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Review on Power Control in Multi-hop Networks

Huda Anwar [1]

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Abstract

This paper reviews power control algorithms through interference management in a variety of network types, such as Device-to-Device (D2D) Networks, Unmanned Aerial Vehicles (UAVs), healthcare systems, and Low Power Wide Area Networks (LPWAN). The growing requirement for effective and consistent wireless communications advanced approaches to mitigate interference, ensuring optimal power usage and network performance. We explore the exceptional interference challenges and requirements of each network type. As wireless networks progress, managing interference becomes essential to maximize power usage and maintain network performance. This paper systematically reviews the latest advancements and methodologies that adjust power levels to mitigate interference. Additionally, we analyze these techniques and discuss their impact on spectral efficiency, supported by recent case studies. Our findings aim to guide researchers and practitioners in developing more effective power control and interference management solutions for next-generation wireless networks.

Keywords—Power control, Interference management, D2D communications, UAVs, Healthcare systems, LPWAN.

1 Introduction

In recent years, the next generation of network communication technologies has been developing rapidly. With the massive increase in the number of users accessing diverse applications and services, the need for greater reliable and efficient communication networks has been increased (Shafique et al., 2020). Users' demand for higher data rates and consistent communication is rising daily (Meng & Liu, 2019). Wireless networks that require messages be transmitted utilizing multiple nodes prior to arriving at their destination are known as multi-hop networks (Shomorony & Avestimehr, 2014)(Qamar et al., 2019). Multi-hop networks are integral to modern communication systems, reshaping the scene of wireless connectivity and enabling various applications (Li et al., 2020). By enabling data transmission through intermediate nodes, multi-hop networks extend the reach of communication beyond the limitations of direct links, enhancing coverage, reliability, and scalability (Wheeb & Naser, 2021). In an age defined by the Internet of Things (IoT), 5G, and beyond, the role of multi-hop networks continues to grow, offering solutions to the challenges posed by dynamic environments, mobility, and resource constraints. Recent research highlights the pivotal role of multi-hop networks in various domains, including urban sensing, D2D communications, UAVs, LPWAN, and healthcare. With the advent of emerging technologies, multi-hop networks are poised to play an even more central role in enabling seamless, decentralized communication infrastructures (Scalambrin et al., 2023). This introduction sets the stage for exploring the latest advancements and emerging trends in multi-hop networking, reflecting the ongoing evolution of communication systems in the digital age. However, these networks' increasing density and diversity introduce significant challenges, particularly concerning power control and interference management, which are vital for maintaining competent and reliable communication. Interference is thought to be one of the primary factors limiting the performance of wireless networks as the volume of connected devices rises (Kim et al., 2022). In multihop networks, interference can be challenges by affecting signal clarity and overall throughput, where data travels through multiple midway nodes to reach its destination. As such, addressing

Huda Anwar
huda@utq.edu.iq

[1] Department of Electrical and Electronics Engineering, College of Engineering, University of Thi-Qar, Thi Qar, Iraq

interference becomes principal in ensuring the operation of multihop (Parissidis et al., 2011). Effective interference management has become a crucial field of research and development as wireless networks becoming denser and more varied in their application scenarios (Heath et al., 2013). The main concern in wireless system is to enhance the signal power to noise power ratio (Cheng et al., 2021). More precisely, signal-to-noise (SNR) ratio enhancement is accomplished through power control. The main objective of managing the power control concern is to manage the interference level that degrade the system performance. The purpose of the power control technique is confirm that the power in transmitter is not so high that it interferes with other users but strong enough for the receiver to detect it (Raziah et al., 2022). The amount of power transmitting is a central factor in defining the quality of service. Though, different networks have been discussed. In brief, D2D communications facilitate direct interaction between devices without need to traditional network infrastructure, boosting spectral efficiency and reducing latency (Lai et al., 2020). When the adjacent devices in the network interact directly, sometimes interfering with the infrastructure networks and other nearby users. In order to provide an operative communication in these contexts, effective interference management techniques are fundamental (Kamruzzaman et al., 2022). UAVs have used in many applications including agriculture, environmental monitoring, and surveillance (Al Radi et al., 2024). These applications depend on wireless communication for control and data transmission. UAV networks, characterized by high mobility and dynamic topologies, require robust interference management to ensure stable and reliable communication links amid frequent changes in network configurations and interference patterns (Vaezi et al., 2024). In healthcare systems, the reliability and energy efficiency of communication are paramount, as these factors directly impact patient outcomes. Effective power control is essential to ensure the reliable operation of medical devices while prolonging battery life (George & Jacob, 2020). Furthermore, LPWANs, designed for long-range communication with minimal power consumption, face the dual challenge of managing interference over extensive areas while adhering to strict power constraints (Cotrim & Kleinschmidt, 2020). This review paper provides techniques in power control and interference management across these diverse network types. We will explore a variety of advanced methodologies to assess their effectiveness in addressing the specific challenges associated with each network. Through this review, we aim to equip researchers and practitioners with a deeper understanding of the current landscape and potential advancements in power control and interference management. By addressing the unique requirements and constraints of D2D Networks, UAV networks, healthcare systems, and LPWANs, we can foster the development of more efficient, reliable, and sustainable wireless communication systems. The rest of this paper is outlined as follows. Section 2 presents the interference management for D2D Networks. Section 3 shows the interference management in healthcare applications. Section 4 Interference Management in Low LPWANs. Interference Management in UAVs are standardized in Section 5, the conclusion is provided in Section 6.

2 Interference Management in Device to Device (D2D) Networks

Commercial and medical technologies use sensors and cellphones to collect data, which is then processed by cloud frameworks enabled by the Internet of Things (IoT) (Chakraborty & Rodrigues, 2020). For multi-hop D2D communications every transmitter requires less transmission, thus reduce the interference caused by other receivers. Users in D2D communications improve throughput, reduce central coordinator load, and increase cellular capacity by directly or multi-hop. According to the manner in which D2D interactions divide into cooperative and peer-to-peer communications (Tran et al., 2021). Managing interference is essential to minimize the effects of interference and improve efficiency of the cooperative D2D network.

The proposed scheme in (Kamal & Kader, 2020) shown in Figure 1, utilizing spatial modulation (SM) at all communication nodes equipped with multiple antennas, guarantees system interference-free communication due to its essential characteristics of SM. The system consists of Base Station (BS), two users; Near User (NU) and Far User (FU) and D2D users (D1 and D2); D1 act as a relay. The transmission occurs in two phases, the first phase involves BS using SM to arrange bits in two groups: antenna index (far user signal) and modulation bits (near user signal). To gain their required data bits, near user and relay D1 employ the iterative-maximum ratio combining (i-MRC) technique. The total amount of bits that BS is capable of transmitting is (Kamal & Kader, 2020) :

$$X_1 = log_2(M_1) + log_2(A_{Bs}) \quad (1)$$

where, M_1: modulation order and A_{Bs}: number of antennas at BS. The D2D allowed D1 further uses SM during phase-2 to convey far user signal obtained from BS along with its particular data bits for a different user D2. Subsequently then, far user and D2 use i-MRC to get the data they need. In this phase the amount of data that can be transmitted by D1 is (Kamal & Kader, 2020).

$$X_2 = log_2(A_{Bs}) + log_2(A_{D1}), \tag{2}$$

where A_{D1} is number of transmit antennas at D1. Since SM is triggered at both BS and D1, there cannot be interference in or among cellular and D2D.

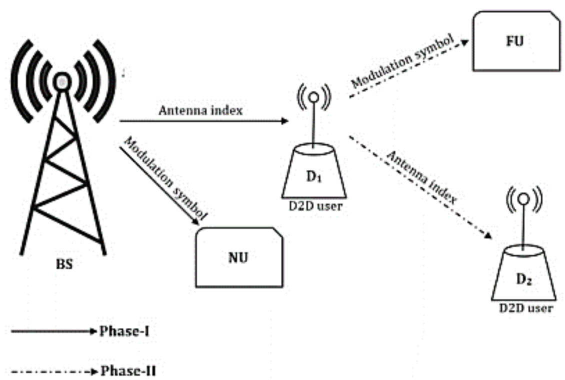

Figure 1: system model (Kamal & Kader, 2020)

They used bit error rate (BER) and spectral efficiency (SE) to study the performance of the presented model. In (Raziah et al., 2022)the proposed an adaptive power control (APC) based on the low-energy adaptive clustering hierarchy (LEACH) protocol to decrease the interference by boost the quality of service (QoS). In suggested model consider a several of device user (DU) and cellular user (CU) that have been clustered using the LEACH. The LEACH procedure consists of two phase the setup and steady-state phases. The setup phase is for cluster creation. On the other hand, data transfer is the steady-state phase, during which the device transmits its data to the designated cluster for forwarding to every device that is a member of the cluster. They used the Pout and throughput with signal to interference plus noise ratio (SINR) for statement among clusters in the uplink and downlink phases. The SINRs for the both phases are in the following equations (Raziah et al., 2022):

$$SINR_{DUk}^{DL} = \frac{P_{eNB,DUk}\, G_{eNB,DUk}}{rd\ (k)\, P_{TUEk}\ CUE_k\ G_{TUEk}\ CUE_k} + N, \tag{3}$$

$$SINR_{DUk}^{UL} = \frac{P_{CUk,eNB}\ G_{CUk,eNB}}{rd\ (k)\, P_{TUEk}\ CUE_k\ G_{TUEk}\ CUE_k} + N, \tag{4}$$

where $SINR_{DUk}^{DL}$ is the SINR at DU in the downlink phase, $SINR_{DUk}^{UL}$ is the SINR at DUE in the uplink phase, $P_{eNB,DUk}$ is the power from Bs to DU, $G_{eNB,DUk}$ is the channel gain from Bs to DUE, rd (k) is the equality of using resources in the downlink and N is the noise power. The results show that the outage probability reduces as SINR growth, while high throughput is achieved after using the proposed APC.

The research article in (F. Yang et al., 2020) looks on D2D communication resource allocation and interference management in multi-hop vehicular ad hoc networks (VANETs). It suggests an interference neutralization model, a cooperative communication approach, and a vehicle clustering algorithm. The clustering technique that groups cars according to their location and speed in order to increase intra-cluster resource efficiency in VANETs. To extend the duration of sustained D2D connections, the algorithm chooses cars whose speeds are closer to the average. Resources for D2D communications are allocated using orthogonal frequency division multiplexing (OFDM), which manages interference. Through D2D communications, vehicles are sharing information about driving behavior changes, trajectory, and speed. TDMA scheduling is used for channel access management. Interference neutralization (IN) method used to management interference that caused due to data transmitting between vehicles in different clusters. The suggested system classifies vehicles into two groups: those on the routing path and those in idle mode. Each vehicle's position is calculated based on its speed and the interference radius. In order to neutralize interference, eligible supporting vehicles are allocated based on their position. The results of the simulation in Figure 2 display that significant throughput may be achieved using the strategy that combines IN and cooperative communication. Additionally, in VANETs, the throughput improvements rise as the vehicle density increases.

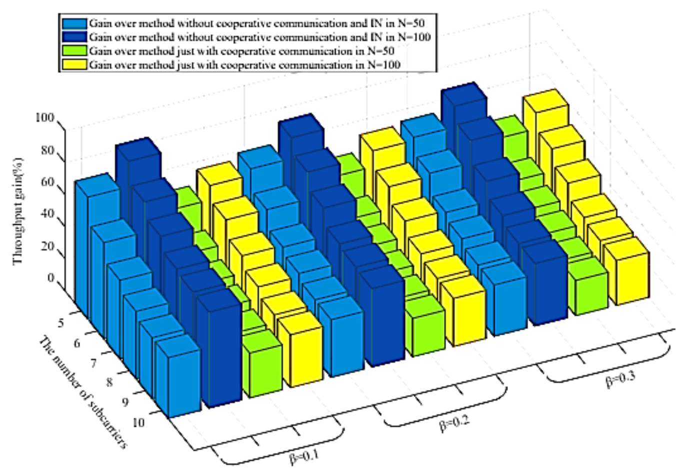

Figure 2: Impact of vehicle density on the throughput (F. Yang et al., 2020)

An algorithm for optimizing transmit power is attached which involves beamwidth selection and device association in (Zhang et al., 2018). An mmWave D2D network is developed, the challenge related to transmitting power optimization in mmWave D2D networks is specifically solved by the beamwidth scheme that is optimized by the particle swarm optimization (PSO) algorithm and the device association performed through distributed framework (Zhang et al., 2018). The system model of mmWave D2D network design, on the assumption that the heights of all transmitters and receivers are identical. The sector antenna model's directional gain remains constant across all major lobe angles. In order to provide a comprehensive optimization problem, the optimization problem concentrates on suppressing interference, maximizing transmitter transmitting power, and conserving energy in mmWave D2D networks as presented in Equations 5,6 and 7 (Zhang et al., 2018):

$$Minimize\ \{\textstyle\sum_{k=1}^{L} p_k^t\}, \tag{5}$$

$$0 \le p_k^t \le P_{max}, \tag{6}$$

$$SINR_i \ge \gamma, \tag{7}$$

where the beamwidth and transmit power are the primary optimal parameters. Equation 6 represents a budgetary restriction on transmission power for every transmitter, and Equation 7 is the requirement that every receiver's SINR necessity to be larger than the γ, meeting QoS criterion to ensure the fundamental communication.

In (Solaiman et al., 2021) authors developed resource allocation for downlink communications supporting the MIMO-NOMA cellular network to maximize SE while ensuring the QoS of D2D pairs and cellular user equipment, as well as shielding cellular user equipment and receiver device user equipment from interference. An optimal power distribution strategy based on particle swarm optimization (PSO) was suggested for both CUEs and D2D user equipments in order to improve network SE, while also protecting CUEs from induced interference and guaranteeing QoS for both CUEs and D2D Pairs. The results obtained from the simulation show that associated to conventional D2D communications operating MIMO-OMA cellular networks, the suggested resource allocation algorithm for D2D communications at mmWave underlays MIMO-NOMA cellular network offers higher spectral and energy efficiency.

In (Anwar et al., 2024) authors proposed a system of multiple users that allows to share the same frequency resources used cooperative NOMA and the transmission of signal is consider over more realistic noise channel known as Symmetric α-Stable Noise Channels. NOMA is consenting for more effective use of the available spectrum. They used the achievable rates and outage probabilities as performance metrics with impact of Symmetric α-Stable

Noise Channels, the rate for different user (near, middle and far user) as shown in Equations 8, 9 and 10 (Anwar et al., 2024):

$$R_{coop}^{n} = \frac{1}{\alpha} log_2(1 + \frac{|h_{sn}|^{\alpha}\ c_n^{\alpha}}{\gamma_N^{\alpha}}) \qquad (8)$$

$$R_{coop}^{m} = \frac{1}{\alpha} log_2(1 + \frac{|h_{nm}|^{\alpha}\ c_m^{\alpha}}{\gamma_N^{\alpha}}) \qquad (9)$$

$$R_{coop}^{f} = \frac{1}{\alpha} log_2(1 + \frac{|h_{nf}|^{\alpha}\ c_f^{\alpha}}{|h_{nf}|^{\alpha}\ c_m^{\alpha} + \gamma_N^{\alpha}}) \qquad (10)$$

Where*:*

- $c_n = w_n\ P_t$, $c_m = w_m\ P_t$ *and* $c_f = w_f\ P_t$.
- h_{sn} *: Fading coefficient between the BS and the D_n.*
- h_{nm} : Fading coefficient between the D_n and the D_m.
- h_{nf} : Fading coefficient between the D_n and the D_f.
- γ_N: symmetric α-stable noise channel

The results display those higher achievable rates show better interference management and enhanced system performance as shown in Figure 3.

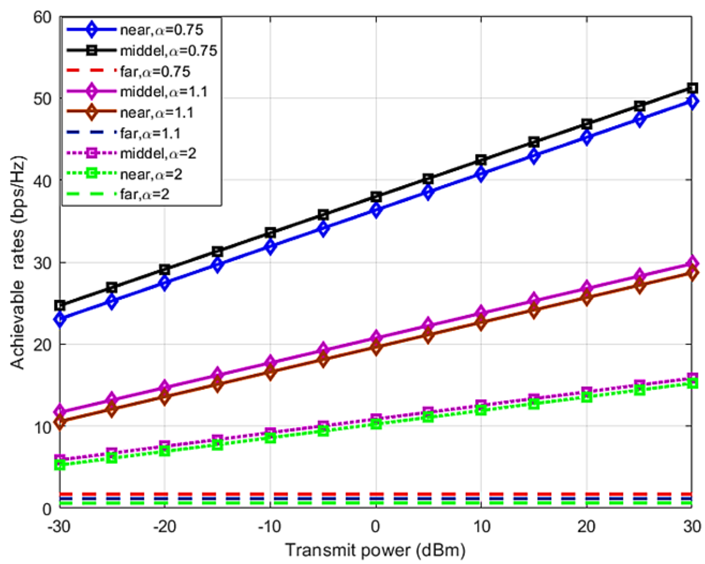

Figure 3: The achievable rate of near, middle and far users for different α values (Anwar et al., 2024)

In (Ding et al., 2015) the authors proposed a cooperative non-Orthogonal multiple access to reduce interference and enhance system reliability, through the use of successive interference cancelation and user collaboration. Stronger channel characteristics users can use this strategy to decode their own signals first, then clear signals indicated for users in less channel conditions. All users are guaranteed a cleaner signal reception owing to this systematic interference elimination. Strong channel characteristics also minimize the requirement for retransmissions by serving as relays for less reliable users. In (Yener & Ulukus, 2015), authors see interference as a protection tool for the transmitted information. In some situations, according to the suggested approach emphasizes how wireless physical-layer security can be greatly increased by strategically utilizing interference and cooperating among transmitters. Valid users can establish scenarios where secure communication is possible even in the aspect of effective eavesdroppers by utilizing cooperative jamming. With this method, interference is no longer a problem but rather a tool for launching reliable and secure wireless connection.

3 Interference Management in Healthcare Applications

Development in healthcare is inspired by the rising number of people need to it and health care costs in many wealthy countries. Wireless Body Area Networks (WBANs) are the result of these developments. They are made to be maintained or attached, monitor physiological signals, and assign those signals to specialist medical servers without significantly interfering with the patient's regular activities (Bouazzi et al., 2022) . In (Alabdel Abass et al., 2024) the proposed system consists of two WBANs with coordinator as shown in Figure 4. Each coordinator is checked of coordinating transmission throughout a network of implanted devices. With its strong battery, the coordinator node makes sure that no node within the same WBAN interferes with any other node. According to a game theoretic model there are a player; which represent every excited WBAN; and a strategy for that player represented by transmission decision.

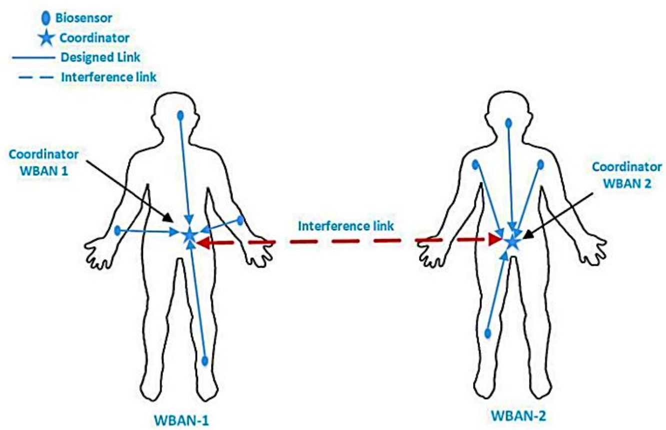

Figure 4: The assumed system in (Alabdel Abass et al., 2024)

Relaying and network coding nodes are two methods that WBANs can use to control transmission power. Relay nodes can cause delays but also decrease the power transmission. Alternatives to network coding are more flexible, but they involve higher processing costs and delays. With a different approach for every node, each WBAN has the ability to choose from among several options for controlling the transmission power levels. A reinforcement learning approach was indicated for the interference management of WBANs by using QIM-MAC that efficiently reduce interference in (Ahmad et al., 2020). In reinforcement learning, agents can communicate on states in order to optimize rewards. They improve their conduct by taking note of the feedback they receive from their behaviors as shown in Figure 5.

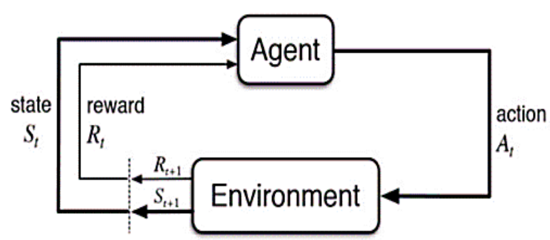

Figure 5: Reinforcement learning (Ahmad et al., 2020)

Also, using a value function to calculate the expected benefit of taking an action and following to the optimal policy, Q-learning is a model reinforcement learning technique that saves the q rate of each action as in Equation 11. It facilitates online learning without the need for a transition model (Ahmad et al., 2020):

$$Q_{t+1}(i,k) = Q_t(i,k) + I(r - Q_t(i,k)) \quad (11)$$

Equation 11 modifies the Q rate for every node i for a certain slot k, where r is a reward and I is the learning rate, which is typically more than zero and less than one (0 < I < 1). $Q_t(i,k)$ is the former Q value of node i on slot k whereas $Q_{t+1}(i,k)$ is the Q value for next frame. According to simulations, QIM-MAC significantly increases network performance while lowering interference.

In (He et al., 2021) authors to minimize inter-network interference, a distributed power controller utilizing a deep Q-learning algorithm is designed. By using distributed coordinators to optimize sensor transmission power, it achieves increased energy efficiency and performance advantages as network scale increases. Massive medical WBAN is organized onto three layers: coordinator nodes, terminal nodes, and central nodes. Large-scale servers connected to the internet compose the central node. Medical sensors on the skin or within the body are designated as terminal sensor nodes, and coordinators are in charge of them. Applications in subnetworks made up of coordinator and terminal nodes are beneficial to the majority of users. Numerous variables, including channel conditions, node power usage, and information transmission rate, are involved in the learning process. Coordinated nodes learn the best policies by being trained and validated.

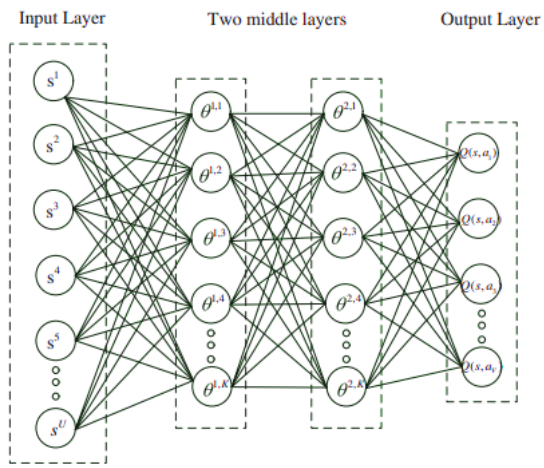

Figure 6: The neural network model (He et al., 2021)

An LSTM channel prediction framework for long-term WBAN radio channel prediction is proposed in (Y. Yang et al., 2019). The technique is appropriate for regular on-body WBAN channels since it lowers circuit power consumption and boosts communication dependability. The design of the suggested LSTM network consists of an input layer, the output layer, a dense layer with batch normalization, multiple stacked LSTM layers, and a fully-connected layer.

Table 1: Detailed Configuration of the LSTM Network (Y. Yang et al., 2019)

Description	Value
Number of layers in the LSTM network	2
Size of the hidden state of an LSTM cell	64
Number of sequences in each mini-batch	64
Input size of the network	100
No. of epochs for initial training	50
No. of epochs for model fine-tuning	20
Training Time	10s
Learning Rate	0.0003
Dropout Probability	0.8

Using new sets of data, an originally trained LSTM network is iteratively fine-tuned as part of the suggested online training method for WBAN operating scenarios. In addition to ensuring a constant low prediction error, this enables the hub to record channel gains while making predictions on the WBAN channel at every time step.

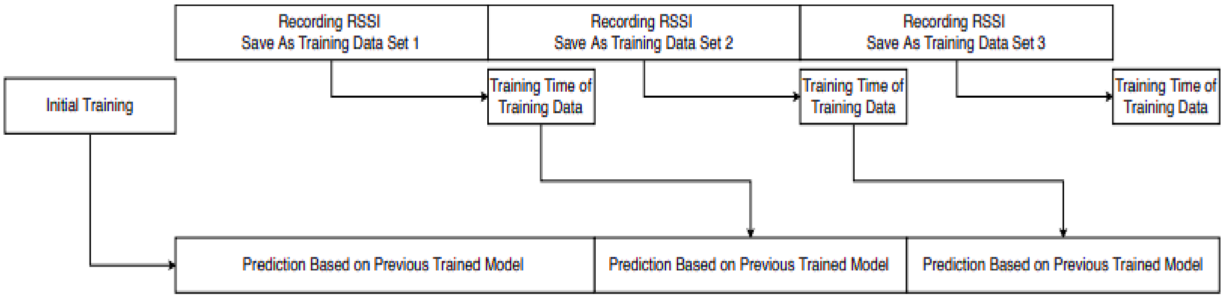

Figure 7: The Flow Chart of the Online Prediction Mechanism (Y. Yang et al., 2019).

4 Interference Management in Low Power Wide Area Networks (LPWANs)

There are two types of radio technologies: short and long ranges. Despite being widely benefited in the Internet of Things (IoT), short-range technologies like Bluetooth and ZigBee, and others not fully satisfy all network connectivity needs (Bembe et al., 2019). To meet the requirement for long-range connectivity of IoT, LPWANs are proposed, which offer energy-saving, scalability, and coverage metrics, making them a potential wireless technology for Internet of Things connectivity (Chilamkurthy et al., 2022). A star topology network that enables nodes to send data directly to the gateway characterizes. The star topology structure is made up of several nodes, the nodes in the gateway are linked to several branches (Misbahuddin et al., 2019). The nodes in each branch are spaced out from the gateway by a specific amount on a ring. In this instance, LoRa technology is being utilized as the wireless communication device. On the other side, send it a packet across a few intermediary nodes through multihop as shown in Figure 8 (Misbahuddin et al., 2019).

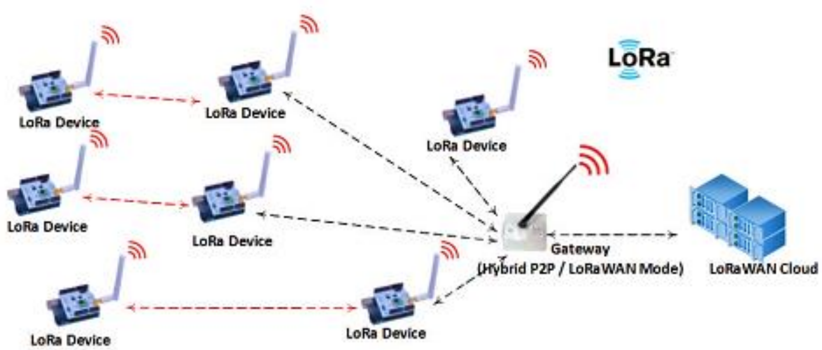

Figure 8: multi hop network in LoRa technology (Misbahuddin et al., 2019)

Long Range (LoRa) is a spread spectrum modulation technique that use a sweep tone to gradually encode messages, reducing their susceptibility to noise and interference (Sallum et al., 2020). In order to address interference in a LoRa network, authors in (Voigt et al., 2016) looks into the use of several base stations and directional antennae. Multiple base stations boost message reception in noisy situations, whereas directional antenna increase signal intensity without raising the cost of transmission energy. The result of their research is to develop the simulation tool LoRaSim. LoRaSim permits to place N LoRa nodes and M LoRa base stations in a 2-dimensional space. They used Data Extraction Rate (DER) as performance metric which definite as the ratio of received messages to transmitted messages over a period of time.

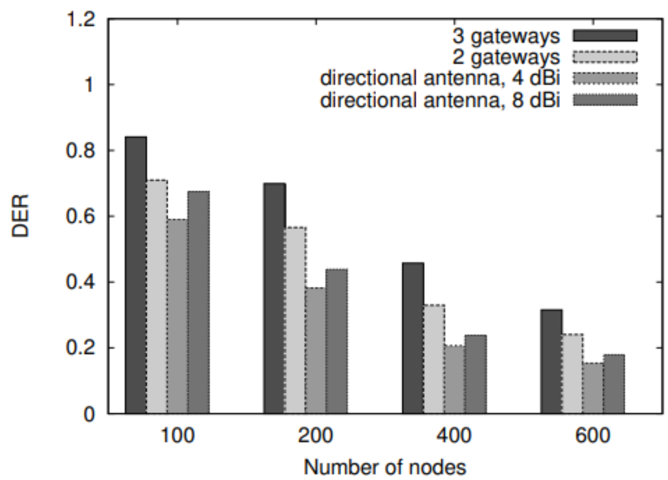

Figure 9: Data Extraction Rate vs Number of nodes (Voigt et al., 2016)

According to simulation, positioning multiple base stations is more effective than using directional antennae.
In (Anedda et al., 2018) authors proposed the energy efficient multi-hop solution over LPWAN by making the system more energy-efficient thus reduce interference The simulator OMNeT++ is used to obtain the results.In their model a smart node known as a LoRa Node (LN) can transmit data to another LoRa Node (LN) that is located nearer the access point, known as a LoRa gateway (LGW). The algorithm aims to find national LNs with a distance lower than the considered LN and LGW, resulting in energy-saving through a multi-hop data sending alternative solution. The algorithm evaluates neighbor LNs, calculates distances, compares distances, determines the best neighbor, and if available, uses the lowest distance dj for multi-hop.

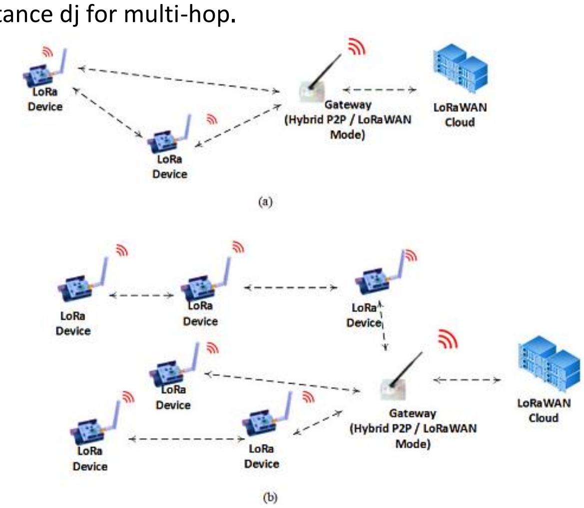

Figure 10: LoRaWAN system model (Anedda et al., 2018)

5 Interference Management in Unmanned Arial Vehicle (UAV)

UAVs have many interesting applications, including construction, agriculture, traffic monitoring, and emergency services (Alnakhli et al., 2024)(Mei & Zhang, 2019). However, in remote locations, they might present difficulties due to limited wireless infrastructure. UAVs can rapidly gather data, reach to different places, and complete tasks that would take a lot of time for humans. They are affordable, easily available, and productive. In addition to being used in the Internet of robotic things (IoRT) to construct autonomous robotic systems, UAVs are being investigated for wireless communications in remote places (Zhu et al., 2020) . In (Zhu et al., 2020), the authors proposed a system consisting of a source node and a destination node with a full-duplex UAV (FD-UAV) relay placed An alternating interference suppression (AIS) approach for the power control and beamforming vectors (BFVs) is proposed. The interference is gradually decreased as the beam gains for the (Source node) SN-to-UAV (S2V) and the UAV-to-DN (destination node) (V2D) links' target signals are alternately maximized in each iteration. They develop an equivalent optimization problem to maximize the achievable rate between the DN and the SN. The authors in (Ghavimi & Jantti, 2020) present study addresses an aerial-terrestrial cellular mobile network uplink system as shown in Figure 11. Every decision phase determines the minimum and maximum flight altitude, maximum velocity, and related BS for the UAV's trajectory. For wireless communication requirements, the position, target BS, resources, and transmit power of the UAV are determined at each time slot.

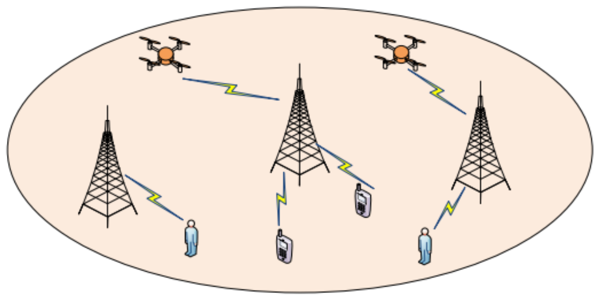

Figure 11: System model (Ghavimi & Jantti, 2020)

The algorithm purposes to optimize EE and SE for cellular users by minimizing interference and maximizing their energy usage. The suggested DQN architecture optimizes energy efficiency by functioning three layers: Input Layer, Hidden Layer, and Output Layer. Input Layer epitomizes user state, including distance, path-loss measurements, interference, and buffer queue size. Output Layer contains the number of neurons and actions specific to user aiming to maximize the reward function. The reward function considers EE, SE, and interference from users, defining a reward function for user k at time t (Ghavimi & Jantti, 2020):

$$r_k(t) = \sum_{t=1}^{T} \eta_e EE(t) + \sum_{t=1}^{T} \frac{\eta_s b(t)}{X(m,n,t,k)} + \sum_{t=1}^{T} \frac{\eta_f}{1+Int(t)}, \tag{12}$$

where η_e , η_s and η_f are weights verified from importance of the energy efficiency and spectral efficiency of aerial users, and the interference from aerial to terrestrial users, b(t) is the amount of information data to be transmitted by a UAV user, $X(m,n,t,k)$ is set of allocated resource blocks. The achieved results illustration that the proposed algorithm enhances energy efficiency and reducing interference from aerial users to terrestrial users.

The authors in (Singh et al., 2018) present distributed algorithms that enhanced inter-cell interference coordination (ICIC) and cell range expansion (CRE) techniques defined in 3GPP. They used system-wide 5th percentile spectral efficiency metric while the performance is enhancing using a deep Q-learning algorithm. The advanced architecture of deep Q network used is in Figure11; their activation function is the rectified linear unit (ReLU).

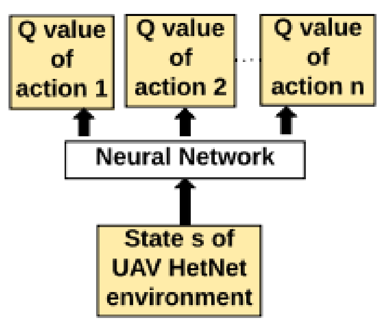

Figure 12: deep Q network architecture (Singh et al., 2018)

For obtaining the results, they assumed specific a neural network consideration as presented in Table 2.

Table 2: Neural network architecture (Singh et al., 2018)

Layer	Number of neurons	Activation
Input layer	Size of state space	ReLU
Full connected 1	24	ReLU
Full connected 2	24	ReLU
Output layer	Size of action space	Linear

In (Yajnanarayana et al., 2018) authors investigate power control mechanism that regulates the transmit power of uplink channels, ensuring they are received at the appropriate power level for demodulation and not excessively high for interference. They used Physical Uplink Shared Channel (PUSCH) as an example, which expressed as (Yajnanarayana et al., 2018):

$$P_{PUSCH}(i) = min\{P_{\ CMAX}\big(10log_{10}(M_{PUSCH}(i) + P_0 + \alpha PL + \Delta_{TF}(i) + f(i))\big)\} \quad (13)$$

Where:

- $P_{\ CMAX}$ is the configured maximum UE transmitting power in dBm.
- $M_{PUSCH}(i)$ is the bandwidth of the PUSCH resource assignment.
- P_0 is an open loop power control parameter in dBm.
- α is a fractional path loss compensation power control parameter.
- PL is the downlink pathloss estimate computed at the UE in dB.
- $\Delta_{TF}(i)$ is an offset which can be used to ensure that the received SINR matches the SINR required.
- $f(i)$ is the closed loop power control adjustment

The authors in (Abass et al., 2024) discusses the interference caused by untrained UAVs in their transmission in a multi-hop UAVs in the presence of jammer.

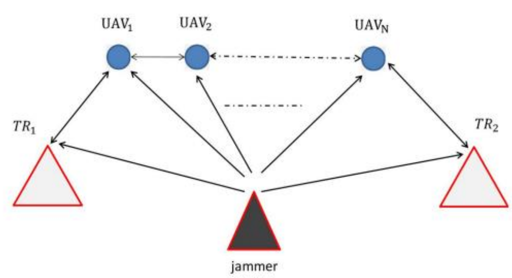

Figure 13: The proposed system model (Abass et al., 2024)

The downlink transmission is assumed to be jammable by an effective jammer, which would reduce the received SINR at ground stations. In response, relay-UAVs boost their transmission power; nevertheless, this causes inter-UAV interference, which lowers the SINR at ground stations. The paper models this by a game theoretic viewpoint, where players P and their strategies are captured by the set U. The game model makes the assumption that terrestrial base stations have the ability to adjust relaying UAVS power preferably to prevent mutual interference.

6 Conclusion

In conclusion, power control through interference management is critical for optimizing the performance and security of diverse networks, including D2D communications, LPWAN, healthcare systems, and UAV networks. Each of these networks presents unique challenges and requirements, necessitating tailored strategies for effective interference management. Current technologies, such as reinforcement learning and neural networks, are at the forefront of developing sophisticated power control mechanisms. These technologies enable adaptive and intelligent interference management by learning from the network environment and dynamically adjusting power levels to mitigate interference. In D2D networks, efficient power control reduces interference and enhances connectivity, enabling more reliable and high-capacity communication. LPWANs, characterized by their long-range and low-power communication, benefit significantly from adaptive power control strategies that balance energy consumption with interference minimization. This ensures prolonged device operation and reliable data transmission, critical for IoT applications relying on these networks. Healthcare systems, which demand high reliability and low latency, require stringent interference management to maintain the integrity and timeliness of critical data transmission. Power control mechanisms tailored for medical environments, supported by neural networks, can reduce electromagnetic interference, ensuring that vital health monitoring and diagnostic systems operate without disruption. For UAV networks, power control is essential for maintaining stable communication links, especially in dynamic and mobile environments. Effective interference management strategies enable UAVs to perform coordinated tasks. The scope of this investigation encompasses the examination of current and emerging power control strategies in various network types, with the aim of identifying effective methods for interference management. Key research directions include further integration of machine learning and artificial intelligence to create adaptive and context-aware interference management systems. By addressing the specific needs and challenges of each network, future research can ensure robust communication infrastructures that support the growing demands of modern applications and technologies. The continuous development and implementation of these sophisticated power control techniques are imperative for advancing the reliability, efficiency, and security of these diverse network types.

7 References

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