Each time a local optimum is found by LocalSearch, it is stored in the archive A of the set approximating the Pareto global optima set. Since the solution to the multiobjective problem is a set of all non-dominated objective vectors in A, the FilterArchive procedure is applied in a post-processing step; it deletes all dominated solutions and returns A^*. This last procedure can be excluded if it is applied every time the UpdateArchive procedure is called.

One obvious advantage of TPLS is its modularity, which enables us to focus on the solution methods embedded in GenerateInitialSolution and LocalSearch. Once the choice for these operators is taken, the only numeric parameter needed is the number of different aggregations of the objective functions. In a weighted sum approach, a high number of weight combinations should return a better approximation to the Pareto global optima set. However, some care must be taken, since increasing the number of weight combinations may not be enough to escape from local optima, resulting in a waste of computation time. A study of the trade-off between computation time and solution quality should be carried out according to the real application and together with the decision maker.

3 The Multiobjective TSP

Given a complete, weighted graph $G = (N, E, c)$ with N being the set of nodes, E being the set of edges fully connecting the nodes, and c being a function that assigns to each edge $(i, j) \in E$ a vector $(c^1_{ij}, \dots, c^K_{ij})$, where each element c^k_{ij} corresponds to a certain measure like distance, cost, etc. between nodes i and j. For the following we assume that $c^k_{ij} = c^k_{ji}$ for all pairs of nodes i, j and objectives k, that is, we consider only symmetric problems. The multiobjective TSP is the problem of finding "minimal" Hamiltonian circuits of the graph, that is, a set of closed tours visiting each of the $n = |N|$ nodes of G exactly once; here "minimal" refers to the notion of Pareto optimality.

Usually there is not only one, but many Pareto global optimum solutions, which form the *Pareto global optima set*. This set contains all solutions that are not dominated by any other solution. The problem of finding the Pareto global optima set is $\mathcal{NP}$-hard [5] and, since for many problems determining exact solutions quickly becomes infeasible with increasing instance size, the goal typically shifts from identifying Pareto global optima solutions to obtaining a good approximation to this set. For this latter task, algorithms based on local search seem to be a suitable approach and already have shown to yield good performance [7,10].

In this article, we apply TPLS to the biobjective case, i.e., $K = 2$. As benchmark instances we use combinations of single-objective TSP instances that are available at TSPLIB via `http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/` with 100 cities (kroA100 and kroB100), 150 cities (kroA150 and kroB150) and 200 cities (kroA200 and kroB200) as defined in [7]. For convenience, were refer to them as instances kroAB100, kroAB150 and kroAB200, respectively. The first instance was also attacked in [2,7,10] and at least for the approach by Jaszkiewicz the solutions are publically available.