Energy-Efficient Access Point Deployment for Industrial IoT Systems

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Abstract. Internet of Things (IoT) technologies have impacted many fields by opening up much deeper and more extensive integration of communications connectivity, sensing, and embedded processing. The industrial sector is among the areas that have been impacted greatly — for example, IoT has the potential to provide novel capabilities for more effective tracking, control and optimization of industrial processes. To maintain reliable embedded processing and connectivity in industrial IoT (IIoT) systems, including systems that involve intensive use of smart wearable technologies, energy consumption is often a critical consideration. With this motivation, this paper develops an energy-efficient deployment strategy for access points in IIoT systems. The developed strategy is based on a novel genetic algorithm called the Access Point Placement Genetic Algorithm (AP2GA). Simulation results with our proposed deployment strategy demonstrate the effectiveness of AP2GA in optimizing energy consumption for IIoT systems.

Keywords: Green Communication · Wireless Industrial IoT · Genetic Algorithm

1 Introduction

Wireless communications technologies are of increasing interest in industrial environments because of their important potential benefits compared to full reliance on wired communications [3]. As such, Industrial Internet of Things (IIoT) is playing a huge role in industry due to the connectivity capabilities provided by wireless technology, revolutionizing the sector. For example, various sensors can be deployed to monitor temperature, humidity, and vibrations of machines to create safer production environments and to report early warnings of possible malfunctions. By seamlessly connecting various devices and sensors, IIoT enables more efficient data collection, analysis, and process control, bringing productivity into higher levels.

However, with ever-increasing system complexity, the increasing amounts of energy consumed by wireless communication devices has attracted significant attention from both academia and industry. The large amount of energy consumption also poses challenges to the environment, as renewable green energy is typically not used as a power source for wireless networks [2].

The energy consumption attributable to Information and Communication Technology (ICT) has exhibited large increases with the advent of new technologies, such as Fifth Generation (5G) and Multiple-Input and Multiple-Output (MIMO), as such technologies require more power consumption to increase response speed and accommodate more users. Therefore, innovation in green communications technologies is in urgent need.

To help address this need, we propose and demonstrate a systematic Access Point (AP) deployment strategy for energy-efficient IIoT systems. The remainder of this paper is organized as follows. Section 2 discusses background and related literature about AP deployment strategies. Section 3 explains the proposed energy-efficient AP deployment strategy. Section 4 reviews the factory system flow model used in our simulation experiments. Section 5 presents the results of the proposed strategy, which are obtained from the aforementioned simulation experiments. Finally, the paper is concluded in Section 6.

2 Background and Related Work

In wireless networks, an AP plays a crucial role by providing wireless connectivity and forwarding communication between devices or even networks as a relay node. To effectively support these functionalities and meet users' requirements, proper deployment of APs is essential. In this paper, by deployment of APs, we specifically mean the physical placement of the APs for operation in a given site.

A range of approaches regarding AP deployment has been proposed in the literature, with a goal of seeking optimal positions based on various objectives, such as reducing the number of APs used [8] or improving network performance [6, 10, 12–14].

In [8], the authors apply a continuous optimization technique known as A new Global OPtimization algorithm (AGOP) to minimize the number of APs used to cover a service area containing obstacles. The authors of [6] employ a multiobjective Tabu algorithm to search the set of candidate locations. The algorithm jointly considers coverage, interference, and Quality of Service (QoS). The final selection is made based on the most important factor to the end user. In [10], AP deployment and channel allocation are optimized together with a computationally-efficient local search algorithm to maximize system throughput and achieve fair resource sharing. In order to reflect the dynamic movement of users in an indoor wireless local area network (WLAN) system, the authors of [12] first use statistical theory to model the location and probability of the user distribution, and then model and solve the corresponding AP deployment problem with the fuzzy C-clustering algorithm.

In addition to the above algorithms, Genetic Algorithms (GAs) have also been widely used in identifying efficient AP deployment locations, especially under relevant multi-objective constraints. GAs are heuristic optimization methods inspired by Darwin's Theory of Evolution. They form an important sub-class of evolutionary algorithms [1]. A GA iteratively evolves to a solution of the given problem by using principles of natural selection. GAs have been shown to perform well on complex optimization problems where it is infeasible to derive optimal solutions with manageable time-complexity [1].

In [13], the authors take non-uniform user distribution into account, using a GA to cooperatively optimize the coverage, number of APs, and interference. In [14], an optimized placement of APs is selected with a GA such that the transmit power and overlap rate are minimized under the constraint of full coverage. The average transmit power is substantially optimized; it is reduced by about 61%. However, this average value may not be very useful in real-life situations, since it is possible that the device in the system with the smallest transmit power only processes a limited amount of traffic. The communication energy consumption would be a better metric to consider to more accurately inform system analysis and optimization.

Motivated by the above observations, we propose a novel energy-efficient AP placement method. The method mutually considers non-uniform user distribution and unbalanced communication activity on the premise of complete coverage. Our method considers total communication energy consumption as a key metric to guide the optimization process. This is a complex optimization problem, and a GA is designed to derive an efficient deployment setup for a given deployment scenario.

3 Proposed Methods

In the problem formulation that is addressed in this work, the energy cost to be optimized refers to the energy consumed by communication activities that occur during normal operation of the IIoT system. Specifically, the problem definition targeted in this work is the optimization of communication energy given a placement of networked devices, which may be unevenly distributed, and a characterization of the traffic demand for each device.

The communication energy considered in this paper refers to the transmission energy. Energy associated with communication reception for the devices is not taken into account in the methods developed in the paper, as it is common in related analysis contexts to focus on transmission power, and consideration of the transmission energy provides an approximation of the overall energy consumption due to communication. Incorporation of models for reception energy into the developments of this paper is an interesting direction for future work.

To save energy, we consider optimal placement of the APs so that they can deliver packets to all stations (STAs) in an area with an appropriate transmit power according to their activity rates. The fitness function can be mathematically expressed as follows:

$$
\begin{aligned}
&\min_{x_i, y_i, \alpha_{i,j}} \sum_{i=1}^{n} \sum_{j=1}^{s} \mathbb{1}_{i,j} \alpha_{i,j} t_{i,j} \beta_{i,j} && (1) \\
s.t. \quad & C1 : (x_i, y_i) \in \mathbb{Q} \\
& C2 : \sum_{i=1}^{n} \mathbb{1}_{i,j} = 1, \ \forall\, j \in [1, s] \\
& C3 : \alpha_{min} \leq \alpha_{i,j} \leq \alpha_{max}, \ \forall\, i \in [1, n], \ \forall\, j \in [1, s] \\
& C4 : \alpha_{i,j} + G_{i,j} - L_{i,j} \geq \alpha_0, \ \exists\, i \in [1, n], \ \forall\, j \in [1, s]
\end{aligned}
$$

Here, n and s denote the number of used APs and STAs respectively, (x_i, y_i) is the position of AP_i, $\mathbb{1}_{i,j}$ indicates whether STA_j is associated to AP_i, $\alpha_{i,j}$, $t_{i,j}$, $\beta_{i,j}$ are the used transmit power, transmission time, and total communication activity rate (including both downlink and uplink activity) occurring in the link between AP_i and STA_j respectively, $\mathbb{Q}$ constrains the service area, α_{min} and α_{max} set the lower and upper bound for the transmit power, $G_{i,j}$ and $L_{i,j}$ are the antenna gains and losses of the communication link between AP_i and STA_j, and α_0 refers to the receiver sensitivity of signal detection. For simplicity we assume a single transmit power setting for both directions of a link; the framework can readily extended to handle differing transmit power values.

The antenna gains add both the transmitter antenna gain and receiver antenna gain. Similarly, the loss $L_{i,j}$ of each link contains three components: cable and connector losses on both sides, path loss, and miscellaneous losses such as fading margin. The propagation loss is estimated using the log-distance path loss model:

$$L = L_0 + 10\gamma log_{10}(\frac{d}{d_0}), \tag{2}$$

where L_0 is the path loss at the reference distance d_0, γ is the decay component, and d is the distance between transmitter and receiver.

Fig. 1 illustrates the communication activities in a simple network consisting of two STAs and one AP. Different colors (i.e., blue and black) are used to distinguish different directions of transmission. Dashed lines represent expected/imagined communication paths, while solid lines represent the corresponding actual occurring communication paths. Suppose STA_1 needs to send 3 messages to STA_2. After receiving and analyzing the messages, STA_2 sends a message back to STA_1. The intermediate AP AP_1 acts as a relay node to perform the above operations. In this case, $\beta_{1,1} = 3(uplink) + 1(downlink) = 4$ and $\beta_{1,2} = 1(uplink) + 3(downlink) = 4$. Note that they are equal because there are only two links existing in this scenario. $\alpha_{1,1}$ is the transmit power used by STA_1 and AP_1, and $t_{1,1}$ is the transmission time of packets in the link between AP_1 and STA_1. $\alpha_{1,2}$ and $t_{1,2}$ have similar meaning but between AP_1 and STA_2.

If the constraints *C1*, *C3*, and *C4* are jointly satisfied, then STA_j is efficiently covered by AP_i in the given environment. Depending on the settings, it

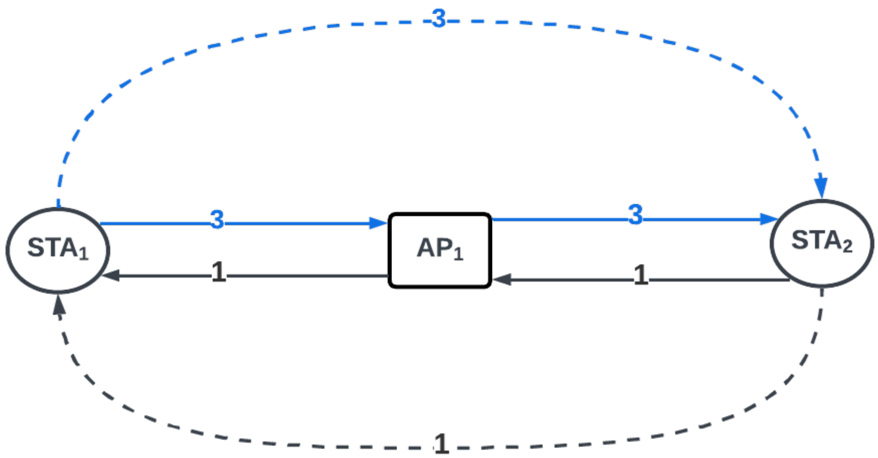


Fig. 1: An illustration of communication activity between two STAs.

is possible that an STA is covered by multiple APs. The constraint *C2* takes this situation into account and restricts an STA to only communicate with the AP offering the best cost.

We have developed a GA to solve the multivariate optimization problem formulated above, and we refer to our GA-based AP placement approach as the AP Placement GA (AP2GA). We have developed a prototype implementation of AP2GA using the DEAP Framework for GA implementation [4]. AP2GA iterates through a series of genetic operations to evolve the population (current set of candidate solutions). After a pre-determined number of iterations, AP2GA produces its final population, and from the final population, a solution with maximum fitness (see Equation 1) is selected as the final solution to the optimization process. Fig. 2 illustrates this operation of AP2GA in a flowchart.

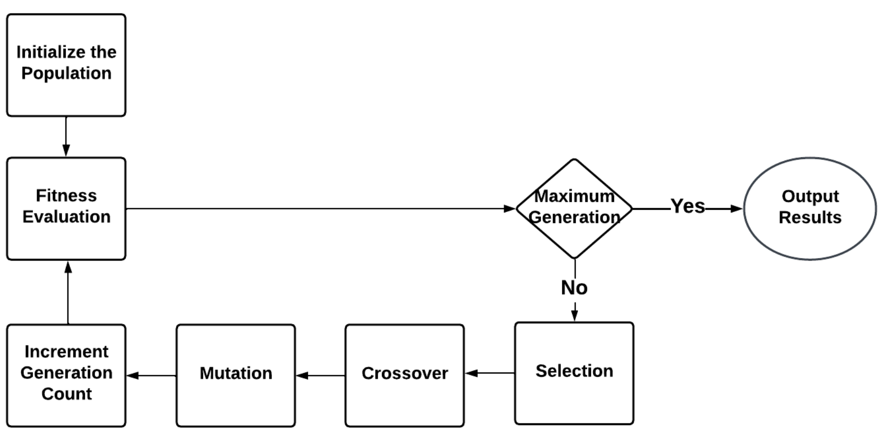


Fig. 2: A flowchart of the proposed deployment strategy.

AP2GA starts by randomly initializing a set of candidate solutions, which will form the initial population for the optimization process. Each candidate solution in a GA population is referred to, in its encoded form, as a chromosome. A candidate solution in a GA population is also referred to as an individual. Each chromosome in the population consists of a set of genes (bits) that encode x_i, y_i, and $\alpha_{i,j}$ ($i = 1, \ldots, n, j = 1, \ldots, s$) in binary format. The crossover and mutation operations, which are used to evolve the population, operate directly on the bits of the chromosome. A gene bit-string is initialized under the constraints *C1* and *C3*, and its length depends on a user-specified precision value.

After that, the fitness function is called iteratively for each individual. Based on the obtained fitness score, a tournament selection process is used to select parents to breed offspring. There is a feasibility check to see if each individual violates any constraint. If so, a large penalty value is added to the fitness score of the individual. The subsequent tournament selection process selects the parents to breed offspring based on the fitness score, so invalid individuals with large fitness scores are less likely to be selected for survival. In our formulation, higher fitness scores correspond to lower-quality solutions, so more "fit" individuals (higher levels of fitness) in the GA population correspond to lower fitness scores.

A two-point crossover follows to exchange information between the selected parents. As the name suggests, two crossover points are randomly chosen and the genes in-between are swapped to reproduce different offspring (derived candidate solutions) with different bit patterns as chromosomes. Subsequently, mutation is applied on the chromosomes. Mutation refers to the unpredictable change in certain genes during the genetic process, which is not guaranteed to have a positive or negative influence on fitness, but will enhance genetic diversity in the population [7]. The above process of evaluation and genetic manipulation (selection, crossover, and mutation) is repeated until a pre-determined number of generations has been reached.

4 Factory System Modeling

We extend our previously proposed factory process-flow model to evaluate our new deployment strategy [5]. An illustration is shown in Fig. 3.

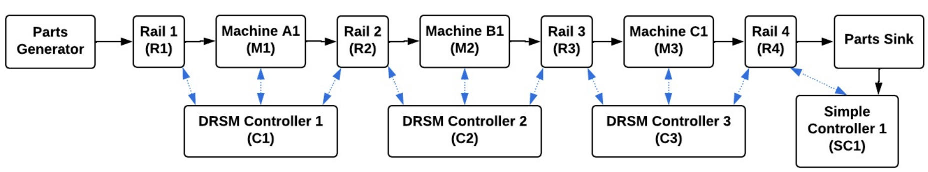


Fig. 3: The factory process flow model that we use in our experiments.

Five types of functional units (actors) are used in the system: part generator, rail, machine, controller, and part sink, where they cooperatively model a basic work cell in a production environment. Each actor effectively encapsulates a finite state machine, where each state (mode) of the actor corresponds to a specific sub-function executed by the actor. The raw components produced by the part generator undergo processing by machines that add features, and are ultimately stored in the part sink once all processing is completed. There are two types of edges shown in the figure: the one-way black edges represent physical links, including both physical entity transport and any associated information flow, while the two-way blue edges represent the transfer of data across wireless communication links.

Rails, machines, and controllers in the environment are equipped with communication devices. Rails and machines report their status to the controller whenever mode transitions happen. After receiving state information, the responsible dual-rail-single-machine (DRSM) controller performs some computation and sends instructions back to the actors to which it is connected. Additionally, there is a special controller, called a simple controller, as shown in the lower right side of Fig. 3. The simple controller records the capacity information of the part sink and controls the release of the last rail. Thus, the modeled workflow can run smoothly with continuous information exchange.

Communication capability is enabled by a specific type of actor called a communication interface actor. Communication tasks are divided into sending and receiving sub-tasks, which are undertaken by the send interface actor (SIA) and receive interface actor (RIA), respectively. For more details on the factory system modeling approach that we build upon in this paper, including the modeling of communication functionality, we refer the reader to [5, 9].

In [5, 9], it is assumed that the machines used in the factory floor are homogeneous. However, in general the operation of a factory may involve the cooperative work of different types of machines, which are specialized for diverse tasks. This diversity generally results in varying processing times and varying levels of communication traffic. Therefore, unbalanced processing and communication activities need to be considered for more general system modeling scenarios.

5 Experiments

In this section, we present simulation results that demonstrate the effectiveness of the proposed AP2GA approach. Our simulations are carried out using ns-3 [11].

The service area for our simulated systems is 20 m x 20 m. There is a total of 13 actors involved in the factory system model of which 11 of the actors involve data communication to other actors (the part generator and part sink do not involve data communication in this model). The communication relationships between the actors are illustrated in Fig. 3.

Each actor is characterized by an activity rate, which characterizes both the outgoing and incoming traffic for the actor. Except for the first rail, each rail has a fixed activity rate of 5 messages/cycle. Here, by a "cycle", we meant the entire processing of a single part through the entire factory pipeline, from the part source to the part sink. Three types of machines are used, and they have activity rates of 8, 6, and 3 messages/cycle, representing high activity, medium activity, and low activity, respectively. The activity rate of a DRSM controller D is the sum of the activity rates of the two rails and one machine that are connected to D, while the simple controller is only responsible for the last rail.

Considering the different volumes of machines and different lengths of conveyors that are typically found in practice, the spacing between actors is nonuniform in our experiments.

We apply the same channel configuration across the entire system model. Unless otherwise stated, the activity rate and placed location of each actor is as listed in Table 1, and other aspects of the simulation setup are as listed in Table 2.

Regarding the threshold for signal detection, two similar values are used in related literature: -65 dBm [13], and -70 dBm [14]. We used the value of -65 dBm to account for the severe multipath fading typical in industrial environments.

Table 1: Communication activity rate and position for each actor. The units for the activity rate are messages/cycle.

Actor	R_1	M_1	R_2	M_2	R_3	M_3
Activity	3	8	5	6	5	3
Position	$(0,0)$	$(0,2)$	$(0,5)$	$(0,7)$	$(0,9)$	$(0,15)$
Actor	R_4	C_1	C_2	C_3	SC_1	
Activity	5	14	11	8	2	
Position	$(0,18)$	$(1,2)$	$(1,6)$	$(1,14)$	$(1,17)$	

Table 2: Other simulation parameters.

Parameter	Value
Number of GA generations	1000
Population size	300
Crossover rate	0.5
Mutation rate	0.2
Tournament selection size	10
Number of bits in each variable	6
Maximum transmit power of AP (α_{max})	17 dBm
Minimum transmit power of AP (α_{min})	0 dBm
Path loss exponent (γ)	3
Reference distance (d)	1 m
Threshold for signal detection (α_0)	-65 dBm

Two scenarios are intensively considered in our experiments: (1) all devices are cable-connected to their power supplies, and (2) all devices are powered by batteries.

5.1 Devices with Cable-Connected Power Supplies

In this simulation, the goal of our deployment strategy is to minimize the communication energy consumption of the network. The position of each actor is listed in Table 1. The actors are non-uniformly distributed in this layout.

First, we do not take into account the non-uniform distribution of actors, nor do we take into account unbalanced communication activity, and we place the AP at the center position $(0.50, 10.00)$ of the pipeline. This center position is a simple and intuitive choice if we do not take into account non-uniform distribution and unbalanced communication, as described above. We execute the simulator for 1000 cycles and record the obtained energy consumption.

Next, we execute AP2GA to take into account the non-uniform actor distribution and unbalanced communication activity, and derive an optimized position for a single AP. The resulting AP position is $(0.70, 7.90)$. We move the AP to this position in our simulation model, and again execute 1000 simulation cycles. We compare the energy consumption brought by (1) deploying the AP in the center position ("middle"), and (2) deploying the AP based on the result produced by AP2GA. The results are shown in Fig. 4.

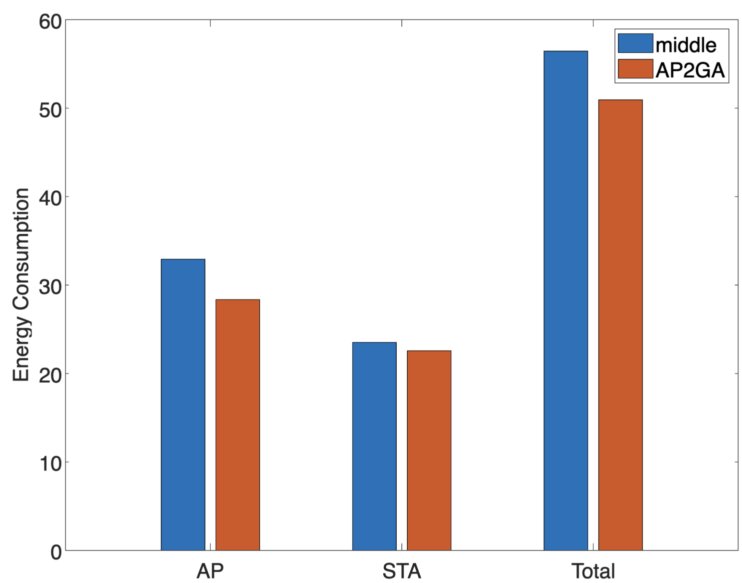


Fig. 4: Energy consumption in different locations.

In Fig. 4, the total energy consumption is the summation of the energy consumed by both the AP and the STAs. The AP column represents the overall downlink energy consumption, while the STAs column represents the overall uplink energy consumption. Since the maximum/minimum allowed transmit power and available power levels are all set to be the same for every communication node in the simulation model, the differences in the energy consumption between the downlink and uplink come from the uneven inflow and outflow the actors.

It can be clearly seen from Fig. 4 that even for this relatively simple and small-scale example, AP2GA results in a significant reduction in total energy consumption compared to the simple/intuitive strategy of placing the AP at the center position. The relative energy savings provided by AP2GA is about 10%, which will amount to significant absolute energy savings over long-term operation. Since the uneven outgoing and incoming traffic makes the downlink bear more long-distance workload, there is more significant reduction in the energy consumed by the AP. For example, when *Rail* 2 sends packets to *DRSM Controller* 1, the downlink transmission distance (from the AP to the controller) is longer than the uplink transmission distance (from the rail to the AP).

5.2 Battery-Powered Devices

In Section 5.1, we optimized the total energy consumption supposing that all of the STAs and the AP are cable connected to power supplies. However, due to their low-price and easy installation, an increasing proportion of communication devices in industrial environments are powered by batteries.

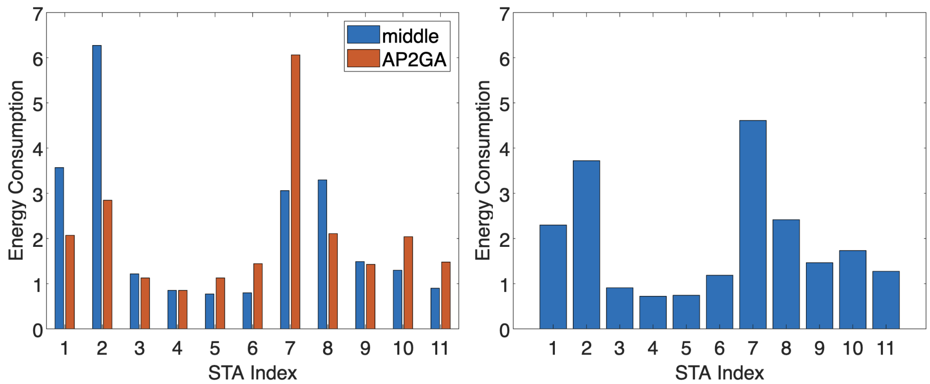
When battery-powered communication devices are employed, it is important to consider the network durability when designing and configuring the network. Intuitively, by network durability, we mean the length of time that the network remains operational as batteries in the communication devices are drained. There are various ways to measure the network durability depending on the particular kinds of operational scenarios that are of interest. Since our scenario requires the mutual work of all devices in the network, we use a measure of network lifetime to assess durability, and we regard the time until one STA's battery is drained as the network lifetime. That is, the network lifetime is the time from the beginning of operation until the time when the first STA stops operating due to insufficient energy availability.

Assuming that all devices have the same battery capacity, maintaining a long network lifetime requires that all devices consume energy at approximately the same average rate — that is, the variance of energy consumption across the battery-powered devices should be low. To assess energy consumption variance, we plotted the energy consumption of each STA under both the center-position and AP2GA-based AP deployment obtained from case 1 in Fig. 5a, and tabulated their corresponding standard deviations ("Std.") values in Table 3.

Table 3: Standard deviation of STA energy consumption.

Label	center pos.	AP2GA pos. 1 with cables	AP2GA pos. 2 with battery
AP Position	(0.50, 10.00)	(0.70, 7.90)	(-0.16, 8.57)
Std.	1.74	1.38	1.26

From Fig. 5a, we can see that the energy consumption of the STAs is unbalanced in both deployment scenarios — center-position and AP2GA-based. Peaks appear on different devices depending on the combination of communication distance and activity rate. However, the distribution of STA energy consumption



(a) In cable-connected configuration and AP2GA position 1.

(b) In AP2GA position 2 with constraint C5 (Equation 3).

Fig. 5: Energy consumption levels of the different STAs under different AP deployment configurations.

under AP2GA-based deployment from case 1 has better performance in terms of standard deviation.

To prolong network lifetime and ameliorate the imbalance described above, the dispersion of STA energy consumption can be taken into account in AP2GA. For this purpose, a maximum value for the standard deviation std_{max} can be imposed as another constraint:

$$C5 : \sqrt{\frac{\sum_{j=1}^{s}(e_j - \mu)^2}{s}} \leq std_{max}, \text{ where } e_j = \alpha_{i,j} t_{i,j} \beta_j, \ \mu = \frac{\sum_{j=1}^{s} e_j}{s}. \quad (3)$$

Moreover, when optimizing deployment for battery-powered devices, the activity rates used in the AP2GA are changed to only include the outgoing traffic for each device (i.e. $\beta_{i,j} \rightarrow \beta_j$). In our formulation, the updated fitness function measures the total transmission energy consumed by all STAs in the network, rather than the combination for all the STAs together with the AP, which was assumed in Section 5.1.

Through simulation experiments, we empirically determined that for our deployment case study, an effective maximum standard deviation value — for use in Equation 3 — is $std_{max} = 1.3$. We executed AP2GA to find optimized deployment positions for this value of the maximum standard deviation. Then for the resulting deployment, we ran a simulation for 1000 cycles and plotted the energy consumption, as shown in Fig. 5b. In comparison with Fig. 5a, we can see that the results in Fig. 5b are more concentrated and the peak value has decreased. The standard deviation of 1.26, which results from imposing $std_{max} = 1.3$, represents a significant improvement compared to 1.74, which is the standard deviation measured from center-position deployment.

AP2GA can be applied in or extended for a wide variety of design space exploration scenarios to incorporate different combinations of decisions that are involved in deploying communication devices. For example, in our experiments, we assumed that the STAs have identical battery capacities. This condition can be relaxed to explore design spaces where batteries of different types are considered — ranging from small and less costly low-capacity batteries to large and more costly high-capacity batteries. The AP2GA fitness function may be extended in such a case to consider the cost of the deployment as well as the energy consumption, while taking into account the different available battery types. A candidate network configuration C would then include an an assignment of battery types to the STAs. Various candidate configurations $C_1, C_2, \ldots, C_n$ can be optimized using AP2GA and evaluated through simulation to determine a single configuration to select among those that are evaluated. Such extension of AP2GA to assist with more general or comprehensive design space exploration is an interesting direction for future work.

5.3 Summary

In summary, from the study and experimental results presented in this paper, two main findings and implications emerge. First, in environments where users are unevenly distributed and their communication traffic varies, proper deployment of APs can significantly reduce the transmission energy consumption of the entire network. Second, the original formulation of AP2GA can be readily extended to other energy-related scenarios by manipulating selected parameters and introducing additional constraints. Averaging the transmission energy of battery-powered devices is an example, and there are many additional possibilities for performing other types of design space exploration.

6 Conclusion

In this paper, we have introduced an energy-efficient AP deployment strategy for industrial Internet of things (IIoT) environments. The developed strategy, which is based on a novel genetic algorithm called the Access Point Placement Genetic Algorithm (AP2GA), optimizes energy consumption in an environment with uneven distribution of communication stations that can have varying levels of communication traffic. Simulation results involving two factory process flow scenarios demonstrate the effectiveness of the AP2GA approach in improving the energy efficiency of AP deployments. For environments in which stations have cable-connected power supplies, we demonstrate the use of AP2GA in optimizing total energy consumption, while in environments that involve battery power, we demonstrate the use of AP2GA in maximizing the operational network lifetime. A current limitation of AP2GA is that the algorithm assumes a single communication channel configuration, which is used uniformly in the modeled industrial environment. Interesting directions for future work include incorporating diverse channel configurations, and also extending the approach to consider additional metrics, such as communication throughput and deployment cost.

Declaration of Generative AI and AI-assisted technologies in the writing process. During the preparation of this work the authors used ChatGPT in order to correct possible grammatical errors and improve the readability of the paper. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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