Integration of Knowledge Discovery into MOEA/D

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1 Context

Extracting knowledge from solutions and then using it to guide the search is a complex task, which has not been highly explored in a discrete multi-objective optimization context. Considering the papers on that subject leads to the following terminology for *Knowledge Discovery* (KD) processes. A KD process is built upon two main procedures called *Knowledge Extraction* (K_{ext}) and *Knowledge Injection* (K_{inj}). The K_{ext} procedure aims to extract problem-related knowledge from one or several solutions. Then the extracted knowledge can be used by the K_{inj} procedure to build new solutions taking into account past iterations.

In this article, we investigate how a KD mechanism can be integrated into MOEA/D. To that purpose, we consider a bi-objective Vehicle Routing Problem with Time Windows (bVRPTW). In this problem, we minimize both the total traveling time and the total waiting time of drivers. With these two objectives, we obtain more diverse and dense fronts than those obtained when minimizing the number of vehicles and the total traveling time.

A study of existing works in KD and its hybridization with metaheuristics [2] leads to four main questions : *What*/*Where*/*When*/*How* is the knowledge extracted/injected ? Question *What* is problem-dependent, since each problem may have specific relevant knowledge. In the context of this article, we use sequences of consecutive customers, excluding the depot, from generated solutions. Questions *Where* and *When* are algorithm-dependent since the extraction and injection steps have to be integrated into the process of the algorithm. Question *How* deals with strategies that are used during the KD process (e.g. intensification or diversification). The answer to this question needs to take into account the multi-objective context of the problem. Our contribution focuses on this question and is detailed in Section 2.

2 Knowledge Discovery Mechanism

In the following, we make the assumption that solutions sharing some similarities are more likely to be in the same region of the fitness space. We propose to divide the fitness space into $k_{\mathcal{G}}$ regions each representing a *knowledge group*. Therefore, a knowledge group is defined by a delimited region of the fitness space. The region can be either explicit (represented by equations) or implicit (represented by sets). If a solution belongs to the region of a knowledge group, then its associated knowledge is added to that group.

Evolutionary algorithms use intensification and diversification mechanisms to explore the search space more in-depth or more largely. We propose to transpose these mechanisms of intensification and diversification to the KD for the extraction and injection mechanisms. When following an intensification strategy, the procedure has access to a small number of groups, in order to focus on close regions. On the other hand, with a diversification strategy, the procedure has access to a large number of groups, in order to bring diversity to the solutions.

Category	*Base*	A^3_{int}	A^3_{div}	A^5_{int}	A^5_{div}	A^M_{int}	A^M_{div}
R	0.730	0.627	0.703	**0.764**	0.667	0.682	0.706
RC	0.738	0.590	0.695	**0.781**	0.665	0.713	0.705
C	0.889	0.848	0.848	**0.959**	0.831	0.934	0.919
All	0.780	0.684	0.745	**0.828**	0.716	0.767	0.770

TAB. 1 – Average uHV of the variants according to their average uHV over the different categories of instance. Bold results are statistically significant.

3 Integration of the KD Process within MOEA/D

MOEA/D [3] is a genetic algorithm that approximates the Pareto front by decomposing the multi-objective problem into M several scalar objective subproblems.

The KD process is integrated as follows. At the start of MOEA/D, M weight vectors are given. Initially, a random population (of size M) is generated and evaluated. The $k_{\mathcal{G}}$ knowledge groups are defined implicitly by a set of subproblems. Four possibilities are considered : $k_{\mathcal{G}} \in \{1, 3, 5, M\}$. When optimizing subproblem i, a new solution is generated by using genetic operators. Then, an injection procedure K_{inj} adapted from [1] is applied. K_{inj} can be used following either an intensification strategy, where the knowledge comes from the closest group of the subproblem, or a diversification strategy, where the knowledge can come from any group. Then a Local Search (LS) is applied. Finally, the resulting solution is added to a set S of solutions generated during the iteration, and a few neighbors of the subproblem i are updated. When all subproblems have been seen, the set S is merged with the archive A, containing the non-dominated solutions, and the extraction procedure K_{ext} is applied to all the solutions of S. The groups are updated accordingly to the chosen strategy. Here, we only considered an intensification strategy for the extraction, thus a solution contributes to only one group. If the termination criterion is reached, the archive A is returned, otherwise, a new iteration is started.

This integration leads to 7 experimental variants : *Base*, A^3_{int}, A^3_{div}, A^5_{int}, A^5_{div}, A^M_{int}, A^M_{div}. *Base* is the variant containing only one group, where intensification and diversification are similar. The other variants follow the form $A^{k_{\mathcal{G}}}_{strat}$, where $k_{\mathcal{G}}$ is the number of groups, and *strat* is the strategy followed by the injection.

4 Conclusion and Perspectives

We compared the seven variants mentioned above, through Solomon's benchmark, after tuning all of them. The average unary Hypervolume obtained over 30 runs is reported in Table 1. The results show that the variant using five knowledge groups with an intensification strategy for both injection and extraction is statistically better than the other propositions.

In future works, we would like to investigate more deeply the impact of the strategies presented for injection and extraction. It could be interesting to use a different framework than MOEA/D, to know whether the conclusions remain similar. Finally, we aim to create an adaptive algorithm, which automatically adapts the number of groups and the strategies implemented by the operators.

Références

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