A Cluster-based Approach to provide Energy-Efficient in WSN

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Summary
Wireless Sensor Networks (WSNs) play an important role in pervasive and ubiquitous systems. Even though the advances in embedded systems, the energy consumption is still open issue in WSNs. In this context, hierarchical routing protocols provide energy-efficiency, scalability and reliability for WSN applications. With this goal in mind, this paper proposes to adopt a Cluster-based approach for ENERgy-efficiency in the WSN (CLENER) protocol. The main purpose of CLENER is to provide energy-efficiency by using fuzzy logic for cluster formation and a probability function for Cluster Head election. Simulations were conducted to show the benefits of CLENER compared with LEACH and EECHS. According to the simulation results, CLENER extends the network lifetime by 19% and 18%, and increases the packet delivery ratio of LEACH and EECHS by 15% and 14%, respectively.
Key words:
Wireless sensor networks, Energy-efficiency, Hierarchical routing protocol.

1. Introduction

Wireless Sensor Networks (WSNs) are resource-constrained networks, which are expanding as a result of a wide range of potential applications. However, there are several difficulties in developing energy-efficient, scalable and reliable WSN applications. This is due to the fact that WSNs are constrained in terms of energy, short communication range, low bandwidth, and limited processing and storage [1], [2].
In this work, we focus on applications for environmental monitoring, where sensor nodes can be scattered in forests or rivers to detect fires or floods. In habitat monitoring, sensor nodes can be used to monitor the conditions of wild animals or plants, as well as to lay down the environmental parameters of the habitats [2].
Routing protocols based on clustering are an alternative to improve Quality of Service (QoS) and energy-efficiency for a set of Internet of Things (IoT) applications [3]. A hierarchical architecture has nodes with different roles or functionalities (heterogeneous nodes can be classified into cluster-head (CH) and non-head nodes). Where, the nodes inside a cluster communicate with each other (sensor-to-sensor), and mainly with the leader node (cluster-head), responsible for communicating outside the cluster (sensor-to-Base Station (BS)). Moreover, some nodes (CH) can have cameras to retrieve multimedia content [4]. There are many algorithms of CH election, they analyze key features as follows: residual energy, link quality and location [5]. These algorithms require time for cluster formation, generating additional delay and complexity, which are unsuitable for many IoT applications.
In this context, the performance of routing protocols affects both the network performance, and the lifetime of the network [6]. Furthermore, recent technological advances in embedded systems lead us to believe that processing and memory constraints in WSNs are tending to disappear [7]. However, external power supply is usually unavailable and the replacement of batteries is not feasible WSNs, especially in environmental monitoring scenarios. Thus, the main design objectives continue to reduce energy consumption and prolong the network lifetime.
In hierarchical architecture, the nodes are divided into clusters and a set of nodes are periodically elected as a leader of each group CH. CHs are used for more complex tasks, such as: the controlling of each cluster, collecting data from non-CHs, data aggregation, and sending the collected data to the BS [8]. For this reason, CHs consume more energy when they are located further away from the BS, which causes communication interference and network partitioning. Thus, it is important to use metrics that can provide an energy-efficient mechanism for CH election and load balance to enable a uniform clustering distribution and homogeneous energy consumption [9]. Furthermore, the cluster formation process can lead unfair energy consumption, if the CHs are only elected on the basis of a single objective metric [1].

In this context, there are several hierarchical routing protocols. However, these proposals have the following drawbacks: ineffective CH selection, low energy-balancing, network lifetime, and scalability.
To address the above issues, this paper proposes an extension of LEACH, called a CLuster-based approach for ENERgy-efficiency in WSNs (CLENER). CLENER combines multiple metrics to solve the above- mentioned drawbacks regarding CH election and cluster formation. Thus, it is possible to balance and reduce the energy consumption between the nodes, while providing data transmission reliability.
The main contributions of CLENER are as follows: (i) a fair distribution of the network resources between the sensor nodes; (ii) a load balanced cluster formation; and (iii) support for resource management. To achieve these aims, CLENER proposes that each node should determine the degree of probability necessary to become a CH, based on the remaining energy and random probability factors. Additionally, the non- CHs choose the CH in accordance with a cost function that is computed through a Takagi-Sugeno fuzzy system (TS) [10].
Simulations were carried out to show the impact and benefits of CLENER for cluster formation and CH election. This paper includes an analysis of energy-efficiency, packet delivery and cluster formation. The results show that CLENER is able to prolong the network lifetime, provide a uniform clustering distribution and increase the Packet Delivery Ratio (PDR) unlike LEACH and Energy Efficient Cluster- Head Selection (EECHS).
The rest of this work is organized as follows: Section 2 outlines the related works and their main drawbacks. Section 3 describes the proposed CLENER protocol. Simulations were carried out and are described in Section 4. Section 5 summarizes our contributions and results of this paper.

2. Related Works

LEACH (low-energy adaptive clustering hierarchy) divides the protocol operation into rounds, and each round is subdivided into two phases: setup and steady-state phase. In the setup phase, the nodes create clusters and elect CH. The nodes choose a random number between 0 and 1, and if the number is less than a threshold T(n) (Equation 1), the node becomes the CH for the current round. After the CH election, CHs must create a schedule for the transmission of non-CHs in accordance with a TDMA (Time Division Multiple Access) scheme. On the other hand, non-CH nodes elect the CH on the basis of minimum energy communication.

$$T(n) = \begin{cases} \frac{P}{1-P\left(r \ mod \ \frac{1}{P}\right)} & \text{if n} \in \text{G} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

In the case of the steady state phase, non-CHs transmit the sensed data to their CH. CHs receive the data, aggregate it into a single packet and forward it to the BS. After a certain period of time (determined a priori), the network returns to the setup phase.
However, LEACH has some drawbacks, such as the fact that CH election does not take account of the energy level of the sensor nodes, since the decision is a simple probabilistic function and not energy-aware. Moreover, LEACH does not employ any scheme to control the cluster formation, which means that a node with almost no energy can become a CH. Additionally, the cluster can be formed in a disproportional way, which causes furthermore communication interferences and network partitioning. Thus, LEACH cannot provide reliability, energy-efficiency or a fair distribution of resources.
Energy Efficient Cluster-Head Selection (EECHS) [11] extends LEACH to solve the problem of CH election. EECHS extends the capacity of the probability model for CH election to allow the CHs to distribute the energy load between all the nodes. In this way, the probability model is based on the remaining energy, energy consumption for data transmission, the monitored area and the distance between a node and BS.
Overall, the main drawback of EECHS [11] is that it uses an inadequate equation for CH election, which prevents it from providing an optimal cluster formation. This equation is based on a centralized proposal, i.e. LEACH-C, which needs additional information, such as the number of nodes and length of the nodes in distributing fields [12]. Hence, each node has a different view of the network in every round and during the CH election each node computes different parameters to choose its CHs. It should be emphasized that EECHS elect many CHs, but does not deal with a real situation in the network and as a result, it will have high energy cost, fast network partitioning and an inefficient load balancing.
There are other proposals that apply Fuzzy logic to help the process to elect CHs. In this context, Barolli et al. proposed a powerful reduction algorithm for sensor networks based on fuzzy logic and a number of neighbor nodes called F3N [13]. F3N uses four input parameters for FLC (Fuzzy Logic Control) to make the CH selection, i.e. cluster- centric distance, the remaining energy, and the degree and number of the neighbor nodes.
The Energy-Efficient Cluster-Head Selection (NECHS) [14] proposes a solution based on fuzzy logic for CH selection. The selection of the CHs is based on the number of neighbor nodes and remaining energy, which are the input for the fuzzy system. The output is the degree of probability that each node will become a CH. The node with a higher degree of probability has a greater chance of becoming a CH.
Both, F3N and NECHS use the compositional rule of inference to infer the output of the system, and hence incur a high computational cost and a poor response performance.
From the analysis of the related work, it is evident that uniform clustering distribution, load balancing and a fair distribution of resources are needed to increase reliability, reduce network resource usage and save energy.

3. CLuster-based approach for ENERgy-efficiency in the WSN (CLENER)

CLENER was developed for application where there are sensor nodes periodically collecting scalar data and send them to BS for further analysis. The physical scalar sensor measurements are processed by means of existing models or methods, with the aim of predicting the occurrence of events, such as flooding, fire or intruders. CLENER considers a network with the following characteristics:

- The sensor nodes fixed, are energy-constrained and they have the same capability;
- The BS has not subject to energy restrictions and is located inside the sensing field;
- There is no batteries recharge after node deployment;
- The sensor nodes can transmit with enough power to reach the BS;
- Each sensor node can change its transmission power level dynamically.

This general scenario may be used for various applications ranging from civilian and military areas. For example, monitoring in rainforest area to measure environmental factors, such as: temperature, humidity, and wind speed. These information can be used to predict event occurrence.

3.1 CH election

As mentioned earlier, in hierarchical architectures, the nodes are divided into clusters and a set of nodes is periodically elected as a CH. CHs are used for more complex tasks, such as: the management of each cluster, collecting data from non-CHs, data aggregation, and sending the collected data to the BS. In this context, it is important to use multiple metrics for CH election to provide an energy-efficient and load balance model. Furthermore, the cluster formation process can lead to poor energy use, if the CHs that are elected are only based on a single metric. In this context, CLENER proposes an equation, which is used by nodes to enable them to become a CH.

During the initialization of the network, BS broadcasts a *startup message*, which enables the node to compute the distance to BS. The distance is computed by means of Received Signal Strength Indicator (RSSI) [15]. Following this, the nodes are able to adjust the transmission power according to distance, which reduces the energy consumption since higher transmission power consumes more energy.

After adjusting the transmission power, each node generates a random number (μ), which ranges from 0 to 1. Then, the node decides to become a CH by comparing μ with the *T(n)*, which is computed by means of Equation 2. If μ is less than *T(n)*, the node becomes a CH for the current round.

$$T(n) = \eta \frac{P}{1-P\left(r \bmod \frac{1}{P}\right)} + \alpha\left(1 - e^{\frac{-RE^2}{2\sigma^2_{RE}}}\right) \qquad (2)$$

Where η and α are weights to give importance, the sum is exactly 1. The Residual Energy is denoted as RE, and σre means the energy variance, which is used to produce better CH candidates.

Equation 2 uses a gauss function, due to the fact that has better result in terms of energy efficiency and representation in the context of an imprecise environment.

The node that becomes CH broadcasts a ch message, which contains the value of its remaining energy. Then, CH waits for a join message from the non-CH nodes. However, if the CHs do not receive a join message, this CH should not become CH. Algorithm 1 describes the steps for CH election and cluster formation.

The proposed CLENER algorithm has a computational complexity of O(n). Additionally, the communication complexity can be analyzed as follows: the most expensive communications are the reception of ch and join messages from non-CH and CH respectively. In the worst case, n non-CHs receive a ch message from all CHs a with a complexity O(log n).

3.2 Cluster Formation

During this sub-phase, non-CHs select the best CH by considering a multiple metrics, i.e. residual energy and a distance from non-CH to CH. Then, non-CHs compute a probability value to each CH candidate using TS. The non-CH chooses the CH with a higher probability value and sends a join message to CH.

The use of fuzzy logic is appropriate, whenever it is not possible to employ a mathematical model for the system. Additionally, fuzzy can reduce the complexity of the model, computational effort and memory [16]. In this context, TS is able to provide higher computational efficiency and better Gain-scheduling controllers than Mamdani fuzzy system, which is expected for resource constrained WSN [10].

TS receive context information from nodes as input and converts into fuzzy linguistic variable input. The defuzzifier process produce a crip output from the fuzzy set and rules that is the output of the inference engine. TS is formed of four modules: rules, inference engine, fuzzifier and defuzzifier. The architecture of the fuzzy system used is shown in Figure 1.

Fuzzy logic provides a rigorous algebra for dealing with inaccurate information [20]. The linguistic input variables of the system are the remaining energy, expressed in percentages and the distance between non-CH and CH (expressed in meters), which these linguistic input have been determined based on the simulation result, presented in Sec. 4. The specifications related for the input and output functions of the system and their respective Linguistic Values (LV) are as follows:

- Residual energy: u=[0,100]: LV = low, average, high;
- Distance: u=[0,100]: LV = small, average, big;
- Probability: u=(0,1]: LV = very high, high, moderately high, fairly high, average, fairly low, moderately low, low, very low.

Algorithm 1 CLENER

```
StartUp
if BS then
    Broadcast startupMessage( ID )
end if
On receiving a startupMessage
μ ← rand(0, 1)
probability ← Equation 2
if μ < probability then
    beCandidate ← TRUE
end if
if beCandidate = TRUE then
    Broadcast chMessage( ID,residualEnergy )
end if
On receiving a chMessage
if !beCandidate then
    c.rssi ← estimateDistance( chMessage )
    c.residualEnergy ← chMessage.residualEnergy
    c.id ← chMessage.id
    ADD c to candidateClusterHead set S
end if
Join a Cluster Head Candidate
if !beCandidate then
    CH = fuzzySystem( S,residualEnergy,RSSI )
    Broadcast joinMessage( CH[0].ID,id )
end if
```

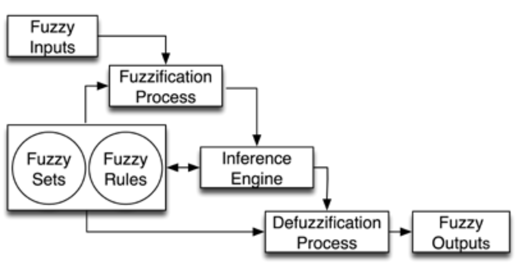

Figure 1: Fuzzy Diagram

A suitable means of determining the appropriate membership functions and meaningful fuzzy operations in the context of each particular application is crucial to make the fuzzy set theory useful in practical terms [17].
For the representation of the linguistic states (low, high, small and large) of the input variables, the degrees of membership to these sets must remain constant for certain values of the universe of discourse. The functions in the form of S and Z, Equations 3 and 4 respectively, are chosen because they have proved to be the most suitable for the representation states.

$$f(x) = \begin{cases} 0, & x < a \\ 2x^2, & a \le x \le \frac{a+b}{2} \\ 1 - 2(1-x)^2, & \frac{a+b}{2} \le x \le b \\ 1, & x \ge b \end{cases} \tag{3}$$

$$f(x) = \begin{cases} 1, & x \le a \\ 1 - 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ \left(\frac{b-x}{b-a}\right), & \frac{a+b}{2} \le x \le b \\ 0, & x > b \end{cases} \tag{4}$$

Experiments were conducted for the linguistic intermediaries representing the states of the input system and the cost function of output. These results were as follows: unsatisfactory with the trapezoidal and triangular functions, fairly satisfactory with the bell-shaped function, good with the small parameter values for the central curve, and better when the Gaussian function provided a better description of the nonlinearity and there was uncertainty about the variables. The function is given below:

$$f(x, \sigma, c) = e^{\frac{-(x-c)^3}{2\sigma^2}} \tag{5}$$

The membership functions designed for the system are shown in Figure 2. The rules are expressed as logical implications in the form of *IF-THEN* statements in a mapping from fuzzy input sets to output functions.

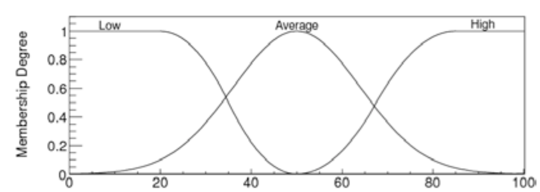

Figure 2: Membership Functions

The rules are determined on the basis of an analysis of the whole network behavior through extensive simulations over time. They result in a class of higher probability, ensure an excellent chance these nodes will be elected, and differentiate depending on their distance from each CH.
However, the behavioral analysis of the network showed that the average levels of energy for CH can lead them to death quickly, and thus although the nodes represent good candidates to be chosen, they should be avoided in order to prevent their death. Table 1 shows the fuzzy inference rules used in the system.

Table 1: Fuzzy Inference Rules

Energy	Distance	Probability	
high	small	very high	**y=1**
high	average	high	**y=0.9**
high	big	moderately high	**y=0.8**

average	small	fairly high	**y=0.6**
average	average	average	**y=0.5**
average	big	fairly low	**y=0.2**
low	high	moderately low	**y=0.1**
low	average	low	**y=0.07**
low	low	very low	**y=0.02**

All the available data are submitted to an expert system, which uses them to evaluate the relevant production rules and draw all possible conclusions [10]. Hence, the fuzzy implication R_i is defined by a set of rules and the final output y inferred from *n* which is given as the average of all y_i with their respective weights. The calculation is given as follows:

$$IF\ f(x_1 is A_1, ..., x_k is A_k)\ THEN\ y = g(x_1, ..., x_k), \quad (6)$$

$$y_i = p_0 + p_1 x_1, ..., +p_k x_k, \quad (7)$$

Where *p* is the order of the output function, then the truth value of the proposition is calculated by the equation:

$$w_i = \prod_{i=1}^{n} A(x_i), \quad (8)$$

Where $A(x_i)$ is the grade of the membership of x_0 and w_i is the degree of truth of rule R_i. The output *y* inferred from *n* implications is given by the weighted averages of $\{y_1, \ldots, y_n\}$:

$$y = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \quad (9)$$

Where $\{x_0,...,x_k\}$ is the set of input systems, $\{A_1,...,A_k\}$ the set of membership functions that defines the rule, being *y* the output of rule, *f* is the logical function connecting the propositions in the premise, *g* is the function that implies the value of *y*. Therefore, for each implication R_i, y_i is calculated by the function g_i in the consequence.

4. Performance Evaluation

Simulation experiments were conducted to analyze the performance of CLENER in WSNs by using the Castalia Framework [18]. Castalia is a widely used network simulator for WSNs based on OMNET++. The simulations were carried out and repeated 30 times with different number of seeds. The data analyzes use the 10 percentiles, in order to provide a confidence interval of 95%. The performance of CLENER was compared with LEACH and EECHS in terms of network lifetime, number of clusters, non-CH per clusters and PRR. The basic parameters used for simulations are listed in Table 2.

Table 2: Parameters Employed in our Performance Evaluation

Parameter	Value
Field Size	50m X 50m
Location of Base Station	(0m,50m)
Number of Nodes	100
Probability of cluster	0.05
Initial Energy of sensor node	20J
n	0.4
α	0.6
The data packet size	26bytes
Time Round	20s
Radio Model	CC2420
Channel Model	Tewari, Swarup and Roy
Width of Trees	0.8m
Length of Trees	40m

We evaluate CLENER under characteristics of rainforest areas, which have various effects on wireless communications, such as attenuation, scattering, and absorption. In this context, Tewari et al. [19] propose a propagation model that is based on an empirical model and consider the natural features of the forest region[1]. Thus, by using this propagation model, it is possible to evaluate CLENER in real-life conditions and improve the accuracy of the results.

In the hierarchical architecture, CHs are responsible for more complex tasks, e.g. they receive the collected data sent by non-CHS, aggregate the non-CHs packets into a single packet, and send it to the BS. At the same time, non-CHs can turn off the radio after transmitting their packets, reducing energy consumption and avoiding communication conflicts.

In resuming, the routing protocols must have the best number of cluster per round, i.e. a number near to the selected probability, which defines the best number of the cluster so that it can reduce energy consumption, interference and the problem of disconnection. Table 3 shows the average and standard deviation of clusters in each round.

When the results are analyzed, it can be concluded that in general CLENER has a better number of clusters per round, i.e. a value near to 5, which is the defined probability (see Table 3). This is due to the fact that CLENER proposes the residual energy as the principal variable in the CH election. In this way, it can establish the correct numbers of CH per round with regard to all the nodes that are alive.

The worst performance of LEACH can be explained by the fact that it only uses a probabilistic equation without considering residual energy, or the relative positions of each non-CH, which can improve the accuracy of the cluster formation.

Table 3: Numbers of clusters

Protocol	Cluster/Round (average)	Standard deviation
LEACH	6.3	2.045
EECHS	8.1	2.652
CLENER	5.8	1.577

EECHS employs a correct variable but at the wrong time. During a CH election in EECHS, each node has a different view of its parameters, which have different values. Hence, each node has different ways of making a decision, and at different stages the network will have smaller or larger clusters. In view of this, it may not be a satisfactory method for CH election.

Table 4 shows the numbers of non-CHs obtained in each cluster per round. CLENER has a low average and standard deviation for the number of non-CHs. This is due to the use of the fuzzy system, which makes it possible to indicate the most eligible CHs for each non-CH during the cluster formation, where there was efficient energy consumption. On the other hand, LEACH and EECHS obtained a higher standard deviation, because these proposals do not improve the fast convergence response with regard to energy.

Table 4: Non-CHs per Cluster

Protocol	Numbers of non-CH (Average)	Standard deviation
LEACH	21.23	11.737
EECHS	19.34	12.745
CLENER	20.77	7.709

Since the proposal has a low variance with regard to numbers of clusters and non-CHs, it can be inferred that CLENER provides a better cluster formation regardless of distance. Thus, CLENER has a better system of clusterization than LEACH and EECHS.

Additionally, an analysis was conducted of the number of nodes that were still alive after some rounds (i.e. the network lifetime), as shown in Figure 3. The network lifetime was measured as the period of time until the point where 10% of the nodes had run out of energy. The results show that LEACH and EECHS protocols consumed their energy at a faster rate than CLENER.

CLENER increases the network lifetime by 19%, and 18%, compared with LEACH and EECHS protocols respectively (Figure 3). The reason is that the CHs are used for more complex tasks, which consume more energy. Additionally, the CHs located farther away from the BS also consume more energy. Therefore, the CH election in CLENER is determined through a combination of random probability, residual energy and a stochastic equation. Thus, the nodes with low energy levels have a lower probability to become CH.

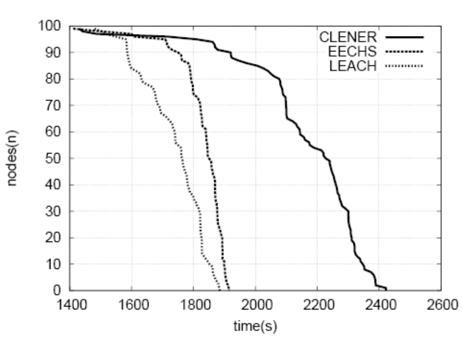

Figure 3: Number of nodes alive over time

Unlike CLENER, LEACH does not consider energy consumption for the CH election sub-phase. Additionally, EECHS do not have an ordinary objective during a CH election. Thus, since LEACH and EECHS does not have a significant resource management system, they did not achieve a higher network lifetime.

It can be assumed that the network lifetime is the time until the point when 1%, 50% and 100% of the nodes run out of energy, as shown in Figure 4. This is useful to evaluate the capability of the routing protocols to dynamically adapt to the new topologies that are caused by the death of the nodes.

CLENER increases the network lifetime in all cases, especially after the first nodes consume the energy resource. This is due to the fact that CLENER always creates the expected number of clusters (see Table 2). Additionally, the cluster formation takes account of fuzzy system residual energy and distance to CH, which balances the energy consumption.

However, LEACH does not consider an important variable that is needed to provide energy-efficiency, i.e. residual energy, and thus reduces the network lifetime. On the other hand, the CH election of EECHS has more candidates than necessary (see in Table III) and hence the non-CH has more candidates to choose. However, its criteria for choice is aware that the non-CH elects the correct CH, because the minimum energy communication shows wide variations and changes in accordance with the environment.

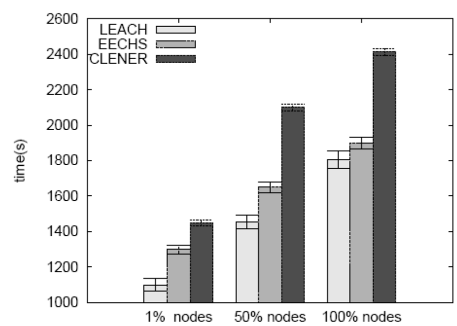

Figure 4: Network Lifetime

The reliability of CLENER, LEACH and EECHS were measured by means of PDR. Table V shows the PDR for all the aggregated packets transmitted from CH to BS. CLENER increases the PDR by 15% and 14%, compared to LEACH and EECHS, respectively. This can be explained by the fact that CHs are selected on the basis of their remaining energy. This reduces the probability of a node exhausting its energy sources after becoming a CH, and thus increases the PDR.

Table 6: Packets Received at BS

Protocol	PRR
LEACH	77%
EECHS	80,5%

CLENER	95,5%

Unlike CLENER, EECHS and LEACH consider the minimum energy communication needed for cluster formation, although this does not guarantee that a correct method is employed for the CH choice. This can cause the node to use up its energy resources, after the CH has been elected. This fact explains the reason why CLENER increases its packet delivery by 15% and 14%.

5. Conclusion

This paper presented CLENER, a CLuster-based approach for Energy-efficiency for WSNs. CLENER proposes two sub-phases for the setup phase, namely CH election and cluster formation. In the former of the CH, each node determines a new probability function to become a CH, based on its remaining energy and a stochastic equation. The cluster formation, the non-CHs select the most reliable CH based on residual energy, and the distance between them. This information is used as input to TS, which seeks to overcome any uncertainties and thus be able to estimate the correct CH. Simulations were carried out to show the impact and benefits of CLENER in terms network lifetime and PDR. We found that CLENER increases the network lifetime in 18%, and PDR in 14% compared to LEACH and EECHS.

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