scientific reports

OPEN

Centralized two tier clustering method for wireless sensor networks based on a coupled cascaded fuzzy system

Antonio Jesus Yuste-Delgado[1,4], Alicia Triviño[2,4], David Diaz-Jimenez[3,4] & Juan Carlos Cuevas-Martinez[1,4]✉

Current applications in the Internet of Things generally rely on wireless sensor network deployments that measure and control a restricted area. Most of those applications use sensor nodes powered with batteries, so efficient energy management is required to maximize the lifetime of the network. To tackle this issue, clustering becomes a suitable solution to prolong energy sources, being the selection of the cluster heads crucial for its optimal operation. The application of soft computing techniques (e.g. fuzzy logic) to clustering has improved the wireless network performance significantly. Therefore, this approach proposes a centralized, two-tier clustering method in which there are cluster heads and super cluster heads. This hierarchy is defined based on a sustainability filter and a two-stage cascaded fuzzy system. Initially, the sustainability filter removes unsuitable nodes in the process of selecting the cluster heads. The decision is based on the node residual energy, eliminating those with low battery levels. The remainder nodes use a first fuzzy system where some of them are promoted as cluster heads. Then, for each CH, a second stage is run, which takes as input the output of the first fuzzy system and three other variables to allow the selection of super cluster heads. The findings of the simulation of this approach have demonstrated that cascaded fuzzy systems have the capacity to circumvent issues such as rapid depletion of energy at the node in close proximity to the base station. Additionally, the simulation results of the proposed method demonstrated a substantial enhancement in the lifetime across the various scenarios applied. Furthermore, they have been shown to exhibit a substantial degree of adaptability to varying base station locations.

Keywords Wireless sensor network, Internet of things, Clustering algorithm, Energy-efficient management, Fuzzy logic

Wireless sensor networks (WSNs) have become a fundamental component of numerous applications of the Internet of Things (IoT), as evidenced by Gulati et al.[1]. Their importance is further underscored by the growing number of IoT deployments, including those in smart cities[2]. Thus, a WSN serves as the foundation for many IoT applications, especially those based on sensing and acting in the environment. A typical WSN is composed of a multitude of compact devices, commonly referred to as nodes or motes. They are strategically placed within the designated sensing area to monitor a wide range of physical parameters, including temperature, humidity, gas concentration, noise, vibrations, and more[3]. The nodes are generally equipped with constrained processing and storage capabilities, and are typically powered by batteries. These features limit their ability to perform demanding tasks. Several of these restrictions are attributable to the fact that such nodes are frequently expendable[4], since the cost of replacing or charging their batteries is ordinarily greater than that of the node itself. The primary function of those nodes is to measure the physical parameters of its surrounding environment and transmit those measurements to a central device, referred to as a base station (BS) for further processing. The BS is typically equipped with enhanced hardware and a more reliable power source than the nodes. Consequently, data transmission represents the most energy-intensive process a node must undertake. Due to the limitations of the nodes, a WSN needs precise energy management to continue operating for as long as possible. For this

[1]Department of Telecommunication Engineering, Universidad de Jaén, Linares 23700, Spain. [2]Department of Electrical Engineering, Universidad de Malaga, Malaga 29071, Spain. [3]Department of Informatics, Universidad de Jaén, Jaén 23071, Spain. [4]Antonio Jesus Yuste-Delgado, Alicia Triviño, David Diaz-Jimenez and Juan Carlos Cuevas-Martinez contributed equally to this work. ✉email: jccuevas@ujaen.es

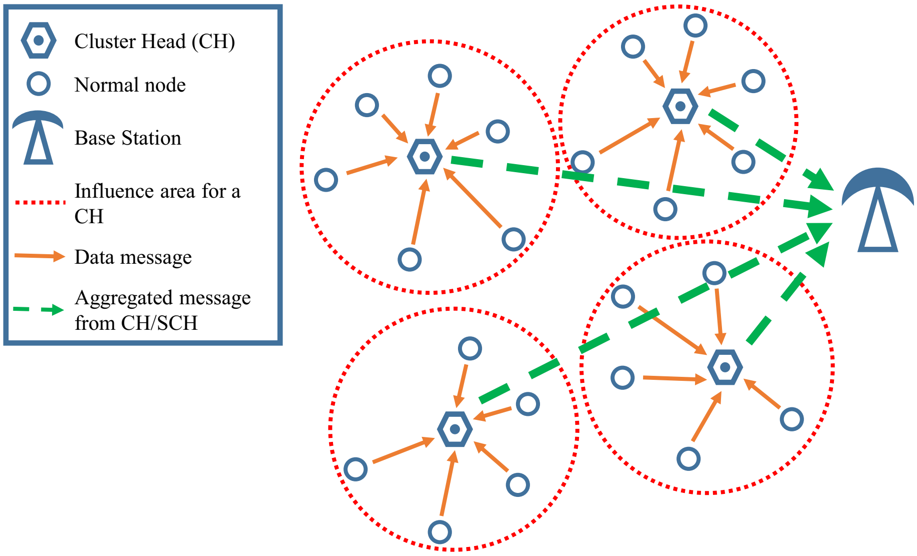

Fig. 1. Tier-1 clustering.

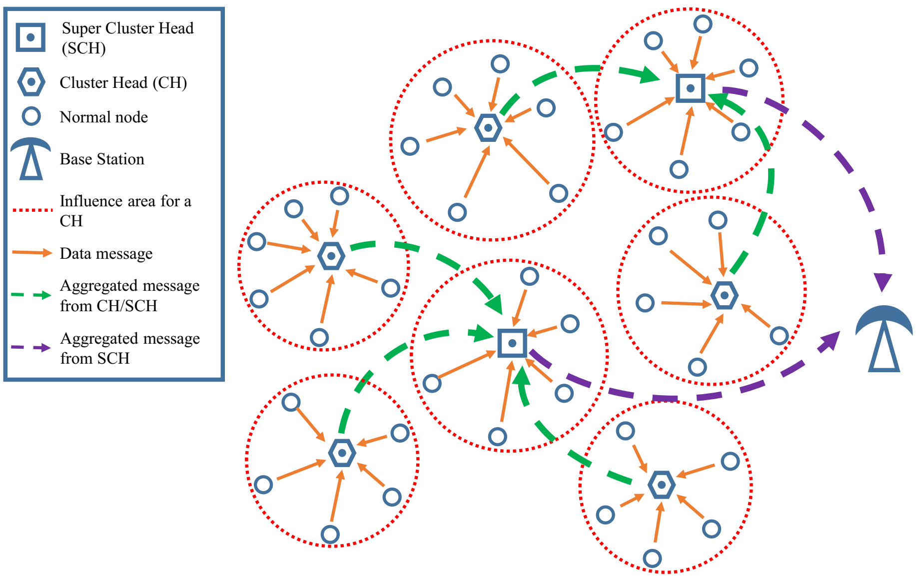

Fig. 2. Tier-2 clustering example.

purpose, topology control techniques, and more precisely clustering, emerge to address this issue together with data aggregation[5]. The primary objective of clustering is to minimize the distance between the node and the intended destination for data transmission. This is achieved by establishing a hierarchical structure comprising one or more levels of specialized nodes, designated as cluster heads (CHs). Therefore, it is essential that these CHs are selected with great care in order to achieve a significant reduction in the energy expenditure associated with data transmission by normal nodes, which send their data to those CHs. This hierarchical process can be seen in Fig. 1.

In this paper, this particular type of clustering will be referred to as ”Tier-1.”. Subsequently, each CH aggregates the collected data in their area and transmits it to the subsequent stage, which is typically the BS. However, in some cases, the data may be transmitted to a new layer of CHs within the hierarchy. In this final scenario, the data are transmitted through the various layers of CHs until they reach the BS. This structure will be referred to as ”Tier-n” clustering. Figure 2 illustrates a Tier-2 WSN. There are cluster heads in tier 1 and super cluster heads (SCH) in tier 2. The methodology for selecting the CHs and SCHs depends on the specific approach employed and will be discussed in more detail in the following section.

It is important to note that Tier-1 strategies are prone to a significant challenge: selected CHs can be situated at a considerable distance from the BS, particularly when the BS is located outside the node deployment area. As a result, the energy expenditure by the CHs transmitting the aggregated data to the BS has the effect of reducing the network lifetime. To circumvent this issue, a Tier-2 strategy can be employed to establish a supplementary layer of CHs, designated as super cluster heads (SCHs). The designation of these SCHs reduces the distance that CH messages must travel. Consequently, each of these SCHs receives aggregated data from a group of CHs, which are then aggregated and subsequently transmitted to the BS. This process reduces the energy expenditure of the CHs and, if conveniently designed, the network lifetime is prolonged. Similarly to simple clustering techniques, the decision of CHs and SCHs in Tier-n methods can be accomplished in a central node or in a distributed way.

Several strategies for two-layer or Tier-2 clustering can be identified:

- A single SCH is selected. In this instance, the remaining CHs establish a transmission chain for routing, as illustrated in Fig. 3.
- Multiple SCHs are selected. In this instance, each SCH is capable of transmitting its aggregated data directly to the BS (see Fig. 2). Alternatively, they can form a chain through routing to send the information to the BS.

This document presents a centralized Tier-2 clustering method that includes a new stage in the cluster head selection system (a sustainability filter), which discriminates nodes that are not suitable to be selected as CHs based on their low residual energy. Subsequently, for those nodes that satisfy the filter criterion, a Type-1 fuzzy system in the BS, representing the initial stage in the cascade, calculates the probability of those nodes becoming a CH. Thereafter, the CHs are selected at random based on the already computed individual probability. For each CH, the system then evaluates its chance of becoming an SCH by means of the second stage of the system. This is another Type-1 fuzzy system that employs the output of the previous fuzzy stage and two additional input variables to derive the probability of becoming a SCH. Finally, the selection of SCH is determined by this newly calculated probability. In consideration of the system's centralized nature, the BS disseminates a configuration message for each round, thereby specifying the nodes designated as CHs and SCHs to initiate the information aggregation process.

Compared to other recent approaches, the results obtained show that this method can outperform them while maintaining favorable metrics for a wide range of BS locations.

The following section presents a comprehensive review of the existing literature on clustering in wireless sensor networks. In section "Proposed clustering method", we present the proposed Tier-2 clustering algorithm, and in section "Results", we provide a detailed comparison of its results with those of other similar clustering approaches. In conclusion, section "Discussion" presents the findings of this study and outlines potential avenues for future research.

Related work

Clustering approaches have become a common topology control technique in wireless sensor networks, offering an effective means of managing energy resources at nodes. As stated previously, the primary objective of clustering is to organize the nodes around a CH in order to minimize the distance that the messages with the collected data must travel. In addition, CHs gather the received data and send them to the base station (Tier-1 methods), or to the next layer or CHs. This is depicted in Fig. 2 for a two-tier hierarchical model (Tier-2) or in Fig. fig:2-tier-chain, which shows a chained model to connect CHs. The process of nodes taking measures from the environment, selecting the CHs, collecting data in the CHs and sending it to the base station is commonly known as a round. This means that clustering is a round-scheduled network management system. It also has to take into account the media access for wireless communications and the idle time of the nodes between

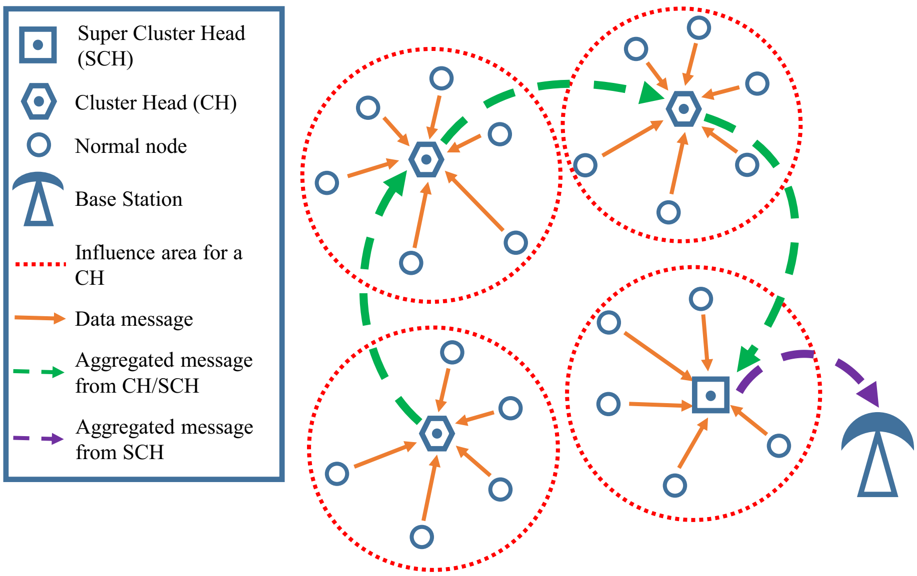

Fig. 3. Tier-2 clustering chain example.

data acquisition and transmission. Therefore, based on an analysis of the relevant literature, four distinct Tier-1 approaches to CH selection can be identified:

- Stochastic. In this case, nodes are designated as CH based on a mathematical or statistical function that usually only considers the residual energy of each node or the number of rounds[6].
- Type-1 fuzzy logic. In these approaches, CHs are selected by a Type-1 fuzzy system, which typically produces a fitness factor for a node to become a CH[78].
- Type-2 fuzzy logic. Similarly to the preceding point, a fitness factor is generated by a Type-2 function to decide the CHs. The use of a Type-2 fuzzy system allows for a more robust tolerance of the inherent uncertainty associated with this type of problem, usually achieving better results with increasing complexity[9].
- Artificial intelligence (AI). CHs are selected according to algorithms that typically require an iterative process, such as genetic algorithms, particle swarm organization (PSO), ant colony optimization (ACO), etc.[10].

It is important to note that the aforementioned strategies may also be implemented centralized or distributed. In a centralized approach, the base station (BS) performs all the necessary processing to select the CHs, subsequently communicating the results to the entire network so that the CHs can initiate the aggregation of data collected by the nodes. Centralized approaches typically necessitate the transmission of control and configuration messages from each node, as well as continuous updates, to maintain precise information regarding the status of active nodes[11]. However, some methods rely on estimated data from nodes to maintain the status of the network[12]. In contrast, distributed solutions allow each node to independently determine whether or not to assume the role of a CH or not. Distributed approaches often require the precise definition of the parameters utilized in the selection process, whereas they tend to necessitate fewer transmissions of control data. However, the uncertainty in the parameters used in the clustering methods is usually high.

It is evident that the selection of SCHs can also be categorized into two distinct methods: centralized and distributed. This classification is analogous to that of CH selection. As illustrated in Fig. 4, the following representative examples are provided for the described categories. One of the most relevant and well-known distributed method is Low Energy Adaptive Clustering Hierarchy (LEACH)[6]. LEACH is a stochastic distributed method in which nodes become CHs with a probability that changes each round. The objective is to ensure that all nodes become CHs in a fixed number of rounds while ensuring that the energy wasted in the process is distributed within the network. For Type-1 fuzzy systems, one of the clustering methods based on this technique is Cluster Head Election mechanism using Fuzzy logic(CHEF)[7]. CHEF is a centralized method in which the BS determines which node is the best candidate to become a CH based on a fuzzy rule-based system (FRBS). Moreover, Energy-Efficient Distributed Clustering based on Fuzzy (EEDCF)[8] employs fuzzy logic for the selection of the CH, albeit in a distributed manner. The selection of CHs can also be accomplished using Type-2 fuzzy logic as described in Statistically Adaptive with Enhanced normalization (SAEZ)[9]. In the method titled Interval Type 2 Fuzzy Unequal Clustering and Sleep Scheduling (IT2FUSS)[13] the authors present an algorithm that uses a type 2 fuzzy system which uses a fuzzy system to determine who is the CH. Additionally, in IT2FUSS there is another mechanism in which the nodes go to sleep to avoid energy consumption. In[14] the authors proposed a centralized algorithm, named LEACH-C, which uses a simulation annealing algorithm to determine the optimal nodes to become CHs. Other recent contribution is an adaptive clustering routing protocol[15] in which the authors use a memetic algorithm (MA) that minimizes a multi-objective function, seeking to ensure that the nodes have the same energy and that consumption is low.

In consideration of the number of stages in the CH selection process, TL-LEACH[16] proposes a two-stage stochastic algorithm. In this approach, the authors present a LEACH-based method in which CHs are selected according to that algorithm. Then, from those selected CHs, the SCHs are chosen among those with higher residual energy. Another example is the fuzzy logic based distributed clustering protocol (FLBDC)[17] in which

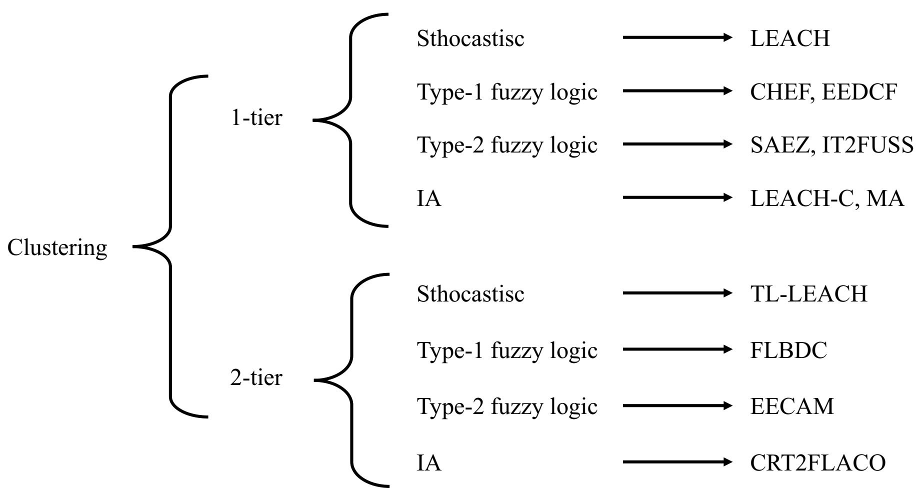

Fig. 4. Clustering in WSN: classification and representative protocols.

clusters are randomly formed and then, among the nodes in each cluster, a Type-1 fuzzy system selects the CH. Subsequently, the SCHs are obtained from those CHs with a different fuzzy system. Taking into account Type-2 fuzzy approaches, for the EECAM method[18], the authors propose this method to select CHs as well as the last substitute of the chain just before BS. Furthermore, the CRT2FLACO method ([19]) utilizes a Type-2 fuzzy system to select the CHs, subsequently employing an ACO to establish a chain of CHs that leads to the BS.

In addition to the aforementioned proposals, hybrid proposals have been submitted, including one entitled 'Fuzzy Logic LEACH Technique-Based Particle Swarm Optimization' (FLLTBPSO)[20]. This proposal involves the selection of cluster centers by a PSO, which then selects a primary and secondary CH by a Type-1 fuzzy system. Another proposal is that of the optimized system, in which the authors seek to enhance the efficacy of the fuzzy system's rule base employed for the selection of CHs through the utilization of a PSO[21].

Furthermore, the classification of clustering algorithms can include the way in which the number of CHs is calculated as can be seen in Fig. 5. One strategy that can be employed is the utilization of a predetermined number based on various methodologies (e.g. equation, K-Means, etc.). Subsequently, each node is allocated to one of the CHs, and the contributing nodes are maintained as linked to the same CH for the duration of the lifetime of the network. This strategy is typically implemented in the context of centralized methods, wherein an optimization process is initiated at the beginning of the deployment phase. Subsequent re-evaluations of network conditions are not a common feature of this strategy. For instance, in[22], the authors utilize the Silhouette index to determine the number of CHs to select from the duration of the WSN application.

Conversely, the dynamic selection of CHs is more prevalent in distributed clustering methods, wherein CHs are selected from among all available nodes. Subsequently, other nodes are typically bound to the closed CH. Thus, in[23], the CHs are selected in each round by a Type-2 fuzzy system that also outputs the range to which the advertising message is to be sent to the normal nodes. This enables the nodes to choose the correct CH.

Following the selection of the nodes that become CHs and their contributed nodes, there are also different ways to rotate their roles, as illustrated by Zeng et al.[24] in their algorithm known as intra-cluster multi-hop based cluster head rotation (ICMH-CHR). In essence, the CHs have the capacity to undergo alteration in each round, or alternatively, to remain unaltered for certain rounds. In the second case, the criteria for modifying a CH can be predetermined or established based on specific thresholds, such as energy, as outlined in the EFUCSS method[22]. Alternatively, as described in the study by Prince et al.[25], a sequential selection approach may also be employed. In this method, CHs are chosen successively in each rotation.

It is important to acknowledge that the present proposal introduces two main novelties that are not currently present in the revised WSN clustering bibliography.Firstly, it includes a sustainability filter that facilitates more efficient calculations in the fuzzy stages by eliminating unsuitable nodes from becoming CHs. That prevents those nodes from being selected as CHs, which would result in additional energy being spent and eventually lead to the premature death of a node. It is evident that the application of the sustainability filter represents a refinement of the two-tier methods, such as FLBDC or CRT2FLACO and EECAM, both with a more complex Type-II fuzzy system. Thus, it can be concluded that the implementation of the filter results in a reduction in the number of CH candidates and facilitates a more expeditious calculation of the final CHs. Subsequently, the selection of CHs is conducted from nodes that exhibit higher energy among the total. Second, it incorporates a cascaded architecture that enables the selection of CHs and SCHs within the same process. In contrast to the random selection of CHs and SCHs employed by TL-LEACH, this methodology employs a more effective selection process by incorporating performance parameters that are not utilized by TL-LEACH in a two-stage fuzzy system. Moreover, the cascade facilitates a fine-grained selection of the SCH, based on the information from the preceding stage. This reduces the uncertainty of such systems by eliminating candidate nodes in the initial stage. The two stage, which do not include the distance as an input variable in the first stage, is another refinement from EECAM or CRT2FLACO, which selects the CHs based on the distance to the BS and the SCH as the closest node to the BS among the selected CHs, consequently, this can clearly derive a premature dead of that SCH because the rotation in the selection of CHs will only depends in their residual energy. The subsequent section will provide a more comprehensive overview of the method.

Proposed clustering method

As previously stated, the proposed clustering method is a centralized one that establishes a two-tier hierarchy. In this structure, there are cluster heads and super cluster heads. The purpose of this architecture is to convey the

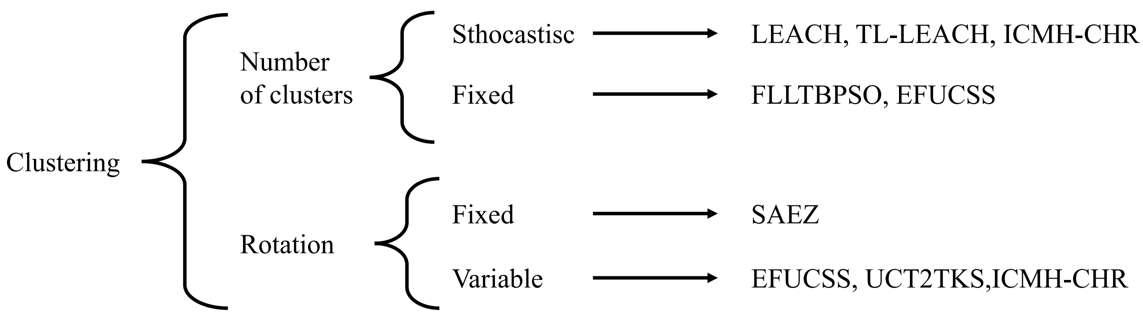

Fig. 5. Clustering in WSN: classification.

information collected by the sensor nodes to the base station more efficiently by reducing the distance between the levels of the network hierarchy.

Each role is set by means of a two-stage cascade fuzzy system named C2TCascade. The CH and SCH selection system is depicted in Fig. 6. It is composed of two cascaded Type-1 fuzzy systems with an initial sustainability filter that removes unsuitable nodes from becoming CHs or SCHs. This filter also allows for a faster calculation in the next stages and the subsequent energy savings in the BS and the degradation of the network lifetime with the selection of inappropriate nodes as CHs or SCHs. In addition, we have found that the moment at which the first node dies in the network is delayed because those nodes are removed from the selection process. Consequently, the network can operate for longer with all its nodes.

The overall process of the clustering method is as follows:

- Startup
  - The BS starts and sends a broadcast message to the WSN.
  - Each node sends a start message with its identification and transmission power.
  - The BS estimates the network conditions from the received messages.
  - The BS begin the clustering process.
- Clustering process (the clustering process is executed in rounds, provided that there are still active nodes.):
  - The BS runs Algorithm 1.
  - The BS transmits the results of the previous step in a configuration message for each node.
  - Each node receives the configuration message, which includes its status (normal node, CH or SCH) and executes the Algorithm 2.
  - Data gathering: After the execution of Algorithm 2 in each node, the BS has received all data.

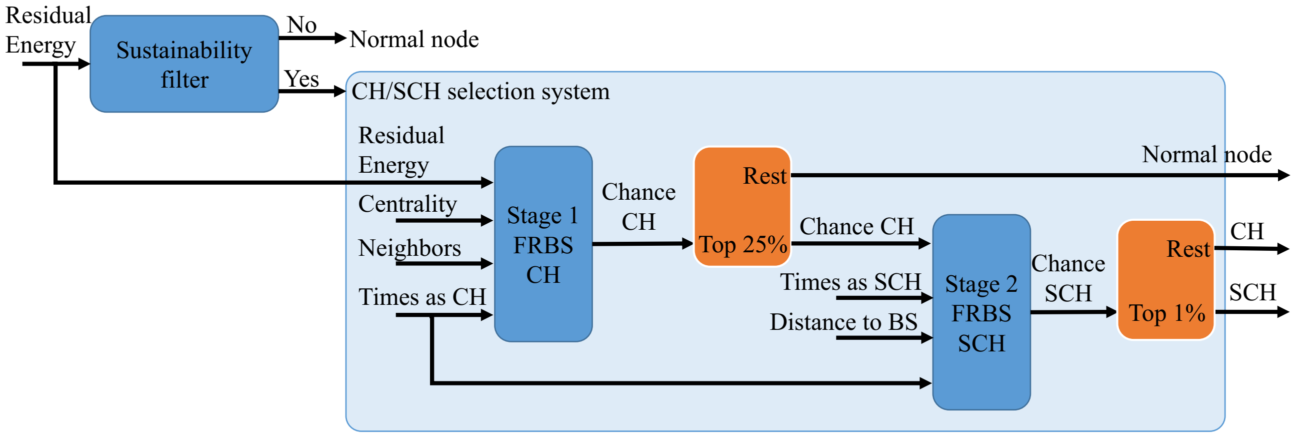

Fig. 6. Two-tier cascade clustering method with sustainability filter.

```
while aliveNodes ≥ 1 do
    while n ≤ totalNodes do
        if energy(n) ≥ 0.01J then
            Update energy of node n;
            if Sustainability(n) = true then
                filteredNodes ← n
            else
                normalNodes ← n
            end if
        end if
    end while
end while
while n in filteredNodes do
    ChanceCH ← stageFRBS_1(n)
    if ChanceCH ≥ 25% of chances then
        ChanceSCH ← stageFRBS_2(n)
        if ChanceSCH ≥ 1% of chances then
            n becomes SCH
        else
            n becomes CH
        end if
    else
        n becomes normal node
    end if
end while
```

Algorithm 1. Algorithm for the process in the BS for each round.

The different parts of the selection system and their configuration parameters are explained next.

```
if node is normal then
    Send data to CH
else if node is CH then
    while n ≤normalNodes do
        Receive data from normal node
        Aggregate data
    end while
    Send aggregated data to SCH
else if node is SCH then
    while n ≤CH do
        Receive data from CH
        Aggregate data
    end while
    Send aggregated data to BS
end if
```

Algorithm 2. Algorithm for the process in nodes after receiving de configuration message from the BS.

Sustainability filter
The objective of the sustainability filter, as previously discussed, is to ensure that nodes with low relative residual energy do not participate in the selection of CHs and SCHs. Therefore, the BS estimates the residual energy of each node after a round, depending on its role (i.e., contributing node, CH or SCH) and calculates the median of the residual energy. Consequently, nodes that exhibit a residual energy level that exceeds the median are allowed to enter the CH/SCH selection system. The remaining nodes are required to wait for subsequent rounds. It is expected that after some rounds the median will have been reduced, thus enabling their re-participation in the CH/SCH selection. Consequently, the sustainability filter ensures that the nodes that are intended to be excluded from the election process do not disrupt it. In this way, the filter favors the selection of more suitable nodes such as CH or SCH in successive rounds.

First stage—Type-1 fuzzy system for CH selection
The initial Type-1 FRBS of the selection system determines whether a node will be promoted as a CH or not, thereby contributing to its potential promotion to a SCH due to the cascaded design of the proposed system. The selection of inputs from this initial stage has been determined by our prior experience in this domain and a comprehensive review of the existing literature. The rationale behind this selection is to identify solutions that

typically yield optimal outcomes while circumventing the undesirable consequences associated with the 'hole', a phenomenon characterized by the rapid depletion of batteries in nodes that are in close proximity to the BS. Consequently, the distance to the BS is negated in this stage of the selection process. Therefore, this fuzzy system has the following inputs:

- Residual energy (E_r): The remaining energy of a node is measured in joules (*J*). This variable is chosen to reduce, or even prevent, the participation of nodes in the selection process that are unlikely to complete the entire clustering process (that is, the aggregation of data from contributing nodes or transmission to a SCH), a node is considered dead (it must be removed from the selection process) when its battery reaches only 0.01 *J*. Consequently, the probability of a node becoming a CH should be low when its energy is low. The selection of a node with low E_r as CH would only be made under optimal conditions, i.e., when other variables are very favorable.
- Centrality (*C*). This variable is calculated based on the distance between the nodes in a CH to the center of the sensing area of their cluster, as used in[26]. In this approach, the K-means function in[27] is used to determine the center of each area. The number of CHs used for K-means is 5% or the total number of nodes in the network. This percentage is used because it is assumed to be an optimal value defined for clustering in WSNs[6]. Subsequently, the distance from each node to the center of that area is calculated. This variable indicates which node acting as CH is better located to have its contributing nodes closer. Thus, during the selection process, nodes with higher *C* values should be selected over nodes with higher energy because they can save more energy by forming a cluster with that CH.
- Neighbors (*N*). This parameter is used as the number of neighbors that a particular node has divided into the maximum number of neighbors that any nodes has computed.[28]. It is assumed that a neighbor is a node that is closer than *d*0 meters (*d*0 is a constant of the first-order radio model that will be detailed later; see Section 4.1). Consequently, this variable is necessary because the number of possible contributing nodes must be high enough in order to be selected as CH. Therefore, nodes with a high *N* value should be selected over others, even if they have lower energy than nodes with fewer neighbors.
- Times selected as CH (*TCH*): The quantity specified herein denotes the number of instances in which a node has been designated as a CH by the BS. It is important to note that a node designated as CH can also be designated as SCH; however, this value will be incremented only once in those circumstances. This variable is important to prevent nodes from becoming CH too many times because they are well-placed in the network (*C* and *N* have high values). Therefore, when nodes are selected multiple times as CH, this variable is used to reduce the likelihood of their being selected again, thereby increasing the possibility that other nodes will be selected to balance the energy among all the nodes.

It is evident that, given the centralized nature of this clustering algorithm, the BS will infer, for every round, the probability of a node being CH for each node that passes the sustainability filter. This probability is referred to as the chance of CH or *cCH*. Consequently, the BS will exclusively select as CHs those with the highest *cCH* probability and no more than 25% of the total number of nodes in the WSN. Subsequently, the recently selected CHs progress to the next stage of the cascade, and the probability of being CH (*cCH*) is utilized as input for the new Type-1 fuzzy system. The selection of only 25% is supported by experimental evidence obtained in our study, which revealed that a sufficient number of CHs are required to promote to SCHs. This study includes an evaluation of different percentages for promoting CHs and SCHs (see section "Network model and simulation scenarios", where the percentage of CHs promoted as SCHs is found). The study utilizes a simulation process that employs three different percentage values to promote CHs and three different percentages to promote SCHs. As outlined in section Network model and simulation scenarios, the simulation scenarios involve three distinct base station locations. Additionally, the simulations were carried out for 100, 500, and 1,000 nodes within the deployment area. From those simulations, we have selected the percentages that maximize the lifetime of the wireless sensor network (also known as LND or Last Node Dies instant). The simulation results of the study commented above are shown in Table 1 where the best LND is achieved (highlighted in bold) for a 25% of CHs in the first stage and 1% of SCHs for the second stage as outlined in the subsequent section.

Second stage—Type-1 fuzzy system for SCH selection

The second stage of the CH/SCH selection system is a new Type-1 fuzzy system in which one of its inputs, the chance of becoming CH for a node (*cCH*), comes from the output of the previous stage, completing the cascaded fuzzy selection system. A key distinction from the preceding stage is the incorporation of the distance of the node to the BS, enabling, in this instance, the selection of previous good CHs (high output value of the first stage) that are more proximate to the BS. Furthermore, this stage infers a new probability that each node will become SCH or *cSCH*.

The complete set of input variables is listed below.

CH/SCH	1%	2%	4%
5%	2333.3	2336.3	2349.4
10%	2335.2	2345.0	2348.7
25%	**2393.4**	2383.6	2350.2

Table 1. Results for mean LND values for different CH and SCH selection percentages.

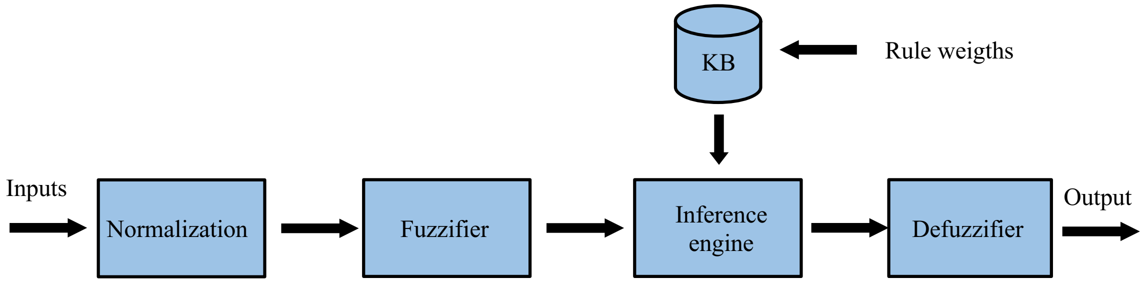

Fig. 7. Type-1 fuzzy inference engine,

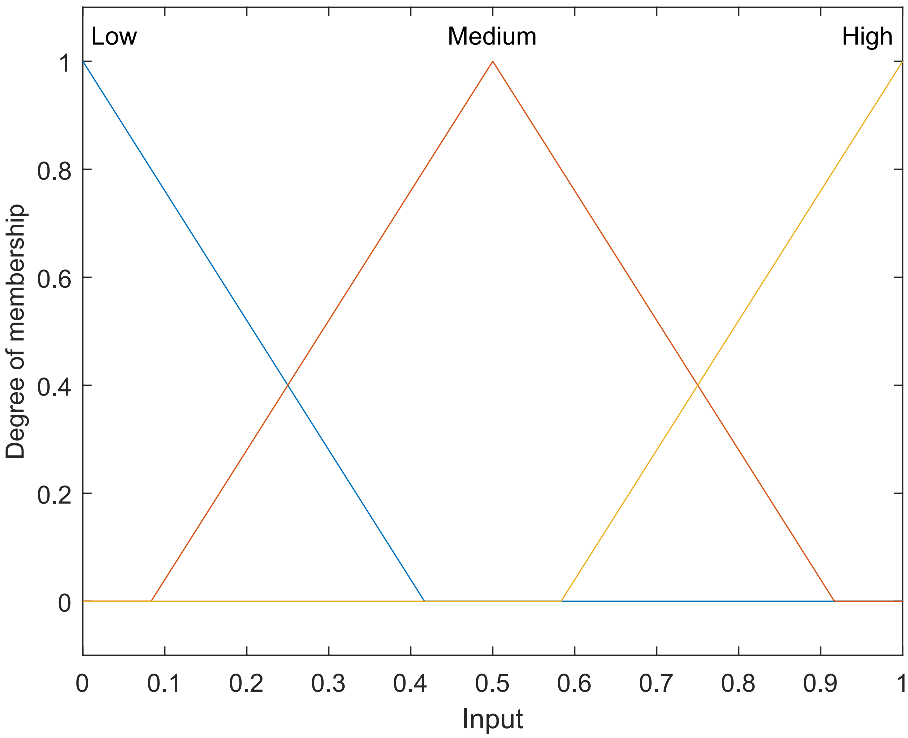

Fig. 8. Example of the fuzzy set layout for E_r input variable. Source: Matlab.

- Chance of being CH (*cCH*): The output of the preceding stage that constitutes the probability of a node becoming CH is used.
- Times selected as SCH (*TSCH*): This input quantifies the number of instances in which a node has been promoted as an SCH by the BS.
- Distance to BS (*dBS*); The purpose of this variable is to measure the normalized distance of each node to BS. To do this, the maximum distance from a node in the WSN to the BS is used as a normalization parameter. The magnitude of the system is indicative of the dispersion of the nodes. This is a factor commonly considered in most fuzzy controllers (see[29]). In this particular instance, as was previously stated, the distance is incorporated into the inputs to facilitate the selection of SCHs that are closer to the BS.
- Times selected as CH (*TCH*): the same value in the previous fuzzy stage.

The final determination of the SCHs is carried out by the BS, which selects only the CHs with the highest inferred probabilities. This results in a SCH comprising no more than 1% of the total number of nodes in the WSN (please, see explanation in section "First stage—Type-1 fuzzy system for CH selection"). As mentioned above, once this selection has been completed, the BS will broadcast a configuration message to the entire network.

Design of the fuzzy rule based systems

Both stages of the CH/SCH selection system are Mamdani[30] Type-1 fuzzy systems or FRBS containing the blocks depicted in Fig. 7. Each FRBS is defined by a set of inputs and outputs (see sections "First stage—Type-1 fuzzy system for CH selection" and "Second stage—Type-1 fuzzy system for SCH selection"). It is important to note that the inputs are first normalized from their crisp values to other new values ranging from 0 to 1. Subsequently,

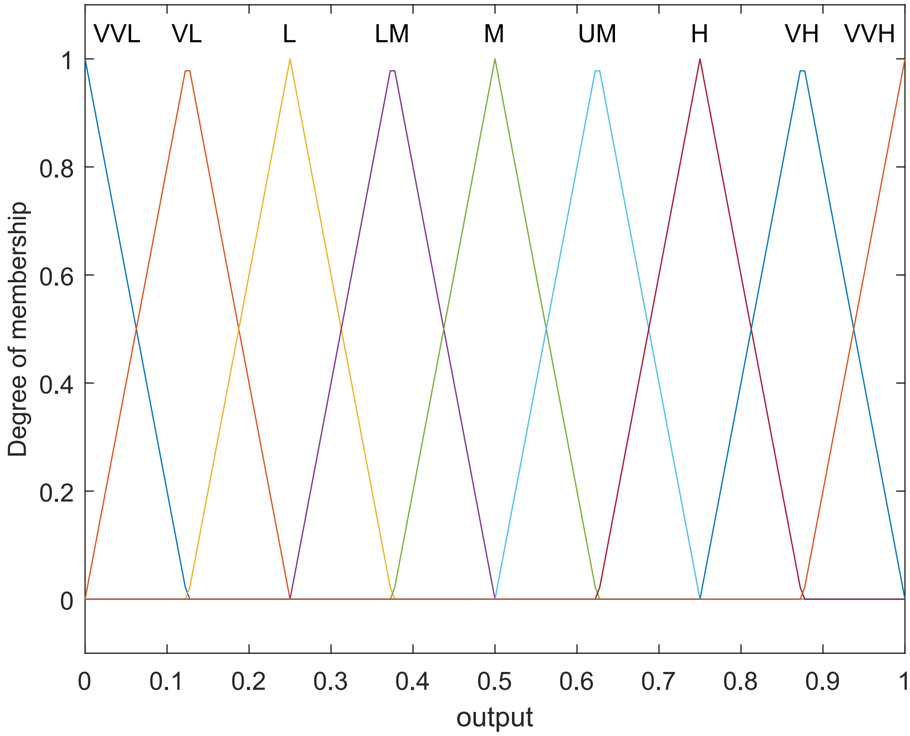

Fig. 9. Example of the fuzzy set layout for both output variables: *chanceCH* and *cSCH*. Source: Matlab.

Centrality	Residual energy	Neighbors	Times CH	Chance CH
L	M	M	F	VVH

Table 2. Example of fuzzy rule of the first stage Type-1 fuzzy system.

all variables are fuzzyfied and passed to the inference engine that uses a knowledge base (KB), which comprises a set of semantic rules that represent the expert knowledge.

In a FRBS, each variable is defined by a set of fuzzy sets, which can vary in shape. In our proposal, all variables have the same three triangular fuzzy sets as can be seen in Fig. 8 for the residual energy. The semantic labels for each variable of the first stage are as follows.

- Residual energy (E_r) and Centrality (C): 'Low' (L), 'Medium' (M), and 'High' (H).
- Neighbors (N) and Times selected as CH (TCH): 'Few' (F), 'Medium' (M) and 'High' (H).

For the second stage, the input variables have the following semantic labels:

- Chance CH (cCH): 'Low' (L), 'Medium' (M) and 'High' (H).
- Distance to BS (dBS): 'Far' (F), 'Medium' (M) and 'Near' (N).
- Times selected as CH (TCH) and Times selected as SCH ($TSCH$): 'Few' (F), 'Medium' (M) and 'High' (H).

The output variables *cCH* and *cSCH* are both defined with the same nine triangular fuzzy sets with stands for the following categories: 'Very Very Low' (VVL), 'Very Low' (VL), 'Low' (L), 'Lower Medium' (LM), 'Medium' (M), 'Upper Medium' (UM), 'High' (H), 'Very High' (VH) and 'Very Very High' (VVH). The layout of those fuzzy sets can be observed in Fig. 9.

However, the KB is not the same for both stages. It can be found in Table 3 for the first stage of the FRBS, and in Table 4 for the second stage. The definition of the base of rules was accomplished from the expert knowledge of the research team based on previous algorithms like CSBA[11] where a centralized clustering method was proposed using similar input variables, and CFC3PSO[21] which optimizes the weights of the KB rules in a centralized clustering method for similar scenarios. For illustrative purposes, let us consider the interpretation of one rule from the KB (see Table 2). It is evident that when a node is poorly positioned in the WSN (Centrality is 'Low') but has sufficient residual energy ('Medium') and neighbors ('Medium'), and it has been selected as a CH only a few times in the past, the rules aim to increase its chance of becoming a CH. Accordingly, the rule sets its output as 'Very Very High' in order to achieve a more equitable distribution of the costs associated with being a CH. Nodes that are unable to be well placed in the WSN but with favorable conditions will also contribute to prolonging the network lifetime thanks to this rule.

C	Er	N	TCH	Chance CH	C	Er	N	TCH	Chance CH	C	Er	N	TCH	Chance CH
L	L	F	F	VVH	M	L	F	F	VVH	H	L	F	F	VVH
L	L	F	M	VL	M	L	F	M	L	H	L	F	M	LM
L	L	F	H	VVL	M	L	F	H	VL	H	L	F	H	L
L	L	M	F	VVH	M	L	M	F	VVH	H	L	M	F	VVH
L	L	M	M	L	M	L	M	M	LM	H	L	M	M	M
L	L	M	H	VL	M	L	M	H	L	H	L	M	H	LM
L	L	H	F	VVH	M	L	H	F	VVH	H	L	H	F	VVH
L	L	H	M	LM	M	L	H	M	M	H	L	H	M	UM
L	L	H	H	L	M	L	H	H	LM	H	L	H	H	M
L	M	F	F	VVH	M	M	F	F	VVH	H	M	F	F	VVH
L	M	F	M	L	M	M	F	M	LM	H	M	F	M	M
L	M	F	H	VL	M	M	F	H	L	H	M	F	H	LM
L	M	M	F	VVH	M	M	M	F	VVH	H	M	M	F	VVH
L	M	M	M	LM	M	M	M	M	M	H	M	M	M	UM
L	M	M	H	L	M	M	M	H	LM	H	M	M	H	M
L	M	H	F	VVH	M	M	H	F	VVH	H	M	H	F	VVH
L	M	H	M	M	M	M	H	M	UM	H	M	H	M	H
L	M	H	H	LM	M	M	H	H	M	H	M	H	H	UM
L	H	F	F	VVH	M	H	F	F	VVH	H	H	F	F	VVH
L	H	F	M	LM	M	H	F	M	M	H	H	F	M	UM
L	H	F	H	L	M	H	F	H	LM	H	H	F	H	M
L	H	M	F	VVH	M	H	M	F	VVH	H	H	M	F	VVH
L	H	M	M	M	M	H	M	M	UM	H	H	M	M	H
L	H	M	H	LM	M	H	M	H	M	H	H	M	H	UM
L	H	H	F	VVH	M	H	H	F	VVH	H	H	H	F	VVH
L	H	H	M	UM	M	H	H	M	H	H	H	H	M	VH
L	H	H	H	M	M	H	H	H	UM	H	H	H	H	H

Table 3. Rule base for the first stage Type-1 fuzzy system.

It must be also noticed that the computational cost of the system is perfectly affordable for common devices that can be used as base stations. For example, the execution of one round of the whole system in an Intel (®) Core (™) I7 CPU of 10th generation at 3.8 GHz with 64 GBytes of RAM in less than 0.1 ms, which is insignificant although the system would be deployed in other devices like the Raspberry PI series with less processing power. Moreover, for devices with very low processing capabilities used as BS, in our previous contributions such as CHEETAH[31] or EUDFC[32], the entire solution space for FRBS is sampled avoiding any processing at the nodes with insignificant variation in the results for the clustering algorithm.

Results

In order to evaluate the proposed method and facilitate a comparison with other approaches, it is necessary to define the parameters commonly used in WSN clustering to measure the performance and effectiveness of those methods. In the context of applying clustering for WSN lifetime maximization, three distinct instants are typically examined: the point at which the initial node depletes its battery (or ceases to function), designated as the first node dies (FND); the moment when half of the nodes have expired, or half of the nodes have been eliminated (HND); and the occurrence of the final node's death, or last node dies (LND). It is important to acknowledge the interdependence of these three parameters, as evidenced by the fact that the maximization of one parameter is contingent upon the minimization of at least two other parameters. This phenomenon, often referred to as a Pareto front in the context of multiobjective optimization, underscores the complexity and interconnectedness of the parameters under consideration.

In addition, the proposed methodology requires the utilization of an energy model to regulate the power expended in communications and data aggregation. A network model is also required to delineate the characteristics of the communication channels and the attributes of each test scenario. This network model must encompass the dimensions of the deployment area, the number of nodes and their initial energy charge, and the location of the base station. These two issues will be discussed next.

Energy model

The energy model used in the simulations was the well-known first-order radio model detailed in Heinzelman et al.[6]. This model defines the energy consumption for the transmission (E_{Tx}) and for the reception (E_{Rx}). The equations of the model are detailed in Eq. (1) for transmission (and in Eq. (2) for energy expenses in reception.

cCH	TCH	TSCH	dBS	cSCH	cCH	TCH	TSCH	dBS	cSCH	cCH	TCH	TSCH	dBS	cSCH
L	F	F	N	M	M	F	F	N	UM	H	F	F	N	H
L	F	F	M	UM	M	F	F	M	H	H	F	F	M	VH
L	F	F	F	H	M	F	F	F	VH	H	F	F	F	VVH
L	F	M	N	LM	M	F	M	N	M	H	F	M	N	UM
L	F	M	M	M	M	F	M	M	UM	H	F	M	M	H
L	F	M	F	UM	M	F	M	F	H	H	F	M	F	VH
L	F	H	N	L	M	F	H	N	LM	H	F	H	N	M
L	F	H	M	LM	M	F	H	M	M	H	F	H	M	UM
L	F	H	F	M	M	F	H	F	UM	H	F	H	F	H
L	M	F	N	LM	M	M	F	N	M	H	M	F	N	UM
L	M	F	M	M	M	M	F	M	UM	H	M	F	M	H
L	M	F	F	UM	M	M	F	F	H	H	M	F	F	VH
L	M	M	N	L	M	M	M	N	LM	H	M	M	N	M
L	M	M	M	LM	M	M	M	M	M	H	M	M	M	UM
L	M	M	F	M	M	M	M	F	UM	H	M	M	F	H
L	M	H	N	VL	M	M	H	N	L	H	M	H	N	LM
L	M	H	M	L	M	M	H	M	LM	H	M	H	M	M
L	M	H	F	LM	M	M	H	F	M	H	M	H	F	UM
L	H	F	N	L	M	H	F	N	LM	H	H	F	N	M
L	H	F	M	LM	M	H	F	M	M	H	H	F	M	UM
L	H	F	F	M	M	H	F	F	UM	H	H	F	F	H
L	H	M	N	VL	M	H	M	N	L	H	H	M	N	LM
L	H	M	M	L	M	H	M	M	LM	H	H	M	M	M
L	H	M	F	LM	M	H	M	F	M	H	H	M	F	UM
L	H	H	N	VVL	M	H	H	N	VL	H	H	H	N	L
L	H	H	M	VL	M	H	H	M	L	H	H	H	M	LM
L	H	H	F	L	M	H	H	F	LM	H	H	H	F	M

Table 4. Rule base for the second stage Type-1 fuzzy system.

$$E_{Tx}(l,d) = f(x) = \begin{cases} l \cdot (E_{elec} + E_{fs} \cdot d^2), & d \leq d_0 \\ l \cdot (E_{elec} + E_{mp} \cdot d^4), & d > d_0 \end{cases} \tag{1}$$

$$E_{Rx}(l) = E_{elec} \cdot l \tag{2}$$

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3}$$

where

- l defines the length in bits of the message sent by a node.
- E_{elec} quantifies the energy expenditure in Joules of the transmitter and receiver circuitry for each bit transmitted or received, respectively.
- d is the distance between the source and destination of the message measured in meters.
- d_0 is the threshold value for using the free-space model or the multi-path model.
- E_{fs} denotes the energy in Joules that the amplifier consumes to achieve an acceptable bit error rate, according to the free space model where $(d \leq d_0)$.
- E_{mp} is defined as the energy consumption of the amplifier in Joules, required to achieve a satisfactory bit error rate in the multipath (MP) model $(d \leq d_0)$.

A further element of energy expenditure in the clustering process is the amount of energy expended in the data aggregation process (E_{Rx-DA}) for each CH[33] defined in Eq. (4):

$$E_{Rx-DA} = (E_{elec} + E_{DA}) \cdot l \tag{4}$$

where

- E_{DA} denotes the energy in Joules expended by the CH when it receives and aggregates data from a contributing node.
- l is the length in bits of the final aggregated message.

Network model and simulation scenarios

For simulation purposes, it is assumed that the communication channels are free from losses and interference. They are also full duplex. The medium access mechanism is based on a time division media access (TDMA) as is commonly used by this kind of networks. For instance, the IEEE Standard for Low–Rate Wireless Networks (IEEE 802.15.4) follows this approach[34].

Furthermore, the proposed method C2TCascade and the other previous approaches have been tested in three different typical WSN scenarios, which are usually used by other clustering methods for comparison. The dimensions of the node deployment area the same for the three variants: a square area of 100×100 m^2, where the nodes were randomly placed. The number of nodes deployed for each scenario has been set in 100, 500 and 1000 nodes. The main difference between the three scenarios was the location of the BS. The three scenarios can be identified as follows.

- Scenario 1: BS is located in a corner of the deployment area at (100, 0) m.
- Scenario 2: BS is located outside the deployment area at (150, 50) m.
- Scenario 3: BS is located in the center of the deployment area at (50, 50) m.

When considering errors or losses in communications in the model used, it should be noted that the BER rate in wireless communications is very low (around $10^{-}4$ or even low with modern techniques[35]). In any case, a distinction must be made between centralized and distributed methods. In centralized methods, the worst case would be one in which a CH/SCH does not receive the message from the BS. This loss has a low probability because the BS has no power limitations and the number of messages of this type is very low.

However, in distributed methods, there is a possibility of loss of several control messages: the broadcast message from candidate CHs (if any), the message from CHs, final SCHs, and the node assignment and data sending messages. It is evident that the number of messages to be transmitted is greater, and the impact of losses, in addition to being more probable, has the potential to further compromise the efficacy of the clustering algorithm. This is due to the fact that, in numerous instances, the execution of the algorithm on each node is contingent on the updating of the information contained within these messages to ascertain whether that node will become a CH. However, as previously stated, even in a noisy environment, the failure of a message transmitted by the base station to a node designated as a CH/SCH would simply result in the node's inability to receive information from the other nodes assigned to it by the base station. Furthermore, since the base station would not receive the message from that SCH, retransmission mechanisms could be implemented to obtain the data not received. Nevertheless, the clustering algorithm would not see its performance degraded, since the new parameters for the new selection could be estimated based on the worst-case scenario (the message sent by the CH/SCH being lost and not that of the base station) and, given the low costs of a single transmission, future estimates would not be significantly affected. Conversely, in the event that the lost message pertains to the configuration of a normal node, only the measurement data would be affected, with minimal impact on the network.

Simulation results

To obtain the results presented in this section for each different method and each scenario, we have carried out 30 simulations in Matlab to assume normality for statistical processing. The parameters used for the energy model, data aggregation, and node setup are detailed in Table 5. Each of those 30 simulations uses a different deployment of the nodes. Each simulation is stopped when 90% of the nodes are dead. This assumption is established to avoid undesirable side effects such as no CH selection or the presence of only CHs. Therefore, for each of the three scenarios, we have used the same 30 different node deployments to allow a better comparison. Taking into account the values in Table 5, the final value of d_0 is 87.7 m.

The methods selected for comparison with the present proposal are: IT2FUSS[13], SAEZ[9], EFUCSS[22], TL-LEACH[16] and FLLTBPSO[20]. A description of these methods is provided in the related work section. The results obtained for the three scenarios are presented in the following subsections. These results were obtained with 100, 500, and 1,000 nodes. Each figure presents the FND, HND, and LND of the simulated method. Furthermore, a variance analysis (ANOVA) has been performed for all experiments, resulting in the presentation of the 95% confidence interval for each method in the figures.

Parameter	Value
Initial energy of nodes	0.5 J
Length of control message	200 bits
Length of data message	2000 bits
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
E_{DA}	5 nJ/bit

Table 5. Values of the setup parameters for the simulations and energy model.

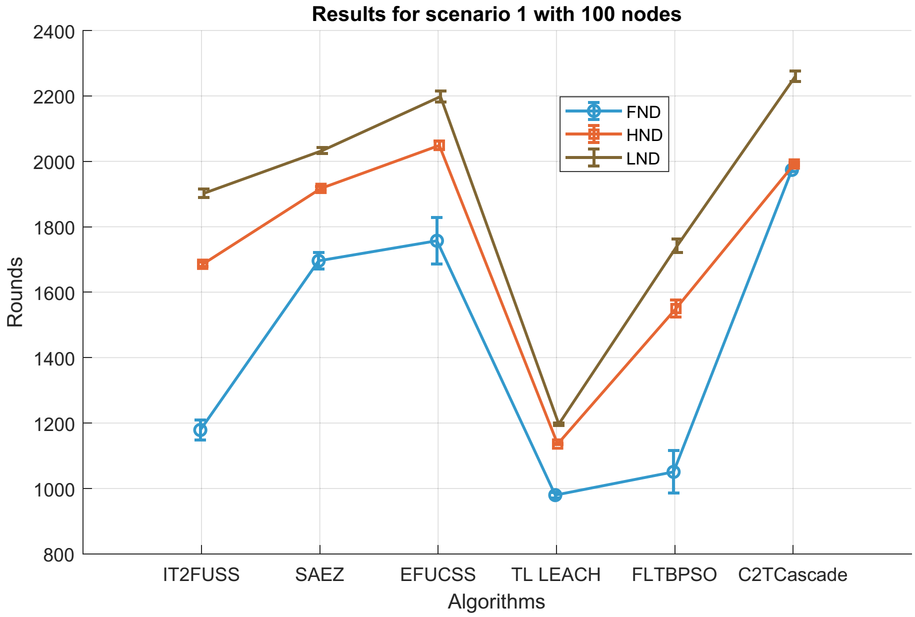

Fig. 10. Scenario 1, 100 nodes. Source: Matlab.

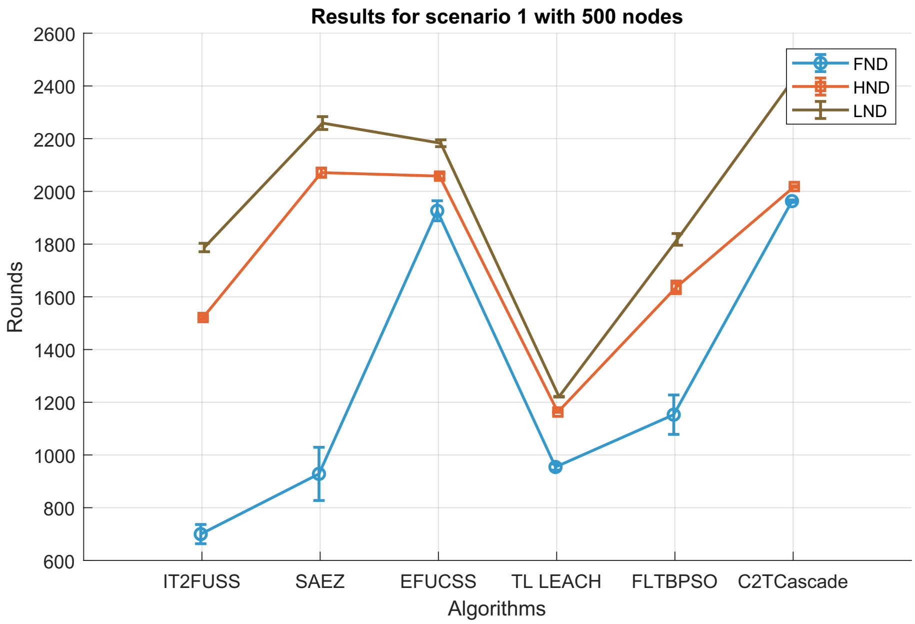

Fig. 11. Scenario 1, 500 nodes. Source: Matlab.

Simulation results for scenario 1

The results for this scenario are presented in Figs. 10, 11 and 12. As can be seen, the results for 100 nodes in Fig. 10, C2TCascade outperform all other methods for FND, HND and LND but the case of HND of EFUCCS which is higher. This situation is similar with 500 nodes (Fig. 11), however, the result for FND of C2TCascade is higher, but similar to EFUCCS FND. In the results for 1000 nodes C2TCascade improves the previous results of 100 and 500 nodes, achieving the best FND, HND (the same result for EFUCCS) and LND. In addition, as can be seen in the figures, C2TCascade maintains good values for LND for the three set of nodes, due to its scalability.

Simulation results for scenario 2

For these simulations, shown in Figs. 13, 14 and 15, C2TCascade is sometimes outperformed by EFUCSS, mainly in HND for the three different number of nodes (FND are similar). However, C2TCascade provides better support for scalability, achieving significantly better results for LND with 500 nodes and 1000 nodes.

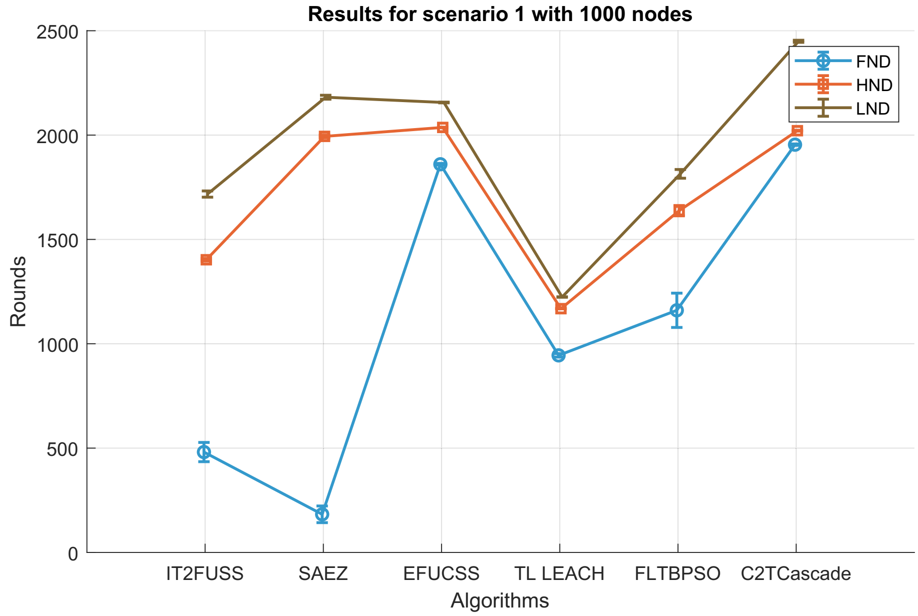

Fig. 12. Scenario 1, 1000 nodes. Source: Matlab.

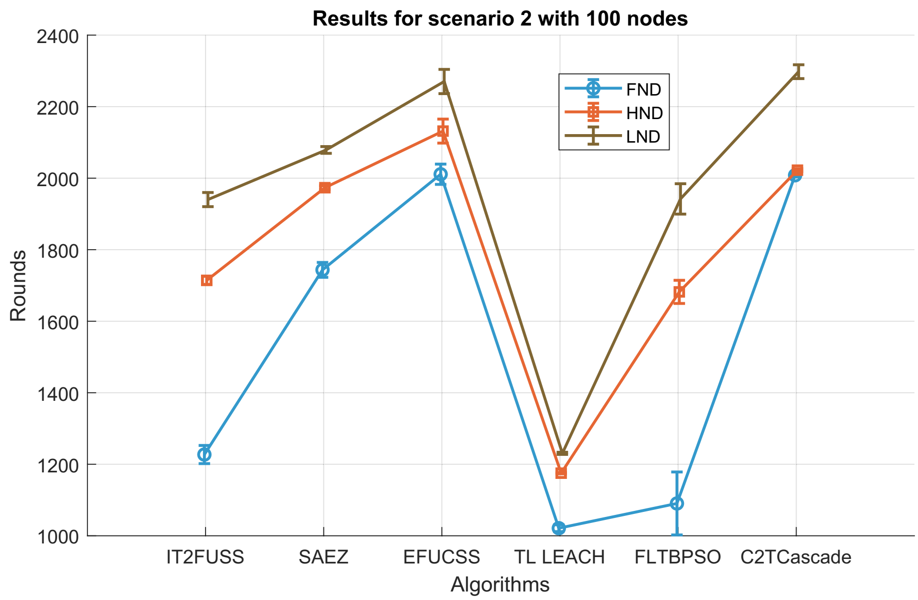

Fig. 13. Scenario 2, 100 nodes. Source: Matlab.

Simulation results for scenario 3

The results for the last set of simulations are plotted in Figs. 16, 17 and 18. For 100 nodes, C2TCascade performs significantly better than any other method, almost doubling the values for TL-LEACH or FLTBPSO FND results. For 500 and 1000 nodes, the behavior of C2TCascade is similar, showing its good scalability, achieves the best LND and FND, while only EFUCSS is slightly better in HND.

Summary

As illustrated in the previous subsections, the results obtained for C2TCascade demonstrate a general superiority over all other methods in the three scenarios. Specifically, C2TCascade achieved a nearly twofold increase in results compared to TL-LEACH and FLLTBPSO, and exhibited a significant enhancement (with the exception of EFUCSS in some cases) over alternative methods in FND. This suggests that C2TCascade has the capability to maintain the functionality of the network with all nodes for an extended period, with the capability to maintain good performance with a large number of nodes showing its scalability.

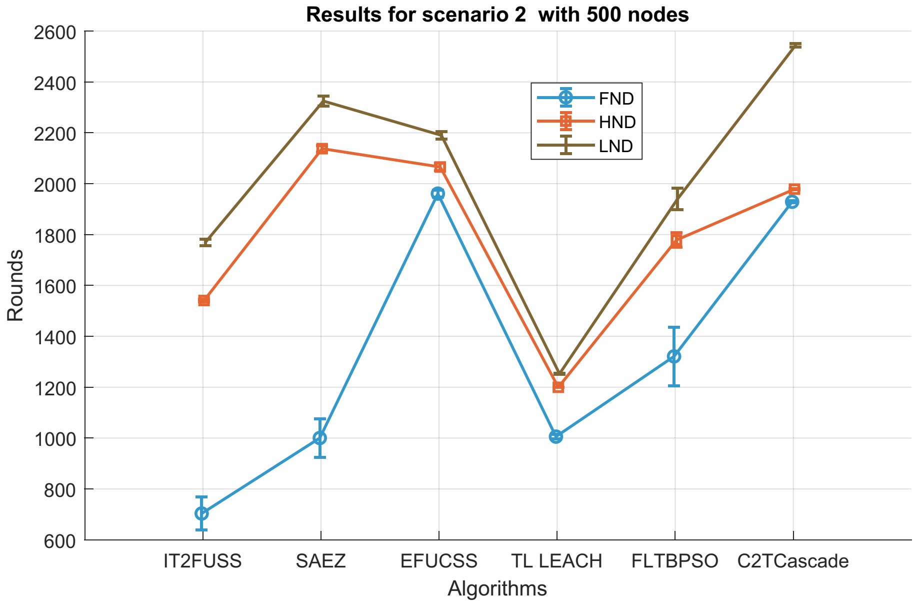

Fig. 14. Scenario 2, 500 nodes. Source: Matlab.

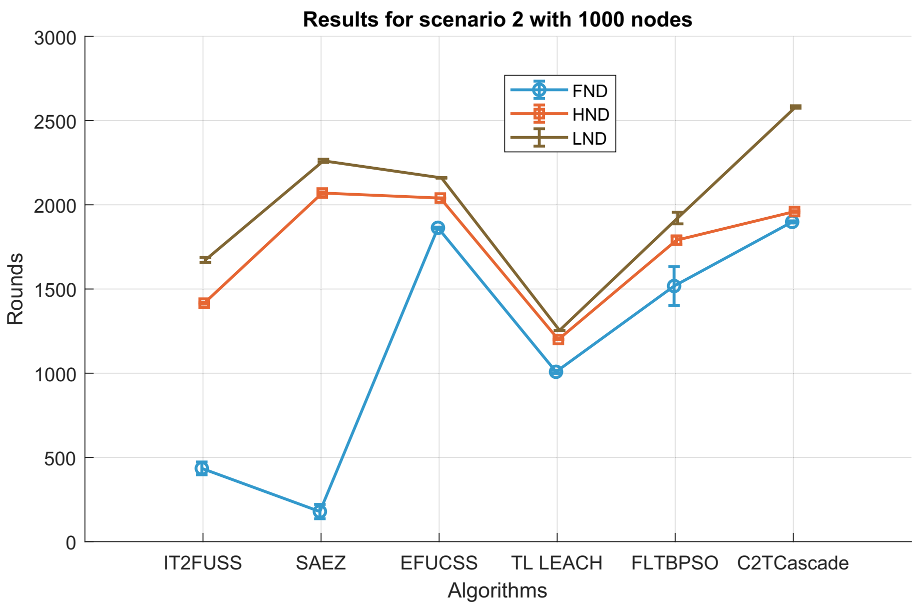

Fig. 15. Scenario 2, 1000 nodes. Source: Matlab.

Furthermore, in order to check the evolution of the total energy in the network of the compared methods, Fig. 19 depicts the evolution for Scenario 1 and 100 nodes (the results are very similar for the rest of the scenarios). Thus, as can be seen in that figure, C2TCascade manages to keep more energy in the network for longer time.

Discussion

The proposed centralized two-tier clustering method, C2TCascade, has been shown to support the selection of CH and SCH in two cascaded Type-1 fuzzy systems. The method also includes a preliminary stage in the form of a sustainability filter. It has been shown that C2TCascade is a reliable and effective method for topology control in WSNs. First, the incorporation of the sustainability filter resulted in a reduction in computation cost, as the BS was required to operate the selection system on fewer occasions and an improvement in the FND parameter of the network. Secondly, the elimination of the distance to the BS of a node from the initial stage of the CHs selection Type-1 fuzzy system has effectively circumvented the 'hole' effect, thereby ensuring the attainment of optimal outcomes by C2TCascade when the BS is not situated at the center of the WSN (scenarios 1 and 3). In conclusion, the two-tier configuration, incorporating CHs and SCHs, has been demonstrated to optimize energy

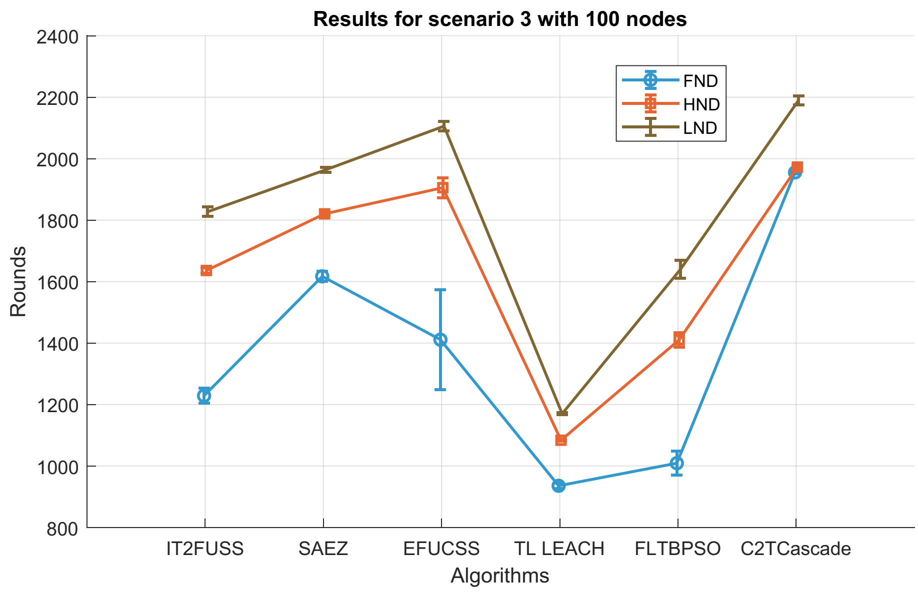

Fig. 16. Scenario 3, 100 nodes. Source: Matlab.

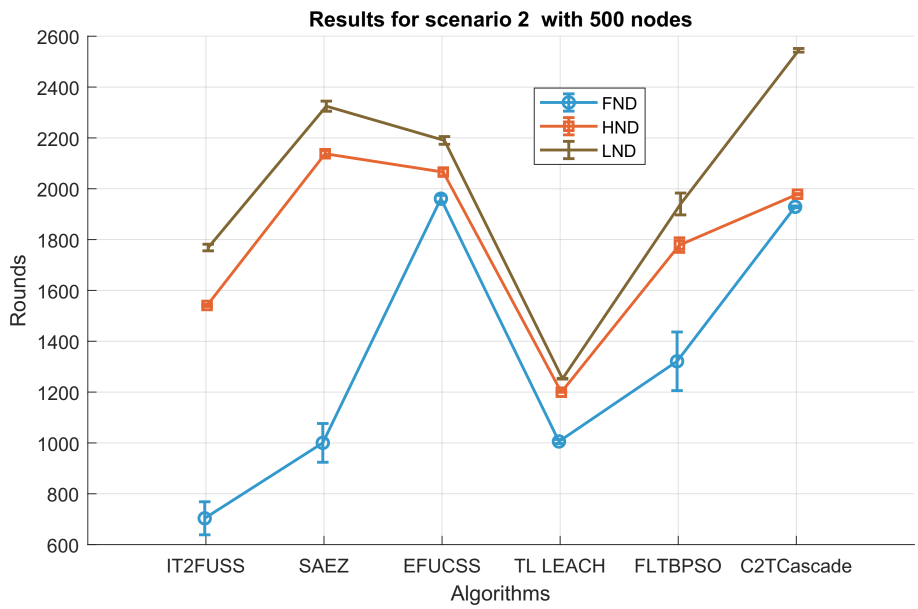

Fig. 17. Scenario 3, 500 nodes. Source: Matlab.

resources, yielding substantial benefits in LND and maintaining HND at a level comparable to the most effective methods.

In future research, the design of the sustainability filter could be improved to incorporate additional parameters that facilitate accelerated calculation in subsequent processing stages. Furthermore, in view of the evident uncertainty surrounding the proposal, the use of a Type-2 fuzzy system could be investigated to achieve improved results for C2TCascade.

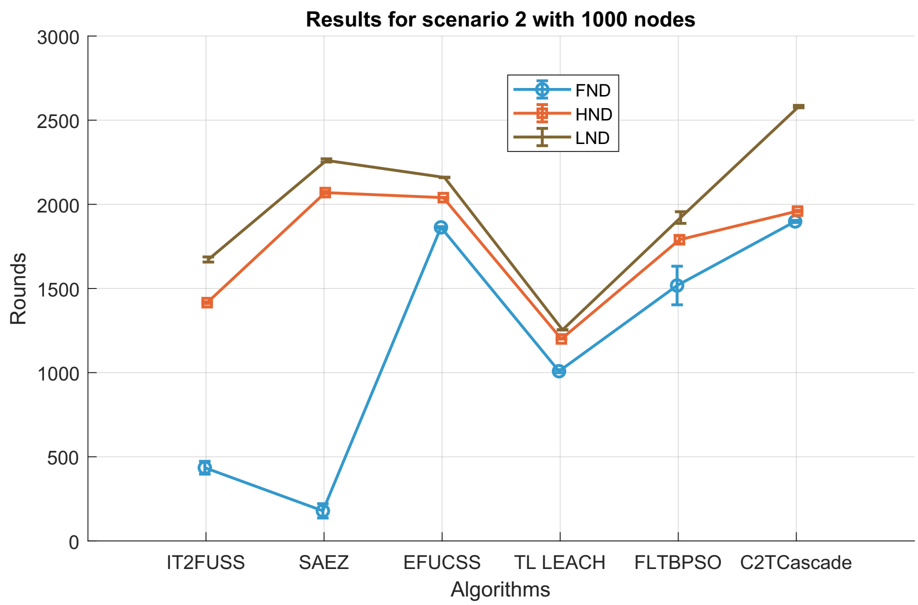

Fig. 18. "Scenario 3, 1000 nodes. Source: Matlab.

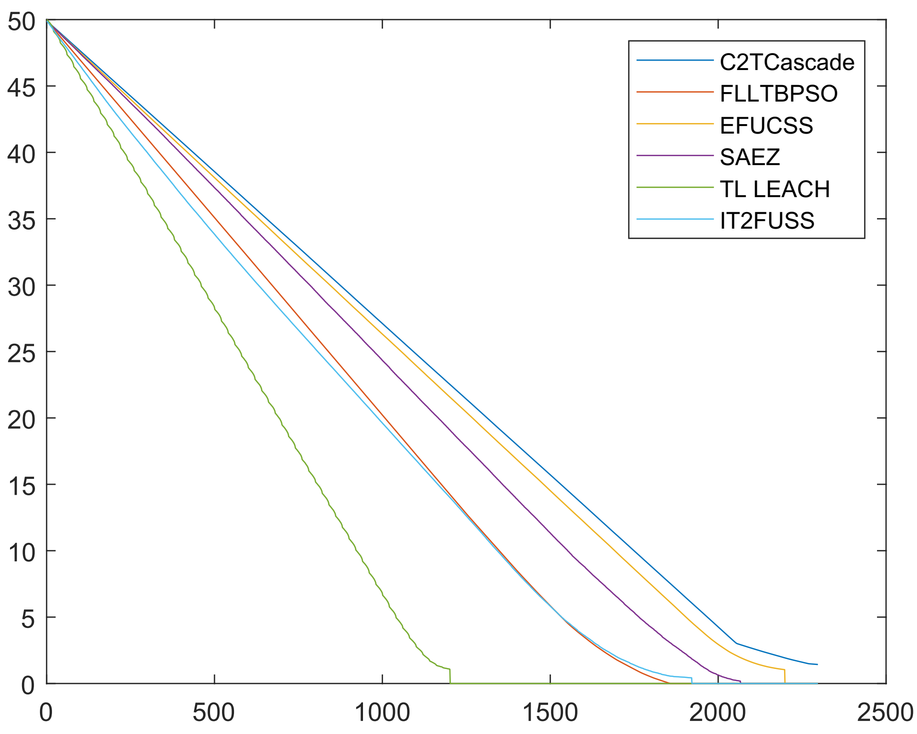

Fig. 19. Total energy in the network per round for scenario 1 and 100 nodes. Source: Matlab.

Data availability

The datasets used and/or analyzed during the current study available from the corresponding author at https://ruja.ujaen.es/home.

Received: 20 June 2025; Accepted: 3 December 2025
Published online: 10 December 2025

References

1. Gulati, K. et al. A review paper on wireless sensor network techniques in internet of things (iot). *Mater. Today Proc.* **51**, 161–165. https://doi.org/10.1016/j.matpr.2021.05.067 (2022).
2. Bajaj, K., Sharma, B. & Singh, R. Integration of wsn with iot applications: a vision, architecture, and future challenges. In *Integration of WSN and IoT for Smart Cities* 79–102 (2020).
3. Sharma, R., Prakash, S. & Roy, P. Methodology, applications, and challenges of wsn-iot. In *2020 International Conference on Electrical and Electronics Engineering (ICE3)* 502–507 (IEEE, 2020).
4. Vivekanand, V. & Mishra, D. Expendable and distributed measurement scheme for acquisition of naturally sparse events. *Wireless Pers. Commun.* **129**, 681–702 (2023).
5. Shahraki, A., Taherkordi, A., Haugen, Ø. & Eliassen, F. Clustering objectives in wireless sensor networks: a survey and research direction analysis. *Comput. Netw.* **180**, 107376 (2020).
6. Heinzelman, W. B., Chandrakasan, A. P. & Balakrishnan, H. An application-specific protocol architecture for wireless microsensor networks. *IEEE Trans. Wireless Commun.* **1**, 660–670 (2002).
7. Kim, J.-M., Park, S.-H., Han, Y.-J. & Chung, T.-M. Chef: cluster head election mechanism using fuzzy logic in wireless sensor networks. In *Advanced communication technology, 2008. ICACT 2008. 10th International Conference on, vol. 1* 654–659 (IEEE, 2008).
8. Zhang, Y., Wang, J., Han, D., Wu, H. & Zhou, R. Fuzzy-logic based distributed energy-efficient clustering algorithm for wireless sensor networks. *Sensors* **17**, 1554 (2017).
9. Yuste-Delgado, A. J., Cuevas-Martínez, J. C. & Triviño-Cabrera, A. Statistical normalization for a guided clustering type-2 fuzzy system for wsn. *IEEE Sens. J.* **22**, 6187–6195. https://doi.org/10.1109/JSEN.2022.3150066 (2022).
10. Bharany, S., Sharma, S., Alsharabi, N., Tag Eldin, E. & Ghamry, N. A. Energy-efficient clustering protocol for underwater wireless sensor networks using optimized glowworm swarm optimization. *Front. Mar. Sci.* **10**, 1117787 (2023).
11. Cuevas-Martinez, J.-C., Yuste-Delgado, A.-J., Leon-Sanchez, A.-J., Saez-Castillo, A.-J. & Triviño-Cabrera, A. A new centralized clustering algorithm for wireless sensor networks. *Sensors* **19**, 1452. https://doi.org/10.3390/s19204391 (2019).
12. Gong, Y., Guo, X. & Lai, G. A centralized energy-efficient clustering protocol for wireless sensor networks. *IEEE Sens. J.* **23**, 1623–1634. https://doi.org/10.1109/JSEN.2022.3224180 (2023).
13. Zaier, A., Lahmar, I., Yahia, M. & Lloret, J. Interval type 2 fuzzy unequal clustering and sleep scheduling for iot-based wsns. *Ad Hoc Netw.* **175**, 103867. https://doi.org/10.1016/j.adhoc.2025.103867 (2025).
14. Heinzelman, W. B., Chandrakasan, A. P. & Balakrishnan, H. An application-specific protocol architecture for wireless microsensor networks. *IEEE Trans. Wireless Commun.* **1**, 660–670. https://doi.org/10.1109/TWC.2002.804190 (2002).
15. Zhang, W., Lan, Y., Lin, A. & Xiao, M. An adaptive clustering routing protocol for wireless sensor networks based on a novel memetic algorithm. *IEEE Sens. J.* **25**, 8929–8941. https://doi.org/10.1109/JSEN.2025.3526831 (2025).
16. Loscri, V., Morabito, G. & Marano, S. A two-levels hierarchy for low-energy adaptive clustering hierarchy (tl-leach). In *VTC-2005-Fall. 2005 IEEE 62nd Vehicular Technology Conference, 2005, vol. 3* 1809–1813 (2005).
17. Rajput, A. & Kumaravelu, V. B. Fuzzy logic-based distributed clustering protocol to improve energy efficiency and stability of wireless smart sensor networks for farmland monitoring systems. *Int. J. Commun. Syst.* **33**, e4239. https://doi.org/10.1002/dac.4239 (2020).
18. Nayak, P. & Vathasavai, B. Energy efficient clustering algorithm for multi-hop wireless sensor network using type-2 fuzzy logic. *IEEE Sens. J.* **17**, 4492–4499 (2017).
19. Zhang, Q., Sun, Z. & Zhang, F. A clustering routing protocol for wireless sensor networks based on type-2 fuzzy logic and aco. In *2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)* 1060–1067 (2014).
20. Gamal, M., Mekky, N. E., Soliman, H. H. & Hikal, N. A. Enhancing the lifetime of wireless sensor networks using fuzzy logic leach technique-based particle swarm optimization. *IEEE Access* **10**, 36935–36948. https://doi.org/10.1109/ACCESS.2022.3163254 (2022).
21. Muñoz-Exposito, J.-E., Yuste-Delgado, A.-J., Triviño-Cabrera, A. & Cuevas-Martinez, J.-C. Optimizing rule weights to improve frbs clustering in wireless sensor networks. *Sensors* **24**, 2563. https://doi.org/10.3390/s24175548 (2024).
22. Abdulzahra, A. M. K., Al-Qurabat, A. K. M. & Abdulzahra, S. A. Optimizing energy consumption in wsn-based iot using unequal clustering and sleep scheduling methods. *Internet of Things* **22**, 100765. https://doi.org/10.1016/j.iot.2023.100765 (2023).
23. Tao, Y., Zhang, J. & Yang, L. An unequal clustering algorithm for wireless sensor networks based on interval type-2 tsk fuzzy logic theory. *IEEE Access* **8**, 197173–197183. https://doi.org/10.1109/ACCESS.2020.3034607 (2020).
24. Zeng, W., Wang, Z., Yang, S., He, D. & Chan, S. Icmh-chr: an intra-cluster multi-hop based cluster head rotation protocol for wireless sensor networks. *Ad Hoc Netw.* **173**, 103829. https://doi.org/10.1016/j.adhoc.2025.103829 (2025).
25. Prince, B., Kumar, P. & Singh, S. K. Multi-level clustering and prediction based energy efficient routing protocol to eliminate hotspot problem in wireless sensor networks. *Sci. Rep.* **15**, 1122 (2025).
26. Gupta, I., Riordan, D. & Sampalli, S. Cluster-head election using fuzzy logic for wireless sensor networks. In *Communication Networks and Services Research Conference, 2005. Proceedings of the 3rd Annual* 255–260 (IEEE, 2005).
27. Silva, A. M. M., Maciel, C. C. & Correa, S. D. C. Multi-hop energy-efficient control for heterogeneous wireless sensor networks using fuzzy logic. arXiv preprint arXiv:1401.5163 (2014).
28. Arjunan, S. & Sujatha, P. Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and aco based routing hybrid protocol. *Appl. Intell.* **48**, 2229–2246 (2018).
29. Sahoo, L., Sen, S., Tiwary, K., Moslem, S. & Senapati, T. Improvement of wireless sensor network lifetime via intelligent clustering under uncertainty. *IEEE Access* **2024**, 253 (2024).
30. Mamdani, E. H. Application of fuzzy algorithms for control of simple dynamic plant. In *Proceedings of the Institution of Electrical Engineers, vol. 121* 1585–1588 (IET, 1974).
31. Cuevas-Martínez, J. C., Yuste-Delgado, A. J. & Triviño-Cabrera, A. Cluster head enhanced election type-2 fuzzy algorithm for wireless sensor networks. *IEEE Commun. Lett.* **21**, 2069–2072 (2017).
32. Yuste-Delgado, A. J., Cuevas-Martinez, J. C. & Triviño-Cabrera, A. Eudfc-enhanced unequal distributed type-2 fuzzy clustering algorithm. *IEEE Sens. J.* **19**, 4705–4716 (2019).
33. Dhand, G. & Tyagi, S. Data aggregation techniques in wsn: survey. *Procedia Comput. Sci.* **92**, 378–384 (2016).
34. Group, I. . W. et al. Ieee standard for low–rate wireless networks. *ANSI/IEEE Std* **802** (2024).
35. Abouzeid, M. S., El-Khobby, H. A., Ali, M. A. & Nasr, M. E. Joint noniterative beamforming schemes for ber minimization in next-generation wireless sensor networks. *J. Electr. Comput. Eng.* **2025**, 5235951 (2025).

Acknowledgements

Figures 1, 2, 3 and 6 have been drawn by J.C. Cuevas-Martinez and Figures 4, 5 and 7 have been drawn by A.J. Yuste-Delgado. Fig. 10 to 19 have been generated by A.J. Yuste-Delgado in Matlab using the simulation results. This research has been funded by the Ministry of Science, Innovation, and Universities, as part of the 2023 call for proposals for grants for proof–of–concept projects under the State Plan for Scientific, Technical, and Innovation Research for the period 2021-2023, within the framework of the Recovery, Transformation, and Resilience Plan, with grant number PDC2023-145863-I00; and by grant M.2 PDC_000756 funded by Consejería de Universidad, Investigación e Innovación and by ERDF Andalusia Program 2021-2027.

Author contributions

AJYD and JCCM. conceived the method and the experiment, AJYD developed the software, AJYD and DDJ tested the software, AJYD, JCCM and ATC conducted the experiments, AJYD and JCCM wrote the original draft, AJYD, JCCM, ATC and DDJ analyzed the results, JCCM and DDJ prepared the final document, AJYD and ATC supervised the research, and the project administration was accomplished by AJYD and JCCM. All authors reviewed the manuscript.

Funding

Open Access funding enabled and organized by, firstly, Microchip4Age project, grant number PDC2023-145863-I00 of the Ministry of Science, Innovation, and Universities. This research has been funded by the Ministry of Science, Innovation, and Universities, as part of the 2023 call for proposals for grants for proof-of-concept projects under the State Plan for Scientific, Technical, and Innovation Research for the period 2021-2023, within the framework of the Recovery, Transformation, and Resilience Plan, with grant number PDC2023-145863-I00, and in addition, by grant M.2 PDC_000756 funded by Consejería de Universidad, Investigación e Innovación and by ERDF Andalusia Program 2021-2027.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to J.C.C.-M.