study, a novel EE-CCSAC technique has been presented to accomplish energy efficiency in WSN. The proposed EE-CCSAC manner is based on the integration of chaotic maps into the traditional sparrow search algorithm (SSA). In addition, the EE-CCSAC technique derives a FF with four variables to properly select the CHs and then organize clusters, thereby achieving energy efficiency. The experimental validation of the EE-CCSAC technique takes place and the outcomes are compared with recent clustering approaches. The simulation outcomes outpeformed the effective outcome of the EE-CCSAC algorithm on the other ones with respect to distinct estimation parameters. In future, multi-hop routing approaches are developed for improving the energy efficiency in WSN.

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