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ORIGINAL RESEARCH ARTICLE

A novel relay placement method for smart energy IoT systems in offices with genetic algorithm

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ABSTRACT

Smart energy in large offices and organizations is an important research area of the Internet of Things (IoT). The energy efficiency of buildings is vital for the environment and global sustainability. To achieve satisfactory performance for this goal, WiFi access point (AP) indoor coverage is of high importance. As it costs a lot to add more WiFi to have good coverage in all parts of the office's buildings, we consider relay node (RN) instead of adding more APs. So in this paper, we propose a novel RN placement in order to improve the indoor coverage of offices considering the signal attenuation using a path-loss model as the main measure for determining positions. The main problem is the placement of these RNs and the required number of them by considering existing APs. At first, we obtain the radio propagation model parameters by considering the data that are collected from the AP. Then based on these parameters, the proposed solution uses a genetic algorithm (GA) for RN placement optimization problem. The experimental results display the effectiveness of the proposed solution for the RN placement problem.

Keywords: smart office; Internet of Things (IoT); energy efficiency; relay node placement; path-loss; genetic algorithm

1. Introduction

The emerging Internet of Things (IoT) systems consist of a large amount of battery-powered controlling devices with limited computation capability composed of low-power, shortrange IoT devices that can not send data over a long distance for monitoring such as pressure, humidity, temperature, and seismic condition[1–6].

One of the main important research IoT devices is for smart energy purposes in large offices and organizations. The energy efficiency of offices buildings is vital for the environment and global sustainability. In addition, traditional fossil fuels cost is increasing and its side effect on the earth and climate changes make us explore new ways to improve energy efficiency in various buildings and offices[7].

Although many factors affect the total energy consumption in buildings, conventional buildings do not have intelligent designs. Therefore, by monitoring the real-time energy consumption and finding major factors, an IoT-based system can be designed to construct appropriate methods and strategies to improve the energy efficiency[8].

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The concept of smart energy in a building based on IoT refers to the monitoring and controlling of the energy appliances that are connected through a complex network. The IoT delivers users adequate information by communicating with various electronic devices through a wireless medium. The IoT has made it a cost-effective and efficient solution in the area of building energy management. The building energy management and information system and IoT are working parallels and so the system controls the indoor physical devices from every place and building, performs the intelligent, energy efficient, green and sustainable[9]. So, the main goal of IoT systems in energy management systems is data gathering, data transferring from the environment to the control systems on the cloud or on local servers and finally data processing. It is noted that, providing connectivity is an important key of each IoT system which needs a device to perform communication with another device or system[10].

There are an increasing number of smart building IoT system such as devices for controlling and monitoring electrical devices that aim to use WiFi as their connectivity access. In consequence, traditional single AP WLANs deployed in buildings may fail to deliver a satisfactory experience due to the existence of areas where the received power from the AP is low, and so we cannot reach the achievable performance. However, due to the cost consideration of APs adding more APs is not so cost-efficient.

In such common conditions, usually there is one AP with Internet access, and there are some RNs that can be added and send data to AP by a wired or wireless backhaul network[11]. Because using the wired network is not feasible all the time, wireless relays are the better choice.

In the study of Redhu and Hegde[12], the authors proposed an online RN selection method based on several machine learning techniques to optimize the reliability of the link and the data latency. In the study of Sarwesh et al.[13], the authors work on the node placement strategy and routing mechanism in the IoT network. The aim of the study was to provide an energy efficient system and reduce the retransmissions of data. Some papers considered the distance for relay placement[14–16]. In the study of Shukla and Tripathi[17], a hierarchical cluster architecture for network deployment is provided and RN selection is considered based on the shortest distance to meet the power consumption requirement of the network. However, most WiFi-based techniques use the Received Signal Strength Indicator (RSSI) as the main measure for determining positions which leads to path-loss models. RSSI is non-linearly related to distance and could fluctuate at any time depending on the surrounding environmental characteristics. Changes in average RSSI readings from one position to the other is very important for WiFi-based systems[18].

In presence of AP/relays, placement of RNs is an important and challenging issue. Since relays should be in a location to both connect the farther devices and also preserve its data rate with the AP.

Consequently, the objective of this paper is to improve the indoor coverage in large building and offices to develop smart energy solutions. This goal happens by enhancing WiFi signal coverage by adding some RNs to the network. So, we propose a RN placement method by considering the signal attenuation using a path-loss model as the main measure for determining position. At first, we obtain the signal propagation model parameters by collecting some dates from the AP. Then, we optimize the problem by utilizing a genetic algorithm (GA) method to find the best placements for the RNs by considering the minimum number of RNs due to the cost considerations and by using learning parameters. The experimental results demonstrate the effectiveness of the proposed method. The following are the main contributions to this paper:

- An efficient GA optimization method is proposed for RN placement for smart energy IoT systems.
- GA method is used to minimize the path-loss by optimizing both the number and coordinates of the RNs placements.
- Signal attenuation parameters are considered based on specific scenario model.

- Some benchmarks are employed to evaluate the efficiency of the proposed method in terms of the number of RNs, path-loss parameters and placement methods.

The remainder of this paper is organized as follows. Section 2 describes our system model and problem statement. In Section 3, the methodology of the proposed solution based on genetic algorithm is provided. The experimental setups and the performance of the proposed algorithm and our system model through different numerical specifications are examined in Section 4. Finally, Section 5 concludes this paper.

2. System model and preliminaries

The goal of this paper is enhancing the indoor coverage with minimum number of RNs and their placement that are added to the connection system among the possible locations. The cost function is calculated in terms of signal attenuation with path-loss (PL), whenever the received power from the RN is high enough at the receiver module. The goal of this problem is to find RNs placements to minimize the cost function, considering the geometry. The optimization variables are the number and coordinates of the RNs placements.

Here, we have one access point, *N* modules which aim to control the energy system of a building. Some of these modules are far from the AP and so the Received Signal Strength (RSS) is low and the path-loss is high and consequently, they cannot work properly. One way to overcome this burden is to add another AP which is not always a good solution as it is not a cost-efficient solution. Another good way is to add some RNs in an optimized place so the modules can get enough RSS and work properly and also the final cost is much lower. Consequently, the number and coordinates of RNs should be optimized[19].

2.1. Signal propagation model

For given system model, if we consider to have M RNs, the PL (in dB) at the n-th module location which is connected to the m-th RN is defined as:

$$pl_{m,n} = P_m - P_n \tag{1}$$

P_n is the received power of n-th module and P_m is the transmit power from m-th RN.

PL can also be defined in dB as shown below,

$$PL_{m,n} = L_0 + 10\gamma \log\left(\frac{d_{m,n}}{d_0}\right) + \chi_\sigma \tag{2}$$

where γ is the PL exponent (PLE) depending on different environments that signal propagates and χ_σ is a random variable with normal distribution, zero mean and standard deviation (STD) of σ and is used to model the shadow fading (SF) in a network. The values of PLE and STD are different across various environments. d_0 is the path-loss reference distance (for indoor environments, $d_0 = 1$ m), L_0 is the path-loss at the reference distance and $d_{m,n}$ is the euclidean distance between m-th RN and n-th module and is given by;

$$d_{m,n} = \sqrt{[(x_m - x_n)^2 + (y_m - y_n)^2 + (z_m - z_n)^2]} \tag{3}$$

When there are multiple RNs, each RN has to serve a group of modules (by considering the capacity of each RN). The n-th module connects to the the relays which creates less PL. So the path-loss function at the n-th module location is given by

$$PL_n = \min_m \left(pl_{m,n}\right) \tag{4}$$

where $pl_{m,n}$ is the path-loss of module n which is connected to the relay m located at the (x_m, y_m, z_m).

2.2. Cost function

To model the cost function definition, we check the worst-case path-loss and then we guarantee that even this path-loss should be less than a threshold value. So the mathematical representation of the cost function which is the maximum pathloss over all the modules is introduced as follows,

$$g = \max_{n} PL_n \tag{5}$$

There is another type of cost function which is the average of the path-losses of all modules. The average cost function aim is to improve the total signal coverage but some few remotely located modules may be ignored in spite of total coverage good quality. So as a comparison, the maximum cost function may need a large number of relays but even the average cost function may use a small number of relays, it might ignore a few remotely located modules which are located in the far areas. Since we aim to control the energy of the whole office even and even the modules in some locations with less RSS and more PL, so the maximum cost function is a better choice.

2.3. System design considerations

It is obvious that when we want to find the best location for RN placement in realistic buildings, there are some practical considerations that should be considered.

The first constraint is that the height and width of relays cannot exceed the height and width of the room. Therefore, the location of relays should be restricted to a certain location.

$$0 \leq y_m \leq y_r \tag{6}$$

$$0 \leq x_m \leq x_r \tag{7}$$

where y_r and x_r are the height and width of the room, and y_m and x_m are the height and width of the m-th relay for $m \in \{1,2,\dots,M\}$.

The second consideration is due to the path-loss threshold. The path-loss at each RN and modules locations must be less than a threshold value, typically associated with the maximum acceptable path-loss:

$$PL_m < th_1 \tag{8}$$

where th_1 is the maximum tolerated path-loss at each RN and PL_m is defined as the path-loss between each RN and AP which is defined as,

$$PL_m = L_0 + 10\gamma \log\left(\frac{d_m}{d_0}\right) + \chi_\sigma \tag{9}$$

where d_m is the distance between the m-th RN and AP. The third constraint is due to the path-loss threshold for modules which should be less than a specified acceptable module pathloss,

$$PL_n < th_2 \tag{10}$$

where th_2 is the maximum path-loss threshold at each module. The fourth constraint is concerned with the capacity of each RN to support the specific number of modules which is defined by C_m and given by;

$$C_m \leq cap_m \tag{11}$$

where cap_m shows the maximum number of modules that are connected to the m-th RN.

2.4. Problem formulation

The optimization problem which is the RN placement that aims to minimize the module path-loss which is shown by minimizing the maximum path-loss among all of the modules, can be mathematically expressed as:

$$\mathcal{P}: \min_{m}\left(\max_{n} PL_n\right) \tag{12}$$

$$\begin{gathered} \text{subject to: } C1: 0 \leq y_m \leq y_r \\ C2: 0 \leq x_m \leq x_r \\ C3: PL_m < th_1 \\ C4: PL_n < th_2 \\ C5: C_m \leq \mathrm{cap}_m \end{gathered}$$

In summary, we aim to minimize the cost function which is the maximum predicted path-loss with some penalty terms subject to constraints $C1-C5$.

3. Methodology

It is difficult to solve the placement problem for large offices. However, heuristic algorithm can be used as a promising method for complex location problems. As the models for the design of RN placement in wireless networks are quite complex and involve generally a lot of parameters, meta-heuristics algorithms like genetic algorithm (GA) can be used. GA algorithm evolves to find a global optimal solution for complex optimization problems by simulating natural behaviour. As GA algorithms are so effective with high efficiency, they have been applied to many placement problems[20]. Here, we optimize the number and placement of relays by utilizing the GA method. Possible positions to place relays are considered based on the coordinates of each room. Here are the steps that we have used to solve the problem:

- The optimization problem is proposed in 12 for giving the minimum number of RN with their placement by minimizing the cost function.
- We obtain the radio propagation model parameters, $\{L_0, \gamma, \chi_\sigma\}$ considering location path-loss.
- The genetic algorithm (GA) is employed to give possible location of RNs.
- The number and placement of RNs are optimized in order to have acceptable path-loss.

3.1. Parameters learning

Based on Equation (2), we have three unknown variables, $\{L_0, \gamma, \chi_\sigma\}$. We can calculate these parameters by gathering a group of observations including the location and the path-loss at this location. Consider that we have L observation groups, so we can have some equations as follow,

$$A = B \cdot x \tag{13}$$

in Equation (13), A, B, and x are as follows,

$$\begin{cases} A = [PL_1, PL_2, PL_i, PL_L] \\ B = \begin{bmatrix} 1 & 10\log\left(\frac{d_1}{d_0}\right) & 1 \\ 1 & 10\log\left(\frac{d_i}{d_0}\right) & 1 \\ 1 & 10\log\left(\frac{d_L}{d_0}\right) & 1 \end{bmatrix} \\ x = [L_0, \gamma, \chi_\sigma], \end{cases}$$

where A is the PL at each module and x is the unknown parameters. B is for path-loss formulation where d_i is obtained by using the distance formula, d_i is $d_{m,i}$ where m is the answer to Equation (4) for RN m, and χ_σ is used to model the shadow fading. Then, by solving the set of Equation (13) we can calculate the parameters.

3.2. GA RN placement

The GA is a series of evolutionary computation methods, and it is famous for its ability to solve various combinatorial optimization problems. In GA, there are structures called chromosomes which represent the candidate solutions to an optimization problem. The group of such solutions is named a population. Evolutionary operators are mutation, crossover, and selection that are applied to this population. In GA population, each individual includes the possible location of RNs and our proposed function in Equation (12) is its fitness. Also, we generate the possible RNs randomly as initialization. By considering elitism and 2-way tournament selection based on our fitness function, the individuals for the next crossover operation are chosen. Also, the crossover operation is the weighted sum of single-point crossover operator, double point crossover, and random crossover. The mutation operator uses random distribution to choose the mutation elements[21].

3.3. Fitness function and selection

The constraints in the objective function are soft and they are combined to the cost function by some penalty coefficients[21]. The penalty coefficients are used to provide an additional term to the cost function whenever the constraints are not satisfied. By combining the soft constraints added to the cost function as penalty terms, the cost function is given by

$$f = \min_{m} \Big\{ \max_{n} PL_n + \lambda \max\{0, PL_m - th_1\} + \mu \max\{0, PL_n - th_2\} + \omega \max\{0, C_m - cap_m\} \Big\} \tag{14}$$

where ω and μ are coefficients for path-loss threshold between a RN and AP and between RN and modules respectively and ω is the penalty coefficient for the maximum capacity of each RN to support modules.

4. Experiments and simulations

In this section, we aim to evaluate the effectiveness of our proposed method, so we perform some experiments in an office building at the University of Hormozgan in IRAN, with a 40×20 floor plan.

In our scenario, there are some IoT modules that should be connected to the network. The goal of this work is to find a minimum number of RNs with their coordinates to ensure the network coverage in the floor and consequently the IoT modules can perform the energy monitoring systems. Here, we have some requirements for example the RN maximum capacity (cap_m), which is considered between 2 to 15 in different simulation scenarios. Genetic algorithm is used to optimize the number and placement of RNs. **Table 1** shows the genetic algorithm parameters which have been chosen based on experimental results.

Table 1. Parameters for genetic algorithm.

Number of generations	Population size	Mutation rate	Crossover percentage on population
1000	100	0.05	0.8

4.1. Snapshot

In this part, a simulation run is selected which shows the results of snapshot. It shows the network visualization for our configurations. In this run there are 30 IoT monitoring sensors with one access point. The GA algorithm suggested 4 RN (each with the maximum capacity of 8 module, $cap_m = 8$) to be added to the system with their optimized coordinate. In this simulation run at **Figure 1**, the dash lines show the connection between IoT modules and AP, and the solid lines show the connection between IoT modules and RNs. Based on our proposed method which relies on minimizing the path-loss, an IoT module usually connects to its nearest RN. However, there are some IoT modules that instead of connecting to their nearest RN, they are connected to the AP. The reason is due to the fact that the goal of adding the RNs to the system is to increase the network coverage for IoT modules that are far from the AP, not the nearest one. Consequently, at first the IoT modules that located near the AP are connected and then the RN placement algorithm would start.

There are also some outliers that should be considered. As an example, there is module that is shown by a red circle. It connects to the RN above instead of the closer RN. This happens due to the maximum capacity of RN. Since the closer RN to the following IoT module already has 8 associated modules so its capacity is full and cannot accept more modules.

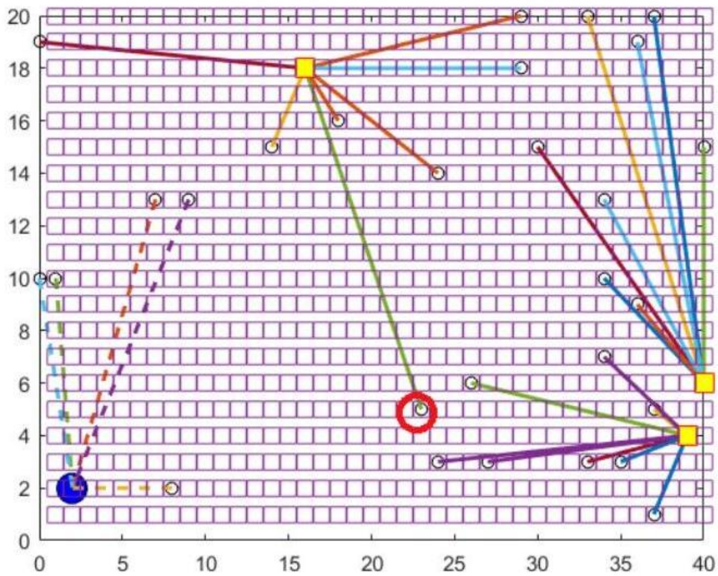

Figure 1. RN locations and device-RN connection. There is one AP that is marked by a large blue circle. Yellow squares show the used RNs and empty squares show unused possible locations without a RN. The empty circles are modules connected to AP and RNs.

4.2. Effectiveness of parameter learning

There are some references that consider the propagation parameters model, $\{L_0, \gamma, \chi_\sigma\}$ as constant[18,19]. But it is obvious that there are not the same in different places. So it is not a suitable choice to use constant parameters for every environment. Therefore, we add a learning parameter section based on AP in the office to calculate the parameters of our office.

Here we compare two methods: learning parameter and constant parameters to evaluate the effectiveness and importance of our proposed method. The constant parameters are set from the study of Rappaport.

The simulation results in **Figure 2** demonstrate that when we use the learning parameters for the RN location scheme, the performance is much better than using constant parameters. It is shown that with the same number of added RNs the cost function is less in the case of learning parameters which indicates the importance of considering parameters of each environment.

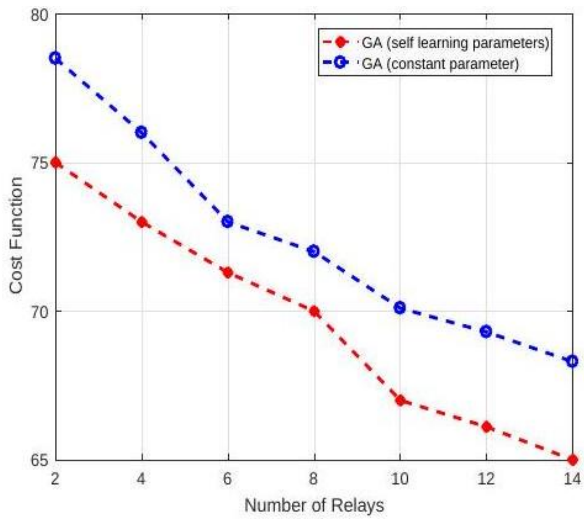

Figure 2. Comparison of the cost function using learning and constant parameters.

4.3. Evaluation of the RN placement method

In this section we aim to evaluate our proposed solution for RN placement in terms of the minimized cost function in **Figure 3**. We use the random and uniform placement methods for comparison with the GA method.

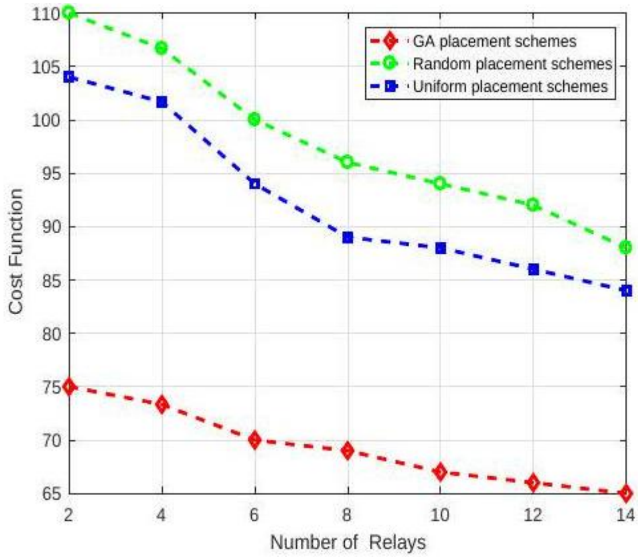

Figure 3. Cost function comparison for different placement methods.

It is obvious that since our problem formulation contains some constraints that should be considered in the placement method, the random and uniform placement method cannot satisfy them and therefore GA method which considers all the constraints is the best solution among these methods. It also can be concluded that the cost function which gives the minimum number of RNs to address the practical limitation of RN placement in a building, limitation on the maximum path-loss of both RNs and nodes and the maximum number of modules that can be connected to each RN, is less in GA method against. Consequently, the proposed GA method is superior in terms of performance, efficiency and costs.

5. Conclusion

The goal of this paper is to propose a novel RN placement method for WiFi connection in smart energy IoT systems in offices. At first, we find the signal propagation model parameters based on some observations from the AP. Then, we use the GA method to optimize the number and locations of added RNs using learning parameters. The simulation results demonstrate that our proposed GA-based solution can minimize the RN placement costs. Also, we validate the effectiveness of parameter learning. It is important to mention that the using GA method for RN placement guarantees both the minimum number of added RNs along with their best placement. Our future work should focus on RN placement in Low Power Wide Area Networks (LPWANs) such as LoRa network. LPWAN are so important for future IoT solutions and meets multiple IoT requirements such as lower cost, better energy efficiency, larger coverage, etc.

Conflict of interest

The authors declare no conflict of interest.

References

1. Ashraf N, Sheikh SA, Khan SA, et al. Simultaneous wireless information and power transfer with cooperative relaying for next-generation wireless networks: A review. *IEEE Access* 2021; 9: 71482–71504. doi: 10.1109/ACCESS.2021.3078703

2. Zannou A, Boulaalam A, Nfaoui EH. An optimal base stations positioning for the Internet of Things devices. In: Proceedings of 2021 7th International Conference on Optimization and Applications (ICOA); 19–20 May 2021; Wolfenbüttel, Germany.
3. Laghari AA, Wu K, Laghari RA, et al. A review and state of art of Internet of Things (IoT). *Archives of Computational Methods in Engineering* 2022; 29: 1395–1413. doi: 10.1007/s11831-021-09622-6
4. Heidari A, Navimipour NJ, Jamali MAJ, Akbarpour S. A green, secure, and deep intelligent method for dynamic IoT-edge-cloud offloading scenarios. *Sustainable Computing: Informatics and Systems* 2023; 38: 100859. doi: 10.1016/j.suscom.2023.100859
5. Heidari A, Jamali MAJ, Navimipour NJ, Akbarpour S. A QoS-aware technique for computation offloading in IoT-edge platforms using a convolutional neural network and Markov decision process. *IT Professional* 2023; 25(1): 24–39. doi: 10.1109/MITP.2022.3217886
6. Ahmadpour SS, Heidari A, Navimpour NJ, et al. An efficient design of multiplier for using in nano-scale IoT systems using atomic silicon. *IEEE Internet of Things Journal* 2023; 10(16): 14908–14909. doi: 10.1109/JIOT.2023.3267165
7. Ahdan S, Susanto ER, Syambas NR. Proposed design and modeling of smart energy dashboard system by implementing IoT (Internet of Things) based on mobile devices. In: Proceedings of 2019 IEEE 13th International Conference on Telecommunication Systems, Services, and Applications (TSSA); 3–4 October 2019; Bali, Indonesia. pp. 194–199.
8. Hossein Motlagh N, Mohammadrezaei M, Hunt J, Zakeri B. Internet of Things (IoT) and the energy sector. *Energies* 2020; 13(2): 494. doi: 10.3390/en13020494
9. Casado-Vara R, Martin-del Rey A, Affes S, et al. IoT network slicing on virtual layers of homogeneous data for improved algorithm operation in smart buildings. *Future Generation Computer Systems* 2020; 102: 965–977. doi: 10.1016/j.future.2019.09.042
10. Rahim A, Rahman A, Rahman MM, et al. Evolution of IoT-enabled connectivity and applications in automotive industry: A review. *Vehicular Communications* 2021; 27: 100285. doi: 10.1016/j.vehcom.2020.100285
11. Azharuddin M, Jana PK. A GA-based approach for fault tolerant relay node placement in wireless sensor networks. In: Proceedings of the 2015 Third International Conference on Computer, Communication, Control and Information Technology (C3IT); 7–8 February 2015; Hooghly, India. pp. 1–6.
12. Redhu S, Hegde RM. Optimal relay node selection in time-varying IoT networks using apriori contact pattern information. *Ad Hoc Networks* 2020; 98: 102065. doi: 10.1016/j.adhoc.2019.102065
13. Sarwesh P, Shet NSV, Chandrasekaran K. Effective integration of reliable routing mechanism and energy efficient node placement technique for low power IoT networks. *International Journal of Grid and High Performance Computing* 2017; 9(4): 16–35. doi: 10.4018/IJGHPC.2017100102
14. George J, Sharma RM. Relay node placement in wireless sensor networks using modified genetic algorithm. In: Proceedings of 2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT); 21–23 July 2016; Bangalore, India. pp. 551–556.
15. Gupta SK, Kuila P, Jana PK. Genetic algorithm for *k*-connected relay node placement in wireless sensor networks. In: Kacprzyk J (editor). *Advances in Intelligent Systems and Computing*, Proceedings of the Second International Conference on Computer and Communication Technologies. Springer New Delhi; 2016. pp. 721–729.
16. Shukla A, Tripathi S. An effective relay node selection technique for energy efficient WSN-assisted IoT. *Wireless Personal Communications* 2020; 112(4): 2611–2641. doi: 10.1007/s11277-020-07167-8
17. Alsmady A, Awad F. Optimal Wi-Fi access point placement for RSSI-based indoor localization using genetic algorithm. In: Proceedings of 2017 8th International Conference on Information and Communication Systems (ICICS); 4–6 April 2017; Irbid, Jordan. pp. 287–291.
18. Saki M, Abolhasan M, Lipman J, Jamalipour A. A comprehensive access point placement for IoT data transmission through train-wayside communications in multi-environment based rail networks. *IEEE Transactions on Vehicular Technology* 2020; 69(10): 11937–11949. doi: 10.1109/TVT.2020.3006321
19. Lembo S, Horsmanheimo S, Honkamaa P. Indoor positioning based on RSS fingerprinting in a LTE network: Method based on genetic algorithms. In: Proceedings of 2019 IEEE International Conference on Communications Workshops (ICC Workshops); 20–24 May 2019; Shanghai, China.
20. Zhou B, Tu W, Mai K, et al. A novel access point placement method for WiFi fingerprinting considering existing Aps. *IEEE Wireless Communications Letters* 2020; 9(11): 1799–1802. doi: 10.1109/LWC.2020.2981793
21. Rappaport TS. *Wireless Communications-Principles and Practice*. Prentice Hall; 2002.