

Highly Effective Online Energy Restoration of Wireless Rechargeable Sensor Networks by a Mobile Charger

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ABSTRACT

Wireless rechargeable sensor network (WRSN) employs a Mobile Charger that mitigates sensor's energy depletion helps to maximize active node counts (operational size) and minimizing node downtime (disconnection time). In this paper, we introduce the Continuous Local Learning (CLL) strategy. CLL is an online replenishment strategy, where MC predicts sensor power consumption rates, calculates the dispatch route and adjusts dispatch decisions during active charging rounds. CLL operates without prior network maps or centralized coordination. CLL relies on single-hop local communication between MC and sensors, with minimum memory allocation, and low computations on the MC. Empirical evaluations confirm that CLL achieves empirical immortality without long-range telemetry and prevents node outages across extended operational horizons. In comparison to a periodic strategy, denoted as H, CLL demonstrates superior performance: CLL consistently expands operational network size while drastically reducing average disconnection time across all evaluated settings.

Keywords: Distributed Systems; Energy Restoration; Effectiveness; Flexibility; empirical Immortality; Local Learning; Mobile Charger; Online Charging; WRSN.

1 Introduction

Wireless sensor networks (WSNs) consist of a large number of sensors (nodes) spatially distributed in network area. These nodes are employed to gather and process environmental data across several applications (e.g., [1], [2]). Sensors have many attractive features including low cost and structural flexibility, which make them an ideal solution for smart cities [3]-[5], healthcare monitoring [6], [7], environmental sensing [8], [9], target localization [10], [11], intruder tracking [12], [13], and barrier surveillance [14], [15].

Small battery capacity presents a crucial challenge to sensor's operational lifetime [16]. Sensors exhaust their battery energy by continuous sensing and radio transmissions. Ultimately causing node failure, which leads to local sensing gap, and eventual network collapse. Mitigating power depletion remains an ultimate goal in the design of WSNs [17],[18].

Existing solutions are classified into endogenous and exogenous strategies. Endogenous solutions augment a node with additional hardware, either by integrating energy harvesters from surrounding environment (e.g., [19], [20]) or by adding self-locomotion equipment to allow the node to reach stationary charging station (e.g., [21], [22]). However, both options lead to higher cost of using WSNs and more complex design.

Exogenous strategies offload energy delivery to external Mobile Charger, a robots or vehicle, which traverse the deployment area to charge depleted nodes. Recent breakthroughs in non-

radiative wireless power transfer (e.g., [23]-[26]) revive the viability of this approach. Using this technology, MC should be able to charge the sensor's battery with energy generated from sources elsewhere. Interestingly, wireless rechargeable sensor network (WRSN) presents a WSN emerging technology (e.g., see [27]).

Both paradigms, endogenous and exogenous, aim to maximum the sensors operational size while minimizing the sensors disconnection time. Performance hinges on two metrics: operational size (the number of active sensors) and disconnection time (the duration of a node's inactive state).

In fact, any appropriate strategy should sustain high operational size that guarantees the minimum connectivity of the network over time (e.g., [28]-[32]). Under favorable conditions an optimal effectiveness is achieved where networks eliminate sensing gaps entirely described as immortality in [33], [34]. In this paper, we will refer to this state as empirical immortality, which we measure over finite evaluation horizons.

The current state of research on online dynamic charging strategies raises important challenges:

Can a highly effective online strategy achieve empirical immortality relying on localized data exchanges without long distance communication? If so, how?

Can dynamic localized strategy surpass the performance of static periodic strategy while preserving low computational overhead?

We address these questions by introducing Continuous Local Learning (CLL), a localized online restoration strategy that sustains operation of WRSN without previous knowledge of initial topology. CLL requires minimal onboard memory and computation steps on MC alongside short-range communication. Eliminates long-distance communication and cluster-head election overhead by locally communicating the sensor's battery states to MC during network traversal. Constructs real-time energy consumption profiles and dynamically updating the MC's traversal order.

Simulations demonstrate that CLL maintains uninterrupted operational states, reaching empirical immortality or near-immortality across scales that exceed the operational limits of traditional periodic benchmarks (H) [33].

CLL achieves high scalability and efficiency with minimal hardware demands. Across all evaluated scenarios, CLL outperforms baseline H by increasing active node availability and shortening sensing hole lifespans.

The rest of this paper is organized as follows. Section 2 reviews related to our work. Section 3 introduces sensors, Mobile Charger, and performance metrics. Section 4 provides detailed description of the proposed CLL strategy. Section 5 presents empirical evaluations of CLL strategy effectiveness. Section 6 presents comparison of CLL with static periodic strategy. Section 7 concludes the paper and presents future research directions.

2 Charging Strategies: Related Work

Several studies on energy restoration in WRSN focus on the mobile charging dispatch under a variety of network and operational assumptions.

Offline global optimization models dominate early research, which assumed full network knowledge a priori available to formulate dispatch sequence (e.g., [4], [34]-[38]). Despite theoretical precision, offline techniques require high computation capabilities and cause a

communication overhead while lacking flexibility during unexpected changes in network behavior [39].

In contrast, online dispatch strategies address dynamic network behavior by using runtime operational communication (e.g., [28], [32], [40]-[44]). Based on the past and the current network status, online strategies made dispatch decisions. Existing online strategies split into two classes:

Global Online Strategies: sensors report residual battery states periodically (e.g., [32]), or at certain energy threshold (e.g., [40], [43]). Base Station receives sensor's energy information, in case of on demand strategies, computing the route and communicating it to the moving Mobile Charger (e.g., [31], [42], [44]-[46]). Other online strategies required nodes to directly send their residual energy levels to MC that is responsible for computing the route and updating it (e.g., [31], [42], [47]). The need for these messages and updates triggers heavy multi-hop communication and cost overhead, sink flooding [28], limiting practical scalability [29], or trajectory tracking costs [35].

Local Online Strategies: Dispatch choices rely strictly on single-hop communication between MC and in proximity sensors. These strategies have a few investigations in literature. Moreover, the existing studies restricted the network arrangement (e.g., circular [19] or linear [23]) or focus on the time elapsed until the first node depletes its battery [29].

Alternatively, charging strategies can also be divided into static and dynamic strategies. In the static (periodic) strategies, MC follows a precomputed route and visits nodes according to an order precomputed at the Base Station (e.g., [21], [30], [33]). These strategies minimize MC processing load and communication energy with the MC. However, the route is fixed and does not adapt to non-uniform rate changes. Conversely, in dynamic strategies, MC continuously modifies the charging order based on evolving sensors' residual energy (e.g., [32], [40]-[44]). Dynamic strategies maximize adaptability but usually incur heavy communication penalties.

3 Model and Terminology

3.1 The Sensors

WRSN is modeled as a connected graph $G(S, E)$, where $S = \{s_1, \dots, s_n\}$ represents n homogeneous sensors randomly distributed across a square region of size $A \times A$. An edge $(s_i, s_j) \in E$ denotes a bidirectional wireless communication link between nodes s_i and s_j . Each node collects information and relays packets to Base Station (BS) via Multi-hop Energy-Aware Routing.

Sensors are randomly deployed in the network area to collect data and communicate information to the Base Station. All sensors are homogenous and powered by wirelessly charged battery that has the capacity of $E_{\max}$. Sensors consume energy for sensing, processing, and communicating. Sensing and processing energy are negligible relative to consumed energy for wireless communication (e.g., [18], [33], [34]). At time t , the instantaneous power consumption $P(s, t)$ for node s depends on its total radio activity:

$$P(s, t) = \varepsilon \cdot \lambda(s, t) \quad (1)$$

where ε represents the radio transceiver energy parameter and $\lambda(s, t)$ is the aggregate transmitted and received throughput. Packet arrivals follow a Poisson process sampled over

discrete steps $\Delta t = 1$ s, yielding an average time-unit power consumption P . Table 1 defines all system notation.

The average node lifetime is expressed as $T_{E_{\max}} = \frac{E_{\max}}{P}$. Sensors deplete their batteries depending on the frequency of activities in the surrounding area. Let $S(s, t)$, or simply $S(s)$, denote the state-of-charge for node s at time t . When $S(s)$ drops below a critical threshold τ , the node becomes non-operational, suspending all sensing tasks and creating a local coverage gap. The node uses the remaining residual energy for short-range communication required during Mobile Charger round.

Table 1: Table of Notations

Notation	Definition
n	Number of sensors
S	Set of sensors
BS	Base station
SS	Service station
$T_{E_{\max}}$	Average sensor lifetime
MC	Mobile Charger
$E_{\max}$	Sensor's maximum battery capacity
τ	Non-operational threshold
E_{MC}	MC battery capacity
E_{Move}	MC Moving energy consumption
μ	Packet arrival Rate
λ	Sensor data rate
v	MC velocity
Δ	Charging rate
Δt	Poisson Sampling interval
η	Charging efficiency
δ	Consumption rate

3.2 The Mobile Charger

Sensors that deplete their residual energy need immediate charge to resume their role and maintain operational size as effectively as possible. To achieve this goal, a vehicle or a mobile robot is deployed in the network to charge depleted sensors. MC has the capabilities of replenishing energy wirelessly. We assume that MC can charge a single sensor in its proximity. The duration of charging a sensor is proportional to its residual energy. For instance, the Mobile Charger will spend t_{charge} seconds when charging a node with $E\%$ energy in its battery

$$t_{charge} = (1 - E) \cdot \frac{E_{\max}}{\Delta \cdot \eta} \quad (2)$$

where t_{charge} is the time needed to charge the sensor's battery; Δ is the charging rate and η is the charging efficiency. Since η is fractional number, then the wireless power transfer loss is $E_{\text{MC}} * (1 - \eta)$. Thus, MC residual energy would decrease by $E_{\text{MC}} \leftarrow E_{\text{MC}} - \frac{\Delta}{\eta} \cdot t_{\text{charge}}$. For simplicity, as in [33], we assume that MC charges any node if the sensor's residual energy is not full.

MC operates on a high-capacity battery E_{MC} (initially fully charged); supplying both locomotion and charging tasks across the network. We assumed that the MC battery is enough to charge all the nodes at least once. When residual energy drops to $5\% \cdot E_{\text{MC}}$, the Mobile Charger returns to the Service Station (SS) located at the Base Station for immediate battery replacement or fast-charging taking t_{ss} seconds before resuming the charging process.

MC travels at constant velocity v , consuming a unit motion cost E_{Move} per meter it traverses. Moving between locations x and y consumes $d(x, y) \cdot E_{\text{Move}}$ energy and requires a time of $t_m = \frac{d(x, y)}{v}$, where $d(x, y)$ denotes the Euclidean distance between x and y .

The Mobile Charger is equipped with sufficient memory to store four $O(n)$ vectors. These vectors maintain node identifiers, locations, estimated energy levels, and time of last visit. These data structures are initialized empty and continuously updated using basic computation capabilities. Moreover, MC estimates consumption rate, at every charging decision, for all nodes constitute to $O(n)$ energy state updates.

3.3 Effectiveness Measures

The process of selecting the targeted node to charge determines the effectiveness of the charging strategy. Recalling that the main objective of using charging strategy is to maximize the network coverage by sustaining the maximum number of operational sensors and minimizing the disconnection duration of the sensors. Two metrics are used to evaluate the effectiveness of a charging strategy: operational size and disconnection time.

Operational size measures the number of active, functioning nodes at time t , denoted by $\text{Size}(t)$. Thus, the number of sensing holes in the network sums to $n - \text{Size}(t)$.

Disconnection time measures the downtime duration for node s starting from depletion time and ending by MC arrival, denoted by $\text{Dis}(s, t)$. If a sensor's charging begins before battery exhaustion, we consider $\text{Dis}(s, t) = 0$. This parameter captures the persistence of sensing holes across the network.

While realistic immortality is hard to achieve, if a strategy eliminates sensing holes entirely over the simulation horizon, we define this state as empirical immortality.

$$\text{Size}(t') = n \quad \text{and} \quad \text{Dis}(s, t') = 0 \quad \forall s \in S, \forall t' \geq t$$

Furthermore, if the sensing holes ratio to n does not exceed 5% of n and disconnection time does not exceed 5% of battery lifespan $T_{E_{\text{max}}}$, we call this near-optimal operating state, near-immortality.

$$\frac{\text{Hole}}{n} \leq 0.05 \quad \text{and} \quad \frac{\text{Dis}}{T_{E_{\text{max}}}} \leq 0.05$$

where Hole represents the average count of concurrent sensing holes and Dis denotes average disconnection time.

4 Continuous Local Learning Strategy (CLL)

The proposed charging strategy executed by the Mobile Charger operates in two phases: an Initialization phase, followed by continuous execution of the Learning and Charging phase.

The Initialization phase begins with a discovery round to construct spatial coordinates and initial state-of-charge vectors; if network topology and energy states are available a priori, this step can be bypassed. Upon completing this round, an estimation round is launched, enabling MC to compute a baseline charging order. Initialization phase takes place immediately after sensors deployment, sensors' batteries are almost full. Thus, the transit time for initialization phase is approximately 4 hours.

In the second phase, the continuous Learning and Charging phase, MC visits nodes using base order, charges nodes, collects state-of-charge information, and dynamically revises the charging order.

Algorithm 1. Initialization.

```

/*Phase 1: Discovery Round (Greedy DFS Traversal)*/
t_start := current_time()
MCloc := Base_Station_Location
Visited0 =:

while |Visited| < |S| do
    Unvisited := S \ Visited
    target := argmin_{s ∈ Unvisited} { distance(MCloc, location(s)) }

    move_to(target)
    t_arr := current_time()

    if target ∉ Visited then
        Visited := Visited ∪ {target}
        Location(target) := get_coordinates(target)
        T1(target) := t_arr
        S1(target) := sample_state_of_charge(target)

        if S1(target) < E_max then
            charge(target, E_max)
        end if
    end if
    MCloc := Location(target)
end while

/*Phase 2: Baseline Estimation Round (Second DFS Traversal)*/
Visited20 =:
while |Visited2| < |S| do
    Unvisited2 := S \ Visited2
    target := argmin_{s ∈ Unvisited2} { distance(MCloc, Location(s)) }

    move_to(target)
    t_arr := current_time()

    if target ∉ Visited2 then
        Visited2 := Visited2 ∪ {target}
        T2(target) := t_arr
    end if
end while

```

```

S2(target) := sample_state_of_charge(target)

*/ Calculate inactive time fraction if depleted before MC arrival/*
if S2(target) <=  $\tau$  then
    t_dep := estimate_depletion_timestamp(T1(target), S1(target),  $\lambda_s$ )
     $\Delta t_{\text{off}}$  := max(0, T2(target) - t_dep)
else
     $\Delta t_{\text{off}}$  := 0
end if

*/ Recalculate baseline consumption rate including forwarding load/*
 $\Delta t_{\text{active}}$  := T2(target) - T1(target) -  $\Delta t_{\text{off}}$ 
 $\delta(\text{target})$  := ( $E_{\text{max}}$  - S2(target)) /  $\Delta t_{\text{active}}$ 

Sold(target) := S2(target)
Told(target) := T2(target)
end if
MCloc := Location(target)
end while

```

4.1 Initialization Phase

The Initialization phase as shown in (Algorithm 1) consists of two sequential discovery rounds: a spatial mapping tour and a baseline estimation round.

During the discovery round, MC executes a depth-first search (DFS) traversal to discover network topology. At each step, the charger greedily moves for the nearest unvisited neighbor and backtracks when encountering a node with fully visited adjacent nodes. Upon its initial arrival at node s at timestamp $T_1(s)$, MC records the node's spatial coordinates and its initial state-of-charge $S_1(s) = S(s, T_1(s))$. The initialization phase is employed to establish a baseline network parameter, thus, the performance evaluation of the proposed CLL strategy is excluded from the results.

The goal of the baseline estimation round is to establish the baseline consumption rate $\delta(s)$ across all sensors. The charger executes a second DFS pass along the mapped graph. Upon reaching node s at time $T_2(s)$, it samples the state-of-charge $S_2(s) = S(s, T_2(s))$. To handle high-traffic nodes that exhaust their battery at time t_{dep} prior to the MC's arrival, the calculation isolates active runtime by subtracting inactive downtime $\Delta t_{\text{off}} = T_2(s) - t_{\text{dep}}$. For those nodes that do not exhaust their batteries before MC arrival, $\Delta t_{\text{off}} = 0$.

The initial consumption rate $\delta(s)$ is calculated as:

$$\delta(s) = \frac{E_{\text{max}} - S_2(s)}{T_2(s) - T_1(s) - \Delta t_{\text{off}}}$$

Using $\delta(s)$, MC projects the remaining lifetime of the battery and moves to the next phase.

4.2 Learning and Charging Phase

Following the Initialization phase, MC has a priori knowledge of all sensors' coordinates and estimated consumption rates. It then continuously runs the Learning and Charging phase (Algorithm 2). At each step, the charger identifies and visits the node with the most critical energy levels.

Let t represent the current timestamp and $d(s, t)$ denote the distance between MC and node s at time t . Traversal time to reach node s is defined as $T(s, t) = \frac{d(s, t)}{v}$, where v is the velocity of the charger. The projected energy $S_{\text{Exp}}(s, t')$ of sensor s upon arrival at time $t' = t + T(s, t)$ is computed as:

$$S_{\text{Exp}}(s, t') = S_2(s) - \delta(s) \cdot (t - T_2(s) + T(s, t))$$

The projected energy, $S_{\text{Exp}}(s, t')$, unifies three distinct routing metrics considered in [17]: inter-node distance, current state-of-charge, and remaining lifetime into a single metric. At decision time t , MC determines the destination node s^* , by identifying the candidate with the minimum expected residual energy upon arrival, with ties resolved arbitrarily:

$$s^* = \arg \min_{s \in S} \{S_{\text{Exp}}(s, t')\}$$

Upon arriving and completing the charging process, MC updates its records of the node's timestamp and consumption rate, before selecting the next destination. The process of updating node's information allows MC to dynamically update expected energy calculations using real-time information.

Algorithm 2. Learning and Charging.

```

Input:  $S, \tau, FL, Told, Sold, \delta$ 
/*  $t$  denotes current time,  $MCloc$  denotes current position of MC */
repeat
   $D := \{\text{distance}(MCloc, l) \mid l \in FL\};$ 
   $S_{\text{Exp}} := Sold - \delta \times (t - Told + (D / v));$ 
   $target := l \in FL : S_{\text{Exp}}(l) = \text{Min}\{s \in FL\}\{S_{\text{Exp}}(s)\};$ 
  move to target;
   $\delta(target) := (Sold(target) - S(target)) / (t - Told(target));$ 
   $Sold(target) := S(target);$ 
   $Told(target) := t;$ 
  if  $S(target) < E_{\text{max}}$  then
    charge target  $\leftarrow E_{\text{max}};$ 
     $Sold(target) := E_{\text{max}};$ 
  end if;
until Forever

```

5 Experimental Analysis

This section evaluates the operational performance of Continuous Local Learning (CLL) through extensive discrete-event simulations, focusing on configuration scenarios where empirical immortality is established in literature.

Performance evaluation relies on two primary metrics: average operational size ($\text{Size}(t)$) and mean node disconnection time ($\text{Dis}(s, t)$), where Operational size presents the number of active, functional nodes during simulation horizon. Disconnection time quantifies the duration a sensor remains non-operational prior arrival of MC to charge it.

5.1 Experimental Setup

Evaluations consider network densities varying from $n = 100$ to $n = 500$ sensors ($n \in \{100, 200, 300, 400, 500\}$) uniformly distributed over a obstacle-free $200 \text{ m} \times 200 \text{ m}$ square

field. The Base Station (BS) and the Service Station (SS) both reside at the central position (100 m, 100 m).

Each sensor is equipped with a 1.2 V/2.5 Ah NiMH battery, with maximum capacity $E_{\max} = 10.8$ kJ. If the state-of-charge of a node falls below $\tau = 5\% \cdot E_{\max}$, it stops working and is counted as non-operational. Nodes generating packets following a Poisson process with arrival rate $\mu_s \in [1,5]$ packets/s, producing individual data rate $\lambda_s \in [1,5]$ kbps with packet size $L_{\text{pkt}} = 128$ B.

The Mobile Charger (MC) is equipped with an onboard battery of capacity $E_{\text{MC}} = 770$ kJ. MC moves in the field at constant velocity $v = 5$ m/s [33] and consumes $E_{\text{Move}} = 5$ J/m for every meter it traverse [33], [34]. Moreover, MC replenishes wireless energy at standard efficiency $\eta = 95\%$ [16]. We assumed that MC charges sensors at one of two rates in the literature, $\Delta = 5$ [24] alongside comparative benchmarks run at $\Delta = 3.4$ [6]. Table 2 details the simulation parameters.

Table 2: Main Simulation Parameters

Parameter	Description	Value
n	Number of deployed sensors	100,200,300,400,500
Area	Deployment Area	$200 \times 200 \text{ m}^2$
$E_{\max}$	Sensor battery capacity	10.8 kJ
τ	Inactivity energy threshold	$5\% \cdot E_{\max}$
E_{MC}	MC battery capacity	770 kJ
E_{Move}	Moving Energy per meter	5 J/m
t_{ss}	Fast-charge duration at the Service Station	15 min
λ_s	Node throughput rate	[1,5] kbps
μ_s	Poisson's arrival rate	[1,5] packets/s
v	MC velocity	{2,5} m/s
Δ	Charging rate	{3.4,5} W
η	Charging efficiency	95%
L_{pkt}	Packet size	128 B
ϵ	Radio transceiver energy parameter	50 nJ/bit
R_c	Communication radius	30 m
$G(V, E)$	Network topology	Connected graph
T_{sim}	Simulation horizon	6 months

Simulations run on a discrete-event simulator in MATLAB 2024b. Every parameter configuration is evaluated 100 independent trials over a 6-month operational timeline. Averages for all performance metrics have been calculated within a 95% statistical confidence interval as shown in Table 3 and Table 4.

5.2 Experimental Results

5.2.1 Operational Size

We initially studied the impact of the charging rate $\Delta = 5W$ [24] on the operational size. The results confirm the empirical immortality of all nodes for all considered network sizes during the simulation horizon. The CLL strategy allows all sensors to stay operational at all times of simulation horizon, even for network of size $n = 500$ (see Figure 1). This result has been reported only for network of size $n \leq 200$ in literature [33].

Summarizing, no other strategy in literature, regardless of communication and computation overhead, can do better than CLL under the considered parameters. To examine the effectiveness of the CLL strategy further, we examined its performance under charging rate of $\Delta = 3.4W$ [6], which is significantly lower than the standard charging rate $\Delta = 5W$. The CLL strategy continues to maintain a high operational size. For instance, it achieves empirical immortality over simulation horizon for networks less than or equal to $n = 300$ sensors. For $n=400$, the number of non-operational sensors is less than 5%, yielding the network of size $n = 400$ to become near immortal.

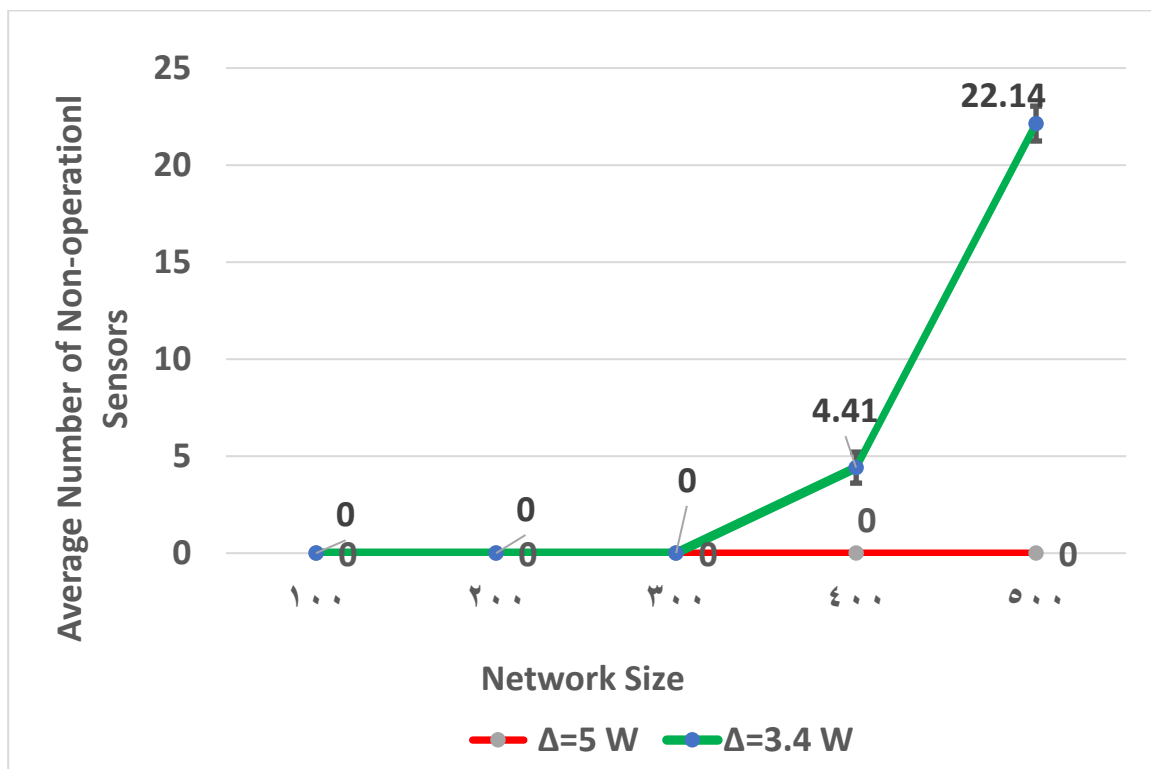
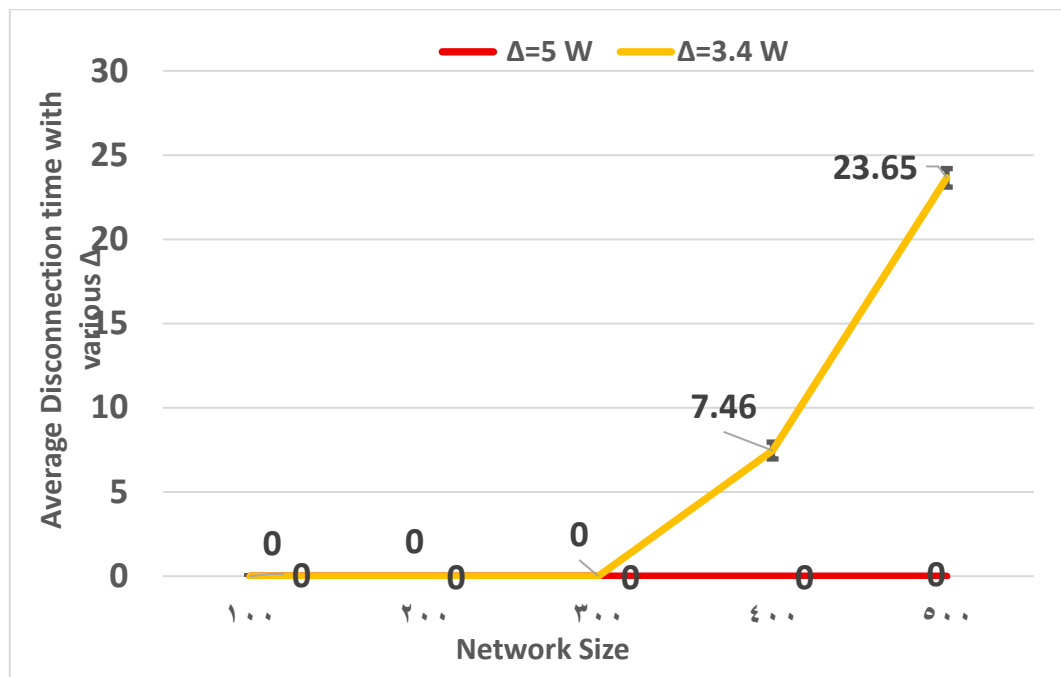


Figure 1. Average non-operational size with various Δ .

Although, increasing network size with slower charging rates reduces operational size, the CLL strategy maintains high operational is for $n \geq 400$. Specifically, for $n = 400$, CLL maintains a 98.8% operational size and keeps non-operational sensors below 5 sensors. Even for $n = 500$, operational size remains above 95%, with 22 non-operational sensors.

Figure 2. Average disconnection time with various Δ .

5.2.2 Disconnection Time

Evaluating node disconnection time captures the lifespan of sensing holes for non-operational sensors. Following the results of previous section, we found that CLL strategy achieves zero disconnection time for all networks ($n \leq 500$) under the standard charging rate $\Delta = 5\text{ W}$. CLL continues to achieve zero disconnection time with $\Delta = 3.4\text{ W}$ for networks of size $n \leq 300$.

Under the lower charging rate ($\Delta = 3.4\text{ W}$), the average disconnection time for $n = 400$ remains less than 5% of total battery operational lifetime $T_{E_{\max}}$, the disconnection time is approximately 7.46 hours (see Figure 2). For $n = 500$, the average disconnection time remains under 24 hours, that is, 13.8% of $T_{E_{\max}}$.

6 Continuous Local Learning vs Periodic Strategies

In the previous sections, we introduced and empirically evaluated the Continuous Local Learning (CLL) charging strategy, demonstrating that the system maintains empirical immortality or near-immortality across large-scale WRSN deployments. CLL achieves these significant results while maintaining simplicity, high scalability, and minimal reliance on communication or computation resources.

These traits, architectural simplicity and lightweight control signaling, are also characteristic of periodic (static) charging strategies. In a typical periodic scheme, MC continuously traverses a predetermined order of sensor nodes X , charging batteries as needed (e.g., [30], [33]). Apart from the offline precomputation of order X , no further global control or real-time calculations occur.

Consequently, periodic dispatch proceeds as a continuous sequence of identical tour cycles. Total round duration equals the total time spent charging nodes' batteries plus the total moving time between consecutive nodes. Minimizing travel overhead requires charging order X to form an optimal Hamiltonian cycle. We denote by H the baseline periodic charging strategy using an

optimal Hamiltonian path. The authors of [33] implement X as traveling salesman path, which is generated offline at the BS using exact solver (e.g., the Concorde TSP Solver), communicated to MC and executed repeatedly by across all operational rounds.

Despite sharing low communication overhead, computation capabilities and short distance communication, CLL and H strategies have many differences. In periodic strategies, the traversal order remains fixed regardless of the changes in network conditions. CLL is dynamic and adaptive, as the charging order continuously adjusted based on real-time energy information collected at visit time. This section investigates the adaptability of CLL compared to static periodic strategy H .

6.1 Experimental Results

To evaluate the performance of Continuous Local Learning (CLL) strategy and the static Hamiltonian baseline strategy H , we expanded the comparison parameters presented in Section 5.1 (Table 2). We studied the impact of battery capacity on the performance of both strategies; thus, we introduced another battery capacity, $E_{max}=15.98$ KJ, in addition to standard battery capacity $E_{max}=10.8$ KJ. Furthermore, we consider lower MC velocity of $v = 2$ m/s (e.g., [36], [44]), in addition to standard velocity of $v=5$ m/s. Across all evaluated network densities, charge rates, and hardware configurations, empirical results confirm that CLL strategy consistently outperforms H strategy.

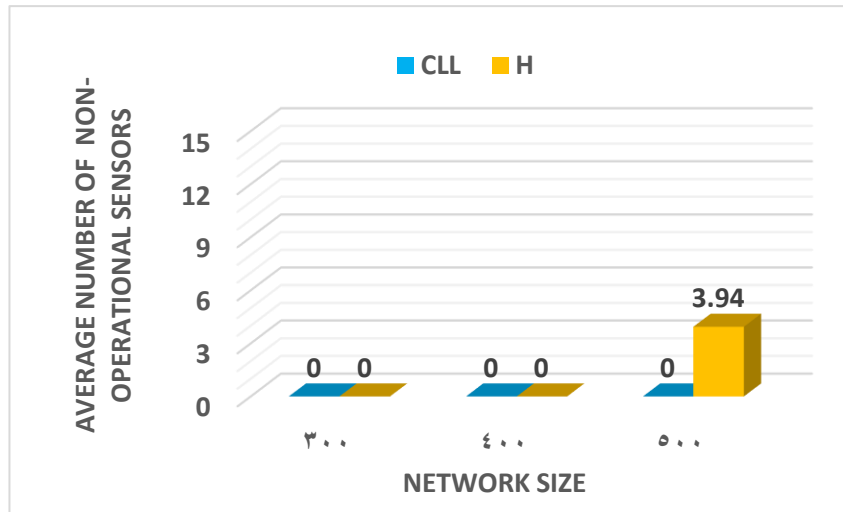
6.1.1 Operational Size

For network sizes up to $n \leq 400$ nodes, both strategies achieve empirical immortality under the standard charging rate $\Delta = 5$ W. However, by increasing network size to $n = 500$, CLL maintains empirical immortality across the entire evaluation horizon, where H suffers from operational size degradation, on average four sensors become non-operational (see Figure 3).

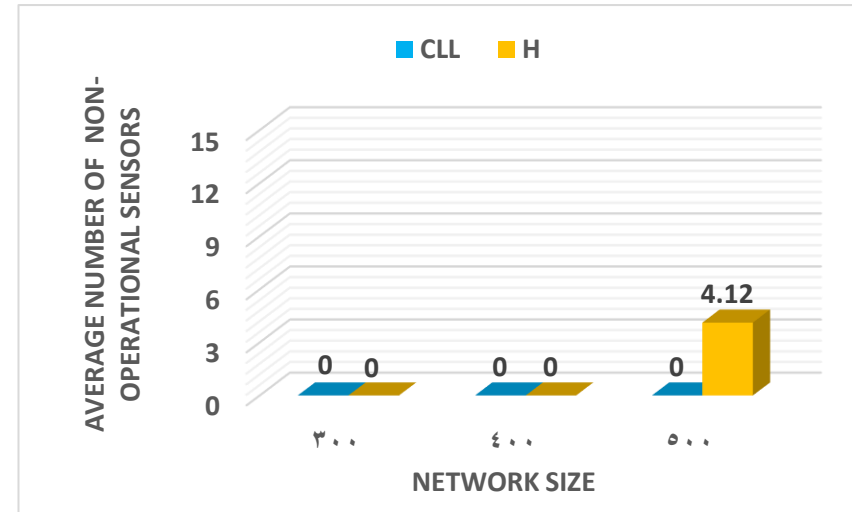
Under the constrained charging rate $\Delta = 3.4$ W, both schemes achieve empirical immortality for smaller deployments ($n \leq 200$). However, for denser networks ($n \geq 300$), performance differences become noticeable across varying combinations of battery capacity E_{max} and charger speed v see Table 3 and Figure 4.

Table 3: Average Non-Operational Size for $\Delta = 3.4$ W

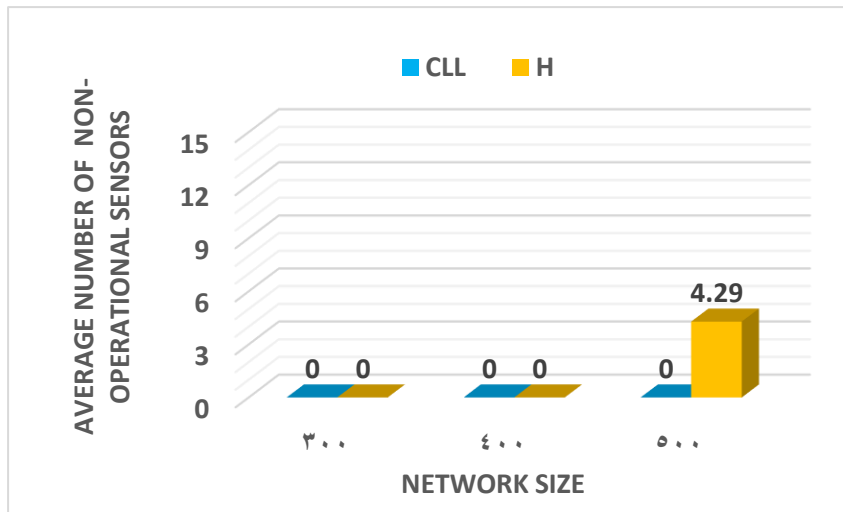
Strategy	n	$E_{max}=10.8,$ $v=5 \pm \text{CI error}$	$E_{max}=10.8,$ $v=2 \pm \text{CI error}$	$E_{max}=15.98,$ $v=5 \pm \text{CI error}$	$E_{max}=15.98,$ $v=2 \pm \text{CI error}$
CLL	300	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.018	0.0 ± 0.0
H	300	0.88 ± 0.12	1.29 ± 0.18	1.03 ± 0.15	1.50 ± 0.21
CLL	400	4.71 ± 0.38	5.57 ± 0.42	5.56 ± 0.41	6.42 ± 0.49
H	400	6.67 ± 0.51	7.09 ± 0.54	7.79 ± 0.58	8.28 ± 0.62
CLL	500	22.14 ± 1.15	23.23 ± 1.2	23.05 ± 1.18	24.90 ± 1.28
H	500	27.16 ± 1.34	28.32 ± 1.4	28.34 ± 1.39	30.17 ± 1.48



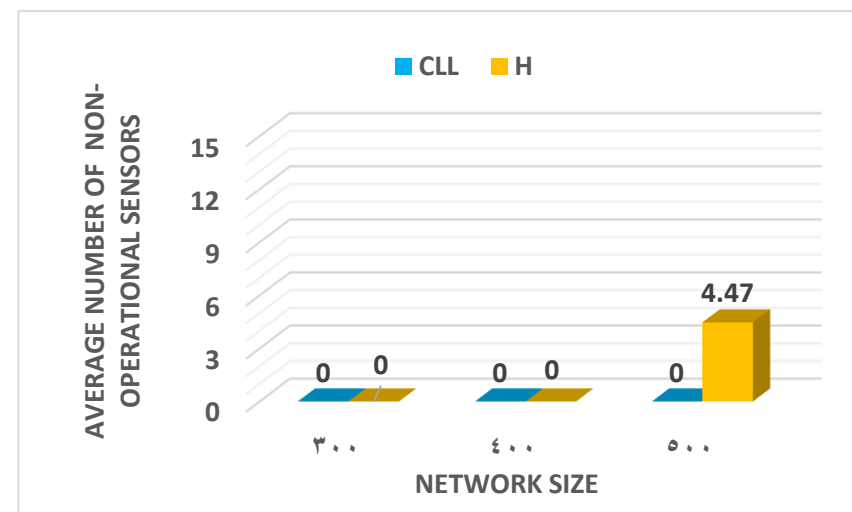
(a)



(b)

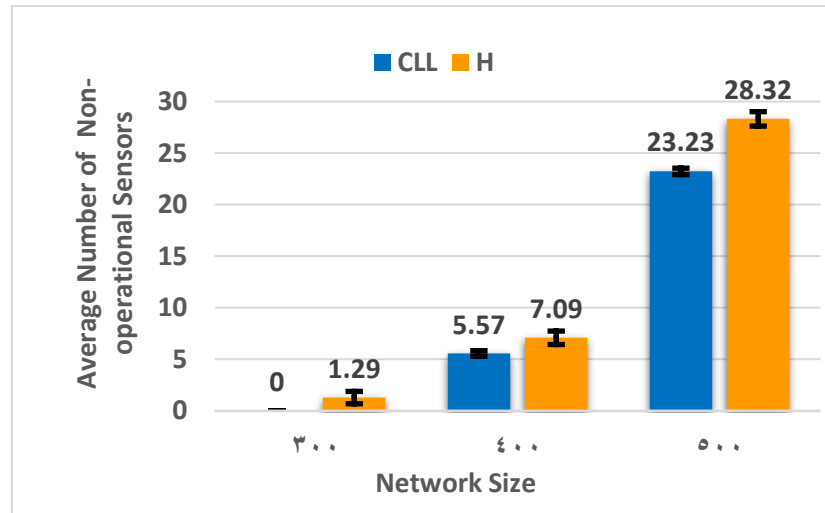


(c)

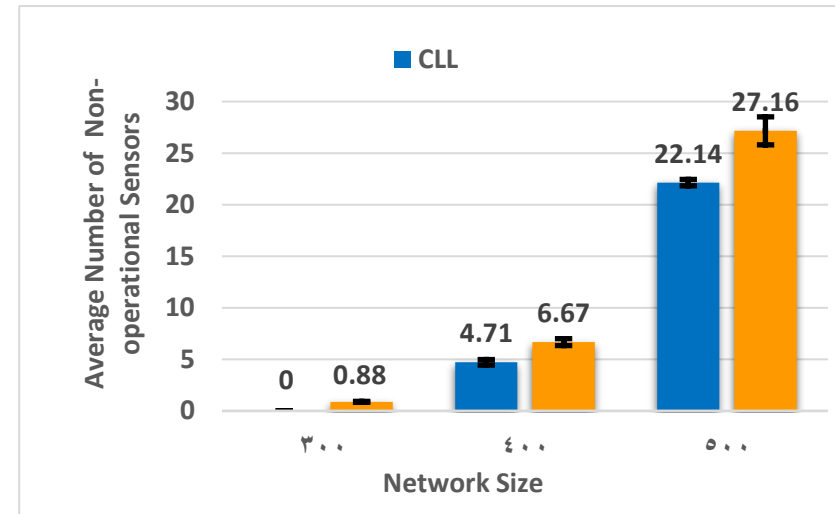


(d)

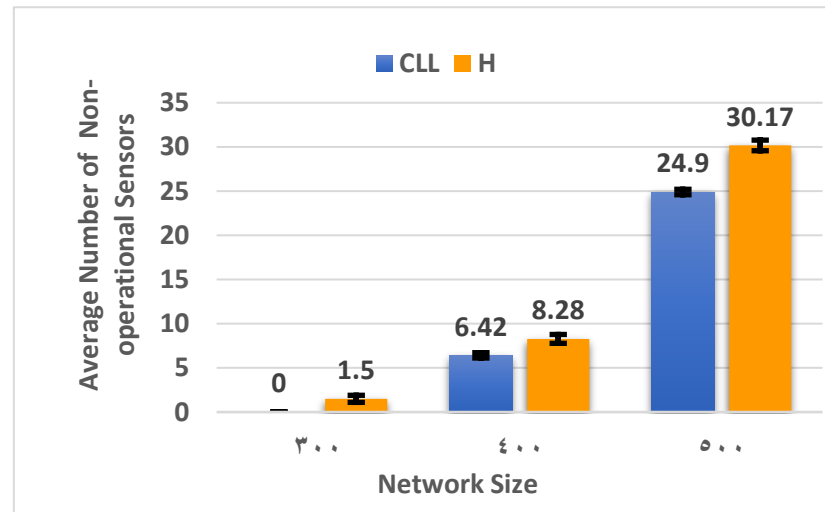
Figure 4. Average non-operational size for $\Delta = 5W$. (a) $E_{max} = 10.8$ KJ; $v = 2$ m/s. (b) $E_{max} = 10.8$ KJ; $v = 5$ m/s. (c) $E_{max} = 15.98$ KJ; $v = 2$ m/s. (d) $E_{max} = 15.98$ KJ; $v = 5$ m/s.



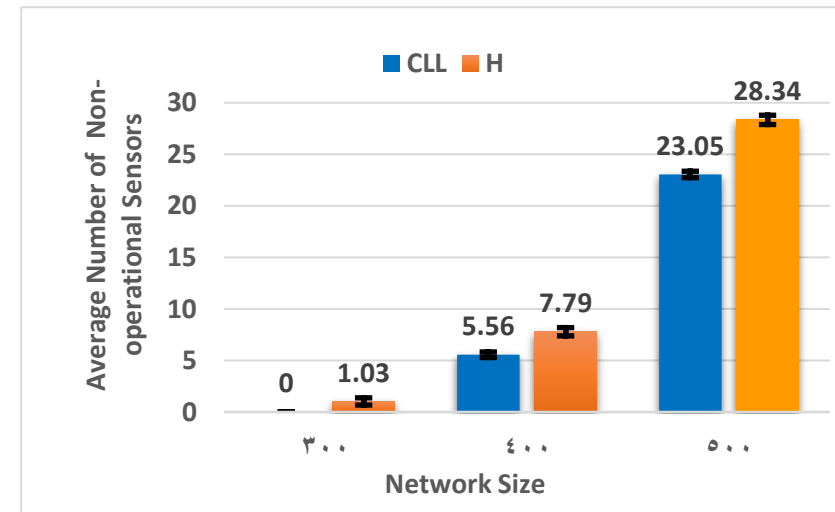
(a)



(b)



(c)



(d)

Figure 5. Average non-operational size for $\Delta = 3.4W$. (a) $E_{max} = 10.8$ KJ; $v = 2$ m/s. (b) $E_{max} = 10.8$ KJ; $v = 5$ m/s. (c) $E_{max} = 15.98$ KJ; $v = 2$ m/s. (d) $E_{max} = 15.98$ KJ; $v = 5$ m/s.

The impact of $E_{\max}$ when $v = 5\text{m/s}$ is shown in Figure 4 (b) and (d). For $n = 300$, with both battery capacities, CLL achieves empirical immortality over simulation horizon, while H has a small but not null number of non-operational sensors. For network sizes $n = 400$ and $n = 500$, the difference between the performance of CLL and that of H becomes slightly more noticeable. In the case of $E_{\max} = 15.98\text{kJ}$, CLL is better than H by 1.40 times with $n = 400$ and 1.23 times better than H with $n = 500$.

At the lower speed $v = 2\text{ m/s}$ (see Figure 4 (a) and (c)), a similar trend is observed. CLL achieves empirical immortality for $n = 300$, whereas baseline H continues to suffer a non-zero count of non-operational sensors.

For larger networks, considering the higher battery capacity $E_{\max} = 15.98\text{ kJ}$, CLL outperforms baseline H by **1.29 times** for $n = 400$ and by **1.21 times** for $n = 500$. Under the standard battery capacity $E_{\max} = 10.8\text{ kJ}$, CLL demonstrates superior performance over H by **1.27 times** and **1.22 times** for network scales of $n = 400$ and $n = 500$, respectively.

6.1.2 Disconnection Time

The operational distinction between the two strategies is most pronounced when examining average disconnection time, which measures the mean lifespan of sensing gaps.

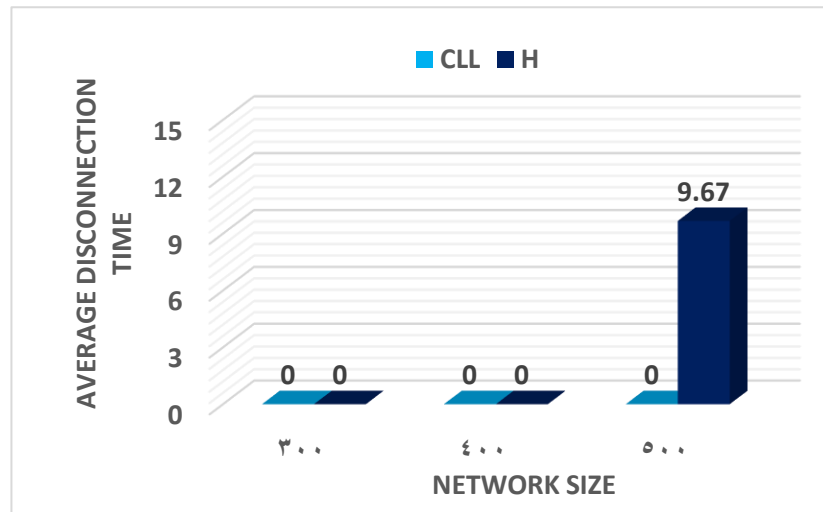
CLL maintains the empirical immortality for all networks of size ($n \leq 500$) under the standard charging rate $\Delta = 5\text{ W}$, which constitutes zero disconnection time over the evaluation horizon. In contrast for $n=500$, H strategy presents an average disconnection time of 9.67 hours under $E_{\max} = 10.8\text{ kJ}$ and $v = 5\text{ m/s}$ and 11.91 hours under $E_{\max} = 15.98\text{ kJ}$ and $v = 2\text{ m/s}$, As shown in Figure 5.

Under the Lower charging rate $\Delta = 3.4\text{ W}$, CLL and H strategies achieve zero disconnection time for networks of ($n < 400$).

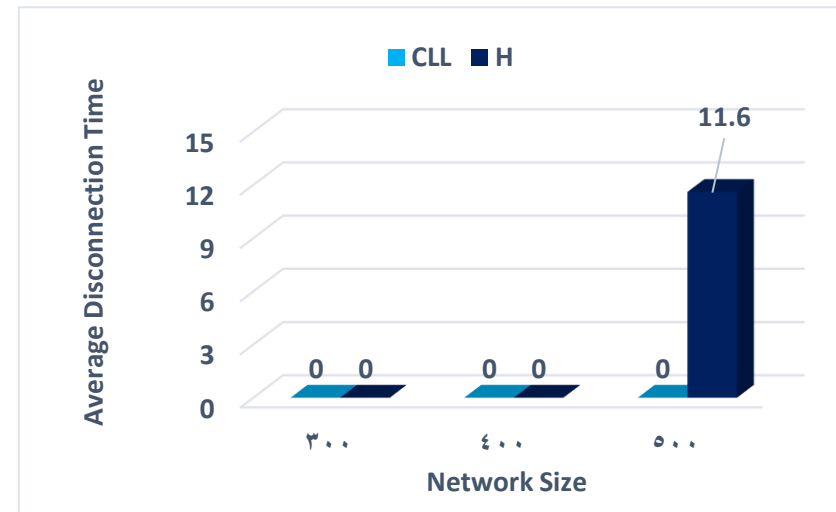
The average disconnection time results of all combinations of battery capacity $E_{\max}$ and charger velocity for network of $n \geq 300$ are shown in Figure 6 and Table 4. For instance, under the combination of $E_{\max} = 15.98\text{ kJ}$ and $v = 5\text{ m/s}$, for $n=300$ CLL maintains a disconnection time of zero hours, whereas H experiences 1.65 hours average disconnection time. For $n=400$, the average disconnection time for CLL strategy is 8.2 hours, which is 2.91 times less than H strategy with 23.83 hours. For $n=500$ CLL limits the disconnection time to 24.67 hours, where H sustained a 40.94 hours.

Table 4: Average Disconnection Time for $\Delta = 3.4\text{W}$ (Hours)

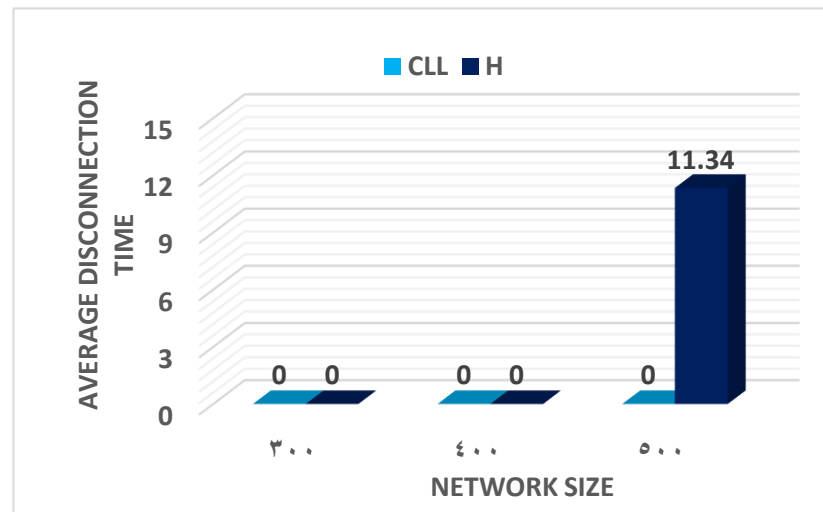
Strategy	n	$E_{\max}=10.8,$ $v=5 \pm \text{CI error}$	$E_{\max}=10.8,$ $v=2 \pm \text{CI error}$	$E_{\max}=15.98,$ $v=5 \pm \text{CI error}$	$E_{\max}=15.98,$ $v=2 \pm \text{CI error}$
CLL	300	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0
H	300	1.25 $\pm$ 0.19	2.48 $\pm$ 0.31	1.65 $\pm$ 0.22	2.82 $\pm$ 0.35
CLL	400	7.46 $\pm$ 0.62	8.49 $\pm$ 0.71	8.20 $\pm$ 0.68	11.76 $\pm$ 0.94
H	400	22.16 $\pm$ 1.45	22.87 $\pm$ 1.53	23.83 $\pm$ 1.58	24.90 $\pm$ 1.63
CLL	500	23.65 $\pm$ 1.52	25.92 $\pm$ 1.67	24.67 $\pm$ 1.61	27.35 $\pm$ 1.76
H	500	38.66 $\pm$ 2.15	40.19 $\pm$ 2.25	40.94 $\pm$ 2.29	43.79 $\pm$ 2.41



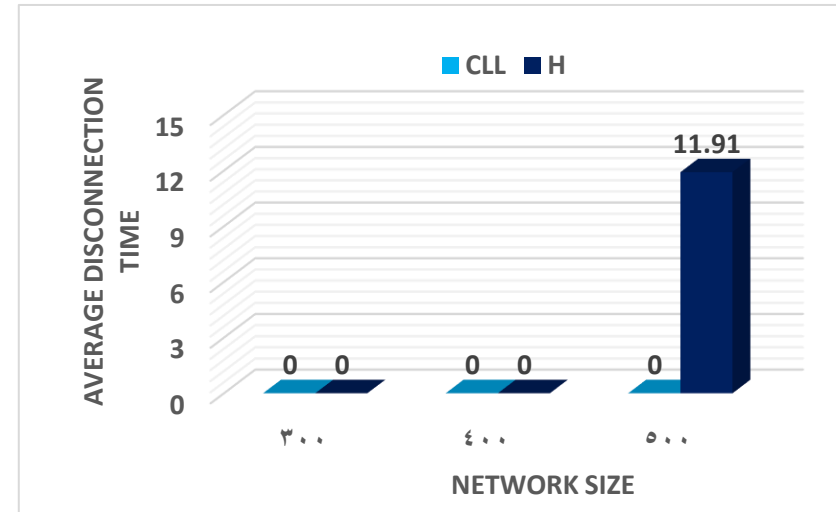
(a)



(b)

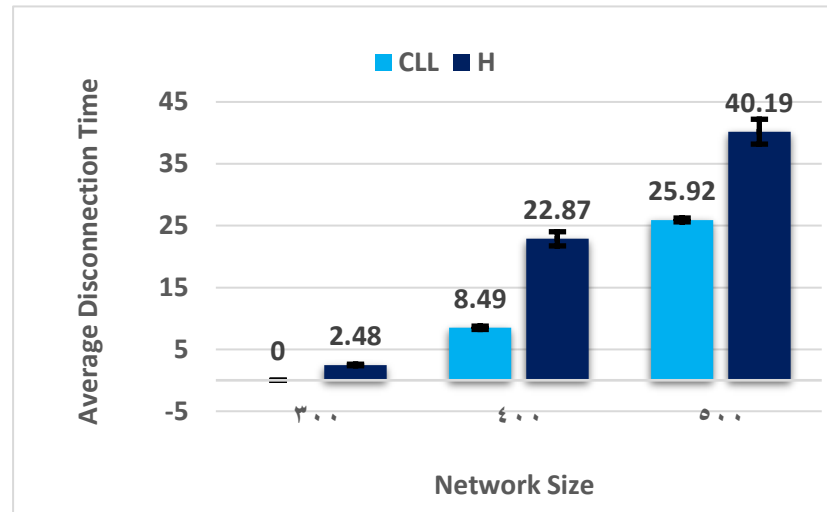


(c)

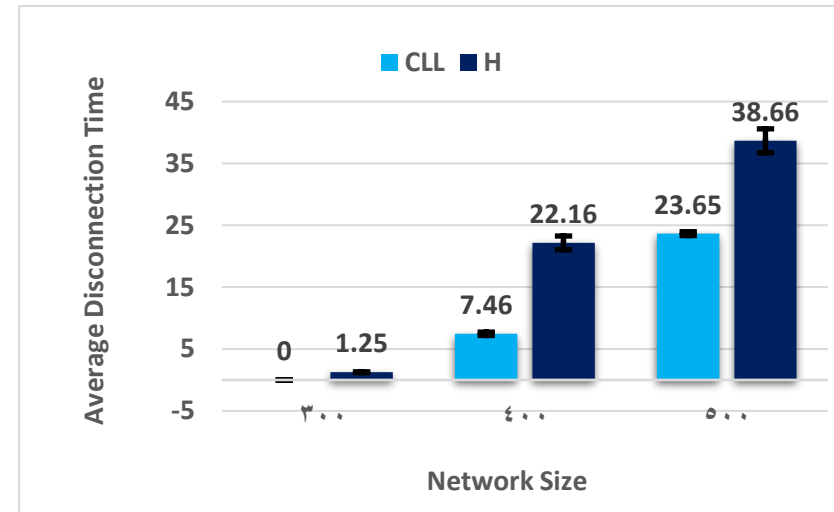


(d)

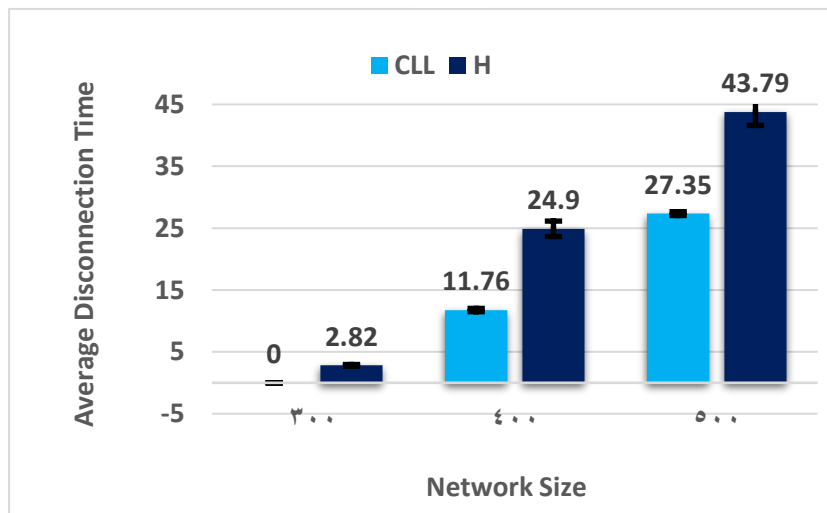
Figure 5. Average Disconnection time for $\Delta = 5W$. (a) $E_{max} = 10.8$ KJ; $v = 2$ m/s. (b) $E_{max} = 10.8$ KJ; $v = 5$ m/s. (c) $E_{max} = 15.98$ KJ; $v = 2$ m/s.(d) $E_{max} = 15.98$ KJ; $v = 5$ m/s.



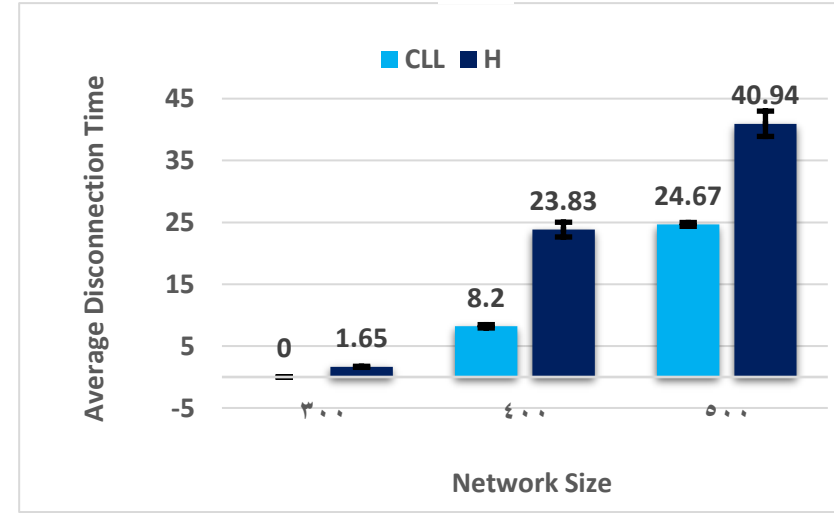
(a)



(b)



(c)



(d)

Figure 6. Average Disconnection time for $\Delta = 3.4W$. (a) $E_{max} = 10.8$ KJ; $v = 2$ m/s. (b) $E_{max} = 10.8$ KJ; $v = 5$ m/s. (c) $E_{max} = 15.98$ KJ; $v = 2$ m/s.(d) $E_{max} = 15.98$ KJ; $v = 5$ m/s.

Turning to another combination of $E_{\max} = 10.8$ kJ and $v = 2$ m/s similar behavior is observable. For instance, CLL achieves better performance than H across all network configurations. For $n = 500$, CLL maintains 1.55 *times* reduction in average disconnection time, that is, CLL experiences 25.92 hours in comparison to 40.19 hours for H . For $n = 400$, the performance difference is higher: CLL yields an average disconnection time of 8.49 hours versus 22.87 hours for H , representing a 2.69 *times* improvement).

6.2 Discussion

Experimental results consistently demonstrate the significance of the Continuous Local Learning (CLL) in comparison with static Hamiltonian strategy H . CLL achieves empirical immortality over simulation horizon across a wider spectrum of operational parameters and network sizes ($n \in [100, 500]$) than H . Under non-immortal configurations, CLL systematically outperforms H . The performance gap between CLL and H in terms of average disconnection time is much higher, while the operational size of CLL remains positive. The average disconnection time of non-operational sensors under H experiences a 50% to 300% longer than those non-operational sensors under CLL.

These findings confirm the significance of CLL on enhancing network availability beyond static charging strategies while retaining their main features (simplicity, scalability, and minimal communication and computational overhead). However, results show that H strategy maintains shorter travel distance and less energy for movement.

The results reveal the influence of hardware parameters (i.e., MC velocity, battery capacity, charging rate) on system performance for both strategies. Moreover, the combination of $E_{\max}$ and v parameters directly affect the performance metrics. For example, the combination of small $E_{\max} = 10.8$ kJ and velocity of $v = 5$ m/s presents the most advantageous option, whereas the combination of $E_{\max} = 15.98$ kJ and $v = 2$ m/s presents the most challenging configuration.

7 Conclusions

In this paper, we proposed Continuous Local Learning (CLL) strategy, a novel online distributed strategy, where the Mobile Charger (MC) dynamically adapts its charging schedule online using single-hop communication during service visits. MC continually updates node depletion estimates, and thus the charging order, without global knowledge of the network state, or charge requests.

Extensive simulations demonstrate that CLL achieves empirical immortality over a finite simulation horizon under a wide range of operational configurations. Nevertheless, it maintains higher operational size and lower disconnection time. CLL maintains near immortality, where less than 5% of nodes become non-operational and the disconnection time does not exceed 5% of sensor's lifespan. This implies that, regardless of the amount of ongoing communications and a priori knowledge, no other strategy achieves better results.

Compared to the static charging strategy (H), CLL shows higher effectiveness while sharing the same features of minimal communication and computation overhead, simplicity, and scalability. Furthermore, CLL preserves adaptability (the ability to change charging order online) while H follows a static, predetermined charging order. Empirical comparisons show the significance of CLL in reducing the average disconnection times by 50% to 300%.

As an extension of this work, we plan first to extend the study of effectiveness using multiple mobile chargers, which introduces a problem of coordination between MCs but helps in achieving empirical immortality for very dense or large-scale networks. Second, investigate the adaptability of CLL to variations in network topology and surges in data rates. Finally, evaluate the effectiveness and adaptiveness of CLL against a testbed of existing online strategies is another research direction.

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Conflicts of interest. [Not Applicable]

Ethics approval. [Not Applicable, authors confirm that the study uses a discrete-event simulation of a wireless sensor network and involves no human or animal subject]

Informed consent. [Not applicable]

Data and code availability. [available at: <https://github.com/oiro81/CLL-Algorithm.git>]

Author contributions. [Osama I. Aloqaily: Conceptualization, Methodology, Formal Analysis, MATLAB Simulation Development), Investigation, Writing Original Draft, Writing Review & Editing. Mohammad F. Al-Hammouri: Formal Analysis, Writing Review & Editing. Islam T. AlMalkawi: Validation, Writing Review & Editing. Eman Omar: Conceptualization, Formal Analysis, Visualization, Writing Review & Editing. Abdullah Aref: Formal Analysis, Validation, Writing – Review & Editing. Md Mahmud Hasan: Conceptualization, Writing Review & Editing, Supervision.]

Use of artificial intelligence. [Not Applicable.]

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