Adaptive Probabilistic Model for Energy-Efficient Distance-based Clustering in WSNs (Adapt-*P*): A LEACH-based Analytical Study

Husam Suleiman* and Mohammad Hamdan
Applied Science Private University, Amman, Jordan
{h_suleiman, mo_hamdan}@asu.edu.jo

Received: July 17, 2021; Accepted: September 2, 2021; Published: September 30, 2021

Abstract

Network lifetime and energy consumption of data transmission have been primary Quality of Service (QoS) obligations in Wireless Sensor Networks (WSNs). The environment of a WSN is often organized into clusters to mitigate the management complexity of such obligations. However, the distance between Sensor Nodes (SNs) and the number of clusters per round are vital factors that affect QoS performance of a WSN. The designer's conundrum resolves around the desire to sustain a balance between the limited residual energy of SNs and the demand for prolonged network lifetime. Any imbalance in controlling conflicting objectives may result in either QoS penalties due to draining SN energies which leaves WSN's environment unevenly covered, or an over-cost environment that is significantly difficult to distribute and operate. Low-Energy Adaptive Clustering Hierarchy (LEACH) is a well-known distributed clustering algorithm proposed to tackle such difficulties. Multiple LEACH-based algorithms have also been proposed to enhance QoS requirements. Proposed algorithms typically focus on residual energies of SNs to compute a probability function that selects cluster-heads. Some algorithms form an optimal energy-efficient path toward a destination SN. Nevertheless, these algorithms do not consider variations in network's state at run-time. Such a state changes in an adaptive manner according to existing network structures and conditions. Thus, cluster-heads per round are not elected adaptively depending on the state and distances between SNs. To tackle such complications, this paper proposes an energy-efficient adaptive distance-based clustering called Adapt-*P*, in which an adaptive probability function is developed to formulate clusters. A near-optimal distance between each cluster-head and its cluster-members is formulated so that energy consumption of the network is mitigated and accordingly the network lifetime is maximized. Distances between and residual energies of SNs are employed to obtain a maximum number of cluster-heads to be elected per round. The cluster-head selection probability is adapted at the end of each round based on the maximum number of cluster-heads permitted per round found a priori and the number of existing alive SNs in the network. The Adapt-*P* based algorithms proposed in this paper improve the performance of LEACH algorithm in term adaptivity and network lifetime.

Keywords: Energy-Efficient Clustering, Cluster-Head Selection, LEACH, WSN

1 Motivation

The implementation of a WSN is influenced by several design factors such as scalability, fault tolerant, topological layout, transmission media, and power consumption [37, 3, 26]. Fault tolerant, for example, ensures that a failure of a SN caused by a lack of power or physical damage should not affect the rest

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), 12(3):65-86, Sept. 2021
DOI:*10.22667/JOWUA.2021.09.30.065*

*Corresponding author: Department of Electrical Engineering, Applied Science Private University, Amman, Jordan, Tel: +962-6-560-9999

of SNs or severely degrade the overall performance. Since a WSN could be in the order of hundreds or thousands of SNs, scalable mechanisms are to be employed to help WSNs adapt to number and density of SNs [38, 13, 17]. Because each SN has limited power resources and may not be rechargeable, effective power-saving mechanisms are needed to extend network lifetime [19, 9, 47]. Therefore, energy efficiency and network lifetime are primarily among the most important QoS obligations to consider in the design of a WSN [12, 29]. There is a need to formalize energy-efficient strategies that preserve SNs' residual energy, reduce the overall energy consumption, and consequently prolong the network lifetime [6, 24, 4].

Energy-efficient algorithms are proposed to address topological complications and energy concerns in WSNs. Heinzelman et al. [15] present LEACH protocol that specifically merges "clustering and media access with application-specific data aggregation" to improve network lifetime, latency, and application quality. LEACH includes a distributed clustering technique that evenly rotates the cluster-head between SNs to avoid power depletion of a specific SN over others. They analytically compute the number of clusters expected per round to minimize the total energy consumption.

Disjoint clustering is accordingly an efficient mechanism effectively employed in WSNs. It is utilized to achieve scalability, stabilize network topology, minimize energy consumption, aggregate sensor data, and alleviate congestion rate. A cluster-head would potentially limit the scope of communication between cluster-members and Base Station (BS), as well as coordinate the channel time among its cluster-members so that the whole network is not burden with extra redundant information. Periodic clustering distributes energy evenly among all SNs, which consequently increases the energy efficiency and extends the network lifetime. With respect to energy consumption, a cluster-member consumes energy when it transmits data to its corresponding cluster-head or directly to BS. On the other side, a cluster-head consumes energy when data is received from its cluster-members, and consumes more energy when data is aggregated and transmitted to the BS.

However, clustering approaches in the literature mostly focus on improving the process of selecting cluster-heads, either randomly or according to SN's residual energy. Some approaches form the best possible energy path toward BS such that network lifetime is increased. Nevertheless, such approaches do not account for variations in network state at run-time. In fact, the state varies often because of frequent changes in network configurations, and thus cluster-heads would not potentially be elected depending on existing conditions of the network and distances between SNs.

To tackle such difficulties, this paper presents a LEACH-based adaptive clustering algorithm in which an adaptive probability function is employed to formulate clusters. A near-optimal distance between each cluster-head and its corresponding cluster-members is formalized such that the overall energy consumption of the network is mitigated and accordingly the network lifetime is maximized. Distances between SNs and residual energy of each SN in the network are utilized to compute the maximum number of cluster-heads elected per round. The cluster-head selection probability is adapted at the end of each round according to the maximum number of cluster-heads permitted per round found in advance and the number of alive SNs currently interacting with the networking environment.

The proposed adaptive clustering scheme helps business organizations and building automation support real-time visibility and remote monitoring on their system operational data, so as to meet a high-level of energy-efficiency and cost-saving. The design is robust to topology changes and can be utilized to tackle interoperability between heterogeneous SNs, so that to it manages security and privacy challenges incurred from a large volume of enterprise data reported from the working environment.

2 Contributions

The communication and computation energy model of the network is mathematically analyzed and examined, which is structured based on LEACH algorithm. An optimal distance (d_{opt}) between each cluster-

head and its cluster-members is formulated, found by deriving the total energy consumption with respect to the distance. The d_{opt} mitigates the total energy consumption of receiving, aggregating, and transmitting data, which as a result prolongs the network lifetime. Thus, the d_{opt} is utilized to formulate the maximum number of clusters permitted per round, κ_{max}. As a result, the cluster-head selection probability is adapted at the end of each round based on κ_{max} found a priori and number of alive SNs ζ currently active in the network. Additionally, distance to and residual energy of cluster-heads are both considered by each SN to select its potential cluster-head. Each SN joins a cluster-head that holds the maximum energy-distance ratio, $F = \frac{E_{res}^{\alpha}}{d_{CH}^{\beta}}$, where E_{res} is the residual energy of cluster-head, d_{CH} is the distance between SN and cluster-head, and α & β are constants. Contributions of this paper are summarized as follows:

- Formulating d_{opt} between each cluster-head and its cluster-members such that network lifetime is prolonged and the overall energy consumption is minimized.
- Formulating κ_{max} based on d_{opt} found a priori and utilizing κ_{max} to optimize the maximum number of cluster-heads permitted per round.
- Adapting the cluster-head selection probability P_{adp} according to existing network's state represented by κ_{max} and number of alive SNs ζ.
- Employing adaptive probability P_{adp}, jointly with κ_{max} and energy factor E, to propose adaptive clustering algorithms.
- Employing the energy-distance ratio (F) to assist SNs effectively select the best cluster-head to join, and to propose adaptive energy-efficient distance-based clustering algorithms jointly with κ_{max}, E, and P_{adp}.
- Verifying the performance of the proposed adaptive clustering algorithms, devised based on LEACH and Stable Election Protocol (SEP) algorithms, on randomly distributed heterogeneous SNs produced with different initial energy-levels.

3 Background and Related Work

Clustering is a systematic practice in WSNs to facilitate routing and collecting data in a timely and energy-efficient manner [45, 10, 28, 46, 7]. Clustering approaches are proposed to prolong the network lifetime, with their focus harnessed on devising cluster-head selection methods that evenly balance the energy consumption among SNs [35, 21, 36, 2, 1]. To efficiently overcome the problem of energy consumption in clustering algorithms, LEACH protocol is proposed by Heinzelman et al. [15] to enable self-organization of SNs and support cluster-head selection. In this protocol, a cluster-head is randomly rotated among all SNs to avoid fast energy depletion of a specific SN, so as to evenly distribute and balance the energy consumption among SNs and thus to prolong the network lifetime. The maximum number of clusters expected to minimize the total energy consumption of the SNs is calculated.

Similarly, Heinzelman et al. [14] evaluate the performance of LEACH algorithm with direct communication, Minimum Transmission-Energy (MTE), and static clustering algorithms. The effectiveness of LEACH algorithm outperforms the other algorithms by reducing the communication energy and increasing SN's lifetime. Nevertheless, LEACH algorithm suffers from numerous drawbacks in that it randomly selects cluster-heads at each round. SNs have equal probabilities to become cluster-heads regardless of their existing residual energy-levels and number of remaining SNs in the network, which in turn may choose a cluster-head with low energy-level.

Smaragdakis et al. [40] propose SEP protocol that selects cluster-heads such that time period to death of first SN is prolonged. SEP assumes SNs with different initial energy so as to tackle heterogeneity of the network. Improvements on SEP algorithm have been proposed to produce enhanced energy consumption and performance [16]. Nurlan et al. [27] extends Z-SEP routing algorithm to propose an EZ-SEP that connects SNs to BS via a hybrid method. Though, some SNs communicate with the BS directly while some other SNs form together clusters to transfer data. Cluster-heads are selected based on residual energy of each SN.

Furthermore, Pranathi et al. [31] present the centralized approach appeared in LEACH, in which a cluster-head is a single-point of failure that leads to information loss when it is transferred to BS. They propose a distributed, robust average-consensus routing protocol that makes SNs exchange information directly to BS to overcome the problem of centralization. Despite the robustness of their consensus algorithm in collecting and transmitting data, it suffers from a high energy consumption required by each SN to transmit its data directly to BS. As such, the proposed algorithm is modified to present an energy-efficient hybrid approach that mitigates the energy consumption to a level close to LEACH protocol.

Several clustering protocols for lifetime maximization of WSNs are also proposed in the literature to tackle such clustering issues. Rawat et al. [34] present an energy-efficient LEACH-based routing protocol for network lifetime's enhancement. Elmasry et al. [11] propose a scalable energy-efficient algorithm that adopts a three-layer hierarchy to minimize workload on cluster-heads and randomize the cluster-head selection procedure. Loganathan et al. [23] propose an energy-efficient clustering algorithm that uses a distance centroid algorithm to design each cluster. The energy centroid of each cluster is computed and employed together with the energy threshold of each SN to choose a cluster-head. Muthukumaran et al. [25] present a hierarchical routing that uses cluster identification, multi-hop, and multi-level routing schemes to evaluate their effectiveness to produce energy-efficient clustering. Priyadarshi et al. [32] propose a clustering algorithm that uses threshold functions and residual energy of each SN to select cluster-heads. Lin et al. [22] modify the threshold function of cluster-head selection to present a strategy for forming clusters of the network.

Qabouche et al. [33] propose a static routing protocol that combines clustering and multi-hop routing. Data is transmitted in each round through independent SNs called gateways, which connect cluster-head SNs with the BS. Pour et al. [30] present an energy-aware cluster-head selection based on residual energy of a SN, centrality of a SN, and number of neighboring SNs. In addition, Chauhan et al. [8] propose a cluster-head selection strategy that splits the WSN into rectangular regions, each of which is managed by a cluster-head. A nature-inspired algorithm employs residual energy of each SN and distance from a SN to a sink node to select cluster-heads of the network. Bhola et al. [5] adopts a genetic-based approach to optimally find route to destination nodes such that energy consumption is mitigated. The genetic algorithm utilizes its fitness function to optimize the network's performance, thus if the network performance is decreased then the genetic algorithm alters the route such that network's efficiency is increased. Wang et al. [44] also present a genetic algorithm that selects the best cluster-heads and combines them in a single chromosome to find the optimal routing path, with a fitness function that considers load balancing among SNs and minimum energy consumption.

In addition, Lata et al. [20] propose a reliable clustering algorithm that adopts a fuzzy-based clustering to formulate cluster, as well as select cluster heads and vice clusters, in a centralized-based manner such that network's lifetime is maximized and energy load is balanced. Ant-colony optimization is utilized by Liang et al. [21] to present an optimized multi-hop routing protocol, where energy consumption per round is employed to compute number of cluster-heads for an improved LEACH-based protocol. Shukry et al. [39] propose a Node Stable Routing protocol that stabilizes data transmission exchanged between SNs. The protocol characterizes a SN's stability by its residual energy and number of successive hops required to reach a destination SN. The source SN formalizes a stable path to destination such that energy consumption is mitigated.

A missing factor in proposed clustering strategies of WSNs is to actively account for network state at run-time [42, 41, 43]. Such a state varies very often because SNs by the time suffer from gradual decrements in their residual energy, which in turn affects the network's configuration. Accordingly, cluster-heads are not adaptively elected based on existing states of the network and hence the total energy of network would not be fairly distributed among SNs leaving network's space proportionally covered. The clustering protocol in this paper employs an adaptive probabilistic function that formulates clusters so that QoS performance is enhanced. It computes a near-optimal distance between SNs such that energy consumption is reduced and thus network lifetime is maximized.

4 Network Model

The network model comprises N heterogeneous SNs with similar computation and communication capabilities. Such SNs are randomly distributed on a space of MxM area, with one BS positioned in the middle. The SNs and BS have fixed locations. However, all SNs are energy-constrained. Each SN starts with different initial amount of energy, has fixed Identifier (ID) address and position, and has enough power to reach the BS if a SN needs to act as a cluster-head. On the other side the BS works without energy constraint because it is assumed to have adequate energy supply; and as such the energy consumption of BS is not considered in the mathematical analysis and design evaluation. As in SEP protocol, SNs are divided into two types: normal and advanced SNs. Normal SNs start with low initial energy-level represented by E_0. Advanced SNs start with high initial energy-level represented by $E_0(1+a)$, where a is constant. Percentage of SNs that are advanced is m. Table I summarizes notations used throughout the paper.

All cluster-members sense the environment at a fixed rate and always have data to send to their corresponding cluster-heads. Each cluster has one cluster-head, and each cluster-member is allocated to one cluster-head, i.e., fuzzy membership is not allowed. Cluster-members communicate with the BS via their corresponding cluster-head by means of symmetric communication channel, i.e., same energy is required to transmit data packets from source to destination SNs and vise versa for a given Signal-to-Noise Ratio (SNR). Each cluster-head aggregates and then transmits data directly to the BS, and the BS receives compressed data.

The size of the transmitted and received data packet is fixed, l bits. Each SN consumes energy when it receives (E_{RX}), aggregates (E_{DA}), and transmits (E_{TX}) data packets of size l bits. Such energy consumption only depends on a distance d between source and destination SNs. For the distance between any two adjacent SNs, the free space model d^2 is employed if the distance between source and destination SNs is smaller than a threshold d_0 ($d \leq d_0$), otherwise ($d > d_0$) the multi-path fading model d^4 is employed. The network simulation parameters are shown in Table II, which illustrates the maximum number of rounds, field dimensions in meters, SN parameters, values for SNs' heterogeneity, and parameters of the energy model.

5 Mathematical Model

A SN typically consumes energy when it receives, aggregates, and transmits data packets. The mathematical model adopts the simple energy dissipation model explained in [15]. A transmitter SN consumes energy to run the radio electronics and power amplifier, and a receiver SN consumes energy to only run the radio electronics.

$$E_{TX} = \begin{cases} lE_{\bar{e}} + l\varepsilon_{fs}d^2, & d \leq d_0 \\ lE_{\bar{e}} + l\varepsilon_{mp}d^4, & d > d_0 \end{cases} \quad (1)$$

Notation	Definition
a	Heterogeneity factor for advanced SNs
α	Energy constant
β	Distance constant
d	Distance between two adjacent SNs
d_0	Distance threshold
d_{BS}	Distance between a SN and a BS
d_{CH}	Distance between a SN and a cluster-head
d_{opt}	Optimal distance between a cluster-head and its cluster-members
ε_{fs}	Energy dissipated by transmitter to run power amplifier using free space (fs) model
ε_{mp}	Energy dissipated by transmitter to run power amplifier using multipath fading (mp) model
E_0	Initial energy-level of normal SNs
E_{init}	Initial energy of a SN
E_{res}	Current residual energy of a SN
$E_{\bar{e}}$	Energy dissipated per bit to run the transmitter and receiver radio electronics
$E_{TX}(l,d)$	Energy dissipated to transmit l bits through a distance d
$E_{RX}(l)$	Energy dissipated to receive l bits
E_{DA}	Energy dissipated to aggregate l bits
E_{member}	Energy dissipated by a cluster-member
E_{CH}	Energy dissipated by a cluster-head
$E_{cluster}$	Energy dissipated in each cluster
E_{Total}	Energy dissipated by all clusters
$\digamma$	Energy-distance ratio
$\mathbb{G}$	Set of non-elected SNs
κ	Number of clusters per round
κ_{max}	Maximum number of cluster-heads permitted per round
l	Size of data packet in bits
m	Percentage of advanced SNs distributed in the field
M	Field's dimension
N	Number of SNs distributed in the field
p	Probability of selecting a cluster-head
P_{adp}	Adaptive probability
r	Current round number
s	A selected SN from the set $\mathbb{G}$
$T(s)$	Threshold for selecting a SN as a cluster-head
$T_E(s)$	Threshold for selecting a SN as a cluster-head based on energy
ζ	Number of alive SNs in the current round

Table 1: Summary of Notations

$$E_{RX} = lE_{\bar{e}} \tag{2}$$

The $E_{TX}(l,d)$ is the energy dissipated to transmit l bits through a distance d, whereas $E_{RX}(l)$ is the energy dissipated to receive l bits. The $E_{\bar{e}}$ is the energy dissipated per bit to run the transmitter and receiver radio electronics. Also, ε_{fs} and ε_{mp} are the energy dissipated by transmitter to run the power amplifier using the free space (fs) model and the multi-path fading (mp) model, respectively. However, the free space (fs) and multi-path fading (mp) models are used depending on the distance between the

Field Dimension - Maximum x and y (in meters)	
Maximum x_m and y_m coordinates in the field	100 x 100m^2
x and y coordinates of the sink node ($0.5x_m$ x $0.5y_m$)	50 x 50
SN Parameters	
Maximum number of rounds	3000
Number of SNs in the field (N)	100
Initial optimal election probability of a SN to become cluster-head (p)	0.1
Values for SNs Heterogeneity	
Percentage of advanced SNs in the field (m)	0.1
Heterogeneity factor (a) for advanced SNs	1
Energy Model (All Values in Joules)	
Initial energy (E_0)	0.5 J/bit
Transmitting (E_{TX}) and receiving (E_{RX}) energy	0.5 x 10^{-9} J/bit
Data aggregation energy (E_{DA})	5x10^{-9} J/bit
Free-space model transmit amplifier energy (ε_{fs})	10 x 10^{-12} $J/bit/m^2$
Multi-path model transmit amplifier energy (ε_{mp})	0.0013 x 10^{-12} $J/bit/m^4$

Table 2: Simulation Parameters

source and destination SNs. The distance is first compared with a threshold value, $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$. The free space model ($d^2$) is employed if the distance d is $d \leq d_0$; otherwise, the multi-path fading model (d^4) is employed. Mathematically, the free space model (d^2) is used in this paper for intra-cluster communication because the distance d is assumed to be $d \leq d_0$, whereas the multi-path fading model (d^4) is utilized for communication between cluster-head and BS because the distance d is assumed to be $d > d_0$.

5.1 Formalizing d_{opt} and κ_{max}

It is assumed that N SNs are randomly distributed over an area of MxM. Since the number of clusters per round is κ, then each cluster comprises $\frac{N}{\kappa}$ SNs. Each cluster-head dissipates energy E_{CH} when it receives data from $(\frac{N}{\kappa}-1)$ cluster-members (denoted by E_{RX}), as well as dissipates energy when it aggregates (E_{DA}) and transmits (E_{TX}) such data to the BS.

$$\begin{aligned} E_{CH} &= E_{RX} + E_{DA} + E_{TX} \\ &= lE_{\bar{e}}(\frac{N}{\kappa}-1) + lE_{DA}\frac{N}{\kappa} + lE_{\bar{e}} + l\varepsilon_{mp}d_{BS}^4 \end{aligned} \tag{3}$$

where d_{BS} is the distance between a cluster-head and BS. Each cluster-member dissipates energy E_{member} when it transmits data to its cluster-head.

$$E_{member} = lE_{\bar{e}} + l\varepsilon_{fs}d_{CH}^2 \tag{4}$$

where d_{CH} is the distance from a cluster-member to its cluster-head. The energy dissipated in a cluster $E_{cluster}$ is equal to the energy dissipated by the cluster-head E_{CH} and its cluster-members $(\frac{N}{\kappa}-1)E_{member}$.

$$\begin{aligned} E_{Cluster} &= E_{CH} + (\frac{N}{\kappa}-1)E_{member} \\ &\approx E_{CH} + (\frac{N}{\kappa})E_{member} \end{aligned} \tag{5}$$

Then, the overall energy consumption E_{Total} dissipated by all clusters is

$$\begin{aligned} E_{Total} &= \kappa E_{Cluster} \\ &= \kappa E_{CH} + N E_{member} \\ &= \kappa\big(lE_{\bar{e}}(\frac{N}{\kappa}-1) + lE_{DA}\frac{N}{\kappa} + lE_{\bar{e}} + l\varepsilon_{mp}d_{BS}^4\big) \\ &\quad + N(lE_{\bar{e}} + l\varepsilon_{fs}d_{CH}^2) \\ &= 2lE_{\bar{e}}N + lE_{DA}N + l\varepsilon_{mp}d_{BS}^4\kappa + Nl\varepsilon_{fs}d_{CH}^2 \end{aligned} \tag{6}$$

The objective is to formulate a distance d_{opt} between each cluster-head and its cluster-members, such that the overall energy consumption of the network is mitigated. The network field is partitioned into equal circles, each of which is of size $2\pi d_{opt}^2$. The expected number of clusters per round is

$$\kappa = \frac{M^2}{2\pi d_{opt}^2} \tag{7}$$

By replacing κ with its new value, replacing d_{CH} with d_{opt}, and deriving the overall energy consumption with respect to d_{opt}, then the final formulation becomes

$$E_{Total} = 2lE_{\bar{e}}N + lE_{DA}N + l\varepsilon_{mp}d_{BS}^4\frac{M^2}{2\pi d_{opt}^2} + Nl\varepsilon_{fs}d_{opt}^2 \tag{8}$$

$$\frac{\partial E_{Total}}{\partial d_{opt}} = 0 \tag{9}$$

$$d_{opt} = \sqrt[4]{\frac{\varepsilon_{mp}M^2}{2\pi N\varepsilon_{fs}}}d_{BS} \tag{10}$$

This means that maximum number of clusters permitted per round to avoid any potential increase in the overall energy consumption of the network is

$$\begin{aligned} \kappa_{max} &= \frac{M^2}{2\pi d_{opt}^2} \\ &= \sqrt{\frac{N\varepsilon_{fs}}{2\pi\varepsilon_{mp}}}\frac{M}{d_{BS}^2} \end{aligned} \tag{11}$$

The value of κ_{max} achieved based on the distance-based clustering is compatible with the expected number of clusters calculated in [15].

5.2 The impact of energy (E) and maximum number of clusters (κ_{max})

The objective is to first design an energy-efficient clustering algorithm that distributes the energy evenly among all SNs, such that no SN is frequently chosen to act as a cluster-head and runs out of energy before others. The d_{opt} and κ_{max} derived formerly are utilized to mitigate the overall energy consumption of the whole network. As explained in [15], all SNs have equal probabilities to become cluster-heads in each round. Each SN selects a random number between $[0,1]$ and elects itself to become a cluster-head in the current round if the random number is less than a threshold $T(s)$.

$$T(s) = \begin{cases} \frac{p}{1-p(r \mod \frac{1}{p})} & , \text{ if } s \in \mathbb{G} \\ 0 & , \text{ otherwise} \end{cases} \tag{12}$$

where r is the current round number, s is the selected SN, p is the probability of selecting a cluster-head, and $\mathbb{G}$ is the set of non-elected SNs. Accordingly, a SN that has not previously been a cluster-head is assumed to have more residual energy than others and qualified to become a cluster-head in next upcoming rounds. In LEACH algorithm, the overall energy is calculated by multiplying the average amount of energy of all SNs in each cluster by the total number N of SNs.

This is accomplished by modifying the cluster-head selection probability to become a function $T_E(s)$ of current SN's energy relative to its initial energy, so that more probabilistic weight is given to SNs that hold high residual energy to become cluster-heads than others.

$$T_E(s) = \begin{cases} \frac{p}{1-p(r \mod \frac{1}{p})} \frac{E_{res}}{E_{init}} & , \text{ if } s \in \mathbb{G} \\ 0 & , \text{ otherwise} \end{cases} \tag{13}$$

where E_{res} represents SN's current residual energy and E_{init} represents SN's initial energy. In this case, SNs with high residual energy are more qualified and have high probabilities to become cluster-heads in the upcoming round. As such, the number of cluster-heads permitted per round κ_{max} developed based on d_{opt} are both employed to devise LEACH-based and SEP-based algorithms.

The number of clusters permitted per round is limited to κ_{max} so that qualified SNs are evenly distributed throughout the network operation. However, κ_{max} combined with E manage and distribute the energy consumption evenly during the network operation instead of having several clusters in such a round. Tradeoff is obvious in applying κ_{max} which may sometimes negatively overload some cluster-heads with extra data traffic and quickly drain their energy, especially when κ_{max} is small and there are many SNs joining the selected cluster-heads. In this paper, the effect of κ_{max} appears when P_{adp} is computed as explained in the next section.

5.3 The impact of adaptive probability (P_{adp})

In LEACH and SEP algorithms, the probability of a SN to become a cluster-head is fixed. Such a probability however becomes inappropriate by the time because of increasing the number of dead SNs; which leads to increase the total number of rounds and decrease the number of elected cluster-heads per round. The probability of selecting a SN as a cluster-head should be adaptive and changed by the time depending on the network's state represented by existing network conditions and structures.

In this paper, the probability of selecting a SN to become a cluster-head is adapted at the end of each round. The P_{adp} depends on the value of κ_{max} permitted per round (calculated a priori) and the number of remaining (alive) SNs ζ in the network. Such a selection scheme in turn increases the probability of electing a SN from the remaining ones to become a cluster-head when the number of alive SNs ζ in the network is decreased.

$$P_{adp} = \frac{\kappa_{max}}{\zeta} \tag{14}$$

Thus, LEACH and SEP algorithms are modified to have LEACH-κP, LEACH-κEP, SEP-κP, and SEP-κEP algorithms. In LEACH-κP algorithm, the probability P is adapted at the end of each round and the number of clusters permitted per round is limited to κ_{max} to independently study the effect of P_{adp}. In LEACH-κEP algorithm, the probability P is adapted at the end of each round, the number of clusters permitted per round is limited to κ_{max}, and the E factor is employed in the cluster-head selection probability function. The same thing is applied for SEP-κP and SEP-κEP algorithms, respectively.

5.4 The impact of the energy-distance ratio ($\digamma$)

In LEACH and SEP algorithms, a SN joins a cluster-head based on the distance between them. The SN first computes the distance between it and all available cluster-heads, and accordingly the SN joins the

nearest cluster-head. However, the difficulty of this practice is that a SN may join a cluster-head that does not have enough energy to serve all its cluster-members. Such a routine drains the energy of the selected cluster-head quickly and as a result leaves some regions uncovered. Though, as explained in [18], a SN selects a cluster-head based on the energy-distance ratio F, where a SN joins the cluster-head with the highest F. The utilization of F ratio is more energy-efficient than joining a cluster-head based on distance only.

$$F = \frac{E_{res}^{\alpha}}{d_{CH}^{\beta}} \tag{15}$$

The κ_{max}, E, P_{adp}, and F are employed. Values of α and β are varied, chosen to be $\alpha = \beta = 1$ to get LEACH-κEF-1-1, and then P_{adp} is employed to get LEACH-κEF-1-1-P. Also, values of α and β are chosen to be $\alpha = 1$ and $\beta = 2$ to get LEACH-κEF-1-2, and then P_{adp} is employed to get LEACH-κEF-1-2-P. Same thing is applied for the proposed SEP algorithms to get SEP-κEF-1-1, SEP-κEF-1-1-P, SEP-κEF-1-2, and SEP-κEF-1-2-P, respectively. For figures of the number of dead SN, the round number period of comparison is chosen to be between $800-2000$, where the major difference between proposed algorithms appears. For figures of the remaining energy, the round number period of comparison is chosen to be between $1000-1600$.

6 Evaluation

The adaptive-based clustering algorithms are developed by utilizing LEACH and SEP. The QoS performance impact of P_{adp} on the probability of dead SNs and the energy consumption are examined. The κ_{max}, E, and F performance parameters are employed and evaluated against each others.

6.1 The impact of P_{adp} on death rate of SNs by utilizing κ_{max}, E, and F

The QoS performance of the proposed LEACH algorithms is evaluated by computing the likelihood of dead SNs as shown in Figure 1. The impacts of κ_{max}, E, and P_{adp} performance factors are examined and analyzed. Commonly, κ_{max} maintains a stable QoS performance throughout the network operation due to the limited number of maximum cluster-heads permitted per round. In this condition, κ_{max} puts more constraints and controls on electing cluster-heads per round by making it optimal, which preserves and defers some qualified SNs to become cluster-heads in upcoming rounds and accordingly distributes the energy evenly among all SNs throughout the network operation. Consequently, κ_{max} positively influences the probability of dead SNs per round. That is because qualified SNs are evenly distributed throughout the network lifetime, instead of having most of them running early as cluster-heads which in turn would deplete their energy rapidly. The effect of κ_{max} appears clearly when P_{adp} is adjusted at the end of each round, because P_{adp} accounts for κ_{max} and number of alive SNs ζ exist in the network.

Examining the impact of utilizing P_{adp}, the formulation of LEACH-κP algorithm developed from employing P_{adp} improves the QoS performance of LEACH algorithm. That is because the cluster-head probability is adapted based on existing network states. Since κ_{max} is fixed throughout the time of network operation, P_{adp} increases when number of alive SNs ζ decreases. Increasing P_{adp}, however, puts less constraint on selecting a SN to become a cluster-head, and hence increases the likelihood of qualified SNs to act as cluster-heads. The formulation of LEACH-κP algorithm increases the stability period and decreases the probability of dead SNs, as compared to LEACH algorithm.

Exploiting E factor to devise LEACH-κEP algorithm improves the stability period and decreases the probability of dead SNs, as compared to LEACH and LEACH-κP algorithms. The probability function of LEACH-κEP algorithm employs the current SNs' residual energy to thus offer more probabilistic weight to SNs with high energy to become cluster-heads than others. Such energy considerations would

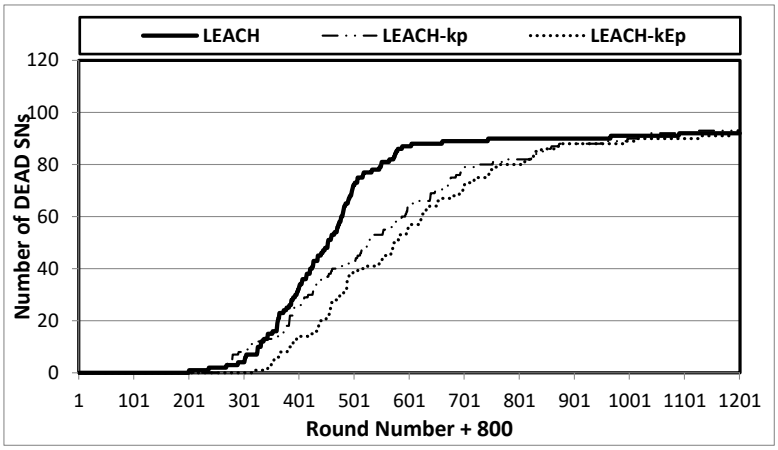

Figure 1: The Effect of κ_{max}, E, and P_{adp} on Dead SNs per Round in LEACH-based Algorithms

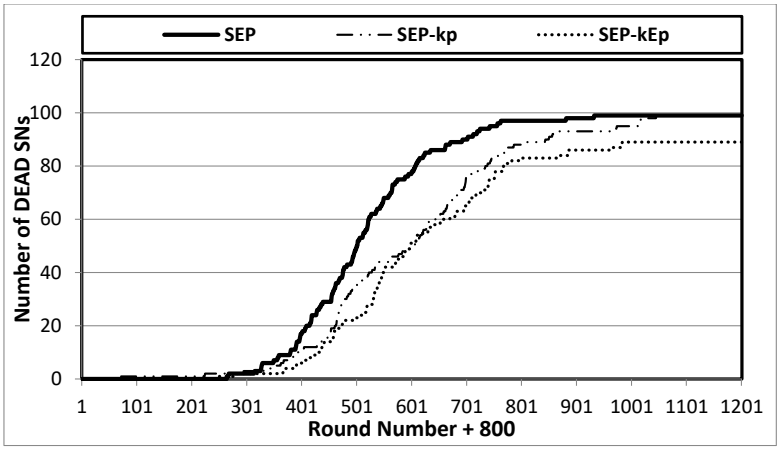

Figure 2: The Effect of κ_{max}, E, and P_{adp} on Dead SNs per Round in SEP-based Algorithms

in turn distribute the energy evenly among all SNs throughout the network lifetime. Overall, engaging E and/or P_{adp} to LEACH algorithm improves the stability period and mitigates the likelihood of dead SNs.

The same thing is applied when SEP algorithms are assessed as shown in Figure 2. SEP-*kP* algorithm surpasses the performance of SEP algorithm by enhancing the probability of dead SNs and stability period throughout most of the network lifetime. In contrast, SEP-κ*EP* algorithm has the greatest stability period in comparison with SEP and SEP-κ*P* algorithms. As well, SEP-κ*EP* algorithm improves the performance of SEP algorithms by decreasing the probability of dead SNs, due to combining the effect of E and P_{adp} performance metrics.

Generally, SEP, SEP-κ*P*, and SEP-κ*EP* algorithms outperform LEACH, LEACH-κ*P*, and LEACH-κ*EP* algorithms, respectively. SEP algorithm basically has different probabilities for advanced and normal SNs; that is P_{adv} for advanced SNs and P_{nrm} for normal SNs. SEP algorithm offers more weight to advanced SNs (by a factor of $(1+a)$) in the original probability function to become cluster-heads than others due to their high residual energy-levels, as compared to LEACH algorithm which allocates equal probabilities to all SNs. Overall, utilizing the effect of P_{adp} and E performance factors together on LEACH and SEP algorithms improves the stability period and mitigates the likelihood of dead SNs per round. The QoS performance of the proposed LEACH algorithms presented in Figure 3 is evaluated

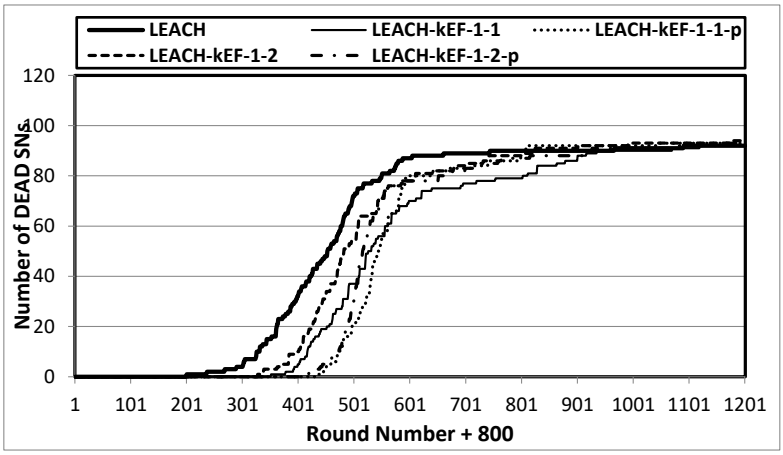

Figure 3: The Effect of P_{adp} and F on Dead SNs per Round in LEACH-based Algorithms

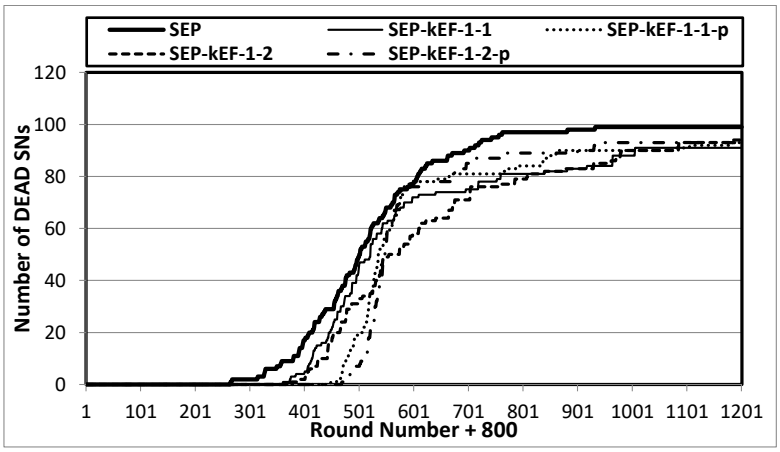

Figure 4: The Effect of P_{adp} and F on Dead SNs per Round in SEP-based Algorithms

on the likelihood of dead SNs by considering the impact of κ_{max}, E, P_{adp}, and F. It is obvious that employing F in combination with κ_{max}, E, and P_{adp} improves the QoS performance of LEACH algorithm - apparently the stability period is increased and probability of dead SNs is decreased. As explained previously, SNs in LEACH algorithm join the nearest cluster-head. However, the nearest cluster-head does not necessarily have adequate energy to serve all its cluster-members for long time. Employing F ratio improves the QoS performance because it also utilizes the residual energy of cluster-heads. In this case, a SN joins a cluster-head with the highest F ratio. P_{adp} combined with F improves the stability period and probability of dead SNs. The same thing is applied when SEP algorithms in Figure 4 are compared together.

6.2 The impact of P_{adp} on death rate of advanced SNs by utilizing κ_{max}, E, and F

The probability of advanced dead-SNs of the proposed LEACH-based algorithms is evaluated in Figure 5 by considering the effect of κ_{max}, E, and P_{adp}. Employing such performance measures on LEACH algorithm gives advanced SNs high probabilities to become cluster-heads and subsequently depletes their energy rapidly. LEACH algorithm by itself, however, selects cluster-heads randomly and does not guarantee to select the most energy-efficient SNs to become cluster-heads.

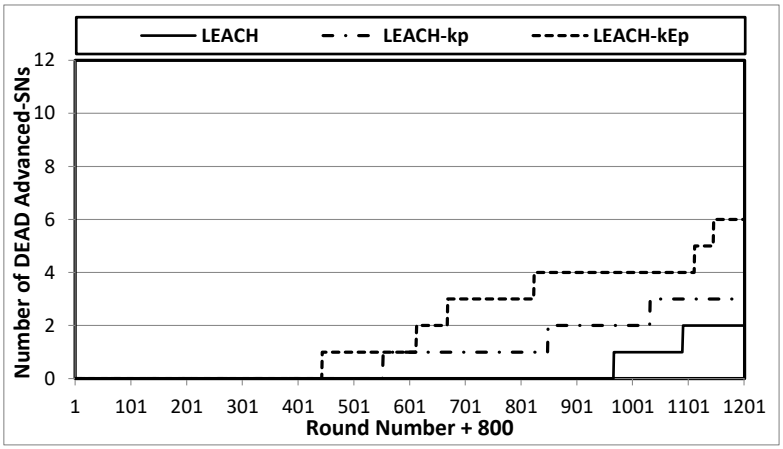

Figure 5: The Effect of κ_{max}, E, and P_{adp} on Advanced Dead SNs per Round in LEACH-based Algorithms

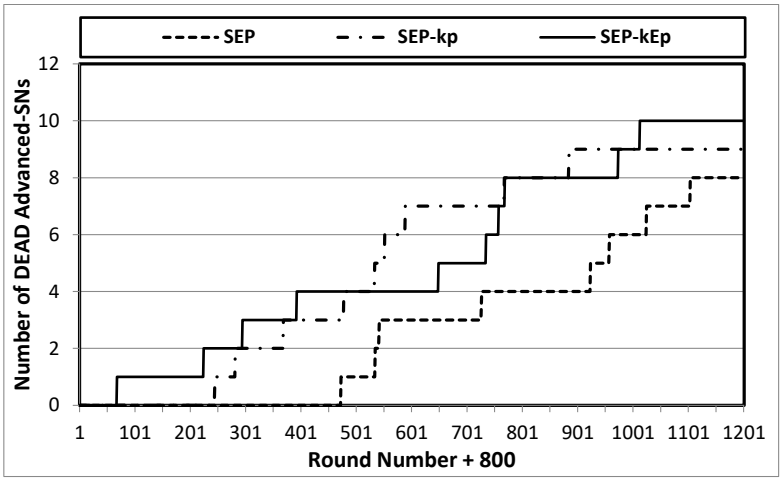

Figure 6: The Effect of κ_{max}, E, and P_{adp} on Advanced Dead SNs per Round in SEP-based Algorithms

In contrast, Figure 6 compares the QoS performance of the proposed SEP-based algorithms on the likelihood of advanced dead-SNs by considering the effect of κ_{max}, E, and P_{adp}. Though, SEP algorithm utilizes high residual energy-levels of advanced SNs to accordingly elect them as cluster-heads early during the network lifetime; which thus decreases the number of advanced SNs throughout the network operation.

However, employing P_{adp} increases the probability of electing advanced SNs and qualifies them more to become cluster-heads in upcoming rounds, especially that advanced SNs have high residual energy-levels as compared to normal SNs. This situation is obvious when SEP-κP algorithm is compared to SEP algorithm, in which P_{adp} factor improves QoS performance of SEP algorithm. The P_{adp} combined with E formulates SEP-κEP algorithm, which in turn improves the performance and stability period, as well as has more impact on enhancing the likelihood of death rate for advanced SNs.

When SEP and LEACH algorithms are compared together, SEP algorithm offers high probabilistic weights to advanced SNs because of their high residual energy as compared to normal SNs. Such weights qualify advanced SNs by increasing their probabilities of being elected as cluster-heads and then die early. Most of advanced SNs are dead in case of SEP algorithm, whereas LEACH algorithm randomly selects cluster-heads without considering SN's residual energy which in turn may leave some of advanced

SNs not being elected very often to act as cluster-heads despite their high residual energy-levels.

Furthermore, the performance impact of P_{adp} together with F ratio for the proposed LEACH-based algorithms in Figure 7 is compared on the likelihood of advanced dead-SNs. Advanced SNs die rapidly because of considering E as a main factor in the modified LEACH-based algorithms to decide on cluster-heads to be elected in each round. Holding $\alpha = \beta = 1$ has more impact on advanced dead SNs than it is in the case of $\alpha = 1$ and $\beta = 2$; and the impact increases when P_{adp} is employed.

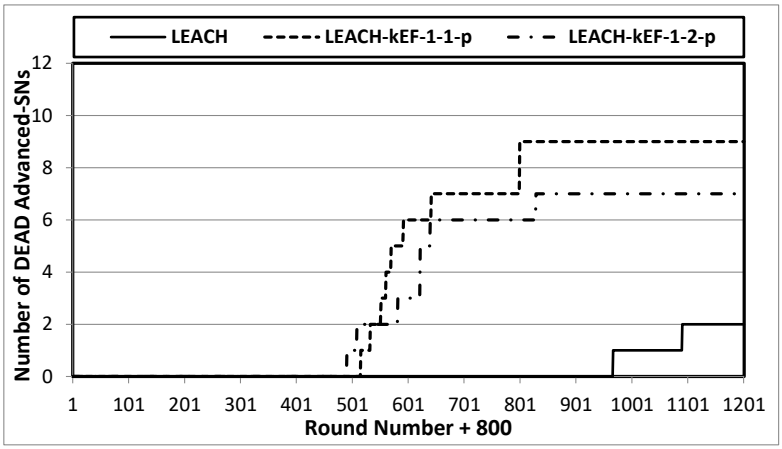

Figure 7: The Effect of P_{adp} and F on Advanced Dead SNs per Round in LEACH-based Algorithms

In contrast, Figure 8 assesses the performance of the proposed SEP-based algorithms on the number of advanced dead SNs by considering the effect of P_{adp} and F. The proposed SEP-based algorithms improve the QoS performance of SEP algorithm by enhancing the stability period and number of advanced dead-SNs. The reason is that the impact of energy and distance, instead of distance only, are considered at each SN to decide on a potential cluster-head to join in each round.

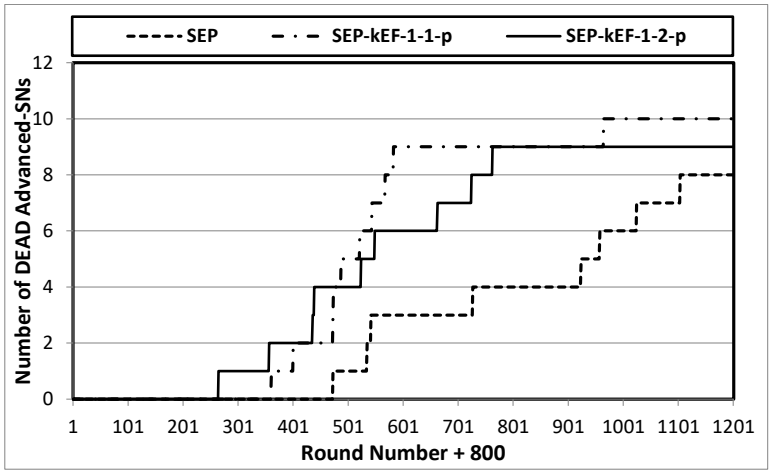

Figure 8: The Effect of P_{adp} and F on Advanced Dead SNs per Round in SEP-based Algorithms

In addition, a cluster-head's energy mostly decreases by increasing the number of cluster-members by the time, by that a cluster-head consumes energy (E_{RX} and E_{DA}) when it accepts a cluster-member. When a distance-based procedure is employed, a cluster-head may keep accepting many SNs because such SNs join the nearest cluster-head, which in turn may rapidly deplete cluster-head's energy. However

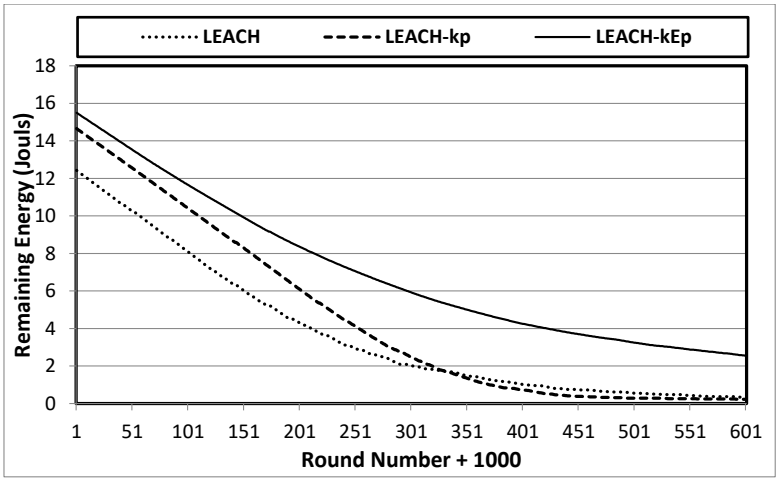

Figure 9: The Effect of κ_{max}, E, and P_{adp} on Energy Consumption per Round in LEACH-based Algorithms

the procedure of utilizing F ratio makes a SN first look at the cluster-head's energy relative to the distance between them, and then the SN joins the cluster-head with the highest F. The latter procedure wisely distributes SNs evenly among existing cluster-heads, each of which with its capacity represented by its residual energy, and hence positively affects the overall QoS performance.

6.3 The impact of P_{adp} on energy consumption

The energy consumption performance of the proposed LEACH-based algorithms is compared in Figure 9, considering the effect of κ_{max}, E, and P_{adp}. Employing P_{adp} decreases the total energy consumption because it increases the probability of qualified SNs to become cluster-heads by the time. LEACH-κEP shows an energy-efficient performance because its cluster-head selection probability accounts for the energy E factor. The same thing is applied for SEP algorithms as shown in Figure 10.

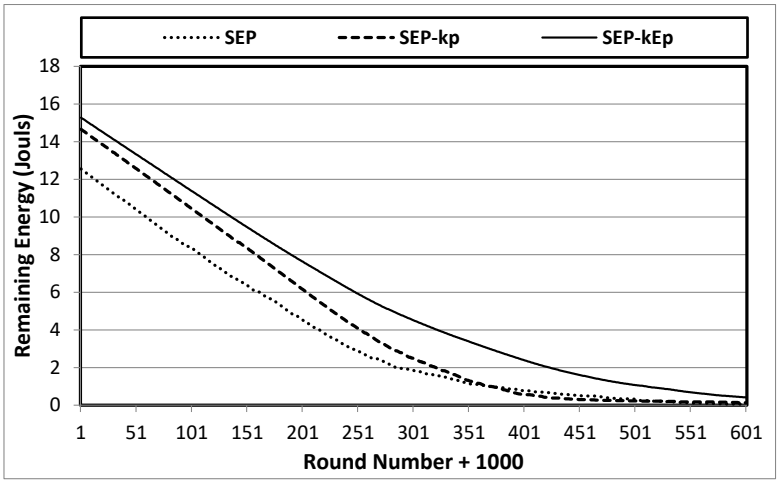

Figure 10: The Effect of κ_{max}, E, and P_{adp} on Energy Consumption per Round in SEP-based Algorithms

The impact of employing F in the algorithms is demonstrated in Figure 11. The adaptive LEACH-κEF-1-1-P and LEACH-κEF-1-2-P algorithms enhance the QoS performance higher than LEACH algo-

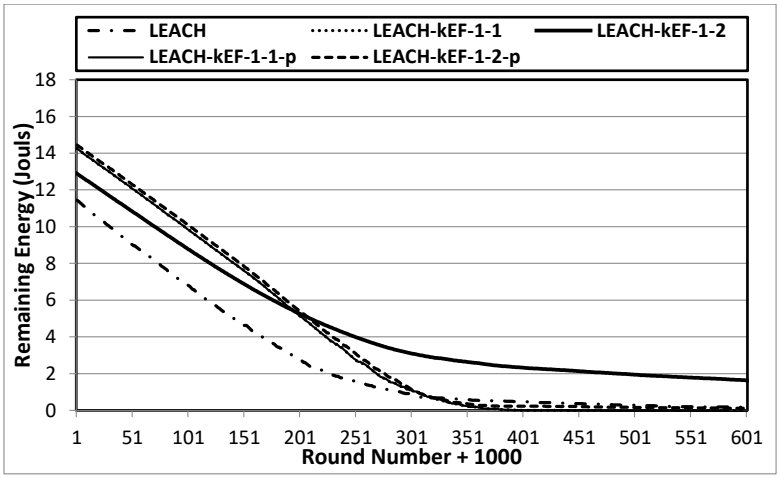

Figure 11: The Effect of P_{adp} and F on Energy Consumption per Round in LEACH-based Algorithms

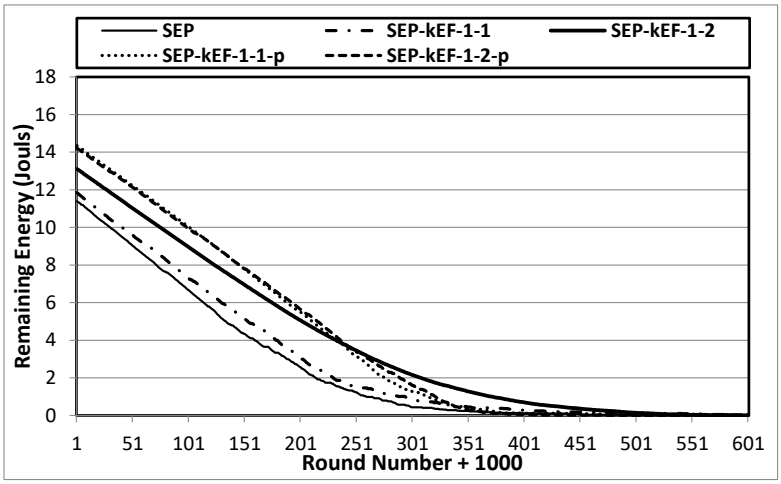

Figure 12: The Effect of P_{adp} and F on Energy Consumption per Round in SEP-based Algorithms

rithm. The same thing is applied for SEP algorithms in Figure 12, where adaptive SEP-κEF-1-1-P and SEP-κEF-1-2-P are the most energy-efficient algorithms.

To conclude, Figure 13 assesses the performance of LEACH and SEP algorithms illustrating the best proposed algorithms according to probability of dead SNs, demonstrating the effect of E and F performance measures. As well, Figure 14 compares the mutual performance impact of such algorithms, utilizing P_{adp} with E and F measures. Overall, the proposed adaptive-based algorithms improve the probability of dead SNs and stability period of original LEACH and SEP algorithms.

6.4 Evolving P_{adp} and κ_{max}

Learning κ_{max}-based algorithms are developed based on the former proposed algorithms, in which the clustering factor κ_{max} is frequently evolved at the end of each round according to the probability of alive SNs ζ, instead of having it fixed a priori in the proposed adaptive algorithms. Accordingly, the probability P_{adp} is adapted according to the evolved κ_{max} clustering and number of alive SNs ζ at the end of each round. Figure 17 compares such learning-based algorithms. The round number period

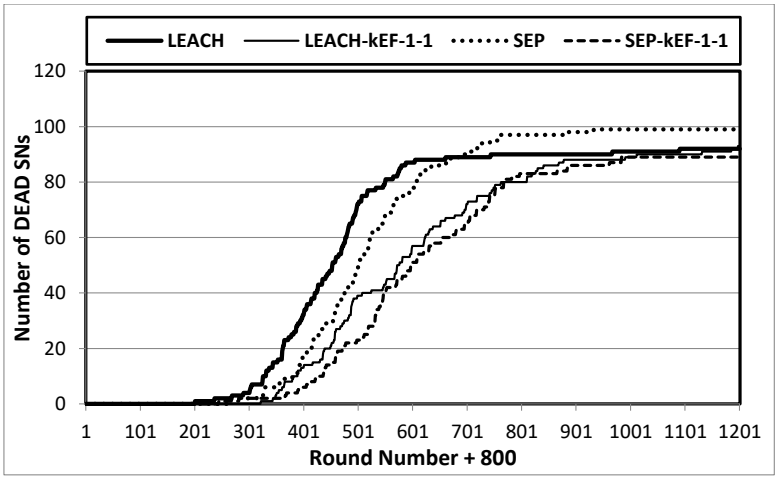

Figure 13: LEACH and SEP Algorithms without P_{adp} for Number of Dead SNs per Round

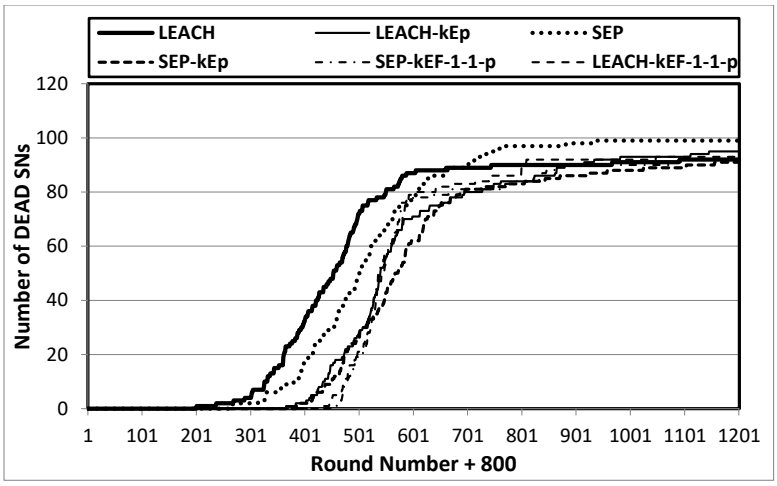

Figure 14: LEACH and SEP Algorithms with P_{adp} for Number of Dead SNs per Round

Algorithm	Round Number	Algorithm	Round Number
LEACH	999	SEP	1052
LEACH-κP	1063	SEP-κP	1081
LEACH-κEP	1164	SEP-κEP	1183
LEACH-κEF-1-1	1135	SEP-κEF-1-1	1150
LEACH-κEF-1-2	1126	SEP-κEF-1-2	1139
LEACH-κEF-1-1-P	1230	SEP-κEF-1-1-P	1241
LEACH-κEF-1-2-P	1217	SEP-κEF-1-2-P	1237
LEACH-κEF-1-1-P-Learning	1308	SEP-κEF-1-1-P-Learning	1367
LEACH-κEF-1-2-P-Learning	1277	SEP-κEF-1-2-P-Learning	1294

Table 3: The Round Number of the Death of First SN for each Clustering Algorithm

of comparison for the likelihood of dead SNs is chosen to be between $1200-1700$, where the major difference between the learning algorithms appears.

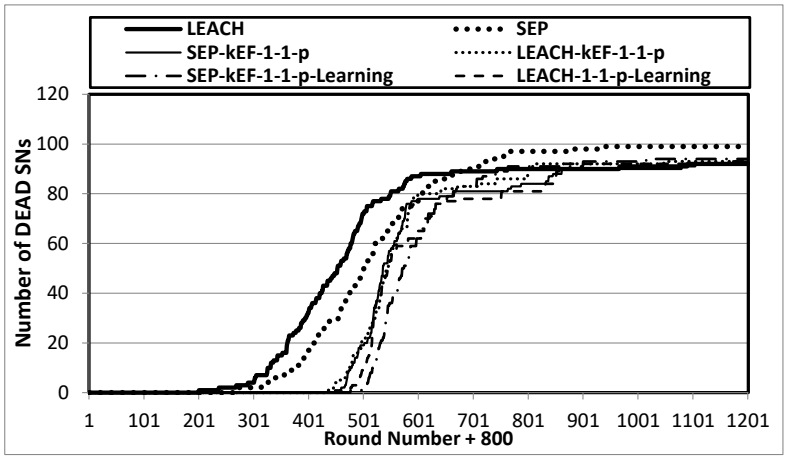

Figure 15: Learning-based LEACH and SEP Algorithms for Number of Dead SNs per Round, $\alpha = 1$ and $\beta = 1$

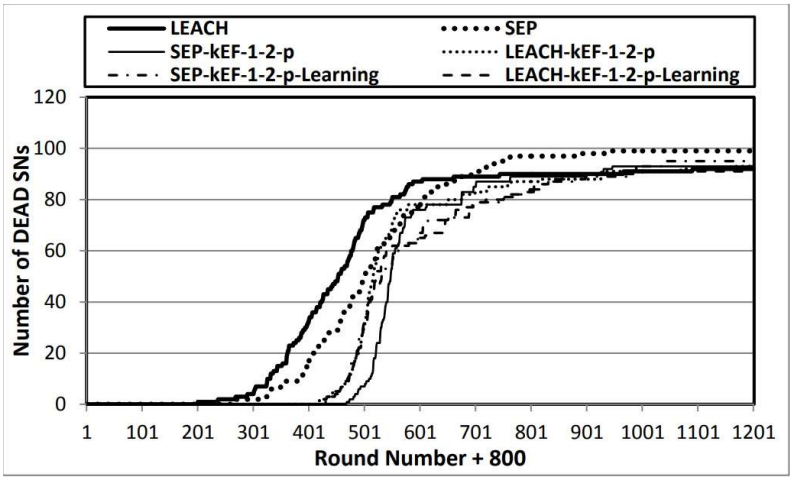

Figure 16: Learning-based LEACH and SEP Algorithms for Number of Dead SNs per Round, $\alpha = 1$ and $\beta = 2$

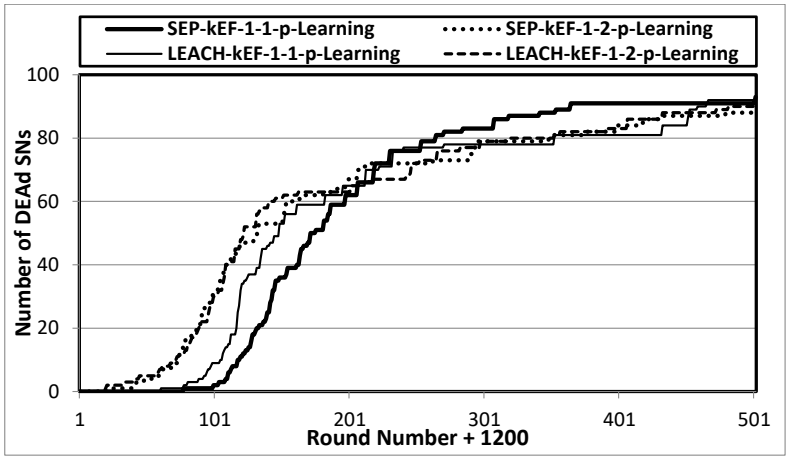

Figure 17: The Effect of P_{adp} on Number of Dead SNs per Round in Learning-based LEACH and SEP Algorithms

The evaluation of the original LEACH and SEP algorithms, the proposed adaptive algorithms, and the learning κ_{max}-based adaptive algorithms are presented in Figures 15-17. The learning-based adaptive algorithms demonstrate better performance and improve the stability period, as compared to both the proposed adaptive and the original LEACH and SEP algorithms. In this case, the round number period of comparison for the likelihood of dead SNs is chosen to be between $800-2000$, where the major difference between the proposed adaptive and learning algorithms appears. To summarize, Table III presents the stability period represented by death of the first SN for each clustering algorithm. The overall QoS performance is improved when κ_{max}, E, P_{adp}, and $\digamma$ are employed together with learning.

7 Conclusion

It is observed that incorporating the residual energy E of a SN in the cluster-head selection probability and limiting the number of cluster-heads permitted per round to κ_{max} improve the overall QoS performance, for LEACH and SEP algorithms. This, however, decreases the likelihood of dead SNs and the total energy consumption, which as a result prolongs the lifetime of network operation. In addition, it is found that P_{adp} improves the cluster-head selection probability because it is adaptive to existing network's state; represented by number of remaining SNs ζ per round and maximum number of clusters κ_{max} permitted per round. Adapting the probability of selecting a cluster-head by P_{adp} and limiting the number of permitted cluster-heads per round to κ_{max} would both distribute the energy and defer qualified SNs evenly throughout the network operation, as well as improve the stability period and QoS performance. Such improvements involve probability of dead SNs and total energy consumption. In addition, incorporating the development of enhanced $\digamma$ ratio improves the performance by considering the residual energy of a cluster-head relative to its distances with its members, instead of only accounting for the distance to compose clusters. Such a relation accounts for the mutual performance impact of member displacements from their corresponding cluster-heads which in turn distributes existing SNs evenly among elected cluster-heads.

8 Future Directions

The cluster-head selection probability will be modified to account for current SN's position to comprise a hierarchical distance-based clustering. Furthermore, a density-based clustering will be developed to formulate SN clusters that do not require a priori knowledge on κ_{max}. A sensitivity analysis will be conducted to study the effect and relationship between input and output performance parameters of the mathematical model. The study will mainly be focused on examining the effect of varying κ_{max} on the probability of dead SNs per round. The QoS performance of the proposed algorithms will be compared with the original LEACH and SEP algorithms, by varying the level of heterogeneity and percentage of advanced SNs in the WSN.

References

[1] M. Adil, R. Khan, J. Ali, B.-H. Roh, Q. Ta, and M. Almaiah. An energy proficient load balancing routing scheme for wireless sensor networks to maximize their lifespan in an operational environment. *IEEE Access*, 8:163209–163224, August 2020.

[2] M. Alharbi, M. Kolberg, and M. Zeeshan. Towards improved clustering and routing protocol for wireless sensor networks. *EURASIP Journal on Wireless Communications and Networking*, 2021(46):1–31, March 2021.

[3] R. Alyousuf. Analysis and comparison on algorithmic functions of LEACH protocol in wireless sensor networks[WSN. In *Proc. of the 3rd IEEE International Conference on Smart Systems and Inventive Technology (ICSSIT'20), Tirunelveli, India*, pages 1349–1355. IEEE, August 2020.

[4] A.-N. Ateeq, I. Obaid, O. Othman, and A. Awad. Lifetime enhancement of WSN based on improved LEACH with cluster head alternative gateway. In *Proc. of the 4th ACM International Conference on Future Networks and Distributed Systems (ICFNDS'20), St.Petersburg, Russian Federation*, pages 1–6. ACM, November 2020.

[5] J. Bhola, S. Soni, and G. Cheema. Genetic algorithm based optimized leach protocol for energy efficient wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 11:1281–1288, July 2019.

[6] L. Chan, K. Chavez, H. Rudolph, and A. Hourani. Hierarchical routing protocols for wireless sensor network: A compressive survey. *Wireless Networks*, 26:3291–3314, January 2020.

[7] D. Chauhan, S. Iyer, and B. Jajal. Enhanced prototype model for energy efficient algorithm of LEACH over wireless sensor network. In *Proc. of the 6th IEEE International Conference on Computing for Sustainable Global Development (INDIACom'19), New Delhi, India*, pages 569–573. IEEE, March 2019.

[8] V. Chauhan and S. Soni. Mobile sink-based energy efficient cluster head selection strategy for wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 11:4453–4466, October 2019.

[9] Y. Chen, L. Jiang, and Y. Mu. A LEACH-based WSN energy balance routing algorithm. In *Proc. of the 2019 ACM World Symposium on Software Engineering (WSSE'19), Wuhan, China*, pages 37—-41. ACM, September 2019.

[10] I. Daanoune, B. Abdennaceur, and A. Ballouk. A comprehensive survey on LEACH-based clustering routing protocols in wireless sensor networks. *Ad Hoc Networks*, 114(1):102388–102409, January 2021.

[11] E. Elsmany, M. Omar, T.-C. Wan, and A. Altahir. Eesra: Energy efficient scalable routing algorithm for wireless sensor networks. *IEEE Access*, 7:96974–96983, July 2019.

[12] A. Faid, M. Sadik, and E. Sabir. EACA: An energy aware clustering algorithm for wireless IoT sensors. In *Proc. of the 28th IEEE International Conference on Telecommunications (ICT'21), London, UK*, pages 1–6. IEEE, June 2021.

[13] L. Guo, J. Liu, P. Qin, X. Zhao, H. Ma, and Z. Chi. Improved strategies of LEACH-based low energy consumption and high reliable multi-hop routing algorithm for wireless sensor network. In *Proc. of the 6th IEEE International Conference on Computer and Communications (ICCC'20), Chengdu, China*, pages 1278–1284. IEEE, December 2020.

[14] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan. Energy-efficient communication protocol for wireless microsensor networks. In *Proc. of the 33rd Annual IEEE Hawaii International Conference on System Sciences (HICSS'00), Maui, Hawaii, USA*, pages 1–10. IEEE, January 2000.

[15] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan. An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, 1(4):660–670, December 2002.

[16] S. Iqbal, S. Shagrithaya, G. Sandeep, and B. Mahesh. Performance analysis of stable election protocol and its extensions in WSN. In *Proc. of the 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies (ICACCCT'14), Ramanathapuram, India*, pages 744–748. IEEE, May 2014.

[17] S. Jain and N. Agrawal. Development of energy efficient modified LEACH protocol for IoT applications. In *Proc. of the 12th IEEE International Conference on Computational Intelligence and Communication Networks (CICN'20), Bhimtal, India*, pages 160–164. IEEE, September 2020.

[18] B. Jiao and Y. Xiong. A novel energy efficient cluster-based algorithm for wireless sensor networks. In *Proc. of the 2011 International Conference on Electronic Engineering, Communication and Management (EECM'11), Beijing, China*, volume 140 of *Lecture Notes in Electrical Engineering*, pages 633–638. Springer, Berlin, Heidelberg, December 2011.

[19] A. Kirsan, M. Al Rasyid, and I. Syarif. Efficient energy for cluster head selection using new LEACH-based routing protocol in wireless sensor network. In *Proc. of the 21st IEEE International Electronics Symposium (IES'19), Surabaya, Indonesia*, pages 70–75. IEEE, September 2019.

[20] S. Lata, S. Mehfuz, S. Urooj, and F. Alrowais. Fuzzy clustering algorithm for enhancing reliability and network lifetime of wireless sensor networks. *IEEE Access*, 8:66013–66024, April 2020.

[21] H. Liang, S. Yang, L. Li, and J. Gao. Research on routing optimization of wsns based on improved leach protocol. *EURASIP Journal on Wireless Communications and Networking*, 2019(194):1–12, August 2019.

[22] C. Lin and F. Jiang. Research of multidimensional optimization of LEACH protocol based on reducing network energy consumption. *Hindawi Journal of Electrical and Computer Engineering*, 2021:1–9, February 2021.

[23] S. Loganathan and J. Arumugam. Energy centroid clustering algorithm to enhance the network lifetime of wireless sensor networks. *Multidimensional Systems and Signal Processing*, 31:829–856, November 2019.

[24] A. Manuel, G. Deverajan, R. Patan, and A. Gandomi. Optimization of routing-based clustering approaches in wireless sensor network: Review and open research issues. *Electronics*, 9(10):1630–1659, October 2020.

[25] K. Muthukumaran, K. Chitra, and C. Selvakumar. An energy efficient clustering scheme using multilevel routing for wireless sensor network. *Computers & Electrical Engineering*, 69:642–652, July 2018.

[26] T. Nguyen, T.-M. Hoang, V.-Q. Pham, T.-T. Nguyen, and N.-S. Nguyen. Enhancing energy efficiency of WSNs through a novel fuzzy logic based on LEACH protocol. In *Proc. of the 19th IEEE International Symposium on Communications and Information Technologies (ISCIT'19), Ho Chi Minh City, Vietnam*, pages 108–112. IEEE, September 2019.

[27] Z. Nurlan, T. Zhukabayeva, and M. Othman. EZ-SEP: Extended Z-SEP routing protocol with hierarchical clustering approach for wireless heterogeneous sensor network. *Sensors*, 21(4):1021–1040, February 2021.

[28] A. Panchal, L. Singh, and R. Singh. RCH-LEACH: Residual energy based cluster head selection in LEACH for wireless sensor networks. In *Proc. of the 2020 IEEE International Conference on Electrical and Electronics Engineering (ICE3'20), Gorakhpur, India*, pages 322–325. IEEE, February 2020.

[29] S. Pandey, K. Dubey, and S. sharma. Performance improvement of LEACH protocol using naïve bayes classifier in wireless sensor networks. In *Proc. of the 2021 IEEE International Conference on Computing, Communication, and Intelligent Systems (ICCCIS'21), Greater Noida, India*, pages 263–267. IEEE, February 2021.

[30] S. Pour and R. Javidan. A new energy aware cluster head selection for leach in wireless sensor networks. *IET Wireless Sensor Systems*, 11(1):45–53, February 2021.

[31] T. Pranathi, S. Dhuli, V. Aditya, B. Charisma, and K. Jayakrishna. A hybrid routing protocol for robust wireless sensor networks. In *Proc. of the 12th IEEE International Conference on Computational Intelligence and Communication Networks (CICN'20), Bhimtal, India*, pages 102–106. IEEE, September 2020.

[32] R. Priyadarshi, P. Rawat, and V. Nath. Energy dependent cluster formation in heterogeneous wireless sensor network. *Microsystem Technologies*, 25:2313–2321, September 2018.

[33] H. Qabouche, A. Sahel, and A. Badri. Hybrid energy efficient static routing protocol for homogeneous and heterogeneous large scale wsn. *Wireless Networks*, 27:575–587, October 2020.

[34] P. Rawat, S. Chauhan, and R. Priyadarshi. A novel heterogeneous clustering protocol for lifetime maximization of wireless sensor network. *Wireless Personal Communications*, 117:825–841, November 2020.

[35] N. Sabor, S. Sasaki, M. Abo-Zahhad, and S. Ahmed. A comprehensive survey on hierarchical-based routing protocols for mobile wireless sensor networks: Review, taxonomy, and future directions. *Wireless Communications and Mobile Computing*, 2017(1):1–23, January 2017.

[36] T. Salam and S. Hossen. Performance analysis on homogeneous LEACH and EAMMH protocols in wireless sensor network. *Wireless Personal Communications*, 113:189–222, January 2020.

[37] S. Saleh, T. Mabrouk, and R. Tarabishi. An improved energy-efficient head election protocol for clustering techniques of wireless sensor network. *Egyptian Informatics Journal*, pages 1–7, February 2021.

[38] D. Sharma, A. Ojha, and A. Bhondekar. Heterogeneity consideration in wireless sensor networks routing algorithms: a review. *The Journal of Supercomputing*, 75:2341–2394, October 2018.

[39] S. Shukry. Stable routing and energy-conserved data transmission over wireless sensor networks. *EURASIP Journal on Wireless Communications and Networking*, 2021(36):1–29, February 2021.

[40] G. Smaragdakis, I. Matta, and A. Bestavros. SEP: A stable election protocol for clustered heterogeneous wireless sensor networks. Technical Report BUCS-TR-2004-022, OpenBU, May 2004.

[41] H. Suleiman and O. Basir. QoS-driven job scheduling: Multi-tier dependency considerations. In *Proc. of the 9th AIRCC International Conference on Cloud Computing: Services and Architecture (CLOUD'19), Toronto, Canada*, pages 133–155. AIRCC, July 2019.

[42] H. Suleiman and O. Basir. Service level driven job scheduling in multi-tier cloud computing: A biologically inspired approach. In *Proc. of the 9th AIRCC International Conference on Cloud Computing: Services and Architecture (CLOUD'19), Toronto, Canada*, pages 99–118. AIRCC, July 2019.

[43] H. Suleiman and O. Basir. SLA-driven load scheduling in multi-tier cloud computing: Financial impact considerations. *International Journal on Cloud Computing: Services and Architecture*, 10:1–24, April 2020.

[44] C. Wang, X. Liu, H. Hu, Y. Han, and M. Yao. Energy-efficient and load-balanced clustering routing protocol for wireless sensor networks using a chaotic genetic algorithm. *IEEE Access*, 8:158082–158096, August 2020.

[45] R. Yadav and M. Gupta. Analysis of modified LEACH protocol for enhancing network lifetime in WSN. In *Proc. of the 4th IEEE International Conference on Electronics, Communication and Aerospace Technology (ICECA'20), Coimbatore, India*, pages 680–683. IEEE, November 2020.

[46] A. Yousaf, F. Ahmad, S. Hamid, and F. Khan. Performance comparison of various LEACH protocols in wireless sensor networks. In *Proc. of the 15th IEEE International Colloquium on Signal Processing and Its Applications (CSPA'19), Penang, Malaysia*, pages 108–113. IEEE, March 2019.

[47] Z. Zhao, G. Li, and M. Xu. An improved algorithm based on leach routing protocol. In *Proc. of the 19th IEEE International Conference on Communication Technology (ICCT'19), Xi'an, China*, pages 1248–1251. IEEE, October 2019.

Author Biography

Husam Suleiman received his PhD in Electrical and Computer Engineering from University of Waterloo, Canada in 2019. His MSc degree is in Computer Engineering from Khalifa University, UAE in 2011 in collaboration with the Massachusetts Institute of Technology (MIT). His BSc degree is in Electrical and Computer Engineering from Hashemite University, Jordan in 2007. Currently, he is an assistant professor in Applied Science Private University, Jordan. His research interests include QoS Optimization in Multi-Tier Cloud Computing, Load Scheduling & Balancing, Big Data Algorithms, Resource Allocation Methods, Performance Prediction Analysis, Security Requirements Engineering Methods for Smart Grids and Systems.

Mohammad Hamdan received his PhD degree in Electrical Engineering from University of Southampton, Southampton, UK in 2019. His MSc degree is in Energy, Sustainability with Electric Power Engineering from University of Southampton, UK in 2014. His BSc degree is in Electrical Engineering from Jordan University of Science and Technology, Irbid, Jordan in 2010. Currently, he is an assistant professor in Applied Science Private University, Jordan. His research interests include smart grid and renewable energy applications.