Hybrid Heuristics for the Probabilistic Maximal Covering Location-Allocation Problem

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Abstract. *The Maximal Covering Location Problem (MCLP) maximizes the population that has a facility within a maximum travel distance or time. Numerous extensions have been proposed to enhance its applicability, like the probabilistic model for the maximum covering location-allocation with constraint in waiting time or queue length for congested systems, with one or more servers per service center. This paper presents one solution procedure for that probabilistic model, considering one server per center, using a Hybrid Heuristic known as Clustering Search (CS), that consists of detecting promising search areas based on clustering. The computational tests provide results for network instances up to 818 vertices.*

General Information

The Maximal Covering Location Problem (MCLP) has been extensively studied in the literature since its formularization by [Church and ReVelle (1974)]. The main objective of the MCLP is to choose the location of facilities to maximize the population that has a facility within a maximum travel distance (or time). Thus, a population is considered covered if it is within a predefined service distance (or time) of at least one of the existing facilities. The MCLP does not require that all demand areas be covered, but offers service to the maximum population, considering the available resources.

Since its proposal, numerous extensions of the MCLP have been proposed to enhance its applicability, both in public and private sectors. Applications range from emergency services to congested systems. Considerable revision of this subject can be found in [Chung (1986)], [Hale and Moberg (2003)], [Serra and Marianov (2004)] and [Galvão (2004)].

[Marianov and Serra (1998)] have proposed models based on the fact that the number of requests for services are not constant in time, but a stochastic process whose stochasticity of demand is explicitly considered in the capacity constraints. Instead of being limited to a maximum value, the authors define a minimum limit for the quality of the service reflected in the waiting time or the number of people waiting for service. The authors have developed the Queuing Maximal Covering Location-Allocation Model (QM-CLAM). Good reviews of the probabilistic models can be found in [Galvão (2004)] and [Brotcorne, Laporte and Semet (2003)].

The purpose of this paper is to examine the QM-CLAM with one server per service center and present a solution using a hybrid heuristic called Clustering Search (CS), which was proposed by [Oliveira and Lorena (2004) (2007)]. The CS consists of detecting promising areas of the search space, using an algorithm that generates solutions to be clustered. These promising areas may then be explored through local search methods as soon as they are discovered. The CS results are compared with those obtained by Constructive Genetic Algorithm (CGA) and by the heuristic proposed by [Marianov and Serra (1998)].

The commercial solver CPLEX [ILOG (2006)] has been used to approximately solve the formulation for all problems, in order to validate the computational results of CS.

The Clustering Search (CS), proposed by [Oliveira and Lorena (2004) (2007)], employs clustering for detecting promising areas of the search space. The sooner these strategic areas can be identified, the sooner a more accurate search strategy can be applied. An area can be seen as a search subspace defined by a neighborhood relationship in metaheuristic coding space. In the CS, a clustering process is executed simultaneously to a metaheuristic, identifying groups of solutions that deserve special attention.

The CS attempts to locate promising search areas by framing them by clusters. A cluster can be defined as a tuple G = {c; r; s} where *c*, *r* and *s* are, respectively, the center and the radius of the area, and a search strategy associated to the cluster.

The center of the cluster is a solution that represents the cluster, identifying its location inside the search space. Initially, the centers of the clusters are obtained randomly; but progressively, they tend to fall along really promising points in the close subspace. The radius r establishes the maximum distance, starting from the center, for which a solution can be associated to the cluster. The search strategy is a systematic search intensification, in which solutions of a cluster interact among themselves along the clustering process, generating new solutions.

The idea of the CS is to avoid applying a local search heuristic to all solutions generated by a metaheuristic, what it can make impracticable the search process because of the time consuming, mainly when the heuristic has a high computational cost. The CS detects the promising regions in the search space during solution generation process, i.e., to detect promising regions becomes an interesting alternative preventing the indiscriminate application of such heuristics.

The CS consists of four conceptually independent components with different attributions: search metaheuristc (SM), iterative clustering (IC), analyzer module (AM), and local searcher (LS).

The SM works as a full-time solution generator. The algorithm is executed independently of the remaining components and must be able to provide a continuous generation of solutions to the clustering process. Clusters are maintained, simultaneously, to represent these solutions.

The IC aims to gather similar solutions into groups, identifying a representative cluster center for them. To avoid extra computational effort, IC is designed as an online process, in which the clustering is progressively fed by solutions generated in each iteration of SM. A maximum number of clusters NC is an upper bound value that prevents an unlimited cluster creation. A distance metric must be defined, a priori, allowing a similarity measure for the clustering process.

The AM provides an analysis of each cluster, at regular intervals, indicating a probable promising cluster. A cluster density, δ_i, is a measure that indicates the activity level inside the cluster. For simplicity, δ_i counts the number of solutions generated by SM and allocated to the cluster i. Whenever δ_i reaches a certain threshold, indicating that some information template has become predominantly generated by SM, that information cluster must be better investigated to accelerate the convergence process on it.

Finally, the LS is a local search module that provides the exploitation of a supposed promising search area framed by a cluster. This process is executed each time AM finds a promising cluster. LS can be considered as the particular search strategy associated with the cluster, i.e., a problem-specific local search to be applied to the cluster.

In this paper, different methods were applied to QM-CLAM. CS got better results than others heuristics (CGA and the heuristic by Marianov and Serra) and it founds good values comparing to CPLEX. CS has two advantages over CPLEX: execution time, and the cost of a commercial solver.

The results show that the CS approach is competitive for the resolution of this problem in reasonable computational times. For some instances of 30-node and 818-node networks, the optimal values were found. Therefore, these results validate the CS application to the QM-CLAM.

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