

# Robust Emergency System Design using Reengineering Approach

Marek Kvet and Jaroslav Janáček

*Faculty of Management Science and Informatics, University of Žilina,  
Univerzitná 8215/1, 010 26 Žilina, Slovakia  
{marek.kvet, jaroslav.janacek}@fri.uniza.sk*

**Keywords:** Robust Emergency System Design, Detrimental Scenarios, Reengineering Approach.

**Abstract:** A robust emergency service system is usually designed so that the deployment of given number of service centers minimizes the maximal value of objective functions corresponding with the specified detrimental scenarios. If the problem is solved by any solving technique based on the branch-and-bound method, the min-max link-up constraints cause bad convergence of the associated computational process. Within this paper, we try to overcome the drawback following from the link-up constraints by usage of an iterative process applied to a series of surrogate problems. The surrogate problems represent a simple emergency system reengineering under a given scenario and chosen values of reengineering parameters. The results of the surrogate problems are used for considerable reduction of the initial set of possible service center locations. The robust emergency service system is obtained as the optimal solution of the reduced problem. We provide the reader with a comparison of the original min-max problem solution to the suggested approach.

## 1 INTRODUCTION

The emergency system design problem is a challenging task for system designer focusing on satisfaction of future demands of the system users in case of emergency. Emergency service system performance is considerably influenced by deployment of the service centers, which send emergency vehicles to satisfy demands on service at the system users' locations. The number of service providing centers is usually limited. As the quality characteristic of the design corresponds to an average response time of the system on a demand raised by a user, then the emergency service system design can be tackled as the weighted  $p$ -median problem, which was studied in (Current et al., 2002, Ingolfsson et al., 2008, Jánošíková, 2007, Snyder and Daskin, 2005).

As far as the usage of a general IP-solver is concerned, the size of the solved integer programming problem must be taken into account. In the real problems, the number of serviced users takes the value of several thousands, and the number of possible service center locations can take this value as well (Avella et al., 2007). The number of possible service center locations seriously impacts the computational time and the memory demands due to used branch-and-bound method, which stores the unfathomed nodes of the inspected searching tree for

the further processing. That is why the direct attempt at solving the problem described by a location-allocation model often fails, when larger instances are solved by a commercial IP-solver. Mentioned weakness has led to the development of so-called radial approach, successfulness of which is based on the fact that there is only finite set of radii, which must be taken into account (Elloumi et al., 2004, Garcia et al., 2011, Janáček, 2008). Simultaneously, several heuristic and approximate approaches have been developed to get a good solution of the problem in a short time (Doerner, K.F., et al. 2005, Gendreau, M. and Potvin, J., 2010).

When the emergency service system is designed, the designer must take into account that the response time might be impacted by various random events caused by partial disruptions of the road network. That is why; the system resistance to such critical events is demanded. Most of approaches to increasing the emergency system resistance (Correia and Saldanha da Gama, 2015, Kvet and Janáček, 2017b, Pan et al., 2014, Scaparra and Church, 2015) are based on incorporating possible failure scenarios into model of the robust service system design problem. Focusing on the objective function value of the robust system design, the most frequently used objective function consists in minimizing the maximal objective function of the individual instances

corresponding with particular scenarios. It follows that the min-sum objective function used in the classical weighted  $p$ -median problem is replaced by the min-max criterion. The associated min-max model uses link-up constraints to limit from above the individual scenario min-sum objectives by their upper bound corresponding to the objective function of the min-max model. In addition, incorporating the scenarios into the mathematical programming model causes that the model magnifies its size proportionally to the cardinality of the scenario set. Both the model structure and its magnified size represent an undesirable burden of the computational process of most available IP-solvers. Thus, complementary approximate approaches to the robustness constitute a big challenge to operational researchers and professionals in applied informatics (Janáček and Kvet, 2017, Kvet and Janáček, 2017a, Kvet and Janáček, 2017b). In this paper, we present an attempt to the robust emergency system design. We based our approximate approach on replacing the computational process of the huge original problem solution with a series of solving processes of the much simpler problems. Each of the simpler problems represents the problem of reengineering (Brotcorne, L. et al., 2003, Guerriero, F. et al., 2016, Schneeberger, K. et al. 2016) of some original service center deployment under a given scenario (Kvet and Janáček, 2018). This approach enables us to identify the most important changes in the service center deployment to react on the individual scenarios. Having inspected all considered scenarios, we can reduce the set of possible center locations and then solve much smaller min-max problem with the original set of scenarios.

The remainder of this paper is organized as follows: Section 2 is devoted to the description of original min-max robust design of emergency system, in which all scenarios and possible center locations are taken into account either as fixed for center location or either free or forbidden for locating a service center. The approach based on system reengineering process used for identification of the important locations is explained in Section 3. The next section contains a description of the complete iterative approach. The fifth Section contains the overview of performed numerical experiments and yields brief comparative analysis of designed service center deployments. The results and findings are summarized in Section 6.

## 2 ROBUST EMERGENCY SYSTEM DESIGN PROBLEM

The robust emergency system design problem can be modelled using the following data structures and decision variables. Symbols  $J$  and  $I$  will denote the set of users' locations and the set of possible service center locations respectively. The set  $I$  will be partitioned into three subsets  $FI$ ,  $FO$  and  $V$ , where set  $FI$  contains the locations, in which a service center must be located. Set  $FO$  consists of center locations, where no center can be temporarily located, and  $V$  is the set of possible locations, from which  $p$  service centers must be chosen. Symbol  $b_j$  denotes the number of users sharing the location  $j$ . Symbol  $U$  denotes the set of considered failure scenarios.

The response time following from the distance between locations  $i$  and  $j$  under a specific scenario  $u \in U$  is denoted as  $d_{iju}$ . In this paper, we consider that each value of  $d_{iju}$  is integer and less than or equal to the maximal value  $D_{max}$ . As we want to make the system resistant to the individual detrimental scenarios, the objective function of the robust system design turns into minimizing the maximal objective function of the individual scenarios.

Complexity of location problems with limited number of facilities to be deployed and the necessity to solve large instances of the problem led the radial formulation of the problem, which could considerably accelerate the associated solving process (Kvet and Janáček, 2017b). As this concept proved to be a suitable tool, we decided to use the radial formulation also for the robust emergency system design.

To complete the associated mathematical model, we introduce the following decision variables. The variable  $y_i \in \{0,1\}$  models the decision on service center location at the location  $i \in V$ . The variable takes the value of 1 if a service center is located at  $i$  and it takes the value of 0 otherwise. In the robust problem formulation, the variable  $h$  denotes the upper bound of the objective functions over the set  $U$  of scenarios. Let us define  $v = D_{max} - 1$ . Next, auxiliary zero-one variables  $x_{jsu}$  for  $s = 0 \dots v$  and  $u \in U$  are introduced to complete the radial model. The variable  $x_{jsu}$  takes the value of 1, if the response time of the nearest service center to the user at  $j \in J$  under the scenario  $u \in U$  is greater than  $s$  and it takes the value of 0 otherwise. Then the expression  $x_{j0u} + x_{j1u} + \dots + x_{jvu}$  constitutes the value of response time  $d_{ju}^*$  under the scenario  $u \in U$ . We introduce a zero-one constant  $a_{iju}^s$  under the scenario  $u \in U$  for each triple  $[i, j, s]$ , where  $i \in V \cup FI$ ,  $j \in J$ ,  $s \in [0..v]$ . The constant  $a_{iju}^s$  is equal to 1, if the response time  $d_{iju}$  of a center located at  $i$  on a

user located at  $j$  is less than or equal to  $s$ , otherwise  $a_{iju}^s$  is equal to 0. Then the model, in which the maximum of the objective function values over the set  $U$  is minimized, follows.

$$\text{Minimize } h \quad (1)$$

$$\text{Subject to: } x_{jsu} + \sum_{i \in V} a_{iju}^s y_i + \sum_{i \in F1} a_{iju}^s \geq 1 \quad (2)$$

for  $j \in J, s = 0, 1, \dots, v, u \in U$

$$\sum_{i \in V} y_i = p \quad (3)$$

$$\sum_{j \in J} b_j \sum_{s=0}^v x_{jsu} \leq h \quad \text{for } u \in U \quad (4)$$

$$y_i \in \{0, 1\} \quad \text{for } i \in V \quad (5)$$

$$x_{jsu} \geq 0 \quad \text{for } j \in J, s = 0, 1, \dots, v, u \in U \quad (6)$$

$$h \geq 0 \quad (7)$$

The objective function (1) represents the upper bound of all objective function values over the individual scenarios. The constraints (2) ensure that the variables  $x_{jsu}$  are allowed to take the value of 0, if at least one center is located in radius  $s$  from the user location  $j$ . The constraint (3) limits the number of service centers located in  $V$  by  $p$ . The link-up constraints (4) ensure that each perceived disutility is less than or equal to the upper bound  $h$ . As the obligatory constraints (6) are concerned, only values zero and one are expected in any feasible solution. Nevertheless, it can be seen that the model has integrality property concerning the variables  $x_{jsu}$ . It follows that the relevant values of  $x_{jsu}$  in the optimal solution will be equal to one or zero without imposing binary constraints upon these variables.

For purpose of conciseness, we introduce the denotation of the set of resulting (optimal) service center locations as  $IR(U, F1, F0)$ . The set includes service centers from both  $F1$  and  $V$ .

### 3 EMERGENCY SERVICE SYSTEM REENGINEERING PROBLEM

The emergency system reengineering was originally studied in (Kvet and Janáček, 2018), where the radial model of the problem was also employed. The basic

idea follows from the analysis of current service center deployment, which may not be optimal due to changing demands and development of the underlying transportation network.

To describe the problem of the system average response time minimization by changing the deployment of centers belonging to a given sub-set of the located centers. Let  $I$  be a finite set of all possible center locations. As above, the response time following from the distance between locations  $i$  and  $j$  under a specific scenario  $u \in U$  is denoted as  $d_{iju}$ . The current emergency service center deployment is described by union of two disjoint sets of located centers  $L$  and  $F1$ , where  $L$  contains  $p$  centers under reconstruction and  $F1$  is the set of fixed centers. The center locations from  $L$  can be relocated within the set  $I - F1 - F0$ , where  $F0$  is the set of temporarily forbidden locations.

When reengineering of an emergency service system is performed, the administrator of the system sets up parameters of rules to prevent a designer of new center deployment from changes, which can be perceived by system users as obnoxious. We consider two formal rules within this study. The first rule limits the total number  $w$  of the centers, which locations can be changed. The second rule limits the time distance between current and newly suggested location of a service center by the given value  $D$ . To be able to formulate the rules in a concise way, we derive several auxiliary structures.

Let  $N_t = \{i \in I - F1 - F0: d_{ti} \leq D\}$  denote the set of all possible center locations, to which the center  $t \in L$  can be moved subject to limited length of the move. Additionally, symbol  $S_t = \{i \in N_t\}$  denotes a set of all centers of  $L$ , which can be moved to  $i \in I - F1 - F0$  subject to the mentioned limitation. Now, we introduce series of decision reallocation variables, which model the decisions on moving centers from their original positions to new ones. The variable  $u_{ti} \in \{0, 1\}$  for  $t \in L$  and  $i \in N_t$  takes the value of one, if the service center at  $t$  is to be moved to  $i$  and it takes the value of zero otherwise.

For the given scenario  $u \in U$  the problem can be formulated as follows.

$$\text{Minimize } \sum_{j \in J} b_j \sum_{s=0}^{m-1} x_{js} \quad (8)$$

$$\text{Subject to: } x_{js} + \sum_{i \in I - F1 - F0} a_{iju}^s y_i + \sum_{i \in F1} a_{iju}^s \geq 1 \quad (9)$$

for  $j \in J, s = 0, 1, \dots, v$

$$\sum_{i \in I-F1-F0} y_i = p \quad (10)$$

$$\sum_{i \in L} y_i \geq p - w \quad (11)$$

$$\sum_{i \in N_t} u_{ti} = 1 \quad \text{for } t \in L \quad (12)$$

$$\sum_{t \in S_i} u_{ti} \leq y_i \quad \text{for } i \in I - F1 - F0 \quad (13)$$

$$u_{ti} \in \{0, 1\} \quad \text{for } t \in L, i \in N_t \quad (14)$$

$$y_i \in \{0, 1\} \quad \text{for } i \in I - F1 - F0 \quad (15)$$

$$x_{js} \geq 0 \quad \text{for } j \in J, s = 0, 1, \dots, v \quad (16)$$

As the constraints (9), (10) and formulae together with used decision variables were explained in the previous section, we restrict explanation only on remainder of the above model. Constraint (11) limits the number of changed center locations by the constant  $w$ . Constraints (12) allow moving the center from the current location  $t$  to at most one other possible location in the radius  $D$ . Constraints (13) enable to bring at most one center to a location  $i$  subject to condition that the original location of the brought center lies in the radius  $D$ . These constraints also assure consistency among the decisions on move and decisions on center location.

To be concise in the next explanation, we introduce the denotation of the set of resulting (optimal) service center locations for given scenario  $u$  as  $I(u, F1, F0, L, w, D)$ . The set also includes the service centers from  $F1$ .

#### 4 APPROXIMATE APPROACH TO THE ROBUST SERVICE SYSTEM DESIGN

To formulate the suggested approximate algorithm for solving of the robust service system design, we employ the procedures  $IR(U, F1, F0)$  and  $I(u, F1, F0, L, w, D)$  introduced in Section 2 and Section 3 respectively. We assume that the data structures  $J, \{b_j\}, I, U, \{d_{iju}\}$  introduced in Section 2 are given and the number  $p$  of centers to be located is also known. As the set  $U$  of scenarios contains one special scenario  $b$  corresponding to standard conditions, we start the process of designing the robust system with

solving the weighted  $p$ -median problem for time distances  $\{d_{ijb}\}$ . This problem can be described by the model (8)-(10), (15), (16). The resulting set of  $p$  center locations will be denoted as  $L$ .

Then we set parameters  $w$  and  $D$  of the algorithm at chosen values from the ranges  $[1 .. p]$  and  $[1 .. D^{max}]$  respectively. We set  $F1 = \emptyset$  and  $F0 = \emptyset$ . The suggested algorithm consists of two following steps.

1. For each  $u \in U - \{b\}$  compute the set  $One(u) = I(u, F1, F0, L, w, D)$ .
2. Set  $F1 = \bigcap_{u \in U - \{b\}} One(u)$  and  $F0 = I - \bigcup_{u \in U - \{b\}} One(u)$  and compute  $Output = IR(U, F1, F0)$ .

The objective function value of the resulting center deployment  $Output$  can be enumerated according to (17).

$$f(Output) = \max \left\{ \sum_{j \in I} b_j \min \{d_{iju} : i \in Output\} : u \in U \right\} \quad (17)$$

## 5 NUMERICAL EXPERIMENTS

The presented numerical experiments were focused on comparison of the presented approximate approach to the exact method of the robust emergency system design from the points of computational time and the solution accuracy. We performed the numerical experiments using the optimization software FICO Xpress 8.3 (64-bit, release 2017). The experiments were run on a PC equipped with the Intel® Core™ i7 5500U processor with the parameters: 2.4 GHz and 16 GB RAM.

The used benchmarks were derived from the real emergency health care system, which was originally implemented in seven regions of Slovak Republic. For each self-governing region from the following list of region names followed by their abbreviations, all cities and villages with corresponding population  $b_j$  were taken into account. The mentioned list contains Bratislava (BA), Banská Bystrica (BB), Košice (KE), Nitra (NR), Prešov (PO), Trenčín (TN), Trnava (TT) and Žilina (ZA). The coefficients  $b_j$  were rounded to hundreds. In the benchmarks, the set of communities represents both the set  $J$  of users' locations and the set  $I$  of possible center locations as well. The cardinalities of these sets are reported in Table 1 together with the number  $p$  of located centers. The network time -

distances from a user to the nearest located center were derived from the real transportation network. Due to the lack of scenario benchmarks for the experiments, the problem instances used in our computational study were created in the way used in (Janáček and Kvet, 2016). There were selected one quarter of matrix rows so that these rows corresponded to the biggest cities concerning the number of system users. Then some of them were chosen randomly and the associated time distance values were multiplied by the randomly chosen constant from the numbers 2, 3 and 4. The rows, which were not chosen by this random process, stay unchanged. This way, 10 different scenarios were generated for each self-governing region.

The first series of experiments was performed so that the exact model (1) - (7) was used to obtain the optimal solution of the robust emergency system design problem. The achieved results of the first series are reported in Table 1. The computational times in seconds are given in the column denoted by  $CT$  and the optimal objective function values are reported in the column denoted by  $ObjF^{robust}$ .

Table 1: Results of the exact approach for robust service system designing applied on the self-governing regions of Slovakia.

Region	$ I $	$p$	$CT$	$ObjF^{robust}$
BA	87	9	52.8	25417
BB	515	52	1605.0	18549
KE	460	46	1235.5	21286
NR	350	35	11055.1	24193
PO	664	67	3078.2	21298
TN	276	28	616.6	17535
TT	249	25	563.8	20558
ZA	315	32	1304.7	23004

The next series of experiments was performed with the goal to find a suitable setting of the parameters  $w$  and  $D$  used in the approximate approach, see model (8) – (16) of the reengineering process. For this study, the benchmark Žilina (ZA) was used. In this portion of experiments, the parameter  $p$  was set at the value 32 reported in Table 1. The maximal radius  $D$  was fixed at one of the values 5, 10, 15, 20 and 25 and the maximal number  $w$  of centers allowed to change their locations was set to  $p/4$ ,  $p/2$ ,  $3p/4$ , and  $p$  respectively. The results of this series of experiments are summarized in Table 2.

Table 2: Detailed results of numerical experiments for the self-governing region of Žilina: computational study of the impact of individual parameters on the results accuracy.

$w$	$D$	$CT$	$SCT$ [%]	$ObjF^{approx}$	$gap$ [%]	$HD$
8	5	231.6	82.25	23411	1.77	14
8	10	430.9	66.98	23377	1.62	14
8	15	502.8	61.46	23236	1.01	6
8	20	516.8	60.39	23359	1.54	10
8	25	529.5	59.42	23359	1.54	10
16	5	234.8	82.00	23411	1.77	14
16	10	455.1	65.12	23377	1.62	14
16	15	516.0	60.45	23236	1.01	6
16	20	529.9	59.38	23359	1.54	10
16	25	542.6	58.41	23359	1.54	10
24	5	232.5	82.18	23411	1.77	14
24	10	434.6	66.69	23377	1.62	14
24	15	508.5	61.02	23236	1.01	6
24	20	531.3	59.28	23359	1.54	10
24	25	534.6	59.02	23359	1.54	10
32	5	231.6	82.25	23411	1.77	14
32	10	427.8	67.21	23377	1.62	14
32	15	509.2	60.97	23236	1.01	6
32	20	531.4	59.27	23359	1.54	10
32	25	534.8	59.01	23359	1.54	10

Each row of the table corresponds to one setting of the parameters  $w$  and  $D$ . In this portion of experiments, several characteristics were studied. The computational time in seconds is reported in the column denoted by  $CT$ . Since the approximate approach proved to be much faster than the exact one, the percentage save of computational time  $SCT$  was computed. Here, the computational time of the exact approach was taken as the base. Furthermore, the objective function associated with the obtained service center deployment is reported in the column denoted by  $ObjF^{approx}$ . To evaluate the accuracy of suggested approximate method, the value of  $gap$  was also computed. It expresses the difference between the objective function values of the exact and approximate models. The objective value of the exact approach was taken as the base. The value of  $gap$  is reported also in percentage. Finally, the resulting service center deployments were compared in the terms of Hamming distance of the vectors of location variables  $y$ . This value is denoted by  $HD$ .

It can be seen that the lowest computational time of the approximate method was reached for the settings  $w = p/4$  and  $D = 5$ . As the associated gap was acceptable, we used this setting in the third series of experiments, which was performed for each self-governing region. The obtained results are reported in Table 3, where the same denotations as in Tables 1 and 2 were used. The table is divided into two sections denoted by EXACT and APPROXIMATE. The first section contains the results from Table 1 for bigger comfort of the readers. The second section

contains the results obtained by the approximate approach for each of considered benchmarks.

Table 3: Comparison of the approximate approach to the exact approach applied on the self-governing regions of Slovakia. Parameters of the approximate approach were set in this way:  $w = p/4$ ,  $D = 5$ .

	EXACT		APPROXIMATE			
	CT	ObjF <sup>robust</sup>	CT	ObjF <sup>approx</sup>	gap	HD
BA	52.8	25417	11.8	26197	3.07	4
BB	1605.0	18549	679.8	18861	1.68	12
KE	1235.5	21286	633.4	21935	3.05	16
NR	11055.1	24193	274.2	24732	2.23	14
PO	3078.2	21298	1601.9	21843	2.56	20
TN	616.6	17535	223.1	17851	1.80	10
TT	563.8	20558	152.4	20980	2.05	10
ZA	1304.7	23004	231.6	23411	1.77	14

## 6 CONCLUSIONS

This paper was focused on mastering dimensionality of the robust emergency system design problem using commercial IP-solver. The robustness follows the idea of making the system resistant to various randomly occurring detrimental events. The original approach with the min-max objective function value proved to be extremely time consuming due to the fact, that the min-max link-up constraints cause bad convergence of the branch-and-bound method. This obstacle can be overcome by presented approximate solving method, which is based on reengineering approach applied on individual scenarios. The approximate approach enables to obtain the resulting robust service center deployment in the computational time, which is much less than half of the computational time demanded by the exact approach. As concerns the accuracy of the resulting solution, it can be observed that the approximate method is very satisfactory. Thus, we can conclude that we have presented a very useful tool for robust service system designing.

The future research in this field could be aimed at other approximate techniques, which will enable to reach shorter computational time under the acceptable solution accuracy. Another future research goal could be focused on mastering the presented problem with larger set of detrimental scenarios.

## ACKNOWLEDGEMENT

This work was supported by the research grants VEGA 1/0342/18 "Optimal dimensioning of service systems", VEGA1/0089/19 "Data analysis methods

and decisions support tools for service systems supporting electric vehicles" and APVV-15-0179 "Reliability of emergency systems on infrastructure with uncertain functionality of critical elements".

## REFERENCES

- Avella, P., Sassano, A., Vasil'ev, I., 2007. Computational study of large scale p-median problems. In *Mathematical Programming*, Vol. 109, No 1, pp. 89-114.
- Brotcorne, L., Laporte, G., Semet, F. 2003. Ambulance location and relocation models. *European Journal of Operational Research* 147, pp. 451-463.
- Correia, I. and Saldanha da Gama, F. 2015 Facility locations under uncertainty. In Laporte, G. Nickel, S. and Saldanha da Gama, F. (Eds). *Location Science*, Heidelberg: Springer Verlag, pp. 177-203.
- Current, J., Daskin, M., Schilling, D., 2002. Discrete network location models. In Drezner Z. (ed) et al. *Facility location. Applications and theory*, Berlin, Springer, pp. 81-118.
- Doerner, K. F. et al., 2005. Heuristic solution of an extended double-coverage ambulance location problem for Austria. In *Central European Journal of Operations Research*, Vol. 13, No 4, pp. 325-340.
- Elloumi, S., Labbé, M., Pochet, Y., 2004. A new formulation and resolution method for the p-center problem. *INFORMS Journal on Computing* 16, pp. 84-94.
- García, S., Labbé, M., Marín, A., 2011. Solving large p-median problems with a radius formulation. *INFORMS Journal on Computing*, Vol. 23, No 4, pp. 546-556.
- Gendreau, M., Potvin, J. 2010. *Handbook of Metaheuristics*, Springer Science & Business Media, 648 p.
- Guerrero, F., Miglionico, G., Olivito, F. 2016. Location and reorganization problems: The Calabrian health care system case. *European Journal of Operational Research* 250, pp. 939-954.
- Ingolfsson, A., Budge, S., Erkut, E., 2008. Optimal ambulance location with random delays and travel times, In *Health Care Management Science*, Vol. 11, No 3, pp. 262-274.
- Janáček, J., 2008. Approximate Covering Models of Location Problems. In *Lecture Notes in Management Science: Proceedings of the 1st International Conference ICAOR*, Yerevan, Armenia, pp. 53-61.
- Janáček, J. and Kvet, M. 2016. Designing a Robust Emergency Service System by Lagrangean Relaxation. In *Proceedings of the conference Mathematical Methods in Economics*, September 6th -9th 2016, Liberec, Czech Republic, pp. 349-353.
- Janáček, J. and Kvet, M. 2017. An Approach to Uncertainty via Scenarios and Fuzzy Values. *Croatian Operational Research Review* 8 (1), pp. 237-248.

- Jánošíková, L. 2007. Emergency Medical Service Planning. *Communications Scientific Letters of the University of Žilina*, 9(2), pp. 64-68.
- Kvet, M. and Janáček, J. 2017a. Hill-Climbing Algorithm for Robust Emergency System Design with Return Preventing Constraints. In 9th International Conference on Applied Economics: Contemporary Issues in Economy, 2017, Toruń, Poland, pp. 156-165.
- Kvet, M. and Janáček, J. 2017b. Struggle with curse of dimensionality in robust emergency system design. In Proceedings of the 35th international conference Mathematical Methods in Economics MME 2017, September 13th -15th 2017, Hradec Králové, Czech Republic, pp. 396-401.
- Kvet, M. and Janáček, J. 2018. Reengineering of the Emergency Service System under Generalized Disutility. In the 7th International Conference on Operations Research and Enterprise Systems ICORES 2018, Madeira, Portugal, pp. 85-93.
- Pan, Y., Du, Y. and Wei, Z. 2014. Reliable facility system design subject to edge failures. *American Journal of Operations Research* 4, pp. 164-172.
- Scaparra, M.P., Church, R.L. 2015. Location Problems under Disaster Events. *Location Science*, eds. Laporte, Nickel, Saldanha da Gama, pp. 623-642.
- Schneeberger, K. et al. 2016. Ambulance location and relocation models in a crisis. *Central European Journal of Operations Research*, Vol. 24, No. 1, Springer, pp. 1-27.
- Snyder, L. V., Daskin, M. S., 2005. Reliability models for facility location; The expected failure cost case. In *Transport Science*, Vol. 39, No 3, pp. 400-416.