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Data collection based on **Q-learning** method in terrestrial networks assisted by **UAV**

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Thanks

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  - The first of them is my God who helped me in everything I ever needed, and I found him in everything that surrounds me
    "*Al Hamdoullillah* "
  - My parents are the two people in whom I found love and support ... Thanks to you, I wouldn't have been here.
  - My family is small, and if it is, it means the whole world to me. My brothers and Sisters.
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First of all to my own self because of her patience, faith and hard work throughout these five years.

Here are the efforts bearing fruit

I dedicate this thesis.

My parents who supported me with love and understanding, without you I could never have reached this current level of success.

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Abstract

Abstract

Nowadays, **Unmanned Aerial Vehicle (UAVs)** are playing an integral and sustainable function in many verticals touching exclusive components of our lives; such as civil, public and military applications. The objective is to appoint a self-trained UAV as a flying cell unit gathering data from ground sensor nodes fairly distributed in a given geographical area through a predefined period of time. In this approach, **Q-learning (QL)** algorithm is employed to train the UAV to learn the environment and provide appropriate scheduling to accomplish its data collection mission while minimizing the data collection time. As a matter of fact, collecting information from sensors may face some noticeable challenges. However, due to use the flexibility of UAVs, collecting information would be much easier. In this thesis, we tried to figure out about UAVs that support data collection over **WSN (wireless sensor network)**, while maximizing the amount of collected data and minimizing the flight duration of time.

Key Words:

- **QL :** Q-learning
- **UAV:** unmanned aerial vehicle
- **WSN:** wireless sensor network

Résumé

De nos jours, les véhicules aériens sans pilote (UAV) jouent un rôle intégral et durable dans de nombreux secteurs verticaux touchant des composants exclusifs de nos vies, tels que les applications civiles, publiques et militaires. L'objectif est de désigner un drone auto-formé en tant qu'unité de cellule volante collectant des données à partir de nœuds de capteurs au sol équitablement répartis dans une zone géographique donnée sur une période de temps prédéfinie. Dans cette approche, l'algorithme Q-learning (QL) est utilisé pour entraîner l'UAV à apprendre l'environnement et fournir une planification appropriée pour accomplir sa mission de collecte de données tout en minimisant le temps de collecte de données. En fait, la collecte d'informations à partir de capteurs peut être confrontée à des défis notables. Cependant, en raison de l'utilisation de la flexibilité des drones, la collecte d'informations serait beaucoup plus facile. Dans cette mémoire, nous avons essayé de comprendre les drones qui prennent en charge la collecte de données sur WSN (réseau de capteurs sans fil), tout en maximisant la quantité de données collectées et en minimisant la durée de vol.

Mots clés :

- **QL :** Q-learning (apprentissage par renforcement)
- **UAV:** le véhicule aérien sans pilote (Drones)
- **WSN:** réseau de capteurs sans fil

ملخص

في الوقت الحاضر ، تلعب المركبات الجوية غير المأهولة (UAVs) وظيفة متكاملة ومستدامة في العديد من القطاعات التي تمس المكونات الحصرية لحياتنا ، مثل التطبيقات المدنية والعامة والعسكرية. الهدف هو تعيين طائرة بدون طيار ذاتية التدريب كوحدة خلوية تجمع البيانات من عقد استشعار الأرض الموزعة بشكل عادل في منطقة جغرافية معينة خلال فترة زمنية محددة مسبقًا. في هذا النهج ، يتم استخدام خوارزمية Q-Learning (QL) لتدريب الطائرات بدون طيار على تعلم البيئة وتوفير الجدول الزمني المناسب لإنجاز مهمة جمع البيانات مع تقليل وقت جمع البيانات. في الواقع ، قد يواجه جمع المعلومات من أجهزة الاستشعار بعض التحديات الملحوظة. ومع ذلك ، نظرًا لاستخدام مرونة الطائرات بدون طيار ، سيكون جمع المعلومات أسهل بكثير. في هذه الأطروحة ، حاولنا معرفة المزيد عن الطائرات بدون طيار التي تدعم جمع البيانات عبر WSN (شبكة المستشعر اللاسلكي) ، مع تعظيم كمية البيانات التي تم جمعها وتقليل مدة الرحلة.

الكلمات المفتاحية :

- **QL :** خوارزميات Q-Learning
- **UAV :** طائرة بدون طيار
- **WSN :** شبكة المستشعرات اللاسلكية

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LIST OF ABBREVIATIONS

A:

AI: Artificial Intelligence.

AODV: Ad-hoc On-demand Distance Vector.

AoI: Age of Information.

B:

BS: Base Station.

E:

EME: Electro Magnetic Energy.

F:

FBS: Flying Base Station.

FWA: Fixed Wing Aircraft.

FBS TD with LS: Learning to Rest: A Q-Learning Approach to Flying Base Station Trajectory Design with Landing Spots.

G:

GR in VANET: Adaptive UAV-Assisted Geographic Routing with Q-Learning in VANET.

H:

HART: Highway Addressable Remote Transducer.

I:

ISA: International Society of Automation.

IoTs: Internet of Things.

L:

LS: Landing Spots.

M:

MDP: Markov Decision Problem.

MPEL with PP in UAV DS: Minimizing Packet Expiration Loss with Path Planning in UAV-Assisted Data Sensing.

N:

NN: Neural Network.

Q:

QL: Q Learning.

QAGR: Q-learning Adaptive Geographical Routing.

QoS: Quality of Service.

R:

RL: Reinforcement Learning.

RS: Road -side Station.

RREQ: Route REQuest.

U:

UAVs: Unmanned Aerial Vehicles.

V:

VANET: Vehicular Ad-Hoc Network.

VE and EaPP via RL: Visual Exploration and Energy-aware Path Planning via Reinforcement Learning.

W:

WSN: Wireless Sensor Network.

WN: Wireless Network.

General Introduction

General Introduction:

Wireless Sensor Network (**WSN**) is an ad hoc network composed of small devices called sensor nodes, which typically have one or more sensors capable of collecting and transmitting data autonomously, these devices are spatially distributed to monitor physical or environmental conditions to detect some phenomena located around them, they communicate by radio and can relay packets received from other nodes to forward them to a special node called **Base station**, which is the interface with the users [1]. As they are usually battery powered, the biggest challenge is to achieve the necessary monitoring while using the least amount of power [2]. As the technologies in the **WSN** and Unmanned Aerial Vehicle (**UAV**s) also known as "**drones**" are integrated together, collaborative drones team up to achieve the data collection task on a WSN [3]. Whereas the processing of data is an essential process for viable WSN, surging via everyone's pockets, homes, vehicles and skies is a never-ending float of information; airborne drones permit humans to survey and investigate the place no one can physically be, this may providing a vast world of industries with real-time insights, when they join to cloud computing to collect and analyze data [4]. **WSN**s have emerged as a solution for an extensive varies of applications. The majority of WSNs architectures consist of static nodes which are densely deployed over a sensing area. Recently, countless WSN architectures based on UAVs have been proposed, most of them exploit the mobility of UAVs to address the problem of data collection [5]. The primary benefit of **UAV**s now is that the delay is significantly reduced and with a travel speed much higher than terrestrial components, the **UAV** components have flying capabilities, which ensures that data spread through multiple sensor nodes can be collected more efficiently and precisely [6].

Traditionally, since each sensor node includes a battery as a power source, the main challenge for this type of network is to capture, collect, store and process sensitive data in an energy-efficient manner [7].

We first define the data collection based on **UAV**s over **WSN**s areas, then we provide the different challenges of data collection. Following this, by taking into account UAV distribution, we will analyze some related works that used **UAVs** to collect data effectively and finally, we proposed a **Q-Learning** algorithm to provide our contribution to achieve the goal of maximizing the data collected with UAV while using the minimum amount of power in a short period of time.

This thesis is composed of three chapters:

- The first chapter is devoted to observe the data collection and its challenges in terrestrial networks.
- In the second chapter, we present Adaptive control based on the **AI** (**Artificial Intelligence**) of drones, we also explore the **Q-Learning** algorithm, widely used in reinforcement learning.
- The last chapter gives an overview of our protocol and showed us the analysis of the results obtained, which are described by graphs. For that, we used Python to simulate the functioning of our protocol.
- Finally, we finish with a general conclusion with the findings obtained and perspectives; we summarize our contribution in this experience by using UAV for collecting data.

Chapter I

Data collection

I.1 Introduction:

While it is important to collect data from wireless sensor network, Collecting data has become a major challenge for engineers, and what makes the challenge more difficult is that it takes a lot of time and great speed to obtain and analyze the data collected to discover solutions in places where it is difficult for a person to be present, but the modern technology that has shown some solutions to rely on UAVs; Since the UAV have the characteristics of stability; it can be deployed in WSN [8], for inclusion in tasks due to their efficiency and speed, which leads to reducing time and distance and preserving people in such critical situations. So, how did the developers rely on them? and how did the **UAV**s prove their efficiency and high ability in achieving this?

In this chapter, we are studying data collection assisted by **UAV**s.

I.2 Data collection definition:

Data collection is the process of gathering and measuring information that has been transformed into a form that can be interpreted by computers**.** Access to collect data in a correct manner will mean that you are able to spot major challenges early on and take action to address them. And it is an important mechanism for **WSN** to be viable [9] & [10].

I.2.a Data collection & Its challenges:

In the Internet of Things (**IoTs**) services and because the IoTs devices generate a big volume of information, the data of wireless sensor network needs to be collected from the ground sensors. Hence, data collection challenges in sensor network nodes can have many types of goals; two common goals to minimize the time and distance required for data collection [11 & 12 & 13 & 14], the energy consumed when collecting data and maximize the data collected [15 & 16 & 17].

I.3 Data collection applications:

The applications are varied, they are differentiated by the challenges they need a solution and they can be defined depending on the fields of operation. Data collection implementations in WSN are found in the most fields of operations, but they are still used predominantly in strategic areas and here we mention some of these applications:

I.3.a **Military:**

In military activities, including information, monitoring and surveillance, the primary sources of information for the Armed Forces are reconnaissance contemporary. In Soldiers' maneuvers in isolated and violent areas, wireless sensor networks are a possible solution [18]. They are used to gather information such as sounds, pictures, detect movement, motion recognition, etc. In the military, WSN applications field require communication protocols that allow sensors to save energy, safeguard data integrity [19] and efficient deployment and collection means are required in hostile areas where it is impossible to place base stations [20] in some places. While several WSN-based military applications have been proposed [21, 22, 23], many challenges continue to be addressed. In reality, installing and securing sensors and base stations remains a real challenge in conflict zones.

I.3.b **Industry:**

In many organizations, like the **ISA** (International Society of Automation) and the Highway Addressable Remote Transducer Protocol Connectivity (**HART**) has strongly encouraged the use of WSN in the industry by providing industry-friendly specifications [24]. There are many aspects of the industry today that require data collection to be implemented for research and preventive maintenance. In order to safeguard manufacturing machines and machinists [25].

I.3.c **Environment:**

The environment is all the factors that encompass a human and some of which at once contribute to its needs. It is the atmosphere, the local weather in which an individual finds himself [26]. According to This definition, functions related to the environment include agriculture, animal husbandry, climatology, seismology, natural world monitoring [27]. The challenges of the local weather disaster on the one hand and of human action on the environment on the different have led to the improvement a number of applications for the protection of our environment. For example, the reconstruction of the habitat of certain species [28] [29], the analysis of the impact of humans on its ecosystem [30], measuring the micro-climate for precision agriculture [31; 32], control of active volcanoes [36], etc.

I.4 Drones assistance in data collection:

These days, in almost every company that needs visual inspections as part of its maintenance processes, drone inspections are being carried out. Drone inspections allowed inspectors prevent having to position themselves in unsafe conditions by using a drone to gather visual evidence on the status [34].

I.4.1 Definition of drones:

(Unmanned Aerial Vehicle) **UAVs** it is an air vehicle without a human pilot that is automatically or remotely controlled**.** Used in both military and non-military uses for security and transport [35]. Contemporary UAV come in all shapes and sizes and can perform a wide array of functions, including surveillance. For example, there is some current aerial drones have the size of insects capable of short-range surveillance operations within buildings, while others weigh seven tons, have a longest wing and are capable of remaining aloft for over 24 hours, flying over 10000 miles [36].

> “Think of drones or any autonomous physical technology as a part or a node in a broader network that’s gathering data and is interconnected with cloud computing,” said *Brian David Johnson*, a futurist in residence and professor of practice at Arizona State University.
>
> “The drone is simply an autonomous data-gathering machine.”

- The size of an aerial drone for miniature models can vary from a few centimeters to several meters for advanced drones (surveillance, intelligence, combat, transport, recreation). The flight time ranges from a few minutes for long endurance drones to over 40 hours, as we cited in the Figure I.1 bellow:

Figure I.1: The size of UAVs

I.4.2 Types of unmanned aerial vehicle (UAVs):

There are so many kinds of drones that you can easily find in the world, and they all function for various purposes, so we cannot identify any particular classification requirements. They may have a variable size and style, depending on the needs or applications. One of the most popular drone technology uses is in the military, as it helps to efficiently monitor surveillance related problems. An air-flying unit can effectively track areas that humans cannot enter directly and can also take images of sensitive locations [37].

We would review different types of drones here (**see figure I.2)** and categorize them into four simple parts to understand it:

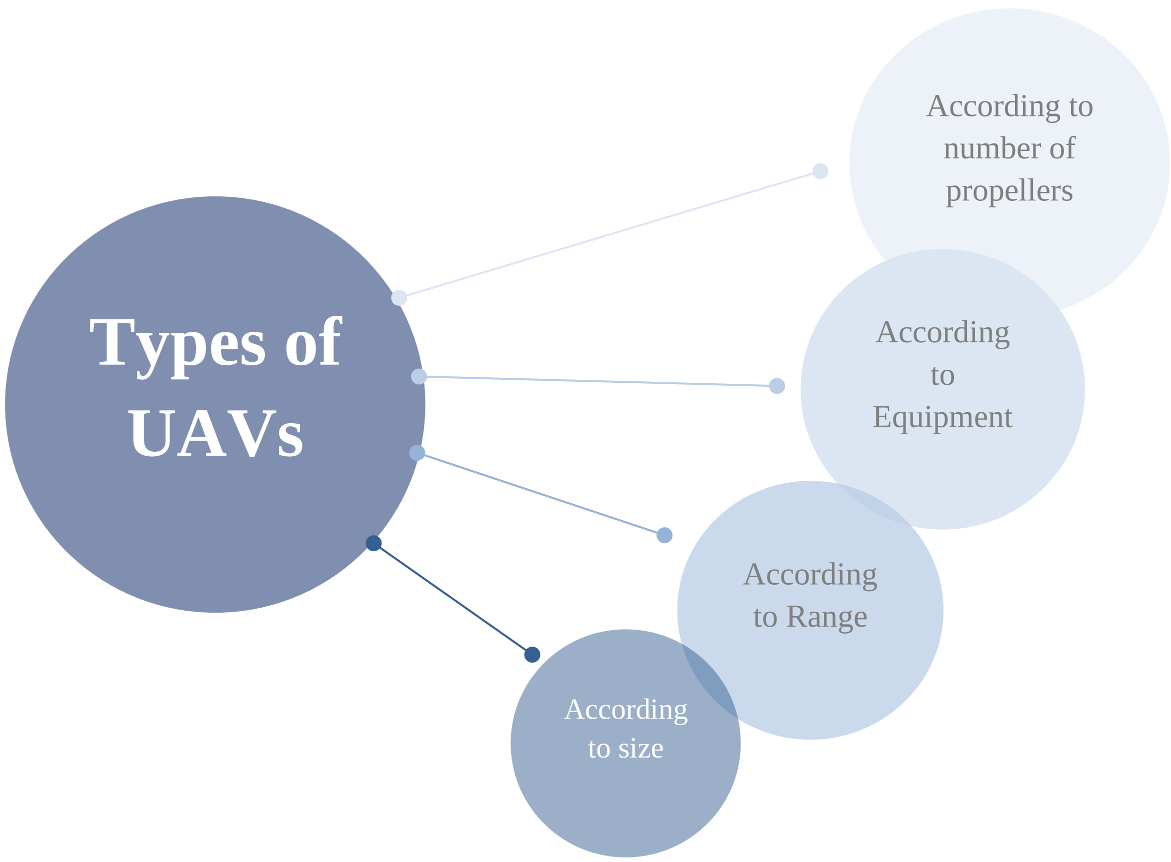


Figure I.2: Types of unmanned aerial vehicle (UAVs)

A. According to Number of Propellers:

The number of propellers used within, flying range and facilities (see figureI.3):

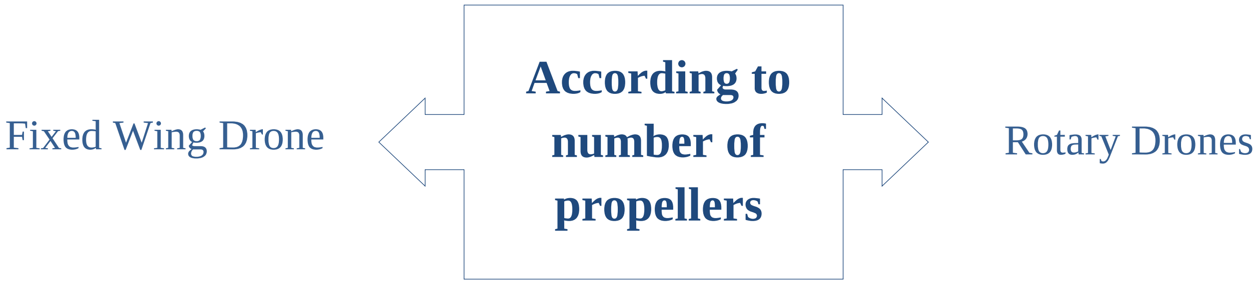


Figure I.3: types of UAVs according to Number of Propellers

A.1 Rotary drones:

Rotary-wing drones may have a single rotor or even up to 8 rotors generating thrust. Rotary-wing drones have the advantage of being easier to fly at first and being able to hover in place, enabling them to perform a wide range of tasks [38].

Figure I.4: Rotary drones

i. Single Rotor Drone:

Single rotor drones are robust and seem comparable in structure and design to actual helicopters (c.f figure I.5). They have one large rotor, which is like one big spinning wing, plus a small sized rotor on the tail for direction and stability [39].

Figure I.5: Single Rotor Drone

ii. Multirotor:

The most popular kind of drone for getting an “eye in the sky” is the multi-rotor drone (c.f figure I.6). This is the popular desire for aerial photography, filmmaking and surveillance, it is used by the authorities and hobbyists alike because of its small measurement and equipped to fly out. Multi-rotor drones are also easiest to manufacturer and the cheapest drone option. They elevate several rotors and can be further categorized based on the variety of them [40]. There are **tricopter** (3 rotors), **quadcopters** (4 rotors), **hexacopter** (6 rotors) and **octocopters** (8 rotors).

- Quadcopters are with the aid of a long way the most popular multi-rotor drones.

a. Tricopter

b. Quadcopter

c. Hexacopter

d. Octocopter

Figure I.6: Multirotor Drones

A.2 Fixed Wing Drone:

Fixed wing drone consists of one rigid wing and is designed to seem to be and work like an airplane. What helps distinguish fixed wing drones from different types is that they cannot continue to be in one location. This capability they can be far greater efficient in contrast to the two other foremost classes of drones. Fixed wing UAVs are nicely acknowledged in the military, as they are often used when manned flight is viewed too unstable or difficult, they are additionally used in the business industry.

We can further categorize within the three main categories of drones:

B. BY SIZE:

- Nano **(The Very Little Drones)**: size of an insect (up to 50 cm)
- Small: (**The small Drones)** bigger than the size of an insect however still pretty small (less than two meters in length). This is the measurement of most client drones. These drones can be handled through one person.
- Medium: Smaller than light aircrafts and normally carried with the aid of two people.
- Large: dimension of a small aircraft, usually used in navy or surveillance situations.

C. BY RANGE:

- Close-range (c.f Figure I.7.1): Most shut range drones typically have a vary of round 3 miles and can stay in the air a common of 20-30 minutes.
- Short-range (c.f Figure I.7.2): Most brief range drones can be controlled up to 30 miles away from users and can continue to be in the air for an average of 1 hour and up to 6 hours.
- Mid-range (c.f Figure I.7.3): Most mid vary drones can be controlled up to ninety miles away and can stay in the air up to 12 hours.

I.7.1. Close-range **I.7.2. Short-range** **I.7.3. Mid-range**

Figure I.7: Types of drones according to range

D. By ENDURANCE:

Most persistence drones can be controlled up to four hundred miles and be up in the air for up to three consecutive days. These are normally used for surveillance and collection of scientific data.

I.4.3 Drone assistance and different applications for data collection:

Drones are being utilized in monitoring, transport, protection and disaster management, and different domains. Envisioning that drones structure autonomous networks incorporated into the air traffic, with help of a single-drone system consisting of quadcopter it can display its attainable in catastrophe assistance, search and rescue and aerial monitoring. The growing popularity with endless possibilities of drones force us to figure out the strategies to data series and evaluation to make use of them in one of a kind fields including:

i. Border Surveillance:

Deploying drone science for the coverage in the area of border surveillance, makes the drones are a valuable tool for border protection because they provide real-time reconnaissance, target acquisition, and tracking of people and illegal activities [41].

ii. Clinical resources:

UAVs or drones are increasingly explored as a solution to transport challenges for medical goods and other clinical resources, including emergency blood supplies, vaccines, medicines, diagnostic samples, and even organs from a distinct clinical facility to remote areas/villages, when the place street tour can be costly and time taking [42].

iii. Engineering:

For engineers, building agencies and clients, drones are an indispensable tool used for shooting data, these tools allow undertaking teams to gather and accumulate giant volumes of highly accurate information in a safer way. After the drones became a part of industry, they have changed the way we collect data. The arrival of drones has supplied engineers with an innovative platform which can hold various kinds of sensors such as high-resolution cameras, video cameras, laser scanners, thermal cameras and electromagnetic energy (**EME**) sensors [43].

I.5. Conclusion:

In this chapter; we talked about the main idea of data collection in wireless sensor networks and what are the different challenges facing us on our way to collect data, and how could the **UAV**s achieve this. Further, The **UAV**s factors have flying capabilities with a travelling speed lots greater than terrestrial elements, meaning that facts scattered across many sensor nodes can be accumulated more quickly and efficiently that's why the use of **UAV**s elements suggested. In the next chapter, we will address the meaning of artificial intelligence and the basic form of reinforcement learning (**QL**) after that we will take an overview about some related works that using the UAVs as a solution of some issues based on **Q-learning** algorithm.

Chapter II

Adaptive control based on the AI of drones

II.1 Introduction :

Questions arise such as “what is intelligence?”, “how can one measure intelligence?” or “how does the intelligence work?”. All these questions are significant when making an attempt to understand **A**rtificial **I**ntelligence (**AI**). However, the central question for the engineer, mainly for the pc scientist is the query of the intelligent laptop that behaves like a person and showing sensible behavior. The intention of **AI** is to enhance machines that behave as through they had been intelligent. **AI** is the potential of digital computers or laptop managed robots to remedy troubles that are commonly associated with the greater mental processing abilities of people [44].

II.2 Q-learning definition:

Q-Learning is a basic form of Reinforcement Learning, which works by approximating the value of state-action pairs, which uses **Q**-values to iteratively improve the behavior of the learning agent. **Q-learning** function composed from five variables {**s**, **a**, **R**, **α**, γ}, where **s** signifies the state of reinforcement learning, **a** signifies the action of reinforcement learning and **α, γ** respectively signify the learning rate of reinforcement learning and the attenuation factor of subsequent reward. The node will update the state value table (**Q-value** table), in which **s’** is the next state resulting from action **a** in state “**s**”. The ‘**Q**’ in **Q-learning** stands for quality. Quality here represents how useful a given action is in gaining some future reward, also **Q-Learning** poses an idea of assessing the ***quality of an action*** that is taken to move to a state rather than determining the possible value of the state being moved to [45].

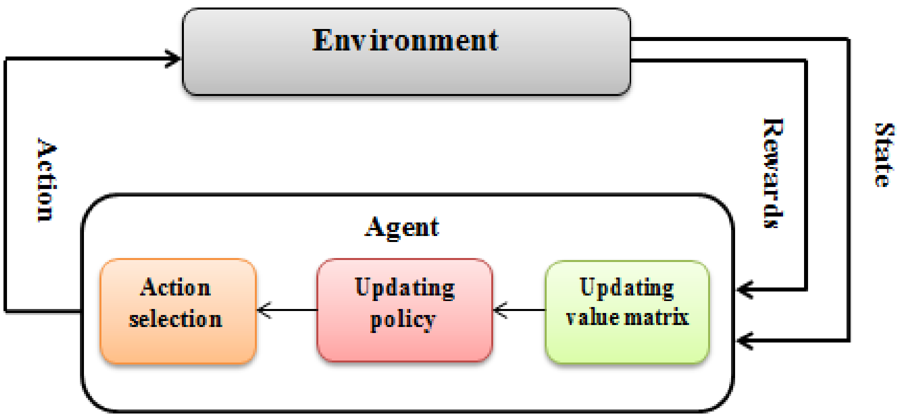


Fig II.1: Standard structure for reinforcement learning algorithm.

In the next section**,** we talk about some of the applications through which Q-learning was used:

II.3. APPLICATION 01:

II.3.1 Description:

VANET (**V**ehicular **A**d-hoc **Net**works) routing faces many difficulties due to the high mobility of vehicles, including regular topology modifications, irregular node distribution, and a shifting climate. The **VANET** routing has been enhanced with the **Q-learning** algorithm to make it more suited for dynamic environments. The neighbor nodes are considered the reinforcement learning state, and the roadside station (**RS**) is considered the fixed destination node that sends **hello packets** "as shown in **Fig II.1"** on a regular basis. When a **hello packet** is sent (*c.f* **Fig II.2**), the node that receives it updates its own Q-value table according to the following rules: The higher is the **Q-value**, the nearest it is to **RS**. For a static destination node, this approach has a greater impact on routing. The **Q-learning** algorithm is combined with the classic **AODV** (**A**d hoc **o**n-**d**emand **d**istance **v**ector) routing**,** by exchanging **hello packets** and **RREQ** (**R**oute **Req**uests) packets during the route discovery period, the nodes update their Q-value tables. **UAV**s were used to assist **VANET** in determining the best path for data transmission. To prevent bad routing route selection due to vehicle contact range limitations, an aerial network made up of several **UAV**s would be deployed to assist ground vehicle communication by broadening the spectrum in **QAGR (Q**-learning **a**daptive **g**eographic **r**outing), since the **UAV**s battery power is limited**,** it should concentrate on selecting the global route. As a conclusion, in this experience **QAGR** is recommended to enhance the converging speed and resources utilization of the geographic routing approaches in **VANET**. Based on this application, **UAV**s are used to guide the global transmission path and **Q-learning** algorithm is exploited to assist nodes choosing the optimal next hop in a given location [46].

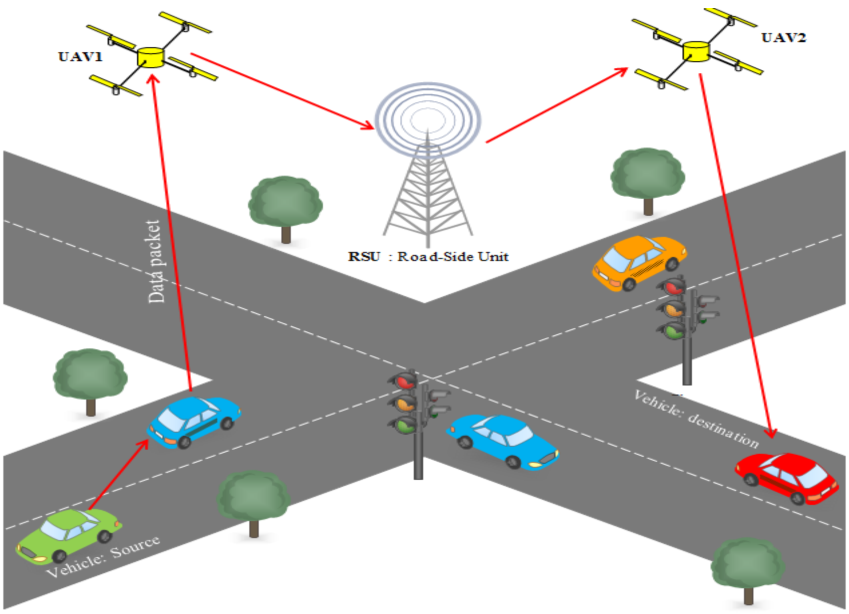


Fig II.2: **QAGR** in **VANET** routing approaches

II.3.2 Inconvenient:

VANETs are used for the purpose of driving assistance, environment surveillance. Due to the limited wireless resources and lossy feature of wireless channel, the high mobility of vehicles along street roads poses daunting challenges to routing protocols and has a great impact on network performance. However, providing a reliable multi-hop communication in VANETs is difficult challenge, when the nodes in the ground network just choose the next hop based on the local information they have on hand, which can easily result in the incorrect route being chosen.

II.4 APPLICATION 02:

II.4.1 Description:

The widespread use of **UAVs** is envisioned for a variety of purposes in the future world. One exciting proposal is to use **UAVs** mobility to develop the mobile connectivity system. Mobile **b**ase **s**tations (**BS**s) installed on **UAV**s could provide network operators the opportunity to respond quickly and effectively to rapid demand spikes in localized environments, such as those triggered by crowded incidents, as well as quickly re-establish disrupted networks in catastrophe and search-rescue scenarios. Alternative carrier technologies, such as “**FWA”** fixed-wing aircraft or balloons, may be used to extend network reach and Internet access to previously unconnected regions around the world. The **Q**uality **o**f **S**ervice (**QoS**) provided to network users is highly dependent on the position of the **UAV BS**, regardless of the networks size. Previous analysis either addressed the problem of finding a **UAV** position that maximizes the systems **QoS** goals. In addition to **QoS**, the developers consider the power consumption of the **UAV** and attached **BS**, there are several studies that look at the general difficulties and opportunities in wireless communications with **UAV**s**.** Power consumption and battery energy limitations are key constraints for **UAV BS** project planning since this application focuses on small and scalable multirotor type **UAV**s, of which the quadcopter is the most commonly used example. Since then, **Q-learning** has seen a lot of attention in a number of fields. Until then, it was thought that the synthesis of a deep **NN** (**Neural Network**) and **Q-learning** was potentially unreliable**.** The authors of use **RL** and a deep recurrent NN to schedule routes for a network of cellular-connected **UAV**s while minimizing ground network interruption proposed the idea of maximizing a **UAV BS**s trajectory using a **NN** trained with reinforcement **Q-learning**, but without taking into account power consumption or **LS**s (**L**anding **S**pots), they considered the **UAV** to be a mobile **BS** serving a group of ground users, with a small amount of energy in the **UAV**s battery at the begin. The **UAV**s current location and battery, as well as the expected total sum rate that can be reached before the battery runs out are used to make movement decisions, while the **UAV** is permitted to land in allocated **LS**s to save energy during the flight, as seen in **Fig. II.3** [47].

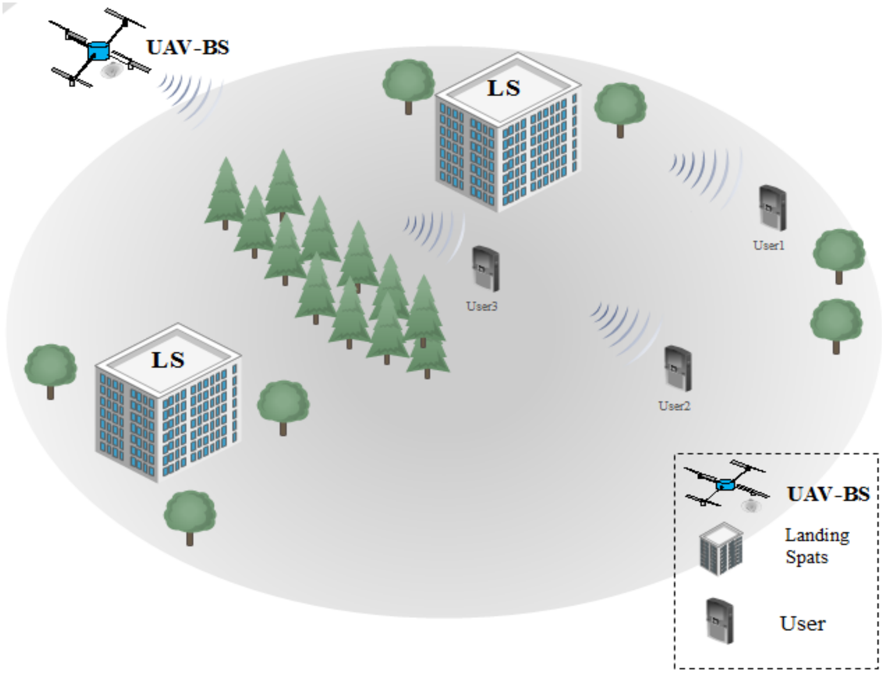


Fig II.3: autonomous **UAV-BS** with the aid of **L**anding **S**pots

II.4.2 <u>Inconvenient:</u>

The most widely studied problem on **UAV-BS**s in **WN**s (wireless networks) is arguably the optimal position assignment to **UAV-BS**s. Actually, many studies have shown that the service time of the **FBS**s (**F**lying **B**ase **S**tations) or **UAV-BS**s is limited and novel approaches should be adopted to increase the energy efficiency. Furthermore, it is improbable that the envisioned application scenarios of **FBS**s will ever receive widespread adoption.

II.5. APPLICATION N°03:

II.5.1 <u>Description:</u>

Because of their high mobility, modular deployment and low operating cost, the use of unmanned aerial vehicles (**UAV**s) to perform sensing in the cellular network has piqued interest**.** UAVs, in particular; have been widely used for critical sensing activities like traffic control, precision agriculture and forest fire surveillance (***c.f II.4***). The sensory data obtained by the **UAV**s in these UAV sensing applications must be sent to the base station (**BS**) immediately for more real-time data processing. This creates a major challenge for the **UAV**s in terms of sensing the mission and transmitting the collected sensory data while retaining a high degree of efficiency, the cellular network-controlled **UAV** transmission is one promising approach for enabling real-time sensing applications, in which the uplink **QoS** is assured relative to ad-hoc sensing networks**.** However, evaluating **UAVs** trajectories in such cellular **UAVs** networks remains a problem**,** when a **UAV** is far from the mission, it runs the risk of receiving incorrect sensing data and when it is far from the **BS**, the poor uplink transmission quality can make it difficult to transmit the sensory data back to the **BS**. As a result, when planning their trajectories, **UAV**s must take into account both sensing precision and uplink transmission quality, it's much more complicated because the UAVs are from separate organizations and aren't cooperating. Therefore, for the UAV trajectory design problem, a decentralized trajectory design approach is required, in which each UAV considers the positions of the mission and the **BS**, as well as the actions of the other UAVs.

In this application, has been imposed a situation in which several **UAV**s in a cellular network conduct various real-time sensing tasks as shown in **Fig II.4.** The **UAV** trajectory architecture problem can be viewed as a **MDP** (Markov decision problem), that making reinforcement learning an appropriate and promising solution, they specifically used the reinforcement learning method to formulate the **UAV** trajectory design problem [48].

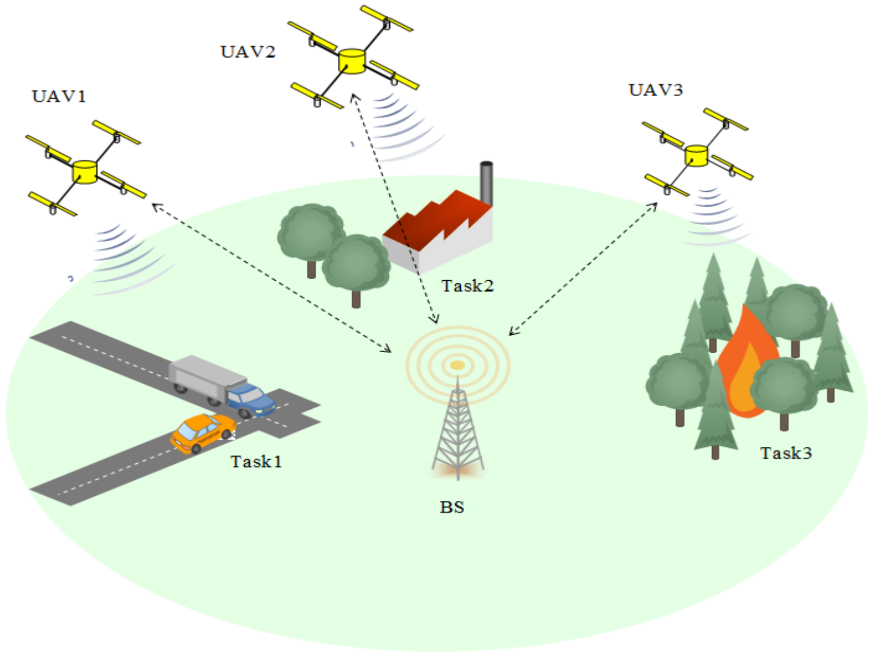


Fig II.4: illustration of the single cell UAV network, in which UAVs execute real-time sensing tasks.

II.5.2 Inconvenient:

Among the negative points is the loss of the battery while performing the task to take the necessary measures to solve problems in real time and thus may lead to the loss of the data collected which leads to a delay in the immediate intervention, in addition to the ability of the **BS** about the informations that can receive from collecting **UAV**s during the missions.

II.6 APPLICATION N°04:

II.6.1 Description:

In a variety of disciplines, visual exploration and smart data collection through autonomous vehicles is a fascinating subject. Wind has a major impact on both the power usage of the flying robots and the camera's efficiency. **UAV**s are used in a wide range of fields, from large-scale agricultural vegetation identification to target search and rescue. Even though **UAV**s are widely used today, their battery life is reduced. Multiple drone flights, which are also conducted through full coverage of the domain are commonly used to obtain sufficient aerial photography of wide fields. Let's start by defining the problem of periodic (i.e. daily) crop monitoring by looking at the farm in ***figure II.5.*** The aim is to provide aerial photography in scattered positions in the field on a regular basis enough to accurately track the health of the crops, but not so often that the drone battery runs out. Although wind can help the drone get to certain remote locations, it can also raise the cost of power when taking other routes. As a result, dealing with such issues requires adaptive route preparation and cautious algorithm architecture for goal prioritization algorithms. One solution for problems like the one seen in ***fig. II.5*** is to use an applied wind-power model in the control unit to test the expected direction at such intervals [49].

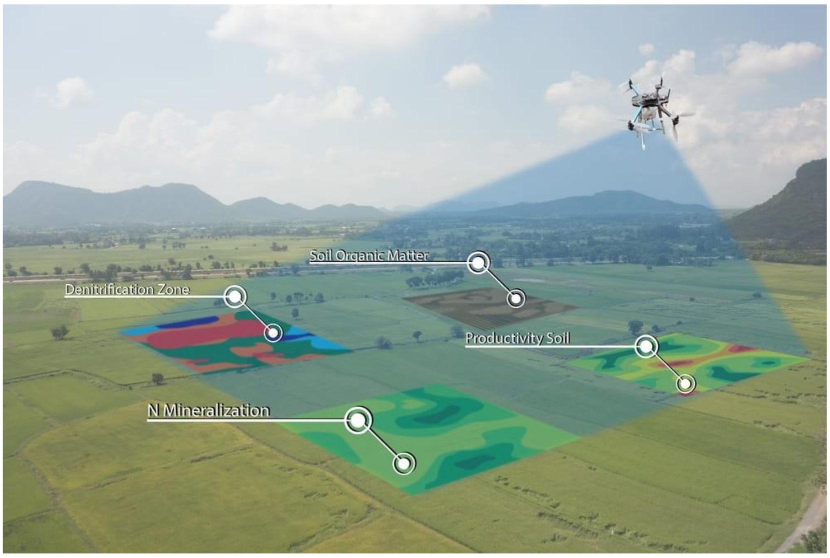


Fig II.5: UAV system in large Fields With sparse goals

II.6.2 Inconvenient:

Besides the wind is the main factor in the power of an aerial vehicle, the conditions of lack or absence of wind the task is almost impossible and the battery life is running out.

II.7. APPLICATION N°05:

II.7.1 Description:

Extensive technological advancements and extensive studies have been implemented in order to improve data processing reliability as a result of the abundance of content. Previous research has focused on how to shorten the time it takes for a UAV mission to complete, whereas this application focuses on the **age of information (AoI). AoI** has become a recent and relevant metric on the freshness of data to calculate how new the sensed information is for the time-effectiveness demand**.** Data must be delivered before a deadline under a number of exceptional situations, or it may lose its meaning. This application focuses on optimizing the **UAV** trajectory to reduce expired packets and lost messages in a UAV-enabled wireless sensor environment, in which the UAV is dispatched to gather data from a group of sensors as shown in ***fig II.6***. Since the data stored in sensors is constantly produced and has a limited lifetime, it would be critical to meticulously plan the UAV trajectory, as the expiration rate of packets is linked to the UAV flight time between sensors and the flight order over them. Furthermore, the reinforcement learning (**RL**) approach is used in this proposed paradigm to improve the time-effectiveness and path design efficiency, as it is a powerful technique for a UAV to learn how to integrate itself into an inconstant environment with different applications based on UAV. This is the first work that incorporates the AoI characteristic, data deadline constraints, and artificial intelligence to optimize the flight trajectory in UAV-assisted information sensing networks for data processing [50].

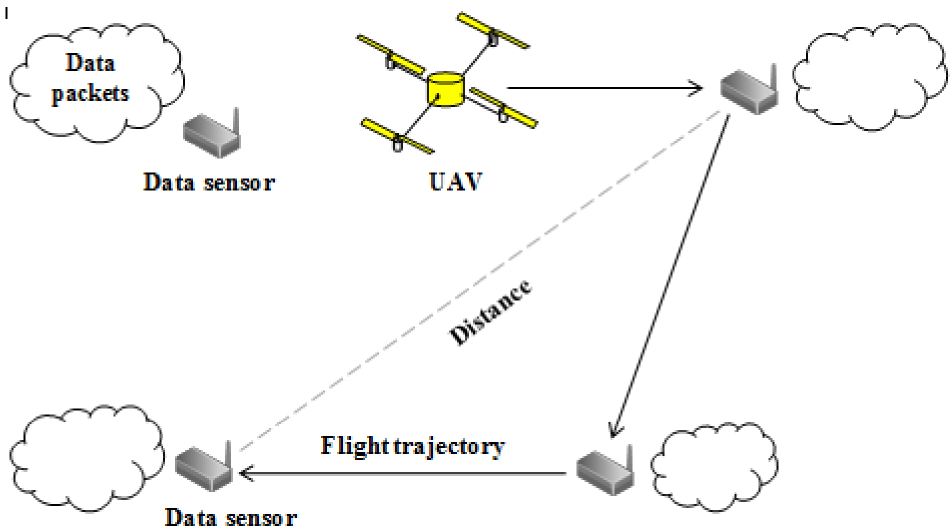


Fig II.6: UAV assisted network for data collection from sensors

II.7.2 Inconvenient:

With the big attention on data sensing services, the **UAV** has been used to accelerate and maximize the data collection. However, with the limited battery life; distance and flying time this was some points that constitute an obstacle and a challenge while doing the mission.

II.8. Conclusion:

We have discussed in this chapter the definition of **Q-learning** and where we need to use it. And we mentioned some of the applications that some experts have mentioned in exploiting the use of **UAVs** based on Q-learning algorithm in many fields, including:

geographic routing in **VANET**, Flying Base Station Trajectory Design with Landing Spots, Decentralized Trajectory Design in Cellular UAV Networks With Sense-and-Send Protocol, Visual Exploration and Energy-aware path Planning, Minimizing Packet Expiration Loss with Path Planning in UAV- assisted data sensing.

Chapter III

Our Protocol

III.1 Introduction :

Have you ever trained a pet and rewarded it for each and every correct command you requested for? Do you comprehend that this simple way of beneficial conduct can be modeled in a robot or a software program to make it do beneficial things? We are going to step into the world of reinforcement learning (***c.f fig III.1)*** [44], some other beautiful branch of artificial intelligence, which lets machines examine on their personal in a way distinctive from traditional machine learning. Now, suppose for a moment, how we would educate robots and machines to do the kind of beneficial duties we people do, be it switching off the television, or transferring matters around, or organizing bookshelves. These are a completely special set of tasks and require an exclusive mastering paradigm for a pc to be capable to operate these tasks. On the other hand, we have the environment is the place where the robot it has been put to use, the agent is itself this robot. For example, a textile factory where a robot is used to move materials from one place to another. We will analyze its states, actions, and rewards later. The missions we discussed now have an advantage in common; these tasks involve an environment and expect the agents to learn from that environment. This is where the reinforcement learning is needed.

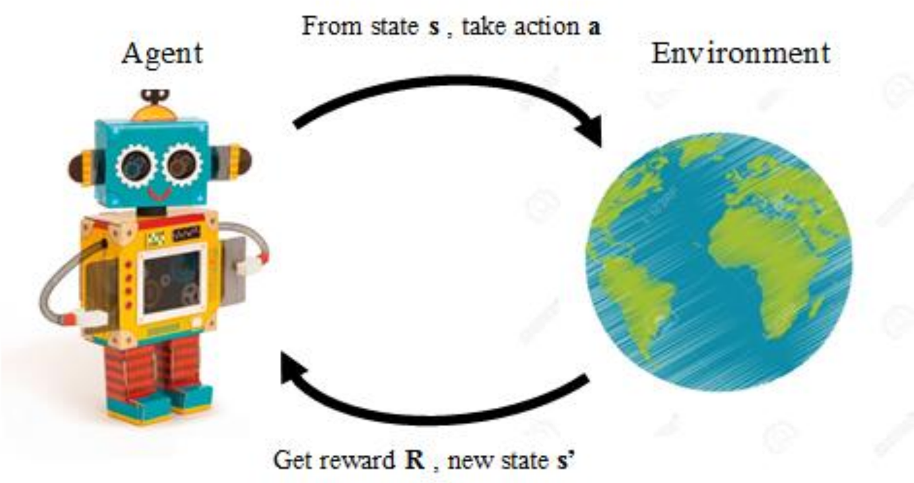


Figure III.1: A rough framework of reinforcement learning

In the first half of this chapter, we discussed artificial intelligent, we commence by way of defining the problem which is very applicable in the discipline of reinforcement learning. After that, we will find out about its **agents**, **environment**, **states**, **actions** and **rewards**, next we present our protocol which is show an idea about collecting data by using programmable

UAVs based on **Q-Learning** algorithm along with an implementation in **Python** the use of **Numpy**.

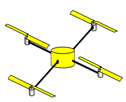
III.2 Motivation of our protocol:

We are in the process of launching a **UAV** in an area that is divided into nine regions to collect data from the wireless sensors randomly distributed in some of those nine positions. So that we will give priority to sites that contain sensors, which we will search for later. The UAV will have to test the ways to these sensors, so that the right path will lead to a reward while the wrong path will lead to a punishment (penalty). The mission is to enable the UAV, so that they can find the shortest route from any given location to another location on their own, with take into account the battery life time while maximizing the data collected and this is the aim of proposing our protocol.

III.3. Description of our protocol:

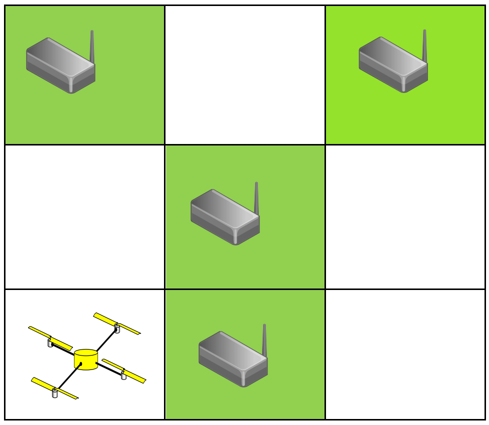
Consider the following square of places which is the same with the actual environment from our original problem.

Table III.1: Table of an environment

Now suppose a drone needs to go to the marked place in green, from its instant position using the specified direction shown in the next figure (*c.f III.2*).

Table III.2: Table of an environment, agent and IoTs



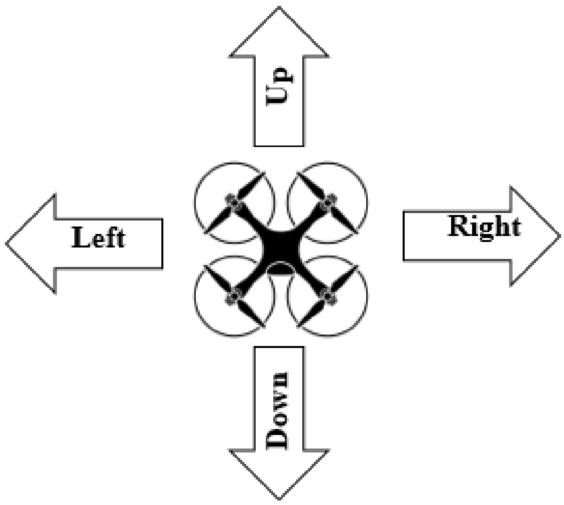
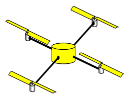


Fig III.2: the possible actions that the agent can take to move

How we can let the drone to do this programmatically? There is an idea would be to insert some types of marks which the drone would be capable to follow. Here, a constant value is specified in each of the places which will come along the drone way if it follows the direction specified above. In this way, if it starts at position **A,** it will be able to scan through this constant value and will move accordingly like below:

Table III.3: Table of an environment with value marks in different directions

1		1
	1	
	1	

- <u>**The Bellman Equation:**</u>

The drone now sees marks in two different directions. It is unable to decide which way to go in order to get to the destination. The drone does not have a way to remember the directions to proceed. So, our job now is to enable the drone with a memory. This is where the Bellman Equation comes to applied:

$$Q_{t+1}(s_t, a_t) = Q(s_t\ , a_t) + \alpha * [R + \gamma\ max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

Where,

- **s =** a particular state (position).
- **a =** action (moving between the positions).
- $\boldsymbol{a_{t+1}}$= next action.
- **s+1 =** state to which the drone goes from **s.**
- $\boldsymbol{\gamma}$ = discount factor.
- **R =** a reward function which takes a state **s** and action **a** and outputs a **reward value.**
- $Q(s_t + a_t)$= value of being in a particular state.

We take into account all the possible actions and take the one that product the maximum value.

- The **max** function helps the drone to always choose the state that gives it the maximum value of being in that state.
- The discount factor γ notifies the drone about how far it is from the destination. This typically specified by the developer of the algorithm that would be instilled in the drone.

- <u>**Moving to Q-learning:**</u>

Q-Learning gives an idea of evaluating the quality of an action that is possessed to proceed to a state rather than determining the possible value of the state being proceeded to. The **UAV** now has four special states to select from and alongside with that the current nation it is in.

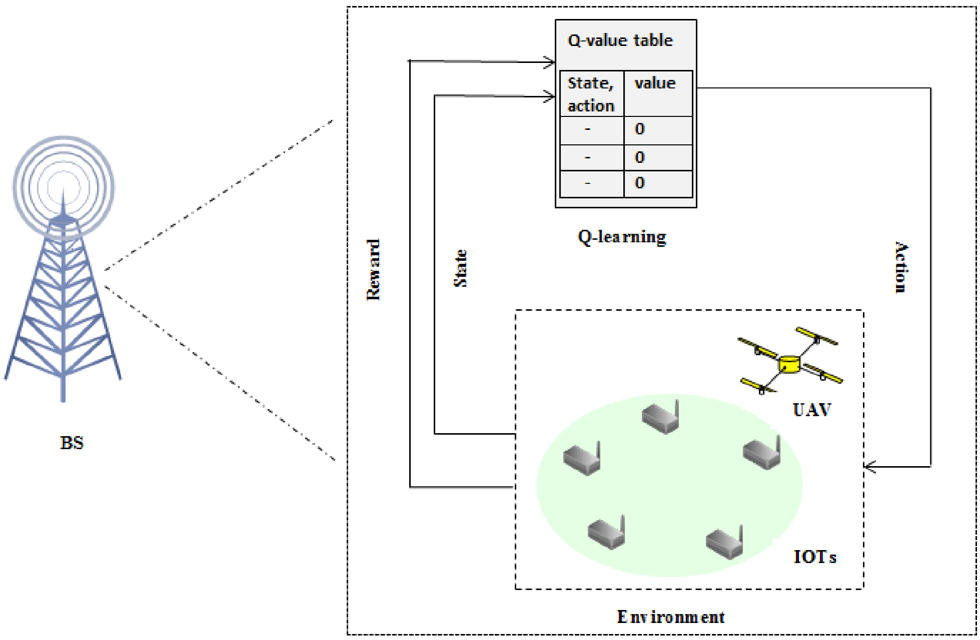


Fig III.3: illustration show **Q-learning** method

<u>In this case:</u>

- **The agent:** the agent is the UAV that has the responsibility to do the mission**.**
- **The environment:** in our case are the **WSN**s which contain the **IoT**s to collect data from.
- **The states:** The states are the positions. The position in which a particular UAV is present in the particular instance of time.
- **The rewards:** We have the following two sets:

- A set states:

  S= 0, 1, 2, 3, 4, 5, 6, 7, 8

- A set of possible actions:

  A= 0, 1, 2, 3

The rewards will be given to a UAV if a position (*state*) is directly reachable from a particular position. Let's take an example:

If a UAV goes from its position to a true position it will be rewarded by **+1**. If a position is not directly reachable from a particular position, we do not give any reward (a reward of **0**), and if the drone goes to a restricted area (position outside of the 9 cases) we will give a penalty equal **-100**. It enables the UAV to make sense of their movements helping them in deciding what positions are directly reachable and what are not.

III.4 Simulation of our protocol:

In this task, the agent is required to initially, explore the environment to find all the objects (**IoT**s in our case) and then generate the path with minimum required power consumption for capturing the data from all **IoT**s. A typical RL framework, the **Q-learning**-based method is applied here, in which the agent selects an action from the feasible action set under the observation on the current state "**s**" at each time step, and then it detects the changes of the environment as well as receiving a reward correspondingly. In our problem, the **UAV** agent is supposed to decide its best path to minimize the consumption of battery. So, the agent needs to select which sensor to visit next step from a feasible set.

III.4.1 Simulation environment:

Python is used to verify the performance advantages of collecting data based on

Q-Learning algorithm using UAV. To make the simulation more realistic, we use an environment composed of **9** states to generate the random movements of our UAV. Additional punishments (negative reward) are given to the drone for stepping out of the **9** grids environment, as well as for failing to return to the final position before the battery runs out and the mission is over.

III.4.2 Presentation of Python [54]:

Python is a popular programming language, an interpreted, multi-paradigm. Python is a programming language that can be used in many contexts and adapt to any type of use thanks to specialized libraries. It was created by Guido van Rossum, and released in 1991.

It is used for:

- web development
- software development
- mathematics
- system scripting.

i. Features of Python simulator:

- Python works on different platforms
- Python has a simple syntax similar to the English language.
- Python runs on an interpreter system, meaning that code can be executed as soon as it is written. This means that can be very quick.

ii. Inconvenient:

- Weak in mobile computing
- Design Restrictions
- Underdeveloped Data base layers

III.4.3 Simulations parameters:

The specific simulation parameters are shown in the next **TABLE (c.t III.1)**, we distinguish an environment grid composed of **9** positions with one UAV and **4** IoTs , we supposed a number of actions equal **4** actions , with a number of steps equal **100** and episodes equal **1000** , next we fixed the battery capacity in **100%** and we put a condition with the consumption of battery with: if the UAV got an IoT and collect data , we will reduce its battery with **-0.5** and if the UAV not got a IoT (take the wrong path) we reduce its battery with **-1**, we choose **α, γ** equal **0.1** , **0.9** respectively which **α :** signify the learning rate of reinforcement learning and **γ:** signify the attenuation factor of subsequent reward, while "epsilon" it is exploration rate and we use to compare the random number to it and the algorithm decide if it picks a random action or picks an action from the Q-table, and *n* is how "epsilon" will be decreased each time, it is called epsilon decay rate.

Table III.4: Table of parameters applied in our simulation

Environment	**9** cases
Number of UAVs	**1**
Number of IOTs	**4**
Number of possible actions	**4**
Discount factor	$\gamma \in [0, 1]$=**0.9**
Battery capacity	**100%**
Number of steps	**100**
Number of episodes	**1000**
α	**0.1**
n	**0.01**
Consumption	**-1** (if the UAV take a wrong action) **-0.5** (if the UAV take a true action above the IOTs)
Penalty	**-100**
Ɛ (epsilon)	**1**

The basis of the reward is formed by the instantaneous sum data collection rate as computed in Equation **(1)**, where:

Reward=100*(IoT + penalty + consumption) … (1)

The next figure shows us the code utilized in our problem by using the Numpy in Python:

```
import numpy as np
from random import randint
import random
import matplotlib.pyplot as plt

class EnvGrid(object):
    def __init__(self):
        self.grid = [
            [1, 0, 1],
            [0, 1, 0],
            [0, 1, 0]
        ]
        self.y = 2
        self.x = 0
        self.actions = [
            [-1, 0],  # Up
            [0, 1],   # Right
            [1, 0],   # Down
            [0, -1]   # Left
        ]

    def reset(self):
        self.y = 2
        self.x = 0
        self.energy = 100
        self.dc=0
        self.movements=0
        return self.y * 3 + self.x + 1

    def step(self, action):
        self.penality = 0
        self.boolean = True
        ycoordinate = self.y + self.actions[action][0]
        xcoordinate = self.x + self.actions[action][1]
        if xcoordinate > 2 or xcoordinate < 0:
            self.boolean = False
        if ycoordinate > 2 or ycoordinate < 0:
            self.boolean = False
        if self.boolean == False:
            self.energy = self.energy - 0.5
            consumption = 0.5
            self.penality = -100

        else:
            self.y = self.y + self.actions[action][0]
            self.x = self.x + self.actions[action][1]
            self.energy = self.energy - 1
            consumption = 1
            self.dc+=1
            self.movements+=1
            if self.grid[self.y][self.x] == 1:
                self.energy = self.energy - 0.1
                consumption = 0.1
        reward = 100*(self.grid[self.y][self.x]) + self.penality+consumption
        return (self.y * 3 + self.x + 1), reward

def take_action(st, Q, eps):
    # Take an action
    if np.random.uniform(0,1) > eps:
        action = np.random.randint(0, 3)
    else:  # Or greedy action
        action = np.argmax(Q[st])
    return action
if __name__ == '__main__':
    env = EnvGrid()
    Q = [
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0],
        [0, 0, 0, 0]
    ]

    num_steps=100
    num_episodes=1000
    alpha =0.1
    discount=0.9
    n=0.01
    total_reward =[]
    energy=[]
    data_collection=[]
    movements=[]

    for episode in range(num_episodes):
        eps = 1
        state = env.reset()
        env.energy=num_steps
        reward_of_episod = []

        for step in range(num_steps):
            #env.show()
            #print("energy     ",env.energy)
            #m= input("$>")
            action = take_action(state, Q, eps)
            #print("action       ",env.actions[action])
            next_state, r = env.step(action)
```

```
            #print("reward     ",r)
            Q[state][action] = Q[state][action] + alpha * (r + discount * max(Q[
            state = next_state
            reward_of_episod.append(r)
            eps-=n
        #print (reward_of_episod)
        data_collection.append(env.dc)
        movements.append(env.movements)
        total_reward.append(sum(reward_of_episod) / len(reward_of_episod))
        energy.append(env.energy)

x=np.arange(len(total_reward))
#plt.plot(x,total_reward)
#plt.ylabel("reward")
#plt.plot(x, energy)
#plt.ylabel("energy consumption")
#plt.plot(x, data_collection)
#plt.ylabel("data collection")
plt.plot(x, movements)
plt.ylabel(" number of movements")
plt.xlabel("episodes")
plt.show()

print(x)
for s in range(1, 9):
    print(s, Q[s])
```

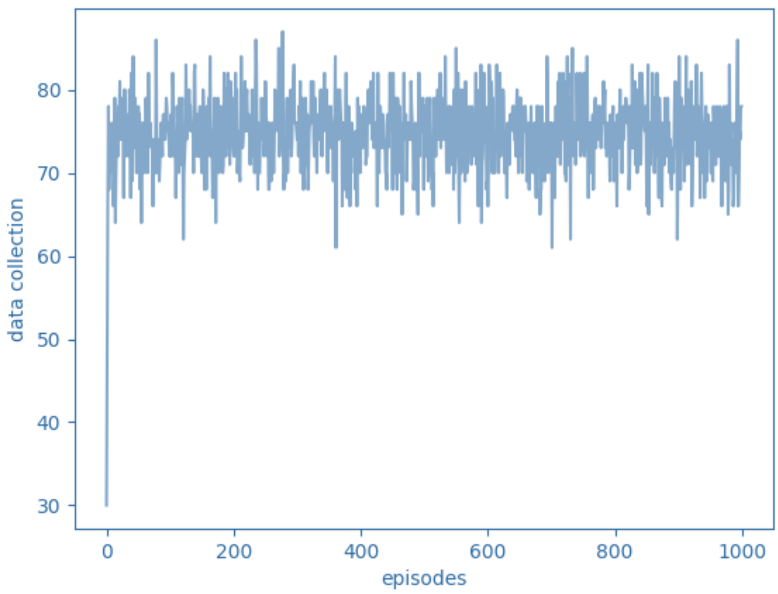
Figure III.4: source code in python

III.5. Simulation Results:

The simulation showed us the following results, as shown in the figures like below:

A. Data collection:

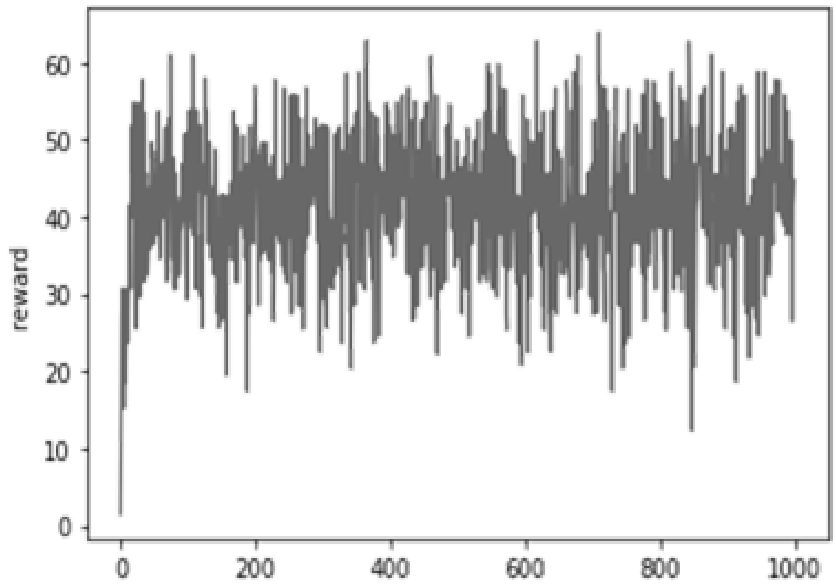
By the curve that shows the percentage of data collected, our protocol achieves the highest percentage of data collection as the highest percentage ranges from **40%** to **70%** **(***c.f. FigIII.5***)**. So, this indicates that the agent (**UAV**) was able to achieve one and the first condition he was assigned to.



FigIII.5: curve showing the data collection rate per episodes.

B. Reward:

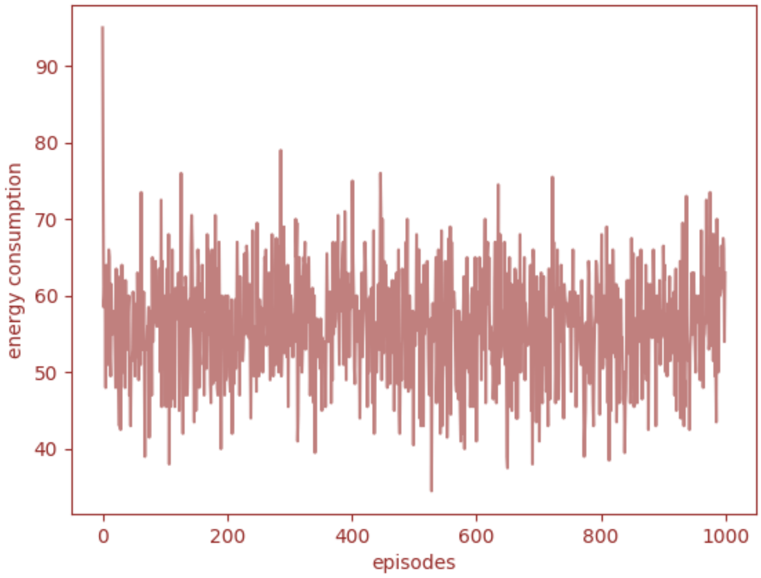
The two curves ***(c.f Fig III.5- III.6)*** appear close to each other, i.e. "*directly proportional*", this is because collecting the data obtained leads to a reward and therefore the percentage of rewards is converges to the highest ratio ***(c.f Fig III.6)*** and this proves that the UAV was able to find its own path, so that it gets more rewards and collected more data.



FigIII.6: curve showing the reward per episodes.

C. Energy consumption:

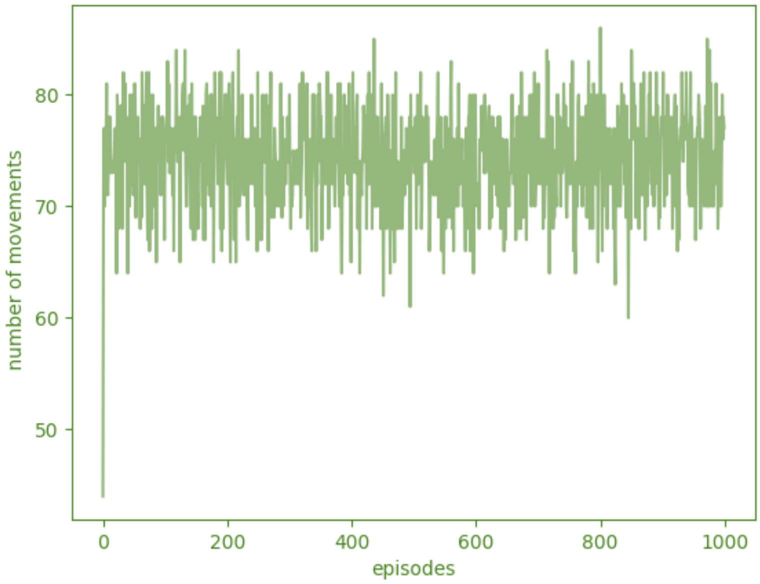
Whereas the proportion of energy consumed is "*inversely proportional*", It is reduced (this is normal), so that energy is consumed as the UAV moves during the mission.



FigIII.7: curve showing the energy consumption per episodes.

D. Number of UAV Movements:

Overall, our protocol performs data collection in number of movements from **35** to **70** steps. This is due to the searching mission for **UAV** paths that takes a time because of the continuous experience if this is the way that leads to the goal.



FigIII.8: curve showing the number of UAV movements per episodes.

III.6. Advantages and Inconvenient of our protocol:

Like every protocol that shows an advantage and inconvenient, and with the good results that we are gets from our protocol, it still presents some inconvenient. Bellow we give some points which present the advantages and the inconvenient of our approach.

A. Advantages:

- The environment is simple and easy to achieve.
- Q-learning with a single UAV is easy to apply.
- UAV with small number of actions is easier to operate.
- A number of actions with an average number of steps / episodes easy to implement.
- For every single correct path that the UAV may take we give a reward.

B. Inconvenient:

- With a simple environment to create, that makes it limited.
- UAV is restrictive to a predefined number of actions.
- Accreditation to a single UAV capable of carrying out the mission a little difficult.
- With every single wrong path that the UAV may take we let a penalty and that's May makes it a little disoriented.

III.7. Comparative table:

Table III.5: Comparative table of some applications with Q-learning algorithm assisted by UAV

	Q-learning algorithm	Agent	Number of UAVs	Simulator
GR in VANET	√	UAV	**25**	NS3
FBS TD with LS	√	UAV	**10**	Eurecom
DTD in Cellular		UAV	**3**	MATLAB

UAV-Net	√			
VE and EaPP via RL	√	UAV	**1**	Unreal engine
MPEL with PP in UAV DS	√	UAV	**1**	MATLAB
Our Protocol	√	UAV	**1**	Python

Table III.6: table of advantages of Q-learning applications

Advantages
The QAGR is proposed to increase the converging speed and resource utilization of **VANET**'s regional routing approaches.
With the aid of LSs, they developed a Q-learning model that trains a NN to make movement decisions for an autonomous UAV BS under an energy constraint.
They used reinforcement learning to solve the distributed UAV trajectory design problem.
The energy-aware target collection and route planning of such vehicles are discussed here using reinforcement learning. The central concept of this study is to combine the compensation from the detected target objects with the expense of the agent's travel.
They proposed a route planning scheme for a UAV to sense deadline-sensitive data for data processing in a variety of contexts, with the aim of reducing expired packets in the device.
We proposed a Q-learning algorithm assisted by UAV to collect data from the wireless sensors in the terrestrial networks with maximizing data and reduce the flying time before the battery runs out.

III.8. Conclusion:

In this chapter we proposed our protocol which illustrates fundamentally a Q-learning algorithm assisted by **UAV** preprogrammed. With the aim of maximizing the data while the

UAV moved over the **IoT**s and minimizing the flying time and distance, we taking into account the energy consumption before the mission is over. Moreover, we programmed a UAV with a python to evaluate the protocol performance and to improve the reliability of our approach.

General Conclusion

General Conclusion:

The main problem is how to find a UAVs tour that minimizes the UAV flying time while gather all data stores in the sensor nodes memories with an environment limited and a number of actions predefined. With the advantages of UAVs that it haves of flying capabilities with a travelling speed much higher than the ground elements; that's means the data scattered cross many sensor nodes can be collected more quickly and efficiently. So, to solve this problem previously mentioned, we propose a Q-learning algorithm to steering the UAV, the goal is to design efficient paths to collect data by using a self-managing UAV; where this UAV acts as a data collector.

In this thesis, as a first step; we talked about the data collection assisted by UAVs and where we are able to use the data collection. Secondly, we discussed some applications based on a Q-learning algorithm. The proposed algorithm proved to be especially useful for missions with few objectives where the agent's battery life is reduced. We demonstrated that Q-learning would find the best trajectories while still being more efficient in terms of time utilization.

Our proposed protocol achieves in the mission of collecting data; however, it implements data collection in a period of time due to the searching mission for UAVs paths that takes a time caused by the sensors randomly discarded in different places of the environment. Basically, the protocol focuses on its goals, the goal of maximizing the data, minimizing energy consumption and reduces the time of the mission…etc.

Finally, the achievement of this research was very beneficial to us where we were able to have new learning on the world of AI and reinforcement learning, dealing with a new simulator, and having a new experience.

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