

# VNS and PBIG as Optimization Cores in a Cooperative Optimization Approach for Distributing Service Points\*

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We consider a variant of the facility location problem [2]. The task is to find an optimal subset of locations within a certain geographical area for constructing service points in order to satisfy customer demands as well as possible. This general scenario has a wide range of real-world applications. More specifically, we have the setup of stations for mobility purposes in mind, such as constructing bike sharing stations for a public bike sharing system, rental stations for car sharing, or charging stations for electric vehicles.

A main challenge with such optimization problems is to come up with reliable data for existing demand that may be fulfilled. Geographic and demographic data is usually combined with the special knowledge of points of interest and upfront surveys of potential users, but almost always this only yields a crude estimate of the real existing demand and final acceptance of the system. Instead of acquiring demand information from potential users upfront, we recently proposed a *cooperative optimization approach*, in which potential users are tightly integrated on a large scale in the optimization process [3]. For a more general review on cooperative optimization methods see [5].

The method iteratively generates solution candidates that are presented to users for evaluation. A surrogate objective function is trained by the users' feedback and used by an optimization core. The process is iterated on a large scale with many potential users and several rounds until a satisfactory solution is reached.

In more detail, one iteration of our approach consists of the following three steps: First, solutions are constructed individually for each user which are then presented to the users and they give feedback by stating how much of their demand would actually be satisfied at which locations. The goal of this step is to find for each user as many relevant locations as possible. Moreover, we are also interested in the relationship between these locations, as a user will prefer some locations to others.

Clearly, care must be taken to not confront users with too many candidate solutions as one cannot expect a user to evaluate hundreds of solutions. Therefore, in the second step a surrogate function [4] is derived for efficiently estimating

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\* Thomas Jatschka acknowledges the financial support from Honda Research Institute Europe.

the total fulfilled demand of intermediate candidate solutions. The surrogate function is repeatedly trained by the feedback so far obtained from each user.

In the last step a metaheuristic is used to find different optimal or close-to-optimal solutions on the basis of the surrogate function. These optimized solutions are then used again to derive new solutions for users to evaluate.

In this contribution, we focus in particular on this last step of our approach. A proper configuration of the used optimization core is vital for the cooperative approach to work. We investigate two different metaheuristics, a Variable Neighborhood Search (VNS) [6] and a Population Based Iterated Greedy Algorithm (PBIG) [1] and experiment with different configurations of these methods. For the VNS we test different local improvement and shaking methods, while for the PBIG we investigate a variety of destruction and construction operators.

We test our approach not with real users but a user and scenario simulation that captures important realistic aspects. In our experiments, we compare the VNS- and PBIG-based cooperative approaches also to stand-alone variants of the VNS and PBIG, in which it is naively assumed that users can evaluate all intermediate solutions. Furthermore, we consider a mixed integer linear programming model that exploits the complete knowledge and structure of our specific benchmark scenarios in order to obtain proven optimal solutions as reference.

## References

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