Intelligent Optimization of Hybrid Networks: Decision-Making with Integrated Approaches

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***Abstract*—The rapid expansion of heterogeneous networks necessitates sophisticated optimization techniques to enhance the overall network performance. Traditional network optimization approaches, such as the per-layer and narrow scope of cross-layer optimization, often fail to capture global network dynamics because of their limited scope. In this study, we propose a comprehensive integrated optimization framework that utilizes a neural network with a decision-making algorithm to optimize gateway selection in hybrid networks comprising local 5G (L5G) and Wi-Fi. Our approach is validated through simulations in EXata, demonstrating improvements in normalized throughput compared to random- and RSSI-based selection strategies. Quantitative results show that our proposed ML-based method enhances network performance by up to 13% compared to the RSSI-based method in dense network scenarios, suggesting its potential utility in next-generation networks.**

***Index Terms*—cross-layer optimization, machine learning, hybrid networks**

I. Introduction

Modern network architectures adhere to the OSI seven-layer model, a key framework for managing network communication complexity. The OSI model divides network functions into layers, each handling specific tasks, to simplify the system, improve interoperability, and enhance fault isolation. Traditionally, each layer operates independently, allowing changes without affecting others. However, these layers are interdependent and collectively influence network performance [1].

Variations in the physical layer, such as fluctuating channel conditions, can affect the error control and retransmission mechanisms of the data link layer, leading to increased delays and reduced throughput. Similarly, routing decisions at the network layer may be affected by the state of the physical layer, further complicating the network dynamics. These interlayer interactions illustrate that traditional optimization approaches that focus on individual layers or specific cross-layer interactions may not sufficiently capture the overall network dynamics or achieve an optimal network performance.

To address these challenges, we propose an integrated optimization method that overcomes the limitations of traditional cross-layer (or per-layer) approaches by optimizing network performance across the entire network stack. This aligns with recent studies that have enhanced cognitive radio through resource allocation [2]–[4]. Our study focuses on optimizing gateway selection in hybrid networks comprising local 5G (L5G) and Wi-Fi. We used machine learning (ML) techniques to model and optimize the complex interactions between network layers, thereby improving network performance.

II. Integrated Optimization of Hybrid Networks

In response to the limitations of traditional optimization methods, we introduce an integrated optimization framework that transcends conventional per-layer and cross-layer approaches. This comprehensive framework encompasses all seven layers of the OSI model, as well as an additional Infrastructure Layer (INF) that incorporates network characteristics such as terrain features, terminal mobility, and the spatial distribution of gateways. This approach was designed to address the complex dynamics of modern heterogeneous networks more effectively.

We define the set of layers as

$$L \in \{\mathrm{INF}, \mathrm{PHY}, \mathrm{DATA}, \mathrm{NET}, \mathrm{TRAN}, \cdots, \mathrm{APP}\}.$$

The integrated optimization aims to maximize the network requirements $J(\cdot)$ and is formulated as follows:

$$\begin{aligned} \vec{\theta}^* &= \arg\max_{\vec{\theta}} J(\vec{\theta}) \\ &= \arg\max_{\vec{\theta}} \left[\sum_{i \in L} U_i(\theta_i) + \sum_{i \in L} \sum_{\substack{j \in L \\ j \neq i}} \lambda_{i,j} C_{i,j}(\theta_i, \theta_j) \right], \end{aligned} \quad (1)$$

where $\vec{\theta} = (\theta_1, \theta_2, \ldots, \theta_n)$ represents the parameter vector for each layer, $(*)$ denotes optimality, $U_i(\theta_i)$ is the utility function for layer i, $C_{i,j}(\theta_i, \theta_j)$ describes the interaction between layers L_i and L_j, and $\lambda_{i,j}$ indicates the weight factors.

The framework distinguishes between cross-layer and integrated optimization based on the composition of L. Cross-layer optimization involves only a subset of layers, optimizing interactions between selected layers such as PHY and DATA. This selective approach provides improvements over per-layer optimization by considering interdependencies between layers; however, it might not capture the overall network dynamics or achieve a global optimum owing to its limited focus.

In contrast, a fully integrated approach, where L includes all layers ($L = L_{\text{total}}$), aims for a global optimum by evaluating and optimizing the performance across all layers. This method provides a more robust solution capable of navigating the complexities of multilayered network environments.

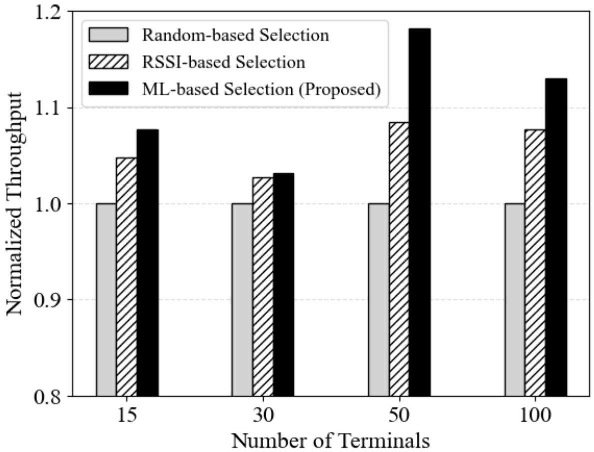

Fig. 1. Comparison of normalized throughput for general and proposed methods across different network densities.

Given the nonconvex and nonlinear nature of the optimization problem, as described by Eq. (1), traditional optimization techniques often fall short [1], [3]. Therefore, we propose tackling this complex problem with data-driven machine learning techniques, which are well suited to managing the intricate dependencies and non-linearities inherent in such tasks.

III. Methodology and Simulation Analysis

A. Gateway Selection via Machine Learning

Building on the approach proposed in [3], this study extends its applicability to dense environments, hybrid network settings, and scenarios with random node positioning, and explores its robustness across various network conditions.

Our optimization strategy is a two-step process that encompasses network performance estimation and intelligent decision-making. In the first step, a feedforward neural network (FNN) is employed to estimate network performance, trained on observable RSSI values (PHY layer) and link connection information (DATA layer). The second step focuses on optimizing gateway selection by identifying the optimal parameter set $\vec{\theta}^*$ that maximizes network performance. Here, end-to-end throughput is treated as a metric within the APP layer because it measures the final data delivery rate received by applications, directly affecting user experience. The optimization criterion $J(\vec{\theta})$ is designed to integrate input parameters from the PHY, DATA, and APP layers to optimize the overall network utility, as described in Eq. (1).

A brute-force search was initially used to evaluate all feasible parameter combinations, validating the concept in a dense network environment and confirming the functionality of our approach under realistic conditions. However, owing to the exponential growth of the search space with increased network complexity, this method became computationally prohibitive. Future work will explore more efficient optimization algorithms to reduce computational demands.

B. Experimental Setup and Performance Evaluation

For our simulations, we used the EXata network simulator configured with three Wi-Fi 802.11ax base stations and three local 5G gNBs. This setup represents a scenario where each terminal device is equipped with multi-interface, allowing it to connect to both Wi-Fi and Local 5G networks. The terrain for the simulation was set to a 100 × 100 m area. The FNN used for this simulation was trained with hidden layers of sizes [256, 128] using the stochastic gradient descent (SGD) optimizer. Data for training were collected at random points, with a total of 1000 samples gathered for each scenario.

We compared three distinct gateway selection strategies: Random-based Selection, RSSI-based Selection, and our proposed ML-based Selection. We evaluated the performance of each strategy using the Normalized Throughput, defined as

$$\text{Normalized Throughput} = \frac{\text{Measured Throughput}}{\text{Offered Load}}.$$

The results are shown in Fig. 1, illustrating the normalized throughput for different numbers of network nodes (15, 30, 50, and 100) under three selection strategies. The results suggest that the ML-based selection strategy generally performs better than other methods, particularly in environments with a high density of network nodes. For example, with 50 network nodes, the ML-based approach achieved a normalized throughput that was approximately 18% higher than the Random-based Selection and 9% higher than the RSSI-based Selection. Similarly, in scenarios with 100 nodes, the ML-based method showed a 13% improvement over the random-based method, and a 5% improvement over the RSSI-based method. These findings indicate the potential advantage of the ML-based approach in more complex and demanding network scenarios.

IV. Conclusion and Future Works

In conclusion, our method used machine learning to enhance gateway selection in hybrid networks, as shown in the simulations. The primary goal of this study was to validate our concept in dense networks by selectively extracting parameters from the chosen layers. Future work will focus on real-world validation, where data may be inconsistent, developing online learning for adaptive responses, overcoming challenges in data collection and overfitting, simplifying decision-making processes, and incorporating additional network layers. These efforts aim to provide scalable, adaptive solutions for managing the complexity of modern networks.

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