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Mitigating Hotspot Problem Using Chaotic Salp Swarm Algorithm for Energy Efficient IoT Assisted Wireless Sensor Networks

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Abstract—Wireless Sensor Networks (WSN) and Internet of Things (IoT) continued to be pro-active study due to their far reaching applications and also a crucial technology for ubiquitous living. In WSN, energy awareness becomes a significant design problem. Clustering can be defined as a renowned energy-efficient method and renders a lot of benefits like energy competence, less delay, scalability, and lifetime; but it resulted in hot spot problems. To sort out this problem a method called unequal clustering is designed. In unequal clustering, the cluster size differs with the Base Station (BS) distance. In this study, a new Chaotic Salp Swarm Algorithm Based Unequal Clustering Approach (CSSA-UCA) methodology to resolve hot spot issues in IoT-assisted WSN is proposed. The major objective of the CSSA-UCA methodology lies in the effectual identification of CHs and unequal cluster sizes. To accomplish this, the CSSA-UCA technique initially derives the CSSA by the incorporation of chaotic notions into the conventional SSA. At the same time, a fitness function incorporating multiple input parameters was considered for unequal cluster construction. A wide range of experimental result analyses is performed to exhibit the supremacy of the CSSA-UCA technique. The experimental results stated that the CSSA-UCA technique proficiently balances energy accretion and improves the network lifetime.

Keywords- Internet of Things; Hot spot problem; Energy efficiency; Unequal clustering; Wireless sensor networks; Salp swarm algorithm

I. INTRODUCTION

Information-centric edge computing and wireless communication are becoming popular in 5G and the IoT with the advancement of communication technologies. WSN is a common example of them [1]. It is centred on a dispersed BS, where WSNs are the IoT devices, and all nodes utilize wireless data transmission to exchange data with each other. WSNs were multi-hop self-organizing networks comprising SNs [2], tiny devices, and other gadgets that monitor occurrences in a targeted area and interact with the collected data to a data centre for processing. WSN comprised hundreds, if not thousands, of interconnected nodes with constrained handling, sensing, and also computing vulnerability, along with restricted energy sources [3]. The nodes, on contrary, are commonly put in inaccessible and hostile atmospheres, making it impossible or difficult to replenish energy or substitute batteries. The WSN's energy efficiency must be prioritized for extending its life as much as possible [4].

Clustering separates the entire network into small networks named clusters; all clusters select a node named CH through a selection and election procedure [5]. Only this authoritative CH was accountable for transferring the data accumulated by the sensors to BS through multi-hop or single-hop transmission [6]. During the selection and election of an SN as CH several parameters like node degree, distance from BS, node density, and remaining energy were considered. With the help of clustering, an SN interacts only with its CH to maintain its residual energy and not to disperse its energy by directly sending data to the BS [7]. In addition to several advantages like bandwidth utilization clustering, reduced overhead, energy consumption, and less delay even causes hot-spot issues. In hot-spot problem, CHs placed near the BS were overloaded with two kinds of data [8]: relay data in the form of inter-cluster data received from other CHs and CH data in the form of intra-cluster data. Because of this overloaded data CHs positioned near BS will drain their battery rapidly and would disturb the overall network functions of the WSN [9]. Several authors have modelled distinct methods to solve hot-spot issues, but one most

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commonly utilized techniques were unequal clustering. In unequal clustering, the size of the cluster can be directly proportional to its distance from BS [10].

In Prabha et al. [11], an Emperor Penguin Colony oriented Unequal Clustering Scheme (EPCUCS-HM) is presented for Hotspot Mitigation in WSN. This abovementioned method intends for mitigating the issue of hot spot by constructing unequal clustering sizes. In this method, the EPC technique depends on the penguin's lifestyle. Also, this method followed the first-order radio energy method for computing power consumption. Furthermore, the EPCUCS-HM method extracted a Fitness Function (FF) for effective cluster size decisions and CH election. Nguyen et al. [12] devise a load balance for mitigating the hot spot issue from WSN, depending on enriching diversity pollens in FPA. The hotspot issue in WSN was spots adjacent to BS that consumed larger energy and drained out energy at a rapid speed compared with other nodes away from the BS. The spots adjacent to BS are hot compared to other areas because of the heavy congestion from other CH and members of the cluster to relay data to BS.

In [13], the authors modelled a Harris Hawk Optimization (HHO) related technique, to capture the hot-spot issue, together called HHO-UCRA (HHO created on routing algorithms and unequal clustering). Initially, the CH selection system was devised depending on the HHO grounded technique. Finally, effective hawk encoding structures and new FFs of HHO-related methods were developed for both algorithms. Anuradha et al. [14] presented a new Seagull Optimization Unequal Clustering (SGOBUC) approach to achieve energy effectiveness in WSNs. The SGO approach was mainly stimulated by the attacking and migrating attitude of seagulls. The SGOBUC approach derived a fitness containing several parameters such that energy effectiveness can be accomplished.

Verma and Gain [15] presented a Political Optimizer-Oriented Unequal Clustering System (POUCS) to mitigate hot-spot issues in WSNs. This POUCS technique chooses CHs and determines unequal clustering sizes. The POUCS method extracted an FF including varied input variables for maximizing network lifetime and reducing energy consumption. In [16], a novel mobile clustering routing protocol related to Thermal Exchange Optimization (TEO) put under simulation by Newton's cooling law, called TEO-MCRP, was introduced for diverse WSN. In this protocol, 2 discrete methods were proposed for Mobile Sink (MS) path recognition and CH selection with main functions comprising autonomous fitness parameter. With the way of minimalizing such main functions, potential MS trajectory determination and CH selection were executed to all the mobile rounds utilizing the temperature formulas in the TEO technique.

In this study, a new Chaotic Salp Swarm Algorithm Based Unequal Clustering Approach (CSSA-UCA) for resolving the issue of hot spot in WSN is proposed. The major intention of the CSSA-UCA method lies in the effectual identification of CHs and unequal cluster sizes. To accomplish this, the CSSA-UCA technique initially derives the CSSA by the incorporation of chaotic concepts into the conventional SSA. At the same time, an FF incorporating multiple input parameters was considered for unequal cluster construction. A wide range of experimental result analyses is performed to exhibit the supremacy of the CSSA-UCA technique.

II. THE PROPOSED MODEL

In the presented article, a novel CSSA-UCA approach for resolving hot spot issues and lifetime maximization in the WSN is developed. The aim of the CSSA-UCA approach lies in the effective recognition of CHs and unequal cluster sizes. Meanwhile, an FF incorporating multiple input parameters was considered for unequal cluster construction. Fig. 1 represents the overall procedure of the CSSA-UCA model.

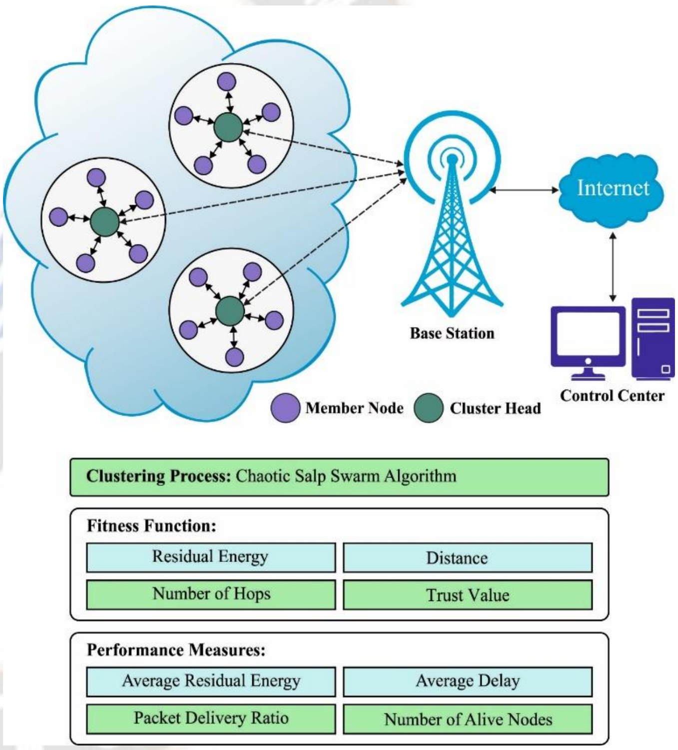

Figure 1. Overall procedure of the CSSA-UCA model

A. *System Model*

The WSN structure is given in. The network architecture is formulated according to the subsequent consideration [17]:

- In WSN, each sensor is similar to one another concerning processing time and initial energy.
- The distance amongst the sensor nodes is assessed according to the Euclidean distance.
- The sensors are installed randomly in the sensing region and the sensor position is constant afterward the deployment.

- BS receives the data regarding the RE and distance from the sensors. By using this data, CH is chosen for each sensor based on a robust CH selection technique. Next, the routing method is utilized for obtaining the path between the CH to BS.

In the proposed work, a 1st order radio model is taken into for calculating the receiver and transmitter energy. The energy consumed to collect and transmit the l-bit packets over the distance d is formulated below.

$$E_{TX}(l,d) = \begin{cases} l \times E_{elec} + l \times \varepsilon_{fs} \times d^2 \; if \; d \le d_0 \\ l \times E_{elec} + l \times \varepsilon_{mp} \times d^4 \; if \; d > d_0 \end{cases} \quad (1)$$

$$E_{RX}(l,d) = l \times E_{elec} \quad (2)$$

Where the quantity of energy dissipated at transmitter/receiver is characterized as E_{elec} and the threshold distance is denoted as d_0. The threshold distance can be evaluated by the subsequent formula:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (3)$$

In Eq. (3), the amplification energy for free space and multipath modelling can be denoted i as ε_{fs} and ε_{mp} correspondingly. ε_{fs} and ε_{mp} depends on the transmitter amplifier.

B. Algorithmic Design of CSSA

Here, the CSSA-UCA technique initially derived the CSSA via the incorporation of chaotic concepts into the traditional SSA. The population is initially divided into two groups for mathematically modelling a salp chain as leader and the followers [18]. The leader is the salp at the front of the chain, and the remaining are followers. The leader steers the group, and the follower follows together. As a result, they indirectly or directly follow the leader. The location of salp can be described in a n-dimensional search space, where n denotes the parameters count of the given issues. Thus, the salp position is stored in a 2D matrix form called x. Additionally, assume that there is a food source called F in the search range that acts as a target. The ensuing equation is employed to update the leader location:

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & C_3 \ge 0 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & C_3 < 0' \end{cases} \quad (4)$$

In Eq. (4), x_j^1 characterizes the initial salp location (leader) at $the \; j^{th}$ dimension, Fj indicates the food source position at $the \; j^{th}$ dimension, ub_j and lb_j represent upper and lower limits at $the \; j^{th}$ dimension, c_1, c_2 and c_3 denotes the randomly generated integers. Eq. (4) depicts that only the leader updates their location concerning the food source. The c_1 coefficient is the key parameter in the SSA since it balances exploitation and exploration, as determined below:

$$c_1 = 2e^{-(\frac{4l}{L})^2} \quad (5)$$

In Eq. (5), l denotes the current iteration, and L shows the overall amount of iterations. c_2 and c_3 parameters are uniform distribution random numbers lying in [0,1] intervals. They specify the second location at the j^{th} parameter must be toward negative or positive infinity, and also, they determine the step size. The subsequent formula is utilized (Newton's law of motion). To upgrade the follower position:

$$x_j^i = \frac{1}{2}at^2 + v_0 \mathrm{t} \quad (6)$$

Where $i \ge 2$, x_j^i denotes the location of i^{th} followers at j^{th} dimension, for the specific time t, an initial velocity $y_0, = \frac{v_{final}}{v_0} tv = \frac{x - x_0}{\tau}$.

Meanwhile, the time corresponding to the similar iteration, the difference between iterations is equivalent to 1. Hence consider$v_0 = 0$, the equation is formulated by:

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right)at^2 \quad (7)$$

Where x_j^i specifies the location of i^{th} followers salp in the j^{th} dimension. The salp chain can be simulated using Eqs. (5) and (7).

Algorithm 1: Pseudocode of SSA

Create and initialize the initial population of salp based on the upper and lower boundaries of lb, ub
While loop (until the ending condition is satisfied)
    Compute the objective function for all the factors
Select the better search engine
Upgrade cl using Eq. (5)
For loop for each salp
    if ($i = 1$)
        Upgrade the leader position salp by using Eq. (6)
    otherwise
        Upgrade the leader salp position by using Eq. (7)
    end
end
Check the range of salp in the range of lb, ub
End

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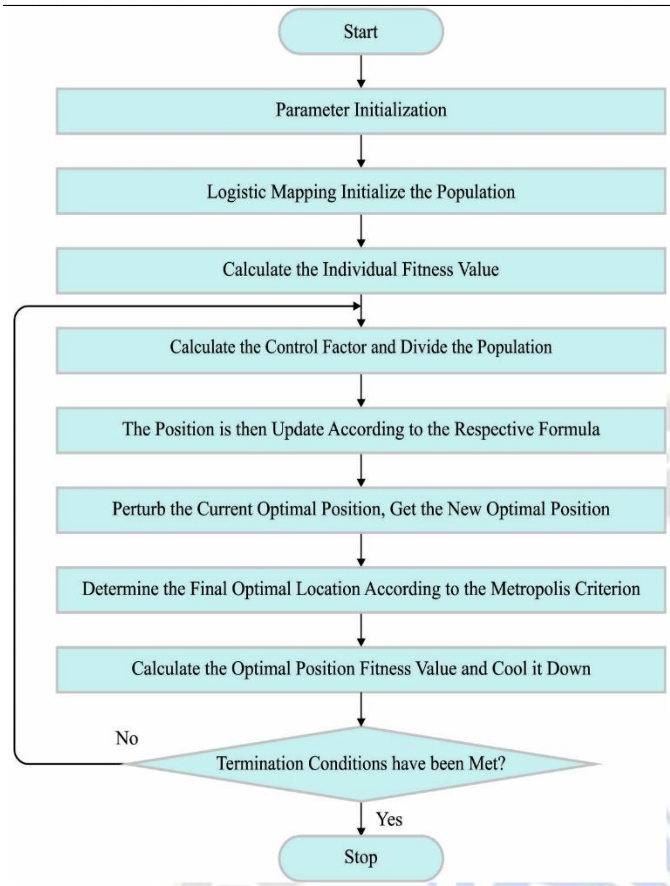

Figure 2. Flowchart of SSA

The chaotic map was used extensively through the initialization period of the optimizer due to the subsequent features: nearness towards the semi-randomness, ergodicity, and initial condition. During the initializing stage, for single feature, the chaotic map can be used for producing arbitrary parameters for replacing the Gaussian or uniform parameter. For additional factors, the chaotic map is adapted for generating a chaotic solution, along with the opposition-based learning role. In the CSSA, the logistic mapping is used for generating the chaotic solution; the distribution of the logistic map is represented as follows:

$$C(t+1) = \mu \times C(t) \times \left(1 - C(t)\right); t = 1,2, \dots, N-1 \quad (8)$$

In Eq. (8), μ refers to the coefficient, which is frequently equivalent to 4, now the chaotic map will be generated; t denotes the present chaotic number index; N shows the size of the populace; $C(1)$ represent the randomly generated value within $(0,1)$ that is not equivalent to 0.25, 0.5, and 0.75; $N-1$ chaotic number is produced by using Eq. (4). The chaotic solution of i^{th} the ith agent is obtained using the following expression:

$$CX_i = C(t) \times X_i \quad (9)$$

In Eq. (9), $C(t)$ denotes the t^{th} chaotic numbers; X_i means the i^{th} agents; CX_i shows the chaotic solution of the i^{th} agents. Fig. 2 demonstrates the SSA flowchart.

C. Design of Unequal Clustering Process

In this work, an FF incorporating multiple input parameters was considered for unequal cluster construction. For unequal clustering, the CSSA-UCA method derives an FF with different input parameters for enhancing energy efficiency and lifetime. Now, distance, trust, number of hops, and RE are four dissimilar parameters used for formulating FF [19]. During the selection of CH, trust is considered a major parameter from the FF to increase safety. The trust value ()utilized to alleviate the DDoS attacks while transferring the data packet is demonstrated as follows.

$$g_1 = \frac{TDP_{ij}}{RDP_{ij}} \quad (10)$$

Distance defines the distance (g_2) amongst the CH and the BS to the subsequent-hop node. While the energy depletion of these nodes is proportional to the transmission path distance. Accordingly, there is a need to define the transmission path with a lower distance to minimise energy consumption. The candidate CH with the highest RE (g_3) is significantly improved in the selection of the CH. Meanwhile, the CH performs various operations such as data aggregation, transmission, and collection.

$$g_3 = \sum_{i=1}^{a} E_{CH_i} \quad (11)$$

Where E_{CH_i} denotes the RE of CH. The amount of normal nodes belonging to the certain CH is defined by the amount of hops. The energy consumption of the CH is smaller when it has a smaller quantity of hops. Hence, the CH with minimal hops is considered in CHS and the amount of hops (g_4) is expressed by.

$$g_4 = \sum_{i=1}^{a} I_i \quad (12)$$

Here, the amount of normal nodes to a particular CH is indicated as I_i. The aforementioned objective value is transformed as the single objective based on the weighted sum approach as in the following.

$$f = \delta_1 \times g_1 + \delta_2 \times g_2 + \delta_3 \times g_3 + \delta_4 \times g_4 \quad (13)$$

Where, δ_1, δ_2, δ_3 and δ_4 indicate the weight allotted to every value of FF.

III. Results and Discussion

In the present segment, the experimental validation of the CSSA-UCA technique was examined in detail.

In Table 1 and Fig. 3, an Average Residual Energy (ARE) assessment of the CSSA-UCA technique with current approaches [14]. The investigational outcomes demonstrate that the CSSA-UCA technique reaches the lowest ARE values over other techniques. For instance, with 1000 rounds, the CSSA-UCA technique obtains an increasing ARE value of 0.9994. Meanwhile, with 5000 rounds, the CSSA-UCA method attains a maximal ARE value of 0.9791. Moreover, with 15000 rounds,

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the CSSA-UCA method acquires an enhancing ARE value of 0.3929.

TABLE I. ARE EVALUATION OF THE CSSA-UCA APPROACH WITH OTHER METHODS UNDER CHANGING ROUNDS

Average Residual Energy (J)						
No. of Rounds	CSSA-UCA	SGOBUC	SUCID	FUCHAR	F5NUCP	KHA
0	0.9994	0.9918	0.9842	0.9740	0.9842	0.9689
1000	0.9994	0.9867	0.9715	0.9360	0.9182	0.8497
2000	0.9969	0.9816	0.9689	0.9283	0.8751	0.7812
3000	0.9943	0.9766	0.9563	0.9157	0.8725	0.7177
4000	0.9928	0.9740	0.9436	0.8827	0.8573	0.6594
5000	0.9791	0.9563	0.9360	0.8624	0.8218	0.6239
6000	0.9766	0.9461	0.9080	0.8015	0.7685	0.5782
7000	0.9309	0.9004	0.8294	0.7355	0.7127	0.5452
8000	0.8877	0.8649	0.7507	0.6721	0.6721	0.4716
9000	0.8725	0.8167	0.7000	0.5553	0.6518	0.4209
10000	0.8269	0.7127	0.6036	0.4970	0.6264	0.3726
11000	0.7406	0.6391	0.5198	0.3803	0.5883	0.3194
12000	0.6924	0.6010	0.4716	0.3371	0.5224	0.2280
13000	0.6213	0.4970	0.4056	0.2737	0.5021	0.1823
14000	0.5122	0.4006	0.2991	0.2331	0.4538	0.0884
15000	0.3929	0.2940	0.2026	0.1747	0.3849	0.0631
16000	0.3676	0.1849	0.1164	0.1164	0.2864	0.0199
17000	0.2991	0.0884	0.0352	0.0681	0.1595	0.0000
18000	0.1037	0.0428	0.0123	0.0352	0.0000	0.0000
19000	0.0605	0.0000	0.0000	0.0000	0.0000	0.0000
20000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

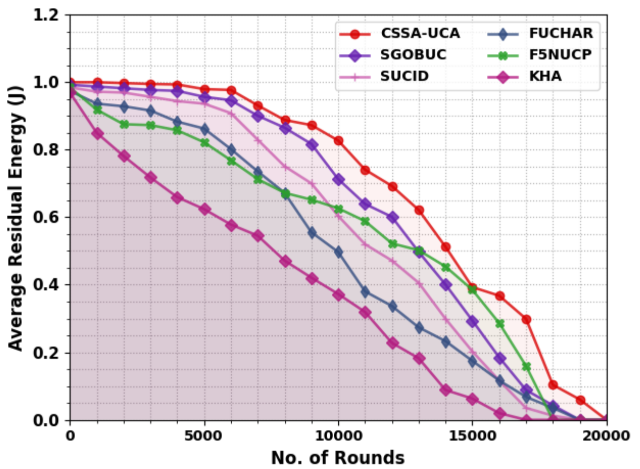

Figure 3. ARE evaluation of the CSSA-UCA method under changing rounds

The ADE inspection of the CSSA-UCA technique is studied with other approaches is demonstrated in Table 2 and Fig. 4. The investigational values portrayed that the CSSA-UCA technique results in decreased ADE of 83.77ms. Concurrently, with 200 nodes, the CSSA-UCA method outcomes in minimal ADE of 91.48ms. Simultaneously, with 500 nodes, the CSSA-UCA methodology results in a reduced ADE of 119.31ms. Finally, with 1000 nodes, the CSSA-UCA methodology outcomes in lower ADE of 137.29ms.

TABLE II. ADE EVALUATION OF CSSA-UCA APPROACH WITH OTHER METHODS UNDER CHANGING NODES

Average Delay (ms)						
No. of Nodes	CSSA-UCA	SGOBUC	SUCID	FUCHAR	F5NUCP	KHA
100	83.77	87.62	92.33	103.46	124.87	135.15
200	91.48	97.90	106.46	123.59	135.57	146.28
300	96.61	104.75	121.02	134.29	146.28	157.84
400	105.61	114.60	129.58	145.85	155.70	165.97
500	119.31	129.58	138.14	151.41	162.55	176.67
600	122.30	133.01	142.85	161.26	170.25	186.09
700	121.87	132.15	148.85	171.11	179.67	192.94
800	132.58	140.71	155.27	179.24	190.80	204.07
900	135.57	150.13	160.41	180.96	204.07	221.63
1000	137.29	154.41	164.26	185.24	212.64	235.76

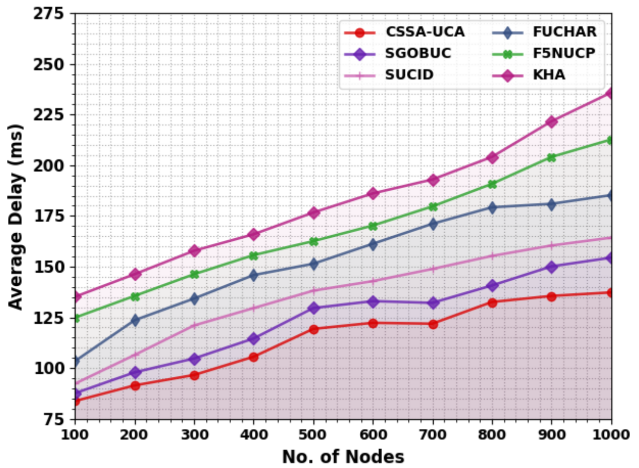

Figure 4. ADE evaluation of CSSA-UCA approach under changing nodes

In Table 3 and Fig. 5, a PDR analysis of the CSSA-UCA methodology with recent techniques. The experimental outcomes demonstrate that the CSSA-UCA methodology gains minimal PDR values over other approaches. For instance, with 100 nodes, the CSSA-UCA methodology obtains an increasing PDR value of 98.57%. In the meantime, with 500 nodes, the CSSA-UCA methodology acquires an increasing PDR value of

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96.89%. Moreover, with 1000 nodes, the CSSA-UCA methodology obtains a maximal PDR value of 88.71%.

TABLE III. PDR ANALYSIS OF CSSA-UCA METHODOLOGY WITH OTHER METHODS UNDER VARYING NODES

Packet Delivery Ratio (%)						
No. of Nodes	**CSSA-UCA**	**SGOBUC**	**SUCID**	**FUCHAR**	**F5NUCP**	**KHA**
100	98.57	97.79	96.37	92.86	87.54	79.88
200	98.44	94.42	91.56	87.02	80.27	73.13
300	98.05	91.56	88.45	81.18	75.20	72.22
400	97.01	89.36	87.02	81.70	75.20	71.18
500	96.89	88.84	85.85	80.79	74.17	70.14
600	95.98	87.41	84.94	80.01	72.87	68.71
700	94.81	88.06	84.42	77.93	70.79	66.12
800	93.90	86.76	79.75	72.74	69.88	65.34
900	92.60	84.68	77.28	72.87	68.84	64.56
1000	88.71	82.86	74.43	71.83	67.41	64.04

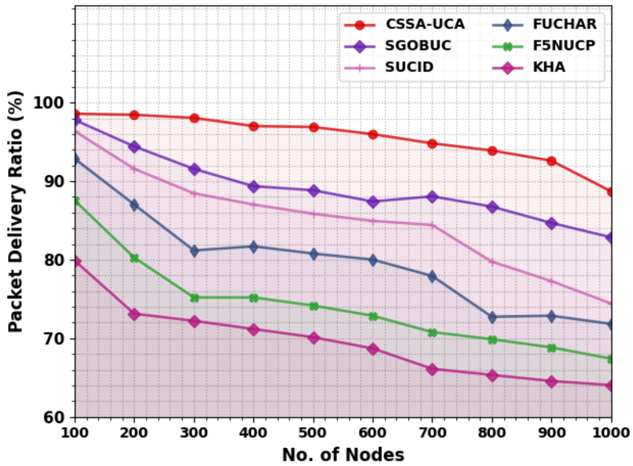

Figure 5. PDR analysis of CSSA-UCA methodology under varying nodes

In Table 4 and Fig. 6, a NOAN investigation of the CSSA-UCA methodology with recent methods. The experimental outcomes exhibit that the CSSA-UCA methodology reaches minimal NOAN values over other methods. For instance, with 1000 rounds, the CSSA-UCA technique obtains an enhancing NOAN value of 995. Followed by, with 5000 rounds, the CSSA-UCA technique gains an increasing NOAN value of 984. Additionally, with 15000 rounds, the CSSA-UCA methodology acquires a maximal NOAN value of 461.

TABLE IV. NOAN ANALYSIS OF CSSA-UCA METHODOLOGY WITH OTHER APPROACHES UNDER VARYING ROUNDS

Alive Node Numbers						
No. of Rounds	**CSSA-UCA**	**SGOBUC**	**SUCID**	**FUCHAR**	**F5NUCP**	**KHA**
0	998	995	987	984	979	965
1000	995	992	979	952	897	842
2000	992	987	965	935	881	755
3000	987	987	946	911	853	657
4000	984	976	930	875	815	600
5000	984	973	924	851	799	540
6000	971	938	872	782	766	504
7000	962	878	799	772	739	436
8000	927	848	714	690	676	371
9000	881	774	684	646	657	324
10000	791	698	551	551	581	278
11000	742	627	471	450	485	226
12000	660	572	406	349	335	182
13000	630	551	343	302	270	144
14000	553	439	286	259	226	128
15000	461	349	215	182	158	76
16000	346	245	128	141	98	30
17000	215	128	79	87	30	0
18000	117	95	34	16	0	0
19000	46	0	0	0	0	0
20000	0	0	0	0	0	0

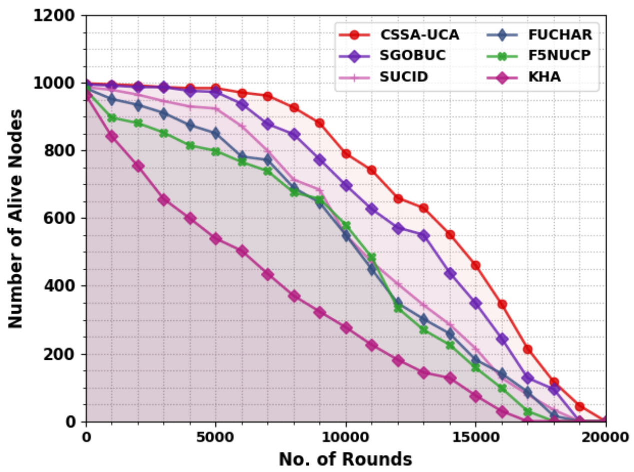

Figure 6. NOAN analysis of CSSA-UCA methodology under varying rounds

TABLE V. LIFETIME ANALYSIS OF CSSA-UCA METHODOLOGY WITH OTHER METHODS

Lifetime (Rounds)						
Dead Nodes	**CSSA-UCA**	**SGOBUC**	**SUCID**	**FUCHAR**	**F5NUCP**	**KHA**
FND	999	991	985	982	976	961
HND	13584	13362	10952	10500	10900	6538
LND	20000	19651	19243	18954	17682	16996

In Table 5 and Fig. 7, the lifetime assessment of the CSSA-UCA method is examined in detail. Based on FND, the CSSA-

UCA technique gains increasing FND of 999 rounds while the SGOBUC, SUCID, FUCHAR, F5NUCP, and KHA attain decreasing FND of 991, 985, 982, 976, and 961 rounds subsequently.

On the other hand, in terms of HND, the CSSA-UCA technique obtains a higher HND of 13584 rounds while the SGOBUC, SUCID, FUCHAR, F5NUCP, and KHA attain decreasing HND of 13362, 10952, 10500, 10900 and 6538 rounds correspondingly. On the other hand, concerning LND, the CSSA-UCA technique obtains a higher LND of 13584 rounds while the SGOBUC, SUCID, FUCHAR, F5NUCP, and KHA attain lower LND of 19651, 19243, 18954, 17682 and 16996 rounds correspondingly. These outputs confirmed the augmented achievement of the CSSA-UCA technique.

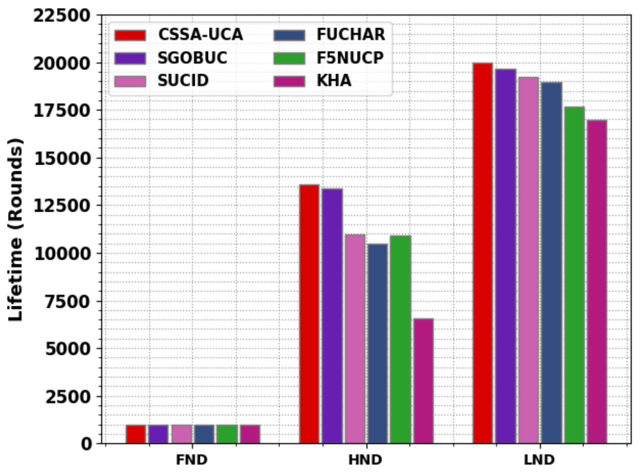

Figure 7. Lifetime analysis of CSSA-UCA methodology with other methods

IV. CONCLUSION

In the presented study, a new CSSA-UCA methodology for determining hot spot issues and lifetime maximization in the WSN is developed. The aim of the CSSA-UCA methodology lies in the effective recognition of CHs and unequal cluster sizes. To accomplish this, the CSSA-UCA technique initially derived the CSSA via the incorporation of chaotic concepts into the traditional SSA. Meanwhile, an FF incorporating multiple input parameters was considered for unequal cluster construction. A wide range of experimental result analyses is performed to exhibit the supremacy of the CSSA-UCA technique. The experimental results stated that the CSSA-UCA technique proficiently balances energy consumption and improves the networking lifetime. In future, node localization techniques can be devised for enhancing the achievement of the overall network.

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