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Determination of Near-Optimal Restoration Programs for Transportation Networks Following Natural Hazard Events Using Simulated Annealing

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Abstract: *Disruptive events, such as earthquakes, floods, and landslides, may disrupt the service provided by transportation networks on a vast scale, as their occurrence is likely to cause multiple objects to fail simultaneously. The restoration program following a disruptive event should restore service as much, and as fast, as possible. The estimation of risk due to natural hazards must take into consideration the resilience of the network, which requires estimating the restoration program as accurately as possible. In this article, a restoration model using simulated annealing is formulated to determine near-optimal restoration programs following the occurrence of hazard events. The objective function of the model is to minimize the costs, taking into consideration the direct costs of executing the physical interventions, and the indirect costs that are being incurred due to the inadequate service being provided by the network. The constraints of the model are annual and total budget constraints, annual and total resource constraints, and the specification of the number and type of interventions to be executed within a given time period. The restoration model is demonstrated by using it to determine the near-optimal restoration program for an example road network in Switzerland following the occurrence of an extreme flood event. The strengths and weaknesses of the restoration model are discussed, and an outlook for future work is given.*

1 INTRODUCTION

Infrastructure networks are essential for economic growth and development. Critical services such as power, water distribution, and transport are provided by these infrastructure networks. The damage of such a network could cause severe disruption to service, probably out of all proportion to the actual physical damage (Vespignani, 2010). With this in mind, the quick restoration of damaged infrastructure following a disruptive event is critical for the society. Managers of these infrastructure networks have the challenging task to determine optimal restoration programs, i.e., the optimal plans of how, and the order in which, the damaged infrastructure objects will be restored so that they provide adequate levels of service (LOS), taking into consideration the possible improvements in service, the costs, and the limited available budget and resources (Cavdaroglu et al., 2011).

In this article, a restoration model using simulated annealing (SA) is formulated to determine the near-optimal restoration program to restore service on transportation networks following the occurrence of a disruptive event. (In the remainder of this work, a "near-optimal solution" in context of SA means an approximated optimal solution, which

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is a good, though not necessarily the global optimal solution). The objective of the model is to minimize the costs, taking into consideration the direct and indirect costs. Direct costs are associated with the execution of interventions, such as cleaning-up, reparation, rehabilitation, or reconstruction. Indirect costs are associated with the traffic flow of the network and include costs for additional travel time, vehicle operating costs, or increased risk of accidents. Constraints, such as limits on available funding and resources, and limits on the type of intervention that can be executed per damage state are taken into consideration. The restoration model can be classified as a multilevel problem, where multiple problems have to be solved dependently (e.g., the minimum costs depend on the planned interventions, which influences the traffic, which in turn causes additional [indirect] costs). Under certain assumptions—e.g., the optimization of the costs depends on the traffic assignment that satisfies Wardrop's user equilibrium conditions (Wardrop, 1952), which can be expressed as first-order optimality conditions for a convex program (Beckmann et al., 1959). The problem can be expressed as a bilevel optimization problem. But also, in this case, classical optimization methods cannot be used for multiple reasons, including nonlinearity, nonconvexity, and nondifferentiability. Hence, in this article SA, is used to solve the problem.

The presented restoration model can be used to determine near-optimal, restoration programs, which include the objects to be repaired and the time and type of interventions to be executed to minimize overall costs. The model is illustrated by using them to develop a restoration program on a part of the road network in the Canton of Grisons, Switzerland, comprised of circa 51 km national roads, 165 km main roads, 395 km minor roads, and 116 bridges. Although the structure of the network is real in the example, fictive damage states following a fictive flood event were used, as were fictive origin-destination data for the traffic assignment and fictive costs. The use of fictive but realistic data in no way diminishes the illustration of the usefulness of the model applied. The restoration model is shown to work in situations where the network topology, traffic demand, and the available resources are to be taken into consideration.

The proposed restoration model is novel in the sense that it is the first model that schedules a tactical restoration program by minimizing direct and indirect costs for multiple object types, damage states, and different interventions associated with each state of each object. Thereby, the model accounts for time-dependent resource limitations and budget constraints as well as varying traffic assignment caused by the applied restoration strategies. Furthermore, the restoration model is applicable to real-world networks by utilizing heuristic processes to solve the complex bilevel optimization problem, as illustrated in a realistically sized case study in Switzerland. Computing such a network, shows that the restoration model presented here can be of great use for infrastructure managers overseeing the reliability and resilience of critical infrastructures to disruptive events, by obtaining relevant information concerning the investment in recovery operations such as insights on the trade-off between recovery budget and quality of the resulting restoration program.

The remainder of the article is organized as follows. In Section 2, related work about restoration modeling for transportation networks after the occurrence of disruptive events is summarized and discussed. The restoration model is presented in Section 3, and the SA is presented in Section 4. The example is given in Section 5. In Section 6, a discussion about the advantages and disadvantages of the restoration model is given. A summary of the work and suggestions for future work in this area are given in Section 7.

2 RELATED WORK

Consequences of transportation network failure depend greatly on how all of the objects within the affected transportation network behave, and on the restoration program adopted to, again, provide an adequate LOS (Hackl et al., 2016). Insight into how such network-related consequences can be classified and estimated is given in Hackl et al. (2015), Adey et al. (2016), Hackl et al. (2016), and Lam and Adey (2016). In particular, Lam and Adey (2016) discusses the interrelationship that exists between the restoration program for damaged objects and the ability of networks to provide an adequate LOS over time. Understanding the restoration process is critical for evaluating risks related to transportation networks, and for designing and operating robust transportation networks to provide an adequate LOS.

The determination of the optimal restoration program for transportation networks has been the focus of a substantial amount of research over the past few decades. These have focused on modeling the restoration program after disruptive events, including earthquakes (Çagnan and Davidson, 2004; Luna et al., 2011; Isumi et al., 1985; Chen and Tzeng, 2000; Bocchini and Frangopol, 2012), storms (Liu et al., 2007; Ramachandran et al., 2015), and floods (Lertworawanich, 2012), considering different individual infrastructure networks such as road networks (Chen and Tzeng, 1999, 2000; Chen and Miller-Hooks, 2012; Bocchini and Frangopol, 2012; Lertworawanich, 2012), power networks (Çagnan and Davidson, 2004; Liu et al., 2007), water distribution networks (Luna et al., 2011), or interdependent networks (Isumi et al., 1985; Ramachandran et al., 2015). Similar optimization models are used for maintenance and rehabilitation planning (Ouyang and Madanat, 2004; Ng et al., 2009; Kuhn, 2010; Sathaye and Madanat, 2011).

One type of model often used, and the type used in this work, is a deterministic resource constraint model (Çagnan and Davidson, 2004). In this type of model, the restoration program is determined using a set of simple equations and rules. Constraints in resources can be taken into consideration, e.g., the number of work crews available, the rate of repair for different objects, or traffic flow on the network. An advantage of models of this type is that they can determine a restoration program both in time and space. A disadvantage, however, is that they are deterministic, which does not allow for effective modeling of the uncertainties related to inputs such as restoration time and cost, which does not necessarily capture reality (Luna et al., 2011).

Isumi et al. (1985) used differential equations to determine optimal restoration programs taking into consideration the number of available personnel and the efficiency of repair as a function of time, for each supply area. Chen and Tzeng (2000) developed more detailed models using a multilevel approach that takes into consideration intervention costs and travel time costs, where the latter involved determining an equilibrium in the traffic flow on the network at different periods of time during the restoration program. In the developed models, several different objective functions have been used, including the minimization of travel time (Chen and Tzeng, 1999), the minimization of the number of impassable paths (Nolz et al., 2011), the minimization of the amount of freight that cannot be shipped (Chen and Miller-Hooks, 2012), and the minimization of the total cost of the restoration activities (Bocchini and Frangopol, 2012). In most cases, these objective functions have been constrained due to a limited budget. In a few cases, however, other constraints, such as limited resources have been considered. In the majority of these models, it is possible to take into consideration different intervention types (Vugrin et al., 2010) and different damage states of the objects (Bocchini and Frangopol, 2012).

To solve many of the models, due to the computational complexity of the problem, the optimal restoration program has been determined either using stochastic mixed-integer programs solved by Monte Carlo simulations (Chen and Miller-Hooks, 2012) or using heuristic procedures, such as genetic algorithms (GA) (Chen and Tzeng, 1999), ant colony system (ACS) (Yan and Shih, 2012), or SA (Vugrin et al., 2014). Although many of these models can be run relatively quickly to find near-optimal restoration programs, none of them have been used in real-world situations of comprehensive complexity (e.g., networks larger than a dozen of edges).

Notable work in determining restoration programs by using SA has been conducted by Vugrin et al. (2010, 2014). They used a modified resource-constrained project schedule approach (Boctor, 1996) to optimize the tasks within an intervention.

In addition to the research that has used Monte Carlo simulations or heuristic procedures to determine near-optimal intervention programs, some have been conducted to determine the optimal intervention programs directly, such as Hajdin and Adey (2005, 2006), Lethanh et al. (2014), and Eicher et al. (2015). Although these models allow for very realistic representations of the world, their use becomes severely difficult, if not intractable, when intervention programs are to be determined for large networks and actual traffic flow has to be considered.

3 RESTORATION MODEL

The mathematical model used in the work to determine the optimal restoration program for a transportation network minimizes the weighted sum of direct and indirect costs that occur over the time period between the occurrence of the hazard event and the moment that the restoration of the network is complete.

Preliminaries and an introduction to the network model and the definition of damage states and functional losses are given in Sections 3.2 and 3.3. The mathematical model is explained in Section 3.5. The notation used is given in Section 3.1

3.1 Notation

3.1.1 Sets and graphs.

$\Gamma(v)$	set of incident edges of vertex v
$\mathcal{D}$	set of destination or demand vertices
$\mathcal{E}$	set of edges of the network
G	transportation network graph
H	demand graph
$\mathcal{I}(n\|s)$	set of interventions for object n given state s
$\mathcal{N}^s$	set of usable objects in state $s \in \mathcal{S}$
$\mathcal{O}$	set of origin or supply vertices
P	specific path in the network
$\mathcal{P}$	set of all nonempty paths
$\mathcal{P}_{od}$	set of all od-paths
$\mathcal{P}_{od}^{g}$	set of all disconnected od-paths
$\mathcal{P}_{od}^{s\setminus g}$	set of all usable od-paths

$\mathcal{S}$ set of all states
$\mathcal{V}$ set of vertices of the network
$\mathcal{W}$ set of all considered vehicle types

3.1.2 Indexes.

e edge in the network
g state of complete damage $g \subseteq s$
i intervention
n object
od demand from o to d
s state
t time period
u, v, o, d vertices in the network
w vehicle type

3.1.3 Parameters.

α, β, γ parameters
κ decay rate
ν mean fuel price
ρ_w operating costs (without fuel) for a vehicle of a specific type
υ labor productivity
ℓ_e length of edge e
w vehicle type
T control parameter (temperature)

3.1.4 Variables.

$\delta_{n,i,t}$ binary variable, which has a value of 1 if an intervention i is executed on object n, initiated at period t and 0 otherwise
$\epsilon_{n,i}$ fixed costs of intervention i on object n
$\zeta_{n,i}$ variable costs of intervention i on object n
$\eta_{n,i,k}$ resource related costs of resource k for object n due to intervention i
$\xi_{e,w}$ value of travel for a vehicle of type w on edge e
$\tau_{n,i}$ intervention time for intervention i on object n
$\Delta y_{n,i}$ restored capacity of n due to intervention i
ΔZ change in value of the objective function
$\Psi_{k,t}$ available resource k in period t
Ω_t available budget in period t
d_{od} flow demand between origin o and destination d
$f_{od}(P)$ path flow between origin o and destination d, on path P
$\mu_{e,w}$ proportion of vehicles of type w on edge e
$r_{n,i,k}$ resource requirement for resource k on object n due to intervention i
t_e^0 free flow travel time at edge e
$t_{e,t}$ travel time at edge e in period t
$x_{e,t}$ link flow on edge e in period t
X state of the variables of Z
y_e capacity of edge e
$y_{n,t}$ capacity of n in period t

3.1.5 Functions.

Λ cost function for loss of connection
Π cost function for prolongation of travel
C^{DC} direct costs
C^{IC} indirect costs
$C_{n,i}$ intervention costs for object n due to intervention i
C_e^T travel cost function for edge e
F_w mean fuel consumption depending on the vehicle type w
$P(X)$ penalty function
Y functions of the constraints of Z
Z objective function
Z^R objective function for the restoration problem
Z^T objective function for the user equilibrium assignment

3.2 Network design

A transportation network is denoted by $G = (\mathcal{V}, \mathcal{E})$ and hereinafter referred to as *the network*. Formally, G is a mathematical structure, which describes a set of vertices $\mathcal{V}$ and a set of edges $\mathcal{E}$. Both vertices and edges correspond to objects in the physical network. Vertices are well suited to represent objects that are to be seen as points in the physical network, e.g., bridges or road crossings, whereas edges are well suited to represent objects that are to be seen as objects with length, e.g., road sections and rail sections. The choice depends on the purpose of the model. Here, the notation $n \in \mathcal{N}$ refers to any object in the network G, where $\mathcal{N} = \mathcal{V} \cup \mathcal{E}$ is the set of all considered objects.

The movement of vehicles on the network is defined by the graph $H = (\mathcal{V}^H, \mathcal{E}^H)$ where the vertex set $\mathcal{V}^H \subseteq \mathcal{V}$ contains origin vertices $\mathcal{O} \subseteq \mathcal{V}^H$ and destination vertices $\mathcal{D} \subseteq \mathcal{V}^H$. Two vertices $o \in \mathcal{O}$ and $d \in \mathcal{D}$ are connected by an edge in H if and only if there is a traffic demand with positive demand value between them, hence an edge in this graph is also called od-pair.

Graphs are assumed to be *directed*. An edge is, therefore, an ordered pair $e = (u, v) \in \mathcal{E}$ indicating that u and v are directly connected and vehicles travel only from u to v. A set of capacities is defined for each edge. The capacity y_e of an edge $e = (u, v)$ is the upper limit on flow in a specific time interval, e.g., in vehicles per hour. A demand from o to d is denoted by od and stands for the directed demand (o, d).

Vehicle movements from origin to destination vertices, which occur along edges, are represented as *paths*. A path $P \in \mathcal{P}$ is considered to be a sequence of edges that are ordered so that two vertices are adjacent if and only if they are consecutive. $\mathcal{P}$, therefore, denotes the set of all nonempty simple paths in $G = (\mathcal{V}, \mathcal{E})$. The set of *od*-paths is denoted by $\mathcal{P}_{od} \subseteq \mathcal{P}$.

3.3 Damage states and functional losses

The occurrence of a hazard event can result in the loss of functionality of the objects within a transportation network, which in turn results in the loss of functionality of the network. These functionality losses may occur due to objects being damaged by a hazard, e.g., a bridge being knocked off its bearings due to excessive ground motions, a road section being eroded by scour, or is blocked by flood waters. More detailed examples for road objects can be found in Lethanh et al. (2015).

The set of considered states is denoted $\mathcal{S}$. These states are defined taking into consideration the ability of the objects to provide the required LOS, which involves the consideration of aspects such as the capacity, i.e., the maximum number of vehicles that can travel over the object in a specified period of time. The objects in a normal state are denoted by 0 and all other states are denoted by $s \in \mathcal{S}$. For example, $n \in \mathcal{N}^s$ describes objects with reduced functionality, where $\mathcal{N}^s \subseteq \mathcal{N}$ denotes the set of objects in state $s \in \mathcal{S}$. Full functional loss, i.e., the state when no traffic flow over an object is possible, is denoted by $g \subseteq s$.

3.4 Costs

3.4.1 Direct costs. Direct costs are intervention costs, i.e., the costs of restoring objects to states where they function again as intended. For each object with reduced functionality $n \in \mathcal{N}^s$, a (finite) set of possible interventions $\mathcal{I}(n|s)$ is assigned. Only one of these can be selected at a time to restore functionality of n. Associated with each intervention $i \in \mathcal{I}(n|s)$ are (i) the flow capacity $\Delta y_{n,i}$ following the execution of the intervention, (ii) the length of time required to execute the intervention $\tau_{n,i}$, (iii) the amount of resources required $r_{n,i,k}$ for resource $k \in \mathcal{K}$, and (iv) the cost of the intervention $C_{n,i} \geq 0$. This cost is composed of a fixed part, a length-dependent part, and a variable part dependent on the used resources. The overall direct costs C^{DC} are the sum of the direct costs for each intervention executed. It is assumed that intervention costs are not affected by the selected restoration program.

$$C^{DC} = \sum_{n \in \mathcal{N}^s} \sum_{i \in \mathcal{I}(n|s)} \sum_{t \in T} \delta_{n,i,t} \cdot C_{n,i} \tag{1}$$

where $\delta_{n,i,t}$ is a binary variable, which has a value of 1 if intervention $i \in \mathcal{I}(n|s)$ is executed on object n in state s, initiated at period t and 0 otherwise. Because at most one intervention is executed on an object at a time (i.e., at most one of the $\delta_{n,i,t}$ has to be 1 and all others have to be 0), the capacity of object $n \in \mathcal{N}^s$ at time t is

$$y_{n,t} = y_{n,0} + \sum_{i \in \mathcal{I}(n|s)} \sum_{j \in t - \tau_{e,i}} \delta_{n,i,j} \cdot \Delta y_{n,i} \quad \forall n \in \mathcal{N} \tag{2}$$

where $y_{n,0}$ is the capacity immediately following the disruptive event.

3.4.2 Indirect costs. Indirect costs are divided into two categories: (1) those associated with temporal prolongation of travel and (2) those associated with the loss of connectivity, as suggested by Adey et al. (2004). Both can be associated with states of the objects. In the case of prolongation of travel, indirect costs are principally caused by such things as additional travel time, additional vehicle operating costs, and additional accidents. Whereas, in the case of a loss in connectivity, indirect costs are principally due to the loss of economic activity that occurs while travel is not possible. The magnitude of each depends on the network design and the traffic flow. A complete list of both types of indirect costs can be found in Adey et al. (2012).

Indirect costs C^{IC} are measured as the difference between indirect costs at t and the indirect costs at $t = 0$, when the network was fully functional.

$$C^{IC} = \sum_{t \in T} \left[\sum_{P \in \mathcal{P}_{od}^{s \setminus g}} \sum_{e \in P} \Pi(t|x_{e,t}) - \Pi^0(t|x_{e,0}) + \sum_{P \in \mathcal{P}_{od}^{g}} \Lambda(t) \right] \tag{3}$$

where Π is a cost function dependent on the link traffic flow $x_{e,t}$ on edge e in period t, and Λ is a cost function dependent on a loss of connectivity. Π^0 is associated with the costs if the network is fully functional. $\mathcal{P}_{od}^{s\setminus g} \subseteq \mathcal{P}_{od}$ refers to the set of *od*-paths where at least some flow is still possible, whereas $\mathcal{P}_{od}^{g} \subseteq \mathcal{P}_{uv}$ refers to the set of *od*-paths where no flow is possible. The former refers to those containing no objects with zero functionality g. A vertex v^g that has zero functionality g renders all incident edges nonfunctional. Thus,

$$\mathcal{P}_{od}^{s\setminus g} = \left\{ P \in \mathcal{P}_{od} \mid e^g, \Gamma(v^g) \notin P \right\} \tag{4}$$

where $\Gamma(v)$ denotes the set of incident edges of a vertex $v \in \mathcal{V}$ in G.

3.5 Mathematical model

The objective of the mathematical model is to find a restoration program that minimizes the sum of costs, considering Equation (1) for the direct costs and Equation (3) for the indirect costs. The mathematical model allows considerations of the functional losses of edges and vertices in the network. The objective function is written as:

$$\min Z^R = \sum_{t \in T} \left[\sum_{n \in \mathcal{N}^s} \sum_{i \in \mathcal{I}(n|s)} \delta_{n,i,t} \cdot C_{n,i} + \gamma \sum_{P \in \mathcal{P}_{od}^{s \setminus g}} \sum_{e \in P} \Pi(t|x_{e,t}) - \Pi^0(t|x_{e,0}) + \sum_{P \in \mathcal{P}_{od}^{g}} \Lambda(t) \right] \quad (5a)$$

subject to

$$\sum_{i \in \mathcal{I}(n|s)} \sum_{t \in T} \delta_{n,i,t} \leq 1 \qquad \forall n \in \mathcal{N} \quad (5b)$$

$$\sum_{n \in \mathcal{N}^s} \sum_{i \in \mathcal{I}(n|s)} \sum_{t \in T} \delta_{n,i,t} \cdot C_{n,i} \leq \Omega_t \qquad \forall t \in \mathcal{T} \quad (5c)$$

$$\sum_{n \in \mathcal{N}^s} \sum_{i \in \mathcal{I}(n|s)} \sum_{j \in t-\tau_{n,i}+1} \delta_{n,i,j} \cdot r_{n,i,k} \leq \Psi_{k,t} \qquad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (5d)$$

$$x_{e,t} \in \min Z^T = \sum_{e \in \mathcal{E}^s} \int_0^{x_{e,t}} C_e^T(\omega) \mathrm{d}\omega \quad (5e)$$

subject to

$$\sum_{P \in \mathcal{P}_{od}^{s \setminus g}} f_{od}(P) = d_{od} \qquad \forall od \in V^H \quad (5f)$$

$$f_{od}(P) \geq 0 \qquad P \in \mathcal{P}_{od}^{s \setminus g}, \ \forall od \in V^H \quad (5g)$$

The optimization problem presented, is a bilevel optimization problem, i.e., a problem where a subset of the variables from a part of the model are constrained to the optimal solution of another part of the model. Here, the indirect costs (Equation (3)), which are part of the upper level optimization (Equation (5a)) depend on the link traffic flow $x_{e,t}$. Beckmann et al. (1959) established that the solution to the traffic assignment (network equilibrium) problem, in the case of user travel cost functions C_e^T, in which the cost on a link only depends on the flow on that link and is assumed to be continuous and an increasing function of the flow, can be obtained by solving the (lower level) optimization problem (Equation (5e)) (Nagurney, 2007). In return, the travel cost function C_e^T and the feasible paths $P \in \mathcal{P}^{s \setminus g}$ are determined by the interventions selected in the upper level optimization.

The accompanying constraints of Equation (5a) are continuity constraints, budget constraints, and resource constraints. The continuity constraints Equation (5b) force the model to select only one intervention per object, which is executed in one time interval, throughout the investigated time period. The budget constraint Equation (5c) forces the model to select no more interventions than for which funding is available, i.e., the total cost of all interventions cannot exceed Ω for the investigated time period t. The resource constraint Equation (5d) forces the model to select no more resources than available in a time interval t, i.e., the amount of resources k in time interval t, needed for the interventions, cannot exceed $\Psi_{k,t}$. Other constraints for the direct costs could be added if desired, for example, time constraints, accessibility constraints, or maximum or minimum work-zone constraints (Lethanh et al., 2016).

The link traffic flow $x_{e,t}$ is estimated, by solving the user equilibrium assignment, Equation (5e) subjected to Equations (5f) and (5g). The costs of travel on each edge change with the flow and, therefore, the costs of travel on several of the network paths change as the edge flow changes. A stable state is reached only when no traveler can reduce his costs of travel by unilaterally changing routes (Sheffi, 1985).

The lower level optimization Equation (5e) for the user equilibrium assignment corresponds to the sum of the integrals of the travel cost function C_e^T for all edges e in the network. The demand constraint Equation (5f), stating that the flow on all od-pairs has to equal the demand $d_{od} \geq 0$ for all $od \in \mathcal{V}^H$. The nonnegativity constraints Equation (5g) are required to ensure that the solution of the program will be physically meaningful. Equation (5e) is formulated in terms of edge flows, whereas the constraints are formulated in terms of path flows. Equation (6) expresses the relationship between edge and path flow, and incorporates the network design into the optimization problem.

$$x_e = \sum_{od \in \mathcal{V}^H} \sum_{P \in \mathcal{P}_{od}^{s \setminus g}} \sum_{e \in P} f_{od}(P) \quad (6)$$

An overview of traffic assignment methods can be found in Nagurney (2007), de Dios Ortuozar and Willumsen (2011), Hoogendoorn and Knoop (2012), and Patriksson (2015). A similar approach can be used for other transportation networks such as, power grids (Quelhas et al., 2007; Van den Bergh et al., 2014), utility networks (Geidl and Andersson, 2007; Leong and Ayala H., 2013; Sarbu, 2014), or communication networks (Riley et al., 2004; Casalicchio et al., 2011).

Because the quantification of indirect costs is a nontrivial task, and there are high levels of uncertainty associated with the estimated values, a weighting factor γ is used to allow a relative weighting between both costs; i.e., decision makers can decide to which extent indirect costs will affect the determination of the optimal restoration program.

4 HEURISTIC OPTIMIZATION

Although there are solution strategies for solving the upper level and lower level optimization separately, classical methods fail to solve this multilevel optimization model exactly. This is due to the computational complexity, including nonlinearity, nonconvexity, and nondifferentiability of the combined problem. Furthermore, the upper level optimization can be classified as a combinatorial optimization, where the optimal restoration program comes from a finite set of restoration programs, i.e., the combinations of different interventions in time are finite. In many such problems, an exhaustive search is not feasible, but heuristic procedures can provide a way of computing near-optimal solutions.

In this work, an SA-based metaheuristic procedure is used to approximate an optimal solution of the upper level optimization. The lower level optimization is embedded in the SA but solved with classical methods. Other metaheuristics, including GA, ACS, and tabu search (TS) might also be possible procedures, but often perform, for this type of optimization, worse than SA (Adewole et al., 2012; Antosiewicz et al., 2013; Mukhairez and Maghari, 2015; Fredrikson and Dahl, 2016).

4.1 Simulated annealing

SA was introduced by Kirkpatrick et al. (1983) and Černý (1985) for solving combinatorial optimization problems. This heuristic procedure originated from an analogy with the physical annealing process of finding low energy states of a solid in a heat bath (Metropolis et al., 1953). In the process of physical annealing, a crystalline solid is heated and then allowed to cool very slowly until it reaches its most regular possible crystal lattice configuration, i.e., its minimum lattice energy state. SA establishes the connection between this type of thermodynamic behavior and the search for the global minimum for a discrete optimization problem (Henderson et al., 2003).

In computational terms, the typical SA-based heuristic seeks to minimize a given objective Z by applying small random changes to the control variables and considering the change in the value of the objective function, ΔZ. When there is an improvement of the value of the objective function, the resulting change in the solution is accepted and a further search is initiated in the neighborhood of this point. If the resulting new solution yields no improvement, it is accepted with probability $\exp(-\Delta Z/T)$, where T is a control parameter referred to as the *temperature* of the system. The probability of accepting a new solution is high for large temperatures and conversely small for low temperatures. This acceptance criterion is helpful in avoiding convergence to local optima. One can think, here, of temperature as representing the level of *disorder* in the search process. Thus, the search is initiated under a high temperature to allow as much exploration of the design space as possible and, as the temperature is then decreased to zero in some regulated fashion, the search, converges onto a globally near-optimal solution (Suppapitnarm et al., 2000).

The design of a good SA-based heuristic is nontrivial and problem specific. The following elements are required: (1) a specific objective function; (2) a rule to create randomly a neighbor solution from the current solution; and (3) a cooling schedule to control the temperature during the annealing process (Eglese, 1990).

4.2 Choice of objective function for SA

In general, a classical SA can handle complex objective functions but without constraints. Finding constrained global minimums is challenging because nonconvex and highly nonlinear constraints make it difficult to even find a feasible solution or a feasible neighborhood. Additionally, it is possible that feasible neighborhoods may be disjoint and the search may need to visit multiple feasible neighborhoods before finding the global minimum (Wah and Wang, 1999).

To avoid infeasible solutions for Equation (5a), the constraints (Equations (5b)–(5d)) were taken into consideration by using a dynamic penalty function, known as annealing penalty (Michalewicz and Schoenauer, 1996). In other words, infeasible solutions were penalized by adding a penalty to the solution of the objective function, such that it becomes worse than a feasible solution.

$$\text{eval}(X) = \begin{cases} Z(X) & X \in \text{feasible} \\ Z(X) + P(X) & \text{otherwise} \end{cases} \tag{7}$$

where the penalty function $P(X)$ is zero if no violation occurs and otherwise it is positive. In addition, the penalty function accounts for the degree of infeasible solutions by weighting the distance to a solution from a feasible neighborhood. In the case of an annealing penalty, the penalty function also depends on the temperature:

$$P(X) = \frac{1}{2T} \sum_{j \in m} Y_j(X)^2 \tag{8}$$

where $Y(X)$ is a constraint of Z, and $m \geq 0$ the amount of constraints. The initial penalty value is relatively low and gradually increases as the temperature reduces. This construct allows a wider solution space in the beginning but puts increasing pressure on infeasible solutions as the simulation goes on.

4.3 Choice of neighborhood

The efficiency of SA is highly influenced by the neighborhood function, which is used to create a neighbor solution from the current solution. The definition of the neighborhood function is mainly a problem-specific choice. The problem of finding an optimal restoration program can be reduced to a combinatorial optimization problem with finite solution space. For example, for a specific object type, three different intervention types exist, i.e., in an SA process the object can only be in three stages. Furthermore, $\delta_{n,i,t}$ can be decomposed in a sequence of tuples $[(n_j, i_j), (n_k, i_k), \ldots]$ where the order indicates the period in which an intervention of type i is executed on object n. The problem is solved by generating a number of sequences in a feasible neighborhood and choosing the best. To generate a neighbor solution, one of the tuples in the sequence is chosen randomly and assigned to a new position, additionally, the intervention type is changed with a certain probability.

4.4 Choice of cooling schedule

The lowering of the system temperature through a cooling schedule is required to reduce the amount of time required to find a near-optimal solution. In literature many heuristic cooling schedules are available, e.g., for engineering applications a comprehensive review of different cooling schedules is given by Siddique and Adeli (2016). However, the effectiveness of these schedules is highly problem specific and can only be compared through experimentation (Henderson et al., 2003). The cooling schedule implemented is as follows. An initial temperature T_0 is set at the beginning. At every ith iteration out of J, the temperature T_0 is multiplied by $\exp(\kappa \cdot i/J)$, where κ is a parameter for the decay rate and here defined as $\kappa = -\ln(T_0/T_{\min})$. The initial temperature is estimated based on the work of Ben-Ameur (2004).

5 EXAMPLE

The restoration model is demonstrated by using them to determine the near-optimal restoration program for an example road network in Switzerland following the occurrence of an extreme flood event. The road network investigated is in the area around the city of Chur, the capital of Grisons the largest and easternmost canton of Switzerland. Grisons is a mountainous area and includes parts of both the Rhine and Inn river valleys. The investigated area of Grisons includes the districts of Imboden and the northern part of Plessur. This area is located next to the river Rhine and contains the city of Chur and Grisons' industrial area, together with the most important transportation links in the canton. The considered road network is comprised of circa 51 km national roads, 165 km main roads, and 395 km minor roads. The canton is crossed in a north-south direction from the A13 motorway. The example network consists of 2,153 objects, which include 2,011 road sections and 116 bridges, as shown in Figure 1.

Table 1
Sample of considered bridges and their assigned attributes

Object				*Affected components*	
ID	*Class*	*Type*	*Material*	*Piers*	*Abutments*
2052	Major	Box girder	Concrete	1	0
2064	Minor	Single span	Concrete	0	1
2070	Major	Single span	Concrete	0	2

5.1 Investigated network

The network investigated is shown in Figure 1 and was assumed to consist of only motorways, main roads, and minor roads. The information of the Chur road network was extracted from the VECTOR25 data set, provided by swisstopo (JD100042). This set of data exhibits a full national coverage and describes approximately 8.5 million objects with their position, shape and its neighborhood relations (topology), as well as the kind of object and further special attributes. The accuracy of the spatial data is in the range of 3–8 m and available as an ESRI Shapefile for the Swiss coordinate system CH1903/LV03 LN02 (ESPG code: 21781). The road sections were described by their direction, length, free flow speed, capacity, and the parameters of the capacity restraint function. Bridges were modeled as vertices with a degree of 2, i.e., the bridge location was defined in the middle of the river where two road segments are joined. This assumption allowed to account for both, local scouring and inundation of the bridges. A sample of bridges and road sections are shown in Tables 1 and 2. For reasons of brevity, the complete list of 2,153 objects is not given.

The trips in the region were considered to start and end in the 37 zones based on judicial districts as shown in Figure 1. All trips made from an origin to a destination during a particular time period are stored in a so-called OD matrix. Because not enough trip distribution information was available for the area of interest, a gravity distribution model (de Dios Ortuozar and Willumsen, 2011) was used to estimate the trips based

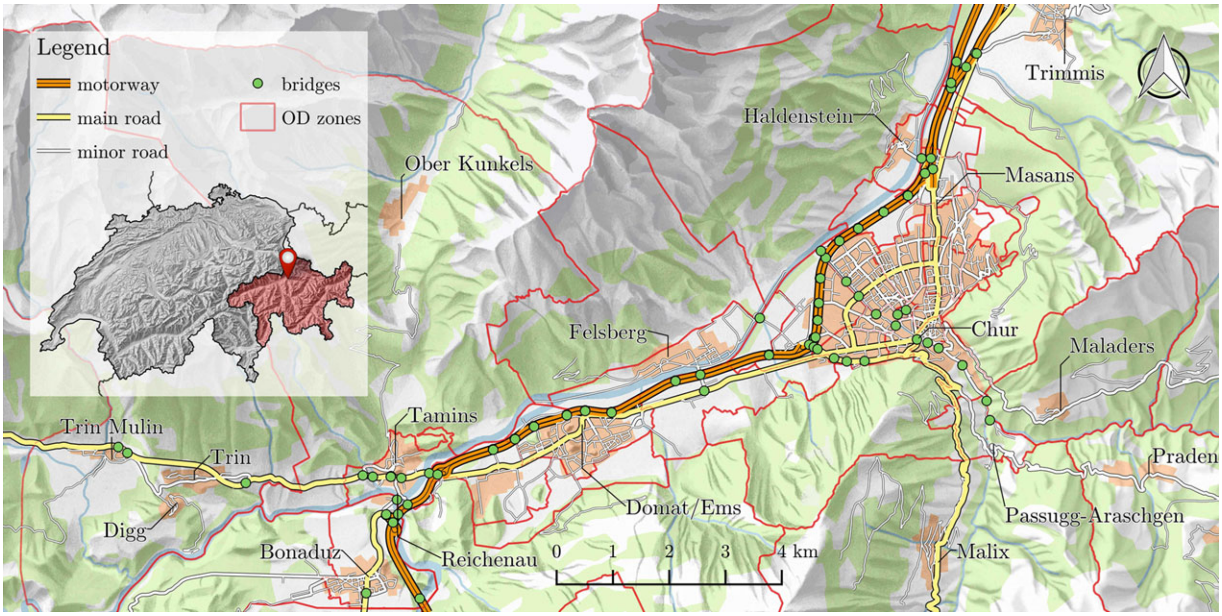

Fig. 1. Investigated road network around the city of Chur, Grisons, Switzerland.

Table 2
Sample of considered road sections and their assigned attributes

Object		*One way*	*Capacity*	*Speed limit*	*Length*	*Width*
ID	*Class*	*(t/f)*	*(veh/h)*	*(km/h)*	*(m)*	*(m)*
461	Motorway	t	4,000	120	193	10.0
554	Major	f	1,200	100	47	6.0
1279	Minor	f	850	30	92	4.0
1692	Minor	f	600	30	902	2.8
1702	Major	f	900	50	40	4.0

Note: t, true; f, false.

on the population of zones. The obtained gravity model was calibrated based on the Swiss national traffic model (FOSD, 2015), which provides data for the motorway and main roads.

5.2 Determine damage states and functional losses

Functional losses due to local scour at bridge piers and inundation of road sections caused by an extreme flood event were considered. The states of the objects were derived by fragility and functional loss functions (Lam and Adey, 2016), which were used in a flood simulation with a 500-year return period. The detailed quantification and computer-supported model used to determine the damage state and functional losses are described in Hackl et al. (2016). The relationships between the hazard event, which caused physical damage, and functional losses of the objects used are given in Tables 3 and 4.

Table 3
State and level of service loss for bridges due to local scour

State s	*Description*	*LOS loss (%)*
0	*No damage*—object is in a normal state	0
1	*Minor damage*—local scour at pier(s) and/or abutment(s) observed; some service can be provided	50
2[a]	*Major damage*—pier(s) and/or abutment(s) with footing(s) exposed; structural reliability is no longer guaranteed; Object cannot provide any service	100

[a] $s_2 = g$.

Table 4
State and level of service loss for road sections due to inundation

State s	*Description*	*LOS loss (%)*
0	*No damage*—object is in a normal state	0
1	*Minor damage*—debris lying on the road; some service can be provided	70
2[a]	*Major damage*—road is washed out by the flood; passing of the road is no longer possible; object cannot provide any service	100

[a] $s_2 = g$.

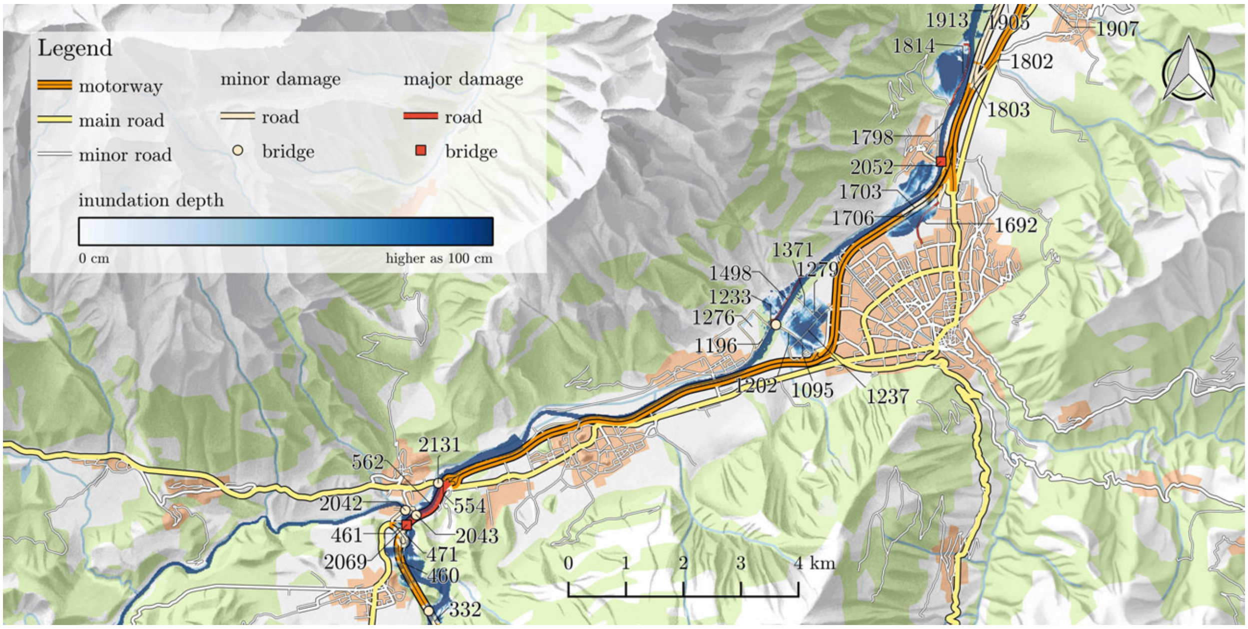

Fig. 2. States of objects following occurrence of extreme flood event. Displayed numbers correspond to the IDs of the damaged objects.

The scenario for which the near-optimal restoration program was determined contains 3 bridges in State 1, 2 bridges in State 2, 20 road segments in State 1, and 4 road segments in State 2. The spatial distribution of the objects is illustrated in Figure 2.

5.3 Setup restoration model

The objective function introduced in Equation (5a) was used, considering Equation (1) for the direct costs and Equation (3) for the indirect costs, where Equation (3) depends on the traffic assignment specified by Equations (5e)–(5g).

5.3.1 Estimation of the direct costs. The intervention cost was calculated using the following equation:

$$C_{n,i} = \epsilon_{n,i} + \zeta_{n,i} + \eta_{n,i,k} \qquad \forall n, i \tag{9}$$

The total costs for intervention $i \in \mathcal{I}(n|s)$ executed on object n in state s were considered to be the summation of the fixed costs ϵ (e.g., building site facilities), the variable costs ζ (e.g., mu/m^2 pavement, mu/m^3 concrete), and resource-related costs η (e.g., labor costs) to execute the intervention. The terms fixed and variable costs are used for non–resource-related material costs, where resource costs are used to describe labor and construction machinery cost of the restoration work crews.

These costs vary depending on the type of object and the type of intervention. For each type of object, three different intervention types are considered: level 1 interventions, level 2 interventions, and level 3 interventions. Level 1 interventions require less time than level 2 interventions, but more resources and additional costs. Level 2 interventions restore the capabilities in a default way. Level 3 interventions require less time and costs than a level 2 intervention. Both level 1 and level 2 interventions restore objects so that they once again provide the expected LOS, level 3 interventions do not.

The LOS recovery, durations, resources, and costs related to interventions of each type for road sections and bridges are given in Tables 5 and 6. Costs taken from the literature are adapted to the price level of 2015. To avoid overinterpreting of the specific values that are being generated in the example, monetary units are used instead of real currency.

5.3.2 Estimation of indirect costs. The indirect costs are comprised of costs for the temporal prolongation of travel Π and costs due to a loss in connectivity Λ. The costs attributed to traffic flow include travel time Φ and vehicle operation costs Υ.

$$\Pi(t|x_{e,t}) = \Phi(t|x_{e,t}) + \Upsilon(t|x_{e,t}) \qquad \forall t, e \in P, P \in \mathcal{P}_{od}^{s\backslash g} \tag{10}$$

Travel time: Travel time costs are estimated as the increased amount of time that people spend traveling. They are linked directly to the flow on an edge, due to

Table 5
Intervention types and associated recovery rate, resources, and costs for bridge local scour

State s *damage*	*Intervention* i *type*	*LOS recovery* Δy *(%)*	*Duration* τ *(hour/elem)*	*Resources* r *(# rwc)*	*Fixed costs* ϵ *(mu)*	*Variable costs* ζ *(mu/elem)*	*Resource costs* η *(mu/(rwc · hour))*
1 minor	Level 1	100	20	2	16,000	24,000	900
	Level 2	100	40	1	10,000	15,000	900
	Level 3	20	35	1	10,000	13,000	900
2 major	Level 1	100	90	2	48,000	64,000	1,200
	Level 2	100	160	1	30,000	40,000	1,200
	Level 3	10	145	1	30,000	37,000	1,200

Note: elem, affected elements of the bridge (e.g., pier(s) and/or abutment(s)); rwc, restoration work crews; mu, monetary unit (e.g., USD, EUR, CHF).

Table 6
Intervention types and associated recovery rate, resources, and costs for inundated road sections

State s *damage*	*Intervention* i *type*	*LOS recovery* Δy *(%)*	*Duration* τ *(hour/m²)*	*Resources* r *(# rwc)*	*Fixed costs* ϵ *(mu)*	*Variable costs* ζ *(mu/m²)*	*Resource costs* η *(mu/(rwc · hour))*
1 minor	Level 1	100	0.001	2	5,250	22.00	500
	Level 2	100	0.003	1	3,500	16.50	500
	Level 3	30	0.003	1	3,500	14.50	500
2 major	Level 1	100	0.006	2	14,400	110.00	700
	Level 2	100	0.012	1	9,600	82.50	700
	Level 3	10	0.010	1	9,600	78.50	700

the cost–flow relationship C_e^T where cost is handled in terms of travel time per unit distance (de Dios Ortuozar and Willumsen, 2011). The cost–flow relationship used is the function proposed by the Bureau of Public Roads (Bureau of Public Roads, 1964):

$$C_e^T := t_{e,t}(x_{e,t}) = t_e^0 \left(1 + \alpha_e \left(\frac{x_{e,t}}{y_{e,t}}\right)^{\beta_e}\right) \quad (11)$$

where $t_{e,t}$ is the travel time at edge e in period t given the traffic flow $x_{e,t}$, t_e^0 is the free flow travel time, $y_{e,t}$ the edge capacity, and α and β are parameters for calibration, typically chosen as $\alpha = 0.15$ and $\beta = 4$, which corresponds to the design capacity (normally LOS C) of the Highway Capacity Manual. The travel time multiplied by the value of travel results in the travel time costs.

$$\Phi(t|x_{e,t}) = t_{e,t}(x_{e,t}) \cdot \sum_{w\in\mathcal{W}} \mu_{e,w} \cdot \xi_{e,w} \quad (12)$$

where $w \in \mathcal{W}$ represent different vehicle types, $\mu_{e,w}$ the proportion of vehicles of type w on edge e, and $\xi_{e,w}$ the value of travel. Only two types of vehicles are considered, i.e., cars and trucks. Based on the work of the Swiss Association of Road and Transport Experts (VSS, 2009b), $\xi_{e,w}$ was assumed to be 23.02 mu/hour for cars and 130.96 mu/hour for trucks. There was assumed to be the same proportion of cars and trucks on all roads. Hence, the overall fraction of trucks ($\mu_{w=\text{truck}}$) was estimated as 6% of the total traffic volume (FEDRO, 2015).

Vehicle operation: Vehicle operation costs are incurred for fuel consumption and maintenance of vehicles. They were estimated as the sum of the operating costs for all vehicle types

$$\Upsilon(t|x_{e,t}) = x_{e,t} \cdot \ell_e \cdot \sum_{w\in\mathcal{W}} \mu_{e,w} \cdot (\nu \cdot F_w + \rho_w) \quad (13)$$

where ℓ is the length of edge e, ν is the mean fuel price (1.88 mu/L), F_w is the mean fuel consumption, depending on the vehicle type (6.7 L and L per 100 km for car and truck, respectively), and ρ_w is the operating costs without fuel for different vehicle types (14.39 mu/(100 · vehicle-km) for cars and 32.54 mu/(100 · vehicle-km) for trucks) (VSS, 2009a).

Loss in connectivity: The costs due to a loss in connectivity are estimated based on the unsatisfied demand per time period t and the resulting costs due to a loss of labor productivity. Labor productivity is an economic indicator that measures the value of goods and services,

Table 7
Considered scenarios and their resources and budget constraints

Scenario	*Resources* $\Psi_{k,t}$	*Budget* Ω
1	$\Psi_{k=2,t\in[0,4]}=0, \quad \Psi_{k=3,t\in[10,15]}=0$	Unlimited
2	$\Psi_{k=2,t\in[0,4]}=0, \quad \Psi_{k=3,t\in[10,15]}=0$	3,630,000
3	All available	Unlimited

produced in a period of time, divided by the hours of labor used to produce them (Freeman, 2008).

$$\Lambda(t) = f_{od,t}(P) \cdot \upsilon(t) \qquad \forall t,\, P \in \mathcal{P}^g_{od} \tag{14}$$

where $f_{od,t}(P)$ is the demand loss and υ is the labor productivity at period t. Based on the data from the Federal Statistical Office (Reutter and Bläuer Herrmann, 2016), the labor productivity per hour worked is 83.27 mu/hour.

5.4 Considered scenarios

To estimate the optimal restoration program, different assumptions were made, including the number of restoration work crews available (#rwc = 3), the considered time intervals ($\Delta t = 4$ hours), the working hours per day (8 hours), and the weighting factor for indirect costs ($\gamma = 1$). The investigated scenarios vary in context of different levels of available resources and different levels of budget and are shown in Table 7.

Scenario 1 had resource constraints but no budget constraints. Here, the second restoration work crew (resource B) was not available in the first four days, whereas restoration work crew three (resource C) was not available between the 10th and the 15th day of the restoration program. Scenario 2 had the same resource constraints as 1 but additionally budget constraints of 3,630,000 mu. The budget constraint was set low enough to force the use of the penalty function Equation (8), i.e., all interventions had to be of type 3. Scenario 3 had no available resources and budget constraints. Additionally, a sensitivity analysis was conducted using scenario 1 by varying the value of the weighting factor.

Due to the complexity of the problem and the extensive solution space, it is not possible to solve this mathematical model exactly by analytics or an exhaustive search. To evaluate the obtained results, a comparison between the proposed model and a (standard practice) benchmark model was made.

The traditional methods to develop restoration programs are mostly heuristic and based on subjective ranking and priority rules developed by domain experts. These prioritization rules can be based either on economic or engineering criteria, such as structure vulnerability, road class, traffic volume, and various socioeconomic factors. For example, Buckle et al. (2006) prioritize road object based on expected damage ranks, where the object with the highest damage or functional loss are given the highest priority for restoration. Because this ranking does not account for the importance of the object in the network, Miller (2014) proposed a prioritization based on the average daily traffic volume for each object under normal conditions, as a benchmark model. Because this model does not account for disconnected parts of the network, a modified version was implemented as the benchmark:

1. sorting the objects based on their average daily traffic volume under normal conditions,
2. restoring objects that cause a loss of connectivity, and
3. restoring the remaining objects.

5.5 Implementation

The model was programmed in python. A conjugate direct Frank–Wolfe (CFW) algorithm (Mitradjieva and Lindberg, 2013), was implemented to solve the traffic assignment problem (Equation (5f)). The convergence criterion was set to a *relative gap* of 10^{-4}. The SA was based on the python package `simanneal` (https://github.com/perrygeo/simanneal) and modified according to Section 4. A GIS interface was developed, allowing easy import and export of GIS data. Furthermore, the program code was optimized for parallel computing, to reduce the computational time of the optimization process.

The optimization for the example was conducted on a 2x10 Core Intel Xenon E5-2690v2 3.0Ghz, 384GB DDR2 server running on Linux 64 bit operating system (Ubuntu 14.04). A simulation of $J = 10{,}000$ steps took approximately 10 hours. In total 10 searches per scenario were conducted. The initial temperature, estimated based on Ben-Ameur (2004), was $T_0 = 25{,}323$.

5.6 Results

In 1, the near-optimal restoration program obtained from the model (Table 8), include level 1 and level 2 interventions at the beginning of the restoration period to first restore network connectivity. Once network connectivity is restored, level 3 interventions are included. The majority of the damaged objects are located in regions where there is little traffic flow as shown in Figure 2. The overall costs for the restoration are 7,935,172 mu, with 3,735,844 mu direct and 4,199,328 mu

Table 8
Near-optimial restoration program for scenario 1, ordered according to the importancies of the objects

	Object		*State*	*Interv.*	*Schedule*			*Res.*	*Costs*			
Nr	*ID*	*Type*	*Damage*	*Type*	*Start*	*End*	*Dur.*	*rwc*	*Fixed*	*Variable*	*Resources*	*Sum*
1	2042	Bridge	1 minor	Level 1	0.0	2.5	2.5	A,C	16,000	24,000	36,000	76,000
2	554	Road	1 minor	Level 2	2.5	3.0	0.5	A	3,500	4,624	2,000	10,124
3	332	Road	1 minor	Level 3	2.5	3.0	0.5	C	3,500	20,739	2,000	26,239
4	461	Road	1 minor	Level 3	3.0	3.5	0.5	A	3,500	28,026	2,000	33,526
5	1803	Road	1 minor	Level 3	3.0	4.5	1.5	C	3,500	50,441	6,000	59,941
6	1095	Road	1 minor	Level 3	3.5	4.0	0.5	A	3,500	11,722	2,000	17,222
7	2052	Bridge	2 major	Level 1	4.0	15.0	11.0	A,B	48,000	64,000	211,200	323,200
8	1802	Road	1 minor	Level 3	4.5	6.0	1.5	C	3,500	60,800	6,000	70,300
9	1706	Road	1 minor	Level 3	6.0	8.0	2.0	C	3,500	72,107	8,000	83,607
10	460	Road	1 minor	Level 3	8.0	10.0	2.0	C	3,500	76,329	8,000	87,829
11	562	Road	2 major	Level 3	15.0	27.5	12.5	A	9,600	799,868	70,000	879,468
12	2069	Bridge	2 major	Level 3	15.0	33.0	18.0	B	30,000	37,000	172,800	239,800
13	1913	Road	1 minor	Level 3	15.0	24.0	9.0	C	3,500	347,907	36,000	387,407
14	1703	Road	1 minor	Level 3	24.0	26.0	2.0	C	3,500	72,349	8,000	83,849
15	1692	Road	2 major	Level 3	26.0	29.0	3.0	C	9,600	198,257	16,800	224,657
16	1279	Road	1 minor	Level 2	27.5	28.0	0.5	A	3,500	6,095	2,000	11,595
17	2131	Bridge	1 minor	Level 3	28.0	32.5	4.5	A	10,000	13,000	32,400	55,400
18	1907	Road	1 minor	Level 3	29.0	30.0	1.0	C	3,500	34,454	4,000	41,954
19	1905	Road	1 minor	Level 3	30.0	30.5	0.5	C	3,500	28,146	2,000	33,646
20	1237	Road	2 major	Level 3	30.5	33.0	2.5	C	9,600	153,816	14,000	177,416
21	1276	Road	1 minor	Level 3	32.5	34.0	1.5	A	3,500	53,835	6,000	63,335
22	1202	Road	1 minor	Level 3	33.0	33.5	0.5	B	3,500	25,309	2,000	30,809
23	1233	Road	1 minor	Level 3	33.0	33.5	0.5	C	3,500	4,541	2,000	10,041
24	1798	Road	1 minor	Level 3	33.5	34.5	1.0	B	3,500	40,023	4,000	47,523
25	1814	Road	2 major	Level 3	33.5	38.0	4.5	C	9,600	267,668	25,200	302,468
26	2043	Bridge	1 minor	Level 3	34.0	38.5	4.5	A	10,000	13,000	32,400	55,400
27	1498	Road	2 major	Level 3	34.5	38.0	3.5	B	9,600	216,257	19,600	245,457
28	471	Road	1 minor	Level 3	38.0	38.5	0.5	B	3,500	27,499	2,000	32,999
29	1371	Road	1 minor	Level 2	38.0	38.5	0.5	C	3,500	19,132	2,000	24,632
									228,500	2,770,944	736,400	3,735,844

indirect costs over a period of 39.5 days. Restoring 1 with the benchmark model, the incurred restoration costs were 9,032,603 mu. This is 1,097,431 mu or 13.83% above the estimated optimum.

Table 8 contains the near-optimal restoration program for scenario 1, including the optimal order, the objects that should be restored, the interventions to be executed with the estimated restoration duration (i.e., start and end time of the task), the assigned restoration work crews and direct costs.

Figure 3 shows the restoration program over time for scenario 1, showing the allocated resources per object, the development of the direct and indirect costs, and the consequences on the network flow, average travel time and change in connectivity. Objects 1 and 7 are these objects, which yield the highest net improvement, i.e., increase in the provided service minus the costs of intervention. The economic costs due to lost connectivity are mainly caused by object 7, whereas object 1 causes the highest additional travel time.

Figure 4 shows the evaluation of the values of the objective function during the SA optimization for scenario 1. All 10 searches for the near-optimal restoration program show a convergence to 7,935,172 mu. Nine out of 10 searches reached this value exactly.

The changes in direct, indirect, and total costs, for various weighting factors γ are shown in Figure 5. The considered values for γ are 0.001, 0.01, 0.5, 1, 2.5, 5, and 10. The indirect costs were normalized by the corresponding γ value. A weighting factor of $\gamma = 0$ means that indirect costs (Equation (3)) are not considered in the optimization while increasing weights give more significance to the impact of flows on the total costs.

Figure 6 shows the evolution over time of the required resources per object and the development of the direct and indirect costs for all three scenarios. Similar

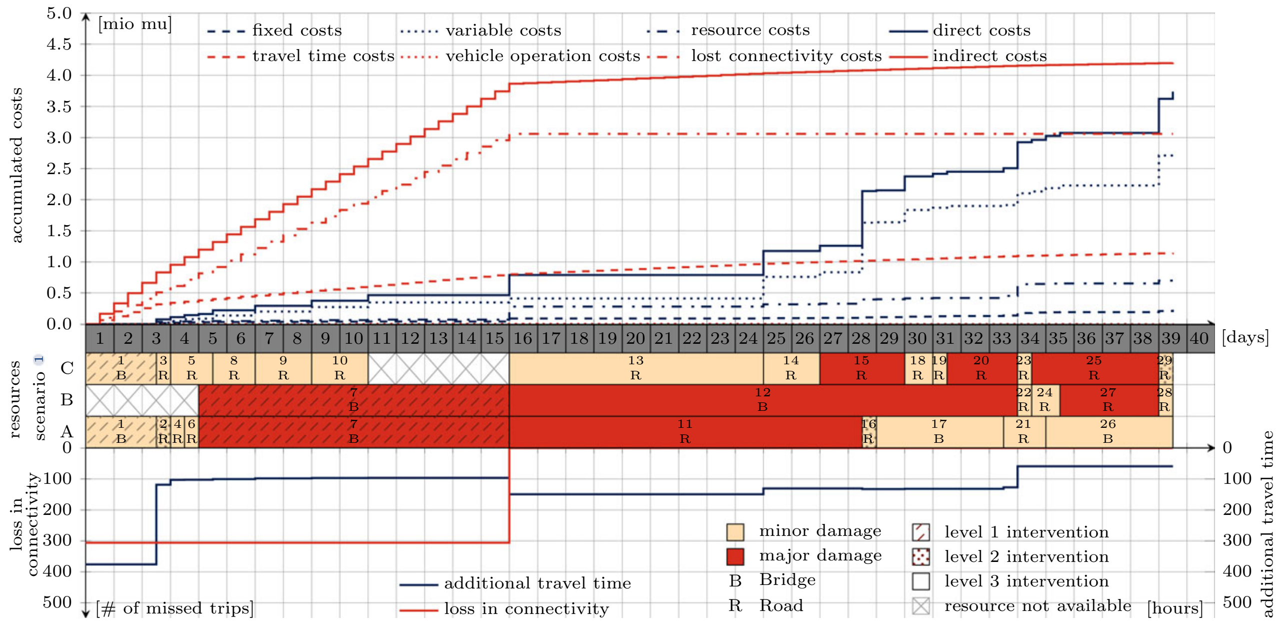

Fig. 3. Near-optimal restoration program for scenario 1 over time. Top: accumulated direct and indirect costs and their cost components (fixed, variable, resources, travel time, vehicle operation, and lost connectivity). Middle: restoration schedule for the work crews A, B, and C over time. The observed damage states are indicated by the fill colors and the assigned intervention types by the hatchings. Bottom: functional losses (loss of connectivity and additional travel time) of the network over time.

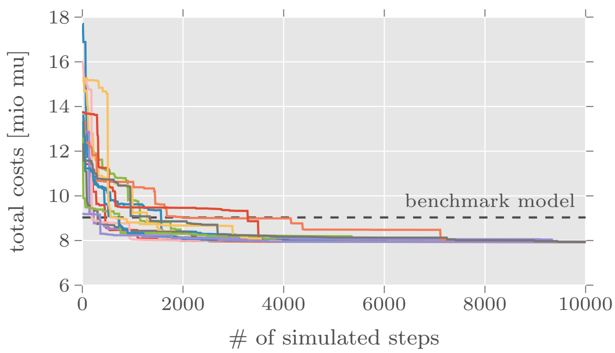

Fig. 4. Illustration of the convergence process for all searches for the near-optimal restoration program of scenario 1. Total costs plotted against the number of simulated steps.

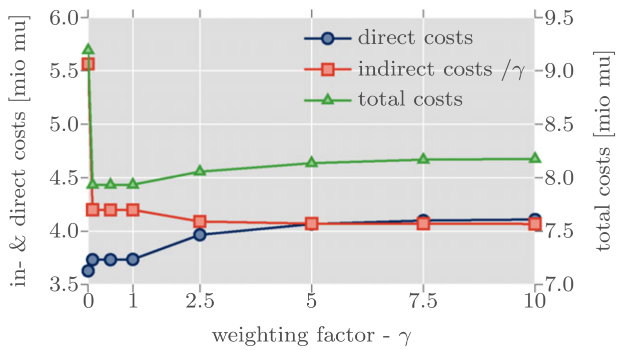

Fig. 5. Costs for different weighting factors γ for scenario 1. Indirect costs normalized by γ and direct costs plotted against various weighting factors.

to the restoration program associated with scenario 1, the restoration programs associated with scenarios 2 and 3 include objects 1, 2, 3, 4, and 7 at the beginning of the restoration program. This is because the restoration of these objects has the largest net improvement. Considering, the resource constraints in scenarios 1 and 2, object 1 and 7, which yield the highest net improvement, cannot be executed in parallel, as in 3. Due to the additional budget constraints in scenario 2, only level 3 interventions are included in the near-optimal restoration program, i.e., only the minimum possible effort to restore the network is made (e.g., execution of clean-up). An overview of all costs is given in Table 9.

6 DISCUSSION

The presented restoration model using SA has been described and its use was demonstrated by determining the near-optimal restoration program on a road network around the city of Chur following an extreme flood event. It is suspected that this model enables improved estimates of the costs incurred due to the loss

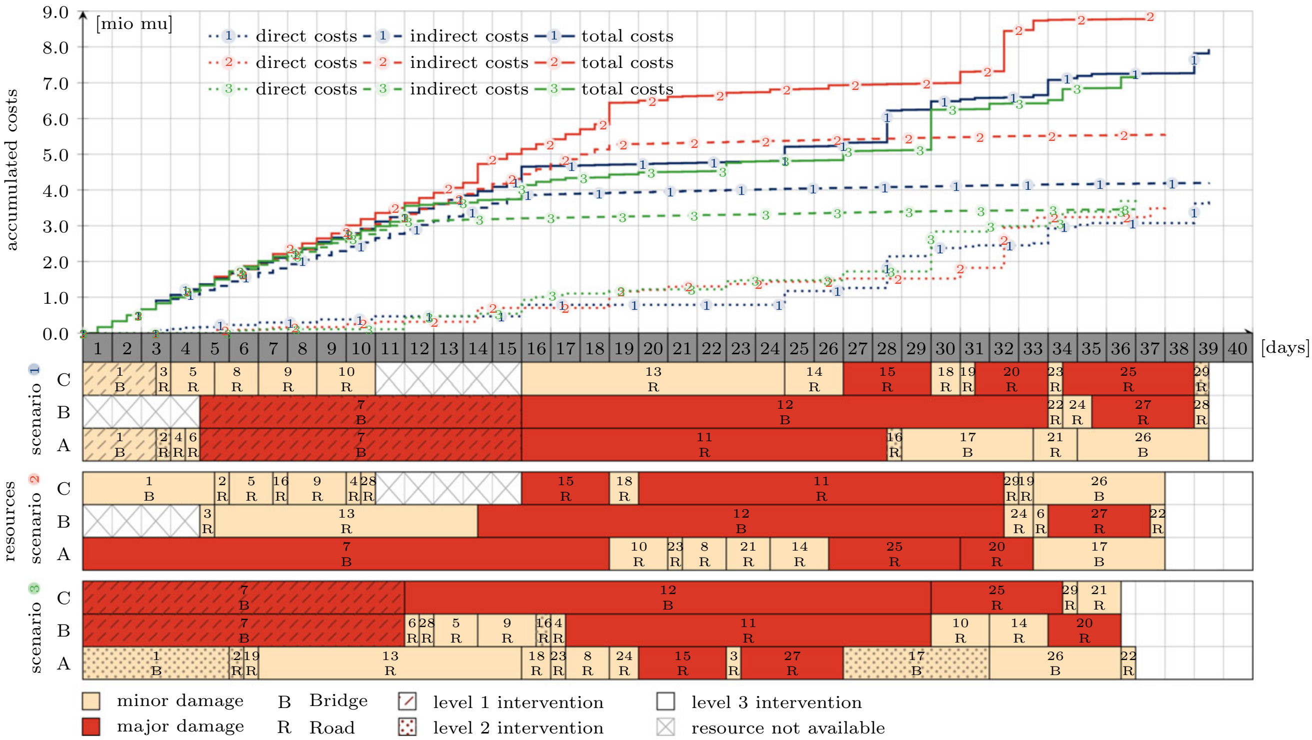

Fig. 6. Near-optimal restoration programs for all considered scenarios over time, where scenario 1 has only resources constraints, scenario 2 has resources and budget constraints, and scenario 3 has no constraints. Top: accumulated direct, indirect, and total costs over time. Bottom: restoration schedule for the work crews A, B, and C over time for each scenario.

Table 9
Costs of the scenarios in comparison with the benchmarks

	Costs			*Benchmark*		
Scenario	*Direct*	*Indirect*	*Total*	*Costs*	*Difference*	*Improvement*
1	3,735,844	4,199,328	7,935,172	9,032,603	1,097,431	13.83%
2	3,628,226	5,547,319	9,175,545	9,841,807	666,262	7.26%
3	3,724,125	3,462,792	7,186,918	7,784,687	598,485	8.33%

of service following a disruptive event and, therefore, enables the development of restoration programs that are better than would be determined with state-of-the-art models. Additionally, it is suspected that use of the restoration mode enable higher order dependencies to be discovered and taken into consideration, which otherwise might not. For example, in some cases it might be more beneficial to restore an object slowly (a level 2 intervention instead of a level 1 intervention), because over the entire restoration period this brings more benefits (e.g., the execution of an intervention on one road section does not need to progress quickly if the traffic flow over the road section in hindered by the execution of an intervention on a bridge within the same road link).

In any case, however, the methodology is useful in the estimation of risks due to natural hazards, where an estimate of the resilience of the network is considered, i.e., when the network will provide service following the natural hazard event.

It is also interesting to note that the model identifies the critical objects in the network, i.e., the objects whose failure will result in relatively large disruptions to service. For example, the restoration determined includes an intervention of level 1 on Bridge 2042 (object 1) in time interval 1, as this intervention would reduce to a large amount the additional travel time from 378 to 119 hours per half day on the network. Additionally, Bridge 2052 (object 7) is scheduled as soon as possible with an intervention of level 1, because this reduces the number of missed trips by 306 (see Figure 3). These large improvements are because of the restoration of Bridge 2052, as it is the only connection from Haldenstein to Chur (see Figures 1 and 2), and reconnects the people to the main region of Chur. Without resource constraints, object 7 would be scheduled first (see Figure 6), because lost trips have higher costs than prolonged travel.

The restoration programs of all scenarios outperform those developed using the benchmark model based on traffic volume-based importance measure. Even in the early phase of the SA process, better solutions than those found using the benchmark model could be observed (see Figure 4). In general, larger improvements could be observed with scenarios with constraints, which is because the benchmark model cannot adapt well to this. Although the used benchmark model represents the current state in practice, it does not indicate how good the observed near-optimal restoration program actually is, hence the lack of such a benchmark model makes it difficult to truly test the solutions found and the computational complexity.

The extent with which indirect costs are considered in the analysis is important. Without considering network flows ($\gamma = 0$), the model yields the restoration program with minimum direct costs; however, the impacts on the users might be out of all proportion. Increasing the importance of indirect cost, leads to more efficient but also more costly restoration programs. As the value of γ is increased, there are decreasing benefits, i.e., there is a decreasing benefit of restoring objects so that they can be used in their full capacity faster.

The assumptions with respect to the damage states and functional losses used in the example are very general. There is, however, no conceptual problem with making them more detailed. A practical problem though is that increasing detail in the descriptions of damage states and functional losses leads to increasing complexity of the computational models (e.g., computational fluid dynamics, finite elements) to be used. The appropriate level of detail needs to be determined in cooperation with appropriate stakeholders and experts, utilizing existing knowledge of how the objects function.

Accurate estimates of restoration times and costs are important for the quality of the near-optimal restoration programs. The provision of this quality is challenging because they often depend on the extent and severity of the damage, the considered object, and on the number of interventions that are being simultaneously executed in the same area. Using historical data, public and private records, and expert knowledge-based evaluations, these estimates can be improved, and so, therefore, can the restoration programs. Unfortunately, the deterministic resource constraint models do not allow effective modeling of the uncertainties related to these estimates. One way to quantify uncertainties related to restoration time and costs, is to conduct a sensitivity analysis to analyze how much the results are affected by changes in these parameters.

The restoration program determined, depends greatly on the underlying traffic assignment model. In this work, a static user equilibrium traffic assignment model, based on the BPR functions to emulate the traffic flow conditions, was implemented to simplify the problem to a bilevel optimization problem. Although this model is mathematical rather simple, computationally inexpensive and widely used in literature, it has some limitations when it comes to a realistic representation of traffic flow, e.g., it is assumed that travelers have full knowledge of the traffic conditions, which is clearly not the case. It also does not account for changes in the travel pattern after a disruptive event, although studies show this behavior is considerably different than before a disruptive event (e.g., Chang and Nojima, 2001; Kontou et al., 2017). Although BPR functions are widely used as travel cost functions, they have several disadvantages, as Horowitz (1991) pointed out, including the use in urban areas (e.g., traffic controlled intersections) and the inability to represent dynamic traffic phenomena like queues, spillbacks, wave propagation, capacity drops, and so forth. To improve this, more sophisticated traffic assignment models (e.g., dynamic traffic assignment) could be used (e.g., Nagurney and Dong, 2002; Smith, 2013; Bliemer et al., 2014; Bliemer and Raadsen, 2017). However, in this case the assumption of a bilevel optimization problem has to be relaxed.

Although it may be theoretically possible to determine a restoration program for a network of basically any size, substantial and practical difficulties exist regarding modeling, and data availability and quality. For example, as infrastructure networks are often owned, operated, and maintained by different entities, data are often not accessible, of considerably different quality and in different forms. Cost data is particularly difficult to obtain. Another challenge for infrastructure managers is the determination of the correct balance between the level of detail and speed of analysis (Adey et al., 2016). Abstraction and simplifications are thus necessary for viable modeling. One needs to keep in mind here that the developed model needs to be detailed enough but not overly detailed.

In the work presented in this article one such tradeoff was made by using a metaheuristic procedure. Although this enables the solving of complex problems, where no analytic solution can be found, the results are only an approximation of the optimal solution. Consequently, it is hard, or in most cases impossible, to quantify how close the observed solutions are to the global minimum. Beyond that, it is also difficult to compare the results within different heuristics. For example, the performance of SA depends as much on the specific problem as on the heuristic itself, i.e., the choice of an appropriate neighborhood function, of an efficient cooling schedule, and of sophisticated data structures that allow fast manipulations can substantially reduce the error as well as the running time (Aarts et al., 2005).

An additional challenge lies in the efficient and effective implementation of the restoration model. To use it as a near-real-time decision support, the computational time has to be reduced (e.g., using compiled languages such as C++ and utilizing parallel computing). Besides technical challenges, optimal disaster response and restoration planning are made even more complex, due to the contribution of different agencies and people, legal requirements, and different policies.

7 CONCLUSIONS

This article introduces a restoration model for identifying near-optimal recovery responses that allow a quantitative analysis of the costs, resources, and time needed for a disrupted network to regain full operation after a disruptive event. An optimization problem to determine the most effective restoration program is presented, aiming to minimize the sum of the direct costs, which are related to the execution of the interventions, and the indirect costs associated with the traffic flow on the network until service is restored. This involves a bilevel optimization problem, which is heuristically solved using the SA method, to overcome the issue of the computational complexity.

The model is general enough to be applicable to a variety of infrastructures, including the road, power, water, wastewater, or communication infrastructures. As a realistic case study, a part of the Swiss road network, damaged by an extreme flood event, is considered. Solving the model on the realistic size network shows that the restoration model can produce solutions that are within 7–14% above the best possible solution observed by currently used prioritization schemes. Furthermore, the analysis shows that the restoration model presented here can be of great use for infrastructure managers overseeing the reliability and resilience of critical infrastructures to disruptive events, by obtaining relevant information concerning the investment in recovery operations such as insights on the trade-off between recovery budget and quality of the resulting restoration program.

This type of information can be useful in several ways. Immediately following a disruptive event, the model could be run to offer early estimates of how long it is likely to take to restore service after the occurrence of the event. By running the model for a suite of disruptive events, it could provide estimates of the range of possible restoration scenarios that might affect the system. This can be useful for utilities that have not experienced recent hazards, as well as for those that have and are tempted to assume future events will be similar to the last ones. It is also a means to compare different approaches to efficiently revise operational plans, e.g., by simulating different restoration strategies and mitigation measures (e.g., increasing the number of restoration work crews or adding redundancy to the network), and then compare the resulting output with the original output to determine their effectiveness in making the restoration faster and more efficient.

At the current state, the proposed restoration model is at a tactical level. To bring it to an operational level future work will be required, including the development, calibration, and validation of more accurate damage states and intervention types. Further, more sophisticated and accurate traffic assignment strategies (e.g., dynamic traffic assignment) will create a more realistic and robust traffic analysis, allowing to account for elastic demands, queues, spillbacks, wave propagation, capacity drops, etc. Additionally, to increase the usability the computational efficiency has to be improved and a straightforward user interface has to be developed that can input local data for infrastructure managers to develop restoration strategies.

The used benchmark also requires increased sophistication in its design. Currently, there is no established benchmark procedure such that the solutions found and the computational complexity can be truly tested. Especially, in the context of resilience infrastructure, there is an urgent need to test and compare the performance of different approaches.

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