Machine Learning for Combinatorial Resource Allocation

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***Abstract*—This project investigates the potential of machine learning methods for optimizing resource allocation problems of combinatorial nature in large, heterogeneous networked systems. Traditional heuristic algorithms, while computationally less intensive, often result in sub-optimal solutions that lead to resource wastage and increased energy consumption. As a milestone in the project we introduce DeepGANTT, a novel learning-based scheduler that leverages Graph Neural Networks and Transformers to solve an NP-hard combinatorial resource allocation problem for IoT networks with battery-free sensor tags. DeepGANTT offers up to 50% reduction in resource consumption compared to the state-of-the-art heuristic, and is capable of scaling to networks significantly larger than those used for training without the need to be retrained. The scheduler is designed for generalizability and elasticity, adapting to varied network sizes and conditions while maintaining efficient runtimes. Our findings pave the way for future research in applying machine learning techniques to enhance resource allocation in diverse networked systems.**

***Index Terms*—machine learning, combinatorial optimization, resource allocation, GNNs, backscatter networks**

I. Context & Motivation

Computer and communication networks are increasingly becoming more complex and heterogeneous due to recent technological advances, such as the Internet of Things (IoT), the development of 5th and 6th generation broadband cellular networks (5G & 6G), and its integration with the compute continuum (Cloud & Edge Computing). This trend is only expected to increase in the upcoming decades, with the introduction of new application domains, and the recent advances in the area of Artificial Intelligence (AI).

Managing such resources implies solving a plethora of resource allocation problems, many of them typically NP-hard optimization problems. Traditional methods for solving such problems rely on carefully-crafted heuristic algorithms, which exhibit polynomial time complexities but are prone to suffer from sub-optimal performance. The sub-optimality of such methods typically implies resource over-provisioning, which ultimately leads to a waste of resources, and to an even steeper increase in energy consumption. Finding more optimal algorithms for managing compute and communication resources is paramount for transitioning towards a more sustainable future.

Additionally, there has been an increasing trend of applying ML methods for solving traditional combinatorial optimization problems (COPs) due to its capabilities of finding more optimal solutions compared to heuristics through a data-driven learning approach [1]. Since several resource allocation problems in computer and communication networks can be traced back to traditional COPs, there is high potential in applying ML in the resource allocation domain to reduce the optimality gap, thus mitigating the waste of computational, communication and energy resources.

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II. Objectives

The project aims at evaluating the applicability of machine learning methods for solving resource allocation problems of combinatorial nature for heterogeneous networked systems that span across Cloud, Edge, and IoT. We emphasize on two aspects for the devised approaches: generalizability and elasticity. First, the approaches are meant to be generalizable in terms of both their scalability to varied network sizes, and their adaptability to changing network conditions while ensuring performance requirements. Moreover, the approaches are meant to be elastic in terms of exhibiting short runtimes for them to be practically applicable.

Research Question: Can machine learning methods be applied in a practical a generalizable manner to solve combinatorial optimization problems in the context of resource allocation for dynamic networked systems?

The research methodology consists of applied exploratory research based on quantitative data obtained from experimentation with simulations and real test-beds.

III. Achieved Milestones

First, we performed a descriptive review of ML methods specifically applied to solving combinatorial optimization problems in networked systems' resource management applications. The results from this review were published as part of a survey in IEEE Access [2], which has received considerable attention from the research community. Among the most important findings from the selected set of works reviewed, we identified the applicability of Graph Neural Networks (GNNs) as key enabler for reaching scalability to larger networks and adaptability to larger problem instances. Furthermore, we also identified a lack of in-depth analysis regarding the deployed ML method's complexity and runtime, as well as a predominance of reinforcement learning over other learning paradigms due to the lack of available data.

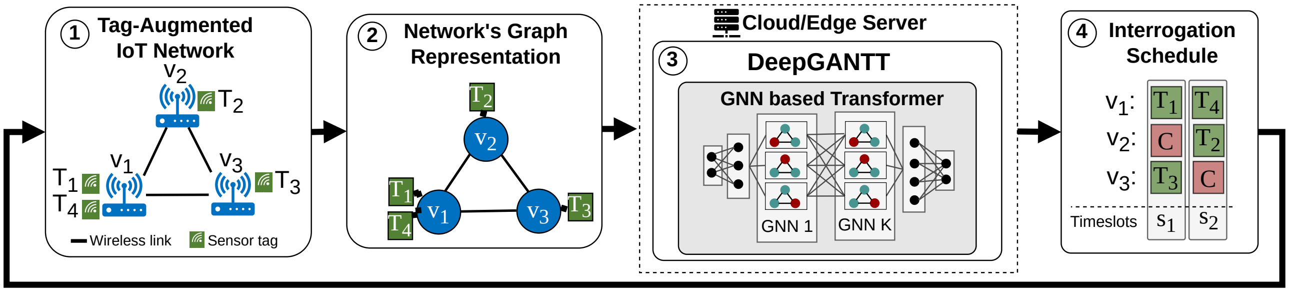
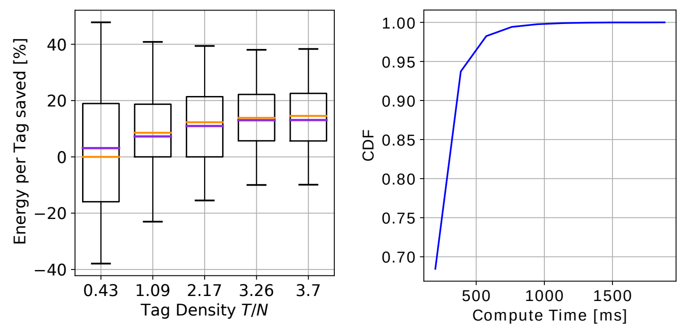


Fig. 1: *DeepGANTT generates interrogation schedules using a GNN based Transformer ML model.* Step 1: collect MAC and routing protocol information. Step 2: build the graph representation of the IoT network. Step 3: generate interrogation schedule through iterative node classification. Step 4: disseminate the schedule using existing network flooding mechanisms and appended it to the IoT device's regular schedule.

In the second stage we tackled an NP-Hard combinatorial resource allocation problem in the area of IoT networks. We considered the scenario of a network of IoT devices that is augmented with battery-free backscatter tags that do sensing in their behalf [3]. The battery-free backscatter devices – *tags* for short – can perform bidirectional communication with its hosting IoT devices, for which they require the provision of an external unmodulated carrier by a neighboring IoT device. A schedule then coordinates the provision of carriers for the communications of the battery-free tags with IoT devices. The schedule consist of a series of one or more timeslots $\mathtt{S}$, each of which assigning a role for each IoT in the schedule: either do nothing ($\mathtt{O}$), interrogate one of its hosted tags (T), or generate a carrier ($\mathtt{C}$) for neighboring nodes to perform tag interrogation (see Fig. 1). The objective of the carrier scheduling problem is to reduce the resources needed to interrogate every tag in the network by minimizing the number of carrier generators (relates to energy and spectrum occupancy), and the number of timeslots (relates to latency and thoughput) in the schedule.

For tackling the carrier scheduling problem we developed DeepGANTT, the first learning based scheduler that leverages GNNs and Transformers to efficiently schedule the communications of battery-free tags and the supporting carrier generation [4]. DeepGANTT iteratively performs node classification, assigning each node in the network to one of the three possible actions for every timeslot until all of the tags in the network are scheduled to be interrogated (see Fig. 1).

We trained DeepGANTT using optimal schedules for networks of small sizes (up to 10 IoT nodes and 14 tags) for which we could deploy a constraint optimizer to generate the training data. Without the need to be re-trained, DeepGANTT scales to previously unseen networks $6\times -10\times$ larger than those used for training, while reducing resource consumption by up to 50% compared to the state-of-the-art heuristic (see Fig. 2). This directly translates to energy and spectrum savings. DeepGANTT's inference time is polynomial on the input size, achieving on average 429 ms, a radical improvement over deploying the constraint optimizer (several days or hours).



(a) In average 13% and up to 50% energy savings compared to heuristic.

(b) DeepGANTT's inference time is polynomial and in average 429ms.

Fig. 2: DeepGANTT is deployed to generate schedules for a real IoT network of $N = 24$ nodes and varying number of tags T. (purple: median, orange: mean, box extents: 25 and 75 percentiles, whiskers: 5 and 99 percentiles).

IV. Concluding Remarks

The achieved milestones described in Sec. III provide a solid basis for a continued development of applying ML methods to solve combinatorial resource allocation problems in networked systems. Future work will focus on deploying ML methods to schedule workload requests and to manage resources in the Edge and Cloud compute continuum.

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