Population Management Based on Data Mining Analysis

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1 Introduction

In this research, we use supervised machine learning to enhance a metaheuristic algorithm designed for solving the Capacitated Vehicle Routing Problem (CVRP). The CVRP, a combinatorial optimization problem, involves determining the min-cost routes from a depot node for a fleet of capacitated vehicles to fulfill the demands of various customer nodes [1]. Traditionally, the algorithms solving this problem start from a new solution each time, even when dealing with similar problem types. However, utilizing historical data could offer valuable insights for achieving more efficient and effective solutions [2]. Moreover, the integration of machine learning (ML) holds the potential for real-time problem learning, guiding the algorithm toward more efficient problem-solving [3]. Therefore, the objectives of this research is to establish an effective learning process combined with a robust optimization algorithm for solving problems with increased efficiency.

2 Related research

The Capacitated Vehicle Routing Problem (CVRP) is defined as an undirected graph with a specific number of nodes. The main objective is to explore permutation sequences of nodes, identifying the most cost-effective routes for each vehicle. These routes collectively aim to minimize the total cost while considering vehicle capacity constraints and meeting all customer requirements [1]. In this context, the weight of each edge denotes the Euclidean distances between the corresponding pair of nodes. Generally, the problem's complexity, in terms of the number of variables and computational time, escalates with the increasing number of edges in the graph. The CVRP has numerous applications in logistics and supply chain distribution [4]. On the other hand, machine learning (ML) is designed to utilize historical data for handling new problem [5]. Then, by integrating optimization algorithms with ML, the algorithm can extract knowledge from previous experiences, effectively guiding towards optimal solutions [3]. The integration of machine learning (ML) and optimization algorithms can be classified into three strategies, as outlined by [2]: (1) end-to-end learning, (2) learning based on problem properties, and (3) learning repeated decisions. In the end-to-end learning approach, ML serves as the optimization algorithm to solve the optimization problem. Then, in the learning based on problem properties, ML can also be employed to generate offline guidance for the optimization algorithm. Lastly, the strategy of learning repeated decisions involves constructing an in-loop ML-assisted optimization algorithm. This method enables the algorithm to learn from its own decisions, adapting its behavior for improved performance.

3 Proposed method

In this research, we use the MNS-TS algorithm from [3] as a benchmark of our proposed algorithm. From [6] and [7], we know that larger capacity utilization for every route is a sign that we may achieve a better quality solution. Then, in this research, we hypothesize that we may use that conclusion to manage the population of solution. To do that, we try to develop guidance based on the capacity utilization of every member of a population of solutions. We apply the guidance to improve the proposed metaheuristic algorithm from [7]. The computational experiment is conduted by solving randomly-sampled instances from [8]. The preliminary results show that the proposed guidance is able to improve the benchmark algorithm and a proposed metaheuristic algorithm from [7].

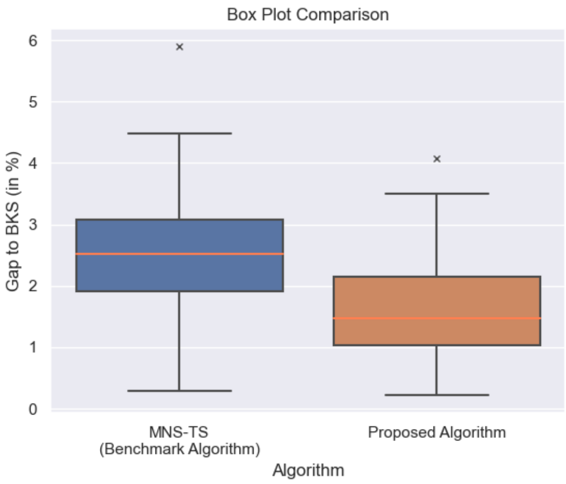

FIG. 1: Preliminary Computational Results

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