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Report

By a member of the dissertation committee of the dissertation of Sun Qiushi on the theme: "Machine Learning for Optimization of Resource Allocation in Wireless Networks", submitted in conformity with requirements for the degree of Candidate (PhD) of technical sciences in Speciality 1.2.2 — Mathematical modeling, numerical methods and software packages. The dissertation of Sun Qiushi is dedicated to the study of optimizing resource allocation in wireless communication network systems.

The main research motivation of the thesis by Sun Qiushi comes from the growing complexity and demand in wireless communication networks, particularly with the advent of 5G and beyond, which require efficient resource allocation to optimize performance. Traditional optimization methods struggle with the scale, non-linearity, and dynamic nature of modern networks, making them inadequate for real-time applications. By using advanced machine learning and metaheuristic algorithms, the developed research proposes innovative, scalable, and adaptive solutions for resource allocation, enhancing network efficiency, reducing latency, and meeting diverse Quality of Service (QoS) requirements. The thesis also seeks to provide new AI-driven frameworks that can dynamically manage network resources. All these are very important and contemporary research topics.

The thesis of Sun Qiushi consists of five technical chapters as well as of Introduction, Conclusions and Bibliography. In the Introduction, the candidate carefully described the motivation of the work, the main contributions of the thesis and the main methodologies.

The first technical chapter addresses power allocation in cellular networks using metaheuristic algorithms. It introduces various algorithms like Particle Swarm Optimization (PSO) and Differential Evolution (DE), comparing their performance in optimizing resource allocation. The simulations demonstrate the effectiveness of these algorithms in different network scenarios, highlighting their strengths and limitations.

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The second chapter focuses on D2D (Device-to-Device) networks and proposes a resource allocation scheme that combines heuristic algorithms with deep neural networks (DNNs). It emphasizes supervised learning to train models that can provide near-optimal solutions for real-time applications. The approach significantly reduces computational complexity while maintaining high performance.

The third chapter extends the previous work by incorporating graph learning methods such as Graph Neural Networks (GNNs) to enhance resource allocation in D2D networks. By using GNNs, the approach captures the topological features of the network, leading to more efficient allocation strategies that consider spatial relationships between devices.

The fourth chapter explores heterogeneous D2D networks using Graph Attention Networks (GATs) with enhanced edge features. The unsupervised learning approach allows the network to learn optimal allocation strategies without labeled data, focusing on maximizing overall system performance by considering both node and edge characteristics.

Finally, the fifth chapter introduces a novel reinforcement learning approach using multi-type mean field reinforcement learning (MFRL) for large-scale, dense heterogeneous networks. The method groups devices based on connection types and uses mean field theory to train agents, aiming to achieve optimal resource allocation with improved scalability and efficiency.

I found chapters 3 and 5 to be very innovative. Specifically, chapter 3 introduces the use of Graph Neural Networks (GNNs) for resource allocation in Device-to-Device (D2D) networks, leveraging the spatial and topological features of the network. The application of GNNs to optimize resource allocation represents a novel approach that addresses the unique challenges of D2D communications, particularly in modeling complex network interactions and capturing dependencies between nodes, which is a significant departure from more traditional methods. Chapter 5 presents a novel reinforcement learning approach using multi-type mean field reinforcement learning (MFRL) tailored for large-scale, dense heterogeneous networks. The originality and practical importance lie in modeling the complex interactions among multiple transceiver pairs as a multi-agent system and addressing scalability through mean field theory.

While each chapter presents a different method and an important contribution to optimizing resource allocation, the transitions between the chapters could be more cohesive. A clearer narrative explaining how each chapter builds upon the previous one would help the reader understand the progression of ideas and the overall flow of the research. A more detailed, side-by-side comparison of the performance, strengths, and weaknesses of each method (especially methods of chapters 2,3 and 4) would provide deeper insights into their practical applicability. Including direct comparisons in terms of computational complexity, accuracy, scalability, and suitability for different network scenarios would be valuable. These are not crucial comments.

Sun Qiushi has published his research results in two journal papers (in high-level journals) and in several conference proceedings.

For all the above reasons, I conclude that the dissertation of Sun Qiushi on the topic "Machine Learning for Optimization of Resource Allocation in Wireless Networks" meets the requirements established by Order No. 11181/1 of 19 November 2021, “On the procedure for awarding academic degrees at Saint Petersburg State University”, and Sun Qiushi deserves the award of the degree of Candidate (PhD) of technical sciences in the Speciality 1.2.2 — Mathematical modelling, numerical methods and software packages. Clauses 9 and 11 of the aforementioned Order by the author of the thesis is not broken.

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