

# Energy-Aware Optimization of Communication and Computation in Indoor IoT Swarm Networks

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**Abstract** – In this paper, we propose an Energy-Aware Cross-Layer Communication and Computation Optimization (EACCO) framework to maximize energy efficiency and operational lifetime of indoor Internet of Things (IoT) swarm robotic networks. The method takes into account energy harvesting, adaptive scheduling, communication and computation altogether in a single cross-layer optimization framework. Results of simulation show that EACCO reduced the energy consumed per day to 2.0-2.3 Wh/day and obtained the energy neutral ratio (ENR) of 1.05-1.18, increased the packet delivery ratio (PDR) to 95-97% and increased mission lifetime to 30-36 hours compared to other energy-only, EDF and FIFO schedulers under the same operating conditions. The results show the effectiveness of EACCO to design reliable, energy neutral and sustainable indoor IoT swarm robotic systems.

**Keywords** – Indoor Internet of Things, Swarm Robotics, Cross-Layer Optimization, Energy Harvesting, Energy Neutrality, Adaptive Scheduling, Communication Reliability, Wireless Sensor Networks.

## I. INTRODUCTION

In swarm robotics, machines solve problems by exhibiting collective behaviors similar to those in natural systems such as bird flocks, bee swarms or fish schools. Their collective behavior is determined by a few simple transactions. Nevertheless, the dynamics of swarms emerging from local interactions remain difficult to predict. The development of swarm robotic systems for practical applications faces many software and hardware obstacles at many stages of the design process, including issues related to the modelling of swarm systems, simulation, software implementation and deployment on real systems.

Swarm robotics is introduced as a larger system, which shows emerging behaviors via distributed local communication [1], and differs dramatically from typical multi-robot models in its management and scalability framework. It often uses a self-organizing control system instead of a centralized work allocation, and resilience is obtained by characteristics allowing anonymity. Furthermore, we have proven that in practice there might be one or more human supervisors supervising the robot swarm. For example, in a human-swarm collaboration task, a human operator collects data from a swarm of robots and delivers commands to adjust their behaviors. This cooperative behavior is called HIS (human-swarm interaction) and has been studied extensively in the last decades.

Optimization measures are required to enable energy efficient IoT devices to operate for a long time without exhausting their power reserves. Examples of such advancements are dynamic energy management, dynamic data communication and energy-efficient routing protocols. All of these try to match energy usage with availability. IoT devices are always on and intentionally adjust communication parameters like data rate, duty cycles and transmission energy to enhance network efficiency. For sustainability, the power efficiency of these gadgets needs to be enhanced as it reduces the costs of regular battery changes.

New communication technologies are required to adequately transmit the data and to make optimal use of energy. Energy efficient communications protocols like MQTT, LoRaWAN and Zigbee can be used to boost energy efficiency of communications [2]. They all have their advantages and are most suitable for a specific IoTs deployment. It is extremely

crucial to be aware of the reliability of the power used particularly if it needs to be sustained output. Systems are complex and often they are hard to integrate into existing systems, involve extra time and financial resources for research and development. The market of energy-efficient IoT connectivity is always growing. The gap between ideas and the implementation of creative ideas. This is compared to the global dialogue about sustainability and viability of technology since gadgets can now “talk” better and this will lead to greater operational efficiencies.

The several techniques for improving energy efficiency in swarm coordination have been discussed in previous works. It has been proved that cluster communication architectures such as those above can drastically cut down on computational duration and energy usage as opposed to complete mesh-based networking. In a similar fashion, the adaptive transfer systems can be coupled with learning algorithms to allow adaptive trading-off between energy and dependability. But there are some techniques that deal with communications and computation separately [3]. We propose the first single model to solve communication-based energy minimization problems considering also local computation costs.

The challenge is to find methods and techniques that will help improve the energy efficiency of the robotic clusters that are operating in different environments. Robotic systems should be successful in the future to function in ensembles, which need less minimal energy. Main issue is to develop employment and robotic systems with less energy resources. The battery is used to power the electronics, sensors, mechanical systems and other components of the robot. Each segment consumes a significant amount of energy, depending on the number of sensors, the power of the processing, how it communicates, size etc. There is a need for study of all aspects of the system to optimize the value of this energy contribution.

This work aims at designing and evaluating an Energy-Aware Cross-Layer Communication and Computation Optimization (EACCO) framework in the indoor IoT swarm robotic network. The proposed architecture includes integrated energy harvesting, communication, computing and adaptive scheduling for energy-efficient, reliable communication, sustainability and long-term autonomous operation considering the changing conditions inside the building. The following section (Sections II) reviews the related studies regarding energy-saving IoT swarm robotics. The system, energy, communication and scheduling models are described in Section III. The simulation environment, the experiment setup, the performance indicators are discussed in Section IV and the energy, computational and communication results are provided in Section V. Lastly, in section VI, we present a summary of key findings and contribution of the study.

## II. RELATED WORK

Several tactics and protocols have been developed for enhancing energy efficiency of swarm robots [4]. Distributed job allocation techniques based on PSO (particle swarm optimization) has been presented for load balancing and indirectly minimizing of idle period time to conserve energy. PSO is a stochastic global optimization method that is based on a swarm of particles with velocities and locations. In PSO, each particle has a velocity which shows its travel in the search space and this velocity is modified adaptively depending upon its past behavior as described by Juneja and Nagar [5]. Thus, the particles migrate to more promising spots in the search space and explore the solution space by changing their position and velocity. Today various SI algorithms are in use, however in large scale settings, PSO has demonstrated better outcomes in terms of performance and complexity.

As described by Ingber and Rosen [6], it decreases the computing time in comparison with other SI algorithms like Genetic algorithms. It also uses the actual numerical values and does not require to encode them to binary, as in GA. Therefore, a PSO technique for the optimization will be adopted in the present work. In distributed environment like cloud computing, the PSO method has proved better efficiency in terms of computational speed than meta-heuristic algorithms such as GA and ACO.

According to Rahmat-Samii [7] PSO is more effective and easier to process and implement than GA. It has the smallest number of parameters to achieve faster convergence rate. Thus, the job scheduling problem will be enhanced by the application of the Particle Swarm Optimization (PSO) in this study. They state that improvements in communications like clustered messaging can lower latency and energy consumption by eliminating unnecessary communications. Duty cycles and transmission energy in different IoT systems have been optimized using reinforcement learning, achieving up to 25% longer device lifetime. The use of data compression and aggregation techniques are useful in reducing payloads to be communicated, which is important as up to 80% of the power of IoTs nodes can be consumed by the communication. Unlike most previous works which consider energy control for computation offloading or communication scheduling separately, our system simultaneously optimizes computation offloading and communication scheduling, particularly aiming at reducing the communications energy.

Ameen, Islam, and Kwak [8] are committed to energy reduction at the connection/ protocol layer through adaptive energy management, protocol decision, MAC scheduling and duty cycling. For the IoT/edge domain, research and comparative studies have showed that protocol attributes (transmission energy, duty cycle, and modulation scheme) as well as application layer methods (data aggregation, data compression) can be effective in the real world to limit the transmission cost. Energy per bit, reliability and latency trade-offs have been studied in the case of LPWAN solutions (e.g., NB-IoTs, LoRaWAN) and short-range protocols (e.g., BLE). These suggest that retransmission strategies and protocol-related overhead have a significant influence on the energy bit-by-bit basis, and require communication strategies based on the payload. However, there are several transmission-centric studies that consider the computational costs as externalities, and the trade-offs introduced by offloading computation that might be required to reduce the message size or alter the energy/latency issues are neglected.

Ouyang et al. [9] argue that offloading computation to cloud or edge computing resources is an extensively evaluated approach to minimize the computational power of the device and improve processing. In conventional models, offloading is treated as optimization problems subject to energy or latency limitations on the energy and time of local processors and the energy and time of transmissions. Several works propose analytical convex models of divisible tasks aiming at globally optimal offloading ratios. Several works study isolated task distribution with combinatorial complexity and resort to mixed-integer or heuristics programming. In research offloading, normally a high-capacity and uniform edge is used, without considering explicitly the effect of numerous devices competing for controlled wireless resources as is common in ensemble settings.

Feng et al. [10] highlight a recent trend that closely relates communication and computation expenses. The joint optimization systems combine the transmission cost per bit and the computation cost per cycle into one target with restrictions of network, energy and CPU. These solutions demonstrate considerable benefits from co-design such as selective data batching/compression before transfer, or selective offloading based on the network type. But exact solutions are not sustainable given the swarm size and variety, which asks for scalable heuristics and approximations.

According to Darvishpoor et al. [11], nature-inspired optimization approaches are generally known as meta-heuristic algorithms. Meta-heuristics are general methods that guide search agents to iteratively improve the global result. Meta-heuristic algorithms, which are employed to mitigate optimization issues, start by generating random solutions and then go toward optimization through its operators and by changing the created random answers. Usually, all meta-heuristic algorithms use similar methods to search for the best solution. Most of these methods start by generating one or more random solutions within the allowed range of the variables. Population-based algorithms generate a population, colony, or group as their main output, and each individual solution is called a chromosome, particle, ant, etc.

According to Gad [12], swarm-based approaches comprise of simple agents or particles that interact locally with each other and their ecosystem. Each particle follows to one or more rules without a central authority directing its behavior. Thus, local and stochastic interactions between the particles result in a coherent global behavior. The algorithms use two methods for optimal performance: local exploitation and global exploration. Exploration refers to the ability to increase the search space whereas corruption is the capability to find the ideal solution near a satisfactory (near-optimal) answer. Because of the lack of knowledge about the search space in the early stages, the swarm has to do more exploration so that it does not get trapped in local extremes. In contrast, the absence of phases requires more exploitation, where the algorithm can self-tune at semi-optimal points. An effective search needs a good tradeoff between exploration and exploitation.

In the work of Dorigo et al. [13], the robots are heterogeneous and need a lot of communication to coordinate, while the tasks are restricted by the power supply of the robots. Previous work on swarm systems has addressed work allocation according to energy constraints, formation control subject to energy constraints, and duty cycling to extend the life of a swarm. Conversely, many swarm studies work on coordination and control approaches without any whole energy frameworks, or use heuristics, which reduce communications efficacy without attempting to efficiently optimize communications and processing expenses. To date, there are only few empirical evaluations of embedded systems such as the TX2 or Jetson Nano, showing the relation between processing and communication for real-world applications.

The incorporation of IoT technology with swarm robots has resulted into a substantial amount of study on energy-efficient communications, resource assignment, and computation offloading. Adaptive energy regulation, duty cycling and protocol level optimization can reduce the energy consumption of energy constrained network elements; and optimization at the protocol level and selection of the protocol can contribute to improving energy effectiveness in IoTs edge model [14]. In the meantime, computation offloading has been extensively studied to balance the pros and cons between local power consumption for CPU computations vs transmission cost with CPU, battery and latency constraints.

### III. MODEL DESCRIPTION

In this paper, we propose an energy-efficient architecture for indoor IoT swarm robotic systems that leverages energy harvesting, computing, communication and adaptive scheduling in order to improve the energy efficiency and operational lifetime of the system, as shown in **Fig. 1**. An IoTs node regularly senses its surroundings, performs local processing, interacts with other nodes and dynamically alters its operation depending on the amount of residual battery life and the amount of available gathered energy. The proposed method is designed to solve all these interdependent processes in parallel, towards the ultimate goal of energy neutrality, with a focus on improving communications reliability and extending the network's lifespan. This section describes the analytical models such as network topology, battery dynamics, energy consumption, wireless communication and cross-layer scheduling approach that form the foundation of the proposed framework.

#### *System and Energy Model*

Consider an indoor IoT swarm robotic network consisting of  $N$  heterogeneous sensor nodes deployed in the monitoring environment. The communication topology is denoted by the undirected graph

$$G = (V, E), \quad (1)$$

Where

$$V = \{v_1, v_2, \dots, v_N\}, \quad (2)$$

denotes the set of sensor nodes and

$$E = \{(v_i, v_j), \mid v_i, v_j \in V, d_{ij} \leq d_{max}\}, \quad (3)$$

indicate the communication links between neighboring nodes at distance less than or equal to the maximum communication range  $d_{max}$ . Every node is equipped with sensing, processing, wireless communication, battery storage and interior energy harvesting modules that work simultaneously during the whole observation period.

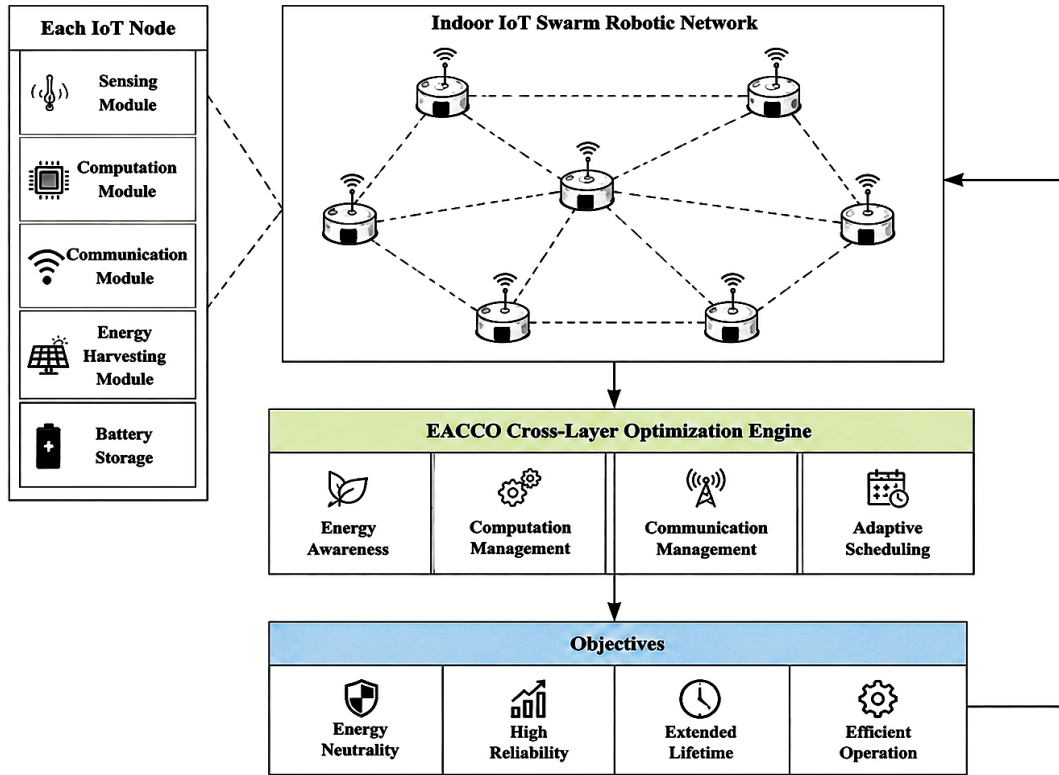


Fig 1. The Global Architecture of Proposed EACCO Framework.

The battery status of node  $i$  evolves as a function of the harvested energy and the total energy consumption due to sensing, computation, transmission, reception and idle operation,

$$B_i(t + \Delta t) = \min\{B_{\max}, \max[0, B_i(t) + \eta_i \int_t^{t+\Delta t} H_i(\tau) d\tau - \sum_{k=1}^m E_{i,k}(t)]\}, \quad (4)$$

Where

$$\sum_{k=1}^m E_{i,k}(t) = E_i^{sense} + E_i^{comp} + E_i^{tx} + E_i^{rx} + E_i^{idle}, \quad (5)$$

where  $B_i(t)$  is the remaining battery energy,  $B_{\max}$  is the battery capacity,  $H_i(t)$  is the harvested power and  $\eta_i$  is the energy conversion efficiency.

The energy consumption per each scheduling period is calculated as

$$\begin{aligned} E_i^{tot} &= E_i^{sense} + E_i^{comp} + E_i^{tx} + E_i^{rx} + E_i^{idle} \\ &= P_i^{sense} T_i^{sense} + P_i^{cpu} T_i^{cpu} + P_i^{tx} T_i^{tx} + P_i^{rx} T_i^{rx} + P_i^{idle} T_i^{idle}, \end{aligned} \quad (6)$$

where  $P$  and  $T$  signify the power and execution time of each activity, respectively. The total network energy usage in an observation interval of  $T$  scheduling cycles is computed as

$$E_{net} = \sum_{i=1}^N \sum_{k=1}^T E_i^{tot}(k), \quad (7)$$

and the equivalent collected energy is given by

$$E_{harv} = \sum_{i=1}^N \sum_{k=1}^T \eta_i \int_{t_k}^{t_{k+1}} H_i(\tau) d\tau. \quad (8)$$

Thus, the energy neutrality ratio (ENR), which quantifies the sustainability of the network, is defined as

$$ENR = \frac{E_{harv}}{E_{net}} = \frac{\sum_{i=1}^N \sum_{k=1}^T \eta_i \int_{t_k}^{t_{k+1}} H_i(\tau) d\tau}{\sum_{i=1}^N \sum_{k=1}^T (P_i^{sense} T_i^{sense} + P_i^{cpu} T_i^{cpu} + P_i^{tx} T_i^{tx} + P_i^{rx} T_i^{rx} + P_i^{idle} T_i^{idle})}. \quad (9)$$

Likewise, a predicted lifetime for the mission is estimated by

$$L = \frac{\sum_{i=1}^N [B_i(0) + \sum_{k=1}^T \eta_i \int_{t_k}^{t_{k+1}} H_i(\tau) d\tau]}{\sum_{i=1}^N \bar{P}_i}, \quad (10)$$

where  $B_i(0)$  is the beginning battery energy and  $\bar{P}_i$  is the average node power consumption during operation.

#### Communication and Cross-Layer Scheduling Model

The wireless communication between neighbor nodes is based on the traditional log-distance propagation model,

$$PL(d) = PL(d_0) + 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma, \quad (11)$$

where  $PL(d_0)$  is the reference path loss,  $n$  is the path-loss exponent and  $X_\sigma$  is the log-normal shadow fading.

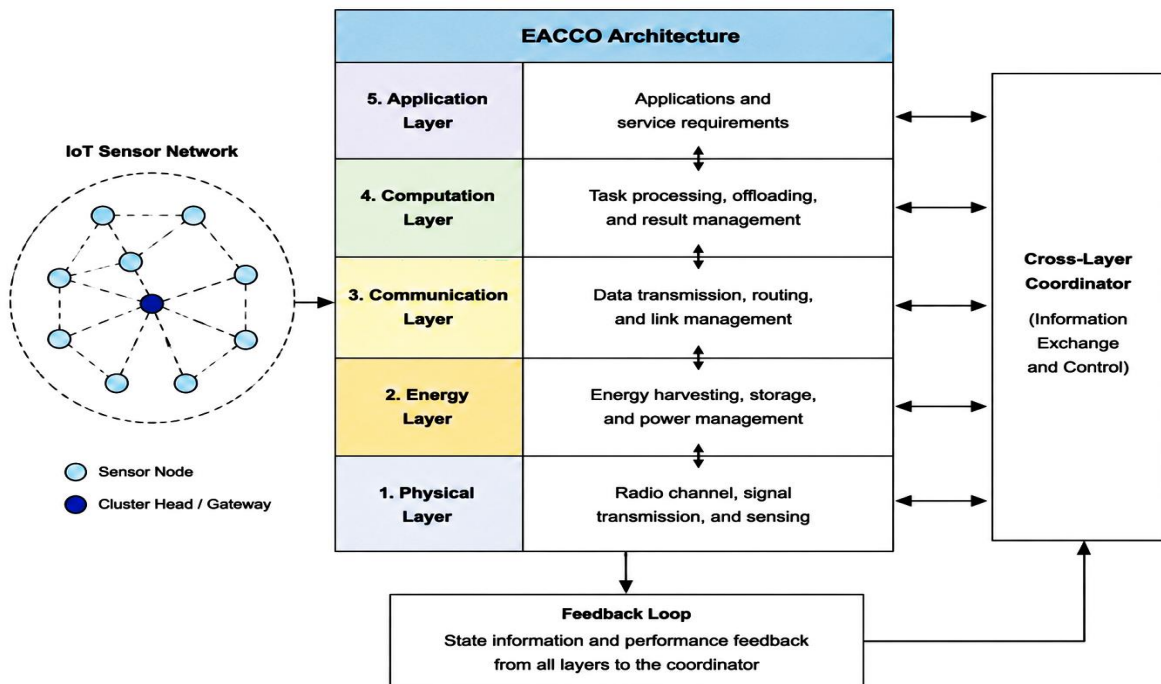


Fig 2. The Cross-Layer Communication and Scheduling Scheme.

The received signal power is thus expressed as which affects the communication quality by the signal-to-noise ratio

$$P_r = P_t - \left[ PL(d_0) + 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma \right], \quad (12)$$

which determines the communication quality by the signal to noise ratio

$$SNR = \frac{P_r}{N_0 B}, \quad (13)$$

where  $N_0$  signifies the noise spectral density and  $B$  represents the transmission bandwidth. Packet Delivery Ratio (PDR) is a measure used to evaluate the reliability of communication,

$$PDR = \frac{\sum_{i=1}^N N_i^{received}}{\sum_{i=1}^N N_i^{transmitted}} \times 100\%. \quad (14)$$

The computational effort to be assigned to each node depends on the processing complexity and execution time and is represented as

$$C_i(t) = \lambda_i f_i \tau_i, \quad (15)$$

where  $\lambda_i$  is the computational intensity,  $f_i$  is the processor operating frequency and  $\tau_i$  is the execution time. The total workload imposed on node  $i$  is characterized as to characterize the relationship between communication and computation.

$$W_i(t) = \alpha E_i^{comp}(t) + \beta E_i^{tx}(t) + \gamma E_i^{rx}(t) + \delta E_i^{sense}(t), \quad (16)$$

subject to  $\alpha + \beta + \gamma + \delta = 1$ ,

where the weighting coefficients control the amount of calculation, transmission, reception and sensing contributing to the scheduling choice.

The framework checks in every scheduling interval, the remaining battery energy, the harvested energy, the computation workload, the communication cost and the transmission requirement and assigns communication possibilities to neighboring nodes. The packet forwarding is preferred to node with high residual energy and low communication overhead, which results in energy neutrality and reliable communication performance [15]. This interaction between the layers enables the framework to respond to different loads and energy availability conditions, and avoids performing without need any unnecessary energy spending in order to assure the operation of the network in the long term. The analytical models are the mathematical foundation for the evaluation of the proposed EACCO framework here (as shown in **Fig. 2**). In this work, we explain the experimental methodology, parameter settings, and performance evaluation metrics to showcase its usefulness in representative indoor IoT operation environments.

#### IV. EXPERIMENTAL METHODOLOGY

To test the proposed Energy-Aware Cross-Layer Communication and Computation Optimization (EACCO) framework in **Fig. 3** in regular situations of the indoor IoT operation, simulation and hardware-aware experiments were carried out. The test is focused on the following: Battery dynamics, energy consumption, communication efficiency, computing workload and scheduling performance. The workload and network configuration of all experiments were identical, and therefore, EACCO was compared fairly with classic scheduling algorithms.

##### *Simulation Environment*

This simulation approach explores a distributed IoT swarm robotic network in an indoor scenario where the energy harvesting sensor nodes have sensing, computing, wireless communication and battery storage capabilities. Every node collects the energy from the ambient indoor environment and locally senses and interprets data and broadcasts a packet periodically. The Battery status is updated regularly with collected and used energy, for a realistic assessment of long-term operation of the network. The communication model considers the effect of the transmission loss, wireless interference and the periodic data exchange between neighboring nodes. We model real world indoor monitoring scenarios with computational workloads comprising event-driven sensing tasks of varying levels of processing intensity. Additionally, part of the simulation is the charging and discharging process of the battery, which can also include the change of available harvested energy.

##### *Experimental Configuration*

Strength of the proposed structure was checked for various operation conditions. In a hybrid scenario, harvested energy with extra charging has been studied under extended operating conditions, considering different energy availability scenarios by using energy harvesting profiles for both indoor and outdoor operating conditions. The communication subsystem was

explored, considering LoRaWAN, BLE, WiFi and cellular communication models, depending on the experiment. The corner detection tasks were used to investigate the relationship between the processing complexity and the energy consumption, in order to vary the workload of the low and high processing. For comparison with EACCO, the earliest-deadline first (EDF), first-in-first-out (FIFO) and an energy-only scheduler baseline scheduling rules were also used under the same workload and communication and energy parameters.

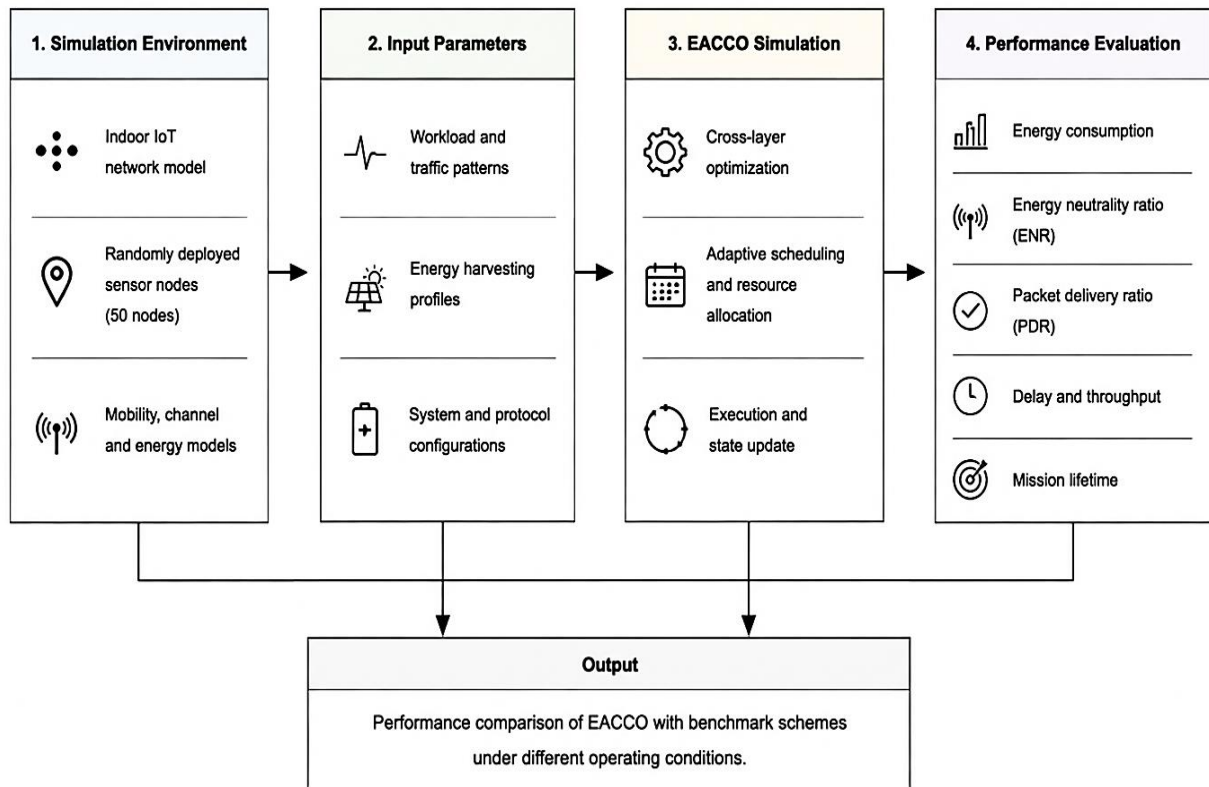


**Fig 3.** Experimental Simulation Framework.

**Table 1.** Simulation Parameters

| Parameter                  | Value                                          |
|----------------------------|------------------------------------------------|
| Number of IoT nodes        | 50                                             |
| Simulation duration        | 24 h                                           |
| Simulation time step       | 5 min                                          |
| Deployment area            | 100 × 100 m <sup>2</sup>                       |
| Initial battery capacity   | 3 Wh                                           |
| Maximum battery capacity   | 3 Wh                                           |
| Energy harvesting source   | Indoor ambient light                           |
| Harvesting efficiency      | 0.20                                           |
| Wireless protocols         | LoRaWAN, BLE, Wi-Fi, Cellular                  |
| Communication frequency    | 868 MHz (LoRa)                                 |
| Transmission power         | 14 dBm                                         |
| Transmission range         | 100 m                                          |
| Packet size                | 25 Bytes                                       |
| Packet generation interval | 5 min                                          |
| Sensor current             | 1.8 mA                                         |
| Transmission current       | 28 mA                                          |
| Sleep current              | 1.5 μA                                         |
| Processor platform         | MSP430 MCU                                     |
| Radio module               | LoRa Transceiver                               |
| Scheduling methods         | FIFO, EDF, Energy-only, EACCO                  |
| Performance metrics        | ENR, PDR, Energy Consumption, Mission Lifetime |

In an effort to make the energy estimates more realistic, the simulation model was updated with measured power characteristics of a prototype consisting of an MSP430 microprocessor and a LoRa transmitter. Energy harvesting traces were harvested under representative indoor lighting conditions and added in the battery model described in Section II. The important simulation parameters used in the experimental evaluation are summarized in **Table 1**.

### Performance Metrics

Various quantitative metrics were used to test the performance, both in terms of energy efficiency and the reliability of the communication. Energy consumed by sensing, computation, transmission and reception and idle operation during the assessment time is added together to calculate the total energy consumption. The remaining battery energy and the energy neutrality ratio (ENR), which is the ratio of the collected energy to the consumed energy, were used to analyze the battery dynamics. The communication performance was measured using packet delivery ratio (PDR) where the ratio of the number of successfully delivered packets to the total number of packets is calculated. The calculation performance was investigated in terms of workload dependent power consumption for different workload intensities. The communication efficiency was determined based on the comparing energy features of LoRaWAN, BLE, Wi-Fi and cellular transmission.

Lastly, the network's sustainability was measured by the mission life, which is the time the network will be active before nodes' battery runs out. These free measurements are used as a basis to evaluate the proposed framework in a holistic way in terms of energy consumption, communication reliability, computation efficiency and long-term autonomous operation. The experimental results based on such measures are presented and discussed in Section V.

## V. RESULTS AND DISCUSSION

In this section, the experimental assessment results of the proposed EACCO framework are presented. We investigate and contrast battery dynamics, energy consumption, computing effort, communication overhead, and scheduling performance with classical methods.

### Battery and Energy Analysis

As shown in **Fig. 4**, there is a fast discharge, a slow recharge and a higher recharge rate. The variable energy sources are assumed to be able to meet the load requirement. At the beginning of depletion, the entire system is not able to sustain rapid rates of harvesting. The next level of excess, however, indicates that the framework can take care of less energy or has more responsibilities. As stated in [16] the preferable operating mode is to set the transmission energy level at the PDR modulation point and to match the energy consumption with the harvesting. This will ensure the system's stability and prevent the battery from rapidly (dis)charging.

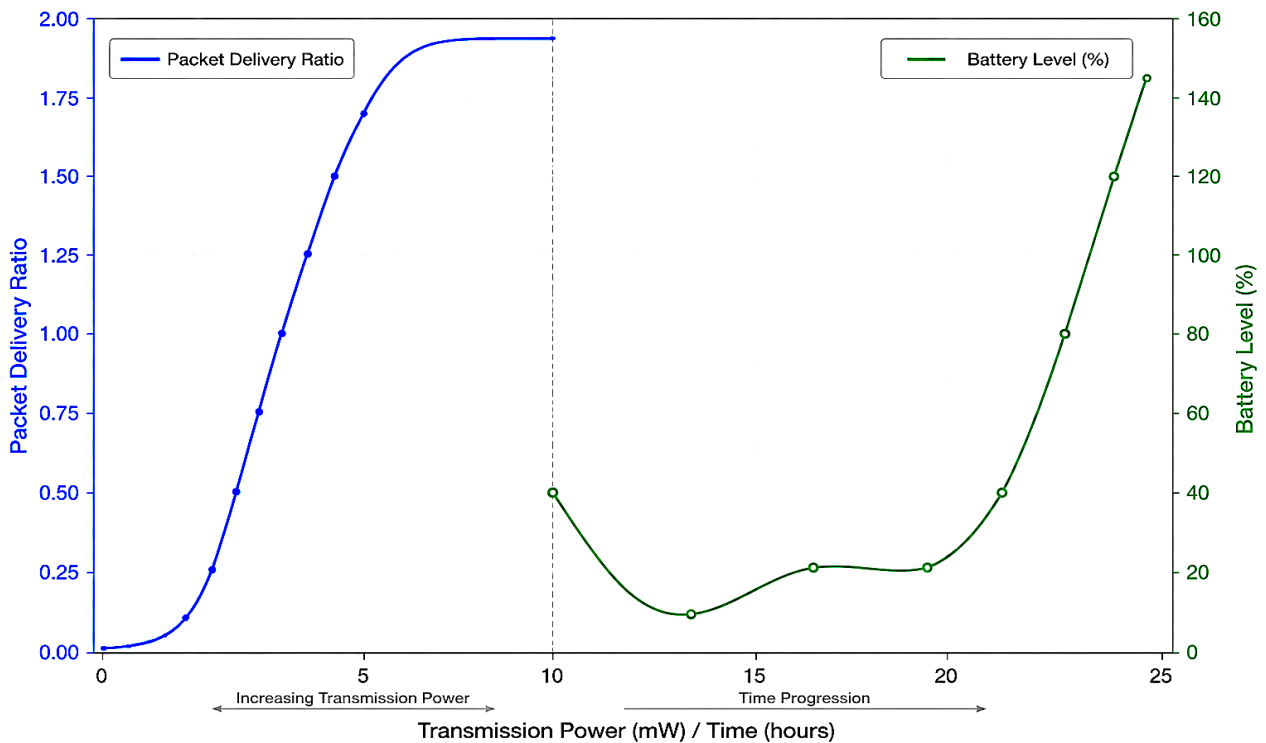


**Fig 4.** Battery Analysis and Power of Transmission.

Energy consumption of every element was measured during the typical activity. The per-occurrence energy usage is shown in **Table 2**.

**Table 2.** EACCO Comparison Against Typical Baselines

| Methods                    | Joint Opt.      | Prio/DL + ENR | Relay | HW + Model |
|----------------------------|-----------------|---------------|-------|------------|
| EACCO (Our framework)      | Yes (T + C + C) | Yes           | Yes   | Yes        |
| Liu [17]                   | No              | Partially     | No    | Partially  |
|                            | No              | Partially     | No    | Partially  |
| Cross-layer (e.g., Alippi) | Partial         | Partially     | No    | Partially  |
| ER-HEED/H-HEED             | No              | No            | Yes   | Partially  |

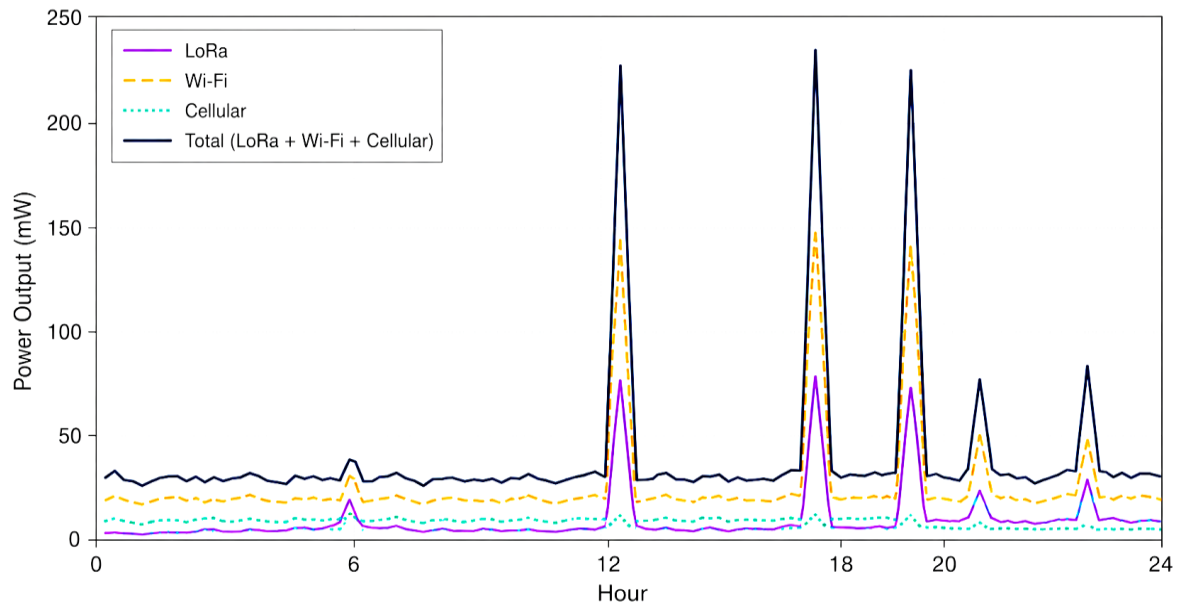


**Fig 5.** Energy Use Analysis.

**Fig. 5** depicts the daily energy usage behavior of an indoor IoT device during its sensing, processing and communication activities. Indoor IoT devices typically use around 20-40 mW of energy, with a constant baseline consumption. Sensing processes are the smallest, most consistent fraction of the entire power allocation. However, the requirements for calculation and transmission are around average with some minor variations, but there are few intervals with considerable but short surges, especially around 12-17 hours and 23 hours. The computing needs during these peaks surpass 200 mW, and the sensor and gearbox power increase concurrently. Short intervals are the main factor that affects the amount of energy consumed by most devices on a regular basis. The maximum power need is identified by intermittent data processing and transmission events and not continuous surveillance. In IoT networks, the communication power is mostly steady, but it is delivered irregularly by periodic uplink scheduling and overhead transmission mechanisms.

The results show that average usage is not a fair estimate of real energy pressure and duty-cycled job design and peak-sensitive power management are essential to avoid brownout incidents. Thus, the increases in both spike frequency and computational load lead to greater savings in energy than small decreases in baseline monitoring load. Therefore, there is a need to monitor the energy consumption associated with a workload in indoor IoT contexts.

#### Computational Power Analysis

The fluctuation of the power consumption of corner identification tasks with the variation of computation energy and transmission protocols (LoRaWAN and BLE) is shown in **Fig. 6**. Systems with high computing always show higher and more volatile energy profiles compared to systems with minimal computation over the observation time. This confirms that the instantaneous energy consumption in resource-constrained nodes is mostly determined by the computational workload. LoRaWAN is usually more energy-consuming compared to BLE since it has to transfer data across long ranges. In contrast, BLE costs less energy and is steadier, particularly in low computational resource contexts.

The temporal fluctuations observed in all the curves are due to the occasional occurrence of event-driven IoT operations (processing, sensing, transmission) [18]. However, the optimized low-computation design maintains the power consumption throughout a narrower spectrum (approximately 1.31 to 2.32 W) whereas computationally-intensive configurations often reach 3W. This means that the use of on-board processing on a large scale requires large amount of additional energy. The results show that the reduction of computing complexity and the use of energy-efficient communication protocols can greatly control the power consumption and extend the lifetime of nodes in IoTs swarm robotic models. Every 5-minute sampling session (288 times daily) used approximately  $9.72 \mu\text{Wh} \times 288$  (~2.8 mWh daily) for sensing and processing (see **Fig. 7**)

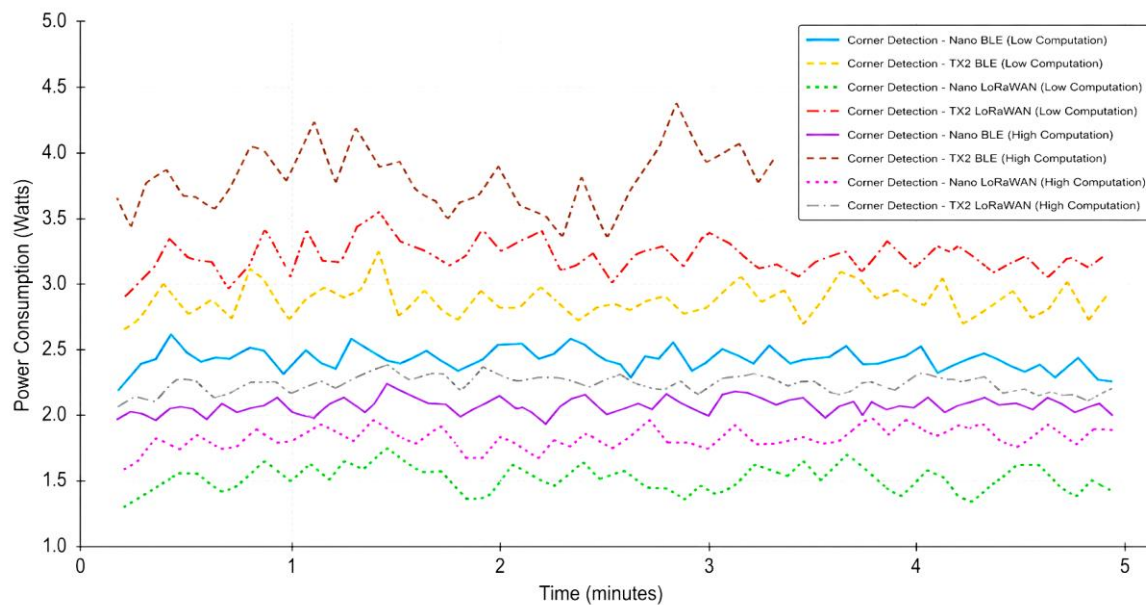


**Fig 6.** Power Analysis for Various Load Intensities.

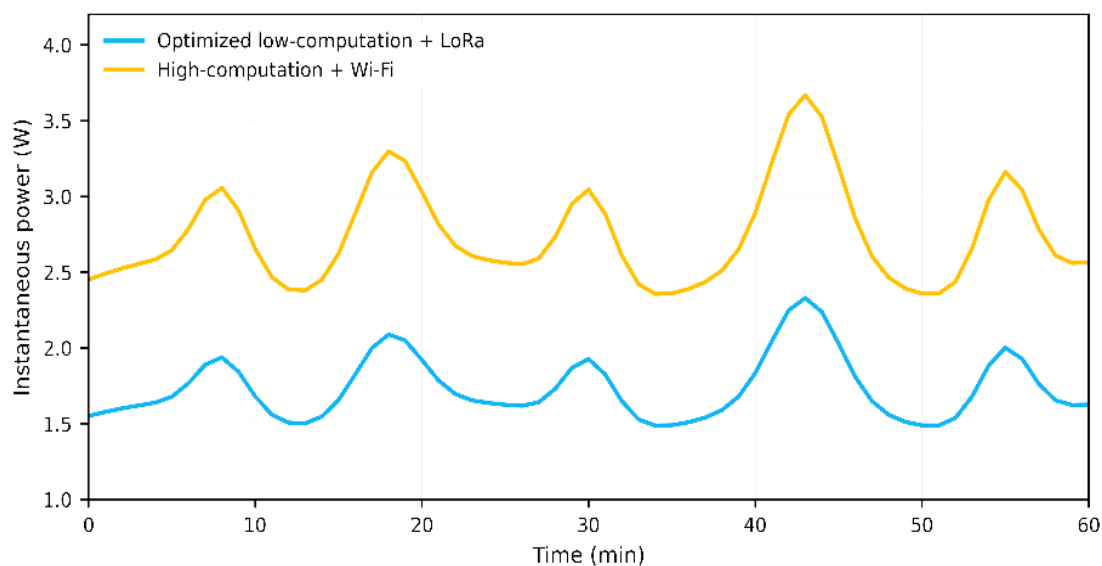


**Fig 7.** Computation Configurations.

As can be seen from **Table 3**, the transmission of a 25.0 B packet, lasting 0.5 seconds, costs 37.81  $\mu\text{Wh}$ . In each interval, the major expenditure was the expenditure on the gearbox which was over 11 times the sensing expenditure. The energy used between events in idle or sleep states was practically non-existent.

**Table 3.** Standard Energy Usage for Every Activity

| Activity                    | Current            | Time   | Energy               |
|-----------------------------|--------------------|--------|----------------------|
| Sensor reading + loading    | 1.81 mA            | 1.9 s  | 9.76 $\mu\text{Wh}$  |
| LoRa communication (14 dBm) | 28.02 mA           | 0.49 s | 37.83 $\mu\text{Wh}$ |
| Low-power MCU model         | 1.52 $\mu\text{A}$ | Varied | Low                  |

**Fig. 8** illustrates the transmission energy assessment of an indoor IoTs node. It is observable that the most significant power consumption is caused by the transmission events, and the baseline communication overhead remains consistently small during the operating cycles. LoRa has a reduced-energy long-range architecture which makes it consumes less power in sleep mode. However, Wi-Fi and wireless connections need to stay on longer when idle because of their greater bandwidth and maintenance requirements. There are sporadic spikes at critical transmission stages consistent with burst data transfers.

### Communication and Scheduling Systems Review

Wi-Fi has the highest peak power ( $> 200$  mW) followed by LoRa and cellular communications. But these heights are short lived, and the average energy for communication is not high, as the transmissions are not steady but erratic. It illustrates that the energy jumps when the aggregated power trace is used for communication. They can thus be computed via transmission-batching and dynamic scheduling schemes [19]. The results show that the transmission energy consumption of indoor IoTs nodes in swarm robotics with power constraints can be greatly reduced by utilizing a communication scheme that employs energy-efficient protocols such as LoRa for regular monitoring data and high-energy interfaces for high-throughput and rate events.

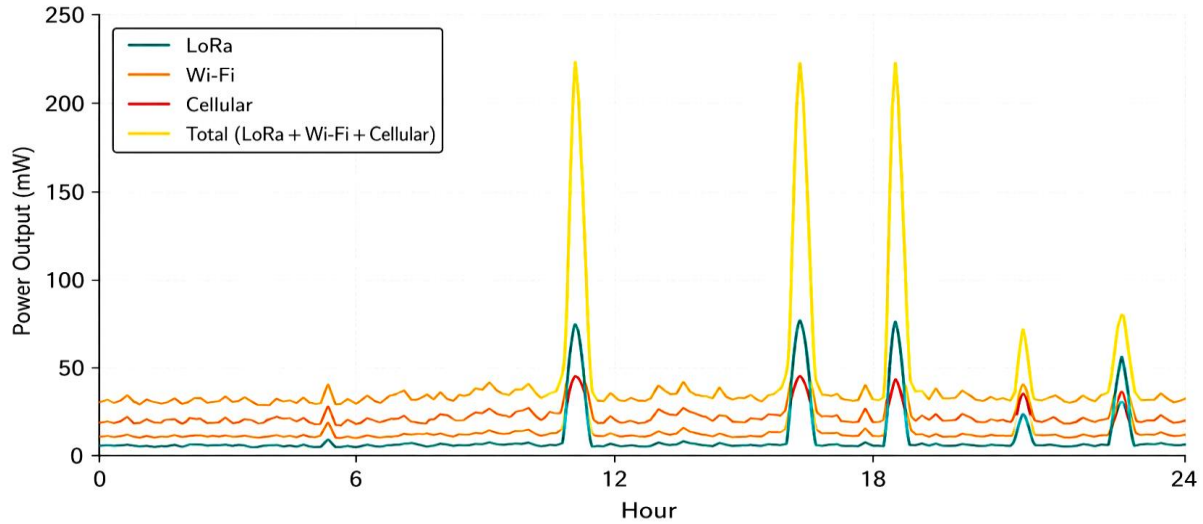


**Fig 8.** Indoor Communication Analysis.

**Table 4** shows results for an augmented/hybrid energy system, which can be achieved by either (i) supplementing the indoor energy harvest with other energy sources (such as hybrid harvesting or intermittent recharge), or (ii) reducing workload thru an improvement in EACCO. Results of EDF, energy-only and FIFO schedulers are provided with simulation models similar to those used for evaluation of EACCO. In our occurrence-based energy and communication framework these basic concepts are realized by the quantifiable physical prototype energy profiles (LoRa + MSP430 transceiver) and by the computation-based collection of energy data (outdoor and indoor). That way the schedulers can be tested successfully under the same channel, energy and workload availability, which provides a controlled and fair comparison.

**Table 4.** Baseline Schedulers Evaluation (Hybrid, Indoor, and Outdoor) vs EACCO

| Environment | Scheduling Method | Mission Duration (h) | PDR (%) | Energy Consumption (Wh/day) | ENR  |
|-------------|-------------------|----------------------|---------|-----------------------------|------|
| Outdoor     | EACCO             | 36                   | 97      | 2.3                         | 1.18 |
| Indoor      | EDF               | 20                   | 82      | 5.2                         | 0.76 |
| Outdoor     | FIFO              | 22                   | 80      | 6.5                         | 0.85 |
| Indoor      | EACCO             | 30                   | 95      | 2.0                         | 1.05 |
| Outdoor     | Energy-only       | 26                   | 87      | 5.6                         | 0.92 |
| Indoor      | FIFO              | 18                   | 78      | 5.8                         | 0.72 |
| Outdoor     | EDF               | 24                   | 84      | 6.0                         | 0.88 |
| Indoor      | Energy-only       | 22                   | 85      | 4.9                         | 0.81 |

### VI. CONCLUSION

The EACCO framework was introduced to address the energy constraint of indoor IoT swarm robotic network in this work. The proposed model can optimize energy harvesting, battery management, communication and computing and adaptive scheduling simultaneously, which can offer a reasonable compromise solution for energy consumption and energy harvesting while still guaranteeing the desired network performance. The experimental evaluation results show the advantages of EACCO in comparison to the traditional FIFO, EDF and energy only scheduling systems in terms of energy efficiency, energy neutrality ratio, packet delivery ratio and mission lifetime in indoor and hybrid operating conditions. The results show that the cross-layer optimization is a practical solution in long term autonomous IoT deployments. Further study will involve multi-robot implementations in the real world and the use of machine learning for adaptive scheduling, and integration with the next generation of wireless communication technologies, to further enhance scalability and resilience.

### CRedit Author Statement

The author reviewed the results and approved the final version of the manuscript.

### Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

### Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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### Competing Interests

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