Intelligent Channel Utilization Discovery in Drone to Drone Networks for Smart Cities

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Abstract. Drone networks are playing a significant role in a wide variety of applications such as the delivery of goods, surveillance, search and rescue missions, etc. The development of the drone to drone (D2D) networks can increase the success of these applications. One way of improving D2D network performance is the monitoring of the channel utilization of the link between drones. There are many works about monitoring channel utility; however, either they sense channel physically, which is not reliable and effective due to noise in the channel and miss-sense of signals, or they have protocol-based solutions with high time-complexity. Hence, we propose a less time and power-consuming MAC layer protocol based monitoring model, which works on the IEEE 802.11 RTS/CTS protocol for D2D communication. We work on this protocol because it solves the hidden terminal problem, which can be seen widely in drone communication due to the characteristics of wireless networks and mobility of drones. Our model consists of Searching & Finding and Functional Sub-layers. In the Searching & Finding Sub-layer, we locate the other drones in the air with a specific flying pattern; we also sense and collect frame information on the channel. With a Functional Sub-layer, we calculate channel utilization with Network Allocation Vector (NAV) vector sizes, showing the duration of the drone about how long it must defer from accessing the link. Also, we create a visualization map with Voronoi Diagram. In that diagram, according to drone coordinates, each region is generated after the k-means clustering algorithm, which is one of the simplest and popular unsupervised machine learning algorithms. Hence, each Voronoi section shows channel utility in terms of percentage in a more precise and discretized way. Furthermore, with our model, we decrease the sensing time of the channel by about 25%, and we reduce the power consumption of sensing drone approximately 26%. Also, our model uses about 57% less area during the calculation phase.

Keywords: Monitoring of channel utilization · IEEE 802.11 RTS/CTS · Drone to drone networks · Voronoi diagram · NAV vectors

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1 Introduction

Low Altitude Platforms (LAVs), also called drones, are rapidly developing and becoming extremely useful in a variety of areas, from civil applications to military missions due to the structural advantages and moving flexibility on air. Surveillance, search and rescue missions, delivery of goods, construction, and natural disaster monitoring are most standing out applications of drones [1]. The achievement of these applications depends on improvements in network performance. Hence, there are a significant number of challenges in aerial networks to increase network performance [2–4]. In this aspect, to provide reliable, efficient, and stable drone to drone networks, monitoring resources of aerial systems is a crucial mission because that minimizes the cost of maintenance of data flow. Thus, we focused on the topic of resource monitoring, which is channel utilization for the drone to drone (D2D) networks.

D2D network complexity is dramatically expanding in terms of services and topology, which causes challenging network management problems on network resources. Hence, the diagnosing channel utilization as resource monitoring takes crucial place in D2D networks. As mentioned in [5], monitoring characteristics of wireless networks is critical to many management tasks such as fault diagnosis and resource management. Also, in that work, monitoring types are introduced as PHY and MAC behaviors. In this aspect, we focus on the discovery of channel utilization for D2D networks in the field of smart city applications. It is known that smart cities enhance life quality with intelligent things. Therefore, drone collaboration and D2D networks play a vital role in supporting a lot of smart city applications such as D2D communication and network resource management [6]. Thus, in this work, we work on monitoring of channel utilization as resource management of D2D networks in smart cities.

There exist many studies in the recent literature about evaluating channel utilization in many ways for D2D networks. In [7], MIT LL has developed a data collection and visualization framework to monitor and analyze the performance of a high-capacity backbone (HCB) network, which is an example of Mobile AdHoc Networks (MANETs). In that work, the monitoring implemented at various layers of the OSI stack. Furthermore, the channel utilization can be measured with PHY(physical) layer methods. In [8], with the proposed Channel Quality Indicator (CQI) feedback scheme, each cellular-UAV can evaluate link quality by the reference signal. Also, in [9], Negative Acknowledgement (NACK)-related regular feedback system is considered. In this work, if Signal to Interference and Noise Ratio (SINR) is less than the threshold of a special Modulation and Coding Scheme (MCS), the user transmits NACK back to the base station. Moreover, [10] provides novel channel feedback schemes that solve the problem of finding the right feedback mechanism to convey channel information. With this scheme, it is possible to measure channel quality for wireless networks.

None of these works presented on PHY layer are accurate and reliable measurement methods for link quality because PHY layer can be affected by other signals or signal cannot reach the destination due to shadowing effect and mobility of UAVs. Also, it is impossible to obtain any information about chan-

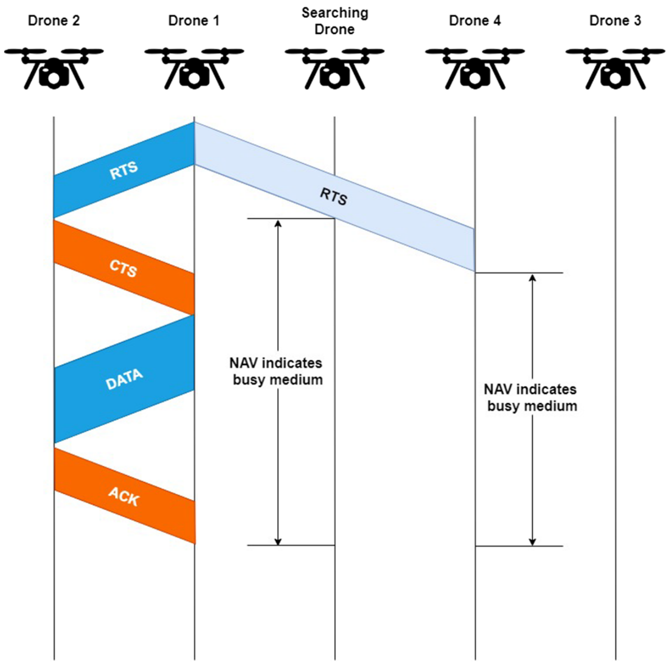


Fig. 1. The RTS/CTS mechanism [11] of scenario Fig. 4

nel quality for the base station, if no NACK is sent. The flow management and logical connection are necessary for more accurate and reliable monitoring of channel utilization; however, these works do not provide these MAC layer properties. Shortly, to be sure about there is a communication in the channel, the MAC layer protocol based approach is needed. Moreover, they have a very complicated implementation of monitoring channel utilization.

Consequently, keeping these studies in mind, we propose a novel monitoring approach of D2D network channel utilization and network traffic type in the field where drones are actively communicating with the IEEE 802.11 protocol. Also, our model works on the MAC layer with flow management and logical connection advantages. Even though the most preferred way of calculating channel utilization is the sensing channel always on the PHY layer, we present a protocol-based method that uses the NAV vector, which is originated from IEEE 802.11 RTS/CTS enabled protocol. In our approach, we calculate channel utilization using the duration field of the frames, which determines the NAV vector size. Furthermore, only one participant can communicate in the channel with IEEE 802.11 RTS/CTS (see Fig. 1); thus, calculating the channel utilization with our method becomes applicable. With our model, we prevent the sensing channel on the PHY layer, which is not an optimal approach due to the power consumption of the searching drone and noise in the channel. The MAC protocol-based system we offered shows there exists absolutely communication in the MAC layer, which is a more exact sensing way rather than blindly sensing the channel. Furthermore, we propose a visualization method using the Voronoi diagram in our work to show channel utilization in the area. Due to a Voronoi map that can be used to find the largest empty circle amid a collection of points, the drone environment where drones are communicating can be represented this method in a more precise way. With this method, drone groups can be visualized more centralized manner within regions because we use one of the unsupervised machine learning algorithms called the k-means clustering method according to drone coordinates. This algorithm clusters drone coordinates and helps to create Voronoi regions. Shortly, the main contributions of this paper include the following:

– We propose a new system model consists of Searching & Finding Sub-layer and Functional Sub-layer Modules, which is responsible for locating drones and creating a Voronoi Diagram. This model works on the MAC layer of IEEE 802.11 RTS/CTS protocol.
– We introduce a practical and more straightforward channel utilization calculation using the properties of the IEEE 802.11 RTS/CTS protocol.
– We present a novel monitoring approach with a k-means clustering algorithm to visualize and analyze network traffic in the Voronoi diagram with a more effective and faster way.
– We can also apply our implementation to future technology WIFI 6, which is the data-driven protocol as we propose. Hence, our model will present a compelling and more uncomplicated novel monitoring method in the future.

The rest of this paper is organized as follows. The network architecture is explained in Sect. 2. In part 3, the system model is indicated. The simulation environment is described in Sect. 4. In Sect. 5, we evaluate the performance of

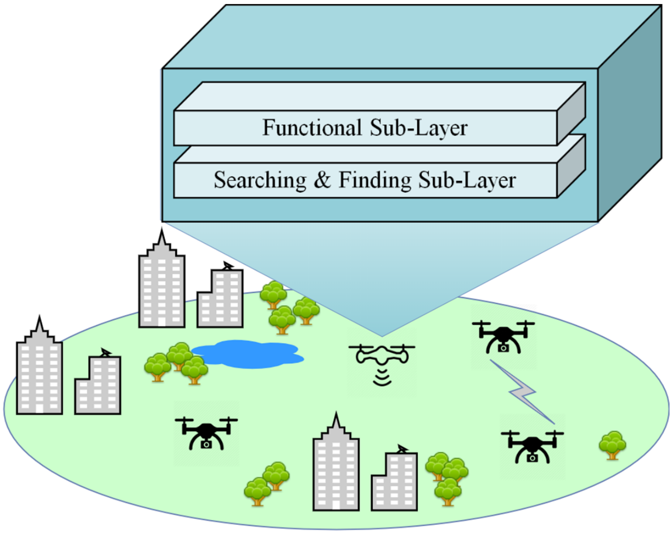


Fig. 2. Network architecture

our proposed model. Finally, we conclude the paper by summarizing the achievements in Sect. 6.

2 Network Architecture

The network topology for our model consists of n drones with one searching drone. These drones are communicating with the IEEE 802.11 wireless networking protocol with RTS/CTS (Request To Send/Clear To Send) mechanism. The RTS/CTS mechanism is created for avoiding the hidden terminal problem in wireless networks and allows only one pair to communicate in the channel. Drones can fly at different heights with the specific moving pattern. However, the searching drone always flies at the pre-determined height. All drones repeat their flying patterns after reaching destination coordinates. Furthermore, we assume that all drones are completed authentication stage for wireless communication. Hence, they communicate directly with each other on the same channel without authentication messages. Moreover, the channel is always busy, and the frame size is randomly generated in the network. We represent the whole network architecture and the component models of the searching drone in Fig. 2.

3 System Model

We divide the proposed system model into two coherent sub-layers titled Searching & Finding Sub-layer and Functional Sub-layer. Searching & Finding Sub-layer is responsible for searching on the area with a specific movement pattern and gathering information from D2D communication. Moreover, we dedicate the Functional Sub-layer to process information belongs to the Searching & Finding Sub-layer. Each of the sub-layers additionally owns some modules. Searching & Finding Sub-layer has two modules entitled Sensing and Data Classification; furthermore, the Functional Sub-layer has two modules entitled Calculation and Visualization. In Fig. 3, we represent the entire system model and the associations between its segments.

3.1 Searching and Finding Sub-layer

Searching & Finding Sub-layer includes Sensing and Data Classification Modules. The Sensing Module determines the movement pattern of the searching drone and executes it. Furthermore, this module performs the classification of data operations and gives the meaning of them.

Sensing Module. This module handles the movement pattern of the searching drone and operations of collecting data from the channel with sensing. This information contains coordinates of communicating drones, source and destination address of the frame, Duration ID in the frame to keep Network Allocation Vector (NAV) timer and frame types such as RTS, CTS, DATA or ACK. After the sensing channel for gathering this information, this module transfers collected data to the next layer called Data Classification.

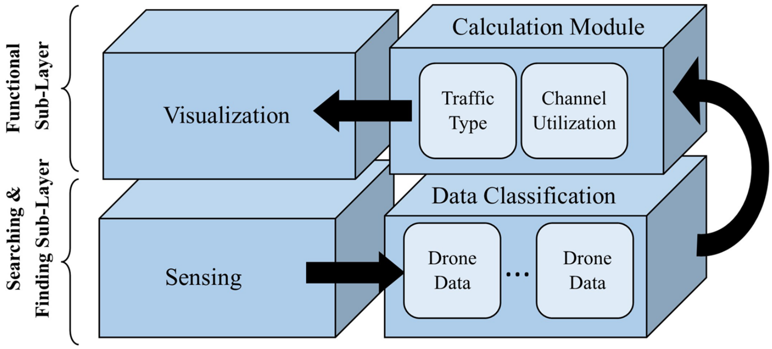


Fig. 3. Layered architecture of proposed system model

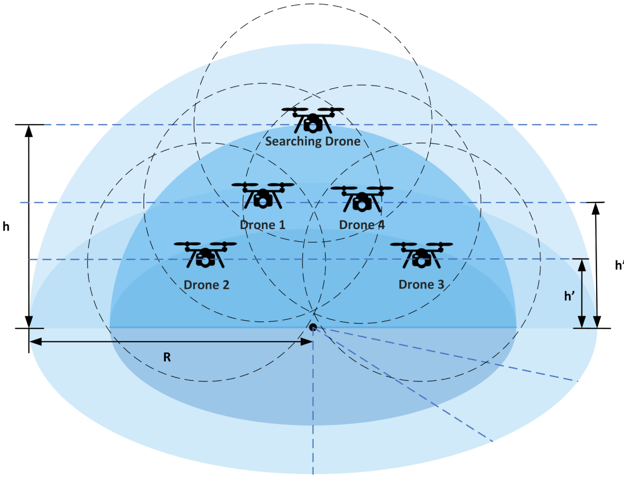
Data Classification Module. This module exists at the end of the Searching & Finding Sub-layer. The transferred data from Sensing Module is classified here to match that data with Drone Data sections. The coming information from the below layer is assigned to Drone Data if there exists. In the case of a new drone whose information does not exist in the Drone Data section, is discovered, then the new part is created in the Data Classification Module. All other information about this drone will be assigned this section in the future data gathering. This module's main aim is grouping collected data with corresponding drones to make it easier for calculations in the future. After all these operations, the classified data is transferred to the upper layer named Calculation Module.

3.2 Functional Sub-layer

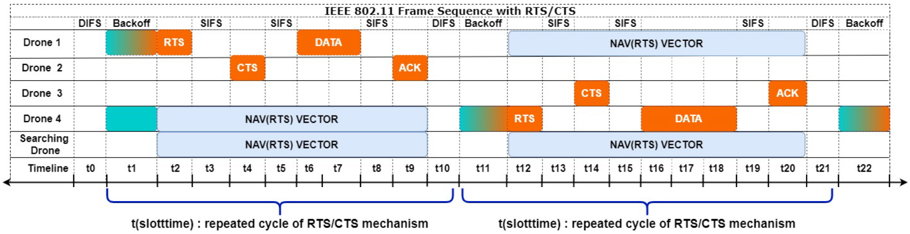
The functional Sub-layer includes Calculation and Visualization Modules. The Calculation Module calculates channel utilization, and the Visualization Module creates a Voronoi diagram with calculated channel utilization and network traffic type.

Calculation Module. This module exists between Data Classification and Visualization Module. It calculates channel utilization and type of network traffic for each drone. To do that, this module uses the information coming from the Data Classification Module. Furthermore, this module contains submodules called Channel Utilization and Traffic Type Sub-Modules.

Channel Utilization Sub-Module. This module is responsible for computing the channel utilization of the area. To do that, this module uses the properties of the IEEE 802.11 RTS/CTS protocol. Due to this protocol, only one pair can communicate at a certain time. Other drones should wait until the NAV vector reaches zero; after that, if they win back off timer before other drones, then they can transmit their data. The Fig. 4 shows sample scenario. This scenario is an example of our model with less number of drones with the searching drone.



(b) The placement of drones in the area



(a) The communication sequence diagram

Fig. 4. The sample scenario of IEEE 802.11 RTS/CTS

The communication sequence diagram of the area can be seen in the below part of the figure. In our model, we concentrate on the repeated cycle of RTS/CTS mechanism denoted as $t_{slottime}$ and natural outcome of IEEE 802.11 RTS/CTS protocol, known as sequentially repeated cycles like in the Fig. 4b. It can be understood that $t_{slottime}$ can be calculated focusing on starting time with the RTS frame after the Backoff timer until the ACK frame is transferred, which showed in Fig. 4b. In this interval, only one drone pair can transmit, and the total transmission time for data always has the same sub-time intervals except for the data frame size. Other time intervals like DIFS duration denoted as t_{DIFS} are constant values determined by the protocol as in work [12]. Hence, $t_{slottime}$ can be denoted as following:

$$t_{slottime} = t_{RTS} + 3 \times t_{SIFS} + t_{CTS} + t_{DATA} + t_{ACK} + t_{DIFS} + t_{Backoff} \quad (1)$$

where $t_{Backoff}$ is a random value between [1, CW], and other time intervals are the part of the IEEE 802.11 RTS/CTS protocol. The CW(contention window) is an integer between $CW_{min} = 32$ and $CW_{max} = 1024$. In our model, we consider this value as average value as $CW = 528$. The other components of $t_{slottime}$ is constant values which depends on the standard of the IEEE 802.11 protocol except t_{DATA}. The t_{DATA} can be changed according to the data frame size.

In this time interval, due to data frame size shows us real traffic in the channel, we focus on the t_{DATA} to calculate channel utilization of the area. Other values are minimal and constant. Hence, rate of t_{DATA} and $t_{slottime}$ gives us channel usage in the time interval $t_{slottime}$ as following:

$$rate = \frac{t_{DATA}}{t_{slottime}} \times 100 \tag{2}$$

In our model, there is no idle time interval between each $t_{slottime}$. Hence, total utilization can be expressed as a summation of the $rate$ using Eq. 2 as following:

$$Total_{utilization} = \sum_{n=1}^{N} rate \tag{3}$$

where N is the total number of repeated cycles $t_{slottime}$ in the channel.

The successful IEEE 802.11 RTS/CTS transmission contains multiple $t_{slottime}$ time intervals successively, as in our model. These intervals are independent; hence, average utilization can be calculated, taking the average of the $Total_{utilization}$ using Eq. 3 as following:

$$Average_{utilization} = \frac{Total_{utilization}}{N} \tag{4}$$

Equation 4 provides a powerful and simple calculation of channel utilization only sensing once in the time interval of $t_{slottime}$. The calculation of the channel utilization can be possible when t_{DATA} internal is known. Hence, we present a novel approach for determining t_{DATA} interval using the NAV vector. After sensing once the channel, the NAV vector is created for sensing drone called searching drone in our model and average channel utilization using the Eq. 4 can be calculated with the size of the NAV vector. Thus, we use four types of NAV vector, and the duration of these vectors can be calculated as follows:

$$NAV_{RTS} = t_{RTS} + 3 \times t_{SIFS} + t_{CTS} + t_{DATA} + t_{ACK} \tag{5}$$

$$NAV_{CTS} = t_{CTS} + 2 \times t_{SIFS} + t_{DATA} + t_{ACK} \tag{6}$$

$$NAV_{DATA} = t_{DATA} + t_{SIFS} + t_{ACK} \tag{7}$$

$$NAV_{ACK} = t_{ACK} \tag{8}$$

It can be seen from Eq. 5–8 that all NAV vector types contain t_{DATA} interval except NAV_{ACK}. In our model, the searching drone can only sense the mentioned frames. Except NAV_{ACK} interval, with all sensed NAV vector types, t_{DATA} can be determined because except t_{DATA}, all other time intervals are known by the protocol. Hence, in this module, it is possible to calculate t_{DATA} interval using the proposed algorithm whose flowchart is given in Fig. 5. Using this flowchart, we decide which equation we can use according to the type of frame received and use the proper equation. Each frame type has a different calculation equation given as Eq. 5–8 and using these equations and Eq. 2–4 following equation can be derived:

$$Average_{Utility} = \frac{\sum_{n=1}^{M} \left(\frac{t_{DATA}}{t_{slottime}} \times 100\right)}{M} \tag{9}$$

where M is the number of the sensed frame number, and t_{DATA} is calculated using our proposed algorithm, whose flowchart is given in Fig. 5. Also, $t_{slottime}$ is determined according to sensed frame type.

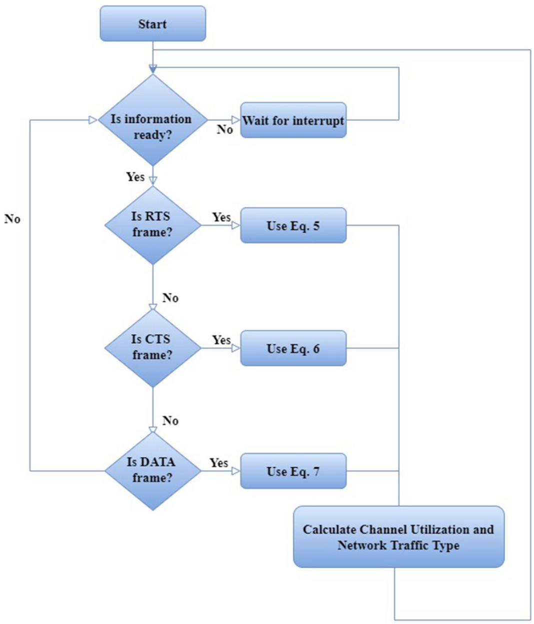


Fig. 5. The flowchart for Calculation Module

Shortly, in this module, according to the frame type, the NAV vector is activated in the searching drone. Using these types of NAV vector, t_{DATA} interval is determined using Eq. 5–7. After that, Eq. 9 gives us individual channel utility for each drone. With Eq. 3–4, known t_{DATA} interval allow us to calculate $Average_{utilization}$. Hence, knowing t_{DATA} interval provides an accurate calculation of the average channel utilization, as mentioned above.

Traffic Type Sub-Module. This module is responsible for determining the traffic type of the region in the Voronoi Diagram. According to the $Average_{utilization}$ of the channel traffic, which is calculated in the Channel Utilization Sub-Module, we determine the traffic type of a region in the Voronoi Diagram in terms of three-level which are low, medium, and high traffic. We define the low level as a percentage of less than 30%, and the medium level as a percentage of between 30% and 60%. Also, we specify the high level as a percentage of more than 60%. After the calculation of these types, this information is transferred to the next module named Visualization Module.

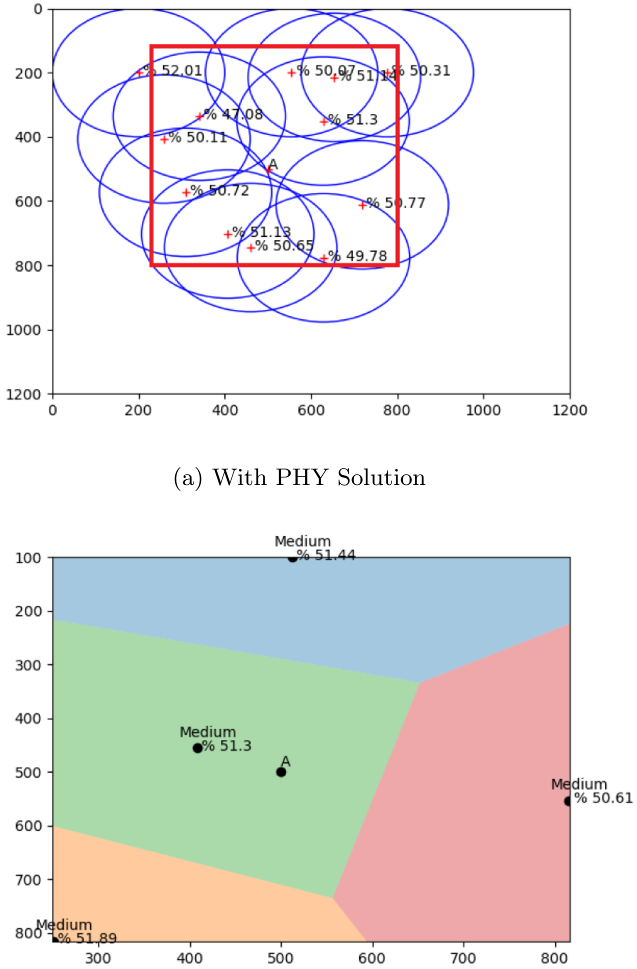
Visualization Module. This module exists after the Calculation Module. After the channel utilization and network traffic type are calculated for each drone, the Voronoi Diagram is created and visualized with each drone's coordinates in this module. This diagram contains regions with average channel utilization and network traffic types. After each iteration, we recreate the map with new data, and we examine the difference in the traffic in this module. The searching drone completes each iteration when it reaches the starting coordinates after visiting all areas.

In this module, as a novel approach, the drone coordinates are grouped, and after that, we construct the Voronoi Diagram. The grouping operation is done with the k-means Clustering Algorithm, which is one of the simplest and popular unsupervised machine learning algorithms. K-means clustering results in a partitioning of the data space into Voronoi cells, which helps us to create Voronoi regions in our model. According to [13], continuous geometric problems can be converted into a discrete graph problem, as in our model.

4 Simulation Environment

The proposed system model is simulated with the pygame library of Python programming language. In the simulation, the drones are placed in the area with Poisson Distribution because it provides centralized distribution with proper lambda value. We choose the lambda value as 10, and the sample size as 1000000. We use the Poisson Distribution for both the x-axis and the y-axis on the map. Though the distribution also provides the same values, we applied the discretization method to these values. However, this method decreases the produced values by Poisson Distribution. Creating values for the x and y-axis with Poisson Distribution is applied multiple times until the coordinates are generated for each drone. Furthermore, drones that are communicating with other already placed drones are also identified with Poisson Distribution. Moreover, we made the placement with some restrictions; the minimum distance with pair drones must be more than ten units.

The model has some assumptions which are mentioned as following. We assume that the searching drone is always flying at the same height; hence, we create the area as a 2D map. Furthermore, we take that all drones are running with a specific movement pattern. The searching operation starts from a



(a) With PHY Solution

(b) With MAC (Our Model) Solution

Fig. 6. The visualisation model of the area with PHY and MAC

particular location and continues on the map until all regions are visited. These regions have the same size as the radius of all other drones, which decreases miss sensed areas when searching and detecting. When the searching drone visits all parts, the backward movement pattern starts. End of this pattern, the searching drone reaches the starting location, and the total movement pattern begins again.

In the model, each drone communicates only with one drone on the map. The communication between them to be possible, each pair of drones placed within the communication range. The communication range of all drones is the same size unit. The direction of communication is determined randomly. Furthermore, we set the data frame size to random size, and the drones are communicating all the time. Hence, there is no idle time on the channel. All drones have the frame to send when the backoff timer starts decreasing.

There are different monitoring types in terms of the number of drones, such as 8, 12, 16, and 20 in the model. We place drones considering the rate of drone communication range and the map. Hence, a more significant number of drones have a smaller communication range in the model. Also, the searching drone moves with a speed vector that scaled for the map. We discretize the movement of the searching drone and communication time of the other drones in terms of units. Furthermore, the searching drone can move with different sizes of the unit of time; however, communication occurs in each unit of time. Table 1 shows the overall simulation parameters.

Table 1. Simulation Parameters

Map Properties			Poisson Parameters	
Vehicle Number	Radius of drones	Map Size	Lambda	Sample Size
8	250	1000×1000	10	1000000
12	200	1000×1000	10	1000000
16	150	1050×1050	10	1000000
20	100	1000×1000	10	1000000
Drone Receiver Power			0.2 W	

5 Performance Evaluation

We evaluate the performance of our proposed system model based on the visualization of the drone environment. If we create a channel utilization map using only drone coordinates, then there might be miss-sensed drones in the map because, according to IEEE 802.11 RTS/CTS protocol, only one drone can use the channel at a time. Hence, we classify drone locations with the k-means clustering algorithm, and we create Voronoi regions after clustering. Furthermore, we show the comparison of the PHY (Physical Layer) and MAC Layer (our model) solutions with different parameters such that average sensing time, power consumption, and used area during calculation in our simulation results.

Figure 6 shows the results of our novel model as a visualization approach. The figure consists of two parts, which first part shows a map of before our work as PHY, and the second part shows a diagram of using our model as the MAC layer. Each section of the figure has a point A on the same location to offer the same place for evaluation channel utility. Furthermore, we create all maps for the same altitude, in which the searching drone flies denoted as h in the figures. Also, we divide all Voronoi diagrams into four regions.

When we examine Fig. 6, we can see for point A; it is not reliable to find out channel utilization in the first part of the figures. For some samples, there is no specific channel utilization, or there are multiple values that we should consider all of that. With our model, as in part b, we can detect channel utilization more reliably and accurately. Furthermore, we show network traffic types in regions, which cannot be seen in the first part of the figures.

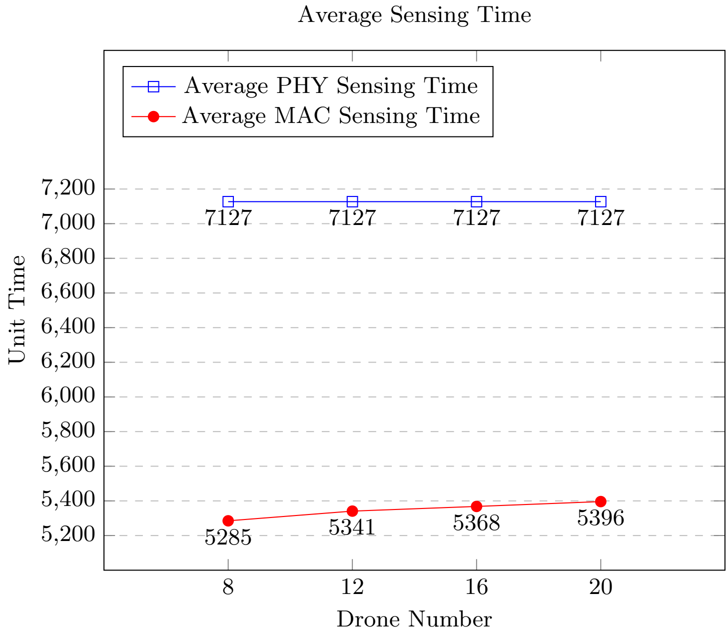


Fig. 7. Average sensing time

In additional visualization evaluation, we experiment average sensing time of the searching drone with MAC solution (our model) and PHY method. Figure 7 shows our model decreases average sensing time about 25%. We also examine power consumption and used area during the calculation of the searching drone as parameters with our simulation. Figure 8 shows the power consumption of the searching drone during the sensing phase, according to PHY and MAC (as our model) layer solutions. It shows that our model decreases power consumption of the searching drone by about 26%. Furthermore, Fig. 9 shows the area used during the calculation phase measured by the searching drone according to PHY and MAC (as our model) layer solutions. It shows that our model decrease used area during the calculation phase about 57%.

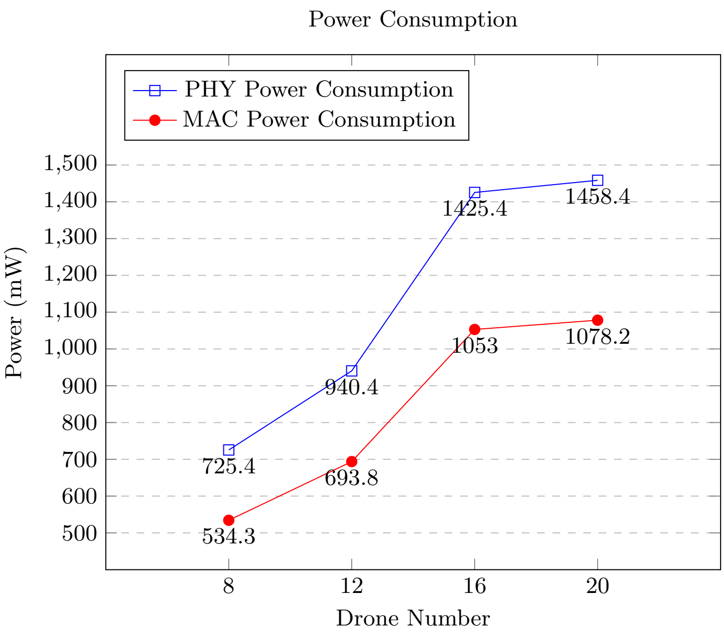


Fig. 8. Power consumption of the searching drone

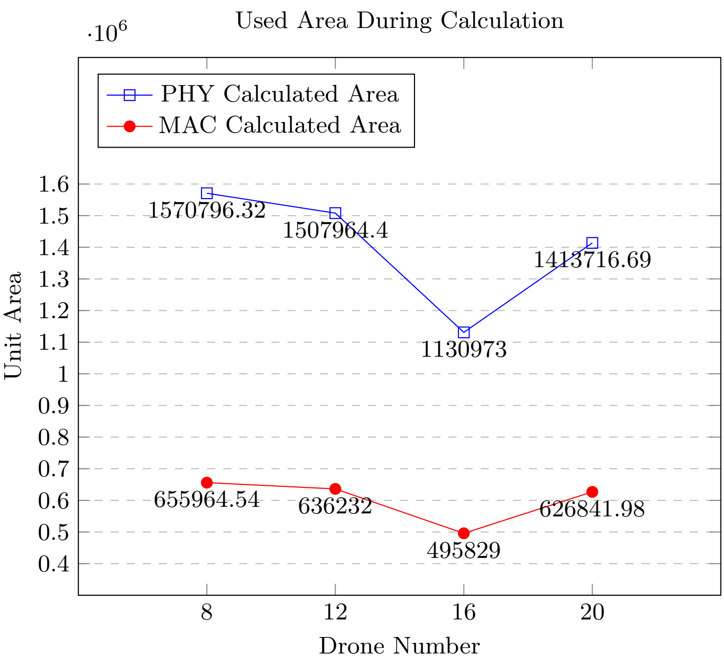


Fig. 9. Used area during calculation

6 Conclusions

In this paper, we propose a novel channel utilization monitoring approach for D2D networks to evaluate the performance of the wireless link. The searching drone flies in the air with a specific flying pattern and senses the channel to locate other drones. Our protocol-based system model process all sensed information and calculate channel utility with our novel method. This method benefits from the IEEE 802.11 RTS/CTS protocol, which allows continuous and discrete communication with one communicating pair at a time in the channel. Furthermore, we provide novel visualization methods with Voronoi Diagram. The power and simplicity of the Voronoi Diagram are applied, and we create the channel utilization map in our work. We divide the map into Voronoi regions with a k-means clustering algorithm for corresponding heights and show channel utility of each area. Furthermore, we decrease the average sensing time of channel 25% with our model. We also reduce the power consumption of the searching drone by about 26%, and we fall used area during the calculation phase, about 57%. In future work, this protocol-based approach for monitoring channel utility can be applied on WIFI 6, which is the data-driven protocol as we propose, and a 3D Voronoi diagram can be created to get a more robust examination of link performance. Artificial Intelligence (AI) based evaluation of channel utility and network traffic type also can be applied to the work.

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