Optimization of the scheduling of medico-social activities at multiple sites: a clustering approach

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1 Introduction

This article focuses on SESSAD-type structures (Service d'Éducation Spéciale et de Soins A Domicile) that provide individualized support to children and adolescents with disabilities in their normal living and educational environment. Multidisciplinary teams are responsible for this support, including speech and language therapists (SLT), physiotherapists, and psychologists, and accompaniments take place in various places of life (at home, at school, etc.).
In this paper, the goal is to propose an efficient model to schedule the activities of SLT within a SESSAD that can be used on a real case, based on our previous work [1], which proposed a first solution, limited to 6 SLT. In order to improve the efficiency of the model, different clustering techniques are investigated.
Our case study is the OVE Foundation, based in Lyon. This foundation is a SESSAD that welcomes and accompanies children and teenagers, from 4 to 20 years old, with or without disabilities, to promote their integration into society. We focus on the accompaniment of children by SLT and taking place only within the schools.
The data used in the experiments are defined as follows: We have 12 SLT and 99 patients. Patients are pre-assigned to SLT. The time horizon is 5 days. Each day is divided into 10 60-minute slots. The treatment time is 45 minutes. There are 3 different skills for the SLT and each SLT has one, two, or three of these skills that match the patient's needs. The number of days separating two sessions of one SLT with one child is known and fixed.
The problem is defined as follows: the objective is to minimize the travel time of the SLT, but also to minimize the waiting time before the start of a session.

2 Method

The above-described problem is modeled as a vehicle routing problem with time windows (VRP-TW). Each patient is represented by its location and requires treatment with a specific frequency and a minimum number of days between sessions, as well as a specific skill. SLT are also represented by their location and each has daily work hours. Availability time slots are defined for each patient and for each SLT according to their schedule. The time is then divided into slots of one hour. One SLT cares for one patient per slot. The main goal is to minimize the travel time of the SLT by finding a match between the schedules and the skills of each SLT and taking into account the capacity of the schools.

The objective of this paper is to optimize this model in order to make it efficient and usable for a real case. The problem is thus divided into sub-problems using clustering methods in order to find a feasible and acceptable solution in a short time since we have seen that the resolution time increases exponentially when the limit of 6 SLT is exceeded. Then it is optimized to find the best possible solution and to minimize travel time as much as possible. We thus create two clusters using different methods, as explained below, and in order to improve the results of the different clustering methods performance, neighborhood operators, and optimization processes are studied.

Basic clustering on SLT, or on patients. Clustering is first based on the group of SLT. Then, the patients are distributed in clusters according to which SLT is currently accompanying them. The 3 methods used and compared are classical ones, namely: K-Means, Agglomerative Hierarchical Clustering (AHC), and DBSCAN. As the SLT are few in number, the effectiveness of the above methods is affected and they can lead to unequal clusters if they are simply applied. We thus change the SLT assigned to each patient in order to improve the results. The algorithm consists then in taking the patient who is geographically farthest from the others, calculating the distance of that patient from all the others, and then forming the cluster of the closest patients. The second cluster is composed of all other patients. The condition of equal cluster size is respected. After that, to assign employees to the clusters, we calculate the distance between the SLT and the barycenter of the first cluster. We take half of the SLT closest to this cluster and add them to it. The other half is assigned to the second cluster. Thus, we finally get two clusters that we can run.

Neighborhood operators. In order to improve cluster solutions to get a shorter travel time, the idea is to use neighborhood operators on clustering solutions, defined using a transformation. Two neighborhood operators are coded and compared: permutation and addition-deletion.

Optimization process Still, with the idea of minimizing the travel time as much as possible, optimization techniques that use the neighborhood permutation operator are employed. Three heuristics are then proposed and compared: iterative permutation between the SLT of the two obtained clusters, record-to-record, and multistart.

3 Results and conclusion

All clustering methods were coded in Python and the library sklearn and applied to the data described above. We could observe that clustering on patients and more specifically the multistart method proposes a shorter total travel time than clustering on SLT because they are more numerous and the patient-employee assignment plays a major role. This clustering uses the hierarchical bottom-up clustering algorithm by assigning the nearest neighbors to the two most distant patients. From these clusters, neighborhood operators are used to improving the clustering solutions. The permutation operator was preferred because the results were better. Finally, this operator has been pushed further with record-to-record acceptance rule and iterative exchanges but the final solutions are globally not better than those of simple permutations in our application case.

To conclude, this paper presents a clustering method, improved using neighborhood operators and optimization processes. To complete this analysis, it would be interesting to study other clustering methods to broaden the comparison spectrum and the behaviors of different neighborhood operators and optimization processes on patients and not only on SLT.

References

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