Parameter-less (Meta)heuristics for Vehicle Routing Problems

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ABSTRACT

Solving rich vehicle routing problems (VRPs) is a vital research topic due to their wide applicability. Although there exist various (meta)heuristics to tackle VRPs, most of them require a practitioner to tune their parameters before the execution. It is challenging in practice, since different algorithm variants often perform well for different scenarios. In this work, we present our adaptive heuristics for this task, in which we benefit from the adaptation schemes executed before the optimization. Extensive experiments backed up with statistical tests revealed that our heuristics is automatically adapted to effectively solve a given transportation problem, and retrieve routing schedules of the state-of-the-art quality.

CCS CONCEPTS

• **Computing methodologies** → *Planning and scheduling*; *Unsupervised learning*; • **Applied computing** → *Operations research*;

KEYWORDS

PDPTW; guided ejection search; adaptation

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1 INTRODUCTION

Route scheduling is one of the most important real-life optimization problems due to its numerous applications. In the pickup and delivery problem with time windows (PDPTW), the customers are divided into the pickup and delivery ones (each request is a pair of the pickup and delivery operations). An PDPTW schedule is feasible, if (i) the service of each customer is *started* within its time window, (ii) the vehicle capacities are not exceeded, (iii) the vehicles get back to the depot within its time window, and (iv) the delivery request is served after the corresponding pickup.

Exact approaches are still difficult to apply in the case of massively-large VRP tests (due to their time requirements). Therefore, the approximate methods—which do not ensure retrieving the globally-optimal solution, but work in an acceptable time—are of the main research interest. In such algorithms, two objectives are usually considered separately: the number of vehicles (K) is minimized at first (main objective), and then—the total travel distance (T) is optimized (secondary objective). Hence, efficient techniques for both optimization phases can be developed independently.

In [2], we tackled the PDPTW using the adaptive guided ejection search (AGES–PDPTW). The pivotal part of AGES–PDPTW is its pre-processing step, in which the structure characteristics of the problem instance are extracted in the clustering and histogram-based analyses. Afterwards, the k-nearest neighbor (k-NN) algorithm is used to classify the test into an appropriate class. Based on this classification outcome, the most suitable AGES–PDPTW variant is adaptively chosen to minimize K in this problem instance. Such data-driven analysis has not been exploited for this purpose so far. The experiments showed that our pre-processing allows for obtaining very high classification accuracy, thus for elaborating the best-suited AGES–PDPTW to tackle a specific problem instance. Importantly, our adaptation algorithm is fairly generic and can be easily used in other (meta)heuristics for discrete optimization problems. Also, we show that it can be coupled with parameter-less approaches for minimizing the travel distances in rich VRPs [1], and be a part of a larger parameter-less VRP framework.

2 ADAPTIVE EJECTION SEARCH

In our adaptive guided ejection search for the PDPTW (abbreviated as AGES–PDPTW), the initial number of routes in a feasible solution (equal to the number of requests) is being iteratively decreased by one at a time. The requests are ejected from the solution and put into the *ejection pool*. Then, these requests are inserted back into the partial solution so that they do not cause violating the constraints. Although we proposed additional refinements which include *squeezing* of infeasible solutions or randomizing the AGES–PDPTW, they work well only for some classes of instances.

In [2], we introduced a data-driven pre-processing step, in which certain characteristics of an input instance are analyzed. To extract the structural information about the travel points, we determine the number of travel-point clusters within the test instance using several aggregation (linkage) techniques (i.e., Ward, McQuitty, Centroid, and k-means) together with 27 clustering validity indices. These measures reflect the inter-cluster isolation and intra-cluster compactness, and they are coupled with the number of clusters retrieved using the affinity-propagation clustering. Additionally, the feature vector includes the histogram-based features (kurtosis, skewness, standard deviation, and entropy) extracted at various scales (the map is divided into several grids which are used to quantify the scatteredness of the customers; see an example rendered in Table 1). Also, the theoretically minimal (feasible) number of trucks that can serve the requests is inserted into the vector. Finally, these vectors are classified into one (out of 6) class using the k-NN classifier. Based on this classification, the best-fitted variant of AGES–PDPTW is selected and applied.

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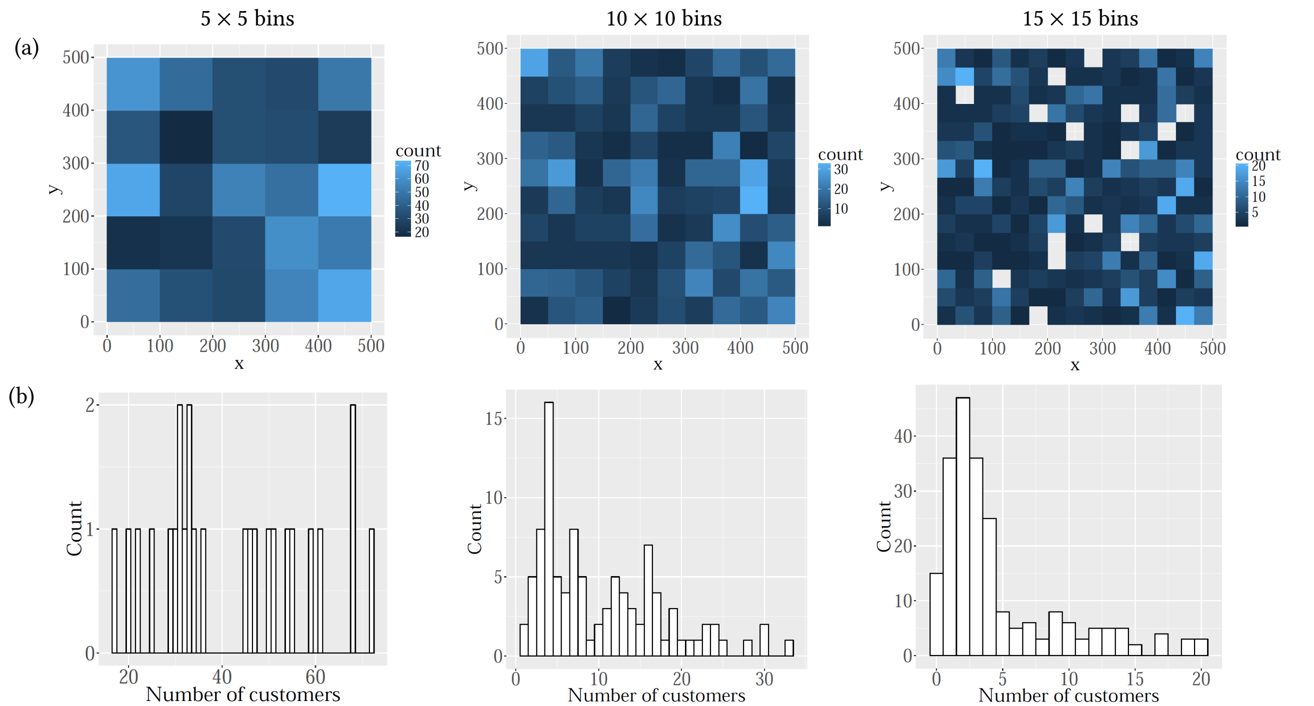
Table 1: Extracting histogram-related features from a PDPTW instance: (a) two-dimensional histograms at various scales, (b) histograms showing the numbers of each-size bins in the corresponding two-dimensional histograms.



3 THE RESULTS

An extensive experimental study performed on the full Li and Lim's benchmark (encompassing 354 problem instances belonging to 6 classes) revealed that our pre-processing allows for achieving very high classification accuracy, thus for selecting the *best* variant of the enhanced guided ejection search (by the best variant of the algorithm we mean the one that elaborated the best routing schedule, i.e., with the minimal number of routes, in the course of our experimental study). The AGES–PDPTW experiments showed that we can achieve the optimal algorithm variant—the classification performance was quite high, and the accuracy was equal to 100% for $k = 2$ with k-NN (in the 10-fold cross-validation setup). The two-tailed Wilcoxon tests proved that the differences in the classification accuracy obtained using various feature vectors (with and without certain features appended) are statistically important, thus utilizing all of the extracted features is beneficial.

4 CONCLUSIONS

In the adaptive guided ejection search for the PDPTW, we proposed a data-driven pre-processing step. Its aim is to select the most appropriate algorithm variant based on the features of the test instance to be solved. Our experiments revealed that the extracted features are discriminative, and applying a simple k-NN classifier gave the perfect classification scores (in the multi-class classification of the PDPTW tests). Hence, the best algorithm variant was always selected to solve a test instance.

The proposed adaptive guided ejection search requires no user interaction. Therefore, it can be considered as the important steps towards hands-free approximate methods for tackling rich VRPs, that are able to automatically adapt themselves according to the search progress or the input data. Importantly, AGES–PDPTW was coupled with our adaptive memetic algorithm [1] to build an automated framework for solving rich VRPs. Also, our adaptation scheme which exploits the structural information about an instance being tackled can be extrapolated onto different parameterized algorithms for solving discrete (especially scheduling) problems. Hence, we believe it will be of interest to the GECCO community since tuning (alongside auto-tuning and adaptation) of critical parameters in evolutionary algorithms is an important issue in practical applications of such approaches.

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