FLOC: HESITANT FUZZY LINGUISTIC TERM SET ANALYSIS IN ENERGY HARVESTING OPPORTUNISTIC CLUSTERING USING RELATIVE THERMAL ENTROPY AND RF ENERGY TRANSFER

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ABSTRACT

Limited energy resources and sensor nodes' adaptability with the surrounding environment play a significant role in the sustainable Wireless Sensor Networks. This paper proposes a novel, dynamic, self-organizing opportunistic clustering using Hesitant Fuzzy Linguistic Term Analysis- based Multi-Criteria Decision Modeling methodology in order to overcome the CH decision-making problems and network lifetime bottlenecks. The asynchronous sleep/awake cycle strategy could be exploited to make an opportunistic connection between sensor nodes using opportunistic connection random graph. Every node in the network observe the node gain degree, energy welfare, relative thermal entropy, link connectivity, expected optimal hop, link quality factor etc. to form the criteria for Hesitant Fuzzy Linguistic Term Set. It makes the node to evaluate its current state and make the decision about the required action ('CH', 'CM' or 'relay'). Our proposed scheme leads to an improvement in network lifetime, packet delivery ratio and overall energy consumption against existing benchmarks.

KEYWORDS

Graph Theory, Wireless Sensor Networks, Hesitant Fuzzy Linguistic Term Set, Opportunistic Routing and RF Energy Transfer.

1. INTRODUCTION

Power-constrained WSNs have to adjust their sleep/wake cycle according to the application requirements in order to maximize the network lifetime and overall energy consumption [1]. Sectional failure and thermal exposure can cause significant damage to sensor nodes. Moreover, different units of a sensor node behave differently when exposed in sunlight for long period of time for example; the performance of a typical transceiver is degraded with the increase in temperature. The purpose of deploying WSNs is to achieve a shared goal through sensor collaboration and data aggregation. In order to allocate the resources to sensor nodes effectively, topology architecture is needed in which sensors are organized in clusters [1]. The multi-hop routing in this clustering topology can result in the decrease of overall energy consumption and interference among sensor nodes due to specific timeslots allocation [2]. In addition to it, it could also effectively optimize the data redundancy by significantly reducing the collected data size using data aggregation techniques at Cluster Head (CH) level [1-2].

Researchers have proposed different node scheduling techniques to save battery power of sensor nodes i.e. synchronous and asynchronous sleep/awake scheduling. Asynchronous sleep/awake scheduling is designed to prolong the network lifetime and improve energy utilization by creating an opportunistic node connection between sensor nodes in the network [3-6]. Opportunistic Routing (OR) is a popular technique to ensure sustainable operation of sensor nodes in which WSNs can benefit from wireless medium broadcasting characteristics by selecting appropriate candidate forwarders. The performance of OR significantly depends on several key factors, such as OR metric, candidate selection algorithm, and candidate coordination method. Based on the asynchronous sleep/awake scheduling in OR, a node can sense, process, and transmit/receive during its active state [3-4]. Researchers have also worked on temperature adaptive sleep/awake scheduling techniques [7-8].

The Hesitant Fuzzy Linguistic Term Set (HFLTS) is the best way to deal with this uncertainty. The fuzzy multi-criteria analysis presents an effective framework where the alternative actions are ranked according to the nodes' assessments concerning each criterion. This motivated us to work on this problem [9]. Keeping in view OR and temperature adaptive sleep/awake scheduling, we have selected multiple parameters including time-frequency parameter, node's gain energy, relative thermal entropy, expected optimal hops, link quality factor in terms of signal-to-noise ratio, as our attributes of hesitant fuzzy linguistic term set. These attributes are used to assess the role of nodes and self adaptively make the appropriate decision in a round of operation. Furthermore, our proposed scheme FLOC uses this information in a Multi-Attribute Decision Modelling (MADM) framework to efficiently utilize our hesitant fuzzy linguistic term set to incorporate a qualitative assessment of the parameters by a node and help the node observe a situation adaptive role transition.

The rest of the paper is organized as follows: Section 2 contains the discussion on some related works. System modelling is presented in Section 3. Our proposed scheme FLOC is presented in Section 4. HFLTS analysis is provided in Section 5. Section 6 presents the simulation framework and performance evaluation of the proposed technique. Finally, section 7 concludes the paper with some targeted future works.

2. RELATED WORK

Various researchers have focused on proposing different routing protocols for WSNs based on different parameters such as end–end delay, packet delivery ratio, network lifetime, overall energy consumption, control packet overhead etc. Ogundile et al. [1] presented a detailed survey for energy-efficient and energy balanced routing protocols for WSNs including the taxonomy of cluster-based routing protocols for WSNs. Routing protocols in WSNs can be segmented into two main categories, i.e., hierarchical and non-hierarchical routing protocols. Non-hierarchical routing protocols are designed in accordance with overhearing, flooding, and sink node position advertisement, whereas hierarchical routing protocols are designed on the basis of grid, tree, cluster and area [1-3][10]. The multi-dynamic (higher-tier and lower-tier) roles of sensor nodes in hierarchical routing can be useful in reducing energy consumption and traffic overhead. Higher-tier nodes are responsible to store the information related to current position of mobile sink whereas lower-tier nodes acquire this information by soliciting the higher-tier nodes [11]. Different hierarchical routing protocols have their own merits and demerits, but as far as cluster-based hierarchical routing protocols are concerned, researchers have been challenged with a task of achieving an optimal balance between end–end delay and energy consumption [10-11].

Yang et al. [5] introduced the utilization of sleep/awake cycle of sensor nodes to prolong the network lifetime. The sleep/awake cycle can be segmented into two categories—synchronous and asynchronous sleep/awake cycle. Depending on the network connectivity requirements in terms of traffic coverage, Mukherjee et al. [12] proposed an asynchronous sleep/awake scheduling technique with a minimum number of sensor nodes to achieve the required network coverage. As a result of asynchronous sleep/awake scheduling, opportunistic node connections are established between sensor nodes and their neighbours, which brings the need of Opportunistic Connection Random Graph (OCRG) theory to properly model the opportunistic node connections by forming a spanning tree. Anees et al. [6] proposed an energy-efficient multi-disjoint path opportunistic node connection routing protocol for smart grids (SGs) neighbourhood area networks (NAN). Anees et al. [10] also proposed a delay-aware energy-efficient opportunistic node selection in restricted routing for delay-sensitive applications. In this protocol, the information related to updated position of sink is advertised by multiple ring nodes and data is forwarded to mobile sink using ring nodes having maximum residual energy.

In a few asynchronous sleep/awake scheduling techniques, the sensor nodes are found to remain inactive listening mode for a long amount of time, resulting in unnecessary consumption of energy. A popular WSN MAC protocol, Sensor Medium Access Control (SMAC), has been proposed by Ye et al. [13]. SMAC protocol lets the node listen for a fixed interval of time and turn their radio off (sleep state) for a fixed duration. Barkley-MAC (BMAC) [14] provides an adaptive preamble sampling technique to effectively reduce the duty cycle and idle listening by the sensor nodes. Shah et al. [22] devised a guaranteed lifetime protocol in which the sink node assigns sleep/awake periods for other nodes depending on residual energy, sleep duration, and coverage by the nodes. A mathematical model for temperature adaptive sleep/awake strategy is developed by Bachir et al. [8] with three proposed algorithms i.e. Stop Operate (SO), a Power control (PC), and Stop-Operate-Power-Control (SOPC). The sensor nodes running any of the algorithms are supposed to observe the contemporary state based on a pre-calculated relationship between node-density and temperature. Thermal entropy of the sensor nodes has been explored in the intelligent sleep-scheduling technique iSleep [15]. Reinforcement Learning based sleep-scheduling algorithm RL-Sleep has been proposed in [7] in which the authors have used a temperature model and Q-learning technique to switch the sleep/awake states adaptively, depending on the environmental situation.

It has been revealed through a detailed literature review that most of the clustering schemes consider energy efficiency, traffic distribution, or coverage efficiency as the prime criteria for state-scheduling and decision modelling of sensor nodes instead of relative thermal entropy, temperature adaptability or hesitant fuzziness used for nodes' role transition etc. A few entropy-based clustering schemes have been proposed in which entropy weight coefficient method is adopted for decision making in cluster-based hierarchical routing protocol [16-18]. Multi-Criteria Decision Analysis (MCDA) and Multi-Attribute Sensors Decision Modelling (MADM) using entropy weight coefficients are also types of entropy weight-based multi-criteria decision routing [16]. Anees et al. [19] proposed hesitant fuzzy entropy based opportunistic clustering and data fusion algorithm for heterogeneous WSNs. In this algorithm, the local sensory data is gathered from sensor nodes by utilizing hesitant fuzzy entropy based multi-attribute decision modelling for cluster head election procedure.

Afsar et al. [20] proposed an unequal size clustering method known as CREST in which the probability of becoming CH in a cluster is based on a function of the distance between BS and the node by employing track-based algorithms. Varshney et al. [21] proposed an emerging concept of simultaneous wireless information and power transfer (SWIPT) in which both energy and data are transferred over RF links simultaneously. Guo et al. [22] utilized the concept of the SWIPT to extend the network lifetime of a clustered WSN by wirelessly charging the relay nodes which are responsible to share data with BS. Zhou et al. [23] proposed dynamic power splitting (DPS) to adjust the power ratio of information encoding and energy harvesting in EHWSNs. Anees et al. [24] proposed harvested energy scavenging and transfer capabilities in opportunistic ring routing in which a distinguishing approach of hybrid (ring + cluster) topology is used in a virtual ring structure and then a two-tier routing topology is used in the virtual ring as an overlay by grouping nodes into clusters.

Overall, to the best of our knowledge, there is no published literature which focuses on thermal entropy-based HFLTS analysis for energy-efficient opportunistic clustering. In this paper, we have considered a set of attributes that regulate the nodes' decisions about its role transition conducive to the current situation in a cluster and provided a detailed solution for optimally handling problems in energy efficient opportunistic clustering using relative thermal entropy based HFLTS analysis. The comparison between FLOC and various scheduling algorithms is given in Table 1.

Table 1. Comparison between FLOC and various scheduling algorithms

Attributes / Articles	Network Lifetime	Heterog--eneity	Conectivity	Mobility pattern	Energy Efficiency	Thermal Entropy	Traffic Distribution	Energy Harvesting	Coverage
[6]	√	√	√	√	√	x	x	x	x
[7]	√	√	x	x	√	x	√	x	x
[8]	√	√	√	x	√	√	x	x	x
[34]	√	x	√	x	√	√	x	x	x
[10]	√	√	√	√	√	x	x	x	x
[12]	√	√	√	√	√	x	x	x	x
[15]	√	x	√	x	√	x	x	x	x
[13]	√	x	x	x	√	x	x	x	x
[14]	√	x	x	x	√	x	√	x	x
[35]	√	x	√	x	√	x	√	x	√
[15]	√	√	√	x	√	x	x	x	x
[36]	√	x	x	x	√	x	x	x	√
[37]	√	x	√	x	√	x	x	x	√
[38]	√	x	x	x	√	x	x	x	√
[24]	√	√	√	√	√	x	x	√	x
[29]	√	x	√	x	√	x	x	x	x
[33]	√	x	√	x	√	x	√	x	x
FLOC	√	√	√	√	√	√	√	√	√

3. SYSTEM MODELLING

3.1. Network model

A MxM network area denoted as A is considered for FLOC in which N sensor nodes are deployed randomly and independently. We have assumed that sensor nodes follow a uniform distribution. The node-density of the network is denoted as $\lambda_0 = \frac{N}{A}$. All sensor nodes use short radio range (RS) for sensing and transmission purposes whereas sink nodes can use RS for transmission & reception and long radio range (RL) for data collection tasks using a tag message. However, all sensor nodes can exploit the power control function and communicate with different neighbouring nodes within various power levels. A probe message is shared by each sensor node to acquire the neighbour information as discussed in [6]. Each sensor node is equipped with a power splitting radio, which is composed of a signal processing unit to transfer energy to or from neighbours using RF link. Moreover, it is also assumed that every sensor node is aware of its position using the energy-efficient localization method [25-28]. Each sensor node is characterized by a set of k attributes named as $C = \{c_1, c_2, \dots . c_k\}$ and a set of weights $w_t = \{w_{t1}, w_{t2}, \dots . w_{tp}\}$ is assigned by sensor node to the p criteria of C. Furthermore, the sensor node undergoes y states i.e. $ST = \{ST_1, ST_2, \dots . ST_y\}$, where ST_1 represents the favorable state (attribute values are above threshold) and ST_y represents the stressed state. Depending on multiple parameters, the sensor node decides about the most suitable action against the contemporary state i.e. $AC = \{CH, CM, Relay\}$.

3.2. Energy Model

The energy consumption model [10] for radio energy dissipation during transmission and reception is considered in which the energy required to transmit l bits of data over distance d can be given in (1) as:

$$E_{Tx}(V_i, V_j) = \begin{cases} E_{elec}l + \varepsilon_{fs} l d^2_{V_iV_j} & d < d_0 \\ E_{elec}l + \varepsilon_{mp} l d^4_{V_iV_j} & d \geq d_0 \end{cases} \tag{1}$$

where E_{elec} is the energy spent by transmitter on running the radio electronics, ε_{fs} is the free space energy dissipated by power amplifier depending on the Euclidean distance $d_{V_iV_j}$ between the transmitter and receiver, ε_{mp} is the muti-path fading factor for energy dissipated by power amplifier depending on Euclidean distance $d_{V_iV_j}$ between transmitter and receiver. The threshold distance d_o is given as $d_o = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$. Likewise, the energy required to receive l bits of data over distance d is given in (2) as:

$$E_{Rx} = E_{elec}l \tag{2}$$

The energy used for sensing l bits of data in the virtual ring at the beginning of each round can be given as $E_{sense} = E_{elec}l$. Accordingly, the total energy consumed by cluster member (CM) can be computed in (3) as:

$$E_{CM} = E_{sense} + E_{Tx} = E_{elec}l + E_{elec}l + \varepsilon_{fs} l d^2_{V_iV_j} \tag{3}$$

Each CH is responsible for data gathering, aggregating the received data and then relaying that data towards sink, so the total energy consumed by a CH can be computed in (4) - (5) as

$$E_{CH} = E_{sense} + \left(\frac{N}{N_C} - 1\right) E_{Rx} + \left(\frac{N}{N_C}\right) l E_A + \left(\frac{N}{r}\right) E_{Tx} \tag{4}$$

$$E_{CH} = E_{elec}l + \left(\frac{N}{N_C} - 1\right) E_{elec}l + \left(\frac{N}{N_C}\right) l \frac{E_{elec}}{R_{CC}} + \left(\frac{N}{r}\right) E_{elec}l + \left(\frac{N}{r}\right) \varepsilon_{mp} l d^4_{V_iV_j} \tag{5}$$

where N_C represents the number of clusters in the network, $\frac{N}{N_C}$ is the number of working sensor nodes per cluster in which we have 1 CH and $\frac{N}{N_C} - 1$ CMs. E_A signifies the data aggregating energy at CH level, r represents the compression ratio and R_{CC} symbolizes the communication to computation ratio.

4. PROPOSED SCHEME FLOC

In this section, the proposed scheme FLOC is discussed in detail. The sink node launches data collection by broadcasting a tag message containing the mobile sink address and data collection duration. Sensor nodes calculate their working-sleeping cycle keeping in view the data collection duration of the mobile sink. Subsequently, each sensor node broadcasts a probe message containing source address, broadcast address, working-sleeping schedule, neighbour address, total energy, thermal entropy and Expected Optimal Hop (EOH) [6].

4.1. Ambient Temperature and Relative Thermal Entropy

Keeping in view the diurnal temperature variation caused by solar radiation, the sensor nodes placed under direct sunlight absorb higher heat energy than the sensor nodes in shadow. According to temperature model in [7], the temperature of a sensor node i after solar heat absorption for amount of time Δt can be represented in (6) as,

$$T_{t+\Delta t}^{i} = max\left\{T_t^i + \frac{(S_{SUN}(t)\alpha(t) - \eta T^4)}{c_p\theta} Area_{sen}\Delta t, T_t^i\right\} \quad (6)$$

where T_t^i is the temperature of a node i at time t, $S_{SUN}(t)$ denotes the amount of radiation by the sun at that time, $\alpha(t)$ is the temporal variation of sun exposure, $Area_{sen}$ is the exposed area through which the sensor node absorbs solar heat, η is Boltzman constant, θ represents the mass of the sensor node, c_p represents the specific heat and $T_{t+\Delta t}^{i}$ symbolizes the ambient temperature. The change in temperature of a sensor node can be extracted from equation (7) i.e.

$$\Delta T_i = \frac{(S_{SUN}(t)\alpha(t) - \eta T^4)}{c_p\theta} Area_{sen}\Delta t \quad (7)$$

The resultant temperature T_i of a sensor node i is given as $T_i = T_{t+\Delta t}^{i} = T + \Delta T_i$. Foregoing in view, the solar radiation pattern for a day can be represented as $S_{SUN}(t) = S_{SUN}^{max} exp^{\frac{-(t-\rho)^2}{2\sigma^2}}$, $0 \leq t \leq 2\rho$ where S_{SUN}^{max} is the peak value of the solar radiation during the day [7]. Let T_i be the temperature of the ith node and T_H be the highest temperature for which the ith node becomes non-operational. The probability of failure of a sensor node due to temperature increase can be represented as $p_i = \frac{T_i}{T_H}$, where T_i can be acquired from equation (6) & (7) and T_H symbolizes the highest temperature the sensor node can withstand. Here we have assumed that T_H is the same for all sensor nodes in the network. The cumulative effect of failure likelihood leads to network instability; therefore we need a probability distribution function (PDF) to measure the degree of uncertainty in the sensor network. This hesitancy or irresolution resembles entropy.

The entropy H(X) of a random variable $X = \{x_1, x_2, \ldots x_n\}$ having probability distribution as p(X) can be given as $H(X) = -\sum_{x \in X} p(x) log_2 p(x)$ for $0 \leq$ H(X) ≤ 1 [10]. Similarly, the Shannon's entropy at ith node can be defined as $H(p_i) = -p_i log_2 p_i$. The relative contribution of a sensor node towards the probable instability of the network can be estimated using relative thermal entropy by calculating the entropy in neighborhood i.e.

$$H_{rel}^{therm} = \frac{H(p_i)}{\sum_{j \in nbr_i} H(p_j)} \quad (8)$$

where H_{rel}^{therm} indicates the relative thermal entropy and nbr_i represents the neighbourhood dataset in equation (8).

4.2. Energy Transfer and Asynchronous Sleep/Awake Cycle

We have assumed that the sensor nodes in the network are able to control their power levels in order to communicate with the neighbours. In this perspective, the amount of energy a node i could acquire from its neighbouring sensor node j through RF transfer can be defined in equation (9) and (10) as:

$$E_{trans(V_j,V_i)} = \eta_1 \mu P_j |h_{V_i,V_j}|^2 = \eta_1 \mu P_j |\beta_1 d_{(V_i,V_j)}^{-\alpha_1}|^2 \tag{9}$$

$$\Gamma_{V_i} = \sum_{j=1}^{k} E_{trans(V_j,V_i)} = \sum_{j=1}^{k} \eta_1 \mu P_j |\beta_1 d_{(V_i,V_j)}^{-\alpha_1}|^2 \tag{10}$$

where $E_{trans(V_j,V_i)}$ is the amount of energy node j can transfer to its neighbor i, η_1 is the energy conversion efficiency 0 <η_1< 1, μ is the energy and data splitting ratio 0 <μ< 1, P_j is the signal power received from node j, h_{V_i,V_j} is the channel gain, β_1 is a constant which depends on the radio propagation properties of the environment, α_1 is the path loss exponent, and $\Gamma_{V_i}$is the node V_i's gain degree. Furthermore, the total available energy at node i can be computed as:

$$E_{T(V_i)} = \Gamma_{V_i} + E_{Bat(V_i)} \tag{11}$$

where $E_{Bat(V_i)}$ is the remaining battery energy of node i in (11). In contrast to conventional routing algorithms in WSNs, our proposed scheme can serve both data and energy in its routing topology. We used opportunistic connection random graph (OCRG) in FLOC to model the opportunistic node connections between sensor nodes. Let $G(S_{SN}, O_C, L)$ be the graph representing OCRG in which S_{SN} represents the set of nodes in the network, O_C represents set of opportunistic connections existing between any two adjacent neighbours and L represents the link connectivity of any two adjacent nodes in S_{SN}. The link connectivity also depends on the data routing cost $DR_C: O_C \rightarrow R$ such that $DR_C(i,j)$ is the cost associated with link (i,j). Our routing metric can be defined as: $Min \sum_{i=1}^{n-1} DR_{C(V_i,V_{i+1})}$, $DR_{C(V_i,V_{i+1})} \geq 0$. The data routing cost can be computed using $E_{C(V_i,V_j)}$, $E_{T(V_i)}$ and $E_{T(V_j)}$ and is given in (12).

$$DR_{C(V_i,V_j)} = \frac{E_{C(V_i,V_j)}}{(E_{T(V_i)} + E_{T(V_j)})} \tag{12}$$

where $E_{C(V_i,V_j)}$ is the transmission energy consumed over link (i,j), $E_{T(V_i)}$ is the available total energy (including battery and gained energy through RF transfer) of node i, $E_{T(V_j)}$ is the available energy (including battery and gained energy through RF transfer) of node j. It is pertinent to mention that energy is also transferred along with the data in the routing process to compensate for the transmission energy consumed over each link and more energy is conserved than consumed as the sensor nodes are using strong signals for transmission purposes.

As far as asynchronous sleep/awake cycle is concerned, we have proposed the concept of sleep/awake cycle schedule (W_v/S_v) and status transition frequencies (F_{ST}) to investigate the opportunistic node connection between sensor nodes in each data collection period. We calculated the time-frequency parameter $TF_{V_iV_j}$ based on working time W_{V_i} and W_{V_j} of sensor nodes V_i and V_j, data collection duration T_{CP}, status transition frequencies F_{ST_i} and F_{ST_j} in equation (13) and (14) as,

$$TF_{V_iV_j} = \left(\frac{F_{STV_i}}{F_{ST_{max}}} \times \frac{W_{V_i}}{T_{CP}}\right)\left(\frac{F_{STV_j}}{F_{ST_{max}}} \times \frac{W_{V_j}}{T_{CP}}\right) \tag{13}$$

$$TF_{V_iV_{SINK}} = \left(\frac{F_{STV_i}}{F_{ST_{max}}} \times \frac{W_{V_i}}{T_{CP}}\right)\left(W_{V_{SINK}}\right) \quad (14)$$

Using the time-frequency parameter $TF_{V_iV_j}$ and data routing cost DR_C, our link connectivity $L_{V_iV_j}$ can be computed in (15) as,

$$L_{V_iV_j} = \alpha_2 DR_C(i,j) + (1-\alpha_2)TF_{V_iV_j} \quad (15)$$

$$L_{V_iV_j} = \alpha_2 \left(\frac{E_{C(V_i,V_j)}}{(E_{T(V_i)} + E_{T(V_j)})}\right) + (1-\alpha_2)\left(\frac{F_{STV_i}}{F_{ST_{max}}} \times \frac{W_{V_i}}{T_{CP}}\right)\left(\frac{F_{STV_j}}{F_{ST_{max}}} \times \frac{W_{V_j}}{T_{CP}}\right) \quad (16)$$

where α_2 is the appropriate weight assigned to data routing cost and time-frequency parameter in (16).

4.3. Expected Optimal Hop (EOH):

In order to minimize the energy consumption, we employed the expected optimal hops (*EOH*) approach. *EOH* can be defined as the number of hops needed to forward a probe message from any node to the mobile sink node with minimum energy consumption [6]. Assuming that there is B-bit data from node V_i to be forwarded to the mobile sink V_{SINK} along the path (V_i,V_{SINK}, k), where k is the hops on the path and satisfies $1 \le k \le N-1$. To unify the path representation, V_{SINK} is represented by V_{i+k} which means that it needs k hops to forward a probe message from V_i to V_{SINK} . Then, the energy consumption function with respect to k for this forwarding can be calculated in equation (17) as follows:

$$\begin{aligned} C_{V_i}(k) = \sum_{j=0}^{k-1}(E_T + E_R) &= \sum_{j=0}^{k-1}\left\{\left[E_{elec} + \varepsilon_{amp} d^2_{(V_{i+j},V_{i+(j+1)})}\right]B + E_{elec}B\right\} \\ &= 2kE_{elec}B + \varepsilon_{amp}\sum_{j=0}^{k-1}\left[d^2_{(V_{i+j},V_{i+(j+1)})}\right]B \end{aligned} \quad (17)$$

To get the minimum value of $C_{V_i}(k)$, we can use the average value inequality to derive inequality of $C_{V_i}(k)$ which can be described in equation (18) as:

$$C_{V_i}(k) \ge 2kE_{elec}B + \frac{\varepsilon_{amp}\left[\sum_{j=0}^{k-1} d_{(V_{i+j},V_{i+(j+1)})}\right]^2 B}{k} \quad (18)$$

Since the sum of the distances for any two adjacent nodes on the path (V_i, V_{i+k}, k) satisfies the following inequality in equation (19):

$$\sum_{j=0}^{k-1} d_{(V_{i+j},V_{i+(j+1)})} \ge d_{(V_i,V_{i+k})} \quad (19)$$

Therefore, the minimum energy consumption function $C_{V_i}^{min}(k)$ with respect to k satisfies equation (20):

$$C_{V_i}^{min}(k) = 2kE_{elec}B + \frac{\varepsilon_{amp}\left[d_{(V_i,V_{i+k})}\right]^2 B}{k} \quad (20)$$

To get the value of k that can minimize $C_{V_i}^{min}(k)$, we can take the first derivative of $C_{V_i}^{min}(k)$ with respect to k in equation (21) as follows:

$$\frac{\partial\, C_{V_i}^{min}}{\partial k} = 2E_{elec}B - \frac{\varepsilon_{amp}\left[d_{(V_i,V_{i+k})}\right]^2 B}{k^2} \tag{21}$$

Let $\frac{\partial\, C_{V_i}^{min}}{\partial k}$ equal to 0, so that we can get a value of $k_{expected}$ as $\sqrt{\frac{\varepsilon_{amp}}{2E_{elec}}}d_{(V_i,V_{i+k})}$. Therefore, the $C_{V_i}^{min}(k)$ has a minimum value at $k = k_{expected}$, and since V_{i+k} represents V_{SINK}, so the value of EOH for node V_i in equation (22) will be:

$$EOH_{V_i} = \sqrt{\frac{\varepsilon_{amp}}{2E_{elec}}}d_{(V_i,V_{SINK})} \tag{22}$$

where E is the basic energy consumed during transmission and reception per bit, ε_{amp} is the energy consumed by the transmission amplifier, $d_{(V_i,V_{SNK})}$is the distance between node V_i and V_{SINK} and EOH_{V_i} is the expected optimal hops of node V_i needed to select proper forwarders to the mobile sink with minimum energy consumed.

4.4. Energy-welfare (EW)

Energy balance is required for a properly active WSN. The measure of energy distribution pattern among sensor nodes can be represented by a parameter known as Energy welfare. We use EW to provide us an estimate of energy balance within sensor node's neighborhood. Equation (23) can be used to formulate the EW.

$$EW = \left(\frac{1}{nbr_i}\sum_{j\in NB_i}\left(Energy_j\right)^{(1-\varepsilon)}\right)^{\frac{1}{(1-\varepsilon)}} \tag{23}$$

where nbr_i is the number of neighbors of node i, NB_i is the set of actual neighbors of i, $Energy_j$is the residual energy of actual neighbors. ε is the inequality aversion factor and its value will be 1.5, 2.0 or 2.5. In our case, we have chosen $\varepsilon = 2.0$. We have also normalized the value of EW as its one of the attributes involved in decision modeling and also a member of hesitant fuzzy set. The normalized value of EW can be represented as,

$$EW_{norm} = \frac{EW_{recent}}{EW_{max}} \tag{24}$$

where EW_{recent} is the recent value of EW obtained during the current iteration in equation (24).

4.5. Link Quality Factor (LQF)

We measure the link quality factor in terms of the signal-to-noise ratio between sensor nodes. The acceptable dynamic range of sensor nodes for signal-to-noise ratio is 10-15 dB [6]. The ambient temperature increase due to solar radiation could affect the As we are dealing with opportunistic clustering environment where the mobility of sink node could result in the intermittency of communication links between sensor nodes and sink, LQR should be selected as one of the decision attributes in HFLTS analysis.

5. HESITANT FUZZY LINGUISTIC TERM SET (HFLTS) ANALYSIS

A generalization of the basic fuzzy set which deals with the uncertainty starting from the hesitation in the assignment of membership degrees of an element is known as Hesitant Fuzzy Set (HFS) [9-10,16-18]. We start the HFLTS analysis with a set of inputs containing a total number of nodes, sink, neighbour information, context-free grammar, transformation function, set of alternatives, set of criteria and weight assignment. In FLOC, a node can attain two states based on the node's gain energy and energy welfare. The state evaluation of a node will be 'optimistic' if its total energy is greater than the threshold and the normalized energy welfare is greater than half of the maximum value of energy welfare. Likewise, the state evaluation of a node will be 'pessimistic' if its total energy is less than the threshold and the normalized value of energy welfare is less than the half of the maximum value of energy welfare. After evaluating the state and acquiring the neighbourhood information, the node calculates the relative thermal entropy with reference to neighbourhood. The next step is to store different attributes in an array and perform the data standardization by normalizing different attributes to obtain the fractional representation of attributes within [0 1] before defining the criteria [29-33]. The pseudo code for FLOC is given in Algorithm 1.

$\boldsymbol{Algorithm\ 1}: \boldsymbol{FLOC}$
$\boldsymbol{INPUT}$: 1. $Number\ of\ nodes\ \boldsymbol{N}$, $Sink\ node \boldsymbol{V_{SINK}}$ 2. $Context\ free$ grammar $\boldsymbol{G_{CF}}$ $(\boldsymbol{V_N}, \mathbf{V_T}, \boldsymbol{I}, \boldsymbol{P})$, $transformation\ function\ \boldsymbol{E_{GCF}}$ 3. $\boldsymbol{Alternatives} = \{CH, CM, Relay\}$ 4. $\boldsymbol{Criteria}$, $\boldsymbol{w_t} = \{w_1, w_2, \ldots w_{\lvert Criteria \rvert}\}$ 5. $Linguistic\ term\ set\ \boldsymbol{S} = \{\boldsymbol{s_1} : \boldsymbol{negligible(n)}, \boldsymbol{s_2} : \boldsymbol{very\ low(vl)}, \boldsymbol{s_3} : \boldsymbol{low(l)}, \boldsymbol{s_4} : \boldsymbol{medium(m)}, \boldsymbol{s_5} : \boldsymbol{high(h)}, \boldsymbol{s_6} : \boldsymbol{very\ high(vh)}, \boldsymbol{s_7} : \boldsymbol{perfect(p)}\}$ 6. $Mobile\ sink\ broadcasting\ SID\ and\ data\ collection\ duration\ to\ all\ nodes\ within\ Rl$ 7. $Sensor\ nodes\ within\ Rl\ receive\ the\ data\ collection\ message$ $\boldsymbol{OUTPUT}$: 8. State Evaluation of the node $\boldsymbol{BEGIN:}$ 9. $\boldsymbol{For}$ $each\ node\ i \in (N - V_{SINK})$, $\boldsymbol{do}$ 10. $\boldsymbol{If\ Energyremain}(i) \le E_{Thresh}$ 11. $\boldsymbol{Action(i)} = 'Sleep'$ 12. $\boldsymbol{EndIf}$ 13. $\boldsymbol{End\ For}$ 14. $\boldsymbol{Calculate}$ $the\ working\text{–}sleeping\ cycle\ and\ status\ transition\ frequencies$ 15. $\boldsymbol{Estimate}$ $the\ distance\ between\ sensor\ node\ and\ mobile\ sink\ using\ RSSI$ 16. $\boldsymbol{Find}$ $own\ temperature\ Ti \leftarrow T + \Delta T$ using (6) 17. $\boldsymbol{Calculate}$ $probability\ of\ failure\ pi \leftarrow \frac{T_i}{T_{H_i}}$ 18. $\boldsymbol{Calculate}$ $Entropy\ H(p_i) = -p_i log_2 p_i$ 19. $\boldsymbol{Calculate}$ $Entropy\ of\ neighborhood\ subgraph\ as\ H(SG_i) \leftarrow \sum_k H(SG_i), k \in C_i$ 20. $\boldsymbol{Find}$ $relative$ thermal entropy using (8) 21. $\boldsymbol{Find}$ $Node\ gain\ degree\ and\ total\ energy\ using$ (10) and (11) 22. $\boldsymbol{Find}$ $Energy\ Welfare\ (EW)\ using$ (23) 23. $\boldsymbol{Calculate}$ $Link\ connectivity\ for\ each\ opportunistic\ connection\ using$ (16) 24. $\boldsymbol{Find}$ $Expected\ Optimal\ Hops\ (EOH)\ using$ (22) 25. $\boldsymbol{Determine}$ $the\ Link\ Quality\ Factor\ (LQF)$ 26. $\boldsymbol{Form\ Criteria} = \{E_{T(V_i)}, EW, H_{rel}^{therm}, L_{V_iV_j}, EOH, LQR\}$ 27. $\boldsymbol{Normalize}$ $the\ values\ in$ $\boldsymbol{Criteria}$ 28. $\boldsymbol{Use}$ $triangular\ fuzzy\ membership\ function\ and\ G_{CF}\ to\ generate\ equation$ (27) 29. $\boldsymbol{Use}$ $transformation\ function\ E_{GCF}\ to\ generate\ the\ HFLTS$ i.e. H_S 30. $\boldsymbol{Use}$ $1 - cut\ HFLTS\ to\ generate\ the\ decision\ matrix\ Y$ 31. $\boldsymbol{State} = State\_Evaluatio(E_{T_{initial}}, E_{T_{remain}}, EWnormalized, EWmax)$ 32. $\boldsymbol{If}$ $state = \boldsymbol{Optimistic}$ 33. $\boldsymbol{Action} = \boldsymbol{RetainFunc}(Alternatives, Criteria, Y)$

34. ***EndIf***
35. ***If*** *state* = ***Pessimistic***
36. ***Action*** = ***ChangeFunc***(*Alternatives*, *Criteria*,*Y*)
37. ***EndIf***

The set of required actions of a sensor node is known as alternatives which can be denoted as {'CH', 'CM', 'Relay'} and the suitable action chosen by the sensor node i from alternatives is based on the criteria defined in equation (25) i.e.,

$$Criteria = \left\{ \begin{array}{c} Node\ gain\ degree \\ Energy\ Welfare \\ Relative\ thermal\ entropy \\ Link\ Conn \\ Expected\ Optimal\ Hop \\ Link\ quality\ factor \end{array} \right\} = \{E_{T(V_i)}, EW, H_{rel}^{therm}, L_{V_iV_j}, EOH, LQR\} \quad (25)$$

And the corresponding weights assigned to the members defining the criteria will be $w_T = \{w_1, w_2, \ldots w_{|Criteria|}\}$, $|Criteria|$ is the cardinality of Criteria. Now we assume our linguistic term set as,

$$S = \left\{ \begin{array}{c} s_1{:}Extremely\ low(el) \\ s_2{:}very\ low(vl) \\ s_3{:}low(l) \\ s_4{:}medium(m) \\ s_5{:}high(h) \\ s_6{:}very\ high(vh) \\ s_7{:}perfect(p) \end{array} \right\} \quad (26)$$

The normalized attribute values after data standardization in the hesitant fuzzy set are converted to linguistic term set S using triangular membership function as depicted from Figure 2. A context-free grammar G_{CF} [7] has been used to produce linguistic terms for the alternatives against different values of the criteria. These HFS membership values are then transformed into HFLTS using a transformation function E_{GCF} as shown in equation (27) and (28).

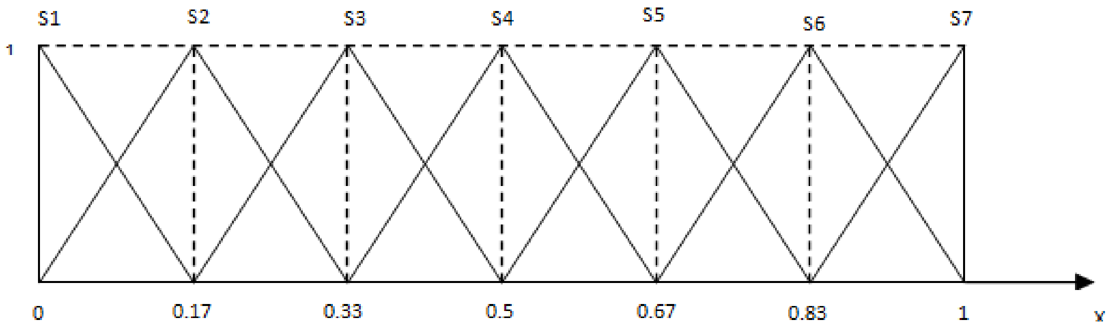

Figure 1. Linguistic term set conversion using triangular membership function

$$H = \begin{array}{c} \\ x_1 \\ x_2 \\ x_3 \end{array} \begin{array}{cccccc} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \\ \end{array}$$
$$\begin{array}{c} x_1 \\ x_2 \\ x_3 \end{array} \begin{bmatrix} greater\ than\ h & greater\ than\ h & lower\ than\ m & greater\ than\ h & lower\ than\ m & between\ h\ and\ p \\ between\ l\ and\ h & between\ v_l\ \&\ h & between\ l\ and\ v_h & greater\ than\ m & between\ l\ and\ v_h & between\ m\ and\ v_h \\ greater\ than\ l & between\ v_l\ \&\ h & lower\ than\ h & greater\ than\ m & lower\ than\ m & between\ h\ and\ p \end{bmatrix} \quad (27)$$

where, $c_1 = Node\ gain\ degree$, $c_2 = Energy\ Welfare$, $c_3 = Relative\ thermal\ entropy$, $c_4 = Link\ Connectivity$, $c_5 = Expected\ Optimal\ Hop$, $c_6 = Link\ quality\ factor$, $x1$ = CH state, $x2$ = CM state, $x3$ = Relay state. Subsequently, the decision matrix D_M is then converted to HFLTS by using a transformation function E_{GCF}.

$$H = \begin{array}{c} \\ x_1 \\ x_2 \\ x_3 \end{array} \begin{array}{cccccc} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \end{array} \left[\begin{array}{cccccc} \{v_h, p\} & \{v_h, p\} & \{el, v_l, l\} & \{v_h, p\} & \{el, v_l, l\} & \{h, v_h, p\} \\ \{l, m, h\} & \{v_l, l, m\ h\} & \{l, m, h, v_h\} & \{h, v_h, p\} & \{l, m, h, v_h\} & \{m, h, v_h\} \\ \{m, h, v_h, p\} & \{v_l, l, m\ h\} & \{el, v_l, l, m\} & \{h, v_h, p\} & \{el, v_l, l\} & \{h, v_h, p\} \end{array} \right] \quad (28)$$

The decision matrix D_M includes the members h_{ij} where $i \in \{x_1, x_2, x_3\}$ and $j \in \{c_1, c_2, c_3, c_4, c_5, c_6\}$. According to the definition of hesitant fuzzy linguistic term set, we can easily calculate the envelope of its members h_{ij} using upper bound and lower bound rules. Accordingly, the new decision matrix Y containing the envelopes of H is given in equation (29) as,

$$Y = \begin{array}{c} \\ x_1 \\ x_2 \\ x_3 \end{array} \begin{array}{cccccc} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \end{array} \left[\begin{array}{cccccc} \{v_h, p\} & \{v_h, p\} & \{el, l\} & \{v_h, p\} & \{el, l\} & \{h, p\} \\ \{l, h\} & \{v_l, h\} & \{l, v_h\} & \{h, p\} & \{l, v_h\} & \{m, v_h\} \\ \{m, p\} & \{v_l, h\} & \{el, m\} & \{h, p\} & \{el, l\} & \{h, p\} \end{array} \right] \quad (29)$$

Now we utilize the node gain degree and energy welfare to classify the status of a node as 'Optimistic' and 'Pessimistic'. The 'RetainFunc' will be called if the status of a node is evaluated as 'Optimistic' and 'ChangeFunc' will be called if the status of a node is evaluated as 'Pessimistic' depending upon the status evaluation criteria already discussed.

Function: RetainFunc (***Alternatives***, ***Criteria***, ***Y***)
1. ***For*** $i = 1$ *to* $\|Alternatives\|$ of Y, 2. ***For j*** $= 1$ *to* $\|Criteria\|$ of Y 3. Get 1-cut hesitant fuzzy set $H_S^j(xi)_{\alpha=1}$ for $H_S^j(xi)$, where, $H_S^j(xi)_{\alpha=1} = [\{H_{S^-}^j(xi)_{\alpha=1}, H_{S^+}^j(xi)_{\alpha=1}\}]$ 4. ***End For*** 5. ***End For*** 6. ***For e = 1 to*** $\|Alternatives\|$ of Y 7. ***For f = 1 to*** $\|Criteria\|$ of Y 8. ***Get*** *the intervals* $I_{max}(xe)$ *for each alternative* x_i *with respect to each criterion* f; *where*, $I_{max}(xe) = [Max(H_{S^-}^f(xi)_{\alpha=1}), Max(H_{S^+}^f(xi)_{\alpha=1})]$ $f \in Criteria = [u_{e1}^{max}, u_{e2}^{max}]$ 9. $Rank_{e1}^{opti} = \max\left(1 - max\left(\frac{1-u_{i1}^{max}}{u_{i2}^{max} - u_{i1}^{max} + 1}, 0\right), 0\right)$ 10. ***End For*** 11. ***End For*** 12. ***Return*** $max(Rank_{e1}^{opti})$

Function: ChangeFunc (***Alternatives***,***Criteria***, ***Y***) ***Algorithm***:
1. ***For*** $i = 1$ *to* $\|Alternatives\|$of Y 2. ***For*** $j = 1$ *to*$\|Criteria\|$ of Y 3. Get 1-cut hesitant fuzzy set $\mathrm{H}_S^j(xi)\alpha{=}1$ for $\mathrm{H}_S^j(xi)$, where, $\mathrm{H}_S^j(xi)\alpha{=}1 = [\{\mathrm{H}_{S^-}^j(xi)\alpha{=}1, \mathrm{H}_{S^+}^j(xi)\alpha{=}1\}]$ 4. ***End For*** 5. ***End For*** 6. ***For*** $e = 1$ *to*$\|Alternatives\|$ of Y 7. ***For*** $f = 1$ *to* $\|Criteria\|$ of Y 8. Get the intervals $Imin(xe)$ for each alternative xi for each criterion f;

where $Imin(xe) = [Max(\mathrm{H}_{S^-}^{f}(xi)\alpha{=}1), Max(\mathrm{H}_{S^+}^{f}(xi)\alpha{=}1)]\ f \in Criteria =$ $[\mathrm{u}_{e1}^{max}, \mathrm{u}_{e2}^{max}]$

9. $\mathrm{Rank}_{e1}^{pessi} = \max\left(1 - max\left(\frac{1-\mathrm{u}_{i1}^{max}}{\mathrm{u}_{i2}^{max} - \mathrm{u}_{i1}^{max} + 1}, 0\right), 0\right)$

10. ***End For***

11. ***End For***

12. ***Return*** $max(\mathrm{Rank}_{e1}^{pessi})$

The 'RetainFunc' and 'ChangeFunc' functions applies the 1-cut HFLTS to fuzzy sets in Y to generate the envelope for each criteria against every alternative and calculates the probabilistic ranking of the alternatives based on the interval calculated from the envelopes. For instance, if the probabilistic ranking of alternatives is $[x_{1>}x_3 > x_2]$, it indicates that the corresponding sensor node in its current state will probably retain its state and perform the role of a CH instead of CM or Relay node. But if the probabilistic ranking of alternatives is $[x_{2>}x_3 > x_1]$ or $[x_{3>}x_2 > x_1]$, it indicates that the sensor node's preferred action will be to change its role as CM or relay instead of CH.

6. RESULTS

6.1. Simulation Environment

We have evaluated the performance of FLOC in MATLAB 2019b and OMNET++ using cross-platform library (MEX-API). This Application Programming Interface (API) can provide the user an easy bidirectional connection interface between MATLAB and OMNET++. Nodes are arranged in random topology. We have utilized low rate, low cost, short-range, flexible and low power consumption standard IEEE 802.15.4 for our PHY and MAC layer. The performance metrics like active node ratio, average energy consumption, and packet delivery ratio are analyzed against parametric benchmarks viz. node density and temperature variation. The performance of FLOC is compared with three different approaches i.e. 1) SOPC [8], 2) BMAC [14], 3) RL-Sleep [7]. Stop-Operate Power-Control (SOPC) is a temperature-aware asynchronous sleep-scheduling algorithm in which energy, link connectivity and network coverage are preserved by putting a few sensor nodes in hibernation mode and controlling the rest of the sensor nodes' transmission power. The communication range and a number of active nodes are adjusted to maintain the critical density for consistent connectivity in the network. Berkley-MAC (BMAC) is a low-traffic, low-power-consuming MAC protocol based on adaptive preamble sampling for duty cycling to preserve energy, provide effective collision avoidance and high channel utilization. RL-Sleep is an asynchronous reinforcement learning based procedure based on the adaptive state transition determined by sensor nodes. The state transition is based on temperature sensing and collecting information from the neighbourhood. The effect of various parameters on the performance of FLOC with other existing benchmarks is provided in this section.

Table 2. Simulation parameters

Parameter	**Value**
Deployment area	500 m X 500 m
N	60-90
T_H	80°C
S_{SUN}^{max}	1

Maximum Temperature	80°C
$Area_{sen}$	20cm^2
d_0	20m
R	200m
ε_{fs}	50nJ/bit/m^2
ε_{mp}	10pJ/bit/m^2
E_{elec}	50nJ/bit
Initial Energy for nodes	5J(for neighbors of sink node) 3J (For other nodes)
n_p	2
c_p	0.5
$mass$	50g
r	0.25
Number of packets	1024
Length of packet	8000bits

6.1.1. Active node ratio

Figure (3) depicts the active node ratio comparison of FLOC with SOPC, BMAC, and RL-Sleep. It is evident from the figure that the ratio of an average number of active nodes to total number of sensor nodes in the network is higher for FLOC than in any other benchmark. Furthermore, the active node ratio for all approaches is optimum for N=80. We also evaluated the performance of FLOC against SOPC, BMAC and RL-Sleep for varying diurnal temperatures. Figure (4) shows the comparison of active node ratio of FLOC and other benchmarks for diurnal temperature variations. It has been observed that FLOC outperforms all three approaches in terms of active node ratio. The number of active sensor nodes in the network varies inversely with the diurnal temperature.

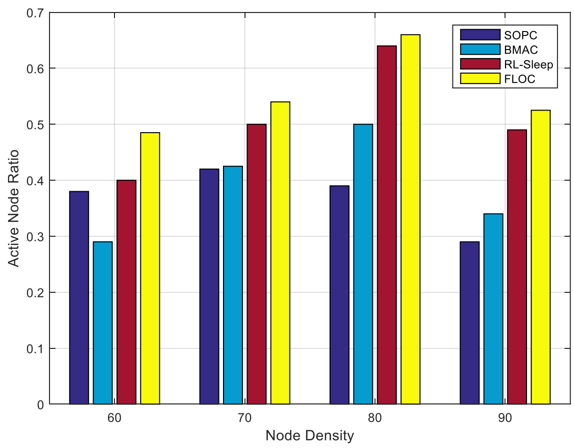

Figure 2. Active node ratio against node density

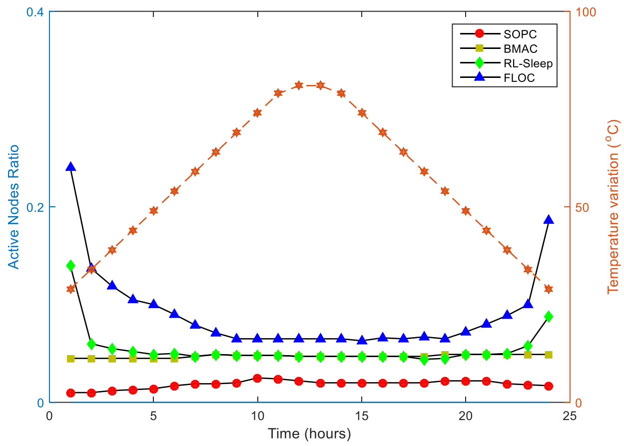

Figure 3. Active node ratio for diurnal temperature variations

6.1.2. Average energy consumption

Figure (5) shows the performance comparison of FLOC with SOPC, BMAC, and RL-Sleep in terms of average energy consumption. BMAC outperforms all other algorithms due to its adaptive preamble strategy and short duty cycle which play a significant role in preserving energy. The adaptive adjustment of temperature with respect to communication range leverages higher energy consumption for SOPC. FLOC performs better than SOPC and RL-Sleep but exhibits a higher amount of energy consumption against BMAC due to packet broadcasting in the neighbourhood. Figure (6) depicts the average energy consumption of FLOC against other approaches for diurnal temperature variation. FLOC and BMAC exhibit almost similar profile for average energy consumed whereas SOPC and RL-Sleep consumed higher amount of energy for N=80.

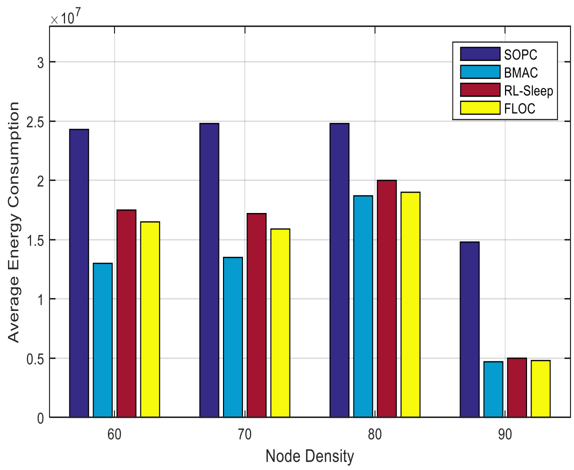

Figure 4. Average energy consumption against node density

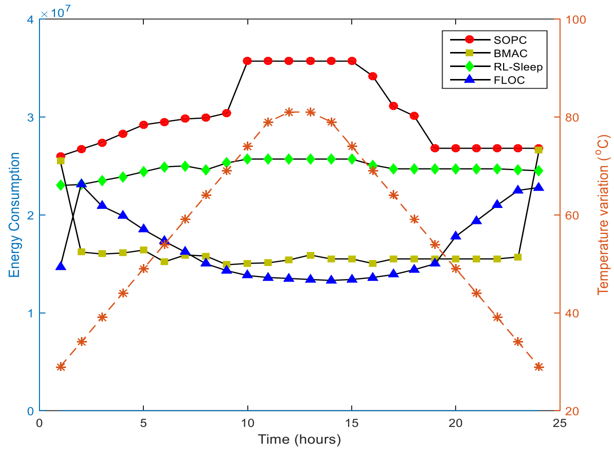

Figure 5. Average energy consumption for diurnal temperature variations

6.1.3. Packet Delivery Ratio (PDR)

Figure (7) depicts the comparison of FLOC with existing benchmarks in terms of PDR. FLOC outperforms other approaches in the case of PD. Due to its opportunistic and environment adaptive sleep scheduling strategy, the additional power loss in FLOC can be compensated due to control packet overhead. BMAC shows the worst performance against existing benchmarks. Figure (8) shows the PDR of FLOC with other approaches for diurnal temperature variations. FLOC leverages a better packet delivery ratio in comparison to other techniques. It is pertinent to mention that the PDR of FLOC decreases with the increase in diurnal temperature.

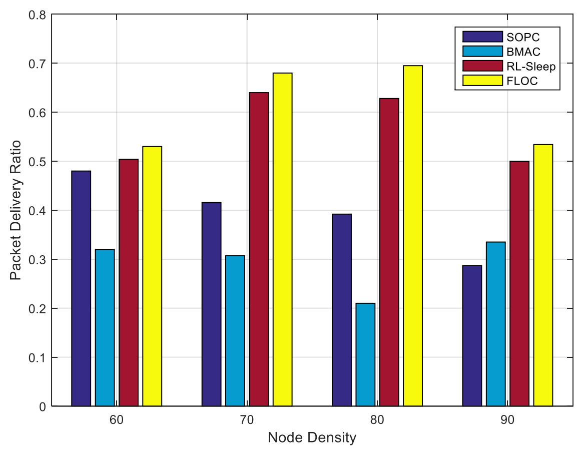

Figure 6. Packet delivery ratio against node density

6.1.4. Network Lifetime

Network lifetime can be evaluated in terms of the dead node ratio in the network. The time when 25% or 50% of the nodes present in the network have no residual energy left to continue their data delivery tasks can be treated as the network lifetime [10]. Here, we considered two such time intervals, i.e., (i) when the first sensor node dies (FND) and (ii) when half the nodes in the network die, i.e., 50% of the sensor nodes have no residual energy left to continue their data sensing tasks (HND). The stacked bar chart in Figure (9) demonstrates the network lifetime of FLOC with SOPC, BMAC, and RL-Sleep against the node density in terms of FND and HND. In every stack, we have four bars representing four different schemes, i.e., SOPC, BMAC, RL-Sleep and FLOC. In each bar, we have two groups, i.e., FND and HND. It can be observed from the figure (9) that our proposed scheme FLOC outperforms other schemes for both FND and HND scenarios. The best performance is achieved when number of nodes in the network are 80.

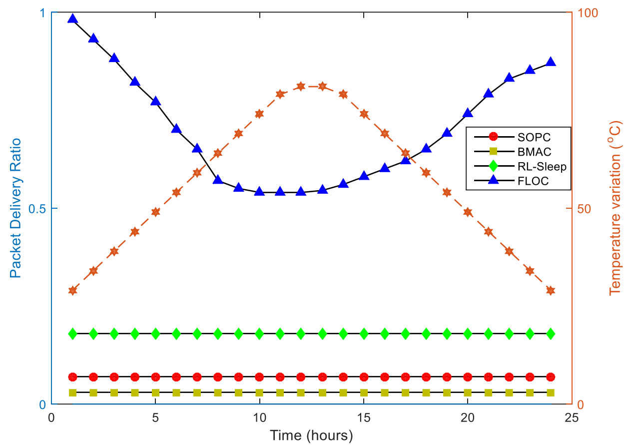

Figure 7. Packet delivery ratio for diurnal temperature variations

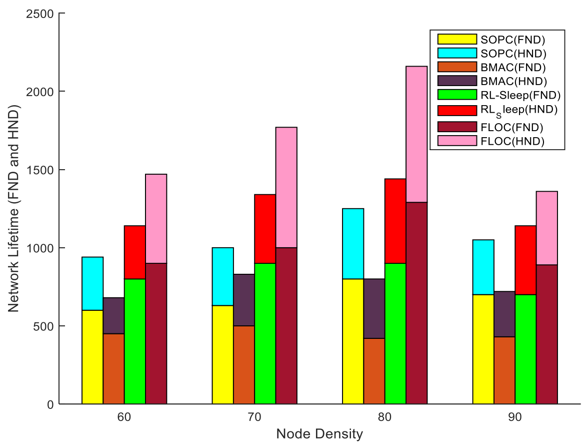

Figure 8. Network lifetime against node density

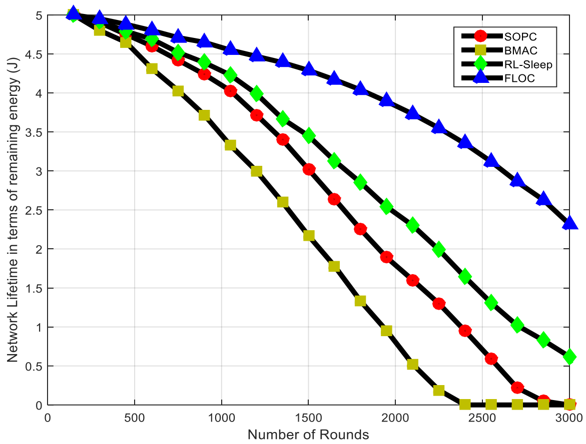

Figure 9. Network lifetime in terms of remaining energy against number of rounds

Similarly, we can also observe the network lifetime against a number of communication rounds in terms of total remaining energy of sensor nodes in Figure (10). Dense deployment of the nodes provides a healthy neighborhood which drives the proposed technique to perform better than others. SOPC outperforms RL-Sleep as it completely depends on its perception of the environment. FLOC, on the other hand, performs better than others as it adapts itself to the status of the neighborhood.

7. Conclusions

In this paper, a novel, distributed, FLOC algorithm is proposed based on the hesitant fuzzy linguistic term set (HFLTS) analysis in order to resolve the CH decision-making problems and network lifetime bottlenecks using a dynamic network architecture involving opportunistic clustering. The attributes such as energy transfer-based opportunistic routing, energy welfare, relative thermal entropy; expected optimal hops and link quality factor are utilized to form the criteria for Hesitant Fuzzy Linguistic Term Set and make a decision about the contemporary role of the node based on its current state. The effectiveness of FLOC is confirmed after carefully analyzing and evaluating its performance against several existing benchmarks. The simulation results have clearly shown that employing FLOC algorithm results in the improvement of the active node ratio, average energy consumption and packet delivery ratio. The possible future work would be to perform the hesitant fuzzy linguistic term set analysis for harvested energy scavenging and transfer capabilities in opportunistic clustering.

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Conflicts of Interest

The author declares no conflict of interest.

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