# Integration of Knowledge Extraction Processes into Metaheuristic Algorithm

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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. Understand the connection between the quality of the solutions, their features, and the associated problem instances, and
2. Construct an efficient learning process consolidated with a powerful optimization algorithm to solve the problems quickly and effectively.

## 2 Literature Review

Mix optimization approaches via learning algorithm to improve optimization algorithms have become increasingly interesting [1][2]. Furthermore, mostly optimization algorithms still solve the problem from scratch, and still nothing useful is extracted from past solutions.

Meanwhile, 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 [5]. 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 [6]. Furthermore, the idea about the integration of ML and optimization algorithm can be divided into three ways [1]:

1. End-to-end learning:

   The idea of end-to-end learning means the ML have a role as the optimization algorithm to solve the optimization problem. However, we may need a huge amount computation resource [2].

2. Learning by properties:

   The idea of learning by properties means that we will use the ML to develop guidance to the optimization algorithm in a very broad way. However, in 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][3].

3. Learning repeated decisions:

   The idea of learning repeated decisions means we will construct an in-loop ML-assisted optimization algorithm. 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 powerful optimization algorithm so that we can achieve not only better quality of solutions but also faster computation time.

# 3 Proposed approach

## 3.1 Knowledge Extraction Processes

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 XML100 instances by [7], for developing an efficient learning process.

## 3.2 Developing Optimization Algorithm

In this research, we also formulate a heuristic algorithm, an improved version of the FG-MNS [6]. We will adapt the path-relinking processes [9][10] to the optimization algorithm to enhance the search capability of the optimization algorithm.

### 3.3 Implementing Learning Processes into 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.

## 4 Preliminary Experiments

### 4.1 Knowledge Extraction Processes

Here, we only consider the three most important features from previous analysis: S18, S19 and S20. All of them are features related to the solution of the VRP model. S18 is a solution feature related to average value of degree neighborhood. S19 is a solution feature related to average value of capacity utilization in every route. And, S20 is a solution feature related to standard deviation value of capacity utilization in every route. From the graph, we learn that a high level of S18, has a negative impact to the target variables, which is meaning that closer neighborhood will have positive impact the improvement of quality solution. Also, it shows that a high level of S19 and S20 have a positive impact to the target variables, meaning that the larger of capacity utilization for every route, will the better the quality solution of VRP.

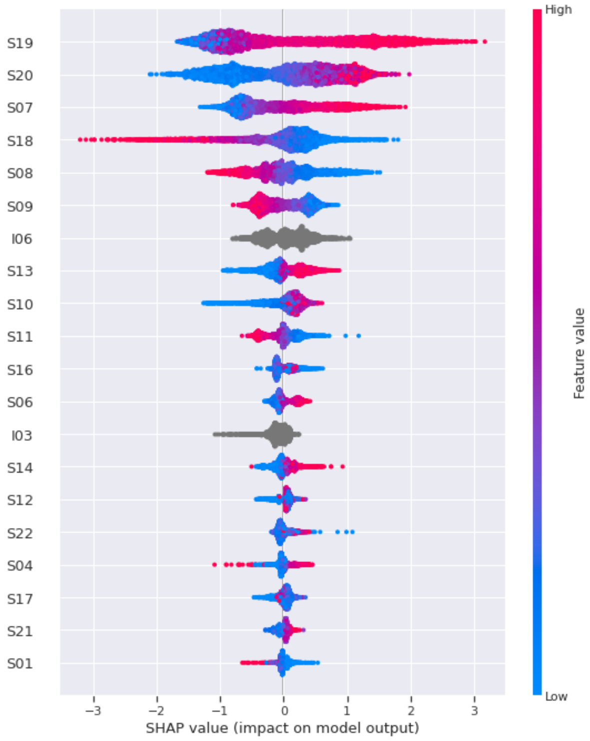


Figure 1: Result from knowledge extraction of VRP.

### 4.2 Developing Optimization Algorithm

In this research, we also develop a heuristic algorithm, named as the MNS-TS-PR algorithm. The proposed algorithm is based on MNS-TS from [7] with several modification using path relinking processes [8]. Then, the computation result of the proposed algorithm will be compared with the TS-PR from [9], and the MNS-TS from [6].

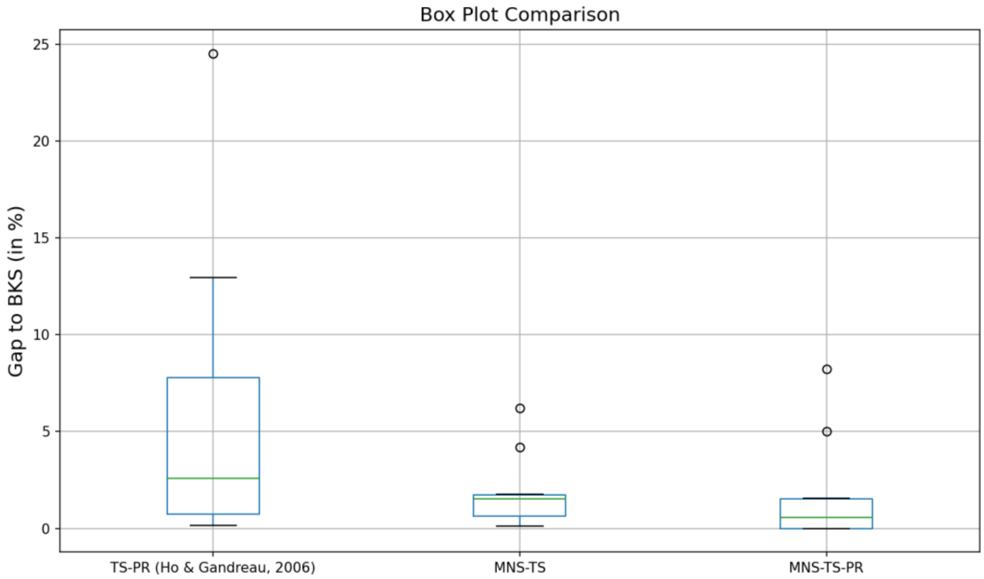


Figure 2: Box plot comparison of the proposed algorithm.

Also, we try to compare the computation result of the proposed algorithm and the MNS-TS from [6] using XML100_2231_20 instances from XML100 instances by [7].

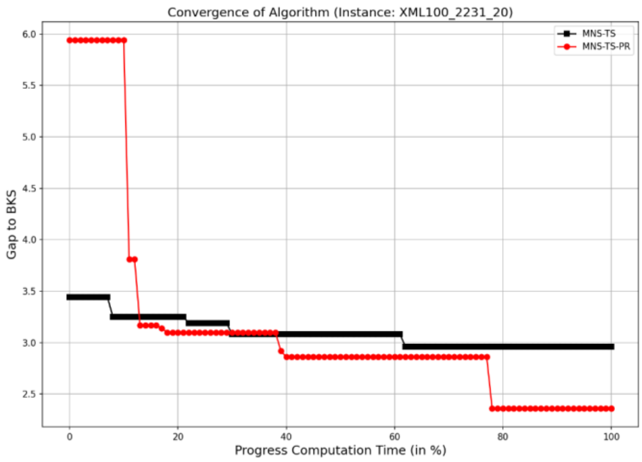


Figure 3: Comparison MNS-TS and MNS-TS-PR using XML100_2231_20 instance.

# 5 Preliminary Results and Next Target

## 5.1 Preliminary Results

From the literature review, we know that the integration of ML and CO can be divided into three ideas: end-to-end learning, learning by properties and learning repeated decisions. Then, the knowledge extraction analysis shows that the S18, S19, and S20 have significant contribution to the solution quality, which meaning that closer the neighborhood will have a larger probability to improve and the larger of capacity utilization, the better the quality of solution of the VRP model. Also, we already developed a new heuristic algorithm, named as the MNS-TS-PR algorithm, that adapt the path-relinking processes [8] to the optimization algorithm.

## 5.2 Next Target

Based on result from knowledge extraction processes, and a new proposed heuristic algorithm, we will develop a new alternative for path relinking processes that will be guided by a learning algorithm for solving CVRP.

# References

[1] Bengio, Yoshua, Andrea Lodi, and Antoine Prouvost (2021): "Machine learning for combinatorial optimization: a methodological tour d'horizon." In: *EJOR*.

[2] Bogyrbayeva, Aigerim, et al (2022): "Learning to solve vehicle routing problems: A survey." In: *arXiv preprint arXiv:2205.02453*.

[3] Herdianto, Bachtiar, and Komarudin (2021): "Guided Clarke and Wright Algorithm to Solve Large Scale of Capacitated Vehicle Routing Problem." In: *2021 IEEE 8th ICIEA*.

[4] Lucas, Flavien, et al (2021): "Some insights about the use of machine learning for solving VRP." *In: 2021 31st EURO*.

[5] Russell, Stuart J (2010): *Artificial intelligence a modern approach*. Pearson Education, Inc.

[6] Lucas, Flavien, et al (2020): "Reducing space search in combinatorial optimization using machine learning tools." In: *Learning and Intelligent Optimization: 2020 14th LION*.

[7] Queiroga, Eduardo, et al (2022): "10,000 optimal CVRP solutions for testing machine learning based heuristics." In: *AAAI-22 Workshop on ML4OR*.

[8] Resende, Mauricio GC, et al (2010): "Scatter search and path-relinking: Fundamentals, advances, and applications." In: *Handbook of metaheuristics*.

[9] Ho, S. C., & Gendreau, M. (2006): "Path relinking for the vehicle routing problem." In: *Journal of heuristics*.

[10] Arnold, Florian, and Sörensen, Kenneth (2019): "What makes a VRP solution good? The generation of problem-specific knowledge for heuristics." In: *CAOR*.