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Access point selection in the network of Internet of things (IoT) considering the strategic behavior of the things and users

Payam Porkar Rezaeiye[1] · Arash Sharifi[1] · Amir Masoud Rahmani[2] · Mehdi Dehghan[3]

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Abstract

With the expansion in the use of IoT, increasing the efficiency of these networks has become even more significant. Objects need reliable communications at suitable speed to be able to reach the expected performance. In a heterogeneous network of IoT, the objects can include users and related devices. Despite the hybrid Li-Fi and Wi-Fi networks, IoT needs were somewhat met. However, the efficiency of these networks depends on the choice of access points at the network level. In this study, a new algorithm was proposed based on the access point selection model, considering the strategic behavior of the objects and users. In this algorithm, inspired by access point selection model, a new adaptive algorithm was selected by choosing the access point by Markov game to enhance the load balancing and efficiency in IoT networks based on Wi-Fi and Li-Fi combination. According to the simulation results, it is seen that the proposed method could greatly increase the efficiency of IoT network and better distributes network load between access points with different technology. Overall network throughput was estimated at an average of at least 10% compared to the load-balancing method with fuzzy logic approach proposed in before research.

Keywords Access point selection · Hybrid Wi-Fi/Li-Fi · IoT · Markov game theory · Enhancing efficiency · Heterogeneous networks

✉ Mehdi Dehghan
dehghan@aut.ac.ir

[1] Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

[2] Future Technology Research Center, National Yunlin University of Science and Technology, 123 University Road, Section 3, Douliou, Yunlin 64002, Taiwan

[3] Computer Engineering Department, Amirkabir University of Technology, Tehran, Iran

1 Introduction

In today's IoT systems, optical technology with the Li-Fi standard plays an important role due to its good features [1], although Wi-Fi is also used. A Li-Fi access point covers a smaller Wi-Fi environment [2]. Thus, to cover a larger environment, a combined network of Wi-Fi and Li-Fi, which is a combination of high-speed Li-Fi transmission and coverage of a wider range of Wi-Fi, is intended to provide a solution for data transfer in indoor environments [3]. Research shows that combining Li-Fi and Wi-Fi technologies thus increases system efficiency much more than when these technologies are used alone. In some studies, all users or objects were connected to the Li-Fi network. The rest of the users or objects that were outside the network were then transferred to the Wi-Fi network and connected [4]. This type of APS method will not work with the fact that the required data transfer rate may vary with objects or users. The problem of APS in a hybrid network is much more complex than in a homogeneous network [5]. In a hybrid network, the areas covered by different networks overlap. So even if the information requests sent by users are evenly distributed, the Wi-Fi network still faces more traffic than Li-Fi in widely covered areas. This disables the SSS method for using in a hybrid network where balanced loading is critical.

An access point for Li-Fi covers a smaller Wi-Fi environment. Thus, a Li-Fi access point covers a smaller area of Wi-Fi. Thus, to cover a larger environment, a hybrid Wi-Fi and Li-Fi network, which is a combination of high transmission speed of Li-Fi and coverage of more area of Wi-Fi, is considered to provide a solution for data transmission in indoor environments [6]. The studies have suggested that the combination of Li-Fi and Wi-Fi technologies increases the network efficiency much more than it does when these technologies are used alone [3]. Network efficiency in our research means network performance in terms of data transfer, which typically includes throughput and delay.

In some studies, all users or objects were connected to the Li-Fi network via a Li-Fi access point. Then, the rest of the users or objects, outside the network range, were transferred and connected to Wi-Fi network and its access point. This type of access point selection (APS) method is not effective in this matter as the data rates required by objects or users can differ [2]. APS problem in a hybrid network is much more complicated than a homogeneous network. In a homogeneous network, the simplest APS method, called signal strength strategy (SSS), is that an AP is selected so that the object receives the strongest signal from it, which is currently widely used in wireless networks when balanced data download is not a concern in the network. In a homogeneous network, access points are deployed to overlap with each other to prevent inter-cell interference (ICI) [3]. In this condition, the unbalanced load of data occurs when the number of objects or users or the data transmission rate required by them are distributed unequally within the covered range. However, in a hybrid network, the areas covered by different networks overlap. Thus, even if the information requests sent by users are equally distributed, Wi-Fi network will continue to face widespread coverage with more traffic than Li-Fi [7]. This makes SSS use and method in a load-balancing network of critical importance to be impractical.

Given the created problems and the low efficiency of the network, regardless of proper load balancing, the network will attempt to achieve a combination of load-balancing control in two Wi-Fi and Li-Fi networks, considering the constraints on the operation of the two networks [8]. Constraints include switching the user in Wi-Fi connection area, as well as the radio frequency band while using Wi-Fi network and the existence of some constraints in emerging Li-Fi technology such as limited space. The idea of combining these two methods and the load balancing in both substrates to reach a more reliable substrate is a problem that has been able to partially reduce these constraints [9].

In this study, the difference between heterogeneous and homogeneous networks according to the choice of access point will be discussed and in order to properly select the access point of heterogeneous networks and a combination of Wi-Fi and Li-Fi has been taken. The contribution of this research is in the field of how to select the access point in the combined network of Li-Fi and Wi-Fi through game theory with high performance. There are not many methods in this field because it is completely new and needs more research. In general, in the new combined network of these two technologies, the discussion of selecting the access point and its location has been discussed more than the theoretical aspect and mathematical problems, while in this research look at it from the point of view of networking and its efficiency in Communication,

In fact, in this study, considering that the objects in the IoT network show different behaviors in terms of networks and their activity will be based on different patterns, the access point selection according to this is done through a game theory-based approach that seems to have a good effect on network performance.

In this research, we have tried to reach the appropriate access point in terms of equilibrium in the hybrid network according to the behavior of nodes and network load, and this has been done through an algorithm based on game theory.

In the rest of the paper, the second part has discussed the general Wi-Fi and Li-Fi hybrid networks and the previous work in this field and the load balancing. The third part has been the proposed method for implementing the mechanism of access point selection using Markov's game theory to show the efficiency and permeability of the network. Section 4 has presented the results of simulation and evaluation. Finally, Sect. 5 has presented the conclusions and future work.

2 Review of literature

In this section, the hybrid Wi-Fi and Li-Fi network model has described the concepts and different methods with the background of selecting access points in similar networks.

2.1 The components of Wi-Fi and Li-Fi hybrid network

Consider a hybrid network of Li-Fi and Wi-Fi for communication of several rooms within a building. As shown in the Fig. 1, the number of LED lamps is mounted on

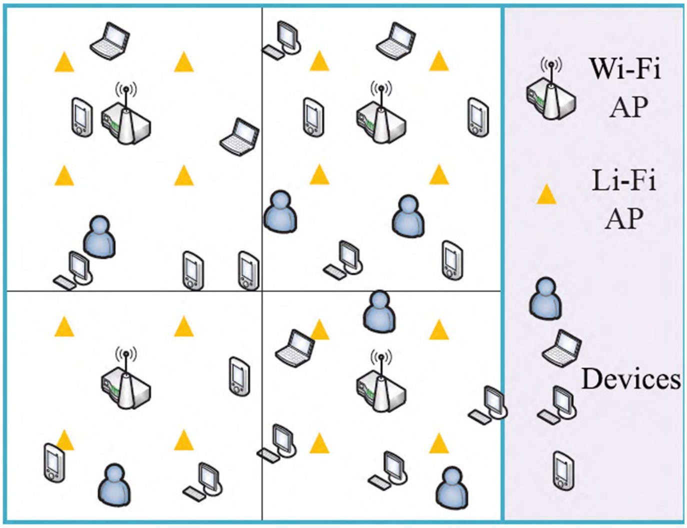

Fig. 1 A schematic of the hybrid model of Li-Fi and Wi-Fi

the ceiling of each room, and each bulb covers a specified range as an access point for Li-Fi. There is also a Wi-Fi access point in each room.

Although in practice Li-Fi access point may be irregular in the environment, they are arranged in a rectangle to simplify the layout and Wi-Fi access point is at its center. Each Wi-Fi has multiple carrier access capabilities (Collision Avoidance) [3]. Thus, no information collision or interference occurs at the Wi-Fi access point. Given the system used in Li-Fi, all of Li-Fi access points use the same bandwidth. Since no light passes the wall, information collisions only occur between Li-Fi in the same room. At each point, Li-Fi access has time division multiple access (TDMA) for multiple users simultaneously. In Fig. 1, a schematic of hybrid and heterogeneous Wi-Fi and Li-Fi networks has been shown, including the users and devices, and IoT devices.

Li-Fi technology mechanism is such that instead of invisible waves, data transfer is done through LED light bulbs. The process consumes less energy, is cleaner and has more speed as well. Li-Fi is a new type of wireless-based light-based connection. Fidelity has two meanings: one refers to loyalty and the other refers to match and similarity, where the second meaning is used in electronic science. This match means that the output of a signal is consistent with the input and not subject to change and destruction [4].

Li-Fi is a two-way, fast and wireless connection. The purpose of the two-way communication is the need for a sender and receiver to work. The transmitter is an optical source and the receiver is either an optical receiver or a photodetector (light detector). With Li-Fi technology, one can have 100-gigabit-per-second wireless Internet connection. The word wireless can be used for anything, say; Bluetooth technology is a wireless connection, so one can communicate without the need for wires. This means that one can transmit information needless of a wire [4, 5].

In actual real-world case studies, Li Fi technology has been able to send data at speeds of 1 Gbit / s, which is up to 100 times more popular than conventional Wi-Fi and up to 10 times faster than fiber optic. The key difference between Li-Fi and Wi-Fi is in using light for wireless data transfer. Although Li-Fi is far faster than Wi-Fi, its being light-based creates some constraints. Unlike Wi-Fi, Li-Fi connection cannot cross wall and other obstructive barriers. However, these constraints themselves can provide more security for Li-Fi connection. Currently, anyone can connect to Wi-Fi, but in Li-Fi connection, it should be directly exposed to radiation.

In Li-Fi technology, special LED lights are designed with a driver and a power supply (the drive is considered to be a controller). Information is sent to these lamps by wire or wireless. These data are controlled by the control circuit (driver) processed and sent through a light bulb to an optical receiver module. The optical module can be mounted on the device or be used as a flash memory. If it be separate, it would be similar to a dongle that has an optical receiver on its head and the other is a connector that connects to a mobile device, laptop, or other digital devices. The light received by the optical sensor is amplified and processed by the internal circuits of the module.

For the mathematical model of Wi-Fi and Wi-Li hybrid technology, there is a need to calculate SINR of these two networks, which will be in line with the following equations [6]:

For Li-Fi,

$$\mathrm{SINR}^{i,u}_{\mathrm{Li-Fi}} = \frac{\left(R_{\mathrm{pd}} H^{i,u}_{\mathrm{Li-Fi}} P_{\mathrm{opt}}/k\right)^2}{N_{\mathrm{Li-Fi}} B_{\mathrm{Li-Fi}} + \sum_{j \neq i} \left(R_{\mathrm{pd}} H^{j,u}_{\mathrm{Li-Fi}} P_{\mathrm{opt}}/k\right)^2} \tag{1}$$

here $N_{\mathrm{Li-Fi}}$ is the value of power spectral density (PSD) of the noise absorbed in PD and $B_{\mathrm{Li-Fi}}$ is the value of bandwidth of Li-Fi Access Point. R_{pd} is the sensor and responsively wave finder. P_{opt} is the light sent and k shows the electric power agent. The coefficient of P_{opt}/k is equal to the light`s signal strength.

For Wi-Fi

$$\mathrm{SINR}^{i,u}_{\mathrm{Wi-F}i} = \frac{G^{i,u}_{\mathrm{Wi-Fi}} P_{\mathrm{Wi-Fi}}}{N_{\mathrm{Wi-Fi}} B_{\mathrm{Wi-Fi}}} \tag{2}$$

here $N_{\mathrm{wi-Fi}}$ is PSD value of the noise received in the receiver. $P_{\mathrm{Wi-Fi}}$ and $B_{\mathrm{Wi-Fi}}$ are, respectively, the transmission power and the used bandwidth by Wi-Fi Access Point.

Understanding features and network specifications for Wi-Fi and Li-Fi, with the precise equations, can determine how the level of parameters such as SINR, which is certainly an effective parameter, correlates with the delay in passing the proposed method. Furthermore, the proposed method, which will be discussed below, can cover mathematical analysis of the network without directly using formulas by examining the strategic behavior of things and measuring performance parameters. Since network performance variables are diverse and unstable conditions, especially in wireless media, lead to many changes in network performance, balancing performance is one of the simplest and most effective methods, and this study shows its effectiveness.

2.2 Previous studies

There have been many studies on load balancing in similar networks. Some work has considered the allocation of resources or the formation of cells in the network, such as research [4] and some have considered the choice of access point and handover between the two networks in the hybrid mode, such as research [2] and [7].

Generally, data traffic distribution on network devices using load-balancing algorithms is called load-balancing operations or process. Load-balancing (LB) process occurs when two or more data transfer sources, such as wireless and fiber optic, receive loads from the network in proportion to their bandwidth and efficiency. Using two or more connecting resource increases the reliability of the system because if one of the Internet lines faces a problem and be disconnected, there will still be access to the Internet [3], [5], [7] and [8]. A load-balancer device or algorithm transmits internet traffic optimally through two or more high-speed connections, providing better services for users who simultaneously use high-speed broadband.

Load-balancing methods usually consider the availability of the source as well as the quality of the channel. These methods can be divided into two categories: channel lending and traffic transfer. As Li-Fi and Wi-Fi operate in different spectra, channel lending is unusable in a hybrid Wi-Fi network. Here, we consider the simple method of transferring traffic, whereas LB is based on optimization as an optimization method. Using this LB method, if an AP can meet user data speed needs, the user connects to the AP that has the highest SNR. Otherwise, the user selects the AP that gives the user the highest satisfaction. Note that this AP can still provide the highest SNR. If several APs reach the highest user satisfaction, the AP with the highest SNR is selected. In other words, the LB method initially maximizes user satisfaction and then channel quality.

Some other aspects are also expressed. The load-balancing function is used to increase efficiency and speed in network affairs. Overall, load balancer is between a client and a host [2], and its performance makes working faster, and in fact reduces the response time, thereby increasing the utilization of the source.

The response time is equal to the waiting time plus the service time. Apparently, the load-balancing algorithm needs a lot of messages for its decisions, which is undesirable. In the distributed project, the dynamic load-balancing algorithm is implemented by all the nodes in the system, and the burden balance is shared between them. In the centralized plan, the load-balancing algorithm is only implemented by the central node of the distributed system; the central node is responsible for load balancing across the distributed system.

Besides the proposed methods in load balancing in related networks, some studies have dealt with similar combinations of networks. For instance, in [7], with the goal of maximizing returns, a central optimization method is described that requires complex and heavy computing. Both of these methods have been developed from APS solutions in homogeneous networks, although both methods failed to exploit the distinctive features and characteristics of Wi-Fi and Li-Fi technologies. Overall, the combination of Wi-Fi and Li-Fi networks challenges the approaches and strategies of the access point selection (APS) in two respects: A Wi-Fi access point often attracts users close to them, and Li-Fi access point, where the user is in the range, and a Wi-Fi access point covers a larger area than a Li-Fi access point, so it is more sensitive to the overload it is imposing.

In study [6], an APS-based fuzzy logic method has been used to select the access point in Li-Fi and Wi-Fi hybrid networks. The method in this paper had two steps. In the first step, fuzzy logic has been developed to identify users connected to the Wi-Fi network. Then, in the second step, if a user is left in Li-Fi homogeneous network, it will remain. The proposed method in [6] is a centralized algorithm, and unlike distribution methods, it does not require repetition to achieve a stable state. However, unlike the centralized optimization method, this method can significantly reduce process operations using fuzzy logic. Unlike most research, such as the [9] research that has been done in this field, this paper considers an internal scenario, with various and different parts that have been generalized. Additionally, the proposed method is optimized and improved. According to this paper`s claim, this method significantly reduces complexity as well as the differences between the paper's proposed method and the conventional APS method.

Among the methods for selecting AP, SSS is a simple method that always selects the AP with the highest performance spectrum. In a homogeneous network, the receiver experiences the same noise when collecting signals from different APs. Thus, for the intended user, SSS method simply selects an AP that delivers the highest signal strength. However, in a hybrid network, different signals are needed to receive light and radio signals, resulting in different noise power at any bandwidth between Li-Fi systems and Wi-Fi. Moreover, these two systems can use various bandwidths. Hence, signal-to-noise ratio (SNR) is usually received instead of the signal strength for the SSS method in a hybrid network.

Every network technology has limitations that make it difficult to use. For example, in addition to the technologies discussed, optical camera communication technology is also based on light and slightly different from Li-Fi, but has data rate limitations. In order to provide a suitable solution to compensate for the limitations of Li-Fi and OCC, a combined OCC / Li-Fi system is proposed in the paper [10]. In this research, both technologies are not to be used simultaneously, but the access point is selected based on fuzzy logic, taking into account different application scenarios. The main focus involves selecting a network at a specific time according to the application scenario and technical requirements. In this paper, two scenarios are considered and an access point selection factor called NS factor is measured for each network based on FL. The network is selected in a specific environment with a higher NS coefficient.

In the study [11], the authors first provide a comprehensive analysis of IoT communication strategies and applications for smart devices based on a systematic literature review (SLR). After that, communication strategies and programs are categorized into four main topics including device-to-device,

device-to-cloud, device-to-gateway, and device-to-application scenarios. In addition, a technical classification is provided for classifying existing articles based on a search-based method in scientific databases. The technical classification offers five categories of IoT communication applications, including monitoring-based communication, routing-based communication, health-based communication, penetration-based communication, and resource-based communication. The authors observed that resource-based communication is the most popular type of method with 35% usage. It also found that device-to-cloud communication is the most popular type of communication, with 52% used in IoT communication strategies. In each group, important evaluation criteria are analyzed according to time, latency, bandwidth, energy and latency in IoT communication strategies with the highest evaluation compared to other factors such as availability, throughput, cost and usage. In addition, the authors found that ubiquitous scenarios with 38% are most useful for evaluating IoT communication strategies. In addition, messaging technology is the most common communication technology that can be used to connect smart devices and IoT applications.

5G networks with better connectivity and coverage can be achieved with a technique called non-orthogonal multiple access (NOMA), which changes the power level of each user. Authors in the study [12] to deal with the limited bandwidth of Wi-Fi and Li-Fi, an algorithm based on mass intelligence and specifically cuckoo search to reuse the frequency of the combined Wi-Fi-Li-Fi network in the outdoor environment and with benefit have suggested the NOMA technique. The combined Wi-Fi and Li-Fi system is modeled by emitting LOS outdoors. The paper's proposed method uses two-way visible light emission with NOMA, a new approach for fifth-generation wireless networks. NOMA can help different users at the same frequency and multiple power levels. The power and spectral efficiency of the system are improved by reusing the dynamic frequency. In this paper, the concept of NOMA is demonstrated for the first time in external communications using a dynamic FR scheme, using the latest LDPC codes in the latest 5G standard.

In the study [13], an efficient resource supply approach is presented. Using an autonomous computing model and a Bayesian learning method, this method tries to make decisions to increase and decrease the fog resources with dynamic scale to adapt the workload of IoT services in the fog computing environment. This method uses a combination of time series prediction models and Bayesian learning-based method, respectively, as a decision-maker to analyze and plan the MAPE-k control loop steps. This research has also designed an independent resource provision framework based on the three-layer architecture of the general fog environment.

The study [14] presents a new RPL-based method for minimizing IoT device power consumption, in which a priority-based and energy-efficient routing (Prinergy) method is proposed. This method is based on the routing protocol for the low consumption and low-power and lossy network (RPL) model. In this QoS method, IoT applications are considered, so that with time division multiple access (TDMA) is used to synchronize between sender and receiver and reduce power consumption.

However, according to previous research, there are several issues that need to be addressed. For example, the need for mathematical calculations that lead to computational complexity and heaviness, and second, the lack of attention to the strategic behavior of objects. At different time intervals, the network can change a lot and the behavior of objects in relation to the network can change, so considering this, methods can show more realistic and appropriate performance for load distribution on the Internet of Things. These, as well as several other things, such as the need to upgrade IoT hybrid systems, led to this research.

3 Proposed method

Considering the above, the use of the strategic behavior model of things in IoT, whose strategic behavior is one of the concepts of game theory, can help the dynamic process of access point selection method (APSM). This method directly considers the efficiency of the network, as it uses network information and strategic and network behavior of things to select the access point. Therefore, it will be able to improve the access point selection function with a more open view than it. To use this design, this paper uses a method based on Markov's game theory, which is an effective strategic game for dynamic environments that it also has learning capability.

This section deals with APSM by Markov's game in the hybrid network of two Li-fi and Wi-Fi technologies, at first about Markov's game, then about the hypothesized network, and finally about APSM by Markov's game. It should be noted that in doing so, the strategic behavior of objects in the game is considered.

Uncertain environments can be modeled as a multivariate environment with a random Markov process [15]. Additionally, the process of training agents in a multi-agent environment is considered as a random game, called Markov's game, which is Markov decision process with several agents [16]. Markov's games are closely related to the reinforcement learning method and are among the solutions used to solve Markov decision problems. In Markov's process, the solution means finding a policy for selecting actions by agents in each state to maximize the mathematical expectation or average of the reduced rewards values for all agents. In Markov-based access point selection, agents are the nodes trying to enhance the important agents in traffic flow in hybrid IoT networks like throughput and delay. Thus, when a path is selected by a node, re-selecting that route by the same node is less likely as the agents want to select a path where the justice between the other agents is established and the network can move toward balance (Nash equilibrium). In the Markov's game, the solution means finding a policy for selecting a solution by agents in each state to maximize the mathematical expectation or average of the reduced total rewards for all agents.

Markov's model has a Markov decision process and a random game theory [17].

In this model, players are defined and follow a set of policies, and parallel to that the players use Markov decision process and make decisions at any time defined in the system. A defined revenue or benefit function that enables players to understand the profitability of their performance, along a strategy of equilibrium that, according to that game, is a relative benefit to all its players. This is a multi-stage and multimode game, which is attainable to the original goal.

In Markov decision process (MDP) section, the model needs to be defined. MDP is defined by a set of modes namely "*S*," and "*A*" modes [18]. A transfer function *T*: $S \times A \rightarrow \text{PD}$ (*S*) defines the effects of different actions on the environment. Probability distribution (PD) shows the discrete-probability distribution set on *S* set. The reward or payoff function *R*: $S \times A \rightarrow R$ specifies the task of the agents [19] (in fact *R* (*s*, *a*) specifies the reward of act "*a*" in state "*s*," in which case each agent will know its task.

Generally, the purpose of the agents is to find a suitable policy to map the history of interactions into the current selection, so that the sum of the discounted rewards is maximized. Mathematically, $E\{\sum_{j=0}^{\infty} \gamma^j r_{t+j}\}$ is defined where r_{t+j} is the reward received for the steps j for the future. A discounted agent γ controls the effect of future rewards on optimal decisions. With small values of γ, more emphasis is placed on short-term utility, and large values of weight are added to future rewards [18].

This model of MDP is seen in the Markov's model. The only difference between MDP and Markov's game model is that in Markov's game model, instead of the parameter A, the associated formulas representing the action of an agent considers an action for each of the agents. Hence, for instance, the transfer function is used as follows, and the same applies to the reward function [18].

In most models related to MDP process and Markov's game, reinforced learning has been added as a way to complement the model from the learning dimension, and the formula for rewarding in the above model has been added for this reason. Indeed, the system in Markov's model that ends in machine learning and the improvement of the environment over time, is the learning system existing in this model, which is here incorporated by the concept of rewards.

For the network model, a hybrid VLC/Wi-Fi system model (Li-Fi) is considered, where IEEE 802.11 wireless local area network (WLAN) is complemented by a light optical network. A hybrid network is a set of VLC access points, as well as a Wi-Fi access point in limited place, but this scenario can easily extend to other AP configurations. Each VLC access point relies on a LED made from multiple LEDs. However, in our scenario, each room has a Wi-Fi access point and several Li-Fi access points. Several IoT devices in each network use the network. The network can include users as well. A schematic for such a network is shown in Fig. 1, which has been used in this study (Figs. 2 and 3).

IoT devices are sensors/actors that operate on the network to transfer data to the Internet as well as execute commands for users associated with objects. Now that the network configuration is specified, the problem should be specified as well:

In an IoT network composed of some sensor/actor devices, this includes users who operate with Li-Fi / Wi-Fi hybrid technology, selecting the optimal access point at a time will be a major problem. This means, which of the Li-Fi or Wi-Fi devices is considered for each device as an Internet access point. Given the definitions of the Markov's model, as well as IoT network needs and the strategic behavior of devices over time, this problem is more specifically modeled. IoT network is composed

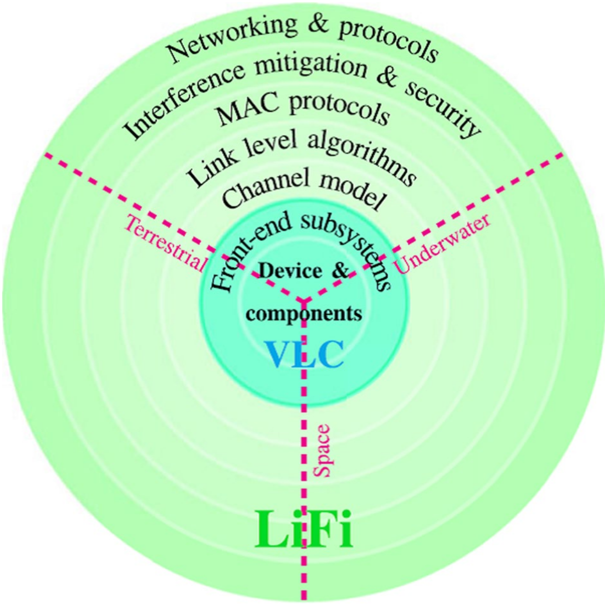

Fig. 2 Definable sections on Li-Fi technology

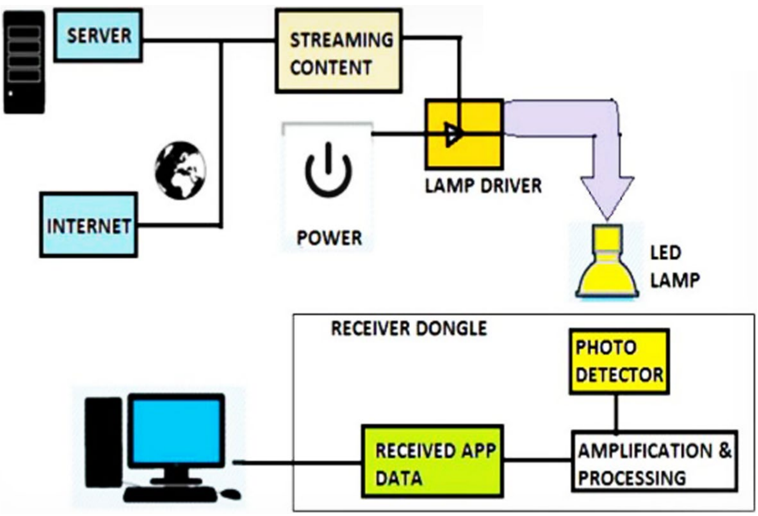

Fig. 3 Li-Fi network components

of nodes with different capabilities and changes in the needs that will exist in the model.

In this model, k agents are considered where k is the number of sensors / actors and users in a room of the network. Each agent in a set of states, i.e., S needs a decision for an operation. The operation of each sensor / actors node is to select from different access points. According to the definition of Markov's model:

$$T : S \times A_1 \times A_2 \times \dots \times A_k \rightarrow \mathrm{PD}(S) \tag{3}$$

here A_1 is the operation of the sensor/actor 1 node and A_k is the actions of the sensor/actor node k, and these actions take the network state into a discrete state of states. Network states are actually node selections for their access points. The reward function has to be defined now, which will be defined according to the network's performance in communications.

Additionally, how the function of each agent affects the network will be effective on MDP. The results of the computations done on the network are communicated to the sensor nodes to make their selection. In the reward function, the values function in terms of a combination of network performance. For example, transmission values and network latency are two important agents: the better the transmission and the less the delay, the better it will be. This is defined in revenue function of interest according to Fig. 4. Therefore, a reward function, with respect to the revenue function by reducing delay, improves performance and, in parallel, increases the yield by increasing the transmission. Finally, depending on different agents, the final reward is performed, and this depends on the magnitude of the increase or decrease of transmission and the delay and the value generated in the revenue function.

$$R : S \times A_1 \times A_2 \times \dots \times A_k \rightarrow R \tag{4}$$

Transmission function (transmission ratio).

First, setting the transfer rate is determined:

$$\mathrm{Trans}_{\mathrm{Rate}} = \frac{\text{Number of Successful transmission(bits)}}{\text{connection time to AP}} \tag{5}$$

where the transfer rate is equal to the number of successful transfers in bits divided by the AP connection time

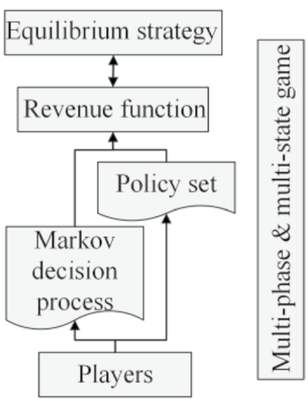

Fig. 4 Markov's Games Model [16]

$$\mathrm{Thr}_{\mathrm{Ratio}} = \frac{\mathrm{Trans}_{\mathrm{Rate}}}{\mathrm{Bandwidth}} \tag{6}$$

Transmission ratios equals to the transmission bandwidth rate.

3.1 Delay function (delay ratio)

$$\mathrm{Delay}_{\mathrm{Ratio}} = \frac{1}{\mathrm{RTT}} * \mathrm{minRTT}_{\mathrm{network}} \tag{7}$$

The calculated delay ratio equals to RTT inverse ratio on the minimum RTT in the network calculated through the AP communications, and at first the nodes provide minimum RTT to APs and then APs to the nodes.

3.2 Revenue function

$$\mathrm{RevF} = \mathrm{Thr}_{\mathrm{Ratio}} + \mathrm{Delay}_{\mathrm{Ratio}} \tag{8}$$

where transmission ratio to the delay ratio is summed up, and the sum of these two ratios determines the usefulness of the AP selection by the node.

3.3 Reward function

$$r_t = \mathrm{ScoreAP}_{\mathrm{i}} = \mathrm{ScoreAP}_{\mathrm{i}} + \mathrm{RevF} \tag{9}$$

In the reward function, any point of access to the AP_{i} is given a score, that is ScoreAPi, calculated according to the revenue function. This formula is a raw formula, but here the total rebates should be calculated. As previously stated, the discounted reward is calculated due to the fact that it adjusts the effect of the new rewards to previous rewards. If γ is 0, then only the action moment reward is considered, and the more the number is, the bigger the rewards of the post-action stages will be.

It should be noted that the calculation of discounted rewards is at the point of access and is at the disposal of the nodes. Overall, it is tried to put a little computational burden on the sensor/actor nodes because these nodes have limited resources. The total value of discounted rewards according to Markov's game will be as follows:

$$E\{\sum_{j=0}^{\infty} \gamma^j r_{t+j}\} \quad 0 \le \gamma < 1 \tag{10}$$

Moreover, the subject is to reach the balance of load on the network, which can be equivalent to achieving the Nash equilibrium in the Markov's game. In this case, there is an effective balance between Wi-Fi and Li-Fi systems. By changing the network, this behavior of objects affects the balance and disturbs it, in which case the model will try to reach a balance in the future.

It is necessary to have the mean revenue function available to the nodes to examine the equilibrium in the network. This function is calculated in the form of the mean in the network by APs. Thus, the calculation of the mean revenue function will be as follows:

$$\mathrm{RevF_{mean}} = \sum_{i=0}^{n} \mathrm{RevF_i} \tag{11}$$

Here, n shows the number of nodes in the entire network. However, to calculate APs first, the amount of revenue function is received from the connected nodes, and then calculates the mean of it to the other APs, so that all APs can ultimately compute the final mean. After calculating the mean, if each node compares the value of the utility function with the mean value, these two values must be equal to find that equilibrium node. The proposed algorithm chart for selecting an access point and load balancing in the Li-Fi and Wi-Fi hybrid network is shown in Fig. 5. Then, algorithms for both Node and AP side are present in algorithm 1 and algorithm 2, respectively.

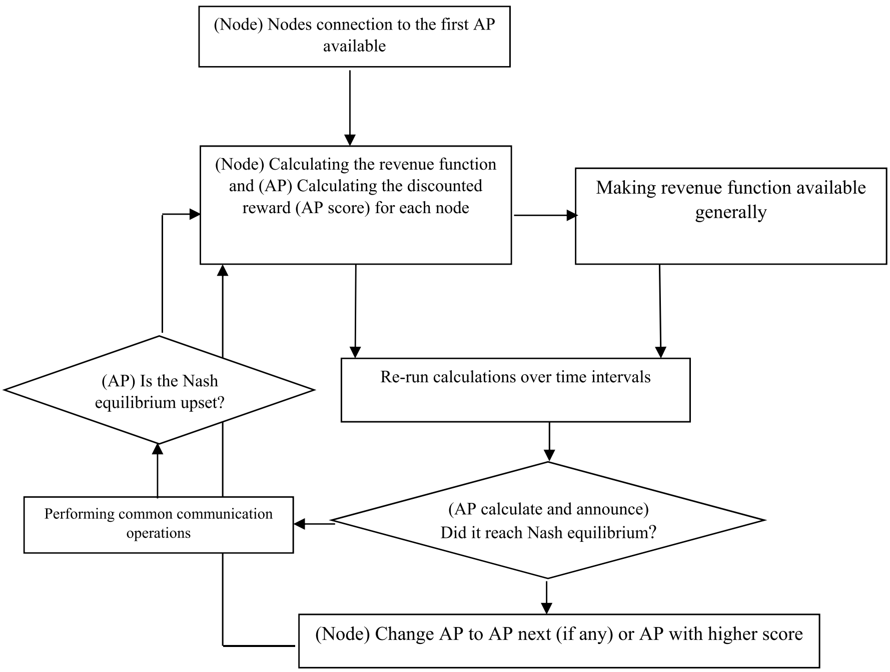

Fig. 5 Flowchart of the proposed method

Algorithm 1
Node (User) side algorithm
1. Connect node to first available AP
2. Calculate revenue function
3. Making revenue function available generally (Send to APs)
   3.1. Re-run calculation over time intervals
4. if exist better selection (didn't reach Nash equilibrium)
   Change AP to AP next (if any) or AP with higher score

Algorithm 2
AP side algorithm
1. Calculating the discounted reward (AP score) for each Node
2. Making discounted reward available generally (Send to Nodes)
   2.1. Re-run calculations over time intervals
3. if didn't reach Nash equilibrium
   announce to nodes for AP selection
4. if Nash equilibrium upset
   announce to nodes for calculate revenue function

3.4 Method overhead

In this research, a method based on Markov game theory algorithm is proposed. From an algorithmic point of view, this method is based on a linear algorithm of order n (number of devices and users) because there is no need for a decision loop for each device or user and a decision is needed for each device. However, further examination of each algorithm determines the time order more accurately. This method requires decision-making at predetermined time points, and as a result, the time interval of checking the condition is added to the complexity analysis. The smaller these intervals, the greater the complexity, and the larger the temporal complexity. As a result, the time complexity is also multiplied by $1/\Delta t$, where Δt represents the time interval between checks.

4 Evaluating the proposed method

Simulation has been used to evaluate the performance of the proposed method compared to the usual methods used in the past. The full realization of the proposed method in real environments needs the assimilation and coordination of software, where due to the lack of proper coordination between software and the existence of incompatibility between them, it is not easy to implement it in real environments [10]. Thus, we selected simulation method for evaluation. In this section, the framework for simulation environment will be explained first. Then, the proposed method is evaluated compared to the method proposed in previous study, [6]. It will be seen that the proposed method has higher transmission and less delay compared to this study and the case of absence of AP strategy.

4.1 Simulation environment

NS3 software environment along Python and C+ +programming language was used for simulation, where the implementation scenario was specified through Python. Also, the VLC module is used in NS3 to simulate Li-Fi. Accordingly, we compared the proposed method with other methods and presented the simulation results as diagrams based on transmission and delay criteria. Finally, the final conclusion was made based on the simulation results.

4.2 Simulation parameters

Assume an internal scenario with 4 rooms as shown in Fig. 1, where each room is a square with a side length of 10 m. At the ceiling of each room, 16 AP Li-Fi is placed in a square matrix design, with a distance of 2.5 m between their closest ones. Users are randomly distributed with the same probability distribution. This means that if

Table 1 Software simulation parameters

#	Parameter	Value
Li_Fi Parameters		
1	Room height (vertical distance between ceiling and user)	2 m
2	Physical surface of photon diode	1 square centimeter
3	Light filter efficiency	1
4	Failure index	1.5
5	Half intensity radiation angle	60 degrees
6	Half-angle domain of photon diode	90 degrees
7	Optical transmission power at any point of access	3 watts
8	Optical conversion factor to electronic force	3
9	Tracker sensitivity	0.53 A/W
10	The reflection on the wall	0.8
11	Bandwidth	40 MHz
12	Power spectral density (PSD) of noise	10^{-21} A^2/Hz
Wi_Fi parameters		
1	Breakpoint distance (dBP)	5 m
2	Standard deviation of shadow fading before dBP	3 dB
3	Standard deviation of shadow fading after dBP	5 dB
4	Central carrier frequency	2.4 GHz
5	LOS entrance and exit angle	45 degrees
6	Transmission power	20 dBm
7	Bandwidth in channels	20 MHz
8	Power spectral density (PSD) of noise	– 174 dBm/Hz

Table 2 Hardware parameters

#	Hardware	Model
1	CPU	intel core i7 2.20Ghz
2	RAM	16G DDR3
3	HDD	1 TB

we have 60 users or devices, when it is spread between 4 rooms, there will be an average of 15 users or devices in each room.

Moreover, the number of available Wi-Fi channels, except for the time it takes to analyze its effects on network performance, is equal to the number of Wi-Fi APs. Some other parameters of the environment by Wi-Fi and Li-Fi are shown in Table 1. The hardware parameters of the simulation system are described in Table 2.

In addition, in the scenario, each user or device sends traffic based on the usual traffic on the Internet of Things and at a variable rate with a certain average. The full package size on the network is 1024 bytes and the type of tcp traffic. In simulation, data rates are obtained through the application defined in the network system, which is used in Internet of Things and smart building applications and has the required average.

The network environment changes in terms of traffic rates and is a dynamic environment, which means that different users and devices have their own strategic decisions and strategic behavior in sending traffic on the network, which determines the main issue in the network.

4.3 Efficiency comparison

The charts show the two important parameters of the transmission network and the delay of packets, considered crucial to assess the quality of sending and receiving in the network against the change in user data demand and increased interference in the network. For brevity, other agents that could be investigated, such as the number of the packets received by delay and the number of received duplicate packets, as well as the drop in packets were ignored. The results have been obtained from five times simulation and then averaging thus.

- *Light traffic* For this mode, 60 nodes were considered on the network, causing small network traffic and relatively light. If the traffic volume on the network be low, it means that the effect of competition on the transmission is low and the quality of the data stream transmitted over the competition between the flows is affected by the channel conditions. Additionally, given the low flow of traffic, the transmission with good choice of efficiency will be very efficient.
- *Heavy traffic* When the number of nodes increased, there was a high volume of traffic on the network, the problem of congestion as well as the re-transmission of packets increased. The number of nodes in this case was considered 100.

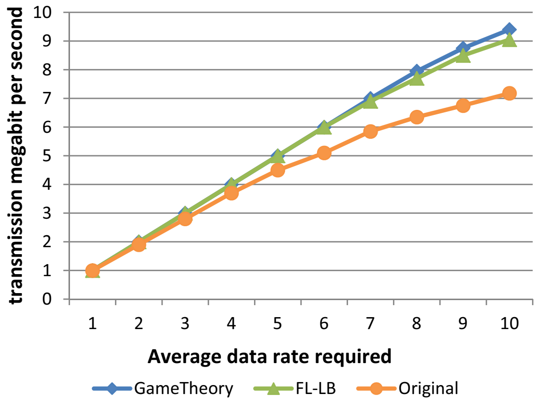

Fig. 6 Comparing transmission in light traffic mode

Figure 6 shows the comparison of transmission in light traffic mode with algorithms. As is seen in the diagram, the distance between the results of the proposed method with the default protocol, without AP selection algorithm, was very high. The reason is clear as well since in the proposed method, it was tried to select the appropriate access point, but this did not happen in the base method. Another point is that in the fuzzy balance method, due to the increase in congestion, an increase in the average required data rate delayed transmission. While in the proposed method high-performance data transfer was performed by Markov's theory of game due to the use of high permeability infrastructures and did not increase the impact of the congestion agent by increasing the requested rate.

In the charts, the original method is to run the network without balancing the load and the FL-LB method is the method of balancing the load with the fuzzy algorithm mentioned in article [6].

Figure 7 shows a comparison of the delay in the first scenario, light traffic, which shows that the performance of the proposed method above the graph was better than the original and the default method was better, which was increased by increasing the data rate. The reason for this is that the data flow rate was not

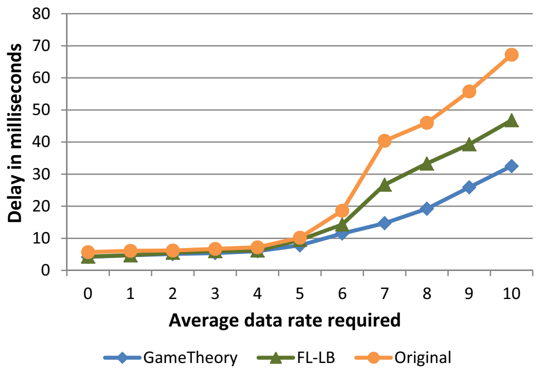

Fig. 7 Comparison of delay in light traffic mode

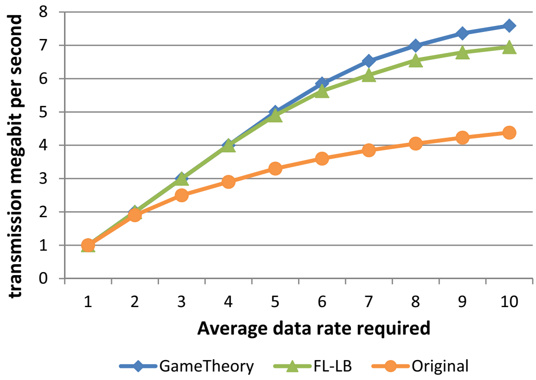

Fig. 8 Comparison of transmissions in heavy traffic

significantly affected by the delay in the proposed method as with the increase in the data rate of the Markov's game theory algorithm, the nodes did not increase the congestion in the network by selecting the best APs. This problem showed itself as compared to FL-LB method.

In comparing transmission in Fig. 8 for heavy traffic, one can state that the difference in methods was more intense in this case. Moreover, the efficiency of the proposed method has not changed much compared with the previous one. The reason is that, first, selecting the appropriate AP using game theory increased the efficiency so that there was not much loss as traffic increased. Secondly, using high-bandwidth infrastructure efficiently has been able to significantly help maintain efficiency. Thus, even FL-LB method has been dropped, with a much less proposed approach.

Figure 9 compares the delay in the proposed method and other methods in heavy-traffic mode. The diagram trend is largely similar to the previous one, and with respect to the graph numbers (vertical axis), the slope of the graph seems to be slower for all methods, including the proposed method. The main protocol certainly had more delay than the previous ones. On the other hand, there was a high traffic volume, and on the other hand, as demands increased, there was a lot of crowd in

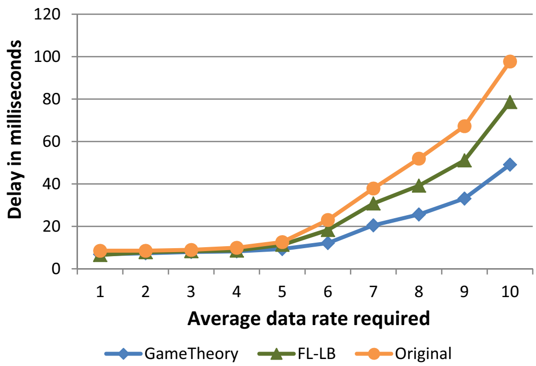

Fig. 9 Comparing delay in heavy traffic

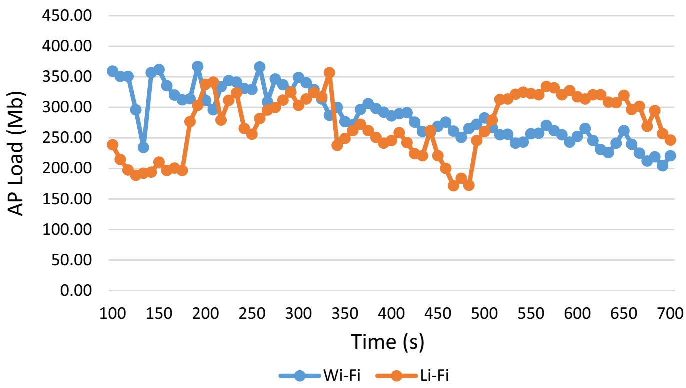

Fig. 10 Load in APs over time in the proposed method

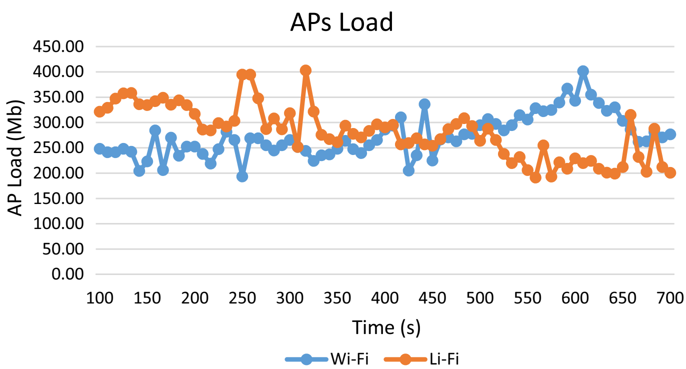

Fig. 11 Load in APs over time in the FL-LB method

the environment that caused a lot of delay. In the proposed method, the delay was from about 8 ms to about 50 ms and in FL-LB protocol, it has increased from about 8–80 ms, which showed a relatively high effect.

Different parameters like packet drop, average overhead energy consumption, and so on can be used to evaluate AP selection methods in wireless networks. Overall, the purpose of all methods was to improve efficiency and performance, and the more this performance increased, the more efficient the algorithm would be. In heavy load conditions, the efficiency of the proposed method was fully characterized to prevent congestion. As nodes could not fully predict network conditions, they made predictions with relative errors in many cases.

Given the obtained results, the proposed mechanism had an acceptable performance and, overall, showed good returns. This optimal output can be found on the network especially in high-noise situations and high noise levels. The proposed method was good compared with the previous FL-LB method and worked best in all cases. In general, regard to the results obtained, more than 10% of routing performance in the proposed method has improved Compared with FL-LB protocol in terms of delay. Moreover, much better performance was reached compared to non-strategy case, and one can state that its performance was at least 100%, which was 2 times better than the other one.

The results of the load balance on Wi-Fi and Li-Fi access points are shown below, in which the total load in the access points is calculated with the relevant technology. These times are expressed in megabits, and the average data rate of 6 megabits per node, including the user or device, and the number of nodes was 80 nodes.

Figure 10 shows the load current of two local area networks between 100 and 700 when sending packets in the proposed method. Figure 11 shows the same for the FL-LB algorithm. In appearance, there is not much difference between the two, but a few points are clear in the diagrams. One is that the maximum load that the controllers have suffered is less than 370 in the proposed method, while in the FL-LB between, in several cases about 400 is also observed. It is important to note that the load on the controllers is kept at a lower range and at a lower point. The next thing is that the course of change in the proposed method is a little softer and decisions do not happen very quickly, but on the FL-LB the speed of change is higher. The peak loads on the FL-LB were higher, resulting in more handover, which in turn increased the handover overhead. Of course, keeping the network conditions moderate is more important than fluctuations in improving network conditions.

The peaks in the algorithms indicate that congestion occurs and the load on the control load increases rapidly during load congestion, and if not controlled, the load will remain at these values and even higher. The parameters that cause this issue are the high load on the nodes due to the different currents that send a lot of packets, and consequently the high load on the relevant APs. By changing the conditions, especially through the node handover, the AP load is reduced. As a result, the proposed method seems to have a better load balance in APs than a load balance in the FL-LB algorithm.

5 Conclusion and future work

The study proposed a Markov-theory-based approach for selecting access points in IoT that used the combination of Li-Fi and Wi-Fi networks, which was a completely dynamic method. Moreover, the proposed method was a reliable method with suitable load balancing, helping the network reach the balance point in any situation. With the structure expressed in this study, this method was able to show a great performance when the server traffic was high, even in cases when network noise was high. This was perfectly consistent with the goals that have already been put in place to put forward a new mechanism for IoT networks to balance load and transmit more efficiently information, especially delayed traffic and events information on IoT networks. Moreover, it increased the network transmission. However, this method can still be enhanced significantly, and besides its different configurations and combination with other solutions, one can change its parameters for decision-making or even add new parameters to it. Therefore, this method is a useful mechanism in the field of wireless local networks, and especially hybrid Wi-Fi and Li-Fi networks for IoT, which has been targeted to address the specific constraints and conditions of these networks to provide the highest possible quality of service [19–26].

Though the results were somewhat variable, for the proposed re-transmission method in this study, a 30% increase can be considered as opposed to AP-free strategy and a growth of approximately 10% compared to the proposed base mechanism in [6]. The usefulness of the proposed AP selection algorithm can be improved using it with a more powerful media control method compared to the standard one.

In this study, there was no chance to deal with some parameters like calculation overhead, the degree of fairness on the network, and so on. It is hoped that future studies will provide this chance. Moreover, traffic engineering is a widespread topic with many arguments and variables. Entering this topic necessarily needs much information and background not available in this category. Dealing with this topic can be a good idea in the future from IoT perspective so that the proposed method can be improved.

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