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Fuzzy with Metaheuristics Based Routing for Clustered Wireless Sensor Networks

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Abstract: Wireless sensor network (WSN) plays a vital part in real time tracking and data collection applications. WSN incorporates a set of numerous sensor nodes (SNs) commonly utilized to observe the target region. The SNs operate using an inbuilt battery and it is not easier to replace or charge it. Therefore, proper utilization of available energy in the SNs is essential to prolong the lifetime of the WSN. In this study, an effective Type-II Fuzzy Logic with Butterfly Optimization Based Route Selection (TFL-BOARS) has been developed for clustered WSN. The TFL-BOARS technique intends to optimally select the cluster heads (CHs) and routes in the clustered WSN. Besides, the TFL-BOARS technique incorporates Type-II Fuzzy Logic (T2FL) technique with distinct input parameters namely residual energy (RE), link quality (LKQ), trust level (TRL), inter-cluster distance (ICD) and node degree (NDE) to select CHs and construct clusters. Also, the butterfly optimization algorithm based route selection (BOARS) technique is derived to select optimal set of routes in the WSN. In addition, the BOARS technique has computed a fitness function using three parameters such as communication cost, distance and delay. In order to demonstrate the improved energy effectiveness and prolonged lifetime of the WSN, a wide-ranging simulation analysis was implemented and the experimental results reported the supremacy of the TFL-BOARS technique.

Keywords: Type II-fuzzy logic; uncertainty; WSN; energy; lifetime; route selection

1 Introduction

Wireless sensor networks (WSNs) comprised number of sensors using single-hop or multi-hop transmission [1]. It is a self-organized and dynamic network to transmit and gather the data in specific region, lastly deliver the data to base station (BS) [2]. In practical application, the sensors are often deployed in complex environments and energy-constrained, making it complex to preserve the constrained energy [3]. Thus, the major problem for WSN is to reduce the overall power utilizing and balance the network loads, as well as extend lifetime of the network. In order to resolve the issue, the researcher has presented several routing protocols for extending the lifetime of WSN. Now, clustering routing method is widely employed where all the clusters are created by many adjacent nodes, which comprises of various cluster members and cluster head (CH), further it is separated into clusters [4]. Clustering routing protocol has a different types of benefits namely less load, more scalability, more robustness and less energy consumption. The CH of lower-level system is the clustering members of higher-level system and the CH of topmost level network communicates with the BS network.

Various methods use fuzzy logic system (FLS) [5] for handling uncertainty in WSN. But the abovementioned protocol uses type-1 FLS that could not simply model and handle the uncertainty existing in WSNs since they use precise and crisp type-1 FLS (that is., membership function (MF)) that doesn't enable uncertainty regarding membership value. Since an expansion of concepts of ordinary fuzzy sets (that is, type-1 FS), the model of type-2 FS was presented by Zadeh. A type-2 FS (T2FS) is considered as a fuzzy MF, that is., the membership values for all the elements of FS. The MF of T2FS are 3D and include footprint of uncertainty (FOU) that offer further degrees of freedom which allows us to handle and model directly the uncertainty in WSN [6]. Fig. 1 illustrates the structure of WSN.

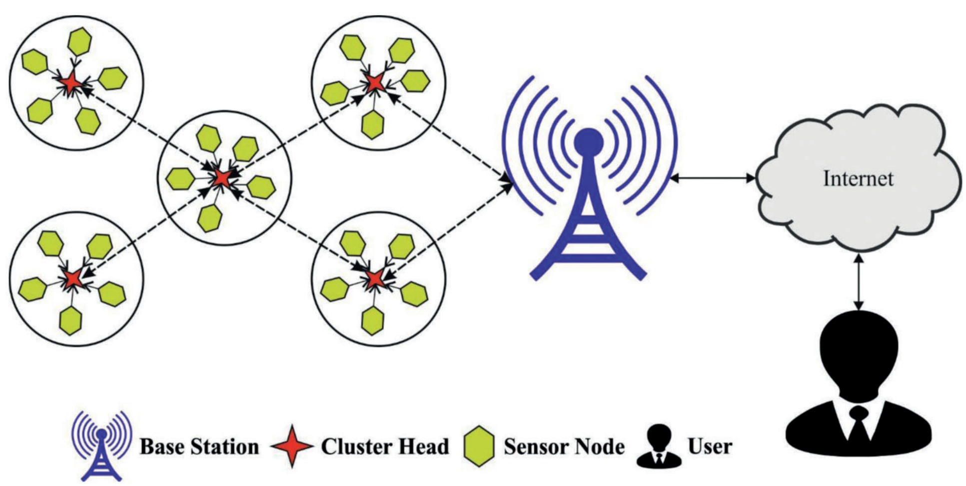

Figure 1: WSN structure

In WSN, routing is difficult to process because of some natural features of WSN that distinguish it from transmission systems, for example, Adhoc network [7]. In the beginning, it isn't possible to create a global addressing system for the placement of several nodes. Thus, traditional IP-related protocol could not be utilized in WSN. Next, different from the transmission systems, most of the WSN application requires flow of the sensed information from various nodes to a certain sink [8]. Then, node senses similar information within the neighborhood of phenomenon, the data traffics has considerable redundancy in it. This redundancy must be applied by the routing approach for improving energy efficacy bandwidth and. AT last, sensors in WSN are extremely controlled interms of processing capacity, transmission power, bandwidth and energy supply. Thus, they needed resource management and careful routing to minimize the overall power utilization [9,10].

This article develops an effective Type-II Fuzzy Logic with Butterfly Optimization Based Route Selection (TFL-BOARS) for clustered WSN. The TFL-BOARS technique applies T2FL technique with distinct input parameters namely residual energy (RE), link quality (LKQ), trust level (TRL), inter-cluster distance (ICD) and node degree (NDE) to select CHs and construct clusters. Moreover, the butterfly optimization algorithm based route selection (BOARS) technique is derived to select optimal set of routes in the WSN. Furthermore, the BOARS technique has computed a fitness function using three parameters such as communication cost, distance and delay. For examining the enhanced energy effectiveness and prolonged lifetime of the WSN, a wide-ranging simulation analysis is carried out.

2 Prior Works on Clustered WSN

Wang et al. [11] introduced an energy-effective clustering routing method. Considering the non-uniform traffic distribution, uneven cluster formation system is presented for energy efficiency and load balancing. Furthermore, a distributed CH rotation method is proposed for balancing power utilization within all the clusters. Since for longer distance communication to BS, we developed a dynamic multi-hop routing method amongst CH nodes-based distance-and-energy-aware cost function for avoiding the energy hole problems. Han et al. [12] an energy-effective clustering routing method has been proposed. To attain the aim of energy preservation, this method considered several clustering factors based on power utilization to choose CHs like number of neighbors through weighting, RE, distance from node to BS and neighbors. Lastly, transform the questions of effective Clustering into the optimization of two variables: weight coefficient W and neighbor transmission range R of cluster factor.

Zhao et al. [13] proposed network architecture and integrates the original power utilization method for constructing a novel methodology for determining the optimum amount of clusters for the overall power utilization reduction. According to the balanced power utilization, we optimized AGglomerative NESting (AGNES) approach includes: (1) the dual-CH (D-CH) divisions of energy balance approach, (2) the node dormancy method and (3) introduction of distance variance. Additionally, the CH priority function is created according to position of node and RE.

Wang et al. [14] introduce a hybrid multiple hop partition-based clustering (HMPBC) routing method that meets interests and needs, fits certain environment, extend lifetime and balance load of the networks. In HMPBC, the single-chain structure within CHs selection and clusters based on RE are functioned using self-organization, as well the region minimal spanning tree model amongst clusters is determined using BS model. Xu et al. [15] presented an energy-effective clustering routing protocol with higher node placement based intercluster routing method (EECRP-HQSND-ICRM) in WSN. Firstly, introduces a formula definition for data redundancy, integrity and validity from the coverage rates as well as presented a node placement method based on two-fold coverage. Next, to fulfill the uniform distribution of CHs, the monitoring fields are separated as the CH is carefully chosen in the separate cells and smaller areas centered on the BS.

3 Design of TFL-BOARS Technique

In this study, a novel TFL-BOARS technique has been developed for clustered WSN to optimally select the CHs and routes in the clustered WSN. Besides, the TFL-BOARS technique incorporates T2FL technique with distinct input parameters to select CHs and construct clusters. Also, the BOARS technique is derived to select optimal set of routes in the WSN.

3.1 Network and Energy Model

Consider N sensor which is located arbitrarily from network domain for monitoring the location and their physical feature periodically [16]. All sensors have neighboring sensors and it transfers information to most neighboring sensors. It can be considered an immobile sensor with equivalent primary energy. The calculation abilities of all sensors were similar. The symmetric radio connects are assumed that amongst some 2 neighboring sensors. The sink was placed inside the network area. Assume that the maximal broadcast of all sensors is R. The adaptive broadcast was regarded as utilizing distance amongst some 2 adjacent sensors. The 1st-order radio method for analyzing the energy utilization of the presented routing. Assume that 7 mm is the size of packet from bits. The energy has required to transmit a m bits of packet across d unit distance amongst sender sensors and among their adjacent sensor is demonstrated as:

$$E_{TX}(m,\ d) = \begin{cases} m * E_{elect} + m * \varepsilon_{fsp} * d^2 \ if\ d < d_o, \\ m * E_{elect} + m * \varepsilon_{mpf} * d^4 \ if\ d \geq d_o. \end{cases} \tag{1}$$

For receiving a m bits of packet, the energy necessity is provided as:

$$E_{RX}(m) = m * E_{elect}, \tag{2}$$

where E_{elect} implies the statistics on the energy dissipate to transmits electron per bit. Many factors like acceptable bit-rate, digital coding and modulation affect the E_{elect}. The ε_{fsp} and ε_{mpf} represents the require of energy from the free-space as well as multipath environments, correspondingly. If the 2 adjacent sensors to that energy procedure were computed are divided with the distance lesser than or equivalent to $\left(l_o = \sqrt{E_{fsp}/E_{mp}}\right)$, the radio method executes Eq. (1) else Eq. (2) for calculating the energy required to broadcast the data.

3.2 Steps Involved in TFL Based Clustering Process

At the initial stage, the TFL-BOARS technique incorporates T2FL technique with distinct input parameters namely RE, LKQ, TRL, ICD and NDE to select CHs and construct clusters [17].

In order to choose the CH, a novel method was utilized named fuzzy logic (FL). This FL is 5 input variables such as RE, LKQ, TRL, ICD and NDE were utilized. Then, the resultant feature is contained with probability of developing as CH (PRCH). Primarily, RE represents the RE of node, LKQ demonstrates the quality of connection, TRL illustrates the intensity of stabilities, ICD defines the distance amongst the nodes and NDE indicates the amount of nodes located towards place. T2FL has 4 levels as demonstrated below:

Fuzzifier

It can be utilized for converting the actual input as fuzzified value. In some input features with respect to linguistic attributes were utilized to choose the CH as well as cluster size which is listed in Tab. 1. At this point, there are any linguistic parameters to RE that are low, medium and high. Likewise, the linguistic feature of DBS is near, far, farthest but ND is minimum, moderate, maximum, correspondingly.

Table 1: Variables with linguistic values

Variables	Linguistic values
RE	LO, AG, HH
LKQ	LO, MM, HH
TRL	LO, MM, HH
ICD	NR, FR, FT
NDE	LO, AG, HH
PRCH	VP, PR, BAG, AG, AAG, SG, VSG

Fuzzy rules/Inference engine

The framework of T1FL and T2FL are the same. At this point, the group of 27 rules was implemented. Afterward, a set of fuzzy rules to CH and decided cluster size. So, the rule was offered in Eq. (3).

$$Rule\ (i) IF\ x1\ is\ A_1(i)\ AND\ x2\ is\ A_2(i)\ AND\ x3\ is\ A_3(i)$$

$$THEN\ y1\ is\ B_1(i) AND\ y2\ is\ B_2(i) \tag{3}$$

where i is i^{th} rule in a fuzzy rule, A_1, A_2 and A_3 are matching fuzzy sets of x_1, x_2 and x_3. The rule base suggestion engine has constrained with 27 rules and created based on Mamdani Inference method. The group of fuzzy rules is provided in Tab. 2. Evaluation of union as well as intersection is important. Fig. 2 demonstrates the process of Type-II Fuzzy Logic technique.

Table 2: Sample Fuzzy rule set

Input parameters					Output parameters
RE	LKQ	TRL	ICD	NDE	PRCH
L	LO	LO	NR	LS	VP
L	MM	MM	NR	LS	PR
L	HH	HH	NR	LS	BAG
L	LO	LO	FR	LS	PR
L	MM	MM	FR	LS	BAG
L	HH	HH	FR	LS	AG
L	LO	LO	FRT	LS	BAG
L	MM	MM	FRT	LS	AG
L	HH	HH	FRT	LS	AAG
A	LO	LO	NR	AG	PR
A	MM	MM	NR	AG	BAG
A	HH	HH	NR	AG	AG
A	LO	LO	FR	AG	BAG
A	MM	MM	FR	AG	AG
A	HH	HH	FR	AG	AAG
A	LO	LO	FRT	AG	AG
A	MM	MM	FRT	AG	AAG
A	HH	HH	FRT	AG	AG
H	LO	LO	NR	HH	AAG
H	MM	MM	NR	HH	SG
H	HH	HH	NR	HH	BAG
H	LO	LO	FR	HH	AG
H	MM	MM	FR	HH	AAG
H	HH	HH	FR	HH	AG
H	LO	LO	FRT	HH	AAG
H	MM	MM	FRT	HH	SG
H	HH	HH	FRT	HH	VSG

Note: where LS-Less, A-Average, HH-high, NR-Near, FR-Far, FT-Farthest, LO-Low, MM-Medium, VP-Very poor, PR-Poor, BAG-Below Average, AAG-Above Average, SG-Strong, VSG-Very Strong.

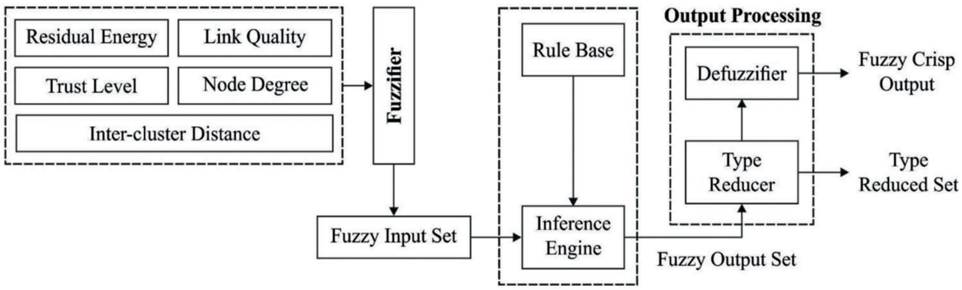

Figure 2: Process of Type-II fuzzy logic

T2FL has been demonstrated as supervised membership function (MF) and inferior MF. This expression is demonstrated in the application of T1FL MF. Then, the space in 2 functions represents the Footprint of Uncertainty (FOU) which explains the T2FL set. Supposing FOU was offered as f. When $f \in [0, 1]$ and f →0, so MF is named as T1FL. Once $f \rightarrow 0$ to 1, afterward T2FL contains distinct range in FOU amongst zero to one. But, the progress of rules from T2FL is same as T1FL which is written as:

$$Type2\ FL = Principal\ MF\ (Type\ 1\ FL) + FOU \tag{4}$$

If the PRCH was received, it transmits the message to target node. This message was enclosed with node ID and PRCH measures. The sensor node (SN) that is superior probabilities was chosen as CH and broadcasts CH_WON to equivalent SN less SN receives many CH_WON in neighboring SNs. In this regard, it sends a CH_JOIN message and merges with nearer CH. During the retrieve CH_JOIN message, neighboring CH verifies the provided cluster size from previous to get novel member.

If the SN receives a CM_REJECT message, afterward it re-transmission CM_JOIN message to future CH without assumptions of distant CH that is repeating still a novel CH was explored. Besides, the SN is not be integrated with another CH that endures inside a coverage area 'R', afterward, it chooses as CH. Therefore, all SNs go to cluster where the divided SN is from VANET. From the processing of different rounds, for eliminating the premature death of CH, rotation function was implemented by CH. If the RE of CH was superior if related to threshold value, afterward CH rotation exists. But RE of CH exceeds a threshold value, a novel CH is chosen utilizing PRCH. As function remove the initial death of CH and improve the network lifespan.

Type reducer/Defuzzifier

This technique generates a T1FL outcome that is restructured to mathematical outcome afterward the execution of defuzzifier was done.

3.3 Steps Involved in BOARS Technique

Once the clusters are constructed, the BOARS technique is derived to select optimal set of routes in the WSN using three parameters such as communication cost, distance and delay. The BOA imitates the natural performance of butterflies on mating and food source find [18]. This technique implements 2 distinct navigation designs for searching the area. During the exploration stage $(r_1 \leq p)$, butterfly move near optimum butterflies of colony but during the exploitation stage $(r_1 > p)$, butterflies carry out an arbitrary search inside the search spaces by moving near arbitrary butterflies from the colony [19]. These 2 search designs are mathematically expressed as:

if $r_1 \leq p$, Global search

$$^{t+1}X_i = {}^{t}X_i + \left(r_2^2 \times g^* - {}^{t}X_i\right) \times \varphi_i \tag{5}$$

if $r_1 > p$, Local search

$$^{t+1}X_i = {}^{t}X_i + (r_3^2 \times {}^{t}X_j - {}^{t}X_k) \times \varphi_i \tag{6}$$

where t and $t+1$ correspondingly represent the present and upgrade state of equivalent variable. Besides, the place of optimum butterflies from the colony was demonstrated by g^*, and ${}^{t}X_i$ and ${}^{t}X_k$ signifies the places of 2 arbitrarily chosen butterflies; r_1, r_2 and r_3 stands for the 3 arbitrary scalars uniformly selected in zero and one, φ_i implies the fragrance factor and it can be determined as under:

$$\varphi_i = cI^a \tag{7}$$

where, φ_i refers the fragrance magnitude to i^{th} butterfly; I and a signifies the intensity of stimulating and fluctuating absorption degree and c has been coefficient. I has connected to main function value and to i^{th} butterflies it can be obtained as $f(X_i)$,where f returns main function value of problem. The coefficients of a and c are chosen in intervals of zero and one,· p stands for the probability switch that defines the search performance of this technique.

The BOARS method focuses on simultaneously reducing the delay, cost and distance of the BS. Where S indicates a set of $\xi\ (i,\ j\ =\ 1,\ 2,\ \ldots,\ m)$ and ξ represent a sojourn point, $d_{i,j}$ shows the distance from ξ_i to ξ_j, $C_{i,j}$ represent the cost of moving from ξ_i to ξ_j, as well as $\tau_{i,j}$ signifies the traveling delay from ξ_i to ξ_j. The decision parameter 0 is shown below. When the objective function to minimize the delay, cost and distance are shown in the following.

$$\Gamma_{i,j} = \begin{cases} 1\ if\ \ \xi_j\ is\ visited\ from\ \xi_i \\ 0\ otherwise \end{cases} \tag{8}$$

$$\mathbb{C} : Min \sum_{i}^{m} \sum_{j}^{m} C_{i,\,j}\,\Gamma_{i,\,j} \tag{9}$$

$$\mathbb{D} : Min \sum_{i}^{m} \sum_{j}^{m} d_{i,\,j}\,\Gamma_{i,\,j} \tag{10}$$

$$\mathbb{T} : Min \sum_{i}^{m} \sum_{j}^{m} \tau_{i,\,j}\,\Gamma_{i,\,j} \tag{11}$$

when the optimization constraint is $\sum_{i}^{m} \Gamma_{i,j}\ = 1$ for every i and j, the estimated path mustn't be selected repeatedly $\left(\Gamma_{i,j} + \Gamma_{j,i} \leq 1\right)$ and $\Gamma_{i,j} \geq 1$.

4 Experimental Validation

The experimental result analysis of the TFL-BOARS technique takes place with recent methods [12] under varying measures. A comparison study is made with Energy efficient cluster formation (EECF), Energy Aware Clustering Hierarchy Protocol (EACHP) and Well Pattern Optimization with Energy Efficient Chain-based Routing Protocol (WPO-EECRP). Tab. 3 and Fig. 3 demonstrates the number of alive node (NOAN) analysis of the TFL-BOARS system with other models under the node count of 100.

The results show that the TFL-BOARS algorithm can attain higher NOAN over the other methods. For instance, with 100 rounds, the TFL-BOARS system has offered an increased NOAN of 100 nodes but the EECF, EACHP and WPO-EECRP algorithms have obtained lower NOAN of 89, 94 and 97 nodes respectively. Likewise, with 300 rounds, the TFL-BOARS algorithm has gained a superior NOAN of 87 nodes while the EECF, EACHP and WPO-EECRP algorithms have resulted in inferior NOAN of 22, 39 and 73 nodes respectively. Moreover, with 600 rounds, the TFL-BOARS algorithm has exhibited improved NOAN of 11 nodes whereas the EECF, EACHP and WPO-EECRP approaches have accomplished reduced NOAN of 0, 0 and 1 node respectively.

Table 3: NOAN analysis of TFL-BOARS technique under 100 nodes

No. of alive nodes (100 nodes)				
No. of rounds	EECF	EACHP	WPO-EECRP	TFL-BOARS
0	100	100	100	100
50	97	99	100	100
100	89	94	97	100
150	84	79	92	98
200	76	75	87	98
250	51	56	80	92
300	22	39	73	87
350	6	19	67	79
400	4	14	55	72
450	3	8	43	63
500	2	5	34	52
550	0	3	19	42
600	0	0	1	11

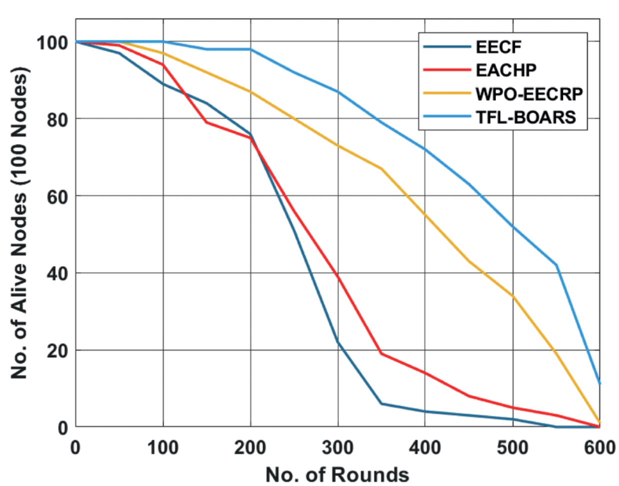

Figure 3: Comparison NOAN study of TFL-BOARS technique under 100 nodes

A comparative number of dead node (NODN) analyses of the TFL-BOARS algorithm with existing algorithms under 100 nodes are offered in Tab. 4 and Fig. 4. The results exhibited that the TFL-BOARS system has exhibited maximum lifetime with the minimal NODN. For instance, with 100 rounds, the TFL-BOARS algorithm has provided a least NODN of 0 nodes whereas the EECF, EACHP and WPO-EECRP approaches have offered higher NODN of 11, 6 and 3 nodes. Concurrently, with 300 rounds, the TFL-BOARS technique has provided a least NODN of 13 nodes whereas the EECF, EACHP and WPO-EECRP techniques have offered higher NODN of 78, 61 and 27 nodes. Simultaneously, with 600 rounds, the TFL-BOARS technique has accomplished minimal NODN of 0 nodes whereas the EECF, EACHP and WPO-EECRP techniques have resulted in maximum NODN of 100, 100 and 99 nodes.

Table 4: NODN analysis of TFL-BOARS technique under 100 nodes

No. of dead nodes (100 nodes)				
No. of rounds	EECF	EACHP	WPO-EECRP	TFL-BOARS
0	0	0	0	0
50	3	1	0	0
100	11	6	3	0
150	16	21	8	2
200	24	25	13	2
250	49	44	20	8
300	78	61	27	13
350	94	81	33	21
400	96	86	45	28
450	97	92	57	37
500	98	95	66	48
550	100	97	81	58
600	100	100	99	89

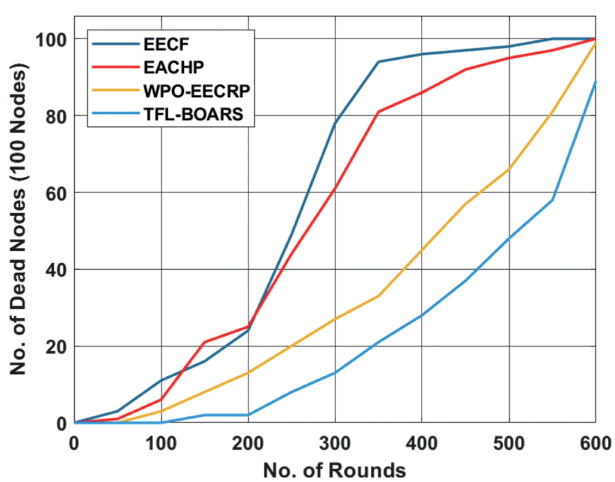

Figure 4: Comparison NODN study of TFL-BOARS technique under 100 nodes

Tab. 5 and Fig. 5 illustrate the NOAN analysis of the TFL-BOARS approach with other methods under the node count of 200. The outcomes demonstrated that the TFL-BOARS approach has the offered of achieving superior NOAN over the other methods. For instance, with 100 rounds, the TFL-BOARS algorithm has offered an increased NOAN of 198 nodes whereas the EECF, EACHP and WPO-EECRP systems have obtained lower NOAN of 169, 175 and 194 nodes correspondingly. At the same time, with 300 rounds, the TFL-BOARS algorithm has reached a superior NOAN of 174 nodes whereas the EECF, EACHP and WPO-EECRP techniques have resulted in inferior NOAN of 88, 114 and 157 nodes correspondingly. Besides, with 600 rounds, the TFL-BOARS approach has demonstrated higher NOAN of 87 nodes whereas the EECF, EACHP and WPO-EECRP methods have accomplished reduced NOAN of 0, 4 and 47 nodes correspondingly.

Table 5: NOAN analysis of TFL-BOARS technique under 300 nodes

No. of alive nodes (200 nodes)				
No. of rounds	EECF	EACHP	WPO-EECRP	TFL-BOARS
0	200	200	200	200
50	197	191	200	200
100	169	175	194	198
150	137	162	184	195
200	124	155	175	189
250	116	136	165	181
300	88	114	157	174
350	68	83	144	162
400	42	55	128	148
450	16	30	114	136
500	8	13	94	120
550	5	8	72	105
600	0	4	47	87
650	0	0	24	65
700	0	0	5	33

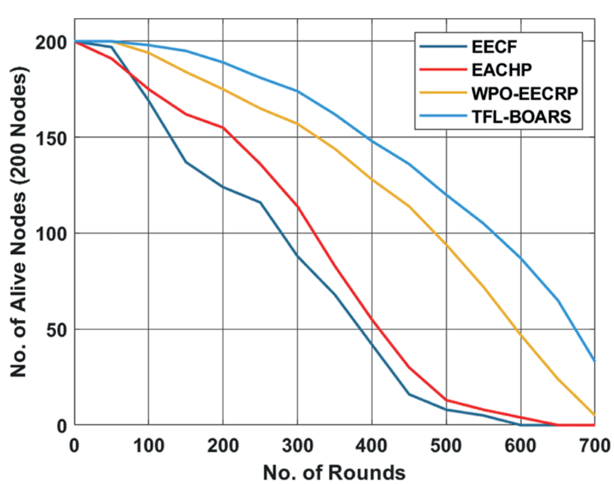

Figure 5: Comparison NOAN study of TFL-BOARS technique under 200 nodes

A comparative NODN analysis of the TFL-BOARS method with existing systems under 200 nodes is offered in Tab. 6 and Fig. 6. The results exhibited that the TFL-BOARS technique has exhibited increased lifetime with the minimal NODN. For instance, with 100 rounds, the TFL-BOARS approach has provided a worse NODN of 2 nodes whereas the EECF, EACHPs and WPO-EECRP techniques have obtainable higher NODN of 31, 25 and 6 nodes. Concurrently, with 300 rounds, the TFL-BOARS algorithm has provided a least NODN of 26 nodes whereas the EECF, EACHP and WPO-EECRP techniques have offered higher NODN of 112, 86 and 43 nodes. Concurrently, with 600 rounds, the TFL-BOARS system has accomplished lesser NODN of 113 nodes whereas the EECF, EACHP and WPO-EECRP methodologies have resulted in increased NODN of 200, 196 and 153 nodes.

Table 6: NODN analysis of TFL-BOARS technique under 200 nodes

No. of dead nodes (200 nodes)				
No. of rounds	EECF	EACHP	WPO-EECRP	TFL-BOARS
0	0	0	0	0
50	3	9	0	0
100	31	25	6	2
150	63	38	16	5
200	76	45	25	11
250	84	64	35	19
300	112	86	43	26
350	132	117	56	38
400	158	145	72	52
450	184	170	86	64
500	192	187	106	80
550	195	192	128	95
600	200	196	153	113
650	200	200	176	135
700	200	200	195	167

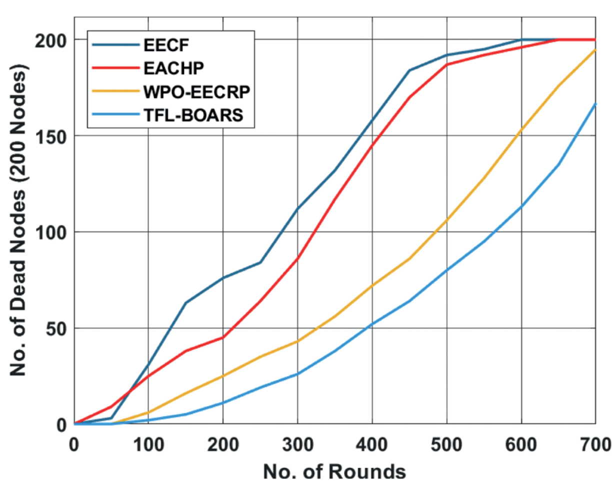

Figure 6: Comparison NODN study of TFL-BOARS technique under 200 nodes

A detailed RE analysis of the TFL-BOARS technique with other methods under 100 nodes is provided in Fig. 7. The experimental values reported the supremacy of the TFL-BOARS technique with the higher RE. For instance, with 100 rounds, the TFL-BOARS approach has obtainable an increased RE of 43J whereas the EECF, EACHP and WPO-EECRP methodologies have reached lesser RE of 38J, 38J and 41J correspondingly. Also, with 300 rounds, the TFL-BOARS method has achieved a superior RE of 29J whereas the EECF, EACHP and WPO-EECRP methodologies have resulted in inferior RE of 13J, 15J and 24J correspondingly. In addition, with 500 rounds, the TFL-BOARS methodology has exhibited improved RE of 14J whereas the EECF, EACHP and WPO-EECRP techniques have accomplished reduced RE of 0, 0 and 10J correspondingly.

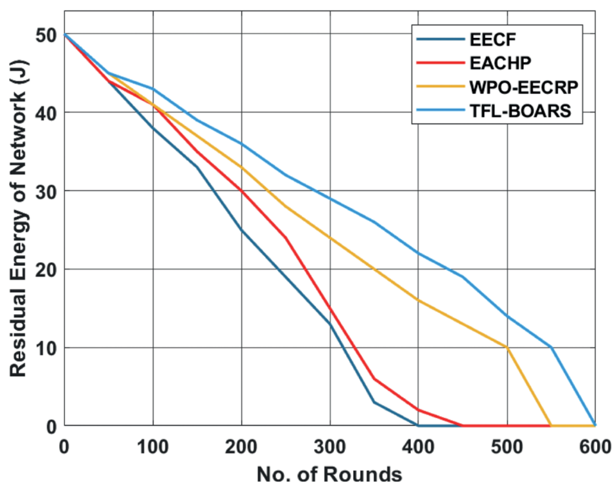

Figure 7: Comparison RE study of TFL-BOARS technique under 100 nodes

Finally, a detailed RE analysis of the TFL-BOARS technique with other algorithms under 200 nodes is offered in Fig. 8. The experimental values reported the supremacy of the TFL-BOARS technique with the higher RE. For instance, with 100 rounds, the TFL-BOARS technique has offered a higher RE of 184J whereas the EECF, EACHP and WPO-EECRP approaches have obtained reduced RE of 159J, 167J and 185J respectively. Followed by, with 300 rounds, the TFL-BOARS system has reached a superior RE of 132J whereas the EECF, EACHP and WPO-EECRP techniques have resulted in inferior RE of 63J, 99J and 114J correspondingly. Eventually, with 500 rounds, the TFL-BOARS system has exhibited improved RE of 72J whereas the EECF, EACHP and WPO-EECRP methods have accomplished reduced RE of 22J, 27J and 58J correspondingly. From the above mentioned result analysis, it is ensured that the presented model has the ability to prolong the lifetime of the WSN.

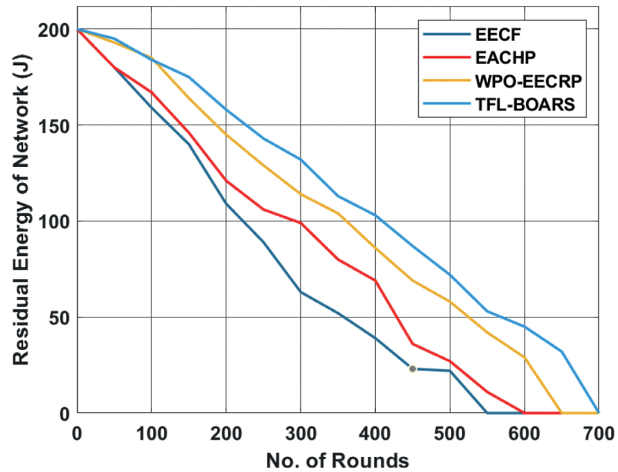

Figure 8: Comparison RE study of TFL-BOARS technique under 200 nodes

5 Conclusion

In this study, a novel TFL-BOARS technique has been developed for clustered WSN to optimally select the CHs and routes in the clustered WSN. Besides, the TFL-BOARS technique incorporates T2FL technique with distinct input parameters namely RE, LKQ, TRL, ICD and NDE to select CHs and construct clusters. Followed by, the BOARS technique is derived to select optimal set of routes in the WSN. In addition, the BOARS technique has computed a fitness function using three parameters such as communication cost, distance and delay. For examining the enhanced energy effectiveness and prolonged lifetime of the WSN, a wide-ranging simulation analysis is carried out. The comparative experimental results reported the supremacy of the TFL-BOARS technique over the recent approaches. In the future, the lifetime of WSN can be further prolonged by the design of data compression approaches.

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