Multi-Objective Large Neighborhood Search

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The large neighborhood search (LNS) framework introduced by Shaw [11] provides a powerful hybridization of Local Search (LS) and Constraint Programming (CP). The idea of LNS is to combine the expressiveness of CP and the efficiency of Local Search (LS) without requiring any meta-heuristic. LNS consists in improving a best-so-far solution by iteratively relaxing it and optimizing this solution using CP at each *restart*. This framework was successfully applied to tackle several large-scale single objective industrial problems [3, 5, 8, 9].

We extend the LNS framework into the so called Multi-Objective LNS (MO-LNS) to tackle Multi-Objective Combinatorial Optimization (MOCO) problems ubiquitous in real life applications [1, 2, 4]. The criteria to optimize in MOCO are usually conflicting. It is thus necessary to provide the decision maker with a set of non-dominated solutions reflecting all the optimal combinations of the conflicting goals. Instead of maintaining a best-so-far solution, the MO-LNS framework maintains the best-so-far approximation of the non-dominated set. At each restart (iteration), a non-dominated solution is chosen and one criteria to optimize is chosen, while preventing the other ones to deteriorate, in order to improve the set of non-dominated solutions.

The MO-LNS framework is implemented into OscaR solver [12]. Our experiments show that this new framework is competitive with state-of-the-art methods [6, 7] on academic problems such as the well-studied, bi-objective Traveling Salesman Problem (bTSP). We also demonstrate the flexibility of our framework by considering a more complex industrial problem i.e. a bi-objective version of the Tank Allocation Problem (TAP) [10].

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