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Alexander Valach

Dissertation Thesis Abstract

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Submitter: Alexander Valach
Institute of Computer Engineering and Applied Informatics
Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava

Supervisor: Prof. Pavel Čičák
Institute of Computer Engineering and Applied Informatics
Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava

Consultant: Assoc. Prof. Dominik Macko
Institute of Computer Engineering and Applied Informatics
Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava

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Prof. Ing. Ivan Kotuliak, PhD.

Dean of FIIT STU in Bratislava

Abstrakt

S narastajúcim počtom koncových zariadení v sieťach Internetu vecí (IoT) vzniká potreba vytvoriť škálovateľné riešení a vysokou mierou adaptácie. Výskumy v oblasti nízko-energetických široko-oblastných sietí ukázali, že decentralizovaný prístup s využitím strojového učenia ľahko prekonáva centralizované riešenia a predstavuje aktuálne smerovanie vývoja technológií.

Technológia LoRa je vhodnou alternatívou pre mobilné uzly, ale chýba jej potenciál nie je naplnený bez spoľahlivých mechanizmov na adaptáciu uzlov na zmeny v sieti a efektívne nastavenie komunikačných parametrov s cieľom minimalizovať stratovosť paketov a maximalizovať spoľahlivosť siete. S tým je spojený problém spotreby energie, ktorú je potrebné dôkladne preskúmať, aby boli uzly schopné konkurovať existujúcim riešeniam, pretože existuje dopyt po zariadeniach IoT, ktoré môžu byť napájané niekoľko rokov na jednej batérii.

Táto dizertačná práca sa zaoberá súčasným stavom výskumu zefektívnenia komunikácie zariadení komunikujúcich pomocou technológie LoRa. Dôraz je kladený na zefektívnenie komunikácie pomocou decentralizovaného strojového učenia a porovnávajú sa dostupné algoritmy určené na riešenie problémy viacrukého banditu. Vzhľadom na nižšiu zložitosť a sľubné simulačné výsledky je algoritmus Thompsonovho vzorkovania vhodným kandidátom pre decentralizované učenie v sieťach LoRa. Práca pokračuje analýzou dvoch prístupov k detekcii obsadenia kanála, pričom sa v praxi uprednostňuje prístup, ktorý je viac šetrný k batériám a využíva mechanizmus vstavanej hardvérovej detekcie aktivity kanálu. Naša práca sa tiež zameriava na známe simulačné prostredia sietí, od čisto matematických modelov po vlastné riešenia a moduly pre známe nástroje na simuláciu sietí (NS-3). Po dôkladnom preskúmaní bola vybratá najvhodnejšia alternatíva v podobe úpravy existujúceho simulátora. Vyššie spomenuté body majú pripraviť siete využívajúce technológiu LoRa na nasadenie v mestskom prostredí s vysokou hustotou komunikácie a rizikom rušenia.

V ďalších kapitolách sme navrhli naše riešenie, ktoré zlepšuje proces učenia koncových uzlov pri výbere spoľahlivého primárneho (frekvencie) a sekundárneho (faktor rozprestretia, angl. Spreading Factor) kanála. Tento proces je dôležitý najmä v mestských oblastiach, kde sa zvyšuje riziko zahltenia kvôli nehostinnému prostrediu v nelicencovaných pásmach. Realizovali sme experimenty s 10 fyzickými koncovými zariadeniami vo fyzickom prostredí na hodnotenie výkonu navrhnutých algoritmov, vrátane tzv. Adaptive Data Rate, tzv. Upper Confidence Bound s detekciou aktivity kanálu a Thompsonovho vzorkovania s detekciou aktivity kanálu a alebo prístupu bez detekcie, tzv. metóda ALOHA. Okrem toho sme vyhodnocovali účinnosť algoritmu Thompsonovo vzorkovanie pre stacionárne a pohybujúce sa uzly a ukázalo sa, že ide o energeticky najefektívnejšie a spoľahlivé riešenie v husto osídlených mestských prostrediach s cieľom dlhodobej prevádzky koncových zariadení a častou potrebou odosielať správy.

Kľúčové slová: problém viacrukého banditu, lora@fiit, škálovateľnosť, lora, komunikačné parametre, zefektívnenie komunikácie, energetická úspora, iot, mabp, internet vecí, strojové učenie

Abstract

With an increasing number of connected end devices in Internet of Things networks, a demand for scalable and adaptable solutions arises. In recent years, research on low-power wide area networks proved that a distributed learning strategy easily outperforms a centralized solution, representing the current state-of-the-art.

LoRa is a very promising technology for utilization in mobile nodes but lacks a proper mechanism to adapt to network changes and effectively set communication parameters to minimize the collision rate and maximize network reliability. Another concern is power consumption, which should be closely examined to compare with currently available solutions as there is a demand for end devices to last on a single battery for several years.

In this document, the current state of research in the optimization of communication of LoRa devices is examined. The analysis focuses on the optimization of communication using a distributed learning strategy, where available multi-armed bandit algorithms are compared. Due to a lower complexity and simulation results, Thompson Sampling is a candidate for a distributed learning solution in LoRa networks. The thesis continues with an analysis of two different lightweight carrier sensing approaches, favoring a more battery-friendly approach utilizing a built-in hardware mechanism, called Channel Activity Detection. Popular network simulators are further examined ranging from purely mathematical solutions, through custom simulators, to modules for popular network simulators (NS-3). We have briefly examined each of them and selected the most appropriate one. All of this is to prepare LoRa networks for deployment in a dense urban environment.

In the later chapters, we have proposed our solution, which enhances the learning process of the End Nodes in terms of selecting a reliable primary (Carrier Frequency) and secondary (Spreading Factor) channel. The nodes have to select the proper parameters in a harsh and dense environment similar to network congestion. We have designed experiments with 10 physical End Nodes in a real-world environment to evaluate the performance of the proposed approaches, namely Adaptive Data Rate, Upper Confidence Bound with Channel Activity Detection, Thompson Sampling with Channel Activity Detection, and pure ALOHA channel access. Additionally, Thompson Sampling has been evaluated for both stationary and mobile nodes, proving to be the most power-efficient and reliable solution in dense urban environments for the long-term operation of the End Nodes.

Keywords: multi-armed bandit, iot, multi-armed bandit problem, smart cities, mabp, long-range, energy-wise, low-power, lora, lora@fiit, internet of things, communication parameters selection, reinforcement learning, communication parameters

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1 Introduction

The surge in Internet-connected sensors and devices, especially in the Internet of Things (IoT), is growing exponentially [1]. Many of these devices weren't originally designed for the demanding IoT environment, compounded by numerous wireless devices sharing the same or similar license-free radio bands. Additionally, the prevalence of low-power devices, expected to function on a single battery for multiple years, raises concerns about power consumption [1].

In a low-power wide area network with only a few connected devices, the collision risk is relatively low due to infrequent uplink message transmissions (usually 10 – 30 per hour). LoRa technology emerges as one of the most promising solutions for such low-power wide area networks [1]. The current go-to solution for optimizing communication parameter selection in LoRa networks is adaptive data rate [2], but it faces challenges in dynamic environments, particularly when nodes start to move [3].

Recent research proposes an alternative to the centralized adaptive data rate solution [3]–[6]. It suggests a distributed learning strategy utilizing reinforcement learning, a subset of machine learning, which proves effective even in non-stationary settings like those involving mobile nodes. However, this approach requires message acknowledgment, posing challenges within duty cycle restrictions, where devices in license-free radio bands can only occupy the shared medium for a limited time (usually 1% within an hour) [7]. This limitation, known as duty cycle, hinders the scalability of distributed reinforcement learning.

A second challenge arises with the growing number of end nodes requiring message acknowledgment. The current method of determining channel occupation by sending an uplink message and waiting for acknowledgment leads to faster depletion of duty cycles and energy waste due to failed transmissions. To address this, the suggestion is to implement a lightweight carrier sensing mechanism to minimize collision risks [8], [9].

Despite the inevitable increase in power consumption per transmission with reinforcement learning and carrier sensing, cumulative energy consumption is generally lower due to the incorporation of collision mitigation mechanisms [8], [9]. The main culprits for the low reliability of low-power wide area networks lie in slow adaptiveness, the absence of collision-mitigation mechanisms, and imperfectly orthogonal spreading factors. To ready mobile LoRa nodes for real-world deployment, additional research is imperative to improve the adaptiveness and scalability of LoRa networks.

The document's structure involves a detailed analysis of current research on LoRa technology and optimization techniques for communication in LoRa nodes. Chapters cover challenges for LPWANs, an introduction to LoRa technology, its protocol, modern approaches for optimizing communication parameters, focusing on distributed learning and carrier sensing mechanisms, and a concluding chapter [1].

2 Low-Power Wide-Area Networks

In this chapter, the focus is on low-power wide-area networks (LPWANs), particularly addressing the challenges associated with ensuring scalability, efficient energy management, and communication parameters selection, with a specific emphasis on LoRa technology [10].

LPWANs encompass diverse devices with constrained resources such as limited power supply, memory, and processing capabilities, transmitting small data amounts over extensive distances. The coverage area varies based on environmental factors, making them suitable for both urban and rural settings. End devices in LPWANs are generally low-cost and may be physically inaccessible, emphasizing the need for prolonged battery life [12].

The document delves into technical details, focusing on LoRa technology and its link layer protocol, LoRa@FIIT. LoRa operates in unlicensed ISM bands, exhibiting interference resistance and immunity to the Doppler effect. LoRa networks cater to devices transmitting small data amounts over long distances, with a unique feature allowing downlink messages to follow uplink messages. However, LoRa devices face duty cycle constraints due to the unlicensed band operation [18].

Efficient energy management is crucial for LPWAN end devices with limited power supplies, necessitating prolonged battery life. Studies explore optimal end node configurations, considering power supply limitations and communication parameter selection [11], [23], [29]–[31]. Battery lifetime evaluations and considerations of battery types emphasize the importance of energy efficiency [33], [35].

Communication parameters selection algorithms, a recent area of interest, aim to minimize collisions, increase packet delivery ratios, and optimize battery efficiency. Challenges arise as more devices join networks, requiring effective solutions for rapid device increase and interference from other technologies [3], [26], [27]. The need for testing proposed solutions in dense environments is underscored, particularly for applications in smart cities facing increased collision risks [39].

3 LoRa Technology

This chapter dives into the analysis of LoRa's physical layer modulation technology and its associated link layer protocol, LoRa@FIIT, known for its enhanced battery efficiency compared to the widely deployed LoRaWAN [32]. While briefly introducing the concepts of LoRaWAN [19] for comparative purposes, the focus remains on the more efficient LoRa@FIIT.

3.1 LoRa Physical Modulation

LoRa, a prominent IoT technology, operates across expansive geographical areas with minimal power demands and low data rates. Utilizing Chirp Spread Spectrum (CSS) modulation, LoRa ensures a consistent frequency and time offset between sender and receiver, simplifying complexity [10]. The chapter outlines key configuration parameters for LoRa networks, including Carrier Frequency, Transmission Power, Spreading Factor, Coding Rate, and Bandwidth [26], [33], [34]. Emphasis is placed on the efficient communication-parameters selection process, aiming for partial independence of end devices from the network server [48].

The discussion encompasses the Capture Effect, a phenomenon impacting packet delivery ratio (PDR), and Spreading Factor Collisions, highlighting intra-SF and inter-SF collisions in LoRa networks [4], [8], [9], [37]. Specific use cases are presented where well-known rules cannot be applied, necessitating a careful consideration of network behavior in real-world scenarios.

3.2 LoRa@FIIT Protocol

In response to the limitations of LoRaWAN, the LoRa@FIIT protocol has been developed, offering notable advantages [32]. With a shorter header, optional acknowledgments, and inherent support for Quality of Service, it utilizes the XXTEA encryption algorithm tailored for IoT devices [53]. Unlike LoRaWAN, LoRa@FIIT employs a single key for communication with both the Network Server and Application Server, limiting its use to scenarios where the owner of the network server is also the owner of all communicating devices. It supports only Class A devices, offering a more energy-efficient solution [32], [54].

LoRa@FIIT Messages

LoRa@FIIT introduces four message types [32]:

1. **Register message**. Used for end devices to register with the network, employing over-the-air activation (OTAA) for enhanced security. Acknowledgment is mandatory for network joining.
2. **Data message.** Sends actual data to all access points (APs) with optional or mandatory acknowledgment, providing flexibility based on application requirements.
3. **Emergency message.** Prioritizes important data, processed ahead of other messages, with mandatory acknowledgment.
4. **Hello message.** Functions as a keepalive mechanism, ensuring communication between end devices and APs. This message also requires mandatory acknowledgment.

Depending on the message type, various packet structures for both uplink and downlink messages are introduced in LoRa@FIIT [32]. These structures undergo encryption using the XXTEA cipher, with specific fields such as device ID, message type, and Diffie-Hellman keys remaining unencrypted [32].

LoRa@FIIT Network Architecture

LoRa@FIIT simplifies network architecture, eliminating the need for roaming support and MQTT communication between Network Server and APs. It employs the Secure TCP for IoT (STIoT) for communication [32]. The architecture, illustrated in Figure 1, ensures secure communication channels through TLS encryption, with the current implementation using TLSv1.3 [43].

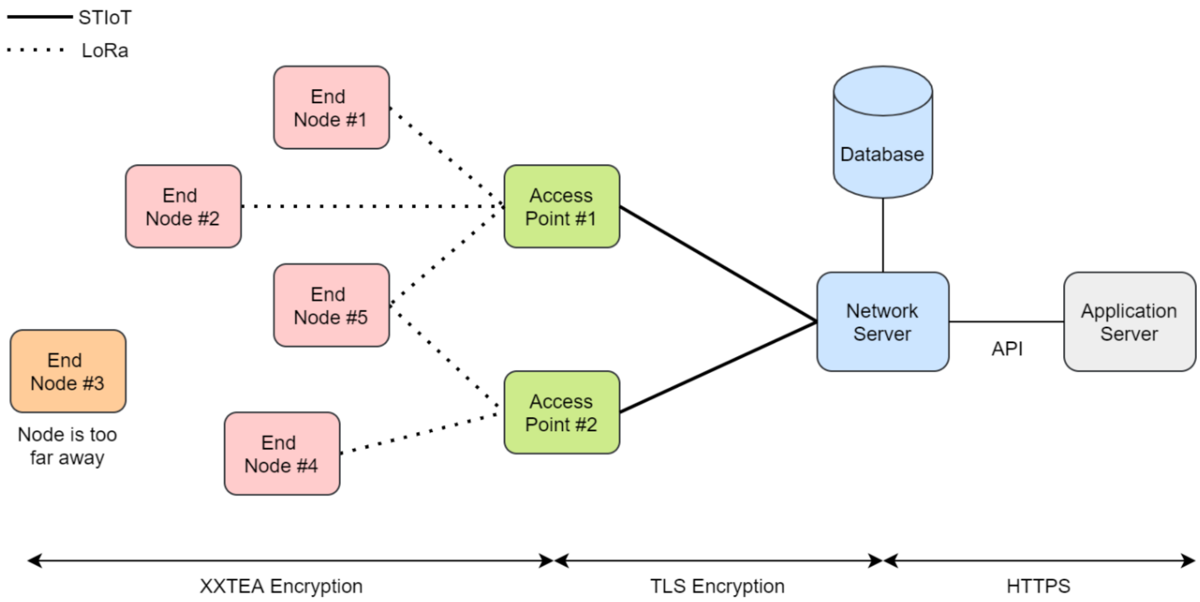

Figure 1: Typical LoRa@FIIT network architecture

4 Optimization of Communication in LoRa Networks

The selection of communication parameters (CP) for end devices can significantly impact battery life, with a potential 47% loss due to suboptimal decision-making or insufficient information from the network server [29]. This issue not only hampers further development but also challenges the fundamental IoT device feature of long-lasting battery performance, often measured in months to years.

In this chapter, we delve into algorithms aimed at enhancing communication efficiency, focusing on key aspects:

1. **Collision Mitigations:** Strategies involve reducing collision rates by choosing less congested channels and preventing collisions through pre-transmission listening.

2. **Energy Consumption:** Prioritizing power efficiency through battery-friendly parameters and adapting swiftly to network changes.

3. **Packet Delivery Ratio (PDR):** Emphasizing increased PDR while ensuring Quality of Service (QoS), tailored to specific application needs.

4. **Learning Process Enhancement:** Addressing the challenge of discovering the network state for end devices, considering the energy and duty cycle costs associated with frequent information exchange between the Network Server (NS) and end nodes (EN).

4.1 Overview of Distributed Learning Strategy Using Reinforcement Learning

The challenge of selecting optimal communication parameters is likened to a multi-armed bandit problem (MABP), where dynamic rewards necessitate a careful balance between exploration and exploitation. Various Multi-Armed Bandit Algorithms (MABAs) have been employed, including:

1. **Upper Confidence Bound (UCB):** A stochastic MABA that sets upper bounds for each arm (CP combination). While easy to implement, it performs suboptimally in dynamic scenarios compared to other algorithms like EXP3.S or Global Switching Thompson Sampling with Bayesian Aggregation (STSBA) [3], [5].

2. **Thompson Sampling (TS):** A stochastic and probability matching algorithm designed for stationary environments but proven effective in non-stationary ones. Its modified version maintains similar performance in non-stationary settings with a lower impact on battery life [3], [5] [56].

3. **EXP3:** An adversarial MABA that theoretically performs worse than stochastic algorithms but adapts well to non-stationary settings, making it crucial for the rapid growth of ENs and support for mobile nodes. Its enhanced version, EXP3.S, significantly shortens learning time [4], [47].

Stochastic algorithms tend to find local maxima quickly but might be less effective. In contrast, adversarial algorithms like EXP3 adapt well to different environments but suffer from longer conversion times. The choice between them depends on the specific requirements of the IoT deployment [56].

In conclusion, the selection of communication parameters and the adoption of appropriate multi-armed bandit algorithms are essential for optimizing communication efficiency in IoT networks, ensuring prolonged battery life and robust performance.

4.2 LoRa Network Simulators

LoRaWAN, a cost-effective and low-power communication technology for IoT devices, is gaining prominence. As the number of IoT devices continues to surge, there's a growing need to simulate network conditions for power and communication efficiency estimation before actual deployment. Network simulators play a pivotal role in this research, allowing the simulation of thousands of End Nodes (ENs) connected to multiple Access Points (APs) to assess communication parameter selection strategies.

LoRa network simulators fall into distinct categories based on various sources. These include purely mathematical simulations, NS-3 simulations leveraging developed plugins, and custom network simulators catering to specific needs. While purely mathematical simulations offer abstraction with potential application in real-world scenarios, NS-3 simulations, particularly with an energy framework, provide a closer representation of actual conditions. Custom network simulators address specific aspects not fully covered by existing solutions [9], [10], [12], [28], [37], [38], [41], [47], [49], [60], [62].

Noteworthy NS-3 modules for LoRa include LoRaWAN ns-3 module, LoRaWAN Partial Network Implementation, and LoRa ns-3 dev module. These modules, integrated into the popular open-source network simulator NS-3, facilitate comprehensive LoRa and LoRaWAN simulations with support and contributions from a vibrant community.

In addition to NS-3, custom network simulators like LoRaSim contribute to the simulation landscape. LoRaSim, a discrete event simulator implemented in Python, incorporates features such as setting transmission parameters, custom payload definition, and modeling communication range based on a log-distance path loss model. The simulator also considers receiver sensitivity, collision behavior, and the capture effect [SimPy].

IoT-MAB, a decentralized intelligent resource allocation approach for LoRaWAN networks, stands out as a solution for optimizing resource allocation in LoRaWAN. Furthermore, the LoRa@FIIT Access Point and End Nodes simulator, an open-source STIoT packet generator, specifically simulates LoRa wireless access points and end nodes using the LoRa@FIIT protocol. The simulator boasts a range of features, including QoS support, emergency message handling, duty cycle constraints, and parameter selection strategies such as Upper Confidence Bound and Thompson Sampling.

As LoRa technology continues to evolve, these simulators play a crucial role in advancing research, testing, and optimization, ensuring the efficient deployment of LoRaWAN networks in diverse scenarios. Researchers can leverage these tools to analyze and enhance the performance, reliability, and energy efficiency of LoRa-based IoT systems [70].

5 Thesis Goals

Previous research has demonstrated that the utilization of reinforcement learning can effectively minimize power consumption in dense and harsh environments. In this study, we seek to evaluate real-world scenarios and further enhance the learning process by incorporating channel activity detection where feasible. All aspects of the research are meticulously designed with energy consumption in mind. Additionally, a simulator will be developed to verify scalability and delve deeper into the optimization of IoT communication.

1. **Improvement of Communication-Parameters Selection:**
   - Utilize a decentralized learning process instead of a fully centralized solution.
   - Propose a solution capable of selecting an appropriate carrier channel (carrier frequency) and sub-channel (spreading factor) based on minimal energy consumption (transmission power).
2. **Implementation of Multi-Armed Bandit Algorithm:**
   - Implement a selected multi-armed bandit algorithm to establish a fully distributed learning strategy for dense and harsh environments.
   - Modify and optimize the algorithm as necessary.
3. **Estimation and Measurements of Energy Consumption:**
   - Assess the energy consumption of autonomous bandit nodes.
   - Compare the energy consumption with the current state-of-the-art solution, which involves the centralized selection of communication parameters.
4. **Evaluation of Performance Metrics for Mobile Nodes:**
   - Evaluate performance metrics for mobile nodes operating in a dynamic environment with multiple wireless access points.
   - Assess the performance as each end node switches between different access points.

6 Design and Implementation

In this chapter, the authors present a novel approach to communication parameter selection using a reinforcement learning algorithm. The end nodes store statistics from previous parameter selections, determining whether they can transmit on selected Spreading Factors (SF) and Coding Rates (CF). To improve the learning process, a channel activity detection mechanism minimizes collisions and prevents duty cycle depletion.

The chapter covers the design of firmware for end nodes, the LoRa@FIIT network architecture, methods for power consumption estimation, and changes to the network server, access point, and end node for enhanced learning. The proposed solution introduces key enhancements, including the design of the end node, utilization of a multi-armed bandit algorithm, channel activity detection, LoRa@FIIT architecture, and power estimation methods. A LoRa@FIIT simulator is developed to assess scalability.

6.1 Hardware Stack

The hardware stack of the proposed end node is discussed, presenting two possible hardware options: the LilyGo LoRa ESP32 and LoRa Radio Node v1.0. Details of the hardware components, such as the ESP32 microcontroller, LoRa transceiver, antenna connectivity, GPIO pins, programmability, and battery management, are provided. The section compares two hardware options: LilyGo ESP32 and LoRa Radio Node.

The use of EEPROM data memory in the ATmega328P processor is explained, highlighting its advantages, such as non-volatile storage, limited SRAM impact, reduced wear, flexibility, and data integrity. Trade-offs and considerations for EEPROM usage are discussed. The authors emphasize the practical choice of using EEPROM for network data storage in systems with limited SRAM and the need for non-volatile storage.

6.2 Software Stack

In this section, the authors conduct an analysis of the original software stack for LoRa@FIIT communications, incorporating modifications detailed in [94, 95, 96]. The focus is on examining the main features and limitations of the LoRa@FIIT software library.

The improved implementation of the LoRa@FIIT library for ATMega328P-based processors includes various functionalities, many of which were added in previous research ([94, 95, 96]). The library, available online [53], encompasses features such as transmission and reception of LoRa@FIIT messages, network data configuration (manual or automatic), key management during join procedures, counter value overflow handling, estimated calculation of message transmission time, and the selection of the best Spreading Factor using the Upper Confidence Bound algorithm. Additionally, lightweight carrier sensing utilizing Channel Activity Detection for LoRa preambles has been introduced.

6.3 Implementation of the Reinforcement Learning Algorithm Using Upper Confidence Bound

The UCB (Upper Confidence Bound) algorithm's objective within the LoRa@FIIT Software Library is to select the Spreading Factor (SF) likely to optimize performance, emphasizing minimal energy consumption and maximal Packet Delivery Ratio (PDR). The library utilizes the "pickBestSF(float bw)" method for SF selection before transmission, with the current implementation exclusively supporting the UCB algorithm.

In the proposed modifications to the end node component, various considerations are addressed. Hardware availability in the Slovak market limits the choice of LoRa transceivers, prompting the use of available devices at the faculty. Time synchronization becomes crucial, leading to the exploration of timing possibilities and reboot memory retention on the Arduino Pro Mini platform (ATmega328P) chosen for fast prototyping.

6.4 Utilization of Thompson Sampling Algorithm for Communication Parameters Selection

In this section, the focus is on the application of the proposed Thompson Sampling algorithm in the Communication Parameter (CP) selection process. The aim is to enhance efficiency for ultra-low-power devices, where code optimization significantly impacts performance and energy consumption, especially for low-power devices with limited resources.

The proposed Thompson Sampling algorithm implementation is built on [97], with necessary steps for code optimization targeting the low-power ATmega328P processor. The functionality of SF (Spreading Factor) selection is divided into three main functions: init, pull, and update. The init function initializes variables and generates sample rewards. The pull function selects the SF for the next transmission based on mean values of probability, while the update function updates relevant parameters after a transmission.

6.5 Utilization of Channel Activity Detection to Enhance Learning Process

To enhance the learning process of the Multi-Armed Bandit (MAB), the authors propose incorporating short period listening during CAD, enabling the MAB to learn not only from acknowledged messages (which can lead to fast duty cycle depletion and is not scalable) but also from short periods of listening when the selected wireless channel is unoccupied by other nodes. The CAD process involves initialization, CAD operation, signal reception, and subsequent decision-making based on the correlation results.

The CAD mechanism, as implemented in the LoRa@FIIT library, detects LoRa preamble signals rather than very weak or intermittent signals, making it less reliable for longer distances [96]. The provided code snippet showcases the CAD implementation using the RadioHead library on an Arduino Pro Mini with the LoRa Radio Node, offering a practical example of CAD integration.

The Finite State Machine (FSM) diagram in Figure 2 illustrates the proposed solution using Thompson Sampling (TS) with CAD. The node transitions through states such as IDLE, SEL (selection), CAD, TX (transmission), INC (increase probability), DEC (decrease probability), SLP (sleep), WUP (wake up), CLR (clear channel), BSY (busy channel), ACK (acknowledged), and nACK (not acknowledged). The FSM depicts the process of CP selection, CAD, message transmission, acknowledgment handling, and the subsequent transition to sleep or idle states based on channel conditions and acknowledgment status.

Additionally, an alternative solution without a CAD mechanism, utilizing a primary ALOHA channel access. In this scenario, the node wakes up, selects CP using TS, and immediately transmits a message. The process includes states such as IDLE, SEL, TX, INC, DEC, SLP, WUP, ACK, and nACK, illustrating the CP selection, message transmission, acknowledgment handling, and state transitions.

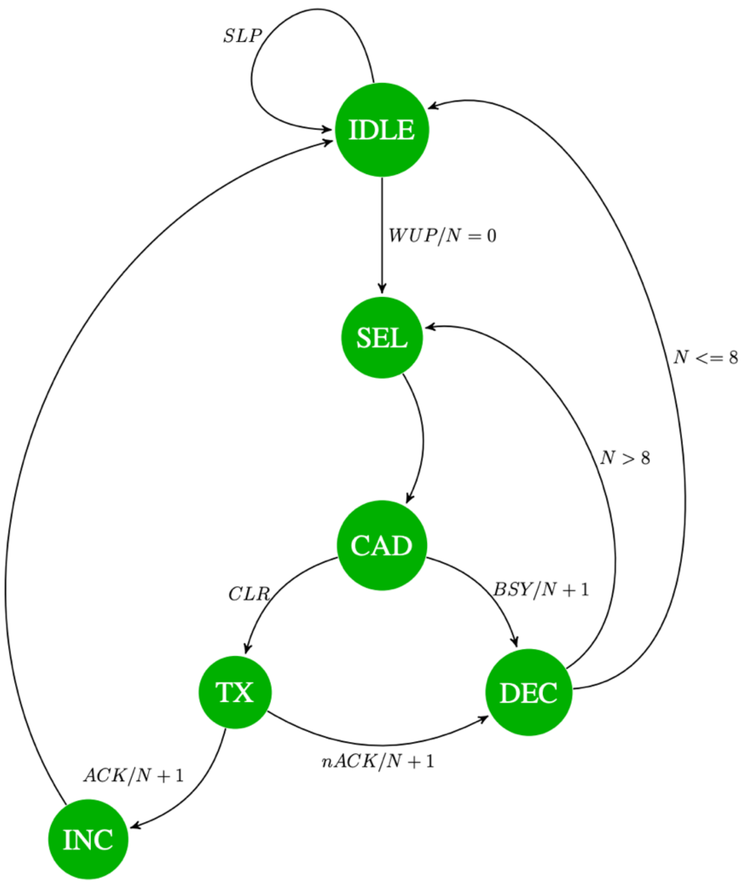

Figure 2: The description of TS with CAD using a FSM

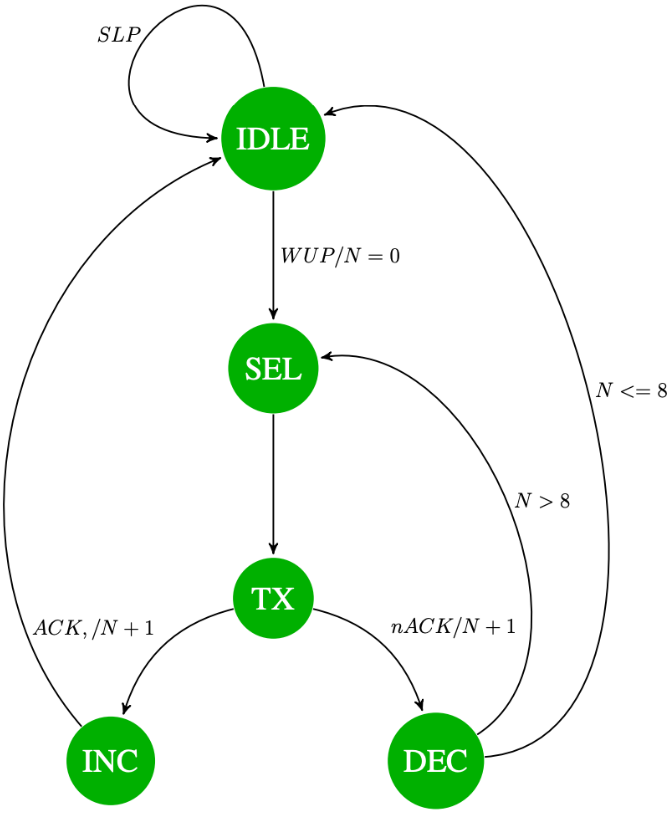

Figure 3: The description of TS with ALOHA channel access using a FSM

6.6 Proposed Network Architecture

In this section, we present the network architecture designed for the evaluation of proposed modifications. The architecture comprises the following components:

1. **LoRa@FIIT End Nodes (ENs).** Ten nodes utilizing LoRa radio modules for communication with the network server.
2. **LoRa@FIIT Access Points (APs).** Two access points strategically placed in different rooms.
3. **LoRa Network Server.** Central management point for the LoRa@FIIT network, leveraging PostgreSQL for data persistence.
4. **Jupyter Notebook and Bash Script.** Specifically crafted for experiment evaluation, streamlining the assessment process.

The design incorporates a limited number of ENs and APs, aligning with duty-cycle restrictions in Europe and constraints posed by hardware availability at the faculty.

6.7 Experiments Setup

To assess the impact of proposed modifications, we have designed specific scenarios utilizing the LoRa@FIIT network architecture:

1. **Scenario 1.** Static nodes with pure ALOHA channel access and Adaptive Data Rate (ADR).

2. **Scenario 2.** Static nodes with Channel Activity Detection (CAD) and Upper Confidence Bound (UCB).
3. **Scenario 3.** Static nodes with CAD and Thompson Sampling.
4. **Scenario 4.** Dynamic nodes with pure ALOHA channel access and Thompson Sampling.
5. **Scenario 5.** Dynamic nodes with CAD and Thompson Sampling.

Each scenario involves 10 - 11 LoRa Nodes, 2 Access Points, and a Network Server supporting LoRa@FIIT protocol. End Nodes (ENs) dependent on the Network Server are distinguished from Bandit Nodes utilizing Thompson Sampling, UCB, or any other Multi-Armed Bandit Algorithm.

All scenarios run five times over 3 hours, with periodic uplink messages every 70 seconds, creating a challenging environment. The communication parameters (CR: 4/5, BW: 125 kHz) remain constant. ENs cover a 261 m^2 area across three rooms within the FIIT STU building, focusing on utilizing CAD to enhance Multi-Armed Bandit Algorithm (MABA) learning rather than long-distance communication.

Key metrics for performance evaluation include:

1. **Packet Delivery Ratio (PDR).** The ratio of successfully delivered packets to the network server over all sent packets, including failed attempts.
2. **Energy Consumption of EN (EC).** Measured current consumption using PPKII.
3. **Distribution of Spreading Factors (SF) and Carrier Frequency (CF)**. Ensuring uniform utilization across SF and CF values, especially focusing on lower SFs near Access Points.

7 Results

Following the successful implementation of Thompson Sampling (TS) and the integration of Channel Activity Detection (CAD) to enhance the learning process of Bandit Nodes (BNs), the code was published on GitHub as open source [53]. Subsequent experiments were conducted to validate the proposed contributions, and this chapter provides a summary of the experimental results.

The initial set of experiments focuses on demonstrating the effectiveness of the proposed communication parameter selection methods and the node-centered approach for code optimization. Stationary nodes scenarios (1-3) are detailed in Section 7.1, while scenarios involving mobile nodes (4-5) are covered in Section 7.2. The second set of experiments delves into illustrating the benefits of energy profiling for Energy Nodes (ENs), as discussed in Section 7.3.

To facilitate result evaluation, an open-source LoRa Jupyter Notebook, named LoBook, was developed and released. This notebook aids in the analysis of collected data, and its processing is accessible to anyone interested in verifying or conducting further analysis [102].

A detailed description of the evaluated dataset, created using the collected data, is available in Appendix A. Additional photo documentation of the proposed solution is provided on GitHub [102]. Guidelines for embedded system development, based on the necessary optimization steps, can be found in Appendix C.

To streamline the evaluation process, a simple bash script was designed to export the database table from a PostgreSQL instance running in a Docker container on lora.fiitacademy.fiit.stuba.sk (or previously lora.fiit.stuba.sk) to a CSV file. This file is then ingested into LoBook for analysis. Further details on this process can be found in Appendix B. The aim is to empower users to assess and verify the data, aligning with the goal of transparency and openness in the experimental analysis.

7.1 Results of Experiments with Stationary Nodes

In this section, the results of experiments involving stationary nodes and the optimization of communication parameters are discussed. The experiments utilized 10 stationary nodes, generating numerous uplink messages stored in a PostgreSQL database and later exported to CSV format. Three approaches, centralized ADR, distributed node centric UCB, and TS, were employed in an indoor physical environment.

The experiments covered a 261 m² area, creating a congested network environment with challenges like high collision rates and limited access points (APs). The primary objective was to evaluate whether nodes could adapt to the environment without prior information. The experiments involved a short learning period, and each node used static settings for communication parameters, including coding rate (CR), bandwidth (BW), payload size, and uplink periodicity.

The communication process selection algorithms aimed to detect and adapt to the unknown environment based on limited knowledge within a constrained time. The experiments consisted of five rounds, each lasting three hours, assessing the adaptability of nodes to changing conditions.

Results were analysed based on CF and SF distribution, as well as the Packet Delivery Ratio (PDR), Signal-to-Noise Ratio (SNR), and Received Signal Strength Indicator (RSSI). The experiments demonstrated that the TS algorithm showed stability and scalability, outperforming ADR and UCB in terms of PDR and efficient CF and SF distribution.

The summary of rounds revealed that ADR struggled with SF12 usage, leading to poor scalability. UCB improved scalability but had a slow learning curve. TS consistently distributed the load effectively, achieving the best PDR and suitable CF and SF selection. Challenges and recommendations for further optimization were discussed, emphasizing the need for accurate implementation and in-depth traffic analysis to enhance the communication parameter selection process.

7.2 Results of Experiments with Mobile Nodes

This section presents the findings from four rounds of Scenario 4-5 experiments, examining the performance of mobile nodes.

The initial round analyzes mobile node experiments over 3 hours. SF8 and SF9 dominate, with SF7 and SF10 following. Mobile nodes, distant from APs, utilize SF11 and SF12 more than stationary nodes. CF 866.9 MHz and 866.1 MHz lead in uplink messages, favoring ALOHA on CF 866.9 MHz. CAD achieves higher PDR (43.80%) than ALOHA (26.80%). Examining results after 6 hours, CAD demonstrates improved PDR (70.06%) over ALOHA (28.57%). Both algorithms evenly use frequencies, with CAD surpassing in message count. CF distribution remains consistent.

Results after 9 hours exhibit CAD's superior PDR (47.66%) compared to ALOHA (14.03%). Both maintain even frequency distribution, but CAD excels in message delivery on specific CF and SF. Results after 12 hours reveal CAD's continued superiority with a PDR of 52.45%, outperforming ALOHA's 19.84%. Both algorithms exhibit even CF distribution, with CAD excelling on SF8 and SF9. In the final round, CAD maintains superiority with a PDR of 42.40%, surpassing ALOHA's 15.39%. Both algorithms exhibit consistent CF and SF distributions.

The experiments demonstrate the scalability and adaptability of the MAB node-centric approach in dynamic environments. The CAD approach consistently outperforms ALOHA in PDR, emphasizing its effectiveness in dense environments. However, challenges persist in certain operations without NS intervention. The experiments, conducted in real-world conditions, highlight the need for future simulator development.

7.3 Energy Consumption Profiling

In this section, the energy profiles of different scenarios are meticulously examined, utilizing the Power Profile Kit II by Nordic Semiconductors [100]. The scenarios include:

1. Energy profile of the original solution using ADR and ALOHA channel access.
2. Energy profile of the UCB with CAD being enabled.
3. Energy profile of the stationary TS with ALOHA channel access.
4. Energy profile of the mobile TS with ALOHA channel access.
5. Energy profile of the mobile TS with CAD approach.

For the original solution (ADR with ALOHA), the mean current consumption was 23.79 mA with a meager mean PDR of 18.30%. The UCB with CAD exhibited a lower mean current of 16.89 mA but with a moderate PDR of 54.80%. However, the stationary TS with CAD outperformed others with a mean current of 18.41 mA and a significantly higher mean PDR of 72.40%.

Table 1: The comparison of current consumption and Packet Delivery Ratio for stationary nodes

Algorithm	Round	Average current [mA]	Peak current [mA]	Mean PDR [%]
Adaptive Data Rate with ALOHA	1	21.57	106.50	215.19
	2	25.28	107.25	18.38
	3	23.31	107.25	20.65
	4	23.80	107.25	15.20
	5	25.00	107.25	18.96
Upper Confidence Bound with Channel Activity Detection	1	16.39	115.53	55.59
	2	14.58	109.51	60.06
	3	14.98	109.51	54.04
	4	17.44	109.51	50.26
	5	21.07	109.51	54.03
Thompson Sampling with Channel Activity Detection	1	17.39	109.51	87.21
	2	18.43	112.52	80.97
	3	18.75	112.52	55.78
	4	18.77	112.52	84.29
	5	18.71	112.52	53.76

The energy consumption profiles are further detailed for each scenario. In the original solution, power optimization steps were applied, resulting in a mean current of 23.79 mA. The UCB with CAD achieved a mean current of 16.89 mA but with only moderate PDR. Notably, the stationary TS with CAD proved to be the most successful with a mean current of 18.41 mA and a high PDR of 72.40%.

In the mobile TS with ALOHA scenario, average current values ranged from 27.15 mA to 18.70 mA across five rounds, with consistently poor mean PDR results. Conversely, the TS with CAD for mobile nodes demonstrated improved results, with mean current ranging from 23.19 mA to 16.66 mA and more favorable PDR values.

Table 2: The comparison of current consumption and Packet Delivery Radio for mobile nodes

Algorithm	Round	Average current [mA]	Peak current [mA]	Mean PDR [%]
Thompson Sampling with ALOHA	1	27.15	106.50	26.80
	2	32.25	109.51	28.57
	3	25.84	109.51	14.03
	4	19.56	109.51	19.84
	5	18.70	109.51	15.39
Thompson Sampling with Channel Activity Detection	1	23.19	105.00	43.80
	2	20.74	110.26	70.06
	3	23.92	110.26	47.66
	4	16.72	110.26	52.45
	5	16.66	110.26	42.40

The experiments highlight the effectiveness of the TS with CAD approach, particularly for stationary nodes, demonstrating stable energy consumption and superior PDR results in congested environments. The findings suggest tailored approaches based on specific requirements and environmental considerations.

7.4 Summary

The experiment outcomes and summary are presented in Table 1 and Table 2, evaluating the overall current flow and mean Packet Delivery Ratio (PDR) for various approaches with stationary and mobile nodes. The PDR values are color-coded for easy interpretation, with red indicating very poor performance, orange for poor performance, yellow for moderate performance, and green for good performance in congested environments.

The ADR_A algorithm exhibits high average current consumption (CC) and exceptionally poor PDR, notably 215.19% in the 1st round due to unexpected unique uplink messages. The UCB_C algorithm achieves the lowest CC but only moderate PDR. The UCB algorithm demonstrates power efficiency but with lower PDR compared to TS, attributed to its simple implementation and zero reward calculation.

TS for stationary nodes initially displays moderate power consumption (17.39 mA) in the 1st round, maintaining a balanced CC-PDR trade-off. The later rounds show slight fluctuations, with TS offering a favorable compromise between power efficiency and PDR.

Table 2 focuses on mobile nodes, where TS_A and TS_C exhibit variations in EC and PDR across rounds. The 1st round of TS_C shows optimal power efficiency. Despite lower PDR with mobile nodes, it aligns with expectations in certain unreachable areas.

The experiments emphasize evaluating reliability in congested environments for long-term operation. Results indicate that Thompson Sampling proves beneficial in such settings, especially for extended durations. ADR may be preferred for environments prioritizing minimal energy consumption, suitable for rural areas with lower congestion probability and longer node distances.

Conversely, CAD's impracticality for distances exceeding 1 km in rural areas is noted, prompting consideration of the Multi-Armed Bandit (MAB) approach with CAD for urban areas. This approach enhances security, minimizing the risk of channel jamming. The MAB with CAD is deemed beneficial for urban scenarios with frequent message transmissions and shorter payloads, improving solution security and minimizing single-channel or channel jamming probability.

In conclusion, the experiments recommend tailored approaches based on the environmental context, advocating for Thompson Sampling in congested settings and ADR or MAB with CAD in rural or urban scenarios, respectively.

8 Conclusion

This document delves into the existing challenges faced by low-power wide area networks (LPWANs), focusing on the contemporary LoRa technology and the LoRa@FIIT MAC protocol. It explores the complexities of communication parameter selection using a reinforcement learning approach and highlights the significance of carrier detection in LoRa networks. Additionally, the document provides a brief overview of publicly available LoRa simulators.

One major challenge discussed is the adaptiveness of end devices in mitigating collisions within LPWAN networks. The document emphasizes the need for distributed learning mechanisms to enhance reliability. However, it acknowledges the limitations of solely relying on end node observations for communication parameter selection, prompting the consideration of centralized intervention in dynamic network conditions.

The document also addresses concerns about how end devices learn about beneficial channels without acknowledgment from the network server. It introduces the concept of lightweight carrier sensing to improve the learning process in dense smart city environments, enabling devices to assess channel occupancy and mitigate collisions effectively.

The selection of appropriate channels and sub-channels is likened to a multi-armed bandit problem, where end devices, with limited knowledge, must make choices to minimize collision risks. Despite the promising aspects of LoRa technology, which enables long-lasting battery life for devices in IoT scenarios, challenges arise due to limited time occupancy within unlicensed radio bands.

The LoRa@FIIT protocol is introduced as an energy-efficient alternative to the LoRaWAN protocol, offering QoS support, a shorter header, different message types, and optional acknowledgments. The document explores ways to enhance adaptiveness for mobile devices and proposes modifications to the LoRa@FIIT library, incorporating the Thompson Sampling algorithm for SF selection and Channel Activity Detection to improve the learning process.

The main contribution of the dissertation lies in the enhanced process of communication parameter selection for the LoRa@FIIT protocol, partially independent of the network server. Experiments demonstrate significant improvements in Packet Delivery Ratio (PDR) and current consumption using the Thompson Sampling algorithm with Channel Activity Detection compared to existing solutions.

In conclusion, the document outlines the positive impact of the proposed modifications on PDR and current consumption for both stationary and mobile nodes. It underscores the potential of the Thompson Sampling algorithm with Channel Activity Detection in overcoming challenges associated with adaptive data rate and channel access in LPWAN networks.

Bibliography

[1] *LoRa and LoRaWAN: Technical overview | DEVELOPER PORTAL*. en. URL: https://lora-developers.semtech.com/documentation/tech-papers-and-guides/lora-and-lorawan/ (visited on 04/28/2023).

[2] *What is an Adaptive Data Rate?* en. URL: https://lora-developers.semtech.com/library/tech-papers-and-guides/understanding-adr/ (visited on 04/28/2023).

[3] Raouf Kerkouche et al. "Node-based optimization of LoRa transmissions with Multi-Armed Bandit algorithms". In: *2018 25th International Conference on Telecommunications (ICT)*. 2018, pp. 521–526. DOI: 10.1109/ICT.2018.8464949.

[4] Duc-Tuyen Ta et al. "LoRa-MAB: Toward an Intelligent Resource Allocation Approach for LoRaWAN". In: *2019 IEEE Global Communications Conference (GLOBECOM)*. 2019, pp. 1–6. DOI: 10.1109/GLOBECOM38437.2019.9013345.

[5] Hiba Dakdouk et al. "Reinforcement Learning Techniques for Optimized Channel Hopping in IEEE 802.15.4-TSCH Networks". In: MSWIM '18. Montreal, QC, Canada: Association for Computing Machinery, 2018, 99–107. ISBN: 9781450359603. DOI: 10.1145/3242102.3242110. URL: https://doi.org/10.1145/3242102.3242110.

[6] Rémi Bonnefoi et al. "Multi-Armed Bandit Learning in IoT Networks: Learning Helps Even in Non-stationary Settings". In: Jan. 2018, pp. 173–185. ISBN: 978-3-319-76206-7. DOI: 10.1007/978-3-319-76207-4_15.

[7] *LoRaWAN® Specification v1.1*. en-US. URL: https://lora-alliance.org/resource_hub/lorawan-specification-v1-1/ (visited on 10/05/2022).

[8] Edward M. Rochester et al. "Lightweight Carrier Sensing in LoRa: Implementation and Performance Evaluation". In: *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*. 2020, pp. 1–6. DOI: 10.1109/ICC40277.2020.9149103.

[9] Thanh-Hai To and Andrzej Duda. "Simulation of LoRa in NS-3: Improving LoRa Performance with CSMA". In: *2018 IEEE International Conference on Communications (ICC)*. 2018, pp. 1–7. DOI: 10.1109/ICC.2018.8422800.

[10] Alexandru Lavric and Valentin Popa. "Internet of Things and LoRa™ low-power wide-area networks challenges". In: *2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*. 2017, pp. 1–4. DOI: 10.1109/ECAI.2017.8166405.

[11] Husam Rajab, Tibor Cinkler, and Taoufik Bouguera. *Evaluation of Energy Consumption of LPWAN Technologies*. Mar. 2021. DOI: 10.21203/rs.3.rs-343897/v1.

[12] Alexandru Lavric and Valentin Popa. "Internet of Things and LoRa™ Low-Power Wide-Area Networks: A survey". In: *2017 International Symposium on Signals, Circuits and Systems (ISSCS)*. 2017, pp. 1–5. DOI: 10.1109/ISSCS.2017.8034915.

[13] Vignesh Mahalingam Suresh et al. "Powering the IoT through embedded machine learning and LoRa". In: *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*. 2018, pp. 349–354. DOI: 10.1109/WF-IoT.2018.8355177.

[14] *NB-IoT, LoRaWAN, Sigfox: An up-to-date comparison*. en-US. URL: https://dt.iotsolutionoptimizer.com/LoadDocument/3047/NB-IoT,\%20LoRaWAN,\%20Sigfox\%20-\%20An\%20Up-to-date\%20Comparison.pdf (visited on 03/01/2021).

[15] Haifeng Fang et al. "An Experimental Analysis of SNR Performance for LoRa Communication". In: *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*. 2018, pp. 57–64. DOI: 10.1109/CompComm.2018.8780989.

[16] *LORAWAN® AND NB-IOT: COMPETITORS OR COMPLEMENTARY?* en-US. June 2019. URL: https://docs.loriot.io/display/LNS6/LoRaWAN+and+NB-IoT\%3A+competitors+or+complementary?preview=/14878627/14878628/lorawanr_and_nb-iot.pdf (visited on 06/23/2022).

[17] Ondrej Perešíni and Tibor Krajčovič. "More efficient IoT communication through LoRa network with LoRa@FIIT and STIOT protocols". In: *2017 IEEE 11th International Conference on Application of Information and Communication Technologies (AICT)*. 2017, pp. 1–6. DOI: 10.1109/ICAICT.2017.8686837.

[18] Maria Rita Palattella and Nicola Accettura. "Enabling Internet of Everything Everywhere: LPWAN with Satellite Backhaul". In: *2018 Global Information Infrastructure and Networking Symposium (GIIS)*. 2018, pp. 1–5. DOI: 10.1109/GIIS.2018.8635663.

[19] *LoRaWAN® L2 1.0.4 Specification (TS001-1.0.4) 49*. en-US. URL: https://lora-alliance.org/wp-content/uploads/2021/11/LoRaWAN-Link-Layer-Specification-v1.0.4.pdf (visited on 06/23/2023).

[20] RocketScream. *Lightweight low power library for Arduino*. URL: https://github.com/rocketscream/Low-Power (visited on 06/23/2023).

[21] Sigfox Build. *Sigfox Payload*. URL: https://build.sigfox.com/payload (visited on 06/23/2023).

[22] Jakub Pullmann and Dominik Macko. "A New Planning-Based Collision-Prevention Mechanism in Long-Range IoT Networks". In: *IEEE Internet of Things Journal* 6.6 (2019), pp. 9439–9446. DOI: 10.1109/JIOT.2019.2940994.

[23] Lluís Casals et al. “Modeling the Energy Performance of LoRaWAN”. In: *Sensors* 17.10 (2017). ISSN: 1424-8220. DOI: 10.3390/s17102364. URL: https://www.mdpi.com/1424-8220/17/10/2364.

[24] Menno Jan Faber et al. “A Theoretical and Experimental Evaluation on the Performance of LoRa Technology”. In: *IEEE Sensors Journal* 20.16 (2020), pp. 9480–9489. DOI: 10.1109/JSEN.2020.2987776.

[25] D. Howe. *Free On-Line Dictionary of Computing*. 1985. URL: https://foldoc.org/ (visited on 06/23/2023).

[26] Martin C. Bor et al. “Do LoRa Low-Power Wide-Area Networks Scale?” In: MSWiM ’16. Malta, Malta: Association for Computing Machinery, 2016, 59–67. ISBN: 9781450345026. DOI: 10.1145/2988287.2989163. URL: https://doi.org/10.1145/2988287.2989163.

[27] Duc-Tuyen Ta et al. “LoRa-MAB: A Flexible Simulator for Decentralized Learning Resource Allocation in IoT Networks”. In: *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*. 2019, pp. 55–62. DOI: 10.23919/WMNC.2019.8881393.

[28] Alexander Valach and Dominik Macko. “Optimization of LoRa Devices Communication for Applications in Healthcare”. In: *2020 43rd International Conference on Telecommunications and Signal Processing (TSP)*. 2020, pp. 511–514. DOI: 10.1109/TSP49548.2020.9163432.

[29] Ashirwad Gupta and Makoto Fujinami. “Battery Optimal Configuration of Transmission Settings in LoRa Moving Nodes”. In: *2019 16th IEEE Annual Consumer Communications Networking Conference (CCNC)*. 2019, pp. 1–6. DOI: 10.1109/CCNC.2019.8651707.

[30] Merin Susan Philip and Poonam Singh. “Energy Consumption Evaluation of LoRa Sensor Nodes in Wireless Sensor Network”. In: *2021 Advanced Communication Technologies and Signal Processing (ACTS)*. 2021, pp. 1–4. DOI: 10.1109/ACTS53447.2021.9708341.

[31] Hafiz Husnain Raza Sherazi et al. “Energy-Efficient LoRaWAN for Industry 4.0 Applications”. In: *IEEE Transactions on Industrial Informatics* 17.2 (2021), pp. 891–902. DOI: 10.1109/TII.2020.2984549.

[32] Martin Bor, John Vidler, and Utz Roedig. “LoRa for the Internet of Things”. In: *EWSN* (Feb. 2016), pp. 361–366.

[33] Andre Gloria et al. “LoRa Transmission Power Self Con?guration for Low Power End Devices”. In: *2019 22nd International Symposium on Wireless Personal Multimedia Communications (WPMC)*. 2019, pp. 1–6. DOI: `10.1109/WPMC48795.2019.9096197`.

[34] Mukul Jain et al. “Analysis of a Lithium/Thionyl Chloride Battery under Moderate-Rate Discharge”. In: *Journal of The Electrochemical Society* 146.11 (1999), p. 4023. DOI: `10.1149/1.1392587`. URL: `https://dx.doi.org/10.1149/1.1392587`.

[35] Ruben M. Sandoval, Antonio-Javier Garcia-Sanchez, and Joan Garcia-Haro. “Optimizing and Updating LoRa Communication Parameters: A Machine Learning Approach”. In: *IEEE Transactions on Network and Service Management* 16.3 (2019), pp. 884–895. DOI: `10.1109/TNSM.2019.2927759`.

[36] Alston Lloyed Emmanuel et al. “Optimization of Spreading Factor Distribution in High Density LoRa Networks”. In: *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*. 2020, pp. 1–5. DOI: `10.1109/VTC2020-Spring48590.2020.9129498`.

[37] Eduardo Sallum et al. “Performance optimization on LoRa networks through assigning radio parameters”. In: *2020 IEEE International Conference on Industrial Technology (ICIT)*. 2020, pp. 304–309. DOI: `10.1109/ICIT45562.2020.9067310`.

[38] Statista. *Number of IoT devices 2015-2025*. URL: `https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/` (visited on 06/23/2023).

[39] Yujun Hou, Zujun Liu, and Dechun Sun. “A novel MAC protocol exploiting concurrent transmissions for massive LoRa connectivity”. In: *Journal of Communications and Networks* 22.2 (2020), pp. 108–117. DOI: `10.1109/JCN.2020.000005`.

[40] HopeRF. *HopeRF RFM96W Datashee*. 2019.

[41] LoRaAlex Team. *LoRa@FIIT Network Server*. URL: https://github.com/loraalex/LoNES (visited on 06/23/2023).

[42] Orne Brocaar. *ChirpStack Network Server*. URL: https://github.com/brocaar/chirpstack-network-server (visited on 06/23/2023).

[43] The Things Network. *The Things Stack, an open source LoRaWAN Network Server*. URL: https://github.com/TheThingsNetwork/lorawan-stack (visited on 06/23/2023).

[44] Martin Bor and Utz Roedig. "LoRa Transmission Parameter Selection". In: *2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. 2017, pp. 27–34. DOI: 10.1109/DCOSS.2017.10.

[45] Shengmin Cui and Inwhee Joe. "Collision prediction for a low power wide area network using deep learning methods". In: *Journal of Communications and Networks* 22.3 (2020), pp. 205–214. DOI: 10.1109/JCN.2020.000017.

[46] Raghad M. Abdulghani et al. "Vulnerabilities and Security Issues in IoT Protocols". In: *2020 First International Conference of Smart Systems and Emerging Technologies (SMARTTECH)*. 2020, pp. 7–12. DOI: 10.1109/SMART-TECH49988.2020.00020.

[47] John Thomas et al. "Man in the Middle Attack Mitigation in LoRaWAN". In: *2020 International Conference on Inventive Computation Technologies (ICICT)*. 2020, pp. 353–358. DOI: 10.1109/ICICT48043.2020.9112391.

[48] Jolan Rokan Naif, Ghassan H. Abdul-Majeed, and Alaa K. Farhan. "Secure IOT System Based on Chaos-Modified Lightweight AES". In: *2019 International Conference on Advanced Science and Engineering (ICOASE)*. 2019, pp. 1–6. DOI: 10.1109/ICOASE.2019.8723807.

[49] The Things Industries. *The Things Stack Reference*. 2021. URL: https://www.thethingsindustries.com/docs/reference/ (visited on 06/23/2023).

[50] Khaled Abdelfadeel et al. "How to Make Firmware Updates over LoRaWAN Possible". In: *2020 IEEE 21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*. 2020, pp. 16–25. DOI: 10.1109/WoWMoM49955.2020.00018.

[51] Chékra El Fehri et al. “An Uplink Synchronization scheme for LoRaWAN Class B”. In: *2019 International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2019, pp. 47–52. DOI: `10.1109/WiMOB.2019.8923189`.

[52] Elbert M. Galas and Bobby D. Gerardo. “Feasibility Assessment on the Implementation of the Enhanced XXTEA on IoT Devices”. In: *2019 IEEE 9th International Conference on System Engineering and Technology (ICSET)*. 2019, pp. 178–182. DOI: `10.1109/ICSEngT.2019.8906473`.

[53] LoRaAlex Team. *LoRa@FIIT Library*. URL: `https://github.com/loraalex/LoRaFIIT` (visited on 06/23/2023).

[54] Aurélien Garivier and Eric Moulines. “On Upper-Confidence Bound Policies for Switching Bandit Problems”. In: *Proceedings of the 22nd International Conference on Algorithmic Learning Theory*. ALT’11. Espoo, Finland: Springer-Verlag, 2011, 174–188. ISBN: 9783642244117.

[55] Olivier Chapelle and Lihong Li. “An Empirical Evaluation of Thompson Sampling”. In: *Proceedings of the 24th International Conference on Neural Information Processing Systems*. NIPS’11. Granada, Spain: Curran Associates Inc., 2011, 2249–2257. ISBN: 9781618395993.

[56] Joseph Mellor and Jonathan Shapiro. “Thompson Sampling in Switching Environments with Bayesian Online Change Point Detection”. In: (Feb. 2013).

[57] Ruben M. Sandoval et al. “Deriving and Updating Optimal Transmission Configurations for Lora Networks”. In: *IEEE Access* 8 (2020), pp. 38586–38595. DOI: `10.1109/ACCESS.2020.2973252`.

[58] Team SimPy. *SimPy Library*. URL: `https://simpy.readthedocs.io/en/latest/about/index.html` (visited on 06/23/2023).

[59] Mariusz Slabicki, Gopika Premsankar, and Mario Di Francesco. “Adaptive configuration of lora networks for dense IoT deployments”. In: *NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium*. 2018, pp. 1–9. DOI: `10.1109/NOMS.2018.8406255`.

[60] Jun Peng and Liang Cheng. “Revisiting Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA)”. In: *2006 40th Annual Conference on Information Sciences and Systems*. 2006, pp. 1236–1241. DOI: 10.1109/CISS.2006.286654.

[61] Muhammad Rizky Eka Arlin et al. “LouPe: LoRa Performance Measurement Tool”. In: *2018 2nd East Indonesia Conference on Computer and Information Technology (EIConCIT)*. 2018, pp. 168–171. DOI: 10.1109/EIConCIT.2018.8878525.

[62] MCCI Catena. *Arduino-LMIC library ("MCCI LoRaWAN LMIC Library")*. URL: https://github.com/mcci-catena/arduino-lmic (visited on 06/23/2023).

[63] Thanh-Hai To and Andrzej Duda. “Simulation of LoRa in NS-3: Improving LoRa Performance with CSMA”. In: *2018 IEEE International Conference on Communications (ICC)*. 2018, pp. 1–7. DOI: 10.1109/ICC.2018.8422800.

[64] He Wu, Sidharth Nabar, and Radha Poovendran. “An Energy Framework for the Network Simulator 3 (NS-3)”. In: SIMUTools ’11. Barcelona, Spain: ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2011, 222–230. ISBN: 9781936968008.

[65] Kerlink. *Wirnet Station*. 2021.

[66] Alexander Valach. *LoRa@FIIT Access Point and End Nodes Simulator*. URL: https://github.com/alexandervalach/lora-ap-sim (visited on 06/23/2023).

[67] Joseph Finnegan, Stephen Brown, and Ronan Farrell. “Evaluating the Scalability of LoRaWAN Gateways for Class B Communication in ns-3”. In: *2018 IEEE Conference on Standards for Communications and Networking (CSCN)*. 2018, pp. 1–6. DOI: 10.1109/CSCN.2018.8581759.

[68] Furqan Hameed Khan and Marius Portmann. “Experimental Evaluation of LoRaWAN in NS-3”. In: *2018 28th International Telecommunication Networks and Applications Conference (ITNAC)*. 2018, pp. 1–8. DOI: 10.1109/ATNAC.2018.8615313.

[69] NSNAM Team. *NS-3 Network Simulator*. URL: https://www.nsnam.org/ (visited on 06/23/2023).

[70] GNU Project Free Software Foundation. *GNU Library General Public License v2.0*. URL: https://www.gnu.org/licenses/old-licenses/lgpl-2.0.html (visited on 06/24/2023).

[71] University of Padova SIGNET Lab DEI. *LoRaWAN ns-3 module*. 2022. URL: https://github.com/signetlabdei/lorawan (visited on 06/24/2023).

[72] networkedsystems. *LoRa-NS3*. 2020. URL: https://github.com/networkedsystems/lora-ns3 (visited on 06/24/2023).

[73] imec idlab. *LoRa-NS3*. 2017. URL: https://github.com/imec-idlab/ns-3-dev-git (visited on 06/24/2023).

[74] Drakkar LIG. *LoRa NS3 Module*. 2021. URL: https://github.com/drakkar-lig/lora-ns3-module (visited on 06/24/2023).

[75] Jéssika Silva et al. "A Survey of LoRaWAN Simulation Tools in ns-3". In: *Journal of Communication and Information Systems* 36 (Jan. 2021), pp. 17–30. DOI: 10.14209/jcis.2021.2.

[76] Davide Magrin, Marco Centenaro, and Lorenzo Vangelista. "Performance evaluation of LoRa networks in a smart city scenario". In: *2017 IEEE International Conference on Communications (ICC)*. 2017, pp. 1–7. DOI: 10.1109/ICC.2017.7996384.

[77] Martina Capuzzo, Davide Magrin, and Andrea Zanella. "Confirmed traffic in LoRaWAN: Pitfalls and countermeasures". In: *2018 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)*. 2018, pp. 1–7. DOI: 10.23919/MedHocNet.2018.8407095.

[78] Nikos Kouvelas, V. Srinivasa Rao, and R. V. Prasad. "Employing p-CSMA on a LoRa Network Simulator". In: *ArXiv* abs/1805.12263 (2018).

[79] Michele Luvisotto et al. "On the Use of LoRaWAN for Indoor Industrial IoT Applications". In: *Wireless Communications and Mobile Computing* 2018 (May 2018), pp. 1–11. DOI: 10.1155/2018/3982646.

[80] Brecht Reynders, Qing Wang, and Sofie Pollin. “A LoRaWAN Module for Ns-3: Implementation and Evaluation”. In: WNS3 ’18. Surathkal, India: Association for Computing Machinery, 2018, 61–68. ISBN: 9781450364133. DOI: 10.1145/3199902.3199913. URL: https://doi.org/10.1145/3199902.3199913.

[81] Brecht Reynders et al. “Improving Reliability and Scalability of LoRaWANs Through Lightweight Scheduling”. In: *IEEE Internet of Things Journal* 5.3 (2018), pp. 1830–1842. DOI: 10.1109/JIOT.2018.2815150.

[82] Haiahem Rahim, Cherif Ghazel, and Leila Azouz Saidane. “An Alternative Data Gathering of the Air Pollutants In the Urban Environment using LoRa and LoRaWAN”. In: *2018 14th International Wireless Communications Mobile Computing Conference (IWCMC)*. 2018, pp. 1237–1242. DOI: 10.1109/IWCMC.2018.8450329.

[83] Floris Van den Abeele et al. “Scalability Analysis of Large-Scale LoRaWAN Networks in ns-3”. In: *IEEE Internet of Things Journal* 4.6 (2017), pp. 2186–2198. DOI: 10.1109/JIOT.2017.2768498.

[84] Semtech Corporation. *SX1301 datasheet*. 2017.

[85] Dr. Gilles Callebaut. *LoRaEnergySim*. URL: https://github.com/GillesC/LoRaEnergySim (visited on 08/29/2023).

[86] G. Callebaut, G. Ottoy, and L. van der Perre. “Cross-Layer Framework and Optimization for Efficient Use of the Energy Budget of IoT Nodes”. In: *2019 IEEE Wireless Communications and Networking Conference (WCNC)*. 2019, pp. 1–6.

[87] Gilles Callebaut, Geoffrey Ottoy, and Liesbet Van der Perre. “Optimizing Transmission of IoT Nodes in Dynamic Environments”. In: *2020 International Conference on Omni-layer Intelligent Systems (COINS)*. 2020, pp. 1–5. DOI: 10.1109/COINS49042.2020.9191674.

[88] M. Bor. *LoRaSim*. 2021. URL: https://github.com/mcbor/lorasim (visited on 06/24/2023).

[89] M. Bor. *LoRaSim*. 2021. URL: https://github.com/mcbor/lorasim (visited on 06/24/2023).

[90] IOT-MCU. *LoRa Radio Node v1.0*. 2018. URL: https://github.com/IOT-MCU/LoRa-Radio-Node-v1.0 (visited on 08/17/2023).

[91] Atmel Corporation. *ATmega328P Datasheet*. 2015. URL: https://ww1.microchip.com/downloads/en/DeviceDoc/Atmel-7810-Automotive-Microcontrollers-ATmega328P_Datasheet.pdf (visited on 08/17/2023).

[92] Arduino Documentation. *Bootload the Arduino Mini*. 2023. URL: https://docs.arduino.cc/hacking/software/MiniBootloader (visited on 08/17/2023).

[93] Rajguru Electronics. *FT232RL USB TO TTL 5V 3.3V Convertor Datasheet*. 2023. URL: https://components101.com/sites/default/files/component_datasheet/FT232RL-USB-TO-TTL-Converter-Datasheet.pdf (visited on 08/29/2023).

[94] Alexander Valach and Dominik Macko. "Optimization of LoRa Networks Using Multi-armed Bandit Algorithms". In: *Artificial Intelligence and Sustainable Computing*. Ed. by Manjaree Pandit et al. Singapore: Springer Nature Singapore, 2022, pp. 371–389. ISBN: 978-981-19-1653-3.

[95] Alexander Valach and Dominik Macko. "Upper Confidence Bound Based Communication Parameters Selection to Improve Scalability of LoRa@FIIT Communication". In: *IEEE Sensors Journal* 22.12 (2022), pp. 12415–12427. DOI: 10.1109/JSEN.2022.3174663.

[96] Michal Greguš. *Carrier Sensing of LoRa IoT Devices*. 2022.

[97] Daniel Russo et al. "A Tutorial on Thompson Sampling". In: *CoRR* abs/1707.02038 (2017). arXiv: 1707.02038. URL: http://arxiv.org/abs/1707.02038.

[98] Mike McCauley. *RadioHead Packet Radio library for embedded microprocessors*. URL: https://www.airspayce.com/mikem/arduino/RadioHead (visited on 08/29/2023).

[99] Benyamin Teymuri et al. "LP-MAB: Improving the Energy Efficiency of LoRaWAN Using a Reinforcement-Learning-Based Adaptive Configuration Algorithm". In: *Sensors* 23 (Feb. 2023), p. 63. DOI: 10.3390/s23042363.

[100] *Power Profiler Kit II*. en. URL: https://nsscprodmedia.blob.core.windows.net/prod/software-and-other-downloads/product-briefs/power-profiler-kit-ii-pbv10.pdf (visited on 09/07/2023).

[101] URL: https://support.arduino.cc/hc/en-us/articles/360013825179-Reduce-the-size-and-memory-usage-of-your-sketch.

[102] LoRaAlex Team. *LoRa Jupyter Notebook*. URL: https://github.com/loraalex/LoBook.git (visited on 08/03/2023).

[103] LoRaAlex Team. *LoRa@FIIT Access Point*. URL: https://github.com/loraalex/LoAP.git (visited on 08/03/2023).

[104] Michal Greguš, Alexander Valach, and Pavel Čičák. “Carrier Sensing of LoRa@FIIT Devices”. In: *2023 Communication and Information Technologies (KIT)*. 2023, pp. 1–9. DOI: 10.1109/KIT59097.2023.10297081.

Appendix E

About the Author

Alexander Valach received bachelor's and master's degrees in computer engineering from the Faculty of Informatics and Information Technologies, Slovak University of Technology in Bratislava, in 2018 and 2020, respectively, where he is currently pursuing a Ph.D. degree in applied informatics. In his work, he focused on low-power communication in the IoT networks, especially researching the possibilities of application of the LoRa technology.

E.1 Publication Activity

This section summarizes the publication activity of the author divided into multiple categories.

E.1.1 International Journal

1. A. Valach and D. Macko, "Upper Confidence Bound Based Communication Parameters Selection to Improve Scalability of LoRa@FIIT Communication," in IEEE Sensors Journal, vol. 22, no. 12, pp. 12415-12427, 15 June 15, 2022, doi: 10.1109/JSEN.2022.3174663.
   Citations:
   (a) Urabe, Ikumi, et al. "Combinatorial MAB-Based Joint Channel and Spreading Factor Selection for LoRa Devices." Sensors 23.15 (2023): 6687.

(b) Dakdouk, Hiba, et al. "Massive Multi-Player Multi-Armed Bandits for IoT Networks: An Application on LoRa Networks." (2022).

E.1.2 International Conference

1. A. Valach, L. Zemko, P. Čičák and K. Jelemenská, "LoRa™ Lab: Laboratory Network for Educational Purposes," 2023 21st International Conference on Emerging eLearning Technologies and Applications (ICETA), 2023, In press

2. D. Bucko, A. Valach, P. Čičák, M. Baláž and O. Kachman, "LoRa Industrial Monitoring and Management Network," 2023 Communication and Information Technologies (KIT), Vysoke Tatry, Slovakia, 2023, pp. 1-6, doi: 10.1109/KIT59097.2023.10297022.

3. M. Greguš, A. Valach and P. Čičák, "Carrier Sensing of LoRa@FIIT Devices," 2023 Communication and Information Technologies (KIT), Vysoke Tatry, Slovakia, 2023, pp. 1-9, doi: 10.1109/KIT59097.2023.10297081.

4. K. Rončkevič, A. Valach and P. Čičák, "Improved Visibility of LoRa Networks Using LoRa Performance Evaluation Tool," 2023 Communication and Information Technologies (KIT), Vysoke Tatry, Slovakia, 2023, pp. 1-7, doi: 10.1109/KIT59097.2023.10297107.

5. Valach, A., Macko, D. (2022). Optimization of LoRa Networks Using Multi-armed Bandit Algorithms. In: Pandit, M., Gaur, M.K., Rana, P.S., Tiwari, A. (eds) Artificial Intelligence and Sustainable Computing. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-1653-3_29

6. Hroš, D., Valach, A. (2022). System for Management and Visualization of LoRa Network Components. In: Pandit, M., Gaur, M.K., Rana, P.S., Tiwari, A. (eds) Artificial Intelligence and Sustainable Computing. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-1653-3_30

7. A. Valach and D. Macko, "Optimization of LoRa Devices Communication for Applications in Healthcare," 2020 43rd International Conference on Telecommunications and Signal Processing (TSP), 2020, pp. 511-514, doi: 10.1109/TSP49548.20

20.9163432.

Citations:

(a) Tasoglu, Savas. "Toilet-based continuous health monitoring using urine." Nature Reviews Urology 19.4 (2022): 219-230.

(b) Lalle, Yandja, et al. "Routing strategies for LoRaWAN multi-hop networks: A survey and an SDN-based solution for smart water grid." IEEE Access 9 (2021): 168624-168647.

(c) Wei, Yang, et al. "Priority-Based Resource Allocation Optimization for Multi-Service LoRaWAN Harmonization in Compliance with IEEE 2668." Sensors 23.5 (2023): 2660.

(d) Zemko, Ladislav, and Pavel Čičák. "IoT and LPWAN Networks: Increasing Efficiency by Communication Planning." 2022 45th International Conference on Telecommunications and Signal Processing (TSP). IEEE, 2022.

8. A. Valach and D. Macko, "Exploration of the LoRa Technology Utilization Possibilities in Healthcare IoT Devices," 2018 16th International Conference on Emerging eLearning Technologies and Applications (ICETA), 2018, pp. 623-628, doi: 10.1109/ICETA.2018.8572032.

Citations:

(a) R.O. Andrade and S.G. Yoo, “A comprehensive study of the use of LoRa in the development of smart cities,” in Applied Sciences, vol. 9, no. 22., article no. 4753, 2019.

(b) B. Buurman, J. Kamruzzaman, G. Karmakar and S. Islam, “Low-Power Wide-Area Networks: Design Goals, Architecture, Suitability to Use Cases and Research Challenges,” in IEEE Access, vol. 8, pp. 17179–17220, 2020.

(c) P. Pistek and M. Hudec, “Using SMS for Communication with IoT Devices,” in Mobile Networks and Applications, vol. 25, pp. 896–903, 2020.

(d) D. Taskin and S. Yazar, “A Long-range Context-aware Platform Design for Rural Monitoring with IoT in Precision Agriculture,” in International Journal of Computers Communications & Control, vol. 15, no. 2, article no. 3821, 2020.

(e) A. Moradbeikie, A. Keshavarz, H. Rostami, S. Paiva, S. Lopes, “GNSS-Free Outdoor Localization Techniques for Resource-Constrained IoT Architectures: A Literature Review”, In APPLIED SCIENCES-BASEL, 2021, vol. 11, no. 22, pp.

(f) S. Tasoglu, “Toilet-based continuous health monitoring using urine”, In Nature Reviews Urology, 2022-01-01, pp. ISSN 17594812.

(g) L. Zemko, P. Cicak, “IoT and LPWAN Networks: Increasing Efficiency by Communication Planning”, In: 2022 45th International Conference on Telecommunications and Signal Processing, TSP 2022. IEEE, 2022. ISBN 978-166546948-7, pp. 116-121. DOI: 10.1109/TSP55681.2022.9851258.

(h) M. Vigil-Hayes, M. Hossain, A. Elliott, E. Belding, E. Zegura. "LoRaX: Repurposing LoRa as a Low Data Rate Messaging System to Extend Internet Boundaries," 2022, pp. 195-213. doi: 10.1145/3530190.3534807.

(i) N. S. Chilamkurthy, O. J. Pandey, A. Ghosh, L. R. Cenkeramaddi and H. -N. Dai, "Low-Power Wide-Area Networks: A Broad Overview of Its Different Aspects," in IEEE Access, vol. 10, pp. 81926-81959, 2022, doi: 10.1109/ACCESS.2022.3196182.

E.1.3 Conference with International Participation

1. P. Čičák, L. Zemko, A. Valach and M. Marko, "Secure LoRa infrastructure for educational purposes", In Bezpečnosť elektronickej komunikácie 2023 : zborník príspevkov z vedeckej konferencie s medzinárodnou účasťou konanej dňa 11.05.2023. 1. vyd. Bratislava : Akadémia policajného zboru, 2023, S. 23-30. ISBN

E.1.4 Student Conference

1. L. Zemko, A. Valach, "LoRa Lab: Laboratory Network for Educational Purposes" in Proceedings of Informatics and Information Technologies Student Research Conference, 2023.

2. A. Valach, "Optimization of LoRa Networks Using Multi-Armed Bandit Algo-

rithms" in Proceedings of Informatics and Information Technologies Student Research Conference, 2021.

3. A. Valach, "Optimization of LoRa Devices Communication for Applications in Healthcare" in Proceedings of Informatics and Information Technologies Student Research Conference, 2020.

4. A. Valach, "Exploration of the LoRa technology utilization possibilities in healthcare IoT devices" in Proceedings of Informatics and Information Technologies Student Research Conference, 2018.