State of Health Optimization Based Unequal Clustering in IoT Networks

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***Abstract*—Energy optimization is an imminent worldwide issues for green computing, it constitutes a major concern and a critical aspect especially for energy constrained wireless networks. To overcome this issue, clustering techniques were introduced as a prominent method that arranges the system operation in correlated manner to attend the energy preservation and prolong the network lifespan. However, existing clustering works only focus on preserving the battery charge to operate until it drains out. This approach is most appropriate for non-rechargeable batteries. However, rechargeable batteries become commonly used and need to be considered. The full discharge of rechargeable battery does not mean the device obsolescence. Therefore, the system lifetime optimization should take into consideration the degradation of the rechargeable batteries performances. In this context, we proposed an improved long-term energy efficient unequal clustering approach based on the battery state of health for IoT networks ($ILEC\_SOH$). This work represents an initial step in the integration of the battery health degradation into the unequal network clustering. The obtained results show that the consideration of battery state of health (SOH) significantly improve the network lifespan in the long term compared to the conventional energy efficient approaches.**

***Index Terms*—IoT, WSN, Energy-aware protocols, Unequal Clustering, Rechargeable Batteries lifespan, Battery SOH.**

I. Introduction

The IoT paradigm comes forth as a robust and dynamic technology approved in many real-world applications. Due to its great convenience, it becomes a point of interest for many researchers and technological solutions in several fields such as military, medical, environmental sciences, traffic management, smart industry and more [1]. The IoT networks constitute a significant source of inspiration for legacy systems pillared by a wireless sensor network (WSN) [2]. These networks are set by a myriad number of wireless electronic devices (objects) distributed over a large area. These objects collect and process data from the environment and work together to communicate them to the base station (BS). The integration of this technology will ensure convenience in the user's daily life whereby the devices have access to the internet [2], [3]. However, the lifetime of these device's is mainly related to their batteries, accordingly, prolonged network durability is considered as a critical challenge.

Multi-hop routing and network clustering are two popular energy efficient techniques proposed to improve the energy consumption [4]. However, with multi-hop clustering, the major part of energy is consumed for aggregating the received packets of other nodes. Therefore, the closest nodes to the BS dissipate their energy earlier compared to distant nodes, which creates the hot-spot problem. Moreover, the majority of clustering work regarding lifetime maximization consider single discharging cycle represented by the state of charge metric (SOC), while the battery health degradation is neglected in the management strategies [5]. With the emergence of modern IoT devices, rechargeable batteries become typically exploited and ought to be regarded. Although the cost of the battery itself might be cheap, its substitution leads to high maintenance cost. Therefore, an effective consideration of these batteries ought to be applied to guarantee the longevity of the network in the long-term.

Rechargeable batteries follow a rude aging mechanism that degrades their capacity and modifies their internal structure. A great variety of research works in the literature have shown a particular concern to the modeling of the battery degradation behavior [5], [6]. These researches deliver a promising concept of battery degradation for vehicular systems [7]. However, this notion was not introduced to wireless networking systems. We notice that the approaches which focus on improving the energy consumption of wireless networks do not provide optimal network longevity. Indeed, these approaches only address the amount of energy consumed (short-term vision) without assuming the battery aging (long-term vision). In this regard, we elaborate on the problem of considering battery degradation to optimize the lifetime of IoT networks. We propose a new state of health based unequal clustering approach for long-term energy optimization in IoT networks.

The idea is to take into consideration the battery aging effect during the election of the cluster heads (CHs) instead of the conventional metrics such as the battery deep of discharge (DOD) or the battery SOC. Thereby, the nodes that endure a considerable battery degradation will not be granted as CH to preserve their durability and increase the network lifetime in the long-term (over several recharging cycles). To the best of our knowledge, this proposal is the first work that considers the integration of the rechargeable battery SOH in the unequal clustering structure to extend the network life and alleviate the hot spot problem. In the adopted structure (illustrated in fig. 1), the network is partitioned into uneven size clusters. Smaller size clusters are placed approximately to the BS. These clusters waste less energy on intra-cluster routing and concentrate on inter-cluster data relaying. In contrast, the size of clusters scales to cover more nodes as we go away from the BS. These clusters employ more energy on intra-clustering traffic and preserve their energy for inter-clustering routing.

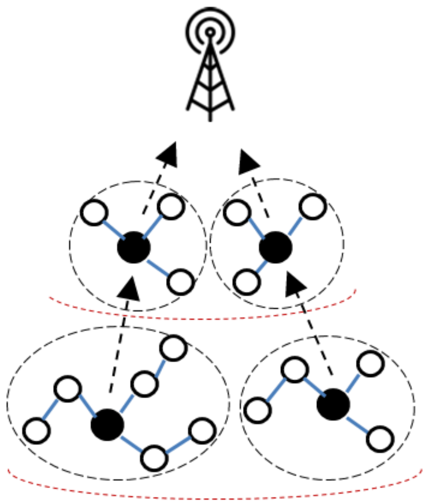

Fig. 1. unequal network clustering topology

The rest of the paper is organized as follow. The following section II describes some related conventional energy efficient approach. Then, we describe the transmission reliability model and the battery degradation model in sections IV and V respectively. Section III presents the contribution. Simulation settings and results are discussed in Section VI. Finally, We conclude our work in Section VII.

II. Related Works

Several studies on the efficient use of network energy have been proposed in the field of wireless networks [4], [8], [9]. Research community developed several topologies for routing protocols to address the energy consumption problem [4]. Among these proposals, hierarchical topology protocols are characterized by their network lifetime durability and offers balanced energy consumption [2]. Several energy efficient clustering protocols have been proposed, specially for unequal clustering [10], [11]. The difference between these diverse proposed approaches mainly rely on the criteria of CHs election.

MH-LEACH [12] mitigate the scaling problem faced in the conventional LEACH [13] by using Multi-hop communication to improve the energy efficiency. The approach is distributed and considers the residual energy of nodes during the CHs election. Some specific nodes are considered as gateways to aggregate the collected data toward the BS and CHs use a data fusion methods to reduce the flow of communication. Optimized LEACH (O-LEACH) proposed in [14] is another amelioration of LEACH based on Genetic algorithm (GA) for energy efficient wireless networks. CHs are formed using the hierarchical LEACH protocol and a fitness function that consider nodes residual energy. The GA is used to find the optimal route toward the BS and improve the packet delivery ration, throughput, and the energy consumption. In [15] the authors presented An optimized clustering method based on Fuzzy-C means for wireless networks called OCM-FCM. Clustering is performed using a C-means mechanism where CHs are elected based on the degree and the distance of each node from the BS. The authors in [16] proposed a new Distributed Unequal Clustering algorithm using Fuzzy logic (DUCF) where the primary set of CHs is designated using a fuzzy logic function combined with an uneven clustering algorithm based on the residual energy, the distance toward the BS and the centrality of network nodes. The final CHs are selected using the fuzzy inference algorithm. Baradaran et al. [17] proposed an improved clustering algorithm and an optimized cluster head selection method using fuzzy logic for wireless networks (HQCA-WSN). The CHs are selected based on fuzzy logic which considers the residual energy criteria in addition to the lowest and highest energy threshold within clusters and the distance between CMs.

Although a considerable part of literature works address the longevity improvement of wireless networks [4], [8], [10]. However, researches in this area, up to this point, are based on devices residual energy and on SOC optimization for non-rechargeable batteries and focus on maximizing the period at which the devices battery remain operational (short-term enhancement). Even though these approaches realize a longer network lifetime by adopting ideal structuring models, the mutual problem facing such approaches is the negligence of the battery behaviors by using a linear energy depletion assumption. Therefore, in the following, we are going to introduces our new distributed clustering scheme based on the battery state of health (SOH), which considers the rechargeable battery degradation aspect to optimize the CHs election in a way that extends the network durability (long-term enhancement).

III. The Proposed scheme

The wireless network is charted by a graph $G(V, E)$ where V represents the set of nodes (devices) and the edges $E \in V^2$ constitutes the communication links. $N(i) = \{j \in V \mid (i, j) \in E\}$ is the set of node i neighbors and $D(i, j)$ represent the distance separating node i and j. The transmitting range is denoted by T_{range}, where nodes communicate through bidirectional links.

In this part, we present a new distributed clustering scheme based on the battery SOH for the long-term energy optimization of IoT networks ($ILEC\_SOH$). The objective is to increase the battery durability (over several recharging cycle) by considering the rechargeable battery aging aspect during the clustering process (Instead of considering the conventional SOC). Therefore, nodes with higher battery degradation will not be granted as CH to preserve their longevity. In addition, we also consider the unequal clustering scheme to alleviate the hot spot energy problem faced by CHs near the BS. This work represents an initial step that considers the integration of the rechargeable battery SOH in the unequal clustering structure.

It is worthy to note that the modelization work of rechargeable battery degradation aspect is an outcome of the electronics specialist and is not adequately used by the networking community. Accordingly, the aim of this work is to illustrate that taking into consideration the long-term usage of devices batteries could greatly expend the network durability. To clarify our perspective, let's consider the network routing example illustrated in Fig 2. In this routing scheme, three nodes can relay the data of node S to the BS. With classical approaches, either the node 1 is selected 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, when considering a long-term energy efficient vision, the optimization of batteries SOH leads to select node 3. Although that this node has the lowest residual energy ($SOC = 40\%$), it presents a better SOH ($SOH = 51\%$) and the sustained damage is minimal ($\Delta_{SOH} = 0.8\%$).

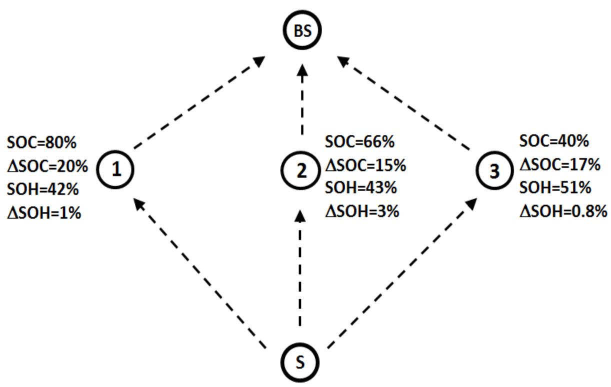

Fig. 2. Short-term vs long-term energy efficient routing scheme

The proposed scheme is distributed and uses a weight-based technique that selects as CHs, nodes that hold the maximum weight within their neighborhood. The weight value is calculated according to the following factors.

1. **The battery SOH** (SOH_i): the battery health value of a network node i deteriorates with time (in the long term) as a consequence of degradation. It decreases from 1 (representing a new battery) to 0 (in reference to a completely degraded battery). This metric is expressed as in eq. 1.

$$SOH_i = 1 - \Omega_i \tag{1}$$

2. **Neighborhood connectivity** (Θ_i): due to the aggregation and interference problems, the energy consumed by a node increases according to its degree. Thus, this parameter is taken into consideration. It evaluates the relative attachment of a node within the neighborhood, this value is computed using eq. 2.

$$\Theta_i = |N(i)| = |\{j \in V \mid (i,j) \in E\}| \tag{2}$$

According to the previous factors, the weight value W_i of a node i is computed as in eq. 3.

$$W_i = \alpha \times SOH_i + \beta \times \Theta_i \ \wedge \ \alpha + \beta = 1 \tag{3}$$

α and β represent the weighting coefficient of the two previous metrics. The significance of each metric, comparatively to the other, is stated by its related weighting coefficient. Simulation results show that using a linear combination of the weight metric with equal weighted coefficients produce better performance. Hence, in this work, these coefficients are equivalent, i.e. $\alpha = \beta = 0.5$

The approach carries multi-hop communication for the intra-clustering. Therefore, multi-hop spanning trees [18] are shaped within each cluster to aggregate data using the shortest paths between CMs and their CHs in order to consume less energy. During the clustering, each node compares its W_i value with that of its surrounding nodes and of CHs that dominate its neighbors ($CH_j / j \in N(i)$). The node holding the maximum weight (i.e. nodes with less battery degradation) broadcast a CH announcement packet. On the other hand, nodes receiving this packet join the cluster and establish the minimum routing path leading to the CH in single or multi hop manner based on their location. The CH adds progressively the potential CMs and updates the cluster information. To enable the clusters to be more tolerant to disconnection incidents that may appear during the operation of the dynamic system. The maintenance is locally enabled by the surrounding nodes to prevent the generation of inadequate topology. According to the role interpreted by the leaving node (following mobility event, death or energy failure or coverage issue), nearby nodes either re-elect a new CH or join another adjacent CH and complete the essential routes upgrades. The clustering process is outlined in Algorithm 1.

IV. Energy dissipation model

To make a better analysis about communication energy consumption, we assume a simplified network energy consumption model discussed in [2]. The energy consumption of network devices generally comprises three main elements: transmission energy consumption E_T, the receiving energy consumption E_R and the sensing and processing energy consumption E_S. E_T and E_R consume the significant part of the energy. Whereas, E_S is commonly marginal and, thus, it is ignored in this work. To forward a l bits packet over a distance d, E_T can be articulated as in 4.

$$E_T(l,d) = E_{elec} \times l + E_{amp} \times l \tag{4}$$

$$E_{amp} = \begin{cases} \varepsilon_{FS} \times d^2 : d < d_0 \\ \varepsilon_{MFS} \times d^4 : d \geq d_0 \end{cases} \tag{5}$$

The receiving energy consumption E_R is formulated by the eq. 6.

Algorithm 1 $ILEC\_SOH$ clustering process

Initialization
$CM_{list} = \emptyset$ //list of cluster members
$Dist\_to\_BS$=0 //approximate distance to the BS
$Dist_{MAX}$, $Dist_{MIN} \in \{10, 1000\}$ // maximum and minimum distance between the BS and a network nodes.

Begin
STEP 1: Compute the node weight (W_i) using equation 3
$W_i = \alpha \times SOH_i + \beta \times \Theta_i$
STEP 2: Determine the cluster Size CS
$CS = 3 \times (1 - \frac{Dist_{MAX} - Dist\_to\_BS}{Dist_{MAX} - Dist_{MIN}})$
STEP 3: **If** the current node has the greatest weight among the neighborhood **then**
$W_i = Max(W_j \mid \forall j \in N(i))$
Broadcast a $CH\_Announcement$ message
else
Upon receiving $CH\_announcement$ **Do**
Send a join request CM_{join} to the CH with the highest weight
Upon receiving a reject message (CM_{reject}) **Then**
Repeat STEP 3
STEP 4: **Upon** receiving CM_{join} from node j **Do**
Update the list of cluster members CM_{list}
$CM_{list} = CM_{list} \cup j$
End

$$E_R = E_{elec} \times k \tag{6}$$

Where E_{elec} is the required energy to operate the transmitter or the receiver circuit. The quantity of energy consumption depends on different parameters, like communication coding, packet filtering, digital modulation and signal dissemination. ε_{FS} and ε_{MFS} represent the characteristics of the transmitter amplifier. Particularly, ε_{FS} is used for free space and ε_{MFS} for multi-path. d_0 represented by eq. 7 is the distance between the transmitter and the receiver. According to the distance d, the loss of propagation can be addressed as a free-space model (d^2 power loss) or multi-path fading model (d^4 power loss).

$$d_0 = \sqrt{\varepsilon_{FS}/\varepsilon_{MFS}} \tag{7}$$

V. Battery Degradation model

The SOC and SOH represent two mutual metrics used to define the actual battery state. The SOC measures the portion of residual energy and estimates the charge remaining before the battery is depleted. Whereas, the SOH evaluates the battery ageing and detect the potential battery degradation. This latter gives substantial information to predict the battery failure and prevent the nodes final death.

Non-rechargeable batteries are substituted ones they are completely depleted, in this case, the SOC is exploited to measure the remaining battery useful life. On the other hand, rechargeable batteries also have a constrained life and need alternation due to aging. However, they can withstand multiple recharging cycles. The SOH indicator is used then to evaluate the health state of the battery. The degradation of rechargeable batteries is mainly due to the calendar and cycle effects [19].

The calendar aging denotes the battery intrinsic deterioration over time, it represents the degree alteration endured by the battery due to the temperature and the charging level. Through continuous charging/discharging cycles, diverse stress factors cause the degradation of the battery and accelerate the calendar aging, such as the ambient temperature, depth of discharge (DoD), number of charging/discharging phases, etc. The cycle aging represents the life expectancy lost over the battery charge and discharge cycles. It also changes according to the battery utilization method [5].

In this work, the battery degradation model is inspired by the work [19]. The battery's life expectancy lost Ω is formulated as in eq. 8.

$$\Omega = (S_{DoD} + S_t) \times S_T \times S_\sigma \tag{8}$$

Where $S_{DoD}, S_t, S_T, S_\sigma$ outline the different stress factors considered in this work, respectively, the DoD, $calendar\ aging$, $Temperature$ and the SOC. These stress factor are estimated with the following equations. Table I represents the variable values employed in the stress models.

$$S_{DoD} = \alpha_{DoD} \times DoD \times e^{(\beta_{DoD} \times DoD)} \tag{9}$$

$$S_t = \alpha_t \times t \tag{10}$$

$$S_T = e^{\left(\alpha_T \times (T - T_{ref}) \times \frac{T_{ref}}{T}\right)} \tag{11}$$

$$S_\sigma = \alpha_\sigma \times e^{\sigma - \sigma_{ref}} \tag{12}$$

TABLE I
Parameters value of the battery degradation stress model

Parameter	value
α_{DoD}	0.05
β_{DoD}	0.03
α_σ	1.04
σ_{ref}	0.50
α_T	6.93E-2
T_{ref}	$25 \circ C$
α_t	4.14E-10/s

VI. Experimental analysis

The performances of the proposed scheme were simulated using JUNG [20], a Java-based library framework that enables visualization, modeling and analysis of wireless networks as graphs. With a variable number of $n \in [200, 1100]$ nodes distributed uniformly in the generated deployment zones of size $1000 \times 1000 m^2$. Each node has a communication range $T_{range} = 90m$. The connectivity model employed is the UDG (Unit Disk Graph [21]) model, in this model, two nodes are considered neighbors if they are within each other's communication scope. A group of 80 random networks were generated using these parameters. The values of the experiment variables are specified in table II. The performances of the proposed approach are compared with MH-LEACH [12] and O-LEACH [14]. The main consideration of these protocols is to reduce the energy consumption and optimize the network lifetime. Three metrics are employed for the performance evaluation of the proposed approach, specifically, the cardinality of clusters, the average energy consumed and the long-term network lifetime. Simulation results are discussed in the following subsections.

TABLE II
EXPERIMENT SETTING PARAMETERS USED DURING THE SIMULATION

Parameter	Value
Network size	$1000 \times 1000\ m^2$
Network density (δ)	$\delta \in [200, 1100]$
Nodes distribution	Uniform random
Transmitting range (T_{range})	90 m
α, β	1/2, 1/2
E_{elec}	$50nJ/bit$
ε_{FS}	$10\ pJ/bit/M^2$
ε_{Mfs}	$0.0013\ pJ/bit/M^4$
Data packet size	100 $bytes$
Initial energy	1 Joule

A. Clusters cardinality

A reduced clusters cardinality can enhance the efficiency of the clustering scheme. Indeed, the number of clusters allows us to measure the efficiency of the clustering approach. Fig. 3 shows the average number of clusters generated using the proposed approach versus O-LEACH and MH-LEACH protocols by using an increased network density $n \in [200, 1100]$. From this figure, we observe that the cardinality of the proposed approach $ILEC\_SOH$ stabilize between $[30, 40]$ compared to the other algorithms where the clusters cardinality tends to increase. The justification behind is that $ILEC\_SOH$ generates a reduced number of dense clusters according to the nodes connectivity and on the battery state, which improve the clustering efficiency and lead to a better preservation of energy. Therefore, $ILEC\_SOH$ reveals better performance and exhibits an improvement of 39% and 60% compared to O-LEACH and MH-LEACH respectively.

B. Average energy consumption

Comparing the energy required for the clustering overhead is also a convenient metric to assess how efficient is the clustered topology. Fig. 4 shows the energy consumed by network nodes to elaborate the structured topology by considering a variable network density. According to this figure, the energy required for the clustering increase along with the network density. This is due to the amount of messages that need to be exchanged to develop the structure, which further expands when the unequal clustering scenario is considered. From the curve of fig. 4, MH-LEACH consumes the lowest energy where it consumed less energy than $ILEC\_SOH$. Indeed, $ILEC\_SOH$ requires additional messages to measure

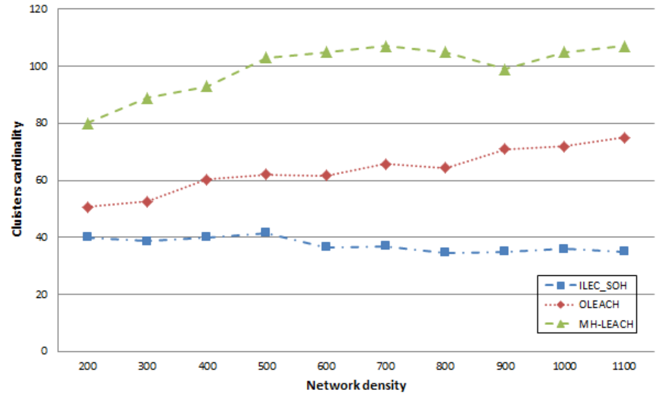

Fig. 3. Average number of clusters versus network density

the weight metric (using eq. 3) which consume more energy (requires 31% more energy compared to OLEACH). This point may be regarded as a short-come. However, the result is tolerable because the consideration of the SOH in the weight metric display a better lifetime performance in long-term as discussed in the following result.

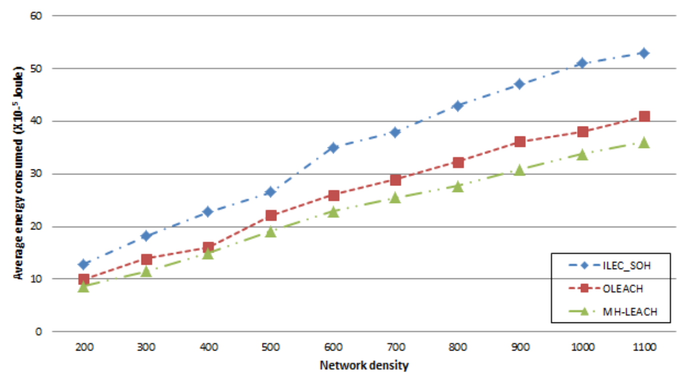

Fig. 4. Average energy consumption

C. Long term network lifetime

The measure of the network lifetime shows the periode during which network nodes can operate the clustering protocol. Indeed, the premature death of nodes can cause a disconnection of some network parts. This metric represents the number of rounds elapsed before the first node with completely dead battery emerge in the network (i.e. the rechargeable battery SOH of this node is fully deteriorated and needs to be substituted). We assume that the network lifetime correspond to the period until the first node death (FND). We consider that after the FND, the efficiency of the current network topology decrease owing to loss of performance, which weakens the network rendering in the coming rounds.

Fig. 5 illustrate a comparison of our clustering proposal compared to the conventional approaches by considering the long-term network lifetime with variable nodes density. According to this figure, initially, the network lifespan of the three approaches is relatively short due to the low density.

At this stage, nodes are isolated and transmit their data directly to the BS. The connectivity increases among with the density which lower the clusters cardinality and load balances the network energy consumption. The curve allure of fig. 5 (a) demonstrates that the proposed approach features better performances, the FND node in $ILEC\_SOH$ withstand up to 4900 rounds compared to 2890 rounds in O-LEACH and 2200 rounds in MH-LEACH. This enhancement comes as a result of exploiting the battery SOH metric. Indeed, rather than using the conventional battery SOC during the clustering. $ILEC\_SOH$ consider the total battery degradation before the election of the potential CHs. Moreover, the proposed approach assume an unequal clustering scheme which alleviate the hot spot energy problem and further balance the energy consumption among CHs. Accordingly, $ILEC\_SOH$ exhibits better lifetime performances compared to the classic approaches (improved by an average of 58.6%).

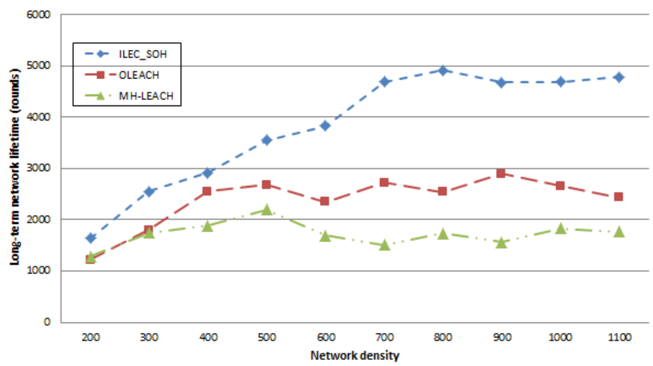

Fig. 5. Long-term network durability

VII. Conclusion and Future Works

The present work focuses on the long-term optimization of IoT networks lifetime. More particularly, it addressed a novel energy efficient unequal clustering based approach called $ILEC\_SOH$. The proposed approach considers an unequal clustering scheme to balance the energy usage among CHs and mitigate the hot spot energy problem. The originality of this approach is the integration of the batterys' State of Health during the clustering to expand the network durability. $ILEC\_SOH$ depicts a long-term energy optimization vision and represents an initial step in the consideration of the rechargeable battery deterioration aspect in wireless network clustering. The obtained results show that the aging based approach outperforms the conventional clustering methods in terms of clusters cardinality and network durability with an average gain of 39% and 58%, respectively. As a future perspective, we aim to integrate a deep learning mechanism in the clustering process of IoT networks to exploit the behavior of smart devices and further preserve the batteries' durability.

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