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HYBRIDIZATION OF METAHEURISTICS BASED UNEQUAL CLUSTERING FOR ENERGY AWARE DATA AGGREGATION TECHNIQUE IN WIRELESS SENSOR NETWORKS

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Abstract

This research work develops an unequal clustering for data aggregation technique in WSN to accomplish maximum energy efficiency. Firstly, a hybridization of social spider with krill herd optimization algorithm based unequal clustering technique is designed to construct clusters of unequal sizes and elect CHs. Secondly, Bit Reduction with Burrows Wheeler Transform called BR-BWT for data aggregation process. The experimental results highlighted the effectual outcome of the proposed techniques over the other techniques in terms of energy efficiency and compression performance.

***Keywords*: Data aggregation, Unequal Clustering, Wireless Sensor Networks, Compression Efficiency, Energy Efficiency.**

1. Introduction

Wireless sensor network (WSN) consists of a huge amount of sub and sensor nodes with a constrained battery power supply. In general, the sensors are arbitrarily dispersed in the monitoring area for aggregating the gathered information and transfer data to the sink node/BS using single/multi hops [1, 2]. The data are transmitted to the terminal system via transmission links like an internet/satellite using the BS [3, 4]. Finally, users would gather information from the terminal system and control the operation over this. But, it has few drawbacks in utilizing WSN, includes higher energy consumption, shorter network lifetime, complicated network management instability, additional network overheads, and run on a large scale [5, 6]. Because of the low cost execution, WSNs are broadly utilized in many applications like transportation, industry, medical industry, agriculture, smart home systems, and environmental monitoring [7], and so on. But, the battery powered sensors have restricted energy, and a complex battery can alter the process procedure that influences lifetime, quality, and performance of WSNs. Because of this factor, managing energy utilization is a vital issue regarding WSNs. A significant detail to note when an attempt to decrease this problem, i.e., data transmission of wireless transmission expend more energy than data processing.

WSNs could function in 2 manners: event-triggered/transmission sensing afterward transmission and continuous periodic sensing [8]. WSN, being a comparatively novel technology, results in various problems, few of which haven't been encountered fully. They include power management, real time, privacy, and security features [9]. One of the solutions presented by the scientists is clustering. In clustering process of WSNs, nodes are separated into an amount of smaller groups named clusters. Clustering provides few benefits like data aggregation performed at the CH, distribution of load through each node isn't fixed permanently to one specific node; thus the rotation of CH is presented. CH deals with 2 kinds of traffic: intra-cluster and inter-cluster transmission; the prior transmission among member nodes of a cluster and CH and last being the relay or transmission of packet from CH to CH till it achieves the BS. Intercluster transmission could utilize single/multi hops transmission [10]. In single hop transmission, every CH directly transmits to BS which might create extreme usage of energy for CH farther from BS makes it crucial nodes. The nodes nearer to the BS tends to terminate earlier compared to the rest and consequently, sensing coverage gets decreased and network partition turns into obvious, [11-14] determined as hot spot problems.

In WSNs, data aggregation is a procedure of combining and collecting beneficial data in a specific area. The efficacy of the transmissions between nodes are depends on the data aggregation model. Data aggregation could be deliberated as a basic process for reducing energy utilization [16] and storing the constrained resources.

2. The Proposed Technique

2.1. Unequal Clustering Process using SS+KH Technique

The proposed SS-KH method performs in 2 phases as FCH utilizing KH method and TCH utilizing SS method. The SS-KH method functions in 4 major phases such as initialization, TCH utilizing SS approach [15], FCH utilizing KH approach [17], and cluster creation. When the sensors endure placement, the initialization stage would be performed. Now, the node gathers data regarding its adjacent nodes and distance to BS. Then, the SS method uses the nature of social spiders for selecting TCH. Later, the TCH suffer election of FCH and its corresponding CHs utilizing the KH approach. Lastly, the selected FCH forms the cluster in the network.

The SS optimization method is depending upon the performance of SS and it is applied to elect the TCHs. The fundamental procedure lies in the deliberation of the SS method in the manner of illustrating the spiders. A set of $\boldsymbol{k}$ cluster center points is denoted by every set is determined by every spider i.e., the optimal solutions to uneven clustering problems. E.g., where $\boldsymbol{x} = \{(\mathbf{10.5};\ \mathbf{20.4}), (\mathbf{15.2};\ \mathbf{25.0})\}$ denotes a spider having $\boldsymbol{m} = \mathbf{2}$ cluster center contains {(10.5; 20.4) and (15.2; 25.0)}, every center has a dimension of $\boldsymbol{n} = \mathbf{2}$. Every spider in early population is created by considering $\boldsymbol{k}$ random points of the provided dataset whereas m denote the amount of clusters.

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As the spider endures shaping by the set of cluster centers, it is essential for determining the distance among 2 spiders and not by point set. Thus, the distance among a pair of spiders is denoted as the amount of Euclidean distances among its cluster centers. The spider with minimal distance keeps small cluster size. E.g., consider $\boldsymbol{a} = \{(\boldsymbol{a_{x1}};\ \boldsymbol{a_{y1}}), (\boldsymbol{a_{x2}}; \boldsymbol{a_{y2}})\}\ \boldsymbol{and}\ \boldsymbol{b} = \{(\boldsymbol{b_{x1}}; \boldsymbol{b_{y1}}), (\boldsymbol{b_{x2}}; \boldsymbol{b_{y2}}\mathbf{2})\}$denotes the pair of spiders which contain $\boldsymbol{m} = \mathbf{2}$ clusters centers, with every center consists of a group of 2D. Then, the distance among the pair of spiders are given as

$$\boldsymbol{d_{a,b}} = \boldsymbol{d}\left((\boldsymbol{a_{x1}}; \boldsymbol{a_{y1}}), (\boldsymbol{b_{x1}}; \boldsymbol{b_{y1}})\right) + \boldsymbol{d}((\boldsymbol{a_{x2}}; \boldsymbol{a_{y2}}), (\boldsymbol{b_{x2}}; \boldsymbol{b_{y2}})) \quad (1)$$

Assume $d\left((a_{x1}; a_{y1}), (b_{x1}; b_{y1})\right)$is the Euclidean distances among the centers$d((a_{x1}; a_{y1})\&(b_{x1}; b_{y1}))$.

The FF of every spider is defined with the help of metric $\boldsymbol{M}$, a pointer to denote an optimum solution that could be created. The major focus of SS method is the decrease of population fitness. Thus, in the population, the spider that has lesser fitness is the optimal one that could be elected as TCH in the cluster. The spider $\boldsymbol{i}$ is determined as the weight and fitness that has negative relation, and it is defined by.

$$w_i = \frac{worst_s - J(s_i)}{worst_s - best_s} \quad (2)$$

$$best_s = \min\left(J(s_k)\right), k\epsilon \{1,2, \dots, N\} \quad (3)$$

$$worst_s = \max\left(J(s_k)\right), k\epsilon \{1,2, \dots, N\} \quad (4)$$

Whereas $J(s_i)$ denotes the fitness rate of spider. If the TCHs are elected, they would perform KH method for the election of FCH i.e., deliberated in the following subsection.

KH method is depending upon the herding nature of krills. It is depending upon the krill's individual result. The set of krill's hunt for food and interact with swarm members. The group of 3 motions where the position of a krill was proposed:

- Endeavor convinced by another krill,
- Foraging behaviour and
- Physical diffusion.

KH takes into account the Lagrangian method is provided by Eq. (5).

$$\frac{dX_i}{dt} = N_i + F_i + Di \quad (5)$$

Whereas N_i denotes the motion of another krill's, Fi represents the seeking movement and Di indicates the physical distribution [18].In the early motion, a repulsive, target and local outcomes compute the direction of motion, αi. For krill i, Eq. (6) is determined as:

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \quad (6)$$

In which $N^{\max}$ represents the most tempted speed, ω_n and N_i^{old} represents the inertia weight and final movement correspondingly.

In the following motion, the location of food is recognized and previous knowledge. At each ith krill, it can be given below:

$$F_i = v_f\beta_i + \omega_f F_i^{old} \quad (7)$$

$$\beta_i = \beta_i^{food} + \beta_i^{best} \quad (8)$$

Whereas v_f, ω_f and F_i^{old} denotes the inertia, searching speed, and last motion, β_i^{food} denotes the attraction of food, β_i^{best} represents the result of optimum fitness of ith krill.

In the last motion, a random process performs in 3 manners such as maximal diffusion speed and a random direction vector. Eq. (9) is indicated by:

$$D_i = D^{\max}\delta \quad (9)$$

Whereas $D^{\max}$&δ signifies the arbitrary vector. With the group of 3 motions, the location of krill at time t to $t + \Delta t$ and is given by:

$$X_i(t+\Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \quad (10)$$

The value of Δt is achieved using:

$$\Delta t = C_t \sum_{j=1}^{NV}(UB_j - LB_j) \quad (11)$$

In which NV signifies the amount of parameters, UBj & LBj represents the upper bound and lower bound of the jth parameters, Ct denotes a constant value of 0.5. There is a need for the energy to execute the procedures related to the CH. decision is created using the election of proper node using the KH. An effective CH at certain level is selected on the basis of energy owned by the distance and node from CH member nodes that aren't CH. At the setup phase, the sensor nodes would transmit the data interrelated to the location and residual energy level to the BS.

Step 1. Consider a set of I krills that keeps a collection of K arbitrarily selected CHs among the proper CH candidates.

Step 2. Define the cost function of every individual krill:

(i) For every node $n_i = 1,2,..,N$

- Define the distance d(ni,CHp,k) among the nodes ni and each CHp,k.
- Allocate the nodes ni to CHp,k whereas;

$$d(n_i, CH_{p,k}) = f_1 = min_{\forall k=1,2,\ldots k}\{d(n_i, CH_{p,k})\} \quad (12)$$

(ii) Calculate the cost function.

Step 3. Decide the optimum value of every krill and recognize the optimum location of the krill.

Step 4. Upgrade the position of every krill in the search region using Eqs. (13) and (14).

$$dXi = delta_t * (N(i) + F(i) + D(i)) \quad (13)$$

$$X(i) = X(i) + dXi \quad (14)$$

Step 5. Repeat steps 2–4 until the maximal amount of rounds are achieved. The BS interacts with the data having the id of the CMs & CHs.

1.2. Data Aggregation Process using BR-BWT Technique

The newly deployed BR-BWT model depends upon a single bit, dictionary relied single character encoding method exploits a 4-bit code allocation dictionary (CAD) for allocating codewords for input series. The exclusive feature of BR-BWT approach is that it uses 4-bit codewords for all characters. The BR-BWT model requires a lower C_{bits}which stores compressed file as calculated in Eq. (15):

$$C_{bits} = \sum_{i=1}^{N} N_{CAD}(i) \quad (15)$$

whereN_{CAD} shows the bit count and i represents the data instance. In specific, the bits required to save a character is around 4. Then, the bits which are essential for storing each character in BR-BWT model is estimated by Eq. (16).

$$CAD_{ch\_av} = \frac{C_{bits}}{N} \approx 4 \quad (16)$$

Eq. (16) states that, the average count of bits required for storing a character results in effective compression operation.

2.2.1. Bit Reduction Process using Codeword Allocation

The complete process of BR-BWT compression as well as decompression task and the optimal CAD is provided in Table 1. Initially, the BR-BWT method retains a BR-BWT that captures the codewords of 12 characters. As the BR-BWT model is deployed for WSN data is composed of arithmetic characters and dot characters. It is mainly applied for reducing the difficulty of a model. The BR-BWT is predetermined, compression and decompression contains a BR-BWT apriori. After receiving the input sequence, the BR-BWT method applies BR-BWT and designates a codeword to them. Consequently, the final outcome of codewords are encoded and integrated for producing the compressed file with actual size which is then offered to receiver end. Here, the newly deployed BR-BWT method applies symmetrical compression in which decompression task is an opposite function of compression process. Since the BR-BWT model contains similar BR-BWT as an encoding device, there is no requirement to send extra data with the compressed file for reformation task. At the initial stage, the BR-BWT method learns the compressed file with binary codewords. Here, compressed data is divided as 4 bits where the BR-BWT is applied for codeword mapping. Once the codewords are identified, decoded characters are integrated for reconstructing actual data. In the next stage, BWT is applied to further compress the data.

2.2.2. BWT based Compression Process

In BWT, the text is assumed as blocks. An effective lossless source code is said to be the sequence of source code that obtains optimal function for each source. The exact function is constrained with the following. Suppose the class of $\{P_\theta : \theta \in \Lambda\}$ of stationary ergodic sources with definite source alphabet $\mathcal{X}$. For all $\theta \in \Lambda$, let $H_\theta(X^n)$ and $H_\theta(\mathcal{X})$ be nth order entropy and entropy rate of P_θ which has been depicted as follows.

$$H_\theta(X^n) = \sum_{u^n \in \mathcal{X}^n}[-P_\theta(u^n) \log P_\theta(u^n)] \quad (17)$$

and

$$H_\theta(\mathcal{X}) = \lim_{n\to\infty} \frac{1}{n} H_\theta(X^n) \quad (18)$$

for all $\theta \in \Lambda$. The applied variable-rate lossless source coding principle for coding n-sequences from $\mathcal{X}$, for $u^n = (u_1 \dots, u_n) \in \mathcal{X}^n$, let $\ell_n(u^n)$ defines the certain length applied in the lossless description of u^n with decided coding principle. For all $\theta C \Lambda, \delta_n(\theta)$ shows the essential redundancy for coding the samples from distribution P_θ. Thus, $\delta_n(\theta)$ demonstrates the difference over the target rate for each symbol $E_\theta \ell_n(X^n)/n$ using block length-n code and better rate for all symbols $H_\theta(X^n)/n$ for coding $n - vectors$ from P_θ; hence,

$$\delta_n(\theta) = \frac{1}{n} E_\theta l_n(X^n) - \frac{1}{n} H_\theta(X^n) \quad (19)$$

The sequence of coding principles are described by the redundancy functions $\{\delta_n(\cdot)\}_{n=1}^{\infty}$, showcases a periodical min-max universal lossless source code on Λ if $\delta_n(\theta) \to 0$ for all $\theta \in \Lambda$ and rapid min-max universal lossless source code on Λ if the convergence is same in θ. These estimated bounds show the code function on sequence X^n by means of "empirical entropy" of X^n related to distribution method which is same as basic sources.

3. Performance Validation

This section investigates the energy efficiency and compression performance. Table 1 examines the performance of the SS+KH technique in terms of different measures. Fig. 1 showcases the results analysis of the SS+KH technique in terms of energy consumption. The figure portrayed that the SS+KH technique has gained effectual energy efficient performance over the other techniques. For instance, with 10 nodes, the SS+KH technique has achieved a minimal energy consumption of 43mJ whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have obtained a maximum energy consumption. Similarly, with 50 nodes, the SS+KH technique has offered a lower energy consumption of 114mJ whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have accomplished a higher energy consumption.

No. of Nodes	**Energy Consumption (mJ)**					
	SS+KH	SS	FUCHAR	DEEC	TEEN	LEACH
10	43	48	51	54	64	74
20	65	72	76	79	89	114
30	81	93	100	106	116	149
40	90	107	115	119	149	167
50	114	134	143	154	174	192
No. of Nodes	**Network Lifetime (Rounds)**					
	SS+KH	SS	FUCHAR	DEEC	TEEN	LEACH
10	6100	6000	5800	5700	5200	5000
20	6000	5800	5600	5400	5000	4800
30	5800	5500	5400	5200	4900	4600
40	5600	5400	5300	5100	4500	4300
50	5400	5200	5100	4900	4300	4100
No. of Nodes	**Packet Delivery Ratio (%)**					
	SS+KH	SS	FUCHAR	DEEC	TEEN	LEACH
10	95.00	90.00	91.00	91.00	90.00	89.00
20	93.00	91.00	91.00	90.00	89.00	88.00
30	92.00	90.00	89.00	89.00	88.00	86.00
40	92.00	90.00	89.00	88.00	87.00	85.00
50	***91.00***	89.00	88.00	87.00	86.00	84.00

Table 1. Result Analysis of Existing with Proposed SS+KH Method in terms of Various Parameters

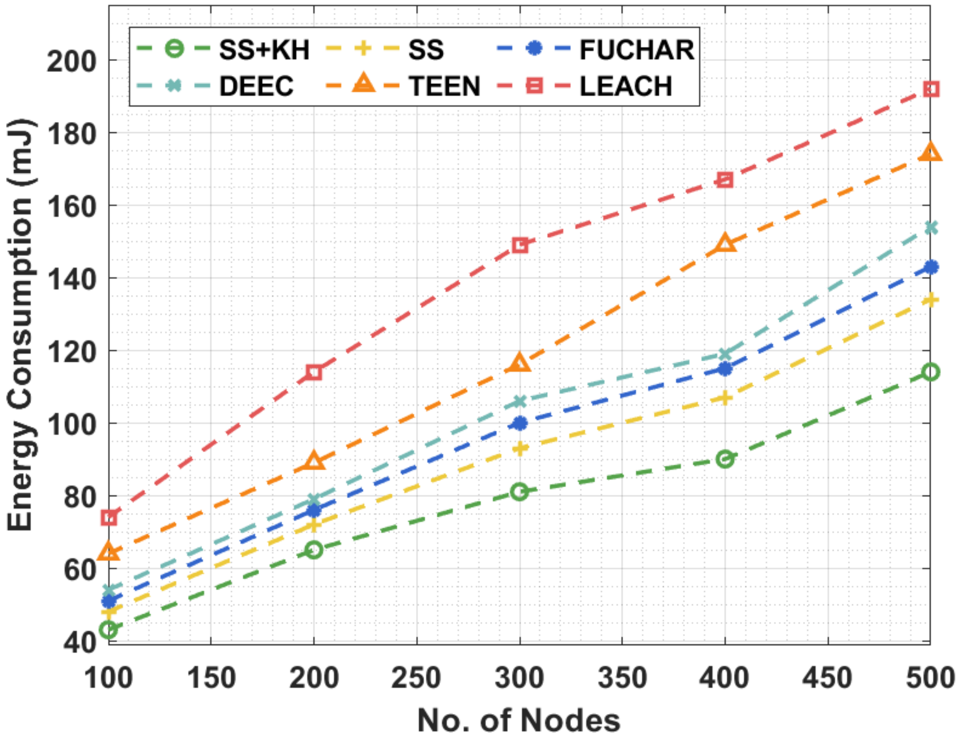

Fig. 1. Energy consumption analysis of SS+KH model

Next, a detailed network lifetime analysis of the SS+KH technique takes place in Fig. 2. The figure reported the enhanced network lifetime performance of the SS+KH technique under varying nodes. For instance, with 10 nodes, the SS+KH technique has demonstrated an improved network lifetime of 6100 rounds whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have attained a decreased network lifetime of 6000, 5800, 5700, 5200, and 5000 rounds respectively. Moreover, with 50 nodes, the SS+KH technique has demonstrated an improved network lifetime of 5400 rounds whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have attained a decreased network lifetime of 5200, 5100, 4900, 4300, and 4100 rounds respectively.

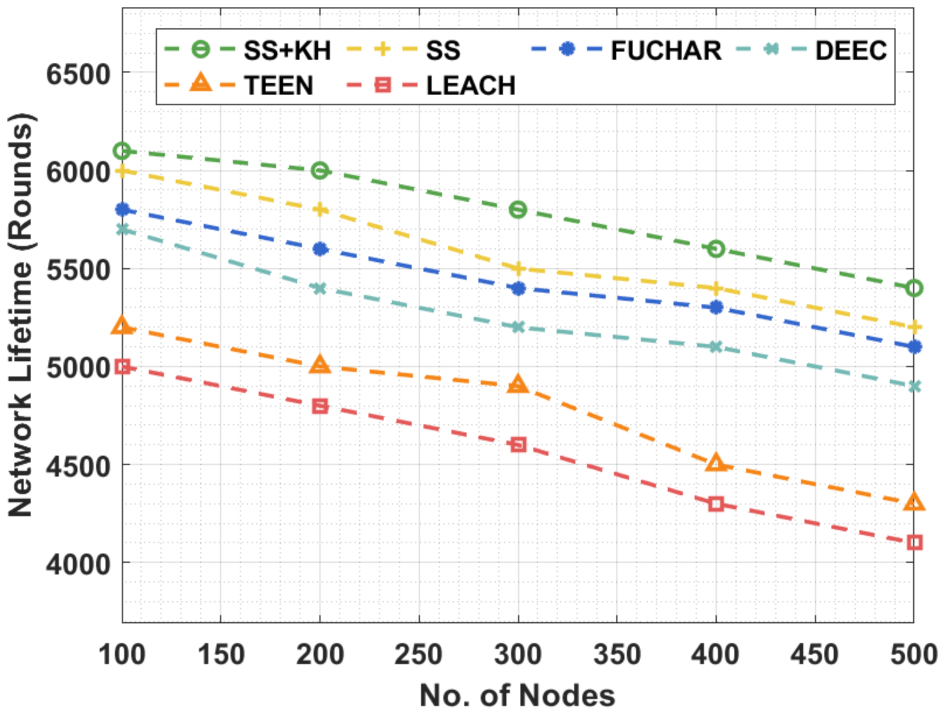

Fig. 2. Network lifetime analysis of SS+KH model

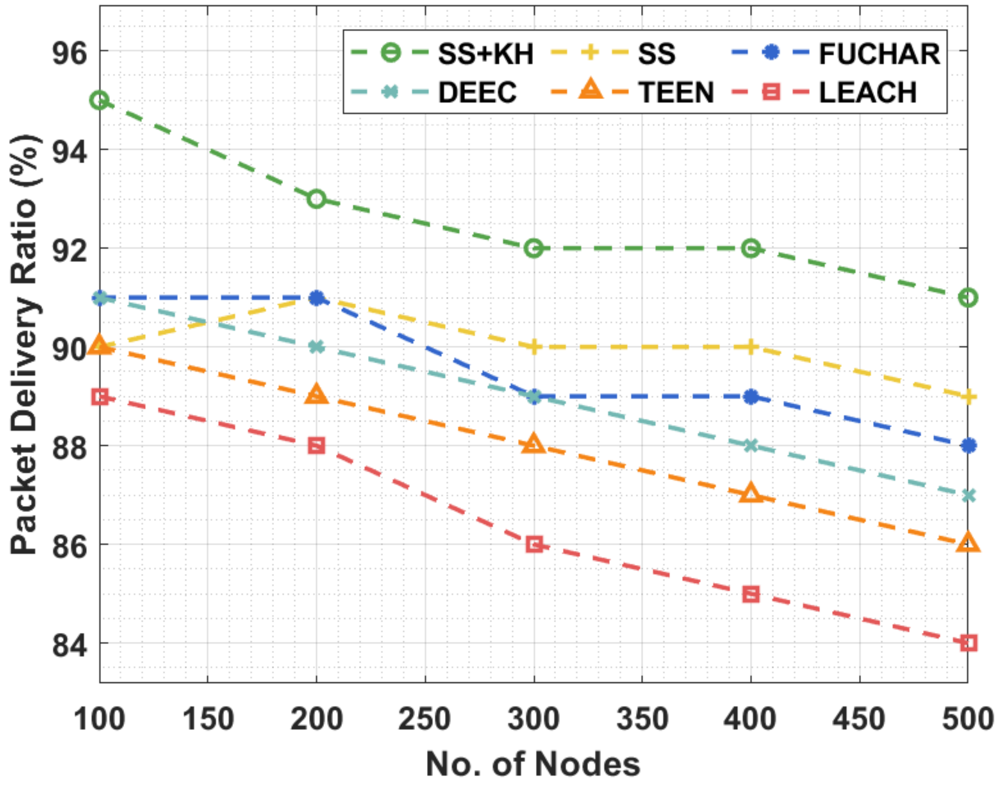

Fig. 3. Packet delivery ratio analysis of SS+KH model

Afterward, a brief PDR analysis of the SS+KH method takes place in Fig. 3. The figure described the higher PDR performance of the SS+KH manner under varying nodes. For instance, with 10 nodes, the SS+KH technique has portrayed a higher PDR of 95% whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have obtained a lesser PDR of 90%, 91%, 91%, 90%, and 89% respectively. Followed by, with 50 nodes, the SS+KH technique has demonstrated an improved PDR of 91% whereas the SS, FUCHAR, DEEC, TEEN, and LEACH methodologies have gained a minimal PDR of 89%, 88%, 87%, 86%, and 84% correspondingly.

Table 2 examines the comparative analysis of the SS+KH technique in terms of distinct measures. Fig. 4 demonstrates the result analysis of the SS+KH technique with respect to ETE delay. The figure outperformed that the SS+KH manner has reached effectual energy efficient performance over the other methods. For instance, with 10 nodes, the SS+KH manner has attained a lesser ETE delay of 2.3s whereas the SS, FUCHAR, DEEC, TEEN, and LEACH manners have achieved a maximal ETE delay. Also, with 50 nodes, the SS+KH manner has offered a minimum ETE delay of 5.4s whereas the SS, FUCHAR, DEEC, TEEN, and LEACH methodologies have accomplished a higher ETE delay.

No. of Nodes	End to End Delay (sec)					
	SS+KH	SS	FUCHAR	DEEC	TEEN	LEACH
10	2.30	2.40	2.45	2.50	3.10	4.40
20	2.60	2.90	3.20	4.00	5.20	5.50
30	3.20	3.60	3.90	5.10	6.40	6.70
40	4.10	4.50	5.10	5.90	8.10	8.40
50	5.40	6.10	6.30	6.50	9.20	9.60
No. of Nodes	Throughput (Mbps)					
	SS+KH	SS	FUCHAR	DEEC	TEEN	LEACH
10	0.96	0.95	0.94	0.93	0.89	0.78
20	0.93	0.89	0.83	0.80	0.76	0.67
30	0.87	0.82	0.74	0.70	0.67	0.58
40	0.79	0.74	0.68	0.63	0.56	0.51
50	0.76	0.70	0.63	0.59	0.51	0.44

Table 2. Result Analysis of Existing with Proposed SS+KH Method in terms of Various Parameters

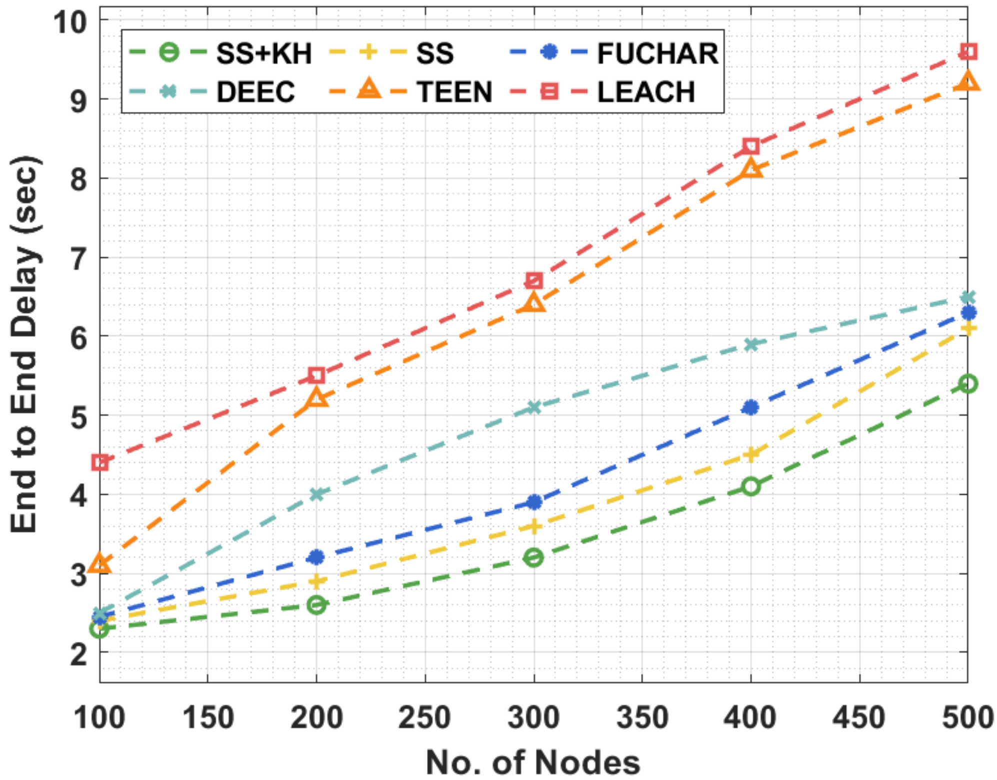

Fig. 4. ETE delay analysis of SS+KH model

Followed by, a detailed throughput analysis of the SS+KH approach takes place in Fig. 5. The figure stated the increased throughput performance of the SS+KH technique under different nodes. For instance, with 10 nodes, the SS+KH technique has exhibited a higher throughput of 0.96Mbps whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have attained a lower throughput of 0.95Mbps, 0.94Mbps, 0.93Mbps, 0.89Mbps, and 0.78Mbps correspondingly. Also, with 50 nodes, the SS+KH method has outperformed an improved throughput of 0.76Mbps whereas the SS, FUCHAR, DEEC, TEEN, and LEACH techniques have gained a minimal throughput of 0.70Mbps, 0.63Mbps, 0.59Mbps, 0.51Mbps, and 0.44Mbps correspondingly.

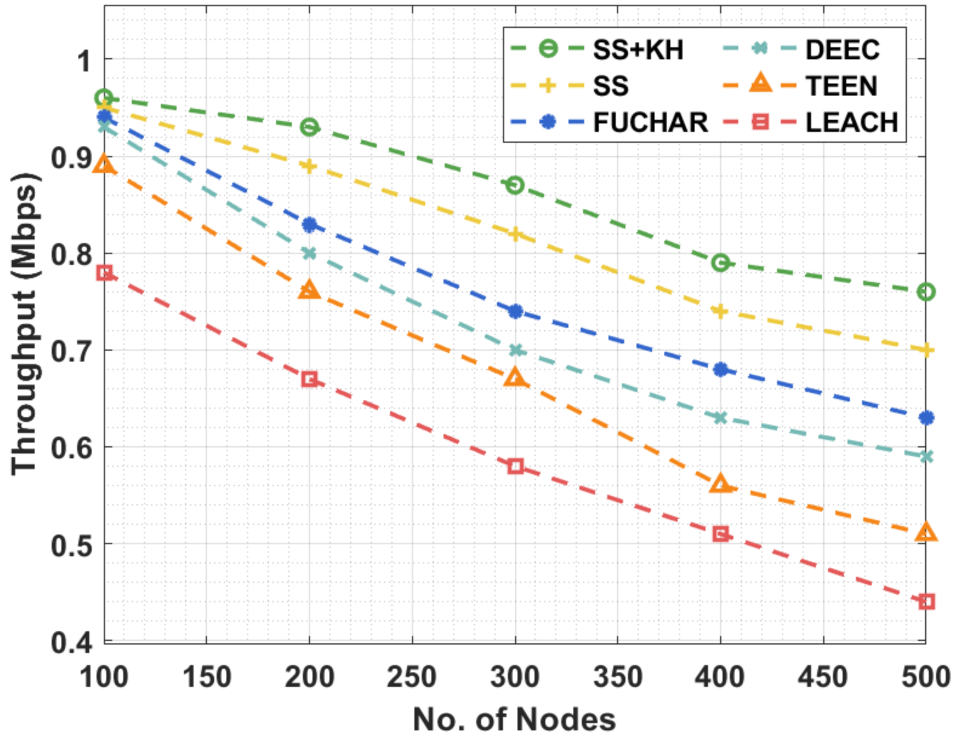

Fig. 5. Throughput analysis of SS+KH model

The compression performance of the BR-BWT technique can be examined in terms of distinct measures in Table 3. The outcomes are analyzed under varying sets. For instance, with set-1, the BR-BWT technique has compressed the original data of 25764 bits into 10363 bits with the CR of 0.402 and CF of 2.486. Moreover, with set-2, the BR-BWT method has compressed the original data of 28061 bits to 12745 bits with the 0.454 of CR and CF of 2.202. Furthermore, with set-3, the BR-BWT methodology has compressed the original data of 27954 bits into 11755 bits with the CR of 0.421 and CF of 2.378. Meanwhile, with set-4, the BR-BWT technique has compressed the original data of 26853 bits into 10628 bits with the 0.396 of CR and 2.527 of CF.

Real Time Data	Original Size (Bits)	Comp. Size (Bits)	Comp. Ratio	Comp. Factor
Set-1	25764	10363	0.402	2.486
Set-2	28061	12745	0.454	2.202
Set-3	27954	11755	0.421	2.378
Set-4	26853	10628	0.396	2.527

Table 3. Result Analysis of BR-BWT on various WSN datasets in terms of Compressed Size, CR, CF

Table 4 investigates the compression performance of the BR-BWT technique in terms of packet size. The table values demonstrated that the proposed BR-BWT technique has significantly reduced the packet sizes on all the applied real time datasets. For instance, with set-1, the BR-BWT technique has compressed the original packet size of 111.051724 bits into 44.668103 bits. Concurrently, with set-2, the BR-BWT manner has compressed the original packet size of 120.952586 bits into 54.935345 bits. Simultaneously, with set-3, the BR-BWT method has compressed the original packet size of 120.491379 bits into 50.668103 bits. Eventually, with set-4, the BR-BWT manner has compressed the original packet size of 115.745690 bits into 45.810345 bits.

Real Time Data	Original packet size (bits)	Compressed packet size (bits)
Set-1	111.051724	44.668103
Set-2	120.952586	54.935345
Set-3	120.491379	50.668103
Set-4	115.745690	45.810345

Table 4. Result Analysis of BR-BWT on various WSN datasets in terms of Packet Size

Real Time Data	Power saving (%)					
	LEC	S-LZW	ALDC	FELACS	BCAT	BR-BWT
Set-1	65.38	66.37	69.02	71.46	74.57	77.02
Set-2	62.18	64.01	66.35	70.45	72.85	74.05
Set-3	48.36	49.29	51.04	56.48	69.48	75.97
Set-4	49.09	50.90	54.38	60.58	69.65	73.61

Table 5. Performance comparison between various compression algorithms in terms of Power saving

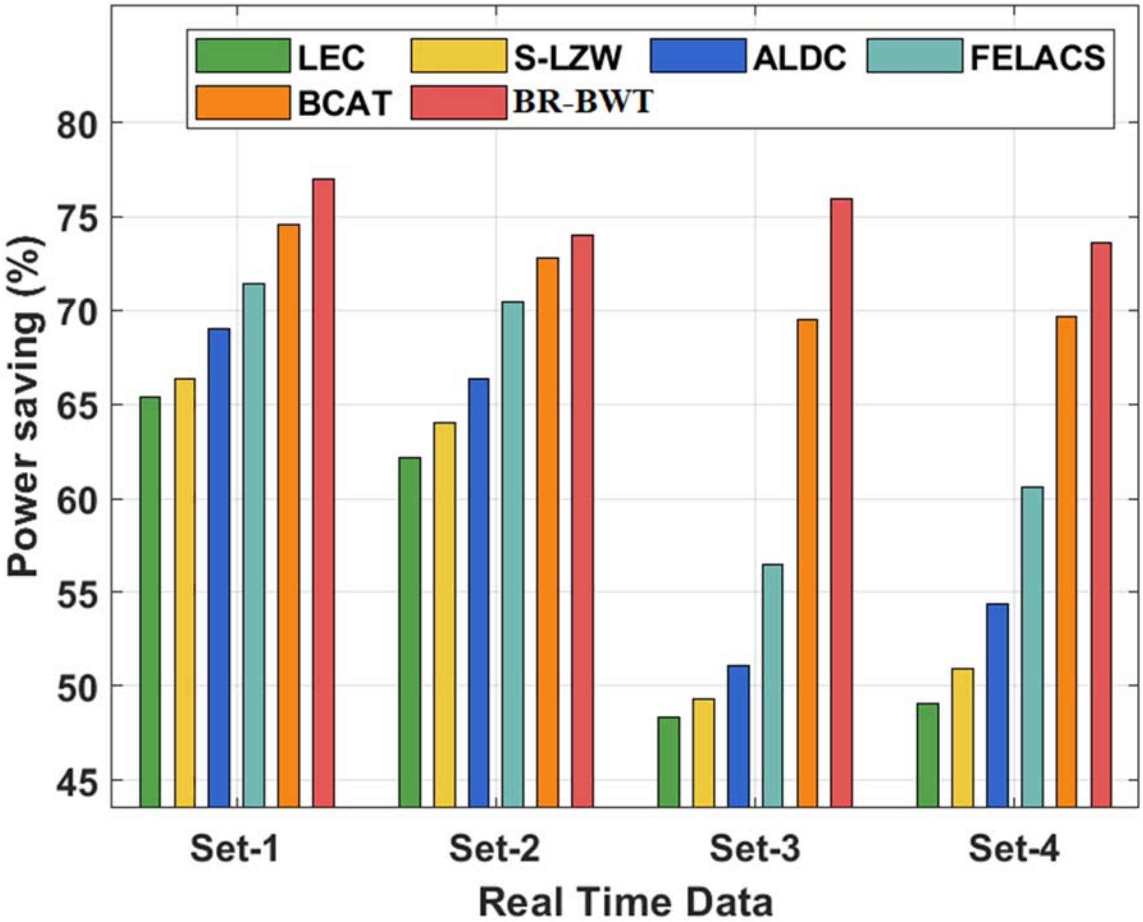

Fig. 6. Power saving analysis of BR-BWT model with existing techniques

Finally, a power saving analysis of the BR-BWT technique with existing techniques is performed in Table 5 and Fig. 6. The simulation outcome demonstrated that the BR-BWT technique has accomplished maximum power saving over the other techniques. For instance, on set-1, the BR-BWT technique has attained a higher power saving of 77.02% while the LEC, S-LZW, ALDC, FELACS, and BCAT techniques have obtained a lower power saving of 65.38%, 66.37%, 69.02%,71.46%, and 74.57% respectively. Also, on set-2, the BR-BWT manner has gained an improved power saving of 74.05% while the LEC, S-LZW, ALDC, FELACS, and BCAT methods have achieved a minimum power saving of 62.18%, 64.01%, 66.35%, 70.45%, and 72.85% correspondingly. Additionally, on set-3, the BR-BWT approach has obtained a superior power saving of 75.97% whereas the LEC, S-LZW, ALDC, FELACS, and BCAT systems have obtained a lower power saving of 48.36%, 49.29%, 51.04%, 56.48%, and 69.48% correspondingly. At last, on set-4, the BR-BWT technique has attained a higher power saving of 73.61% while the LEC, S-LZW, ALDC, FELACS, and BCAT techniqueshave reached a least power saving of 49.09%, 50.90%, 54.38%, 60.58%, and 69.65% correspondingly.

4. Conclusion

This paper has developed a new unequal clustering protocol for data aggregation approach in WSN. Once the nodes are placed, they are initialized and clustering process gets executed using the SS+KH technique. Secondly, The BR-BWT technique has implemented for data aggregation process. An extensive range of simulation analyses is implemented to portray the enhanced performance of the proposed techniques. The experimental results portrayed that the proposed techniques has accomplished maximum energy efficiency. In future, the performance can be extended to the design of lightweight cryptographic techniques to achieve security in WSN.

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