Optimal Placement of Internet of Things Gateways in Modern Electric Vehicle Charging Communication Systems

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ABSTRACT

This paper presents the use of the optimal placement and number of the Internet of Things (IoT) gateway method to support home Electric Vehicle (EV) charging scheduling within an IoT system. A research was conducted for two scenarios. In scenario 1, a single IoT gateway was placed, while in scenario 2, the optimal number of IoT gateways was placed. The evaluation method for both scenarios utilized random placement, Equally Distributed Placement (EDP), and Genetic Algorithm (GA) placement. The optimization result ensures that the Path Loss (PL) value in the communication system does not exceed the specified PL threshold. This research aims to minimize the IoT gateways while ensuring quality data transmission, specifically maintaining a data rate above 31.72 kbps and a throughput of 24 kbps. The results indicate that both the random placement and EDP require more than three IoT gateways. Meanwhile, the GA placement requires only three IoT gateways, making it a more cost-effective communication solution.

Keywords-internet of things; gateway; path loss; optimal placement; LoRa

I. INTRODUCTION

The growing awareness of sustainability issues has led to a corresponding increase in EV users [1, 2], which has driven advancements in the EV charging station technology, leading to more efficient and accessible charging solutions. Residential EV charging stations in every home [3-5] have become a preferred option because they offer convenience and easy access for the EV users. To achieve a fully sustainable technology, the power source should come from renewable energy resources. In the context of a residential charging station with a centralized Photovoltaic (PV) system, energy limitations must be considered. Additionally, renewable energy sources may face intermittency. EV charging scheduling is a strategy to balance the energy between the source and loads [6, 7]. Currently, IoT plays an important role in achieving this goal [8-10]. IoT seamlessly connects data from the source and load devices. Then, the former enables automated EV charging scheduling decisions without human intervention. In [11], IoT was integrated with EV charging in a specific case. The IoT-driven benefits enable better management of power distribution and the ability to obtain real-time reports on the charging behavior. These reports are used for predictive maintenance and to reduce downtime. In [12], a smart EV charging station was prototyped utilizing the IoT Thing Speak cloud service. This prototype is equipped with the ability to automatically switch between solar, wind, or main power sources based on their availability. In [13-15], an IoT framework or infrastructure was developed to facilitate the coordination between the EVs and charging stations. The main role of the IoT-driven technology in charging stations is to facilitate a seamless communication between the EV charging stations and charging sources. Therefore, reliable data transmission processes need to be further examined to enhance this research. The Long Range (LoRa) 2.4 GHz communication mode can be utilized for IoT communication [16]. The typical LoRa data transmission starts with sensors (IoT nodes), which relay information to an IoT gateway before it is sent to a server or cloud [17]. The volume of data generated by the IoT nodes must be processed using a reliable and cost-effective communication method to facilitate the exchange and processing of such large amounts of data. Based on [18, 19], the throughput needed for home EV charging systems can range from 10 to 100 kbps. Therefore, the throughput of the communication link should be considered when designing and planning a network. Reliable data transmission is highly dependent on PL which affects the strength and quality of the signal as it travels through various environments [20]. Consequently, the placement of the IoT gateway plays a crucial role in determining the PL value. The optimal placement of the IoT gateway will reduce cost and enhance network performance [21-24]. Therefore, the appropriate placement of the IoT gateway can significantly maintain signal integrity and data reliability in an IoT network. This research aims to evaluate the IoT gateway placement for a home EV charging station. Specifically, this research focuses on identifying the optimal placement that minimizes the number of IoT gateways while ensuring the quality of data transmission.

In this research, three methods were evaluated to determine the optimal placement and number of IoT gateways in the IoT system for residential PV charging stations. In a large residential area, the data transmission between the IoT nodes (EV devices and PV) and IoT gateways must be considered. The criterion for the optimization function is to minimize the total of PL while ensuring that the PL of all IoT nodes does not exceed the specified PL threshold constraint. The minimum PL indicates the reliability of the IoT system performance. Therefore, the optimal placement is in the minimum PL area. Meanwhile, minimizing the number of IoT gateways contributes to cost-effective communication. Random placement, EDP, and GA placement are applied for comparison.

The main contributions of this research are:

1. Determining the optimal placement and number of IoT gateways in an IoT system specifically designed for residential PV charging stations.
2. Analysing two scenarios to evaluate the performance of the implemented optimal placement. In scenario 1, one IoT gateway is placed as the initial condition. In scenario 2, the optimal number of IoT gateways is placed based on random placement, EDP, and GA placement, which are applied for each scenario.
3. Maintaining the data rate and throughput value in the communication between the IoT nodes and IoT gateways to ensure that the system meets the specific performance standards.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The proposed model in this research is a residential PV charging station. This model is typically located in urban and suburban areas. Firstly, the residential area model is determined and the coordinates of each house are identified. In this research, a residential study was conducted in Pakuwon City Surabaya, Indonesia, since this residential area has the potential for the implementation of home EV charging systems. The placement of IoT gateways is done using random placement, EDP, and GA placement. The IoT gateway is connected to each house equipped with an EV charging station and a centralized PV, functioning as IoT nodes. Figure 1 presents an overview of the tasks to be performed in this research. This system enables seamless data exchange to determine the EV charging schedule.

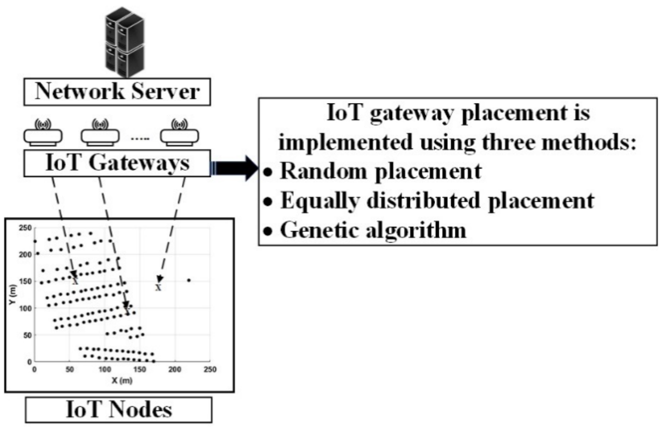

Fig. 1. IoT network architecture with optimal IoT gateway placement strategy.

The present research implements the Electronic Communication Committee-33 (ECC-33) model, which is a modification of the Okumura-Hata model. The latter is designed for Ultra High Frequency (UHF) frequencies, but its accuracy remains uncertain at high frequencies [25]. Meanwhile, the ECC-33 modifies the assumptions of Okumura-Hata to make it suitable for signals at a frequency of 2 GHz, which corresponds to the 2.4 GHz used in LoRa [16]. The ECC-33 model also classifies the urban areas into categories of large cities with dense building structure, such as Tokyo, and medium-sized cities, such as those found in typical European suburban areas [25]. Therefore, the ECC-33 model is suitable for the propagation model in residential areas. The residential model in this research is classified as a part of the medium city category. Therefore, the ECC-33 model is used in this research.

The linear PL of a wireless channel is characterized as the ratio of the transmitter power (P_{tx}) to the receiver power (P_{rx}) [26]. Equation (1) represents the PL for the channel between an IoT gateway located at point i and an IoT node at point j. The PL formulation using the ECC-33 model is defined by:

$$PL_{i,j} = \frac{P_{tx_i}}{P_{rx_j}} \quad (1)$$

$$PL_{i,j} = A_{fs} + A_{bm} - G_t - G_r \quad (2)$$

where $G_r \in \{G_{r1}, G_{r2}\}$ and:

$$A_{fs} = 92.4 + 20\log_{10} d_{ij} + 20\log_{10} f \quad (3)$$

$$A_{bm} = 20.41 + 9.83\log_{10} d_{ij} + 7.89\log_{10} f + 9.56[\log_{10} f]^2 \quad (4)$$

$$G_t = \log_{10}\left(\frac{h_t}{h_r}\right)\left\{13.958 + 5.8\left[\log_{10} d_{ij}\right]^2\right\} \quad (5)$$

$$G_{r1} = [42.57 + 13.7\log_{10} f] \times [\log_{10}(h_r) - 0.585] \quad (6)$$

$$G_{r2} = 0.759h_r - 1.86 \quad (7)$$

$$d_{ij} = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \quad (8)$$

In (2-8), A_{fs} is the free space attenuation, A_{bm} is the basic median PL, G_t is the transmitter height gain factor, G_r is the receiver height gain, which can be either G_{r1} or G_{r2}, G_{r1} and G_{r2} are the receiver height gain factors for medium and large cities, respectively, f is the frequency (GHz), h_t is the transmitter height (m), h_r is the receiver height (m), d_{ij} is the Euclidean distance between the i^{th} IoT gateway and the j^{th} IoT node (km), and (x_i, y_i) and (x_j, y_j) represent the Cartesian coordinates of the i^{th} and j^{th} IoT nodes, respectively.

Minimizing the PL in a communication channel, results in improving the data rate, which refers to the actual rate at which data are successfully transmitted over a communication channel in a given period of time. Therefore, this research aims to find the optimal placement and number of IoT gateways to achieve the minimum PL. The optimization problem is formulated in (9-10) with constraints defined in (11):

$$F_{objective} \Rightarrow min\ (PL) \quad (9)$$

$$PL = \sum_{j=1}^{M}\sum_{i=1}^{N} PL_{ij} \quad (10)$$

$$PL_{ij} \leq PL_{th},\ \forall i,j \quad (11)$$

The constraint of the objective function ensures that the PL does not exceed a specified threshold. In this research, LoRa 2.4 GHz is utilized with a spreading factor (SF) of 5, receiver power (P_{rx}) of -109 dBm, P_{tx} of 12.5 dBm, bandwidth (B) of 203 kHz, and data rate (R_b) of 31.72 kbps [27]. The power reduction during transmission or PL_{ij} determines the P_{rx} in the communication channel in (12). Based on the previous parameters, PL_{th} is 121.5 dB to achieve the minimum P_{rx}. Meanwhile, M is the number of IoT nodes and N is the number of IoT gateways. If the PL is kept below the PL_{th}, the LoRa module can continue to operate with $SF = 5$. As a result, the data rate and throughput can be maintained at a minimum of 31.72 kbps and 24 kbps, respectively. Furthermore, the formulation for R_b is presented in (13) and the throughput (Thr) is detailed in (14-17). In this context, T_s represents the symbol duration in seconds, N_{sym} is the number of symbols needed for the payload, CR is the coding rate of 4/5 [27], PS is the payload size (bytes), and T_{total} is the total transmission time (s):

$$PL_{th} = P_{tx} - P_{rx} \quad (12)$$

$$R_b = \frac{SF \times B}{2^{SF}} \quad (13)$$

$$T_s = \frac{2^{SF}}{B} \quad (14)$$

$$N_{sym} = \frac{8 \times PS + 4.25}{PS \times (1 - CR)} \quad (15)$$

$$T_{total} = N_{sym} \times T_s \quad (16)$$

$$Thr = \frac{PS \times 8}{T_{total}} \quad (17)$$

III. OPTIMIZATION OF PLACEMENT AND NUMBER OF IOT GATEWAYS

Assume that each home charging station and the central PV are integrated with an IoT system and a LoRa network. The IoT system design connects all IoT nodes to the IoT gateways before sending data to the server. An optimal placement of the IoT gateways is required to ensure reliable communication for the IoT nodes. The placement is approached employing three placement methods, which are random placement, EDP, and GA placement. Figure 2 illustrates the data transmission flow.

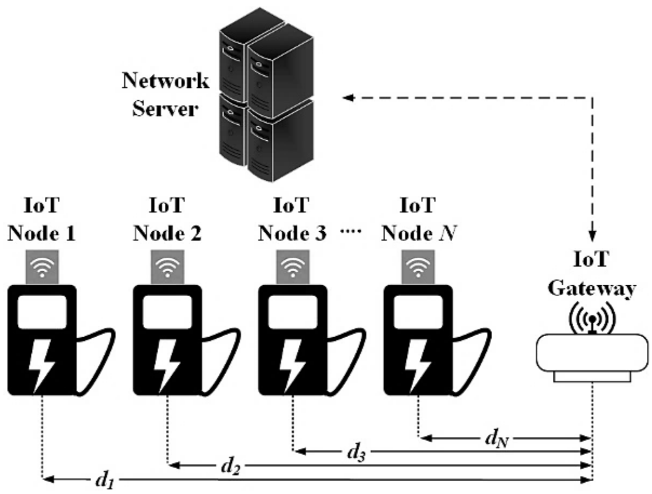

Fig. 2. The data transmission flow.

A. *Random Placement*

The random placement of the IoT gateway determines the location points that randomly surround the IoT nodes without considering any factors or specific patterns. This method is very simple, but the optimization is often not achieved. This method is utilized as a baseline for comparison with other methods to evaluate performance.

B. *Equally Distributed Placement*

EDP placement is a straightforward method for determining the placement of the IoT gateways. The total number of the IoT nodes (M) is divided into the R regions, where each region contains an equal or approximately equal number of IoT nodes.

The number of regions corresponds linearly to the number of IoT gateways (*N*). Each IoT gateway is placed in the center of each region to ensure an even distribution of the IoT nodes. First, one IoT gateway will be placed at the center. Then the PL is calculated. If the PL exceeds the threshold (PL_{th}) at any points, another IoT gateway is added. Therefore, the area is divided into several clusters according to the minimum number of IoT gateways required. Figure 3 displays the EDP method used in this research.

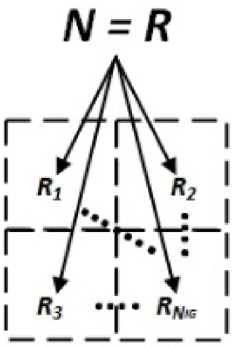

Fig. 3. EDP method for optimal placement and number of IoT gateways.

C. Genetic Algorithm

The third method for optimal placement of the IoT gateways is through the application of a GA. GA employs evolutionary principles to iteratively identify the optimal position of the IoT gateways, thereby ensuring that the PL values of the IoT nodes do not exceed the threshold. The implementation of GA in this research is carried out as follows: A population of 50 individuals is generated at each randomly selected location. Each individual contains PL values that represent the chromosomes. Based on the optimization formulation, the selection process will choose the best individuals. The coupled selected individuals will undergo crossover to produce new individuals that have the potential to become an optimal solution. Then, the new individual is mutated at a rate of 0.01 and re-evaluated using the optimization formulation. This process is repeated for 100 iterations to obtain the optimal placement. Figure 4 presents the optimal placement method using GA, where N_{IG} represents the number of IoT gateways and IG represents the IoT gateway.

IV. SIMULATION AND RESULTS

To evaluate the proposed method, this research conducted residential mapping, with data collected using Google Maps ©2024 Google, as depicted in Figure 5, to obtain the necessary real position data. The residential site location is classified as a medium city. Then, the residential site data are converted into Cartesian coordinates to calculate the distance between the i^{th} IoT gateway and the j^{th} IoT node. It is assumed that LoRa 2.4 GHz is used as the communication mode for the data transmission. The objective of this research is to minimize the PL so that it does not exceed the PL threshold (121.5 dB). To achieve this goal, the number and placement of IoT gateways should be optimized. The implemented optimization demonstrates the ability to constrain the PL to a specified threshold for all IoT nodes. The result of the optimal placement and number of IoT gateways will lead to maintained quality of service.

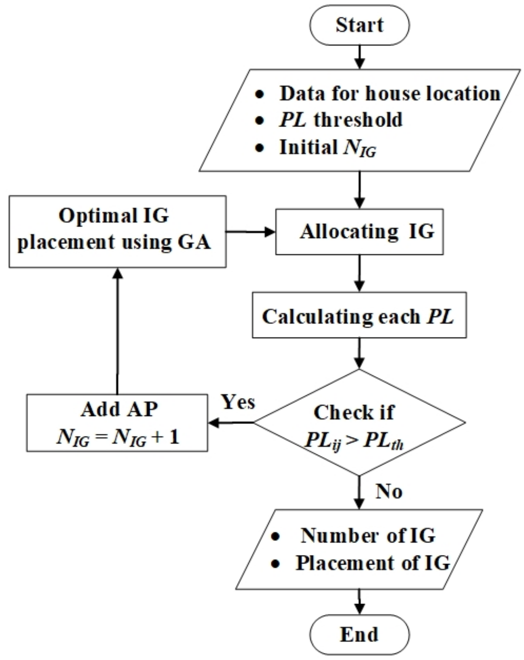

Fig. 4. The GA method for optimal placement and number of IoT gateways.

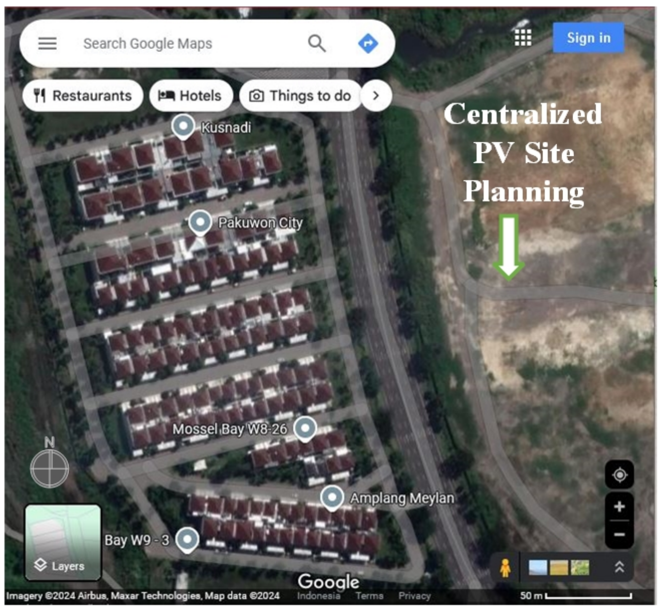

Fig. 5. Screenshot of the residential site location from Google Maps ©2024 Airbus, SNES / Aribus, Maxar Technologies.

As described in section III, the process of optimizing the placement and number of IoT gateways is performed until it is found that PL does not exceed the PL threshold for all IoT nodes. In scenario 1, the IoT gateway allocation is performed for one IoT gateway using the random placement, EDP, and

GA placement methods. The results demonstrate that having only one IoT gateway is insufficient across all placement methods. This is because there are 37 IoT nodes that exceed the PL threshold for the random placement, whereas ten IoT nodes exceed the PL threshold for both the EDP and GA placement. The IoT gateway placement positions of each method in scenario 1 are presented in Figure 6. Therefore, the process continues for the optimal number of the IoT gateways placement. The results indicate that the GA placement successfully satisfies the PL threshold for three IoT gateways. Meanwhile, the random placement and EDP methods still fail to meet the threshold. The EDP method has one IoT node that exceeds the PL threshold, whereas the random placement method has eight IoT nodes that exceed the PL threshold. The results of the optimal IoT gateway placement positions are portrayed in Figure 7. The GA placement optimization method for the IoT gateway placement can reduce the number of the required IoT gateways, contributing to more cost-effective communication, as demonstrated in Figure 8. Additionally, the optimal IoT gateway placement kept the PL below the threshold value, as exhibited in Figure 9.

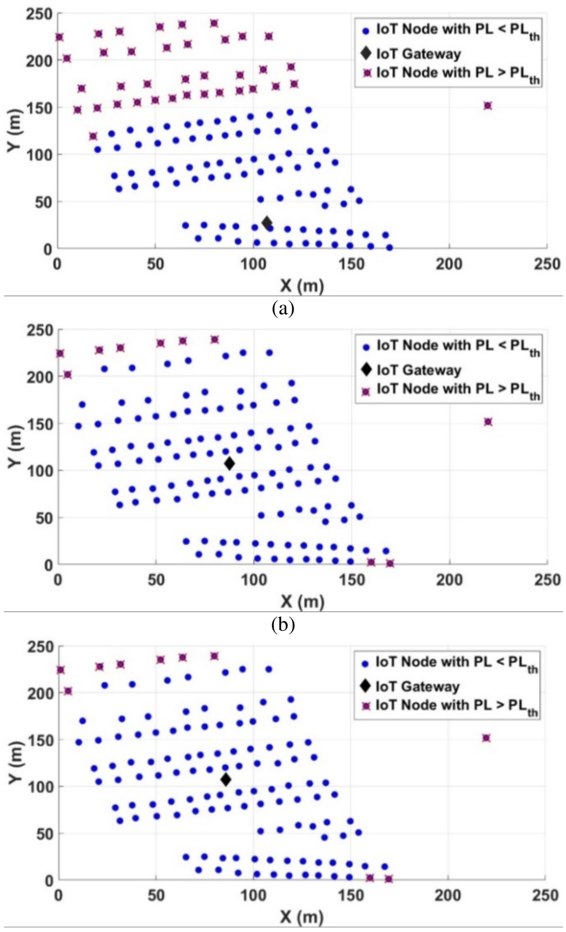

Fig. 6. Cartesian image in scenario 1 condition: (a) random placement, (b) EDP, (c) GA placement for one IoT gateway.

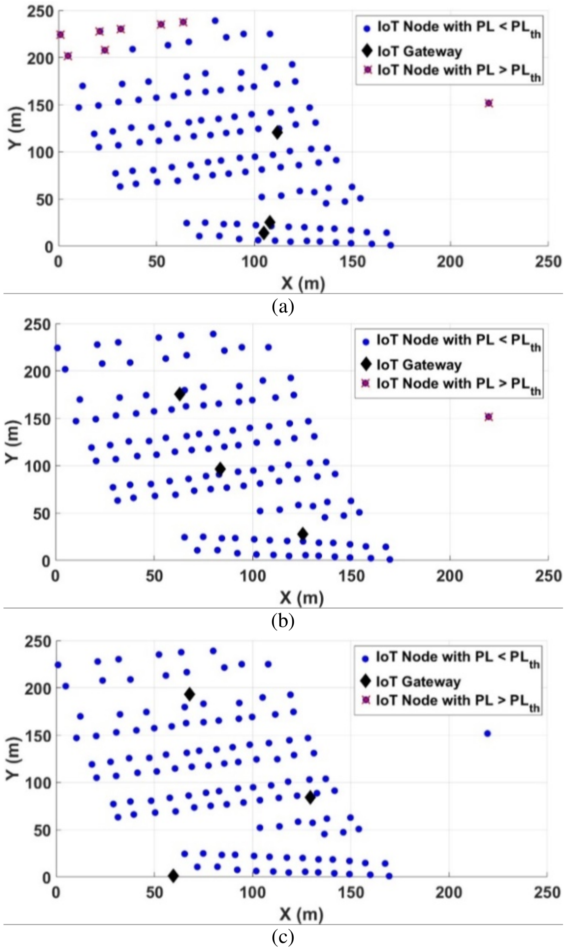

Fig. 7. Cartesian image in scenario 2 condition: (a) random placement, (b) EDP, (c) GA placement for three IoT gateways.

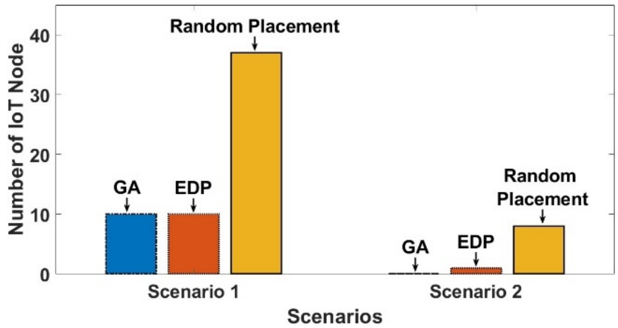

Fig. 8. The number of IoT nodes that do not meet the objective constraint.

As a result of the optimal placement and number of IoT gateways, the quality of data transmission is maintained. Figure 10 demonstrates that the communication system operates above the desired data rate of R_b =31.72 kbps. Maintaining PL and SF affects the throughput value, which is maintained at 24 kbps. This condition facilitates reliable communication between devices in residential charging stations and maintains performance in managing energy consumption and charging processes.

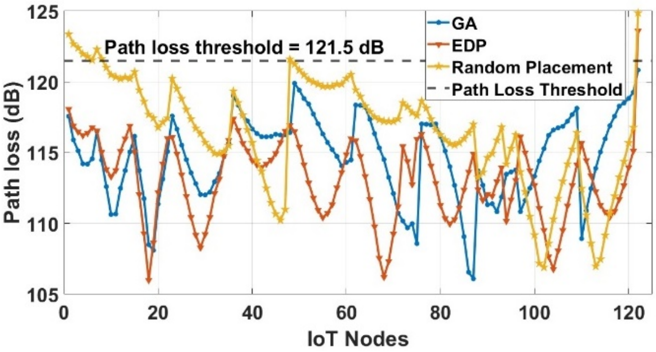

Fig. 9. PLs.

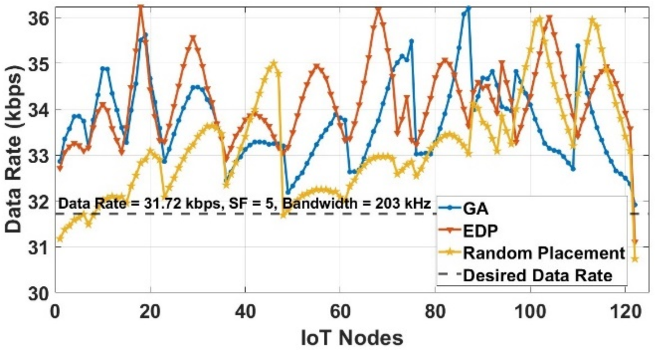

Fig. 10. System data rate results.

The simulation results show that a shorter distance results in lower PL compared to a longer distance between the IoT node and gateway. As a result, the required power consumption varies for each IoT node. Therefore, the adaptive transmission power can be considered as a future work to reduce the power consumption in IoT nodes. Distance is one of the criteria for determining the adaptive transmission power. The transmission power for both the fixed and adaptive transmission power is presented in Figure 11. As an initial hypothesis, fixed transmission power requires 2169.501 mW, whereas adaptive transmission power with distance criteria requires only 546.6569 mW for all IoT nodes. The energy saving efficiency of adaptive transmission power compared to the fixed transmission power is 74.80%. This approach will improve energy efficiency across the IoT systems and support the use of limited renewable energy resources.

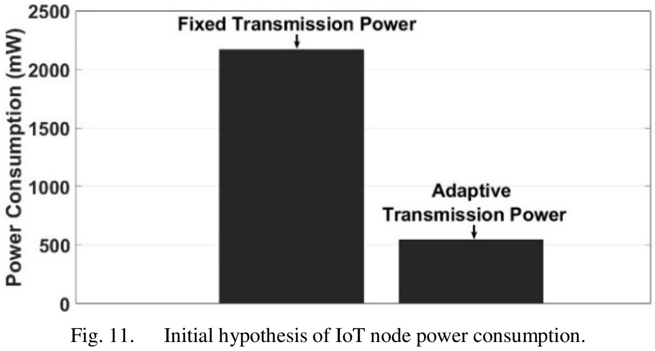

Fig. 11. Initial hypothesis of IoT node power consumption.

V. CONCLUSION

In this research, the optimal placement and number of Internet of Things (IoT) gateways for home charging are considered to implement Electric Vehicle (EV) charging scheduling within an IoT system. In other works, the IoT gateway placement is treated as a cluster assignment problem and IoT gateways are load balanced. In contrast, this work focuses on finding the optimal placement of the IoT gateways by considering the Path Loss (PL). The key contribution is finding the optimal placement with a specific PL threshold to achieve performance that meets the requirements of home EV charging using Long Range (LoRa) 2.4 GHz. There are two scenarios to compare the IoT gateway placement using three methods. Scenario 1 is implemented for the minimum or least number of IoT gateways, whereas scenario 2 is implemented for the optimal number of IoT gateways. Each scenario is investigated using random placement, Equally Distributed Placement (EDP), and Genetic Algorithm (GA) placement. The objective function of the three methods is to find the minimum PL between the IoT nodes and IoT gateways that does not exceed the desired PL threshold. This objective is achieved through the optimal placement method of the IoT gateway. The optimal placement of the IoT gateway is able to maintain the data rate value above 31.72 kbps and a throughput of 24 kbps. This system contributes to the overall performance of the IoT infrastructure needed for home EV charging. The simulation results demonstrate that the GA placement achieves better outcomes compared to the random placement and EDP. The GA placement can achieve the objective function with three IoT gateways, while the other two methods require more than three IoT gateways. Adaptive transmission power might be required to reduce the power consumption in the IoT node devices. According to the initial hypothesis, the energy saving efficiency of the adaptive transmission power in IoT nodes is 74.80% compared to the fixed transmission power. This approach will improve the overall energy efficiency of the IoT systems and benefit the limited renewable energy sources.

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