Multi-Criteria Service System Designing Using Tabu Search Method

Marek Kvet and Jaroslav Janáček
University of Žilina, Faculty of Management Science and Informatics, Univerzitná 8215/1, 010 26 Žilina, Slovakia

Keywords: Multi-Criteria Location Problems, Pareto Front, Tabu Search Heuristics, Algorithm Efficiency Improvement.

Abstract: Designing a good public service system that provides a geographical region with service through a specified number of service centers is a very difficult task, particularly when multiple quality evaluation criteria are applied. A Pareto front of public service system designs is a very useful instrument for any designer who must consider multiple requests from public representatives. Due to the computational difficulty of determining the Pareto front, a number of heuristic approaches have been developed. One of these techniques, gradual refinement, proved to be quite effective, but its performance could be enhanced by eliminating the repetition of some rudimentary swap routines. This contribution focuses on the application of tabu search features to enhance and increase the efficacy of the gradual refinement process by suspending the routines' few useful applications. The resulting metaheuristic is validated through numerical experimentation using benchmarks, and the approximations of the Pareto front are compared to the exact Pareto fronts.

1 INTRODUCTION

Establishing a new service system, improving an existing one, or solving other similar issue involving a public service system involves figuring out the best locations for service centers, stations, or facilities that are stocked with the tools, personnel, or other resources required to meet customers' demands. It goes without saying that the combinatorial nature of the aforementioned challenges necessitates the use of various mathematical modeling techniques, software development expertise, or other advanced abilities. As a result, while making strategic decisions, professionals in operations research cannot be disregarded. Because of enormous and quick advancements being made in practically all relevant domains, we are able to quickly and effectively produce good results for significant problem instances (Ahmadi-Javid et al, 2017, Current, Daskin and Schilling, 2002, Ingolfsson, Budge, Erkut, 2008).

Speaking of the designing of service systems, it must be recognized that we do not study private service systems in this study because they are primarily focused on maximizing profit regardless of the number of users covered by the system or the degree of equity in service accessibility. As a result, we exclusively focus on public service systems, the existence of which is typically guaranteed by legislation. Public service systems are designed to ensure that all local citizens will receive services, regardless of financial gain or loss (Jánošíková, 2007, Jánošíková, Žarnay, 2014). According to science, the discrete network location problem family includes the public service system design problem, which has been researched and successfully resolved by numerous authors (Brotcorne, Laporte, Semet, 2003, Doerner et al, 2005, Marianov, Serra, 2002). The weighted *p*-median problem is the most concrete form of the problem, and one of the most popular modeling notions is what comes next.

Common mathematical models may have a number of serious drawbacks, one of which is the limitation that only one objective function can be maximized/minimized. Large service systems are complicated systems with a variety of competing demands made by various stakeholder groups involved in the decision-making process, and not all of them lend themselves to abstraction. Therefore, multi-objective service system optimization is the focus of attention. Only two opposing aims will be taken into account for the sake of simplicity in this paper. Another obstacle connected with large mathematical models consists in the complexity of most exact methods, which usually disables their application for practice. On the other hand, experts have found a solution also for such a situation.

As well as existing conventional exact methods based usually on the branch and bounds principle,

Kvet, M. and Janáček, J.
Multi-Criteria Service System Designing Using Tabu Search Method.
DOI: 10.5220/0012262800003639

In *Proceedings of the 13th International Conference on Operations Research and Enterprise Systems (ICORES 2024)*, pages 193-199
ISBN: 978-989-758-681-1; ISSN: 2184-4372

newer heuristic algorithms, metaheuristics, and more advanced evolutionary approaches to the optimization issues have been created. Verifying that the best answer identified is the optimal solution is a particular weakness of practically all exact approaches. Some modeling strategies, such as the radial approach (Avella, Sassano, Vasil'ev, 2007, Kvet, 2014, Kvet, 2018), can greatly speed up the associated solving process. Nonetheless, the time it takes to verify these accurate methods is sometimes prohibitive. However, heuristic approaches allow us to get a decent answer in much less time. Furthermore, public service system design can address bi-criteria location challenges, which present a similar challenge with the same precise techniques of slow performance. The Pareto front is a unique collection of solutions that must be looked for when there are two or more objectives to be optimized. Since completing the complete inextensible Pareto front requires a lot of effort (Grygar, Fabricius, 2019, Janáček, Fabricius, 2021), academics have focused on developing approximate methods and efficient heuristics (Arroyo et al, 2010, Gendreau, Potvin, 2010, Gopal, 2013).

This contribution is focused on application of tabu search features to enhance the gradual refinement process developed especially to approximate the original Pareto front. The main goal is to increase its efficiency by suspending the little useful applications of associated routines. Obviously, suggested algorithm has been experimentally verified and the obtained results are reported here.

The structure of this paper is organized according to the following scheme: The main goal of the first section was to introduce the problem and to place it into a wider scientific context. The second section discusses the Pareto front of bi-criteria location problem solutions. In section 3, we introduce the neighborhood search with tabu moves. The fourth section summarizes the numerical experiments. Here, we provide the readers with several comments on the computational study. The last section is dedicated to the conclusions and future research directions.

2 PARETO FRONT OF BI-CRITERIA LOCATION PROBLEM SOLUTIONS

A discrete location problem can be concisely described as the task to select p locations from the set of m candidate locations so that a given criterion value is minimal. Thus the set of all feasible problem solutions $\boldsymbol{Y}$ can be defined as $\boldsymbol{Y}=\{\boldsymbol{y}: \boldsymbol{y}\subset\{1, \ldots, m\}, |\boldsymbol{y}|=p\}$.

As concerns quantified criteria of the individual elements of $\boldsymbol{Y}$, they depend on the sort of the real problem formulated as the location problem. In the case of private service system design, the objective is often minimal total cost of service distribution from service centers to the customers. The total cost is usually proportional to the sum of weighted distances from customers to the closest service center. Considering a public service system design, the situation is more complex due to more points of view at the system utility. In principle, the applied criteria can be divided into two classes called system criteria and fairness criteria. The system criterion minimizes disutility perceived by an average system user and the fairness criterion minimizes disutility perceived by the worst situated minority of the system users. The system criterion can be represented by an average response time of the system subject to the assumption that a user's demand is satisfied from the nearest available service center. The fairness criterion can be represented by the number of users' demands, which are situated outside a radius R from the nearest located service center.

Taking into account random occurrence of the users' demands and limited capacity of the service centers, the nearest available center need not mean the nearest center due to possible occupancy of the nearest center. This situation can be modelled by series $q_1, q_2, \ldots, q_r$ of probability values, where q_k expresses the probability that the k-th nearest service center is the nearest available one. If t_{ij} denotes time necessary for transport of service from a possible service center location i to a user located at location $j\in\{1, \ldots, n\}$ and if b_j denotes frequency of the demand occurrence at a user's location j, then the system objective function $f_1(\boldsymbol{y})$ can be defined by (1).

$$f_1(\boldsymbol{y})=\sum_{j=1}^{n}\sum_{k=1}^{r}q_k b_j \min{}_k\left\{t_{ij}: i\in \boldsymbol{y}\right\} \tag{1}$$

In formula (1), the $\min_k$ operation performed on a set of values returns the k-minimum value from the set.

The fairness criterion can be expressed by (2), see (Bertsimas, Farias, Trichakis, 2011, Buzna, Kohányi, Janáček, 2013).

$$f_2(\boldsymbol{y})=\sum_{j=1}^{n}b_j sign\Big(\max\Big\{0, \min\Big\{t_{ij}-R: i\in \boldsymbol{y}\Big\}\Big\}\Big) \tag{2}$$

The criteria f_1 and f_2 are in conflict, which means that a decrease in one of them is paid for by an increase in the other. It follows that there is no optimal solution, but a usable result of the two-criterion problem can be seen in determining such a set PF of solutions that satisfy clauses (3) and (4).

$$\begin{aligned}&\text{For each } \boldsymbol{x} \in \boldsymbol{Y},\ \text{there exists } \boldsymbol{y} \in PF:\\ &f_1(\boldsymbol{y}) \le f_1(\boldsymbol{x}) \text{ and } f_2(\boldsymbol{y}) \le f_2(\boldsymbol{x})\end{aligned} \tag{3}$$

$$\begin{aligned}&\text{For each pair } \boldsymbol{y}, \boldsymbol{z} \in PF,\ \text{it holds that}\\ &\text{either } f_1(\boldsymbol{y}) < f_1(\boldsymbol{z}) \text{ and } f_2(\boldsymbol{y}) \ge f_2(\boldsymbol{z})\\ &\text{or } f_1(\boldsymbol{y}) \ge f_1(\boldsymbol{z}) \text{ and } f_2(\boldsymbol{y}) < f_2(\boldsymbol{z})\end{aligned} \tag{4}$$

Such a set PF is called a Pareto front. If two solutions $\boldsymbol{x}$ and $\boldsymbol{y}$ satisfy (3), it is said that solution $\boldsymbol{y}$ dominates solution $\boldsymbol{x}$.

As determination of exact Pareto front demands extremely big portion of computational time, our attention is focused on approximation of the Pareto front by a set of *noNDSS* non-dominated solutions, which will be denoted by symbol *NDSS*. The used implementation of *NDSS* will be kept in the form of ordered sequence of feasible solutions $\boldsymbol{y}^1, \ldots, \boldsymbol{y}^{noNDSS}$, for which the following inequalities hold $f_2(\boldsymbol{y}^1) < f_2(\boldsymbol{y}^2) < \ldots < f_2(\boldsymbol{y}^{noNDSS})$ and $f_1(\boldsymbol{y}^1) > f_1(\boldsymbol{y}^2) > \ldots > f_1(\boldsymbol{y}^{noNDSS})$. Furthermore, the first and last members of *NDSS* must correspond to the first and last bordering members of the Pareto front, i.e. the solutions which have the minimal and maximal value of f_2 respectively. These properties of *NDSS* enable fast decision on arbitrary element $\boldsymbol{y}$ of $\boldsymbol{Y}$ concerning its suitability for improving the current approximation. That can be used for construction of procedure *Update*(*NDSS*, $\boldsymbol{y}$), which returns the value of "true" if $\boldsymbol{y}$ improves the current *NDSS* and it returns the value of "false" otherwise. At the same time, the procedure updates *NDSS* inserting the admissible $\boldsymbol{y}$.

The procedure starts with determination of such $k \in \{1, \ldots, noNDSS\text{-}1\}$ that $f_2(\boldsymbol{y}^k) \le f_2(\boldsymbol{y})$ and $f_2(\boldsymbol{y}) < f_2(\boldsymbol{y}^{k+1})$. If such k does not exist, $\boldsymbol{y}$ is dominated by $\boldsymbol{y}^{noNDSS}$ and the result of the procedure is "false". If k is found, then either $f_1(\boldsymbol{y}) \ge f_1(\boldsymbol{y}^k)$ or $f_1(\boldsymbol{y}) < f_1(\boldsymbol{y}^k)$. In the former case, $\boldsymbol{y}$ is dominated by $\boldsymbol{y}^k$ and the procedure returns "false". In the latter case, $\boldsymbol{y}$ is included into *NDSS*, which can be accompanied by exclusion of some original members, when $f_1(\boldsymbol{y}) < f_1(\boldsymbol{y}^{k+1})$ holds. In this case, the procedure returns the value of "true" and updated *NDSS*.

Proximity of *NDSS* to *PF* can be measured by so-called *NDSS-Area,* which is computed according to (5). The complementary constants f_1dif_k and f_2dif_k can be computed by (6) and (7) respectively.

$$NDSS\text{-}Area = \sum_{k=1}^{noNDSS-1} \left(f_1 dif_k\right)\left(f_2 dif_k\right) \tag{5}$$

$$f_1 dif_k = f_1(\boldsymbol{y}^k) - f_1(\boldsymbol{y}^{noNDSS}) \tag{6}$$

$$f_2 dif_k = f_2(\boldsymbol{y}^{k+1}) - f_2(\boldsymbol{y}^k) \tag{7}$$

Each update of the *NDSS* by a new solution y is followed by a reduction of the *NDSS-Area* and the associated value is bounded from below the *PF-Area*.

3 NEIGHBORHOOD SEARCH WITH TABU MOVES

The neighbourhood search algorithm has proved to be a massive source of feasible solutions, which represent candidates for *NDSS* improving. In general, the neighbourhood of a given current solution is defined by a set of permitted operations, which can be used to modify the current solution keeping feasibility of the operation result. Each feasible result of a permitted operation is considered to be an element of the neighbourhood.

The neighbourhood search algorithm comes from an initial solution declared as the starting current solution and searches element-by-element through the neighbourhood of the current solution. If the used searching strategy yields n admissible solution, then this solution is declared to be the new current solution and the neighbourhood search is continued with the new neighbourhood. If the opposite case occurs, the simple neighbourhood search algorithm terminates and returns the last current solution as the result.

Various strategies can be applied to the neighbourhood search. The two most known ones are the first or best admissible strategies. The first admissible strategy provides the first solution found that is better than the current one and the best admissible strategy provides the best admissible solution of the current neighbourhood. These strategies can be generalized using parameters called *MaxNos* and *Threshold*. The parameter *Threshold* gives minimal difference between objective function values of the inspected and current solutions for the inspected solution to be considered admissible. The parameter *MaxNos* gives the number of admissible solutions, which must be met during the neighbourhood inspection to be allowed to stop the inspection prematurely. The best of the found admissible solutions is used as the new current solution. If the parameter *Threshold* equals to zero and the parameter *MaxNos* takes the value of one, then the associated strategy reduces to the first admissible strategy. If the parameter *MaxNos* is set to a bigger value than the number of the neighbourhood elements, then the strategy behaves as the best admissible strategy.

In this paper, we focus on the neighbourhood search algorithm with the generalized strategy and with the only one permitted operation represented by so called swap operation. The swap operation replaces one service center location i of the current solution $\boldsymbol{y}^{curr}$ by a possible service center location j, which is not included in the current solution. The resulting solution is denoted as $swap(\boldsymbol{y}^{curr}, i, j)$. The inspected solution admissibility is evaluated by the *NDSS-Area* decrease caused by insertion of the solution into *NDSS*.

The neighbourhood search algorithm was embedded into the process of *NDSS* improvement in the following way.

The process starts with *NDSS* consisting of exactly two solutions representing the border solutions of the exact Pareto front, i.e. the solutions with the minimal and maximal values of the function f_2. Then, the process continues with selecting an element of the current *NDSS* in some order and applying the neighbourhood search algorithm to the selected solution. During the run of the algorithm, the *NDSS* is updated whenever such solution is inspected, which is not dominated by any solution of the current *NDSS*. This process continues until the given computational time limit is exceeded.

The process in the above described form cannot avoid repeating the neighbourhood search algorithm with the same starting solution. Repeating the algorithm reduces the efficiency of the process because it only produces candidates that have already been inspected once. This drawback evoked an idea of prevent the algorithm from inspecting the series of current solutions, which was already inspected. For the purpose, tabu approach taken from the tabu search approach was implemented here. Time limited prohibition (tabu) is imposed on both locations of the performed swap operation so that each possible center location i is connected with two time instants $In(i)$ and $Out(i)$ initialized by the value of $-Exp$, where Exp is the time of prohibition expiration.

When swap operation i for j should be performed at current time t, then the clauses $t - Out(i) \geq Exp$ and $t - In(j) \geq Exp$ are verified. If the clauses are satisfied, the swap operation is performed and the attributes $Out(i)$ and $In(j)$ are updated by t. The whole process of *NDSS* improvement can be described by following sequence of steps.

0. Initialize *NDSS*, set up the parameters *MaxNos*, *Threshold*, *Exp* and time limit T. Set $In(i)$ and $Out(i)$ at the value if $-Exp$ for all possible locations and set t=0.
1. If $CPU < T$ then continue with the step 2, otherwise terminate and return the current *NDSS*.
2. Set k=1 and continue with the step 3.
3. If $k < noNDSS$, then select $\boldsymbol{y}^k$ from the current *NDSS* and go to the step 4, otherwise go to the step 1.
4. {Application of the neighborhood search algorithm to $\boldsymbol{y}^k$} Substitute $\boldsymbol{y}^k$ for the current solution $\boldsymbol{y}^{curr}$ and continue with the step 5.
5. Define set C of location not contained in $\boldsymbol{y}^{curr}$ by $C = \{1, \ldots, m\} - \boldsymbol{y}^{curr}$, $Area0 = NDSS\_Area$, $Nos = 0$, $BestDecrement = 0$ and continue with the step 6.
6. While $Nos < MaxNos$ choose step-by-step a pair (i, j), where $i \in \boldsymbol{y}^{curr}$ and $j \in C$ and define $\boldsymbol{y} = swap(\boldsymbol{y}^{curr}, i, j)$. If $Updated(NDSS, \boldsymbol{y})$, then compute $Area1 = NDSS\_Area$, $Decrement = Area0 - Area1$. If $Decrement > Threshold$ then perform $Nos = Nos+1$, $Area0 = Area1$ and if $Decrement > BestDecrement$, then set $BestDecrement = Decrement$, $i^{best} = i$ and $j^{best} = j$. After processing of the step 6 has finished, continue with the step 7.
7. If $BestDecrement > 0$, then redefine $\boldsymbol{y}^{curr} = swap(\boldsymbol{y}^{curr}, i^{best}, j^{best})$, $In(j^{best}) = t$, $Out(i^{best}) = t$, $t = t+1$ and continue with step 5. Otherwise, check whether the solution at the k-th position of the current *NDSS* has changed. If it stays the same, set k=k+1. Continue with the step 3.

4 NUMERICAL EXPERIMENTS

This section is used to report the performed numerical experiments aimed at verifying the efficiency of suggested approach.

4.1 Benchmarks and Solving Tools

As far as the technical support like hardware and software tools is concerned, we used the programming language Java within the NetBeans IDE 8.2 environment. The experiments were run on a common PC equipped with the 11th Gen Intel® Core™ i7 1165G7 2.8 GHz CPU and 40 GB RAM.

As the input dataset for the reported computational study, we made use of commonly used benchmarks described in (Grygar, Fabricius, 2019), Janáček, Fabricius, 2021, Janáček, Kvet, 2020, Janáček, Kvet, 2021, Janáček, Kvet, 2022a, Janáček, Kvet, 2022a, Janáček, Kvet, 2022b, Janáček, Kvet, 2022c, Kvet, Janáček, 2022), the origin of which comes from the road network of Slovakia, through which the urgent medical care is provided by the emergency agencies. The list of higher territorial units, frequently referred to as self-governing regions, contains Bratislava (BA), Banská Bystrica (BB), Košice (KE), Nitra (NR), Prešov (PO), Trenčín (TN), Trnava (TT) and Žilina (ZA). It must be noted that all network nodes represent both the set of candidates for service center locating and the set of inhabitants being provided with service.

As the objective function f_1 expressed by (1) follows from the concept of so-called generalized disutility, the parameter r was set to 3. The coefficients q_k were set so that q_1 = 77.063, q_2 = 16.476 and q_3 = 100 - q_1 - q_2. These values were obtained from a simulation model the details of which are discussed in (Jankovič, 2016). Parameter R in the fair objective function described by the formula (2) was set to the value of 10 in accordance with previous experiments.

The basic characteristics of benchmarks are summarized in Table 1. The column denoted by m reports the cardinality of the set of candidates I, from which exactly p center locations are to be chosen. The complete exact inextensible Pareto front is reported by two values. While the number of its elements is referred to by *NoS*, the last column of the table denoted by *PF-Area* contains the area of the complete Pareto front *PF* computed according to (5).

Table 1: Benchmarks sizes and the exact Pareto fronts characteristics.

Region	*m*	*p*	*NoS*	*PF-Area*
BA	87	14	34	569039
BB	515	36	229	1002681
KE	460	32	262	1295594
NR	350	27	106	736846
PO	664	32	271	956103
TN	276	21	98	829155
TT	249	18	64	814351
Za	315	29	97	407293

4.2 Results of Experiments

This subsection is devoted to the results of numerical experiments. The experiments should reveal a dependence of proximity of *NDSS* and *PF* on expiration “time” *Exp*. If the value of *Exp* = 0, no tabu is imposed on the swap operations. If *Exp* reaches the value of p almost each exchange operation is prohibited. Therefore, we have performed the experiments in such a way that the parameter *Exp* was set according to the expression $Exp = coeff*p$. The *coeff* could vary from 0 (no tabu) to 0.8.

Each run of the algorithm was restricted to five minutes of computation. This time threshold of five minutes was chosen on purpose to keep the comparability of the newly obtained results with the results of previously developed heuristic approaches. This is also the reason, why the required computation time is not reported in the following table.

As far as the quality of the Pareto front approximation is concerned, it was necessary to find a suitable metric to compare two sets possibly with different cardinality. As mentioned in previous sections, a good metric is the area formed by the members of *PF* and *NDSS* respectively. The area can be computed easily by the expression (5). To avoid reporting and comparing high values of areas, a simpler coefficient called *gap* can be used. Generally, *gap* can be understood as a relative difference between two values. In our case, it can be expressed by (8).

$$gap = 100 * \frac{NDSS\text{-}Area - PF\text{-}Area}{PF\text{-}Area} \tag{8}$$

The following Table 2 and Table 3 summarize the obtained results. Both tables keep the same structure. Each row corresponds to one setting of *coeff*, which is used to determine the value of *Exp*. Each table contains the results of experiments performed for half of benchmarks. In the tables, the values of gap are reported.

Table 2: Results of numerical experiments – part 1.

coeff	Higher territorial unit			
	BA	BB	KE	NR
0	2.075	1.373	3.031	7.485
0.1	2.005	0.535	3.490	7.483
0.2	2.203	2.483	4.622	6.249
0.3	2.257	3.168	4.607	7.543
0.4	1.485	1.794	5.481	6.218
0.5	1.468	2.906	3.535	0.649
0.6	0.334	4.535	4.004	0.749
0.7	1.699	5.807	2.972	0.764
0.8	0.416	11.449	8.090	2.695

Based on the reported results we can see that the suggested heuristic approach is sensitive to the parameters settings like many other approximate approaches (Janáček, Kvet, 2021, Janáček, Kvet, 2022a, Janáček, Kvet, 2022b). On the other hand, the achieved values of gaps are very promising and they show, that the tabu search-based method is able to produce such a Pareto front approximation that shows a satisfactory level of accuracy.

Table 3: Results of numerical experiments – part 2.

coeff	Higher territorial unit			
	PO	TN	TT	ZA
0	3.203	4.376	0.652	2.068
0.1	3.205	4.376	0.652	2.068
0.2	3.232	4.996	0.652	0.573
0.3	3.373	3.294	0.704	1.488
0.4	3.610	4.795	0.859	0.361
0.5	0.745	3.851	1.158	0.033
0.6	4.793	5.552	0.091	0.045
0.7	14.459	0.724	0.091	0.116
0.8	19.177	1.115	0.091	0.302

5 CONCLUSIONS

This research paper was intended to develop such heuristic approach to Pareto front approximation that incorporates the basics of tabu search principle. Methods for approximating the Pareto front are required whenever there are multiple contradictory objectives to be optimized simultaneously. In this manner, we have attempted to extend the state-of-the-art approaches for solving bi-criteria location problems.

The achieved results show that the suggested tabu search can produce a very precise approximation of the original Pareto front of service system designs in acceptably short computational time. Such a great accuracy makes it suitable for practical applications. Obviously, we cannot omit the sensitivity of the method to the parameter value. Therefore, future research could be aimed at finding possible ways of finding proper value, for which the best possible results could be achieved.

ACKNOWLEDGEMENT

This work was financially supported by the following research grants: VEGA 1/0216/21 “Designing of emergency systems with conflicting criteria using tools of artificial intelligence”, VEGA 1/0077/22 “Innovative prediction methods for optimization of public service systems”, and VEGA 1/0654/22 “Cost-effective design of combined charging infrastructure and efficient operation of electric vehicles in public transport in sustainable cities and regions”. This paper was also supported by the Slovak Research and Development Agency under the Contract no. APVV-19-0441.

REFERENCES

Ahmadi-Javid, A., Seyedi, P. et al. (2017). A survey of healthcare facility location, Computers & Operations Research, 79, pp. 223-263.

Arroyo, J. E. C., dos Santos, P. M., Soares, M. S. and Santos, A. G. (2010). A Multi-Objective Genetic Algorithm with Path Relinking for the p-Median Problem. In: Proceedings of the 12th Ibero-American Conference on Advances in Artificial Intelligence, 2010, pp. 70–79.

Avella, P., Sassano, A., Vasil'ev, I. (2007). Computational study of large scale p-median problems. Mathematical Programming 109, pp. 89-114.

Bertsimas, D., Farias, V. F., Trichakis, N. (2011). The Price of Fairness. In Operations Research, 59, 2011, pp. 17-31.

Brotcorne, L, Laporte, G, Semet, F. (2003). Ambulance location and relocation models. European Journal of Operational Research, 147, pp. 451-463.

Buzna, Ľ., Koháni, M., Janáček, J. (2013). Proportionally Fairer Public Service Systems Design. In: Communications - Scientific Letters of the University of Žilina 15(1), pp. 14-18.

Current, J., Daskin, M. and Schilling, D. (2002). Discrete network location models, Drezner Z. et al. (ed) Facility location: Applications and theory, Springer, pp. 81-118.

Doerner, K. F., Gutjahr, W. J., Hartl, R. F., Karall, M. and Reimann, M. (2005). Heuristic Solution of an Extended Double-Coverage Ambulance Location Problem for Austria. Central European Journal of Operations Research, 13(4), pp. 325-340.

Gendreau, M. and Potvin, J. (2010). Handbook of Metaheuristics, Springer Science & Business Media.

Gopal, G. (2013). Hybridization in Genetic Algorithms. International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, pp. 403–409.

Grygar, D., Fabricius, R. (2019). An efficient adjustment of genetic algorithm for Pareto front determination. In: TRANSCOM 2019: conference proceedings, Amsterdam: Elsevier Science, pp. 1335-1342.

Ingolfsson, A., Budge, S., Erkut, E. (2008). Optimal ambulance location with random delays and travel times. Health care management science, 11(3), pp. 262-274.

Janáček, J., Fabricius, R. (2021). Public service system design with conflicting criteria. In: IEEE Access: practical innovations, open solutions, ISSN 2169-3536, Vol. 9, pp. 130665-130679.

Janáček, J. and Kvet, M. (2020). Adaptive Path-Relinking Method for Public Service System Design. In: 38th International Conference on Mathematical Methods in Economics, Brno: Mendel University in Brno, 2020, pp. 229-235.

Janáček, J., Kvet, M. (2021). Emergency Medical System under Conflicting Criteria. In: SOR 2021 Proceedings, pp. 629-635.

Janáček, J., Kvet, M. (2022a). Adaptive swap algorithm for Pareto front approximation. In: ICCC 2022: 23rd

International Carpathian Control conference, Sinaia, Romania, Danvers: IEEE, 2022, pp. 261-265.
Janáček, J., Kvet, M.. (2022b). Repeated Refinement Approach to Bi-objective p-Location Problems. In: INES 2022: Proccedings of the IEEE 26th International Conference on Intelligent Engineering Systems 2022, pp. 41-45.
Janáček, J., Kvet, M. (2022c). Pareto Front Approximation using Restricted Neighborhood Search. In: Proceedings of the 40th International Conference on Mathematical Methods in Economics, 2022, Jihlava, pp. 141-147.
Jankovič, P. (2016). Calculating Reduction Coefficients for Optimization of Emergency Service System Using Microscopic Simulation Model. In: 17th International Symposium on Computational Intelligence and Informatics, pp. 163-167.
Jánošíková, Ľ. (2007). Emergency Medical Service Planning. In: Communications - Scientific Letters of the University of Žilina 9(2), pp. 64-68.
Jánošíková, Ľ. and Žarnay, M. (2014). Location of emergency stations as the capacitated p-median problem. In: Quantitative Methods in Economics (Multiple Criteria Decision Making XVII). pp. 117-123.
Kvet, M. (2014). Computational Study of Radial Approach to Public Service System Design with Generalized Utility. In: Digital Technologies 2014, Žilina, Slovakia, pp. 198-208.
Kvet, M. (2018). Advanced radial approach to resource location problems. In: Developments and advances in intelligent systems and applications. Cham: Springer International Publishing, 2018, Studies in computational intelligence, 718, pp. 29-48.
Kvet, M., Janáček, J. (2022). Directed Search for Pareto Front Approximation with Path-relinking Method. In: Proceedings of the 40th International Conference on Mathematical Methods in Economics, 2022, Jihlava, pp. 212-217.
Marianov, V. and Serra, D. (2002). Location problems in the public sector, Facility location - Applications and theory (Z. Drezner ed.), Berlin, Springer, pp 119-150.