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Ph.D. THESIS SUMMARY

Seyed salar SEFATI

DENSIFICAREA OBIECTELOR ÎN INTERNETUL LUCRURILOR PENTRU SISTEME ULTRA FIABILE ȘI CU LATENȚĂ REDUSĂ

INTERNET OF THINGS DENSIFICATION FOR ULTRA-RELIABLE AND LOW-LATENCY SYSTEMS

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Abstract

Internet of Things (IoT), an innovation that originated in 1989, initially focused on incorporating small sensors. Over time, it evolved into a globally recognized technology, characterized by a vast network of interconnected devices. This advancement broadens the scope of internet connectivity from standard devices, like computers and smartphones, to include a wide variety of common items, including household appliances, automobiles, and wearable tech. This interconnectedness allows for seamless data exchange and automation in various fields, including healthcare, manufacturing, and urban planning, leading to enhanced efficiency, improved decision-making, and innovative solutions to complex challenges.

Ultra-reliable low-latency Communication (URLLC) is essential for the IoT, particularly in applications requiring maximum reliability and minimal latency. In the IoT ecosystem, URLLC enables real-time, uninterrupted communication between devices, critical for scenarios like industrial automation, healthcare monitoring, and autonomous vehicles. With its ability to deliver data transmission with latency as low as a few milliseconds and reliability as high as 99.999%, URLLC ensures that IoT devices can quickly and reliably share information, facilitating instant decision-making and action. The research presented in this thesis can be classified into five parts:

The thesis initially embarks on an exhaustive literature review that examines the evolving role of URLLC in the IoT. Chapter 2 introduces IoT and URLLC's significance, focusing on 5G's role, Quality of Service (QoS) frameworks, methodologies for URLLC, and implications on QoS. Chapter 3 addresses QoS-oriented service grouping in cloud computing, using advanced algorithms for efficient service selection and composition. Chapter 4 enhances routing and load balancing in Wireless Sensor Networks (WSNs) through a metaheuristic algorithm. Chapter 5 introduces an innovative approach for optimizing smart city services, utilizing Recurrent Neural Networks (RNN) and optimization algorithms to enhance QoS. Chapter 6 summarizes the research's academic contributions through published papers, provides a roadmap for future research avenues, and emphasizes the study's role in driving further advancements in the dynamic field of URLLC and IoT.

The conclusion of the thesis highlights the current contributions to IoT and URLLC and suggests future research directions, such as exploring the scalability of these solutions in larger, more complex IoT networks. This future-oriented perspective indicates the ongoing relevance and potential impact of the research.

Content

Chapter 1

Introduction

Ultra-reliable low-latency communication (URLLC) is crucial to the Internet of Things (IoT), particularly for smart city applications where reliable and rapid data exchange is indispensable. This chapter provides an in-depth introduction to URLLC's transformative role in IoT networks, emphasizing applications within smart city environments where high reliability and minimal latency are critical. The primary objective of this thesis is to investigate URLLC's role in improving reliability and latency for smart cities, industrial automation, and connected vehicle systems.

1.1 Overview

The IoT integrates physical objects into the digital world via intelligent devices equipped with sensors, communication capabilities, and computing power. IoT devices collect environmental data through their sensors, transmitting it to centralized servers for analysis. Actuators can then modify specific conditions based on this analysis. The URLLC framework is particularly important for the Industrial Internet of Things (IIoT) in Industry 4.0 and connected vehicle systems, where reliability and rapid data exchange are crucial for efficient operation [1].

Despite the increasing adoption of Low Power Wide Area Network (LPWAN) technologies for IoT device connectivity, they struggle to meet the low-latency requirements of URLLC due to their inherent limitations. Cellular IoT solutions, such as Narrow Band-IoT (NB-IoT) [2], address this gap by offering expanded coverage and improved latency performance, making them suitable for applications where timing and reliability are paramount. Furthermore, NB-IoT networks can dynamically adjust protocol parameters based on network conditions, enabling them to support increasingly complex real-time applications. This adaptability is crucial in industrial automation and vehicular systems, where network conditions can fluctuate significantly [3].

1.2 Scope of the doctoral thesis

Integrating URLLC into IoT networks is crucial for high-stakes applications where milliseconds can make a substantial difference. This thesis aligns with global research efforts aimed at improving IoT reliability and latency, building upon existing studies and proposing innovative solutions. Despite significant advancements in URLLC and IoT networks, several challenges and limitations persist, affecting their broader adoption and implementation:

Network Reliability and Resilience: Ensuring near-perfect reliability is critical for applications in healthcare, autonomous vehicles, and industrial automation. Maintaining such high levels of resilience remains challenging.

Scalability and Density of IoT Devices: High device density can lead to network congestion and interference, necessitating advanced algorithms for efficient data management.

Security and Privacy: Implementing robust security protocols without compromising performance is crucial. The extensive network of interconnected devices forms a vast attack surface, making them targets for cyber threats.

Energy Efficiency: Effective communication strategies must balance low energy consumption with the need for constant connectivity, which is challenging for battery-operated devices.

Spectrum Management: Efficient radio spectrum management requires dynamic allocation, interference management, and AI-driven prediction algorithms to maximize the efficient use of frequencies.

Cost and Investment: Implementing URLLC and IoT infrastructure requires substantial investment, necessitating strategic planning and cost-benefit analysis.

1.3 Research questions and purpose

The thesis aims to address these challenges and propose solutions for enhancing URLLC and IoT networks, focusing on improving deep architecture development. Research questions include:

- What challenges are faced in integrating URLLC into IoT networks for smart city applications?
- How are methodologies categorized for implementing URLLC in IoT networks?
- What challenges arise in integrating multiple cloud services, and what innovative approaches can meet complex requirements?
- What are the challenges regarding energy consumption and network longevity in IoT-WSN networks?
- What novel approach is proposed for IoT service discovery and composition, and how does it enhance Quality of Service (QoS) in smart cities?
- What future research directions are recommended for dynamic network reconfiguration and energy management in IoT?

1.4 Thesis structure

This thesis encompasses a comprehensive exploration of advanced solutions in smart cities, IoT, and big data environments through innovative algorithms and frameworks. Structured over several chapters, it delves into various aspects of IoT environments, from data routing protocols to cloud computing. The organization of the thsesis is outlined as follows:

Chapter 2: A thorough literature review and classification of URLLC in IoT contexts are presented, with a particular focus on the implications of 5G networks. This work is foundational for future research in understanding 5G's impact on IoT and URLLC.

Chapter 3: In the third chapter, the manuscript introduces an innovative methodology for selecting and integrating services within the cloud computing framework, leveraging the integration of adaptive penalty mechanisms within genetic algorithms alongside the ABC method. This approach significantly improves the allocation efficiency of cloud resources in scenarios involving IoT.

Chapter 4: In the fourth chapter, the development of a cutting-edge QoS-oriented routing protocol, which integrates load balancing strategies through the application of the Markov model and the ABC method. This chapter addresses challenges in wireless sensor networks, focusing on efficient data routing and network congestion management.

Chapter 5: This chapter introduces a comprehensive framework employing Recurrent Neural Networks and optimization algorithms, significantly enhancing service requirements in smart cities. It discusses the novel approach to addressing complex urban service demands in the context of IoT.

Chapter 6: In Chapter 6, the culmination of the research is presented, synthesizing the key findings and contributions from the preceding chapters and proposing directions for future work

Chapter 2

Exploring URLLC in IoT Through 5G

This chapter explores the foundational concepts and methodologies underpinning this thesis. Section 2.1 lays the groundwork by examining the role of IoT in modern technology, particularly emphasizing sensor devices and communication protocols. The chapter progresses by emphasizing the importance of URLLC in the 5G cellular landscape, as defined by the 3GPP standards. Section 2.2 dives into the methodologies used in this study, categorizing them into structural, diversity, metaheuristic, and channel state information (CSI) methods to present a comprehensive view of URLLC applications in IoT. Finally, the chapter addresses the broader implications of URLLC for QoS in IoT networks.

2.1 Architecural overview and diversity of IoT networks

The IoT ecosystem comprises various interconnected technologies and components. Its architecture connects a multitude of sensor-based devices that communicate and interact across different domains, including industrial applications and smart home systems. These devices, along with actuators and communication modules, form the physical layer responsible for data collection and interaction. The network layer ensures seamless communication between these devices and the broader network, often relying on wireless protocols. The middleware layer acts as an intermediary between the physical and application layers, refining the collected data for advanced applications such as smart city management, home automation, and industrial automation [4].

The introduction of 5G into IoT networks brings considerable advancements in network capacity, minimal latency, and exceptional reliability. It enables real-time data exchange for applications demanding rapid response, such as autonomous vehicles and telehealth services. This technology also facilitates the seamless connection of more devices while maintaining consistent performance. Nevertheless, developing IoT networks presents challenges, including scalability, security, and energy efficiency.

Overcoming these obstacles requires innovative protocols, standards, and technologies to handle the growing number of IoT devices effectively.

2.2 Comparative Analysis and Categorization of URLLC Methodologies in IoT networks

Structure-Based Methodology: Orthogonal Frequency-Division Multiplexing (OFDM) [5]exemplifies a strategic approach in telecommunications development. Its flexibility in subcarrier spacing, advanced modulation techniques like Quadrature Amplitude Modulation (QAM), and integration with emerging technologies such as massive MIMO and beamforming make it ideal for high-bandwidth 5G networks [6].

Diversity Approach: This approach enhances system robustness and reliability by navigating issues like error probability and noise interference. Modulation Coding Scheme (MCS) techniques employ redundancy over time to improve signal robustness, and the integration of Frequency/Time/Space Diversity ensures consistent and reliable transmission [7].

Meta-Heuristic Approaches: Inspired by natural phenomena, these methodologies handle global optimization problems by iteratively developing innovative concepts and learning processes to identify effective search regions within networks. This approach enhances network reliability, aligning with URLLC objectives [8].

CSI: CSI provides critical insights into wireless channels, such as signal strength and temporal delays. Channel estimation, often through pilot signals, allows systems to infer channel conditions and adjust parameters like power levels and modulation schemes accordingly. Feedback-based CSI acquisition complements this by enabling real-time response to changing conditions [9]. Table 2.1 shows the pros and cons of each method.

Table 2.1 *General QoS of each method.*

Method	Efficiency	Adaptability	Reliability	Complexity	Latency	Energy
Structure-based	High in data rate handling	Adapts to sub-carrier spacings	Ideal for dense areas	Moderately complex	Low	Moderate
Diversity Approach	Robust in variable conditions	Effective in diverse scenarios	Strong in high-noise areas	Complex analysis	Optimizable	Varies generally efficient
Meta-Heuristic Approaches	Practical for network complexities	Adapts to network changes	Near-optimal reliability	Iteratively complex	Algorithm-dependent	Algorithm complexity-dependent

CSI in 5G IoT	Real-time optimization	Responsive to channel changes	Maintains fidelity and efficiency	Detailed feedback mechanisms	Low	high

2.3 URLLC overview & conclusion

The methodologies explored above were analyzed for their implications on URLLC metrics. Around 40% of studies emphasized energy consumption and availability, while 10% focused on scalability, cost, and complexity.

Risk-Aware Strategy in URLLC: Advances like Enhanced Mobile Broadband (eMBB) and Massive Machine Type Communications (mMTC) aim to improve data speeds and support vast IoT networks. URLLC aims for minimal latency (1 ms) and error rates (under 10), crucial for autonomous vehicles, virtual reality, and industrial IoT. Conditional Value at Risk (CVaR) scheduling strategies help ensure proportional fairness by splitting the problem into scheduling eMBB users and URLLC devices.

Hardware Technology with Low Cost in URLLC: Cost-effective hardware technology is crucial for the proliferation of URLLC-based IoT environments. System-on-Chip (SoC) technology reduces costs by integrating components like processors, memory, and communication interfaces. Software-Defined Radios (SDRs) provide adaptable hardware solutions via software-based reconfiguration. Reduced hardware costs will be vital for the adoption of massive MIMO and the shift to Terahertz (THz) bandwidths, influencing transceiver design for the 5G-to-6G transition.

Scalability and Availability: Machine Learning (ML) enhances the scalability and availability of IoT networks. Learning architectures must evolve to support multiple entities, providing accurate epistemic uncertainty estimates and ensuring efficient communication. Techniques like compensated learning phases can accurately assess network needs and improve QoS.

Energy Consumption and Management: Energy management will be a challenge in 5G networks due to processing massive data and operating extensive antennas. Efficient energy harvesting circuits will allow devices to operate independently, supported by advanced power consumption strategies. Expanded Kalman Filtering (EKF) techniques enable efficient energy control and prediction mechanisms, ensuring optimal energy usage. Additionally, renewable energy sources and adaptable communication protocols will enhance energy efficiency, vital for reliable URLLC in IoT systems.

Chapter 3

Optimizing IoT service selection and composition in cloud computing

This chapter explores the strategies for QoS-oriented service grouping in Cloud Computing (CC). Individual cloud services often fail to meet complex real-world needs, so this research highlights the importance of integrating multiple services to enhance functionality and consumer satisfaction. The problem of service grouping is NP-hard, necessitating advanced metaheuristic algorithms for near-optimal solutions. A novel approach, combining the Artificial Bee Colony and Genetic Algorithm (ABCGA), is introduced. The Genetic Algorithm (GA) selects initial services based on a fitness function, while the Artificial Bee Colony (ABC) algorithm further optimizes selection based on specific QoS criteria. CloudSim simulations demonstrate the method's effectiveness in delivering reliable, accessible, and cost-efficient service groupings. This advanced strategy aims to reduce response times, service costs, and energy usage, enhancing the speed and efficiency of service grouping in the cloud. Additionally, the chapter compares ABCGA with other metaheuristic algorithms and discusses future CC models that could benefit from improved brokering and resource management.

3.1 Overview of cloud service selection

Over recent years, CC has gained immense popularity due to its advantageous features and cost-effectiveness. Users benefit from these services without needing extensive IT skills, paying only for what they use and avoiding technical complexities. CC is evolving to offer services akin to utilities like electricity and water, emphasizing affordability. Its architecture delivers three main services: Software as a Service (SaaS) [10], Platform as a Service (PaaS) [11], and Infrastructure as a Service (IaaS) [12]. Cloud providers assess QoS and handle two types of service requests: single and multiple. While offering a single service is straightforward, selecting multiple services simultaneously is more challenging. Often, users' needs require a combination of multiple resources and services through service composition. Integrating services to meet diverse user needs is complex, making service composition an NP-hard problem, necessitating metaheuristic algorithms to find near-optimal solutions efficiently.

This research introduces a novel approach to selecting suitable services that meet users' QoS demands, employing an adaptive penalty function created using GA [13] and ABC algorithm [14]. GA initially identifies the right services based on a fitness function, and then the ABC algorithm combines these services according to QoS evaluation criteria. The key outputs of this approach include:

- Optimal Service Collection: Identifies an optimal set of services based on QoS criteria, ensuring alignment with user objectives.
- Reduced Response Time and Cost: Decreases the time to respond to service requests and overall service costs, enhancing efficiency.
- Increased Speed of Service Composition: Improves the rate of service composition, leading to faster deployment and user satisfaction.
- Lower Power Consumption: Reduces power consumption compared to other metaheuristic algorithms, promoting energy-efficient cloud computing solutions.

3.2 Proposed method of Service selection

The proposed method involves a multi-step approach combining GA and ABC algorithms to optimize service composition in cloud computing environments.
Here is a step-by-step summary:

Step 1: Initial Population and Fitness Evaluation

Initialization: The GA begins by creating an initial population of chromosomes, each representing potential solutions through numerical sequences.
Fitness Function: Each chromosome's fitness is assessed to determine the most efficient combination of services, considering both quantitative and qualitative dimensions.

Step 2: Chromosome Selection

Selection Process: Chromosomes are selected based on their fitness using a probability function *P(x)*, where a higher fitness value increases the likelihood of selection.

Step 3: Crossover and Penalty Application

Crossover Mechanism: New offspring chromosomes are generated by merging parent chromosomes using a weighted average method.
Fitness and Penalty Functions: The fitness function F_{obj} and the penalty function *P(x)* are applied to evaluate each chromosome, penalizing those with constraint violations to guide the search towards feasible solutions.

Step 4: Transition to ABC Algorithm

ABC Algorithm Initiation: Once the GA identifies the best QoS solutions, the ABC algorithm is employed to further refine service combinations to meet user requirements.

Step 5: Search Space Exploration

Bee Movement: The ABC algorithm explores the search space, adjusting bee positions Q_{ik} to find the most favorable service locations using a random variable to guide the search.

Step 6: Population Representation

Food Source Representation: Each food source (service) is represented by x_{mi} within the population, with parameters defining the limits of the search space.

Step 7: Employed Bees' Search

Service Identification: Employed bees search for new services, representing new food sources, and retain information about the nectar (service quality) near each source.

Step 8: Fitness Function Evaluation

Service Evaluation: The fitness of each service is evaluated using a specific formula. If the fitness meets user requirements, the service is deemed optimal; otherwise, the search continues.

Step 9: Onlooker Bees' Search

Alternative Search: If the initial fitness evaluation is insufficient, onlooker bees search for alternative services, using a mathematical process to navigate and evaluate new food sources.

By combining GA and ABC algorithms, this method systematically enhances the service composition process in cloud computing, aiming to identify and optimize services that meet specific user requirements effectively.

3.3 Experimental results of service selection

The dataset was generated using the Quality of Web Service (QWS) methodology, evaluating qualitative aspects such as functionality, security, and flexibility, alongside six conventional QoS indicators. Security, usability, and flexibility were categorized into low, medium, and high for analysis ease. Response times were divided into intervals (e.g., 0.5, 2, 3 seconds), availability was quantified as exact percentages (e.g., 99.5%, 99.9%, 99.999%), and costs were specified in units (e.g., 5, 20, 30, 40). Using these parameters, 50 services were assembled, adhering to the QWS model and emphasizing practical adaptation by service providers. Communication distances spanned from 20 to 500 units for user-cloud data center interactions and 50 to 400 units for user-service array connections. Cloud SIM was employed for experimental verification, simulating a SaaS platform to provide a tailored resource allocation environment [15].

The proposed method was benchmarked against Moth Flame Optimization (MFO) [16], ABC [17], Greedy (GR) [18], Grey Wolf Optimization (GWO) [19], and Hidden Markov Model (HMM) [20] algorithms on the same dataset. Costs were calculated as the aggregate of selected services, allowing users to convey the significance of each contributing factor, enhancing reliability. Reliability, especially critical in virtual machines for domains like power supply, traffic control, and healthcare, was a focus.

Cost Efficiency: The proposed method achieved superior cost reductions compared to other strategies, with MFO being a close contender. The HMM algorithm showed less favorable outcomes in cost efficiency.

Response Times: The proposed method achieved the quickest response times as the volume of requests increased, followed closely by MFO. HMM struggled with efficient response times for a large number of services due to its complexity.

Availability: The new method outperformed others in terms of availability, crucial for service success, with GWO and GR showing the least impressive results.

Reliability: Results for reliability were comparable across most methods, with the proposed method registering a marginally higher score. However, the predictability of HMM resulted in lower reliability.

Energy Consumption: MFO demonstrated the most efficient energy usage. The proposed method showed similar performance to MFO at low request counts but higher energy consumption beyond 9000 requests. HMM outperformed ABC and GR in energy efficiency, while GWO, MFO, and the proposed algorithm exhibited lower energy consumption.

3.4 Conclusion

CC is favored for its cost-effective provision of hardware and software resources. The integration of various services often presents NP-hard challenges, necessitating service composition for complex demands. This research combines GA and ABC algorithms, where GA selects services based on user needs and ABC evaluates and integrates them. The GA uses a penalty mechanism for constraint handling without eliminating non-viable options, accelerating effective solution development. Cloud-SIM simulations demonstrated the proposed method's superior performance in response time, reliability, and cost, despite higher energy use compared to the MFO algorithm.

Chapter 4

QoS-Driven Routing and Load Balancing in IoT-WSN Networks with Markov Model and ABC Algorithm

In Chapter 4 of the thesis, we explore the pivotal challenges of energy consumption and network longevity in IoT-WSNs, focusing on the development of an innovative routing and load-balancing scheme. This chapter introduces the integration of the Markov Model (MM) and the ABC algorithm to optimize the selection of CHs, utilizing the Low-energy adaptive clustering hierarchy (LEACH) algorithm for initial load balancing. Through MATLAB simulations, the chapter demonstrates the effectiveness of this novel Markov Model Artifical Bee Colony (MMABC) approach in enhancing energy efficiency, prolonging node lifespan, and ensuring reliable data transmission to Base Stations (BS) and Cluster Heads (CHs). This addresses the immediate challenges in WSNs and contributes significantly to the broader field of network management, highlighting potential applications in various real-world scenarios.

4.1 Overview of IoT-WSN

The advent of IoT has revolutionized our interaction with technology, with WSN being a key component. IoT-WSN ecosystems consist of numerous sensors and devices communicating wirelessly, enabling real-time data flow from physical to digital environments. These networks are crucial in urban development, industrial automation, environmental surveillance, and healthcare, offering unprecedented insights and automation capabilities. Effective routing algorithms in IoT-WSNs must be scalable and efficient, addressing sensor node limitations while ensuring reliable data delivery. Load balancing is essential but challenging due to its NP-hard nature, necessitating metaheuristic algorithms for effective solutions.

This paper introduces a novel cluster-based routing method focusing on load balancing and QoS improvement in IoT-WSNs [21]. The proposed method combines the MM and the ABC algorithm to optimize CH selection and reduce energy consumption. It begins with predicting the residual energy of each sensor node using

MM based on their location, followed by the ABC algorithm performing local searches to evaluate CH candidates. Key contributions include:

- MMABC Algorithm for Efficient CH Selection: The MMABC algorithm efficiently selects new CHs, optimizing load balancing and significantly reducing cluster-building time.
- Energy Consumption Reduction: Combining MM's predictive capabilities with the ABC algorithm decreases overall WSN energy consumption.
- Improved QoS Parameters: Enhances various QoS parameters such as the number of live nodes, total packets sent to CH and BS, and average residual energy, thereby improving network performance and QoS.

4.2 Network model of IoT-WSN

In our proposed approach, we employ the LEACH algorithm to group nodes into clusters initially, and starting from the second iteration, we integrate the MMABC algorithm into the network operation. Initially, MM techniques identify several candidate nodes for potential CH roles based on historical data about the network nodes. Subsequently, the ABC algorithm is employed to select and confirm one of the candidates for each CH role. As depicted in Figure 4.1, some CHs can establish direct connections with the BS, while others must resort to multi-hop communication to transmit data to the BS. The primary responsibility of CHs is to aggregate the received data and prepare it for onward transmission to their respective destinations. Subsequently, CHs transmit this data to the BS, using either single-hop (direct) communication for nearby CHs or multi-hop routing for those situated at a greater distance from the BS.

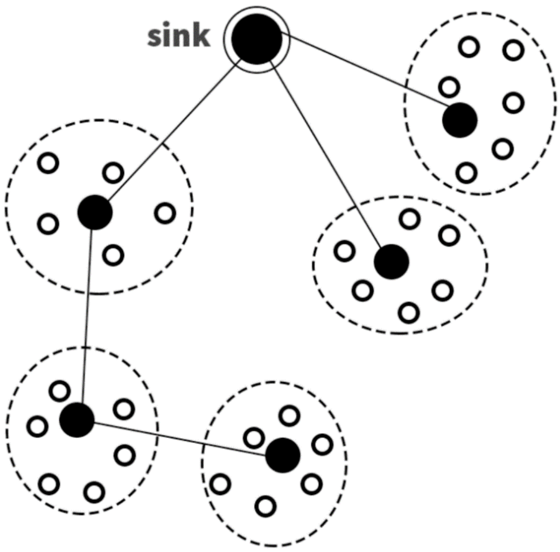

Figure 4.1 : *IoT-WSN network model*

When setting up network nodes within domains, the LEACH algorithm is utilized alongside the MM and the ABC algorithm to choose the optimal CH based on network conditions during each iteration. To clarify, starting from the second iteration onward, the MM identifies the most promising candidates for assuming the role of cluster heads within each domain. The ABC algorithm subsequently selects one of them based on criteria such as location and energy efficiency. Energy transmission occurs through single hops for nearby destinations and employs the nearest neighbor method for multiple hops when dealing with distant destinations. Nodes designated as CHs cannot take on the same role until the P-th iteration, where P represents a specified percentage of clusters. Consequently, in each iteration, a node has a 1/P chance of becoming a CH. Cluster members can only communicate with the CH using Time-division multiple access (TDMA) schemes [22], following the schedule established by the CH. The LEACH algorithm consistently employs single hops for transmitting data from all CHs to the BS.

4.3 Energy consumption in IoT-WSN

The proposed model's energy usage was determined through the application of the LEACH algorithm. To compute the energy needed for transmitting a data packet of size k bits across a distance d (which represents the space between sender and receiver nodes), can employ the subsequent Eqution (4.1).

$$E_{tx}(i) = k(E_{elec} + E_{anp} * d^2) \tag{4.1}$$

Here, E_{elec} represents the energy consumption within the electrical circuit, while E_{anp} signifies the energy needed to amplify the transmitted signals for sending a single bit of data. Additionally, can calculate the energy necessary to receive a data packet containing *k* bits with the following Equation (4.2):

$$E_{rx}(i) = k * E_{elec} \tag{4.2}$$

Furthermore, for nodes positioned at a midpoint between the sender and receiver nodes, the total energy consumed will be the combination of the energy needed for both sending and receiving the data:

$$E_{cons}(i) = \sum_{i=1}^{n} [E_{tx}(i) + E_{rx}(i)] \tag{4.3}$$

Therefore, the energy utilized by any nodes, whether they are sending or receiving, within these networks can be determined using the provided equations.

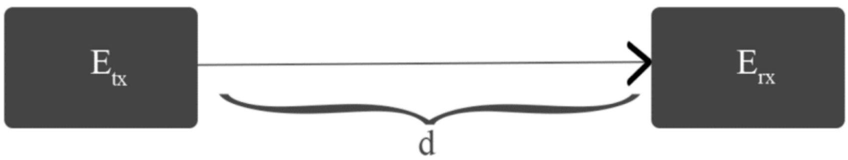

Figure 4.2 : *The transmission of energy*

4.4 Proposed algorithm of IoT-WSN

The proposed approach employs the MM to identify nodes with the highest remaining energy. Then, the ABC algorithm selects CH nodes from those identified by MM, with the least active central node being chosen as the CH in each iteration. The steps are as follows:

Initialization: Sensor nodes are randomly dispersed in the environment.

Initial CH Selection: The LEACH algorithm designates initial CHs.

Advertisement: CH nodes broadcast advertisement packets to nearby cluster members (CMs).

Cluster Formation: Remaining nodes join clusters based on Received Signal Strength (RSS).

Data Transmission: Using the LEACH algorithm, data is transmitted.

Subsequent CH Selection: From the second iteration, MM identifies optimal nodes based on fitness functions and historical data, and ABC finalizes the CH selection.

Fitness Function: The fitness function combines residual energy, distance from the center, and buffer size to evaluate nodes.

The fitness function is given by:

$$\text{Fitness(i)} = \alpha\left(\frac{E_{res}(i)}{E_{init}}\right) + \beta\left(1 - \frac{D_{cen}(i)}{D_{max}}\right) + \gamma\left(\frac{B_{res}(i)}{B_{init}}\right) \quad (4.5)$$

$$\alpha + \beta + \gamma = 1 \quad (4.6)$$

Algorithm Steps:

First Round:

1. Randomly distribute sensor nodes.
2. Select CHs based on a threshold.
3. CHs broadcast signals to attract nodes.
4. Nodes join clusters based on signal strength.
5. Data transmission.

Second Round Onwards:

1. Calculate fitness for all nodes.
2. MM identifies candidate nodes.
3. ABC approves new CHs.
4. Data transmission continues with new CHs.

Nodes start with an initial energy of 1 joule and a buffer size of 65 bytes. CHs are selected in each iteration using MM and ABC, and data is transmitted to the BS using the nearest neighbor approach.

4.5 Experimental results of IoT-WSN

The proposed approach employs the MM and ABC algorithm to optimize CH selection, enhancing energy efficiency and extending network lifespan in IoT-WSNs. This method was evaluated against several algorithms, including Ant Colony Optimization (ACO) [23], Glowworm Swarm Algorithm (GSO) [24], Greedy Meta-heuristic Algorithm, Meta-Heuristic Ant Colony Optimization based Unequal Clustering (MHACO-UC) [25], and Chaotic Discrete Artificial Bee Colony (CDABC) [26], using a consistent dataset. Simulations were conducted in MATLAB R2016b on a system with an Intel Core i7 processor and 16 GB RAM, running Windows 10.

Network Lifespan: The proposed method demonstrated the longest network lifespan, with a significantly higher number of surviving nodes beyond 1500 rounds.

Energy Consumption*:* It showed more efficient energy management from the initial rounds, outperforming other algorithms in conserving total energy.

Data Collection: The proposed method collected the largest amount of data at the CH level.

Packet Transmission*:* It excelled in the total number of packets received by the BS, particularly in the early rounds.

Convergence: The method displayed rapid convergence, reaching stable performance within about 40 cycles.

Stability: The proposed method exhibited strong stability across various tasks and iterations, outperforming other algorithms.

4.6 Conclusion

The integration of MM and ABC techniques in selecting CH nodes ensures a balanced distribution of tasks, significantly improving network energy efficiency and lifespan. The strategic selection of CH nodes is crucial for minimizing energy expenditure, enhancing network longevity. The MMABC algorithm identifies optimal CH candidates based on energy levels and geographical positioning, and the ABC algorithm evaluates their suitability. Simulation results indicate that this methodology surpasses existing algorithms in energy efficiency, data reception rates at CH and BS levels, and overall network performance.

Chapter 5

Optimizing Smart City Services with Recurrent Neural Networks and Optimization Algorithms

This chapter tackles the challenge of identifying and integrating services within the IoT framework for smart urban settings, focusing on improving QoS optimization. We introduce a methodology using an Recurrent Neural Network (RNN) framework enhanced by Long Short-Term Memory (LSTM) networks and Black Widow Optimization (BWO) technology. The RNN leverages LSTM's capabilities for recognizing temporal patterns and uses Backpropagation Through Time (BPTT) for parameter updates. Inspired by black widow spiders, the BWO strategy refines service selection through attraction and repulsion dynamics, pinpointing the optimal top-K services that meet QoS requirements. This approach significantly enhances the speed, accessibility, and reliability of IoT service discovery and integration.

5.1 Overview of service discovery

A smart city is characterized by an advanced urban environment reshaped by IoT, enhancing life quality, urban service efficiency, and economic growth. IoT integrates diverse sensors and devices into common objects like streetlights and water systems, forming a vast network that exchanges and processes information. This network allows real-time supervision and management of urban infrastructures, improving energy allocation, waste management, public safety, and city planning, making cities more sustainable, comfortable, and adaptable to evolving demands. In IoT, service discovery and composition involve linking varied devices using technologies like the semantic web, service-oriented architecture, and cloud computing, creating a dynamic and scalable service framework for smart city applications. A major challenge is ensuring these services meet user requirements, particularly QoS. This study introduces a novel approach to selecting services that optimally fulfill users' QoS expectations, addressing the NP-hard problem of service selection in smart cities. The method employs an RNN algorithm to estimate each service's QoS based on connected devices, traffic volume, and network structure, using historical data to project QoS through recognized patterns. Subsequently, BWO is used for service composition. Key contributions include:

- Integrating QoS to meet user requirements.
- Enhancing latency, energy use, availability, and reliability.
- Conducting comprehensive experiments to evaluate the approach's efficiency across diverse services.

5.2 Proposed method & Experimental results

A RNN is a specialized neural network designed to handle sequential data by preserving important information in its memory through loops, making it suitable for applications like time-series prediction and natural language processing. RNNs incorporate previous network states as inputs, allowing them to remember past inputs and enhance prediction accuracy. LSTM networks, a type of RNN, manage long-term dependencies more effectively. RNNs are trained using BPTT to update weights by minimizing a loss function. However, they face challenges like the vanishing gradient problem, which techniques such as LSTMs and gradient clipping mitigate. In this study, the RNN framework operates on three layers: Input, Recurrent, and Output. The input layer includes user preferences, the number of users, available services, targeted services, and top-K services. The RNN identifies the top-K services by analyzing QoS data, predicting the most suitable services based on various parameters. These values include response time, throughput, reliability, availability, and energy consumption. After discovering available services, the BWO algorithm uses these services to meet user requests by identifying the optimal service combinations. Inspired by black widow spiders, BWO uses attractive and repulsive forces to evaluate service combinations, iteratively refining candidates until the optimal solution is found.

This methodology is evaluated against several algorithms including GA-based QoEaware service composition (GQSC) [27], Artificial Neural Network based Particle Swarm Optimization (ANN-PSO) [27], Deep Reinforcement Learning (DRL) [28], and ML [29], primarily applied in the context of service discovery and composition. Consistent fitness values were observed across all datasets for each algorithm. The research focused on analyzing the variables and their magnitudes, in addition to the factors and results of the simulations. Our city-centric methodology was assessed utilizing the Cooja simulator tailored for mobile applications. This involved a simulated intelligent urban environment where interactions occurred between service providers, citizens, and a network of gateways overseeing services. The configuration allowed for both static and mobile states of providers, citizens, and gateways, with the latter capable of handling service registration, distribution, and discovery. To suit the expansive and evolving nature of a smart city, we applied an overlay maintenance mechanism to both models.

The simulations operated on a Linux OS, powered by a Corie i7 Intel processor with 32GB of RAM. In the realm of government and planning, the service developed generates a street dashboard, integrating data from street videos, temperature readings, and water levels. It leverages Dublin's points of interest (POIs) and their corresponding domains as benchmarks. Each POI receives automatic domain labeling based on its geographic position and the tags in open street maps. City services are delineated using Dublin POIs and their specific domains. The simulation, replicating Dublin city's framework, encompasses 500 gateways, split evenly between 250 mobile and 250 static units. The experiments varied in the number of services and adjusted several parameters for each method . For the technical specifications of our simulation, we adjusted the learning rate to 0.01 and experimented with different configurations of the neural network, including the number of hidden layers set at 3, 5, and 7, and the number of neurons per layer at 50 and 100. Additionally, we varied the batch size, testing both 32 and 64, and conducted experiments over 50 and 100 epochs to thoroughly evaluate the performance and efficiency of our methodology [30].

This study evaluates various algorithms in IoT service discovery and composition by measuring the ratio of successfully processed requests. Our proposed method demonstrates superior performance, achieving higher success rates at increasing service counts compared to the ML algorithm and GQSC, which show lower success rates. This method combines RNN algorithms to forecast QoS with BWO algorithms to enhance request resolution rates, forming a robust framework for IoT service discovery and composition.

Reliability: Reliability is also assessed across different methods, with our proposed method ranking the highest, especially at higher service counts, while others, like the GQSC algorithm, show declining reliability scores.

Cost: Cost analysis reveals that the ML algorithm is the most economical, while the ANN-PSO algorithm is the costliest. Our proposed method incurs higher costs than the ML and DRL algorithms due to its metaheuristic approach for addressing composition challenges.

Availability:, crucial for IoT service accessibility, is ensured at higher levels by our method, reflecting robust design and redundancy protocols.

Energy: Energy consumption, a critical factor in IoT environments, is balanced in our method, showing efficient use of energy, especially for battery-reliant devices.

Latency: Latency in service discovery is another key metric, with our proposed method achieving the lowest latency times across various service volumes, outperforming the ML, ANN-PSO, and DRL algorithms.

5.3 Conclusion

Smart cities powered by IoT technologies promise to enhance living standards through refined infrastructure, services, and sustainability. Service discovery and composition are key to adapting to evolving urban demands while maintaining service quality. This study introduces a novel methodology using RNN and BWO algorithms to improve service composition in IoT frameworks. The RNN-LSTM predicts service quality, while the BWO algorithm integrates services to meet user demands, significantly enhancing service composition accuracy and IoT system performance. Evaluated in a simulated smart city environment, the method proves effective in metrics like latency, reliability, availability, and request resolution, though it incurs higher energy consumption and costs. Future research could involve real-world testing, incorporating deep learning for QoS prediction, exploring metaheuristic algorithms, and introducing new efficiency metrics.

Chapter 6

Synthesis of Findings, Publications, and Future Directions

In this thesis, we explored the integration of URLLC in IoT, focusing on smart city applications. Our major contributions include developing innovative solutions for IoT systems to achieve high reliability and minimal latency, crucial for transforming industries and smart cities. We categorized methodologies for implementing URLLC in IoT into structure-based, diversity-based, metaheuristic algorithm-based, and channel state information-based approaches, providing a comprehensive understanding of URLLC applications. Additionally, we addressed challenges in deep architecture development for URLLC and IoT, enhancing data processing and interpretation capabilities. Our work also highlighted the need for agile, adaptive networks, energy efficiency strategies in 5G/6G, and advanced security and privacy measures. These findings pave the way for future research aimed at improving IoT system efficiency and reliability in smart city environments and beyond.

6.1 Overview of Additional Research Contributions

During this research, several papers were published, significantly contributing to the field, though not included as individual chapters in this thesis:

Improving Security in VANETs via Enhanced Sybil Attack Detection Techniques: This manuscript introduces a novel method for detecting Sybil attacks in Vehicular Ad Hoc Networks (VANETs) using a fitness function and metrics like signal strength index and throughput. It enhances network security comprehension and ensures safer and more reliable vehicular communication systems by addressing Sybil attacks and broader vehicular network threats .

Optimizing Cluster Selection in Flying Ad Hoc Networks (FANETs) for Load Balancing: This research presents a novel clustering mechanism for FANETs, focusing on energy efficiency and resource optimization, addressing unique challenges posed by the mobility and energy constraints of flying networks .

Data Forwarding with Fault Tolerance in IoT Fog Computing: Introducing a robust data forwarding framework emphasizing fault tolerance in fog computing environments, this paper significantly enhances the resilience and reliability of IoT systems and contributes to the growing field of fog computing .

Fuzzy Logic Enhanced Mobile Sink Utilization for URLLC in IoT: By employing fuzzy logic in mobile sink utilization for data gathering, this paper highlights the importance of intelligent and adaptive systems in managing ultra-reliable and low-latency communications in IoT .

Energy-Efficient and Stable Routing in MIoT: This research develops a routing protocol focusing on predicting and optimizing energy consumption and link stability, addressing critical aspects of mobile IoT networks such as energy management and network reliability .

A Hybrid Heuristic Algorithm for Data Replication in Distributed Systems: This work on data replication in distributed systems using artificial agents presents a novel hybrid heuristic algorithm developed in collaboration with Istinye University. It optimally manages data placement and replication, significantly impacting data management in complex network environments .

QoS Enhancement in IoT Big Data Environments Using Harris Hawks Algorithm: Applying the Harris Hawks optimization algorithm to improve QoS in IoT, particularly in big data contexts, this paper contributes to understanding how big data and IoT can be synergized for optimized network performance .

IoT Service Recommendation for Group Users Based on Popularity: This study proposes a method for IoT service recommendation focusing on group users and leveraging service popularity, addressing user-centric aspects and dynamics of service utilization in IoT .

A Bioinspired Test Generation Method Using Discretized and Modified Bat Optimization Algorithm: This approach adapts the Bat Optimization Algorithm for software testing, developed in collaboration with Istinye University, enhancing test generation methods in software engineering .

Enhancing Internet of Things Security and Efficiency: Anomaly Detection via Proof of Stake Blockchain Techniques: Introducing the Proof of Stake (PoS) algorithm for anomaly data detection in IoT, this paper demonstrates superior performance in terms of QoE metrics like Processing Time Reduction Ratio (PTRR), Resource Gain (RG), and latency.

6.2 List of publicitons

6.2.1 Journal publicitions

1. Sefati, Seyed Salar, and Sara Ghiasi Tabrizi. "Detecting sybil attack in vehicular ad-hoc networks (vanets) by using fitness function, signal strength index and throughput." *Wireless Personal Communications* (2022): 1-21. https://doi.org/10.1007/s11277-021-09261-x WOS:000712739400002 Q2 – IF= 2.017
2. Sefati, Seyed Salar, Simona Halunga, and Roya Zareh Farkhady. "Cluster selection for load balancing in flying ad hoc networks using an optimal low-energy adaptive clustering hierarchy based on optimization approach." *Aircraft Engineering and Aerospace Technology* 94.8 (2022): 1344-1356. https://doi.org/10.1108/AEAT-08-2021-0264 WOS:000784089300001 Q3 – IF=1.5
3. Sefati, Seyed Salar, and Simona Halunga. "A hybrid service selection and composition for cloud computing using the adaptive penalty function in genetic and artificial bee colony algorithm." *Sensors* 22.13 (2022): 4873. https://doi.org/10.3390/s22134873 WOS:000825529200001 Q2 – IF=3.9
4. Arasteh, Bahman, Seyed Salar Sefati, Simona Halunga, Octavian Fratu, and Tofigh Allahviranloo. "A hybrid heuristic algorithm using artificial agents for data replication problem in distributed systems." *Symmetry* 15, no. 2 (2023): 487. https://doi.org/10.3390/sym15020487 WOS:000942053900001 Q2 – IF = 2.7
5. Sefati, Seyed Salar, and Simona Halunga. "Ultra-reliability and low-latency communications on the internet of things based on 5G network: Literature review, classification, and future research view." *Transactions on Emerging Telecommunications Technologies* (2023): e4770. https://doi.org/10.1002/ett.4770 WOS:000964150700001 Q1 – IF=4.7
6. Sefati, Seyed Salar, Mehrdad Abdi, and Ali Ghaffari. "QoS-based routing protocol and load balancing in wireless sensor networks using the markov model and the artificial bee colony algorithm." *Peer-to-Peer Networking and Applications* 16.3 (2023): 1499-1512. https://doi.org/10.1007/s12083-023-01502-z WOS:000990428800002 Q2 – IF =4.6
7. Sefati, Seyed Salar, Bahman Arasteh, Simona Halunga, Octavian Fratu, and Asgarali Bouyer. "Meet User's Service Requirements in Smart Cities Using Recurrent Neural Networks and Optimization Algorithm." IEEE Internet of Things Journal (2023). https://doi.org/10.1109/JIOT.2023.3303188 WOS:001163472700080 Q1 – IF= 12.62
8. Arasteh, Bahman, Keyvan Arasteh, Farzad Kiani, Seyed Salar Sefati, Octavian Fratu, Simona Halunga, and Erfan Babaee Tirkolaee. "A Bioinspired Test Generation Method Using Discretized and Modified Bat Optimization Algorithm." Mathematics 12, no. 2 (2024): 186. https://doi.org/10.3390/math12020186 WOS: 001151438900001 Q2 - IF=2.5

6.2.2 Conference publicitions

1. Sefati, Seyed Salar, and Simona Halunga. "Data forwarding to Fog with guaranteed fault tolerance in Internet of Things (IoT)." *2022 14th International Conference on Communications (COMM)*. IEEE, 2022. https://doi.org/10.1109/COMM54429.2022.9817179
2. Sefati, Seyed Salar, and Simona Halunga. "Mobile sink assisted data gathering for URLLC in IoT using a fuzzy logic system." *2022 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*. IEEE, 2022. https://doi.org/10.1109/BlackSeaCom54372.2022.9858268 WOS:000865848800065
3. Sefati, Seyed Salar, et al. "A Novel Routing Protocol based on Prediction of Energy Consumption and Link Stability in Mobile Internet of Thing (MIoT)." *2022 25th International Symposium on Wireless Personal Multimedia Communications (WPMC)*. IEEE, 2022. https://doi.org/10.1109/WPMC55625.2022.10014984 WOS:000947852500005
4. Sefati, Seyed Salar, and Simona Halunga. "Enhancement of Quality of Service (QoS) in Internet of Things based on big data environment using the Harris Hawks algorithm." *Advanced Topics in Optoelectronics, Microelectronics, and Nanotechnologies XI*. Vol. 12493. SPIE, 2023. https://doi.org/10.1117/12.2642727
5. Sefati, Seyed Salar, and Simona Halunga. "Service Recommendation for a Group of Users on the Internet of Things Using the Most Popular Service." *2023 12th International Conference on Modern Circuits and Systems Technologies (MOCAST)*. IEEE, 2023. https://doi.org/10.1109/MOCAST57943.2023.10176696
6. Nor, Ahmed M., Seyed Salar Sefati, Octavian Fratu, and Simona Halunga. "RXs Directions based codebook solution for passive RIS beamforming." In *2023 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*, pp. 330-335. IEEE, 2023. https://doi.org/10.1109/BlackSeaCom58138.2023.10299786
7. Sefati, Seyed Salar, Octavian Fartu, Ahmed M. Nor, and Simona Halunga. "Enhancing Internet of Things Security and Efficiency: Anomaly Detection via Proof of Stake Blockchain Techniques." In *2024 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pp. 591-595. IEEE, 2024. https://doi.org/10.1109/ICAIIC60209.2024.10463516.

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