Matheuristics Algorithm Guided by Machine Learning for Solving the Vehicle Routing Problem

Bachtiar Herdianto[1], Romain Billot[1], Flavien Lucas[2], Marc Sevaux[3]

[1] IMT Atlantique, Lab-STICC, UMR 6285, CNRS, Brest, France
{bachtiar.herdianto,romain.billot}@imt-atlantique.fr

[2] IMT Nord Europe, CERI Systèmes Numériques, Douai, France
flavien.lucas@imt-nord-europe.fr

[3] Université Bretagne Sud, Lab-STICC, UMR 6285, CNRS, Lorient, France
marc.sevaux@iuniv-ubs.fr

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1 Introduction

In recent days, the usage of learning algorithm to improve optimization methods have become increasingly interesting [1, 2]. For example, the Vehicle Routing Problem (VRP) that logistic companies might face daily. The main problem is arising whenever the delivery routes could not be optimal, which causes an increase in delivery costs. To reduce these costs, we need optimize the delivery route [3]. However, most optimization algorithm still solves the problem from scratch, even for the same problem type, and nothing useful is extracted from prior solutions. Meanwhile, the historical data could be useful to gain solutions efficiently and effectively. In term of optimization algorithm, the use of artificial intelligence (AI) for solving VRP promise to learn from past solutions or in real-time and then to guide the algorithm to solve the problem [4]. Moreover, the optimization algorithm could learn from its own decisions and adjust its behaviour accordingly to gain better behaviour [1].

Therefore, the objective of this research is divided into two goals: (1) to get an understanding of the connection between the quality of the solutions, their features, and the associated problem instances, and (2) to construct an efficient learning process consolidated with a simple yet powerful optimization algorithm to solve the problems quickly and effectively.

2 State-of-the-art

Matheuristic is the combination of mathematical tools with an optimization, heuristic, algorithm [5]. The term mathematics tools could be interpreted as a guidance that helps the optimization algorithm find the solution efficiently. However, the current of mostly optimization algorithms still solve the problem from scratch, even for a similar type of problems, and nothing useful is extracted from past solutions. In the other hand, the capabilities of AI can be categorized into several groups, such as knowledge representation, automated reasoning, machine learning (ML), etc. Thus, in terms of ML, the goal of AI is to use the historical data for handling new circumstances [6]. Therefore, by combining the optimization algorithm and ML, the algorithm can learn from past or real-time conditions and use them to obtain the optimal solution effectively [7]. Furthermore, the idea about the integration of ML and optimization algorithm can be divided into three ways: (1) end-to-end learning, (2) learning by properties and (3) learning repeated decisions [1]. The idea of end-to-end learning means the ML have a role as the optimization algorithm to solve the optimization problem (e.g., by employing reinforcement learning to solve VRP). However, we may need a huge amount computation resources, particularly when facing large-scale problems [2].

In the case whenever the first idea is not suitable to solve the problem, we can apply the second idea, that is, use the ML to develop guidance to the optimization algorithm in a very broad way. However, using this idea, the learning paradigm may not have a strong influence on the process, so the full potential of ML may not be fully unlocked yet during optimization processes [1]. Also, we will too rely on the optimization algorithm whenever solving problems [3]. Subsequently, to obtain the full potential of the learning paradigm, we can use the third idea, that is learning repeated decisions by constructing an in-loop ML-assisted optimization algorithm. Moreover, by using this idea, the algorithm will be able to learn from its own decisions and adjust its behaviour consequently to achieve better performance. However, for the implementation of this idea, we need to develop an efficient learning process combined with a simple yet powerful optimization algorithm so that we can achieve not only better quality of solutions but also faster computation time.

3 Proposed approach

To achieve minimum computation time and sufficient quality of solution, we need to develop an efficient learning process consolidated with a simple yet powerful optimization algorithm. To do that, first, we will identify a fully comprehensive set of features that influence the resulting solutions by knowledge extraction process, using XML instances by [8], for developing an efficient learning process. In the meantime, we also formulate a simple yet powerful algorithm. We will adapt the path-relinking strategy [9] to the optimization algorithm to enhance the search capability of the optimization algorithm. Afterward, we will consolidate both the efficient learning process and the powerful optimization algorithm and then use them to solve the problem quickly and effectively.

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