Cluster-based routing protocols in wireless sensor networks: A survey based on methodology

Abstract

In today's world that all sciences and technologies, including Wireless Sensor Networks (WSNs) are dealing with the improvement of the existing solutions, we are looking for time-saving and cost-effective approaches that unveil new methods and concepts in the intended field. Survey studies provide a quick and comprehensive access to these concepts in the intended realm. Having this motivation in mind and considering the impact of clustering process on controlling and managing energy consumption of WSNs, we focus on clustering and cluster-based multi-hop routing protocols to provide an expansive assessment in terms of methodology. In this survey, some parameters are presented

for evaluating the properties of the different methods. Then, the studied methods are classified from the perspective of methodology into four categories: classical approaches, fuzzy-based approaches, metaheuristic-based approaches and hybrid metaheuristic- and fuzzy-based approaches. In each category of the classification, criteria and parameters are presented according to the type of methodology to evaluate the methods; thenceforth, all methods in each class are evaluated in terms of the clustering-based parameters and methodology-based parameters and eventually discussed. In an effort to provide accurate and useful information and motivate audiences, this evaluation, regardless of providing a useful assessment, intends to propose a new approach for examining methods by considering the methodology-based parameters such as capabilities and constraints, examined inputs and outputs in each method, type of algorithm used in the methods, the purpose of using algorithms, etc. This survey can be useful for researchers as the starting point for a quick understanding of shortcomings and deficiencies in this field to carry out further investigations in the future.

Keywords: Clustering, Multi-hop routing, Classical approaches, Fuzzy-based approaches, Metaheuristic algorithms, Wireless Sensor Networks (WSNs).

1. Introduction

Drawing on the recent advances in the design and manufacture of low-consumption, small, and cost-effective sensors for various applications, which are capable of receiving, processing, and transmitting various types of environmental information, it is now possible to create and develop Wireless Sensor Networks (WSNs). Therefore, a WSN is a generation of networks which usually consists of many inexpensive sensor nodes connected via wireless signals, wherein the goal is to collect information on the environment surrounding network sensors. Generally, a WSN includes many sensors, the data of which are considered in groups to measure one or more parameters. All environmentally collected data packets are transmitted to a node of the network, usually called the Base Station (BS), for further processing [1-4]. The sensor nodes are usually used in areas where it is difficult or impossible for humans to operate. An area of interest should entirely be covered, and sensors are provided with limited battery energy. In addition, the lifetime of a WSN depends on energy [5, 6], and sensor nodes are prone to damage when they are distributed. Therefore, a large number of nodes have to be dealt with. Naturally, such networks consist of hundreds or even thousands of nodes. Small sensor nodes include three main phases: receiving information, processing information, and transferring information wirelessly [5].

WSNs are used widely in various fields, including industries [7-9], medicine and healthcare [10, 11], environmental control and military applications [12-14], traffic surveillance [15], environmental monitoring [16, 17], agriculture, disaster management and healthcare monitoring [18, 19], home automation [20, 21], and other fields [22, 23]. WSNs face many challenges, including energy restrictions [24], security [25], communication reliability [26], design, and so on. It is hard to deal with all these challenges because of their conflicts with each other. In this regard and in order to overcome one of the main challenges, i.e. the energy restrictions of the sensor networks, many methods have been proposed to reduce the energy consumption of sensor nodes and increase the network lifetime, such as data gathering, data correlation, energy harvesting, beam forming, resource allocation using cross-layer design, opportunistic transmission schemes (sleep-wake scheduling), mobile relays and sinks, optimal deployment, clustering and multi-hop routing [27]. Clustering is an example of these methods and is considered as an efficient and scalable energy method for WSNs [28-31]. For clustering in WSNs, sensors are divided into certain groups or clusters, each of which has a Cluster Head (CH). The sensors in each cluster transmit the relevant information to CHs periodically or after an event.

Then CHs transmit the information to a BS directly or in a multi-hop way [32-35]. Clustering has a lot of benefits some of which are mentioned [36, 37]:

– Clustering can maintain communication bandwidth and prevent redundancy of exchange messages.

– Clustering can stabilize the network topology at the sensor level and reduce communication overhead due to node interactions only with CHs.

– Clustering can implement optimized management strategies in the network.

In addition to the clustering mechanism, routing for sending their data plays a major role in reducing energy consumption and, consequently, increasing the lifetime of the network. Therefore, the design of routing protocols in WSNs is challenging because it involves limitations for the efficiency of the network energy. A number of effective parameters in the design of routing protocols are outlined in the following [38, 39]:

– *Energy consumption constraints:* All sensor nodes in WSNs are equipped with a limited-energy battery, which turns the computing, sending and receiving of data into a challenging task, and the lifetime of the sensor nodes is heavily dependent on it.
– *How to deploy nodes:* The distribution of sensor nodes in the network's area is program-dependent and without human monitoring, thus affecting the performance of a routing protocol.
– *Node capabilities:* Sensor nodes can perform different roles and functions such as relaying, sensing, aggregation and combining data according to the type of strategy; each of these roles leads to energy consumption and are regarded as challenge in designing these protocols.
– *Data aggregation:* Adjacent sensor nodes in the network may sense duplicate events. Proper aggregation methods can be taken into account to prevent the redundant data from being sent to the BS.
– *Fault tolerance:* Uncertainty in these networks is normal due to wireless connectivity so should consider studying different mobility patterns and dynamic topologies.

Considering the above mentioned issues, many parameters should be considered in order to design an efficient energy protocol in WSNs. On the other hand, the research fields of sensor networks are very extensive and these networks are becoming more widespread due to the expansion of their field of application. In addition, clustering and routing mechanisms are also used in other areas of the sensor networks, such as mobile sink trajectory [40], trajectory design [41], and even fields other than sensor networks. In order to have effective routing and clustering designs considering the various factors affecting their performance, designers should carefully target accurate details of these methods to identify deficiencies and shortcomings. Therefore, this survey focuses on cluster-based routing protocols with limited non-rechargeable battery aiming at a more accurate examination in this extensive field. Accordingly, several methods, algorithms, and protocols with various purposes have been introduced to make the right use of WSNs. However, given the large number of methods and protocols presented in this field, a survey which examines the methods in terms of used methods, parameters of each part of the method and algorithms used, etc. from the perspective of methodology has always been needed; a survey which regardless of providing complex judgments, provides a general perspective on the details of the methods used in this field and shorten the research path for the designers. This survey is designed to be a starting point for researchers in the field of cluster-based routing protocols from the perspective of methodology. Therefore, the main motivation of this survey is to provide an overview of the details of methods, parameters, goals, algorithms, etc. in the field of cluster-based routing protocols of WSNs with the purpose of facilitating the identification of deficiencies and shortages. Figure 1 shows the structure of a clustered WSN. A list of abbreviations used in this paper, along with their brief definitions, is summarized in Table 1.

This survey is organized such that we will review the past surveys on clustering and cluster-based multi-hop routing protocols in Section 2, and delve into the criteria and classification factors along with the description of the parameters presented in Section 3. In Section 4, a summary of each clustering and cluster-based routing technique is presented with the purpose of highlighting the objectives and their evaluation functions, as well as the comparison of the protocols examined with respect to classification in the form of tables and they are subsequently discussed. Finally, in Section 5, the conclusions and some future directions related to the study are stated.

3. Criteria and Classification Factors

In this section, the classification parameters are characterized. First, clustering-based parameters are divided into clustering-based macro parameters and clustering-based micro parameters. These two categories include parameters describing macro- and micro-characteristics of the clustering methods. Then, the methodology-based parameters are introduced with respect to the classification presented in Section 4 based on the methodology used in the reviewed methods and algorithms.

3.1. Clustering-based Parameters

The parameters for the evaluation of the clustering are presented in this section by employing two approaches to the analysis of macro- and micro-characteristics of the clustering methods known as clustering-based macro parameters and clustering-based micro parameters, respectively.

3.1.1. Clustering-based Macro Parameters

This section addresses the clustering-based macro parameters. These parameters provide general information on the evaluated methods, such as hierarchical structure, CH selection method and the general objective of the method. An overview of these parameters is presented in Figure 3.

- Hierarchical: One way to minimize long-distance data transfer is to use a hierarchical network structure as it facilitates the control and management of the network. This provision also prevents congestion. In hierarchical clustering methods, normal nodes are put at one level, whereas CH nodes are put at another level where CH nodes are usually connected directly to a BS. In simpler words, there are two levels of hierarchy. However, there are a few methods in which two types of CHs are selected. One level of CH is responsible for the transmission of information to the next-level CHs which are responsible for transmitting the information to a BS. These methods are characterized by three levels of hierarchy. However, information is sent to the BS in a multi-hop or multilevel way in a large number of methods. Such a structure sometimes is used among the network CHs and

among the nodes of a cluster some other times. The goal of this parameter is to determine the number of levels created in the reviewed methods. Thus, the parameters specifying the number of levels in this criterion are two levels, three levels, and multilevel hierarchical parameters, respectively. A multilevel hierarchy is employed in methods consisting of more than three levels in their network structures.
- CH selection method: A brief account of steps is presented to describe the general procedure for selecting CHs in different methods in a way that benefits the audience. This section presents significant approaches to the CH selection in the reviewed methods.
- Objective: Clustering and routing algorithms and methods have many objectives such as scalability, faulttolerance, data aggregation/fusion, load balancing, stability of network topology, maximizing network lifetime, reducing energy consumption, increasing connectivity, decreasing delay, avoiding collision, utilizing sleeping schemes, removing hot spots problem, maintaining coverage network, and reducing the number of control messages. Some of these objectives may be considered as the main objectives such as scalability, faulttolerance, data aggregation/fusion, load balancing, the stability of the network topology, and maximizing the network lifetime. The rest of them are considered as secondary objectives set to help achieve the main objectives. Secondary objectives are of less importance [61]. Figure 4 presents a summary of the primary objectives in various clustering methods. More details of these objectives may be found in [51, 61, 66].

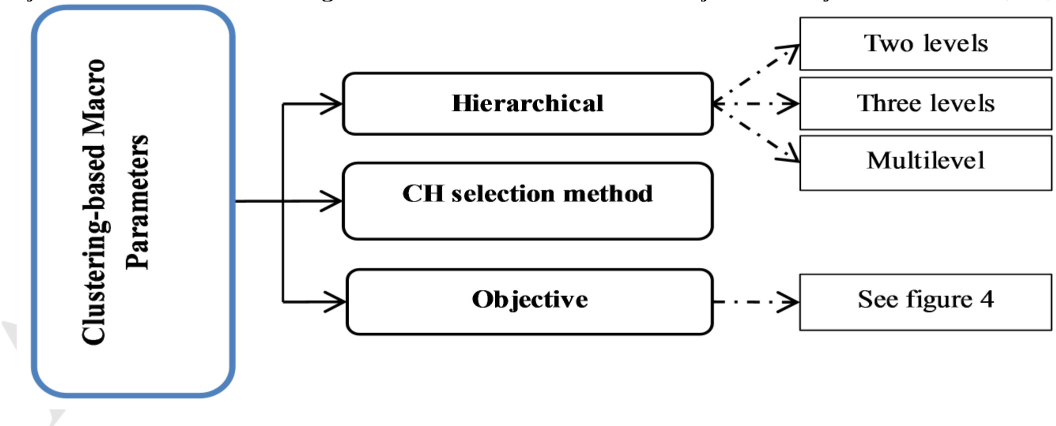
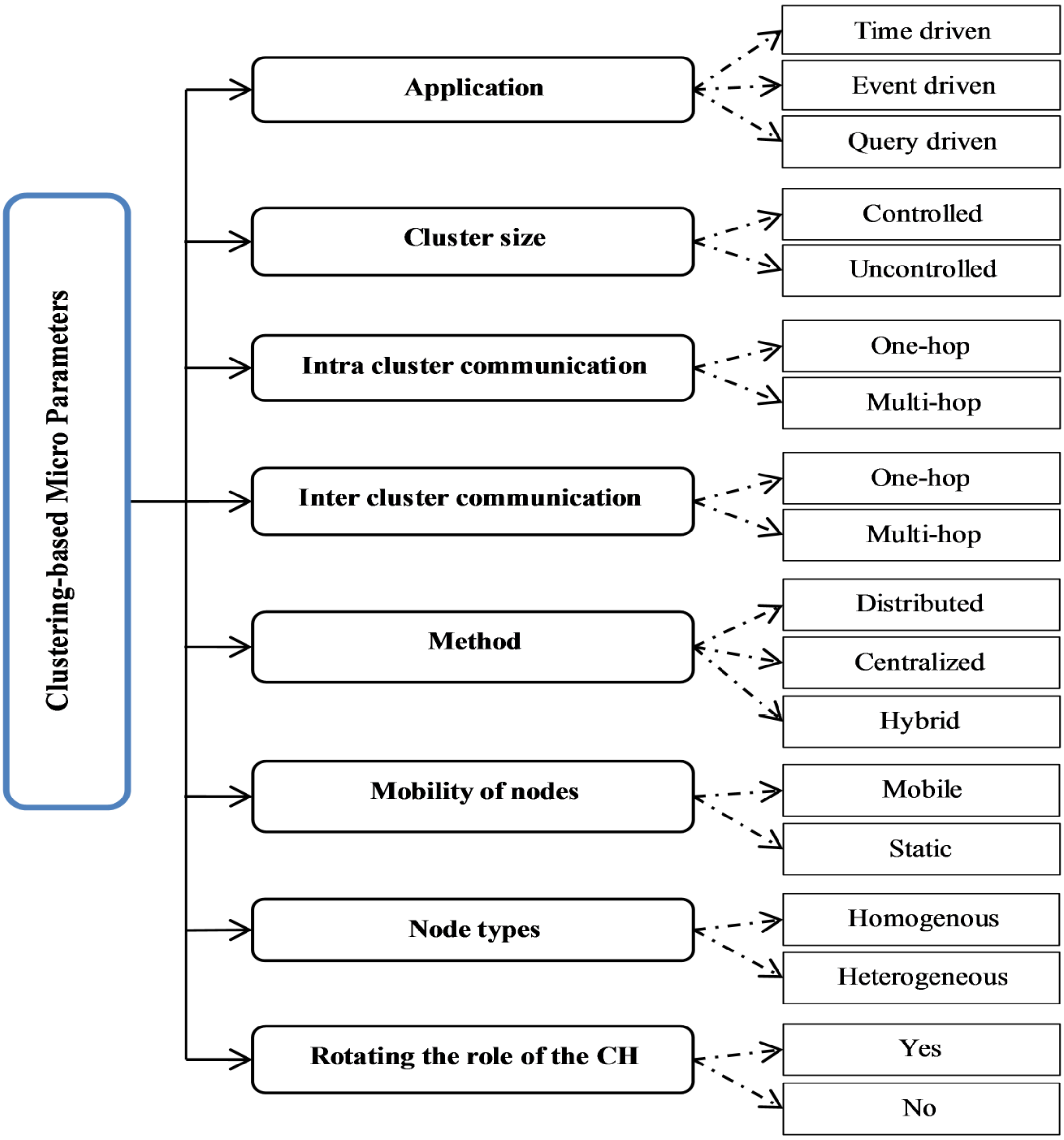


Figure 3. The clustering-based macro parameters in WSNs.

3.1.2. Clustering-based Micro Parameters

This section addresses the clustering-based micro parameters. These parameters define the micro-features and characteristics of a clustering method, which are discussed below. Figure 5 shows an overview of these parameters.
- Application: The algorithms and methods for collecting information from normal nodes by CHs and transmitting them to a BS can be classified into time-driven, event-driven, and query-driven [62, 69]. In timedriven methods, the sensor nodes transmit data to a BS or to gateways periodically. In event-driven methods, the sensor nodes transmit the collected data to a BS when an event occurs or according to a specified threshold. In query-driven methods, a BS sends a query to nodes, and then, the nodes transmit the information back to the BS in response to the query [70, 71].
- Cluster size: A cluster size can be either controlled or uncontrolled. This criterion is used to analyze a method or algorithm to see whether designers paid attention to controlling the size of clusters or the number of members in a cluster. A cluster size can be determined with respect to the distance from a BS or to overcome the hot spot problem. In this case, farther CHs are larger, whereas closer CHs are from smaller clusters. A cluster size may also be based on the density of clustering algorithms to determine the range of clusters [66, 72].
- Intra-cluster communication: In some methods, there is a direct (one-hop) connection between a sensor and a relevant CH. In some other methods, there are multi-hop connections. In the methods where there is a small number of CHs when member nodes are far from CHs or when there are transfer restrictions on sensors, it is better to use multi-hop intra-cluster communications. Hence, the parameters were considered either one-hop or multi-hop in this evaluation criterion.
- Inter-cluster communication: There can be direct or one-hop connections between CHs and a BS. CHs can also be connected to middle nodes in a multi-hop way. If the sensor nodes are equipped with limited-range transmitters and receivers or if there is a large number of sensor nodes in the area, multi-hop mechanisms may be a good choice for WSNs.
- Method: The method of a clustering algorithm can be either distributed or centralized. The process of performing tasks can even be a hybrid distributed and centralized mechanisms in such methods. In fact, it is possible that the clustering phase of a method is distributed (or self-organized and distributed by nodes), whereas the routing phase is centralized with the help of a BS or directly by a BS. This parameter is used to analyze the mechanism adopted in the entire process of an algorithm.

- Mobility of nodes: Normal nodes and CHs can be either motionless (not moving) or mobile (moving). If they are considered mobile, they can move in a limited range.
- Node types: Algorithms can use either normal or homogeneous nodes (in simpler words, such nodes are similar to each other in respect of energy sources and other pieces of equipment) or heterogeneous nodes (which are different in sources and equipment). CHs are usually selected from heterogeneous sensor nodes if algorithms employ such nodes.
- Rotating the role of the CH: This criterion determines whether a method of interest uses a mechanism to replace the nodes playing the role of a CH. In certain methods, CHs are replaced periodically. In some other methods, they are replaced after a predetermined period of time or when the energy levels of CHs reach a predetermined threshold. By adopting the energy threshold mechanism, a method usually tries to unify the network energy consumption.



3.2. Methodology-based Parameters
According to the classification presented in Section 4, methodology-based parameters were classified into classical approaches, fuzzy-based approaches, metaheuristic-based approaches, and hybrid metaheuristic- and fuzzy-based approaches in this section.

3.2.1. Parameters Considered in Classical Approaches
This section deals with parameters used to compare classical approaches. Figure 6 shows the parameters analyzed in this method to express the entire methodology-based features employed in the reviewed methods, including the capabilities, limitations, parameters studied, specific purpose of the method and simulation environment.

3.2.2. Parameters Considered in Fuzzy-based Approaches

This section presents parameters used to compare fuzzy-based approaches in respect of methodology. The parameters considered in fuzzy-based approaches were presented to describe every characteristic of the fuzzy methodology in the reviewed protocols, Such as capabilities, limitations, fuzzy input parameters, fuzzy output parameters, defuzzification method, evaluation method of fuzzy rules, fuzzy rule setting method, the purpose of using fuzzy logic, simulation environment. Figure 7 shows the parameters used to compare fuzzy-based approaches.

3.2.4. Parameters Considered in Hybrid Metaheuristic- and Fuzzy-based Approaches

This section presents parameters used to compare the methods using both metaheuristic algorithms and fuzzy-based approaches. The considered parameters were presented for examining the characteristics of both methods used in these approaches are; capabilities, limitations, fuzzy input parameters, fuzzy output parameters, defuzzification method, evaluation method of fuzzy rules, fuzzy rule setting method, how to do the optimization process, the purpose of using fuzzy logic, optimization algorithm, parameters studied in optimization, the purpose of using the optimization algorithm, simulation environment. Figure 9 shows an overview of these parameters.

4. Classification of Cluster-based Routing Protocols According to Methodology

WSNs benefit from clustering to meet their requirements such as reducing the energy, on which these networks depend highly. Many methods and algorithms have been presented for this purpose in various classifications (according to Section 3). In this section, a new classification of the methodology view is presented to categorize current methods as classical approaches, fuzzy-based approaches, metaheuristic-based approaches, and hybrid metaheuristic- and fuzzy-based approaches (neural network methods were ruled out in this area because they are not widely used [73-75]). Figure 10 presents an overview of the classifications and methods analyzed in every section. They are dealt with briefly here.

4.1. Classical Approaches

Classical clustering-based routing protocols focus on how to select CHs. They can be distinguished from each other in the ways they select CHs. A number of them are discussed here.

– Low Energy –Adaptive Clustering Hierarchy (LEACH)

LEACH was introduced by Heinzelman et al. [32]. This protocol is probably the first dynamic clustering protocol, which considers the requirements of WSNs in particular and uses motionless sensor nodes distributed at random. LEACH is still regarded as a base for other advanced clustering protocols in WSNs. Generally, it is a hierarchical, probabilistic, distributed, and one-hop protocol. LEACH is employed in certain periods, each of which includes a setup phased and a steady-state phase. The setup phase starts when nodes organize themselves into clusters. Every node selects a random number like *T* (between 0 and 1). A node turns into a CH in the current round if *T* is smaller than *T(i)* in Formula (1).

$$T(i) = \begin{cases} \dfrac{p}{1 - p \times \left(r \bmod \dfrac{1}{p}\right)} & \text{if} \quad i \in G \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

In this formula, *p* is the expected percentage of CH nodes in the population of sensors, and *r* represents the number of a current round. *G* is a group of nodes which did not turn into CHs in the last *1/p* rounds (rotations). After selecting CHs, every CH transmits a message to other nodes, and every node (which is not a CH) indicates which cluster it is going to be a member of. In fact, every node selects its cluster to communicate with its CH by spending less energy. A non-CH node becomes a member of a cluster when it receives the strongest announcement signal from the respective CH. Every node sends a new message to its new CH to inform it of the membership in the cluster. After the nodes are formed, the steady-state phase begins. In this phase, the network functions in a number of time frames. In each frame,
the entire nodes of a cluster transmit data to a CH within the specified time slot. In fact, a CH creates a Time Division Multiple Access (TDMA) communication scheduler for the member nodes. Given the fact that the length of a time slot is constant for each node, the length of a time depends on the number of nodes in the cluster. After every member node transmitted the information to a CH, the CH puts the combination of data into a packet and sends it to a BS. Then the period ends after a specified amount of time and a new period begins, periodically assigning the CH role to the nodes to balance the load.

– Maximum Energy Cluster Head (MECH)

Chang and Kuo [76] introduced a method named MECH. In this protocol, every node transmits ‘Hello' to its neighbors first. This message is characterized by a Time To Live (TTL) defined as a period to collect information from neighboring nodes which are as far as a hop. Therefore, a radio range is determined so that every node can register the number of its neighbors. Here there is a systemic parameter named Cluster Nodes

(CN) determining the maximum number of neighboring nodes. If the number of nodes reaches CN, the node transmits an announcement to the neighbors existing in one hop. The announcement states, "I am a CH". Every recipient records this message and turns

on a time. In addition, some nodes do not claim to be a CH, although the number of their neighbors reaches a CN because only one CH is determined in the radio range here. After the timer expires, every node selects a CH based on the strongest signal it has received and sends the CH a message, informing it about the member nodes. After the clusters are formed and data is collected by the CHs, the data is transmitted to the BS according to a set of specified rules, the number of hops, and the energy of the nodes.

– Three Layered routing protocol based on LEACH (TL-LEACH)

Zhixiang and Bensheng [77] introduced a protocol named TL-LEACH consisting of three functional phases: selecting the CH, setup, and data transfer. In the CH selection stage, the first-level CHs are selected randomly by using an enhanced threshold such as LEACH. Formula (2) shows the threshold.

$$T(i)=\begin{cases}(\mathrm{r}+1)\times mod\,\dfrac{1}{p}\times p & if \quad i\in G\\ 0 & otherwise\end{cases} \tag{2}$$

In this formula, p is the expected percentage of CH nodes in the population of sensors, and r is the current round number. Furthermore, G is a group of nodes which did not turn into a CH in the previous $1/p$ round (rotation). Then, the second-level CHs are selected from the first-level CHs based on energy. First, non-CH nodes become members of the first-level CHs. Next, the first-level CHs become members of the second-level CHs based on the shortest distance. Finally, non-CH nodes transmit information to the first-level CHs in the data transfer phase. Then, the first-level CHs transmit the aggregated data to the second-level CHs which transmit them to a BS in turn.

– Threshold-based cluster head replacement – LEACH (T-LEACH)

Hong et al. [78] presented a method named T-LEACH delaying the periodic exchange of CHs in LEACH until the CH energy level would reach lower than the predetermined threshold. The threshold is determined with respect to the energy consumed by nodes in different roles described by the following formulas. In other steps, T-LEACH acts like LEACH.

$$P_{th}=Count_{RND}\times\left(PK_{Tx}+PK_{Rx}\right)P_{Tx} \tag{3}$$

$$Count_{RND}=\frac{P_{HR}}{P_{WEC}}\times 100 \tag{4}$$

$$P_{WEC}=NumofNodesPerCluster\times InitPowerofEachNode \tag{5}$$

where P_{TX} is the energy consumed to transmit 1 byte of data. PK_{TX} and PK_{Rx} indicate the sizes of the transmitted and received data packets, respectively. P_{HR} represents the energy consumed for exchanging the CH; it also includes the energy consumed by a node serving as a CH and the energy of an ordinary node in the network. P_{WEC} shows the total energy of each cluster.

– Power Efficient Clustering Routing Protocol (PECRP)

Liu and Li [79] introduced a protocol named PECRP enhancing the CH selection mechanism in LEACH based on energy and distance. The following formulas show the threshold discussed in this paper:

$$T_{PECRP}\begin{cases}\dfrac{p}{1-p\left[r\,mod\,\dfrac{1}{p}\right]}\times\dfrac{\left[E(i)+\left(1-D(i)\right)\right]}{2} & in \quad n\in G\\ 0 & otherwise\end{cases} \tag{6}$$

$$D(i)=d_{iB}/d_{FAREST} \tag{7}$$

$$E(i)=E_{current}(i)/E_{max} \tag{8}$$

where d_{iB} is the Euclidean distance between node i and the BS. Moreover, $d_{FARBEST}$ was considered 5000 meters, a value which as stored in the Random-Access Memory (RAM), and p indicates the expected percentage of CH nodes in the population of sensors. Finally, r shows the current round number, and G is a group of nodes which did not turn into a CH in the last *1/p* round (rotation). Every node selects a random number. If the selected number is smaller than T_{PECRP}, the node turns into a CH. In this method, to allow for multi-hop CH communications, each CHs select its neighboring CH based on its distance to the BS and the closer CHs directly transmit data to the BS.

– **Energy-Efficient Heterogeneous Clustered scheme (EEHC)**

Kumar et al. [80] introduced a protocol named EEHC. This protocol uses three types of nodes: normal nodes, advanced nodes, and Super Nodes. It has been assumed that a percentage of nodes is equipped with more sources of energy compared with normal nodes in the network. In other words, m is a portion of the entire nodes in the network (n), and mo is a percentage of the entire nodes (m), equipped with more time energy β. These nodes are known as Super Nodes. Other nodes ($n * m * (1 \_ mo)$), equipped with more time energy α compared with normal nodes, are known as advanced nodes. The rest of the nodes are known as normal nodes, which are distributed uniformly in the network. This protocol includes two phases. In the setup phase, every step looks exactly like those of LEACH. The only difference is that three types of nodes with three different energy levels are used in EEHC. To select CH, a weighted probability is used with respect to the initial energy of nodes compared with others. This weight should be equal to the ratio of every node initial energy to the initial energy of normal nodes. Therefore, it is assumed that p_n is the weighted probability of selecting normal nodes, and p_a is the weighted probability of selecting advanced nodes. Moreover, p_s is the weighted probability of selecting large nodes. Accordingly, a threshold is set for selecting CHs in each period in this protocol.

– **Density of Sensor - LEACH (DS-LEACH)**

Bagherzadeh and Samadzamini [81] presented an algorithm named DS-LEACH (density of sensor–LEACH). In every period, this algorithm includes two phases: setup and steady-state. Major tasks are performed in the setup phase, which introduces a node as a CH. In DS-LEACH, the density of nodes is used as a criterion for selecting a CH. The setup phase includes advertisement, cluster-setup, and TDMA scheduling procedures. In the setup phase, every node I calculates the probability of becoming a CH by using the Formula (9).

$$p_i = \max\left(\frac{1}{M_i - (r \bmod M_i)} - \frac{C_i}{r}, 0\right) \tag{9}$$

In this formula, C_i is the number of times when sensor i was a CH, and M_i is the number of nodes in the cluster (or the average number of nodes in the clusters where node i was a CH in previous periods). Furthermore, r is the current round number, and p_i indicates the probability at which node i was a CH in round r. It should be noted that M_i ought to be considered a random number above zero. After a few rounds, if node i becomes a CH, the value of M_i is updated to the number of nodes in that cluster (wherever node i becomes a CH). The value of p_i depends on M_i, C_i, and r. After estimating p_i, every node selects a random number like x between zero and one. Then x is compared with p_i. If $p_i>x$, then node i does not turn into a CH. It waits until another CH receives the message and becomes a member. In the next phase, every node, which has not turned into a CH, decides what cluster it should join based on the highest received signal power. When the node selects a CH, a membership message is sent to that CH. Other steps are like those of LEACH.

– **Multi clustered Energy – efficient Routing Algorithm (MERA)**

Nayak et al. [87] introduced an algorithm named MERA, in which the BS exists outside the network environment and is constant. Based on the information obtained from the BS, the network environment is divided into L levels or L nested clusters. Inside every cluster, sensors are divided into L other levels. By the BS, the nodes of each level are chained to each other using the Dijkstra algorithm (the shortest path) to form a cluster. The CHs are selected from the list of nodes at the shorter distance from the BS randomly with respect to the residual energy. They are not replaced until they run out of energy. After clustering, considering the distance from the BS and the distance from an adjacent node, each CH decides to transmit information to a next-level CH or an adjacent one. This procedure continues until the information reaches the BS.

– **Energy-aware Routing Algorithm (ERA)**

Amgoth and Jana [88] presented the ERA algorithm that consists of two steps, namely clustering, and routing. In the clustering stage, every sensor node has an independent timer before competing to become a CH. This timer shows the maximum time specified for selecting the CH. The time is calculated with respect to the initial and residual energy of a sensor. In other words, a higher energy level result in a shorter period of time to let the node select itself as a CH. If the timer expires and no messages are received from another CH, it will introduce itself as a CH by disseminating an announcement within a specific range. If a node receives a message from another CH before the timer expires, it turns into a non-CH node. Then the relevant time expires. Sensor node timer i is obtained from Formula (16):

$$t(i) = \frac{E_m(i) - E_r(i)}{E_m(i)} \times T_{CH} \tag{16}$$

where T_{CH} is the maximum time determined to select a CH. Moreover, $E_m(i)$ and $E_r(i)$ show the initial and residual energy levels of sensor node i. Based on the received messages, every node stores the CH paths, sending announcements, into a table containing information on neighbors. According to this table, every non-CH node calculates the average residual energy of CHs and joins the closest CH with the highest level of residual energy. In the routing stage, the BS is assumed as the level zero and disseminates a message in a specific range. The CH nodes receiving this message are considered as the first-level CHs which, in turn, send a message containing certain information in another specific range. The recipients of this message that are not at the same level as the transmitting CH are considered as the next-level CHs. This procedure continues until the routes are formed. Therefore, every CH of lower levels may have several parents at higher levels. Then a set of parent CHs is selected if they have equal or greater energy levels compared with the residual energy of the selected CHs. The comparison is drawn as follows:

$$\mu(u) = \frac{\sum_{i=1}^{p} E_r(V_i)}{p} \tag{17}$$

where $\mu(u)$ is the residual energy of parent CHs, and p is the number of parent CHs. Considering the set of parent CHs having more or equal energy compared with $\mu(u)$, data are divided into parent CHs to be sent to the BS.

– Decentralized energy efficient Hierarchical Cluster – based Routing algorithm (DHCR)

Sabet and Naji [89] introduced a method named DHCR using a clustering algorithm with several criteria and a clusterbased routing algorithm simultaneously. In other words, the BS disseminates a message first in a specific range. Upon receiving the message, every node starts competing to become a CH by disseminating a new message (containing information such as residual energy and distance from the BS). Based on such information, every node i of the neighboring nodes existing in the target range receives the message and calculates its $CHSnfun_i$.

$$CHSnfun_i = a \times \frac{Ere_i}{E_{max}} + b \times \frac{1}{DisToBS_i} \tag{18}$$

where Ere_i and E_{max} show the residual and initial energy levels of node i, respectively. $DisToBS_i$ is the distance between node i and the BS. Furthermore, a and b are real values selected between zero and one in a way that $a+b=1$. Then every node compares its $DisToBS_i$ with those of its neighbors. The node with the highest value becomes the CH. Otherwise, it remains a normal node. Every first-level CH disseminates a message in a specific range containing certain pieces of information such as its own residual energy, the number of neighboring nodes, and the distance from the BS via routes. The next-level CH nodes receive the information to continue the procedure. Accordingly, every node determines a redistributor CH to the BS at the same time. Then the nodes join the closest CH. To select a redistributor node, a CH is selected if it has more energy and fewer neighbors (neighboring degree).

– Layered Clustering Routing Protocol with Overlapping Cluster Heads (LCRPOCH)

Agrawal and Kushwah [90] introduced a protocol named LCRPOCH consisting of five steps. In the first step, sensor nodes are distributed in the field randomly with unique IDs. In the second step, the entire network is divided into clusters of constant sizes. Clusters are formed into layers. In the third step, CHs are evaluated and determined. Based on the density of sensor nodes and the proximity of nodes to the center of gravity in a cluster, CHs are selected. In the fourth step, overlapping CHs are evaluated and allocated. The nodes existing near the CH on the boundary between clusters are selected as overlapping CHs. Finally, data are sent to the BS via CHs and overlapping CHs.

– Low Energy Fixed Clustering Algorithm (LEFCA)

Cengiz and Dag [91] presented an algorithm called LEFCA. In LEFCA, the clusters are constructed during the set-up phase. A sensor node which becomes a member of a cluster stays in the same cluster throughout the lifetime of the network. LEFCA uses the clustering approach by partitioning the nodes into fixed clusters. For each cluster a CH is responsible for collecting and delivering the data to the BS. In the algorithm, each node self-elects itself as a CH. Each node generates a random number, and if that number is smaller than the probability threshold (the optimal number of clusters relative to the total number of nodes), then the node becomes the CH. Otherwise, that node becomes a cluster member. It should be noted that in LEFCA, when the data transmission phase of a round is complete, the CH needs to decide whether it will continue to act as a CH for the next round or choose a new CH. This decision is made based on the CH's remaining energy. If a new CH needs to be elected, the current CH chooses the new one randomly among the members of its cluster.

– Hamilton Energy-Efficient Routing protocol (HEER)

Yi and Yang [92] presented a clustering-based routing protocol named HEER benefiting from the concept of a Hamiltonian path. HEER aggregates data and transmits them to the BS via a Hamiltonian path created by the entire cluster of nodes and controls the cluster size by selecting one node as the CH. The probability of being selected as a CH (*p*) is calculated from Formula (19).

$$p = \left(L_{message} \big/ F_{max} \right) \tag{19}$$

In this formula, $L_{message}$ represents the size of every node, and F_{max} is the maximum size of a frame. In this protocol, clusters are created only once in the first round based on LEACH. In other rounds, only the CH role changes according to the energy on the Hamiltonian path after a determined period of time.

– Improving Low Energy Fixed Clustering Algorithm (ILEFCA)

Cengiz and Dag [93] presented an algorithm called Imeproving LEFCA. In this algorithm, the network is initially partitioned and then the CHs are determined only once by the BS and clusters are formed. These clusters are constant throughout the network's lifetime, and CHs within the clusters are changed only when their energy is less than the set threshold based on the energy consumption of the node farthest to BS. In order to carry out the CH substitution process in this algorithm, the current CH will select a node from its cluster members randomly for the next round.

– Multi – Level Route-aware Clustering algorithm (MLRC)

Sabet and Naji [94] introduced the MLRC algorithm. In this algorithm, first, the BS sends a message to every node to start the competition for the CH. The nodes with higher levels of residual energy than the determined threshold participate in the competition and turn into a candidate CH. They disseminate a message in a specific range covering neighbors. Based on the information, every node calculates the information on the value of CHs_i function compared with the values of neighbors. If a node realizes that it has the highest value of CHs_i function, it will be selected as CH.

Otherwise, it remains normal node. Formula (20) is used to calculate CHs_i function:

$$CHs_i = a \times Er_i + b \times \frac{1}{dToBS_i} \tag{20}$$

where Er_i is the residual energy of node *i* and $dToBS_i$ shows the distance between node *i* and the BS. Moreover, *a* and *b* are real values selected between zero and one in a way that a+b=1. The first-level CHs are determined by a message that the BS disseminates in a specific range to create paths in a multilevel structure. The CHs disseminate their positional information in a specific radius. Based on the information in this message, the nodes of every level determine their redistributor nodes at higher levels. This procedure lasts until every CH determines the next-level redistributor node to the BS. Then every node joins the closest CH with respect to Received Signal Strength Indication (RSSI) in the cluster formation phase. To reduce the workload of CHs near the BS, such CHs are considered to have fewer members in this protocol. In other words, every member node considers a set of candidate CH. Then a random number like *x* (ranging between zero and one) is selected and compared with the determined threshold (based on conditions such as the residual energy of candidate CHs and distance) to select the right CH.

– Hierarchical Distributed Management Clustering (HDMC)

Shahraki et al. [95] introduced a protocol named HDMC, the goal of which was to extend the network lifetime, distribute energy consumption between the entire nodes fairly, and increase the network coverage. Based on its history and the current status of resources and information on the visible scope, every node tends to become a CH. However, since a node is not aware of neighboring nodes and their intention to become a CH, the responsibility for making decisions is given to a judge knowing the intention of every node in the area. This judge is the every CH selected in the previous round. The judge wants the nodes in its scope to transmit their tendency information. Every node calculates its tendency using Formula (21) and transmits it to the CH that asked for it.

$$Inc\left(x\left[T_{n+1}\right]\right) = \left(\beta_1 * Act_{hist}\left(x\left[T_{n+1}\right]\right) + \left(\beta_2 * Act_{En}\left(x\left[T_{n+1}\right]\right) + \left(\beta_3 * Act_{Ov}\left(x\left[T_{n+1}\right]\right) \right.\right.\right. \tag{21}$$

In this formula, *x* is the node calculating its tendency for the next round, and Act_{hist} is the history of node activity, and Act_{En} is the history of node energy based on the ratio of residual energy to the initial energy. Furthermore, Act_{Ov} shows how much *x* overlaps with a requesting CH when β_1, β_2, and β_3 show the weights of Act_{hist}, Act_{En}, and Act_{Ov}, respectively. These weights range between zero and one in a way that $\beta_1+\beta_2+\beta_3=1$. Based on the CH selection algorithm, then the right node is selected as the new CH. Therefore, the new CH is selected in the old cluster. It should be noted that if a node does not see itself fit to be selected as the CH, it may still be selected as the CH by the judge to maintain the network coverage.

– Energy Aware Multi-hop Routing Protocol (EAMR)

Cengiz and Dag [96] presented a protocol called EAMR which is an improvement on their M-LEFCA [97] protocol. This protocol consists of two main phases: set-up phase and steady state phase. In the setup phase, the CHs, their members, and the redistributor nodes are assigned so that at first each node can randomly choose itself as a CH (the number of CHs is predefined). Each CH node selects the closest CH node to itself as the redistributor node and the formed clusters are constant over the entire network lifetime (unless the CH nodes have substitution conditions). This phase is performed only once at the beginning of the EAMR. In the steady state phase, the transmission of the collected data, the substitutions of CHs and the redistributor nodes take place. Generally in this phase, a CH is replaced when its energy is lower than the set threshold based on the energy consumption of the node farthest to the BS; in these conditions, the current CH randomly chooses a node from among its member nodes as the new CH. By substituting the CH, if the node also has the role of redistributor, this role will also be passed to the new CH.

4.1.1. Comparison of Classical Approaches

Classical approaches have been investigated in terms of clustering-based parameters and methodology-based parameters. In order to provide a general overview of the characteristics of classical approaches, this evaluation is presented in two macro and micro sections, which are presented in tables 3 and 4, respectively. The classical approaches based on the evaluation presented in Table 3, initially paid more attention to the two levels hierarchical, while they have moved towards the multilevel hierarchical structures in the recent approaches. In other words, in these methods, it has initially been attempted to prevent the direct connection of CHs to the BS by considering the multilevel hierarchy. It is clear that the focus of these methods is to select the appropriate CHs. In these methods, firstly, simple random methods are used for this purpose, and effort has been made to solve the load balance issue in the clustering mechanism with periodic rotation mostly by considering the time driven application and rotation of CHs among all nodes. However, considering the disadvantages of random methods, the methods of CHs selection while considering the network parameters have gained further attention. These methods are more effective in choosing the appropriate CHs using local information based on the distribution method.

From the perspective of methodology-based parameters related to classical approaches in consistence with the above arguments, the main limitation of these methods is the lack of attention to the proper and comprehensive parameters for choosing CHs and their distribution at the network space level and the lack of scalability. In addition, these methods are not application-specific. In other words, there is no any strategy to adaptively adjust and tune the controllable parameters of the protocols based on the application requirements. Although a protocol may have acceptable performance for an application, its performance may be reduced for another application, and they cannot cover the different applications. Table 5 deals with the evaluation of classical approaches from the point of view of methodology-based parameters. According to the parameters studied, most of the classical methods (other than LEACH and some of the initial methods that do not address a particular parameter) considered the energy and distance parameters, but the designers of these methods have turned to combine different parameters in recent years (such as DHCR, MLRC, and HDMC). Finally, with regard to the simulation environment, according to the examined methods, the MATLAB environment is desired by designers for simulation of classical methods. In general, the mechanism considered in these methods is simple and they have low computational and overhead complexity. Usually, CHs selection based on the mechanisms with a few parameters and the rotation of the CHs role in these methods is carried out periodically. In a number of methods of this category, an effort has been made to delay the rotation of the CHs role by the creation of some thresholds. Due to the lack of attention to the size of clusters and their distribution, these techniques do not appropriately create the load balance in the network; thus, they cannot increase the lifetime significantly.

4.2. Fuzzy-based Approaches

Due to uncertain incidents occurring in the environments of WSNs and overlapping parameters affecting the roles of CHs, many protocols have used the fuzzy logic for clustering and selecting the appropriate CHs. A number of such algorithms are discussed here.

– LEACH protocol using Fuzzy Logic (LEACH-FL)

Ran et al. [98] introduced a protocol named LEACH-FL to select CHs by using the fuzzy logic. It is an enhanced version of LEACH. The input variables of the fuzzy system are residual energy, distance to the BS, and node degree to calculate the probability of becoming a CH. This protocol employs a distributed process of clustering and selecting CHs based on fuzzy outputs in the same way as LEACH. In details, if the fuzzy output of every node is smaller than $P_i(t)$, obtained from Formula (22), in every round, the node is selected as a CH. Ultimately, the information, collected by CHs, is sent to the BS in a one-hop way.

$$p_{i(t)} = \begin{cases} \dfrac{p}{1 - p \times \left(r \bmod \dfrac{1}{p} \right)} & \text{if} \quad i \in G \\ 0 & \text{otherwise} \end{cases} \quad (22)$$

In this formula, p is the expected percentage of CH nodes in the population of sensors, and r is the current round number. Moreover, G is a set of nodes which did not become a CH in the last $1/p$ rounds.

– Energy –Aware Unequal Clustering algorithm with Fuzzy (EAUCF)

Bagci and Yazici [99] presented a clustering algorithm named EAUCF mainly to reduce workload inside clusters existing closer to the BS or having lower levels of energy. In EAUCF, conventional CHs are selected using a probabilistic model in every round of node clustering. In other words, every node selects a random number between zero and one. If this number is smaller than the predetermined threshold, the node turns into a conventional CH. The competitive radius of conventional CHs is selected by every node using Fuzzy Inference System (FIS) based on inputs such as residual energy and distance from the BS. If a tentative cluster-head node has a high level of energy and exists at the longest distance from the BS, it will have the longest competitive radius and vice versa. The other values range between these two values. After determining the competitive radius of conventional CHs, every CH competes with other conventional CHs in the radius. If a conventional CH receives a message stating a higher level of energy in that radius, it will withdraw from the competition to become a CH; otherwise, it becomes a CH.

– Multi –Objective Fuzzy Clustering Algorithm (MOFCA)

Alperset et al. [100] proposed the MOFCA method to overcome the problem of hot spots and the early evacuation of energy in WSNs. Similar to EAUCF, this algorithm operates with various fuzzy inputs. In this algorithm, every node selects a number between zero and one in every round. If this number is smaller than *TH* (the favorable percentage of the number of CHs), it decides to become a temporary CH. Then temporary CHs consider fuzzy inputs (residual energy, distance from the BS, and node density) to calculate the competitive radius by using the fuzzy logic. Given the predetermined radius and the maximum competitive radius of temporary CHs, they disseminate an announcement. If a temporary CH receives the message from another with a higher level of energy, it withdraws from the competition. If the two nodes are of the same energy level, their density parameters are compared. The temporary CH with higher density becomes the CH. Otherwise, the temporary CH becomes the final CH, and non-CH nodes join the closest CH.

– Distributed Fuzzy Logic (DFL)

Alaybeyoglu [101] introduced a method named DFL to reduce energy consumption and decrease the number of sent messages. For this purpose, when the energy of a root node becomes lower than the threshold, it informs every node with a message. Then, an FIS is carried out in every node, executing the middle node of the FIS tree based on its information and child nodes. Then, the best node is introduced to the root node via a message and an FIS is carried out in the root node to select the best root. The fuzzy inputs of FIS included residual energy, centrality, distance from BS, the number of hops, and node density.

– Fuzzy based Unequal Clustering Protocol (FUCP)

Gajjar et al. [102] introduced a protocol named FUCP to layer the network in the form of hexagonal sections. Given the three fuzzy inputs (distance from the centers of hexagons, residual energy, and communication quality) CHs are selected by using the fuzzy Logic. Based on the distance between the hexagon and the BS as well as the density of nodes inside the hexagon regarded as fuzzy inputs, the competitive radius of CHs and the number of CHs will be determined inside every hexagon. Then, the protocol tries to overcome the problem of hot spots by increasing the number of CHs and decreasing the competitive radius in the layers of every hexagon near to the BS.

– Fuzzy logic Based Unequal Clustering (FBUC)

Logambigai and Kannan [103] introduced an algorithm named FBUC. In this algorithm, conventional CHs of every node are first determined randomly in the same way as LEACH. Next, conventional CHs use the fuzzy logic considering three parameters (distance from the BS, residual energy, and node degree) to determine the competitive radius. Then final CHs will be the nodes with the maximum fuzzy output in their domain. After that, the nodes use the fuzzy logic and inputs (distance from CHs and the degree of CHs) to calculate the chance of joining them. Finally, they join a CH with the largest fuzzy outputs.

– Distributed Unequal Clustering using Fuzzy logic (DUCF)

Baranidharan and Santhi [104] introduced an algorithm named DUCF consisting of two working phases like LEACH. In the cluster formation phase, every node is qualified to become a CH. Given the FIS inputs (residual energy, the degree of the nodes, and distance from the BS), every node calculates two outputs: chance and size. Then every node disseminates an announcement containing an ID (Identification) and a chance indicator to compete to become a CH. The CHs receiving such an announcement from other CHs will turn into the final CH if they have a higher chance than others. Then, they send an announcement in a certain domain to notify other sensor networks. Considering the messages received from CHs, the non-CH nodes send their membership requests to the closest CH. After a CH receives a membership request from another node, it checks the Size parameter. If it has fewer members than the Size, the request is granted. Otherwise, it is denied. Then the node sends the membership request to another closer CH, from which an announcement has been received. If a non-CH node does not find a CH to connect to, it introduces itself as the CH. This procedure lasts until all of the nodes are clustered.

– **Energy Conserved Unequal Clusters with Fuzzy logic (ECUCF)**

Sundaran et al. [105] introduced a method known as ECUCF. In this approach, every node selects a random number between zero and one. If this number is smaller than the predetermined threshold, the node will become the initial CH. Then the entire network is divided into three sections based on the distance from the BS, residual energy, and node proximity by using the fuzzy logic. In every section, the node energy is compared to the energy threshold. If the node energy is lower, the node will put to sleep. Otherwise, the node will remain active. Every initial CH calculates its competitive radius by considering the inputs (distance from the BS, residual energy, and the node sector information). Then every initial CH disseminates a message within its competitive radius. If the recipient of this message has lower residual energy than the residual energy of redistributor node, it will withdraw from the competition to become a CH. If a normal node receives this message, it will select and join the final CH by considering the fuzzy inputs such as distance, residual energy, and node proximity.

– **Adaptive Multi-Clustering algorithm using Fuzzy Logic (Adaptive MCFL)**

Mirzaie and Mazinani [106] presented an algorithm named the adaptive MCFL. In this paper, three different clustering algorithms were used for clustering sensor nodes. In the first clustering algorithm, every node calculates its chance of becoming a CH by using the fuzzy logic and fuzzy inputs (residual energy and the number of neighboring nodes). Then the node with the highest value of fuzzy output is selected as the CH. If the energy levels of CHs, selected in the first algorithm, do not reach the experimental threshold, every CH of previous round will continue serving as the CH in the second clustering algorithm. If the CH energy reaches the threshold, the algorithm begins executing the third clustering method. In this phase, the fuzzy logic and fuzzy inputs (residual energy and distance from the CH) are employed to calculate the chance of nodes to become a CH. Then, the node with the highest fuzzy output will is as the CH. After this step, the nodes are clustered in the next round using the first type of clustering algorithm. The predetermined threshold is based on an experiment conducted to enter the protocol into the third type of clustering algorithm:

$$TH = \frac{1}{2^{\frac{r}{450}}} - \frac{x^2}{2} \tag{23}$$

where x is the fuzzy output of every node, and r is the current round number. The predetermined threshold (TH) reduces to half gradually in every 450 rounds.

– **Distributed Fuzzy logic-based unequal Clustering approach and Routing algorithm (DFCR)**

Mazumdar and Om [107] presented an algorithm called DFCR which consists of four main steps: information sharing, cluster formation, virtual backbone formation and data routing. In the information sharing step, each node is aware of its distance from the BS and its neighbors. In the cluster formation step, each node decides on becoming a CH in a distributed way, and calculates its cluster radius based on local information. In this algorithm, each node calculates the energy level and its distance to BS as the fuzzy input parameters in order to obtain the competency function 1 for CH selection. Each node, then calculates its latency based on the competency function 1, and when the timer expires, the node calculates its radius according to the competency function 1 and the fuzzy output derived from the consideration of the neighbor density and the cost of the neighbor and the production of output of competency function 2. More specifically, the competency functions 1 and 2 are considered as fuzzy inputs and the cluster radius is calculated as fuzzy output. Each node distributes a message within its own radius notifying that it has become the CH. If a node receives a message before the timer expires, it will ignore the competition for becoming the CH. Each node, then calculates its connection cost to the CH from which the message was received and becomes the CH member with the least cost. At the virtual backbone formation stage, the CHs are classified and their levels are determined. Finally, at the data routing stage, each CH selects a member from among the lower-level CHs from which it has received a message according to the minimum cost function (including total sending and receiving charges).

4.2.1. Comparison of Fuzzy-based Approaches

This section compares clustering and cluster-based routing protocols in the category of fuzzy-based approaches according to the parameters presented in Section 3 and the methodology type. Tables 6 and 7 present the characteristics of the clustering-based macro and micro parameters, respectively. The fuzzy logic in the investigated methods has been used for two types of operations for the selection of the optimal CH or for determining the competitive radius related to the activity of CHs, which are more related to objectives of load balancing and removing hot spots problems. The most hierarchical structure to be considered in these methods along with paying attention to the problem of hot spots, is multilevel structure, in which, the intra-cluster communications are more one-hop and the inter-cluster communications are multi-hop. In these methods, like classical approaches, the time driven application and rotation of the CH role along with their periodic collection have attracted the designers. Considering the problem of hot spots in these methods, their cluster sizes are usually controlled. As the fuzzy-based approaches are a little bit more complex than classical approaches in design, distributed methods are used for performing the protocols' activities in these methods (like the classical methods).

Table 8 analyzes the fuzzy-based approaches by considering the methodology-based parameters. From the perspective of methodology, the main limitation of these methods is the lack of attention to the parameters affecting the determination of the role of CHs and the failure to provide the appropriate mechanism and strategy for routing among the clusters. It should be noted that one of the main objectives in these methods is overcoming the problem of hot spots and one of the most effective solutions considered in these methods is to unequalize the activity radius of the clusters in the multilevel structure. The distance-to-BS factor is the most important parameter for overcoming the problem of hot spots in multilevel structures; therefore, to reduce the load of CHs near the BS, the radius of these clusters is considered to be smaller than the CHs which are located farther from the BS and are not responsible for receiving and sending messages from other CHs. However, special attention is not given to these routing methods in order to better utilize the structure. Parameters considered as the fuzzy inputs in these methods show that energy, distance to BS and a higher node degree in these methods are given special consideration; besides, the fuzzy outputs are the probability of becoming CH and the competitive radius of the CHs. Among all the examined methods, Center Of Area (COA) defuzzification method and Mamdani FIS have been utilized, in which, the regulation of the table of their rules is conducted manually by an expert. In addition, fuzzy logic has been used in a several stages of a number of recent methods, so that the output of a fuzzy phase is considered as an input parameter of another phase of fuzzy logic (methods such as FUCP, FBUC, ECUCF, and MCFL). The simulation environment desired by designers in simulating these types of methods, such as classical methods, is the MATLAB environment.

– **Multipath Routing Protocol (MRP)**

Yang et al. [108] introduced a protocol named MRP based on the ACO algorithm. MRP consists of three steps: cluster formation, multipath construction, and data transmission. Cluster formation is executed whenever an event occurs. According to the rules of cluster formation, nodes can feel how far they are from an event based on RSSI. Nodes are also aware of the residual energy of their neighbors. If RSSI is greater or equal to the threshold, the node exists in the event space, and the CH is selected in a way that it can be closer to the center of the event. The objective function of CH determination is described as follows:

$$q_i = (E_i)^{k_1} \times (K_i)^{k_2} \times (SE_i)^{k_3} \tag{24}$$

where E_i is the residual energy of node i, and K_i is a temporary set of node i used to store the number of neighbors in the event space. Furthermore, SE_i is the RSSI from an event when, k_1, k_2, and k_3 are the weight control parameters. In multipath construction, CH uses ACO to search for and discover paths to the BS. After discovering several paths, the CH selects one path for data transmission based on an evaluation function. Then the information is sent to the BS via the selected path. The evaluation function is as follows:

$$f_1 = (E_{min}(i))^{k_{10}} + 1/\left(E(i)\right)^{k_{11}} + 1/\left(lenght_i\right)^{k_{12}} \tag{25}$$

where k_{10}, k_{11}, and k_{12} are the weighted values, the summation of which is one. $E_{min}(i)$ is the minimum residual energy on path i. $E(i)$ is the total energy consumed on the path i, and $length_i$ indicates the length of path i.

– **LEACH-based Genetic algorithm and Partition (GP-LEACH) and LEACH-based Harmony Search (HSLEACH)**
(HS-LEACH)

Karimi et al. [109] presented two algorithms named GP-LEACH and HS-LEACH to improve the process of selecting CHs in LEACH. These two algorithms act exactly like LEACH. The only difference is that they divide the entire network into several sectors (the number of which is determined by the BS) first. The number of CHs is 3-5% of nodes in every sector. In GP-LEACH, the genetic algorithm is used to select CHs based on the distance and residual energy of nodes in every sector. In HS-LEACH, the HS algorithm is employed to select CHs. Finally, the nodes join the closest CH. The information is sent from CHs to the BS directly in a one-hop way.

– **Evolutionary Approach for Load-Balanced Clustering Problem**

Kuila et al. [110] presented an algorithm (referred to as ELBCP here for simplicity) to balance the workload of the CH. A number of such sensors were regarded as gateways in the network. Every sensor node can only be connected to one of such gateways. For this purpose, the GA was employed. Given the mechanisms for generating the initial population and the processes of mutation and crossover, the algorithm tries to minimize the workload of every CH. In other words, the generation of the initial population is changed from the pure random state by being limited to the connections between sensor nodes and corresponding CHs. The chromosome length was regarded as the number of nodes in the network to generate the initial population. The value of every gene can be selected randomly from the list of CHs on which this node existed and received a message. The following formulas show the objective function calculating the standard deviation of gateways:

$$\sigma = \sqrt{\frac{\sum_{j=1}^{m} (\mu - wj)^2}{m}} \tag{26}$$

$$\mu \ (average\ load\ ) = \sum_{i=1}^{n} d_i \ / \ m \tag{27}$$

In these formulas, σ shows the standard deviation of the gate workload distributed in a cluster, and m is the number of gateways when n is the number of sensor nodes. Moreover, d_i is the load at the sensor node i, and w_j is the total load at gate g_j.

– HSA Cluster-based Protocol (HSACP)

Hoang et al. [111] introduced a protocol known as HSACP based on the Harmony Search Algorithm (HSA). HSACP was implemented to minimize the intra-cluster distance between the members of a cluster and corresponding CHs and to distribute energy in a real environment to detect a fire. It includes two phases named clustering setup and data transmission. In clustering setup, sensor nodes are clustered by HSA and an objective function described in the following formulas:

$$f_{obj} = \alpha \times f_1 + (1 - \alpha) \times f_2 \tag{28}$$

$$f_1 = \max j \in (1, k) \left\{ \frac{\sum \forall\ node_i \in C_j \ d\left(node_i, CH_j\right)}{\left|C_j\right|} \right\} \tag{29}$$

$$f_2 = \sum_{j=1}^{k} \left\{ \frac{\sum \forall\ node_i \in C_j \ V_i^{res}}{V_{CH_j}^{res}} \right. \tag{30}$$

In Formula (29), f_1 is the maximum Euclidean distance between nodes ($node_i \forall i \in$ $cluster\ C_j$) and CH_i when $|C_j|$ shows the number of nodes belonging to C_j. Moreover, f_2 is the total ratio v_i^{res} of the current residual energy of all nodes (Σ $\forall node_i \in C_j$ v_i^{res}) in the network to the energy level of CH_j, i.e. $v_{CH_j}^{res}$. This step ends with the formation of clusters and data transmission begins. In this step, sensor nodes send the information they received to the corresponding CHs with respect to their specific time slots. Then CHs send the information directly to the BS after aggregating data.

– Sink Mobility based Energy Balancing Unequal Clustering (SMEBUC)

Fan and Feiefi [112] presented a protocol named SMEBUC using using Shuffled Frog Leaping Algorithm (SFLA) to select CHs with higher levels of energy and create unequal clusters in a centralized way. To deal with the frequent replacement of CHs in this protocol, CHs work continuously until the predetermined exchange time. This protocol also uses mobile BS routing algorithms to collect information and cope with the problem of hot spots. Formula (31) shows the objective function of this algorithm.

$$
\begin{cases}
E(p_i) = a_1.A_1(p_i) + a_2.A_2(p_i) + a_3.A_3(p_i) \\
A_1(p_i) = \max j = 1,2,\ldots,N \ \Sigma \forall n_k C_{pi,j} D\left(n_i, CH_{pi,j}\right)/N \\
A_2(p_i) = \sum_{k=1}^{M} e(n_k) / \sum_{j=1}^{N} e\left(CH_{pi,j}\right) \\
A_3(p_i) = \sum_{j=1}^{N} D\left(s, CH_{pi,j}\right)/N.D(s, MC)
\end{cases}
\tag{31}
$$

In this formula, $A_1(p_i)$ is the maximum average distance between nodes and the CH, and $A_2(p_i)$ is the ratio of the entire energy of all nodes to all CHs. $A_3(p_i)$ is the ratio of the average distance between a CH and the BS or the BS and an *MC* (Monitoring Center). Furthermore, p_i is a sensor node *i*, and $D(x, y)$ shows the Euclidean distance between two nodes like *x* and *y*. The letter *M* represents the number of CHs, whereas *N* shows the number of sensor nodes. Finally, $E(p_i)$ minimizes the energy consumed by sensor node p_i.

– **Application Specific Low Power Routing protocol (ASLPR)**

Shokouhifar and Jalali [113] introduced a protocol named ASLPR collecting certain pieces of information such as the distance from the BS, residual energy, and the distance between CHs from nodes to select CHs. Then every node selects a random number between zero and one. If this random number is smaller than T_{ASLPR} in Formula (32), the node will become a CH:

$$
T_{ASLPR} = \begin{cases}
Z(n) & if \ E(n) \geq t_1 \times \frac{1}{N} \sum_{i=1}^{N} E(i) \\
0 & if \ E(n) < t_1 \times \frac{1}{N} \sum_{i=1}^{N} E(i)
\end{cases}
\tag{32}
$$

$$
Z(n) = \alpha_1 T_1(n) + \alpha_2 T_2(n) + \alpha_3 T_3(n) + \alpha_4 T_4(n) \tag{33}
$$

where *N* is the entire number of live nodes in the current round, and $E(n)$ is the residual energy of node *n*. In Formula (33), $T_1(n)$ is the subthreshold for the energy of nodes, and α_1 is the weight of this sub-threshold. $T_2(n)$ is the subthreshold for the distance between nodes and the BS, whereas α_2 is the weight of this subthreshold. $T_3(n)$ is the subthreshold for the distance between the node and the CH, and α_3 is the weight of this subthreshold. The subthreshold $T_4(n)$ refers to the number of rounds in which a node has been the CH, and α_4 is the weight of this subthreshold. Then CHs disseminate certain announcements to the entire nodes of the network. After receiving these announcements from different CHs, the non-CH nodes join them if they exist at the shorter distance. In this protocol, GA was combinedwith SA (Simulated Annealing) to optimize certain parameters used to determine the threshold for application-based CHs. The objective functions of GA and SA are described by the following formulas in this protocol:

$$
Maximize : fitness = W_1 \times FND + W_2 \times HND + W_3 \times LND \tag{34}
$$

$$
0 \leq \alpha_k \leq 1 \quad (k = 1,2,3,4), \sum_{k=1}^{4} \alpha_k = 1 \tag{35}
$$

$$
0 \leq t_s \leq 2 \quad (s = 1,2,3,4), t_1 \leq t_2 \tag{36}
$$

$$
0 \leq W_u \leq 1 \quad (k = 1,2,3), \sum_{k=1}^{3} W_u = 1 \tag{37}
$$

W_1, W_2, and W_3 show the weights of FND (First Node Dies), HND (Half Node Dies), and LND (Last Node Dies), respectively. Based on the application, they range between zero and one in a way that they add up to one according to Formula (37). Moreover, t_s refers to the subthreshold values of Formula (33), and α_k of Formula (35) indicate the subthreshold weights in Formula (33).

– Heuristic Algorithm for Clustering Hierarchy (HACH)

Oladimeji et al. [114] presented a protocol named HACH. In this protocol, two mechanisms were employed. The sleep schedule is the first mechanism in which passive nodes are selected from nodes with lower levels of energy at random. Then they are put to sleep in a way that the network coverage is not damaged. In the second mechanism, a heuristic crossover of GA is used to select CH nodes from active nodes in the network. These mechanisms are executed by the BS collecting information from nodes in every round of the network. In this protocol, the risk penalty function is defined, according to Formula (38), to maintain the percentage number of CHs, represented by L, between lower and upper boundaries. The GA objective function is used to select CHs in this protocol:

$$R=\begin{cases} Lower-L, & if\ L<Lower \\ L-Upper, & if\ L>Upper \\ 0, & Otherwise \end{cases} \tag{38}$$

$$F(X)=W_1\times\frac{AvgENCH}{AvgECH}+W_2\times R \tag{39}$$

where $AvgENCH$ is the average energy of non-CH nodes, and $AvgECH$ is the average energy of CH nodes. Moreover, W_1 and W_2 are the weight factors in energy and the penalty function, respectively.

– Genetic Algorithm-based Threshold-sensitive Energy – efficient Routing Protocol (GATERP)

Mittal et al. [115] presented an incident-based reaction protocol named GATERP. The protocol consists of set-up and steady state phases. In the set-up phase, the CH selection is performed based on GA. The objective function for choosing CHs is expressed as follows:

$$f_{obj\_clustering}=\sum_{m=1}^{4}w_m\times f_m \tag{40}$$

$$f_1=\left(\sum_{k=1}^{K}\sum_{node_j\in C_k}E_{TX_{node_j\,CH_k}}+E_{RX}+E_{DA}\right)+\sum_{k=1}^{K}E_{TX_{CH_k\,BS}} \tag{41}$$

Where $\sum_{m=1}^{4}w_m=1$, K is the number of CHs, $node_j\in C_k$ is a member belonging to the k^{th} CH, $E_{TX_{node_a node_b}}$ is the energy consumed to move the data from $node_a$ to $node_b$, E_{DA} is the consumed energy for data aggregation and E_{RX} is the energy consumed to receive data. f_2 is the ratio of the total Euclidean distance of CHs to their members and the minimum distance between two adjacent CHs. f_3 is the total remaining energy ratio of the living sensors of a cluster to the remaining energy of the corresponding CHs in the current period. f_4 is the maximum number of members in the k^{th} cluster, which aims to minimize the total time spent by the k^{th} cluster to transfer its data to the BS. After selection of CHs by GA, each node joins its nearest CH. In the steady state phase, each node sends its information to the corresponding CH at the time of the incident and then goes to sleep mode, but the CHs are active. If the distance between a CH and the BS is greater than the preset threshold, adjacent CHs are checked, and the distributor node for transmitting information from the CH to the BS is selected according to the remaining energy factor f_{RE} and the distance factor f_D using GA. So that if CH_i is far from the BS, it chooses one CH_j to redistribute its information in a way that the link cost is minimized for redistributing the information; the evaluation function is expressed as follows:

$$f_{obj\_routing}=W_R f_{RE}+(1-W_R)f_D \tag{42}$$

where W_R and (1- W_R) are respectively the weights assigned to f_{RE} and f_D.

4.3.1. Comparison of Metaheuristic-based Approaches

In this section, the reviewed metaheuristic-based approaches are compared based on the methodology type. Tables 9 and 10 show different comparisons of the evaluation of metaheuristic-based approaches from the clustering-based parameters point of view in both macro and micro parameters, respectively. The CHs selection in this class of methods takes place with the help of metaheuristic algorithms and their objective function are adjusted to select the optimal and appropriate CHs. Reducing energy consumption is the most important objective considered in these methods. The time driven application, periodic rotation of the CHs role, and the periodic collection of information are used in these methods. Although in these methods, reducing the intra-cluster distance factor is considered in the objective function of some methods, no specific mechanism has been considered in order to control the cluster size and overcome the hot spots problem, especially since most of these methods use one-hop communication for the intra- and inter-cluster communications, and no attention has been paid to scalability of the methods. Additionally, most of the methods in this category use centralized method because of the complexity of implementation and execution of metaheuristic algorithms and sensor node constraints. Therefore, all activities related to the implementation of the metaheuristic algorithm are done in the BS and the necessary information is then sent to the nodes.

The analysis of the methodology-based parameters related to metaheuristic approaches can be shown in Table 11. The limitations of these methods, such as classical and fuzzy methods, are the lack of attention to scalability, increasing the time complexity and delay due to the implementation of metaheuristic algorithms in each period (according to time driven application, the periodic rotation the CHs role, the periodic collection of data, and the necessity of choosing CHs in each period by metaheuristic algorithms). According to the periodic performance, a suitable solution has been taken to overcome this problem in a number of methods (such as ASLPR) with respect to implementation of the process of using the metaheuristic algorithms only once before starting the network operation in order to optimize the parameters required in the protocols. On the other hand, the metaheuristic algorithms are used in an offline scheme, and no online delay and complexity is boosted. In examining the reviewed methods, energy and distance (including inter-cluster and intra-cluster distances) are more attractive to designers of these methods. The most widely used algorithm in this area considering the reviewed methods is GA, and the desired simulation environment is MATLAB. Finally, it is worth mentioning that these methods, which are more recent than the classical methods, are generally more complex than methods of the two previous categories, but offer more appropriate solutions. In addition, these methods allow the designers to adjust the parameters in order to guide the method for the purpose of the application.

4.4. Hybrid Metaheuristic- and Fuzzy-based Approaches

Recently, a few methods have combined the approaches based on fuzzy logic and metaheuristic algorithms to take the advantage of both. Some of such methods are described here.

– Fuzzy and Ant colony optimization based combined MAC, Routing, and unequal clustering cross-layer protocol for WSNs (FAMACROW)

Gajjar et al. [116] introduced a protocol named FAMACROW layering network nodes first. This protocol includes three steps, namely selecting the CH, clustering, and inter-cluster routing. It uses the residual energy, the number of neighboring nodes, and quality of communication as the fuzzy logic inputs to select CHs. Accordingly, every node executes FIS and calculates the fuzzy output by the name of Proficiency. The node with the highest proficiency will become a CH in the predetermined domain. In this protocol, clusters are formed unequally to prevent the problem of hot spots. In other words, closer clusters to the BS are considered smaller, whereas farther clusters from the BS are considered larger. This protocol benefits from the ACO for information routing between clusters and its transmission to the BS. The following formulas show the function used by the ACO to estimate the fitness value of path *S*:

$$w_s = \frac{T}{Rate_s \times Var_i} \tag{43}$$

$$Rate_s = \sum_{x=1}^{m} Rx = \sum_{x=1}^{m} xd^2(S_{x-1}, S_x) \tag{44}$$

$$Rx = d^2(S_{x-1}, S_x) \tag{45}$$

$$Var_i = \frac{1}{m} \times \sum_{x=1}^{m} (Rx - \frac{1}{m} \times \sum_{x=1}^{m} Rx)^2 \tag{46}$$

where T is a constant number, and $Rate_s$ is the communication cost of path S. Moreover, Var_i is the variance of energy balanced among the edges on the path, and x is the impact factor defined for the path between the nodes of a transmitter and a receiver. R_x is the energy consumed on edge (S_{x-1}, S_x), in which S_{x-1} is the transmitter node, and S_x is the receiver node (the consumed energy is proportionate to the squared distance between two nodes) in Formula (44). Furthermore, m is the number of nodes forming a path. The inputs of the ACO algorithm included the distance between the current CH and the BS, the residual energy of the node, length of the queue, and the likelihood of delivering packets to the BS to determine the best redistributor node.

– Swarm Intelligence based Fuzzy routing protocol (SIF)

Molay Zahedi et al. [117] presented a protocol named SIF using the Fuzzy C-Means (FCM) algorithm for clustering sensor nodes. This protocol then selects the right CHs from the cluster members by using the FIS and considering the fuzzy inputs (residual energy, distance from the BS, and distance from the center of gravity) in addition to the fuzzy outputs. In this protocol, Mamdani's rules table of FIS is optimized before starting the network operations by combining the Firefly Algorithm (FA) and the SA algorithms based on an objective function defined for application.
Formula (47) shows the objective functions of SA and FA for the optimization of the fuzzy rules table in this protocol:

$$Maximize: fitness = W_1 \times FND + W_2 \times HND + W_3 \times LND \qquad (47)$$

$$0 \le W_u \le 1, \quad \sum_{u=1}^{3} W_u = 1, \; u = 1,2,3 \qquad (48)$$

W_1, W_2, and W_3 represent the weights of FND, HND, and LND, respectively. According to a certain application, the weights range between zero and one. According to Formula (48), they add up to one.

– Centralized cluster-based routing protocol based on Sugeno Fuzzy inference system (LEACH-SF)

Shokouifar and Jalali [118] introduced an algorithm named LEACH-SF resembling SIF. The only difference is that LEACH-SF benefits from the Sugeno-type FIS instead of Mamdani's inference method in SIF. In addition, the Artificial Bee Colony (ABC) algorithm was used to optimize the Sugeno-type fuzzy rules table. The ABC objective function is described as follows:

$$Maximize: fitness = W_1 \times FND + W_2 \times HND + W_3 \times LND \qquad (49)$$

$$0 \le p_k \le 1, -1 \le q_k \le 0 -1 \le r_k \le 0, -1 \le s_k \le 1, k = 1,2,\ldots,27 \qquad (50)$$

$$0 \le W_l \le 1, \quad \sum_{l=1}^{3} W_l = 1, \; l = 1,2,3 \qquad (51)$$

W_1, W_2, and W_3 are the weights used to regulate the importance of FND, HND, and LND, respectively. Based on a certain application, they can range between zero and one. According to Formula (51), they add up to one. Furthermore, p_k, q_k, r_k, and s_k are the parameters of energy, distance from the BS, distance from the center of gravity, and bias, respectively. They are the Sugeno-type fuzzy input parameters optimized by the ABC algorithm in Formula (50) in the predetermined domain.

– Fuzzy Shuffled Frog Leaping Algorithm (FSFLA)

Fanian and Kuchaki Rafsanjani [119] have introduced an algorithm named FSFLA, which employs SFLA to optimize the Mamdani fuzzy rules based on application. In addition to automatically adjusting the if-then rules, this protocol optimizes five adjustable parameters associated with the inputs to the fuzzy system in an offline procedure prior to launching the network. The inputs of the fuzzy systems include the remaining energy, distance from the BS, the number of neighboring nodes, and node histories. The capability of nodes to be nominated as CHs is determined considering the compromise between the important parameters regarding the node conditions and their respective optimized fuzzy rules. The FSFLA employs two specified thresholds to elect a candidate node as a CH. The protocol can be adjusted according to the application due to having two determined thresholds for turning candidate nodes to final CHs. The objective function of SFLA is described as follows:

1 2 3 4 5 6
Data FND Data HND Data LND
fitness w FND w HND w LND w w w
N N N
= × + × + × + × + × + × (52)
{ }
6
1
0 1 , 1 *i i* , , 1, 2 , 3, 4 , 5 , 6
i
w w i
=
≤ ≤ © = ∀ ∈ ∂ ∂ = (53)

W_1, W_2 to W_6 are the weights used to regulate the importance of the six objectives presented in Formula (52), respectively. They can range between zero and one according to Formula (53). N is the total number of network nodes and (Data FND)/N is, the average number of packets that sent to the BS by a node in the network prior to reaching FND. (Data HND)/N is the average number of packets delivered to the BS by a node prior to reaching HND. (Data LND)/N is the average number of packets delivered to the BS by a node prior to reaching LND.

4.4.1. Comparison of Hybrid Metaheuristic- and Fuzzy-based Approaches

In general, these recently expanding methods have been used to combine the features of both fuzzy-based approaches and the methods based on the metaheuristic algorithms. The evaluation of these methods based on the clustering-based macro and micro parameters can be seen in Tables 12 and 13, respectively. The cluster selection process in these methods is performed using fuzzy logic, and the main objective is to maximize the network lifetime. The application used in these methods is time driven and the periodic collection of information from the network is based on the periodic rotation of the CHs role. Mainly, one-hop communication is used for intra-cluster and inter-cluster
communications, and therefore they are not efficient for large environments. These methods use centralized method due to their high complexity, and all major activities related to protocols are performed in the BS.
Table 14 analyzes these approaches in methodology-based parameters. The main limitation of this category is the high complexity and overhead. The most important fuzzy parameters considered for the selection of CHs in these methods, are energy parameters and distance to the BS. In these techniques Mamdani and Sugeno FIS are utilized, and the method of defuzzification is COA. In addition, in some of these methods, to overcome the delay and complexity of periodic applying the metaheuristic algorithm, it is used only once before beginning the main network operations with the purpose of adjusting the fuzzy rule table according to the intended application. Generally, speaking about these methods is difficult due to their novelty and small number of studies in this category. The complexity of these methods is higher than other categories, but provide more appropriate solutions. The most important point regarding these methods is that their performance depends on the correct adjustment of their parameters.

$$fitness = w_1 \times FND + w_2 \times HND + w_3 \times LND + w_4 \times \frac{Data\ FND}{N} + w_5 \times \frac{Data\ HND}{N} + w_6 \times \frac{Data\ LND}{N} \quad (52)$$

$$0 \le w_i \le 1, \quad \sum_{i=1}^{6} w_i = 1, \ \forall i \in \partial, \ \partial = \{1, 2, 3, 4, 5, 6\} \quad (53)$$

4.5. Discussion and Future Directions

In this section, a general discussion regarding the classification performed in this survey along with some open research areas for future works are presented.

4.5.1. Discussion

According to the compared methods, there have been many efforts to design efficient clustering-based routing protocols. In this survey, each protocol has been discussed based on clustering-based and methodology-based parameters. From the methodology point of view, the existing methods have been classified into four categories of classical, fuzzy-based, metaheuristic-based, and hybrid metaheuristic- and fuzzy-based approaches.
In classical approaches, CHs are mainly selected via classic formula considering different parameters of sensor nodes in a distributed or centralized scheme. These methods are simple and easy to implement, and they have low overhead and complexity. However, they do not consider appropriate criteria and their relative importance for selecting CHs. Moreover, scalability is not efficiently taken into account in these methods. This problem is partially solved in recent studied by combining different parameters and considering the multilevel routing. These methods are not applicationspecific, and their performance is fix for all applications.
Fuzzy-based approaches consider uncertainties of the parameters to partially overcome the difficulties of tuning the relative importance of the parameters for selecting CHs. In these methods, some criteria of the sensor nodes are defined as fuzzy inputs, where fuzzy output is determined to select the appropriate CHs. In contrast to the classical approaches, fuzzy-based techniques utilize the FIS instead of classical formulas to determine the relationship between the input parameters and the output (selecting CHs). In these techniques, the rule base table is typically determined by an expert, and consequently, this category are not also application-specific.
Metaheuristic-based approaches are more efficient than the classical and fuzzy-based approaches in selecting appropriate CHs, however, they suffer from high time- and computational-complexity as the metaheuristic algorithms should be performed to select CHs at the every round. Generally, energy, intra- and inter-cluster distances are used as the main parts of the objective function of the metaheuristic algorithm. Similar to classical and fuzzy-based approaches, the existing metaheuristic-based methods (except ASLPR) are not application-specific. The three above categories are not application-specific; the controllable parameters of the protocols cannot be adaptively adjusted according to the application requirements. Although these methods may have acceptable performance for some applications, their performance may be reduced for some other applications. This problem does not exist in the hybrid metaheuristic- and fuzzy- based approaches, which combine the advantages of both fuzzy logic and metaheuristic algorithms to achieve better clustering performance. In these methods, FIS is typically applied to select the CHs, while the metaheuristic algorithms are utilized to adaptively adjust the fuzzy rule base as well as the controllable parameters of the protocol. The optimization procedure is typically performed in an offline scheme once before the main network operation, just for tuning the protocol

based on the application specifications. These approaches can achieve better performance than the three other categories, however, they boost extra time- and computational-complexity to adaptively adjust the protocols.
Finally, in each of the four categories of evaluated methods, there is an open space in examining the important and influential parameters for performing clustering, routing and, in other words, scalable design, to guide the performance of the methods into adaptive functions.

4.5.2. Future Directions

As mention above, the clustering and routing protocols in WSNs are widely noticed by the researchers in the different fields, but some aspects have not been properly studied. This survey reveals many open areas for future researches, as follows.

– Most of the existing approaches have been presented for general purpose WSNs and the specific applications are less considered in the literature. On the other hand, adaptive protocols based on the network details have been less noticed. Although a few application specific protocols have been presented in the two categories of the metaheuristic-based approaches and hybrid metaheuristic- and fuzzy-based approaches (such as ASLPR, SIF, LEACH-SF and FSFLA), this issue can be considered as an open research area.

– All reviewed application specific protocols (ASLPR, SIF, LEACH-SF and FSFLA) utilize single-hop communications, and consequently, they cannot support large-size area networks. Therefore the scalability problem of the adaptive protocols is another point which can be discussed and solved in the future works.

– Using metaheuristic algorithms to select the proper CHs or redistributor nodes in the category of the metaheuristic-based approaches impose high delay and complexity to the network, because of online running the optimization process at the every round. On the other hand, metaheuristic algorithms are performed in an offline scheme in the category of the hybrid metaheuristic- and fuzzy-based approaches. This issue has been considered in a few of the protocols (such as ASLPR, SIF, LEACH-SF, and FSFLA), so we need to use creative innovations to deal with it.

– From the perspective of methodology, most of the protocols consider simple and insufficient parameters to select the CHs and redistributor nodes. Although in some protocols (such as DHCR, MLRC, HDMC) new ideas have been introduced in which the different parameters are mixed to make new parameters, selecting and combining parameters can be further discussed.

– Regarding the methods studied in this survey and their details, we think there is a research area to present and to use the new metaheuristic algorithms and different fuzzy approaches to select the proper CHs and redistributor nodes.

5. Conclusion

Considering the energy constraints of sensor nodes and the role of clustering as an effective solution and to manage energy consumption in wireless sensor networks, an extensive assessment of clustering and cluster-based routing protocols have been presented to provide an applied view in line with more precise examination of the methods irrespective of any judgments. In this study, the existing protocols have examined from two aspects of clustering and methodology. The compared protocols have been classified into macro and micro classes in terms of clustering features. On the other hand, the methods, according to the methodology, have been classified into four categories in term of methodology: classical approaches, fuzzy-based approaches, metaheuristic-based approaches, and hybrid metaheuristic- and fuzzy-based approaches. In order to evaluate each viewpoint, the parameters that are consistent with the view (including clustering-based parameters and methodology-based parameters) have been presented in order to evaluate the existing techniques. Then, each category of methods has been evaluated and discussed according to the parameters presented. In an effort to provide useful information and motivate readers, this assessment aims to provide a new perspective and a starting point for exploring methods by taking into account the methodology-based parameters (e.g., capabilities, constraints, inputs and outputs examined in each method, the type of algorithm used in the methods, and the purpose of using algorithms) for a quicker understanding of deficiencies in terms of methodology. We aim to develop the methodology-based parameters in this regard and to extend this perspective in other fields of wireless sensor networks such as body area sensor networks, mobile sink scheduling, and rechargeable sensor networks.