Highlights

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- Coordination of spontaneous volunteers requires multi-objective approaches
- Uncertainty during disasters can be addressed through sequences of deterministic instances
- Generic set of objective functions allows for broad applicability of our decision support model
- Computational experiments demonstrate the applicability of the model in practice

Decision Support for Disaster Relief: Coordinating Spontaneous Volunteers

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ABSTRACT

In the aftermath of large-scale disasters, the exploitation of often up to thousands of spontaneous volunteers is crucial to meet the need for surge capacity which cannot be met by official responders. However, the coordination of spontaneous volunteers differs in several regards from that of professional and paid relief workers. Based on empirical requirements identified in interviews with the manager of a professional fire department, we suggest a multi-objective mixed-integer linear optimization problem with lexicographically ordered objective functions, which we refer to as spontaneous volunteer coordination problem (SVCP). Acknowledging that disaster situations are unavoidably linked to uncertainty, we consider uncertainty with a sequence of (deterministic) SVCP instances, where each instance depends on the solutions of previous SVCP instances. We conduct comprehensive computational experiments based on real-world data of a flood disaster that the fire department faced. From our computational results, we derive detailed implications for the fire department on how to use our decision support model. We also derive recommendations for all relief organizations which aim at adopting or adapting our model for the coordination of spontaneous volunteers in a broad set of disasters. Our implications include several recommendations for relief organizations in terms of performing extensive computational tests in order to parameterize and instantiate the generic model before its use during the disaster response phase; thereby we also address tasks to be executed during the preparedness phase of a disaster.

1. Introduction

Managing large-scale disasters, including natural and man-made disasters as well as pandemics, has become and is predicted to remain an important issue for societies. According to the *World Disaster Report* of the International Federation of Red Cross and Red Crescent Societies [31], in the past ten years there have been more than 3 700 natural hazards with an estimated 2 billion people and USD 1 658 billion cost of damages affected. In order to reduce the impact of disasters on humankind, the field of disaster operations management (DOM) has emerged, defined as the management of the "[…] *activities that are performed before, during, and after a disaster with the goal of preventing loss of human life, reducing its impact on the economy, and returning to a state of normalcy*" [5, p. 476]. Research on DOM has a long tradition of now more than 60 years in the fields of operations research (OR) and management science (MS) [59]; literature reviews of OR and MS work on DOM are provided in [26, 5, 22, 11]. The particular role of DOM as an application domain that poses new challenges to the OR discipline has been highlighted by Simpson and

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Hancock [59, p. 126]: *"While OR has traditionally focused on the management of an organization, emergency response ultimately requires the management of disorganization, suggesting an important OR growth area for the next 50 years."*

There is large consensus in the literature that DOM consists of the four phases *mitigation*, *preparedness*, *response*, and *recovery* [5, 22, 64, 57], which are often understood as phases of a cyclic process. Mitigation tasks include activities for reducing the long-term risk of a disaster [61, 40]. The preparedness phase includes all activities performed before a disaster that aim at providing a more efficient processing of tasks once the disaster strikes, including tasks related to training, early warning, risk assessment, asset prepositioning, and the planning and establishment of necessary emergency services [2, 13, 28, 52, 8, 14, 3, 48, 25]. While mitigation and preparedness refer to the time before a disaster, response phase activities take place in the immediate aftermath of a disaster. The main objectives here are the rescue from immediate danger and the stabilization of the condition of survivors. Tasks in this phase focus on the areas of shelter and settlement, telecommunication, emergency health, water and sanitation, tracing and restoring family links, and humanitarian logistics [30, 32, 21]. From a functional perspective, in the response phase mainly issues of locating, allocating and routing resources of disaster relief are addressed [60]. Finally, the recovery stage includes tasks that restore the normal functioning of the community, including post-disaster logistics management, person finding, data analysis, infrastructure repair and the provision of emergency [28, 44, 71].

This article focuses on the coordination of relief persons during the response phase of a disaster; however, our implications also cover tasks to be performed during the preparedness phase when coordination procedures need to be prepared and customized to specific needs. Relief persons can be members of professional relief organizations, such as the International Federation of Red Cross and Red Crescent Societies, volunteers affiliated with such organizations and formally trained for disaster response [47], or spontaneous volunteers, who are citizens willing to offer ad-hoc support for a limited period of time.

For example, in the aftermath of the 1985 earthquake in Mexico City about two million citizens provided assistance [15], and after 9/11, more than $15,000$ people gathered at Ground Zero offering their support [39]. The particular importance of volunteers is highlighted by the fact that *"[t]he Red Cross website shows that 90 percent of the humanitarian work is carried out by volunteers and 95 percent of disaster relief workers are volunteers."* [23, p. 534] In particular, the role of spontaneous volunteers must not be underestimated as *"[t]he study of spontaneous volunteers in 2015/2016 flooding by Harris et al. (2017) in the UK reveals that volunteer management at disasters should be aware of the possibility that there is a need for 'surge capacity' which cannot be met by official responders."* [23, p. 534] The management of spontaneous volunteers has been analyzed in several further case studies in different countries, including Italy [47, 46] and Denmark [43].

The coordination of volunteers differs from that of professional and paid relief workers [54]. In particular, spontaneous volunteers are different as, generally, not much information is known on them in terms of their numbers, times and places of occurrence, periods of availabilities and capabilities. Spontaneous volunteers are often present on disaster sites regardless of a request for their assistance, and their mass movements (also known as convergence) are highly unpredictable [20, 38]. All these issues makes it challenging for relief organizations to coordinate spontaneous volunteers effectively (in terms of exploiting availabilities and capabilities) and efficiently (in terms of deriving decisions quickly). However, as the additional capabilities provides by them pose invaluable resources [19, 41] and on-site coordination of spontaneous volunteers distracts professional responders from their primary duties [20], this coordination task is a highly important component of disaster relief. Unfortunately, *"spontaneous volunteers are rarely incorporated into formal disaster and humanitarian planning,"* according to the review of Twigg and Mosel [62].

While the literature provides a rich set of models and methodologies for the coordination of composite relief units, containing both human and non-human resources, under both certainty [21, 12, 53, 56, 64, 65, 51, 68, 69] and uncertainty [3, 66, 10, 72, 50, 67], the body of literature about how to support the coordination of a (potentially very large) group of individuals, in particular spontaneous volunteers, with mathematical optimization models is scarce; we unfold this literature in the succeeding section. Our literature findings are consistent with those of Garcia et al. [23]. We address this need for research by accounting for a situation in which information on spontaneous volunteers becomes available prior to their appearance at a disaster site. This availability of information is given when, during the preparedness phase, citizens have been informed on the existence and functionality of IT applications which allow providing information to coordinate relief organizations, and then, during the response phase, citizens make use of these applications. Such services are already available and include social-media-based ones, such as the spontaneous volunteering service provided by the Australian *NSW State Emergency Service* [45], and those based on systems dedicated to coordinate volunteers, such as the system *KUBAS* [9, 50]; a general model *EV CREW* for centrally coordinating spontaneous volunteers (and building applications) has been suggested by McLennan et al. [42]. An overview on volunteer management systems is provided by Schönböck et al. [55]. Assuming (input) information becomes available, coordination planning can be launched, resulting in (output) information on which volunteers at what times are asked to appear at a specified site. This output information can then be sent back to volunteers using the same or other IT applications. In summary, we address a situation in which, during the disaster situation, interaction between professional relief organizations and volunteers via modern information and communication technologies occurs.

The particular contributions of this article are manifold: (i) we empirically acquire practical requirements for coordinating a heterogeneous and large set of spontaneous volunteers; (ii) we suggest a generic and, thereby, adaptive mathematical decision model with multiple, lexicographically ordered objectives to solve the coordination issue; (iii) based on the specific requirements of a single fire department, we instantiate the generic model, which results in an optimization problem formulated for the specific fire department; we use this problem formulation and real-world data of a flood disaster to conduct extensive computational experiments and to derive implications for the fire department on how to use our decision support model; (iv) based on insights gained through our computational experiments, we derive recommendations for all relief organizations which aim at adopting or adapting our model for the coordination of spontaneous volunteers in a broad set of disasters.

Our conceptual approach particularly differs from those suggested in the literature in that the set of objectives focuses on various types of "balances", to be considered when volunteers are assigned to tasks in the presence of resource scarcity; these balances are based on our interviews with the manager of a professional relief organization who is experienced with coordinating large numbers of spontaneous volunteers.

Acknowledging that disaster situations are unavoidably linked to uncertainty with regard to the demand for support and the availability of volunteers, and following the argumentation of Garcia et al. [23] that uncertainty in disaster situation cannot be addressed appropriately with stochastic models, we consider uncertainty with a deterministic, yet dynamic mixed integer linear programming (MILP) coordination model. Sequences of model instances are generated over time so that the planning situation gets updated (e.g., volunteers may join and leave in unexpected ways) and as circumstances change and re-optimization can occur.

The remainder of the article is structured as follows: in the succeeding section, we present related work. Then, we describe the problem to be solved, including requirements acquired in interviews with practitioners. Based on the problem description, we proceed with formulating the mathematical optimization model. Then, we present our computational experiments and results before we provide managerial implications and conclude the article.

2. Related work

2.1. Literature review

Volunteerism, in general, and volunteer management, in particular, have been intensively discussed in the field of disaster management; literature reviews are provided by Alexander [4] and Whittaker et al. [70]. In recent years, in particular the use of information systems for volunteer management has gained increasing attention [63, 27, 29, 36, 58, 50]. Although the use of such information systems is not the focus of this work, we assume that some of these are in operation during the response phase in order to provide information required for coordinating spontaneous volunteers. This assumption is in line with most of the succeedingly presented prior works on volunteer coordination, which are based on the availability of information on volunteers prior to their on-site appearances.

Quantitative decision support have been suggested for a variety of situations and goals of volunteer coordination; literature reviews are provided by Rauchecker and Schryen [50] and Garcia et al. [23], for example.

We found a few works which explicitly target the coordination of spontaneously appearing volunteers: Mayorga et al. [41] present a queuing system to model the uncertain arrival and departure of spontaneous volunteers during the recovery phase. They present and computationally analyze several heuristics to assign volunteers to queues. Regarding the response phase, Rauchecker and Schryen [50] suggest a MILP formulation for the assignment of volunteers to tasks at disaster sites. Their study applies the proposed model to a single real-world scenario as a “proof of concept” and describes its integration into the practical volunteer coordination system *KUBAS* [9]. Abualkhair et al. [1] use an agent-based simulation of a disaster relief center to analyze the effectiveness of several heuristic policies for assigning volunteers to two parallel queues, one for donors/donations and the other for beneficiaries. The authors take various sources of uncertainty into account. Minimizing the number of volunteers required to meet all task demands is addressed by Pielorz and

Lampert [49], who present an integer linear program (ILP) model to coordinate the volunteer organization Team Austria.

Further work addresses volunteer coordination in general or focuses on volunteers who are affiliated with or even members of relief organizations; i.e., they do not focus on spontaneous volunteers in particular.

The goal of cost minimization is addressed by Liu and Wang [37], who develop an ILP model to coordinate entire volunteer teams and minimize their travel costs. The works of Lassiter et al. [33] and Lassiter et al. [34] seek to minimize various costs associated with volunteer coordination. Li et al. [35] aim at maximizing the sum of *matching degrees* between rescuers and rescue tasks, with the matching degree being a composite measure of satisfaction degree, competence degree, and time fitness degree. Alwahishie [6] develops quantitative models which consider those factors which may cause turnover or turnover intentions of volunteers.

Several works account for the multi-objective nature of volunteer coordination. Falasca et al. [17] and Falasca and Zobel [16] formulate a bi-objective model to minimize the number of unmet task demands as and the number of volunteer assignments to undesired tasks or time slots. Falasca et al. [18] address the three goals of minimizing the percentage of undesired assignments, the percentage of unmet task demands, and the percentage of budget used; they use one weighted sum objective function. In their approach of minimizing deviations from task demands as well as from the desired number of shifts expressed by each volunteer, Aman et al. [7] propose a goal programming model to schedule volunteer organizations after a volcano eruption. Garcia et al. [23] aim at maximizing the total allocation benefit attained minus the sum of the total shortage and deviation costs, suggesting a MILP.

2.2. Contributions of this work

In our work, we account for the aforementioned multi-objective nature of volunteers coordination by suggesting and computationally evaluating a multi-objective optimization model, which is flexible and generic in terms of objective functions. While our studied problem is based on the problem considered in [50], our work differs from that work. The latter can be considered a “proof-of-concept” of an optimization model as it targets one specific flood scenario and tests the model based on this scenario with two model instances and fixed values of model parameters. Albeit being valuable research in its own right, the study [50] suggested a model that worked well for the tested scenario but did not produce sufficiently acceptable and generalizable results for other scenarios and, thus, provided only limited scientific insights into the decision problem studied.

Based on these shortcomings, we conducted a new study, which differs substantially from [50] in the following ways: First, regarding the requirements for a decision support model, we conducted new rounds of interviews with practitioners and also considered requirements obtained from the literature. This approach resulted in a different set of requirements, which describe a more general problem setting than that in [50]. Second, in contrast to the single-objective model in [50], our suggested model is a multi-objective optimization model with lexicographically ordered objective functions. In addition, the set of objective functions in now generic in the sense that they can be adapted to specific situations of spontaneous volunteers coordination. In our work, the elaboration of the new system of objective functions has become a substantial part of the overall modeling procedure. We also revised the set of constraints based on the new set of requirements, which also account for the existence of priority classes. Overall, this approach led to a model that is more generally applicable than that suggested in [50]. Third, we conducted comprehensive computational experiments. More precisely, we systematically varied the values of model parameters in a full-factor design, resulting in a set of 16 scenarios. For each of these scenarios, we developed a temporal series of 20 model instances to analyze how the coordination of spontaneous volunteers evolves over time. Thereby, we emphasize the analysis of the dynamic and uncertain nature of disaster situations. As in each scenario, the parameter values of all 20 instances were determined using stochastic distributions, we ran 10 different sets of 20 instances per scenario. To sum up, in contrast to the study [50], which solves two single-objective model instances, we conducted a simulation containing ($20 \cdot 16 \cdot 10 =$) 3 200 multi-objective model instances. Finally, the comprehensive simulation of our multi-objective model allows for analyzing each objective function separately and also in relationship to other objective functions in terms of achieved objective values and required wall times[1], depending on different values of model parameters. Thereby, we develop general insights into the problem studied, which go beyond those gained in [50] from conducting a "proof of concept" of a single-objective optimization model in a single scenario with fixed parameter values.

3. Problem description and requirements

In this section, we focus on the description of coordinating spontaneous on-site volunteers during disaster responses and the resulting requirements for this purpose. Note that we write volunteers as a short-hand notation for spontaneous on-site volunteers, and that the requirements which we are going to define apply to off-site volunteers as well.

3.1. Problem description

The problem description is based on several in-depth interviews and workshops with practitioners of rescue organizations. While requirements for the coordination of volunteers are largely homogeneous across organizations, preferences of coordinators may slightly vary between organizations. In particular, preferences of single coordinators turned out to be multi-dimensional, with dimensions and their relative importance varying slightly across different coordinators. In order to develop a broadly applicable and adaptable model, we decided to adopt those preferences acquired in interviews with the manager of a professional fire department, who already gained experience with coordinating volunteers during floods and who was able to express a sophisticated set of preferences. The broad set of requirements and preferences that we identified can essentially be grouped by three types of issues: assigning volunteers to appropriate specific activities of a task (e.g., *filling sandbags* as part of the overall task *flood control*) in terms of their capabilities and availability, sequential scheduling of volunteers' task activities, and balancing volunteer assignments in times of volunteer shortage. Thus, we refer to this problem as *spontaneous volunteer coordination problem* (SVCP).

Firstly, we explain what a task is, how it is divided into task activities, and how the volunteer capabilities are related to task activities. A *task* is defined by its type, required activities, required volunteers per

[1] Wall (clock) time refers to the actual (elapsed) time that a program takes to execute its task.

each activity, location, time period, and priority level. The *level of priority* is based on the judgement of professional relief organizations in terms of how urgent a task needs to be processed. Specifically in times of a shortage of volunteers, it is useful to draw on the *workload* of an activity of a task, defined as the ratio of assigned volunteers to requested volunteers. This concept allows balancing workloads according to preferences of decision makers. For example, we might want to assign, at the same time, volunteers to tasks with priority level *high* and to tasks with priority level *low* in a workload ratio of 2 : 1. This means that the overall workload of all activities belonging to high-priority tasks should be twice as high as the overall workload of all activities belonging to low-priority tasks.

Figure 1 illustrates a problem setting with two tasks to which volunteers need to be assigned.

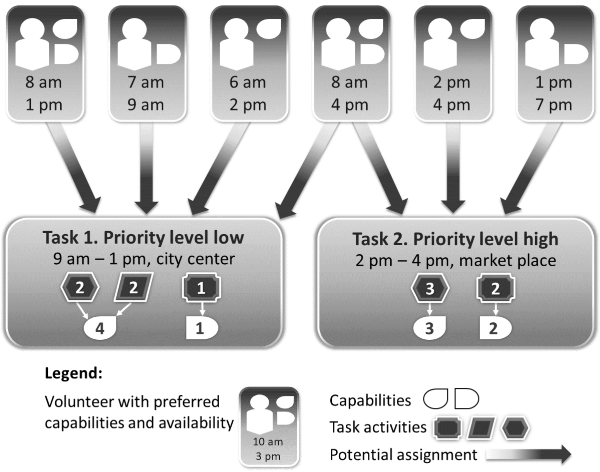

Figure 1: Sample situation. Scheduling six volunteers to two tasks.

Note that both tasks differ in terms of their priority level, time period, task activities and (the number and capabilities of) volunteers required for each activity. For example, task 1 has a low priority level and needs to be processed between 9am and 1pm. It could be of type *food supply*, for example. The task consists of three different task activities with two different needs of capabilities for volunteers. For example, activities *serving meals* and *care* require 2+2 volunteers with the capability *care work*, and activity *documentation* requires 1 volunteer with the capability *writing*. In our problem setting, an overall set of 6 volunteers are available and need to be assigned to the 5 task activities. The assignment needs to ensure that each volunteer is assigned to task activities according to his/her *preferred available times* and *preferred personal capabilities*. For example, volunteer 1 can be assigned to each activity of task 1 but (due to a mismatch of time periods) to no activity of task 2.

Note that the problem setting above does not only address assigning volunteers to task activities but also scheduling volunteers as a single volunteer may be used to process more than one task activity subject to his/her availability and capabilities.

A problem setting as shown in Figure 1 occurs at a specific point of time when a decision maker needs to assign and schedule volunteers based upon the current situation. Acknowledging that situations during a disaster are likely to change frequently in an often unpredictable manner, it should be noted that a sequence of (related) problem settings (often periodically) occurs and needs to be solved over time. Based on our interviews, we do not re-assign or re-schedule volunteers and thereby base our work on non-preemptive scheduling in and across problem settings; we expect non-preemptive scheduling to reduce the turnover (intention) of volunteers.

3.2. Requirements

In alignment with the above problem formulation, related work, the interviews conducted by Rauchecker and Schryen [50], and our more recent interviews with the manager of a professional fire department, we derived a set of requirements (see Table 1) for coordinating spontaneous volunteers.

Unsurprisingly, the distribution of volunteers on task activities is largely affected by the urgency with which tasks need to be processed (priority level). When relating the urgencies of two tasks that have different priority levels, our interviews have revealed that relief organizations use two different ways to cope with priority differences when it comes to distributing the set of available volunteers on tasks:

i. A pair of priority levels (p, p') may be ordered in a *strong* way; i.e., as many volunteers as possible should be assigned to tasks with priority level p before any volunteers are assigned to tasks of priority level p'.
ii. A pair of priority levels (p, p') may be ordered in a *weak* way; i.e., the assignment of volunteers to tasks of priority levels p and p' follows a predefined ratio. For example, a ratio of $3:1$ means that the overall number of volunteers assigned to all tasks of priority level p should be three times higher than the overall number of volunteers assigned to all tasks of priority level p'.

Accounting for these more complex yet more flexible and realistic perspectives, we suggest grouping priority levels by priority classes in the following way: priority levels that follow a weak order are assigned to the same priority class; priority levels that follow a strong order are assigned to different priority classes. Using both priority levels and priority classes allows us addressing both ways how practitioners cope with tasks of different priorities.

It should be noticed that the concepts of ordering priority levels in an either *strong* or *weak* way can be extended to more than two priority levels. Regarding the pairwise *strong* relationship between priority levels, an extension requires generating a total order of all priority classes. Regarding the pairwise *weak* relationship between priority levels of the same priority class, an extension is possible through, first, generating a total order of all priority levels in the given class and, second, the determining of all ratios of two priority levels that are *adjacent* in the total order.

We can now formulate the requirements for coordinating volunteers as listed in Table 1.

The requirements are grouped by three categories. The first category contains three requirements (1a–1c), which refer to the abovementioned different urgencies that tasks may have. In our interviews, these requirements have been considered most relevant when coordinating volunteers, with requirement 1a being more important than requirement 1b, and requirement 1b being more important than requirement 1c. Furthermore, practitioners stated that the fulfillment of these requirements are non-compensatory, which calls for considering 1a–1c as a set of lexicographically ordered goals. The second category addresses

Table 1
Requirements for volunteer coordination.

No.	Requirement	Rationale
	Urgencies of tasks	
1.	Tasks belonging to	
a)	different priority classes (use strong order): Assign as many volunteers as possible to activities of those tasks that have a priority level of the highest priority class; when no more volunteers can be assigned to such task activities, then assign as many of the remaining volunteers as possible to activities of those tasks that have a priority level of the second-highest priority class; remaining volunteers are assigned to task activities in descending order of priority classes.	Interviews, [54]
b)	same priority class but different priority levels (use weak order): If a priority class consists of more than one priority level, assign volunteers to task activities in a way that predefined workload ratios of priority levels apply.	Interviews
c)	same priority level: Assign volunteers to task activities in a way that all affected activities have identical workloads (all ratios are 1:1).	Interviews, [16]
	Relationships between volunteers and tasks	
2.	It is more important to assign volunteers at earlier times than at later times of the planning horizon.	Interviews, [50]
3.	Balancing workloads between task activities of identical workloads (see requirement 1c) becomes less important with increasing overcapacity of volunteers for task activities in terms of required volunteers.	Interviews
4.	Do not assign more volunteers than requested to each task activity.	Interviews, [50]
5.	A volunteer cannot work on more than one task activity at the same time.	[50]
6.	A volunteer can only be assigned to a task activity, if s/he has the appropriate capability and availability.	[54, 17, 24, 33, 50]
7.	Volunteer scheduling (assignments of volunteers to task activities over time) is non-preemptive	[50, 23]
	Characteristics of volunteers' engagement	
8.	Volunteers need initial travel times to reach the location of their first task activity.	Interviews
9.	Volunteers need travel/setup times when switching from one task activity to another.	[50]
10.	The minimum number of working hours on a task activity is lower-bounded, for each volunteer.	[50, 17]
11.	The maximum number of working hours during the entire planning horizon is upper-bounded, for each volunteer (must not be exceeded by any volunteer).	[50, 17]

requirements that apply when a single volunteer is assigned to a single task activity. Finally, the last category refers to requirements that need to be considered when volunteers are involved regardless of specific tasks.

4. Balanced decision support model

Our requirement analysis and problem formulation presented in the previous section have revealed that decision makers of relief organizations are considering a complex set of requirements when coordinating volunteers. In order to develop an optimization model that accounts for this complexity and that is broadly applicable to many relief organizations, we suggest a model that generalizes several of the empirically acquired requirements; generalizations may be simplified when applied by a particular relief organization as needed. Due to its broad applicability, the optimization model is complex. Accounting for its complexity, we first present all notations and derive objective functions before we present the complete optimization model.

4.1. Notations

Our notation consists of indices, sets, (decision) variables and parameters (see Table 2). Indices refer to concepts already introduced above and specify a volunteer v, a type of capability c that volunteers may have, a task activity a, a priority level p and a priority class k to which a priority level belongs. For both indices p and k, larger numbers indicate "more severe" priority levels and classes, respectively. Furthermore, we introduce the index t in order to discretize the planning horizon into equally long periods.

We use two sets $\hat{\mathcal{A}}_{k,t}$ and $\mathcal{A}_{p,t}$ to refer to all task activities in time slot t with priority levels of priority class k and to all task activities in time slot t with priority level p, respectively.

The coordination of volunteers in disasters situations needs to account for a variety of exogenous factors, which we consider using parameters in the optimization model. The first group of parameters refers to priority levels and classes. Suppose $\{1, \dots, P\}$ is the ordered set of all priority levels, with higher numbers indicating higher priorities. Then, partitioning $\{1, \dots, P\}$ into a set $\{\mathcal{P}_k \mid k = 1, \dots, K\}$ of pairwise disjoint priority classes groups all priority levels by priority classes. Partitions are conducted in the following way: $p \in \mathcal{P}_k \wedge p' \in \mathcal{P}_{k'} \Rightarrow p < p'$ for all $k < k'$, i.e. partitions keep the order of priority levels. For example, with $\{1, \dots, P = 12\}$ being the ordered set of priority levels, we could yield the following partitions: $\mathcal{P}_1 = \{1, 2, 3, 4\}$, $\mathcal{P}_2 = \{5, 6\}$, and $\mathcal{P}_3 = \{7, 8, 9, 10, 11, 12\}$. With $\mathcal{P}_k$ being the set of all priority levels in priority class k, α_k is a binary parameter specifying if $\mathcal{P}_k$ contains more than one priority level or not. The relationship between a priority level and a priority class is given by $cl_{k,p}$. The parameter $\sigma_{p,p+1}$ specifies the intended workload ratio between two priority levels of the same priority class.

The second group of parameters relates to characteristics of task activities. Therein, $r_{a,t}$, $req_{a,c}$ and p_a specify a task activity a with regard to whether it needs to be processed during time slot t or not, whether processing requires a particular capability c or not, and its priority level. Furthermore, $d_{a,t}$ specifies the time-specific ratio of the number of requested volunteers for task activity a to the number of volunteers which are available in a specific time slot t and which are capable of processing task activity a.

The third group of parameters contains information on single volunteers using the parameters $av_{v,t}$, $cap_{v,c}$ and $o_{v,a,t}$. The first two parameters specify the availability and the capabilities of a particular volunteer. The third parameter accounts for the temporal dynamics and uncertainty of the overall planning situation. As unfolded in the introduction, we generate a sequence of model instances over time so that the planning situation gets updated from one instance to the next. In this regard, the parameter $o_{v,a,t}$ specifies whether a volunteer v has already been assigned to task activity a in time slot t in the solution of a previous problem instance.

The fourth group of parameters specifies the number n_a of volunteers required for processing task activity a and the number $n_{p,t}$ required for all task activities that have priority level p and need volunteers in time slot t.

The fifth group refers to information on the number of time slots required for specific procedures. The parameter τ_{min} specifies a lower bound of time slot that a volunteer is required to work consecutively on any task activity in order to avoid high fragmentation and disruption of volunteers' work. An upper bound of the number of time slots that a volunteer may work in total during T consecutive time slots is given by $\bar{\tau}_{max}$; this bound considers the existence of a sequence of i problem instances, with the total number of time slots of all instances amounting to $T + i - 1$ as each additional problem instance considers a period that is time-shifted by one time slot compared to the previous problem instance. The parameters $\tau_{v,a}$ and $s_{a,a'}$ refer to average setup times in terms of how many time periods a volunteer needs to travel from the location of his/her starting position to the location of his/her first task (activity), and the location of his/her current task (activity) to that of his/her next task (activity), respectively. Finally, the parameter w_t is used to weight the numbers of volunteers assigned to task activities in time slot t.

We use five types of decision variables. $X_{v,a,t}$ is a binary variable indicating whether volunteer v is assigned to task activity a in time slot t; we refer to the set of all decision variables $\{X_{v,a,t} | v = 1, \dots, V; a = 1, \dots, A; t = 1, \dots, T\}$ as X. All four remaining types of variables are continuous in the range between 0 and 1 and defined based upon $X_{v,a,t}$. Then, $L_{a,t}(\mathbf{X})$ is the workload of task activity a in time slot t, defined as the ratio of the number of volunteers (assigned to a in t) to the number of volunteers required for task activity a (over all time periods); i.e.,

$$L_{a,t}(\mathbf{X}) := \frac{1}{n_a} \sum_{v=1}^{V} X_{v,a,t}. \tag{1}$$

Similarly, $\bar{L}_{p,t}(\mathbf{X})$ is the average workload of all task activities with priority level p in time slot t; i.e.,

$$\bar{L}_{p,t}(\mathbf{X}) := \frac{1}{n_{p,t}} \sum_{v=1}^{V} \sum_{a \in \mathcal{A}_{p,t}} X_{v,a,t}, \tag{2}$$

with $\mathcal{A}_{p,t} := \{a = 1, \dots, A \mid p_a = p; r_{a,t} = 1\}$ being the set of all task activities in time slot t with priority level p.

We use two further types of decision variables $\Delta_{a,a',t}(\mathbf{X})$ and $\Lambda_{p,p',t}(\mathbf{X})$ to model imbalances between workloads $L_{a,t}(\mathbf{X})$ and $L_{a',t}(\mathbf{X})$ in time slot t, and between average workloads $\bar{L}_{p,t}(\mathbf{X})$ and $\bar{L}_{p',t}(\mathbf{X})$ in time slot t, respectively. We describe these more complex decision variables and the closely related objective functions in more detail in the subsequent section.

Table 2
Indices, sets, parameters and variables of the optimization model.

Notation	Description/Definition
	Indices
$t = 1, \ldots, T$	Time slots
$v = 1, \ldots, V$	Volunteers
$c = 1, \ldots, C$	Capabilities
$a = 1, \ldots, A$	Task activities
$p = 1, \ldots, P$	Priority levels
$k = 1, \ldots, K$	Priority classes
	Sets
$\mathcal{P}_k$	Priority levels in priority class k
$\hat{\mathcal{A}}_{k,t}$	Task activities in time slot t with priority levels of priority class k;
$\mathcal{A}_{p,t}$	Task activities in time slot t with priority level p.
	Parameters
α_k	$= 1$ if $\lvert\mathcal{P}_k\rvert > 1$ (0 else)
$cl_{k,p}$	$= 1$ if priority level p belongs to priority class k (0 else)
$\sigma_{p,p+1}$	Balancing factor for priorities p and $p + 1$ in the same priority class
$r_{a,t}$	$= 1$ if time slot t is within the time frame of task activity a (0 else)
$req_{a,c}$	$= 1$ if task activity a requires capability c (0 else)
p_a	Priority level of task activity a—depends only on the underlying task
$d_{a,t}$	Demand/Supply ratio of volunteers for task activity a in time slot t
$av_{v,t}$	$= 1$ if volunteer v is available in time slot t (0 else)
$cap_{v,c}$	$= 1$ if volunteer v offers capability c (0 else)
$o_{v,a,t}$	$= 1$ if volunteer v has an assignment to task activity a in time slot t from the solution of the previous SVCP instance (0 else)
n_a	Number of volunteers required for task activity a;
$n_{p,t}$	Number of volunteers required for all task activities in $\mathcal{A}_{p,t}$ in time slot t.
τ_{min}	a volunteer must work consecutively on the same task activity;
$\bar{\tau}_{max}$	each volunteer is allowed to work in total, during the past T slots;
$\tau_{v,a}$	volunteer v needs to reach task activity a from his/her current position;
$s_{a,a'}$	are required to travel from task activity a to task activity a'.
w_t	Weight which indicates the severity of unmet demands for volunteers at task activities in time slot t
	Variables
$X_{v,a,t}$	$= 1$ if volunteer v is assigned to task activity a in time slot t (0 else)
$L_{a,t}(\mathbf{X})$	Workload of task activity a in time slot t
$\bar{L}_{p,t}(\mathbf{X})$	Average workload of all task activities with priority level p in time slot t
$\Delta_{a,a',t}(\mathbf{X})$	Imbalance between workloads $L_{a,t}(\mathbf{X})$ and $L_{a',t}(\mathbf{X})$ in time slot t
$\Lambda_{p,p',t}(\mathbf{X})$	Imbalance between the average workloads $\bar{L}_{p,t}(\mathbf{X})$ and $\bar{L}_{p',t}(\mathbf{X})$ in time slot t

4.2. Multiple objectives

In this section, we explain the construction of multiple objective functions (OF). We align the OF with the requirements 1a–1c, referring to the urgencies of tasks (see Table 1). As these requirements have been totally ordered in descending order of importance and in a non-compensatory manner, we model these requirements using a lexicographic set of OF.

Requirement 1a corresponds to the goal of assigning as many volunteers as possible to task activities by considering priority classes in descending order of importance. This approach leads to as many goals as priority classes exist, with higher priority classes leading to higher prioritized objective functions, again in a non-compensatory manner. Thus, we receive K lexicographically ordered OF for K priority classes. From requirements 1b, we derive the goal of balancing the assignment of volunteers to task activities which are within the same priority class but in different priority levels, accounting for predefined workload ratios of two priority levels. Similarly, from requirement 1c, we derive the goal of balancing the assignment of volunteers to task activities which are within the same priority levels, accounting for the predefined workload ratio of (1:1) between two of such priority levels. Overall, our approach results in a total number of $K + 2$ lexicographically ordered OF.

Objective functions of the first goal. The following K objective functions, which have to be considered in lexicographical order starting with (OF 1) and ending with (OF K), fulfill the first goal:

$$\max\left(\sum_{v=1}^{V}\sum_{a\in\hat{\mathcal{A}}_{K,t}}\sum_{t=1}^{T} w_t \cdot X_{v,a,t}\right), \tag{OF 1}$$

$$\vdots \tag{\vdots}$$

$$\max\left(\sum_{v=1}^{V}\sum_{a\in\hat{\mathcal{A}}_{1,t}}\sum_{t=1}^{T} w_t \cdot X_{v,a,t}\right), \tag{OF K}$$

with $\hat{\mathcal{A}}_{k,t} := \{a = 1, \dots, A \mid p_a \in \mathcal{P}_k; r_{a,t} = 1\}$ being the set of all task activities in time slot t with priority levels of priority class k, and $\mathcal{P}_k := \{p = 1, \dots, P \mid cl_{k,p} = 1\}$ for $k = 1, \dots, K$ being the set of all priority levels in priority class k.

Note that (OF 1), …, (OF K) only differ in the priority class of considered task activities. All K objective functions were constructed by combining requirements 1a and 2. Therein, (OF k) is the time-weighted sum of the numbers of volunteers assigned to task activities with priority levels from the k-th highest priority class. The use of weights w_t (with $w_t > w_{t+1} > 0$) accounts for requirement 2, according to which the importance of assigning volunteers to task activities decreases over time for all time slots t.

Objective function for the second goal. In order to formulate the objective function of the second goal, we first define the (composite) decision variable $\Lambda_{p,p',t}(\mathbf{X})$, which reflects the imbalance between the average workloads $\bar{L}_{p,t}(\mathbf{X})$ and $\bar{L}_{p',t}(\mathbf{X})$ in time slot t. As imbalances do not need to be considered in cases where both average workloads $\bar{L}_{p,t}(\mathbf{X})$ and $\bar{L}_{p',t}(\mathbf{X})$ equal 100%, we set $\Lambda_{p,p',t}(\mathbf{X}) := 0$ in these cases. For all other cases, we set

$$\Lambda_{p,p',t}(\mathbf{X}) := \begin{cases} \bar{L}_{p,t}(\mathbf{X}) - \sigma^{-1}_{p',p}\bar{L}_{p',t}(\mathbf{X}) & \text{if } p = p'+1 \text{ and } \bar{L}_{p,t}(\mathbf{X}) - \sigma^{-1}_{p',p}\bar{L}_{p',t}(\mathbf{X}) > 0, \\ \bar{L}_{p,t}(\mathbf{X}) - \sigma_{p,p'}\bar{L}_{p',t}(\mathbf{X}) & \text{if } p = p'-1 \text{ and } \bar{L}_{p,t}(\mathbf{X}) - \sigma_{p',p}\bar{L}_{p',t}(\mathbf{X}) > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

The weight factor $\sigma_{p,p+1} \in (0,1]$ is the ratio of the average workload of task activities with priority levels p and $p+1$; e.g., $\sigma_{p,p+1} = 1/2$ and $\sigma^{-1}_{p,p+1} = 2$ for a $1:2$ ratio. It is sufficient to consider only positive differences in definition (3) since we sum over all imbalances for all $p, p' \in \mathcal{P}_k$ in objective function (OF $K+1$).

We use an example to demonstrate the determination of $\Lambda_{p,p',t}(\mathbf{X})$: Consider a situation with three task activities ($A = 3$). Task activity 1 has priority level 1 and requires 50 volunteers. Both task activities 2 and 3 have priority level 2 and require 20 and 30 volunteers, respectively. We assume an average workload ratio $1:4$; i.e., $\sigma_{1,2} = \frac{1}{4}$. Consequently, we have one priority class $\mathcal{P}_1 = \{1, 2\}$. For simplicity, we fix a time slot t and suppose that there are $V = 50$ volunteers – all being always available and capable of everything. Then, we can determine $\Lambda_{2,1,t}(\mathbf{X})$ and $\Lambda_{1,2,t}(\mathbf{X})$. Now, we compare both expressions for different feasible solutions, which are shown in Figure 2.

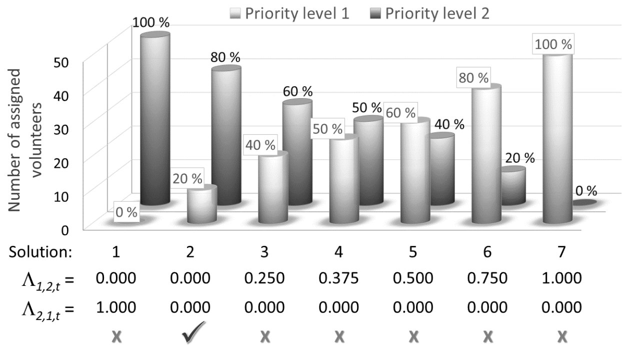

Figure 2: Example for $\Lambda_{p,p',t}$ with 50 available and capable volunteers, $\sigma_{1,2} = \frac{1}{4}$, $\mathcal{P}_1 = \{1, 2\}$.

Therein, the percentage figures above the bars represent the average workloads; i.e., $\bar{L}_{1,t}(\mathbf{X}) = \frac{1}{50}\sum_{v=1}^{50} X_{v,1,t}$ and $\bar{L}_{2,t}(\mathbf{X}) = \frac{1}{20+30}\sum_{v=1}^{50}(X_{v,2,t} + X_{v,3,t})$, cf. Eq. (2), for priority levels 1 and 2, respectively. The objective function (OF $K+1$) is minimal if $\Lambda_{1,2,t} + \Lambda_{2,1,t}$ is as small as possible, rendering the second solution in Figure 2 the optimal one.

We only have to take $\Lambda_{p,p',t}(\mathbf{X})$ values into account if the considered priority class k consists of more than one element, otherwise there is nothing to be balanced; therefore, we multiply $\sum_{p,p' \in \mathcal{P}_k}\sum_{t=1}^{T}\Lambda_{p,p',t}(\mathbf{X})$ by a factor α_k (see Table 2) for each priority class k, with α_k equalling being one in the former and zero in the latter case. Based on the above construction, we can now formulate the objective function for the second goal as follows:

$$\min\left(\sum_{k=1}^{K}\alpha_k \cdot \sum_{p,p' \in \mathcal{P}_k}\sum_{t=1}^{T}\Lambda_{p,p',t}(\mathbf{X})\right). \tag{OF $K+1$}$$

Therein, (OF $K+1$) penalizes the violations of predefined workload ratios of two priority levels by minimizing the sum of all imbalances between the average workloads of all task activities a with *neighboring* priority levels p, p' (e.g. $p' = p+1$ or $p' = p-1$) from the same priority class k, for all priority classes $k = 1, \dots, K$.

Objective function for the third goal. In order to formulate the objective function of the third goal, we refer to the (composite) decision variable $\Delta_{a,a',t}(\mathbf{X})$ as the imbalance between workloads $L_{a,t}(\mathbf{X})$ and $L_{a',t}(\mathbf{X})$ in time slot t, and define it as the difference between both workloads,

$$\Delta_{a,a',t}(\mathbf{X}) := \begin{cases} L_{a,t}(\mathbf{X}) - L_{a',t}(\mathbf{X}) & \text{if } L_{a,t}(\mathbf{X}) - L_{a',t}(\mathbf{X}) > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Note that $\Delta_{a,a',t}(\mathbf{X}) + \Delta_{a',a,t}(\mathbf{X}) = |L_{a,t}(\mathbf{X}) - L_{a',t}(\mathbf{X})|$ holds true. Hence, we need to consider only positive differences in definition (4) as, in objective function (OF $K+2$), we sum imbalance values over all pairs $(a, a') \in \mathcal{A}_{p,t} \times \mathcal{A}_{p,t}$, thereby penalizing imbalances. Balancing workloads between task activities of identical workloads (see requirement 1c) becomes less important with increasing overcapacity of volunteers for task activities in terms of required volunteers, cf. requirement 3. In order to account for this relationship, we define a ("supply") weight factor $d_{a,t}$ as the ratio of the number of requested volunteers for task activity a in time slot t and the number of volunteers who are capable of working on a and available in t,

$$d_{a,t} := \begin{cases} \frac{n_a \cdot r_{a,t}}{req_{a,c} \cdot \sum_{v=1}^{V} av_{v,t} \cdot cap_{v,c}} & \text{if } req_{a,c} \cdot \sum_{v=1}^{V} av_{v,t} \cdot cap_{v,c} > n_a \cdot r_{a,t}, \\ 1 & \text{otherwise.} \end{cases} \tag{5}$$

The factor $d_{a,t}$ is smaller than 1 if and only if the number of requested volunteers (for a in t) is smaller than the number volunteers who are available in t and capable regarding a (i.e., when no shortage of volunteers occurs); otherwise $d_{a,t}$ equals 1 so that it has no effect on (OF $K+2$).

We use an example to demonstrate the determination of $\Delta_{a,a',t}(\mathbf{X})$. We consider an example with $A = 2$ task activities, and both have the same priority level, $p_1 = p_2 = 1$. Furthermore, each task activity requires 50 volunteers. The workload can be obtained as given in Eq. (1). $V = 50$ volunteers are always available and capable of everything. By fixing a time slot t, we get $d_{1,t} = d_{2,t} = 1$, cf. Eq. (5), resulting in $\Delta_{1,2,t}(\mathbf{X}) + \Delta_{2,1,t}(\mathbf{X})$ as the value of objective function (OF $K+2$). Comparing the solutions of $\Delta_{1,2,t}$ and $\Delta_{2,1,t}$, shown in Figure 3, it becomes evident that solution no. 4 is the optimal one (the percentage values over the bars represents the workloads of the two task activities).

The imbalances $\Delta_{a,a',t}$ weighted by $d_{a,t} \cdot d_{a',t}$ need to be summed up over all pairs of task activities, $a, a' \in \mathcal{A}_{p,t}$, in all time slots t and for all priority levels p. This approach leads to the formulation of the following objective function for the third goal:

$$\min \left(\sum_{p=1}^{P} \sum_{a,a' \in \mathcal{A}_{p,t}} \sum_{t=1}^{T} d_{a,t} \cdot d_{a',t} \cdot \Delta_{a,a',t}(\mathbf{X}) \right). \tag{OF $K+2$}$$

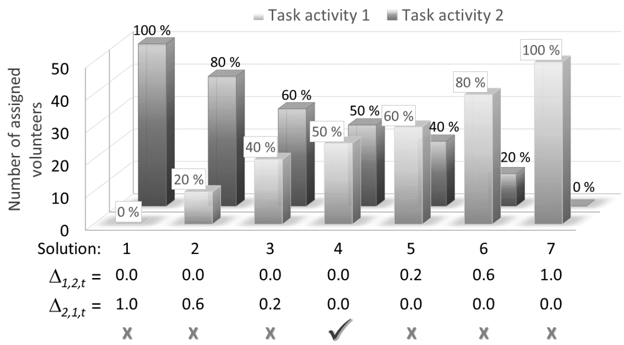

Figure 3: Example for $\Delta_{a,a'}$; 50 volunteers, two task activities with the same priority level.

4.3. Optimization model

Based upon the above described lexicographically ordered objective functions and coordination requirements, we now formulate the complete optimization problem.

$$\max \left(\sum_{v=1}^{V} \sum_{a \in \hat{\mathcal{A}}_{K,t}} \sum_{t=1}^{T} w_t \cdot X_{v,a,t} \right) \tag{OF 1}$$

$$\vdots \tag{OF ⋮}$$

$$\max \left(\sum_{v=1}^{V} \sum_{a \in \hat{\mathcal{A}}_{1,t}} \sum_{t=1}^{T} w_t \cdot X_{v,a,t} \right) \tag{OF K}$$

$$\min \left(\sum_{k=1}^{K} \alpha_k \cdot \sum_{p,p' \in \mathcal{P}_k} \sum_{t=1}^{T} \Lambda_{p,p',t} \left(\mathbf{X} \right) \right) \tag{OF $K+1$}$$

$$\min \left(\sum_{p=1}^{P} \sum_{a,a' \in \mathcal{A}_{p,t}} \sum_{t=1}^{T} d_{a,t} \cdot d_{a',t} \cdot \Delta_{a,a',t} \left(\mathbf{X} \right) \right) \tag{OF $K+2$}$$

subject to

$$\sum_{v=1}^{V} X_{v,a,t} \leq n_a \cdot r_{a,t} \qquad \forall a, t \tag{6}$$

$$\sum_{a=1}^{A} X_{v,a,t} \leq 1 \qquad \forall v, t \tag{7}$$

$$X_{v,a,t} \geq o_{v,a,t} \qquad \forall v, a, t \tag{8}$$

$$X_{v,a,t} \leq av_{v,t} \cdot \sum_{c=1}^{C} cap_{v,c} \cdot req_{a,c} \qquad \forall v, a, t \tag{9}$$

$$\sum_{t=1}^{\tau_{v,a}} X_{v,a,t} \leq \sum_{t=1}^{\tau_{v,a}} o_{v,a,t} \qquad \forall v, a \tag{10}$$

$$\sum_{\substack{a'=1 \\ a'\neq a}}^{A} \sum_{t'=1}^{\min\{s_{a,a'},T-t\}} X_{v,a',(t+t')} \leq T \cdot (1 - X_{v,a,t}) \qquad \forall v, a, t \tag{11}$$

$$\sum_{t'=0}^{\min\{\tau_{min}-1,T-t\}} (1 - o_{v,a,(t+t')}) \cdot X_{v,a,(t+t')} \geq \tau_{min} \cdot \sum_{t'=0}^{\min\{1,t-1\}} (-1)^{t'} \cdot (1 - o_{v,a,(t-t')}) \cdot X_{v,a,(t-t')} \qquad \forall v, a, t \tag{12}$$

$$\sum_{a=1}^{A} \left(\sum_{t'=0}^{t-1} X_{v,a,(t-t')} + \sum_{t'=t}^{T-1} o_{v,a,(t-t')} \right) \leq \bar{\tau}_{max} \qquad \forall v, t \tag{13}$$

$$\Lambda_{p,p',t}(\mathbf{X}), \bar{L}_{p,t}(\mathbf{X}) \geq 0 \qquad \forall p, p', t \tag{14}$$

$$\Delta_{a,a',t}(\mathbf{X}), L_{a,t}(\mathbf{X}) \geq 0 \qquad \forall a, a', t \tag{15}$$

$$X_{v,a,t} \in \{0, 1\}. \qquad \forall v, a, t \tag{16}$$

As the lexicographically ordered objective functions (OF 1) to (OF $K + 2$) have been described in the preceding section, we focus here on the set of constraints and their relationships with the empirical requirements described in Section 3.2.

Constraint (6) assures that not more than the requested numbers of volunteers are assigned to each task activity a in a time slot t. Assigning a volunteer to more than one task activity in one time slot t is prevented through constraint (7). Constraint (8) implements non-preemptive scheduling across problem instances: we set $o_{v,a,t} = 1$ if volunteer v has an assignment to task activity a in the time slot t from the solution of a previous SVCP instance, resulting in $X_{v,a,t} = 1$. Constraint (9) ensures the assignment of volunteers to task activities a if and only if they have the required capability and availability.

Constraint (10) considers travel times $\tau_{v,a}$ that volunteers need to travel from their current location to the location of the first task activity a when volunteer v becomes available. Hence, a volunteer v cannot get a new assignment in the first $\tau_{v,a}$ time slots. Analogously, constraint (11) accounts for travel times $s_{a,a'}$ between the locations of two task activities a and a' that a volunteer works on successively.

Constraint (12) ensures that each assigned volunteer continuously works on a task activity a for at least τ_{min} time slots. With constraint (13), an upper bound on the overall working time for each volunteer is guaranteed by limiting the total number of his/her working slots to $\bar{\tau}_{max}$ over the full planning horizon.

Constraints (14)–(16) ensure non-negativity of all decision variables and the binary nature of $X_{v,a,t}$. Note that variables $\Lambda_{p,p',t}(\mathbf{X}), \bar{L}_{p,t}(\mathbf{X}), \Delta_{a,a',t}(\mathbf{X})$ and $L_{a,t}(\mathbf{X})$ are further specified in definitions (1)–(4).

An overview of the mapping of empirical requirements on objective functions and constraints of the optimization model is provided in Table 3.

5. Computational experiments

Our computational experiments are based on empirical data, generated during the disaster management of a flood that stroke the city of Halle (Saale), Germany, in 2013 (see Appendix B for further information). We further conducted several interviews with the manager of the fire department who was responsible for the

Table 3
Mapping of empirical requirements on objective functions and constraints.

Objective functions and constraints	Requirements
(OF 1)–(OF $K+2$)	1, 2, 3
In particular:	
(OF 1)–(OF K)	1a, 2
(OF $K+1$), (14)	1b
(OF $K+2$), (15)	1c, 3
(6)	4
(7)	5
(8)	7
(9)	6
(10)	8
(11)	9
(12)	10
(13)	11

disaster relief operations. We use the information gained during this data acquisition process to generate a series of simulations in which we apply our model. We vary the values of several parameters of our model in order to evaluate the robustness of our computation results and the sensitivity of parameters. In our simulations, we use up to 10 000 volunteers to be assigned to emerging tasks during an overall planning period of 33.5 hours, thereby our model undergoes a computational "stress test".

According to our interviews, the fire department of Halle distinguishes three priority levels $p = 1$, $p = 2$, and $p = 3$ as *green*, *yellow*, and *red* priority levels, with the red priority level belonging to the highest priority class, and the green and yellow priority levels belonging to the second-highest priority class. Overall, we yield four objective functions (OF 1) to (OF 4) in decreasing order of importance. With objective function

- (OF 1), we maximize the time-weighted sum of the number of volunteers assigned to (activities of) tasks with red priority level,
- (OF 2), we maximize the time-weighted sum of the number of volunteers assigned to (activities of) tasks with green or yellow priority levels,
- (OF 3), we minimize the sum of deviations from the intended ratio of $1:3$ between the average workloads of (activities of) tasks of green priority level and yellow priority level, and
- (OF 4), we minimize the supply-weighted sum of derivations from the intended ratio of $1:1$ between the workloads of activities of tasks with the same priority level, considering the red, yellow, and green priority levels.

5.1. Data generation

In our simulations, we refer to a *scenario* as a disaster relief situation during which volunteers are assigned to tasks periodically during a period of time. Thereby, we account for the dynamics of and uncertainty in a relief operation, during which the planning situation gets updated periodically. Each update involves generating and solving an instance of the suggested optimization model, where solving a particular instance requires considering all assignments of volunteers included in solutions of previous instances.

Based on our interviews, the high dynamics in a disaster situation requires relief organizations to update their schedules after 30 min at the latest. Thus, we generate a new instance every 30 min, which thereby provides an upper bound of the computation time that is available to solve each instance. We set the number of instances per scenario to 20, which reflects a period of 9.5 hours. While, in practice, scheduling instances would need to be solved also beyond this period, the computational difficulty of solving those instances becomes relatively low compared to the difficulty of the first 20 instances, during which most of the volunteers appear. This effect is also indicated by our results shown in Figures 4 and 7 in Appendix C, which show the low computation times and low gaps to optimal values for the first and last instances. Thus, we decided to limit our computational evaluations to 20 instances per scenario. While an instance reflects a planning situation that occurs at a particular point of time, we further need to specify the time period in which volunteers are scheduled. Based on our interviews, we set this planning horizon to 24 hours, which corresponds to $T = 48$ time slots. In summary, each scenario consists of $i = 20$ instances, with each of the instances covering a period of 48 time slots, which results in an overall planning period of $T + i - 1 = 67$ time slots (= 33.5 hours) per scenario. Figure 5 in Appendix A illustrates the aforementioned relationships in a scenario. Table 4 provides values of all parameters which remain constant over all scenarios. Details on the parameter values can be found in Appendix B.

Table 4
Constant parameter values.

Parameter	Value	Rationale
T	48 (representing 24 hours)	Interview
C	6	Interview (cf. Tab. 9)
P	3	Interview
K	2	Interview
$\mathcal{P}_1$	$\{1,2\}$	Interview
$\mathcal{P}_2$	$\{3\}$	Interview
α_1	1 for $\mathcal{P}_1$	Def. of α_k (cf. Tab. 2)
α_2	0 for $\mathcal{P}_2$	Def. of α_k (cf. Tab. 2)
$cl_{1,p}$	1 for $p = 1,2$	Def. of $cl_{k,p}$ (cf. Tab. 2)
$cl_{1,3}$	0	Def. of $cl_{k,p}$ (cf. Tab. 2)
$cl_{2,p}$	0 for $p = 1,2$	Def. of $cl_{k,p}$ (cf. Tab. 2)
$cl_{2,3}$	1	Def. of $cl_{k,p}$ (cf. Tab. 2)
$\sigma_{1,2}$	$\frac{1}{3}$	Interview
τ_{min}	4 (representing 2 hours)	Interview
$\bar{\tau}_{max}$	16 (representing 8 hours)	Interview
$s_{a,a'} = \tau_{v,a}$	2 (representing 1 hour)	Interview
w_t	$1 - \frac{t-1}{T}$	Requirement 2, interview

Based on the data of the 2013 flood, we define a set of 27 tasks, and we assume that in the first instance, for each scenario, four tasks exist, with the set of these tasks varying across runs. The characteristics of all

27 tasks and contained task activities, including required capabilities, demand of volunteers, period of time, and priority level, are described in detail in Appendix B. From Tables 5, 9, 12 and 13 the number of added tasks for each instance, the values of the parameters $A, \hat{\mathcal{A}}_{k,t}, \mathcal{A}_{p,t}, r_{a,t}, req_{a,c}, p_a, n_a$ and $n_{p,t}$ can be derived.

In order to simulate volunteers' individual appearances and periods of availability realistically, we draw on stochastic distributions based on the interviews with the manager of a professional fire department. For each volunteer, we determine his/her appearance in terms of the first time slot t_0 in which the volunteer is available, using a Poisson distribution (with parameter λ); we use two different values for λ to define different scenarios (see Table 6). We only consider a volunteer in our scheduling when s/he appears during the planning horizon of a scenario; i.e., we require t_0 not to be greater than $T+i-1$. Based on our interviews, we determine a volunteer's period of availability in terms of (the number d of) time slots during which s/he is consecutively available using a (discrete) uniform distribution over the set $\{6, \dots, 16\}$, which corresponds to a period of at least 3 hours and at most 8 hours. Based on the abovementioned two randomly generated values t_0 and d, we consider a volunteer to be available during the time slots $\{t_o, \dots; t_o + d - 1\}$, and we can now determine all $av_{v,t}$ values (cf. Table 2) accordingly.

Considering variations in disaster relief situations, we distinguish scenarios along four dimensions: First, the number of tasks getting added to an instance may differ. We use the two values "1" and "2" to model different intensities of task arrivals. From the set of overall 27 tasks, we add the corresponding number of tasks (and related task activities) to each instance. Second, the intensity with which new volunteers appear in an instance may differ. We chose to use the time slot $\lambda = 7$ or $\lambda = 11$, so that we have both a sharp rise and a sharp decline in the number of new volunteers, within our generated instances (as it was observed during the 2013 flood in Halle). Third, the maximum number of volunteers available during a scenario may differ. We use two different numbers: $5,000$ and $10,000$ volunteers (in the case of the 2013 flood, up to $10,000$ volunteers were available in the course of a day). Based on λ as the parameter of the distribution for simulating volunteer availabilities and the maximum number of volunteers, we determine the numbers of actual volunteers, i.e. V, for each instance. An example of the volunteer generation process can be found in the Appendix B in Table 10. Finally, we simulate capabilities of volunteers varying the probability (we use values of 0.3 and 0.5 based on results of our empirical data[2]) with which each volunteer has a particular capability. We can then determine all $cap_{v,c}$ values. The values of parameters $d_{a,t}$ can be determined based upon the values of $r_{a,t}, req_{a,c}, av_{v,t}, cap_{v,c}$ and n_a.

Combining the different values of the four dimensions, we derive $2^4 = 16$ different scenarios (see Table 5 and Table 6), with each scenario including 20 model instances over time.

5.2. Computational environment

Our hardware setup contains an Intel Core i9-9900K CPU @ 3.60 GHz 3.60 GHz, x64-based processor and 64 GB RAM. We coded the model in Java, used PostgreSQL as database and solved the model-instances with the off-the-shelf solver *Gurobi* (version 9.1.1). Based on results achieved in computational pretests, we

[2]Using probabilities 0.3 and 0.5 leads to an expected number of capabilities of each volunteer of about 2 and 3, respectively, in the presence of six different capabilities (see Table 9 in Appendix B

Table 5
Variations of scenarios.

Dimension	Range
Tasks	
Number of added tasks for each instance	$\in \{1, 2\}$
Volunteers	
Poisson-distributed time slot λ	$\in \{7, 11\}$
Maximum number of volunteers	$\in \{5\,000, 10\,000\}$
Probability of capability	$\in \{0.3, 0.5\}$

Table 6
Scenarios.

Scenario	Parameter			
Number	Volunteers	Added tasks	Probability of capabilities	Time slot λ
1	5000	1	0.3	7
2				11
3			0.5	7
4				11
5		2	0.3	7
6				11
7			0.5	7
8				11
9	10000	1	0.3	7
10				11
11			0.5	7
12				11
13		2	0.3	7
14				11
15			0.5	7
16				11

use the *initial presolve* option, and we set the value of parameter *NumericFocus* to its maximum *3* in order to employ more expensive techniques to avoid potential numerical issues.

5.3. Results

For each of the 16 scenarios, we sequentially solve its 20 model instances. In our experiment, we use a wall time limit per objective function of 5 min, resulting in an upper bound of the wall time of 20 min for the four objective functions. The wall time required for the initial presolve, which cannot be upper-bounded in *Gurobi*, must not exceed 10 minutes in order to keep the total wall time below 30 min, which is the temporal gap between two consecutive instances. In our experiments, we used the default *Relative MIP optimality gap* of *Gurobi*, which is 0.01%.

As some data in our simulations are generated using stochastic distributions, we computationally evaluated each scenario and its 20 instances through ten independent runs. All results provided are thus averaged over these ten runs[3]; i.e., a gap of $x\%$ provided for a particular objective function, particular instance and particular scenario means that, over all five runs, an average relative gap to the optimal objective value of $x\%$ has been achieved. Figure 4 visualizes the results (x values) for each of the four objective functions; detailed figures can be retrieved from Tables 14–17 in Appendix C.

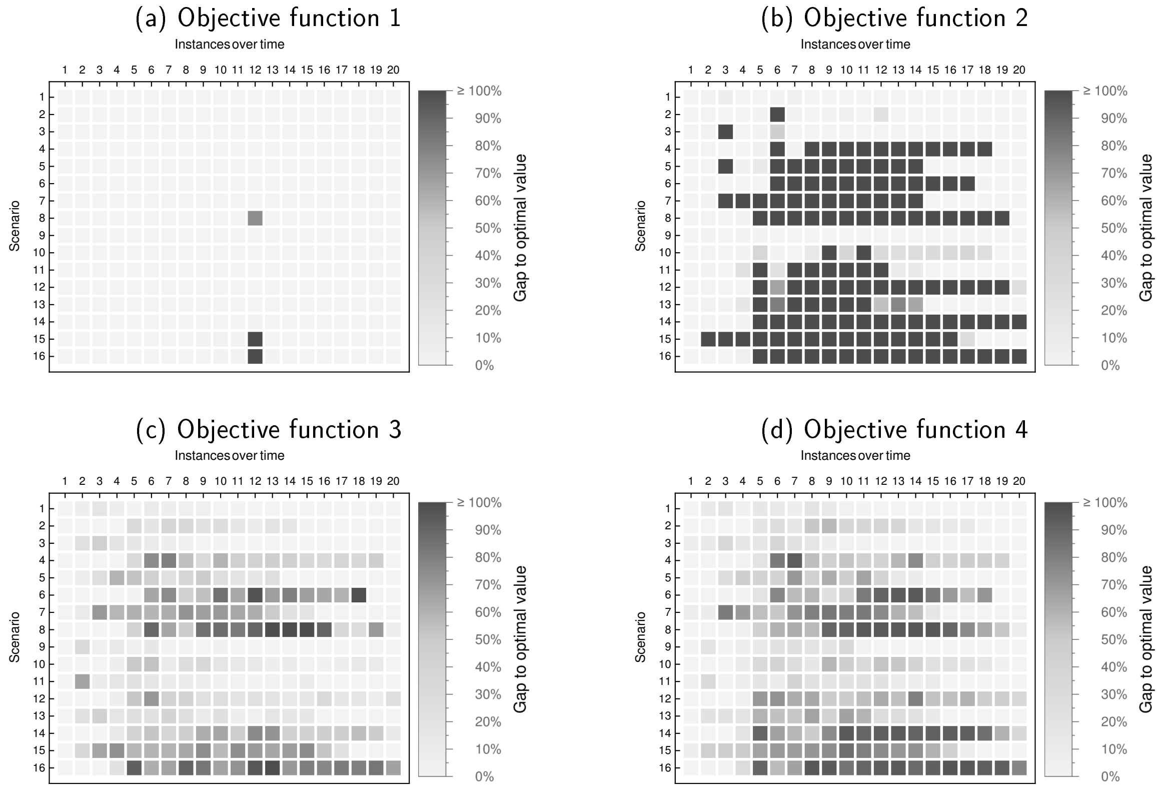

Figure 4: Gaps to optimal values for all objective functions [in %], with a wall time of 5 minutes.

The actual wall times required to obtain the solutions for the four objective functions shown above can be obtained from Figure 7 in Appendix C, with detailed figures being included in Tables 19–22 in Appendix C. The wall times required for solving the initial presolve phase and the total wall times[4] can be retrieved from Figure 8 and Tables 18 and 23 in Appendix C.

As Figure 4 (a) indicates, (OF 1) can be solved to optimality in almost all scenarios and instances; i.e., the (time-weighted) number of volunteers assigned to tasks of the highest priority class and level (*red*) is almost always set to the highest possible value. The (averaged) wall times required for solving (OF 1) (see Figure

[3]We excluded results from those runs where at least one problem instance could not be solved by Gurobi due to numerical issues. Appendix C provides more details on this issue.

[4]The wall time limit of 30 min was not exceeded in any instance. Furthermore, access to faster computers, for example using a high-performance cloud web service, may allow to further reduce required times.

7 (a) in Appendix C) indicate that, except for the complex scenarios 8 and 14-16, problem instances are solved in less than 85 seconds regarding the most important objective function; wall times in the remaining scenarios amount to a maximum of 238 seconds (see Figure 7 (a) and Table 19 in Appendix C). As solving (OF 1) is predated by an initial presolve phase, we need to also account for wall times required in this phase (see Figure 8 (a) in Appendix C), which are similar to those needed to solve (OF 1). The sum of both wall times determines the time after which solutions for (OF 1) are finally found. In all but the abovementioned scenarios, this sum is upper bounded by 182 seconds while the remaining scenarios require 656 seconds at most; i.e., the sum of times required for both initial presolving and solving (OF 1) is upper bounded by 11 minutes. Overall, for the most important goal – the maximization of the time-weighted sum of the numbers of volunteers assigned to task activities with the highest priority level (*red*) – in a lexicographically ordered set of objectives, optimal solutions in all scenarios and instances can be determined in less than 11 minutes (in most cases even in less than three minutes).

Figure 4 (b) reveals that for (OF 2) gaps to the optimal value vary substantially over scenarios and instances, with some patterns being observable. In four scenarios, 1–2 and 9–10, which are less complex in terms of the numbers of tasked added per time slot and the extent of capabilities of volunteers, optimal solutions are obtained in most instances; i.e., in these scenarios the (time-weighted) number of volunteers assigned to tasks of the second-highest priority class (levels *yellow* and *green*) is almost always set to the highest possible value. The remaining, more complex scenarios reveal a more diverse picture: during the medium period (instances 5–14) when many tasks and volunteers have entered the system, gaps may become quite high, which impedes the ultimate assessment of solution qualities (it is unclear whether solutions and/or upper bounds are of low quality). During early and late instances (1–4 and 15–20, respectively), the quality of gaps depends on the distribution of volunteer appearances over time. When volunteers tend to appear early ($\lambda = 7$, odd scenario numbers), assignments of volunteers to tasks become difficult in the early instances and easier in the later instances. Unsurprisingly, this difference is mirrored in low-quality solutions during early instances and almost optimal solutions during later instances. Converse results can be found when volunteers tend to appear late ($\lambda = 11$, even scenario numbers). To sum up, the quality of solutions for (OF 2) – the (time-weighted) number of volunteers assigned to *green* or *yellow* tasks – largely depends on the complexity and characteristics of the scenario and the affected instances. Although the nature of (OF 1) and (OF 2) are the same, results for (OF 2) are overly worse than those for (OF 1) as the number of (*green* or *yellow*) tasks to be considered in (OF 2) is larger than the number of *red* tasks to be considered in (OF 1).[5] The wall times required for solving (OF 2) (see Figure 7 (b) in Appendix C) show a diverse landscape, with the maximum time limit of 5 min often been fully used. While this pattern is not surprising in the presence of high gaps in many scenarios and instances, the observation of wall times and achieved gaps together reveal a more nuanced picture. In less complex scenarios (in particular scenarios 1–3 and 9–10), exploiting the time limit leads to achieving low gaps, while in the other scenarios the existence of low gaps coincides with low wall times much below the time gap of 5 min.

[5] In the Halle disaster, the number of *green* and *yellow* tasks amounted to $7 + 12 = 19$, the number of *red* tasks amounted to 8.

Figures 4 (c) and (d) show similar results for (OF 3) and (OF 4). While gaps to optimal solutions are overly much smaller than those achieved for (OF 2), results show the same relative patterns across scenarios and instances: while in the medium phase (instances 5-15), gaps can amount to almost 100%, in the remaining phases, solution qualities largely depend on the complexity of scenarios, the temporal phase (instances), and the distribution of volunteer appearances over time.

The wall times required for solving (OF 3) and (OF 4) show similar patterns across all scenarios. When gaps are low, their determination proceeds quickly; otherwise the time limit is (nearly) exploited.

6. Managerial Implications

6.1. Managerial implications for the fire department of Halle

The suggested (optimization) model for computationally supporting coordination decisions to be made by relief organizations is based upon the academic literature as well as a series of interviews with the manager of the Halle fire department. While the former analysis aims at developing a model that is widely applicable by many relief organizations (see Section 6.2), the latter approach ensures the applicability of our model for the Halle fire department, considering its specific perspective on coordinating spontaneous volunteers. As a result, the suggested model is both generic and instantiable to meet (all) the demands of the Halle fire department acquired in our empirical requirement analysis. In particular, the generic model addresses the expectations of the Halle flood department to have multiple, lexicographically ordered objectives, different priorities of tasks, goals to maximize the time-weighted sum of the number of volunteers assigned to tasks of a specified priority class ((OF 1) - (OF K)), and goals to optimize pre-specified balances of volunteer assignments ((OF $K+1$) - (OF $K+2$)). In our computational validation, we have demonstrated the applicability of our generic model to the Halle environment by instantiating the model in a way that it considers all current specific requirements, including three priority levels, two priority classes (i.e., $K = 2$), and specified ratios that allow for balanced assignments of volunteers. Our instantiation of the generic model accounts for requirements specified by the Halle fire department also by instantiating constraints (6)-(13) of the model. More precisely, this part of model instantiation involves specifying values of model parameters (see Table 4); for example, the maximum time a volunteer is allowed to work in total equals eight hours ($\bar{\tau}_{max} = 16$, which corresponds to 16 30min time slots). As a result, the Halle fire department may use our instantiated model unaltered to implement their current setting of volunteer coordination (implication 1a, see Table 7).

However, it also can (and has to) adapt the model to changing needs when objectives need to be modified (in terms of the number and order of objectives, and ratios) and/or when further parameter values change which require re-instantiating model constraints. Our model instantiation may serve as a blueprint for this process (implication 1b). However, when new or altered requirements for volunteer coordination occur which are deviate from our empirically acquired requirements (summarized in Table 1), then the instantiation of the suggested generic model needs to be substituted by a modification of the model. In this case, the Halle flood department may benefit from our implications unfolded in the succeeding subsection.

Our computational results are valid for model instantiation as it results from the requirement specification of the Halle fire department. The validity of results is also limited to those flood scenarios which we defined

Table 7
Implications for the fire department of Halle

No.	Implication
1a	The (instantiation of the generic) optimization model used in the computational experiments reflects all specific requirements expressed by the Halle fire department and can thus be used unaltered unless requirements undergo changes.
1b	The generic optimization model may (and has to) be newly instantiated when modifications of the objective functions and/or of the values of further model parameters are required. However, when new or altered requirements for volunteer coordination occur which deviate from the empirically acquired requirements, then the suggested generic model needs to be modified rather than only instantiated.
1c	Our computational results are valid for the model instantiation and the flood scenarios as they result from the specifications of the Halle fire department. When scenarios used in our computational experiments undergo substantial changes, then the Halle fire department should reconduct computational experiments using our model instantiation using adapted scenarios. The department may draw upon our computational procedure (as a methodological blueprint) to guide their experiments.
1d	When both model and scenario specifications are still valid, our computational results indicate that (a) the most important objective is achieved under all scenarios in almost all instances during a few minutes and the department is advised to use our model to optimize this objective under all scenarios; (b) they are appropriate for predicting the quality and required computation time of solutions of the remaining three objective functions, which, in turn, allows deciding when to accept or manually improve solutions (using visualization techniques) and to abort computations.

based upon data provided by the Halle fire department and some further assumptions (see Tables 5 and 6). When (some characteristics of) scenarios change substantially, then our computational results may no longer be valid and we recommend the Halle fire department to reconduct computational experiments using our model instantiation but adapting to new scenarios. Although new experiments may be required, the department can draw upon our computational procedure, which may serve as a methodological blueprint (implication 1c).

When both model and scenario specifications are still valid, our computational results indicate some recommendations for the Halle fire department (implication 1d): (1) The most important goal, the maximization of the (time weighted) number of volunteers assigned to red tasks, is achieved under all scenarios in almost all instances during a few minutes. Thus, the department is advised to use our model and the assignments of volunteers to red tasks (regardless of the results for the remaining, less important objectives). (2) The second most important goal, the maximization of the (time-weighted) number of volunteers assigned to green or yellow tasks, is achieved at different quality levels. The quality largely depends on the complexity and characteristics of the scenario and instances and can be well anticipated based on our experiments. When solution qualities are predicted to be of low quality, the Halle fire department should provide a tool for visualizing suggested assignments, which would allow decision makers to adjust generated solutions manually. As our results also indicate that in such situations, the quality of solutions does not substantially improve over time, we recommend that computations of the second objective function be aborted for the sake of increasing the computation time available for addressing objectives 3 and 4. However, when results are predicted to be of high quality, the time limit for determining solutions for the second objective function should be fully exploited as solution qualities may substantially increase over time. (3) For the two least important goals, the achievements of various balances between workloads in order to distribute volunteers according to specified ratios, the quality of results depend on the temporal phase of the disaster during which volunteers need to be coordinated and the specific characteristics of the scenario. Our identification of patterns in results allows distinguishing situations in which generated solutions can be accepted automatically (due to proven, high level of quality) from those in which solutions may be visualized and adjusted manually. The identified patterns of required wall times imply that, across all scenarios, good solutions (when achieved) are usually obtained quickly so that computations may be aborted early for the sake of increasing the computation time available for achieving objective 4 or terminating the whole decision process for the current model instance earlier.

6.2. General managerial implications

As our decision model is generic and intended to be instantiated and used by a broad range of relief organizations in various disaster situations, we suggest some general implications and recommendations for relief organizations; these are summarized in Table 8. The suggestions go beyond opportunities and needs to adapt and/or instantiate our generic model from a (model) implementation perspective, they also point to any relief organization's need for specifying their principles of volunteer coordination.

As the generic nature of the suggested mathematical model allows (and requires) relief organizations to instantiate it, prior or parallel to model instantiation as a modeling task they inherently have to specify their (potentially yet unspecified) requirements of volunteer coordination (see implication 2a). Relief organizations are recommended to align their expectations and needs with our empirically acquired requirements (see Table 1). One key task for relief organizations is to define their objectives of volunteer coordination. If their objectives are in line with our concept of urgencies of tasks, the organizations may adhere to our lexicographically ordered objective functions and instantiate these by quantifying priority levels, priority classes, and balancing factors in order to finally define all $(K + 2)$ objective functions. Otherwise, relief organizations have to redefine objective(s) (functions) and/or their relationships beyond the framework included in the generic model. For example, decision makers of relief organizations may want to remove or add new types of objectives or deviate from a lexicographic order by weighting objectives. In the latter case, other methodologies of multi-objective optimization are required, including the practically challenging determination of weights. A second key task of relief organizations is to align their constraints which apply to volunteer coordination with our assumptions on the relationships between volunteers and tasks and on the characteristics of volunteers' engagement (see Table 1). Decision makers may want to modify, remove and/or add constraints.

The instantiation of our (potentially altered) generic model requires relief organizations to fix some more values of (endogenous and exogenous) parameters, including the definition of capabilities and of the upper bound on the time that a volunteer is allowed to work (see implication 2b); Table 4 which includes a list of all model parameters, can be used as a "checklist" in this regard. It should be noticed that fixing these parameter values as a task of model implementation also requires relief organizations to previously clarify all issues that may affect parameter instantiation. For example, work times may be regulated by national laws, and

Table 8
General managerial implications

No.	Implication
2a	Relief organizations have to specify their (potentially yet unspecified) requirements of volunteer coordination. They are recommended to align their expectations and needs with our empirically acquired requirements (see Table 1). These tasks include defining their objectives of volunteer coordination as well as their constraints applying to volunteer coordination. Both objectives and constraints may deviate from our requirements and would then also need to be specified mathematically.
2b	The instantiation of the generic model requires relief organizations to fix values of several (endogenous and exogenous) parameters; Table 4) includes a list of all model parameters and may be used as a "checklist". Fixing these parameter values as a task of model implementation requires relief organizations to previously clarify all practical issues that may affect parameter instantiation.
2c	We recommend that relief organizations conduct extensive computational experiments in the preparedness phase. Insights gained into the computational behavior of the model solution process can then be used to adjust the time available for any objective function and, thereby, also an upper bound for the overall solution time. The design of our computational experiments may serve as a blueprint for relief organizations to plan and conduct these experiments.
2d	The lexicographical order of objective functions allows decision makers to exploit the sequential nature of the optimization process by making partial assignments of volunteers without having to optimize all objectives. This process of incremental decision making requires decision makers to conduct computational experiments to define rules which fit their specific needs.
2e	Decision makers need to determine the temporal characteristics of the overall planning process in terms of the number of time slots as planning horizon, the number of model instances to be solved consecutively, and the delay between two consecutive instances. Decision makers face a trade-off between the temporal grain of planning iterations and the time available to solve instances. We recommend decision makers to perform extensive computational experiments to determine temporal characteristics.

the definition of capabilities may require drawing on experience gained in prior disasters to forecast needed skills of volunteers.

Our computational results show that the quality of assignments and times required to determine volunteer assignments can substantially vary across objective functions, scenarios, and points of time at which coordination decisions need to be made. We recommend that relief organizations conduct extensive computational experiments in the preparedness phase. Insights gained into the computational behavior of the model solution process can then be used to adjust the time available for solving any objective function and, thereby, also an upper bound for the overall solution time (see implication 2c). The design of our computational experiments may serve as a blueprint for relief organizations to plan and conduct these experiments.

The lexicographical order of the objective functions in our generic model results in a "sequential nature", which can be exploited by making (partial) assignments of volunteers without having to optimize all objectives. For example, when balanced assignments of volunteers to tasks are much less important, then, the overall number of assigned volunteers, then the sequence of (disjoint) decisions resulting from optimizing (OF 1) to (OF K) (K being the number of priority classes) can be used to assign volunteers to tasks of priority class k before searching for assignments of volunteers to tasks of priority class $k+1$. The resulting process of incremental decision making contributes to the flexibility with which our optimization model can be used in practice but requires decision makers to conduct computational experiments to define rules which fit their specific needs (see implication 2d).

Our generic model allows for temporal flexibility in two regards. First, the number of time slots T as a parameter of the model can be set to a chosen value, allowing to control for the size of the time window for which each single model instance generates volunteer assignments. Second, the number of model instances i to be solved consecutively and the delay between two instances needs to be determined to define the temporal characteristics of the overall planning process. Decision makers face a trade-off between the temporal grain of planning iterations and time available to solve instances. We recommend decision makers to perform extensive computational experiments adopting a scenario approach (as applied in our computational experiments) and implementing different alternatives of temporal settings prior to determining the (final) temporal characteristics (see implication 2e).

To our best knowledge, today's coordination of spontaneous volunteers by relief organizations only rarely apply decision support models and methods of operations research like those proposed here. Although relief organizations apply a variety of information systems to coordinate professional and/or paid relief workers, the integration of volunteer coordination into these efforts is still in its infancy, despite its large need as expressed by practitioners with which the authors are connected to. When implemented in (ideally, open source) software with interfaces to existing information systems of relief organizations, our proposed optimization model and computational approach may find entrance into the application of information systems by a broad set of relief organizations. Then, it may help leverage the large potential of spontaneous volunteers to respond not only to flood disasters but to other types of disasters as well.

7. Conclusion

In this work, we address the issue of coordinating a heterogeneous and large set of spontaneous volunteers during the immediate aftermath of a disaster in the response phase. Based on empirically acquired requirements, we suggest a generic multi-objective mixed-integer linear optimization problem with lexicographically ordered objective functions, which we refer to as *spontaneous volunteers coordination problem (SVCP)*. Acknowledging that disaster situations are unavoidably linked to uncertainty, we consider uncertainty with a sequence of (deterministic) SVCP instances, where each instance depends on the solutions of previous SVCP instances. Drawing on an exact state-of-the art solver, we conduct comprehensive computational experiments based on real-world data of a flood disaster and vary several parameter values in order to control for the robustness and sensitivity of results.

From our requirement specification, mathematical model formulation, and computational experiments, we derive implications for the Halle fire department in terms of developing principles which guide their volunteer coordination, instantiating and parameterizing our generic decision support model, and conducting extensive computational experiments to control the model solution process. We also provide implications for all relief organizations which aim at adapting, adopting, and/or applying our requirements, decision support model and computational pre-evaluations for the coordination of spontaneous volunteers in a broad range of disasters. Thereby, we also address tasks to be executed during the preparedness phase of a disaster.

Our work has several limitations, which open avenues for further research. First, our computational experiments and computational results are based on a single flood case (Halle, 2013). Further computational case studies are useful to evaluate the appropriateness of our model for other model instantiations and (types of) disaster situations. Second, in the presence of high time pressure on decision makers, shorter wall time limits than that used in our study may occur. Future computational studies should be conducted to elaborate more detailed how qualities of generated schedules (regarding different goals) improve or worsen with increased or reduced wall times, respectively. When these qualities fall behind expectations, the development and application of (mat/meta)heuristics may be useful. Future research may focus on such heuristic approaches. Finally, our problem description and the resulting decision model refer to disaster situations in which (spontaneous) volunteers appear in an unpredicted way, are available only for a few hours, and are scheduled in a non-preemptive way to avoid or to reduce their turnover (intention). Future work may deviate from these assumptions, for example, to develop schedules spanning a period of several days and to achieve more effective schedules through re-scheduling volunteers, which may be useful in the presence of pre-registered, trained, and/or paid relief workers.

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A. Temporal arrangement of instances in a scenario

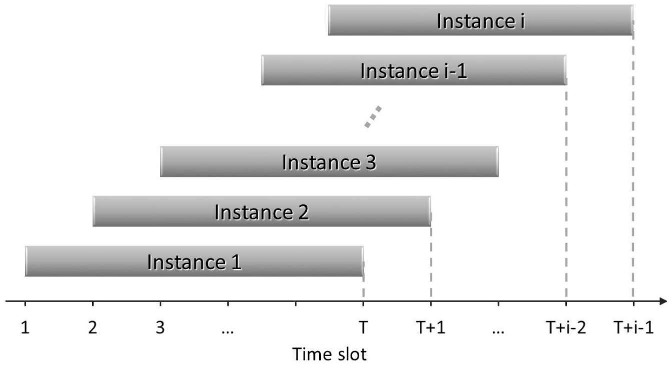

Figure 5: Temporal arrangement of instances in a scenario.

B. Data of experiments

In our experiment, we use six different capabilities, referred to as *hard physical labor*, *medium physical labor light physical labor*, *care work*, *writing*, and *care work, including one's own car*. Furthermore, we distinguish three priority levels: *green* ($p = 1$), *yellow* ($p = 2$), and *red* ($p = 3$). These levels are assigned to two priority classes (i.e., $K = 2$), resulting in the two sets $\mathcal{P}_1$ and $\mathcal{P}_2$ of priority classes. Here, the highest priority class $\mathcal{P}_2$ contains the red priority level ($p = 3$) and the lowest priority class $\mathcal{P}_1$ contains priority levels green ($p = 1$) and yellow ($p = 2$).

Due to the two priority classes, we get 4 objective functions for the model, cf. Section 4.3, with the parameter $\sigma_{1,2} = \frac{1}{3}$ for the third objective function. Based on the requirements of decision-makers, a linear decreasing importance of volunteer assignments over time is ensured by setting $w_t = 1 - \frac{t-1}{T}$. Furthermore, we set the minimum number of time slots that a volunteer must consecutively work on the same task activity to two hours, represented by $\tau_{min} = 4$, and the maximum number of time slots that a volunteer is allowed to work to eight hours, i.e. $\bar{\tau}_{max} = 16$. As described in the previous sections, we schedule on-site volunteers in an urban region of the city of Halle where travel times between two locations are not high and are estimated to be one hour on average. Thus, we use the fixed value of 1 hour for all initial travel times $\tau_{v,a}$ and for all travel times $s_{a,a'}$ to simplify our computational experiment. An overview about all task activities and required capabilities as identified in our interviews is given in Table 9.

Table 10 shows an example of how we simulated volunteers for each instance of a scenario in case that the maximum number of volunteers equals 5 000.

In addition, we had two types of tasks with three possible priority levels (see Table 11). Detailed information about tasks, task activities and required numbers of volunteers are listed in Table 12. Figure 6 visualizes the food area in Halle in 2013 and the locations of the tasks. Table 13 contains the randomly generated order of tasks for each run.

Table 9
Mapping of task activities on volunteer capability.

Task activity	Requires capability	Reason
Carrying sandbags	Hard physical labor	Interview
Filling water canister Filling sandbags	Medium physical labor	Interview
Information transfer	Light physical labor	Interview
Serving meals Care	Care work	Interview
Documentation	Writing	Interview
Movement command	Care work, including one's own car	Interview

Table 10
Sample. Simulation of newly available volunteers and V for each instance, with time slot $\lambda = 11$ and $5,000$ volunteers.

Instance	New volunteers	V
1	1	1
2	6	7
3	19	26
4	47	73
5	126	199
6	214	413
7	335	748
8	430	1178
9	551	1729
10	654	2383
11	646	3029
12	487	3516
13	454	3970
14	315	4285
15	275	4560
16	197	4757
17	115	4872
18	54	4926
19	29	4955
20	25	4980

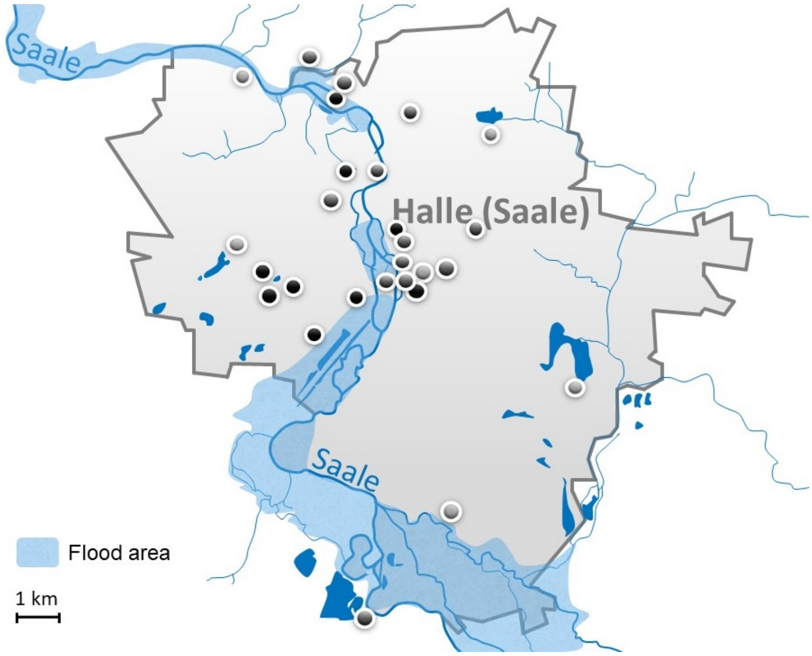

Figure 6: Flood area and location of tasks.

Table 11
Types of tasks and priority levels.

	Priority level: red ($p = 3$)	Priority level: yellow ($p = 2$)	Priority level: green ($p = 1$)
Task type: Flood control			
Task type: Food supply			

Table 12: Task activities and required numbers of volunteers.

ID	Task type	Task activities	Number of volunteers
1		Documentation	1
		Carrying sandbags	25
		Serving meals	3
2		Documentation	2
		Carrying sandbags	96
		Serving meals	10
3		Documentation	1
		Carrying sandbags	25
		Serving meals	3
4		Documentation	1
		Carrying sandbags	25
		Serving meals	3
5		Documentation	1
		Carrying sandbags	25
		Serving meals	3
6		Documentation	1
		Carrying sandbags	25
		Serving meals	3
7		Documentation	1
		Carrying sandbags	40
		Serving meals	4
15		Documentation	1
		Carrying sandbags	25
		Serving meals	3
16		Documentation	1
		Carrying sandbags	25
		Serving meals	3
17		Documentation	8
		Filling sandbags	90
		Carrying sandbags	270
		Serving meals	36
18		Documentation	22
		Filling sandbags	270
		Carrying sandbags	810
		Serving meals	108
19		Documentation	3
		Filling sandbags	30
		Carrying sandbags	90
		Serving meals	12
20		Documentation	1
		Information transfer	8
		Movement command	8
		Serving meals	8
		Care	16
21		Documentation	1
		Information transfer	8
		Movement command	8
		Serving meals	8
		Care	16

Table 12: Task activities and required numbers of volunteers. (cont'd)

ID	Task type	Task activities	Number of volunteers
8		Documentation Carrying sandbags Serving meals	1 25 3
9		Documentation Carrying sandbags Serving meals	1 25 3
10		Documentation Carrying sandbags Serving meals	1 30 3
11		Documentation Carrying sandbags Serving meals	9 440 44
12		Documentation Carrying sandbags Serving meals	1 25 3
13		Documentation Carrying sandbags Serving meals	1 25 3
14		Documentation Carrying sandbags Serving meals	1 25 3
22		Documentation Information transfer Filling water canister Serving meals Care	1 8 8 8 16
23		Documentation Serving meals	1 25
24		Documentation Serving meals	1 25
25		Documentation Serving meals	1 25
26		Documentation Serving meals	1 25
27		Documentation Serving meals	1 25

Table 13
Randomly generated orders of task IDs for different runs.

Run	List oft task ID's
1	$\{12, 13, 17, 11, 24, 23, 3, 15, 20, 4, 2, 19, 21, 14, 5, 9, 26, 27, 10, 7, 22, 16, 6, 8, 1, 25, 18\}$
2	$\{19, 13, 15, 25, 10, 16, 23, 11, 7, 18, 14, 8, 17, 20, 24, 5, 12, 4, 22, 26, 9, 6, 1, 21, 27, 2, 3\}$
3	$\{22, 21, 25, 20, 16, 11, 15, 5, 6, 9, 14, 23, 3, 18, 27, 7, 10, 26, 24, 1, 2, 24, 4, 13, 17, 8, 12\}$
4	$\{15, 17, 26, 25, 20, 18, 11, 13, 5, 4, 2, 9, 6, 12, 23, 22, 24, 21, 7, 10, 3, 8, 14, 27, 19, 1, 16\}$
5	$\{25, 21, 6, 1, 18, 11, 24, 23, 4, 3, 22, 9, 26, 16, 14, 7, 12, 10, 2, 13, 19, 27, 8, 20, 17, 5, 15\}$
6	$\{[26, 20, 9, 7, 1, 3, 14, 18, 16, 25, 19, 17, 22, 11, 6, 2, 13, 4, 24, 12, 10, 15, 23, 5, 27, 8, 21\}$
7	$\{25, 15, 2, 3, 21, 6, 22, 4, 24, 26, 1, 7, 10, 27, 18, 20, 17, 14, 16, 12, 5, 23, 13, 9, 11, 8, 19\}$
8	$\{27, 13, 12, 4, 3, 16, 22, 26, 15, 18, 21, 8, 9, 7, 1, 6, 2, 19, 10, 23, 24, 25, 20, 17, 5, 11, 14\}$
9	$\{14, 18, 13, 6, 27, 10, 16, 19, 5, 8, 22, 25, 15, 9, 26, 17, 1, 7, 21, 4, 23, 2, 12, 3, 20, 11, 24\}$
10	$\{1, 21, 10, 23, 5, 17, 26, 14, 22, 4, 20, 13, 25, 12, 27, 3, 19, 16, 11, 15, 9, 7, 6, 24, 8, 18, 2\}$

C. Results of experiments: Gaps to optimality and wall times

In this part of the Appendix, we provide the detailed results of our computational experiments in terms of the gaps to optimal values (in percent) and wall times (in seconds) needed for achieving these gaps; results are provided for each of the four objective functions.

Tables 14–17 show, for each of the four objective functions, the gaps to optimality. Each table entry can be interpreted as follows: *opt* means that in all ten runs the relative optimality gap was below 0.01% so that the corresponding solution is considered to be optimal.[6] In case at least one of the ten runs exceeded the gap, we provide the average gap over all ten runs; superscript values indicate the number of runs in which the abovementioned gap was exceeded and the corresponding solution was not considered optimal.[7] Figure 7 shows, for each of the four objective functions, the average wall times required to find the solutions, averaged over all ten runs. In Figure 8, wall times required for the initial presolve and for the complete model are shown. Tables 18–23 provide the corresponding figures. In a few runs, the Gurobi solver could not find a feasible solution for at least one instance. These issues varied across different configurations of the solver, which leads us to conclude that these issues are of numerical nature. We did not consider those runs in our evaluations; Table 24 lists the numbers of finally considered runs per scenario.

[6]Note that instances might not have been solved to optimality although the gap was below 0.01%.
[7]The solution might be optimal but without proof of optimality.

Table 14
Gaps to optimal values for objective function 1 [in %], with a wall time of 5 min.

Scenario	Instances									
No.	1	2	3	4	5	6	7	8	9	10
1	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
2	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
3	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
4	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
5	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
6	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
7	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
8	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
9	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
10	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
11	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
12	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
13	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
14	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
15	opt.	opt.	opt.	opt.	opt.	opt.	0.15^{1}	0.15^{1}	2.31^{3}	2.67^{1}
16	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	0.00^{1}	0.69^{1}

Scenario	Instances									
No.	11	12	13	14	15	16	17	18	19	20
1	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
2	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
3	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
4	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
5	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
6	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
7	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
8	opt.	74.04^{1}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
9	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
10	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
11	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
12	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
13	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
14	opt.	1.14^{1}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
15	0.65^{2}	306^{2}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
16	0.80^{3}	228^{5}	0.72^{3}	opt.	opt.	opt.	opt.	opt.	opt.	opt.

Table 15
Gaps to optimal values for objective function 2 [in %], with a wall time of 5 min.

Scenario	Instances									
No.	1	2	3	4	5	6	7	8	9	10
1	opt.	1.01^{2}	5.72^{5}	0.17^{3}	0.00^{2}	0.56^{2}	3.36^{2}	0.14^{4}	0.02^{2}	0.01^{1}
2	opt.	opt.	opt.	opt.	1.20^{3}	121^{3}	2.35^{5}	0.24^{6}	0.73^{4}	5.04^{5}
3	opt.	1.68^{2}	$*^{4}$	opt.	0.61^{1}	45.97^{2}	0.03^{2}	0.04^{3}	opt.	opt.
4	opt.	opt.	opt.	opt.	3.95^{2}	$*^{5}$	2.84^{6}	137^{5}	736^{3}	134^{4}
5	opt.	opt.	154^{4}	3.53^{6}	12.52^{5}	521^{5}	679^{5}	208^{5}	522^{6}	296^{4}
6	opt.	opt.	opt.	opt.	opt.	100^{4}	515^{5}	$*^{5}$	$*^{5}$	531^{5}
7	opt.	0.77^{1}	$*^{7}$	105^{6}	410^{6}	978^{6}	$*^{8}$	$*^{7}$	$*^{8}$	$*^{7}$
8	opt.	opt.	opt.	0.84^{1}	871^{5}	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$
9	opt.	0.59^{4}	0.09^{1}	1.15^{1}	1.24^{2}	0.16^{1}	0.01^{1}	0.10^{2}	0.03^{1}	0.01^{3}
10	opt.	opt.	opt.	0.92^{2}	35.58^{7}	1.15^{5}	0.02^{1}	13.36^{4}	198^{5}	37.02^{4}
11	opt.	0.87^{6}	0.15^{1}	24.26^{3}	152^{3}	22.61^{1}	729^{2}	$*^{3}$	$*^{1}$	$*^{2}$
12	opt.	opt.	opt.	0.06^{1}	$*^{5}$	66.32^{7}	$*^{5}$	$*^{6}$	398^{5}	239^{5}
13	opt.	0.88^{2}	1.48^{4}	16.87^{2}	602^{4}	80.42^{3}	131^{5}	$*^{4}$	$*^{4}$	$*^{4}$
14	opt.	opt.	opt.	1.32^{3}	$*^{7}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$
15	opt.	$*^{2}$	306^{3}	$*^{4}$	392^{5}	$*^{4}$	$*^{4}$	$*^{4}$	$*^{4}$	$*^{4}$
16	opt.	opt.	opt.	5.29^{6}	$*^{9}$	$*^{10}$	999^{10}	$*^{10}$	$*^{10}$	$*^{10}$

Scenario	Instances									
No.	11	12	13	14	15	16	17	18	19	20
1	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
2	0.01^{1}	23.17^{2}	0.14^{5}	0.20^{2}	opt.	opt.	opt.	opt.	opt.	opt.
3	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
4	115^{3}	163^{3}	$*^{4}$	$*^{4}$	$*^{3}$	346^{3}	356^{3}	262^{3}	0.15^{3}	opt.
5	337^{4}	338^{2}	397^{2}	124^{1}	opt.	opt.	opt.	opt.	opt.	opt.
6	725^{5}	$*^{5}$	$*^{5}$	$*^{5}$	$*^{5}$	$*^{5}$	$*^{5}$	0.38^{5}	opt.	opt.
7	$*^{7}$	$*^{7}$	335^{7}	$*^{5}$	0.05^{1}	opt.	opt.	opt.	opt.	opt.
8	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{7}$	opt.
9	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
10	754^{3}	32.89^{4}	26.80^{4}	29.28^{4}	30.77^{5}	32.54^{5}	36.99^{3}	26.36^{2}	0.04^{1}	opt.
11	472^{1}	461^{1}	10.37^{1}	12.64^{1}	0.01^{1}	opt.	opt.	opt.	opt.	opt.
12	$*^{4}$	$*^{5}$	$*^{5}$	$*^{5}$	$*^{4}$	$*^{4}$	$*^{4}$	$*^{4}$	181^{4}	27.02^{3}
13	$*^{3}$	54.55^{2}	77.39^{2}	64.52^{2}	0.01^{1}	opt.	opt.	opt.	opt.	opt.
14	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	848^{10}	968^{10}
15	$*^{5}$	$*^{4}$	$*^{4}$	$*^{4}$	334^{4}	279^{4}	29.28^{1}	opt.	opt.	opt.
16	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$	$*^{10}$

Agenda: $*$ . . . indicates a value $> 1,000$.

Table 16
Gaps to optimal values for objective function 3 [in %], with a wall time of 5 min.

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	opt.	5.96^{2}	17.42^{5}	7.59^{4}	1.36^{2}	10.00^{3}	7.88^{4}	4.18^{5}	4.86^{4}	0.16^{1}
2	opt.	opt.	opt.	opt.	32.79^{3}	18.96^{3}	38.37^{6}	34.67^{6}	22.90^{6}	28.74^{6}
3	opt.	23.86^{3}	45.41^{4}	20.31^{2}	15.69^{3}	11.81^{2}	7.22^{3}	2.95^{4}	0.12^{1}	1.05^{3}
4	opt.	opt.	opt.	opt.	33.34^{3}	75.02^{6}	79.83^{6}	54.79^{6}	33.92^{5}	59.58^{4}
5	opt.	7.01^{1}	26.39^{6}	59.99^{7}	53.44^{6}	45.64^{6}	24.70^{7}	38.60^{5}	49.91^{6}	26.81^{6}
6	opt.	opt.	opt.	opt.	0.97^{1}	65.03^{5}	75.59^{5}	43.64^{5}	54.26^{5}	85.22^{5}
7	opt.	11.26^{3}	69.85^{8}	58.60^{7}	61.61^{8}	58.93^{7}	62.00^{8}	72.10^{8}	67.71^{8}	70.21^{8}
8	opt.	opt.	opt.	0.23^{1}	42.33^{7}	89.25^{10}	64.48^{10}	50.01^{10}	85.58^{10}	86.68^{10}
9	opt.	31.73^{7}	4.18^{2}	13.43^{2}	4.72^{2}	15.00^{3}	0.84^{3}	2.04^{2}	opt.	3.09^{4}
10	opt.	opt.	opt.	6.17^{2}	51.08^{7}	53.91^{6}	11.43^{5}	28.90^{6}	34.50^{7}	18.24^{6}
11	opt.	65.60^{7}	9.67^{2}	18.16^{3}	23.59^{3}	17.05^{3}	10.31^{4}	9.87^{4}	6.95^{2}	3.57^{3}
12	opt.	opt.	opt.	5.86^{2}	52.06^{6}	70.76^{7}	43.16^{6}	40.91^{6}	24.19^{5}	26.30^{5}
13	opt.	22.53^{3}	43.57^{3}	17.98^{4}	26.23^{5}	23.63^{4}	40.57^{5}	27.11^{4}	11.72^{4}	25.81^{5}
14	opt.	opt.	opt.	13.34^{4}	41.94^{9}	52.69^{10}	38.44^{10}	46.73^{10}	62.09^{10}	65.03^{10}
15	opt.	36.10^{4}	65.20^{4}	73.67^{5}	58.16^{4}	59.32^{4}	59.80^{5}	63.87^{4}	74.15^{4}	56.96^{4}
16	opt.	opt.	opt.	22.00^{5}	92.40^{10}	62.01^{10}	66.10^{10}	90.90^{10}	83.46^{10}	65.57^{10}

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	0.26^{1}	0.04^{1}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
2	15.17^{5}	9.89^{5}	20.33^{6}	16.11^{4}	1.41^{3}	0.30^{3}	0.01^{1}	opt.	opt.	opt.
3	0.06^{2}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
4	45.21^{4}	43.01^{5}	47.27^{4}	43.65^{5}	35.20^{5}	32.97^{4}	38.50^{4}	35.01^{4}	48.37^{3}	opt.
5	18.68^{5}	16.98^{2}	26.75^{2}	0.01^{1}	opt.	opt.	opt.	opt.	opt.	opt.
6	63.81^{5}	97.45^{5}	67.98^{5}	79.91^{5}	68.02^{5}	64.45^{5}	60.33^{5}	98.71^{5}	0.24^{1}	opt.
7	64.21^{8}	62.27^{7}	50.58^{7}	24.96^{6}	20.56^{3}	opt.	opt.	opt.	opt.	opt.
8	81.26^{10}	90.27^{10}	99.13^{10}	99.39^{10}	99.58^{10}	90.76^{10}	35.00^{9}	27.63^{8}	70.09^{9}	7.43^{1}
9	0.09^{1}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
10	13.61^{5}	12.18^{6}	5.76^{4}	9.85^{7}	2.48^{6}	4.07^{4}	6.70^{3}	14.55^{3}	11.45^{2}	opt.
11	2.71^{2}	1.32^{4}	1.89^{1}	3.73^{1}	10.78^{1}	opt.	opt.	opt.	opt.	opt.
12	19.38^{4}	23.75^{5}	21.02^{4}	14.22^{6}	16.82^{5}	32.83^{4}	15.33^{5}	17.64^{4}	7.17^{4}	27.04^{3}
13	6.74^{6}	4.30^{2}	17.99^{2}	16.83^{2}	15.45^{1}	opt.	opt.	opt.	opt.	opt.
14	47.61^{10}	76.04^{10}	71.81^{10}	44.96^{10}	44.41^{10}	46.33^{10}	46.76^{10}	55.39^{10}	48.58^{8}	12.88^{6}
15	74.10^{4}	69.43^{5}	65.03^{4}	68.75^{4}	74.69^{4}	52.72^{4}	22.66^{2}	opt.	opt.	opt.
16	72.67^{10}	95.74^{10}	99.32^{10}	70.57^{10}	80.48^{10}	76.98^{10}	81.57^{10}	79.68^{10}	83.87^{10}	66.57^{9}

Table 17
Gaps to optimal values for objective function 4 [in %], with a wall time of 5 min.

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	0.09^{1}	12.72^{5}	20.83^{8}	3.28^{7}	14.59^{6}	14.57^{5}	6.83^{5}	21.01^{5}	13.36^{5}	1.60^{4}
2	opt.	opt.	opt.	0.09^{1}	19.50^{6}	28.68^{8}	16.72^{7}	51.72^{6}	57.91^{7}	37.70^{7}
3	7.21^{4}	14.04^{5}	34.89^{7}	15.12^{4}	16.75^{4}	38.64^{5}	22.51^{3}	18.00^{5}	6.04^{4}	1.75^{4}
4	opt.	opt.	0.99^{1}	2.46^{1}	20.20^{4}	81.98^{6}	93.12^{6}	55.46^{6}	43.42^{6}	52.93^{5}
5	0.12^{1}	2.62^{3}	29.31^{6}	47.58^{7}	40.68^{5}	39.34^{7}	70.86^{7}	44.89^{7}	62.74^{6}	46.91^{6}
6	opt.	opt.	0.42^{1}	0.54^{2}	20.33^{3}	76.83^{5}	56.89^{5}	58.74^{5}	25.95^{5}	40.81^{5}
7	7.18^{4}	10.10^{5}	81.72^{7}	69.27^{7}	55.29^{8}	51.51^{7}	72.26^{8}	79.62^{8}	83.65^{8}	80.62^{8}
8	opt.	opt.	2.08^{1}	4.37^{4}	44.44^{10}	60.70^{10}	62.19^{10}	56.87^{10}	90.31^{10}	89.73^{10}
9	1.00^{4}	20.61^{8}	1.26^{3}	6.07^{3}	12.17^{3}	22.19^{3}	25.40^{4}	20.84^{4}	20.97^{3}	35.22^{4}
10	opt.	opt.	opt.	10.22^{5}	33.69^{9}	41.09^{9}	28.91^{7}	15.01^{6}	58.62^{8}	46.70^{7}
11	3.89^{4}	33.17^{9}	1.86^{2}	7.79^{3}	19.69^{3}	10.34^{3}	42.12^{6}	23.68^{5}	20.99^{5}	21.45^{5}
12	opt.	opt.	opt.	4.90^{5}	70.54^{6}	72.80^{7}	62.65^{7}	63.93^{6}	48.58^{6}	49.71^{5}
13	1.40^{3}	22.32^{5}	22.34^{6}	19.92^{5}	59.76^{5}	54.59^{6}	52.21^{5}	66.02^{6}	40.75^{5}	66.40^{6}
14	opt.	opt.	opt.	20.20^{8}	90.24^{10}	66.58^{9}	58.38^{10}	50.08^{10}	75.16^{10}	94.36^{10}
15	5.64^{3}	45.49^{5}	48.16^{4}	50.55^{5}	66.31^{5}	69.71^{4}	68.57^{5}	71.21^{5}	74.50^{4}	86.61^{5}
16	opt.	0.54^{1}	1.64^{2}	30.05^{8}	89.88^{10}	56.58^{10}	66.41^{10}	95.41^{10}	94.11^{10}	84.10^{10}

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	1.54^{5}	0.03^{1}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
2	37.09^{6}	39.15^{7}	37.40^{7}	16.87^{7}	17.72^{7}	13.75^{5}	13.48^{4}	0.27^{1}	opt.	opt.
3	2.55^{2}	0.84^{2}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
4	43.90^{5}	41.55^{4}	58.36^{5}	74.97^{6}	45.08^{5}	41.38^{5}	48.68^{5}	47.83^{4}	41.00^{3}	opt.
5	65.97^{7}	41.14^{5}	12.02^{2}	9.89^{1}	0.16^{1}	opt.	opt.	opt.	opt.	opt.
6	81.66^{5}	91.15^{5}	93.43^{5}	94.63^{5}	81.59^{5}	69.58^{5}	55.47^{5}	71.12^{2}	0.05	opt.
7	82.55^{8}	75.77^{7}	60.85^{7}	56.03^{6}	16.06^{3}	opt.	opt.	opt.	opt.	opt.
8	94.87^{10}	95.19^{10}	94.91^{10}	95.40^{10}	95.26^{10}	89.54^{10}	74.60^{9}	63.59^{9}	52.05^{9}	7.07^{1}
9	1.98^{3}	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.	opt.
10	33.35^{6}	53.23^{8}	51.98^{7}	40.03^{7}	23.89^{7}	24.40^{6}	21.24^{5}	15.05^{2}	2.87^{1}	opt.
11	22.80^{4}	21.14^{3}	11.09^{1}	7.36^{1}	10.95^{1}	opt.	opt.	opt.	opt.	opt.
12	55.48^{5}	63.25^{6}	54.84^{5}	79.52^{7}	53.46^{5}	54.65^{5}	60.84^{6}	47.22^{4}	48.18^{5}	35.15^{3}
13	59.38^{5}	29.85^{3}	28.04^{3}	23.92^{2}	12.25^{1}	opt.	opt.	opt.	opt.	opt.
14	89.93^{10}	92.80^{10}	93.97^{10}	91.08^{10}	91.98^{10}	92.71^{10}	92.69^{10}	86.48^{10}	60.58^{10}	34.16^{9}
15	80.27^{5}	75.26^{5}	70.34^{4}	73.02^{4}	60.56^{4}	43.67^{4}	8.24^{2}	opt.	opt.	opt.
16	90.23^{10}	93.19^{10}	94.78^{10}	87.89^{10}	92.22^{10}	96.03^{10}	95.46^{10}	92.66^{10}	92.51^{10}	78.02^{10}

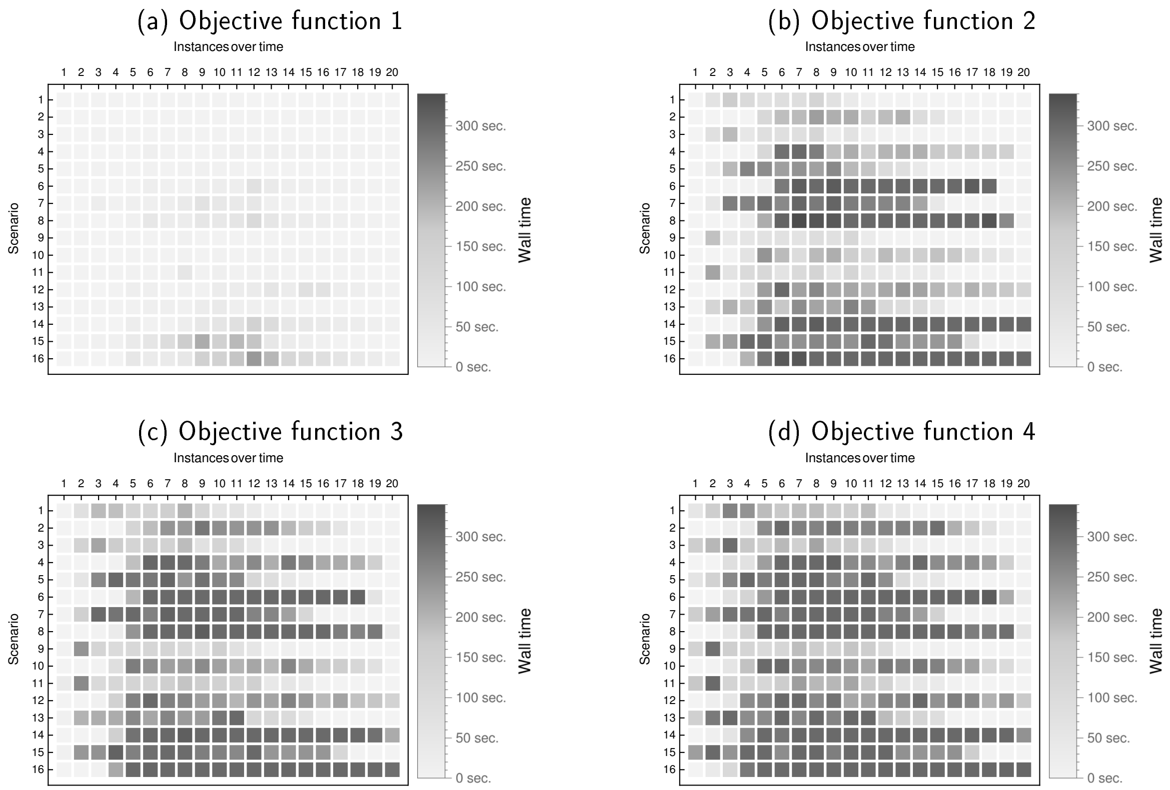

Figure 7: Wall times for all objective functions [in sec.], with a wall time of 5 min.

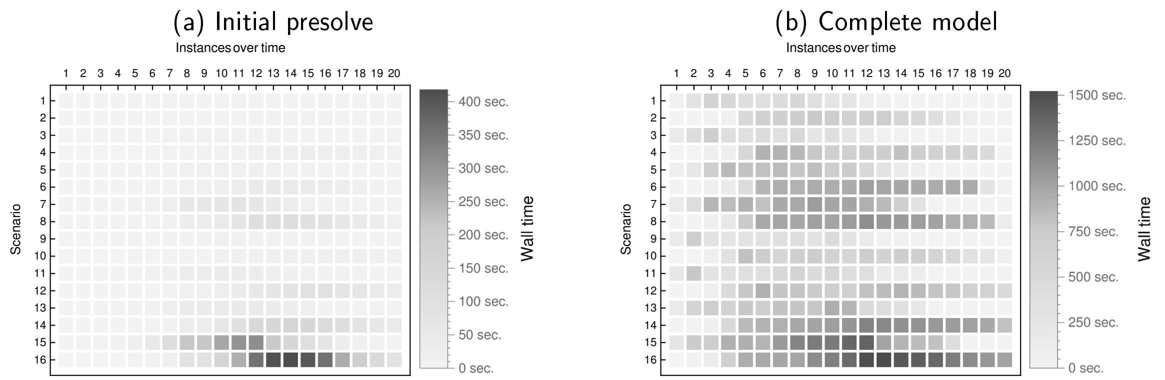

Figure 8: Wall times for initial presolve and the complete model [in sec.].

Table 18
Wall times for initial presolve [in sec.].

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	0.07	0.18	0.57	0.89	1.42	2.26	3.07	4.43	4.43	4.62
2	0.00	0.02	0.10	0.18	0.42	1.07	1.42	3.25	3.25	3.93
3	0.10	0.30	1.16	1.61	2.52	3.90	5.20	8.24	8.24	8.79
4	0.00	0.03	0.15	0.27	0.69	2.19	3.03	6.54	6.54	9.51
5	0.07	0.22	1.02	1.97	3.57	5.90	9.44	15.51	15.51	17.06
6	0.00	0.03	0.16	0.31	0.87	2.58	4.16	13.49	13.49	19.81
7	0.10	0.39	1.87	3.86	7.97	15.80	27.95	64.77	64.77	66.92
8	0.00	0.04	0.19	0.51	1.66	6.01	9.99	30.72	30.72	47.85
9	0.12	0.41	0.77	1.63	2.88	5.06	7.49	11.69	11.69	13.32
10	0.01	0.05	0.14	0.29	1.09	1.63	2.42	6.37	6.37	10.62
11	0.15	0.78	1.51	3.10	5.72	14.65	22.27	37.42	37.42	43.18
12	0.01	0.06	0.21	0.54	2.04	3.39	4.94	16.62	16.62	27.75
13	0.12	0.54	1.51	3.23	7.26	14.31	22.96	41.83	41.83	49.08
14	0.01	0.06	0.20	0.50	2.21	4.39	9.21	35.80	35.80	61.66
15	0.15	1.15	3.05	8.66	20.60	50.70	109.95	218.25	218.25	269.32
16	0.01	0.08	0.29	0.93	4.55	9.89	18.43	89.32	89.32	160.28

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	4.66	4.39	4.02	3.64	3.06	2.63	2.12	1.69	1.29	1.00
2	4.96	6.06	6.69	7.01	6.88	6.76	6.49	5.61	5.04	4.33
3	8.76	7.88	7.34	6.53	5.68	4.80	3.97	3.11	2.45	1.91
4	15.68	19.42	26.38	27.87	29.52	27.06	23.07	19.78	15.80	8.01
5	16.96	16.83	14.12	10.41	6.72	5.01	3.74	2.65	1.97	1.33
6	30.51	47.44	51.60	48.02	42.46	35.56	30.91	21.80	7.95	6.09
7	77.73	71.79	48.59	29.70	16.28	9.56	7.14	5.14	3.72	2.64
8	76.14	109.40	112.37	111.59	99.92	83.64	63.35	46.60	29.01	12.60
9	12.68	11.28	10.15	8.91	7.35	6.04	4.72	3.78	3.04	2.24
10	14.30	16.88	19.14	20.63	22.50	22.27	21.36	19.18	14.42	9.87
11	36.51	33.83	24.81	20.40	17.15	10.90	8.50	6.95	5.38	4.09
12	41.06	56.86	69.72	78.28	96.42	90.60	74.70	67.14	49.52	35.12
13	50.72	47.86	39.44	30.19	18.12	10.92	8.24	6.04	4.44	2.95
14	100.11	143.66	152.83	155.57	150.13	131.40	110.99	86.91	64.53	46.46
15	301.63	310.08	213.43	148.03	108.60	75.74	32.35	13.17	8.07	5.83
16	256.09	354.95	409.41	417.37	400.99	358.04	261.75	196.62	133.21	89.38

Table 19
Wall times for objective function 1 [in sec.], with a wall time of 5 min.

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	0.04	0.33	2.23	1.02	0.76	1.45	0.87	3.24	1.01	1.62
2	0.00	0.01	0.05	0.15	0.79	3.44	1.47	2.41	2.04	2.94
3	0.08	0.78	5.95	2.50	1.53	1.71	1.26	5.11	1.49	2.03
4	0.00	0.01	0.10	0.34	4.36	17.41	5.80	3.85	5.09	5.94
5	0.06	0.41	9.14	2.83	5.13	6.58	4.77	5.99	10.29	7.72
6	0.00	0.02	0.12	0.38	2.07	22.03	11.44	8.02	18.77	23.06
7	0.08	0.80	24.08	7.96	15.15	14.26	20.24	40.50	75.54	47.02
8	0.00	0.01	0.16	0.56	9.76	52.85	30.85	30.55	55.02	48.86
9	0.12	2.52	0.64	1.32	1.36	3.37	1.45	13.94	2.37	5.06
10	0.00	0.02	0.10	0.43	5.00	2.67	1.38	5.64	2.58	6.77
11	0.24	3.28	1.33	5.06	6.87	7.88	5.70	55.19	8.73	14.59
12	0.00	0.04	0.22	1.03	20.26	14.26	4.38	12.78	9.23	29.71
13	0.15	2.40	4.58	3.96	8.22	17.87	18.09	13.25	30.82	38.97
14	0.00	0.03	0.18	0.69	23.99	8.30	9.30	23.38	51.52	62.41
15	0.14	4.95	10.01	10.13	37.88	55.77	94.54	168.98	212.43	149.10
16	0.00	0.04	0.32	4.45	53.91	32.50	38.56	52.38	148.45	145.28

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	0.98	0.77	0.72	0.61	0.46	0.40	0.32	0.24	0.20	0.16
2	1.61	2.06	2.03	1.90	1.35	1.47	1.21	1.07	0.85	0.72
3	1.51	1.24	1.21	0.97	0.80	0.66	0.60	0.42	0.33	0.29
4	14.19	12.94	16.10	10.95	12.71	12.98	7.02	5.90	3.20	1.18
5	5.84	3.81	2.89	1.76	0.93	0.74	0.52	0.35	0.27	0.19
6	21.47	76.82	37.35	20.59	16.87	13.15	11.13	6.59	1.37	1.04
7	44.52	53.46	14.91	5.70	2.28	1.16	0.97	0.64	0.45	0.36
8	61.33	109.06	54.61	34.55	30.07	23.87	18.35	12.69	6.47	1.85
9	2.79	1.72	1.70	1.32	1.03	0.89	0.69	0.55	0.44	0.32
10	4.94	6.02	9.15	6.16	9.42	8.12	5.80	6.88	2.64	1.43
11	8.31	11.57	10.65	3.55	3.52	1.46	1.11	0.91	0.71	0.56
12	27.79	36.22	59.05	29.97	84.67	73.55	24.00	21.28	9.98	6.96
13	14.87	17.38	12.67	5.45	2.56	1.46	1.09	0.80	0.65	0.42
14	81.70	143.93	99.67	51.22	46.85	37.00	31.13	23.58	16.31	11.02
15	195.85	179.22	49.93	29.73	18.75	10.81	4.10	1.48	0.99	0.73
16	180.15	237.72	197.94	124.72	103.28	88.22	60.32	43.47	28.88	17.76

Table 20
Wall times for objective function 2 [in sec.], with a wall time of 5 min.

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	0.16	68.26	167.92	108.11	71.93	89.49	91.77	136.93	79.97	37.61
2	0.00	0.01	0.20	0.79	120.29	189.00	192.61	231.99	208.32	211.44
3	0.37	81.18	192.79	52.73	88.02	86.19	85.76	125.16	29.28	72.11
4	0.00	0.02	0.48	2.38	120.33	292.82	300.24	274.03	189.61	211.24
5	0.20	38.39	195.78	267.77	253.78	229.92	245.83	227.76	258.72	195.88
6	0.00	0.02	1.42	2.46	22.46	279.54	315.85	300.48	319.49	300.16
7	0.37	51.29	273.68	265.65	294.26	259.32	306.19	278.82	306.74	277.25
8	0.00	0.02	3.79	33.12	211.21	308.47	339.77	327.16	321.75	300.57
9	0.89	185.36	47.03	61.48	75.24	78.76	68.16	96.26	82.67	120.94
10	0.01	0.06	2.33	69.96	245.14	192.48	101.43	194.79	210.60	161.83
11	2.08	224.11	69.90	108.54	116.18	67.55	109.26	135.96	64.87	131.46
12	0.01	0.09	2.50	72.07	232.37	302.24	227.42	260.95	217.72	219.86
13	0.77	129.48	205.60	176.52	253.43	175.43	253.94	223.59	217.39	267.93
14	0.01	0.05	4.17	100.16	244.36	311.81	302.68	316.80	300.73	300.74
15	0.56	211.02	229.94	300.32	300.41	247.85	248.92	261.87	263.52	249.19
16	0.00	0.09	7.42	202.90	286.66	323.70	326.24	301.06	302.33	302.40

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	11.06	2.85	2.21	0.87	0.21	0.11	0.07	0.02	0.01	0.02
2	153.42	190.61	206.79	101.27	65.05	31.66	9.87	2.84	1.22	0.77
3	19.60	6.35	2.26	1.67	0.60	0.20	0.22	0.13	0.04	0.19
4	167.89	200.34	207.73	205.93	173.43	166.55	168.00	156.44	151.38	1.59
5	179.16	103.21	87.89	44.24	1.87	0.36	0.15	0.03	0.04	0.04
6	300.19	300.73	300.70	300.78	300.21	300.16	316.18	300.58	5.09	1.23
7	268.54	263.33	267.02	221.26	48.54	0.46	0.47	0.17	0.08	0.27
8	302.08	302.91	301.89	301.55	300.61	300.86	300.26	327.29	258.59	20.37
9	32.16	9.45	3.58	5.00	1.17	0.51	0.15	0.05	0.06	0.02
10	118.28	193.12	162.95	158.80	184.25	174.35	115.85	71.59	37.67	2.25
11	63.50	49.43	39.28	38.92	35.10	0.77	0.16	0.10	0.07	0.06
12	196.33	217.89	240.44	224.34	197.67	177.54	206.33	178.36	174.80	132.86
13	232.79	117.08	102.17	101.40	51.54	0.76	0.17	0.05	0.11	0.02
14	302.15	302.64	303.20	302.02	301.75	300.72	300.67	300.67	300.77	301.84
15	303.21	288.12	241.58	241.04	240.76	241.63	102.13	0.30	0.04	0.08
16	302.93	304.49	305.00	303.07	302.84	303.19	301.72	302.04	301.80	300.61

Table 21
Wall times for objective function 3 [in sec.], with a wall time of 5 min.

Scenario No.	Instances 1	2	3	4	5	6	7	8	9	10
1	1.80	84.57	192.37	185.78	135.44	129.74	156.72	205.40	130.33	63.05
2	0.00	0.10	0.73	3.67	129.46	190.10	245.23	237.55	283.78	251.08
3	4.69	139.38	222.83	169.03	135.39	153.02	143.01	191.10	78.29	134.23
4	0.00	0.05	0.78	8.00	186.22	302.87	301.80	300.55	276.30	214.94
5	1.71	58.97	259.16	302.17	283.49	281.43	302.69	240.86	291.16	265.30
6	0.00	0.03	0.63	6.04	198.08	300.65	300.90	300.24	300.70	300.27
7	4.65	153.21	300.32	286.65	300.17	269.70	308.57	300.45	300.63	301.01
8	0.00	0.12	1.23	36.25	245.17	301.04	303.06	302.14	316.90	300.62
9	8.49	245.43	132.89	104.61	118.10	128.78	132.57	115.12	86.39	155.10
10	0.03	0.51	4.10	87.12	275.49	253.99	229.64	233.32	256.40	227.14
11	38.75	257.42	109.51	120.62	133.70	125.69	156.05	181.14	160.44	148.88
12	0.02	0.30	12.75	143.31	269.20	300.68	269.76	263.36	232.80	237.16
13	12.49	204.02	209.70	213.44	259.28	220.48	264.03	234.98	232.66	283.49
14	0.04	0.26	8.65	153.72	290.35	301.87	302.31	314.50	301.60	301.35
15	13.95	240.16	247.03	309.22	271.88	293.91	300.88	297.42	274.16	270.03
16	0.02	0.65	7.13	216.63	301.23	304.54	301.30	300.56	301.16	301.14

Scenario No.	Instances 11	12	13	14	15	16	17	18	19	20
1	68.03	37.42	5.91	1.32	0.37	0.15	0.09	0.03	0.02	0.02
2	243.01	245.73	247.99	197.16	164.74	139.14	60.92	15.80	3.08	2.09
3	105.65	47.97	9.36	3.04	1.72	0.33	0.37	0.15	0.05	0.10
4	231.24	259.62	210.37	281.03	252.53	215.60	213.52	205.54	152.42	6.95
5	258.95	124.52	89.83	45.53	18.88	0.45	0.21	0.04	0.03	0.03
6	300.64	301.04	300.37	301.13	300.50	302.72	300.49	306.70	66.64	4.21
7	302.41	267.84	265.26	227.25	123.80	1.00	0.82	0.20	0.08	0.28
8	301.82	302.07	301.07	300.78	301.39	300.65	274.41	266.24	280.35	36.66
9	79.29	55.01	7.38	15.87	4.30	0.72	0.15	0.05	0.06	0.02
10	203.12	220.81	196.71	264.62	214.32	174.11	164.38	124.11	80.26	7.53
11	135.96	153.55	46.27	54.58	35.86	1.01	0.18	0.10	0.08	0.07
12	200.66	243.57	224.11	267.79	237.37	194.56	222.87	184.07	178.30	141.40
13	300.26	121.39	119.49	103.98	58.16	1.94	0.18	0.03	0.19	0.02
14	300.99	301.51	301.21	301.07	300.94	300.72	300.44	300.57	291.50	214.65
15	260.25	301.22	241.86	241.00	245.22	242.63	123.15	0.88	0.03	0.07
16	301.63	303.51	301.99	303.34	301.41	301.19	301.32	302.16	300.61	293.91

Table 22
Wall times for objective function 4 [in sec.], with a wall time of 5 min.

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	56.60	162.24	267.52	246.37	191.04	174.49	190.50	192.08	169.92	160.82
2	0.00	0.66	24.72	53.87	256.27	300.44	270.81	266.71	284.02	273.89
3	164.21	198.37	297.04	175.76	154.90	196.08	151.96	224.14	166.29	169.17
4	0.00	0.25	86.78	75.08	231.26	300.51	300.09	301.76	309.76	257.96
5	65.67	142.73	260.93	301.72	275.79	300.61	302.04	301.93	265.83	261.65
6	0.00	0.30	75.23	135.16	238.36	300.10	300.08	300.67	300.62	305.15
7	164.16	230.58	285.82	287.00	303.38	270.50	300.89	300.83	301.31	300.77
8	0.00	1.82	58.40	150.03	300.45	304.22	302.08	304.02	300.78	301.77
9	141.04	292.83	156.36	129.70	107.50	125.05	188.48	164.34	149.05	179.41
10	0.11	3.22	60.45	183.43	300.45	300.51	261.04	260.02	271.75	239.94
11	175.48	300.10	137.66	129.91	123.33	167.73	231.18	196.76	198.35	222.24
12	0.07	20.87	56.94	254.93	266.28	300.10	300.10	259.27	288.58	219.84
13	151.61	279.34	300.60	256.03	257.19	301.99	261.64	300.77	265.41	303.05
14	0.12	16.44	66.05	255.60	300.08	283.52	302.95	300.28	301.12	301.11
15	230.93	300.17	245.23	300.16	300.38	254.03	301.80	301.27	273.36	302.21
16	0.04	37.99	114.53	280.88	300.89	301.12	303.12	301.45	301.29	303.02

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	190.70	52.03	44.61	8.81	1.30	0.64	0.16	0.03	0.01	0.02
2	261.21	265.46	270.56	266.04	293.71	208.24	174.86	75.94	16.81	6.57
3	134.44	94.62	33.75	17.65	4.07	0.70	0.91	0.12	0.04	0.12
4	257.74	224.30	266.01	300.88	255.84	251.27	254.25	229.22	158.82	17.29
5	300.93	252.46	110.04	57.61	50.35	0.88	0.64	0.04	0.03	0.02
6	300.35	302.97	303.23	302.01	302.05	300.55	300.39	318.05	214.49	34.95
7	301.21	269.22	271.81	230.54	143.87	2.45	4.46	0.18	0.07	0.13
8	302.33	302.10	301.84	302.24	303.26	300.45	275.32	276.18	293.30	58.45
9	160.92	98.34	24.41	13.94	13.94	3.51	0.56	0.09	0.16	0.02
10	222.56	282.39	265.88	282.40	270.19	235.40	227.49	132.83	106.17	22.21
11	170.94	146.24	56.62	50.29	40.37	6.95	0.41	0.16	0.10	0.06
12	226.01	265.59	262.28	301.55	247.22	272.23	260.18	205.41	239.13	172.80
13	300.19	191.77	157.73	130.19	90.70	8.43	0.44	0.05	0.69	0.01
14	302.43	302.22	301.20	301.53	302.36	301.67	301.68	302.31	301.86	247.54
15	302.18	303.14	248.84	243.52	243.45	248.90	160.97	3.59	0.04	0.10
16	302.35	304.07	303.89	303.20	303.05	302.23	302.09	302.22	304.53	304.56

Table 23
Wall times for the complete model [in sec.].

	Instances									
Scenario No.	1	2	3	4	5	6	7	8	9	10
1	58.7	315.6	630.6	542.2	400.7	397.6	443.2	542.3	386.1	268.2
2	0.1	0.8	25.8	58.7	507.3	684.1	711.6	740.9	781.6	743.5
3	169.5	420.0	719.8	401.7	382.5	441.2	387.6	553.8	284.2	387.1
4	0.0	0.4	88.3	86.1	542.9	915.9	911.1	884.5	787.6	700.0
5	67.8	240.7	726.1	876.6	821.9	824.7	865.2	789.2	842.1	748.4
6	0.0	0.4	77.6	144.4	461.9	905.0	932.6	916.5	953.4	948.8
7	169.4	436.3	885.8	851.3	921.2	830.0	964.4	967.5	1 049.9	994.0
8	0.0	2.0	63.8	220.5	768.3	972.7	985.9	981.3	1 025.6	1 000.3
9	150.7	726.6	337.7	298.9	305.3	341.4	398.7	401.5	333.1	474.8
10	0.1	3.9	67.2	341.3	827.2	751.4	596.1	698.3	748.1	646.8
11	216.7	785.7	320.0	367.4	386.2	384.1	525.2	604.7	471.1	561.9
12	0.1	21.4	72.7	472.0	790.3	920.8	806.8	806.1	765.6	735.2
13	165.2	615.8	722.1	653.4	785.8	730.7	821.6	806.8	789.8	944.4
14	0.2	16.8	79.3	510.7	861.1	910.1	926.8	974.3	991.4	1 028.1
15	245.7	757.5	735.4	928.7	931.6	903.2	1 057.4	1 188.3	1 243.5	1 242.2
16	0.1	38.9	129.7	705.9	947.4	972.0	988.0	995.9	1 143.5	1 213.5

	Instances									
Scenario No.	11	12	13	14	15	16	17	18	19	20
1	275.9	97.9	57.9	15.6	5.8	4.2	2.9	2.1	1.6	1.3
2	664.6	710.4	734.6	574.0	532.3	387.9	254.0	101.8	27.5	14.9
3	270.7	158.8	54.7	30.5	13.4	7.1	6.3	4.1	3.0	2.7
4	687.3	717.3	727.3	827.4	724.9	674.3	666.7	617.7	482.4	35.8
5	762.7	501.8	305.7	160.4	79.4	7.9	5.5	3.2	2.4	1.7
6	953.7	1029.7	994.1	973.3	962.9	952.8	959.8	954.4	296.3	48.1
7	995.5	926.8	868.8	715.7	335.8	15.4	14.3	6.6	4.6	3.8
8	1 044.6	1 126.6	1 073.0	1 051.9	1 036.4	1 010.6	932.9	930.1	868.7	130.9
9	289.0	176.9	48.3	46.1	28.6	12.4	6.7	4.8	4.0	2.8
10	564.0	720.3	654.9	733.8	702.0	615.6	536.1	355.8	242.3	44.3
11	416.9	396.3	179.2	169.2	133.3	22.3	11.1	8.8	6.7	5.1
12	693.0	821.5	857.2	903.8	865.2	810.2	789.9	658.1	653.5	490.6
13	900.9	497.6	433.3	372.8	222.5	24.8	10.8	7.3	6.4	3.6
14	1 088.6	1 195.3	1 159.7	1 113.1	1 103.6	1 072.9	1 046.3	1 015.2	975.9	822.5
15	1 365.4	1 384.1	998.1	905.3	858.4	821.1	423.9	20.3	9.5	7.1
16	1 345.0	1 506.8	1 520.6	1 454.3	1 414.0	1 355.3	1 229.3	1 148.4	1 070.6	1 007.6

Table 24
Evaluated runs for each scenario.

Scenario No.	No. of considered runs
1	10 of 10
2	8 of 10
3	8 of 10
4	6 of 10
5	7 of 10
6	5 of 10
7	8 of 10
8	10 of 10
9	9 of 10
10	9 of 10
11	9 of 10
12	7 of 10
13	6 of 10
14	10 of 10
15	5 of 10
16	10 of 10