Battery State-of-Health Prediction based Clustering for Lifetime Optimization in IoT Networks

Mohamed Sofiane BATTA, Hakim MABED, Zibouda ALIOUAT, and Saad HAROUS

***Abstract*—The Internet of Things (IoT) represents a pervasive system that continuously demonstrates an expanded application in various domains. The energy efficiency problem has always been a crucial issue linked to this type of network where the system lifetime strongly depends on devices' batteries. Numerous energy efficient networking protocols have been proposed in the literature to increase the system lifetime. However, most of the proposed approaches deal with the short-term vision of energy consumption and omit to consider the rechargeable battery degradation when evaluating the network lifetime. Indeed, the major parts of the network devices use rechargeable batteries that age and degrade over time due to several factors (temperature, voltage, charging/discharging cycle, etc.). Therefore, it is essential to promptly detect these internal and environmental degradation factors to avoid network failures. Clustering represents one of the main wireless network protocols and plays an essential role in network self organizing. In this work, we propose a novel Long-term Energy optimization Clustering Approach based on battery State Of Health (SOH) prediction, called $LECA\_SOH$. The objective is to predict the impact of Cluster Heads election on the rechargeable batteries SoH before applying the clustering. $LECA\_SOH$ fosters the selection of the nodes, which will less suffer from battery degradation during the future rounds, leading to extend the system lifetime. The obtained results demonstrate that the proposed clustering approach improves the network lifetime in the long term and extends the number of recharging cycles compared to the conventional energy efficient approaches.**

***Index Terms*—IoT, WSN, Rechargeable battery lifespan, State of Health prediction, Energy-aware protocols, Distributed Clustering.**

I. Introduction

An expanding number of modern electronic devices are being connected to the Internet at an exponential scale, realizing the idea of the Internet of Things (IoT). This paradigm is a hot research area that is rapidly growing and covers a broad range of research. The basic concept of the IoT is to enable everyday devices (smartphones, sensors, laptops, RFID tags, vehicles, etc.) to communicate and share information and, therefore, transforms these conventional devices into smart systems by exploiting their underlying technologies (pervasive computing, embedded systems, wireless communication, Internet protocols, sensing, etc.). Nowadays, IoT has substantial home and business applications and a huge impact on the world's economy. Indeed, there are various domains where the IoT plays an outstanding role and improves the quality of our daily lives. These domains cover intelligent transportation, smart healthcare, industrial automation, smart city, smart home and more [1].

Wireless Sensor Networks (WSNs) constitute an essential part of the IoT field that offers the required technological foundations used within IoT systems [2]. Indeed, WSNs integration in IoT networks provides efficient and cost-effective networking solutions to manage the Internet access issue in massive IoT systems [3]. WSNs are composed of a substantial number of small electronic devices fitted with limited sensing, computing, communication ability and a constrained power supply. The aim of these devices is to cover a certain region of interest by collecting data from their surrounding environment and transmitting it to a Base Station (BS) for further treatment. The BS may be connected, via a private or public network (e.g. Internet), to a particular remote service as shown in Figure 1. Since each device has a limited power supply, prolonging the network lifetime constitutes a critical challenge that requires the implementation of energy efficient protocols.

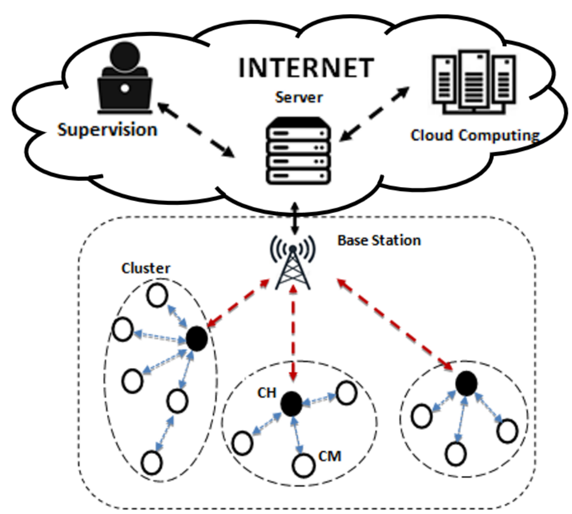

Fig. 1. IoT network architecture

Commonly, devices' batteries represent the unique source of energy and therefore are central for the nodes' operation. The energy source problem undermines the integration of the traditional wireless network protocols into the IoT [4]. Therefore, the self rechargeable battery concept has draw much attention [4], [5]. This kind of batteries benefit from prolonging the lifetime of devices by fitting them with recharging systems [6] (e.g. piezoelectric generators, RF harvesters, solar panels and wind turbines), which transform environment sources, such as body heat, foot hit, wind and sunbeams into electric energy

Mohamed Sofiane BATTA and Hakim MABED are with the FEMTO-ST Institute, University of Bourgogne Franche-Comté, Montbéliard 25200, France ({mohamed.batta, hmabed}@femto-st.fr).

Mohamed Sofiane BATTA and Zibouda ALIOUAT are with the LRSD Laboratory, Computer Science Dept, Ferhat Abbas University - Setif 1, Setif, Algeria (e-mail: {mohamedsofiane.batta, zaliouat}@univ-setif.dz).

Saad HAROUS and is with the College of Computing and Informatics, University of Sharjah, Sharjah, UAE (e-mail: harous@sharjah.ac.ae)

[4]. However, the durability of rechargeable batteries is not unlimited and omitting the degradation aspect may lead to a high substitution and maintenance costs. Hence, preserving battery state of health (SoH) is crucial even with rechargeable batteries. The State of Health of a rechargeable battery refers mainly to the ability of the battery to be fully recharged again in the future.

To ensure a proper connectivity to the Internet network, the IoT nodes are often organized into clusters. Clustering protocols represent an essential function in reducing the energy consumption and extending the network durability [7]. During a period or round, each cluster comprises one Cluster Head (CH) device and several cluster members (CMs). The clusters' composition changes from period-to-period. The CH node is responsible for collecting and processing the data acquired by the CMs and relying it to the remote BS (Figure 1). The CHs election is a crucial component to ensure the efficiency of the wireless network operation [8]. That is why, CHs election has received much attention from the research community [3]. However, the energy-aware clustering protocols assume that the battery is non-rechargeable. Whereas, rechargeable batteries are nowadays widely used and the contact less harvesting solutions have evolve into a reality [9]. Furthermore, works dealing with rechargeable batteries all neglect the batteries aging over time.

Conventional works either focus on static battery-powered networks (with one discharging cycle) or merely consider the current state of charge (SoC) of the batteries in order to improve, in the short time, the network lifetime. Therefore, we propose a novel Long-term Energy optimization Clustering Approach based on battery SoH prediction ($LECA\_SOH$). Since battery aging is one of the prevalent failures that cause material replacement [10], considering the long-term exploitation of devices batteries in networking design can considerably decrease the carbon footprint and extend the network durability. The modeling of rechargeable battery degradation is an outcome of the electronics specialists but it is not exploited enough by the networking community.

A. Contributions

The proposed clustering approach uses an original SoH prediction model to guide decisions about the next selected cluster head nodes. To the best of our knowledge, there is no prior work on clustering protocols studying the problem of maximizing the network lifetime based on a prevision model of the rechargeable battery degradation. In summary, as CH nodes have more functionalities, their batteries deteriorate faster. The proposed approach uses the current nodes' SoH and the battery degradation prediction for the selection of the next round's CHs. The devices with less expected battery degradation level are then elected, which leads to prevent the fast battery aging, and in turn improves the network long-term durability. The proposed degradation model is inspired from many works [11] [12] [13], and combines a computation simplicity and a good accuracy due to the consideration of different degradation factors such as cycle aging, depth of charge or discharge, internal temperature, charging and discharging voltage. Furthermore, conventional clustering approach aim to delay the recharging procedures. However, recharging procedure leads to short-time interruption, while hardware or battery replacement provokes a long-term unavailability.

The rest of this paper is organized as follow. Section II describes the batteries features and discusses the literature on system lifetime optimization in wireless networks. In section III, we describe the proposed clustering protocol $LECA\_SOH$ and how the predicted State of Health degradation is used to guide the cluster heads selection. Then Section IV depicts how the degradation of the rechargeable battery is predicted on the basis of internal temperature estimation, the prediction of energy consumption devoted to the communication activities and the prediction of battery heating according to the device activities. Section V is devoted to the discussion of experimental settings and simulation results. We conclude our work in section VI.

II. Related works

In this section, we discuss the major differences between rechargeable and non rechargeable batteries from an energy optimization point of view. Then we discuss the works on the wireless network lifespan optimization from the literature.

The measurement of battery lifespan differs according to the nature of the battery: rechargeable or not. In non-rechargeable batteries, also called primary batteries [14], [15], the remaining battery life is measured using the SoC. The Zinc–carbon battery is an example of a non-rechargeable battery [16]. In contrast, rechargeable batteries [15], [17], [18] (also called secondary batteries) can undergo multiple charge/recharge cycles. Combined with energy harvesting methods such as solar cells or thermal energy, the operational duration of the rechargeable batteries may be extended without interruption. The battery State of Health SoH is used to estimate the battery operational quality. This parameter provides important information to prevent battery malfunctioning and the consequent network failures [6]. The first commercial lithium-ion batteries (LIB, developed by Sony Corp. in 1991 [19]) triggered a revolution of the rechargeable battery market. Subsequently, the development of secondary batteries has increased quickly, LIB exhibits the highest energy density and maintains an exceptional working performance; they are currently leading the rechargeable battery market and are widely used in several areas [15]. Rechargeable batteries have a limited lifetime and need replacement due to aging. Indeed, SoH optimization in networking protocols helps to extend the devices' global lifetime and offers a better impact on the carbon footprint.

A considerable amount of literature addresses the lifetime improvement of wireless networks [8], [20]–[25]. However, researchers in this area commonly consider non-rechargeable batteries with restricted energy supply and focus on slowing the batteries discharging [22]. Commonly, these approaches neglect the batteries behavior by using a linear energy depletion model. Low-Energy Adaptive Clustering Hierarchy (LEACH) [26] is among the earliest classical clustering techniques. CHs are selected by a probabilistic rotation pattern where each node gets an equivalent chance to be a CH.

LEACH uses the probability formula defined in equation 1, each node randomly chooses a number $n \in [0,1]$. If this number is lower than the threshold value $f(i)$, the current node is selected as a CH for the next round. The other nodes select their CH according to their proximity from the CHs.

$$f(i) = \begin{cases} \frac{n}{1-n\times(r\times mod(1/n))} & i \in G \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

r is the current round, p is the probability of being a CH, G represents the group of nodes that have never been CH during the previous $1/p$ rounds. LEACH provides significant energy saving and prolongs the network lifetime compared to the flat topology approaches. However, it still possible to select a CH with critical energy, which may lead to a quick death and degrade the network performance. Therefore, many clustering protocols have been inspired by LEACH to provide higher network durability [27], [28], including MH-LEACH [29], O-LEACH [30], S-LEACH [31] and others [32].

A Multi-Hop version of LEACH protocol (MH-LEACH) was introduced in [29]. MH-LEACH proposes a multi-hop architecture within each cluster to promote energy preservation. Some specific CM nodes are considered as intermediate nodes to relay the collected data toward the CH. In [30], the authors combine LEACH algorithm and Genetic (GA). LEACH algorithm determines the clusters, while the GA is used to locate the optimal routing paths using a fitness function. This latter uses the residual energy of the nodes for the selection of the CHs. O-LEACH outperforms the classic LEACH by improving the packet delivery rate, throughput, and energy saving. Residual energy-based LEACH (R-LEACH) protocol [33] selects the CH by combining multiple parameters, such as the remaining energy and the optimum number of network CHs. The approach applies the same mechanism for the CH election as LEACH. However, the new CH is selected at the end of the round based on nodes energy.

In [34], Hamzah et al. proposed a new clustering method called FL-EECD based on the minimum separation distance between CHs. The CHs are selected based on the residual energy, location suitability, density, and distance from the BS. The approach sets a minimum separating distance between CHs and uses a Gini index [34] to measure the energy efficiency of the clustering approach to ensure an even distribution of energy through nodes. Authors in [35] presented an energy harvesting scheme for CH rotation (EH-CHRS) in green wireless networks based on the double chain Markov model. The main motive of the approach is to perform a CH rotation and minimize the energy overflow during high data traffic by assigning the CH role to nodes that consume less energy during the data aggregation phase.

In [36], the authors proposed to combine a gravitational search algorithm (GSA) with a Power Distance Sums Scaling (PDSS) mechanism to determine the optimal number of clusters in each round. This method uses the location and the remaining energy of nodes to reduce the number of active CHs and decrease the energy consumption. It uses a fuzzy logic controller which considers the residual energy and the transmission link quality to improve the performance of the method. Improved Energy-Efficient Clustering Protocol (IEECP) [3] determines the optimal number of balanced clusters, which are formed based on a modified fuzzy C-means algorithm, which balances the energy consumption of nodes. The approach uses a CH rotation mechanism combined with a CH back-off timer mechanism to select CHs at optimum locations.

WPO-EECRP protocol [37] considers diverse clustering factors for CHs election, namely, the residual energy, the average distance toward the BS, and the number of nodes in the neighborhood. It aims to ensure the scalability of the protocol and to provide a proper clustering control by altering the clustering parameters. The approach is completely distributed and requires the exchange of control packets to estimate the distance separating the nodes and their CH.

The proposed clustering protocols, up to this point, have been mostly based on devices' residual energy optimization for non-rechargeable batteries. These solutions focus on slowing the batteries discharging process (short-term vision) and ignore the impact of operational activities of the devices on the SoH of the batteries. Therefore, such approaches does not optimize rechargeable batteries lifespan (in long-term). In this work, we introduce a distributed clustering scheme based on the battery SoH prediction. In the subsequent sections, we are going to present the different models used for the implementation of our solution. Table I outlines a brief comparison of the clustering approaches presented in this section.

TABLE I
CLUSTERING ALGORITHMS PROPERTIES COMPARISON

Algorithm	**Distr.**	**Multi-hop**	Lifetime vision	**Clustering parameter**
LEACH [26]	✓	X	Short	load balance
MH-LEACH [29]	✓	✓	Short	SoC, reliability
O-LEACH [30]	✓	✓	Short	SoC, latency
R-LEACH [33]	✓	X	Short	SoC, density
EH-CHRS [35]	X	X	Short	SoC, load balance
PDSS-GSA [36]	X	X	Short	SoC, position, reliability
DWCA [38]	X	X	Short	SoC, Distance to BS
IEECP [3]	✓	✓	Short	SoC, position
WPO-EECRP [37]	✓	✓	Short	SoC, distance to BS
GCA [39]	X	✓	Short	SoC, cluster size
FL-EECD [34]	X	X	Short	SoC, position, density
LECA-SOH	✓	✓	Long	**SOH Prediction**, density

III. THE PROPOSED APPROACH: $LECA\_SOH$

In this section, we present a new distributed clustering technique based on the state of health prediction of rechargeable batteries called $LECA\_SOH$. CHs nodes perform more functionalities than CMs and accordingly deteriorate more quickly. The novelty of the proposed solution consists of predicting the degradation effect of a potential selection of the node as a CH. $LECA\_SOH$ selects as CHs the nodes that undergo less estimated battery deterioration during the forthcoming round, which in turn extends the network long-term lifetime.

Let $G = (V, E)$ the graph representation of the wireless network, where V is the set of nodes and $E \subseteq V^2$ is the set of short-range communication links. The edges correspond to the couples of nodes i and j where the distance between i and j, $Dist(i, j)$, is lower than the transmission range Tr.

We note $N(i)$ the set of node i direct neighbors, $N_k(i)$ the set of nodes reachable in k hops from the node $i \in V$, and $N_{<k}(i)$ the set nodes that can be reached in less than k hops from i.

$LECA\_SOH$ computes a weight for each node, and the node holding the highest weight among its surrounding area is selected as a CH. The weight of a node i is computed using two metrics. First, the ratio of neighborhood cardinality $\theta_i \in [0,1]$ (equation 2) that depicts the connectivity ratio of a node relative to its neighborhood. Indeed, a high node degree strengthens the cluster connectivity and reduces the intra-cluster communication.

$$\theta_i = \frac{|N_1(i)|}{Max(|N_1(j)| \mid j \in N_1(i) \cup i)} \tag{2}$$

Secondly, a predicted battery state of health degradation ($\Delta_{SOH} \in [0,1]$) metric that estimates the potential degradation of the node battery if it is selected as CH during the subsequent round. Although, nodes cardinality and the battery degradation represent two different physical units, the combination of the ratio of these two units (θ, Δ_{SOH}) allows the election of CHs possessing the highest connectivity proportion and holding the minimal battery degradation among each cluster. Indeed, the ratio of the connectivity $\theta \in [0,1]$ varies from 0 (referring to an isolated node) to 1 (depicting a fully connected node). On the other part, with $\Delta_{SOH} \in [0,1]$, On the other hand, with SOH [0, 1], the closer the value is to 0 the lower the degradation, while the higher the degradation, the more the battery undergoes further degradation.

The computation of Δ_{SOH} is detailed in section IV-D. The future SoH is then expressed by Equation 3, where p refers to the current round.

$$SOH_{p+1}(i) = SOH_p(i) - \Delta SOH_p(i) \tag{3}$$

The weight W_i of a node i is computed based on the two previous metrics as follow:

$$W_i = \alpha \times \theta_i + \beta \times (1 - \Delta_{SOH}(i)) \tag{4}$$

Where α and β depict the decision maker defined coefficients of the two criteria: the battery state of health (SOH) and node degree respectively. α and β are chosen regarding the target application and the surrounding context. These weight factors are altered comparatively to the others to acquire the best performance result for a specific network configuration. For instance, within a reduced density network, the device's residual energy should be privileged. Whereas, with an elevated density network, the nodes connectivity needs to be explored. The proposed scheme is designed to work under a typical network with various configurations to cover different use-case scenarios. Hence, in this experiment, the weight coefficients are considered equal.

A. Weights computation

To compute the weights W_i at the beginning of a new round p, $LECA\_SOH$ assumes that each node i broadcasts a $Neighbor\_Discovery(ID_i)$ packet to all surrounding nodes. A Neighbor j receiving this packet, updates its local state by inserting node i information into $NeighborsList_j$. Next, node j replies by sending its local state $Local\_State_j(ID_j, W_j)$ to i. Progressively, node i knows the local state of its surrounding neighbors using the state list ($NeighborsList_i$). Every time, the node i updates its weight due to a received $Local\_State$ packet from a neighbor, i broadcasts its new computed weight. Figure 2 outlines the weight computation phase.

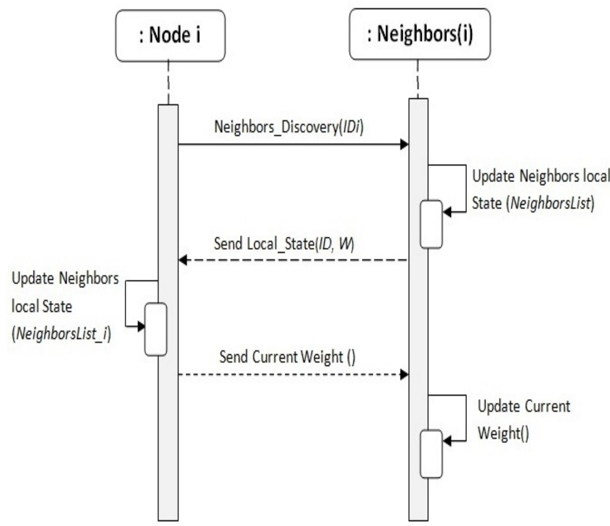

Fig. 2. Sequence diagram of the weight computation procedure

B. CHs election phase

CHs election algorithm is inspired from the self-stabilization works [40], which allows $LECA\_SOH$ to adapt to transient events and network dynamic topology. We note CH_i the cluster head of the node i. $LECA\_SOH$ organizes each cluster into k-hop routing tree where the root is the cluster head node. The rooting tree defines how the data sensed by the devices are aggregated and forwarded to the CH. The CHs rely then the data to the BS using long range communication mode.

The clustering process of $LECA\_SOH$ is illustrated in Figure 3. Whence the weights of the nodes are computed, each node checks if it meet the conditions to be the cluster head during the next round. CH_i is the cluster head of i ($CH_i = i$ means that i is a CH), CH_i is within a range of k hops from i and its weight is the highest among all the weights of nodes that dominate the neighborhood of i ($N_{\leq k}(i)$). More formally:

$$CH_i \Leftrightarrow \begin{cases} CH_i \in N_{\leq k}(i) \cup i \\ W_{CH_i} \geq W_i \\ W_{CH_i} = \underset{j \in (N_{\leq k}(i) \bigcup \{i\}) \,\wedge\, j = CH}{Max(W_j)} \end{cases} \tag{5}$$

If two or more nodes in $N_{<k}$ possess the same highest weight, the distance is used as a tie-breaker (by choosing the nearest CH). Furthermore, if node i is isolated or no CH satisfies the multi-hop constraint, then node i elects itself as CH. After CHs election, each node exploits its direct neighbors knowledge to shape the multi-hop cluster topology. The nodes update their distance toward the CH and select their parents,

P_i, in the routing tree by following the shortest path to the selected CH as expressed in following equation.

$$P_i = m \Leftrightarrow \begin{array}{l} \forall j \in N(i), Ch_i = CH_j : \\ HopsToCH_j \geq HopsToCH_m \end{array} \quad (6)$$

$HopsToCH_i$ refers to the minimum number of hops to reach the CH_i from i and it is measured using the recursive formula:

$$HopsToCH_i = \left(\min_{\substack{j \in N(i) \\ CH_i = CH_j}} HopsToCH_j \right) + 1 \quad (7)$$

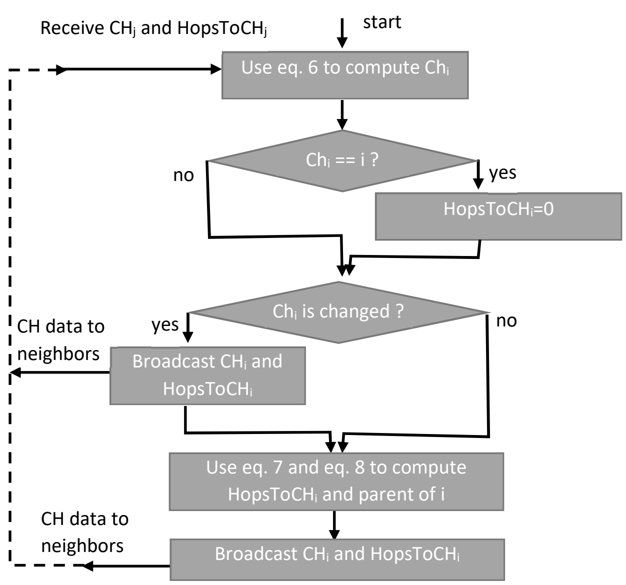

Fig. 3. Flowchart of $LECA\_SOH$ leader election phase

To illustrate the intended idea of $LECA\_SOH$, let's consider the routing example illustrated in Fig 4. In this routing scheme, four potential CH's can relay the data of node S to the BS. With conventional energy efficient approaches, either the node 1 is selected as CH because it residual energy is the highest ($SOC = 80\%$) or the node 2 because it consumes the lowest amount of energy ($\Delta_{SOC} = 15\%$). However, for a long-term energy efficient perspective, the optimization of batteries health leads to select node 3 or 4. Indeed, these nodes present a better SOH (node 3 with $SOC = 53\%$ and node 4 with $SOC = 51\%$). In this scenario, $LECA\_SOH$ grants node 4 as CH because this latter will endures less battery health degradation after the data aggregation ($\Delta_{SOH} = 0.4\%$) compared to the other nodes. Therefore, the predicted state of health of node 4 after routing is the best, which is more convenient for a long-term durability.

The proposed approach is distributed and the re-clustering procedure is locally operated and does not strike the whole network when interruption events occur due to devices displacement, battery discharge or a coverage failure, etc. Indeed, the re-clustering process is triggered by the CH and the local state information are exchanged only when the current cluster undergone a considerable topology changes. This approach reduces the messages overhead and preserve the node's energy.

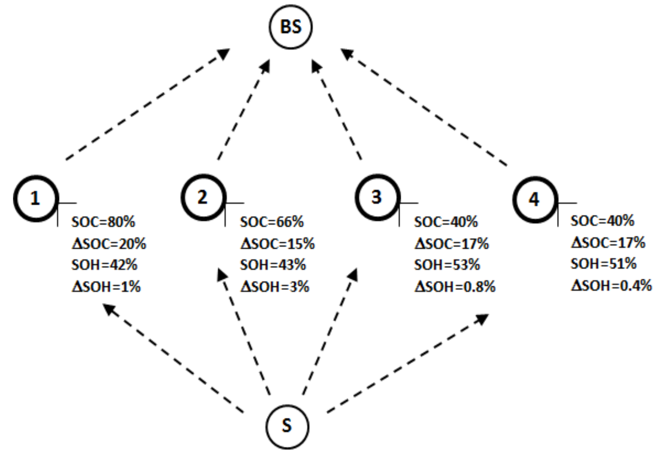

Fig. 4. Short-term vs long-term energy efficient routing scheme

C. Clusters complexity

***Lemma** 1:* The maximum number of clusters that can be generated with $LECA\_SOH$ when considering a related graph is $1+n/(k+1)$, where $n = |V|$ and k is the maximum number of hops within each cluster.

Proof:

$LECA\_SOH$ partitions the related graph G into several clusters where each cluster has the node with the highest weight as its root (the cluster head) and it's surrounding neighbors at k hops form the rest of the cluster (cluster members). Therefore, within a related graph, the minimum number of nodes that can be in a cluster is $k+1$ (the maximum degree of each node $i \in G$ in this case is: $0 < |N(i)| \leq 2$) and the graph can contain $n/(k+1)$ clusters. As each cluster is represented by only one CH, the maximum number of clusters formed by $LECA\_SOH$ within a related graph is $\frac{n}{k+1}$, where $n = |V|$ and k is the maximum number of hops within each cluster.

In the subsequent section IV, we are going to present the different models used for the implementation of our solution.

IV. Battery Modeling

$LECA\_SOH$ functioning is mainly depending on the ability to estimate the battery degradation if a node is CH. In this sections, we present the different models used for the implementation of our solution.

A. Battery Internal Temperature Evaluation

Increasing the battery operating temperature above the recommended scope intensifies the aging process and leads to a fast battery degradation. Typically, the acceptable temperature scope of a LIB battery is between [-20- 60]°C [15]. When the temperature is out of these interval, the battery degrades faster with a high risk of causing a safety issues including fire and explosion [15]. The acceptable temperature range should lie within [20-40]°C to ensure a proper balance between performance, battery life and safety [41]. Low temperature affects the properties of electrolyte in LIB's. Indeed, with the diminution of temperature, the viscosity of the electrolyte increases, which reduces the ionic conductivity [15].

High battery's internal temperature is due to a high electric current including operations with quick charging and the discharging speed. Therefore, the appropriate management of the battery temperature is crucial to ensure efficient performance and safe functioning. In our approach, temperature monitoring is one of the fundamental management processes. However, monitoring the temperature distribution within the batteries is not straightforward. We adopted the thermal model proposed in [13] for monitoring the internal battery temperature. The internal battery temperature (T_p) at a period p is estimated according to the observed temperature at the surface of the battery T_{surf} and the ambient temperature T_{amb} as follow:

$$T_p = T_{surf} \times \left(1 + \frac{R_{in}}{R_{out}}\right) - T_{amb} \times \frac{R_{in}}{R_{out}} \tag{8}$$

R_{in} and R_{out} represent the thermal resistance inside and outside the battery.

B. Energy consumption prediction

Wireless communications represent a large portion of the consumed sensors energy [8]. For instance, transmitting one bit over 100 meters requires an equivalent energy as executing 3000 machine instructions [37]. To predict the battery charge diminution if a node is selected as a CH, we used the energy consumption model proposed in [3], [30], [36]. In this model, dissipated energy due to the data processing is ignored. Data transmission energy is spent on radio equipment's and the power amplifier activation. In contrast, the receiving node spent energy to detect and decode the radio signal as shown in Figure 5.

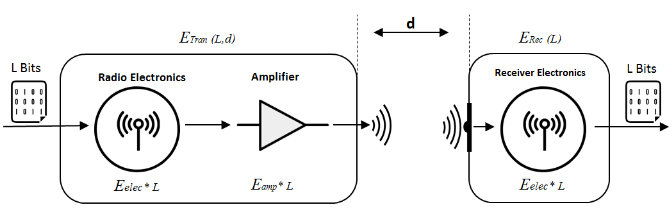

Fig. 5. Radio energy dissipation model

The energy consumed by a node for transmitting a packet of l bits over a distance d is measured as follows:

$$E_{Tran}(l, d) = E_{elec} \times l + E_{amp}(d) \times l \tag{9}$$

E_{elec} corresponds to the consumed energy per transmitted bit. The quantity of energy consumption relies on different elements, including the digital coding, modulation, signal filtering and spreading. $E_{amp}(d)$ is the power amplification coefficient, it relies upon the distance to the receiver d and the tolerable bit-error rate. E_{amp} is formulated as in eq. 11.

$$d_0 = \sqrt{\varepsilon_{FS}/\varepsilon_{MFS}} \tag{10}$$

$$E_{amp} = \begin{cases} \varepsilon_{FS} \times d^2 : d < d_0 \\ \varepsilon_{MFS} \times d^4 : d \geq d_0 \end{cases} \tag{11}$$

On the other side, the energy required for the reception of a message of size l bits is given by equation 12.

$$E_R(l) = E_{elec} \times l \tag{12}$$

In this model, the energy consumption by a transmitter is proportional to the threshold transmission distance d_0. According to the distance value d_0 (Eq. 10), the propagation loss can be modeled as a free-space model or a multi-path attenuation model. ε_{FS} and ε_{MFS} are used for the free space and multi-path model respectively, they represent the characteristics of the transmitter amplifier which depend on the required receiver sensitivity and receiver noise pattern [42].

C. Heating prediction model

The operating temperature of the battery is a determinant factor of its deterioration. To predict the impact of the node selection as a CH on its state of health, it is crucial to predict the effects of CH's activities on the battery temperature rise. In [43], Taheri and Bahrami studied the Lithium-Ion batteries temperature rise according to the activity degree. The results of this work show that, under a constant discharging intensity, LIB's temperature curves follow the same global scheme corresponding to three stages. When the battery is full charged (75%-100%) the temperature rises moderately. When the battery is averagely charged (10%-75%) the battery temperature rises slowly. Finally, when the battery is almost discharged, the temperature rises quickly. However the global rapidity of the temperature rise depends on the convective transfer coefficients of the battery surface h (the ability of the device to evacuate the heat) and the discharging intensity.

Based on the provided results in [43], we modeled the temperature rise when a node is a CH as follow :

$$T_{p+1} = T_p + \Delta T \times |p| \tag{13}$$

The values of ΔT are given in Kelvin per hour (K/h) and depends on the electrical intensity and the discharging stage as shown in Table II. The presented values are those related to a Lithium Ion battery of $18mm \times 16mm \times 0.2mm$ size, a capacity of $0.27Wh$ (1000 joules) and a voltage of $3.7V$, and convective transfer coefficient h of $5w/(m^2K)$. The temperature T_{p+1} corresponds to the next period predicted temperature based of the measured temperature T_p probably computed using equation 8. $|p|$ corresponds to the time during which the node is CH.

TABLE II
TEMPERATURE RISING RATE ACCORDING TO THE DISCHARGING INTENSITY AND THE CHARGE LEVEL OF THE BATTERY

Intensity	$SoC \in [75, 100]$	$SoC \in [10, 75]$	$SoC \in [0, 10]$
1.5A	2.6	1.07	8
3A	6.4	8.30	43
6A	40	36.9	140

D. Battery State of Health prediction model

The SoH refers to the operational status of the battery and declines over time from 1 representing a healthy battery to 0 where the battery is completely inoperative due to degradation. Rechargeable batteries are impacted by diverse aging factors that lead to a considerable effect on their performance. These factors not only impact the performance of the battery, they also reduce their lifetime [18]. Several aspects that influence the battery life and provide the appearance of aging effects, such as the calendar aging and cycle aging [17], [44].

The calendar aging stands for the battery inherent degradation over time (in the long-term). It reflects the battery depletion caused by keeping the battery under given operating conditions, including the temperature and the charge degree [18]. These factors determine the aging speed over time. Meanwhile, the cycle aging is due to the charging/discharging cycles. It affects the degradation of the battery due to the complex composition and working process of the battery.

The selection of a proper model to estimate the current SoH is of primary importance. Indeed, there are many methods proposed in the literature to determine the battery SoH [17], [44]–[46]. However, most of the proposed methods are too complex to run on low-cost micro-controllers. Therefore, in this work, we adopted the simplified battery degradation model used in [44].

In the adopted degradation model, the previous factors are used to estimate the battery additional degradation level during a laps of time p. In this model, T_p defines the internal battery temperature during p, SoC_p represents the portion of available battery capacity, and DoD_p describes the portion of charge consumed during p. Hence, the State of Health loss during p, ΔSOH_p is formulated by:

$$\Delta SOH_p = (S_p^{DoD} + S_p^t) \times S_p^T \times S_p^\sigma \qquad (14)$$

Where $S_p^{DoD}, S_p^t, S_p^T, S_p^\sigma$ represent respectively, the battery degradation contributions of DoD, calendar aging, battery internal temperature and the average SoC during the period p. These terms are computed using the following equations, where $|p|$ is the duration of the round.

$$S^{DoD} = \alpha_{DoD} \times DoD_p \times e^{(\beta_{DoD} \times DoD_p)} \qquad (15)$$

$$S_p^t = \alpha_t \times p \qquad (16)$$

$$S_p^T = e^{\left(\alpha_T \times (T_p - T_{ref}) \times \frac{T_{ref}}{T_p}\right)} \qquad (17)$$

$$S_p^\sigma = \alpha_\sigma \times e^{SOC_p - \sigma_{ref}} \qquad (18)$$

In our simulations, we considered the following values of the model: $\alpha_{DoD} = 0.05$, $\beta_{DoD} = 0.03$, $\alpha_\sigma = 1.04$,$\sigma_{ref} = 0.50$, $\alpha_T = 6.93E-2$, $T_{ref} = 25°C$ and $\alpha_t = 4.14E-10/s$.

V. Simulation

A. Experimental parameters

The performances of the proposed algorithm are evaluated using JUNG (Java Universal Network/Graph) [47], a Java based library that enables the analysis and the modeling of wireless networks as graphs. Simulation parameters used in this experiment are mentioned in Table III. The network topology corresponds to a variable number of nodes $\delta \in [200, 1000]$ dispersed over a square area of size $1000 \times 1000\ m^2$ where the BS is located in the top left side of the network. Sensor networks typically use wireless communication standards with low power consumption, such as IEEE 802.15.4 Zigbee (with a maximum transmitting range of 100 m) or the 802.11n [48] (with a transmitting range of 90 m). Accordingly, based on the wireless communication standards used by conventional wireless networks, in this experiment, we assume that network nodes have a transmission range of $Tr = 90m$ and are randomly distributed to generate a random network topology. We adopt the classic Unit Disk Graph (UDG) connectivity model [49] with symmetric communications. It's worth mentioning that the proposed method works when considering uneven transmission ranges. However, in this case, communications among adjacent nodes become asymmetric and, in turn, isolated devices may emerge and connectivity will be difficult to ensure. Nodes have an initial energy of 1 KJoule and the size of a data packet is $l = 100$ bytes.

The battery degradation model used and the pattern adopted in the prediction of the battery temperature are presented in section IV-D and section IV-C respectively. The thermal model used to estimate the internal battery temperature is inspired from [13] and is illustrated in section IV-A. We assume that when a node is no longer a CH, its temperature gradually cools until reaching the ambient temperature. The performance of our clustering approach is evaluated by considering the single-hop and multi-hop (with K=2 hops) intra-clustering scenarios. The proposed scheme is tested with different network density to analyze the performance under different scenarios.

$LECA\_SOH$ is, to the best of our knowledge, the first clustering approach that considers the prediction of the battery SoH in the clustering process. To show the relevance of this new paradigm, the performances of the proposed scheme are compared with IEECP [3] and O-LEACH [30]. These protocols belong to the same clustering class and their primary goal is the energy efficiency and extending the network lifetime. Five parameters are considered for the analysis of the protocols performance, namely, the CHs cardinality, the energy consumption, the network lifetime (in short and long-term), the number of recharging cycles and the average number of dead nodes.

B. Experimental Results

1) *CH's cardinality:*

Typically, a reduced CH's cardinality reveals efficient clustering performance as it depicts the number of wireless communication channels formed with the BS and the number of clusters generated. Figure 6 illustrates the average number of CHs of the proposed approach versus O-LEACH and IEECP

TABLE III
EXPERIMENT SETTING PARAMETERS

Parameter	Value
Network size	$1000 \times 1000\ m^2$
Node density (δ)	$\delta \in [200, 1000]$
Transmitting range (Tr)	90 m
α, β	0.5, 0.5
E_{elec}	$50mJ/bit$
ε_{FS}	10 $nJ/bit/M^2$
ε_{Mfs}	0.0013 $nJ/bit/M^4$
R_{in},R_{out}	$3.2KW^{-1}$,$8.44KW^{-1}$
Data packet size	100 $bytes$
Battery's full charge	1 KJ

protocols under different density values $\delta \in [200, 1000]$. For the case of a single hop transmission (Figure 6), the number of clusters generated by the proposed scheme is stabilized between 70 and 95 clusters. Whereas, this value increases up to 105 and 115 with IEECP and O-LEACH respectively. Figure 6 also illustrates the case when the multi-hop scheme is considered. In general, the clusters cardinality decreases. The average CHs generated is reduced by an average of 31.4% as compared to the single-hop scheme, the CHs cardinality in this case varies between [40-55]. This can be explained by the fact that clusters coverage area increases, in multi-hop scheme, which allows the clusters to manage more nodes. $LECA\_SOH$ maintains the lowest CH cardinality, it shows an enhancement of 10.3% and 6.1% compared to O-LEACH and IEECP respectively. This improvement is due to the consideration of the nodes connectivity metric in the clustering process of $LECA\_SOH$, which leads to the election of CHs with high connectivity. Therefore, more nodes are covered by a single cluster.

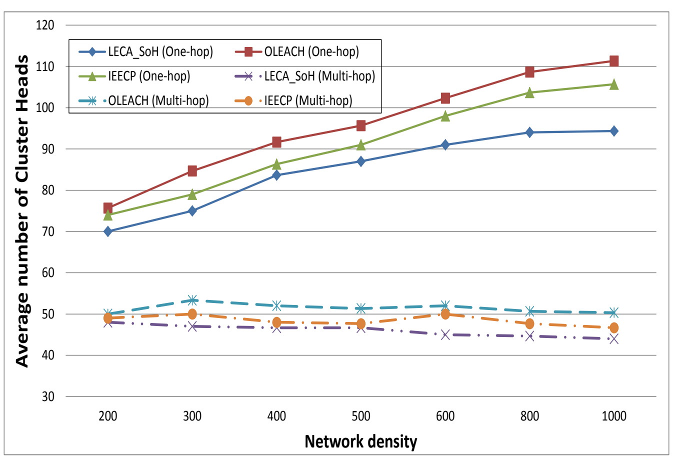

Fig. 6. Average Cluster Heads cardinality considering the single-hop clustering and the multi-hop clustering.

2) *Average energy consumed*:

Figure 7 exhibits the average energy consumed by network nodes by considering a variable network density $\delta \in [200 - 1000]$ and by assuming the single-hop and multi-hop scenario. From these figures, we observe that the energy required for the clustering is affected by the network density and the clustering scheme used. When the number of nodes increases, the energy required to build the cluster structure increases as well. This value is bounded by 0.95×10^{-3} KJoule when the single hop scenario is considered, while it reaches up to 1.4×10^{-3} KJoule when the multi-hop clustering is employed. This is due to the amount of messages exchanged to construct the structure. According to Figure 7, IEECP consumes the highest amount of energy compared to the other approaches owing to the modified fuzzy C-means algorithm used during the clustering which requires the exchange of additional setup packets to form the clusters. Accordingly, O-LEACH consumes 39% less energy compared to IEECP.

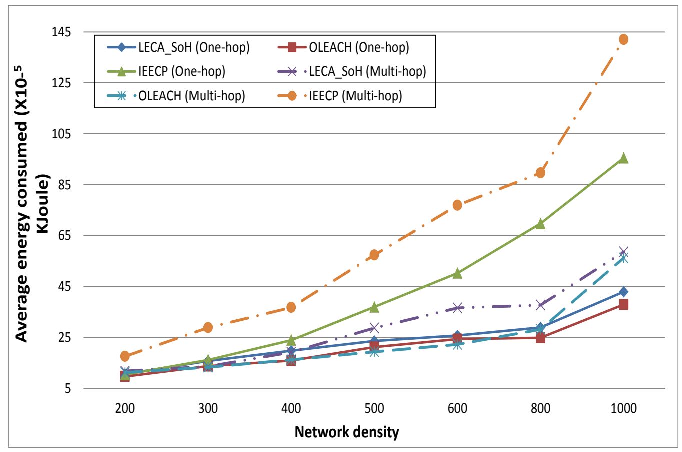

Fig. 7. Average energy consumed with the single-hop and the multi-hop clustering.

$LECA\_SOH$ shows an average improvement of 27.3% compared to IEECP. O-LEACH consumes the lowest energy. It consumes slightly less energy than $LECA\_SOH$ (11% less) because this later requires more messages to compute the weight metric (computed using Equation 4), which consumes an extra more energy. However, the result is acceptable because the topology generated by the proposed approach carries less clusters (as illustrated in previous section V-B1) and exhibits a better lifetime performance in the long-term (which is discussed in section V-B4 and V-B5).

3) *Network lifetime (in the short-term)*:

This measure stands for the average number of rounds elapsed before the first network device spend all of it energy and its battery needs recharging. This measure is typically used in the literature to evaluate the energy consumption of devices. It also depicts the lifespan of one battery cycle by considering only the residual energy (short-term vision).

Figure 8 illustrates the average battery cycle lifetime of the studied approaches by considering the single hop and multi hop clustering modes. From this figure, we observe that the network lifetime increases when the multi-hop is considered, as compared to the single-hop clustering. The battery cycle lifetime varies between $[900 - 2600]$ rounds in the single-hop scenario and it increases to $[1200 - 2800]$ rounds in the multi-hop scenario. Indeed, as the network scales, ensuring the connectivity tends to be more difficult. Therefore, multi-hop communications are advantageous to reduce the energy cost devoted to wireless transmission. Moreover, we observe that the network lifespan, for the three schemes, increases

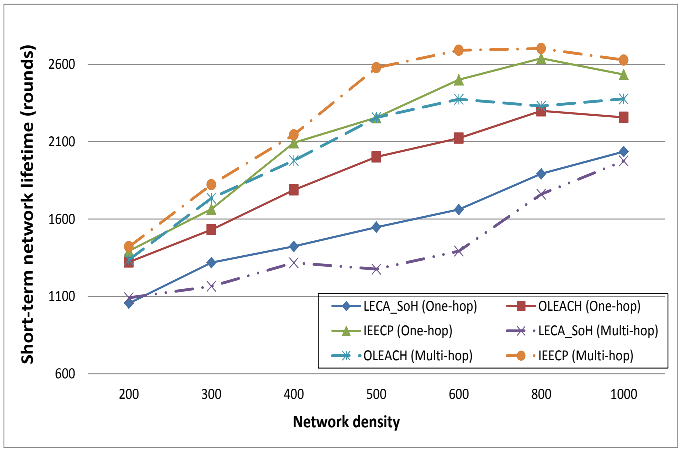

Fig. 8. Average network lifetime (short-term) in single-hop and multi-hop scenario.

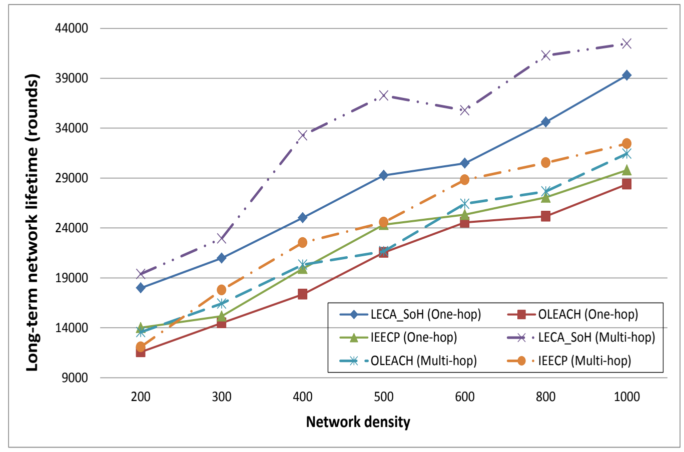

Fig. 9. Average network lifetime (long-term) in single-hop and multi-hop clustering.

because the network starts to be more connected. Indeed, when the density scales, the clusters connectivity increases and the CHs are able to cover more nodes (Figure 6), which in turn reduces the long range transmission and boosts the energy preservation.

Based on the shape of Figure 8, we observe that IEECP maintains the highest durability, it shows an average improvement of 9% compared to O-LEACH. This improvement is due to the consideration of communication reliability in IEECP in addition to the residual energy of nodes. Both O-LEACH and IEECP show an average improvement of 19.7% compared to our approach. This is because O-LEACH and IEECP consider the residual energy of devices, which result in a longer lifetime in the short-term (over one battery cycle only). In the next paragraph we study the performances of the three approaches according to the long-term durability (the batteries life over several recharging cycles).

*4) **Network lifetime (in the long-term)**:*

This metric depicts the average number of rounds elapsed before the appearance of the first completely dead node in the network (i.e. the SoH of its rechargeable battery is totally exhausted and needs to be altered). This metric enables the evaluation of the network durability and estimates the devices battery degradation aspect in the long-term. Usually, the network lifetime is described in different manners e.g. the interval from network initialization to the last node death round (LND) [29] or the interval from the initial deployment until a predefined percentage of nodes death. In this experiment, we consider the lifetime as the period until the first node death (FND).

Figure 9 shows the average network lifetime in long-term of our approach versus IEECP and O-LEACH. Initially, nodes tend to be isolated due to the low connectivity, they are self elected as CH to send their data toward the BS. Hence, at this point, the lifetime of the three protocols is relatively short. When the density increases, nodes connectivity increases, which in turn lower the CHs cardinality and balances the consumption of energy within CMs. From Figure 9, we observe that nodes using O-LEACH tend to die earlier and the FND only reached 28400 rounds (with $\delta = 1000$) compared to IEECP where the nodes survive up to 29800 rounds. This figure shows that our proposed approach exhibits better performances, the FND node in $LECA\_SOH$ reached 32500 rounds. This improvement is due to the use of the prediction metric Δ_{SOH}. Indeed, instead of performing the clustering based on the actual state of charge, $LECA\_SOH$ predicts the amount of battery degradation for the following round before the election of the potential CH's. Accordingly, inadequate nodes are avoided and the battery aging process is delayed, which strengthens the network durability. Moreover, we observe that considering the SoH prediction in the clustering process balances the temperature fairly among devices, which further reduces the battery degradation. Figure 9 illustrates a comparison of the three approaches by considering the multi-hop clustering. $LECA\_SOH$ shows better lifetime performances compared to the classic approaches in both single-hop and multi-hop scenarios (improved by 23% and up to 44% respectively).

*5) **Average number of recharging cycles and dead nodes (long-term)**:*

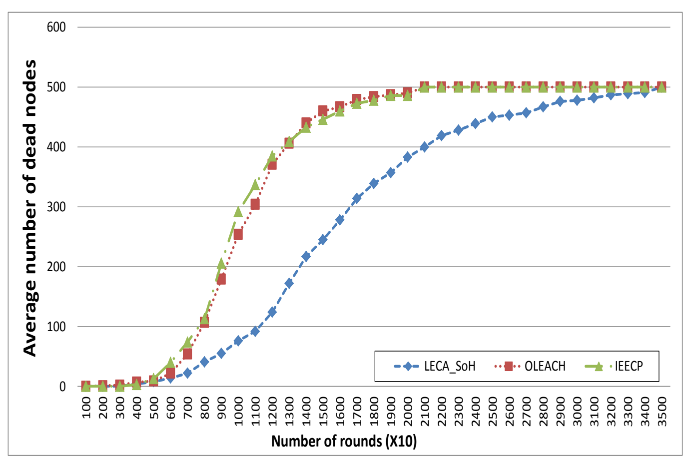

Fig. 10. Average number of dead nodes ($\delta = 500$ nodes)

The average number of recharging cycles and the average number of completely dead nodes (i.e. nodes with a completely

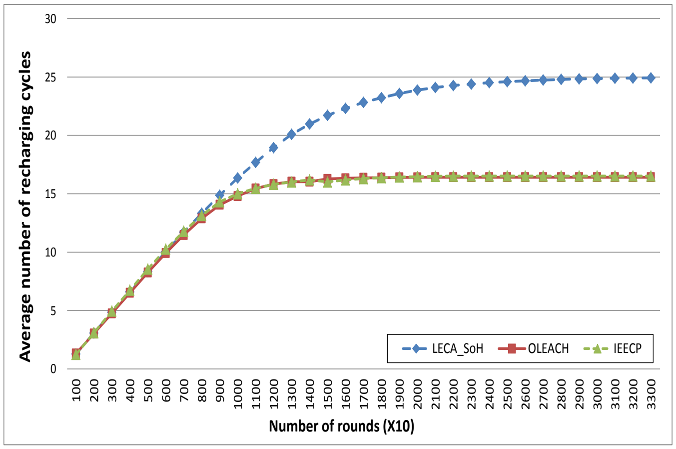

Fig. 11. Average number of battery recharging cycles

damaged battery, $SOH = 0$) represent two significant parameters to demonstrate the lifetime efficiency of the proposed approach. These parameters depict the elapsed period before a rechargeable battery is entirely dead and needs to be changed, i.e. it depicts a vision of the material substitution frequency.

Figures 10 and 11 illustrate the average number of completely dead nodes and the number of battery recharging cycles (measured in rounds) of $LECA\_SOH$ vs O-LEACH and IEECP with $\delta = 500$ nodes. It can be observed from the shape of Figure 11 that O-LEACH and IEECP withstand approximately the same number of cycle (up to 16 cycles). Whereas, in $LECA\_SOH$ the average number of recharging cycle reached 25 cycles. This lifespan improvement is mainly due to the use of the SoH prediction metric in the clustering process. This reduces the battery degradation and allows batteries to last extra number of recharging cycles. Therefore, the number of completely dead nodes is considerably reduced as shown in Figure 10. The proposed approach improves the number of recharging cycles by an average of 31% and reduces the average number of nodes death by 34.6% when compared to the conventional energy efficient approaches [3], [30].

VI. Conclusion and Future Work

In this work, we proposed an energy efficient prediction based clustering approach called $LECA\_SOH$. The approach is distributed and aims to optimize the network lifespan in long-term by considering the battery degradation aspect in the decision making process of the wireless networking protocols. More precisely, $LECA\_SOH$ uses an SoH prediction based mechanism during the CHs election in order to elect nodes that will endure less potential degradation during the forthcoming rounds, which in turn extends the system lifetime. To the best of our knowledge, this work is a first step in the integration of the battery degradation prediction in the clustering process to extend the network lifespan in the long-term. Moreover, the approach contemplates the behavior of the rechargeable batteries and considers the thermal effect on the battery degradation.

The obtained results are encouraging as the lifespan of the network is extended with the use of the prediction criterion. The aging based approach outperforms conventional methods in terms of clusters cardinality and network lifetime in the long-term (exhibits an average improvement of 44%). As a future work, we aim to incorporate a deep learning mechanism in the clustering process and consider both thermal and electric aspects of the rechargeable battery [12] to further improve the network durability.

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Mohamed Sofiane BATTA received the Master 2 degree in networks and distributed systems from the University of Ferhat Abbas Setif-1, Algeria, in 2018. He is currently pursuing the Ph.D. degree with the LRSD laboratory (Setif, Algeria) and the DISC/Femto-ST institute (Montbéliard, France). He is working on the field of networks fault tolerance and distributed systems. His research interests include the modeling and optimization of wireless networks, communication management in IoT networks.

Hakim MABED is currently an associate professor at the UFC University (France) and is a member of the FEMTO-ST institute (France) where he does his research. He obtained the Ph.D. degree from the University of Angers, (France, 2003) and the M.S. degree from the USTHB university (Algeria, 2000). His research interests are in the modeling and optimization of radio networks and swarms of modular robots.

Zibouda ALIOUAT is currently a professor in Computer Engineering Department at Sétif University (Algeria). She obtained the engineer degree (1984) and the M.Sc. (1993) from the University of Constantine (Algeria). She received the Ph.D. degree from the University of Setif, (Algeria, 2011). Her research interests include wireless networks, mobile networks modelling and simulation, fault tolerance of embedded systems and security and privacy in the IoT.

Saad HAROUS is currently chair and professor at the College of Computing and Informatics at the University of Sharjah (United Arab Emirates). He obtained the Ph.D. degree in computer science from Case Western Reserve University (USA, 1991). He has more than 30 years of experience in three different countries (USA, Oman and UAE). His research interests are in distributed computing, technology based learning, fault tolerant computing, communication networks. He has published more than 200 journal and conference papers. He is an IEEE senior member.