In this paper we consider a large scale Multi Depot Vehicle Routing Problem with Time Windows (MDVRPTW) that was derived from a large Austrian logistics provider. The developed algorithm is based on the PopMusic framework developed by Taillard and Voss [2] and uses a specially designed Memetic Algorithm (MA) as optimizer. The MA was chosen as it is easy to be integrated into the framework as well as the fact that the generated populations can be saved and used as starting solutions for the subproblems within the PopMusic framework. The MDVRPTW was defined by Cordeau et al. [1] and is a generalization of the well known Vehicle Routing Problem with Time Windows but with the addition of more than one depot. A fixed and homogenous vehicle fleet that is distributed between the depots needs to serve a set of customers with respect to time window constraints, a maximum allowed tour length as well as a maximum allowed load on each vehicle. The developed MA consists of the following core components. A special modification of a 1 insertion heuristic based on a stochastic insertion criterion was chosen to generate the initial population $pop$. An evaluation function that penalizes violations in load, maximum tour length and time window violations is used to interpret solution quality. The selection procedure then follows the idea of the binary tournament selection procedure, where two solutions are selected randomly from the population and are then compared by the evaluation function. The better of the two individuals is then assigned as the first partner for recombination, and the whole process is repeated to yield a second recombination partner. A route based two-point crossover operator is used to mate two solutions with each other. After the recombination operator has generated an offspring, $pop$ is updated in a steady state fashion. A Stochastic Local Search procedure that is based on the Variable Neighborhood Search Procedure and uses a CROSS-Exchange operator in the shaking phase and a 3-opt operator in the local search phase, is applied to mutate existing solutions as well as newly generated ones.

The PopMusic framework follows the basic concept provided by Taillard and Voss [2]. The idea is that a given solution $S$ can be decomposed in $p$ subsolutions $s_1, \ldots, s_p$ (also named parts). Once these parts are defined, we aggregate parts that are related to each other, in order to build subproblems and solve these with a given optimizer. In our algorithm parts where defined as sets of routes (cluster). The initial clustering was done by a $p$-Median
clustering algorithm to get a good initial solution. Subproblems where then created by randomly choosing a seed cluster, and then adding a close route of a related cluster into the seed cluster, where relatedness is defined as the closeness in distance between two centroids of clusters. These newly created subproblems are then solved by the MA that functions as an optimizer.

To analyze the effectiveness of our approach we decided to form three solving strategies. **Strategy I** is the most basic one, which tries to solve the problem as a whole by the described MA until a certain amount of runtime is elapsed. **Strategy II** is based on the initial clustering by the $p$-Median algorithm. In this case all clusters where treated as individual problems and solved by the MA respectively. **Strategy III** was executed two times with different parameter settings. The PopMusic Algorithm was implemented with longer runtime in IIIa and shorter runtime in IIIb. Furthermore the optimizer was given less time in IIIb to improve the subproblems then in IIIa to put some emphasis on faster descend of the solution quality. Each strategy was executed 10 times with 8 hours runtime for Strategy I, II and IIIa and 30 minutes for Strategy IIIb.

As expected the solving of the problem as a whole resulted in the generation of solutions with the worst quality. Strategy II is a very simple and easy to implement strategy that is able to provide significantly better results about $-13\%$ compared to Strategy I. In comparison Strategy III is more sophisticated and exploit the problem by decomposing it into related parts. In difference to Strategy II some kind of interaction occurs between the parts of the solution so that better results can be reached. Looking at the average results of strategy IIIa compared to strategy I, nearly $20\%$ improvement in solution quality shows that the PopMusic framework can solve large scale problems efficiently. This fact is underlined when looking at the results of the short PopMusic results IIIb. Even though the algorithm has only about $6\%$ of the time available it can beat the simple Strategy I by nearly $14\%$ and the decomposing Strategy II by around $0.75\%$ when comparing average results.

Support from the Austrian Science Fund (FWF) by grant #L362-N15 (Translational Research) is gratefully acknowledged.

**References**
