Selecting Between Evolutionary and Classical Algorithms for the CVRP Using Machine Learning*

Optimization of Vehicle Routing Problems †

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ABSTRACT

Solutions for NP-hard problems are often obtained using heuristics that yield results relatively quickly, at some cost to the objective. Many different heuristics are usually available for the same problem type, and the solution quality of a heuristic may depend on characteristics of the instance being solved. This paper explores the use of machine learning to predict the best heuristic for solving Capacitated Vehicle Routing Problems (CVRPs). A set of 23 features related to the CVRP were identified from the literature. A large set of CVRP instances were generated across the feature space, and solved using four heuristics including a genetic algorithm and a novel self-organizing map. A neural network was trained to predict the best performing heuristic for a given problem instance. The model correctly selected the best heuristic for 79% of the CVRP test instances, while the single best heuristic was dominant for only 50% of the test instances.

CCS CONCEPTS

• **Applied computing** → **Operations research**; • **Computing methodologies** → **Neural networks**; **Genetic algorithms**; **Massively parallel algorithms**; **Machine learning approaches**;

KEYWORDS

Vehicle routing, Algorithm Selection, Evolutionary Algorithm, Neural Network, Genetic Algorithm, Self-Organizing Map, Machine Learning

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1 INTRODUCTION

The Algorithm Selection Problem (ASP) is concerned with selecting the best performing algorithm to solve an instance of a particular problem type by creating a model which maps problem features to algorithm performance [13]. The ASP has been studied for search problems since the 1970s [7–9, 13–15, 17, 20] and more recent work includes algorithm selection for the Travelling Salesman Problem [10] and advances in the information retrieval community [2]. This work investigates the ASP in the context of the CVRP, for which existing work is limited to only six problem features [5]. To the best of our knowledge, this is the first significant ASP for the CVRP in which evolutionary algorithms are considered.

2 THE VEHICLE ROUTING PROBLEM

The CVRP is one of the most studied operations research problems. Formulated by Dantzig and Ramser in 1959 as the Truck Dispatching Problem, it minimizes the cost incurred for organizing a fleet of vehicles to service a set of spatially disparate customer demands [4]. Finding a good solution for the CVRP and assessing its quality relative to the optimal using exact methods is an NP-Hard problem [1, 17, 19, 21]. Therefore, the historical record of creating heuristics for the CVRP is extensive; however, the improvements of one algorithm can often be isolated to certain instance types [7, 17, 20]. These disparities in performance motivate this study's ASP for the CVRP, which considered a set of four state-of-the-art heuristics comprised of two evolutionary and two classical algorithms.

3 ALGORITHM SELECTION FOR THE CVRP

The problem space for this study was generated organically from novel methods adapted from *New Benchmark Instances for the Capacitated Vehicle Routing Problem* by Eduardo Uchoa et al. This study compliments this existing work by generating a larger problem set, considering a more exhaustive set of features, and expanding node positioning possibilities. In total, 4987 instances were created.

As a static portfolio, this study's set of heuristics was assembled prior to solving any of the instances and remained unchanged throughout the study, including the values of initialization parameters [7]. All CVRP instances were solved with each algorithm and the best performing (that attaining the lowest cost to the CVRP objective function) was mapped to the instance. The classical heuristics included the Clarke and Wright Algorithm (CW) [3] and the Sweep Algorithm with 2-Opt (SP) [6], which were implemented as outlined in [11, 18], respectively. The two evolutionary algorithms included an accelerated Genetic Algorithm (GA) implemented by Adbelatti entirely on a GPU [1] and a novel Self-Organizing Map (SOM) implemented by Steinhaus that incorporates an updated bias term [16] and fuzzy logic for automatic parameter control [17].

The Neural Network (NN) used in this study is a supervised machine learning method that optimizes feature-to-label relationships. Applied to the CVRP, instances are represented as a vector of features with its best algorithm as the label. This work considered 23 features, which are defined in [17] and largely capture the size, spatial attributes, and capacity constraints of each problem. For this study, an arbitrary CVRP instance i is represented in the $(\vec{x}_i, y_i)$ form where $\vec{x}_i$ is a 23 dimensional vector of features and y_i is the best performing algorithm. The data set, D, is a 4987×24 matrix. The NN uses D to create a prediction model from known instances, or training data, capable of classifying new CVRP instances, or test data, based upon its feature values.

D may be visualized through Principal Component Analysis (PCA), a compression technique used to capture the most information in a data set. By the first three principal components, which contain 65% of the original signal encoded in D, a proxy of the label boundaries can be visualized in figure 1.

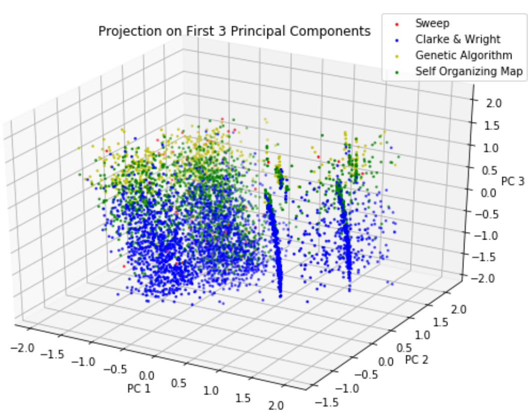

Figure 1: Projection of data using PCA.

4 RESULTS AND CONCLUSION

The NN achieved 79.4% prediction accuracy, which may be compared to a simulated Single Best Solver (SBS) model that assigns the most frequently occurring label to all test instances [12]. Where the SBS model achieves 49.8% accuracy with the CW algorithm, the NN improvements clearly indicate machine learning algorithms can effectively learn from past data to select CVRP heuristics for new instances based upon feature values.

Generating a labeled CVRP data set is a computationally expensive endeavor. Indeed, the GA alone required nearly 12 weeks of run time to solve the problem space. Future work may evaluate the effectiveness of data set size on the learners' abilities to generalize, as the effect of using fewer instances may yield comparable results. Lastly, the initialization parameters used in the GA and SOM will also be explored to increase their competitiveness - extended tests are planned for the future.

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