DECONN: Combining Minimum and Neutral Energy Consumption Strategies in IoT Networks

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***Abstract*—In Low-Power Internet-of-Things (IoT), energy provisioning is often heterogeneous, meaning that nodes with rechargeable and non-rechargeable batteries coexist and collaborate to support data communication. Non-rechargeable nodes pose the requirement of minimum energy consumption for maximizing their network lifetime. Nodes powered by rechargeable batteries, in turn, must foster neutral energy consumption to avoid battery depletion and overflow. In this context, keeping one subset of nodes in neutral consumption and another subset in minimum consumption while maintaining proper network operation is a complex challenge to solve. To tackle this problem, we propose in this paper the Dual Energy COnsumption for interNet-of-thiNgs (DECONN). DECONN is a distributed solution designed to combine minimum and neutral consumption for IoT networks with heterogeneous energy provision. Using DECONN, nodes with the lowest amount of energy determine the energy consumption of the nodes located in the communication path. We compare DECONN with current IoT low-power standard protocols, such as RPL and CoAP. The results achieved provide evidence that DECONN may outperform standard protocols regarding the amount of saved energy for non-rechargeable and time in neutral operation for rechargeable nodes.**

***Index Terms*—Internet-of-Things; Energy Sources; Renewable;**

I. Introduction

A massive number of Internet-of-Things (IoT) devices have been deployed to provide data monitoring to many IoT applications, such as smart metering, e-health, Industry 4.0, and precision agriculture [1]. For many years, the main research challenge in terms of power provision was to save energy and extend the network lifetime of non-rechargeable battery-powered devices [2], [3]. In recent years, a new era for IoT power provision based on energy harvesting [4] emerged. Energy harvesting replenishes energy for the IoT device by extracting energy from solar power, ambient radio frequency, and thermal energy. The harvested energy is stored in the nodes' rechargeable battery. Since the harvested energy is renewable, it may be a sustainable and greener solution in comparison to the traditional non-rechargeable batteries [5].

Given the large number of deployed IoT devices using non-rechargeable batteries, a tendency when deploying IoT devices with rechargeable batteries is to make them inter-operate. It means that nodes with rechargeable and non-rechargeable energy provision will be online in the same network, handling communication channels for transferring data generated by the IoT devices. In this context, devices powered by renewable and non-renewable sources must collaborate and coexist for data communication. However, combining these two energy sources in the same network is challenging since they follow different energy consumption strategies. Traditional devices, i.e., non-rechargeable, seek to minimize energy consumption since they have a limited energy supply. On the other hand, rechargeable devices aim to achieve neutral consumption, which means the node must consume the same amount of energy that has been harvested to avoid battery overflow and depletion.

Most of the current approaches do not propose solutions considering both energy sources in the same network. There are proposals for controlling the parent selection and data aggregation levels to optimize the energy consumption and achieve a long-term neutral operation for a low-power IoT network. However, all nodes have batteries replenished by energy harvesting [6], [7] . Despite the benefits of energy harvesting, it is not realistic to assume only renewable energy sources for low-power IoT networks.

To address this challenge, we propose in this paper the Dual Energy COnsumption for interNet-of-thiNgs (DECONN). DECONN is designed to tackle the problem of having renewable and non-renewable energy sources in the same IoT Network. It can reduce energy consumption for non-rechargeable nodes and seek neutral operation for rechargeable IoT devices, applying data aggregation and computing tree-oriented routing schemes. With regard to routing, DECONN takes into account the energy type, i.e., renewable or non-renewable, and the level of the batteries in the paths. Using DECONN, the node with the lowest amount of energy determines the energy consumption of the nodes in the communication path.

The contributions of this paper are threefold: (i) It proposes a distributed solution for tree-based routing that combines minimum and neutral energy consumption in the same network; (ii) It extends the Routing Protocol for Low-Power Lossy Networks (RPL) [8] and Constrained Application Protocol (CoAP) [9] protocols to embed the DECONN code in emulated real low-power IoT devices; (iii) It evaluates traditional and renewable nodes using a non-linear battery model in an evaluation environment that replicates actual indoor light measurements as a source of energy harvesting.

The remainder of this paper is organized as follows. We discuss related work in Section II. We introduce and discuss DECONN, our solution for combining minimum and neutral energy consumption in IoT in Section III. We describe our experimental evaluation in Section IV and discuss the results achieved. Finally, we close the paper in Section V with concluding remarks and prospective directions for future research.

II. Related Work

Nguyen et al. [7] proposed the Energy-Harvesting-Aware Routing Algorithm (EHARA), a solution that chooses the best routes by using two different cost metrics defined as combinations of the consumed energy, the harvested energy, and the residual energy at nodes. Their work considers a network where the nodes have heterogeneous energy harvesting sources, including solar, movement, and RF-based. Similar to DECONN, EHARA selects the routes based on the residual energy on the batteries in the upward path. However, EHARA does not consider a network with rechargeable and non-renewable nodes.

Said et al. [10] proposed Energy Management Scheme (EMS), a solution that considers heterogeneous types of energy-constrained nodes. EMS applies data aggregation to control the volume of data sent over the network to regulate energy consumption. EMS also proposes schedule and fault tolerance for the IoT environment, and considers heterogeneous energy sources, including traditional and renewable batteries. EMS focuses on providing different fault-tolerance strategies based on the energy source type. Besides, EMS is centralized and is evaluated in NS2, which does not emulate real low-power IoT devices.

Gambín et al. [11] addressed a smart-city scenario in which the IoT Gateways (GWs) are connected to an electrical grid and equipped with a backup battery to provide resilience to power network outages. In this scenario, IoT devices have energy harvesting capabilities, but they are not satisfactorily served by energy harvesting due to the instability of ambient energy arrivals. The authors formulated a convex optimization problem that finds the optimal solution to allocate energy, including the possibility of transferring energy from the GWs to the IoT devices with scarce energy resources.

In [12], [13], Tipantuna et al. proposed solutions involving renewable energy and IoT. In their work, the IoT network provide the communication infrastructure for a response-demand architecture that promotes the interaction between generators and consumers of an urban electric system. Therefore, their focus is not to optimize the energy consumption of the IoT but to seek efficient management of renewable and non-renewable energy sources in an urban electric grid system.

Sadek et al. [14] proposed Hybrid Protocol for heterogeneous devices in IoT (Hy-IoT). The Hy-IoT solution considers the nodes may have renewable and non-renewable energy sources. This solution divides the network into superior and regular regions. The regular region is composed of sensors, actuators, and RFIDs. The superior region has mobile phones and smart controllers. Hy-IoT uses the following cluster-based algorithms: Stable Election Protocol (SEP) and Low Energy Adaptive Clustering Hierarchy (LEACH). Cluster-head selection is carried out in the superior region by LEACH, while nodes in the regular region compute the cluster-head using SEP. Although Hy-IoT considers nodes with rechargeable batteries, these nodes are not charged by an energy harvesting process, such as solar or vibration. The rechargeable devices are smartphones, which have batteries with high capacity and are recharged regularly using the electric grid. Therefore, Hy-IoT does not address the challenge of combining IoT nodes powered ambient energy harvesting and traditional batteries in the same network.

To sum up, the existing literature does not cover the problem of having renewable and non-rechargeable batteries providing energy for nodes in the same low-power IoT network. This is a relevant open issue, not only from the point of view of energy efficiency, but also for the environment to support the integration of both energy sources. This is a more feasible approach for handling legacy networks than promoting a massive replacement of devices with non-rechargeable batteries.

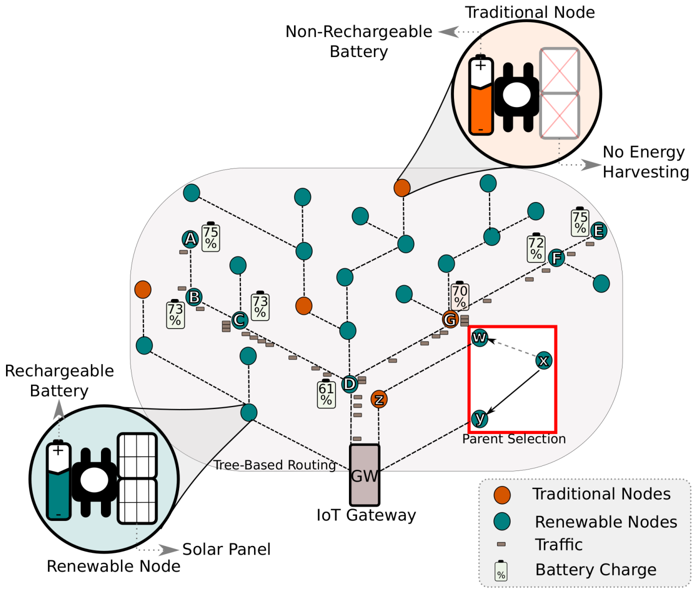
III. DECONN: Dual Energy Consumption for Internet-of-Things

In this section we present our solution for Dual Energy COnsumption for interNet-of-thiNgs (DECONN). We begin with an overview in Section III-A. In Section III-B, we introduce the DECONN parent selection process and in Section III-C we discuss data aggregation. Finally, we provide implementation details of DECONN in Section III-D.

A. Overview

Figure 1 depicts an overview of DECONN, considering a network with heterogeneous (renewable and traditional) nodes. The renewable nodes are equipped with hardware that can do energy harvesting (e.g., solar panels). The traditional nodes have only non-renewable batteries. The illustrated network executes a tree-based routing, where each node selects one parent node to create a route towards the IoT gateway (GW).

The primary objective of DECONN is to select the parent toward the GW that maximizes the minimum energy available energy on the path, giving preference for full renewable routes over traditional batteries. For instance, the red box in Figure 1 shows the parent selection executed by node X. Node X has two possible parents towards GW. If node X chooses Y, it is a path where all the nodes have renewable energy. If node X selects W, it is not a full renewable path since node Z is a traditional node. Therefore, node X must select node Y as a parent because DECONN prefers routes where all node is renewable nodes. When a node has multiple full renewable paths to choose from, it selects the parent that leads to the



From	To	Route	Min. Energy on Route	Type	Data Agg. Level on Route
A	GW	A - B - C - D - GW	61%	Renewable	40%
E	GW	E - F - G - D - GW	70%	Traditional	100%

Fig. 1: A conceptual overview of DECONN.

route with the maximum value among the minimum energy available on the route.

After the parent selection, the produced traffic flows towards the GW from the nodes. Each node can apply data aggregation to the routed traffic. DECONN computes the data aggregation level for each route according to the minimum energy available on the route and the type of energy source. For instance, the route from A to GW includes the nodes B, C, and D. Among these nodes, node D is the one that has the minimum energy available on the route, and it is a full renewable path. So, DECONN sets the aggregation level for this route at 40% (the actual computation of this number is shown in Section III-B). Let us consider another route, from E to GW. This route includes F, G, and D. Among these nodes, node D has the minimum energy available, with 61%, but node G is a traditional node with 70% of battery charge. In this case, DECONN sets the data aggregation level in 100%, i.e., maximum. The maximum data aggregation level for this case is since node G will deplete its battery before node D since it cannot recharge its battery, considering similar consumption for both. With the maximum data aggregation level in this route, the lifetime of node G will be prolonged.

B. DECONN Parent Selection

Algorithm 1 presents the DECONN algorithm for parent selection. To illustrate, consider node A running this algorithm. DECONN stores in A the *pathEnergy* information received from the set of parent candidates. The received *pathEnergy* reveals what is the minimum energy level on the path for each candidate. In case *pathEnergy* is zero, there is at least one node in the path that has a non-rechargeable battery. For node A, DECONN selects as a parent the candidate with maximum *pathEnergy*. In the end of this process, node A has to announce its *pathEnergy* to other nodes which are considering A as a parent candidate. Before this announcement, Node A assigns zero to *pathEnergy* if it uses traditional battery. Besides, the announced value is the minimum value between the maximum *pathEnergy* and the residual energy on the node's A battery.

Algorithm 1 Parent Selection.

Start
  while (*Rx from candidate_set*) **do**
    PathEnergy[ ] ← *Receive msg with PathEnergy*
  end while
  Select p with max(PathEnergy[ ])
  maxPathEnergy ← *max(PathEnergy[ ])*
  Announce(*maxPathEnergy*)
  AjustDataAgg(*maxPathEnergy*)
End

---

procedure ANNOUNCE(*maxPathEnergy*)
  if my Battery type == Traditional **then**
    my_Energy ← *zero*
  end if
  newPathEnergy ← *min(my_Energy, maxPathEnergy)*
  Send msg with newPathEnergy
end procedure

---

procedure AJUSTDATAAGG(maxPathEnergy)
  Normalize maxPathEnergy
  DataAggLevel ← *function(Normalized maxPathEnergy)*
end procedure

When a node is executing Algorithm 1, after knowing what is the maximum *pathEnergy* for its selected parent, DECONN adjusts the data aggregation of the node. DECONN normalizes the maximum *pathEnergy*, i.e., computing the percentage, and transforms it to a data aggregation level that is executed on the network traffic flowing through that particular node.

C. DECONN Data Aggregation

Figure 2 illustrates how the data traffic is aggregated in a particular node. As can be observed, the input data considered for aggregation can be received from a neighbour (Label 1.a), or it can be produced by the node itself (label 1.b). In the application layer, the input data is stored (label 2). When the data aggregation timer expires, the input data is aggregated according to the level set by the Algorithm 1 (Label 3). After the aggregated message is produced (Label 4), it passes through the communication layer to be transmitted (Label 5).

Algorithm 2 presents further details on how a node computes the data aggregation. As can be noticed, not all traffic is aggregated. So, when a new message arrives, the node must check if the code in the message's header indicates it is an application data message, e.g., CoAP or Message Queuing Telemetry Transport (MQTT). If the traffic is an application

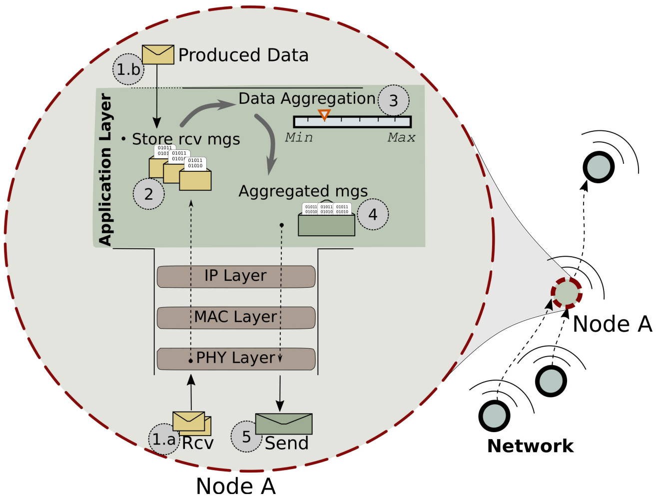


Fig. 2: Data Aggregation approach to control the data traffic.

Algorithm 2 Data Aggregation Algorithm

```
Start
    function NEW_PACKET_ARRIVES(msg)
        typeCode ← parseCode(msg)
        address ← parseAddrs(msg)
        if isDataTrafic(typeCode) and notMyAdd(address) then
            buffer(msg)
            if timer_not_set() then
                set_aggregation_timer()
            end if
        end if
    end function

    function TIMEOUT_AGGREGATION_TIMER( )
        buffer(data_produced)
        p_num ← count_payloads(buffer)
        p_data ← extractPayloads(buffer)
        DataAggLevel ← getAggLevel()
        newPayloadLen ← (DataAggLevel -1) * p_num
        if newPayloadLen == 0 then
            newPayloadLen == 1
        end if
        newPayload ← assembly(p_data, newPayloadLen)
        forward_next_layer(header, newPayload)
    end function
End
```

layer and it is not the final destination, the node stores it and sets a data aggregation timer.

When the timer expires, the node counts the number of stored payloads, including self-produced, and extracts them. Then, it computes the number of payloads the aggregated message must have, using the aggregation level set in Algorithm 1. Then, Algorithm 2 processes the input payloads, applying data aggregation operations, to obtain as an outcome the aggregated payloads. After that, the aggregated payload is inserted in a new application layer message and forwarded.

D. Implementation

We used Contiki [15] – an operating system for tiny and low-power IoT devices – to implement DECONN. The main functionalities were implemented in the routing and application layers. The Constrained Application Protocol (CoAP) [9] and Low-Power Lossy Networks (RPL) [8] were selected for DECONN, as they are standard protocols designed for IoT devices with memory and processing constraints.

RPL is a suitable protocol to implement DECONN's parent selection. It adopts a proactive protocol that establishes a Destination Oriented Directed Acyclic Graph (DODAG) based at a single destination. The RPL DODAG Information Object (DIO) message informs the neighbour nodes about the parent candidates. The RPL code responsible for sending and receiving DIO messages was modified to carry *pathEnergy* information in Algorithm 1. To enable the *pathEnergy* information, we have implemented the Kinetic Battery Model (KiBaM) [16], which is a non-linear battery model. This module allows each node to know its residual battery level.

With regard to data aggregation, extra code was required in the IPv6 layer running the IPv6 over Low-Power Wireless Personal Area Networks (6LowPan) protocol. It was necessary to inspect the header information in the messages to identify the CoAP messages. Every CoAP message in the IPv6 layer is checked. If the message is not in its destination, it goes to the application layer to be stored for aggregation.

We implemented the following data aggregation components in the application layer: (i) Buffer for CoAP messages, (ii) data aggregation timer, and (iii) extraction and computing aggregated payloads. We have considered the following protocol stack: IEEE 802.15.4, 6LowPAN, RPL, UDP, and CoAP. Figure 3 shows how many bytes were used for each protocol header and describes the format for aggregated payloads.

PHY MAC	IPv6	UDP	CoAP	Payload Lenght	Payload 1			Payload N		
					Type	Data		Type	Data	
33	7	8	7	1	2	2	...	2	2	(bytes)

Fig. 3: Header and Payload Format for Aggregated CoAP message.

As can be observed in Figure 3, the payload in the aggregated message uses 2 bytes to indicate the data type and 2 bytes to store the data. Using this specific protocol stack, it was possible to insert up to 17 payloads in the same CoAP message without causing 6LowpAN fragmentation.

IV. Performance Evaluation

Next, we present the experiments carried out to evaluate DECONN. Section IV-A introduces the testing settings and metrics, and Section IV-B shows the obtained results.

TABLE I: Parameter Settings.

Parameter	Value
Protocol Stack	IEEE 802.15.4, 6LowPAN, RPL, UDP, CoAP
Model for (Non-)Rechargeable Batteries	Kinetic Model
Energy harvesting Trace	Columbia University's [18]
Total Number of nodes	80
Number of Rechargeable nodes	72
Number of Non-Rechargeable nodes	8
Simulated Time	72h
Battery Capacity	1000000 microAh

A. Environment Settings and Performance Metrics

DECONN has been implemented in Contiki OS and tested in the Cooja simulator [17]. Table I presents the main settings used for the evaluation tests.

Cooja embeds Contiki code emulating real IoT hardware. The emulated hardware was the following: MSP430 series 5, which has a MicroController Unit (MCU) of 16 bits with 16kB internal RAM and 128kB Flash. The transceiver is TI CC2520 (2.4GHz), compatible with IEEE 802.15.4 and 6LoWPAN.

The Kinetic Battery Model (KiBaM) was set to measure the residual energy on the battery, supporting rechargeable and non-rechargeable nodes. The rechargeable nodes read a data-trace that contains indoor radiant light measurements collected by the Columbia University's [18]. The theoretical solar panel with 170 cm^2 provides an input electric current for KiBaM at 5v. The conversion efficiency is set to 20%. Regarding energy consumption, it is based on Powertrace [19] functionalities, which can measure energy consumption related to Transmit, Receive, Idle Listen, Active CPU, and Low Power CPU.

The objective of this evaluation is to measure the performance of DECONN mainly in terms of (i) Residual Energy (RE) in the battery; and (ii) Energy Consumption. RE is a metric to measure the performance of the rechargeable nodes, and the energy consumption is an evaluation metric for non-renewable nodes.

In this evaluation, DECONN is compared to the Standard Protocol Stack (SPS), which uses the standard version of RPL and does not execute any data aggregation on the network traffic. Besides, SPS uses Minimum Rank with Hysteresis Objective Function as metric for parent selection [20].

Two simulation scenarios have been set to represent a network with Low and High Residual Energy. These scenarios are detailed as follows.

- **Low RE Scenario**: This scenario was set up to simulate a situation where the nodes have low energy on their batteries. To achieve that, at the beginning of the simulation, we set all the batteries with 50000 microAh, which represents 5% of the battery capacity. Besides, each node produces and sends 30 CoAP messages per minute.
- **High RE Scenario**: In this scenario, the nodes have abundant energy in their batteries. In this case, the batteries begin the simulation with 85000 microAh, which is 85% of the battery capacity. Besides, each node produces and sends 120 CoAP messages per minute.

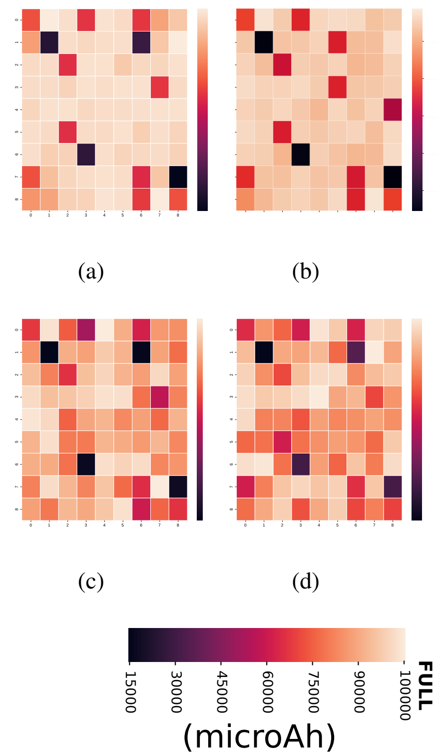


Fig. 4: Heat Map of Residual Energy. a) DECONN in High RE Scenario; b) SPS in High RE Scenario; c) DECONN in Low RE Scenario; d) SPS in Low RE Scenario.

B. Obtained Results

The obtained results shown in this section were computed with a confidence interval of 95% and based on 30 samples.

Figure 4 displays the residual energy for DECONN and SPS at the end of the simulations. Figure 4.a and 4.b depict the High RE scenario. The Low RE scenario is presented in Figure 4.c and 4.d. Visually, it is possible to notice a slight advantage for DECONN, mainly for Low RE scenario. To provide further analysis in High RE scenario, Figure 5 shows the probability distribution function of the residual energies in the network, at the end of the simulation. Based on the data supplied by Figure 5, it is possible to find out the percentage of nodes that have at least a certain amount of residual energy. According to these results, it is possible to notice a superior performance of DECONN. For instance, the SPS probability for residual energy of ≤ 0.97 is 100% and DECONN probability for this same value is around 60%.

Figures 6 and 7 introduce the results in terms of residual energy over time. Figure 6 and 7 are the obtained results for scenarios Low RE and High RE, respectively. In Figure 6, there is a trend line to indicate the tendency of the results. The trend line was computed using the Least Square Method (LSM). It is possible to notice that DECONN tendency is negative at the beginning of day 1. However, at the end of day 3, DECONN has a positive tendency, which indicates that the balance between the harvested and consumed energy is

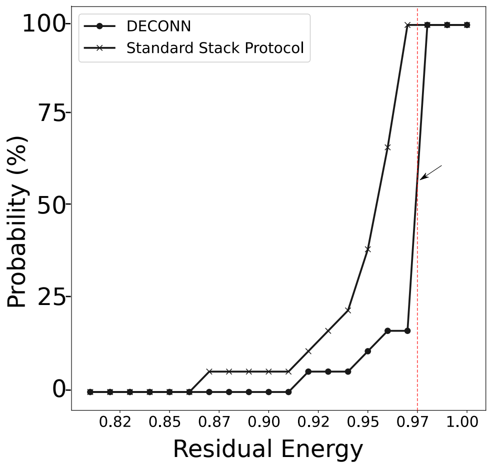


Fig. 5: The probability distribution function of the residual energy in High RE Scenario after 3 simulated days.

positive. This positive tendency benefits the nodes because it indicates that the rechargeable batteries will not deplete in the short-term, which means an extended neutral operation time.

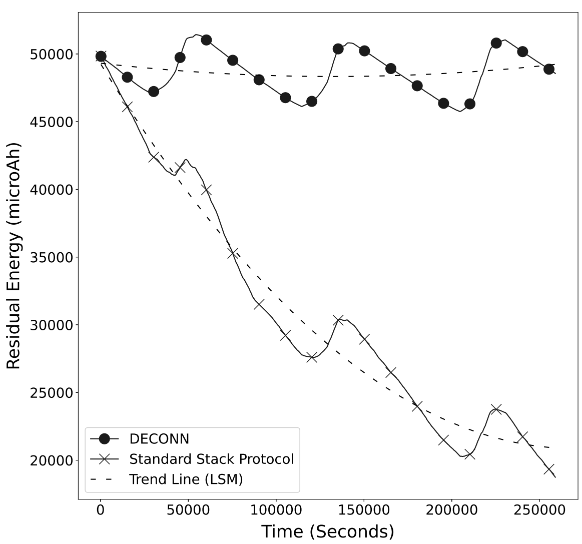


Fig. 6: Residual Energy Over Time of Rechargeable Nodes in Low RE Scenario.

On the other hand, a negative tendency is observed for SPS. Regarding Figure 7, both solutions are discharging the batteries, as expected. If the solutions do not present this behaviour, the batteries will overflow after some days, representing a waste of energy.

So far, the results have focused on residual energy, showing the results for nodes with rechargeable batteries. Figure 8 and 9 present the energy consumption for non-rechargeable batteries.

As can be observed, in both scenarios, DECONN enables lower energy consumption than SPS. This energy consumption

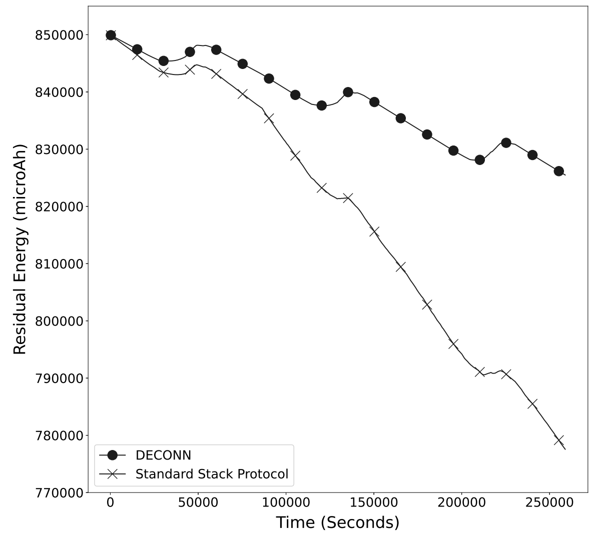


Fig. 7: Residual Energy Over Time of Rechargeable Nodes in High RE Scenario.

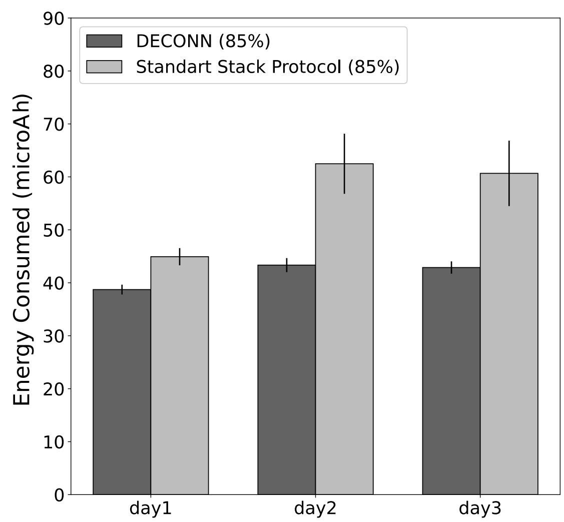


Fig. 8: Energy Consumption of Non-Rechargeable Nodes in High RE Scenario.

reduction prolongs the lifetime of the nodes.

Table II presents the average data aggregation executed by DECONN. This percentage represents the amount of CoAP messages aggregated using data aggregation operations such as average, maximum, minimum, or sum. It is possible to notice that in the Low RE scenario, the aggregation level is 31% on average for three days. In High RE, the average data aggregation percentage is 11%. The results of Table II is expected since, in the Low RE scenario, the nodes have %5 of charge, which means that the network has to save energy by applying higher data aggregation on the traffic.

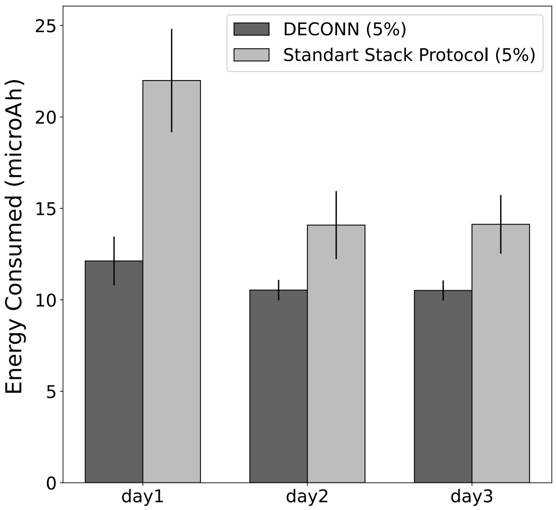


Fig. 9: Energy Consumption of Non-Rechargeable Nodes in Low RE Scenario.

DECONN Data Aggregation Statistics		
	Low RE	**High RE**
day 1	36.35%	13.94%
day 2	29.33%	10.99%
day 3	28.96%	10.99%

TABLE II: Data Aggregation performed by DECONN.

V. Conclusions

While the industry promotes low-cost IoT devices that present interesting trade-offs between resource consumption and effectiveness, environmental issues related to power provisioning in IoT devices can not be neglected. The massive number of nodes powered by non-disposable and non-rechargeable batteries has to be replaced gradually with renewable energy sources. In the meantime, traditional and renewable IoT devices must cooperate to support IoT data monitoring.

To promote the coexistence of renewable and non-renewable energy sources in the same IoT network, we presented and discussed in this paper the Dual Energy COnsumption for interNet-of-thiNgs (DECONN). DECONN is a distributed solution designed to combine minimum and neutral consumption for IoT networks with heterogeneous energy provision. From our experimental evaluation, we observed that DECONN can reduce the energy consumption of traditional nodes and extend the neutral operation of the renewable nodes. As prospective direction for future work, we intend to perform practical experiments in a testbed to validate DECONN and highlight its potential benefits.

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