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Spectral and Energy Efficiency Trade-Off in UAV-Based Olive Irrigation Systems

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Abstract: Precision agriculture, also referred to as smart farming, is one of the main pillars of modern society to achieve the Sustainable Development Goals (SDGs). Precision agriculture aims to improve the quality and quantity of production while conserving scarce natural resources. Smart farming has grown in recent years thanks to the adoption of modern technologies, including artificial intelligence (AI) and the Internet of Things (IoT). In this work, we consider an irrigation system for olive orchards based on unmanned aerial vehicles (UAVs). Specifically, UAVs ensure remote sensing (RS), which offers the advantage of collecting vital information on a large temporal and spatial scale (which cannot be achieved with traditional technologies). However, UAV-based irrigation systems face tremendous challenges due to the various requirements of a powerful computing ability, battery capacity, energy efficiency, and spectral efficiency for different connected devices. This paper addresses the energy efficiency and spectral efficiency trade-off problem of UAV-based irrigation systems. We propose to adopt massive multiple input, multiple output (M-MIMO) technology to ensure wireless communication. In fact, this technology plays a significant role in future sixth-generation (6G) wireless mobile networks and has the potential to enhance the energy efficiency as well as the spectral efficiency. We design a network model with a three-layered architecture and analytically compute the achievable spectral efficiency and the energy efficiency of the studied system. Then, we numerically determine the optimal number of ground base station antennas as well as the optimal number of IoT devices that should be used to ensure the maximum energy efficiency while guaranteeing a high spectral efficiency. The numerical results prove that the proposed UAV-based irrigation system outperforms conventional systems and demonstrate that the best spectral and energy efficiency trade-off is obtained by using the M-MMSE combiner.

Keywords: precision agriculture; irrigation; olive; unmanned aerial vehicles (UAVs); remote sensing; massive MIMO; spectral efficiency; energy efficiency; 6G



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1. Introduction

By 2050, the United Nations (UN) predicts that the world's population will increase by approximately 2 billion people. As a consequence of this expected dramatic growth, 70% more food is required, as reported by the United Nations Food and Agriculture Organization (FAO) [1]. Additionally, climate change presents one of the most critical issues challenging humanity nowadays. In this context, the KSA's (Kingdom of Saudi Arabia) agricultural sector aims to enhance the quantity as well as the quality of production. However, water scarcity remains one of the most challenging issues, especially regarding

the fact that most Saudi regions suffer from a desert climate and a meager precipitation rate. Consequently, it is hard to achieve sustainability goals with traditional farming methods. To deal with such challenges, smart farming, also called precision agriculture or Agriculture 5.0, is one of the main pillars of modern society and is considered as a key solution to guarantee food safety and food security [2]. Precision agriculture represents the adoption of new technologies to strengthen the efficiency of a bio-based economy while conserving scarce natural resources. Specifically, smart farming is growing thanks to the adoption of new technologies, including artificial intelligence (AI), the Internet of Things (IoT), and 5G/6G networks [3–5]. This can assist farmers in taking appropriate measures at the appropriate moment by monitoring soil moisture, temperature, and other environmental factors, consequently making the production process more scientific in terms of fertilization, pest control, and improving crop yields.

In the paper, we introduce an overview of the literature on precision agriculture with a focus on smart irrigation systems. We present a review regarding the deployment of 5G/6G in precision agriculture, the M-MIMO technology as a keystone of 5G/6G networks, and precise irrigation systems.

1.1. 5G/6G in Precision Agriculture

Third and fourth generation wireless communication technologies are not guaranteed to meet the requirements of smart agriculture applications (particularly precise irrigation), mainly in terms of their delay, speed, scalability, and bandwidth. Therefore, recent studies proposed deploying 5G/6G technology in the agricultural field to overcome the limitations mentioned above (see, for example, [4–11] and the references therein). In fact, 5G/6G networks are characterized by ultra-low delays, super large-scale connections, and high speeds. These systems have been integrated into precision agriculture in several applications like real-time monitoring, predictive maintenance, virtual consultation, artificially intelligent robotics, and data analytics. In [4], the authors thoroughly surveyed 5G networks in the agricultural industry. The authors also detailed the benefits of 5G in smart and precision farming and its applications. In [4], Tang et al. discussed how deploying 5G technologies will alter the agricultural field to boost productivity. In [6], the author developed the MERLIN (sMART framEwork foR agricuLture In iNdia) project in India. Indeed, MERLIN is an intelligent framework based on artificial intelligence, a 5G wireless communication system, and the IoT. The proposed project used cloud-based (supervised and semi-supervised) databases to acquire data and further process them for decision making. The author showed that the proposed 5G-based framework significantly improves production. In [7], the authors proposed an intelligent farming system using 5G communications. The authors showed that the proposed innovative system could transfer data at high speeds of up to 20 Gbps, and could link massive amounts of IoT devices in a square kilometer. The work in [8] was based on studying architecture for smart agriculture environments based on robotics, MEC (Mobile Edge Computing), and 5G technologies. The principal purpose of this study was to design a system appropriate for a huge-scale adoption of robotics in agriculture. In [9], the authors explored the opportunities and challenges of applying 5G/6G technology in precision agriculture. In [10], Liu et al. presented a survey on the development status of 5G networks and the IoT in precision agriculture in recent years. This work analyzed the related key technologies and challenges and raised some critical scientific problems. Liu et al. also showed the development trend and application value of 5G networks and the IoT in precision agriculture. Javaid et al. explained in [11] how smart farming can improve Agriculture 4.0 and increase efficiency, productivity, and sustainability. In this research, the authors emphasize using cutting-edge technologies, namely, cloud computing, edge computing, AI, the IoT, big data, and 6G in agriculture. The authors also discuss the benefits of “smart farming”, including precision farming, resource optimization, and predictive maintenance. Furthermore, they explore the problems related to traditional farming, such as increasing food production, water scarcity, and the need for climate change.

1.2. M-MIMO

The concept of M-MIMO was first introduced in [12]. This technology plays a significant role in 5G and the future sixth-generation (6G) wireless mobile networks [13]. Indeed, M-MIMO has the potential to enhance the energy efficiency and spectral efficiency of communications systems [13]. The idea behind M-MIMO is to deploy a vast (massive) number of antennas at the base station and use multiuser MIMO transmission to serve a smaller number of terminals simultaneously (in the same time and frequency sample). In the downlink transmission (from the base station to the terminal), beamforming exploits the uplink–downlink reciprocity of the radio channel, since M-MIMO uses the time division duplex (TDD) mode. The base station array mainly exploits channel estimates acquired from uplink pilots transmitted by the terminals. The application of massive MIMO in precision agriculture has not been widely considered in the literature. The authors of [14] detailed the state-of-the-art deployment of massive MIMO technology in precision agriculture. Zhang et al. also discussed the M-MIMO channel characteristics that should be thoroughly considered when deploying an M-MIMO system in smart agriculture, mainly for beamforming design, network planning, and signal processing. Paper [15] considered a massive MIMO as a large-scale communications solution for IoT-based smart agriculture. In [16], Fang et al. proposed an M-MIMO network model with multiple cells and users. The authors analyzed the M-MIMO system's spectral and energy efficiency with pilot contamination and hardware impairment. Moreover, Zhang et al. in [17] studied the energy efficiency of trajectory optimization schemes for UAV-assisted IoT networks. Notably, the authors optimized the UAV trajectory design by simultaneously considering the total energy consumption, the average data rate, and the fairness of coverage for the IoT devices. The authors also evaluated the effectiveness of the developed scheme by carrying out extensive numerical simulations.

1.3. Precision Irrigation

In the literature, various methods and systems have been developed for precise irrigation. Millan et al. developed in [18] an automated irrigation protocol for olive farms, where RDI (regulated deficit irrigation) strategies were implemented. The authors used a decision support system (DSS) to evaluate the productive response of a heterogeneous plot in a super high-density plantation olive grove. The irrigation process was carried out automatically based on the information obtained through wired sensors. However, using cables to communicate data in smart farming presents several drawbacks, such as scalability, deployment costs, absence of mobility, and cable corruption. Therefore, adopting wireless communication technologies like LoRaWAN (Long-Range Wide-Area Network), ZigBee, Bluetooth, and the IEEE 802.15.4 protocol presents an attractive alternative to wired networks [5,19]. In [19], Valente et al. developed an IoT-based system to monitor the water scarcity of a vineyard, where different types of ground-based sensors were implemented. The LoRaWAN standard was adopted to ensure data transmission. The results showed that the proposed system outperforms other IoT systems based on Bluetooth or WiFi communications. However, as aforementioned, these wireless communication technologies do not guarantee precise irrigation, mainly in terms of delay, speed, scalability, and bandwidth. Therefore, other recent studies proposed using 5G/6G technologies to deploy smart irrigation systems. For example, in [20], Xue et al. proposed a framework for a drip irrigation remote control system (DIRCS) based on mobile application and IoT-enabled 5G technology. Precisely, the DIRCS framework is managed remotely through a mobile application. Data storage and sharing are ensured by IoT-enabled 5G technology.

One of the most crucial variables in a precise irrigation system is soil moisture, which provides information about the water content in agricultural fields and the vegetation indices used in precision agriculture [21]. The traditional way to measure soil moisture is with the use of moisture sensors that are installed directly in the soil. There are four methods for measuring soil moisture: (i) resistance blocks, (ii) travel time sensors, (iii) capacitance sensors, and (iv) neutron thermalization [22]. Unfortunately, directed measurements have

different issues depending on the sensor type [23]. All these shortcomings encourage the development of remote sensing (RS) approaches. They will allow for data acquisition of soil moisture measures without physical contact with a sensor [24]. Therefore, remote sensing applied in smart irrigation offers the advantage of collecting vital information on a large temporal and spatial scale which cannot be achieved with traditional technologies. In recent years, using unmanned aerial vehicles has enhanced remote sensing approaches for measuring soil moisture [25]. In fact, remote sensing systems based on UAVs are efficient, cost-effective, and have great geometric accuracy. UAVs can potentially reduce the data acquisition gap between conventional ground-based methods and satellites [26]. The combination of the IoT and UAVs in precise irrigation has been widely considered by researchers in many existing works (see, for example, [27] and the references therein). In [27], Ahansal et al. considered the problem of water scarcity in arboriculture and proposed a smart irrigation solution based on UAVs and ML. The deployment of UAVs in irrigation systems was studied to save both waste and time. The UAVs were equipped with different remote sensors and collected the necessary data (such as soil moisture) for the irrigation process. The collected data were processed using ML techniques, allowing the smart IoT system to make better decisions.

1.4. Motivation and Contributions

Internet of Things technologies have revolutionized agricultural value chains when deployed in advanced data analysis. Conversely, despite the benefits of IoT implementation in precision agriculture, the energy efficiency and spectral efficiency trade-off problem could impact the agricultural and food sectors in the coming decades. Indeed, on the one hand, the large amount of data transmitted by IoT nodes can be overwhelming, requiring new approaches to data management/analysis and raising exigencies concerning spectral efficiency. On the other hand, in an IoT-based environment, most sensors and actuators encounter the limited energy issue. In particular, unmanned aerial vehicles (UAVs) require significant energy to maintain flight and perform various tasks such as remote sensing. If a drone runs out of battery mid-flight, it could crash and cause damage to the crops or other equipment. In practice, to avoid this problem, the drone will automatically return to its launch location when the drone's battery runs out. Then, depending on the drone's model, the battery will be recharged or replaced. However, frequent battery recharging (or replacement) can be costly and time-consuming and reduce UAV applications' efficiency and productivity. Consequently, guaranteeing sustainable energy to these devices represents another critical challenge.

In this work, we aim to design a smart irrigation system for olive orchards in the Al Jouf region, a province in the northern region of Saudi Arabia. This region is the largest plant-producing region producing olive oil in the Middle East, with an area of about 7700 hectares and more than 30 million olive trees [28]. Therefore, the design of an IoT-based irrigation system in such open-field farming represents a challenging issue, especially regarding the communication network's energy efficiency and spectral efficiency. To solve this problem, we propose a smart irrigation system based on UAVs and M-MIMO (massive multiple input, multiple output) technology [12]. Specifically, UAVs ensure remote sensing (RS), which offers the advantage of collecting vital information on a large temporal and spatial scale (which cannot be achieved with traditional technologies), whereas M-MIMO ensures low delays, a large scale, and high-speed communications among different IoT devices.

In this work, we aim to accomplish the following contributions:

- Design a network model with a three-layered architecture for a UAV-based olive irrigation system.
- Analytically compute the achievable spectral efficiency as well as the energy efficiency of the studied system when a swarm of single antenna UAVs simultaneously communicate with a ground base station equipped with a large number of antennas.

- Numerically determine the optimal number of ground base station antennas, as well as the optimal number of IoT devices (UAVs and actuators) that should be used to ensure the maximum energy efficiency while guaranteeing a high spectral efficiency.

The remainder of the paper is organized as follows: In Section 2, we describe our proposed UAV-based olive irrigation system with the deployment of M-MIMO communication. The evaluation experiments and results are described in Section 3. Section 4 presents the results of the proposed method. Then, the conclusion and future works are given in Section 5.

2. Method

To the best of the authors' knowledge, and in light of the previous description of related works, researchers have not considered the combination of unmanned aerial vehicles and massive MIMO technology in smart irrigation systems. Therefore, we consider in this section the problem of water scarcity for olive orchards. We propose a smart irrigation system where multiple drones (equipped with onboard sensors) are deployed to gather information (on humidity, temperature, and soil moisture) through remote sensing techniques. As aforementioned, UAVs are used in this work to leverage their advantages in flexible deployment and low cost. However, in such a considered system, the olive farm spans a large area, and thus, providing power to UAVs and gathering data from them may be an issue, especially since these vehicles are limited in energy. In addition, the enormous number of connected devices increases the demand for spectral efficiency. To address these challenges, we adopt massive MIMO (multiple input, multiple output) technology in the UAV-based irrigation system. Indeed, this technology will play a significant role in future sixth-generation (6G) wireless mobile networks and can potentially enhance the energy efficiency and spectral efficiency [13].

In the following, we will describe the architecture of our proposed UAV-based olive irrigation system.

2.1. Architecture of the Proposed UAV-Based Olive Irrigation System

This research deploys a network model with a three-layered architecture, as shown in Figure 1. The uppermost layer represents the cloud layer; the middle layer is referred to as the fog layer; finally, the lower layer is composed of IoT or smart devices. A three-layered network model is a prevalent architecture in the Industry 5.0 paradigm, which has gained significant global traction as a fundamental driver of industrial growth and transformation.

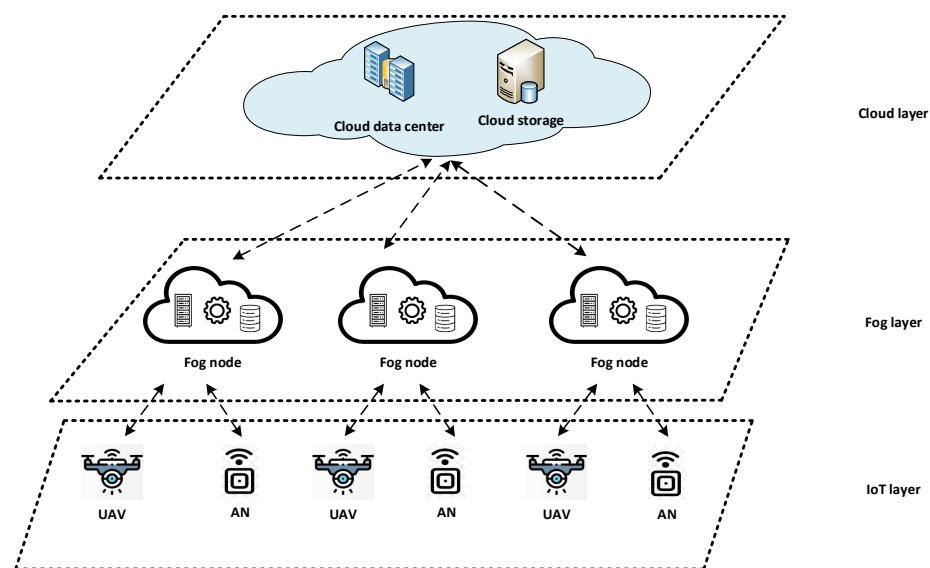


Figure 1. Architecture of the proposed UAV-based olive irrigation system.

- The topmost layer is the cloud layer, consisting of a cloud storage node and a cloud data center. The cloud layer provides scalability and resilience for storing and processing large amounts of data. It serves as a centralized storage unit for updated information on the behaviors of various IoT devices (UAVs and actuators). Additionally, the IoT devices in the lower layer receive regular updates from the cloud layer, ensuring that their behavior is up-to-date. Additionally, the user/farmer can instantaneously and remotely visualize (via the internet) the information and running activities of the olive farm. The user can also control the UAV movements around the orchard.
- The intermediate layer is called the fog layer, consisting of fog nodes (it can be based on Raspberry Pi, Arduino, or any micro-controller) for data processing and storage. It is designed to provide low latency and efficient processing power to meet the needs of the applications running on the devices in the lower layer. These nodes offer services to nearby IoT devices and maintain timely behavior records. This intermediate layer acts as a bridge between different IoT systems and the cloud layer, thus facilitating the interoperability of IoT systems. A cloud gateway (CG) connects the fog layer to the upper layer. Communication between the fog layer and the lower/upper layer is facilitated through M-MIMO technology (see Figure 2).
- The lower layer, also known as the IoT or smart device layer, consists of drones and actuators. In this layer, drones are equipped with cameras and onboard sensors. Specifically, these vehicles ensure remote sensing (RS), which offers the advantage of collecting vital information on a large temporal and spatial scale (which cannot be achieved with traditional technologies). Indeed, by flying over fields, the drones measure soil conditions, namely temperature, humidity, light, soil moisture, and nutrient levels. UAVs can also monitor crop health, detect anomalies, and respond to all end-user requests. As mentioned earlier, IoT devices in this layer have limited storage and computational capacity. Therefore, UAVs send a substantial amount of collected data to the fog layer to conduct speedy computation and services. Then, according to the obtained results, the fog nodes communicate with actuator devices (placed directly in the soil beside each olive tree) to activate/deactivate the corresponding solenoid valve that irrigates the olive tree.

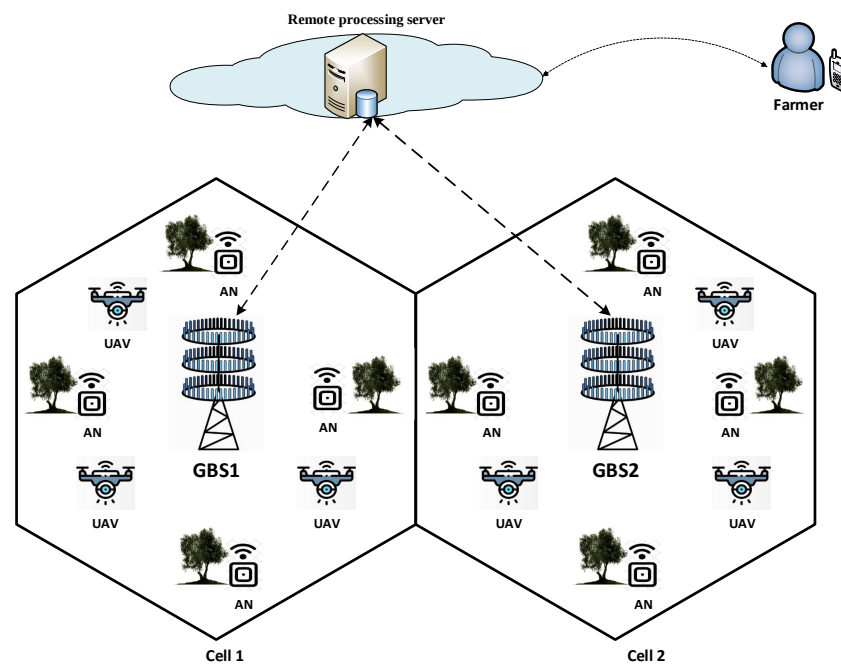


Figure 2. Network model of the proposed UAV-based olive irrigation system.

2.2. Network Model

We illustrate in Figure 2 the network model of the proposed UAV-based olive irrigation system. As represented in Figure 2, we separate the olive farm into N cellular networks. We use M-MIMO technology, where every cellular network has a single ground base station (GBS). Equipped with very large number of antennas M_n , ($1 \leq n \leq N$), the n -th GBS simultaneously serves K_U UAVs with onboard sensors, K_A actuators nodes (ANs), and K_F fog nodes. The actuators devices are placed directly in the soil beside each olive tree. We assume in the present work that all these devices are geographically distributed in the cellular network and are equipped with a single antenna.

The n -th GBS receives data from the UAVs and also from the fog devices in uplink communication. The received signal at the n -th GBS is denoted as $\mathbf{r}^{UL} \in \mathbb{C}^{M_n}$. We denote by $\mathbf{h}_{nk}$ the channel between the UAV (or the fog device) and the n -th GBS. We assume that the channel vectors are independent and identically distributed (i.i.d.) complex Gaussian samples of a random variable with zero mean and unit variance. We also denote by $\mathbf{x}_{nk} \sim \mathcal{N}_{\mathbb{C}}(0, p_{nk})$ the signal from the UAV (or the fog device) to the n -th GBS, where $p_{nk} = E(|\mathbf{x}_{nk}|^2)$ represents the power of the transmitted signal. The noise, $\mathbf{b} \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2 \mathbf{I}_{M_n})$, is assumed to be independent additive white noise. The received signal in the uplink at the n -th GBS is modeled as [29]:

$$\mathbf{r}^{UL} = \sum_{n=1}^N \sum_{k=1}^{K_U+K_F} \mathbf{h}_{nk} \mathbf{x}_{nk} + \mathbf{b}. \quad (1)$$

Correspondingly, in downlink communication, the n -th GBS sends data to different IoT devices (i.e., the UAVs, the fog nodes, and the actuators nodes). We denote by $K_I = K_U + K_F + K_A$ the total number of connected devices in the cell. The data signal intended for the k -th connected node in the n -th cell is $\mathbf{x}_{nk}$, ($1 \leq k \leq K_I$) and ($1 \leq n \leq N$). This signal is precoded using the beamforming vector $\mathbf{w}_{nl} \in \mathbb{C}^{M_n}$. In this work, we deploy the TDD (time division duplex) mode and we assume that the CSI (perfect channel state information) of all channels is available at the GBS. In this case, the GBS performs channel estimation using only the uplink pilot transmission from each IoT device. Consequently, the received signal in the downlink at an IoT device is modeled as [29]:

$$\mathbf{r}_k^{DL} = \sum_{n=1}^N \sum_{l=1}^{K_I} (\mathbf{h}_{nk})^H \mathbf{w}_{nl} \mathbf{x}_{nl} + \mathbf{b}_k. \quad (2)$$

2.3. Spectral Efficiency

The spectral efficiency (SE) of an encoding / decoding communication system is defined as the average number of bits of data that can be accurately transmitted (measured in bit/s/Hz). Specifically, in this work, the enormous number of connected devices in the proposed irrigation system (UAVs, fog nodes, and actuators) increases the demand in terms of spectral efficiency. We adopt M-MIMO technology to deal with this challenge, since it significantly enhances the system's spectral efficiency. This motivated us to derive, in this subsection, the analytical expression of the spectral efficiency that can be achieved within the proposed UAV-based irrigation network. In this study, we consider two diversity combining techniques: the M-MMSE (Multicell Minimum Mean Squared Error) combiner and the MR (Maximum Ratio) combiner.

The SE of the proposed network in the uplink transmission, i.e., from the k -th UAV (or the fog device) to n -th GBS, is denoted as SE_{kn}^{UL} (for $1 \leq k \leq K_U + K_F$ and $1 \leq n \leq N$) and is expressed as [29]:

$$SE_{kn}^{UL} = \frac{\tau_u}{\tau_c} \mathbf{E} \left\{ \log_2 \left(1 + SINR_{kn}^{UL} \right) \right\}, \quad (3)$$

where:

- τ_u (respectively, τ_c) is the data sample in uplink (respectively, the total number of samples) for every coherence block;

- $SINR_{kn}^{UL}$ represents the signal to interference plus noise ratio (SINR) of the k -th UAV (or the fog device) in uplink of the n -th cell.

Likewise, the SE of the proposed network in the the downlink transmission, i.e., from the n -th GBS to the k -th IoT device (UAV or the fog node or actuator), is denoted as SE_{nk}^{DL} (for $1 \leq k \leq K_I$ and $1 \leq n \leq N$) and is expressed as [29]:

$$SE_{nk}^{DL} = \frac{\tau_d}{\tau_c} \mathbf{E} \left\{ \log_2 \left(1 + SINR_{nk}^{DL} \right) \right\}, \quad (4)$$

where:

- τ_d is the data sample in the downlink for every coherence block;
- $SINR_{nk}^{DL}$ represents the signal-to-interference plus noise ratio (SINR) of the k -th IoT device in downlink of the n -th cell.

2.4. Energy Efficiency

The energy efficiency (EE) of a cellular network (measured in bit/Joule) is categorized as how much energy it takes to transmit a number of bits accurately. As previously mentioned, most sensors and actuators encounter limited energy issues in a UAV-based IoT environment. For this reason, guaranteeing sustainable energy for these devices represents another critical challenge. Drones, in particular, require significant energy to maintain flight and perform various tasks such as remote sensing. This motivated us to analyze the energy efficiency of our proposed irrigation system. Accordingly, we drive the expression of EE as follows [30]:

$$EE = \frac{T}{PC}, \quad (5)$$

where:

- T denotes the throughput of the proposed system and is measured in bit/s/cell. This throughput can be calculated using the downlink (or the uplink) SE expressions given in the previous subsection;
- PC denotes the power consumption of the proposed system and is measured in W/cell. This power is equal to the sum of the effective transmit power (ETP) and the circuit power (CP), i.e., $PC = ETP + CP$. Note that the circuit power is consumed by the transceiver hardware at the GBS and different IoT devices. In this work, we adopt the circuit power model in [31].

3. Results

In this section, we numerically evaluate the performance of our proposed UAV-based olive irrigation system. Specifically, we focus on the consumed circuit power of the studied system. We also analyze the energy efficiency and spectral efficiency trade-off. We determine the optimal network parameters in order to obtain the maximum energy efficiency. In Table 1, we give the simulation parameters.

Table 1. Simulation parameters.

Parameters	Value
Number of cells (L)	10
Cell radius	250 m
SNR	0 dB
τ_u	90
τ_d	90
τ_c	200

In Figure 3, we present the circuit power (CP) of the proposed UAV-based olive irrigation system with reference to the number of IoT devices K_I . We consider two diversity

combining techniques: the M-MMSE (Multicell Minimum Mean Squared Error) combiner along with the MR (Maximum Ratio) combiner. Further, two amounts of GBS antennas were selected: $M = 100$ and $M = 200$. In Figure 4, we present the circuit power (CP) of the proposed UAV-based olive irrigation system with reference to the number of GBS antennas. As in Figure 3, we consider two diversity combining techniques: the M-MMSE combiner along with the MR combiner. Additionally, two different numbers of IoT devices are examined: $K_I = 10$ and $K_I = 20$. In Figure 3 (respectively, in Figure 4), we notice that for the two considered combiners, the total circuit power increases with K_I (respectively, with M). The previous figures also illustrate the fact that the M-MMSE combining technique consumes a higher CP than the MR combining technique. Indeed, the M-MMSE scheme requires the inversion of an M -dimensional matrix, whereas no matrix inversions are required in the MR scheme.

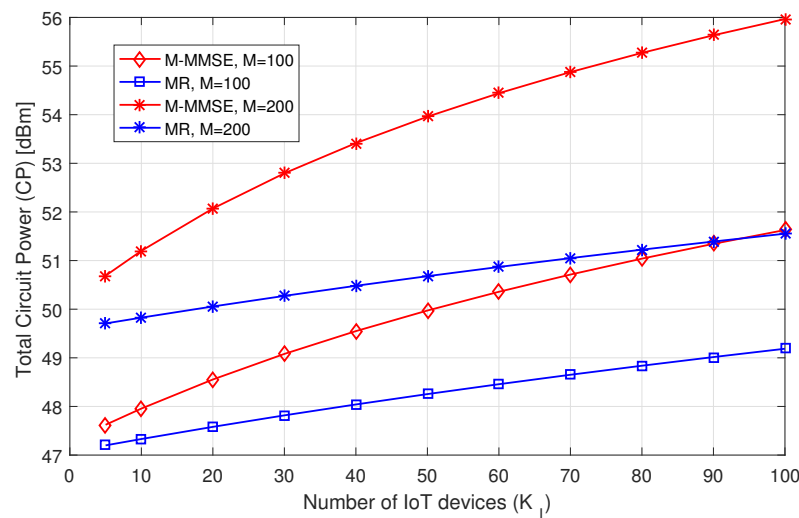


Figure 3. Circuit power (CP) of the proposed UAV-based olive irrigation system with reference to the number of IoT devices K_I , for a multi-cell MMSE combiner, an MR combiner, and different numbers of GBS antennas, M .

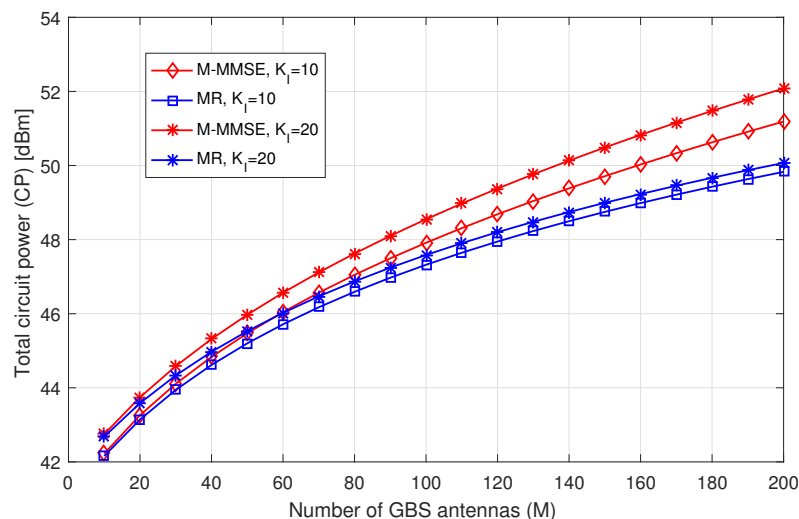


Figure 4. Circuit power (CP) of the proposed UAV-based olive irrigation system with reference to the number of GBS antennas M , for a multi-cell MMSE combiner, an MR combiner, and different numbers of IoT devices K_I .

We analyze in Figures 5 and 6 the proposed UAV-based olive irrigation system's energy efficiency and spectral efficiency trade-off problem. We consider different numbers of GBS

antennas $M \in \{20, 40, 100, 200\}$ and $K_I = 20$ in Figure 5. However, we consider different numbers of IoT devices $K_I \in \{5, 20, 50\}$ and $M = 20$ in Figure 6. From both figures, one can see that the energy and the spectral efficiency trade-off curve is an unimodal function of M (as it is for K_I).

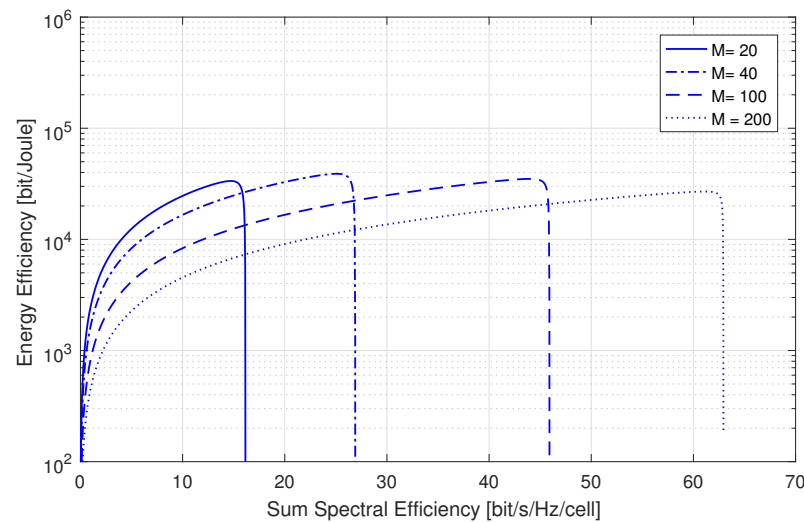


Figure 5. Energy efficiency versus spectral efficiency of the proposed UAV-based olive irrigation system for different numbers of GBS antennas M with the number of IoT devices as $K_I = 20$.

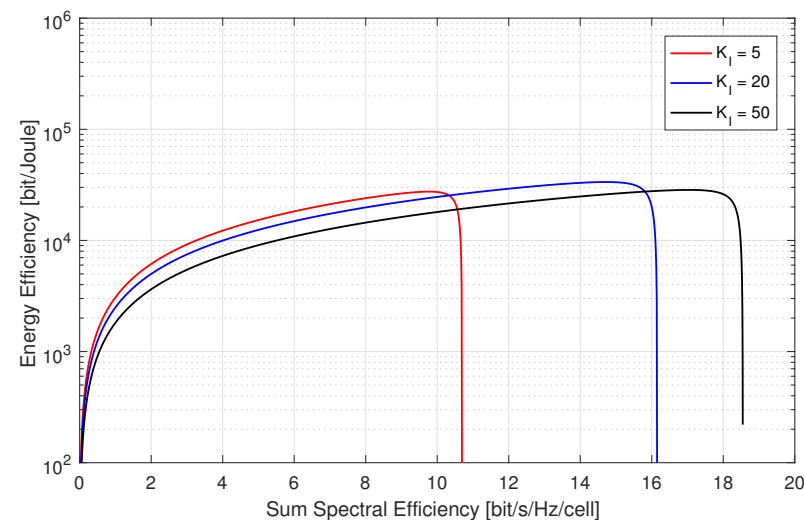


Figure 6. Energy efficiency versus spectral efficiency of the proposed UAV-based olive irrigation system for different numbers of IoT devices K_I with the number of GBS antennas as $M = 20$.

In Figure 7, we plot the energy efficiency of the proposed UAV-based olive irrigation system as a function of the throughput. We also consider two diversity combining techniques: the M-MMSE combiner along with the MR combiner. The results are obtained by varying the number of IoT devices K_I as well as the number of GBS antennas M . As illustrated in Figure 7, the maximal energy efficiency value with the MR combiner (respectively, the M-MMSE combiner) is about 9 Mbit/Joule (respectively, 20 Mbit/Joule), which corresponds to a throughput of 330 Mbit/s/cell (respectively, 600 Mbit/s/cell) when $K_I = 10$. Consequently, the M-MMSE combining technique performs better and achieves the maximal EE. This can be explained by the fact that in massive MIMO communication, the M-MMSE scheme exploits the spatial degrees of freedom (offered by multiple antennas) to focus signals on intended receivers, reduce interference, and consequently increase the system throughput [32]. Hence, M-MMSE improves the energy efficiency, since the higher

the throughput, the higher the circuit power (CP), due to the larger number of antennas deployed in massive MIMO communication.

In Figures 8 and 9, we illustrate the energy efficiency of the proposed UAV-based olive irrigation system as a function of K_I and M . We consider the MR combiner (respectively, the M-MMSE combiner) in Figure 8 (respectively, in Figure 9). We aim to determine the optimal number M of GBS antennas as well as the optimal number K_I of IoT devices (UAVs and actuators) that can be served. We note that the energy efficiency surfaces are concave and a global optimum exists for each combiner. Indeed, with the M-MMSE combiner, a maximal energy efficiency of 19.57 Mbit/Joule is achieved with $(K_I, M) = (20, 50)$. Moreover, with the MR combiner, a maximal energy efficiency of 9.68 Mbit/Joule is achieved with $(K_I, M) = (10, 40)$. As we can see, the M-MMSE combiner outperforms the MR combiner.

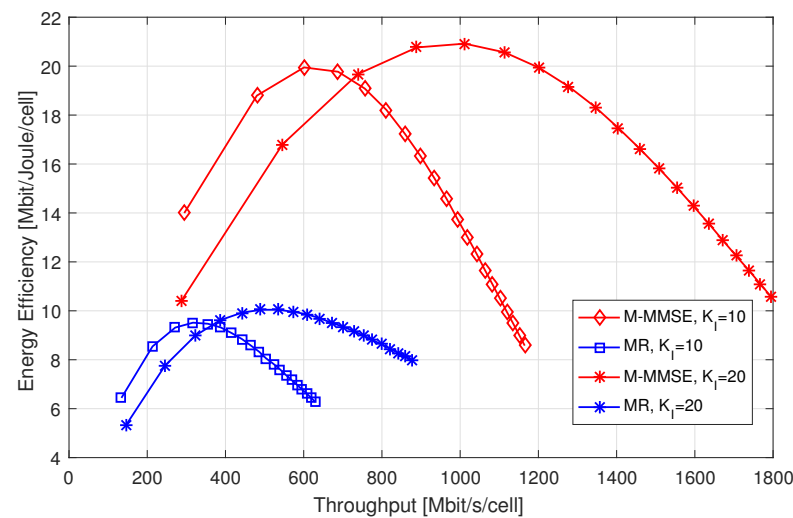


Figure 7. Energy efficiency versus throughput of the proposed UAV-based olive irrigation system for the multi-cell MMSE combiner, the MR combiner, different numbers of IoT devices K_I , and different numbers of GBS antennas M .

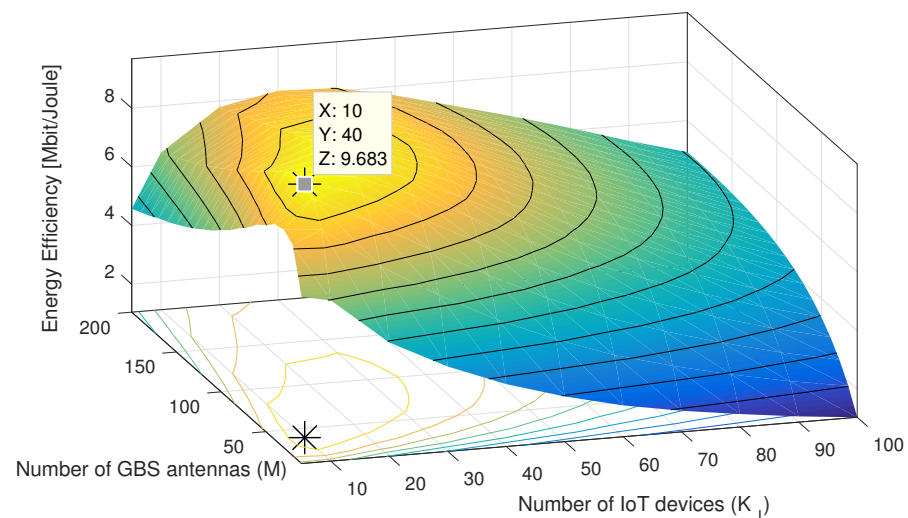


Figure 8. Energy efficiency of the proposed UAV-based olive irrigation system with reference to the number of IoT devices K_I and the number of GBS antennas M , for the MR combiner.

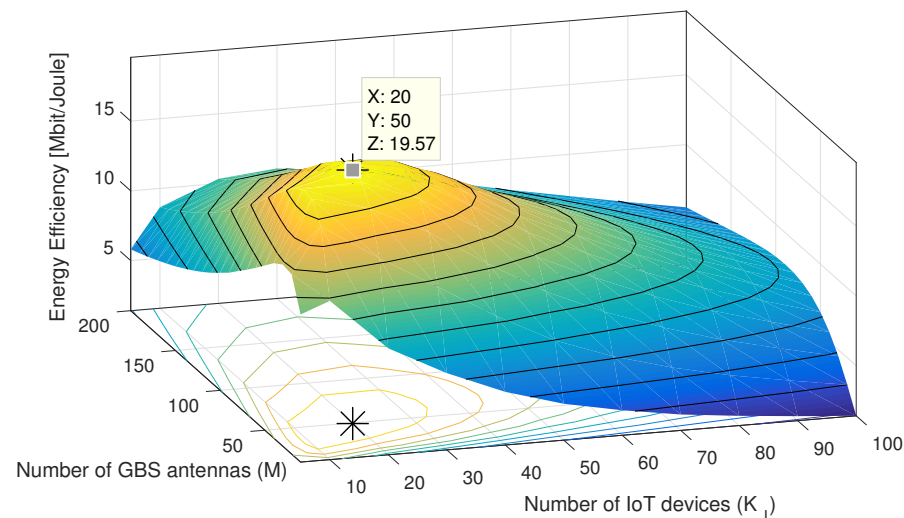


Figure 9. Energy Efficiency of the proposed UAV-based olive irrigation system with reference to the number of IoT devices K_I and the number of GBS antennas M , for multi-cell MMSE combiner.

4. Discussion

This section discusses the results of the proposed UAV-based olive irrigation system. We start by emphasizing the significance and reasonability of the results. Then, we analyze the limitations and areas for improvement of the study.

Firstly, as mentioned earlier, to the best of the authors' knowledge, and in light of the previous description of related works, researchers have not considered the combination of unmanned aerial vehicles and massive MIMO technology in smart irrigation systems. Furthermore, this study is general, and the obtained simulation results can be easily extended for any other parameters. Moreover, unlike previous studies in the literature that analyzed the spectral and energy efficiency trade-off (for example, [2,16]), our analysis takes into account not only the transmit power and throughput but also the circuit power (CP). Indeed, in Figure 3 (respectively, Figure 4), we plot the CP of the proposed UAV-based irrigation system as a function of the number of IoT devices K_I (respectively, the number of GBS antennas M). The simulation results showed that the M-MMSE combining technique consumes a higher CP than the MR combining technique. Clearly, as aforementioned, the MR scheme does not require matrix inversions, whereas the M-MMSE scheme requires the inversion of an $M \times M$ -dimensional matrix.

In addition, in Figure 7, we plot the energy efficiency of the proposed system as a function of the throughput. We noticed that the M-MMSE combining technique performs better and maximizes the energy efficiency. Thus, the M-MMSE combining technique finds a non-trivial trade-off between a high signal power and low interference and noise, which maximizes the instantaneous SINR. This can be explained by the fact that in massive MIMO communication, the M-MMSE scheme exploits the spatial degrees of freedom (offered by multiple antennas) to focus signals on intended receivers, reduce interference, and consequently increase the system throughput [32]. Hence, M-MMSE improves the energy efficiency since the higher the throughput, the higher the circuit power (CP), due to the larger number of antennas deployed in massive MIMO communication. In this way, the corresponding energy efficiency gain comes from suppressing intra-cell interference from the massive antennas and by sharing the per-cell CP costs among multiple IoT devices.

Moreover, the results given in Figures 8 and 9 show how to determine the optimal number M of GBS antennas as well as the optimal number K_I of IoT devices (UAVs and actuators) that can be served. Additionally, Figures 8 and 9 illustrate that the proposed UAV-based irrigation system outperforms conventional ones regarding the energy efficiency, while conserving network spectral efficiency. In fact, when the number of GBS antennas M increases proportionally to K_I ($M/K_I \gg 1$), inter-user interference (that increases with

K_I) is suppressed. Note that the case when $M/K_I = 1$ represents the traditional scheme adopted in the literature. We can clearly deduce that our proposed UAV-based method ($M/K_I \gg 1$) outperforms the traditional one ($M/K_I = 1$).

Hence, through qualitative and quantitative analyses of the simulation results, it was verified in this work that the proposed irrigation system is effective and optimal in terms of energy efficiency and conserving network spectral efficiency. However, this research still has some limitations, mainly regarding the following two aspects:

- Although M-MMSE combining is optimal, it is not frequently used in the research literature. There are several reasons for this. One is the high computational complexity of computing the inverse $M \times M$ matrix, especially when M is large. The complexity is also affected by the need to estimate the channels and acquire the channel statistics of all IoT devices. Another reason is that M-MMSE performance is hard to analyze mathematically, while other schemes can give more insightful closed-form spectral efficiency expressions. A third reason is that receiver combining methods are often developed for single-cell scenarios and then applied heuristically in multi-cell systems.
- Additionally, as mentioned earlier, olive farming at Al Jouf, with an area of 7730 hectares and over 30 million olive trees [28], leads to a massive amount of collected data. Given this, it is essential to deploy real-time control, and data should be protected from unauthorized access or interception.

5. Conclusions

The present study addressed precision agriculture's water scarcity and energy efficiency challenges. We proposed a novel UAV-based olive irrigation system, which leverages the combination of unmanned aerial vehicles and massive MIMO technology. This approach encompasses the integration of the IoT, drones, and sensors to optimize the irrigation process. The UAVs ensure remote sensing through onboard sensors and collect necessary data (such as soil moisture) for the irrigation process, whereas M-MIMO communication is adopted to meet the increasing requirements regarding spectral efficiency and to guarantee the energy efficiency of the studied system. The numerical results proved that the proposed UAV-based irrigation system outperforms conventional ones regarding energy efficiency, while conserving the network's spectral efficiency.

In future work, we plan to deploy drones equipped with cameras to capture images of olive leaves to identify leaves with different types of infections, including *Aculeus olearius*, olive peacock spot, and olive scab, from healthy leaves. Additionally, since collected data should be protected from unauthorized access or interception, we plan also to study the physical layer security issue.

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