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Variable neighborhood search for the pharmacy duty scheduling problem

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ABSTRACT

In this paper, we study on the Pharmacy Duty Scheduling (PDS) problem, where a subset of pharmacies should be on duty on national holidays, at weekends and at nights in order to be able to satisfy the emergency drug needs of the society. PDS problem is a multi-period p-median problem with special side constraints and it is an NP-Hard problem. We propose four Variable Neighborhood Search (VNS) heuristics. The first one is the basic version, BVNS. The latter two, Variable Neighborhood Decomposition Search (VNDS) and Variable Neighborhood Restricted Search (VNRS), aim to obtain better results in less computing time by decomposing or restricting the search space. The last one, Reduced VNS (RVNS), is for obtaining good initial solutions rapidly for BVNS, VNDS and VNRS. We test BVNS, VNRS and VNDS heuristics on randomly generated instances and report the computational test results. We also use VNS heuristics on real data for the pharmacies in central İzmir and obtain significant improvements.

1. Introduction

The Pharmacy Duty Scheduling (PDS) problem arises from the society's need for emergency drugs. The goal of the PDS problem is to assign duties to the pharmacies on national holidays, at weekends and at weekday nights. Ağlamaz and Özpeynirci [2] defined PDS problem as a multi-duty p-median problem and showed that PDS problem is an NP-Hard problem by reducing to the p-median problem. In this study, we develop four Variable Neighborhood Search (VNS) based heuristics for the PDS problem; (i) basic, (ii) initial solution provider, (iii) decomposed, and (iv) with restricted local search.

PDS problem is a society related real life problem and its solution affects many people. There are many studies related with healthcare problems, such as ambulance location, nurse scheduling and emergency facility location.

The Chamber of pharmacists is responsible for the duty scheduling of the pharmacies, which is currently prepared manually in a decentralized approach. In the current system, the pharmacies are grouped into regions based on their geographical locations and there is a representative pharmacist in each region. These representative pharmacists manually prepare duty schedules for their regions independently. The current decentralized system may involve excessive customer travel in order to reach the closest on duty pharmacy. On the other hand, PDS problem considers all regions simultaneously. The mathematical model and algorithms developed in this paper propose central duty schedules.

The rest of the paper is planned as follows. We provide a literature review in Section 2. We introduce the mathematical model of the problem in Section 3. We present the VNS heuristics in Section 4 and the computational results in Section 5. Finally, we conclude the paper in Section 6.

2. Literature review

We present an extensive literature review of Variable Neighborhood Search (VNS) heuristic and its extensions in this section. We also discuss the facility location problem, the p-median problem and the emergency facility location problem.

Hale and Moberg [15] define facility location problems as exploring where to physically locate a set of facilities so as to minimize the cost of satisfying some set of customer nodes, while satisfying some set of constraints. They also emphasize that facility location models can differ in their objective function, the distance metric applied, the number and the size of the facilities to locate and several other decision indices. ReVelle et al. [37] classified the developments in location modeling into four categories: firstly, analytic models based on a large number of simplifying assumptions; secondly continuous models assuming facilities can be located anywhere, while demands

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are often at discrete locations; thirdly network models assuming the location problem are embedded in a network composed of links and nodes; and finally discrete location models in which demands and locations are discrete, as in the Pharmacy Duty Scheduling (PDS) problem case.

The p-median problem is a commonly used model in location science. Kariv and Hakimi [25] classified the p-median problem as an NP-hard problem. Researchers use the p-median problem to model many real life problems regarding the location of industrial plants, warehouses, public facilities [30]. Researchers have also applied the p-median problem to other research areas, such as cluster analysis [17] and data mining [33].

The computational complexity of the p-median problem has led the researchers to develop heuristics. Mladenović et al. [30] identified two groups of heuristics for solving the p-median problem: classical heuristics and metaheuristics. Classical heuristics contained greedy, stingy, dual ascent, composite, alternate, interchange, dynamic programming, lagrangian relaxation and aggregation heuristics. Metaheuristics consisted of tabu search (TS), variable neighborhood search (VNS), genetic algorithm (GA), scatter search, simulated annealing (SA), heuristic concentration, ant colony optimization (ACO), neural networks, decomposition heuristics and hybrid heuristics (HH).

Alp et al. [4] applied an efficient GA to the p-median problem and tested the algorithm on 80 test problems ranging 100–1000 nodes. Levanova and Loresh [28] proposed the SA algorithm and completely solved 17 out of the first 20 (among 40) OR-library test instances [6]. Resende and Werneck [36] and Kochetov et al. [26] suggested two different improvements of ACO and were able to solve all 20 OR-library instances.

Mladenović and Hansen [29] introduced a new metaheuristic, VNS, an approach that avoids entrapment in local optima. They defined this simple and effective metaheuristic as a systematic change of neighborhood within a local search algorithm. Instead of following a normal trajectory, VNS searches in increasing distant neighborhoods of the current incumbent solution and jumps to a new solution if and only if an improvement was obtained.

Hansen and Mladenović [18] proposed VNS heuristic for solving p-median problem and compared VNS with TS heuristics. They obtained better results against TS heuristics, but VNS heuristic took several hours for the large scale problems. In order to decrease computation time of the VNS heuristic, Hansen et al. [19] developed Variable Neighborhood Decomposition Search (VNDS). VNDS heuristic decomposes the search space and applies local search in a relatively smaller space. They illustrated VNDS on the p-median problem and tested on instances of 1400, 3038 and 5934 users from the TSP library [35]. They showed that VNDS improved notably upon VNS in less computing time.

Hansen and Mladenović [20] proposed several extensions of VNS for solving large scale problem instances: Reduced VNS (RVNS) heuristic discards the local search step of basic VNS heuristic in order to decrease the computation time for the large scale problems in which local search step takes long time. This allows a jump to a solution worse than the incumbent, with some probability, and allows easy exploration of valleys far from the incumbent solution. It also provides an efficient Skewed VNS (SVNS) heuristic, and these extensions of VNS were applied (by the researchers) to some classical optimization problems. Later, those researchers used the extensions of VNS to solve 0-1 mixed integer programming (MIP) problems with hybrid algorithms (see for example [27,16,40]).

Combining VNS with other heuristic methods generates new variants of VNS. Pérez et al. [34] developed a new method, the variable neighborhood tabu search (VNTS), by combining VNS and TS method. García-López et al. [13] developed the parallelization of VNS metaheuristic, parallel Variable Neighborhood Search (PVNS), which allowed high efficient exploration of space through the distribution of the steps of the algorithm among the available processors and then they tested PVNS on large scale instances of the p-median problem from TSP library. Crainic et al. [10] defined Cooperative Parallel VNS (CPVNS) which cooperates several independent VNS metaheuristics by the asynchronous exchange of information about the most recent best solution. They experimented this method by using the classical TSP library problem instances with up to 11,948 customers and 1000 medians. The results showed that cooperative method outperforms the recent methods in terms of computation time with no loss in solution quality.

In the literature, VNS heuristic and its extensions are applied to several optimization problems. Şevkli and Aydın [38] proposed VNS heuristic to solve job shop scheduling problems, with better results than other proposed methods. Other problems solved by the VNS heuristics include minimum berth allocation problem [22], location routing problem [24], bandwidth reduction problem [32], constrained and unconstrained continuous optimization problems [31], harmonic means clustering problem [3], local branching problem [21], k-cardinality tree problems [7,39] and the capacitated p-median problem [12].

Fire brigades, ambulances, police stations and hospitals are examples of important emergency service stations. The emergency service station (ESS) location problem is a very important problem that received great attention in the literature. Başar et al. [5] propose a taxonomy for ESS location problems. Adenso-Díaz and Rodríguez [1] suggested tabu search (TS) heuristic for locating ambulances in the Spanish province of León. Çatay et al. [11] analyzed single and multi-period emergency station location problem for İstanbul, Turkey and propose heuristics to solve the large scale instances. Harewood [23] proposed a multi-objective programming problem to locate ambulances on the island of Barbados. Carreras and Serra [8] study on locating new pharmacies in the rural areas of Spain considering the service threshold levels and propose a TS heuristic. The PDS problem is also a special ESS problem. However, in PDS the locations of the pharmacies are known, and we deal with assigning duties to pharmacies in order to provide good quality service to emergency drug needs of the society.

3. Mathematical model

Ağlamaz and Özpeynirci [2] introduced the Pharmacy Duty Scheduling (PDS) problem and developed a mixed integer mathematical programming model for the PDS problem in cooperation with the Chamber of Pharmacists. The chamber is responsible for planning the duty schedules of pharmacies, which are clustered (for this purpose) into regions based on geographical locations. The number of pharmacies in regions may differ based on several factors such as the population density, hospital locations and preferences of the pharmacists.

Ağlamaz and Özpeynirci [2] have made assumptions regarding the demand points and the distances between the demand points and the pharmacies. They assume an aggregate customer node where a group of people living in the same neighborhood will be represented. They also assume that the customer nodes are located at the centers of the districts and the demand at each customer is proportional to the population. The distance between the customer nodes and pharmacy locations are known. The length of the planning horizon (T) and the total number of duties in which each of the pharmacies must take on during the planning horizon are inputs for the mathematical model.

Indices and Sets

i customer node (demand point), $i = 1, \ldots, I$

j pharmacy (facility site), $j = 1, \ldots, J$