Performance of TVWS-based LoRa Transmissions using Multi-Armed Bandit

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Abstract *– Low Power Wide Area Networks (LPWANs) support long-range communication that suits them for varied IoT applications such as asset tracking, environmental monitoring, agricultural management, work site monitoring, fleet management, and smart cities. Even with the large number of connected devices, LPWANs are more power efficient than traditional IoT networks. Long Range (LoRa) is a noteworthy LPWAN technology that employs the ISM band, which experiences congestion due to the growing IoT and smart network applications. LoRa networks can utilize the available TV white spaces to overcome the congestion problem. Performance enhancement of the LoRa network in terms of energy efficiency is a significant concern. This paper proposes, for the first time, Multi-Armed Bandit (MAB) to improve the performance of the LoRa network using TVWS. We have developed a novel algorithm, LoRaT-MAB, for TVWS-based LoRa, and results show that the mean rewards increase by about 12.5% over conventional LoRa and the energy consumption for TVWS-based LoRa using LoRaT-MAB decreases by about 11.7% over conventional LoRa. The findings are encouraging and provide a basis for further research on the TVWS-based LoRa and other IoT applications.*

Keywords: *Internet of Things, LPWANs, LoRa, TV White Spaces, Multi-Armed Bandit, UCB*

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1. INTRODUCTION

The Internet is still expanding due to advancements in wireless and mobile technology. The rapid and easy adoption of the Internet of Things (IoT), thanks to the emerging new technologies, has changed the way we live and work. Low Power Wide Area Networks (LPWAN) are a leading network paradigm for IoT as they support range connectivity for tiny edge nodes with lower power and cost than conventional wireless networks. LPWANs provide scalability and can accommodate the varied IoT requirements, enabling applications including smart metering, smart homes, and smart cities, tracking and monitoring applications such as wildlife, agriculture, industrial assets, infrastructure, and so on. Long Range (LoRa), Weightless-N, Weightless-P, SigFox, SNOW, IQRF, DASH7, RPMA, NB-IoT, and 5G are some of the LPWAN technologies. Semtech's LoRa LPWAN technology enables low power, low throughput, and long-range communication. It employs spread spectrum modulation at the physical layer, which improves link budget and interference resistance. It also takes advantage of Forward Error Correction (FEC). It functions in the 433, 868, or 915 MHz Industrial, Scientific, and

Medical (ISM) band. It employs Chirp Spread Spectrum (CSS) modulation with quasi-orthogonal spreading factors and supports up to 50 kbps data rate [1].

With the expansion of wireless applications and due to the restricted availability, fixed resource allocation techniques are unable to meet the growing demand of frequency spectrum from the expansion. With cognitive radio, underutilized TV bands and TV White Spaces (TVWS) may be made available for these kinds of applications. Without interfering with the primary licensed users' ability to communicate, cognitive radio makes it easier for secondary, unlicensed users to take advantage of the unused licensed bands. The White Space Devices (WSD) identify and use the unoccupied spectrum using spectrum sensing. These days, a lot of applications using 2.4 GHz ISM protocols, such as Wi-Fi, Bluetooth, and others, are prevalent, particularly in indoor and urban environments. Herein, the data rate and Quality of Service (quality of service) are affected by interference and coexistence. Using the 5 GHz range for indoor communication raises the issue of fading brought on by obstructions. For such scenarios, TVWS can be used instead. Compared to the ISM band, the VHF and UHF bands show superior signal propagation and greater obstacle penetration.

Various TVWS applications have been researched in the last few years. Regulations governing the maximum duty cycle in the unlicensed ISM bands have a significant im-pact on network capacity. Performance is affected when node density is high. According to studies in [2], using TVWS for LPWAN may lessen co-existence and interference problems. One potential solution for LPWANs operating in the unlicensed yet restricted spectrum is to employ non-ISM spectrum, including whitespaces [3]. Using whitespaces for LPWAN can significantly minimize ISM band conflict, even if it could require improved time synchronization, listen-before-talk functionality, and channel information transmission. Since available spectrum is limited and unlicensed spectrum is susceptible to interference, TVWS offers an excellent alternative to LPWANs. Studies have shown that current LPWAN technologies face challenges such as coexistence, coverage, lack of spectrum, mobility, scalability, and security. As LPWAN drives the visibly growing IoT domain, addressing these issues is imperative. The unlicensed ISM band is commonly used in most current LPWAN solutions. Access to this frequency range is not controlled at the global level except by duty cycle guidelines. An available TVWS can be used to deal with interference, coexistence, and scalability issues in LPWAN networks.

A LoRa-based LPWAN is constructed using stars topology and consists of several nodes that use the CSS modulation technique and the LoRaWAN MAC layer protocol to communicate with a gateway. The gateways send packets received from end devices to the network server [4]. Transmission channels, spreading factors, transmit power, channel bandwidth, and transmission rate are the essential parameters that can be customized with LoRa modulation. The network's overall performance, coverage, capacity, time-on-air, transmission energy, and range are all impacted by the selection of these parameters [5]. One of the six spreading factors and an available subchannel are used by the end devices to communicate with the gateway. When multiple devices use the same channel and spreading factor at the same time, a collision could happen. The likelihood of a collision increases as the number of end devices in the network increases, which leads to a decline in network performance. In this situation, choosing the best parameters to reduce interference and increase energy efficiency may be done using machine learning techniques, which will ultimately improve network performance [6]. Adaptive transmission and efficient resource use are the two strategies for improving low power IoT energy efficiency [7].

In LoRa networks, resource distribution and parameter selection can be done via centralized or distributed methods. Devices have two options: either they allow the network to control the transmission power and data rate, or they take control themselves. The network server manages the end node's transmission parameters. By adjusting the data rate, it lowers a node's transmit power. In this scenario, the network needs to know the node's transmitted power for roughly the last twenty transmissions. It then adjusts the data rate to estimate the transmit power for the upcoming transmission and sends it to the node. The node then modifies its parameters based on the data it receives from the server. This approach's drawback is that it can only be used in stable radio frequency scenarios in which the end nodes remain stationary [4]. In practice, the end node can be mobile, and hence, for the low-complex network with uniformly distributed nodes, considering a single frequency channel and uniform transmit power, the best parameter selection is still challenging.

Additionally, the adaptive data rate approach has certain drawbacks where it as-signs SF to a node based on the uplink signal-to-noise ratio (lower SF for the nodes close to the gateway and higher SF for nodes away from the gateway). ADR may assign the same SF to all nodes that are closer together, which could result in collisions from using one SF more and not using the other SFs [8]. ADR also tends to use less energy but has significant packet losses [5]. In such situations, distributed learning algorithms could be employed so that the edge nodes can select the best parameters for enhancing the performance.

The aim is to optimize energy efficiency and reduce interference at the edge nodes of LoRa-LPWANs that use the TVWS band for transmissions. These two LoRa network performance metrics are affected by the selection of the spreading factor. The network performance is also influenced by several other factors, including channel frequency, bandwidth, coding rate, and transmission power. Multi-Armed Bandit (MAB) is reinforcement learning algorithms that conform to such a structure. A new strategy employing the MAB algorithms is proposed to achieve energy efficiency in this work.

The significant contributions of this work are as given. First is the use of licensed TVWS for LoRa transmissions in contrast to the typical use of the unlicensed spectrum to avoid possible congestion and improve LoRa network performance. Second is the use of MAB algorithm such as DUCB for TVWS-based LoRa is experimented first time in this work, as per our literature study. The third contribution is that we have also developed a novel algorithm, LoRaT-PLM, based on MAB, for the use of TVWS in LoRa, which demonstrates improved performance and enhanced energy efficiency.

The structure of the paper is as follows. Section 2 discusses the relevant works. A brief description of LoRa technology and TVWS is given in Section 3. In Section 4, a novel policy for TVWS-based LoRa using MAB algorithms is proposed. In Section 5, simulations conducted and results obtained are discussed, and Section 6 presents the conclusions.

2. RELATED WORK

Different approaches for the selection of transmission parameters that boost energy efficiency and enhance performance for IoT and LoRa-based LPWANs are being studied and investigated. There are roughly 6720 possible configurations for a LoRa device based on the different transmit power levels, coding rates (CR), spreading factors (SFs), and bandwidths that can be used. As a result, choosing the optimal course of action to maximize network performance is extremely difficult. The technique developed by [9] examines the link and effectively decides a suitable transmission parameter value. The method performs channel estimation based on the data extraction rate and modifies the spreading factor to adapt to the changing channel. In dense networks, experiments show that the suggested scheme outperforms other spreading factor provisioning strategies in terms of capacity and reliability [10]. Utilizing the K-means clustering algorithm for LoRa SF al-location offers added flexibility, enhancing coverage likelihood and enabling uniform resource distribution [11].

Allocating resources at the end node through decentralized learning is an intriguing strategy [12]. To improve energy efficiency and reliability, the end device can choose various parameters for each packet transmission, including sub-channel, spreading factor, transmission power, and others. This method focuses on applying MAB algorithms. To lessen collisions with other nodes, the first application of learning algorithms on LoRa network devices is suggested. The MAB-based upper confidence bound (UCB) algorithm is used for channel selection in LoRa, and the experimental results show that it is possible to double the device's battery life with less memory and processing requirement and achieve better outcomes as compared to random selection. These algorithms are lightweight and can be used to avoid interference coming from other gateways. MAB-based GNU radio implementation also illustrates how such approaches help improve network connectivity [13]. It suggests that both the UCB1 as well as TS are effective and attain convergence quickly in stationary environments; UCB1 learns more quickly than TS, while TS provides slightly superior average performance. If the end nodes in a network are based on learning algorithms, it is possible to accommodate more nodes. Recent works also analyze TS and UCB1 in conjunction with a time and frequency slotted ALOHA, validating an increase in packet delivery ratio even in non-stationary scenarios [14].

The EXP3 algorithm takes into account inter-spreading factor collision, and adversarial MABs are used in the design of a simulator for allocating the resources in LoRa-based LPWANs [15] and improving the overall performance. The EXP3 algorithm's lengthy convergence time is one of its limitations. Compared to EXP3, the improved version, the EXP3.S algorithm, requires less convergence time and is computationally efficient. It performs well for the non-uniform distribution of devices, but the convergence rate might become worse as the number of parameters increases [16].

Reinforcement learning-based resource management techniques that take into account the channel and energy correlation are also developed that exhibit improved energy efficiency [17]. As dense LoRa network deployments experience more packet collisions, a deep reinforcement learning-based transmission parameter assignment algorithm for LoRaWAN is proposed that demonstrates an enhanced packet delivery ratio [18]. A multi-agent cooperative Q-learning approach for resource allocation in LoRa networks demonstrates an improved packet delivery ratio and reduces energy consumption in a deep reinforcement learning-based PHY layer transmission parameter assignment algorithm for LoRaWAN [19]. A multi-agent Q-learning algorithm for dynamic allocation uplink power and SF in LoRa is designed to decrease the power requirement and improve reliability giving an advantage for signal-to-interference noise ratio (SINR) and data rate [20].

Several studies have suggested employing stochastic and adversarial-based distributed learning like updated UCB (UUCB) and its variations, along with updated EXP3 (UEXP3), to fine-tune the communication parameters of devices according to the surrounding conditions. The simulations yield encouraging results for enhancing low-power IoT networks' dependability and energy efficiency [6]. In recent times, scholars have also investigated the UCB for channel selection and various retransmission strategies based on UCB. The technique is equally efficient and raises the transmission rate in dense networks [21].

LoRa specifies the centralized adaptive data rate (ADR) algorithm. The studies show that various MAB algorithms perform better in terms of energy consumption and packet loss than the conventional ADR algorithm. From a cognitive radio (CR) perspective, MAB learning algorithms are also being studied for spectrum sensing and MAC perspectives. To improve detection efficiency in varying scenarios, a discounted UCB algorithm is proposed for cooperative spectrum sensing [22]. In terms of energy transmission, the results demonstrate higher throughput when compared to the current ADR method [23]. DUCB policy for frequency band selection in a non-stationary CR is also studied, and according to the application requirements, discount functions and exploration bonuses are taken into account; as a result, the policy offers reduced regret [24]. In one of our previous works, new discount functions and exploration bonuses for DUCB were developed to meet LoRa requirements. In comparison to other existing algorithms, the developed algorithm exhibits superior performance and lower complexity [25].

MAB has been used in literature for various wireless network applications for dynamic spectrum access, and modified algorithms have also been proposed. In [26], the authors investigate a dynamic spectrum access problem as a budget-constrained MAB. A modified UCB-MAB algorithm is proposed for dynamic spectrum access and transmission power selection for data rate maximization, resulting in improved performance. Two Thompson sampling-based methods that detect the channel variations and adjust the channel access policy for dynamic spectrum access are suggested [27]. The methods proposed do not consider any information exchange between the end nodes but display a better success rate. A deep learning-based approach for CR results in improved channel access success probability and reduced interference probability [28]. Implementation of UCB-based Reinforcement Learning (RL) algorithm for opportunistic spectrum access on real radio environment using USRP N210 platforms is demonstrated [29]. The UCB algorithm favors the best solution and converges faster, validating the use of RL for dynamic spectrum access. A new approach to a non-stationary MAB problem that uses the predictive abilities of a Large Language Model (LLM) to guide the decision-making process is introduced [30]. Conventional bandit strategies such as epsilon greedy and UCB struggle in case of dynamic variations. An LLM-informed policy that provides guidance dynamically exhibits improved performance. Wireless networks are emerging as self-evolving networks where the use of Generative AI (GenAI) can be beneficial. LLMs, a subfield of GenAI promise to facilitate autonomous wireless networks. A large model trained over various network data can be adapted to accomplish tasks, thus leading to what can be termed artificial general intelligence-enabled wireless networks. The fast growth of LLM offers vast opportunities for network optimization and management in future networks [31]. A TVWS database with a prediction feature that is suitable for different TV frequencies is suggested. It forecasts TVWS availability using RL depending on the time, day, location, and device [32]. Studies show that there are several tools employing geo-location spectrum databases to estimate and guide the TVWS availability to promote efficient radio frequency utilization and dynamic spectrum access [33].

In summary, there are databases available that provide information about the TVWS at a particular location and time. MAB algorithms are shown to perform better for parameter selection in LoRa networks. TVWS database can be exploited in an LLM-like manner along with MAB for parameter selection with additional channels, giving the advantage of faster learning and enhanced success rate. We used a combination of an informed strategy along with the developed UCB-P-1/2+O MAB algorithm [25] for parameter selection in TVWS-based LoRa.

3. LORA, TV WHITE SPACES AND MAB

3.1. LORA TECHNOLOGY

LoRa employs the low-power CSS modulation technique [9] and LoRaWAN medium access control (MAC) [4]. LoRa can operate over different frequency ranges [34]. Although it typically utilizes unlicensed ISM bands like 433 MHz, 868 MHz, and 915 MHz, it operates in licensed bands as well [35]. The packets transmitted by an end node can be received by several gateways in the neighborhood, as shown in Fig. 1.

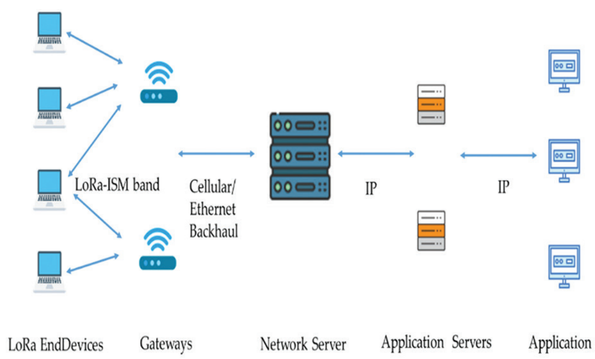

Fig. 1. LoRa Network Architecture

Every gateway uses a backhaul (either satellite, cellular, Ethernet, or Wi-Fi) to forward the packets to the network server for handling sophisticated and intricate tasks like adaptive data rates, sending acknowledgments via the appropriate gateway, and eliminating unnecessary packets. The LoRa network's asynchronous nodes only communicate utilizing pure ALOHA. The number of channels, data rate, and frequency of transmission by the nodes all affect capacity. Variations in the data rate and orthogonal signals are caused by various spreading factors. As a result, the gateway can receive several packets with different data rates on the same channel concurrently [4, 36]. There are also other options being investigated to improve coverage with minimal interference [37].

Different parameters, including SF, CR, transmit power, frequency, and channel bandwidth, can be set for any LoRa device [10]. According to the rules, transmission power can be adjusted roughly in steps of 1 dB, ranging from 2 dBm to 17 dBm. A higher spreading factor corresponds to increased SNR, sensitivity, range, and packet airtime. Spreading factor is defined as the ratio of symbol rate to chip rate. Any value between 7 and 12 can be chosen for SF [36]. A bandwidth of 125 kHz, 250 kHz, or 500 kHz is typically used by LoRa networks. A larger bandwidth increases data rate but at the expense of decreased sensitivity. Forward error correction (FEC) is used by the LoRa modem, and its coding rate can be adjusted to 4/5, 4/6, 4/7, or 4/8. Although it lengthens time on air, a higher coding rate improves error prevention. For transmission, a LoRa packet consumes an average amount of energy, as given by

$$\boldsymbol{E_{avg}} \cdot \!=\! \cdot \boldsymbol{P_t T_{pkt} N_p} \tag{1}$$

where P_t is transmit power, T_{pkt} is transmission time, and N_p is per packet transmissions required for successful transmission. T_{pkt} depends on SF [36]; thus, selecting optimal SF can facilitate optimal energy consumption. If the SINR at the desired LoRa node is higher than the receiver sensitivity for a given SF, a signal is detected at the gateway. The signal power must be high, and the interference power must be low for a high SINR value. It is implied by the above equations that when SF rises, sensitivity improves, and a lower SINR is needed. Time on Air (ToA) or packet time, average energy, and throughput are likewise low for lower SF. The likelihood of a successful transmission decreases as the size of the network grows because there are more devices with the same SF. Achieving energy efficiency and interference avoidance are always trade-offs.

3.2. TV WHITE SPACES

TVWS includes free bands at different times and some TV broadcast frequency bands that are unutilized as a result of TV services being digitalized. TVWS's lower frequency ranges (50–698 MHz) are better at passing through obstructions and are, therefore, less susceptible to fading as well as multipath, allowing for indoor and other applications [35]. Because TVWS offers much bandwidth, it can also support several high-bit-rate applications. Sufficient TVWS may be generally accessible, in contrast to ISM bands, particularly in rural areas, because of the small number of broadcast stations [38, 39]. TVWS presents a promising option for numerous critical indoor and outdoor wireless applications due to its superior indoor penetration, higher spectral efficiency, and good propagation characteristics. Applications requiring a broad transmission range could use TVWS. The Indian government has granted experimental licenses in the 470–590 MHz band, unlocking the possibility of using the TVWS spectrum. Numerous TVWS applications for home networks, smart metering, WLAN, and rural wireless broadband access are demonstrated by literature reviews. For LPWAN, several hardware and software platforms operate over different frequency ranges [35]. Presently, LoRa transceivers for 137 MHz to 1020 MHz frequency bands (*Semtech SX126** and *SX127** series) are available [36]. We have investigated the use of TVWS frequencies, primarily the licensed bands for LoRa, using MAB for optimal parameter selection.

3.3. MULTI-ARMED BANDIT ALGORITHM

Multi-armed bandit is a reinforcement learning structure where an agent must choose arms or actions to maximize its cumulative reward. The end device must choose SF or a strategy $s(t) = \{SFs\}$ from the provided set of SFs. The devices are unaware of their location or the state of the channel. Therefore, any SF that is a part of the set, $s \in S$ may be chosen by the device. Each end device selects a strategy $s(t)$ at each packet arrival time t based on a specific distribution over S, yielding a reward of $rs(t) \in \{0, 1\}$. The transmission may be successful or unsuccessful after the device transmits a packet after choosing a specific value for SF. The LoRa gateway notifies the device of its successful packet reception by sending an acknowledgment. The selection of SF that leads to a successful transmission and receipt of acknowledgment can be modeled as the reward, while SF value can be modeled as the arm or action. It is apparent that the end device receives a reward of 1 if it receives an acknowledgment; otherwise, the reward is 0. The end device chooses an optimal value of SF based only on locally available information, i.e., the received acknowledgment, and experiences the fewest collisions. Since the end nodes are dynamic, it is possible to model the SF selection problem as a non-stationary MAB problem.

Discounted UCB for LoRa:

Stochastic MAB algorithms such as TS and UCB are applicable for stationary distribution scenarios, whereas the advanced DUCB algorithm is suitable for a non-stationary problem. By using an appropriate discount factor, the UCB algorithm can be modified to suit a non-stationary problem. This is the idea behind the Discounted UCB algorithm. The discount factor gives more weightage to the most recent plays and averages past rewards in the DUCB policy. This approach fits the time-varying wireless environment. Therefore, the DUCB policy can also be optimized by modifying the discount factor and exploration bonus to adapt to the varying and complex LoRa network environment. The DUCB algorithm core index $U_k(t)$ is given as

$$\boldsymbol{U_k(t) = \ X_k(t) \ + \ B_k(t)} \tag{2}$$

$X_k(t)$ is the discounted average for exploitation, $B_k(t)$ is the exploration bonus [24]. If the discount function is a power function that is defined as $f(x)=\gamma^x$, then the term $X_k(t)$ can be written as

$$\boldsymbol{X_k(t) = \frac{\sum_{s=1}^{t} \gamma^{t-s} X_t^k 1_{i_s=i}}{\sum_{s=1}^{t} \gamma^{t-s} 1_{i_s=i}}} \tag{3}$$

Here, $X_k(t)$ gives the average reward of action k at time step t, s is the sample, B is the upper bound, γ^{t-s} denotes the discount function, 1_{i_s} is the indicator function with value 1 if true and 0 if false. The $B_k(t)$ can be written as

$$B_k(t) = 2\mathbf{B}\sqrt{\frac{\xi\,(\log \sum_{i=1}^{k} Ni(t))}{N_k(t)}} \tag{4}$$

where N is the maximum number of trials, i is the index of actions, X_k is the average reward for action k, N_k is number of times action k is chosen, ξ is the bias parameter. $N_k(t)$ is given as

$$N_k(t) = \sum_{s=1}^{t} \gamma^{t-s} \mathbf{1}_{i_s=i} \tag{5}$$

Multi-armed bandit algorithms such as DUCB can be modified to suit the LoRa networks.

4. MAB ALGORITHM FOR TVWS-BASED LORA

The use of MAB algorithms such as modified Discounted Upper Confidence Bound for LoRa using TVWS bands is discussed below subsections.

4.1. UCB-P-1/2+O ALGORITHM FOR LORA

In our previous work, an exhaustive study related to DUCB for LoRa is carried out and a modified DUCB policy for LoRa, UCB-P-1/2+O is proposed [26]. The core index of this policy is as given.

$$U_k(t) = X_k(t) + \mathbf{0.5}\sqrt{\frac{(X_k(t) - X_k(t)^2)}{N_k(t)}} \tag{6}$$

where $X_k(t)$ is the discounted average with the discount function as $[(N\text{-}x)/N]^{1/2}$. Fig. 2 illustrates the flowchart of the developed UCB-P-1/2+O policy, which is utilized by an intelligent node to choose the SF.

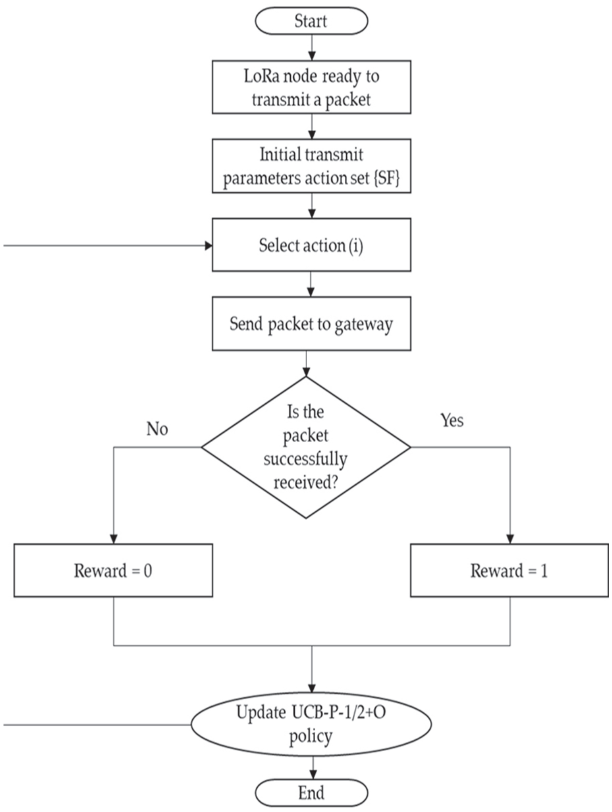

Fig. 2. Flowchart of UCB-P-1/2+O Policy

The node first chooses any SF value from $\{SF\}$ to transmit a packet. The reward is equal to one if a packet is successfully received at the gateway, which sends an acknowledgment. If the packet is not received successfully, the reward is equal to zero and there is no acknowledgment. The UCB-P-1/2+O policy is therefore updated, and the subsequent selection is carried out as per the revised policy.

4.2. LORA OVER TVWS – PATH LOSS MODEL (LORAT-PLM)

The received signal strength varies as a result of hills, trees, buildings, and other similar objects standing between the transmitter and the receiver; this phenomenon is known as shadowing. This effect is seen in wireless networks and TV broadcasts, and it must be taken into account when determining the appropriate transmission power by adding a margin. A hybrid path loss model for LoRa transmissions over TVWS frequencies is developed after a thorough literature review and analysis of the results of various existing path loss models for TV and LoRa transmissions [39]. Based on the Okumura Hata model, the proposed LoRa over TVWS – Path Loss Model (LoRaT-PLM) takes shadow fading into account as given. For urban settings

$$L_u = 69.5 + 26.16\,log_{10}\,f - 13.82\,log_{10}h_B - C_H + [44.9 - 6.55\,log_{10}h_B]\,log_{10}\,d + C_s \tag{7}$$

where L_u is the path loss in urban regions (dB), f is the transmission frequency (MHz), h_B is the base station antenna height (m), h_M is the mobile station antenna height (m), C_H is a factor for antenna height correction, d is the distance between the transmitter and receiver in kilometers. For rural settings

$$L_0 = L_u - 4.78(log_{10}f)^2 + 18.33(log_{10}f) - 40.94 + Cs \tag{8}$$

where L_o is the path loss in open regions (dB), L_u is the average path loss from a small city form of the model (dB), and f is the transmission frequency in MHz. In (7) and (8), shadow fading is taken into account by the newly designed C_s, a correction factor with a log-normal distribution. When there is an obstruction in the line of sight, when one turns a corner, passes behind a large building, or enters a building, shadow fading can be experienced. The C_s for urban settings would be higher than those for rural ones because these cases are more frequent in urban settings than in rural ones.

4.3. LORAT- MAB ALGORITHM

We developed a modified MAB algorithm, UCB P-1/2+O algorithm, for parameter selection in a LoRa network [24]. The developed algorithm is analyzed for SF selection and gives better performance in terms of mean rewards and execution time. In terms of energy cost, the algorithm demonstrates enhanced energy efficiency as compared to other algorithms. This algorithm is designed and the analysis is carried out in the context of LoRa operating in the 867 MHz frequency band in India. The use of 470 - 590 MHz TVWS bands, specifically in the Indian context for LoRa, is further investigated by using the developed LoRaT-PLM model [39]. It is demonstrated that TVWS-based LoRa performs better for path loss, energy consumption, and uplink delivery rate. Both the proposed approaches (MAB and TVWS) utilize different techniques for energy efficiency, be it parameter selection or the use of TVWS. The rationale is to combine the two approaches to get the advantages of both. It has been shown previously that the UCB P-½+O algorithm for LoRa at ISM bands performs better than conventional LoRa. Performance analysis of UCB P-½+O algorithm for LoRa at 470 MHz (TVWS) is carried out and compared with the conventional LoRa at ISM band for mean rewards and energy consumption. It is observed that the UCB P-½+O algorithm for LoRa at 470 MHz (TVWS) gives better rewards and the energy consumption is less as compared to the conventional LoRa at the ISM band. This corroborates the use of the UCB P-½+O algorithm for LoRa at TVWS frequencies.

LoRaT-MAB algorithm uses the core index of the UCB-P-½ +O algorithm. It works on the strategy of explore and exploit. The additional information on TVWS availability can be obtained from an authorized database. This information is used by the LoRaT-MAB algorithm to exploit the available channels, thus reducing the exploration requirements. The developed UCB-P-½+O algorithm, as given in (6), has the core index, which is derived from the standard DUCB policy as given in (2). It consists of the addition of two terms: $X_k(t)$, which decides the exploitation of the action depending on the discounted averages, and $Bk(t)$, which decides the exploration of actions done by the policy. Based on this, a novel algorithm is proposed that exploits the database-assisted information effectively to its benefit. This presents an important contribution as a new method to assist the decision-making process of complex stochastic MAB problems. This type of decision-making can adapt to the changing rewards and their distribution patterns and perform better in a non-stationary scenario. This approach can ensure better selection by the algorithm, which will finally lead to improved performance [31]. The strategy to select the transmit parameters can be defined as explore or exploit according to the MAB concept as Strategy $S = \{explore, exploit\}$. The strategy to explore or exploit as decided by the UCB-P-½+O algorithm is S_{actual}. The strategy to explore or exploit according to the information from the TVWS database is Sinformed. The decision D to explore or exploit is made by the LoRaT-MAB algorithm, depending on the strategies S_{actual} and $S_{informed}$, given as

$Decision\ D(S_{actual}, S_{informed})=$

{*'exploit'*, if both S_{actual} and $S_{informed}$ are *'exploit'*}

Or {*'explore'*, if S_{actual} &/ or $S_{informed}$ are *'explore'*}

The flowchart of the developed LoRaT-MAB algorithm is illustrated in Fig. 3.

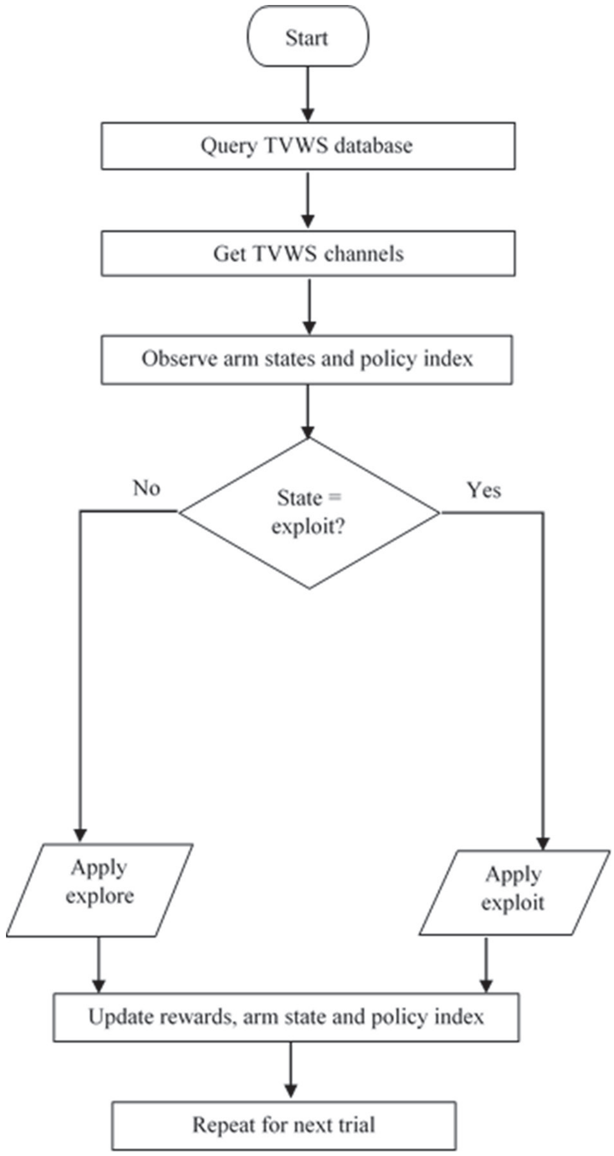

Fig. 3. Flowchart of LoRaT-MAB Algorithm

The important steps of LoRaT-MAB algorithm are as given. At first, a query to the TVWS database is made. The database provides information about TVWS availability. The MAB policy state and the arm states are observed, and then it is verified whether the channel selected by the UCB-P-½+O MAB algorithm is free or busy and whether it should be used at that time instant or not. Depending on the data from the TVWS database, the channel is exploited if free; if the state is exploiting. Otherwise, a new channel is explored. The process is repeated for the subsequent trial.

5. RESULTS AND DISCUSSION

This section presents the performance analysis of the proposed LoRaT-MAB algorithm for LoRa at 470 MHz (TVWS) and a comparison with the UCB-P-½+O algorithm and conventional LoRa using the Random Selection (RS) method. Table 1 lists the various simulation parameters and their settings. All the methods compared consider the selection of SF as the primary

LoRa transmit parameter for selection. Uplink delivery rate (UDR) is the percentage of packets correctly received at the gateway. The simulations also consider the designed LoRaT-PLM path loss model and it shows an improved uplink delivery rate [37, 39]. Results show that LoRaT-MAB gives better rewards, better success rate, and lower energy consumption.

Table 1. Simulation Parameters for TVWS-based LoRa

Parameters	Values
End Devices	5
Area Radius	1 km
Bandwidth	125 kHz
Preamble Symbols	8
Packet Length	11
Header Disabled (H)	1
Data Rate Optimization Disabled (D)	0
Coding Rate	4/5

To investigate the performance of TVWS-based LoRa using the LoRaT-MAB algorithm, LoRa transmissions are simulated using 470 MHz transmission frequency. The results are compared with the performance of TVWS-based LoRa using 470 MHz frequency and UCB-P-½+O algorithm, as well as conventional LoRa using ISM band transmission frequency. Fig. 4 shows the mean rewards per device in a multiple intelligent node scenario as a function of a number of trials.

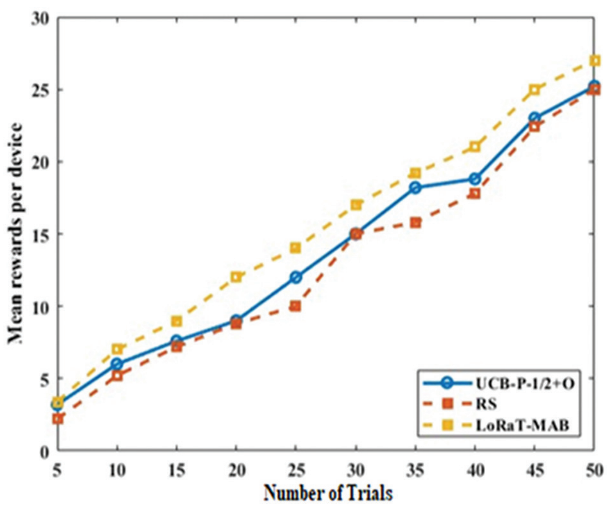

Fig. 4. Mean Rewards vs. Number of Trials for LoRa with LoRaT-MAB and UCB-P-½+O, and Conventional LoRa

The results in Fig. 4 show that TVWS-based LoRa using the LoRaT-MAB algorithm gives better mean rewards per device than TVWS-based LoRa using the UCB-P-½+O algorithm and the conventional LoRa using the ISM band. It is also observed that as the number of trials increases, the mean rewards also increase, as expected. For example, the mean rewards for TVWS-based LoRa using LoRaT-MAB increase by about 12.5% over conventional LoRa and 8.3% over TVWS-based LoRa using UCB-P-½+O for 50 trials. It is also seen that the proposed LoRaT-MAB algorithm gives consistent rewards and outperforms the other two methods. Fig. 5 depicts the changes in average energy consumption for TVWS-based LoRa using the LoRaT-MAB algorithm. It is seen that when the LoRaT-MAB algorithm is applied for TVWS LoRa, it results in lesser energy consumption than TVWS LoRa employing the UCB-P-½+O algorithm and also the conventional LoRa using the ISM band. For example, the energy consumption for TVWS-based LoRa using LoRaT-MAB decreases by about 11.7% over conventional LoRa and 5.8% over TVWS-based LoRa using UCB-P-½+O for 50 trials. It is also seen that the proposed LoRaT-MAB algorithm consistently demonstrates less energy consumption and outperforms the other two methods.

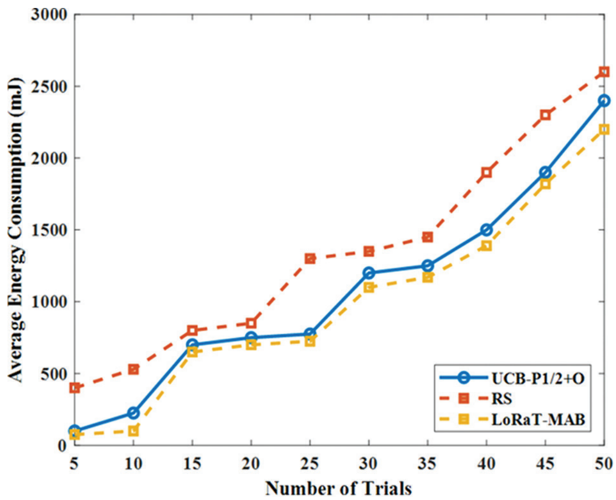

Fig. 5. Average Energy Consumption for LoRa with LoRaT-MAB and UCB-P-½+O, and Conventional LoRa

The consistent and enhanced performance of the proposed LoRaT-MAB algorithm can be attributed to the fact that the algorithm benefits both the MAB and the TVWS database. The database query reduces unnecessary explorations and exploitations. Thus, this additional input from the TVWS database ensures that the decision to exploit or explore is more tolerant and robust to the non-stationary wireless channel environment.

The analysis discussed in the previous sections is carried out for conventional LoRa using ISM band and TVWS-based LoRa using UCB-P-½+O and LoRaT-PLM algorithms separately. Instead of being executed separately, these methodologies can be combined. This would enable the LoRa end device to operate in the ISM band and TVWS band. Initially, the LoRa device would work in the ISM band using the UCB-P-½+O algorithm. If the ISM band is occupied and the selected transmit parameters yield lesser rewards than the required threshold, the transmissions would shift to the TVWS frequencies according to the LoRaT-PLM algorithm. In case the TVWS band operations also yield lesser rewards than the required threshold, the system will reset and repeat the process. The entire procedure is repeated for further trials. A combination of the methodologies, such as making use of ISM and TVWS band channels and MAB algorithms, may increase the probability of successful transmissions, thus improving energy efficiency and network performance.

6. CONCLUSIONS

To improve the energy efficiency in LoRa along with the network performance, the UCB-P-½+O algorithm has been developed and investigated for ISM band LoRa. It is employed on TVWS-based LoRa transmissions and exhibits improved performance compared to other studied methods. TVWS is beneficial in terms of interference avoidance, reduced path loss, and reduced energy consumption for LoRa networks. These approaches are combined, and a modified MAB algorithm is developed, the LoRaT-MAB algorithm. Simulation results validate the enhanced performance of the LoRaT-MAB algorithm for TVWS-based LoRa transmissions. The methods are compared for the selection of SF as the transmit parameter and can be easily extended for multiple parameter selection. LoRaT-MAB also takes into account the channel frequency selection and displays better performance in terms of rewards obtained and energy consumption. Further, work can be carried out for the selection of multiple parameters simultaneously to increase the network performance. The findings serve as a foundation for future study of MAB-based algorithms, TVWS-based LoRa, and the use of such techniques for other machine-to-machine and 6G applications.

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