Future proofing strategies FOr RESilient transport networks against Extreme Events

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Final versions of the algorithms to determine optimal restoration and risk reduction intervention programs

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1 INTRODUCTION

Building on the work in WP1, in which guidelines for the evaluation of resilience were developed, this deliverable contains algorithms to be used in the assessment of resilience when simulations are to be run, and how resilience indicators can be used to select resilience enhancing interventions (Part 1 and 2), and in situations where the values of the resilience indicators are not tied directly to reductions in service or intervention costs (Part 3). The former was principally developed by the EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH (ETH Zürich). The latter was principally developed by the CENTRO DE ESTUDIOS DE MATERIALES Y CONTROL DE OBRA SA (CEMOSA). All partners involved in each task contributed to each. The example use of the guidelines developed in WP1 on case study 2 shown in the appendix was done by the EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH (ETH Zürich) with considerable input from Autostrade per l'Italia, AISCAT SERVIZI SRL (AIS), WSP Spain (Formerly Louis Berger) and FUNDACION TECNALIA RESEARCH & INNOVATION (TEC).

The deliverable is divided into three parts:

Part 1 - Algorithms to determine optimal restoration programs. It contains a description of all required inputs, a complete mathematical model and multiple search algorithms to be used to determine optimal restoration programs, for all objects in a network following the occurrence of a hazard event. It is demonstrated on the road network in the region of Chur, Switzerland.

Part 1 - An algorithm to determine the optimal risk reduction programs. It contains a description of all required inputs, a complete mathematical model and a search algorithm to be used to determine optimal risk reduction programs, for all objects in a network based on the maximization of the difference between risk reduction and intervention cost. It is demonstrated on a small but realistic railway network.

Part 1 - An algorithm to select resilience enhancing interventions using resilience indicators, in situations where the values of the resilience indicators are not tied directly to reductions in service or intervention costs. This methodology uses hierarchical diagrams. It is illustrated using case study 2, and the results are compared with the selection of the optimal interventions following the guideline given in D1.2 (included in the appendix).

In addition to the value of the work presented here in its own right, it has formed the foundation for the work conducted in WP7. To enable the work in WP7

- The first algorithm in part 1 and the algorithm in part 2 have been successfully containerized as Docker containers. The first tool is an algorithm programmed in python to determine the optimal restoration intervention programs following the occurrence of a flood, landslide or earthquake affection either, a part of a road network, part of a rail network or both. The second tool is an algorithm programmed in R to determine the optimal risk-reducing intervention programs taking into account the possibility of reducing the costs of these intervention programs by grouping them spatially and temporarily. From now on, they can be deployed and used by all partners. The next steps are the integration of the Tools from WP3 "Traffic Module" (T3.4.1) and "Fragility and Vulnerability Analysis and the Decision Support Module (DSM)" (T3.4.2). The integration of the first version of the tools with the expected delivery date in M27, as T2.4 "Virtual Modelling platform", T2.5 "Alerting SAS platform", T4.4 "Hybrid data fusion framework" and T7.1 "Definition of framework: use cases, risk scenarios and analysis of impact". In addition, the containerized tools will be developed as APIs in order to achieve the best possible communication between the tools. These Docker containers are available from FhG at present in anticipation of their availability at RINA-C. The FORESEE tool developers will receive a tool assessment sheet under construction at present informing them about a correct behaviour of their respective tool in the Fraunhofer premises.

- Work has also begun in T4.3, with partners working to understand the functioning of the algorithms so that they can be implemented in the case studies in WP6.

2 PART 1: RESTORATION PROGRAMS

2.1 Notations

Sets and graphs

E	set of edges of the network
$\boldsymbol{G}$	transportation network graph
$\boldsymbol{i}(\boldsymbol{n}\|\boldsymbol{s})$	set of interventions for object $\boldsymbol{n}$ given state $\boldsymbol{s}$
$\boldsymbol{n_s}$	set of usable objects in state $\boldsymbol{s} \in \boldsymbol{S}$
$\boldsymbol{P_{od}}$	set of all $\boldsymbol{od}$-paths
$\boldsymbol{P_{od}^g}$	set of all disconnected $\boldsymbol{od}$-paths
$P_{od}^{s\setminus g}$	set of all usable $\boldsymbol{od}$-paths
S	set of all states
V	set of vertices of the network
W	set of all considered vehicle types

Indexes

e	edge in the network
g	state of complete damage $\boldsymbol{g} \subseteq \boldsymbol{s}$
i	intervention
n	object
od	demand from $\boldsymbol{o}$ to $\boldsymbol{d}$
s	state
t	time
w	vehicle type

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 $\boldsymbol{e}$
T	control parameter (temperature)

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 $\boldsymbol{i}$ on object $\boldsymbol{n}$
$\zeta_{n,i}$	variable costs of intervention $\boldsymbol{i}$ on object $\boldsymbol{n}$
$\eta_{n,i,k}$	resource-related costs of resource $\boldsymbol{k}$ for object $\boldsymbol{n}$ due to intervention $\boldsymbol{i}$
$\xi_{e,w}$	value of travel for a vehicle of type $\boldsymbol{w}$ on edge $\boldsymbol{e}$
$\tau_{n,i}$	intervention time for intervention $\boldsymbol{i}$ on object $\boldsymbol{n}$
$\Delta y_{n,i}$	the restored capacity of n due to intervention $\boldsymbol{i}$
ΔZ	change in the value of the objective function
$\psi_{k,t}$	available resource $\boldsymbol{k}$ in period $\boldsymbol{t}$
Ω_t	available budget in period $\boldsymbol{t}$
d_{od}	flow demand between origin $\boldsymbol{o}$ and destination $\boldsymbol{d}$
$f_{od}(P)$	path flow between origin $\boldsymbol{o}$ and destination $\boldsymbol{d}$, on path $\boldsymbol{P}$
$\mu_{e,w}$	the proportion of vehicles of type $\boldsymbol{w}$ on edge $\boldsymbol{e}$
$r_{n,i,k}$	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 $\boldsymbol{e}$ in period $\boldsymbol{t}$
X	state of the variables of $\boldsymbol{Z}$
y_e	the capacity of edge $\boldsymbol{e}$
$y_{n,t}$	the capacity of $\boldsymbol{n}$ in period $\boldsymbol{t}$

Functions

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

2.2 Introduction

The functioning of societies depends on the transportation of goods and persons. The built infrastructure are required to provide specified levels of service (LOS); however, extreme events, e.g. floods, earthquakes, heavy snowfalls, wind storms, whose frequency of occurrence and severity may change due to climate change can significantly reduce this LOS. Managers of transportation infrastructure are responsible for keeping the extent of these possible service disruptions to a minimum. This includes the development and adoption of strategies to minimize the time and costs of restoring affected infrastructure so that it once again provides an adequate LOS, when service disruptions occur.

Consequences of extreme events on transportation networks depend significantly on the response of the objects within the network to the event (LOS drop), and on the restoration program adopted to restore the damaged objects in the network so that they can provide adequate LOS (Figure 1). The first part of this report will focus on post-disaster restoration strategies and on providing a restoration model and appropriate heuristic algorithms to develop the optimal restoration program after an extreme event. Algorithms for determining optimal risk reducing intervention programs before an extreme event are discussed in Part 2 of the report.

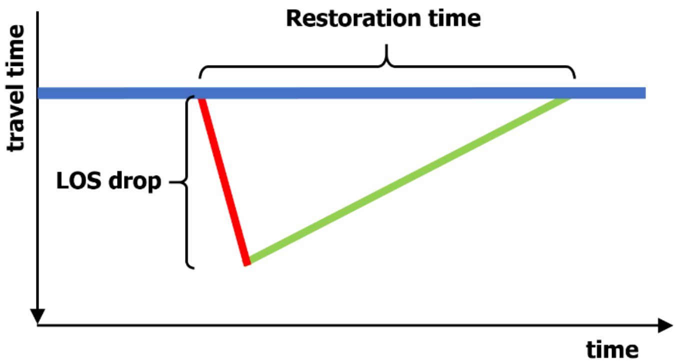


Figure 1. Illustration of resilience, in terms of travel time for transportation of goods and persons from point A to B, where an extreme event occurs and the infrastructure is restored so that it provides the same LOS as it did before the extreme event.

An optimal restoration program refers to the determination of the type and the sequence with which the damaged objects in the network are to be restored, so that they provide adequate LOS, considering the overall costs, and the available budget and resources (Cavdaroglu et al., 2011).

In general, researchers have used two main approaches to develop restoration programs. Some have focused on prioritizing the restoration of the damaged objects using simple equations and rules based on economic or engineering criteria, such as prioritization based on the level of damage (Buckle et al., 2006), average daily traffic volume (Miller, 2014), or based on the importance or the criticality of the objects (Y. C. Liu et al., 2020; Scott et al., 2006). These approaches are mostly used in real-world practices and are time efficient; however, they rarely result in optimal solutions.

Finding the optimal restoration program from a finite set of combinations of different interventions in time might seem a simple task, but in practice, it is not. It may appear that the problem can be solved by simply calculating the overall costs of each combination of interventions in time and then selecting the lowest. As this may be an option for very small networks, the task is almost impossible within a reasonable amount of time for large networks with multiple restoration options for each damaged object. An algorithm is, therefore, needed to find the optimal restoration program.

Algorithms for finding optimal intervention programs can be divided into exact and heuristic algorithms. An exact algorithm guarantees to find the global optimal intervention program while a heuristic algorithm will find a good (near-optimal) intervention program, although it might not be the best available one. Heuristic algorithms, however, have the advantage of having a shorter running time which makes them more suitable for estimating how networks might be restored when estimating risk, requiring many scenarios to be investigated, and for determining the optimal way to restore infrastructure following the occurrence of an extreme event, i.e. in post-disaster decision-making. There are several studies that have focused on the identification of the optimal restoration program after the occurrence of extreme events for infrastructure. Table 1 summarizes the latest studies based on the type of disruptive event and the infrastructure.

A proliferation of objective functions are used in literature to determine optimal intervention programs, including minimizing the travel time, the number of lost trips, disconnected links, and the overall costs of the restoration programs. These objective functions are often minimized by using stochastic mixed-integer programs solved by Monte Carlo simulations (L. Chen & Miller-Hooks, 2012), or using heuristic models such as Genetic Algorithms (GA) (Yuh-Wen Chen & Tzeng, 1999), Ant Colony System (ACS) (Yan & Shih, 2012), or Simulated Annealing (SA) (Hackl, Adey, et al., 2018; Vugrin et al., 2014). These single optimization approaches that use heuristic algorithms have the advantage of finding near-optimal solutions in a relatively short time in comparison to exact algorithms. However, none of the models have been used in real-world networks with larger than a dozen edges. In the few studies where the models were tested on real-world networks, the time required to develop an optimal restoration program was unacceptable (Hackl, Adey, et al., 2018; Orabi et al., 2009). This is because when the time between the occurrence of the disruptive event and the beginning of restoration work increases, the indirect costs related to the travel prolongation and loss of connectivity will also increase. Therefore, there is still a need for developing an approach that can determine the optimal restoration intervention program, in a short period.

In this report, to determine the optimal restoration program for transportation networks, a mathematical model is suggested that minimizes the weighted sum of the direct and indirect costs over the period between the occurrence of the disruptive event and the time the restoration work is complete. The efficiency of common heuristic algorithms, in minimizing the objective and developing the restoration programs are investigated and the most suitable algorithms for this problem are identified. These algorithms were selected due to their ability in providing a balance between complexity and efficiency, which outperform other commonly-used algorithms (Antosiewicz et al., 2013; Ma et al., 2015; Mukhairez & Maghari, 2015; Nolz et al., 2012). This model includes constraints, such as limits on the available budget, resources and the type of intervention that can be executed per damage state, as well as varying traffic assignments caused during the implementation of the restoration program.

Moreover, a novel approach is introduced that identifies the near-optimal solution using a double optimization procedure. In the first stage of the proposed approach, the model optimizes the restoration of the most critical objects in the network and while the restoration work is being carried out on these objects, the second stage optimization will identify the sequence and level of repair of the remaining objects in the network. This novel approach can be used to determine the optimal restoration programs for real-world networks in a short period of time.

Ultimately, the two optimization approaches, i.e. single and double optimization are used in a real-world network and the results are compared with a benchmark model that uses prioritization rules.

The remainder of part 1 is organized as follows: In Section 2.3, the objective function of the proposed restoration model is presented. The comparison of the most commonly-used heuristic algorithms for combinatorial problems is presented in Section 2.4 and the three most suitable heuristic algorithms are introduced in more detail. In Section 2.5, the studied network is introduced along with various steps and procedures for using the proposed restoration model. 2.6 and 2.7 illustrate the procedures for developing restoration programs using the three most suitable heuristic algorithms in single and double optimization approaches respectively. In Section 2.8, the advantages and limitations of the proposed restoration model are discussed along with some suggestions for future work.

Table 1. Examples of studies on the identification of optimal restoration programs after the occurrence of a disruptive event.

Focus of work	Citation
Post-earthquake restorations for lifeline systems	(Isumi et al., 1985)
Post-earthquake restorations for road networks	(Y.W. Chen & Tzeng, 2000)
Post-earthquake restoration modeling of electric power systems	(Çagnan & Davidson, 2004)
Post-earthquake optimal restoration of electric power systems	(Xu et al., 2007)
Post-earthquake restoration of water distribution systems	(Luna et al., 2011)
Post-earthquake restoration for bridges	(Bocchini & Frangopol, 2012)
Post-earthquake restoration strategies for highway bridges	(Tao & Wang, 2019)
Post-earthquake restoration for complex infrastructure networks	(Morshedlou et al., 2019)
Estimation of restoration times of electric power after hurricanes and ice storms events	(H. Liu et al., 2007)
Restoration strategies for supply-chain infrastructure elements after tornados	(Ramachandran et al., 2015)
Highway network restoration after an extreme flood event	(Lertworawanich, 2012)
Restoration of roadway networks after an extreme flood event	(Hackl, Adey, et al., 2018)
Optimal scheduling of emergency roadway repair	(Yan & Shih, 2009)
Post-disaster restoration of critical infrastructure	(Vugrin et al., 2010)
Post-disaster intervention prioritization for bridges along a highway segment	(Bocchini & Frangopol, 2010)
The resilience of freight transport networks to natural or human-caused disaster	(L. Chen & Miller-Hooks, 2012)
Optimal restoration programs for transportation networks	(Vugrin et al., 2014)
Restoration program for infrastructure networks after disruptions	(Hu et al., 2016)
Post-disaster restoration of transportation networks	(Liao et al., 2018)
Post-disaster restoration under uncertainty for power grids	(Fang & Sansavini, 2019)
Post-disruptions restoration of critical infrastructure	(Fang et al., 2019)
Optimization-based decision support framework for coupled pre- and post-earthquake infrastructure risk management	(Gomez & Baker, 2019)

2.3 The objective function

The objective function of the model is to minimize the weighted sum of the direct and indirect costs, i.e. reductions in the cost of the restoration actions but also on the cost of the loss of service, during the implementation of the restoration program following an extreme event.

2.3.1 Direct costs

Direct costs are referred to the expenses related to the execution of the physical interventions, such as cleaning-up, preparation, rehabilitation of damaged objects, or reconstruction. The overall direct costs, C^{DC} is the sum of the direct costs for the interventions that are executed on damaged objects (EQ. 1) (Hackl, Adey, et al., 2018).

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

where for each damaged object $n \in N^s$, only one intervention $i \in I(n|s)$, can be assigned at the time $t \in T$. A binary variable, $\delta_{n,i,t}$, has the value of 1 if at the time t, the intervention i is executed on the object n with a damage state s; otherwise, the value would be equal to 0. The overall costs of intervention i on object n with a damage state s, i.e. $C_{n,i}$, is the summation of the fixed ϵ, variable ζ and resource-related costs (EQ. 2).

$$C_{n,i} = \epsilon_{n,i} + \zeta_{n,i} + \eta_{n,i} \qquad \forall n, i \qquad 2$$

It is noted that the following parameters are associated with each intervention $i \in I(n|s)$:

1 The flow capacity following the execution of the intervention $\Delta y_{n,i}$

2 The duration of the execution of the intervention $\tau_{n,i}$

3 The amount of resources $k \in K$ required for the execution of the intervention $\mathrm{r}_{n,i,k}$

4 The execution costs of each intervention $C_{n,i}$

The capacity of object n at time t can be calculated from EQ. 3.

$$y_{n,t} = y_{n,0} + \sum_{i \in I(n|s)} \sum_{j \in t - \tau_{n,i}} \delta_{n,i,t} \, . \, \Delta y_{n,i} \qquad \forall n \in N \qquad 3$$

where $y_{n,0}$ is the capacity of the object immediately after the extreme event.

2.3.2 Indirect costs

Indirect costs are either due to the travel prolongation $\Pi - \Pi^0$, or are associated with the impassable paths and loss of connectivity Λ (Adey et al., 2004). Indirect costs C^{IC} are estimated to be the difference between the indirect costs at time t and $t = 0$ when the extreme event had not yet happened and the network was fully functional (EQ. 4)

$$C^{IC} = \sum_{t \in T} \left[\sum_{p \in P_{od}^{s\backslash g}, e \in P} \Pi(t|x_{e,t}) - \Pi^0(t|x_{e,0}) + \sum_{p \in P_{od}^{g}} \Lambda(\mathrm{t}) \right] \qquad 4$$

where $P_{od}^{s\backslash g} \subseteq P_{od}$ is the set of od-paths with some possible flow and does not contain any objects with zero functionality g.

The loss in connectivity is estimated by evaluating the unsatisfied demand in a period of time, $f_{od,t}\ (P)$, and the costs due to a loss of labour productivity which is a measure for the produced value of services and goods in unit time period υ (Freeman, 2008).

$$\Lambda(\mathrm{t}) = f_{od,t}\ (P).\upsilon(t) \qquad \forall t, P \in\ P_{od}^{g} \tag{5}$$

The travel time costs are due to the extra time that is spent on travelling and are linked to the traffic flow on the transport link, section or edge (hereafter "edge"). These costs include travel time Φ and vehicle operation costs Υ as indicated in EQ. 6.

$$\Pi(t|x_{e,t}) =\ \Phi(t|x_{e,t}) +\ \Upsilon(t|x_{e,t}) \qquad \forall t, e\ \in P, P \in\ P_{od}^{s\backslash g} \tag{6}$$

where $\Phi(t|x_{e,t})$ and $\Upsilon(t|x_{e,t})$ can be estimated from EQ. 7 and EQ. 8 respectively.

$$\Phi(t|x_{e,t}) =\ t_{e,t}(x_{e,t})\,.\sum_{w \in W} \mu_{e,w}\,.\,\xi_{e,w} \tag{7}$$

where $w \in W$ is referred to the different vehicle types, $\mu_{e,w}$ presents the proportion of vehicles of type w on edge e, and $\xi_{e,w}$ is the estimated cost of travel per unit time.

The vehicle operating costs are due to the fuel consumption and the maintenance of vehicles (Adey et al., 2012), and are estimated as follows:

$$\Upsilon(t|x_{e,t}) =\ x_{e,t}.\,l_e\,.\sum_{w \in W} \mu_{e,w}\,.\,(\nu.\,F_w + \rho_w) \tag{8}$$

where l is the length of edge e, F_w and ν are the mean fuel consumption and mean fuel price respectively, and ρ_w is the operating costs (without fuel) for each vehicle type.

Sometimes, a weighting factor γ is used for the estimation of the total indirect costs. This is due to the high levels of uncertainty that is normally associated with quantifying the indirect costs and the resulting estimated values. Using the weighting factor will allow the decision-makers to decide on the extent that the indirect costs will affect the determination of the optimal restoration program (Hackl, Adey, et al., 2018).

2.3.3 Restoration model

As stated earlier the objective function of the proposed model is to minimize the overall direct and indirect costs which can be written as the minimum of $C^{DC} +\ C^{IC}$:

$$min\ Z^R = \sum_{t \in T}\left[\sum_{n \in N^s}\sum_{i \in I(n|s)} \delta_{n,i,t}\,.\,C_{n,i} + \gamma \sum_{p \in P_{od}^{s\backslash g}, e \in P} \Pi(t|x_{e,t}) - \Pi^0(t|x_{e,0}) + \sum_{p \in P_{od}^{g}} \Lambda(\mathrm{t})\right] \tag{9}$$

It is subject to the following constraints:

$$\sum_{i \in I(n|s)}\sum_{t \in T} \delta_{n,i,t}\ \le 1 \qquad\qquad \forall n \in N \tag{a.}$$

Constraint a is to enforce the model to select only one intervention at a time for each damaged object throughout the restoration planning horizon.

$$\sum_{n \in N^s}\sum_{i \in I(n|s)}\sum_{t \in T} \delta_{n,i,t}\,.\,C_{n,i} \le \Omega_t \qquad\qquad \forall t \in T \tag{b.}$$

Constraint b is to ensure that the total costs of all interventions does not exceed Ω, which is the available budget for time period t.

$$\sum_{n\in N^s}\sum_{i\in I(n|s)}\sum_{j\in t-\tau_{n,i}+1}\delta_{n,i,j}\cdot r_{n,i,k}\leq \psi_{k,t} \qquad \forall k\in K\ ,\ \forall t\in T \qquad \text{c.}$$

Constraint c forces the model to not select more resources than available, i.e. $\psi_{k,t}$, for the period t. Depending on the network situation, it is possible to add other constraints such as accessibility, or time constraints to the model as well. The link flow $x_{e,t}$ in EQ. 9 which is a part of the indirect costs, is estimated by solving a user equilibrium assignment as indicated in EQ. 10.

$$x_{e,t}\ \in \min Z^T = \sum_{e\in\varepsilon^s}\int_0^{x_{e,t}} C_e^T(\omega)d_\omega \qquad 10$$

The costs of travel on each edge can change with the flow (e.g. speed reductions) and result in changes to the costs of travel in the network. A stable state is reached only "when no traveller can reduce his costs of travel by unilaterally changing routes" (Daskin, 1985; Hackl, Adey, et al., 2018). The function proposed by the Bureau of Public Roads (BPR, 1964), can be used to find the cost-flow relationship, C_e^T , where the travel cost is determined by $travel\ time/unit\ distance$, since these costs are directly linked to the traffic flow on an edge (EQ. 11)

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

Where t_e^0 is the free-flow travel time, and $t_{e,t}$ corresponds to the travel time at edge e in period t given the traffic flow $x_{e,t}$. The edge capacity is defined as $y_{e,t}$; and parameters α and β are for calibration purposes.

The user equilibrium assignment defined in EQ. 10 is constrained as follows:

$$\sum_{P\in P_{od}^{s\backslash g}} f_{od}(P) = d_{od} \qquad \forall od\in V^H \qquad \text{a.}$$

$$f_{od}(P)\geq 0 \qquad P\in P_{od}^{s\backslash g}, \qquad \forall od\in V^H \qquad \text{b.}$$

The constraint d states that the flow on all od-pairs has to be equal to the demand $d_{od}\ \geq\ 0$ for all $od\in V^H$. The non-negativity constraint, e, is to ensure that the solution of the optimization will be physically meaningful. EQ. 12 is used to express the relationship between edge flows and path flows; since EQ. 10 is formulated in terms of edge flows while the related constraints (d and e) are expressed in terms of path flows.

$$x_e = \sum_{od\in V^H}\sum_{P\in P_{od}^{s\backslash g},e\in P} f_{od}(P) \qquad 12$$

2.4 Heuristic algorithms

The determination of an optimal restoration program for transportation networks after the occurrence of an extreme event can be categorized as a multilevel optimization problem, where some variables of the objective function are constrained to the optimal solution of another part of the model. In this study, the minimization of the overall intervention costs (EQ. 9) or the upper-level optimization depends on the traffic assignment (EQ. 10) that needs to be solved using another lower-level optimization problem.

The upper-level optimization can be classified as a combinatorial optimization problem, where the optimal restoration program is selected from a finite set of combinations of different interventions in time (Hackl, Adey, et al., 2018). The lower-level optimization which is embedded in the upper one, i.e. the traffic assignment, can be solved using a conjugative direst Frank-Wolfe algorithm (or any other algorithm for traffic assignment). For the upper-level optimization, however, the classical optimization methods cannot be used due to the computational complexity, nonlinearity, non-convexity, and non-differentiability of the problem. Additionally, as the indirect costs increase with time, the computation speed has a significant influence on the efficiency of the algorithm that is selected to solve the optimization problem. Hence, the selected optimization algorithm should accommodate the mentioned challenges in a relatively short amount of time.

Algorithms for finding optimal intervention programs can be divided into exact and heuristic algorithms. An exact algorithm guarantees to find the global optimal intervention program while a heuristic algorithm will find a good (near-optimal) intervention program, although it might not be the best available one. Heuristic algorithms have the advantage of having a shorter computation time, which makes them more suitable for post-disaster decision-making, as delays can significantly influence the costs. Table 2 presents a short overview of common heuristic algorithms suitable for combinatorial problems such as the traveling salesman problem (TSP), with their advantages and limitations.

By comparing the algorithms in Table 2, it can be deduced that algorithms that are very easy and fast to use for most combinatorial problems are not necessarily fast to implement in finding the optimal restoration programs. For example, tour construction algorithms such as the Nearest Neighbour, Greedy heuristic, and tour data structure algorithms such as Ant Colony, require information of the distance (costs) from one point to all other points. While this can be a very simple task for problems such as TSP, it is not the case for the presented restoration model. This is due to the existence of the indirect costs that depend on the traffic model and hence, one should run the traffic model for each set separately that will significantly increase the computation time. Hence, such algorithms are not efficient for this problem. Branch and Bound and Tabu search are also not efficient due to the related computational time. Consequently, the authors have selected the three most promising algorithms, i.e. Simulated Annealing (SA), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO), to compare their potentials in identifying the optimal restoration programs after an extreme event.

Table 2. Comparison of the commonly-used heuristic algorithms for combinatorial problems

Algorithm	Method	Advantages	Limitations	Ref.
Branch and Bound	The set of solutions is formed as a rooted tree. Explores branches of the tree, which present subsets of the solution set. The algorithm checks the estimated upper and lower bounds of the solution for each branch and discards it if it is not possible to find a better solution than what is identified so far. If promising, it enumerates the candidate solution of the branch.	Finds the optimal solution. Suitable for problems with fewer search points.	The efficiency of the algorithm is dependent on the accuracy of the estimated lower and upper bounds of branches. If this estimation is not possible, the algorithm performs an exhaustive search that can be very slow for large networks.	(Carpaneto & Toth, 1980; Carrabs et al., 2013)
Nearest Neighbour	Selects a random point. Finds the nearest (with lowest costs) unvisited point and go there. Any unvisited points left? If yes, it repeats step 2. Returns to the first point.	Very simple and straightforward heuristic, especially for TSP.	Prior knowledge of the costs from one point to all other points is required. Stops when it finds a solution and does not try to improve it.	(Hurkens & Woeginger, 2004; Nilsson, 2003; Rosenkrantz et al., 1977)
Greedy heuristic	Sorts all edges. Selects the shortest unselected edge (with the lowest cost) and add it to the tour. Are there N edges in the tour? If not, repeats step 2.	More efficient than the Nearest Neighbor in finding the optimal solution.	Prior knowledge of the costs for all possible edges is required. Stops when it finds a solution and does not try to improve it.	(Geng et al., 2011; Nilsson, 2003)
Tabu-Search	Checks its immediate neighbours in the hope of finding a better solution. Allows moves with a negative gain if we cannot find a positive one. A tabu-list is created based on the moves to the immediate neighborhood where that move will never be implemented again, while it is on the list unless it provides a better solution.	Avoids getting stuck in a local optimum	Long computation time.	(Knox, 1994; Malek et al., 1989; Nilsson, 2003)
Simulated Annealing (SA)	Starts from a random point and calculates the value of the objective function Z, also known as the initial state. Applies random shifts based on the selected neighborhood and computes ΔZ Decides to accept the new point or to stay with the initial state. If improved, selects the solution. If not, accepts it with a probability of $e^{(-\frac{\Delta Z}{T})}$, where T is the algorithm temperature. During this search, the temperature is gradually decreased from an initial positive value to a value near zero.	Provides a balance between complexity and efficiency which outperforms the other commonly-used algorithms	The embedded parameters such as the acceptance probability function, the initial and end temperature, and the annealing schedule have a significant influence on the effectiveness of the method. However, there is no general way to find the best choices of these parameters for a given problem.	(Geng et al., 2011; Hackl, Adey, et al., 2018; Malek et al., 1989; Nilsson, 2003)
Genetic Algorithms (GA)	Starts with randomly generating a population of feasible solutions. The created population (feasible solutions) mate and produce the next generation. Some undergo a mutation. The excellence of the solutions are evaluated using a fitness value. Selects the fittest candidates for mating and mutation and hence, increases the overall fitness of the solutions.	Parameters are relatively easy to adjust.	Computationally expensive.	(Yuh-Wen Chen & Tzeng, 1999; Grefenstette et al., 1985; Nilsson, 2003; Potvin, 1996)
AC	A group of ants start from various points and move to another (new) point. The ants leave a trail of pheromones that is proportional to the inverse of the length (cost) of the tour. Ants are more inclined to select the path that has the strongest pheromone trail. This process is repeated until a tour being short enough (low costs) is found.	Fast determination of optimal solutions to small problems.	Prior knowledge of the costs from one point to all other points is required.	(Dorigo & Gambardella, 1997; Nilsson, 2003; Yan & Shih, 2012)
Particle Swarm Optimization (PSO)	Uses the physical movements of the individual particles in the swarm. The particles' movements are controlled by their local best-known solution and are ushered toward the best-known solution in the search space, that will be updated as better solutions are found. This procedure will prompt the swarm to move toward the best solutions.	Has a well-balanced mechanism to enhance and adapt to the global and local exploration abilities. Relatively fast and easy to implement.	c_1 and c_2 parameters need to be tuned to get the optimal results in a relatively short time. However, the choices of these parameters are problem-specific.	(Clerc, 2004; Nilsson, 2003; Wang et al., 2003)

2.4.1 Simulated Annealing algorithm

SA is a heuristic approach for approximating the global optimum of a given function in a large search space. This method is often used when the search space is discrete and when an approximate global optimum in a relatively shorter amount of time is preferred over attempting to find the exact global optimum.

The method was inspired by the annealing in metallurgy, where a metal is heated until it melts and then it is gradually cooled to increase the size of its crystals, reducing the defects and reaching a new ground state. The SA was first used in 1983, by Kirkpatrick et al. (1983) to find the solution to the traveling salesman problem.

In principle, the SA seeks to minimize an objective function following the bellow procedure:

- Start from a random point and calculating the value of the objective function Z, also known as the initial state
- Apply small random changes to the variables and compute ΔZ
- Deciding to accept the new point or to stay with the initial state. In this step when there is an improvement, i.e. the value of the objective function is reduced, the resulting change is accepted and a further search is initiated in the neighbourhood of this point. However, if the new solution shows no improvements, it is accepted with a probability of $e^{\left(-\frac{\Delta Z}{T}\right)}$, where T is a control parameter known as the temperature of the system. Hence, the probability of accepting a worse solution is high for high temperatures and small for low temperatures. This will help in avoiding the local optima (Suppapitnarm et al., 2000). During this search, the temperature is gradually decreased from an initial positive value to a value near zero. Hence, at each step, the probability of moving to a better new solution is either kept to 1 or is moved towards a positive value; and the probability of accepting a worse solution is gradually moved towards zero.

To use the SA in an optimization problem it is necessary to define the objective function, the neighbourhood, the acceptance probability function, the initial and end temperature, and the annealing schedule (Eglese, 1990). These parameters have a significant influence on the effectiveness of the method, however, unfortunately, there is no general way to find the best choices of these parameters for a given problem.

2.4.1.1 Objective and penalty function

The objective function and constraints were introduced in the earlier section. It is worth mentioning that finding the global minimum of a constrained and complex objective function can be very challenging. In fact, the existence of non-convex and nonlinear constraints makes it difficult to even find a feasible solution or neighbourhood for the problem. Moreover, the feasible neighbourhoods may be a part form each other and the search for the global minimum may require visiting multiple feasible neighbourhoods (Wah & Wang, 1999).

A dynamic penalty function, also known as the annealing penalty can be used to avoid the selection of infeasible solutions for the objective function (EQ. 9), with respect to the problem constraints (Michalewicz & Schoenauer, 1996). In other words, infeasible solutions become worse than a feasible solution since they are added with a penalty (EQ. 13)

$$eval(X) = \begin{cases} Z(X) & X \in feasible\ solutions \\ Z(X) + P(X) & otherwise \end{cases} \qquad 13$$

where $P(X)$ is dependant on the temperature and can be derived from EQ. 14. This function also accounts for the degree of the infeasible solutions by weighting the distance to a solution from a feasible neighbourhood.

$$P(X) = \frac{1}{2T} \sum_{j \in m} Y_j\,(X)^2 \qquad 14$$

Where $Y(X)$ is a constraint of the objective function and m is the amount of the constraint. It can be observed that at be beginning of the search, where the "temperature" is high, the penalty is relatively low and it gradually increases as the "temperature" drops. This will allow for a wider solution space at the beginning of the search and will penalize infeasible solutions more harshly as the simulation proceeds.

2.4.1.2 Selecting the neighbourhood

The neighbourhood function, which is highly problem-specific, is used to create a neighbour solution from the current solution and can significantly influence the efficiency of SA. As mentioned earlier, the challenge of finding an optimal restoration program is categorized as a combinatorial optimization problem with a finite solution space. This means that, for a specific object type, i different intervention types exist, hence, in the SA process the object can only be in i stages. Consequently, one can write the order in which an intervention of type i is executed on object n as a sequence of tuples $[(n_j, i_j), (n_k, i_k), \ldots]$.

As a result, the problem can be solved by generating several sequences in a feasible neighbourhood and choosing the best. A neighbour solution is generated by randomly choosing one of the tuples in the sequence and assigning it to a new position; additionally, the intervention types for the damaged objects are changed with a certain probability.

2.4.1.3 Selecting the annealing schedule

The annealing schedule is required to reduce the amount of time required to find a near-optimal solution. There are a proliferation of heuristic annealing schedules (also known as cooling schedules) available in the literature. For instance, Siddique and Adeli (2016) have provided a comprehensive review of different cooling schedules for engineering applications. Nevertheless, these schedules are highly problem-specific and their effectiveness can only be compared through experimentation (Henderson et al., 2003).

The annealing schedule can be adjusted as follows:

- The initial temperature is set as T_0.
- At every i^{th} iteration out of J the temperature T_0 is multiplied by $e^{(\mathrm{k}.\frac{\mathrm{i}}{J})}$, where κ is a parameter for the decay rate and is defined as $\kappa = -ln(\frac{T_0}{T_{min}})$.

2.4.2 Genetic Algorithm

The Genetic Algorithm is a heuristic inspired by the theory of natural evolution. It starts with the formation of the initial population that are random restoration programs (i.e. random orders in which interventions are executed on damaged objects). In identifying the optimal restoration programs, the fitness of each individual is the inverse of the total costs of each program. Consequently, a mating pool is formed based on the fitness score of individuals, meaning that the ones with higher fitness have more chances to be selected for mating.

For each pair of parents, a crossover point is randomly selected within the genes and the next generation is created by swapping the genes of parents until the crossover point is reached (Figure 2). Mutation subjects some of the individuals in the new generation to some gene flips with a low probability. This is done to preserve the population diversity and avoid premature convergence. The parameters involved in this algorithm are the population size, elite size, number of generations, and the mutation rate which is normally a very small value. Figure 3 provides a flowchart of this algorithm.

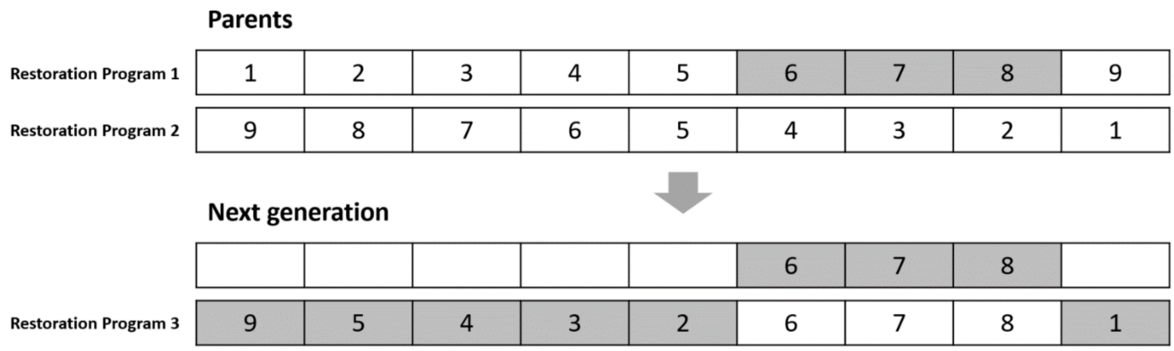


Figure 2. Illustration of the crossover process. The genes are the objects that need to be restored and each program represents the sequence of the objects to be restored.

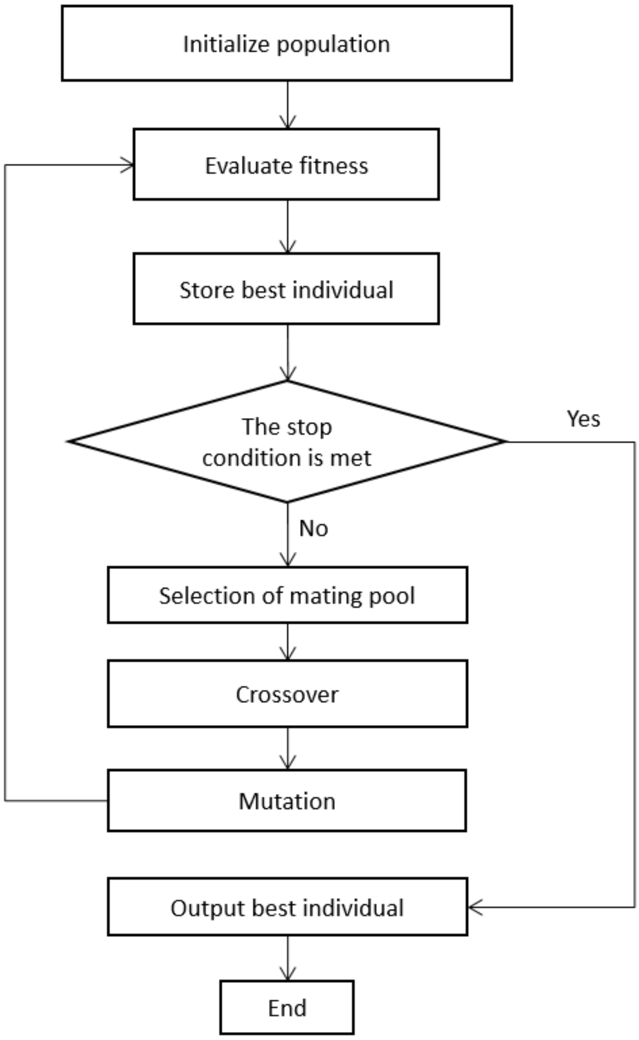


Figure 3. The Genetic Algorithm flowchart

2.4.3 Particle Swarm Optimization algorithm

Particle Swarm Optimization (PSO) is a population-based algorithm where first random solutions are initialized. The algorithm then searches for the optimal solution by updating the direction of movement in the search space, meaning the particles (potential solutions) move through the search space by following the existing best available solutions. This algorithm requires adjustment of some parameters including the number of particles, number of iterations, the individual (c_1), social (c_2), and inertial (w) coefficients. Normally, the inertial coefficient (w) is gradually reduced from 0.9 to 0.4. The individual (c_1) and social (c_2) coefficients are, however, problem-dependent and need tuning to find near-optimal solutions in a timely manner. Figure 4.a presents the pseudocode for PSO, which is very efficient in continuous problems.

However, as the determination of an optimal restoration program is a combinatorial problem, the presented PSO algorithm needs to be modified to be suitable. For this purpose, shifting to new solutions will be through swap operations. A swap operator $\mathrm{SO}(n_i, n_j)$, is a function that swaps node i and j in a solution. A basic swap sequence (SS) represents the sequence of using swap operators to reach solution B from solution A. This basic sequence is presented as demonstrated in Eq. 15 and 16 (Wang et al., 2003).

$$SS = A - B \qquad (15)$$
$$A = SS + B \qquad (16)$$

The operators ⊕ and ⊖ are used to show the merging of two swap sequences, that produces a new swap sequence. As a result, the pseudocode for the discrete PSO can be written as illustrated in Figure 4.b.

<table>
<tr><td>(a)</td><td>(1) Initialize swarm $\boldsymbol{P}$ of $\boldsymbol{n}$ particles $\boldsymbol{p}$:
- Initialize particles positions
- Set all velocities to 0

(2) Update swarm at iteration $\boldsymbol{t}$
- Evaluate swarm with the objective function: $\boldsymbol{f}(\boldsymbol{P^t})$
- for each particle $\boldsymbol{i}$ do
Update the last (historically) best position of the particle: $\boldsymbol{Pbest_i^t}$
Update the last best position of the swarm particles: $\boldsymbol{Gbest^t}$
Update the particle velocity and position with:
$\boldsymbol{v_i^{t+1} = wv_i^t + C_1 u_i^{1,t}(Pbest_i^t - x_i^t) + C_2 u_i^{2,t}(Gbest^t - x_i^t)}$
$\boldsymbol{x_i^{t+1} = x_i^t + v_i^{t+1}}$
- end for

(3) If $\boldsymbol{Gbest^t}$> threshold
- Go to (2).
else:
- Terminate</td></tr>
<tr><td>(b)</td><td>(1) Initialize swarm P of n particles p:
- Initialize particles position sequence
- Set all velocities to $\emptyset$

(2) Update swarm at iteration t
- Evaluate swarm with the objective function: $f(P^t)$
- for each particle i do
Update the last (historically) best position of the particle. $Pbest_i^t$.
Update the last best position of the swarm particles. $Gbest^t$
Update the particle velocity and position with:
If $(c_1^t < rand(0,1))$: exclude swap sequence $Pbest_i^t \ominus x_i^t$ end
If $(c_2^t < rand(0,1))$: exclude swap sequence $Gbest^t \ominus x_i^t$ end
$v_i^{t+1} = wv_i^t \oplus (Pbest_i^t \ominus x_i^t) \oplus (Gbest^t \ominus x_i^t)$
$x_i^{t+1} = x_i^t \oplus v_i^{t+1}$
- end for

(3) If $Gbest^t$> threshold
- Go to (2).
else:
- Terminate</td></tr>
</table>

Figure 4. Part (a) illustrates the pseudocode for continuous PSO where $u_i^{1,t}$ and $u_i^{2,t}$ are random values. Part (b) represents the pseudocode for a discrete PSO

2.5 Example: Near-optimal restoration program for the city of Chur

In this section, the heuristic algorithms presented above will be used to develop near-optimal restoration programs after an extreme flood event on a part of the road network around the city of Chur, the capital of Grisons the largest canton of Switzerland.

Two approaches are used to develop restoration programs. The first one is a single optimization approach, where the sequence and level of restoration for all damaged objects in the network are determined in a single stage. The second approach is a double optimization procedure where initially a program is developed for the most critical objects in the network and while the restoration work is being carried out on these objects, the second stage of optimization will identify the sequence and level of repair of the remaining objects in the network.

The following sub-sections provide an overview of the network, the procedure to determine the damaged objects after the extreme event, the intervention types, and the development of the restoration programs using single and double optimization approaches.

2.5.1 The example network

The studied city has a population of roughly 34’500 people. The network is located next to the river Rhine and according to the historical records of the Swiss Flood and Landslide Damage Database (Hackl, Lam, et al., 2018; WSL Unwetterschadens, 2014), it is prone to floods and landslides on an annual basis.

The network is comprised of approximately 51 km of national roads, 165 km of main roads, and 395 km of minor roads. In total it consists of 2’153 objects, including 2’011 road sections and 116 bridges, as shown in Figure 4.

The related information of the Chur road network was taken from the VECTOR25 data set, provided by swisstopo (JD100042). In this example, it is assumed that the network only consisted of motorways, main roads, and minor roads.

This network is denoted by $G = (V, E)$, where V is a set of vertices corresponding to point-objects such as bridges or road crossings, and E is referred to edges that represent objects with a length such as road sections. Graphs are assumed to be directed and therefore, an edge is an ordered pair. The edges have a defined capacity, y_e which is referred to the upper limit on the flow in a time unit. The od-paths represent vehicle movements from an origin vertex o, to the destination vertex d that occur along edges.

An ESRI Shapefile for the Swiss coordinate system CH1903/LV03 LN02 (ESPG code: 21781) was used that provided information regarding the direction, length, free-flow speed, and capacity of the road sections. In the example, bridges are modelled as vertices and located in the middle of the river where two road segments are joined. A sample of road sections and bridges are shown in Tables 3 and 4.

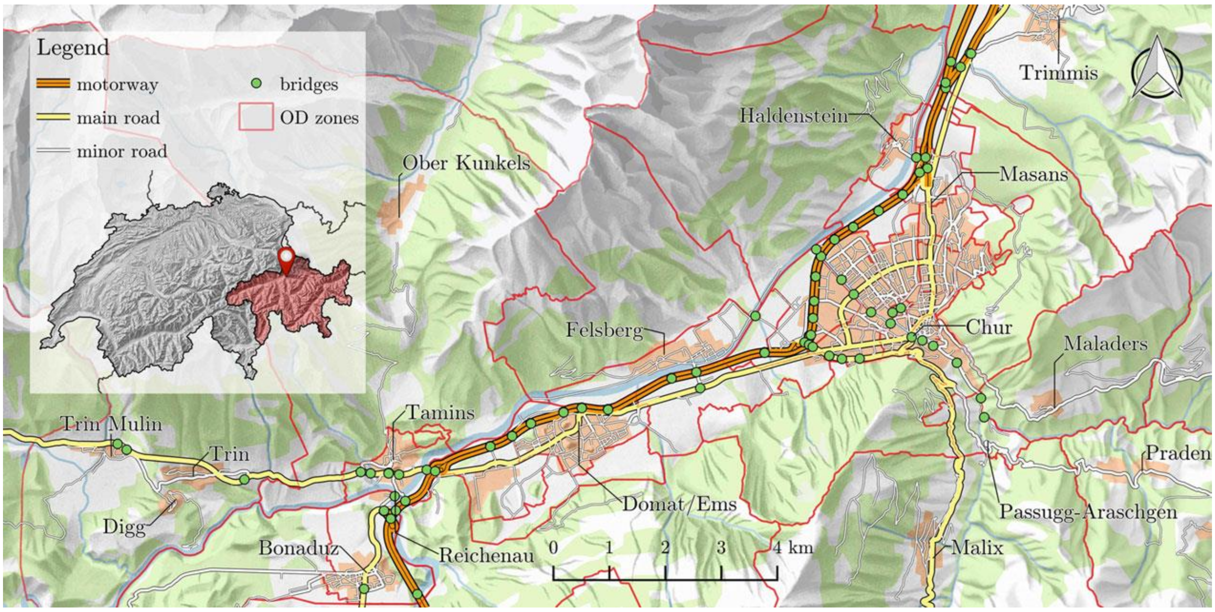


Figure 5. Investigated road network around the city of Chur, Grisons, Switzerland (Hackl, Adey, et al., 2018)

Table 3. Sample of considered road sections and their assigned attributes (Hackl, Adey, et al., 2018)

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

Table 4. Sample of considered bridges and their assigned attributes (Hackl, Adey, et al., 2018)

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

The trips in the network are considered to start and end in the 37 zones based on the judicial districts shown in Figure 5. A gravity distribution model (de Dios Ortuzar & Willumsen, 2011) was used to estimate the trips based on the population of each zone, to construct the OD matrix. This method was used due to the lack of available information regarding the trip distribution for the area of study. The results were then calibrated based on the Swiss national traffic model (FOSD, 2015), which provides data for the motorway and main roads (Hackl, Adey, et al., 2018).

2.5.2 Damage states and functional losses

As mentioned earlier, natural hazards can reduce the functionality of the objects within the transportation infrastructure and disturb the transportation of people and goods.

Evaluation of the damage level following a natural hazard is normally done by performing inspections, however, due to lack of available damage assessment data following a flood event in the area of investigation, the damage states of the objects in the network were estimated using fragility and capacity loss functions (Lam & Adey, 2016), which were used in a flood simulation with a 500-year return period (Hackl, Lam, et al., 2018).

In this simulation, functional losses due to the inundation of road sections along with the local scour at bridge piers caused by an extreme flood were estimated. More information regarding the details of quantification procedures and computer-supported model used to derive the damage states and functional losses are described in (Hackl, Lam, et al., 2018) and its supplemental manuscript. Figure 6 illustrates a schematic overview of the modules used for the simulations. In Figure 6, modules, represented by nodes with certain inputs and outputs, are related to the events that need to be modelled to estimate risk. The assessment starts with the modelling of a random rainfall and its corresponding runoff. Estimated discharge values at river stations of interest are used to simulate the flood propagation, including the inundation of the area. A mudflow can be randomly triggered during the rainfall if accumulated precipitation values exceed certain thresholds. In the next step, expected damages (i.e., bridge local scour, road section inundation, road section mud-blocking), functional losses (i.e., speed reduction, capacity reduction), and restoration needs (i.e., restoration cost, restoration time) are determined for each affected object in the network. The updated states of individual objects help define the new state of the entire network. The traffic through the network is then simulated. Restoration interventions are executed to enable the network to provide an adequate level of service again by changing the state of damaged objects. The costs for the restoration are accounted as direct costs, while the costs related to additional vehicle travel time through the network and missed trips are accounted as indirect costs (Hackl, Lam, et al., 2018).

The state of an object after the occurrence of a disturbing event is demonstrated with $s \in S$. This state demonstrates the capacity of the object to provide the required LOS (in terms of the maximum number of vehicles that can travel over the object in a specified period).

The objects with no loss in the LOS are in normal state and are denoted by 0 and objects with full functional loss, where no traffic flow over them is possible are denoted by $g \in S$. For damaged objects, two states where considered: minor and major where objects with major damage have lost 100% of their LOS (i.e. state g).

Table 5 summarizes the relationship between the damage states and the estimated loss of capacity. The damage states and related functionality losses can be categorized differently depending on the network and at decision-makers' discretion.

The results of the flood simulation determined that following an extreme flood event with a 500-year return period, out of 2'153 objects (roads and bridges), 20 road sections would be in state 1 with minor damage, and 4 road sections will completely lose their capacity and would be in state 2. The numbers for bridges are 3 and 2 for minor and major damage states respectively. Hence, a total of 29 objects need to be restored. The location of each damaged object is demonstrated in Figure 7 and it can be observed that the majority of the damaged objects are located in regions with little traffic flow.

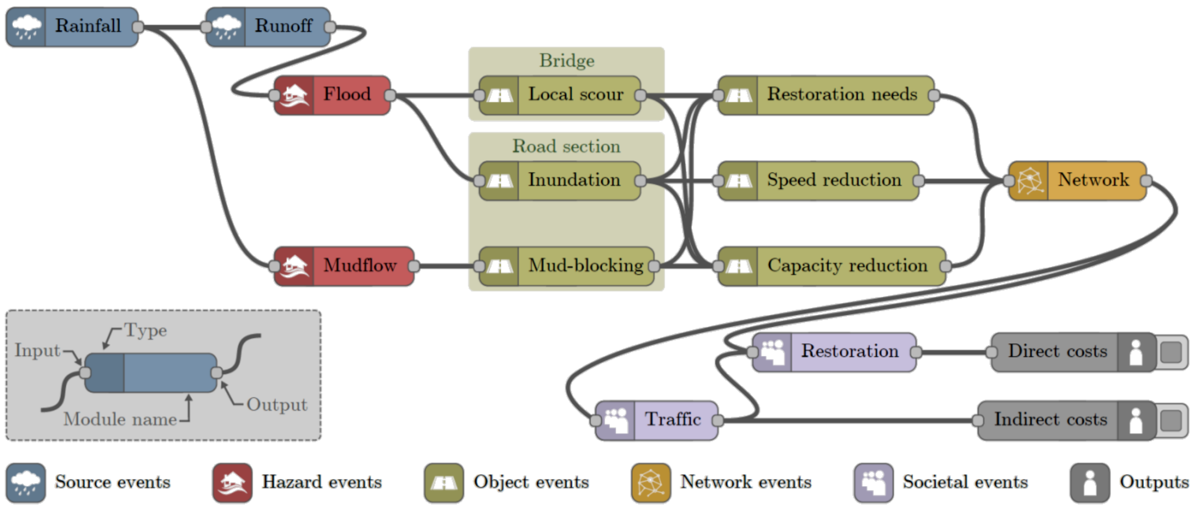


Figure 6. Schematic overview of the modules used for the flood simulation along with the estimation of consequences (direct and indirect costs)

Table 5. State and level of service loss for road sections and bridges due to inundation and local scour, adapted from (Hackl, Adey, et al., 2018)

Object	**State (s)**	**Description**	**LOS loss (%)**
Road	0	No damage—the object is in a normal state	0
	1	Minor damage—debris lying on the road; some service can be provided	70
	2	Major damage—the road is washed out by the flood; the passing of the road is no longer possible; the object cannot provide any service	100
Bridge	0	No damage—the object is in a normal state	0
	1	Minor damage—local scour at the pier(s) and/or abutment(s) observed; some service can be provided	50
	2	Major damage—pier(s) and/or abutment(s) with footing(s) exposed; structural reliability is no longer guaranteed; Object cannot provide any service	100

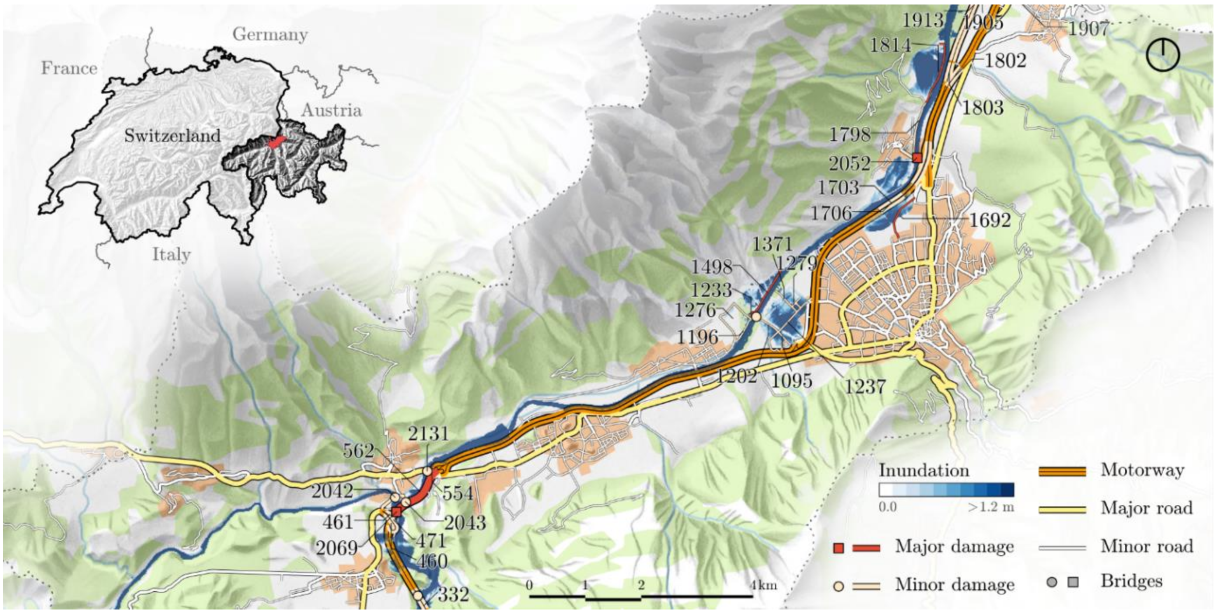


Figure 7. Studied network with damaged segments' ID

2.5.3 Intervention types

For each object type and damage state, 3 types of intervention are considered:

- Level 1 interventions (High priority): Require less time than a level 2 intervention, but more resources and additional costs; full recovery
- Level 2 interventions (Normal priority): Restore the capacities in a default way; full recovery
- Level 3 interventions (Low priority): Less time and costs than a level 2 intervention; partial recovery.

Table 6 provides the information related to the LOS recovery, durations, required resources, and costs for each object type, damage state and intervention level (Hackl, Adey, et al., 2018). The terms fixed and variable costs are referred to the non–resource-related material costs. Resource costs are related to labour and construction machinery costs. Monetary units are used instead of real currency value to avoid over-interpreting the estimated costs.

Consequently, the direct costs of interventions can be estimated using EQ. 1 and EQ. 2, and by using the information provided in Table 7.

Table 6. Intervention types and associated recovery rates, resources and costs for road sections and bridges, adapted from (Hackl, Adey, et al., 2018)

State		Intervention type	Capacity recovery (%)	Duration (1)	Required crews	Fixed costs (2)	Variable costs (3)	Resource costs (4)
Road	1	Level 1	100	1	2	5.25	22	0.5
		Level 2	100	3	1	3.5	16.5	0.5
		Level 3	30	3	1	3.5	14.5	0.5
	2	Level 1	100	6	2	14.4	110	0.7
		Level 2	100	12	1	9.6	82.5	0.7
		Level 3	10	10	1	9.6	78.5	0.7
Bridge	1	Level 1	100	20	2	16	24	0.9
		Level 2	100	40	1	10	15	0.9
		Level 3	20	35	1	10	13	0.9
	2	Level 1	100	90	2	48	64	1.2
		Level 2	100	160	1	30	40	1.2
		Level 3	10	145	1	30	37	1.2

The total indirect costs are calculated using EQ. 4-8, and the parameters summarized in Table 7. Different assumptions were made in the determination of the restoration program for the area of study. These assumptions are summarized:

- The number of restoration work crews available, $rwc = 3$
- Time intervals, $\Delta t = 4\ hours$
- The working hours per day $= 8\ hours$
- The weighting factor for indirect costs, $\gamma = 1$

Table 7. Estimated parameters for calculating indirect costs

Notation	Parameter	Estimated value	Comments
$\mu_{e,w}$	The proportion of vehicles of type w on edge e	Cars: 94% Trucks: 6%	Only two types of vehicles are considered, i.e., cars and trucks and it was assumed to have the same proportion of cars and trucks on all roads. The estimated value was derived from (FEDRO, 2015).
$\xi_{e,w}$	The value of travel	Cars: $23.02\ (\frac{mu}{hour})$ Trucks: $130.96\ (\frac{mu}{hour})$	Based on the work of the Swiss Association of Road and Transport Experts (VSS, 2009b).
ν	Mean fuel price	$1.88\ (\frac{mu}{L})$	
F_w	Mean fuel consumption	Cars: $6.7\ \left(\frac{L}{100\ km}\right)$ Trucks: $33\ \left(\frac{L}{100\ km}\right)$	
ρ_w	The operating costs without fuel for different vehicle types	Cars: $14.39\ (\frac{mu}{100\ km})$ Trucks: $32.54\ (\frac{mu}{100\ km})$	Reference: (VSS, 2009a)
υ	Labour productivity per hour worked	$83.27\ (\frac{mu}{hour})$	Based on the data from the Federal Statistical Office (Reutter, R., & Blauer Herrmann, 2016)

2.6 Development of near-optimal restoration program for the city of Chur using a single optimization approach

In this section, the restoration algorithms introduced earlier, i.e. SA, GA and PSO were used to determine the sequence and type of interventions to restore the 29 damaged objects to an acceptable LOS, in a single optimization procedure. The objective function (EQ. 9) was to choose a program with minimal overall costs.

A conjugate direct Frank–Wolfe (CFW) algorithm (Mitradjieva & Lindberg, 2013), programmed in Julia, was implemented to solve the traffic assignment problem. Then C_e^T is estimated using cost–flow relationship demonstrated in EQ.11. The calibration parameters are selected to be $\alpha = 0.15$ and $\beta = 4$ as suggested by the Highway Capacity Manual (Hackl, Adey, et al., 2018).

SA, GA and PSO were used separately to solve the upper-level optimization problem for a scenario where there are no constraints available. The parameters for each method were tuned to attain optimal solutions with the least number of iterations and are summarized in Table 8.

Table 8. Parameters for SA, GA and PSO to identify the optimal restoration program using a single optimization approach

Simulated Annealing	Genetic Algorithms	Particle Swarm Optimization
Tmax = 2500 Tmin = 2.5 Steps = 100 Updates = 100	Population size = 25 Elite size = 1 Mutation rate = 0.01 Generations = 200	Population size = 10 C_1 = 2 C_2 = 1.8 w = 0.9 - 0.4 Iterations = 100

A GIS interface was used, to easily import and export the GIS data of the city. The algorithm used to solve the upper-level optimization was programmed in Python. The related codes are available from (https://ibi-s01.ethz.ch/ibi-git/Repository/FORESEED4.7). Ultimately, parallel computing was implemented to reduce the computational time of the optimization process.

The running time for the Simulated Annealing with 100 steps and 100 updates (10’000 tests in total) ranged between 13-17 hours. The Genetic Algorithm with a population size of 25 and 200 generations (5’000 tests) took 57-62 hours and the Particle Swarm Optimization with 10 particles and 100 iterations (1’000 tests) took approximately 12-17 hours.

The results of using SA, GA, and PSO for solving the optimization problem and identifying the near-optimal program, with no constraints to the budget and resources, are summarized in Table 9. The results show that the SA is the fastest algorithm for running a single test however, PSO although slower than SA, reaches a slightly better solution with a significantly fewer number of tests (10’000 vs 1’000). Hence, for reaching the near-optimal solution, both methods take almost the same amount of time. GA was relatively slow and within 5’000 tests did not reach the solutions SA and PSO produced.

To assess the efficiency of the methods, the results were compared with a benchmark model that sorts the objects based on the average traffic flow and restores the objects that cause loss of connectivity in the network and then restores the remaining objects (Hackl, Adey, et al., 2018). The overall estimated costs for the benchmark model for the studied network is 7’784’687 mus. Table 9 shows the extent of improvements over the benchmark model for each method.

Table 9. Direct and indirect costs of restoring the network after an extreme flood event using a single optimization approach

Method	Direct Costs (mu)	Indirect Costs (mu)	Total Costs (mu)	Improvements over the benchmark model
SA	3'725'003	3'573'481	7'298'484	6.7%
GA	3'897'025	3'809'705	7'706'730	1%
PSO	3'725'003	3'452'824	7'177'827	8.46%

Figures 8, 9, and 10 demonstrate the intervention level and the sequence of restoring the damaged objects in the networks. On the upper part of the figures, the components of the direct and indirect costs are demonstrated and at the bottom, the system recovery over time is illustrated. The restoration work is completed in 35, 36, and 36.5 days for programs optimized by GA, PSO, and SA respectively. As illustrated in Table 9, the variations in results are mainly due to the indirect costs. Particularly, SA and PSO have the same direct costs and the small difference in the overall costs is due to the indirect consequences. An example of the development of the direct costs is demonstrated in Table 10, for SA. The table includes the damaged objects that need to be restored, the optimal sequence and interventions to be executed along with the restoration duration, designated work crews and the related costs.

In all three programs, low priority interventions are chosen to repair the non-critical objects in the network. This is done to speed up the network recovery and reduce the imposed indirect costs.

The results in Figure 8-10 can help in identifying the critical objects in the network. For example, it can be observed that the object 2052, i.e. the bridge with major damage (B1 in Figures 8 and 10; and B6 in Figure 9) is the reason for the loss of connectivity in the network, and as soon as this bridge is restored the loss in connectivity is eradicated. For this reason, early and fast restoration of this object can reduce the indirect costs incurred by travel prolongations or lost trips. Both SA and PSO choose to initially restore this bridge, while for GA (B6 in Figure 9) the bridge is the 6th item to repair. All three programs have chosen a high priority intervention (level 1) to restore this object.

Moreover, the major travel prolongation is caused by object 2042, i.e. the bridge with minor damage (B5 for SA and GA, and B2 for PSO) that is the 5th object that is repaired in programs generated by SA and GA and the 2nd object repaired in the restoration program optimized by PSO.

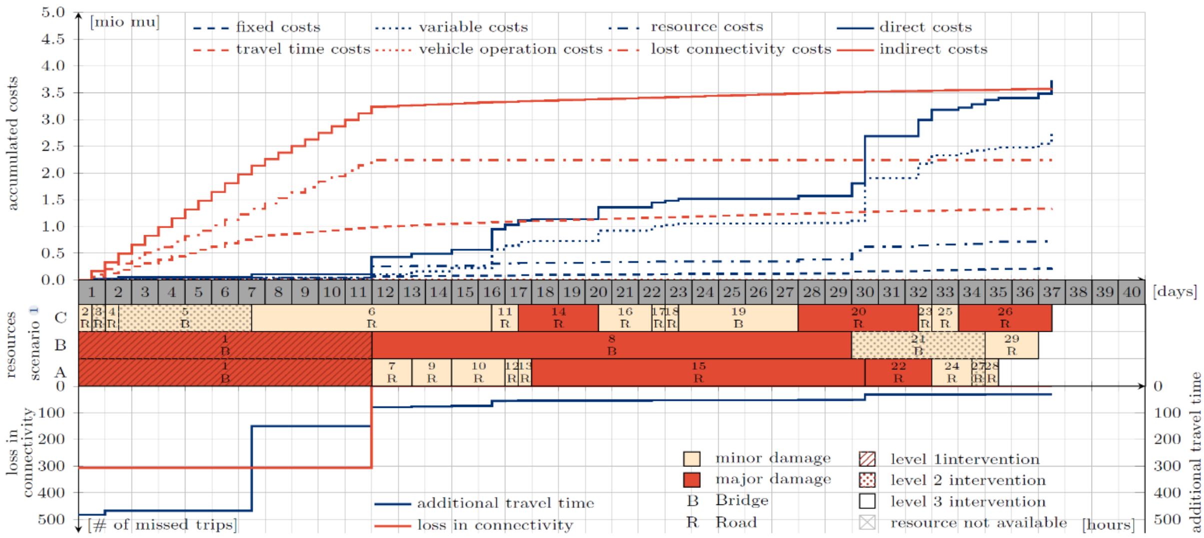


Figure 8. The resulting restoration program using Simulated Annealing

Table 10. Development of the direct costs for SA

	Object		State	Intv.	Schedule			Res.	Costs			
#	ID	Type	Damage	Type	Start	End	Dur.	rwc	Fixed	Variable	Resources	Sum
1	2052	Bridge	2 major	Level 1	0	11	11	A & B	48'000	64'000	211'200	323'200
2	1233	Road	1 minor	Level 3	0	0.5	0.5	C	3'500	4'541	2'000	10'041
3	554	Road	1 minor	Level 2	0.5	1	0.5	C	3'500	4'624	2'000	10'124
4	332	Road	1 minor	Level 3	1	1.5	0.5	C	3'500	20'739	2'000	26'239
5	2042	Bridge	1 minor	Level 2	1.5	6.5	5	C	10'000	15'000	36'000	61'000
6	1913	Road	1 minor	Level 3	6.5	15.5	9	C	3'500	347'907	36'000	387'407
7	1803	Road	1 minor	Level 3	11	12.5	1.5	A	3'500	50'441	6'000	59'941
8	2069	Bridge	2 major	Level 3	11	29	18	B	30'000	37'000	172'800	239'800
9	1802	Road	1 minor	Level 3	12.5	14	1.5	A	3'500	60'800	6'000	70'300
10	1706	Road	1 minor	Level 3	14	16	2	A	3'500	72'107	8'000	83'607
11	1798	Road	1 minor	Level 3	15.5	16.5	1	C	3'500	40'023	4'000	47'523
12	461	Road	1 minor	Level 3	16	16.5	0.5	A	3'500	28'026	2'000	33'526
13	1371	Road	1 minor	Level 3	16.5	17	0.5	A	3'500	16'813	2'000	22'313
14	1692	Road	2 major	Level 3	16.5	19.5	3	C	9'600	198'257	16'800	224'657
15	562	Road	2 major	Level 3	17	29.5	12.5	A	9'600	799'868	70'000	879'468
16	460	Road	1 minor	Level 3	19.5	21.5	2	C	3'500	76'329	8'000	87'829
17	471	Road	1 minor	Level 3	21.5	22	0.5	C	3'500	27'499	2'000	32'999
18	1202	Road	1 minor	Level 3	22	22.5	0.5	C	3'500	25'309	2'000	30'809
19	2043	Bridge	1 minor	Level 3	22.5	27	4.5	C	10'000	13'000	32'400	55'400
20	1814	Road	2 major	Level 3	27	31.5	4.5	C	9'600	267'668	25'200	302'468
21	2131	Bridge	1 minor	Level 2	29	34	5	B	10'000	15'000	36'000	61'000
22	1237	Road	2 major	Level 3	29.5	32	2.5	A	9'600	153'816	14'000	177'416
23	1276	Road	1 minor	Level 3	32.5	33	0.5	C	3'500	5'356	2'000	10'856
24	1276	Road	1 minor	Level 3	32	33.5	1.5	A	3'500	53'835	6'000	63'335
25	1907	Road	1 minor	Level 3	32	33	1	C	3'500	34'454	4'000	41'954
26	1498	Road	2 major	Level 3	33	36.5	3.5	C	9'600	216'257	19'600	245'457
27	1095	Road	1 minor	Level 2	33.5	34	0.5	A	3'500	13'339	2'000	18'839
28	1905	Road	1 minor	Level 3	34	34.5	0.5	A	3'500	28'146	2'000	33'646
29	1703	Road	1 minor	Level 3	34	36	2	B	3'500	72'349	8'000	83'849
									222'500	2'762'504	740'000	3'725'004

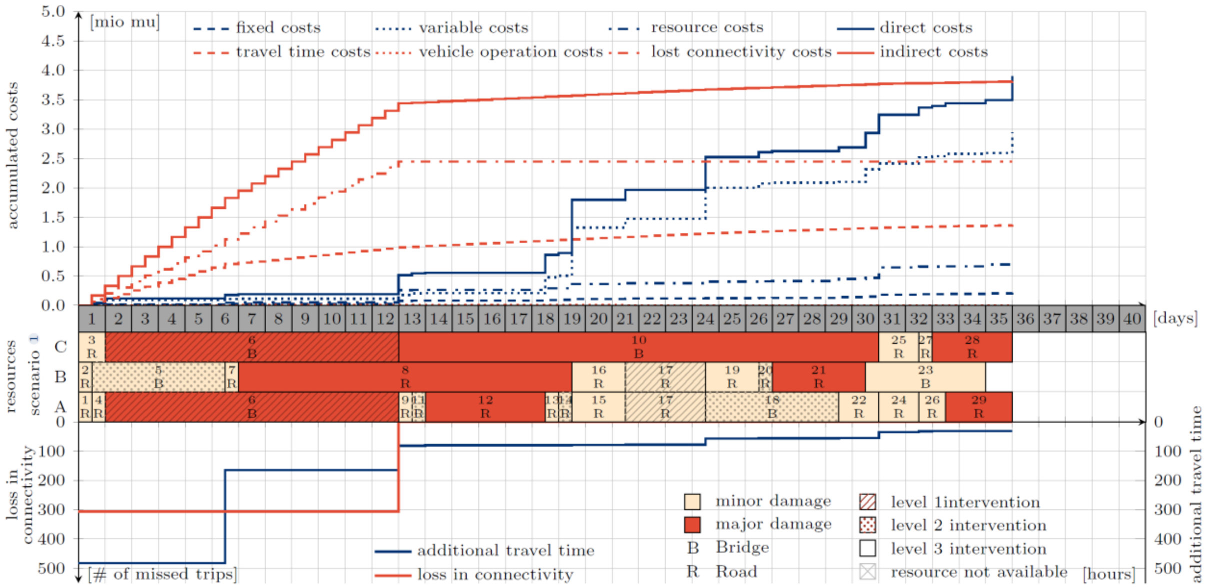


Figure 9. The resulting restoration program using Genetic Algorithms

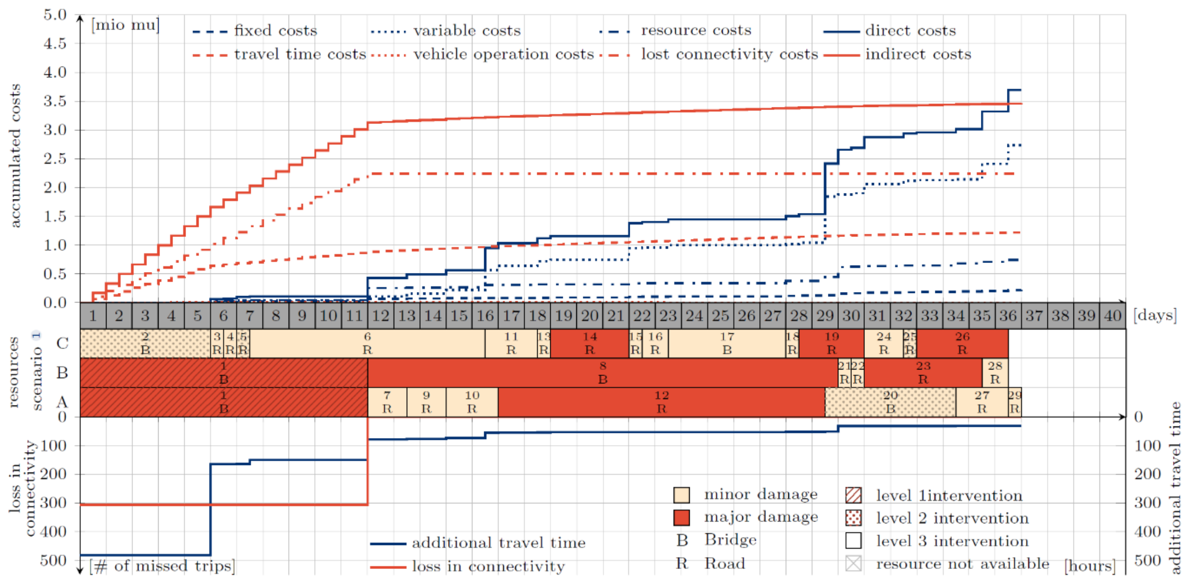


Figure 10. The resulting restoration program using Particle Swarm Optimization

As mentioned earlier, these algorithms have all been used in a scenario where no time or budget constraints were present. However, the model has the flexibility to consider budget limitations by adopting a penalty function that would penalize infeasible solutions so that they become worse than feasible ones (Michalewicz & Schoenauer, 1996), or allow for resource constraints to the restoration schedule. Figure 11 presents an example of a scenario where the work crew B was not available in the first four days, and work crew C was absent between the 10th and the 15th day of the restoration work. The algorithm selected for this example was the Simulated Annealing which provides a restoration program with a total cost of 8.55×10^6 mus.

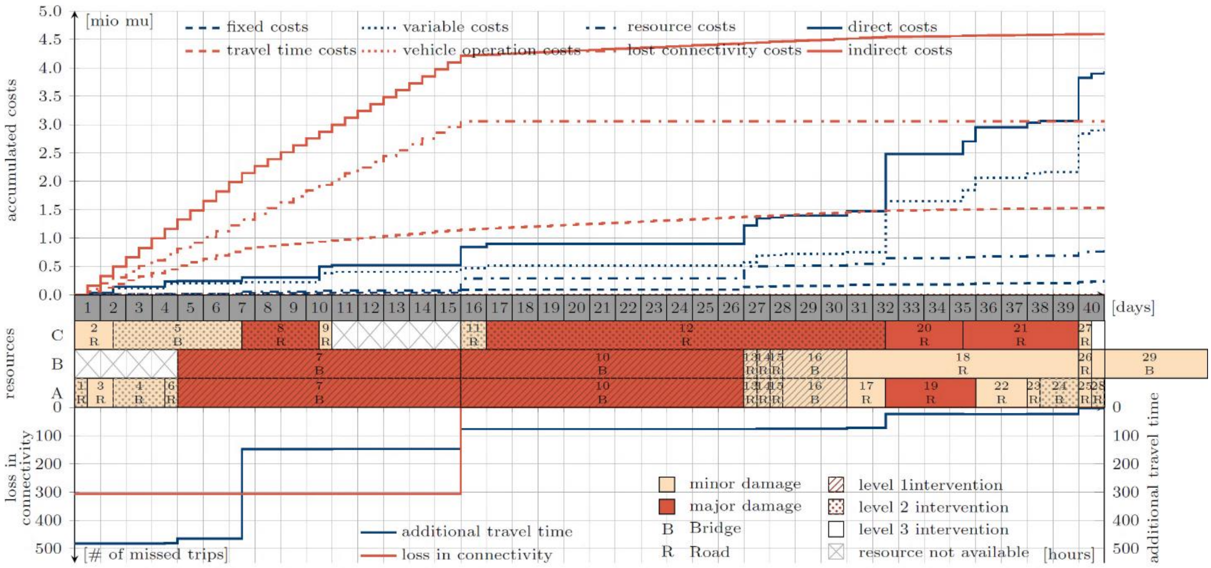


Figure 11. Near-optimal restoration program in presence of resource constraints, using SA

2.7 Development of near-optimal restoration program for the city of Chur using a double optimization approach

The time that each algorithm takes for identifying the near-optimal restoration program significantly depends on the number of objects in the network. Hence, as the network grows the time for the computation will also increase. As the restoration model is mainly proposed for post-disaster decision making, the rapid response of the infrastructure managers in handling the damaged objects in the network is critical. Consequently, a novel approach is proposed that is suitable for very large networks. In this approach, first, an initial optimization is carried out to find the sequence and level of repair of the objects that are most critical to the network, such as lifelines, roads with the highest traffic load, and objects with major damages. As the number of these critical objects is usually small, the identification of the near-optimal program for these objects will take a relatively short amount of time. The result of this first optimization will be the first action plan for the infrastructure managers to start the restoration work. Meanwhile, they will run a secondary optimization to find the restoration plan for the remainder of the damaged objects in the network.

Same as the single optimization approach, a conjugate direct Frank–Wolfe (CFW) algorithm was implemented to solve the traffic assignment problem with the same calibration parameters $\alpha = 0.15$ and $\beta = 4$.

SA, GA and PSO were used separately to solve the upper-level optimization problem for a scenario with no budget or resource constraints. The parameters for each method were tuned to attain optimal solutions with the least number of iterations and are summarized in Table 11.

Table 11. Parameters for SA, GA and PSO to identify the optimal restoration program using a double optimization approach

Stage	SA	GA	PSO
1	T_{max} = 2500 T_{min} = 2.5 Steps = 6 Updates = 10	Population size = 4 Elite size = 1 Mutation rate = 0.01 Generations = 15	Population size = 4 C_1 = 2.2 C_2 = 2 w = 0.9 - 0.4 Iterations = 15
2	T_{max} = 2500 T_{min} = 2.5 Steps = 100 Updates = 100	Population size = 25 Elite size = 1 Mutation rate = 0.01 Generations = 200	Population size = 10 C_1 = 2 C_2 = 1.8 w = 0.9 - 0.4 Iterations = 100

2.7.1 Identification of critical objects in the network

The main concern following a disruptive event would be to facilitate the search and rescue activities, allow for access to hospitals and other required services. Hence, the most critical objects would be those that contribute to improving the network connectivity since some damaged objects can cause loss of connectivity to a part of the network with high travel demands. The importance of objects in the network can be decided by a panel of experts, using prioritizations rules (Buckle et al., 2006; Miller, 2014), or measures to calculate the criticality of objects in a network (Y. C. Liu et al., 2020; Scott et al., 2006).

This study used the method introduced in (Y. C. Liu et al., 2020) to find the most important damaged objects in the network. The method uses a modified network robustness index that was proposed by (Scott et al., 2006), which is calculated for each object by setting the capacity of that object to zero and then computing the increase in travel prolongation costs and the costs due to the loss of connectivity and lost trips.

The results suggest that the following four objects (out of 29) are the most critical ones in the studied network, due to their traffic load and their damage level that resulted in travel prolongation and loss of connectivity

- Object 2052: Bridge with major damage
- Object 2042: Bridge with a minor damage
- Object 1913: Road with minor damage
- Object 554: Road with minor damage

2.7.2 Results

The four selected objects were used as the initial input of the model and the SA, GA, and PSO algorithms were used to find the initial optimal restoration program. Subsequently, the secondary optimization was performed on the remaining damaged objects in the network. Table 12 summarizes the results.

Table 12. Direct and indirect costs of restoring the network after an extreme flood event using a double optimization approach

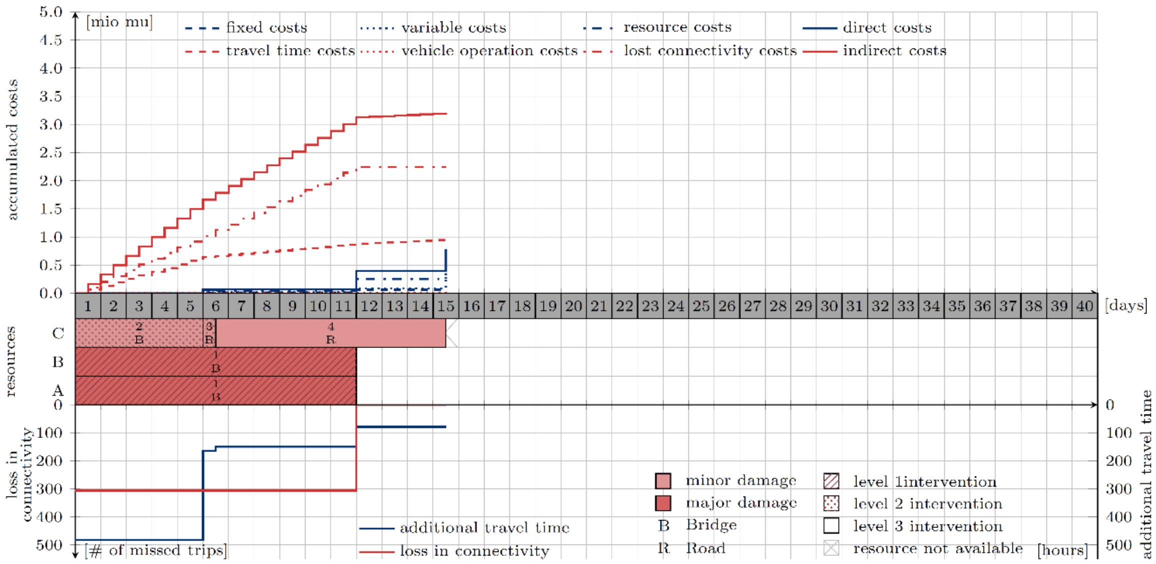
Approach		Algorithm	Direct Costs	Indirect Costs	Total Costs	Approximate running time (hours)
Double-stage optimization	Stage 1	SA	781’731	3’199’447	3’981’178	0.25
		GA	781’731	3’199’447	3’981’178	2.5
		PSO	781’731	3’199’447	3’981’178	1.25
	Stage 2	SA	2’941’655	492’664	3’434’319	13-17
		GA	2’995’591	562’591	3’558’088	55-60
		PSO	2’941’655	467’841	3’409’496	11-17
	Overall	SA	3’723’386	3’692’111	7’415’497	13-17
		GA	3’777’322	3’762’038	7’539’266	58-63
		PSO	3’723’386	3’667’288	7’390’674	12-18
Benchmark		-	3’916’025	3’868’662	7’784’687	0.10

The results in Table 12 suggest that the SA is more suitable for the first stage of the proposed approach, where the search space is smaller (involves 4 critical objects). All three algorithms reach the same solution however, SA is much faster than the other two. For the second part, however, PSO seems to be more suitable. The running time for the SA with 100 steps and 100 updates (10’000 tests in total) ranged between 13-17 hours. The GA with a population size of 25 and 200 generations (5’000 tests) took 55-60 hours and the PSO with 10 particles and 100 iterations (1’000 tests) took approximately 11-17 hours. The significant variations in the running time for each algorithm are due to the variations in the server traffic.

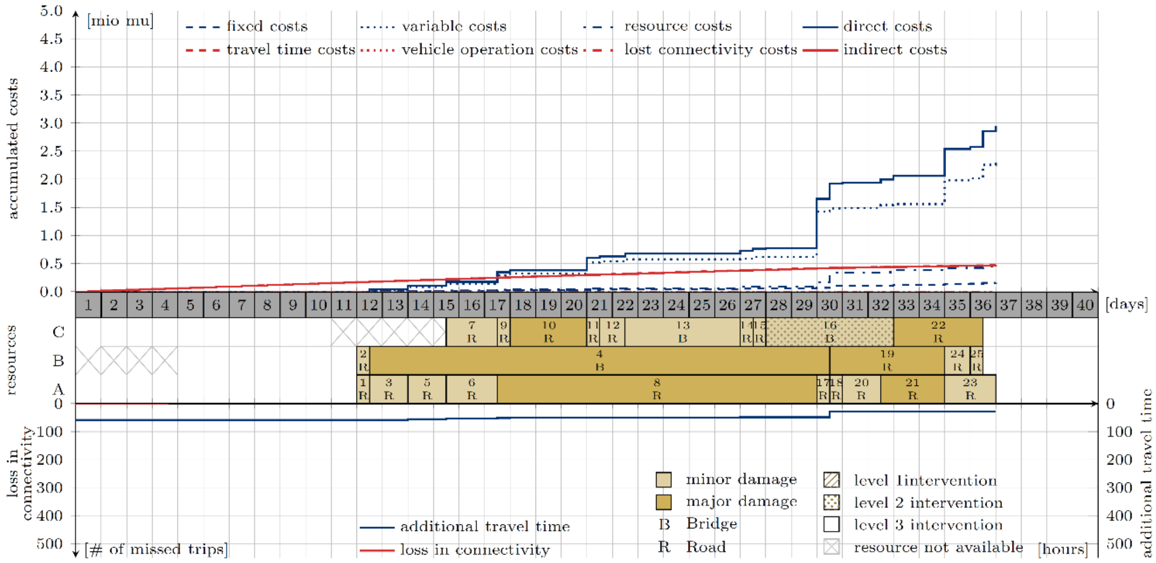
The overall costs using the benchmark model is 7’784’687, which is higher than the solutions proposed by all three algorithms in the double optimization approach. In terms of time efficiency, both approaches are very fast. The double optimization approach provides the first restoration plan within 15 minutes (using SA algorithm) and while the restoration work is been carried out on the critical objects in the network, the PSO algorithm will run to find the optimal restoration plan for the remaining objects in the network. The time to develop the restoration program using the benchmark model is around 5 minutes. The reason for the time difference is mainly due to the necessity of running the traffic model in each iteration.

By comparing the results of the double optimization with the single optimization approach (Table 9 and Table 12), it can be noticed that the total costs for the first option (single optimization method) is slightly lower than the second option. However, it must be noted that the restoration program for the first option would be available after 12-16 hours (in this case study and a longer period for larger networks); while the first action plan for the second approach would be available in less than an hour. This will result in savings on the imposed indirect costs that are caused by the delays from the time the extreme event happens and the time the restoration work starts. In fact, by imposing a delay equal to the running time of the algorithms, an indirect cost of 332’209 mus will be added to the total costs. Hence, the solutions will be worse than those provided by the double optimization approach.

Figure 12 illustrates the identified restoration program using SA for the initial optimization and PSO for optimizing the second part of the restoration work.



(a)



(b)

Figure 12. Near-optimal restoration program for the remaining damaged objects in the network, using a double optimization approach

2.8 Discussion

The examples show that the restoration model presented in this report can be used to:

- identify objects whose failure will result in relatively large disruptions to service. As indicated in the example above object 2052 and 2042 caused the highest loss of connectivity and additional travel time respectively.
- identify when it is advantageous to execute less extensive interventions rather than more extensive interventions in the interest of speeding up the restoration of service. For instance, it might not be beneficial to perform an intensive intervention on a road section if the traffic flow is impeded (for a longer period) by the execution of another intervention on a bridge within that same road section.

While the model is theoretically capable of determining the restoration program for a real network of any size, in practice there would be challenges involved with respect to the required computation time and determination of the correct balance between the level of detail and speed of analysis. Generally, heuristic algorithms in a single optimization approach are used to find the near-optimal solution of a mathematical model that minimizes the overall direct and indirect costs of interventions from the time the extreme event occurs and the time the restoration work is complete. However, the time for developing these programs for real-world large networks is not acceptable. This issue can be resolved by using a double optimization approach as suggested in the report where the algorithm will first generate a program to restore the most critical objects in the network and while these critical objects are being restored, the secondary optimization will work on the determination of the optimal restoration program for the remaining damaged objects in the network.

The optimality of the resulting restoration program depends, of course, on the accuracy of the input data used, including the damage extent, the object type and the number of interventions that are simultaneously executed in the same region. Estimates of appropriate input values should be made as best possible, exploiting where possible historical data, public and private records, and expert knowledge. Sensitivity analyses should be conducted to determine the effect of variations in the input values on the restoration programs.

The importance weight, γ , that is assigned to the indirect costs, can have a significant impact on the restoration program. For example, when $\gamma = 0$, the model yields the restoration program with minimum direct costs; however, the impacts on the users which are not considered might be considerably large. On the other hand, choosing a large weight for indirect costs will result in restoration programs with lower indirect costs but, increased overall costs.

Moreover, although the performance of the optimization algorithms can be improved by tuning the related parameters; it is hard and in most cases impossible to determine how close the generated solutions are to the global minimum. Also, one must consider that large networks have possible issues with the availability and quality of data. Additionally, the contribution of different agencies and people, legal issues and policies add to the complexities of finding optimal post-disaster intervention programs in real-world practices.

One limitation of the proposed restoration model is related to the traffic assignment model. A static user equilibrium traffic assignment model was used which is widely used in the literature and is mathematically simple and computationally inexpensive. Other models could provide more realistic representations of traffic flow. This model assumes that the travellers are informed of the traffic conditions, and does not account for changes in the travel pattern after an extreme event.

2.9 Conclusion

In this report, a restoration model using the Simulated Annealing, Genetic Algorithms and Particle Swarm Optimization algorithms were introduced to determine near-optimal post-disaster restoration intervention programs. The functionality of the model was demonstrated by determining an optimal restoration intervention program for the road network around the city of Chur after a flood event with a 500-year return period. The bi-level optimization algorithm minimizes the overall direct and indirect costs, where the direct costs were related to the physical intervention execution while the indirect costs were associated with the traffic flow.

This model has the flexibility to be used in real-world situations and for a variety of infrastructure types. It can account for various constraints such as limitations on the budget or resources. The presented model can be beneficial for infrastructure managers in charge of the determination of the resilience of critical infrastructures to extreme events. It can also provide estimations on the time required to restore the desired LOS following an extreme event and provide insights on various possible restoration programs and the trade-offs between the direct and indirect costs.

To make the model and algorithm even more operational, the computational time of the algorithm can be reduced by using double optimization methods. A possible future study would be finding appropriate measures to estimate the criticality of the objects in the network to be used in the double optimization procedure. Also, the development of a user interface can facilitate the use of situation-dependent local data. Additionally, it should be kept in mind, that the input values are of utmost importance, and appropriate levels of effort should be made to ensure their correctness.

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3 PART 2: RISK REDUCTION PROGRAMS

3.1 Notations

Optimal intervention programs

C^{IP}	Costs of intervention program $\boldsymbol{IP}$
C^{ref}	Costs of the reference intervention program
C^{IP}_{DC}	Direct costs of intervention program $\boldsymbol{IP}$
C^{IP}_{IC}	Indirect costs of intervention program $\boldsymbol{IP}$
ΔR	Reduction in risks
R^{IP}	Risks of intervention program $\boldsymbol{IP}$
R^{ref}	Risks without the risk reducing intervention program
R^{IP}	Risks with the risk reducing intervention program
ΔFC	Reduction in future costs
FC^{ref}	Future costs without the risk reducing intervention program
FC^{IP}	Future costs with the risk reducing intervention program
$\delta_{n,i}$	Binary variable, which has a value of 1 if intervention $\boldsymbol{i}$ on object $\boldsymbol{n}$ is selected

Network flow optimisation model

G	Graph of the network flow optimisation model
V	Set of nodes of graph $\boldsymbol{G}$
V, E	Set of edges of graph $\boldsymbol{G}$
$\delta_{u,v}$	Binary variable, which has a value of 1 if edge $(\boldsymbol{u}, \boldsymbol{v})$ is selected
$\gamma_{u,v}$	Flow on edge $(\boldsymbol{u}, \boldsymbol{v})$
$\varepsilon_{u,v}$	Sink flow on $(\boldsymbol{u}, \boldsymbol{v})$
$NB_{u,v}$	Net benefit assigned to edge $(\boldsymbol{u}, \boldsymbol{v})$
$d_{u,v}$	Duration assigned to edge $(\boldsymbol{u}, \boldsymbol{v})$
$c_{u,v}$	Intervention costs assigned to edge $(\boldsymbol{u}, \boldsymbol{v})$
Ω_{max}	Budget limitation

Model application

C_k	Unit costs of traffic state $\boldsymbol{k}$
P_f	Probability of failure
p_{CS}	Probability of failure in condition state $\boldsymbol{CS}$
C_f	Consequences of failure
$C_{f,CI}$	Costs of corrective intervention due to a failure
$C_{f,tt}$	Costs of traffic disturbance due to a failure
$C_{f,A}$	Costs of accidents due to a failure
d_{CI}	Duration of corrective intervention
$d_{reaction}$	Reaction time in case of a failure
$p_{f,A}$	Probability of an accident in case of a failure
C_{pd}	Costs for property damage in case of an accident
p_{inj}	Probability of an injury in case of an accident
c_{inf}	Costs of an injury
p_{fat}	Probability of a fatality in case of an accident
c_{fat}	Costs of a fatality
$n_{passengers}$	Number of passengers

Accuracy of input information

$J(IP_x, IP_{x'})$	Similarity of intervention programs $\boldsymbol{IP_x}$ and $\boldsymbol{IP_{x'}}$
$O(IP_x, x')$	Optimality of intervention program $\boldsymbol{IP_x}$ with variable value $\boldsymbol{x'}$
IP_x	Optimal intervention program with variable value $\boldsymbol{x}$
δ_i	Binary variable, which has a value of 1 if intervention $\boldsymbol{i}$ is selected

3.2 Introduction

Transportation infrastructure is the backbone of growing societies. Road and railway infrastructure allow people to travel between different locations, and goods to be transported between origins and destinations. On one side, the railway and road networks are different with respect to their functionality, the vehicles that travel on them, how they are operated, controlled and organised and to some extent, how they are configured. For example, the road network transports people and goods as a more or less self-operated network with relative small units based on point-to-point transportation, while the railway network transports people and goods in large units operated by train operators. On the other side, both networks have similarities with regard to their composition from different object types, high initial construction costs, objects being affected by slow deterioration processes and therefore having long life times when they are not affected by extreme events, exposure to extreme events which can shorten these life-times, and the requirement of the infrastructure to be maintained and renewed over time so that it can continue to provide the required service.

Regarding the similarities, it is essential for infrastructure managers of both road and railway networks to make reasonable decisions about when to execute which interventions on which objects of the network. The further an infrastructure object deteriorates, the higher the probability of the object not being able to provide an adequate level of service. When an object does not provide the required level of service, a corrective intervention has to be executed. Inadequate levels of service lead to direct effects on different stakeholders, e.g. longer travel time for passengers, and to higher probabilities of severe incidents happening, e.g. a derailment with fatalities. In order to prevent inadequate levels of service, preventive interventions are executed to reduce the risks. When making the decision whether to execute preventive interventions on infrastructure objects, the trade-off between the costs related to preventive interventions and the risk related to the infrastructures condition has to be considered.

Infrastructure managers mostly make this decision considering objects of only one type, e.g. road sections, tracks, bridges or tunnels, and then combine the resulting interventions into a single intervention program using exclusively expert opinion. Most methodologies used in literature to develop intervention programs for transportation networks have been focused on objects of one type. In addition to focusing on objects of one type, most research in this area uses rather limited objective functions, e.g. selecting interventions to minimize the costs for the infrastructure manager, or the costs for the people traveling on the network, and much of the research omits the risk of the infrastructure to not being able to provide an adequate service. There is increased interest in the research community in developing methodologies to determine the optimal risk reducing intervention programs, taking into consideration the impact on multiple stakeholders, objects of multiple types, and the dependencies between objects within the network and how they work together to provide service (Burkhalter & Adey, 2018; Lethanh et al., 2018). There does not exist in the existing literature a clear structure that enables to represent the candidate interventions and their dependencies influencing the costs of an intervention program.

In this part of the report, a methodology is presented that enables the determination of the optimal risk reducing intervention programs that is generally applicable for all transportation networks but is specifically designed for railway networks. The methodology consists of a system representation and a mathematical optimisation model. The objective function of the mathematical model is the maximisation of the net benefit of all stakeholders (as described in Adey et al., 2018), where

- the costs are the monetised impacts on stakeholders that are directly related to the execution of the interventions, e.g. the costs for the material and labour to carry out the work and the travel delay caused during the execution of the interventions, and
- the benefits refer to the reduction of risks, i.e. the possible costs due to failure multiplied by the probability of failure, e.g. the costs for the material and labour to carry out the work for the restoration interventions and the travel delay caused until the infrastructure is restored.

The mathematical model is devised to determine the optimal risk reducing intervention program for a railway network taking into consideration the dependencies between different objects, the dependencies between an object and the provided service, and organisational constraints, i.e. budget constraint. It is built as a multilevel network flow model with side constraints, where

- the first level, i.e. the object level, contains all aspects of the model that can be related to the objects, such as the material and labour costs of executing interventions including their variation depending on the execution of interventions on other objects, and
- the second level, i.e. the network level, contains all aspects of the model related to the provided service, such as the amount of travel delay caused by the execution of one or more intervention on the same railway line.

The remainder of this part of the report is structured as followed. Chapter 3.3 contains a literature review. Chapter 3.4 contains the methodology to develop optimal intervention programs for transportation networks. Chapters 3.5 and 3.6 contain the description of the characteristics of the railway infrastructure network, the system representation and the mathematical model proposed to develop optimal risk reducing intervention programs. Chapter 3.6 contains an example of the model on a railway line. Chapter 3.7 contains a sensitivity analysis investigating the influence of the input information accuracy for the example network. Chapter 3.8 contains the conclusion of the report.

3.3 Literature review

3.3.1 Infrastructure management and intervention planning problems

In order to understand the problem faced when developing intervention programs, it is necessary to positioning the development of intervention programs within the infrastructure management process. Adey (2019) presented an infrastructure management process for the road infrastructure, where a clear separation between the establishment of intervention strategies (task 2) and the development of intervention programs (task 3.2) is stated. Intervention strategies define how infrastructure objects should be managed in general, i.e. maintained and renewed, over the long-time considering all possible states an object can be in and all impacts related with the existence of the object, e.g. through life cycle analysis. Usually, they are developed for each object type individual. Intervention programs consider the defined intervention strategies and the current condition of the infrastructure objects and develop a plan of which interventions are going to be executed on which infrastructure objects within the next planning period or multiple periods. In this phase, the state of other infrastructure objects are considered, which may lead to deviations in the intervention program compared with the intervention program purely based on the intervention strategies.

Lidén (2015) summarised and categorised planning problems for railway infrastructures (Table 13). The problems are divided into strategic, tactical and operational problems with respect to their association within the infrastructure management. Even though, the problems in Table 13 refer to the railway infrastructure they can be overlaid with the infrastructure management process for roads proposed in Adey (2019). The service life and maintenance frequency determination problem as well as the network design considering maintenance problem refer to the task of establishing intervention strategies. The renewal scheduling and project planning problem on the strategic level and all the scheduling problems in the tactical level are related to the task of developing intervention programs according to Adey (2019). They can, however, be divided into problems that 1) select and group the interventions to be executed within a period or multiple periods considering dependencies and 2) schedule predefined interventions.

Table 13. Planning problems on railway infrastructures according to (Lidén, 2015)

Level	Problem	Description
Strategic problems	Service life and maintenance frequency determination	Conducting life-cycle analysis to determine the service life and maintenance policies.
	Network design considering maintenance	Including general maintenance consideration in the network design planning.
	Renewal scheduling and project planning	Planning of joint execution of interventions for a period, i.e. 5 years, based on their individual condition.
Tactical problems	Possession scheduling	Scheduling of track possessions for maintenance focusing on regular possession patterns (long term), coordinated maintenance tasks (months – 1 year), or adjustments of given maintenance plans (months).
	Deterioration-based maintenance scheduling	Scheduling maintenance for a limited period, i.e. months to 1 year, based on deterioration prognoses
	Maintenance vehicle routing and team scheduling	Assigning and scheduling given maintenance jobs to maintenance vehicles and teams within the range of months and years
Operational problems	Work timing and resource scheduling	Scheduling resources like machinery and work teams within the short time (days - weeks)

In the following, the literature review concentrates on the research in the area of developing intervention programs, i.e. where decisions are made about which interventions to execute and how to group them within a period or multiple periods. The literature review is divided into research focusing on single types of objects (section 3.3.2) and multiple types of objects (section 3.3.3)

3.3.2 Single object types

There exists a wide variety of research on developing intervention programs for objects of single types within the transportation infrastructures, i.e. road pavement (Abaza & Ashur, 2009; Ferreira et al., 2002; Ouyang & Madanat, 2004; Šetinc et al., 2015), railway track (Budai-Balke, 2009; Higgins et al., 1999; Peng, 2011; Pouryousef et al., 2010), bridges (Frangopol & Liu, 2007; Zhang & Alipour, 2019), and railway power supply system (Chen et al., 2013).

Regarding road pavements, the models developed determine intervention programs for either single time periods using integer linear programming (Abaza & Ashur, 2009) or multiple time periods using non-linear programs that are optimised using heuristic algorithms (Ferreira et al., 2002; Ouyang & Madanat, 2004; Šetinc et al., 2015). All models do not directly consider the impacts for the road users, which are considered at most by using indices for condition state and quality.

Regarding railway tracks, most research is based on Higgins et al. (1999), who developed an integer linear program allocating interventions to time windows in order to minimise traffic delays. The work has been extended by combining short routing maintenance and long unique projects (Budai-Balke, 2009), adding work team capacities (Peng, 2011), combining it with a job-to-project clustering using a vehicle routing based model formulation (Peng, 2011), and multiple track segments (Pouryousef et al., 2010). All mentioned work used heuristic algorithms to solve the track maintenance scheduling problem for real world sized networks.

Two examples for developing intervention programs for bridges, which are the major structures of transportation networks, can be found in Frangopol & Liu (2007) and Zhang & Alipour (2019). While Frangopol & Liu (2007) developed intervention programs for multiple time periods using a multi-objective model optimising the condition state, safety and agency costs, Zhang & Alipour (2019) developed a two-level prioritisation model for a single time period, where the first level minimises the owner and user costs and the second level evaluates the traffic disturbance using a traffic assignment problem.

Further, Chen et al. (2013) developed a bi-objective maintenance scheduling model for the railway power supply system that minimises the agency costs and maximises the reliability of the system.

Most work in the area of developing intervention programs for a single type of objects consider some aspects of the network structure of transportation infrastructures. They neglect, however, the interaction between the objects of different types as well as the risk reduced by the intervention programs.

3.3.3 Multiple object types

Multiple researchers have considered the variety of objects within road and railway networks when developing intervention programs, where the research concentrates more on railway networks. In general, the models proposed in the research can be categorised in bottom-up, top-down and combined approaches.

The research following a bottom-up approach proposes models that first identify optimal and near-optimal interventions for each object separately, and second select the best combination of the individual interventions on the network level (Caetano & Teixeira, 2015; Fecarotti & Andrews, 2017; Furuya & Madanat, 2013; Zhao et al., 2009). How the network is considered varies from work to work. The work consider different objects at the same location (Zhao et al., 2009), objects on neighbouring segments (Caetano & Teixeira, 2015; Furuya & Madanat, 2013), a penalty cost for shifting an intervention out of the individual optimum (Caetano & Teixeira, 2015; Zhao et al., 2009), economical and functional dependencies (Furuya & Madanat, 2013), and petri-net based simulations (Fecarotti & Andrews, 2017).

The research following a top-down approach determines a set of optimal spatial work zones before determine the exact work zones and interventions within the work zones being part of the intervention program (Den Hertog et al., 2005; Jenema, 2011; Lidén et al., 2018; Van Zante-De Fokkert et al., 2007). All the research on the bottom-up and top-down approach minimise infrastructure agency costs and the traffic disturbance. Lidén et al. (2018) in particular, considered the coordinated planning of optimal work zones and train operation in order to minimise traffic disturbance while considering agency costs and resource constraints.

Beside using a clear bottom-up or top-down approach, some research proposed models that combine the intervention selection and the network level within the optimisation, e.g. for road (Bonyuet et al., 2002; Eicher et al., 2015; Hajdin & Adey, 2006; Lethanh et al., 2018) and railway (Burkhalter & Adey, 2018; Burkhalter, Martani, et al., 2018; Dao et al., 2019; Pargar, 2015). For road, Bonyuet et al. (2002) proposed an iterative model to develop intervention programs for roads combining road and bridge renewals that minimise the user travel time within a given budget. Hajdin & Adey (2006) proposed a model based on network flow theory to develop an optimal risk reducing work zone one a road network considering different road sections, i.e. open road, bridge section, tunnel. The optimal work zone is thereby the one that maximises the net benefit considering the benefit in terms of risk reduction and the costs for the infrastructure agency and the road user, while being subject to a budget and a maximum length constraint. This model was further extended to multiple work zones (Eicher et al., 2015) and implemented in a GIS environment (Lethanh et al., 2018). For rail, Pargar (2015) and Dao et al. (2019) proposed models to develop cost minimising intervention programs on entire railway networks considering the grouping effect over all types of objects and the benefit of grouping multiple sections together using linearization (Pargar, 2015) and a non-linear functions (Dao et al., 2019). Burkhalter, Martani, et al. (2018) used the approach of fault tree analysis to model the network effects when developing intervention programs for railway networks, which led to a non-linear model, while the model proposed in Burkhalter, Adey, et al. (2018) is a linear problem formulation based on network flow theory. Similar to Eicher et al. (2015) and Lethanh et al. (2018), the two models of Burkhalter & Adey (2018) and Burkhalter, Martani, et al. (2018) maximise the net benefit considering the risk reduced by the interventions and the cost for the infrastructure agency and the railway users. All of these models, except Burkhalter, Martani, et al. (2018) and Dao et al. (2019), have in common that they are based on mixed integer linear programming, which allow to find the global optimum using Branch-and-Bound. This has, however, the disadvantage of getting computational difficult for large networks.

3.4 Optimal risk reducing intervention programs

3.4.1 Intervention programs

The development of intervention programs is one task of the infrastructure management process. An intervention program consists of the interventions to be executed on the objects of an infrastructure network within the next planning period (Adey, 2019). The duration of the planning period and whether the period is divided into smaller periods, e.g. a 10 year period into two 5 year periods, depend on the infrastructure, the considered objects and interventions, and the expected results. An intervention program provides information about the interventions to be grouped together and the operational state under which the interventions are to be executed, e.g. during the execution of two interventions on a railway line, the railway line is to be closed to traffic from Friday at 22:00 to Monday at 4:00. During which weekend within the period considered these interventions are executed is, however, not part of the intervention program. This is done in a later step when the interventions are scheduled and attributed to particular times, e.g. weekends (see section 3.3.1). Further, an intervention program does not explain that it is better to execute an intervention in this year on an infrastructure object than in another year. This is something that is done in the determination of optimal intervention strategies (Adey, 2019).

In the search for optimal risk reducing intervention programs, the starting point is normally the intervention program generated from the condition of all of the objects in the network and the intervention strategies to be followed. This initial intervention program, however, may not be possible due to multiple reasons, e.g. budget constraints or the inability to close multiple railway lines at one time. These reasons often result in feasible intervention program missing interventions or including more or less expensive interventions than would be optimal to execute from an object point of view.

3.4.2 Network dependencies

An infrastructure network is not the same as a portfolio of objects. Although both consist of the objects, the former also refers to the dependencies within the network of objects. The five main types of dependencies shown in Table 14 are referred to in this report as, resource, structural, economical, topological and stochastic dependencies (Furuya & Madanat, 2013; Olde Keizer et al., 2017; Van Horenbeek & Pintelon, 2013). Economical, structural and topological dependencies are graphically illustrated for the railway infrastructure in Figure 13.

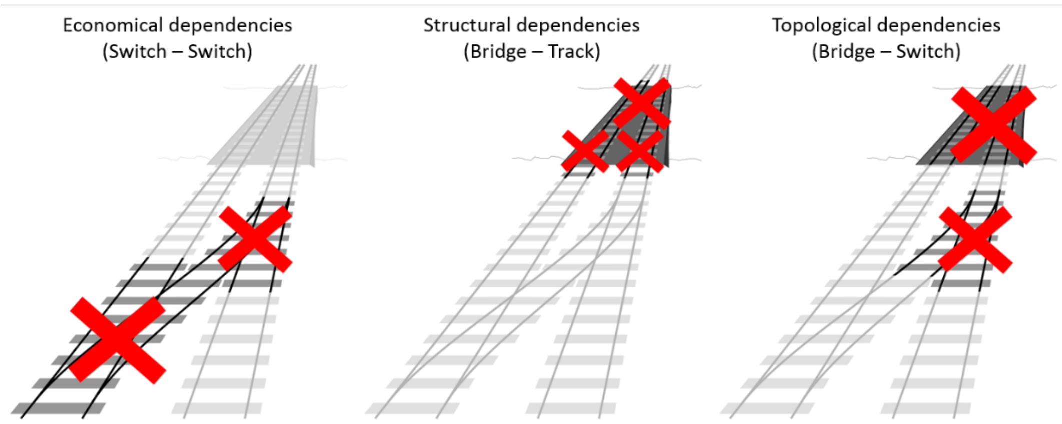

Figure 13. Economical, structural and topological dependencies (Burkhalter & Adey, 2018)

Table 14. Network dependencies regarding interventions on a transportation infrastructure

Dependency	The dependencies refer to …	Example	Consideration
Resource	… common shared resources, i.e. budget, machinery, and work labour.	The total intervention costs cannot surpass the available budget.	Yes, because of limited budgets of infrastructure managers
Economical	… the difference in costs when interventions are grouped together, i.e. due to economies of scale or shared fix costs.	The cost of executing two switch interventions combined is lower than the cost for individual executions.	Yes, because they have a direct effect on the costs of interventions
Structural	… dependencies between objects with respect to their functionality as an object, i.e. when one objects functionality depends on the functionality of another object. They are based on the physical or technical construction of the system, i.e. an object constructed on another object.	A rebuild of a bridge requires the track on top of the bridge to be rebuild too.	Yes, because they lead to mandatory combinations of interventions on different objects.
Topological	… the functional dependencies between the object and the systems performance, i.e. when the ability of an object to provide service depends on other objects ability to provide service. They describe the functional structure of the system, i.e. serial and parallel structure, k-out-of-N, and redundancy.	Executing a switch and a track intervention affecting the same traffic together leads to less traffic disturbance than when the interventions are executed individually.	Yes, because they have a direct impact on the impact on the service.
Stochastic	… correlated objects failures, i.e. due to common cause failures.	A river flooding may cause damage on multiple bridges at the same time.	No, because they would have to be considered in the risk assessment process.

Table 15 lists the potential effect the dependencies have on the intervention program and on the net benefit obtained from the intervention program. While deviations in the intervention programs due to resource and structural dependencies tend to decrease the overall net-benefit, because it may not be possible to execute the theoretically optimal interventions on each object, the economical and topological dependencies tend to increase the overall it, by making use of synergies when grouping interventions.

Table 15. Effect of dependencies on the intervention program

Dependency	Effect on the intervention program	Effect on the optimality
Resource	Not all interventions that are required based on the individual consideration of the objects can be executed due to a limited resource.	Decrease in the overall optimality due to the deviation from the individual optimal point in time for the interventions omitted.
Structural	The execution of an intervention on an object requires the execution of interventions on other objects that would not be necessary based on the objects conditions.	Decrease in the overall optimality due to the execution of interventions on objects at the non-optimal point in time.
Economical	Interventions are grouped together, where interventions can be included that would not be required in order to use synergies between interventions.	Increase in the overall optimality due to the decrease in costs related to the execution of grouped interventions.
Topological		

3.4.3 Optimal risk reducing intervention programs

The optimal risk reducing intervention program is the one that maximises the net benefit consisting of the benefit and the costs of an intervention program compared to those of a reference program (EQ. 17).

$$Net\ Benefit = Benefits - Costs \tag{17}$$

The costs refer to the difference in all the costs related to the execution of the intervention program C^{IP} and the reference program C^{ref} (EQ. 18). The costs of any intervention program (C^{IP}) consist of all effects on stakeholders due to the execution of the interventions, which are divided into direct (C_{DC}^{IP}) and indirect costs (C_{IC}^{IP}) (EQ. 19) (Adey, Martani, et al., 2019). Although it is possible to consider many different costs (Adey, Burkhalter, et al., 2019; Papathanasiou et al., 2019), the costs considered in this report, which are for illustrative purposes, include only the costs of the infrastructure manager for the intervention as the direct costs, and the additional travel time costs of the users due to traffic disturbance caused by the interventions as the indirect costs.

$$Costs = C^{IP} - C^{ref} \tag{18}$$

$$C^{IP} = C_{DC}^{IP} + C_{IC}^{IP} \tag{19}$$

The benefits of an intervention program (EQ. 20) refer to the reduction in risks (EQ. 21) and the reduction in future costs due to the increased probability of not having to execute other risk reducing intervention in future planning periods (EQ. 22). Both reductions are quantified as the difference between an intervention program IP and a reference intervention program of not executing any risk reducing interventions in the planning period. Figure 14 illustrates the net benefit of executing an intervention within the planning period.

$$Benefits = Reduction\ in\ risks + Reduction\ in\ future\ costs = \Delta R + \Delta FC \tag{20}$$

$$\begin{aligned} Reduction\ in\ risks &= R^{ref} - R^{IP} \\ &= Risks\ without\ the\ risk\ reducing\ intervention\ program \\ &\quad - Risks\ with\ the\ risk\ reducing\ intervention\ program \end{aligned} \tag{21}$$

$$\begin{aligned} Reduction\ in\ future\ costs &= FC^{ref} - FC^{IP} \\ &= Future\ costs\ without\ the\ risk\ reducing\ intervention\ program \\ &\quad - Future\ costs\ with\ the\ risk\ reducing\ intervention\ program \end{aligned} \tag{22}$$

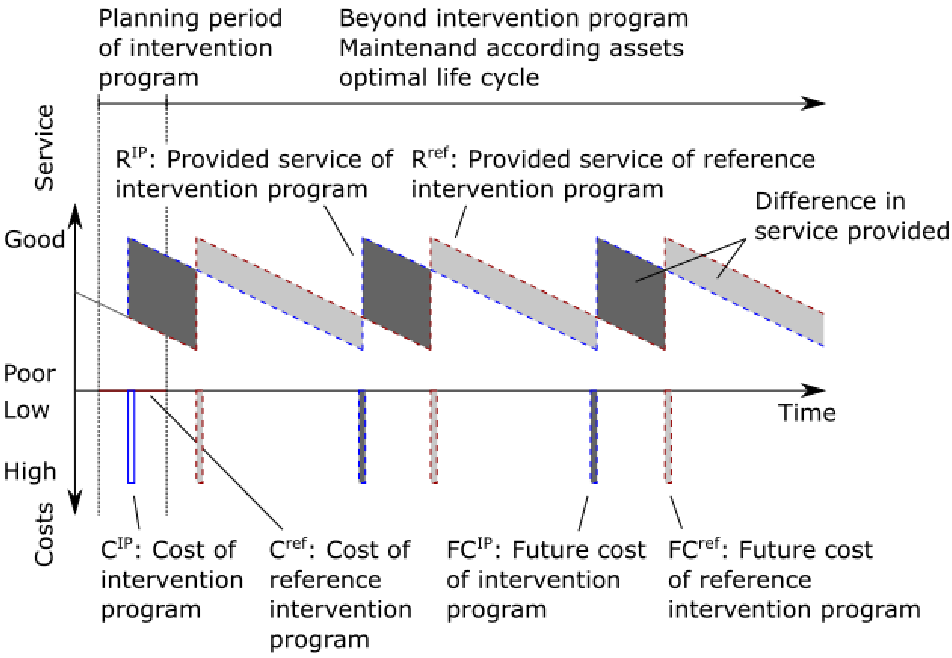

Figure 14. The impacts of executing an intervention

The intervention program optimisation and net benefit estimation introduced above can be written in a general form as shown in EQ. 23 to 27. The objective is to maximise the net benefit of the intervention program, where $\delta_{n,i}$ represents a binary variable that is 1 if intervention i is selected on object n. The benefit is the sum of the benefits of each intervention selected. The costs, consisting of the direct and indirect costs, cannot be written with single summations, as the economical (EQ. 24) and topological (EQ. 25) dependencies are nonlinear functions of the set of the possible interventions $\delta_{n,i}$. The optimal intervention program is subject to resource constraints, i.e. budget, derived from resource dependencies (EQ. 26), and structural dependencies and exclusivity constraints, which vary dependent on the exact modelling of the infrastructure network and are therefore included in a general formulation of EQ. 27.

$$Max\ NB = \left[\sum_{n}\sum_{i}\delta_{n,i}\cdot\left(\Delta R_{n,i,1}^{IP} + \Delta FC_{n,i,1}^{IP}\right)\right] - [\Delta(C_{DC} + C_{IC})] \quad 23$$

Subject to:

$$C_{DC} = f\left(\delta_{n,i}\right) \quad 24$$

$$C_{IC} = g\left(\delta\delta_{n,i}\right) \quad 25$$

$$C_{owner} \leq Budget \quad 26$$

$$\delta_{n,i} \leq q(\delta) \quad 27$$

3.5 Optimal risk reducing intervention programs for railway networks

In this section, a network flow model is presented that allows the determination of optimal risk reducing intervention programs on a specific railway network. It contains a short system description of the railway network (section 3.5.1), a system representation of the infrastructure in the network (section 3.5.2), the network model (section 3.5.3), and a mathematical formulation of the network model based on the general formulation in section 3.5.3 (section 3.5.4).

3.5.1 System description

Determining intervention programs for railway networks requires an understanding of the main characteristics of the infrastructure objects (section 3.5.1.1), the potential interventions on the objects (section 3.5.1.2), and the traffic running on the network (section 0).

3.5.1.1 Objects

The railway infrastructure consists of thousands of objects categorized into different object categories. The major categories with their main characteristics are listed in Table 16. A more complete list can be found in the European Union Commission Regulation No 851/2006 (European Union, 2006).

Table 16. Object categories of railway infrastructures

Category group	Categories	Description and major characteristics
Track bed	Embankments	Elongated infrastructure caring the track elevated to the ground in order to level topological differences.
	Cuttings	Elongated infrastructure to allow the track to lay deeper than the original ground to level topological differences.
	Drainage	Different types of infrastructures to ensure the stability of the subsoil.
Engineering structures	Bridges	Unique engineering structures or elongated viaduct to overpass bigger obstacles. Carries the other entire required railway infrastructure.
	Overpasses	Short and more standardised overpasses.
	Tunnels	Elongated infrastructure to underpass big obstacles. The other entire railway infrastructure is placed into the tunnel.
	Underpasses	Short and more standardised underpass.
	Retaining wall	Location specified designed structure to protect the track stability or the ground stability next to the track.
Level crossing		Stand-alone infrastructure with high safety requirements to allow roads to cross the railway on the same level.
Permanent way	Track	Elongated infrastructure to guide and carry the trains constructed as ballasted track or slap track.
	Switches and Crossings	Stand-alone infrastructure allowing trains to switch paths between different tracks or to cross different tracks.
Public installations		Infrastructure located along the network for passengers and goods to access the railway network.
Safety, signalling and telecommunications installations	Signalling infrastructure	Smaller equipment located all along the track to control the train traffic.
	Interlocks	Centralised infrastructure to control and steer the train traffic by interacting with the signals and switches.
Railway power installations	Catenaries	Elongated infrastructure along the track to provide power to the trains.
	Substations	Centralised stations to transform and control the power supply

The descriptions in Table 16 show the wide variety of objects regarding their extent, functionality, construction, and lifetime. For example, the tracks, switches and crossings guide and carry the train along the network, while bridges, tunnels, embankments and cuttings are required to overcome obstacles. Tracks, embankments, tunnels, and catenaries are elongated infrastructure, which have different logistical requirements for the execution of interventions compared to stand-alone infrastructure such as switches and level crossings. The signalling infrastructure consists of smaller equipment distributed over the entire network.

3.5.1.2 Interventions

All railway objects require having interventions from time to time. The variety of interventions is as extensive as the variety of objects. For detailed information about possible interventions on the railway infrastructure, one has to refer to specific literature (Esveld, 2014; Fendrich & Fengler, 2013; Freystein et al., 2015; Gutsche, 2009; Jänsch, 2016; Profillidis, 2014; SBB Infrastruktur, 2016, 2017).

All interventions cost money to execute, require a certain time to be executed and can be categorised according to their extent, their requirement of track possession and their ability to be executed without disrupting traffic. The extent of an intervention is highly dependent on the form and extent of the object. Interventions on elongated objects are often carried out in a continuous and rolling way, e.g. a track renewal with a renewal train running along the track. Interventions on single stand-alone objects, e.g. single bridges or switches, are localised in a single place. Dependent on the breakdown of the infrastructure, some objects consist of single components distributed along the network, a line, or a route. Interventions on such distributed objects require many small activities at different places distributed in space. They, therefore, have to be considered differently from continuous and local interventions.

The different types of interventions in terms of track possessions and traffic disturbance are shown in Table 17. Type *A*, *B* and *C* refer to interventions that disturb traffic and are either continuous or local executed interventions requiring track possession, or interventions that disturb traffic without requiring track possession. Interventions of type *D* and *E* do not disturb traffic.

Table 17. Intervention types for railway infrastructure

Intervention type	Extent over the network	Track possession	Traffic disturbance	Example
A	Continuous	Yes	Yes	Track renewal with an intervention train
B	Local	Yes	Yes	Switch replacement, bridge renewal
C	Local / Disperse	No	Yes	Renew an interlock requiring closing the track for traffic
D	Local / Disperse	Yes	No	Minor intervention on a switch that can be executed between two trains
E	Local / Disperse	No	No	Rehabilitation of an embankment under traffic

3.5.1.3 Network

The railway network enables the transportation of passengers and goods from their origin to their destinations. From the traffic perspective, the railway network consists of stations, junctions, lines, line sections, track routes, and crossovers (Figure 15). Railway lines are between major stations where multiple lines come together. Beside the major stations, there can be multiple smaller stations along a line. These intermediate stations together with junctions, where two or more lines merge outside of a station area, define the line sections. Lines are either single track lines, i.e. line *C*, double (or multiple) track lines, i.e. line *A*, or partial double track lines, i.e. line *B*. Multiple tracks parallel to each other are called track routes. They are separated by stations, junctions and switches.

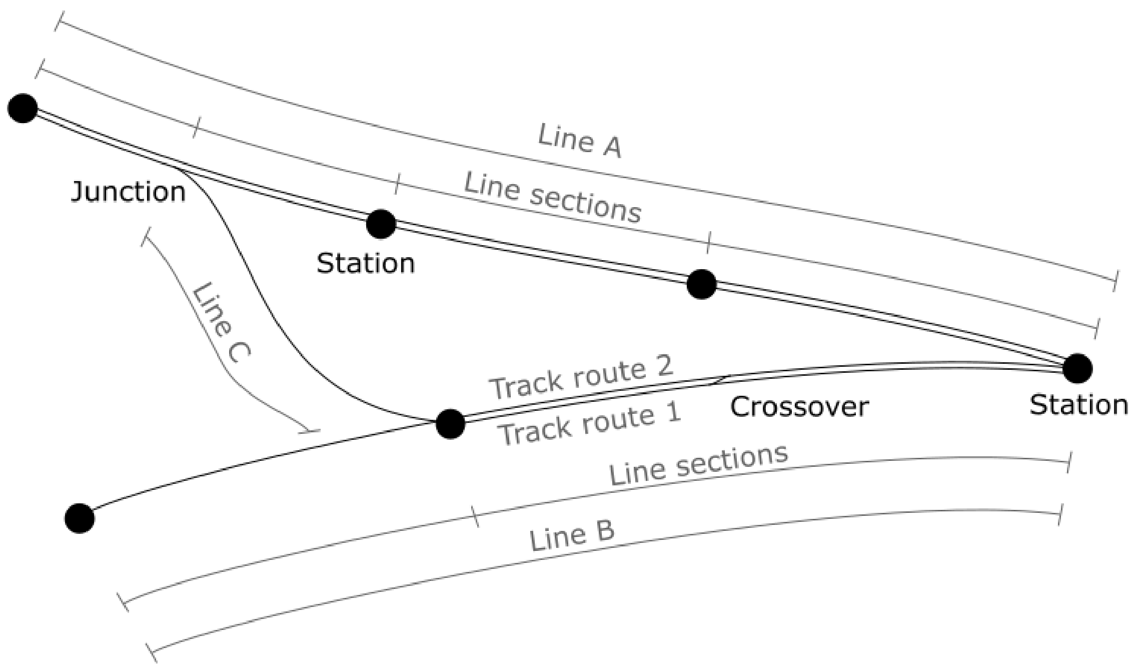

Figure 15. Railway network

The consideration of the network topology is required to estimate the effect of interventions on traffic and therefore the user. Using Figure 15 as a reference, one can see that

- Traffic can be disturbed by closing different parts of the network.
- A closure always affects at least one entire route.
- A closed route on a double track line still allows traffic to run with a lower capacity.
- When the entire cross-section at a specific location is closed, the entire line section has to be taken out of service, as train service has to end at a station.
- While it is possible to take multiple neighbouring line sections out of service, it is also possible to close down an entire line.

This route system is the biggest difference between railway and road networks, where cars can change lanes anywhere within the network allowing local partial closures of the road that only disturb traffic locally. In the railway network, at least an entire route has to be closed for traffic.

3.5.2 System representation

In this section, the railway network described in section 3.5.1 is represented in a systematic structure upon which an optimisation model can be built. The structure takes into consideration how objects are related to each other, how objects are related to interventions and the dependencies identified in section 3.4.2. This is shown in Figure 16 for line *B* in Figure 15. Line *B* consist of two line sections, wherein section *2* consists of the four routes *1* to *4*. The objects consist of 8 track sections *T1* to *T8*, three switches *S1*, *S2* and *S3*, and the two bridges *B1* and *B2*. The system representation is shown in Figure 17.

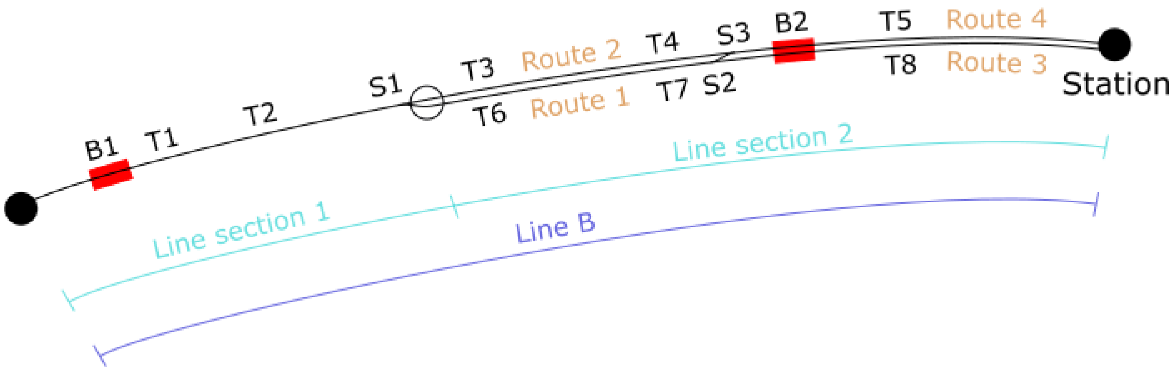

Figure 16. Network structure of line B

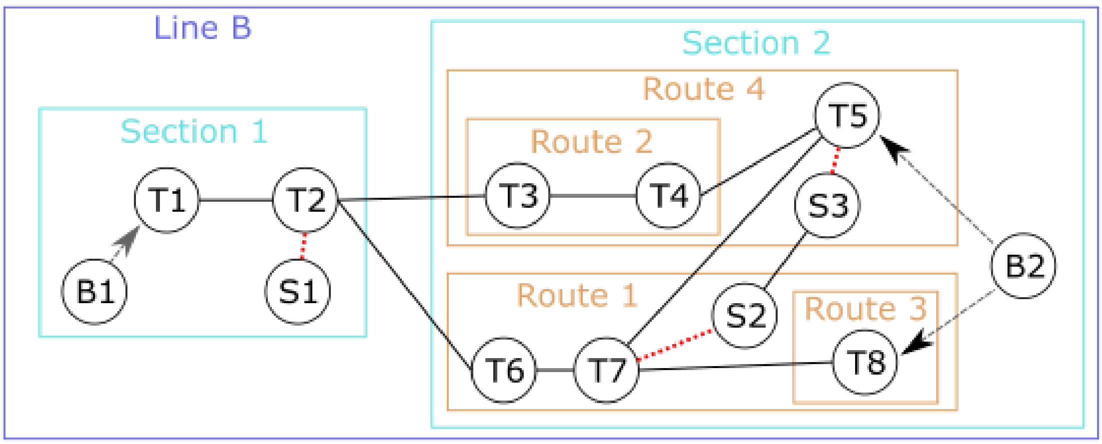

Figure 17. Representation of line B

In Figure 17,

- the objects are represented by nodes and the network breakdown elements, e.g. a line, by rectangles.
- the relationships between objects are represented by lines between two objects referring to
- economical dependencies (black solid lines), which exist when interventions of the same type can be executed on neighbouring objects, where elongated objects such as tracks are considered as neighbours when they are connected together in the track direction, while local stand-alone objects, i.e. switch and bridges, are considered

neighbours when they are within a close geographical distance. For example, switch S2 and S3 are considered to be close to each other, while switch S1 is not within the neighbourhood allowing for economical dependencies.

- structural dependencies (arrows). The arrows of the structural dependencies point to the dependent objects. For example, track segment T1 is structural dependent on bridge B1.
- the relationships between objects and the provided service are represented by the nested structure of the network breakdown elements. Each network element can be associated with a provided service or, in terms of the execution of interventions, when the element is non-functional.
- Within the nested structure, an inner element is functionally dependent on the functionality of an outer element, i.e. route 4 is part of section 2 and therefore functionally dependent on section 2.
- The same is true for the objects, where an object can only provide service when the surrounding network breakdown elements are functional as a whole. For example, T6 is a track segment along route 1 belonging to section 2 and is part of line B. When line B, section 2 or route 1 are out of service, object T1 cannot provide any service.
- In terms of interventions, this means that an intervention on track T1 affecting the traffic can be executed, while either route 1, section 2 or the whole line B is closed.

This nested structure of the network breakdown elements indicates the topological dependencies. Objects that lay within the same network element affect the same traffic and interventions on them can make use of synergies in respect to topological dependencies when grouped together. Based on the intervention characteristics, all intervention types can be executed parallel in time, except interventions that are connected by economical dependencies and type A interventions (see Table 17) that are continuous interventions on stand-alone objects requiring track possession with intervention trains, i.e. track interventions with track renewal trains. This exception are indicated with red dotted links in Figure 17.

3.5.3 Network model

The system representation in section 3.5.2 enables an optimisation model using network optimisation techniques to be developed. Network models are often used to solve combinatorial optimisation problems (Vangelis T. Paschos, 2014; Vangelis Th. Paschos, 2013; Subramanian et al., 2016). They represent real world problems with a set of nodes and edges connecting the nodes to a network, where the flow along the edges represent some kind of a decision. Classical network problems focus on either, 1) maximising a flow in the network or 2) minimising the costs or distances of travel between multiple nodes in the network. In the simplest formulation, network models allow a simple introduction of capacity constraints on each edge beside the flow conservation constraints of a network formulation.

Since many combinatorial optimisation problems cannot be modelled as simply as the classical network problem formulations, more complex network models are widely developed. For example, the job to machine problem, in which binary decision variables representing the assignment of jobs to a machine are transformed into reel variables representing duration (Bertsekas, 1998), and flow problems with gains and losses along the network (Truemper, 1977) require to replace the classical flow conservation constraints in each node with a node flow constraint allowing the flow to increase or decrease. Other problems require a differentiation of edges and the consideration of multiple node flow constraints, i.e. multi-commodity flow problems (Ahuja et al., 1993). Further, additional side constraints have to be implemented to address specific constraints that take into account relationships between the flows on different, not necessary connected, edges, i.e. a shortest path problem with a cost limitation (Beasley & Christofides, 1989).

The network model used to determine optimal intervention programs is a network flow model with additional node flow constraints and side constraints. It is divided into two parts, an object level with binary flows representing the decision as to which intervention to execute under which condition, and a network level with real-valued flows to calculate the duration of different traffic disturbances. The objective of maximising the net benefit includes both levels with the object level providing the intervention benefits and costs considering economical dependencies, and the network level calculating the user costs considering topological dependencies, which is in line with the general formulation in EQ. 23. The resource and structural dependencies are considered through side constraints.

Figure 18 illustrates the structure of the network flow model for the example network in Figure 16. The structure is derived from the system representation described in 3.5.2 and graphically illustrated in Figure 17. In favour of readability, it is reduced to line section *2* and to one intervention per object. The network model consists of two levels, i.e. object and network level, four different types of nodes, i.e. source, interventions, groups and sink consisting of traffic states, and five types of edges, i.e. *a* to *f*.

The source and intervention nodes together with edges *a*, *b* and *c* build the object level, which represents the selection of interventions while considering economical dependencies between objects. An intervention node represents a possible intervention on a specific object executed within a specified time window. Edges of type *a* represent the execution of an intervention without considering economical dependencies, while edges of type *b* consider the execution of another intervention and represent economical dependencies. For example, the edge *Source – T7* represents the execution of the intervention on track segment *7* without considering any previous intervention, while edge *T6 – T7* represents the execution of the intervention on track segment *7* coupled with the execution of the intervention on track segment *T6*. Edges of type *c* represent closure of the network on the object level in order to have flow conservation throughout this part of the network model. The flows on edges type *a*, *b* and *c* are constrained to be binary. The costs and benefits of executing an intervention is attributed to edges of type *a* and *b*, where the intervention costs on edges of type *a* consist of both the fixed and variable costs, while the costs on edges of type *b* only consist of the variable costs.

The edges of type *b* are derived from the lines representing the economical dependencies in the system representation (Figure 17). For example, the edge *T6 – T7* is derived from the economical dependency between *T6* and *T7*. Therefore, the object level network flow model equals the network of the system representation considering only the economical dependencies (black solid lines in Figure 17). The nodes in the system representation representing the objects are replaced in the network flow model by as many nodes as there are different intervention options for that object.

The network level represents the effect on the network due to the interventions and consists of the interventions and group nodes and the edges of type *d*, *e* and *f*. This part of the network model estimates the required duration of each traffic state based on the selected interventions while considering topological dependencies. The flow in it is real-valued and represents durations. The source flow in the intervention nodes are the durations of the interventions, while the edges reaching the sink node hold the unit cost per time unit for a particular traffic state in order to calculate the overall cost related to traffic disturbance. The sink node combines all traffic state nodes into one node, as the differences between the traffic states is already given by the edges.

For each traffic state, the same or similar interventions on different objects are grouped together. For example, node *T-R1* groups all track interventions that can be executed under traffic state *R1*. These group nodes allow consideration of the differences between temporal parallel and serial execution of the interventions. While all interventions within one group are assumed to be executed together, groups of interventions type *B* and *C* in Table 17 can be executed parallel in time. For this reason, edges of type *f* are introduced. Edges of type *f* are sink edges that remove some flow out of the network dependant on the flow on other edges. For example, node *S-S2* represents the group of switch interventions (type *B* interventions) that are executed under traffic state *S2*. They can be executed at the same time as the bridge interventions (also type *B*) under traffic state *S2*. The flow representing a duration on edge *S-S2 – B-S2* is part of the normal flow conservation constraint in node *S-S2*, while it is constrained in node *B-S2* to be smaller than the duration group *B-S2* requires in traffic state *S2*, i.e. the flow on *B-S2 – Sink*.

Regarding the system representation, the group nodes of one traffic state in the network flow model of the network level correspond to the economical connected components of the subgraph of the system representation referring to the network element (rectangular in Figure 17) affected in the traffic state. For example, traffic state *R1* refers to a closure of route *R1*. The subgraph for route *R1* of the entire system representation consists of *T6*, *T7*, *T8* and *S2* with economical dependencies between *T6* and *T7* as well as between *T7* and *T8*. The connected components within this subgraph can be grouped into the components of tracks leading to group *T-R1*, and the single switch intervention leading to group *S-R1*. An edge of type *f* between two groups exists only if all interventions of two groups can be executed parallel in type, which is derived from the system representation by the non-existing of a dotted red line between the two connected components representing the groups. For example in traffic state *S2*, the groups *S-S2* and *B-S2* are linked by an edge of type *f* as their represented individual components of *S3* and *B3* in Figure 17 are not linked with a red dotted line.

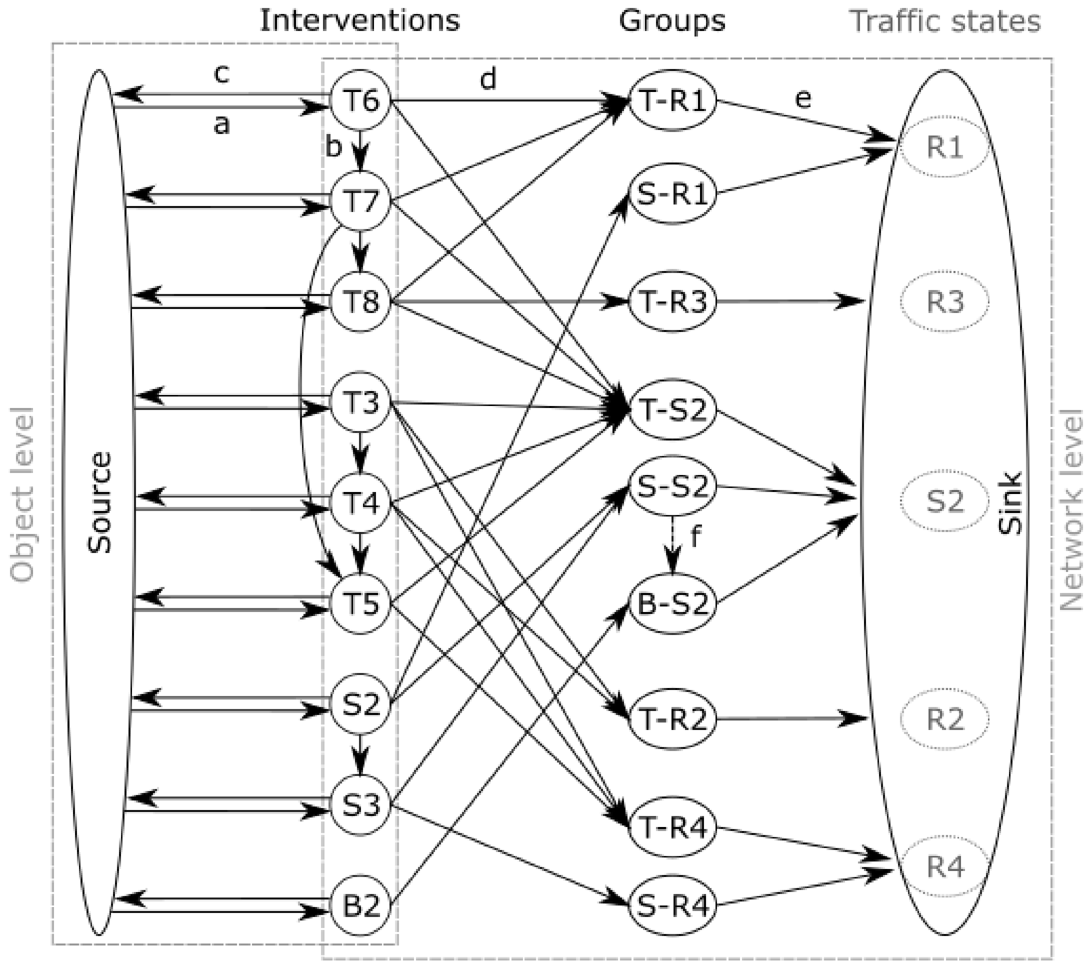

Figure 18. Network flow model

In addition to the network structure, with the objective and the different flow constraints, additional side constraints are required to consider resource constraints, structural constraints and exclusivity constraints, which assure that for each object at most one intervention is selected.

The network model illustrated in Figure 18 considers only one possible intervention per object executed in one possible time window. When considering different time windows, i.e. night shift and day shift, the network consisting of intervention, group and traffic state nodes has to be constructed for each time window separately. This assures that grouping of interventions is only considered when the interventions are selected to be executed within the same time window. When different interventions are possible per object category, these interventions are represented by an intervention node each.

Mathematically, the network model can be formulated as a graph $G = (V, E)$, where V is the set of nodes and E is the set of edges that connect pairs of nodes (u, v). Subsets of the node set are the set of interventions V^I and the set of group nodes V^G. The edges are differentiated into edge subsets $E = E^{OL} \cup E^{NL} \cup E^{TD}$, where E^{OL} represents the binary edges in the object level, i.e. edge *a*, *b*, and *c* in Figure 18, E^{NL} represents the normal duration flow edges in the network level, i.e. edges *d* and *e*, and E^{TD} represents the topological dependency edges, i.e. edge *f*.

3.5.4 Mathematical Formulation

In this section, the mathematical optimisation model is formulated for the network flow model proposed in section 3.5.3 in respect to developing optimal intervention programs described in section 3.4.3.

3.5.4.1 Objective function

The objective of the optimization model is to maximise the net benefit, which is done in the network flow model by maximising the sum product of the flow on each edge and the net benefit associated with each edge (EQ. 28).

$$Max\ NB = \sum_{u\in V}\sum_{v\in V}\delta_{u,v}\cdot NB_{u,v} + \sum_{u\in V}\sum_{v\in V}\gamma_{u,v}\cdot NB_{u,v} \qquad 28$$

where

$\delta_{u,v}$ are binary variables that are 1 if the edge $(u,v)\in E^{OL}$ between the nodes u and v is part of the optimal path and 0 otherwise.

$\gamma_{u,v}$ are non-negative variables that represent the time flow on the edge $(u,v)\in E^{NL}$ between the nodes u and v.

$NB_{u,v}$ is the net benefit associated with the edge between nodes u and v.

3.5.4.2 Constraints

The objective function is constrained by the flow conservation, topological dependency, exclusivity, budget, and structural dependency constraints.

EQ. 29 and EQ. 30 show the flow conservation constraints for the object and the network level, respectively. On the object level (EQ. 29), the flow is conserved between the inflow and outflow of object level edges. On the network level (EQ. 30), the inflow of network level edges together with the source flow is equal to the outflow of network level edges together with the outflow of economical dependency edges, which are sink edges.

$$\sum_{v\in V}\delta_{v,u} = \sum_{v\in V}\delta_{u,v}\,, \qquad \forall\, u\in V \qquad 29$$

$$\sum_{v\in V}\delta_{v,u}\cdot d_{v,u} + \sum_{v\in V}\gamma_{v,u} = \sum_{v\in V}\gamma_{u,v} + \sum_{v\in V}\varepsilon_{u,v}\,, \qquad \forall\, u\in V \qquad 30$$

where

$d_{u,v}$ are the durations associated with the edge between node u and v.

$\varepsilon_{u,v}$ are non-negative variables that represent the time flow on topological dependency edge $(u,v)\in E^{TD}$ between the nodes u and v.

EQ. 31 provides the formulation of the topological dependency constraints, where the flow on a topological dependency edge (u,v) is restricted to at most the sum of the flow on the outgoing normal flow edges in node v.

$$\varepsilon_{v,u} \le \sum_{w\in V}\gamma_{u,w}\,, \qquad \forall\, u\in V \qquad 31$$

The exclusivity constraint in EQ. 32 ensures that only one intervention per object is selected.

$$\sum_{u\in V}\sum_{v\in V_n}\delta_{u,v} \le 1\,, \qquad \forall\, n \qquad 32$$

where

V_n is the set of nodes representing interventions on object n.

EQ. 33 shows the budget constraint that ensures that the intervention costs do not exceed the budget.

$$\sum_{u \in \mathrm{V}} \sum_{v \in \mathrm{V}} \delta_{u,v} * c_{u,v} \leq \Omega_{max} \tag{33}$$

where

$c_{u,v}$ are the intervention costs associated with the edge between node u and v.

Ω_{max} is the budget limitation.

The structural constraints in EQ. 34 ensure that the mandatory intervention of a structural dependent pair is selected when the initial intervention of the structural dependent pair is selected.

$$\sum_{u \in \mathrm{V}} \delta_{u,v} - \sum_{u \in \mathrm{V}} \delta_{u,w} \leq 0\,, \qquad \forall\,(v,w) \in SD \tag{34}$$

where

SD is the set of structural dependent nodes.

3.6 Example

3.6.1 Situation

The presented model to develop optimal risk reducing intervention programs is used to develop an optimal risk reducing intervention program for an example one-line railway network in Switzerland (Figure 19). The line is a single-track line with multiple tracks in 7 of the 10 stations along the line. It is connected to the rest of the network by a junction at station A, while station J is a terminal station of the railway network.

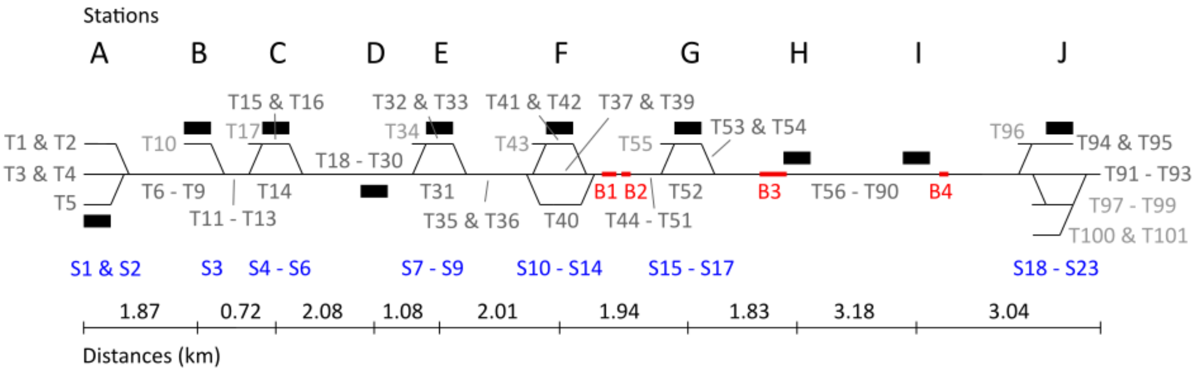

Figure 19. Example network

The network consists of the track, switches, and bridges. They are described in more detail in section 3.6.2. The considered condition states and deterioration are discussed in section 3.6.3, while the interventions considered are provided in section 3.6.4. Section 3.6.5 describes the traffic states and their related effects on the users. The risk estimation is given in section 3.6.6.

3.6.2 Railway network

The track network is divided into track segments that split the track at all switches. In addition to this topological break down, tracks between switches are further divided into segments due to their condition when possible, and due to the existence of a bridge, where the track on top of the bridge is an individual track segment. Table 18 shows the 101 identified track segments also shown in Figure 19. The table provides information about the location, the object extent in meters, and the current condition of the track segments. The location is provided by the section or station to which the track belongs, and further, by the number of the element within this section or station. For example, track *T15* is in station *C* and is numbered *2.1*, which means that it is the *first* segment of track *2* in station *C*. Further, the word *Siding* describes a track beside the main tracks. The total length of all tracks is approximately 20 kilometres.

Table 18. Track segments

ID	Section / Station	Element	Length [m]	Condition state
T1	A	1.1	155	1.5
T2	A	1.2	60	2.4
T3	A	2.1	239	1.4
T4	A	2.2	31	2.0
T5	A	3	197	1.2
T6	A – B	1.1	235	3.2
T7	A – B	1.2	468	1.0
T8	A – B	1.3	104	2.5
T9	A – B	1.4	758	2.0
T10	B	siding	192	2.0
T11	B – C	1.1	306	1.5
T12	B – C	1.2	37	3.5
T13	B – C	1.3	46	1.6
T14	C	1	209	1.0
T15	C	2.1	47	1.3
T16	C	2.2	163	2.0
T17	C	siding	121	1.1
T18	C – D	1.1	126	4.8
T19	C – D	1.2	295	3.2
T20	C – D	1.3	38	2.0
T21	C – D	1.4	268	3.8
T22	C – D	1.5	76	2.0
T23	C – D	1.6	194	3.8
T24	C – D	1.7	296	3.8
T25	C – D	1.8	181	3.2
T26	C – D	1.9	787	2.0
T27	D – E	1.1	120	3.3
T28	D – E	1.2	135	1.4
T29	D – E	1.3	394	4.8
T30	D – E	1.4	72	1.2
T31	E	1	193	3.5
T32	E	2.1	57	2.7
T33	E	2.2	136	2.0
T34	E	siding	180	1.0
T35	E – F	1.1	264	3.6
T36	E – F	1.2	1494	2.0
T37	F	1.1	43	2.0
T38	F	1.2	161	1.1
T39	F	1.3	24	2.0
T40	F	2	229	2.0
T41	F	3.1	37	2.0
T42	F	3.2	124	2.0
T43	F	siding	113	2.7
T44	F – G	1.1	21	2.0
T45	F – G	1.2	97	3.2
T46	F – G	1.3	160	3.2
T47	F – G	1.4	57	3.2
T48	F – G	1.5	11	3.2
T49	F – G	1.6	7	3.2
T50	F – G	1.7	176	3.2
T51	F – G	1.8	1233	1.1
T52	G	1	239	2.0
T53	G	1.1	186	2.0
T54	G	1.2	54	2.0
T55	G	siding	106	1.5
T56	G – H	1.1	102	1.4
T57	G – H	1.2	273	4.3
T58	G – H	1.3	299	2.8
T59	G – H	1.4	299	2.8
T60	G – H	1.5	120	2.8
T61	G – H	1.6	115	2.2
T62	G – H	1.7	272	3.0
T63	G – H	1.8	177	2.0
T64	G – H	1.9	92	1.3
T65	H – I	1.1	112	2.8
T66	H – I	1.2	305	3.6
T67	H – I	1.3	673	5.0
T68	H – I	1.4	164	3.2
T69	H – I	1.5	60	2.4
T70	H – I	1.6	281	3.2
T71	H – I	1.7	396	3.2
T72	H – I	1.8	266	1.7
T73	H – I	1.9	566	5.0
T74	H – I	1.10	102	5.0
T75	H – I	1.11	111	5.0
T76	H – I	1.12	182	2.0
T77	I – J	1.1	90	3.6
T78	I – J	1.2	397	1.0
T79	I – J	1.3	150	3.3
T80	I – J	1.4	161	3.3
T81	I – J	1.5	199	3.0
T82	I – J	1.6	136	3.2
T83	I – J	1.7	6	3.2
T84	I – J	1.8	61	3.2
T85	I – J	1.9	77	2.2
T86	I – J	1.10	174	2.4
T87	I – J	1.11	601	1.5
T88	I – J	1.12	226	2.5
T89	I – J	1.13	431	1.6
T90	I – J	1.14	16	4.5
T91	J	1.1	82	2.0
T92	J	1.2	181	4.5
T93	J	siding 1	58	4.7
T94	J	2.1	57	1.4
T95	J	2.2	182	1.2
T96	J	siding 2	76	3.4
T97	J	3.1	55	2.0
T98	J	3.2	90	4.8
T99	J	siding 3	78	4.9
T100	J	3.3	36	2.6
T101	J	siding 4	169	4.7

Table 19 lists all 23 switches along the line. Their locations are identified by the station to which they belong and the number of the switch within the station. Switches within the same station are numbered in the direction towards station *J*. The triplet of adjoined track segments describes the track segments connected by the switches, where the order represents the track facing the switch, the main line track, and the turnout track, respectively. For example, switch *S5* is the 2nd switch in station *C* connecting *T16* straight with *T17* and has a turnout from *T16* to *T15*.

Table 19. Switches

ID	Station	No.	Adjoined track segments	Condition state
S1	A	1	T4, T3, T5	1.4
S2	A	2	T6, T4, T2	2.6
S3	B	1	T11, T9, T10	4.4
S4	C	1	T13, T14, T15	3.4
S5	C	2	T16, T17, T15	3.6
S6	C	3	T18, T14, T16	2.2
S7	E	1	T30, T31, T32	4.3
S8	E	2	T33, T34, T32	2.7
S9	E	3	T35, T31, T33	4.3
S10	F	1	T36, T37, T40	4.3
S11	F	2	T37, T38, T41	3.1
S12	F	3	T42, T43, T42	1.6

ID	Station	No.	Adjoined track segments	Condition state
S13	*F*	4	T39, T38, T42	2.8
S14	*F*	5	T44, T39, T40	4.3
S15	*G*	1	T51, T52, T53	1.8
S16	*G*	2	T54, T55, T53	1.4
S17	*G*	3	T56, T52, T54	2.4
S18	*J*	1	T90, T91, T94	4.5
S19	*J*	2	T95, T96, T94	3.3
S20	*J*	3	T91, T92, T97	1.9
S21	*J*	4	T98, T99, T97	4.5
S22	*J*	5	T100, T98, T101	4.5
S23	*J*	6	T93, T92, T100	4.5

The example network consists of four bridges with varying size (Table 20). Bridge *B3* is the major engineering structure along the line. Bridge *B1* is a relatively small bridge crossing a small river. Bridges *B2* and *B4* are road underpasses.

Table 20. Bridges

ID	Location	Related track	Extend [m²]	Current condition
B1	F – G	T47	285	2.0
B2	F – G	T49	33	1.6
B3	G – H	T63	883	4.0
B4	I – J	T83	30	4.2

3.6.3 Condition of the infrastructure over time

3.6.3.1 Condition states

The condition states considered are based on the classification scheme of the regulation R RTE 29900 (VöV, 2018), but only refer to the physical condition of the infrastructure. A general description is given in Table 21.

Table 21. Condition states

Condition state	Description
1 – New	There are no discernible difference between the actual and design characteristics. The probability that the design traffic flow capacity will be affected in the next year is negligible.
2 – Good	There are discernible differences between actual and design characteristics. The probability that the design traffic flow capacity will be affected in the next year is non-negligible.
3 – Sufficient	There are small differences between the actual and design characteristics. The probability that the design traffic flow capacity will be affected in the next year is small.
4 – Bad	There are medium differences between the actual and design characteristics. The probability that the design traffic flow capacity will be affected in the next year is medium.
5 – Insufficient	There are large differences between the actual and design characteristics. The probability that the design traffic flow capacity will be affected in the next year is high.

3.6.3.2 Deterioration

Infrastructure deteriorates over time. The deterioration process is described as the speed with which the objects traverse the condition states as described in section 3.6.3.1. Although sophisticated and detailed deterioration models exist for different object categories, only simple approximate deterioration models were used in this case study that help to keep the focus on the optimisation model and algorithm to develop optimal risk reducing intervention programs. The deterioration rates used were developed using the life times suggested in the R RTE 29900 (VöV, 2018).

Table 22. Deterioration process

Object category	Subcategory	Condition range	Deterioration rate
Track	Main track	1 – 5	0.16
Track	Siding track	1 – 5	0.075
Switches		1 – 5	0.12
Bridges		1 – 3	0.025
Bridges		3 – 5	0.1

3.6.4 Interventions

The interventions considered includes two interventions on the track, track renewal and rail replacement, switch replacement, and renewal of bridges. Table 23 lists all interventions with their categorisation into intervention type according to Table 17, the assumed improvement in the objects condition, the unit they are measured, the unit cost in CHF per unit, the shared cost factor, and the required track possession.

Table 23. Interventions considered

Object category	Intervention	Type according Table 17	Improved condition	Unit	Unit cost [CHF/unit]	Shared cost factor	Track possession [h/unit]
Track	Track renewal	*A*	1 – New	m	2’350	20%	0.1
Track	Rail replacement	*A*	2 – Good	m	200	20%	0.04
Switch	Switch replacement	*B*	1 – New	Object	255’000	16%	8
Bridge	Bridge renewal	*B*	1 – New	m^2	4’000	0%	0.5

While track renewal includes the replacement of sleepers, ballast and the rail, the rail replacement is a minor intervention improving the condition to a good state. The unit costs of track renewal and rail replacement are identified to be 2’350 CHF per metre and 200 CHF per metre. Both unit costs are only approximate estimates and do not differentiate between fix and variable costs. In order to show the effect of grouping interventions, the factor of the shared cost has to be considered. Caetano & Teixeira (2016) have shown that 40% of the total track renewal costs are engineering and logistic costs, from which 50% can be assumed to be fix costs, which can be shared among identical interventions on different objects. This leads to 20% fixed costs of the total costs ($0.4 \cdot 0.5 = 0.2$). The required track possession time in hours per units is used to estimate the durations of traffic disturbance due to the execution of the interventions on the objects. Literature provides values of 70 to 100 metre per work shift dependant on the construction method and the shift length (Esveld, 2014). A required track possession time of 0.1 hours per metre is assumed. The productivity rate for rail replacement is assumed to be 100 metre per night break. This is around 0.04 hours per metre under the assumption of four hours of effective worktime during a night break (see section 3.6.5.2).

Regarding switches, only switch replacement is considered. It is assumed that one switch replacement costs 255'000 CHF and takes 8 hours to execute. Regarding cost reduction by grouping interventions, Dao et al. (2019) have identified in their case study a cost reduction of up to 16%. Since this is the best estimated value found in literature, a 16% cost reduction is considered for grouping switch interventions.

Regarding interventions for bridges, only bridge renewal is considered. Minor interventions on bridges are not part of this example. A bridge renewal is assumed to cost 4'000 CHF per m^2 and requires 0.5 hours of track possession per m^2.

3.6.5 Traffic disturbance and traffic states

Traffic states refer to the different closure intervals in which interventions can be executed. Each traffic state specifies which section of the network is closed (*Closure*) during which time of the day or week (*time window*), and is associated with the respective cost of having this traffic state per hour. The cost of a traffic state per hour C_k is calculated by multiplying the number of passengers per hour, the additional travel time per passenger, and the value of time (EQ. 35).

$$C_k = {}^{Passengers}/_{Hours} \cdot {}^{Additional\ travel\ time}/_{Passenger} \cdot \text{Value of time} \qquad 35$$

The following subsections identify the potential closures and their related additional travel time (3.6.5.1), the potential time windows (3.6.5.2), the traffic volume (3.6.5.3), and the value of time (3.6.5.4) in order to estimate the cost per hour for each traffic state considered (3.6.5.5).

3.6.5.1 Closures and additional travel time

The network considered in this example is a single-track line with multiple tracks in some of the stations. A closure on the track between to stations leads essentially to a complete closure of the line section between these stations, while the closure of one track in a station still allows trains to operate. The determination of possible closures and their related additional travel time per passenger is divided into closures of line sections between stations and the closure of one track within a station.

When closing a line section, train replacement bus services has to be operated. Closures are, therefore, only possible between stations that are easy accessible with buses, have enough space for buses to operate, and have a direct road connection. In addition, the operation of remaining trains should still be reasonable. For example, operating trains between the last (station *J*) and second to last station (station *I*) of a line may not be reasonable when the replacement bus could be extended to the last station (station *I*) instead of turning at the second to last (station *J*). All the constraints regarding rail replacement bus operations limit the possibilities for the infrastructure manager of how to set closures in the network, which are shown in Table 24. The table shows the actual travel time by train for these sections, the expected travel time by buses, and the additional time required for passengers to transfer. The additional travel time due to transfer is assumed to be 5 minutes considering that passengers have to transfer from the short-turning train to the bus and some additional buffer time to catch up delays due to congestion.

In stations with multiple tracks, trains can still operate when a single track is closed. Siding tracks and also main tracks in stations where trains do not cross each other according to the schedule can be closed without having any impact on the operation. Sidings are not required for the scheduled train operation, while trains can deviate to another main track when one of multiple main tracks in a station is closed and trains are not supposed to cross each other. Considering the train schedule in the example network, only stations *C* and *G* are stations with train crossings. Based on simple train rescheduling, 5 minutes is estimated as additional travel time due to trains having to cross in other stations.

Table 24. Additional travel time per passenger of possible closures

Closures	Travel time train	Travel time bus	Transfer time	Additional travel time
A – J	32	40	5	13
A – C	5	10	5	10
C – J	25	26	5	6
E – J	21	19	5	3
F – J	18	16	5	3
I – J	6	4	5	3
Main track in C	-	-	-	5
Main track in G	-	-	-	5
A, E, F, J and all sidings	-	-	-	0

3.6.5.2 Time windows

Table 25 shows the possible time windows for executing interventions. Five different time windows are applicable. The night break refers to the time window during the night when no trains are operating, while the night closure is an extension of this time window to 8 hours by replacing the last trains in the evening and the first train in the morning by train replacing buses. The day closure refers to a closure during a weekday for the duration of one shift, i.e. 8 hours. For the weekend closure, it is assumed that it is applied after finishing the operation on Friday and ending before the operation starts again on Monday morning resulting in a total time of 52 hours. The 24h closure refers to the closure for an entire day during the week, when the work is executed in multiple shifts. Unlike all other time windows, the 24h closure is not restricted in length.

Table 25. Time windows

Time window	Start time	End time	Duration [h]
Night break	01:00	05:00	4
Night closure	22:00	06:00	8
Day closure	Sometime during the day		8
Weekend closure	Sa 01:00	Mo 05:00	52
24h closure	00:00	24:00	Inf.

3.6.5.3 Traffic volume

Table 26 shows the passenger volume on all sections that can be closed and where buses can replace its train service. The table shows the passenger volume for weekdays, Saturdays and Sundays in passengers per day. The passengers per night shown in Table 26 refer to the passengers traveling between 22:00 and 6:00. Considering analyses of the Federal Statistical Office, 4% of the average daily traffic is within the time period 22:00 and 6:00 (BFS, 2012).

Table 26. Passenger volume

Closures	Mo – Fr [P/day]	Sa [P/day]	So [P/day]	Night [P/night][1]
A – J	8’338	4’921	3’743	334
A – C	7’004	2’774	2’164	280
C – J	5’026	3’609	2’720	201
E – J	4’318	3’101	2’337	173
F – J	3’268	2’347	1’769	131
G – J	2’288	1’643	1’238	92
Main track in C	8’338	4’921	3’743	334
Main track in G	3’268	2’347	1’769	131

[1] Night passengers refer to passengers between 22:00 and 6:00.

3.6.5.4 Value of time

Time spent traveling between to places can be monetarised using the value of time, which differs dependant on the mode used, e.g. car or public transportation, and the purpose of traveling, e.g. work or leisure. According to Swiss standards, the value of time for traveling with public transportation in Switzerland is 14.43 CHF/h (VSS, 2009c).

3.6.5.5 Traffic states

All traffic states can be defined considering the possible closures (section 3.6.5.1) and time windows (section 3.6.5.2), and their effect per hour can be estimated using EQ 35 considering the passenger volumes (section 3.6.5.3) and the value of time (section 3.6.5.4). Table 27 shows all possible traffic states with their effects.

Table 27. Cost for traffic states in CHF/h

Closures	Night break	Night closure	Day closure	Weekend closure	24h closure
A – J	0	130	1’303	521	1’086
A – C	0	84	842	228	702
C – J	0	36	363	176	302
E – J	0	16	156	75	130
F – J	0	12	118	57	98
G – J	0	8	83	40	69
Main track in C	0	50	501	200	418
Main track in G	0	20	196	95	164

For example, the day closure on $A - J$ has an effect of 1’303 CHF/h, which is the multiplication of the passenger volume of 8’338 passenger/day divided by the operation hours of 20 hours/day, the additional travel time per passenger on this closure of 13 min/passenger, and the value of 14.43 CHF/h (EQ. 36).

$$C_{A-J}^{day} = \frac{8'338 \, {}^{P}/_{day}}{20 \, {}^{h}/_{day}} \cdot \frac{13 \, {}^{min}/_{P}}{60 \, {}^{min}/_{h}} \cdot 14.43 \, {}^{CHF}/_{h} = 1'303 \, {}^{CHF}/_{h} \tag{36}$$

3.6.6 Estimation of risks

Risks are considered to be the expected costs due to the occurrence of an unplanned inacceptable level of service, as outlined in Papathanasiou et al. (2018). For example, a switch failure leading to a partial shutdown of the operation until the failure is fixed. The risks, therefore, include the costs incurred by the infrastructure manager, i.e. those related to the execution of the corrective intervention, and the costs incurred by the user, e.g. longer travel time. In general, the risks are the product of the probability of having an inacceptable level of service and the consequences related to it (EQ. 37). The following subsections discuss the estimation of the probabilities (3.6.6.1) and consequences (3.6.6.2).

$$R = P_f \cdot C_f \qquad 37$$

3.6.6.1 Estimation of the probabilities of inacceptable levels of service

Defining the probabilities of failure for each object in each object category over the different condition states is difficult to do without historical failure data. As a consequence, reliability literature is used to assume probabilities related to the condition states defined in section 3.6.3.1. Many different methods can be used to identify the target reliability index for objects (Mahboob & Zio, 2018; SMARTRAIL, 2014). Target values of reliability indexes are references to the minimal reliability a structure should have dependent on the magnitude of consequences. It is questionable how well they can be used to estimate failure probabilities for existing objects. It is, however, a good reference as long as there is no more detailed failure data available.

The probabilities of failure were estimated using reliability indexes from literature (Mahboob & Zio, 2018; Sykora et al., 2017), and they were assumed to increase exponentially as a function of condition state (EQ. 38), which is an often used simplification, (Fendrich & Fengler, 2013). More sophisticated models could be used if desired. The probabilities of failure used in this example are shown in Table 28.

$$p_{CS} = p_1 \cdot e^{b \cdot (CS-1)} \qquad 38$$

Table 28. Probabilities of failure per condition state and object category

Object category	**Probability of failure $P_{f,cs}$**				
	CS 1	CS 2	CS 3	CS 4	CS 5
Track	$1.0 \cdot 10^{-3}$	$2.5 \cdot 10^{-3}$	$6.3 \cdot 10^{-3}$	$1.6 \cdot 10^{-2}$	$8.0 \cdot 10^{-2}$
Switch	$8.0 \cdot 10^{-3}$	$1.4 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$	$4.5 \cdot 10^{-2}$	$1.6 \cdot 10^{-1}$
Bridge	$4.0 \cdot 10^{-5}$	$1.2 \cdot 10^{-4}$	$3.4 \cdot 10^{-4}$	$1.0 \cdot 10^{-3}$	$6.0 \cdot 10^{-3}$

3.6.6.2 Estimation of the consequences of an inacceptable level of service

The consequences of a failure consist of three elements, 1) the corrective intervention cost $C_{f,CI}$, 2) the traffic disturbance cost $C_{f,tt}$, and 3) the accident costs $C_{f,A}$ (EQ. 39).

$$C_f = C_{f,CI} + C_{f,tt} + C_{f,A} \qquad 39$$

For the cost of the corrective intervention $C_{f,CI}$ that is required after a failure, it is assumed that a failed object is renewed to a like new state. Compared with a preventive planned renewal, the cost of a corrective intervention is assumed to be higher by 10 % (EQ. 40). Table 29 provides the overview of the considered corrective interventions.

$$C_{f,CI} = C_{Renewal} \cdot 1.1 \quad (40)$$

Table 29. Corrective interventions

Category	Intervention	Unit	Unit cost [CHF/unit]	Track possession [h/unit]	Reaction time [h]
Track	Corrective intervention	m	2'780	0.1	4
Switches	Corrective intervention	Object	280'500	8	2
Bridge	Corrective intervention	m^2	4'400	0.5	24

A failure leads to disturbances in the train traffic and, therefore, to user costs due to additional travel times $C_{f,tt}$ which is the multiplication of the traffic disturbance duration and the user cost per time unit related to the resulting traffic state in case of a failure C_k (EQ. 41). The additional travel time occurs between the points in time when the failure occurs until when the infrastructure is back in service after executing a corrective intervention. The productivity of the corrective intervention is assumed to be equal to that of the preventive renewal intervention, while additional 4, 2, and 24 hours are assumed for the reaction time between a failure occurs and the start of the corrective intervention for track, switches, and bridges (Table 29).

$$C_{f,tt} = (d_{reaction} + d_{CI}) \cdot C_k \quad (41)$$

The accident costs $C_{f,A}$ consider all costs related to an accident (EQ. 42). They consist of 1) the property damage in case of a failure, 2) injury costs in case of a failure considering the number of passengers per train and the probability of a passenger getting injured in case of an accident, and 3) fatality costs in case of a failure considering the number of passengers per train and the probability of a passenger getting killed in case of an accident.

$$C_{f,A} = p_{f,A} \cdot \left(C_{pd} + \left(p_{inj} \cdot c_{inf} + p_{fat} \cdot c_{fat}\right) \cdot n_{passengers}\right) \quad (42)$$

Table 30 shows the probabilities used in the example. Regarding the probabilities for tracks and switches of having an accident in case of a failure $p_{f,A}$, of an injury per passenger in case of an accident p_{inj}, and of a fatality per passenger in case of an accident p_{fat} are estimated based on different accident data in Switzerland (BFS, 2019a, 2019b) and in the European Union (European Union Agency For Railways, 2017, 2019; EUROSTAT, 2018). The probabilities referring to bridges are assumed on best knowledge since almost no data about bridge failures exist. The cost for property damage C_{pd} is assumed to be 84'000 CHF per accident (Vasic, 2012), while the cost per injury c_{inf} and fatality c_{fat} are considered as 89'900 and 3'191'400 CHF (VSS, 2013).

Table 30. Probabilities related to accidents

Category	Probability of an accident in case of a failure $p_{f,A}$	Probability of injury per passenger in case of an accident p_{inj}	Probability of fatality per passenger in case of an accident p_{fat}
Track	0.0023	0.18	0.035
Switches	0.0002	0.18	0.035
Bridge	0.1	0.7	0.2

3.6.7 Model application

The optimal risk reducing intervention program is developed for the railway network described in section 3.6.1 for a 12-year planning period, divided into three 4-year periods. The 12-year consideration is the infrastructure managers medium term planning of the intervention program. The 4-year periods within this 12-year planning period correspond to the 4-year service agreement period between the infrastructure manager and the government. Two cases are considered, where one has an unlimited budget and the other a budget limitation of 4 million CHF per 4-year period. In both cases, the intervention program developed using the optimisation model is compared with a reference intervention program developed qualitatively. The intervention program developed quantitatively represents the process currently used in practise, where the interventions required are provided by managers on the object level and manually converted into intervention programs by program managers.

In order to identify the candidate interventions, intervention strategies have to be determined and the future objects condition have to be estimated. The strategies (Table 31) are derived from the definition of condition states in Table 21. Renewal intervention have to be executed when an object reaches State 5. Rail replacement is executed in state 4 to improve the track condition slightly in an earlier state. Additional to the interventions according to the strategy, all interventions have to be considered that are mandatory interventions due to structural dependencies with other interventions. The candidate interventions for the intervention program are identified by predicting the objects future condition based on the current condition states of the objects and the assumed deterioration rates in Table 22, and face them against the defined strategy.

Table 31. Intervention strategies

Category	State 1	State 2	State 3	State 4	State 5
Track	-	-	-	Rail replacement	Track renewal
Switches	-	-	-	-	Switch renewal
Bridge	-	-	-	-	Bridge renewal

The network flow model presented in section 3.5.3 and the optimisation model presented in section 3.5.4 is used to develop the optimal intervention program for the network described in section 3.6.1. The problem and model characteristics are given in Table 32. The problem situation with 128 objects, 145 possible traffic states and three 4-year periods is modelled with a network model with 2’173 nodes and 10’385 edges, which leads to a mixed integer linear program with 10’385 decision variables and 6’441 constraints. The problem formulated as a mixed integer linear program is solved using branch-and-bound with the simplex algorithm to solve the linear sub problems.

Table 32. Model characteristics

Item	Characteristics	Quantity
Problem situation	Objects	128
	Traffic states	145
	Possible interventions	129
	4-year periods	3
Network model	Total nodes	2’173
	Intervention nodes	616
	Group nodes	1’407
	Traffic state nodes	150
	Total edges	10’385
	Intervention level E^{IL}	1’476
	Network level E^{NL}	3’879
	Topological dependency E^{TD}	5’030
Mixed integer linear program	Decision variables	10’385
	Total constraints	6’441
	Object level flow conservation	617
	Network level flow conservation	2’023
	Topological constraints	2’262
	Exclusivity constraints	126
	Budget constraint	3
	Structural constraints	3
	Non-negativity constraint	1’407

3.6.8 Optimal risk reducing intervention program unlimited budget case

3.6.8.1 Results

The optimal risk reducing intervention program developed using the optimisation model is shown in Figure 20, while the intervention program developed qualitatively is shown in Figure 21. The figures highlight all selected interventions, where the colour represents the group of interventions in which they are executed. For example, all interventions in violet in Figure 20 are executed during a weekend closure between station I and J in period 2019-2020. Further information about the groups of interventions can be seen in appendix 6.1. The costs for both programs are shown in Table 33. The optimal intervention program for the unlimited budget case was determined within 1.4 seconds using the optimisation model on an Intel® Core™ i7-8650U powered windows laptop computer with 1.90GHz.

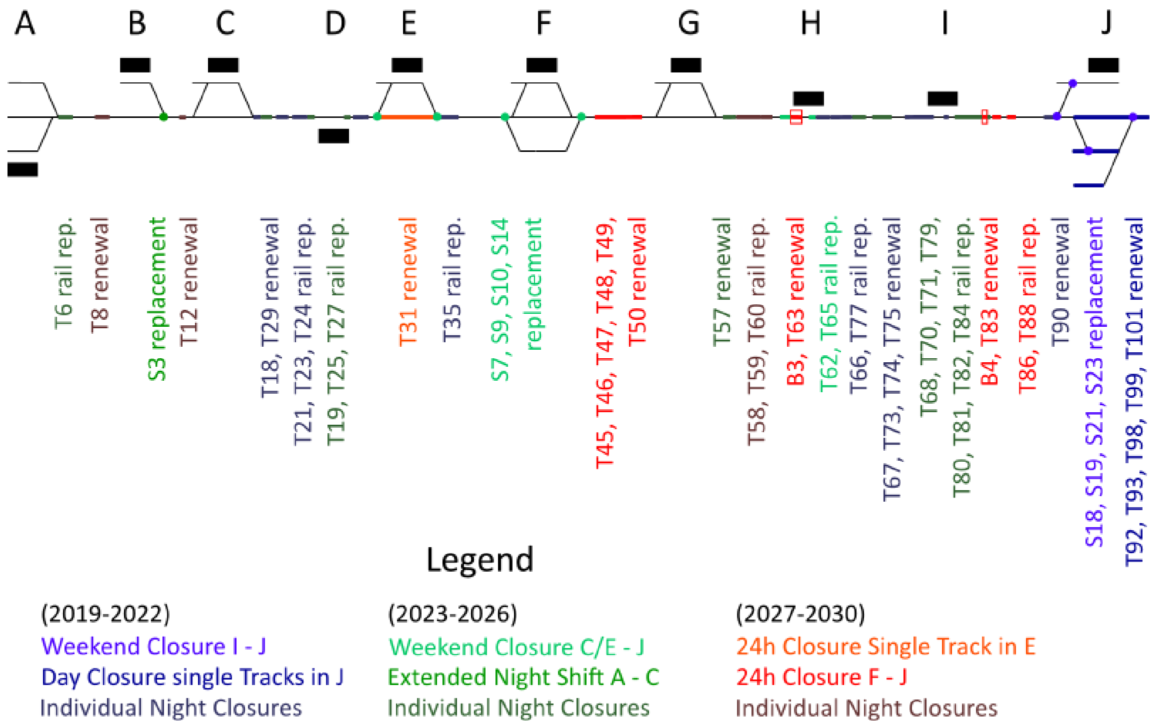

Figure 20. Intervention program developed using the optimisation model in the unlimited budget case

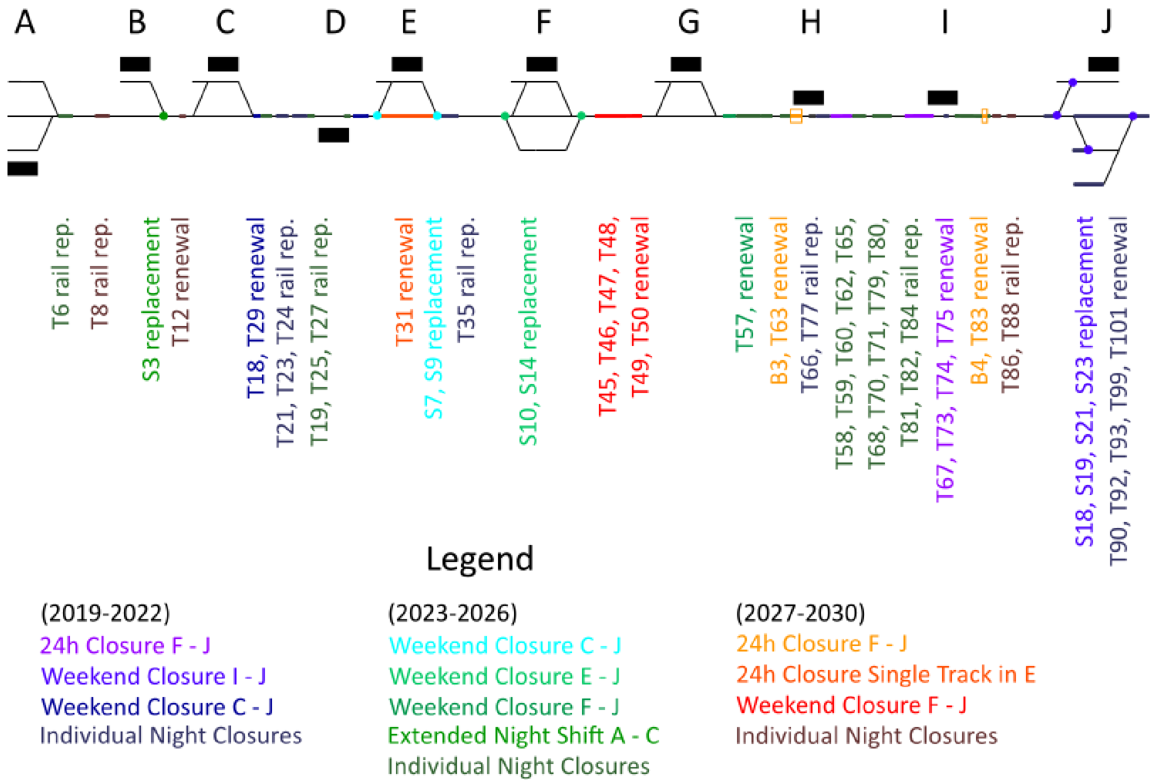

Figure 21. Intervention program developed qualitatively in the unlimited budget case

Table 33. Cost in CHF of the intervention programs in the unlimited budget case

Intervention program	Cost category	Period 2019-2022	Period 2023-2026	Period 2027-2030	Total	Percentage of optimum
Developed using the model	Intervention costs	7'024'890	2'351'870	5'850'820	15'227'580	100%
	Additional travel time cost	320	2'680	45'002	48'002	100%
	Total costs	7'025'210	2'354'550	5'895'822	15'275'582	100%
	Risk reduction	9'935'253	5'930'409	1'387'398	17'253'060	100%
	Future cost reduction	3'702'822	305'419	5'568'138	9'576'379	100%
	Benefit	13'638'074	6'235'828	6'955'536	26'829'438	100%
	Net benefit	6'612'864	3'881'278	1'059'714	11'553'857	100%
Developed qualitatively	Intervention costs	7'106'290	2'531'150	5'723'980	15'361'420	101%
	Additional travel time cost	54'249	6'244	56'027	116'520	243%
	Total costs	7'160'539	2'537'394	5'780'007	15'477'940	101%
	Risk reduction	9'935'253	6'661'941	850'833	17'448'026	101%
	Future cost reduction	3'702'822	10'782	5'665'894	9'379'498	98%
	Benefit	13'638'074	6'672'722	6'516'727	26'827'524	100%
	Net benefit	6'477'536	4'135'328	736'720	11'349'583	98%

The intervention program developed using the optimisation model consists of three groups of interventions (Figure 20). In period 2019-2022, the switch replacements in station J are grouped within a weekend closure. In period 2023-2026, the switch replacements in stations E and F and the rail replacements on track segments *T62* and *T65* are executed in parallel during a weekend closure between C and J. In period 2027-2030, the renewal of track segments *T45* to *T50* and the rail replacements of *T86* and *T88* are grouped parallel to the execution of the bridge renewals of *B3* and *B4*. All other interventions are executed individually ether during regular night closure, i.e. the renewal of *T12*, *T57* and *T67*, during an extended night closure, i.e. the replacement of *S3*, or during day closures without a traffic disturbance, i.e. the renewal of *T31* and *T92*.

The intervention program reaches a net benefit of 11.6 million CHF, where the total cost of 15.3 million CHF face the total benefit of 26.8 million CHF (Table 33). The total cost consists of 15.2 million CHF of intervention cost and 48 thousand CHF of additional travel time cost. The benefit consists of 17.3 million CHF due to the risk reduction and 9.6 million CHF due to the reduction of costs related to future preventive interventions.

The intervention program developed qualitatively focuses on grouping interventions within object categories and within sections of the network (Figure 21). For example, switch replacements are grouped together within stations, i.e. station E, F and J. The two bridge renewals on *B3* and *B4* are executed in parallel during a closure of F – J.

The intervention program developed qualitatively reaches a net benefit of 11.3 million CHF, which equals 98% of the net benefit achieved by the intervention program developed using the optimisation model (Table 33). The total cost of 15.5 million CHF consists of 15.4 million CHF of intervention cost and 117 thousand CHF of additional travel time cost. The total benefit of 26.8 million CHF is the sum of 17.4 million CHF due to the risk reduction and 9.4 million CHF due to the reduction of costs related to future interventions.

3.6.8.2 Discussion

Table 33 shows that the additional travel time cost in the case study situation are significant lower than the intervention cost and the benefit. The reason for the large difference between intervention costs and additional travel time costs are the rather high intervention costs on this particular line due to the difficult topography, and the relative low traffic on the line. The ratio between intervention cost and additional travel time would be more balanced in other situations, i.e. an urban main line with higher traffic volume.

The intervention program developed using the optimisation model (Figure 20) shows the models capability to consider the cost reduction due to the grouping of interventions. For example, the intervention costs of tracks *T45* to *T50* can be reduced by grouping the renewals of these interventions. The additional travel time costs are reduced by executing the renewal on bridge *B3* in parallel to the renewal on bridge *B4* and tracks *T45* to *T50*. The renewal of bridge *B3* requires a closure of F – J for 440 hours during which time the other interventions can be executed without any additional travel time costs.

Comparing the intervention program developed qualitatively with the intervention program developed using the optimisation model indicates, that the qualitative approach can lead to an intervention program that is close to the optimal intervention program. The qualitative approach, however, lacks in the capability to consider all possible combinations and lacks in the comparability of different possibilities. This are the reasons for the deviation from the optimal intervention program. In respect with the two intervention programs developed here, it can be seen that the optimisation model enables to consider and compare the execution of interventions in different periods. For example, the rail replacements on track segments *T58*, *T59* and *T60* are proposed to be executed in period 2023-2026 based on the condition of the obejct. Without a proper quantification of the impacts of an intervention program, which is missing in the qualitative approach, the 1'915 CHF higher benefit of the three interventions together when executed in period 2027-2030 is not detected and considered. The optimisation model is able to consider this slightly higher net benefit and enables to develop intervention program with higher net benefits.

3.6.9 Optimal risk reducing intervention program limited budget case

3.6.9.1 Results

The budget limitation used in this case, i.e. 4 million CHF per 4-year period, requires that some of the interventions optimally executed in the first period are postponed to later period as their total intervention costs of 7 million CHF exceed the 4 million CHF limitation. Further it requires that some of the interventions selected in the unlimited case are omitted with the budget limitation because the total intervention costs over all three periods in the unlimited case, i.e. 15 million CHF (Table 33), exceed the combined budget limitation of 12 million CHF ($3 \cdot 4$ million CHF).

The optimal risk reducing intervention programs in the case of a budget limitation are shown in Figure 22 and Figure 23 for the intervention program developed using the optimisation model and developed qualitative. As for the unlimited case, the interventions selected for execution are highlighted according to the group in which they are executed. Further information about the groups of interventions can be seen in appendix 6.2. All interventions that are moved from one 4-year period into another 4-year period when compared with the unlimited case are framed in a box. For example, the renewal of track *T29* is executed in period

2023-2026 while it has been allocated to the earlier period 2019-2022 in the unlimited case. Table 34 provides the costs of the intervention programs including the percentage of the total values compared to the intervention program developed using the optimisation model in the unlimited situation (Table 33). The optimal intervention program was determined within 1'414 seconds using the optimisation model.

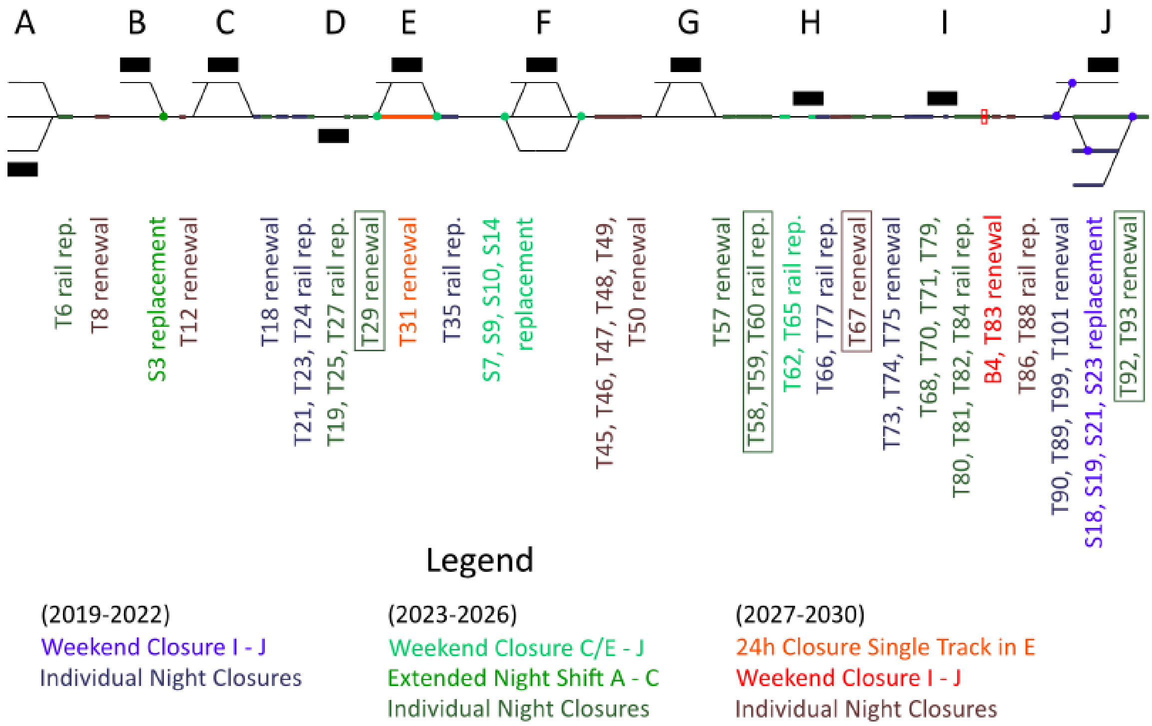

Figure 22. Intervention program developed using the optimisation model in the limited budget case

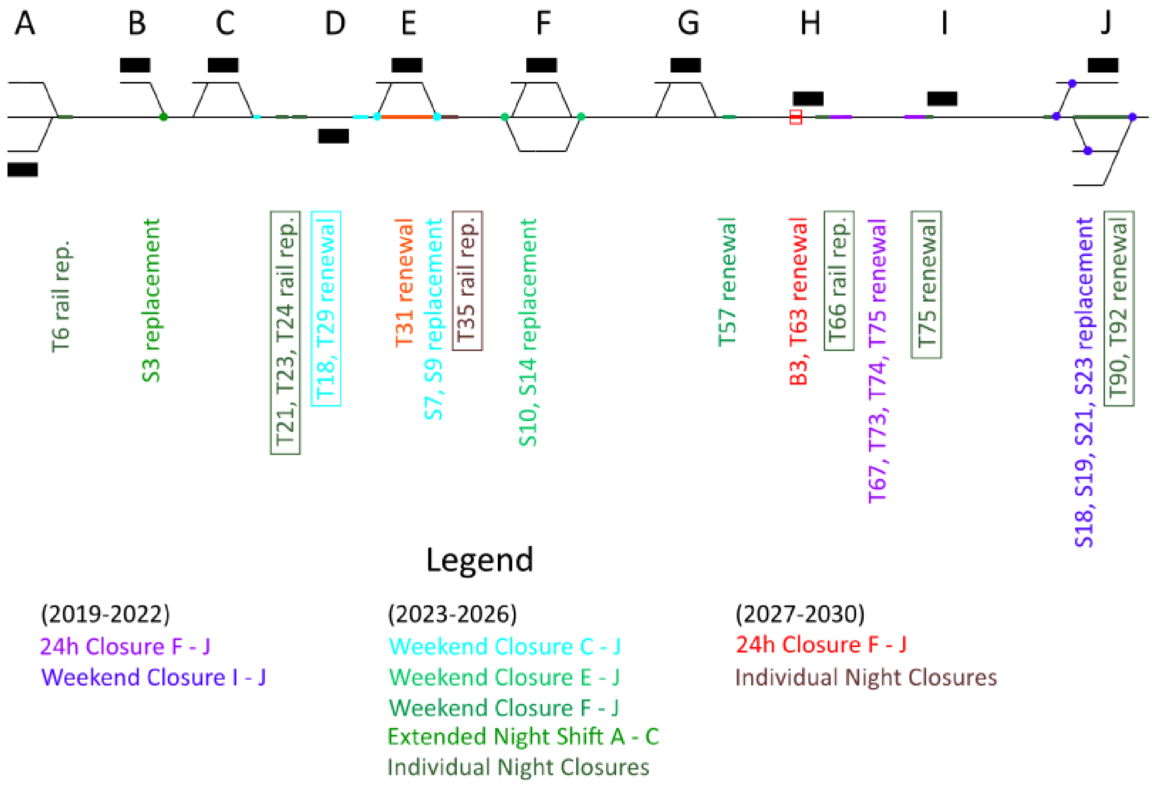

Figure 23. Intervention program developed qualitatively in the limited budget case

Table 34. Cost in CHF of the intervention programs in the limited budget case

Intervention program	Cost category	Period 2019-2022	Period 2023-2026	Period 2027-2030	Total	Percentage of optimum
Developed using the model	Intervention costs	3983050	3937520	3357580	11'278'150	74%
	Additional travel time cost	320	2'680	624	3'624	8%
	Total costs	3'983'370	3'940'200	3'358'204	11'281'774	74%
	Risk reduction	7'135'436	7'810'574	1'206'763	16'152'772	94%
	Future cost reduction	1'693'848	1'150'968	2'928'472	5'773'288	60%
	Benefit	8'829'284	8'961'541	4'135'235	21'926'060	82%
	Net benefit	4'845'914	5'021'341	777'031	10'644'286	92%
Developed qualitatively	Intervention costs	4'001'010	3'993'350	4'000'750	11'995'110	79%
	Additional travel time cost	41'754	15'394	45'002	102'150	213%
	Total costs	4'042'764	4'008'744	4'045'752	12'097'260	79%
	Risk reduction	4'433'123	4'812'248	377'504	9'622'874	56%
	Future cost reduction	2'682'011	2'473'331	4'066'917	9'222'260	96%
	Benefit	7'115'134	7'285'579	4'444'421	18'845'134	70%
	Net benefit	3'072'369	3'276'835	398'669	6'747'873	58%

The intervention program developed using the optimisation model consists of all interventions included in the intervention program developed using the optimisation model in the unlimited situation (Figure 20) except the renewal of bridge *B3* and its related track *T63*. The omission of the renewal on bridge *B3* vanishes the benefit of grouping interventions in the period 2027-2030. The remaining interventions are either executed during regular night breaks, i.e. on track *T45* to *T50*, or over individual weekend closures, i.e. bridge *B4* together with *T83*. In order to reduce the intervention costs in the first period below the limited 4 million CHF, the interventions on tracks *T29*, *T58*, *T59*, *T60*, *T92* and *T93* are postponed to the period 2023-2026 and the renewal on track *T67* is postponed to the third period. With this, the intervention costs sum up at 11.3 million CHF, which equals the total costs due to the marginal additional travel time costs, i.e. 3.6 thousand CHF (Table 34). The benefit achieved equals 21.9 million CHF consisting of 16.1 million CHF of risk reduction and 5.8 million CHF of future cost reduction. Overall, this leads to a net benefit of 10.6 million CHF, which is 94% of the optimal net benefit.

The intervention program developed qualitatively consists of much less interventions due to the inclusion of the track renewal on *T67* and *T73* in period 2019-2022 and the renewal of bridge *B3* in period 2027-2030, which lead to intervention costs of close to 3 million CHF and 4 million for the two periods, respectively. The inclusion of these larger interventions requires to postpone interventions from the period 2019-2022 to period 2023-2026, i.e. *T18*, *T21* and *T23,* and to omit many of the smaller interventions, i.e. *T8*, *T12* and *T84*. Due to the fewer interventions that are possible to be executed under the budget limitation, the possibility of grouping interventions is reduced. The focus of grouping interventions lays in grouping switch interventions within stations, i.e. station E, F and J.The total costs of the intervention program equal 12.1 million CHF consisting of 12.0 million CHF of intervention costs and 102 thousand CHF of additional travel time costs (Table 34). The benefit reaches 18.8 million CHF consisting of 9.6 million of risk reduction and 9.2 million of future cost reduction. Overall, this equals in a net benefit of 6.7 million CHF, which is 58% of the optimal net benefit.

3.6.9.2 Discussion

The intervention program developed using the optimisation model shows the advantage of considering multiple periods within a planning period, as this enables to better consider the different characteristics of railway infrastructure objects. Switches tend to deteriorate faster than tracks and bridges requiring more frequent interventions. The results show that all postponed interventions are either track or bridge interventions as their slower deterioration allows to postpone interventions by four year with less impact, i.e. risk, than a postponement of a switch intervention would imply.

The results in the limited budget case show clearly the difficulty to develop optimal intervention program quantitatively in case of further constraints, i.e. a budget limitation. The net benefit of the intervention program developed qualitatively (6.7 million CHF) reaches 63% of the net benefit of the intervention program developed using the optimisation model (10.6 million CHF) considering the budget limitation. The qualitative approach considered criteria such as the extent of the intervention or the importance of the object in the network, e.g. a large bridge is considered to be more important than a small overpass. The optimisation model uses a structured and comparable quantification, i.e. costs and benefits. The qualitative approach results in a significant less optimal intervention program than the quantitative approach using the optimisation model. For example, the intervention program developed qualitatively includes the renewal on bridge *B3* because bridge *B3* with its length of 180m is the most prominent object in the network, and its condition requires a renewal intervention according to the strategy. The optimisation model considers all possible combinations of interventions and quantifies the costs and benefits of the entire intervention program. Thereby, it is identified that it is more worthwhile to execute multiple smaller interventions instead of the more costly bridge renewal. Additional, the renewal of the bridge would require to include the renewal of the associated track T63 too, which reduces the net benefit of the intervention on the bridge *B3*. The intervention costs of these two interventions together are just below 4 Mio CHF removing the possibility to execute more interventions in the same period. Considering the benefit of both interventions, a net benefit of 240 thousand CHF could be achieved for the period 2027-2030, which is significant lower than the net benefit achieved by selecting multiple smaller interventions, i.e. 780 thousand CHF (Table 34).

Further, the difficulty to select the optimal combination of interventions for an intervention program developed using a qualitative approach can also be seen in the two periods 2019-2022 and 2023-2026. There, the difference in the net benefit of the two intervention programs developed qualitatively and using the optimisation model are more significant, i.e. 1.7 million CHF for both periods. The focus on selecting interventions on objects with larger extent or objects that are further deteriorated than others limit the possibility to consider combinations of interventions that significantly increase the net benefit. The intervention program developed using the optimisation model omits the renewal of track *T67*, which is one of these longer track segments with further deteriorated condition. This enables to include interventions on 12 other objects, which reduce 2.7 million CHF more in risk while only allowing 1 million CHF more in costs related to future preventive interventions compared to when *T67* and *T73* are renewed.

In the considered case study, the intervention program developed qualitatively tends toward a higher reduction in costs related to future preventive interventions and a lower reduction in risk than the intervention program developed using the optimisation model.

3.7 Accuracy of input data

As seen in the former section, a mathematical optimisation model to develop optimal risk reducing intervention programs requires a significant amount of data about the infrastructure and railway network. Infrastructure managers, however, do often not have all required data available or only simple estimations with low accuracy tied to them. In order that infrastructure managers know on which data they should concentrate to make it available or to increase their accuracy, they need a methodology to estimate the required accuracy of their input information. Such a methodology is presented in this section and illustrated for the railway infrastructure of the example in section 3.6.

3.7.1 Methodology to estimate the required information accuracy

3.7.1.1 Ranges of values of input variables

The required accuracy of the values of the input variables depends on the effect of these values on the composition of the intervention program and the net-benefit obtained from the intervention program. The required accuracy will vary from situation to situation and infrastructure manager to infrastructure manager. In order to estimate the required accuracy, three ranges of the values have to be considered, namely

- the range over which the optimal intervention program does not change, i.e. how far can the value of a single variable be changed before the optimal intervention program changes,
- the range over which the optimal intervention program can still be considered similar, using an agreed upon value of similarity coefficients (3.7.1.2), and
- the range over which the net-benefit obtained from the intervention program can still be considered near optimal, using an agreed upon value of the optimality coefficient (3.7.1.3).

3.7.1.2 Similarity of intervention programs

The similarity between two intervention programs can be quantified using a similarity coefficient based on the Jaccard coefficient, which defines the similarity as the intersection over the union of two sets (Jaccard, 1912). The similarity $J(IP_x, IP_{x'})$ is estimated by dividing the sum of the number of interventions selected in both intervention programs by the sum of all interventions selected in either of the two intervention programs (EQ. 43).

$$J(IP_x, IP_{x'}) = \frac{\sum_{i=1}^{I} \delta_i \cdot \delta_i'}{\sum_{i=1}^{I} \left(1 - (1 - \delta_i) \cdot (1 - \delta_i')\right)} \quad (43)$$

Where

I is the set of all interventions.

δ_i is a binary variable that is 1 if intervention $i \in I$ is selected in intervention program IP_x.

δ_i' is a binary variable that is 1 if intervention $i \in I$ is selected in intervention program $IP_{x'}$.

IP_x is the reference intervention program determined using the default value x.

$IP_{x'}$ is the optimal intervention program determined using the varied value x'.

Using this similarity coefficient, the similarity of two intervention programs is expressed by a number between 0 and 1, where 0 means that the two intervention programs have no common interventions and 1 means that both intervention program consists of the exact same interventions.

3.7.1.3 Optimality of an intervention program

In order to determine whether an intervention program obtains an optimal or near optimal net benefit, it is important to consider the correct difference between the net benefits obtained. Figure 24 shows the effect of a variation of an input variable on the net benefit obtained, where x refers to the assumed default value of a variable and x' to the actual value of the variable, e.g. the varied value. The net benefit obtained by the optimal intervention programs are shown in red and the net benefit obtained by the reference intervention program, i.e. the one determined optimal with value x, in blue. Both, the difference between the net benefits obtained by the optimal intervention programs, i.e. between the red columns, and the difference between the net benefit obtained by the reference intervention program, i.e. between the blue columns, are useful considerations when analysing the sensitivity of the maximal net benefit possible or the net benefit of an intervention program. They, however, do not properly state how optimal a decision taken with the default value x is when the actual value varies, i.e. x'.

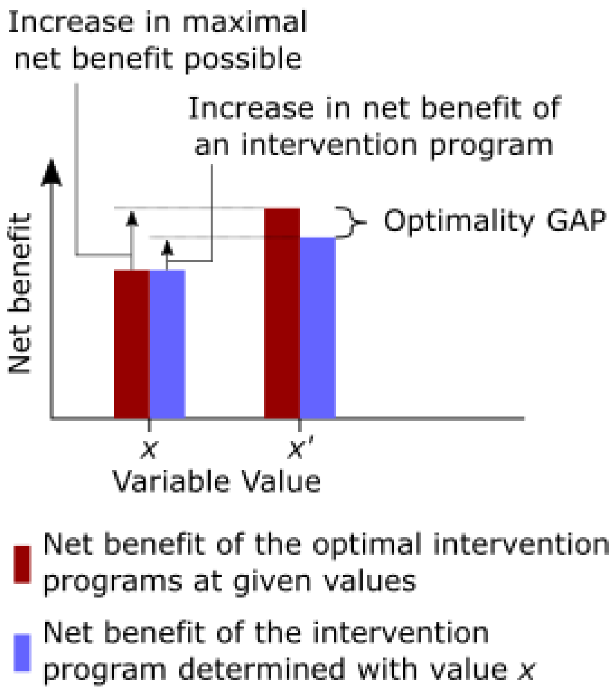

Figure 24. The effect of a variation of an input variable on the net benefit obtained

The optimality of an intervention program can be defined as the division of the net benefit obtained by the reference intervention program through the net benefit obtained by the optimal intervention program given a variation of the input variable x'. In Figure 24, this refers to the one minus the optimality gap, which is the difference between the red and blue column at value x'. EQ. 44 shows the formulation of the optimality coefficient. There, IP_x represents the reference intervention programs that is optimal with the variable values x. $IP_{x'}$ represents the intervention programs that is optimal with the variable values x'. The optimality of IP_x when the value of the variable is x', i.e. $O(IP_x, value = x')$, is the division of the net benefits obtained by IP_x and $IP_{x'}$ estimated using value x', i.e. $NB(IP_x, value = x')$ and $NB(IP_{x'}, value = x')$.

$$O(IP_x, value = x') = \frac{NB(IP_x, value = x')}{NB(IP_{x'}, value = x')} \quad 44$$

Using this optimality coefficient, the optimality of an intervention program given a value of a variable is expressed by a value smaller or equal to 1. 1 means that the net benefit of the reference intervention program is equal to the optimal net benefit. A value between 0 and 1, e.g. 0.5, means that the reference intervention programs reaches a percentage of the optimal net benefit, e.g. 50%. A value of 0 means that the reference intervention program has a net benefit of 0.

3.7.1.4 Identification of ranges

In order to determine the ranges of values of each input variables, they are varied *one-at-a-time* (Saltelli et al., 2000). For each variation, 1) the similarity of the optimal intervention program and the reference intervention program, i.e. the one that is optimal without a variation in the input variables, is measured, and 2) the optimality of the reference intervention program is estimated considering the variation of the value of the input variable. The values of all variables are varied until the defined thresholds are reached for the three ranges defined in section 3.7.1.1. Regarding the first range, the optimal intervention program is unchanged when both, the similarity and optimality coefficient are equal to one. This methodology differs from other similar types of analyses, such as the determination of which uncertainties to quantify (Papathanasiou & Adey, 2020), or the effect of variations in the values of input variables (Lautala & Pouryousef, 2011; Sharma et al., 2018), as the focus of this work is on the methodology to estimate the required accuracy of input information.

3.7.2 Estimation of the required accuracy of input variables for the example railway network

The estimation of the required accuracy of input variables is illustrated for the example railway network in section 3.6, where the algorithm to determine optimal intervention programs developed in section 3.5 is applied. Figure 25 shows the input variables required by the optimisation model to quantify the net benefit of an intervention program. Variables in green refer thereby to intervention related information, variables in blue to traffic related information, variables in orange to object related information, variables in red to risk related information, and the variable in violet to analysis parameters. The values defined in the example in section 3.6 are considered as default values, and the optimal intervention program determined by them is called the reference intervention program.

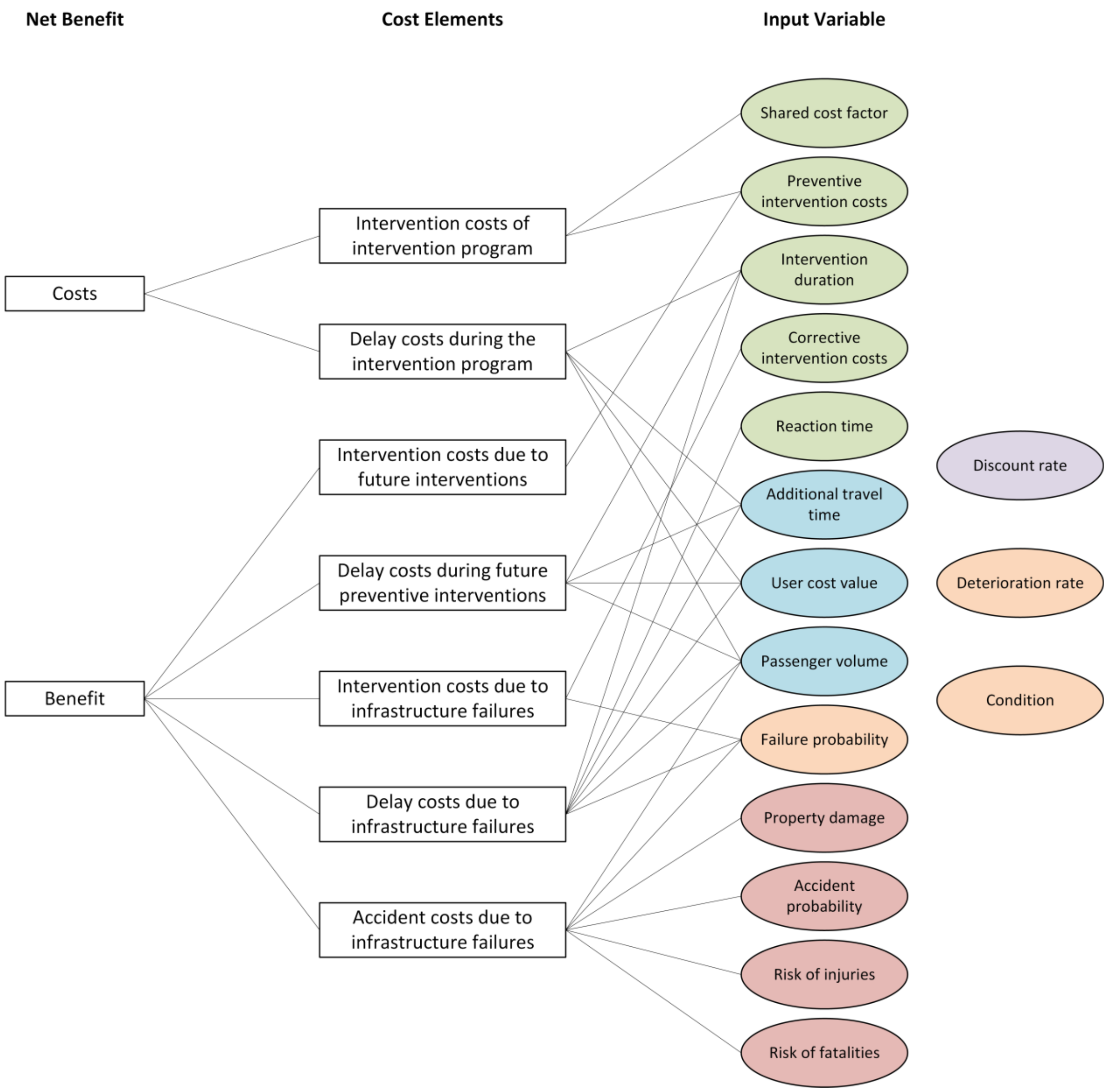

Figure 25. Input data to estimate the cost and benefit of an intervention program

3.7.2.1 Definition of thresholds

In this example, all three ranges defined in section 3.7.1.1 are used to estimate the required accuracy of the input variables. The range over which the optimal intervention program does not change is defined by the range over which both, the similarity and optimality coefficient, are equal to 1. The range over which the optimal intervention program can still be considered similar is defined with a threshold on the similarity coefficient of 0.95, i.e. $J(IP_x, IP_{x'}) \geq 0.95$. This means that an optimal intervention program is still considered to be similar when at least 95% of the interventions are equal to the reference intervention program. Considering the 60 interventions selected in the optimal intervention program determined in section 3.6.8, a similarity of 0.95 refers to the identical selection of 57 interventions and the change in at least 3 interventions, which is considered a justifiable assumption for the similarity. The range over which the reference intervention program is still considered to be near optimal is defined with a threshold on the optimality coefficient of 0.98, i.e. $O(IP_x, value = x') \geq 0.98$. This means that the reference intervention program is still be considered optimal when it obtains a net benefit of at least 98% of the optimal net benefit with a given variation of a variable. This threshold is in the similar range as the accuracy obtained when the optimisation model is applied on large railway networks using a genetic algorithm (Burkhalter & Adey, 2019).

3.7.2.2 Ranges of values of input variables

Figure 26 to Figure 30 show the three ranges, named 1) *unchanged* (green line), 2) *similarity* (orange line) and 3) *optimality* (violet line), for each input variable. They are determined by changing one variable at the time until it reaches the thresholds defined. The figures show the ranges in percentage variations (x-axis) of the variable from the default value, which is highlighted at variation 0. This is favourable especially for the variables that take different values for different categories. For example, the intervention costs are different for each intervention on each type of object. The use of percentage variation enables to show the ranges for the intervention costs of all interventions together. The figures cut some of the ranges in favour of readability. There, the ranges are provided by the value assigned to the graphs.

Figure 26 shows the ranges for the intervention related variables, i.e. the intervention costs, the shared cost factor, the intervention durations, the costs of corrective interventions and the reaction time for corrective interventions. The figure is to be read as follows. The range of the intervention costs over which the optimal intervention program is unchanged is between -21% and +130% of the intervention costs assumed in section 3.6.4. For example, this range in percentage results to a range of 1'857 CHF/m to 5'405 CHF/m for track renewal, which is assumed to cost 2'350 CHF/m. The optimal intervention program can be considered similar to the reference intervention program over the range of a -21% and + 134% variation of the intervention costs. The reference intervention program is near optimal, i.e. obtains a net benefit that is at least 98% of the optimal net benefit, over the range of -91% and +63'397% of the assumed value of the intervention costs, where the later refers to a 633 times higher value than the assumed one. The example of the intervention costs show that the ranges can differ significantly with the *optimality* range being much wider than the other two ranges. This means that the reference intervention program can still be seen as near optimal with higher variations in the value of the intervention costs, even though the optimal intervention programs are not similar.

The shared cost factor has the smallest ranges of the intervention related variables. All three ranges are within ∓60% with the *unchanged* range between -2% and +1%. The only other variable having a range in this scale is the intervention duration with an *unchanged* range of ∓0%. This means that any change in the intervention duration leads to changes in the optimal intervention program. The upper limit of all three ranges of the intervention duration lay at 0% because the reference intervention program becomes unfeasible with longer intervention durations due to intervention executions planned during time windows that are not long enough for the intervention to be executed. The lower bounds of the *similarity* and *optimality* range of the intervention duration as well as all ranges of the costs for corrective interventions and the reaction time in case of a failure are at -100%. This means that the intervention program determined with their value being 0 still lay within the defined thresholds

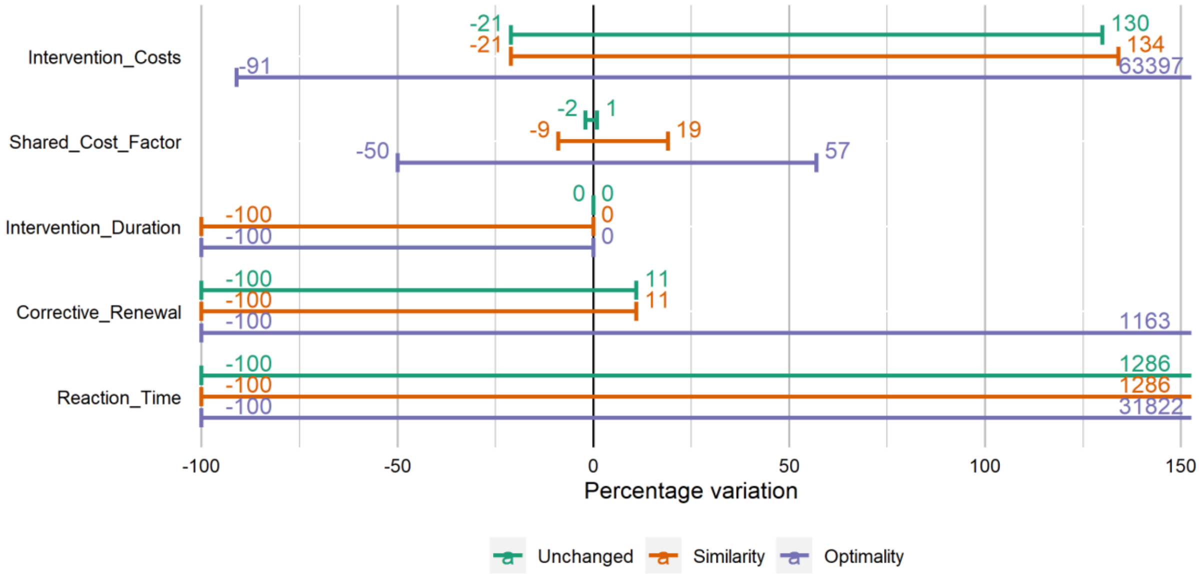

Figure 26. Ranges of intervention related variables

Figure 27 shows the ranges of the traffic related variables, i.e. the passenger volume, the additional travel time and the value of time. Variations in the passenger volume are within the defined threshold in the range of -56% and +31% for an unchanged and similar optimal intervention program, and in the range of -100% and +1'060% for the reference intervention program to be near optimal. The additional travel time and value of time allow for larger ranges, i.e. -100% to +222% for the *unchanged* and *similarity* range and -100% to -8'294% for the *optimality* range.

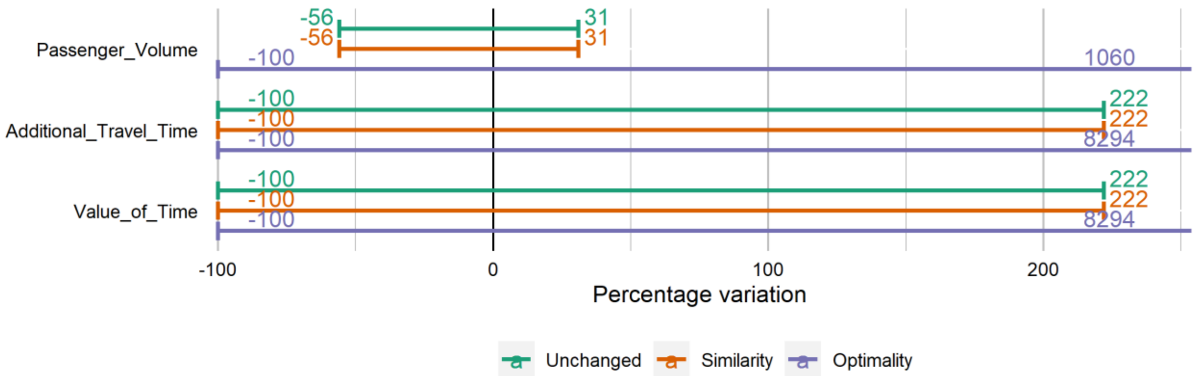

Figure 27. Ranges of traffic related variables

Figure 28 shows the ranges for the object related variables, i.e. the condition of the objects, the deterioration rate and the failure probability. Since the condition is measured in discrete states, the percentage variation refers to the percentage of overestimated (negative variation) and underestimated (positive variation) conditions of the objects. For example, +40% refers to the situation where the condition of 40% of the objects are underestimated, meaning that their actual condition state is higher than the assumed.

All ranges except the *optimality* of the failure probability are within ∓40%. The optimal intervention programs are unchanged and even similar for only small ranges of the condition and the deterioration rate, e.g. ∓0% and -1% to +2% for the *unchanged* ranges. The reference intervention program can still be considered near optimal when at most +6% and 2% of the condition are overestimated and underestimated, respectively. For variations in the deterioration rate, the reference intervention program stays near optimal within the range of -37% and +24%. The ranges for the failure probability show that the optimal intervention program significantly changes when the values are slightly higher than assumed in the example. The reference intervention program, though, remains near optimal until the value is 103% higher than assumed.

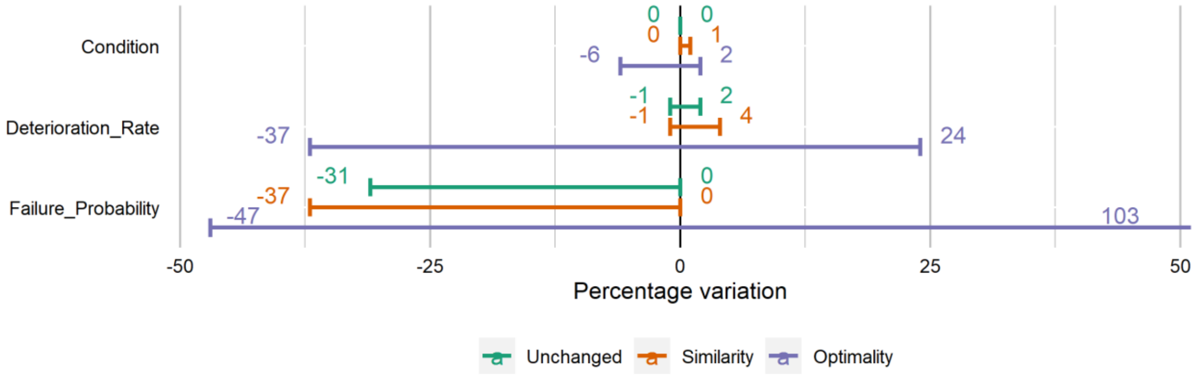

Figure 28. Ranges of object related variables

Figure 29 shows the ranges for the accident related input variables, i.e. the probabilities and costs related to accidents to occur. The accident related variables can be grouped into three groups. First, the accident probability, the fatality probability and the fatality costs all have similar ranges for the optimal intervention program to be unchanged and similar, i.e. roughly -60% to +36%, and for the reference intervention program to be near optimal, i.e. roughly -100% to +1'100%. Second, the injury probability and the injury costs have the identical ranges, i.e. -100% to +248% for the *unchanged* and *similarity* range and -100% to +9'501% for the *optimality* range. Third, the property damage has much higher ranges meaning that this variable can vary much more (in percentage) with being between the defined thresholds.

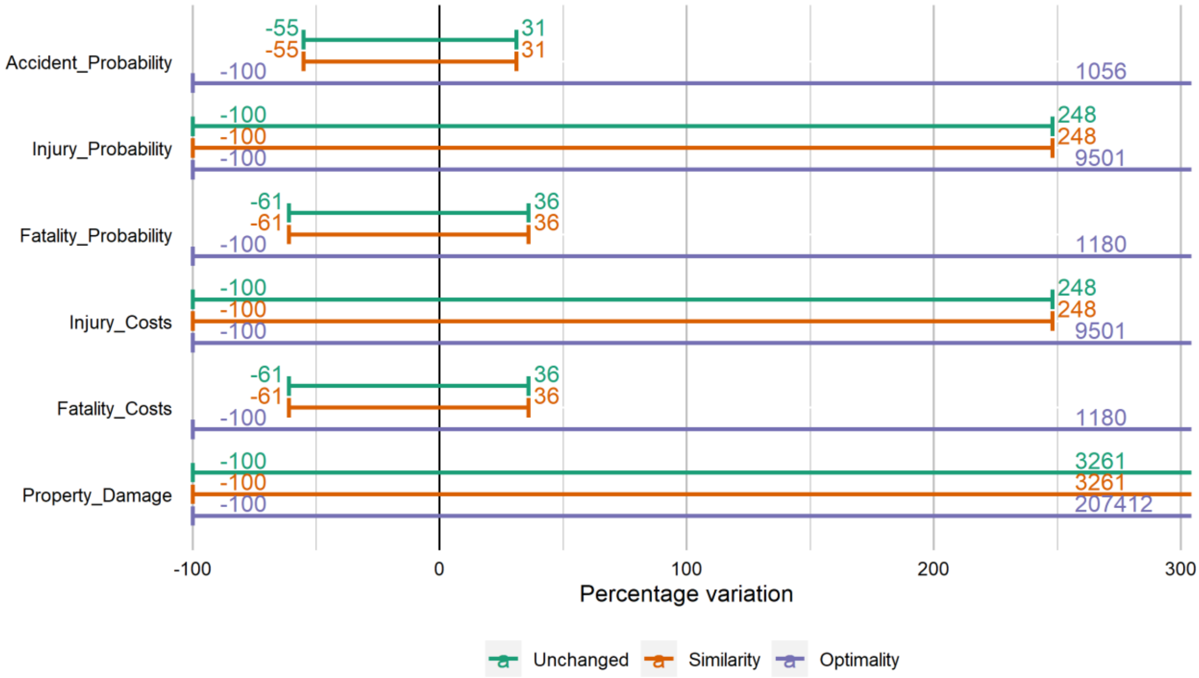

Figure 29. Ranges of accident related variables

Figure 30 shows the ranges over which variations in the discount rate lead to results that are within the defined thresholds. The optimal intervention program is unchanged over the range of -15% and +282%. The optimal intervention program is similar to the reference intervention program over the range of -15% and +325%. The reference intervention program is near optimal over the range of -100% and +1'330%

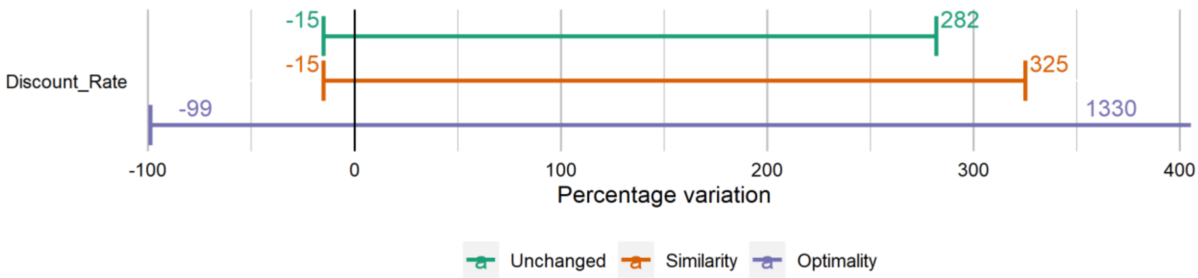

Figure 30. Influence of the analysis related deterioration rate

3.7.2.3 Discussion

Table 35 summarises the ranges for each input variable for the example railway network. The table clearly shows that the three considered ranges increase in their extent, where *unchanged* range < *similarity* range < *optimality* range. The *unchanged* range is by its definition the smallest range as it determines the range over which the optimal intervention program does not change. The difference in the extent of the *similarity* and *optimality* ranges is due to the situation considered and the thresholds defined, and will differ in other situations with other infrastructure networks and infrastructure managers.

Table 35. Ranges of input variables

Input variable	Range over which the optimal intervention program is unchanged		Range over which the similarity is larger than 0.95		Range over which the optimality is larger than 0.95	
	from	to	from	to	from	to
Condition	0%	0%	0%	+1%	-6%	+2%
Deterioration rate	-1%	+2%	-1%	+4%	-37%	+24%
Probability of failure	-31%	0%	-37%	0%	-47%	+103%
Intervention costs	-21%	+130%	-21%	+134%	-91%	+63’397%
Shared cost factor	-2%	+1%	-9%	+19%	-50%	+57%
Intervention duration	0%	0%	-100%	0%	-100%	0%
Cost of corrective interventions	-100%	+11%	-100%	+11%	-100%	+1’163%
Reaction time	-100%	+1’286%	-100%	+1’286%	-100%	+31’822%
Passenger volume	-56%	+31%	-56%	+31%	-100%	+1’060%
Additional travel time	-100%	+222%	-100%	+222%	-100%	+8’294%
Value of time	-100%	+222%	-100%	+222%	-100%	+8’294%
Accident probability	-55%	+31%	-55%	+31%	-100%	+1’056%
Property damage	-100%	+3’261%	-100%	+3’261%	-100%	+207’412%
Injury probability	-100%	+248%	-100%	+248%	-100%	+9’501%
Injury costs	-100%	+248%	-100%	+248%	-100%	+9’501%
Fatality probability	-61%	+36%	-61%	+36%	-100%	+1’180%
Fatality costs	-61%	+36%	-61%	+36%	-100%	+1’180%
Discount rate	-15%	+282%	-15%	+325%	-100%	+1’330%

The results in Table 35 show that the condition of the objects, deterioration rate, failure probability, shared cost factor and intervention duration have in general the smallest ranges. Their ranges over which the optimal intervention program does not change or are similar, are mostly within single digit percentages. This means that already small differences in the actual and assumed value of this variables lead to significant changes in the optimal intervention program. Further, their ranges over which the reference intervention program can be seen as near optimal, i.e. optimality >0.98, are within the range of -50% and +100%, which is a much smaller ranges than for other variables. These other variables have rather large ranges over which the reference intervention program can be seen as near optimal, i.e. variations where the value is at least 10 times higher than assumed. They can be grouped according to the ranges over which the optimal intervention program does not change and remains similar.

- Approximate -60% to +40%: Passenger volume, accident probability, fatality probability and fatality costs
- Approximate -100% to +11%: Corrective intervention costs
- Approximate -20% to +200%: Intervention costs, discount rate
- Approximate -100% to +250%: Additional travel time, value of time, injury probability and injury costs
- Above +1000%: Reaction time and property damage

The ranges determined for traffic related variables are of rather large extends indicating that their accuracy is less important than the variables with tighter ranges, i.e. deterioration rate and intervention costs. This is due to the low traffic volume on the railway line considered, which result in significant lower indirect costs compared to the direct costs (section 3.6.8.1). The ranges for the traffic related variables might be smaller in another situation, where the indirect costs of additional travel time for the user has a higher impact on the total net benefit.

In general, the ranges in Table 35 provide the required accuracy of the input variables for determine a reliable optimal intervention program for the example railway network. The first range, the range over which the optimal intervention program is unchanged, defines the required accuracy in order that the intervention program determined by the infrastructure manager is truly optimal. The second range, the range over which the optimal intervention program can be seen as similar, defines the required accuracy in order that the actual decision made by the infrastructure manager, i.e. which interventions to execute, has at most marginal differences with the optimal intervention program. The third range, the range over which the reference intervention program is near optimal, defines the required accuracy in order that the intervention program determined by the infrastructure manager obtains an at least near optimal net benefit. Which required accuracy to choose, depends on the current situation of information availability, the available resources to improve the accuracy of the input information, and the aim of the infrastructure managers. The required accuracies based on the first range enable the infrastructure manager to determine the optimal intervention program, but requires more effort and time to collect and estimate the input variables. The minimal required accuracies based on the second and third range enable infrastructure managers to determine reliable near optimal intervention program with less strict conditions on the required accuracy. This is of special interests for infrastructure managers when determining the intervention program for large railway networks using heuristic optimisation algorithms, which enable to find near optimal intervention program with less computational effort (Burkhalter & Adey, 2019).

The required accuracies based on the ranges in Table 35 define the required accuracies of the input variables in order that reliable optimal intervention programs can be determined. They do not relate to the accuracy and uncertainties in the existing data. Some of the variables will be available in higher accuracy then their required accuracy. For example, the traffic volume on the example railway line is known with a higher accuracy than the required accuracy in the range of -56% to +31%, as it is based on measured passenger flow data. Other variables, however, may not be available with the required accuracy. For example, the shared cost factors in section 3.6.4 are assumed based on little to know available data and may be much less accurate than the required accuracy in the range of -50% to 75% for the maximal range. By considering the defined required accuracies and the accuracies of the existing data, the infrastructure manger can decide where to focus on to improve data availability.

3.8 Conclusion

In this report, a methodology is presented to determine optimal risk reducing intervention programs on transportation networks, where intervention programs are the result of selecting and grouping the interventions to be executed within the upcoming planning period considering dependencies. An optimal risk reducing intervention program is the one that maximises net benefits, where the benefits consist of the reduction in risks and of the reduction in future costs due to the execution of the interventions. A constrained network flow model is presented that allows the determination of the optimal risk reducing intervention programs for railway networks considering the railway specific dependencies, i.e. budget limitation, structural dependencies referring to the physical functionality between objects, economical dependencies referring to cost reduction when grouping interventions, and topological dependencies referring to the service oriented functionality.

The constrained network flow model consists of two levels, the object level representing the infrastructure objects, and the network level representing the service provided in terms of train traffic. It is constrained by the flow continuity constraint in both levels and side constraints regarding mandatory intervention pairs based on structural dependencies, exclusivity constraints ensuring that at most one intervention is selected per object, and the budget constraint limiting the available money to spend on interventions. The continuity constraints in the network level require the introduction of a new network element, the sink edges. A sink edge $\varepsilon_{u,v}$ is part of the flow continuity constraint in the origin node u, its capacity is constrained by the flow through the destination node v. With these sink edges, the constrained network flow model enables to consider the complex relationships when determining optimal intervention programs for railway infrastructure networks. And it allows the writing of the problem of determining intervention programs as a mixed integer linear program, which can be solved for smaller instances of the problem with the Branch-and-Bound algorithm.

The model presented is used to determine optimal risk reducing intervention programs for an example railway network that is based on a real railway line in Switzerland using approximated condition data. In order to reduce the complexity, the example focuses on objects of three different categories, i.e. track, switches and bridges, and interventions of only four different types, i.e. rail replacement, track renewal, switch replacement and bridge renewal. The optimal risk reducing intervention programs determined for an unlimited and a budget limited situation show that the model can be applied and solved within reasonable time. The example shows that a budget reduction by 64% of the resources required in the unlimited situation still leads to net benefits of 97% of the optimal net benefits. This result, as well as the determined intervention programs, depend on the situation considered and may be different when having another situation. The model, however, can be applied for all situations.

In order to support infrastructure managers where to spend their effort on collecting and estimating the infrastructure and traffic information that is required when determining optimal intervention programs, a methodology is presented that enables to estimate the required accuracy of the input information. Applied on the example railway line, the results show a high required accuracy for object related information such as the condition of the objects, the predicted deterioration and the failure probability. Further, the shared cost factor is of high importance, which defines the amount of the intervention costs that is reduced when the same intervention is grouped on neighbouring objects. This analysis enables infrastructure managers to compare the required accuracy of all input information with the accuracy of their available data and to decide where to focus on to improve their available data.

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4 PART 3: METHODOLOGY FOR PRIORITIZING RESILIENCE ENHANCING INTERVENTIONS

4.1 Notations

IN_i	Intervention *i*
a_{ij}	Element of row *i* and column *j* in a generic matrix
ARI_i	Absolute relevance of indicator *i*
CI	Consistency Index
CR	Consistency Ratio
$[D_{Ii}]$	Decision Matrix of Indicator *i*
DMC	Decision Matrix Component
DV	Decision Value
[H]	Hierarchical matrix
H-Diagram	Hierarchical Diagram
[I]	Interventions Matrix
I_i	Indicator *i*
KDP	Key Design Parameter
KPI	Key Point Indicator
n	Matrix order
RI	Random Index
RRI_{ij}	Relative Relevance Index between indicators *i* and *j*
$\lambda_{[M]}$	Eigenvector which belongs to the principal eigenvalue of matrix *[M]*
λ_{ppal}	Principal eigenvalue

4.2 Introduction

In this section, a methodology is developed for the evaluation of possible interventions to be performed in order to enhance infrastructure resilience. This methodology is aimed to support, at the strategic level, infrastructure managers and operators in decision-making processes where the resilience of the system has been measured using Resilience Indicators and target values not directly tied to reductions in service or interventions costs (as shown in Deliverables D1.1 and D1.2 (Adey et al., 2019)).

As it is exposed in WP1, measuring resilience in terms of Level of Service in detail involves a great deal of complexity. In some cases, due to lack of time, lack of modelling expertise or some other reasons, it might not be desired neither worthwhile to measure resilience directly using the reductions in service. For such cases, a guideline to measure resilience indirectly using *Resilience Indicators* is developed in WP1.

Additionally, in D1.2 (Adey, Martani, & Kielhauser, 2019) a guideline is developed to set target values on those Resilience Indicators. Setting target values on Resilience Indicators and comparing them to actual values gives an idea of how far the system is from reaching the desired level of resilience. However, the range of possible interventions that can be performed to increase resilience might be of quite different kind and it can be difficult to identify the most relevant intervention in terms of increased resilience.

For example, it is intended to improve the resilience of an existing road bridge facing an earthquake. After analysing the actual values of Resilience Indicators following guideline in D1.1 and setting Target Values on those indicators through guideline in D1.2 (Adey, Martani, & Kielhauser, 2019), it is observed:

- The age of replacement of the warning system is between 50 – 80 % of the minimum expected life-time achieved, while it is aimed to be between 20 – 50 % of the minimum expected life-time achieved (please refer to Deliverable 1.1 for more information about indicators scale).
- The emergency plan is only a generic one while it is aimed to be a full operative emergency plan (with tasks, resources, etc.).

Table 36: Example of Target Values and Actual Vales of Resilience Indicators

Indicator	Target Value	Actual Value
Age of replacement of the warning system	2	1
Presence of an emergency plan	2	1

Supposing there are no budget constraints and regarding solely resilience: which intervention would be best to carry out? Would it be better to upgrade the warning system or to develop a full operative emergency plan?

Determining the weight of each intervention is the key to solve the problem in this decision-making process. However, as it can be seen, it is difficult to determine the weight of each intervention as the relationship between them is qualitative. Therefore, a formal process is needed to rationally rank interventions priority according to specific indicators.

The methodology developed in this report will serve as a strategic tool for ranking resilience enhancing interventions taking into account initial and target values of resilience indicators of a particular system facing a hazard.

While previous parts of this deliverable are more related with physical interventions, whether they are restoration intervention programs or risk reducing intervention programs, this methodology comprises an overview of the resilience of the system and allows infrastructure managers and operators to consider different interventions, such as reinforcement interventions, monitoring measures and organisational measures, and to compare them regarding the resilience of the system. This is a strategic tool that will allow to rank intervention focusing on resilience. Once this analysis is performed, detailed planning and scheduling, taking into account budget and resources constraints, will be required.

The aim is to shed light on where it will be better to focus efforts in order to foster the resilience of the system when facing a hazard. This is achieved by integrating the level of resilience (actual and target) measured in previous work of FORESEE project (WP1) and developing a hierarchical process that allows to relate interventions and resilience indicators. The result is a priority order of interventions in terms of its influence on resilience.

The methodology proposed here for prioritizing resilience enhancing interventions is based on *Analytic Hierarchical Process (AHP)* theory*.* AHP, originally developed by Saaty in the 1970s, is a typical system engineering method transforming qualitative analysis into quantitative analysis (Li et al., 2017). This method is widely used for determining weights expressing the relative importance of a set of alternatives based on multiple criteria.

Analytic hierarchy process theory has been deeply studied and it is currently being used as an alternative method to determine intervention priority in many infrastructure's maintenance programs. Some examples are:

- Application of Hierarchy process in network level pavement maintenance decision-making (Li et al., 2017): This is an interesting study in twenty six road sections in which hierarchical diagrams are used to determine a priority order in which pavements should be rehabilitated/replaced depending on indicators as level of traffic, pavement age or road grade.
- District road maintenance priority using analytical hierarchy process (Siswanto et al., 2019): This study is similar to the application in pavements maintenance but, it incorporates more details of the road (i.e. pathologies), economics and land use. Its aim is to set a priority order of different road sections to be maintained.

These are two examples of how hierarchical diagrams are currently being implemented in the same field as FORESEE project. There are several case studies including hierarchical diagrams or a similar process as in (Sabarethinam et al. 2020), where a decision tree algorithm is developed in terms of probability to set the most optimal restoration model for extreme events in bridges.

This Part 3 of Deliverable D4.7 is divided into three sections, the first of which is this Introduction. The following section, Section 4.3, develops the methodology proposed, defining the input parameters needed and the prioritization process to be carried out in order to obtain the decision values of each intervention. Then, Section 4.4 presents an example of the application of this methodology in one of the case studies of FORESEE project, Case Study #2. Finally, Sections 4.5 and 4.6 present the overall conclusions of this study and the various references used respectively.

4.2.1 Previous work

First version of the methodology for prioritizing resilience enhancing interventions was presented in deliverable D4.2: 1st version of the algorithms to determine optimal restoration and risk reduction in intervention programs for transportation networks (Burkhalter et al., 2020). In that deliverable, the methodology was fully developed and a simple theoretical example was included to illustrate the steps of the methodology. In Deliverable D4.7 work has been done to carefully apply the methodology to Case Study #2. As a result of testing this methodology a possible improvement has been detected and it has already been implemented in the algorithm in order to increase results reliability. Section 4.3.8 details how this methodology has been improved by introducing the concept of a null weighting vector for fully fulfilled indicators.

4.2.2 Relation with other WPs

The methodology developed in this deliverable is related with the Resilience Indicators developed in WP1. Resilience Indicators are used here to compare target values (which in this methodology play the role of Key Design Parameters) with the values representing the current resilience of the system (playing the role of Key Performance Indicators). These values, both target and current values of Resilience Indicators, are obtained using guidelines from Deliverables D1.1 and D1.2.

The result of this methodology is a list of ranked interventions for improving the resilience of the infrastructure system in relation to the extreme hazard considered. The weights obtained for ranking interventions are the Decision Values that support the decision making of strategic infrastructure managers and operators.

This methodology will be integrated in the Resilience Schemes to be developed in WP7 as it will support infrastructure managers and operators to decide where to focus efforts in order to improve the resilience of the system.

4.3 Methodology for prioritizing resilience enhancing interventions

4.3.1 Overview

The range of possible interventions that can be applied to an infrastructure system in order to increase its resilience might be of quite different kind. Because of the different nature of each potential intervention, it is very complex to compare them so as to identify the most relevant intervention in terms of increased resilience.

The methodology developed in this deliverable revolves around the construction of a hierarchical model. The main advantage of the hierarchical model is that the decision problem becomes hierarchical and the complexity is decomposed. The hierarchical model proposed consists of three levels:

1. Top level: this level represents the overall goal that, in this case, is to determine the ranking of importance of each proposed intervention in order to improve resilience given the state of the system.
2. Middle level: this level contains the criteria that influence the goal and are used for evaluating alternatives. In this case, the middle level contains the resilience indicators and are used for evaluating the interventions under analysis.
3. Bottom level: this level includes the alternatives to achieve the goal. In this case, the alternatives are the possible interventions that can be performed to increase the resilience of the infrastructure (goal of top level).

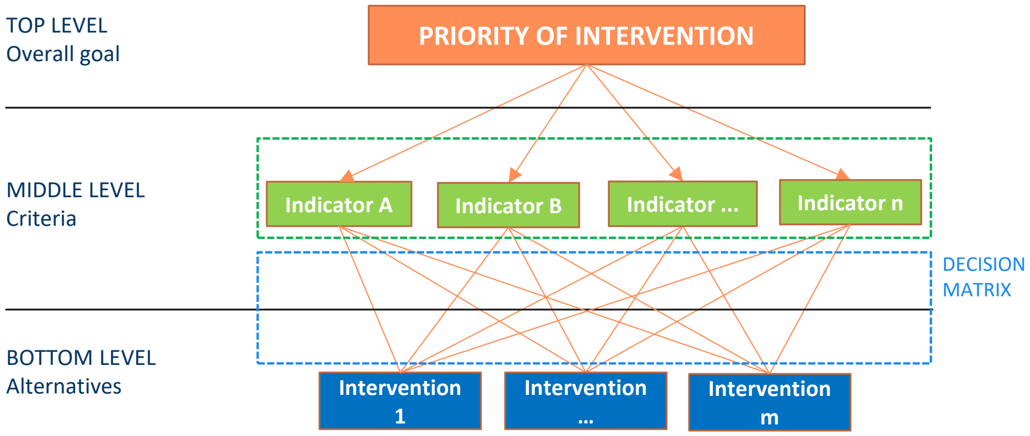

Figure 31: Generic H-Diagram structure

Relations are established within the structure through pairwise comparison that leads to comparison matrices.

Middle level is evaluated through pairwise comparison determining relative importance of each criterion (resilience indicator) in terms of overall goal. This leads to the construction of a *Hierarchy matrix* that is a pairwise comparison matrix of elements from middle level. Thus, it will be a matrix of order $n \times n$ (for n indicators).

Bottom level (interventions) are compared with respect to each of the above indicators, leading in this case to n pairwise comparison matrices of order $m \times m$, being n the number of indicators and m the number of interventions. These are called *Decision matrices.*

After constructing these matrices, the relative importance of each element of one layer to the element of the above layer can be extracted through the calculation of eigenvectors. The final step (top level) is to calculate the weight value of each intervention. These weights constitute the *Decision Values* that will allow to arrange priorities.

However, before initiating this prioritization process and comparisons explained above, a set of parameters must be defined in order to represent the resilience of the infrastructure and the target level of resilience that is aimed to achieve. These parameters are defined through the use of Resilience Indicators defined in WP1 (D1.1). Indicators will constitute the middle level of the hierarchy diagram shown in Figure 31.

The following sections describe the main steps to be followed in the application of this methodology, which can be summarized as follows:

1. Defining resilience indicators and evaluating system performance (KDP and KPI).
2. Defining possible interventions to enhance system resilience.
3. Building the hierarchical model which is based on Hierarchy and Decision matrices referred in steps 4 and 5 below.
4. Constructing Hierarchy matrix.
5. Constructing Decision matrix.
6. Obtaining Decision Values and ranking of interventions.

4.3.2 Definition of indicators and evaluating system performance (KDP and KPI)

The first step is to define a set of parameters that represent the level of resilience of the infrastructure and the objective level which it is aimed to achieve. In other words, an analysis of the infrastructure resilience must be done, where a number of criteria (indicators) are defined and goals regarding resilience are set.

For that purpose, guidelines in Deliverables D1.1 and D1.2 should be used to define the following parameters:

- *Key Design Parameters (KDP):* these are the Target Values of the Resilience Indicators. These parameters represent the level of resilience that is aimed to achieve and are set following guidelines in Deliverable D1.2.
- *Key Performance Indicators (KPI):* these are the actual values of Resilience Indicators. These parameters represent the level of resilience that the infrastructure actually has when facing a particular extreme event (earthquake, flooding, etc.). They are obtained following guideline shown in Deliverable D1.1 for measuring resilience using indicators.

As it can be seen, the parameters that serve as inputs on this methodology are obtained from Resilience Indicators and target values defined in WP1. This allows to integrate goals regarding resilience in the process of selection of different actions.

Example:
Table 37 shows an example of the scale of three indicators (A, B and C), and its target values (what is aimed to achieve) as well as its actual performance (Table 38).

Table 37: Example of Indicators scale and meanings

ID	Indicator	Scale	Meaning
A	Age of replacement of the warning system	0	>80% of the minimum service life achieved
		1	> 50% < 80% of the minimum service life achieved
		2	> 20% < 50% of the minimum service life achieved
		3	< 20% of the minimum service life achieve
B	Presence of an emergency plan	0	No plan
		1	Generic plan
		2	Operative plan
C	Condition state of protection barriers	0	Highly likely to collapse
		1	No information is available
		2	Moderately likely to collapse
		3	Unlikely to collapse
		4	Very unlikely to collapse
		5	Extremely unlikely to collapse

Table 38: Example of KDP and KPI of Indicators

ID	Indicator	Key Design Parameter *(Target Values)*	Key Performance Indicator *(Actual Value)*
A	Age of replacement of the warning system	3	1
B	Presence of an emergency plan	2	1
C	Condition state of protection barriers	3	3

4.3.3 Definition of interventions

Based on developments made in FORESEE project, that will be included in the Resilience Plans developed in WP7, decision-makers will be able to set a range of possible interventions that will enhance the resilience of the transport systems. Therefore, these interventions will increase the current values of resilience indicators (KDP) towards target values (KDP).

<u>Example:</u>
Regarding Indicators A, B and C considered in previous example, four possible interventions could be set:

- *Intervention 1: Replacement of the warning system by a new one.*
- *Intervention 2: Installation of a monitoring system.*
- *Intervention 3: Development of a full operative emergency plan.*
- *Intervention 4: Replace protection barriers.*

4.3.4 Hierarchical Model

Once KDP, KPI and interventions have been defined, a hierarchical diagram is constructed as shown in Figure 31. Then, it starts a process of building the different matrices by pairwise comparison and obtaining relative weights through the calculation of eigenvectors. The following sections describe in detail the construction of these matrices.

4.3.5 Construction of Hierarchy Matrix [H]

The purpose of building a Hierarchy matrix (middle level in Figure 31) is to weight different indicators. This matrix is built by pairwise comparison between indicators.

In Deliverable D1.1, weights are established for each indicator as a percentage. These weights can be translated to an importance scale on the basis of 0-9 as it is shown in EQ. 45. These weights represent the *Absolute Relevance Index (ARI)* of each indicator.

$$ARI = Weight(\%) \cdot \frac{9}{100} \tag{45}$$

Then, the decision-maker compares the indicators in pairs obtaining their relative importance. This pairwise comparison can be done following the scale proposed in the Analytic Hierarchical Process (AHP) theory developed by Saaty and shown in Table 39 (Saaty, R.W., 1987).

Table 39: Pairwise comparison scale and meaning (Saaty, R.W., 1987)

Relative importance index	Definition
1	Equal importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments
Reciprocal values	If indicator *i* has one of the above numbers assigned to it when compared with indicator *j*, r_{ij}. Then indicator *j* has the reciprocal value when compared with *i*, and the reciprocal value is 1/

Alternatively, as an *Absolute Relevance Index* has been defined for each indicator, instead of using the above table, pairwise comparison can be automated by following the algorithm in EQ. 46.

$$\begin{aligned}
&\text{If } ARI_A - ARI_B \geq 0 \\
&\qquad RRI_{AB} = ARI_A - ARI_B + 1 \\
&\text{Else} \\
&\qquad RRI_{AB} = 1/|ARI_A - ARI_B - 1| \\
&\text{End}
\end{aligned} \tag{46}$$

Being:

ARI_i Absolute Relevance Index of indicator *i*

RRI_{ij} Relative Relevance Index between indicator *i* and *j*.

In both procedures, a *Relative Relevance Index (RRI)* is obtained for each indicator that represents their relative importance, thus generating a pairwise comparison matrix. The number of comparisons needed for a matrix of order *n* (being *n* the number of indicators considered) is *n (n – 1)/2* because of Hierarchic matrix is reciprocal and the diagonal elements are equal to unity.

As a result of the above pairwise comparison, a Hierarchy matrix is built as in EQ. 47.

$$[H] = \begin{array}{c|cccc}
 & I_A & I_B & I_i & I_n \\
\hline
\mathbf{I_A} & 1 & RRI_{AB} & RRI_{Ai} & RRI_{An} \\
\mathbf{I_B} & 1/RRI_{AB} & 1 & RRIB_i & RRI_{Bn} \\
\mathbf{I_i} & 1/RRI_{Ai} & 1/RRI_{Bi} & 1 & RR_{in} \\
\mathbf{I_n} & 1/RRI_{An} & 1/RRI_{Bn} & 1/RRI_{in} & 1
\end{array} \tag{47}$$

Example:

To continue the previous example, Table 40 shows Absolute Relevance Index (ARI) considered for each indicator.

Table 40: Considered ARI for the explanation example

ID	Indicator	KDP *(Target Values)*	KPI *(Actual Value)*	Weight (%)	ARI
A	Age of replacement of the warning system	3	1	11.1	1
B	Presence of an emergency plan	2	1	44.4	4
C	Condition state of protection barriers	3	3	88.9	8

Then, applying algorithm in Eq. 46 Relative Relevance Index is obtained

RRI_{AB} = 1/4 (meaning that Indicator A has a moderate importance over Indicator B, according to Table 39)

RRI_{BA} = 4 (reciprocal value, according to Table 39)

The Hierarchy matrix is constructed as shown in EQ. 48:

$$[H] = \begin{array}{c|ccc} & I_A & I_B & I_C \\ \hline I_A & 1 & 1/4 & 1/8 \\ I_B & 4 & 1 & 1/5 \\ I_C & 8 & 5 & 1 \end{array} \qquad 48$$

4.3.5.1 Consistency check and eigenvector ($\lambda_{[H]}$)

The purpose of matrix consistency check is to ensure each comparison is rational and to avoid no conflicting results. A matrix is said to be consistent if $a_{ij} \cdot a_{jk} = a_{ik}\ \forall\, i, j, k$. The matrix built in the previous step will not meet initially this statement but, formulating it as reciprocal, consistency at both sides of diagonal is compensated.

For example, supposing $RRI_{\mathrm{AB}} = 1/4$; $RRI_{\mathrm{BC}} = 1/5$; $RRI_{\mathrm{AC}} = 1/8$, to be consistent $RRI_{\mathrm{AC}} = RRI_{\mathrm{AB}} \times RRI_{\mathrm{BC}} = (1/4) \times (1/5) = 1/20$, but it has the value 1/8. RRI_{AC} is lower than what it should be to fulfil consistency requirements. Analysing the reciprocal, $1/RRI_{\mathrm{AB}} = 4; 1/RRI_{\mathrm{BC}} = 5$; $1/RRI_{\mathrm{AC}} = 8\ \rightarrow 1/RRI_{\mathrm{AB}} \cdot 1/RRI_{\mathrm{BC}} = 20\ \neq 8$. So, RRI_{CA} is larger than what it should be and there is a tendency to compensate (Saaty, R.W., 1987). When a positive reciprocal matrix n-order is consistent, the principal eigen value is n. How far is the principal eigenvalue from n, is the comparison to perform in order to analyse consistency of the matrix by means of Consistency Index (CI) defined in EQ. 49.

$$CI = \frac{\lambda_{ppal} - n}{n - 1} \qquad 49$$

Being:

λ_{ppal} Principal eigenvalue

n matrix order

Consistency Ratio (CR) is obtained by comparing the *CI* with a called *Random Consistency Index (RI)* which is a parameter obtained from a sample of size 500, of a randomly generated reciprocal matrix using the scale 1/9-9 to check whether it is lower than 0.10. If not, Hierarchical matrix is not consistent enough and need to be reformulated. Table 41 shows *RI* values depending on the matrix order (Saaty, R.W., 1987).

Table 41: Random Consistency Index in function of Matrix order

Matrix order	2	3	4	5	6	7	8	9	10	>10
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.50

Finally, *Consistency Ratio (CR)* is obtained as in EQ. 50.

$$CR = \left|\frac{CI}{RI}\right| \cdot 100 \qquad (50)$$

Matrix consistency defines how indicators will influence in interventions. This means that, not having a proper *CR* would mean that there is one indicator whose importance is much higher than others and it would be pointless considering all the other indicators. Also, poor *CR* can means that there is no coherence in Hierarchical Matrix definition (e.g. Indicator A is more important than B and much more important than C - $RRI_{AB} = 3; RRI_{AC} = 9$-, but indicator B is less important than C - $RRI_{BC} = 1/5$).

In order to assure enough consistency for Hierarchy Matrix, Table 42 defines maximum limits for *CR* to be fulfilled depending on matrix order.

Table 42: Limits for Consistency Ratio in Hierarchical Matrix

Matrix order	Maximum Consistency Ratio (CR)
3	5%
4	9%
≥ 5	10%

Once the Hierarchical Matrix consistency has been checked, the next step is to derive the scale of the weights. This is obtained by solving for the principal eigenvector of the matrix and then normalizing the result. This normalised eigenvector ($\lambda_{[H]}$), which belongs to the principal eigenvalue (λ_{ppal}), gives the vector with relative weights normalised to the unit for each indicator. This shows a relative relevance order among all indicators.

<u>Example</u>
Considering Hierarchical matrix shown in EQ. 48. Normalised eigenvector in EQ. 51 shows the relative relevance order for all indicators.

$$\lambda_{[H]} = \begin{pmatrix} 0.07 \\ 0.20 \\ 0.73 \end{pmatrix} \rightarrow \begin{matrix} \text{Indicator A} \\ \text{Indicator B} \\ \text{Indicator C} \end{matrix} \qquad (51)$$

Indicator A has a relative weight of 0.07 while Indicator B has 0.20 and the most weighted is Indicator C with 0.73.

4.3.6 Construction of Decision matrix [D]

The next step is to build Decision matrices (see Figure 31). The purpose of these matrices is to allocate relative weights to each intervention. These weights depend on:

- whether the indicator and the intervention are related, and
- the degree of fulfilment of the indicator.

This requires the estimation of the degree of fulfilment of each resilience indicator, which can be calculated as follows:

$$\% \, fulfilment = \frac{Actual \, performance \, (KPI)}{Target \, Value \, (KDP)} \cdot 100 \qquad 52$$

The relationship between the % fulfilment of indicators and interventions is introduced in the matrix through the element *Decision Matrix Component (DMC)* whose value is linked to the fulfilment of the indicator.

To calculate the value of this element, several algorithms can be used to obtain results using linear piecewise function shown in EQ. 53.

$$DMC = \begin{cases} 1 & \%Fulfilment > 100\% \\ -8/90 \cdot \%Fulfilment + 9 & \%Fulfilment \leq 100\% \end{cases} \qquad 53$$

Figure 32 shows a graphic representation of EQ. 53. As it can be seen, the less the % of fulfilment of the indicator, the higher the value of DMC. Therefore, when introducing this element in the matrix, a higher weight will be assigned to the intervention(s) directly related with that indicator.

It is noted that for indicators with a 100% of fulfilment no actions need to be done to improve this KPI as already meets KDP.

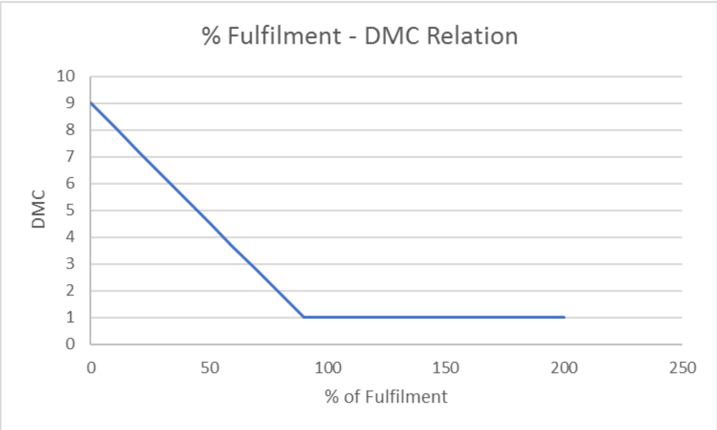

Figure 32: Relationship between % of Fulfilment and DMC

DMC is obtained following EQ. 53 for every indicator. So, being *n* the number of indicators and *m* the number of possible interventions, *n* matrices of order *m x m* elements are obtained $[D_n]_{mxm}$ (one for each indicator). In EQ. 54 an example of Decision matrix is shown. EQ. 54 shows a matrix in which indicator *j* influences only in one of four interventions considered (which is Intervention 3).

$[D_{Ij}] =$

	Intervention1	Intervention2	Intervention3	Intervention4
Intervention1	*1*	*1*	*1/DMC*	*1*
Intervention2	*1*	*1*	*1/DMC*	*1*
Intervention3	*DMC*	*DMC*	*1*	*DMC*
Intervention4	*1*	*1*	*1/DMC*	*1*

54

EQ. 54 can be interpreted as for Indicator I_i, weight will be assigned *DMC* times more to intervention 3 than to the other interventions. Because this indicator does not influence on Intervention 1, 2 and 4, it is assigned a value 1.

As it can be seen, by building *Decision matrices* for each indicator relative weights are assigned to interventions taking into account:

- Whether the indicator influences the intervention: by assigning either value 1 (no influence) or value DMC.
- The degree of fulfilment of the indicator: represented by DMC whose value depends on % fulfilment (the less the fulfilment the higher the value).

Example:
Considering indicators A, B and C from previous steps of the example, % of fulfilments are calculated in Table 43.

Table 43: % of fulfilment analysis for considered indicators in explanation example

ID	Indicator	KDP *(Target Values)*	KPI *(Actual Value)*	% fulfilment
A	Age of replacement of the warning system	3	1	33 %
B	Presence of an emergency plan	2	1	50 %
C	Condition state of protection barriers	3	3	100 %

DMCs are calculated in EQ. 55, EQ. 56 and EQ. 57 as follows:

$$DMC_A = -\frac{8}{90} \times 33 + 9 = 6{,}04 \quad (55)$$

$$DMC_B = -\frac{8}{90} \times 50 + 9 = 4{,}56 \quad (56)$$

$$DMC_C = -\frac{8}{90} \times 100 + 9 = 1 \quad (57)$$

If the decision-maker is analysing four (4) possible interventions, three (3) Decision matrices of order 4x4 are built (one matrix for each indicator). For this example, it has been considered that indicator A influences interventions 1 and 2; indicator B influences interventions 2 and 3; and indicator C influences intervention 4, as it shown in Table 44:

Table 44: Example of proposal of interventions and relation with indicators

ID	Intervention	Related Indicators
INT 1	Replacement of warning system by a new one	Indicator A
INT 2	Installation of monitoring system	Indicators A and B
INT 3	Development of a full operative emergency plan	Indicator B
INT 4	Replacement of protection barriers	Indicator C

Indicator A has a DMC value of 6.04. In order to build the Decision matrix of this indicator, interventions are compared against each other as follows:

- Intervention 1 VS Intervention 2: in this case both interventions influence Indicator A, therefore no emphasis (or same weight) is given to anyone (meaning both are important). Cell (1,2) and cell (2,1) of the matrix will have value 1.
- Intervention 1 VS intervention 3: intervention 1 influences Indicator A while intervention 3 does not. Therefore, DMC value will be assigned to intervention 1 in cell (1,3) in order to give more weight to this intervention over intervention 3. Intervention

3 compared to intervention 1, cell (3,1) of the matrix, will have the reciprocal value 1/DMC.

- Intervention 1 VS intervention 4: this case is similar to the previous one: intervention 1 influences Indicator A while intervention 4 has no relation with it. Therefore, DMC value will be assigned to intervention 1 in cell (1,4) in order to give more weight to this intervention over intervention 4. Intervention 4 compared to intervention 1, cell (4,1) of the matrix, will have the reciprocal value 1/DMC.
- Intervention 2 VS intervention 3: intervention 2 influence Indicator A while intervention 3 does not. Therefore, DMC value will be assigned to intervention 2 in cell (2,3) in order to give more weight to this intervention over intervention 3. Intervention 3 compared to intervention 2, cell (3,2) will have the reciprocal value 1/DMC.
- The same applies to comparisons: Intervention 2 VS Intervention 3; Intervention 2 VS Intervention 4; Intervention 3 VS Intervention 4.

Therefore, following the explained comparison process, Decision matrices are obtained for indicators A, B and C as shown in EQ. 58, EQ. 59 and EQ. 60 respectively.

$$[D_{IA}] = \begin{bmatrix} 1 & 1 & 6.04 & 6.04 \\ 1 & 1 & 6.04 & 6.04 \\ {}^{1}/_{6.04} & {}^{1}/_{6.04} & 1 & 1 \\ {}^{1}/_{6.04} & {}^{1}/_{6.04} & 1 & 1 \end{bmatrix} \quad (58)$$

$$[D_{IB}] = \begin{bmatrix} 1 & 1/4.56 & 1/4.56 & 1 \\ 4.56 & 1 & 1 & 4.56 \\ 4.55 & 1 & 1 & 4.56 \\ 1 & 1/4.56 & 1/4.56 & 1 \end{bmatrix} \quad (59)$$

$$[D_{IC}] = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \quad (60)$$

4.3.6.1 Eigenvector ($\lambda_{[D]}$)

Once all Decision matrices are built, the next step is, for each Decision matrix, obtaining eigenvector ($\lambda_{[D]}$) which belongs to its principal eigenvalue (λ_{ppal}) normalised to the number of interventions influenced by considered indicators. This gives a vector for each indicator with weight assigned to interventions. As they are normalised, if $\lambda_{[D]}$ was not multiplied by number of influenced interventions, it would lead to the more influence, the less weight assigned.

There will be a total of Eigenvectors ($\lambda_{[D]}$) equal to the number of indicators considered (and therefore, equal to the number of Decision matrices calculated).

4.3.6.2 Decision Values (DV)

Final step of this methodology is to obtain the weight of each intervention. These weights represent the relative importance of each intervention and will provide the *Decision Values* that will allow decision-maker to arrange priorities of interventions in terms of resilience.

After obtaining eigenvectors in previous step, the assembly in columns of all of them gives as result, the Interventions matrix (I), shown in EQ. 61.

$$[I] = (\lambda_{IA}; \lambda_{IB}; \lambda_{IC}; \dots; \lambda_{Ii}; \dots; \lambda_{In}) \qquad 61$$

Decision Values are obtained as a vector resulting from the product of Intervention matrix [I] by Hierarchy matrix [H].

$$DV = [I] \cdot [H] = \begin{pmatrix} Weight\ assigned\ to\ Intervention\ 1 \\ Weight\ assigned\ to\ Intervention\ 2 \\ \vdots \\ Weight\ assigned\ to\ Intervention\ i \\ \vdots \\ Weight\ assigned\ to\ Intervention\ N \end{pmatrix} \qquad 62$$

Result in EQ. 62 gives to the decision-maker a quantitative order of interventions according to the state of the system and the relevance of previously defined resilience indicators.

4.3.7 Improvement in Selection methodology

A point of improvement was spotted with respect to the first version of this methodology presented in Part 3 of Deliverable D4.2. In this section, the improvement is further explained:

Following previous step (construction of Decision matrix) if an indicator was fulfilled (that is, its target value was equal to its actual value) its Decision matrix was built as an identity matrix. This meant that for that indicator, no actions were needed to be done to improve its KPI as already met the target value (KDP).

However, by doing that, a certain unrealistic weight is being assigned to all interventions, which means that when weighting at the end of the methodology, the results are homogenized and do not highlight as they should the most important interventions.

To solve this weakness, a condition has been introduced which, if it is detected that the % fulfilment of an indicator is equal to or greater than 100%, a zero weighting is imposed on all interventions.

As shown in EQ. 60 Decision matrix of Indicators C is an identity matrix because this indicator is already fulfilled, and it is considered no action is needed to improve it.

From this point, two different procedures have been developed to obtain the final Decision values and ranking of interventions:

Option A in this procedure the methodology is applied considering a homogeneous weighting vector in those indicators that are fully fulfilled.

Option B: in this procedure the methodology is applied considering a null weighting vector in those indicators that are already fulfilled.

Option A: Considering homogenous weighting vector

Indicators A, B and C eigenvectors are obtained from Decision matrices in EQ. 58, EQ. 59 and EQ. 60. The obtained eigenvector are shown in EQ. 63, EQ. 64 and EQ. 65:

$$\lambda_{IA} = \begin{pmatrix} 0.92 \\ 0.92 \\ 0.15 \\ 0.15 \end{pmatrix} \quad (63)$$

$$\lambda_{IB} = \begin{pmatrix} 0.20 \\ 0.90 \\ 0.90 \\ 0.20 \end{pmatrix} \quad (64)$$

$$\lambda_{IC} = \begin{pmatrix} 1.00 \\ 1.00 \\ 1.00 \\ 1.00 \end{pmatrix} \quad (65)$$

Assembling in columns these vectors, Intervention matrix is built as shown in EQ. 66:

$$I = \begin{pmatrix} 0.92 & 0.20 & 1 \\ 0.92 & 0.90 & 1 \\ 0.15 & 0.90 & 1 \\ 0.15 & 0.20 & 1 \end{pmatrix} \quad (66)$$

Product of Intervention matrix [I] by Hierarchy matrix [H] gives the vector with ranking weights of the relative importance of each intervention in terms of resilience. In EQ. 67 Decision values obtained are shown:

$$DV = \begin{pmatrix} 0.273 \\ 0.384 \\ 0.343 \\ 0.232 \end{pmatrix} \rightarrow \begin{matrix} \text{Intervention 1} \\ \text{Intervention 2} \\ \text{Intervention 3} \\ \text{Intervention 4} \end{matrix} \quad (67)$$

According to the results, Intervention 2 would be the best intervention to perform in terms of resilience.

<u>Option B: Considering null weighting vector</u>

In this case, a null weighting vector is applied to Indicator C which is already fulfilled. Thus, its eigenvector is shown in EQ. 68.

$$[\lambda_{IC}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \quad (68)$$

Assembling vectors in columns, Intervention Matrix is built:

$$I = \begin{pmatrix} 0.92 & 0.20 & 0 \\ 0.92 & 0.90 & 0 \\ 0.15 & 0.90 & 0 \\ 0.15 & 0.20 & 0 \end{pmatrix} \quad (69)$$

Decision values are obtained as a vector with ranking weights of the relative importance of each intervention. This is obtained by multiplying Intervention Matrix [I] by Hierarchy Matrix. In EQ. 70 Decision value results are shown:

$$DV = \begin{pmatrix} 0.191 \\ 0.453 \\ 0.356 \\ 0.093 \end{pmatrix} \rightarrow \begin{matrix} \text{Intervention 1} \\ \text{Intervention 2} \\ \text{Intervention 3} \\ \text{Intervention 4} \end{matrix} \quad (70)$$

According to the results, Intervention 2 would be the best intervention to perform in terms of resilience.

<u>Discussion of results:</u>
Comparison between the results from both procedures is shown in EQ. 71. In both procedures the final vector with Decision Values for each Intervention shows that Intervention 2 has the highest weight, therefore it is the most important intervention in terms of resilience.

$$DV = \begin{pmatrix} 0.273 \\ \boxed{0.384} \\ 0.343 \\ 0.232 \end{pmatrix} \rightarrow \begin{matrix} \text{Intervention 1} \\ \boxed{\text{Intervention 2}} \\ \text{Intervention 3} \\ \text{Intervention 4} \end{matrix} \qquad DV = \begin{pmatrix} 0.191 \\ \boxed{0.453} \\ 0.356 \\ 0.093 \end{pmatrix} \rightarrow \begin{matrix} \text{Intervention 1} \\ \boxed{\text{Intervention 2}} \\ \text{Intervention 3} \\ \text{Intervention 4} \end{matrix} \quad (71)$$

Option A
Decision Values obtained considering a homogeneous weighting vector in fulfilled indicators.

Option B
Decision Values obtained considering a null weighting vector in fulfilled indicators.

However, performing a relative analysis regarding Interventions 2 (the most weighted) and 4 (the one that is only influenced by a fulfilled Indicator), relative relevance is much higher when considering a null weighting vector as it is shown in EQ. 72 (for homogeneous weighting vector) and EQ. 73 (for null weighting vector):

$$Relative\ relevance\ of\ INT_2 = \left(\frac{0.384}{0.232} - 1\right) \cdot 100 = 65\%\ more\ relevant \quad (72)$$

$$Relative\ relevance\ of\ INT_2 = \left(\frac{0.453}{0.093} - 1\right) \cdot 100 = 386\%\ more\ relevant \quad (73)$$

So, it can be concluded that introducing the null weighting vector concept will ease the decision-making process.

4.3.8 Summary

Figure 33 below shows a schematic presentation of the methodology proposed highlighting the main parameters and outcomes.

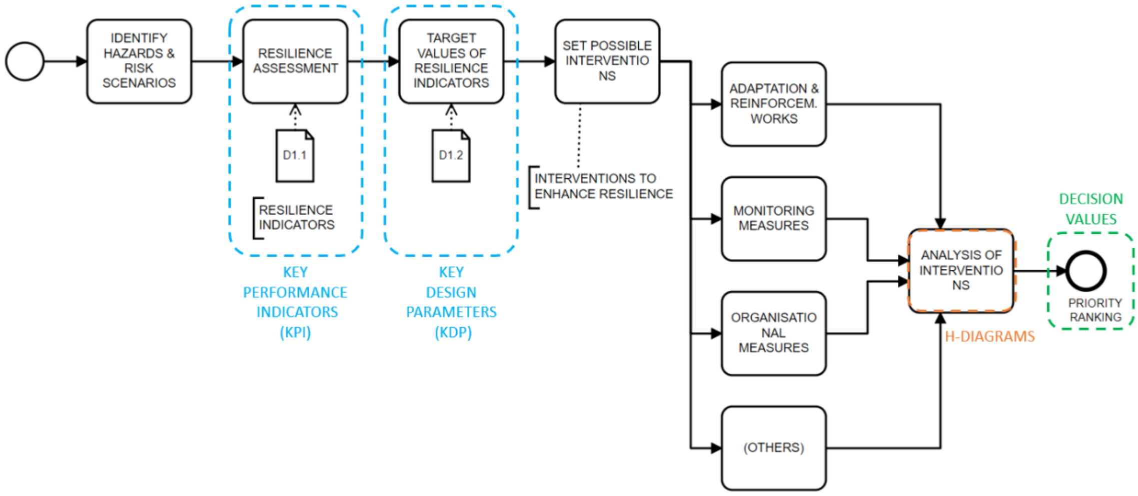

Figure 33: Methodology for prioritizing resilience enhancing interventions

4.4 Application in case study #2

Selection methodology has been applied to Case Study #2 of FORESEE project. The study presented in this section takes as its starting point the work done by (Martani et al., 2020) where a detailed study has been done to estimate the resilience of, and set resilience targets for, this transport system using resilience indicators (full details are provided in the appendix in section 6.3).

In Deliverables D1.1 and D1.2 (Adey et al., 2019) of FORESEE project a methodology is developed to measure the resilience of a transport infrastructure (D1.1) and to set resilience targets (D1.2) with respect a defined service. In the above-mentioned study, both methodologies are applied to a fictive but realistic example transport system based on the A16 highway in Italy. Firstly, resilience is measured following guidelines presented in D1.1 and using resilience indicators with different weights, and then, target values for resilience indicators are set using cost-benefit analysis.

Selection methodology has been applied to the same example with the challenge of comparing both results. In (Martani et al., 2020) targets values of resilience indicators are set using cost-benefit analysis and, therefore, interventions would be oriented towards those targets that make the highest net benefit. In this study, target values are established using the opinion of domain experts, and, afterwards, interventions are prioritised following the selection methodology.

4.4.1 Description of Case Study 2

The transport system to analyse in Case Study 2 is a section of the A16 Highway connecting Napoli to Canosa (see location in Figure 34). The portion of the A16 analysed in this work is a 30 km length section connecting Grottaminarda and Lacedonia.

The hazard event considered is a landslide of a magnitude of up to 19.3 kN/m, which occurs with a frequency of 1/20 years in the section under study. From records on past events, an event of that magnitude is expected to cause the most severe consequences. In light of the importance of such an event, the infrastructure manager wishes to increase the resilience of the system with respect to a landslide of this magnitude[2].

[2] It is to be noticed that both the intensity and the frequency of the event here considered are invented by the authors in order to define a precise hazard, against which measuring the resilience. As such, the event is fictive and does not reflect the real situation of the highway.

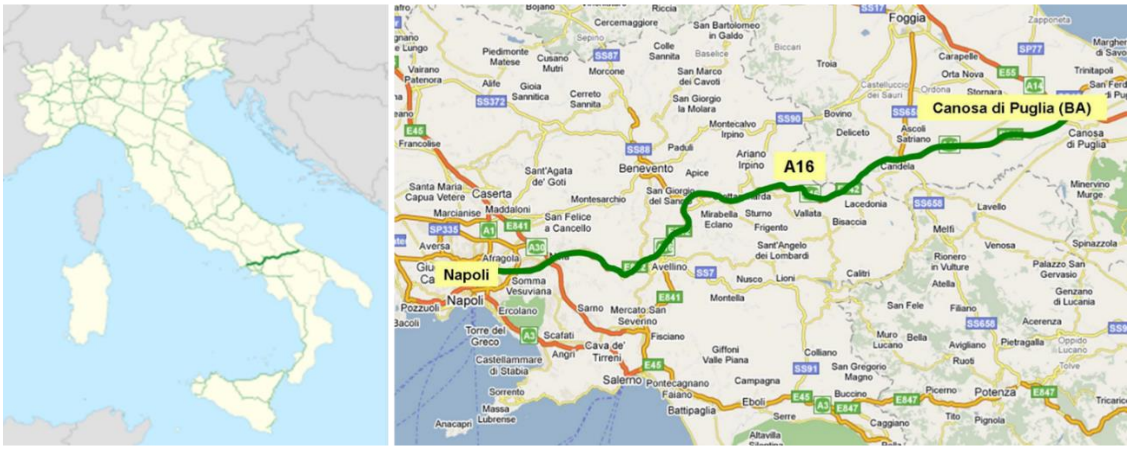

Figure 34: Location and development of the A16 highway[3]

4.4.2 Definition of indicators and performance evaluation (KDP and KPI)

Key Performance Indicators (KPI) are the actual values of Resilience Indicators. These parameters represent the level of resilience of the system analysed has when facing the landslide considered. These values are a sample extracted from the case study developed in (Martani et al., 2020) and contained in appendix 6.3 and are shown in Table 45.

Key Design Parameter (KDP) are the target values of the Resilience Indicators. These parameters represent the level of resilience that is aimed to achieve. Target values can be set using cost-benefit analysis as in (Martani et al., 2020); however, in some cases, due to lack of time or resources, it might be desired to set them based on expert's opinion. In those cases, it is needed to collect all necessary domain expert and stakeholder opinion to formulate a broadly accepted list of resilience indicators targets. There are targets that may not be possible as they are outside of the influence of the infrastructure operator and they are excluded from the list. This is an iterative task of including and excluding resilience indicators until reach a supported agreement on a list of targets. Table 45 shows a fictive example of target values, supposing a panel of experts and stakeholders haven been involved to agree on this final list of selected target indicators.

[3] Source: https://it.wikipedia.org/wiki/Autostrada_A16_(Italia)

Table 45: Selection of indicators and performance evaluation in Case Study 2

Indicator Number	Indicator ID	Indicator Description[4]	KDP *(Target Value)*	KPI *(Actual Value)*	Weight (%)
A	1.1.1	The possibility of building a temporary alternative route for vehicles, reduces the consequences on infrastructure users.	0	0	65%
B	1.1.4	The presence of a warning system allows users to bypass a road section in case of danger, which reduces the consequences of a landslide.	2	2	72%
C	1.1.5	The presence of a safe shutdown system to prevent users from using a damaged road section reduces the consequences of a landslide	1	0	66%
D	1.2.2	The presence of protection barriers prevents the infra. From being hit	0	1	84%
E	1.2.3	The adequacy of protection barriers (e.g. adequately dimensioned and located) prevent the road section from being hit by a landslide.	1	1	62%
F	1.3.2	The condition of the infrastructure providing service affects the probability of the infrastructure being damaged in a landslide	3	4	100%
G	1.3.3	The condition of protection barriers affects the probability that they can provide the level of service for which it was designed during and following the occurrence of a landslide and the harder to repair it if damaged in a landslide.	5	2	78%
H	1.3.4	The condition of the assistance alert systems affects the probability that it can provide the level of service for which it was designed during and following the occurrence of a landslides and the harder to repair it if damaged in a landslide	1	2	18%
I	1.3.5	The expected condition of infrastructure providing service after a landslide affects its ease of repair.	2	1	98%
J	1.3.6	The expected condition of the protective barriers after a landslide affects the likelihood that they will not function as intended after a landslide.	0	2	63%
K	1.3.7	The expected condition of assistance alert systems after a landslide, affects the likelihood that they will not function as intended after a landslide	0	2	6%
L	2.1.12	The extent of vegetation affects the likelihood of future landslides and the probability of restoration interventions / service interruptions	2	1	6%
M	3.1.1	The presence of a monitoring strategy raises the awareness of the state of the road and is likely to increase their preparedness to react when necessary	1	1	13%
N	3.1.2	The presence of a maintenance strategy increases the likelihood that the infrastructure will be in a condition to resist a landslide	2	1	47%
O	3.1.3	The extent of interventions executed prior to the landslide affects the likelihood that the infrastructure will be in a condition to resist a landslide	1	1	81%
P	3.2.1	The presence of an emergency plan reduces the time between the occurrence of a landslide and the moment a manager reacts.	2	1	68%
Q	3.2.2	The practicing of the emergency plan affects the ability of the manager to use it when needed, reducing the time for execution.	2	2	32%
R	3.2.3	The time since the last review/update of the emergency plan affects the likelihood that it will be fit for purpose	2	1	25%

Note: Shaded cells in the table highlight indicators whose target values are above actual ones.

[4] It has been selected only indicators that are possible to modify. Indicators that refer to situations that cannot be modified with interventions (i.e.: amount of hazardous good traffic) have not been considered.

4.4.3 Definition of interventions

After analysing the resilience of the system, a set of possible interventions are established by the decision-maker. The resilience plans to be developed in WP7 will include developments made in FORESEE, as well as other classic interventions, so the decision-maker will be able to set a range of possible interventions that will enhance the infrastructure resilience.

For this case study, analysing indicators above, interventions in Table 46 are proposed. Table 46 also shows the related indicators of each intervention.

Table 46: Proposal of interventions and relation with indicators in Case Study 2

Intervention ID	Interventions	Related Indicators
INT.1	Developing and improving the operative emergency plan	C; P; Q; R
INT.2	Replacing deteriorated nets and piles	D; E; G; I; J
INT.3	Reinforcing pillars and girders of the bridges	F; I
INT.4	Improving maintenance strategy	F; G; I; J; L; N; O
INT.5	Installing instrumented monitoring & alert system	B; H; K; M
INT.6	Installing new safe shutdown system	C
INT.7	Building an alternative route path	A

4.4.4 Hierarchical Model

Once KDP, KPI and interventions have been defined, the hierarchical diagram is constructed as shows Figure 35.

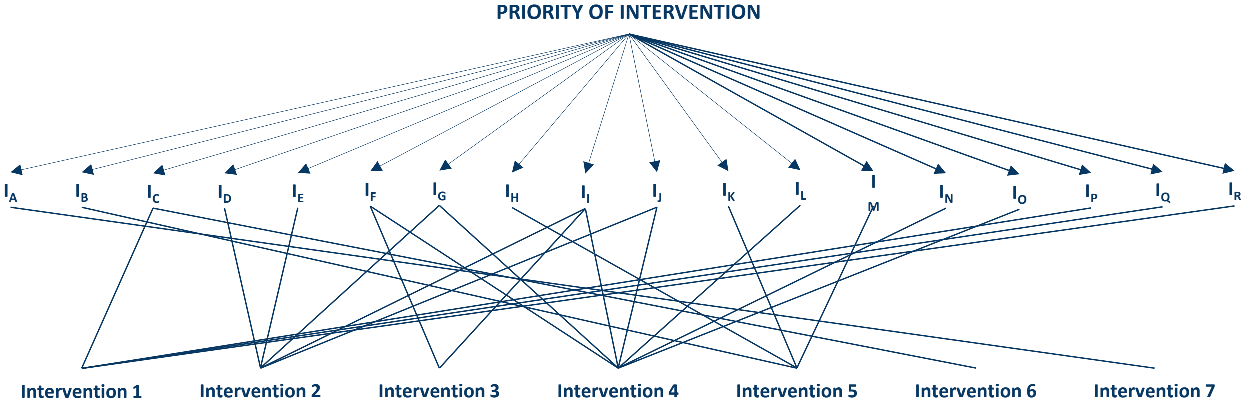

Figure 35: H-Diagram

4.4.5 Construction of Hierarchical Matrix [H]

Prior to build Hierarchical matrix, the Absolute Relevance Index (ARI) of each indicator must be defined. This is done by transforming the importance of the indicator expressed in percentage in Deliverable D1.1 (Adey et al., 2019) to an importance scale on the basis 1-9 in order to tailor weights to the scale proposed by (Saaty, R.W., 1987) and shown in Table 47.

Table 47: Scale of relative importance and meaning

Relative Importance Index	Definition
1	Equal importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments
Reciprocal values	If indicator i has one of the above numbers assigned to it when compared with indicator j, rij. Then indicator j has the reciprocal value when compared with i, and the reciprocal value is 1/

Table 48 below shows Absolute Relevance Index (ARI) obtained for each selected indicator following EQ. 74:

$$ARI = Weight(\%) \cdot \frac{9}{100} \tag{74}$$

Table 48: Indicator classification in terms of Absolute Relevance Index (ARI) for Case Study 2

Indicator Number	Indicator ID	Weight (%)	ARI
A	1.1.1	65%	5.85
B	1.1.4	72%	6.48
C	1.1.5	66%	5.94
D	1.2.2	84%	7.56
E	1.2.3	62%	5.58
F	1.3.2	100%	9.00
G	1.3.3	78%	7.02
H	1.3.4	18%	1.62
I	1.3.5	98%	8.82
J	1.3.6	63%	5.67
K	1.3.7	6%	0.54
L	2.1.12	6%	0.54
M	3.1.1	13%	1.17
N	3.1.2	47%	4.23
O	3.1.3	81%	7.29
P	3.2.1	68%	6.12
Q	3.2.2	32%	2.88
R	3.2.3	25%	2.25

Using algorithm presented in EQ. 75 performing a pairwise comparison among indicators, Hierarchical Matrix shown in Table 49 is then obtained.

$$\begin{aligned}
&\text{If } ARI_A - ARI_B \geq 0\\
&\qquad RRI_{AB} = ARI_A - ARI_B + 1\\
&\text{Else}\\
&\qquad RRI_{AB} = 1/|ARI_A - ARI_B - 1|\\
&\text{End}
\end{aligned} \tag{75}$$

Table 49: Hierarchical matrix obtained in Case Study 2

	I_A	I_B	I_C	I_D	I_E	I_F	I_G	I_H	I_I	I_J	I_K	I_L	I_M	I_N	I_O	I_P	I_Q	I_R
I_A	1.00	1.18	2.44	2.71	2.98	3.52	3.88	4.06	4.15	4.33	4.42	5.77	7.12	7.75	8.38	8.83	9.46	9.46
I_B	0.85	1.00	2.26	2.53	2.80	3.34	3.70	3.88	3.97	4.15	4.24	5.59	6.94	7.57	8.20	8.65	9.28	9.28
I_C	0.41	0.44	1.00	1.27	1.54	2.08	2.44	2.62	2.71	2.89	2.98	4.33	5.68	6.31	6.94	7.39	8.02	8.02
I_D	0.37	0.40	0.79	1.00	1.27	1.81	2.17	2.35	2.44	2.62	2.71	4.06	5.41	6.04	6.67	7.12	7.75	7.75
I_E	0.34	0.36	0.65	0.79	1.00	1.54	1.90	2.08	2.17	2.35	2.44	3.79	5.14	5.77	6.40	6.85	7.48	7.48
I_F	0.28	0.30	0.48	0.55	0.65	1.00	1.36	1.54	1.63	1.81	1.90	3.25	4.60	5.23	5.86	6.31	6.94	6.94
I_G	0.26	0.27	0.41	0.46	0.53	0.74	1.00	1.18	1.27	1.45	1.54	2.89	4.24	4.87	5.50	5.95	6.58	6.58
I_H	0.25	0.26	0.38	0.43	0.48	0.65	0.85	1.00	1.09	1.27	1.36	2.71	4.06	4.69	5.32	5.77	6.40	6.40
I_I	0.24	0.25	0.37	0.41	0.46	0.61	0.79	0.92	1.00	1.18	1.27	2.62	3.97	4.60	5.23	5.68	6.31	6.31
I_J	0.23	0.24	0.35	0.38	0.43	0.55	0.69	0.79	0.85	1.00	1.09	2.44	3.79	4.42	5.05	5.50	6.13	6.13
I_K	0.23	0.24	0.34	0.37	0.41	0.53	0.65	0.74	0.79	0.92	1.00	2.35	3.70	4.33	4.96	5.41	6.04	6.04
I_L	0.17	0.18	0.23	0.25	0.26	0.31	0.35	0.37	0.38	0.41	0.43	1.00	2.35	2.98	3.61	4.06	4.69	4.69
I_M	0.14	0.14	0.18	0.18	0.19	0.22	0.24	0.25	0.25	0.26	0.27	0.43	1.00	1.63	2.26	2.71	3.34	3.34
I_N	0.13	0.13	0.16	0.17	0.17	0.19	0.21	0.21	0.22	0.23	0.23	0.34	0.61	1.00	1.63	2.08	2.71	2.71
I_O	0.12	0.12	0.14	0.15	0.16	0.17	0.18	0.19	0.19	0.20	0.20	0.28	0.44	0.61	1.00	1.45	2.08	2.08
I_P	0.11	0.12	0.14	0.14	0.15	0.16	0.17	0.17	0.18	0.18	0.18	0.25	0.37	0.48	0.69	1.00	1.63	1.63
I_Q	0.11	0.11	0.12	0.13	0.13	0.14	0.15	0.16	0.16	0.16	0.17	0.21	0.30	0.37	0.48	0.61	1.00	1.00
I_R	0.11	0.11	0.12	0.13	0.13	0.14	0.15	0.16	0.16	0.16	0.17	0.21	0.30	0.37	0.48	0.61	1.00	1.00

Once Hierarchical matrix is built, consistency analysis is performed as follows:

- $\lambda_{ppal} = 18.77$
- $RI = 1.50$
- Consistency index obtained in EQ. 76.

$$CI = \frac{\lambda_{ppal} - n}{n - 1} = 0.0454 \tag{76}$$

- Consistency ratio obtained in EQ. 77

$$CR = \frac{CI}{RI} \cdot 100 = 3.03\ \% \tag{77}$$

As it can be observed, a consistency ratio lower than 10% is obtained so this requirement is fulfilled (Saaty, R.W., 1987).

After checking consistency, next step is obtaining the scale of weights of indicators by solving the eigenvector which belongs to λ_{ppal}, (EQ. 78):

$$\lambda_{[H]} = \begin{pmatrix} 0.0491 \\ 0.0647 \\ 0.0511 \\ 0.1006 \\ 0.0438 \\ 0.1641 \\ 0.0809 \\ 0.0120 \\ 0.1547 \\ 0.0454 \\ 0.0087 \\ 0.0087 \\ 0.0104 \\ 0.0276 \\ 0.0903 \\ 0.0553 \\ 0.0180 \\ 0.0147 \end{pmatrix} \rightarrow \begin{matrix} \text{Indicator A} \\ \text{Indicator B} \\ \text{Indicator C} \\ \text{Indicator D} \\ \text{Indicator E} \\ \text{Indicator F} \\ \text{Indicator G} \\ \text{Indicator H} \\ \text{Indicator I} \\ \text{Indicator J} \\ \text{Indicator K} \\ \text{Indicator L} \\ \text{Indicator M} \\ \text{Indicator N} \\ \text{Indicator O} \\ \text{Indicator P} \\ \text{Indicator Q} \\ \text{Indicator R} \end{matrix} \qquad (78)$$

As it can be observed in EQ. 78 $\lambda_{[H]}$ is a normalised vector as $\sum \lambda_{[H]i} = 1$.

4.4.6 Construction of Decision Matrix [D]

Before constructing *Decision matrix*, the degree of fulfilment of each indicator is calculated:

Table 50: Considered indicators with their KDP, KPI and % of fulfilment

Indicator	Indicator ID	KDP *(Target Value)*	KPI *(Actual Value)*	% Fulfilment
A	1.1.1	0	0	100
B	1.1.4	2	2	100
C	1.1.5	1	0	0
D	1.2.2	0	1	100
E	1.2.3	1	1	100
F	1.3.2	3	4	100
G	1.3.3	5	2	40
H	1.3.4	1	2	100
I	1.3.5	2	1	50
J	1.3.6	0	2	100
K	1.3.7	0	2	100
L	2.1.12	2	1	50
M	3.1.1	1	1	100
N	3.1.2	2	1	50
O	3.1.3	1	1	100
P	3.2.1	2	1	50
Q	3.2.2	2	2	100
R	3.2.3	2	1	50

Once % fulfilment is calculated, the element *Decision Matrix Component (DMC)* is obtained for each indicator following piecewise function defined in EQ. 79 and plotted in Figure 36.

$$DMC = \begin{cases} 1 & \%Fulfilment \geq 100\% \\ -8/90 \cdot \%Fulfilment + 9 & \%Fulfilment < 100\% \end{cases} \quad (79)$$

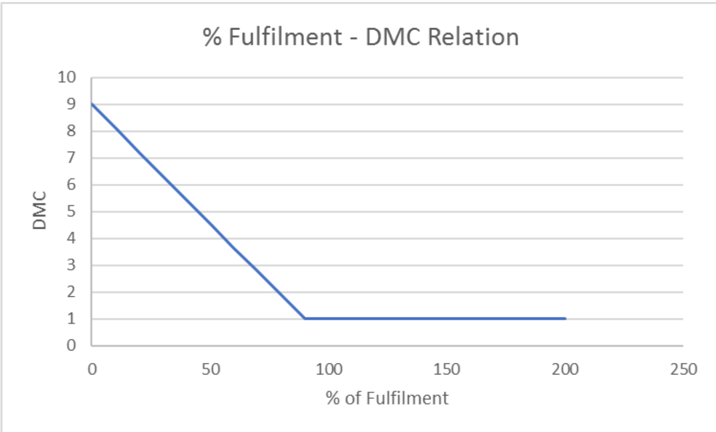

Figure 36: Relationship between % of Fulfilment and DMC

Finally, *Decision matrices* are built (one for each indicator) considering indicator-interventions relationship (shown in Table 46). These matrices are shown from EQ. 80 to EQ. 97. It is noted that *Decision matrices* of Indicators that already fulfil their target values are identity matrices.

$$[D_{IA}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (80)$$

$$[D_{IB}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (81)$$

$$[D_{IC}] = \begin{pmatrix} 1 & 9 & 9 & 9 & 9 & 1 & 9 \\ 0.11 & 1 & 1 & 1 & 1 & 0.11 & 1 \\ 0.11 & 1 & 1 & 1 & 1 & 0.11 & 1 \\ 0.11 & 1 & 1 & 1 & 1 & 0.11 & 1 \\ 0.11 & 1 & 1 & 1 & 1 & 0.11 & 1 \\ 1 & 9 & 9 & 9 & 9 & 1 & 9 \\ 0.11 & 1 & 1 & 1 & 1 & 0.11 & 1 \end{pmatrix} \quad (82)$$

$$[D_{ID}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (83)$$

$$[D_{IE}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (84)$$

$$[D_{IF}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (85)$$

$$[D_{IG}] = \begin{pmatrix} 1 & 0.18 & 1 & 0.18 & 1 & 1 & 1 \\ 5.44 & 1 & 5.44 & 1 & 5.44 & 5.44 & 5.44 \\ 1 & 0.18 & 1 & 0.18 & 1 & 1 & 1 \\ 5.44 & 1 & 5.44 & 1 & 5.44 & 5.44 & 5.44 \\ 1 & 0.18 & 1 & 0.18 & 1 & 1 & 1 \\ 1 & 0.18 & 1 & 0.18 & 1 & 1 & 1 \\ 1 & 0.18 & 1 & 0.18 & 1 & 1 & 1 \end{pmatrix} \quad (86)$$

$$[D_{IH}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (87)$$

$$[D_{II}] = \begin{pmatrix} 1 & 0.22 & 0.22 & 0.22 & 1 & 1 & 1 \\ 4.56 & 1 & 1 & 1 & 4.56 & 4.56 & 4.56 \\ 4.56 & 1 & 1 & 1 & 4.56 & 4.56 & 4.56 \\ 4.56 & 1 & 1 & 1 & 4.56 & 4.56 & 4.56 \\ 1 & 0.22 & 0.22 & 0.22 & 1 & 1 & 1 \\ 1 & 0.22 & 0.22 & 0.22 & 1 & 1 & 1 \\ 1 & 0.22 & 0.22 & 0.22 & 1 & 1 & 1 \end{pmatrix} \quad (88)$$

$$[D_{IJ}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (89)$$

$$[D_{IK}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (90)$$

$$[D_{IL}] = \begin{pmatrix} 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 4.56 & 4.56 & 4.56 & 1 & 4.56 & 4.56 & 4.56 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \end{pmatrix} \quad (91)$$

$$[D_{IM}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (92)$$

$$[D_{IN}] = \begin{pmatrix} 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 4.56 & 4.56 & 4.56 & 1 & 4.56 & 4.56 & 4.56 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0.22 & 1 & 1 & 1 \end{pmatrix} \quad (93)$$

$$[D_{IO}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \tag{94}$$

$$[D_{IP}] = \begin{pmatrix} 1 & 4.56 & 4.56 & 4.56 & 4.56 & 4.56 & 4.56 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \tag{95}$$

$$[D_{IQ}] = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \tag{96}$$

$$[D_{IR}] = \begin{pmatrix} 1 & 4.56 & 4.56 & 4.56 & 4.56 & 4.56 & 4.56 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.22 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \tag{97}$$

As it was done for *Hierarchical matrix*, next step is to obtain the eigenvectors which belongs to principal eigenvalues of each *Decision matrix*. In those indicators that are fulfilled, a null weighting vector is applied. As it was explained in Section 4.3.8, this will yield more accurate results. These eigenvectors are shown in EQ. 98, EQ. 99 and EQ. 100.

$$[\lambda_{DIA}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIB}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIC}] = \begin{pmatrix} 0.78 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.78 \\ 0.09 \end{pmatrix};\ [\lambda_{DID}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIE}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIF}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{98}$$

$$[\lambda_{DIG}] = \begin{pmatrix} 0.13 \\ 0.69 \\ 0.13 \\ 0.69 \\ 0.13 \\ 0.13 \\ 0.13 \end{pmatrix};\ [\lambda_{DIH}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DII}] = \begin{pmatrix} 0.03 \\ 0.26 \\ 0.26 \\ 0.26 \\ 0.06 \\ 0.06 \\ 0.06 \end{pmatrix};\ [\lambda_{DIJ}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIK}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}\ [\lambda_{DIL}] = \begin{pmatrix} 0.09 \\ 0.09 \\ 0.09 \\ 0.43 \\ 0.09 \\ 0.09 \\ 0.09 \end{pmatrix} \tag{99}$$

$$[\lambda_{DIM}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIN}] = \begin{pmatrix} 0.09 \\ 0.09 \\ 0.09 \\ 0.43 \\ 0.09 \\ 0.09 \\ 0.09 \end{pmatrix};\ [\lambda_{DIO}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix};\ [\lambda_{DIP}] = \begin{pmatrix} 0.43 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \end{pmatrix};\ [\lambda_{DIQ}] = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}\ [\lambda_{DIR}] = \begin{pmatrix} 0.43 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \\ 0.09 \end{pmatrix} \tag{100}$$

Assembling vectors shown in EQ. 98, EQ. 99 and EQ. 100 in columns, *Interventions Matrix (I)* is built in EQ. 101.

$$[I] = \begin{pmatrix} 0 & 0 & 0.78 & 0 & 0 & 0 & 0.13 & 0 & 0.03 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.43 & 0 & 0.43 \\ 0 & 0 & 0.09 & 0 & 0 & 0 & 0.69 & 0 & 0.26 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 \\ 0 & 0 & 0.09 & 0 & 0 & 0 & 0.13 & 0 & 0.26 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 \\ 0 & 0 & 0.09 & 0 & 0 & 0 & 0.69 & 0 & 0.26 & 0 & 0 & 0.43 & 0 & 0.43 & 0 & 0.09 & 0 & 0.09 \\ 0 & 0 & 0.09 & 0 & 0 & 0 & 0.13 & 0 & 0.26 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 \\ 0 & 0 & 0.78 & 0 & 0 & 0 & 0.13 & 0 & 0.26 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 \\ 0 & 0 & 0.09 & 0 & 0 & 0 & 0.13 & 0 & 0.26 & 0 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 & 0 & 0.09 \end{pmatrix} \quad (101)$$

4.4.7 Decision Values

Product of *Interventions matrix* by *Hierarchical matrix* gives a vector with ranking weights of the relative importance of each intervention in terms of resilience. In EQ. 102 results for Case Study 2 are shown.

$$DV = \begin{pmatrix} 0.2295 \\ 0.2106 \\ 0.1121 \\ 0.2187 \\ 0.0544 \\ 0.1203 \\ 0.0544 \end{pmatrix} \rightarrow \begin{matrix} \boxed{\text{Intervention 1}} \\ \text{Intervention 2} \\ \text{Intervention 3} \\ \text{Intervention 4} \\ \text{Intervention 5} \\ \text{Intervention 6} \\ \text{Intervention 7} \end{matrix} \quad (102)$$

Results show that the optimal intervention would be Intervention 1 that is to develop and improve the operational emergency plan. The weight of this intervention is 0.2295 and it is followed by Intervention 4 (improving maintenance strategy) with a weight of 0.2187 and by Intervention 2 (replacing deteriorated nets and piles) with a weight of 0.2106.

The priority ranking is as shown below (from most to least relevance):

ORDER	WEIGHT	INTERVENTION
1	**0.2295**	**Intervention 1: Developing and improving the operative emergency plan**
2	0.2187	Intervention 4: Improving maintenance strategy
3	0.2106	Intervention 2: Replacing deteriorated nets and piles
4	0.1203	Intervention 6: Installing a new safe shutdown system
5	0.1121	Intervention 3: Reinforcing pillars and girders of the bridges
6	0.0544	Intervention 5: Installing instrumented monitoring & alert system
7	0.0544	Intervention 7: Building an alternative route path

4.4.8 Discussion

In order to validate this selection, it is needed to perform a critical analysis of inputs and to analyse the veracity of results:

- As it can be observed in Table 46, Table 48, and Table 50, Intervention 1 is related to indicators that are far from being fulfilled such as Indicators 3 (0%), Indicator 16 (50%) and Indicator 18 (50%). As developing and improving the operative emergency plan will directly influence those indicators, it is justified that this intervention should be applied with priority.

- Priority order given previously follows the same path, the more important the indicator and the lower its % of fulfilment, the higher priority is assigned through this selection methodology.

If cost-benefit analysis is used to set target values on resilient indicators, as in the work presented in section 0, it is obtained that the indicator that the greatest net-benefit would be *developing and improving the operative emergency plan* (€ 12.5 million). The order obtained in that study (in a decreasing order from higher to lower net-benefit) is:

- Developing and improving the operative emergency plan: € 12.5 million.
- Improving the condition state of the protective barriers (i.e.: replacing deteriorated nets and piles): € 10.9 million.
- Improving the expected condition of the infrastructure (i.e.: reinforced pillars and girders of bridges): € 3 million.
- Improving the maintenance strategy: € 1.6 million.

After comparing results from both procedures, the following comments are made:

1. In both procedures it is concluded that the optimal intervention would be to develop and improve the operational emergency plan. However, following the selection methodology the second-best option would be to improve the maintenance strategy while following the cost-benefit analysis it would be to replace deteriorated nets and piles.
2. Under a cost-benefit approach, it can happen that the improvement of a certain indicator does not bring a net benefit and, consequently, interventions focused on that indicator might be discarded. This happened, as an illustration, in the following indicators:
    - Presence of a safe shutdown systems.
    - Presence of special measures to help evacuate people.

   After performing the cost-benefit analysis, the target values assigned to these indicators were 0 because they did not bring net benefit and neither they were a legal requirement. However, the presence of a safe shutdown system for closing bridges and/or tunnels so as they are not transited by users considerable reduces the consequences of landslides, thus contributing to the resourcefulness of the system.
3. Another aspect to consider is the fact that in the selection methodology, the improvement of indicators is not analysed one by one (as it is done in the cost-benefit analysis); instead, the study is focused on analysing interventions and how they would improve the resilience of the system. In some cases, there are interventions that upgrade a single indicator, but there are also cases where implementing an intervention may lead to the upgrading of more than one indicator. Such is the case of intervention developing and improving the operative emergency plan that would improve those indicators related with the emergency plan (four in total).
   For that reason, both the methodology presented in this document and the cost-benefit analysis cannot be compared straight forward as they are different in nature and pursue slightly different goals: selection methodology is focused on analysing interventions while cost-benefit is focused on analysing indicators. Nevertheless, both methodologies should be understood as complementary procedures. Selection methodology can be useful when there are no resources to make a cost-benefit analysis, but it can also be very useful as a first approach prior to the cost-benefit analysis.

4.5 Conclusions

In this report, a methodology based on *Design Values, Key Design Parameters and Key Performance Indicators*, conducted by means of Hierarchical diagrams has been applied to FORESEE Case Study #2.

The main purpose of this methodology is to support infrastructure managers and operators in decision-making processes where the target values of resilience indicators are not tied directly to reductions in service or intervention costs. In such cases, comparison among resilience enhancing interventions can be a difficult task as the relationship between interventions is qualitative. With this methodology a scientific process is introduced to rationally rank interventions priority according to specific indicators.

It has been noticed that there is a high dependence on previous analysis such is measuring infrastructure resilience using resilience indicators and setting target values. The more elaborate the resilience indicators analysis, the more accurate the results of the methodology for prioritizing resilience enhancing interventions.

Methodology has evolved from previous FORESEE Deliverable 4.2 modifying the influence of fully fulfilled indicators. Considering a null vector has shown more representative results since weighting all interventions in a fulfilled indicator results in a more homogeneous decision values eigenvector making more difficult the intervention ranking.

Finally, a comparison has been made between results obtained from selection methodology and from cost-benefit analysis carried out by (Martani et al., 2020). Both procedures lead to the same conclusion: the optimal intervention would be to develop and improve the emergency plan; however, the order of priorities differs in the two procedures. This, among other reasons, is due to the fact that in the selection methodology, the improvement of indicators is not analysed one by one (as it is done in the cost-benefit analysis) but the study is focused on analysing interventions and how they would improve the resilience of the system. In some cases, there are interventions that upgrade a single indicator, but there are also cases where implementing an intervention may lead to the upgrading of more than one indicator.

For that reason, both methodologies should be understood as complementary procedures. Selection methodology is aimed to prioritize interventions for strategic planning. Once this analysis is performed, detailed planning and scheduling, taking into account budget and resources constraints, will be required.

4.6 References

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5 CONCLUSION

The work conducted in Task 4.3 was very successful. The success are summarized as follows.

- The algorithms to determine optimal restoration programs (part 1) are suitable for detailed simulations of complex networks, and the variations between them in terms of speed and accuracy are clearly shown. Users in the case studies have a choice of a wide range of options to determination their optimal restoration programs. The algorithms they will be using are a clear advancement on the state-of-the art.
- The algorithm to determine the optimal risk reduction intervention programs (part 2) is sufficiently detailed and fast to allow the determination of optimal intervention programs on large realistic networks. The algorithm proposed is suitable for use in any case study looking to determine the best way to spend money on the physical intervention on complex infrastructure networks. The algorithm is unique on the world stage in terms of structure, its ability to consider synergies between interventions, and accuracy.
- The intervention selection methodology (part 3) can be used to determine the best resilience enhancing interventions when only resilience indicators are used that are not directly connected to service or intervention costs has potential to be used in this situation. An example has been done using case study 2. To compare this methodology with the one proposed in WP1, the one proposed in WP1 was also used to estimate the resilience enhancing intervention in case study 2. The results are very similar, reinforcing the validity for the work and offering those conducting the case study an excellent selection of tools.

In addition to this work substantial work has occurred to enable the use of the tools in the case study. This work includes the following:

- The containerization of algorithms in part 1 and 2 into Docker containers. The first is an algorithm programmed in python to determine the optimal restoration intervention programs following the occurrence of a flood, landslide or earthquake affection either, a part of a road network, part of a rail network or both. The second is an algorithm programmed in R to determine the optimal risk-reducing intervention programs taking into account the possibility of reducing the costs of these intervention programs by grouping them spatially and temporarily. From now on, they can be deployed and used by all partners. The next steps are the integration of the Tools from WP3 "Traffic Module" (T3.4.1) and "Fragility and Vulnerability Analysis and the Decision Support Module (DSM)" (T3.4.2). The integration of the first version of the tools with the expected delivery date in M27, as T2.4 "Virtual Modelling platform", T2.5 "Alerting SAS platform", T4.4 "Hybrid data fusion framework" and T7.1 "Definition of framework: use cases, risk scenarios and analysis of impact". In addition, the containerized tools will be developed as APIs in order to achieve the best possible communication between the tools. These Docker containers are available from FhG at present in anticipation of their availability at RINA-C. The FORESEE tool developers will receive a tool assessment sheet under construction at present informing them about a correct behaviour of their respective tool in the Fraunhofer premises.
- Partners working to understand the functioning of the algorithms so that they can be implemented in the case studies in WP6.

6 APPENDICIES

6.1 Part 2: Intervention program for the unlimited case developed using the optimisation model

The groups of interventions of the intervention program developed using the optimisation model in the unlimited budget case, i.e. Figure 20, are shown in more detail in Table 51 to Table 59.

Group 1 (Table 51), group 2 (Table 52) and group 3 (Table 53) refer to groups of interventions in period 2019-2022. Group 1 and 2 group the same interventions on different objects making use of economical dependencies, i.e. reduced intervention costs. Group 1 consists of the replacement of switches *S18*, *S19*, *S21* and *S23* executed with a weekend closure of section I – J. Group 2 consists of the renewal of track segments *T92*, *T93*, *T98*, *T99* and *T101* executed with a day closure of I – J. Group 3 contains all remaining interventions of period 2019-2022 that are executed with single night break closures without traffic disturbances.

Table 51. Group 1: Weekend closure of I – J in the period 2019-2022

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S18	Switch Replacement	8.0	255'000	509'117	320	Economical dependent
S19	Switch Replacement	8.0	214'200	508'144		
S21	Switch Replacement	8.0	214'200	508'144		
S23	Switch Replacement	8.0	214'200	508'144		

Table 52. Group 2: Day closure of single tracks in station J in the period 2019-2022

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T92	Track Renewal	18.1	37'600	61'876	0	Economical dependent
T93	Track Renewal	5.8	425'350	597'663		
T98	Track Renewal	9.0	109'040	225'363		
T99	Track Renewal	7.8	169'200	333'266		
T101	Track Renewal	16.9	183'300	327'806		

Table 53. Group 3: Single Night break closures without traffic disturbances in the period 2019-2022

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T18	Track Renewal	12.6	296'100	479'599	0	
T21	Rail Replacement	10.7	53'600	399'605		
T23	Rail Replacement	7.8	38'800	296'437		
T24	Rail Replacement	11.8	47'360	438'641		
T29	Track Renewal	39.4	925'900	1'444'494		
T35	Rail Replacement	10.6	52'800	340'950		
T66	Rail Replacement	12.2	61'000	385'209		
T67	Track Renewal	67.3	1'581'550	2'541'270		
T73	Track Renewal	56.6	1'330'100	2'140'063		Economical dependent
T74	Track Renewal	10.2	191'760	400'251		
T75	Track Renewal	11.1	208'680	433'998		
T77	Rail Replacement	3.6	17'995	119'717		
T90	Track Renewal	1.6	37'634	61'923		

Group 4 (Table 54), group 5 (Table 55) and group 6 (Table 56) refer to groups of interventions in period 2023-2026. Group 4 consists of switch replacements on *S7*, *S9*, *S10* and *S14* and rail replacements on track segments *T62* and *T65*. These interventions are executed with a weekend closure of E – J, which is partially extended to C – J for the replacement of *S7*. The replacements of switch *S7* and *S9* as well as the replacements of switch *S10* and *S14* are economical dependent and reduce the intervention costs, i.e. owner costs, when being grouped. The grouping of all these interventions enable to make use of topological synergies, i.e. reduced user costs, due to the parallel execution of interventions. Groups 5 consists only of a switch replacement on *S3* executed with an extended night shift between A – C in the period 2023-2026. Groups 6 contains all remaining interventions of period 2023-2026 that are executed in single night breaks without traffic disturbance.

Table 54. Group 4: Weekend closure of (C/E) – J in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S7	Switch Replacement	8.0	214’200	486’299	2’008	Economical dependent
S9	Switch Replacement	8.0	255’000	483’833		
S10	Switch Replacement	8.0	255’000	483’833		Economical dependent, parallel to S7 and S9
S14	Switch Replacement	8.0	214’200	482’866		
T62	Rail Replacement	10.9	54’400	209’401		Parallel to switch replacements
T65	Rail Replacement	4.5	22’400	72’332		

Table 55. Group 5: Extended night shift between A – C in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S3	Switch Replacement	8.0	255’000.00	492’203	672	

Table 56. Group 6: Single Night break closures without traffic disturbances in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T6	Rail Replacement	9.4	47’000	283’544	0	
T19	Rail Replacement	11.8	59’000	334’538		
T25	Rail Replacement	7.24	36’200	212’394		
T27	Rail Replacement	4.8	24’000	147’036		
T57	Track Renewal	27.3	641’550	897’492		
T68	Rail Replacement	6.56	32’800	185’540		
T70	Rail Replacement	11.2	56’200	309’546		Economical dependent
T71	Rail Replacement	15.8	63’360	431’432		
T79	Rail Replacement	6	30’000	167’040		Economical dependent
T80	Rail Replacement	6.4	25’760	178’681		
T81	Rail Replacement	8.0	31’840	152’736		
T82	Rail Replacement	5.4	21’760	152’225		
T84	Rail Replacement	2.4	12’200	72’857		

Groups 7 (Table 57), group 8 (Table 58) and group 9 (Table 59) refer to groups of interventions in period 2027-2030. Group 7 consists of only the renewal of track segment *T31*, which is executed with a single track closure in station *E* during the day. Group 8 consists of the

renewals of bridges *B3* and *B4* executed with a 24 hour closure of F – J. Both bridge renewals are grouped with the track renewals that are structural dependent on the bridge renewals, i.e. the renewal of track *T83* and *T63*. The parallel execution of the two bridge renewals and the group of economical dependent renewals of track segments *T45*, *T46*, *T47*, *T48*, *T49* and *T50*, as well as of the rail replacement on track segments *T86* and *T88* enable to make use of topological synergies, i.e. reduce the user costs. Group 9 consists of the remaining interventions of period 2027-2030 that are executed in single night breaks without traffic disturbances.

Table 57. Group 7: Single track day closure of in station E in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T31	Track Renewal	19.3	454’066	506’969	89	

Table 58. Group 8: 24 hour closure of F – J in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
B3	Railway bridge renewal	441.5	3’532’000	3’969’561	45’002	T83 is structural dependant on B3
T63	Track Renewal	17.7	415’950	312’026		
B4	Railway bridge renewal	15.0	120’000	206’012		T63 is structural dependant on B4, parallel to B3
T83	Track Renewal	0.6	14’100	15’193		
T45	Track Renewal	9.7	227’950	222’681		Economical dependent, parallel to B3
T46	Track Renewal	16.0	300’800	366’033		
T47	Track Renewal	5.7	107’160	131’664		
T48	Track Renewal	1.1	20’680	26’995		
T49	Track Renewal	0.7	13’160	17’893		
T50	Track Renewal	17.6	330’880	402’439		
T86	Rail Replacement	7.0	34’800	77’559		Parallel to B3
T88	Rail Replacement	9.0	45’200	99’785		

Table 59. Group 9: Single Night break closures without traffic disturbances in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T8	Rail Replacement	4.2	20’800	56’026	0	
T12	Track Renewal	3.7	86’950	106’460		
T58	Rail Replacement	12.0	59’800	181’298		Economical dependent
T59	Rail Replacement	12.0	47’840	181’298		
T60	Rail Replacement	4.8	19’200	76’213		

6.2 Part 2: Intervention program for the budget limited case developed using the optimisation model

The groups of interventions of the intervention program developed using the optimisation model in the budget limited case, i.e. Figure 22, are shown in more detail in Table 60 and Table 67.

Group 1 (Table 60) and group 2 (Table 61) refer to groups of interventions in the period 2019-2022. Group 1 groups multiple switch replacement interventions with a weekend closure of I – J. This enables to make use economical dependencies, i.e. reducing the intervention costs of the owner. Group 2 contains all remaining interventions that are executed with single night break closures without traffic disturbances, where still some economical dependencies apply.

Table 60. Group 1: Weekend closure of I – J in the period 2019-2022

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S18	Switch Replacement	8.0	255’000	509’117	320	Economical dependent
S19	Switch Replacement	8.0	214’200	508’144		
S21	Switch Replacement	8.0	214’200	508’144		
S23	Switch Replacement	8.0	214’200	508’144		

Table 61. Group 2: Single Night break closures without traffic disturbances in the period 2019-2022

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T18	Track Renewal	12.6	52’800	340’950	0	
T21	Rail Replacement	10.7	296’100	479’599		
T23	Rail Replacement	7.8	47’360	438’641		Economical dependent
T24	Rail Replacement	11.8	53’600	399’605		
T35	Rail Replacement	10.6	38’800	296’437		
T66	Rail Replacement	12.2	169’200	333’266		
T73	Track Renewal	56.6	183’300	327’806		Economical dependent
T74	Track Renewal	10.2	18’000	119’750		
T75	Track Renewal	11.1	37’600	61’876		
T77	Rail Replacement	3.6	1’330’100	2’140’063		
T90	Track Renewal	1.6	61’000	385’209		
T98	Track Renewal	9.0	208’680	433’998		Economical dependent
T99	Track Renewal	7.8	191’760	400’251		
T101	Track Renewal	16.9	397’150	638’285		

Group 3 (Table 62), group 4 (Table 63) and group 5 (Table 64) refer to groups of interventions in the period 2023-2026. Group 3 consists of switch replacements on *S7*, *S9*, *S10* and *S14* and rail replacements on track segments *T62* and *T65*. These interventions are executed with a weekend closure of E – J, which is partially extended to C – J for the replacement of *S7*, in period 2023-2026. The replacements of switch *S7* and *S9* as well as the replacements of switch *S10* and *S14* are economical dependent and reduce the intervention costs, i.e. owner costs, when being grouped. The grouping of all these interventions enable to make use of topological synergies, i.e. reduced user costs, due to the parallel execution of interventions. Groups 4 consists only of a switch replacement on *S3* executed with an extended night shift between A – C. Groups 5 contains all remaining interventions of period 2023-2026 that are executed in single night breaks without traffic disturbance.

Table 62. Group 3: Weekend closure of (C/E) – J in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S7	Switch Replacement	8.0	214’200	493’028	2’008	Economical dependent
S9	Switch Replacement	8.0	255’000	490’509		
S10	Switch Replacement	8.0	255’000	490’509		Economical dependent, parallel to S7 and S9
S14	Switch Replacement	8.0	214’200	489’521		
T62	Rail Replacement	10.9	54’400	216’168		Parallel to switch replacements
T65	Rail Replacement	4.5	22’400	74’844		

Table 63. Group 4: Extended night shift between A – C in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
S3	Switch Replacement	8.0	255’000.00	499’061	672	

Table 64. Group 5: Single Night break closures without traffic disturbances in the period 2023-2026

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T6	Rail Replacement	9.4	47’000	291’476	0	
T19	Rail Replacement	11.8	59’000	344’049		
T25	Rail Replacement	7.24	36’200	218’379		
T27	Rail Replacement	4.8	24’000	151’134		
T29	Track Renewal	39.4	925’900	1’314’295		
T57	Track Renewal	27.3	641’550	906’350		
T58	Rail Replacement	12.0	59’800	186’405		Economical dependent
T59	Rail Replacement	12.0	47’840	186’405		
T60	Rail Replacement	4.8	19’200	79’616		
T68	Rail Replacement	6.56	32’800	190’818		
T70	Rail Replacement	11.2	56’200	318’415		Economical dependent
T71	Rail Replacement	15.8	63’360	443’831		
T79	Rail Replacement	6	30’000	171’812		Economical dependent
T80	Rail Replacement	6.4	25’760	183’790		
T81	Rail Replacement	8.0	31’840	157’677		
T82	Rail Replacement	5.4	21’760	156’567		
T84	Rail Replacement	2.4	12’200	15’011		
T92	Track Renewal	18.1	37’600	600’234		Economical dependent
T93	Track Renewal	5.8	425’350	216’737		

Group 6 (Table 65), group 7 (Table 66) and group 8 (Table 67) refer to groups of interventions in period 2027-2030. Group 7 consists of only the renewal of track segment *T31*, which is executed with a single track closure in station *E* during the day. Group 7 consists of the renewal of bridge *B4* and its structural related track renewal on *T83* executed with a weekend closure of I – J. Group 8 consists of the remaining interventions of period 2027-2030 that are executed in single night breaks without traffic disturbances.

Table 65. Group 6: Single track day closure of in station E in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T31	Track Renewal	19.3	453'550	511'549	0	

Table 66. Group 7: Weekend closure of I – J in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
B4	Railway bridge renewal	15.0	120'000	209'246	624	T63 is structural dependant on B4
T83	Rail Replacement	0.6	14'100	7'338		

Table 67. Group 8: Single Night break closures without traffic disturbances in the period 2027-2030

Object	Intervention	Duration [h]	Owner cost [CHF]	Benefit [CHF]	User cost [CHF]	Comment
T8	Rail Replacement	4.2	20'800	59'086	0	
T12	Track Renewal	3.7	86'950	107'868		
T45	Track Renewal	9.7	227'950	223'978		Economical dependent, parallel to B3
T46	Track Renewal	16.0	300'800	368'108		
T47	Track Renewal	5.7	107'160	132'467		
T48	Track Renewal	1.1	20'680	27'229		
T49	Track Renewal	0.7	13'160	18'078		
T50	Track Renewal	17.6	330'880	404'712		
T67	Track Renewal	67.3	1'581'550	1'878'129		
T86	Rail Replacement	7.0	34'800	81'972		Parallel to B3
T88	Rail Replacement	9.0	45'200	105'476		

6.3 Part 3: Estimating the resilience of, and targets for, a transport system using expert opinion

This is a copy of the article submitted to the journal of infrastructure asset management. It is included here for completeness of the document. The article will be published as Open Access once it is accepted. The formatting in this appendix has been adapted to fit the required format of the deliverable.

6.3.1 Abstract

To ensure that transport infrastructure provides acceptable levels of service with respect to extreme events, the resilience of the infrastructure needs to be estimated and targets for it need to be set. Recent work in the European research project FORESEE- Future proofing strategies FOr RESilient transport networks against Extreme Events (Adey et al., 2020) has shown how this can be done in situations with a wide range of available data, a wide range of available time frames for the estimation, and a wide range of expertise available.

This paper gives an example of how an infrastructure manager can use the guideline to estimate the resilience of, and set resilience targets for, a transport system in a relatively short period of time, even in the case of limited expertise in all the relevant areas and limited knowledge and information on all the basic input variables. The example is fictive, but realistic. It is based on the transport system consisting of a section of the A16 highway, in Italy, where a potential landslide could discharge enough material to damage road sections and bridges. The resilience is estimated using resilience indicators with differentiated weights. The resilience targets are set using cost-benefit analysis.

6.3.2 Introduction

The functioning of society depends on the transportation of goods and persons. The infrastructure required to enable transportation is built to ensure that this can happen in specified ways, i.e. built to provide specified levels of service. As reductions in service due to natural hazards, e.g. floods, earthquakes, heavy snow falls, can have significant societal consequences, transport infrastructure managers have the mandate to minimise this risk, i.e. the probability of having consequences if a natural hazard occurs multiplied by the consequences if it occurs.

In order to do so, however, it is necessary for transport infrastructure managers to: (i) on the one side, have a clear idea of the service the infrastructure is providing and an understanding of its resilience, if it is affected by natural hazards, and (ii) on the other, to understand how the resilience of a network can be modified to counteract the loss of service following an hazard and to provide specified levels of service during and following the occurrence of extreme events, i.e. to set resilience targets.

A methodology to measure[5] the resilience of a transport infrastructure[6] with respect to a defined service, and set resilience targets have been proposed in the European research

[5] To measure - To assess the importance, effect or value of (something)

[6] Transport infrastructure is considered to be all infrastructure to enable travel, e.g. road infrastructure and rail infrastructure or combinations of both.

project FORESEE- Future proofing strategies FOr RESilient transport networks against Extreme Events (Adey et al., 2020).

Adey et al, 2020 define service as the ability to perform an activity in a certain way. This definition can be operationalised, for example, as the ability to transport from A to B the required goods and persons, within a specific amount of time, and for goods without being damaged, while for persons without being hurt or losing their lives. They define resilience as the ability to continue to provide service if a hazard event occurs. Resilience, with this definition, is measured, using each measure of service deemed relevant, in order to assess how service is being affected, and the cost of the interventions required to ensure that the infrastructure once again provides an adequate service. When considering natural hazards, resilience is therefore measured as the difference between: (i) the service provided by the infrastructure if no hazard event occurs and the service provided by the infrastructure if a hazard event occurs, and (ii) the costs of intervention if no hazard event occurs and the costs of interventions if a hazard event occurs.

Adey et al, 2020 consider it possible to set targets on the maximum decrease in service / increase in intervention costs from the beginning to the end of the hazard event, the service restoration time, the shape of the restoration curve and the total reduction in service / increase in intervention costs. The targets can be set simply using the opinions of experts or using cost-benefit analysis.

This article demonstrates how the guidelines presented in (Adey et. al, 2020) are to be used, using a fictive, but realistic example transport system based on the A16 highway, in Italy, which could be exposed to hazards causing severe landslides. The remaining of the article is organized as it follows. Section 6.3.3 contains a description of the hypothetical case study situation. Section 6.3.4 contains the definition of the transport system. Section 6.3.5, 6.3.6 and 6.3.7 contain explanations as to how service and resilience are measured. Section 6.3.8 contains an explanation as to how the resilience indicator targets are sets. Section 6.3.9 contains the conclusions.

6.3.3 Situation

The example is developed using a section of the highway A16. The Autostrada A16, is a highway connecting Napoli to Canosa, before merging with the A14 (Figure 37). The road is also known as "Autostrada dei Due Mari" (Motorway of the Two Seas) because it connects Napoli, on the Tyrrhenian coast, with Candela, on the Adriatic coast, playing a strategic role for the connectivity of the Country.

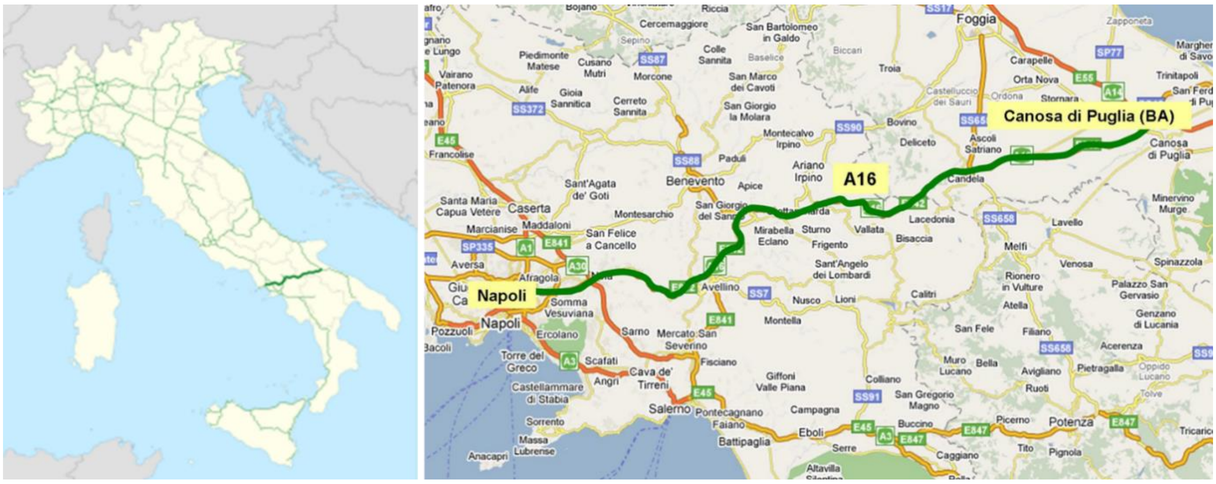


Figure 37 - Location and development of the A16 highway[7]

The highway passes through areas of a high geomorphological hazard zone which renders it subject to landslides of medium to severe intensity. It is considered, for the purpose of the paper, to focus on the 30.1 km section connecting Grottaminarda and Lacedonia. Moreover, it is assumed that the infrastructure manager has registered the hazard events occurred in the past and has realized from the records that the potential event that is associated to the most severe consequences is a landslide of a magnitude of up to 19.3 kN/m, which occurs with a frequency of 1/20 years[8].

In light of the importance of such an event, the infrastructure manager wishes to estimate the resilience of the transport system for the interested section with respect to a landslide of this magnitude, and set resilience targets to optimally balance the cost of preventive interventions and increasing resilience. The three measures of service to be used are the travel time, safety, and the socio-economic impact of people and goods not being able to travel. The infrastructure manager, in addition to the many different activities carried out to provide the required service, are assumed to takes care of surveillance and maintenance of the infrastructure, as well as the planning and exercise of the emergency plans in case a hazard occurs.

According to Adey et al., 2020, for this paper, it is considered that the infrastructure manager has decided to a) estimate the resilience of the transport infrastructure using indicators with differentiated weights, and, b) set resilience indicator targets with cost benefit analysis. The decisions are motivated by the fact that:

- given the dimension of the infrastructure and the complexity of the service considered, it would be computationally too intense to estimate the resilience using simulations.
- using indicators the infrastructure manager wishes to estimate the resilience with the highest possible accuracy, therefore the effort will be made to use the differentiated

[7] Source: https://it.wikipedia.org/wiki/Autostrada_A16_(Italia)

[8] It is to be noticed that both the intensity and the frequency of the event here considered are invented by the authors in order to define a precise hazard, against which measuring the resilience. As such, the event is fictive and does not reflect the real situation of the highway.

weights, i.e. an individual weight will be defined for each indicator to express the impact that each indicator has on each service considered.
- the infrastructure manager wants to set the targets based on a general idea of what might be the optimal balance between costs and benefits.

6.3.4 Transport system

Before the service provided by, and the resilience of, the transport infrastructure are measured and the targets set, it is necessary to define the parts of the transport system to be considered. The transport system is considered to have three main components, namely

1. the infrastructure, i.e. the physical assets that are required to provide the service,
2. the environment, i.e. the physical environment in which the infrastructure is embedded that might affect the provision of service, and the organisational environment in which the infrastructure management organisation is embedded that might affect the provision of service, and,
3. the organization, i.e. the organisation(s) responsible for ensuring that the infrastructure provides service.

Infrastructure

The A16 has a total length of 172'300 km that mainly consists of double-lane road sections, which are predominately on the ground, but occasionally, due to the conformation of the valley, on viaducts and in tunnels (Figure 38). The portion of the A16 analyzed in this work is the section connecting Grottaminarda and Lacedonia. The main physical characteristics of the transport infrastructure are listed in Table 68.

Figure 38. Images of the double-lines road A16 highway[9]

Table 68. Proposed infrastructure characteristics (the data are invented by the authors and does not reflect the actual situation of the infrastructure)

Inputs [units]	Symbol	Value
Length of the infrastructure [m]	Li	30'100
Average width of the infrastructure [m]	$Width$	21
Average height of the infrastructure [m]	$High$	0-3
Average condition of the infrastructure	CS	CS2-Very good

[9] Source: https://www.quotidianomotori.com/sicurezza-stradale/a16-napoli-canosa-chiusura-notturna-e-regolamentazione-del-traffico/

The infrastructure - i.e. the road sections, viaducts and tunnels - is characterized by some features that influence positively and some negatively the resilience of the transport system. Some features are assumed that positively contribute to resilience include:

- The infrastructure is on average in very good condition as well as the slopes around it, that have been designed to comply with the slope stability design code.
- The highway is equipped with warning systems both fixed (road signs) and dynamic (digital signs) used to warn drivers of the presence of landslides, which are in relatively good condition, and of protective structures, i.e. barriers to prevent landslides to hit the road.
- There are existing ways to deviate vehicles, as well as the possibility of using another means of transport, to satisfy transport demand, in case the traffic on the highway is interrupted, i.e. as an alternative to the A16.
- In case a landslide occurs, there are emergency measures to help evacuate people trapped on bridges and tunnels.

To negatively influence resilience, some features are assumed as follows:

- Despite its very good condition, the infrastructure is not designed to withstand all landslide events without consequences. It is, indeed, expected that following the reference landslide both the infrastructure and the protection barriers will be out of service and in need of rehabilitation.
- There are currently neither alert systems, i.e. systems able to detect signals of landslides through environmental monitoring, nor safe shut down systems, i.e. systems able to trigger an immediate blockage of road as soon as a landslide starts.
- In the most part of the chosen section, there are no possibilities to build any nearby temporary alternative route for vehicles in case a landslide damages the highway.

Environment

The A16 covers a diversified set environmental conditions that range from a flatter landscape at the two ends and a green hilly - and even mountainous - one in the central part. The soil along the highway is mainly characterized by a clay-sand component (low permeability), with rare calcareous or lithoid intercalations. In 2005, the section crossing Lacedonia - next to Avellino - has been hit by a landslide that has moved the road embankment at the km 122.5, forcing the closure of the road for several days. During those days traffic was diverted in Grottaminarda.

It is assumed that a landslide of the reference magnitude has occurred in the past with a frequency of circa 1/20 years and it is consider plausible that: (i) it will have a similar frequency in future, and (ii) that it may affect other sections of the highway. The risk on traffic and on the safety due to these events is not negligible, as there is a relatively large traffic flow on the highway. The main physical and traffic characteristics of the environment are listed in Table 69.

Table 69. Proposed environment characteristics (the data are invented by the authors and does not reflect the actual situation of the infrastructure)

Type	Inputs	Symbol	Landslide [_l]
Physical	Landslides severity [m/s]	Ls	20
	Landslides frequency	Lf	1/20 years
	Soil type	*Soil*	Clay and sand
	Expected amount of material to hit the infrastructure [m^2]	Eam	700
	Expected force with which it will hit the infrastructure [kN/m3] - dry and saturated	Efm	15.3 - 19.3
Traffic	Speed limit (average among weather conditions) [km/h]	Sl	120
	No. of people traveling per day	P	5’000
	No. of people traveling for work in a day	Pw	3’000
	No. of people traveling for leisure in a day	Pl	2’000
	Amount of goods travelling per day [trucks]	G	1’000
	Vehicle transporting dangerous goods [% of the total trucks]	$TRdg$	5

Organization

The route is managed by an infrastructure manager that, among the many different activities carried out to provide the service required, takes care of surveillance and maintenance of the infrastructure. The activities performed by the infrastructure manager include conducting periodic monitoring of the condition states, executing maintenance when required, ensuring the functioning of emergency plans to react to hazard events and, when needed, preparing and managing tendering procedures for the extra-ordinary interventions, e.g. after the event the section has been completely rebuilt with a double-curved variant, due to the difficulty in restoring the damaged viaduct. The main physical characteristics of the organization are listed in Table 70.

Table 70 – Proposed organisation characteristics (the data are invented by the authors and does not reflect the actual situation of the infrastructure)

Inputs	Symbol	Value
Annual cost of regular maintenance [€/m]	Cm	0.06
Days to recover in case of the reference landslide	D	9
Cost of intervention after the reference landslide [€/m]	Ci	400
Restoration plans	-	Existing
Average time required for the submission of tenders to repair damaged infrastructure*	Tt	1 year

* The time to tender refers to the required time for selecting the tender to undergo major interventions that cannot be held by the infrastructure manager himself (e.g. the reconstruction of a bridge). It is to be noticed that this does not refers to the time the infrastructure is out of service, which is instead given by the parameter *D*.

6.3.5 Measures of service

The service provided by the transport system is measured as the ability of road users to travel from Grottaminarda to Lacedonia on the A16 highway within a specific amount of time (travel time) and without having their property damaged or being hurt or losing their lives (safety), and the inhabitants of the area to be able to ship and have shipped goods on the highway (socio-economic activities).

The service provided by the infrastructure (in absence of any landslide) is measured as shown in Table 71, where in the last column it is shown how the annual service is estimated, using inputs on the infrastructure, environment and organization (Table 68-4) and the variables affecting the service (Table 72). Table 71 should be read as follows: the measure of travel time (€18’068’000) is estimated as the amount of minutes a vehicle spend on average on the road, which is computed as the ratio of length of the infrastructure in km (Li = 30’100/1’000) and the speed limit (Sl = 120km/h) and converted in minutes (i.e. multiplied by 60 min/h), multiplied by the cost of that time for the users in one year, estimates as the sum of the average number of people traveling for work in a day (Pw = 3’000) for the cost of work time (Cwt = 0.9 €/min) and the average number of people traveling for leisure in a day (Pl = 2’000) for the cost of leisure time (Clt = 0.3 €/min), for 365 days. This number is used as reference number to measure deviations that are caused due to the reference landslide. It is not a measure of the value of the road. The formulas to estimate the costs for safety and socio-economic activities reported in Table 71 follow a similar logic. In total the measures of service have a value of 24.6 million €.

Table 71. Measure of the service provided in one year assuming there is no landslide

Type of service	**Measure**	**Annual estimate [10^3€]**	**Estimated as**
Travel time (Stt)	the travel time for all the people travelling between on the viaduct	18’068	$\left(\left(\left(\frac{\left(\frac{L_i}{1'000}\right)}{(S_l)} \cdot 60\right) . \left((P_w . C_{wt}) + (P_l . C_{lt})\right)\right) . 365\right)$
Safety (Ss)	the cost of repairing damaged property, the number of injuries and deaths due to people travelling on the viaduct	941	$\left(\left(\left(\left(\frac{Pdp_0}{100}\right) . P . PDp_0\right) + \left(\left(\frac{Pi_0}{100}\right) . P . Ip\right) + \left(\left(\frac{Pd_0}{100}\right) . P . Dp\right)\right) . 365\right)$
Socio economic activities (Ssc)	The socio-economic activity facilitated by persons and goods travelling.	5’475	$\left(\left((P . Dpud_0 . SEC_p) + (G . Dpud_0 . SEC_g)\right) . 365\right)$
Total		24’543	$(Stt + Ss + Ssc)$

Table 72. Assumed values of variables used to measure service (the data are invented by the authors and does not reflect the actual situation of the infrastructure)

Variable	**Symbol**	**Value**
Daily injury probability assuming no landslide [%]	Pi_0	0.15
Daily death probability assuming no landslide [%]	Pd_0	0.01
Daily property damage probability assuming no landslide [%]	Pdp_0	0.15
Delay per unit (person or truck) per day assuming no landslide [min/p.u.]	$Dpud_0$	6
Property damage per person in case of no accident [10^3€/p.p.]	PDp_0	0.5
Socio economic costs per person, i.e. the cost of one minute delay of one passenger to the wither society [€/min/p.p.]	SEC_p	0.1
Socio economic costs for goods, i.e. the cost of one minute delay of one truck to the wither society [€/min/truck]	SEC_g	2
Impact of injuries per person [10^3€/p.p.]	Ip	10
Impact of death per person [10^3€/p.p.]	Dp	5’000
Cost of work time [€/min]	Cwt	0.9
Cost of leisure time [€/min]	Clt	0.3

6.3.6 Resilience indicators

The infrastructure manager determined that there were 42 relevant indicators for the example transport system and defined their possible ranges of values (Table 73 - Table 75). The indicators were selected to give an indication of the difference between the intervention costs and the service provided if no landslides occurs and if the reference landslide occurs, from the start of the landslide to the time when service is again provided at the level it was before the landslide. The indicators were grouped at the highest level as infrastructure, environment or organization indicators.

Infrastructure indicators (Table 73) are considered those related to the physical man-made parts of the transport system. They consisted of condition state, protective measure, and preventive measure indicators. Protective measure indicators pertained to how well the physical man-made parts of the transport system can protect the infrastructure providing the service. Preventive measure indicators pertained to how well the physical man-made parts of the transport system can withstand the reference hazard. Condition indicators pertained to how well the physical man-made parts of the transport system can provide the service it was originally designed to provide.

Environment indicators (Table 74) were those related to the physical natural parts, and the non-physical man-made parts of the transport system. An example of the former is the exposure to hazards. An example of the latter would be the available budget.

Organisation indicators (Table 75) are those related to non-physical man-made parts of the transport system, i.e. the activities of the organisation managing the infrastructure. They consisted of pre-event and post-event activities indicators, whereas pre-event and post-event referred to the start of the landslide.

The values of all indicators were taken as averages for the entire 30 km road section, and were thought of only in general terms (Table 73 - Table 75). For example, the condition of the infrastructure was expressed as an average of the condition states of all objects that comprise the A16. If desired, the condition state of each category of objects (e.g. road sections, bridges and tunnels), could be treated separately. For example, if the age of the warning system (1.3.1) along the A16 highway is on average 10 years, and its expected lifetime is 25 years, the indicator value is 2. The relevancy check was used to identify if intervention costs and each measure of service were affected by variation in the values of each indicator. For example, the presence of an emergency plan, has no effect on the safety measure of service, but it does on the travel time measure of service.

Table 73. Proposed infrastructure resilience indicators (part 1)

Type	ID	Indicator	Possible values (the current value is underlined)
Protective measure	1.1.1	The possibility of building a temporary alternative route for vehicles, reduces the consequences on infrastructure users.	0 - No alternative path; 1 – 1 alternative path; 2 - Multiple alternative paths
	1.1.2	The possibility of using another means to satisfy transport demand - reduces the consequences of an infrastructure being out of service.	0 - No alternative means; 1 – 1 alternative mean; 2 - Multiple alternative means
	1.1.3	The number of possible existing alternative ways to deviate vehicles reduces the consequences of an infrastructure being out of service.	0 - No alternative ways; 1 - 1 alternative way; 2 - Multiple alternative ways
	1.1.4	The presence of a warning system allows users to bypass a road section in case of danger, which reduces the consequences of a landslide.	0 - No warning systems; 1 - 1 warning system; 2 - Multiple warning systems
	1.1.5	The presence of a safe shutdown system to prevent users from using a damaged road section reduces the consequences of a landslide	0 - No safe shut down system; 1 - 1 safe shut down system;
	1.1.6	The presence of emergency / evacuation paths allows users to escape in case of danger, which reduces the consequence of a landslide	0 - No emergency path; 1 - 1 emergency path; 2 - Multiple emergency paths
	1.1.7	The presence of special measures to help evacuate persons (e.g. helicopter) allows users to escape in case of danger, reduces the consequence of a landslide.	0 - No extraordinary measures; 1 - 1 extraordinary measure; 2 - Multiple extraordinary measures
Preventive measure	1.2.1	Compliance with the current slope stability design code, increases the likelihood that no landslide will occur and if it does decreases the extent of the landslide.	0 - Below current regulation, e.g. designed according to an older design; 1 - According to current regulation; 2 - Above current regulation
	1.2.2	The presence of protection barriers prevents the infra. From being hit	0 - No protection; 1 - Protection
	1.2.3	The adequacy of protection barriers (e.g. adequately dimensioned and located) prevent the road section from being hit by a landslide.	0 - Not adequate; 1 - Adequate

Table 73. Proposed infrastructure resilience indicators (part 2)

Type	ID	Indicator	Possible values (the current value is underlined)
Condition	1.3.1	The age / age of replacement of the warning system affects the probability of accidents due to a lack of signalling in case of a landslide.	0 - > 80% of min. service life achieved; 1 - > 50%,< 80% of min. service life achieved; 2 - > 20%,< 50% of min. service life achieved; 3 - < 20% of min. service life achieved
	1.3.2	The condition of the infrastructure providing service affects the probability of the infrastructure being damaged in a landslide	0 - highly likely to collapse; 1 - No information is available; 2 - moderately likely to collapse; 3 - unlikely to collapse; 4 - very unlikely to collapse; 5 - extremely unlikely to collapse.
	1.3.3	The condition of protection barriers affects the probability that they can provide the level of service for which it was designed during and following the occurrence of a landslide and the harder to repair it if damaged in a landslide.	0 - highly likely to collapse; 1 - No information is available; 2 - moderately likely to collapse; 3 - unlikely to collapse; 4 - very unlikely to collapse; 5 - extremely unlikely to collapse.
	1.3.4	The condition of the assistance alert systems affects the probability that it can provide the level of service for which it was designed during and following the occurrence of a landslides and the harder to repair it if damaged in a landslide	0 - highly likely to collapse under normal traffic loads; 1 - No information is available; 2 - moderately likely to collapse under normal traffic loads; 3 - unlikely to collapse under normal traffic loads; 4 - very unlikely to collapse under normal traffic loads; 5 - extremely unlikely to collapse
	1.3.5	The expected condition of infrastructure providing service after a landslide affects its ease of repair.	0 - Collapsed, requires rebuilding; 1 - Out of service, requires repair/rebuilding; 2 - In service but repairs are necessary; 3 - In service and no repairs necessary
	1.3.6	The expected condition of the protective barriers after a landslide affects the likelihood that they will not function as intended after a landslide.	0 - Collapsed, requires rebuilding; 1 - Out of service, requires repair/rebuilding; 2 - In service but repairs are necessary; 3 - In service and no repairs necessary
	1.3.7	The expected condition of assistance alert systems after a landslide, affects the likelihood that they will not function as intended after a landslide	0 - Out of service, requires repair/rebuilding; 1 - In service but repairs are necessary; 2 - In service and no repairs necessary

Table 74. Proposed environment resilience indicators

Type	ID	Indicator	Possible values (the current values are underlined)
Physical	2.1.1	The height of the infrastructure providing service affects the consequences of an accident	0 - > 3 meters; 1 - < 3 meters; 2 - At the same level
	2.1.2	The accessibility of the infrastructure affects the ability and time required to restore it	0 - Accessible with telescopic crane; 1 - Accessible with truck mounted crane; 2 - Accessible with steps; 3 - Accessible without equipment
	2.1.3	The presence of persons/property below the infrastructure affects the consequences if a landslide occurs	0 - Yes; 1 - No
	2.1.4	The extent of past damages due to landslides indicates the likelihood of future damages	0 - Collapse; 1 - Serious damage; 2 - Minor damage; 3 - Aesthetic damages
	2.1.5	The hazard zone affects the likelihood of future landslides	0 - High; 1 - Medium; 2 - Low
	2.1.6	The frequency of past landslides affects the likelihood of future landslides	0 - Location in a <1-year landslide zone; 1 - Location in a >1, <5-years Landslide Zone; 2 - Location in a >5, <15-years Landslide Zone; 3 - Location in a >15-years Landslide Zone
	2.1.7	The severity of past landslides affects the probability of restoration interventions / service interruptions	0 - Collapse; 1 - Serious damage; 2 - Minor damage; 3 - Aesthetic damages
	2.1.8	The expected frequency of future landslides affects the probability of restoration interventions / service interruptions	0 - Location in a <1-year landslide zone; 1 - Location in a >1, <5-years Landslide Zone; 2 - Location in a >5, <15-years Landslide Zone; 3 - Location in a >15-years Landslide Zone
	2.1.9	The expected severity of future landslides affects the probability of restoration interventions / service interruptions	0 - Strong increase; 1 - Soft increase; 2 - Soft decrease; 3 - Strong decrease
	2.1.10	The land type affect the likelihood of future landslides and the probability of restoration interventions / service interruptions	0 - Rock mass; 1 - Clayey; 2 - Loose rocks; 3 - Sandy
	2.1.11	The terrain type affects the likelihood of future landslides and the probability of restoration interventions / service interruptions	0 - Rugged; 1 - Hilly; 2 - Flat
	2.1.12	The extent of vegetation affects the likelihood of future landslides and the probability of restoration interventions / service interruptions	0 - Limited; 1 - Light; 2 - Middle; 3 - Dense
	2.1.13	The amount of traffic affects the consequences of a landslide	0 - >80% of capacity; 1 - >50%,<80% of capacity; 2 - >20%,<50% of capacity; 3 - <20% of capacity
	2.1.14	The amount of hazardous goods traffic affects the consequences of an accident	0 - Frequent dangerous goods; 1 - Rare dangerous goods; 2 - No dangerous goods
	2.1.15	The amount of flammable goods traffic affects the consequences of an accident	0 - Yes; 1 - No
Non-physical	2.2.1	The budget availability affects the likelihood that speed of restoration	0 - Enough for <50% of the interventions; 1 - Enough for >50%,<100% of the interventions; 2 - Enough for >100% of the interventions

Table 75. Proposed organisation resilience indicators

Type	ID	Indicator	Possible values
pre-event activities	3.1.1	The presence of a monitoring strategy raises the awareness of the state of the road and is likely to increase their preparedness to react when necessary	0 - No condition monitoring; 1 - Periodic condition monitoring; 2 - Constant condition monitoring
	3.1.2	The presence of a maintenance strategy increases the likelihood that the infrastructure will be in a condition to resist a landslide	0 - No intervention strategy; 1 - Only responsive interventions conducted; 2 - Preventive interventions strategies is conducted
	3.1.3	The extent of interventions executed prior to the landslide affects the likelihood that the infrastructure will be in a condition to resist a landslide	0 - <50% of the benchmark budget; 1 - >50%,<80% of the benchmark budget; 2 - > 80% of the benchmark budget
post-event activities	3.2.1	The presence of an emergency plan reduces the time between the occurrence of a landslide and the moment a manager reacts.	0 - No plan; 1 - Generic plan; 2 - Operative plan (with tasks, resources, ...)
	3.2.2	The practicing of the emergency plan affects the ability of the manager to use it when needed, reducing the time for execution.	0 - No exercise; 1 - 1 exercise every > than 2 years; 2 - 1 exercise every 2 years; 3 - 1 exercise every year; 4 - 1 exercise every 6 months
	3.2.3	The time since the last review/update of the emergency plan affects the likelihood that it will be fit for purpose	0 - >5 years ago; 1 - <2 years ago; 2 - <5 years ago
	3.2.4	The expected time for tendering affects the time required to restore service	0 - > 1 year; 1 - > 8 months and < 1 year; 2 - > 4 months and < 8 months; 3 - < 4 month
	3.2.5	The expected time for demolition of damaged infrastructure affects the time required to restore service	0 - > 1 year; 1 - > 8 months and < 1 year; 2 - > 4 months and < 8 months; 3 - < 4 month
	3.2.6	The expected time for construction affects the time required to restore service	0 - > 1.5 year; 1 - > 1 year and < 1.5 year; 2 - > 6months and < 1 year; 3 - < 6 month

6.3.7 Resilience

6.3.7.1 Estimation

The measures of resilience used were the cumulative differences in interventions costs and the reductions in service if each indicator had its worst and current values. This was determined by first estimating the maximum restoration intervention costs and reductions in service (Table 76) considering the transport system characteristics (Table 68 - Table 70), and the additional assumptions listed in Table 77, and then the expected intervention costs and reductions in measures of service if each indicator had worst possible value (Table 78). An example of the former is the maximum reduction in the travel time for work measure of service (€2.4 million), which is estimated by multiplying the number of workers traveling per day (3’000), by the average delay per person per day (100 minutes), by the cost of working time (0.9 €/min) by the average number of days in which the traffic is delayed due to the restoration interventions (9). An example of the latter is that the value of the safety measure of service between the age of warning system indicator (1.3.1) having its worst value is €14.6 million, which is 26% of the maximum expected reductions in safety if all indicators have their worst possible values, i.e. €54 million. The total measure of resilience is €70 million. The age of the warning system is expected to have no effect on the restoration intervention costs or on the travel time measure of service.

Table 76. Maximum expected restoration intervention costs and reductions in service

Intervention costs / Measure of service	Description	Costs [10^3€]		
		Estimate	Equation	Estimate
Intervention costs (Ii)	The impact of executing restoration interventions	12'040	$(Ci \cdot Li)$	12'040
Travel time (Itt)	The impact of travel condition in terms of time lost the impact of travel condition on the vehicle cost for work and leisure	**2'430**	$(Pw \cdot Dpud \cdot Cwt \cdot D)$	2'970
		540	$(Pw \cdot Dpud \cdot Clt \cdot D)$	
Safety (Is)	The impact due to the user being involved in an accident divided by property damage, injury, deaths	3'000	$\left(\left(\frac{Ppd}{100}\right) \cdot PDp \cdot P\right)$	**54'000**
		1'000	$\left(\left(\frac{Ppd}{100}\right) \cdot Ip \cdot P\right)$	
		50'000	$\left(\left(\frac{Ppd}{100}\right) \cdot Dpp \cdot P\right)$	
Socio-economic activities (Ise)	The impact of people and goods not being able to travel	450	$(P \cdot Dpud \cdot D \cdot SECp)$	1'260
		810	$(G \cdot Dpud \cdot D \cdot SECg)$	
Total		70'270	$(Ii + Itt + Is + Ise)$	**70'270**

Table 77. Assumptions required to estimate how service would be affected by the reference landslide (the data are invented by the authors and does not reflect the actual situation of the infrastructure)

Variable	Symbol	Value
Delay per unit (person or truck) per day after the reference landslide [min/p.u.]	$Dpud$	100
Injury probability given occurrence of the reference landslide [%]	Pi	2
Death probability given occurrence of the reference landslide [%]	Pd	0.2
Property damage probability given occurrence of the reference landslide [%]	Ppd	30
Property damage per person in case of accident [103€/p.p.]	PDp	2

Table 78. Expected intervention costs and reductions in measures of service if each indicator had worst possible value (part 1)

Indicator	Costs and reductions in service [10^3€]					Weight total[1]
	Inter. costs	Measures of service			Total	
		Travel time	Safety	Socio-econ.		
1.1.1 - The possibility of building a temporary alternative route for vehicles	-	1'931	-	819	2'750	65%
1.1.2 - The possibility of using another means to satisfy transport demand	-	2'079	-	882	2'961	70%
1.1.3 - The number of possible existing alternative ways to deviate vehicles	-	1'149	-	488	1'637	39%
1.1.4 - The presence of a warning system	-	2'138	-	907	3'046	72%
1.1.5 - The presence of a safe shutdown system	-	1'961	-	832	2'792	66%
1.1.6 - The presence of emergency / evacuation paths	-	1'040	-	441	1'481	35%
1.1.7 - The presence of special measures to help evacuate persons	-	802	-	340	1'142	27%
1.2.1 - Compliance with the current slope stability design code,	8'910	2'198	39'960	932	52'000	74%
1.2.2 - The presence of protection barriers	10'118	2'496	45'381	1'059	59'054	84%
1.2.3 - The adequacy of protection barriers	7'465	1'841	33'480	781	43'567	62%
1.3.1 - The age / age of replacement of the warning system	-	-	14'273	333	14'606	26%
1.3.2 - The condition of the infrastructure providing service	12'040	2'970	54'000	1'260	70'270	100%
1.3.3 - The condition of protection barriers	9'391	2'317	42'120	983	54'811	78%
1.3.4 - The condition of the assistance alert systems	2'190	540	9'824	229	12'783	18%
1.3.5 - The expected condition of infrastructure	11'799	2'911	52'920	1'235	68'865	98%
1.3.6 - The expected condition of the protective barriers	7'585	1'871	34'020	794	44'270	63%
1.3.7 - The expected condition of assistance alert systems	690	170	3'095	72	4'028	6%
2.1.1 - The height of the infrastructure	-	-	14'925	-	14'925	28%
2.1.2 - The accessibility of the infrastructure	3'367	-	-	-	3'367	28%
2.1.3 - The presence of persons/property below the infrastructure	-	-	44'280	-	44'280	82%
2.1.4 - The extent of past damages	6'104	-	-	-	6'104	51%
2.1.5 - The hazard zone	9'632	2'376	43'200	1'008	56'216	80%
2.1.6 - The frequency of past landslides	-	1'735	31'552	736	34'024	58%
2.1.7 - The severity of past landslides	-	1'723	31'320	731	33'773	58%
2.1.8 - The expected frequency of future landslides	-	2'228	40'500	945	43'673	75%
2.1.9 - The expected severity of future landslides	-	2'228	40'500	945	43'673	75%
2.1.10 - The land type	4'236	-	18'998	-	23'234	35%
2.1.11 - The terrain type	3'251	802	14'580	340	18'973	27%
2.1.12 - The extent of vegetation	722	178	3'240	76	4'216	6%
2.1.14 - The amount of traffic	10'170	2'509	45'612	1'064	59'355	84%
2.1.15 - The amount of hazardous goods traffic	-	-	17'280	-	17'280	32%
2.1.16 - The amount of flammable goods traffic affects	-	-	14'252	-	14'252	26%
2.2.1 - The budget availability	6'863	1'693	30'780	718	40'054	57%
3.1.1 - The presence of a monitoring strategy	1'588	392	7'121	166	9'267	13%

Table 78. Expected intervention costs and reductions in measures of service if each indicator had worst possible value (part 2)

Indicator	Costs and reductions in service [10³€]					Weight total[1]
	Inter. costs	Measures of service			Total	
		Travel time	Safety	Socio-econ.		
3.1.2 - The presence of a maintenance strategy	5'687	1'403	25'508	595	33'193	47%
3.1.3 - The extent of interventions executed prior to the landslide	9'693	2'391	43'475	1'014	56'574	81%
3.2.1 - The presence of an emergency plan	-	2'020	-	857	2'876	68%
3.2.2 - The practicing of the emergency plan affects the ability of the manager to use it when needed, reducing the time for execution.	-	936	-	397	1'333	32%
3.2.3 - The time since the last review/update of the emergency plan affects the likelihood that it will be fit for purpose	-	743	13'500	315	14'558	25%
3.2.4 - The expected time for tendering	5'418	1'337	-	567	7'322	45%
3.2.5 - The expected time for demolition of damaged infrastructure	3'251	802	-	340	4'393	27%
3.2.6 - The expected time for construction	4'575	1'129	-	479	6'183	38%

[1] The expected intervention costs and reductions of service due to the indicator having its current values / the maximum expected intervention costs and reductions of service multiplied by 100.

6.3.7.2 Measures of resilience per indicator

The measures of resilience per indicator were computed as the expected intervention costs and reductions in the measures of service taking into consideration the value of the indicator (Table 73 -Table 75, and Table 78). They are shown in Figure 39, 4 and 5 for all indicators. The exact numbers are shown for a subset of these in Table 79 in terms of both the maximum possible value, the actual expected value and the difference between the two. The figures show, for example, that the measures of resilience of the condition of the infrastructure (1.3.2) in terms of intervention costs, and the travel time, safety and socio-economic measures of services using the worst indicator value (0/5), i.e. the Max measures, are €12, €3, €54 and €1.3 million, and using the actual indicator value (4/5), are €2.4, €0.6, €10.8 and €0.25 million. The former of these values mean that if the condition of the infrastructure indicator had its worst possible values the consequences of the reference landslide would be €12 million in restoration interventions, €3 million in additional travel time, €54 million in terms of injuries and fatalities, and €1.3 million for the regional economy. The latter of these values mean that in the actual situation, the consequences of the reference landslide would be €2.4 million in restoration interventions, €0.6 million in additional travel time, €10.8 million in terms of injuries and fatalities, and €0.25 million for the regional economy. The maximum and actual values of the measures of resilience of the condition indicator in terms of the intervention costs and all measures of service are €269.6 and €120.2 million respectively.

Table 79. Infrastructure: Measures of resilience per condition indicator (1.3)

Indicator	Item	Measures of resilience (10^3€)				
		Intervention cost	Reductions in service			Total
			Travel time	Safety	Socio-econ.	
1.3.1 - The age / age of replacement of the warning system	Max	Not relevant	Not relevant	14'273	333	14'606
	Actual			4'758	111	4'869
	Difference			9'515	222	9'737
1.3.2 - The condition of the infrastructure providing service	**Max**	**12'040**	**2'970**	**54'000**	**1'260**	**70'270**
	Actual	**2'408**	**594**	**10'800**	**252**	**14'054**
	Difference	**9'632**	**2'376**	**43'200**	**1'008**	**56'216**
1.3.3 - The condition of protection barriers	Max	9'391	2'317	42'120	983	54'811
	Actual	5'635	1'390	25'272	590	32'886
	Difference	3'756	927	16'848	393	21'924
1.3.4 - The condition of the assistance alert systems	Max	2'190	540	9'824	229	12'783
	Actual	1'314	324	5'894	138	7'670
	Difference	876	216	3'929	92	5'113
1.3.5 - The expected condition of infrastructure	Max	11'799	2'911	52'920	1'235	68'865
	Actual	7'866	1'940	35'280	823	45'910
	Difference	3'933	970	17'640	412	22'955
1.3.6 - The expected condition of the protective barriers	Max	7'585	1'871	34'020	794	44'270
	Actual	2'528	624	11'340	265	14'757
	Difference	5'057	1'247	22'680	529	29'513
1.3.7 - The expected condition of assistance alert systems	Max	690	170	3'095	72	4'028
	Actual	0	0	0	0	0
	Difference	690	170	3'095	72	4'028
Total	Max	43'696	10'779	210'252	4'906	269'633
	Actual	19'751	4'872	93'344	2'178	120'146
	Difference	23'945	5'907	116'908	2'728	149'487

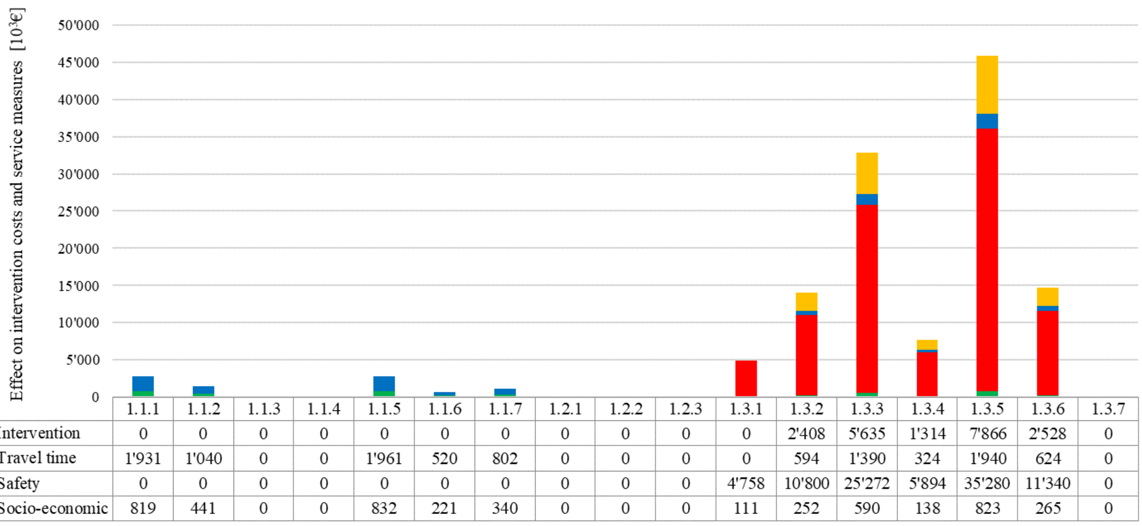
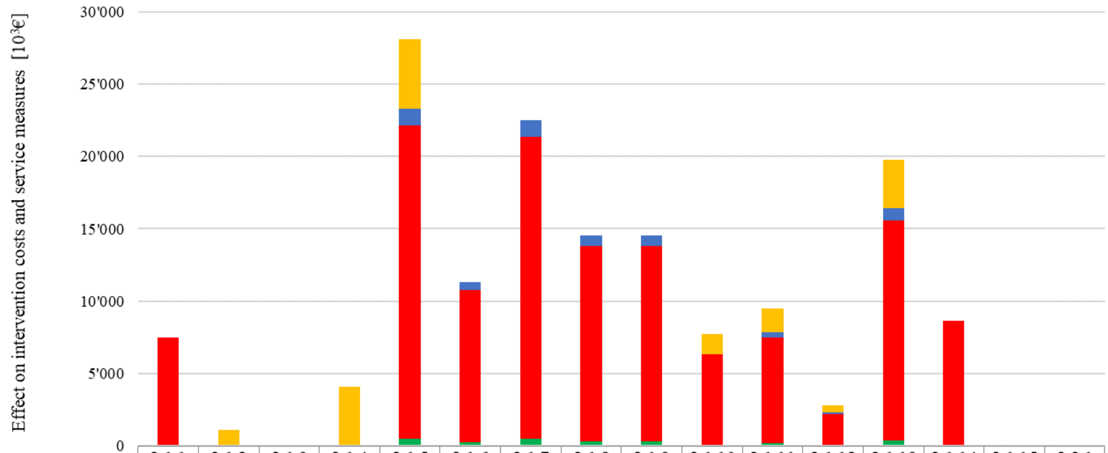
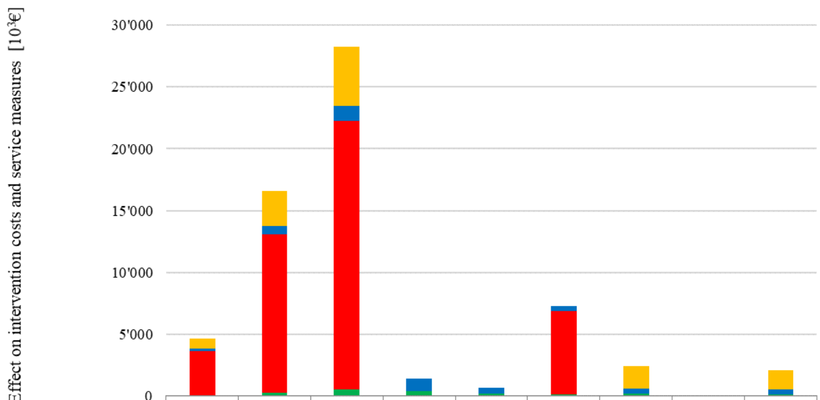


Figure 39. Infrastructure: Measures of resilience for each indicator, using the actual value of all indicators, by intervention costs and each measure of service



	2.1.1	2.1.2	2.1.3	2.1.4	2.1.5	2.1.6	2.1.7	2.1.8	2.1.9	2.1.10	2.1.11	2.1.12	2.1.13	2.1.14	2.1.15	2.2.1
Intervention	0	1'122	0	4'069	4'816	0	0	0	0	1'412	1'625	482	3'390	0	0	0
Travel time	0	0	0	0	1'188	578	1'148	743	743	0	401	119	836	0	0	0
Safety	7'462	0	0	0	21'600	10'517	20'880	13'500	13'500	6'333	7'290	2'160	15'204	8'640	0	0
Socio-Economic	0	0	0	0	504	245	487	315	315	0	170	50	355	0	0	0

Figure 40. Environment: Measures of resilience for each indicator, using the actual value of all indicators, by intervention costs and each measure of service



	3.1.1	3.1.2	3.1.3	3.2.1	3.2.2	3.2.3	3.2.4	3.2.5	3.2.6
Intervention	794	2'844	4'847	0	0	0	1'806	0	1'525
Travel time	196	701	1'196	1'010	468	371	446	0	376
Safety	3'561	12'754	21'738	0	0	6'750	0	0	0
Socio-Economic	83	298	507	428	199	158	189	0	160

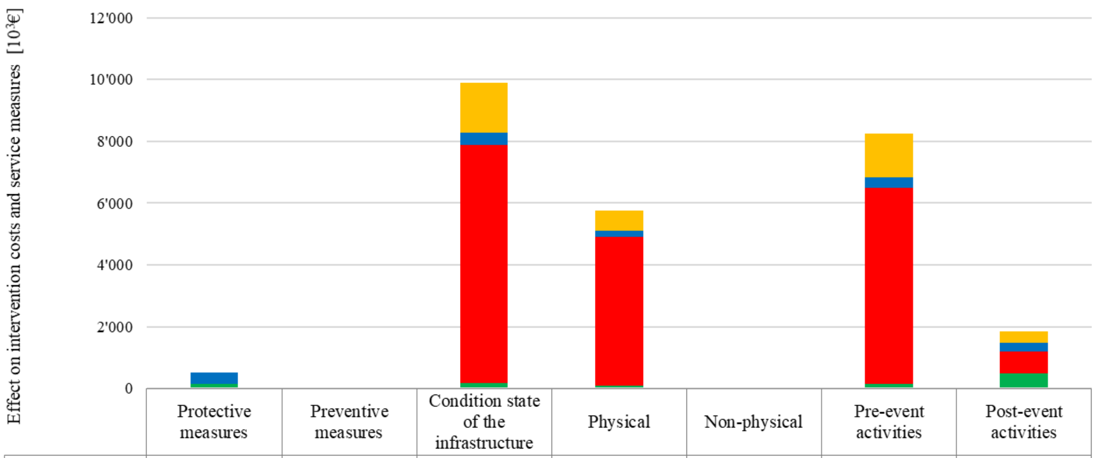
Figure 41. Organisation: Measures of resilience for each indicator, using the actual value of all indicators, by intervention costs and each measure of service

Estimating the measures of resilience for intervention costs and each measure of service in this manner, provides an infrastructure manager with an idea of which of these is the most problematic and where to focus efforts on improving resilience.

It can be seen from the measures of resilience shown in this section, for example, that the safety measure of service is significantly more important than intervention costs, and the travel time and socio-economic measures of service. The safety measure of service accounts for 93% of the measure of resilience for the indicators frequency of future hazards (2.1.8) and severity of future hazards (2.1.9) and 100% for the height of the infrastructure indicator (2.1.1). It can also be seen that the largest potential for improvement is by improving the value of the expected condition state of infrastructure indicator (1.3.5), which would result in an improvement of the measure of resilience by €46 million.

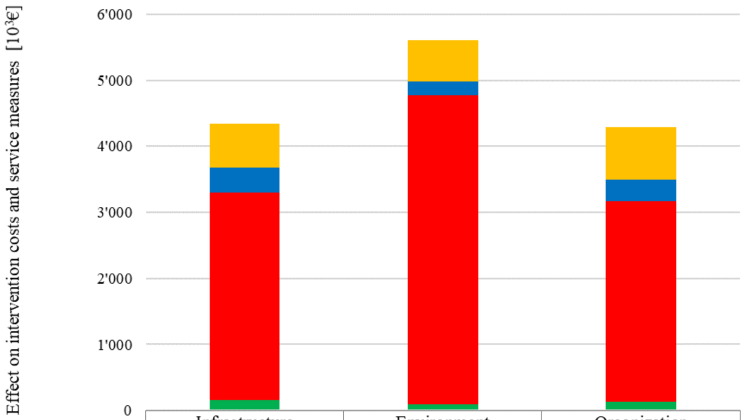
6.3.7.3 Measures of resilience per indicator category

The measures of resilience per indicator category are shown in Figure 42 and Figure 43. A measure of resilience for an indicator category is the ratio between the sum of the actual and the sum of the highest possible values of all indicators in the category multiplied by the average of the values of their individual measures of resilience. For example, the measure of resilience of the indicator category 1.3 "Condition" with respect to intervention costs was given by the sum of the actual values of indicators 1.3.1 to 1.3.7 (i.e. 15) (Table 79) divided by the sum of their highest possible values (i.e. 26), multiplied by the average of the expected intervention costs due to indicators 1.3.1 to 1.3.7 (i.e. €2.8 million). The measure of resilience for the indicator category 1.3 with respect to intervention costs and all measures of services was €1.6 million.



	Protective measures	Preventive measures	Condition state of the infrastructure	Physical	Non-physical	Pre-event activities	Post-event activities
Intervention	0	0	1'628	640	0	1'414	359
Travel time	372	0	402	218	0	349	288
Safety	0	0	7'693	4'809	0	6'342	728
Socio-economic	158	0	180	92	0	148	477

Figure 42. Measures of resilience for the condition state, protection measures, preventive measures, physical and non-physical environment, and pre- and post-event activities indicator categories



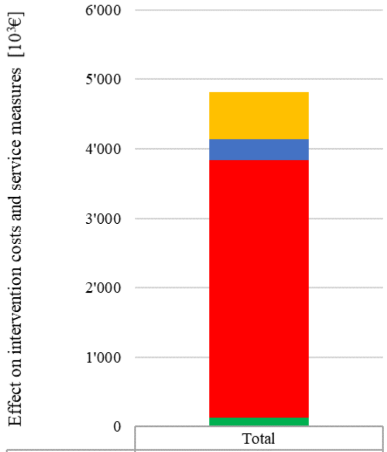
	Infrastructure	Environment	Organization
Intervention	664	624	799
Travel time	374	212	322
Safety	3'138	4'684	3'030
Socio-economic	162	90	137

Figure 43. Measures of resilience for the infrastructure, environment and organisation indicator categories

It can be seen from Figure 42, that there is the most potential to improve resilience by improving the values of the condition state of the infrastructure indicators, the pre-event activities indicators, and the physical environment indicators, which have measures of resilience of €9.9, €8.3 and €5.8 million respectively, and that improvements to their values would have the largest impact on the safety measure of service, followed by intervention costs, with very little of the resilience related to travel time or socio-economic impact. Figure 43 shows that the environment indicators are the largest contributor to resilience, with a value of €5.6, compared to €4.34 and €4.3 million for the organisation and infrastructure indicators. It has to be kept in mind that these values do not, of course, say anything about the ease with which the indicators can be reduced even if it is possible. This is discussed in section 7.

6.3.7.4 Measures of resilience for the transport system

The measures of resilience for the whole transport system are shown in Figure 44. The measure of resilience for the intervention costs and all measures of service was €4.8 million, i.e. the sum of the expected intervention cost (€0.7 million), and expected reductions in the travel time, safety and socio-economic measures of service (€0.3, €3.7, and €0.13 million) if the reference landslide occurs. The measures of resilience for the transport system were obtained with the same logic as for the indicator categories explained in section 6.3.7.3. For example, the safety measure of resilience was the sum of the actual values of indicators 1.1.1 to 3.2.6 (i.e. 60) divided by the sum of their highest possible values (i.e. 104), multiplied by the average measures of resilience per indicator (i.e. €7.34 million).



	Total
Intervention	677
Travel time	302
Safety	3'704
Socio-economic	130

Figure 44. Measures of resilience for the transport system

6.3.7.5 Difference between measures of resilience using worst and actual values of indicators

The differences between the measures of resilience using the worst and actual values of indicators are shown in Figure 45 for the whole transport system and the infrastructure, environment and organisation categories using intervention costs and all measures of service. Figure 46 shows the resilience indicators for the infrastructure, environment and organisation categories using intervention costs and each measure of service. Figure 47 shows the safety measures of service for the indicator categories condition state, protection measures, preventive measures, physical and non-physical environment, and pre- and post-event activities. While Figure 48 show the example of the specific expected condition state of protective barriers indicator (1.3.6). Through these figures, an infrastructure manager obtains an idea of how much better and how much worse resilience can be. For example, although the measure of resilience of the transport system is €4.8 million (Figure 45), which is arguably a high number, it is less than half of what it could be, i.e. €14.4 million. Although alone, even this might not be much information, it would be very useful if being used to track resilience over time. It can also be seen quickly where little or no additional improvements in resilience can be achieved. For example, the protective measures indicator category (Figure 47) is not relevant with respect to safety so if safety is of concern no improvements are possible through the improvements of these measures. As well, improvements are not possible by improving the values of the preventive measures indicators, as they all already have their best values. On the contrary, improvements are possible by improving the values of the indicators, such as the expected condition state of protective barriers indicator (Figure 12).

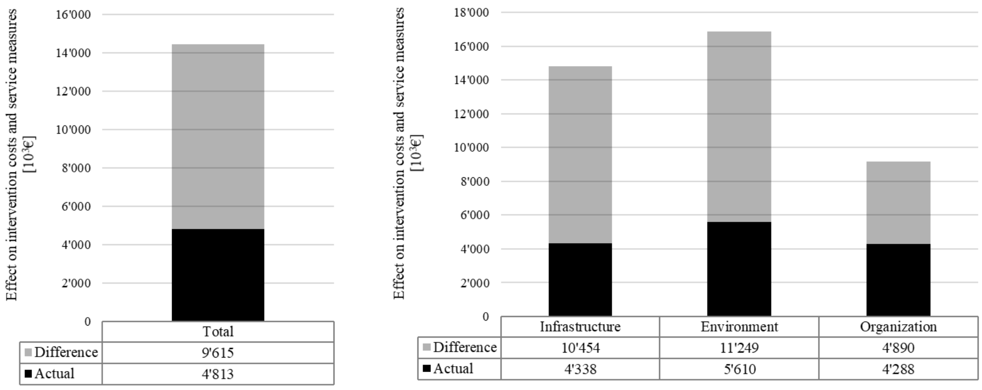


Figure 45. Difference between measures of resilience for a) the transport system, and b) the infrastructure, environment and organisation categories

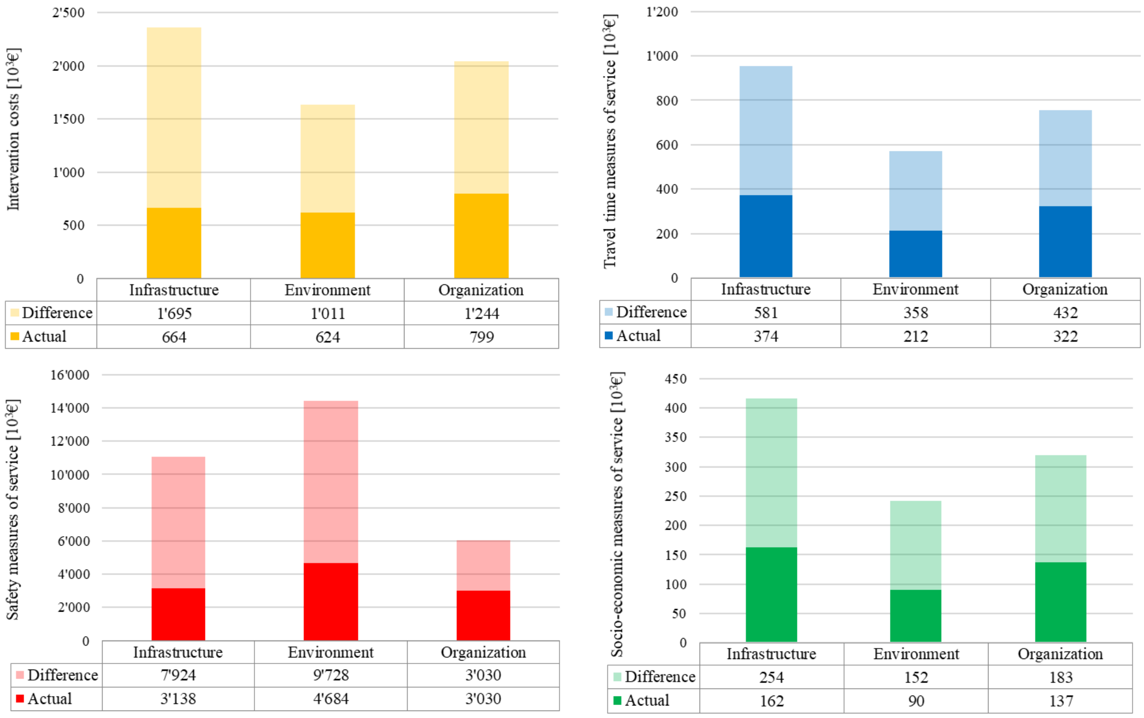


Figure 46. Difference between measures of resilience for the infrastructure, environment and organisation categories using only a) intervention costs, b) the travel time measure of service, c) the safety measure of service, and d) the socio-economic measure of service.

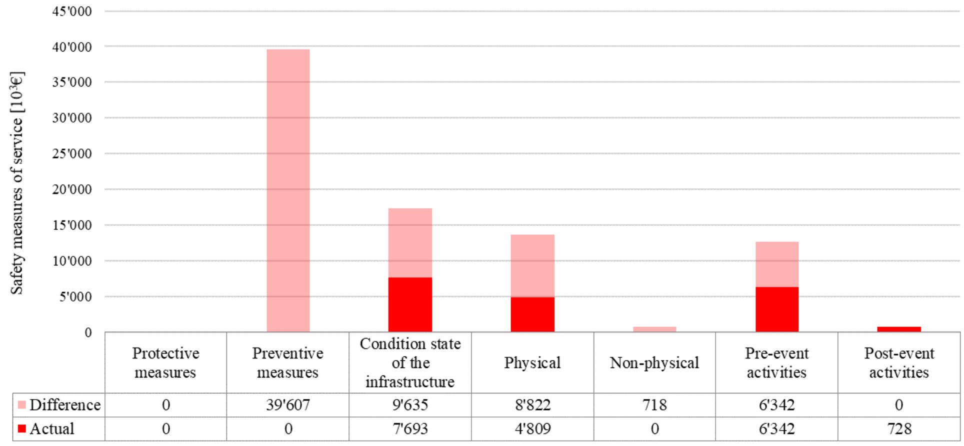


Figure 47. Difference between measures of resilience for the indicator categories condition state, protection measures, preventive measures, physical and non-physical environment, and pre- and post-event activities

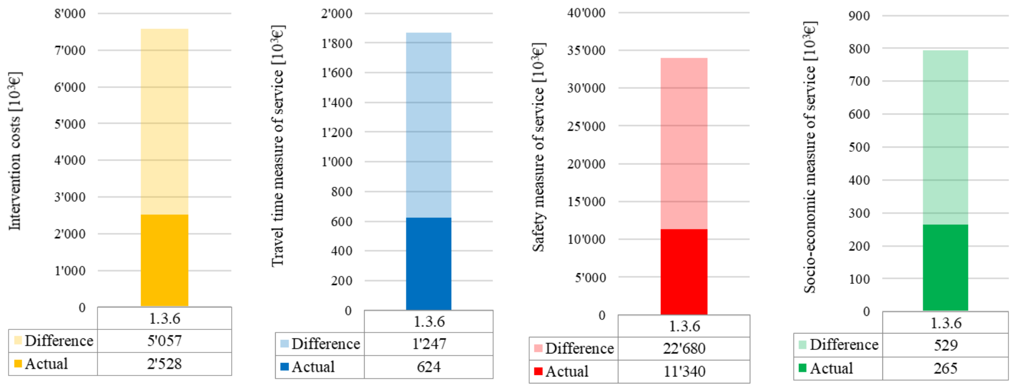


Figure 48. Difference between measures of resilience for the indicator expected condition state of protective barriers (1.3.6)

6.3.7.6 Summary

The resilience of the transport system is relatively good (€4.8 million compared to the maximum possible value of €14.4 million (only 33.3%). The greatest contributor to the €4.8 million is that of the environment, followed by the organization, and the infrastructure, with measures of resilience of €5.6, €4.34, and €4.3 million. This is mainly due to the fact that, for the example , the infrastructure is assumed to be out of service, and the protection barriers moderately likely collapsed following the occurrence of a reference landslide. Although both the infrastructure and the barriers are designed to withstand reference landslides, they are still expected to be severely damage if they occur, and consequently significant repair or even a replacement is likely to be required.

These facts can be clearly seen by looking closely at the indicator categories and indicators themselves. Looking at the indicator categories, it can be seen that the greatest contributors in terms of indicator categories are the infrastructure condition indicators, the pre-event activities indicators, and the physical environment indicators, with measures of resilience of

€9.9, €8.3 and €5.8 million, respectively. Looking at the specific indicators, the greatest contributors are the expected condition of infrastructure (1.3.5), €46 million, the condition of protection barriers (1.3.3), €33 million, the extent of interventions executed prior to the landslide (3.1.3), €28.3 million, and the hazard zone (2.1.5), with €28.1 million.

With the goal of improving resilience, i.e. decreasing the measure of resilience for the transport system, the infrastructure manager should focus his attention in improving the values of the above indicators. It should be kept in mind from the beginning on though that some of these are relatively easy to modify, i.e.: the expected condition of infrastructure (1.3.5), currently 1/3; the condition of the protection barriers (1.3.3), currently 2/5; and the extent of interventions executed prior to the landslide (3.1.3), currently 1/2, and an other that is impossible to modify, i.e. the hazard zone of the infrastructure (2.1.5). Once clarity is achieved on the measures of resilience, the infrastructure manager can proceed with setting targets on the values of the indicators taking into consideration the ease with which values can be improved.

6.3.8 Targets

The resilience indicators targets for the example infrastructure were set for the indicators that were considered to be in the control of the infrastructure manager (31 out of the 42). In general, the infrastructure manager should first identify both the legal requirements and his own, as well as the owners', requirements, i.e. the things that they empirically know had to be done. He then systematically estimated the approximate costs and benefits of improving the values of each of the indicators, with respect to the likely restoration costs and the likely reductions in service with respect to the reference landslide. Finally, he then selected the target values that were likely to give the maximum net-benefit, while satisfying all of the requirements. Each of these steps is explained in the following sections in more detail, though in this example it was considered that no requirements, i.e. neither legal nor stakeholders' requirements, bounded the decision. So the process to set the targets starts directly with the estimate of the net-benefit.

6.3.8.1 Net-benefit

Beyond the requirements for the indicator values, the targets were determined using incremental cost-benefit analysis, i.e. for each indicator estimating the approximate net-benefit from the lowest acceptable level to the level where the incremental net-benefit of a further increase is negative (which is equivalent to the benefit/cost ratio being less than 1.0). An example of how this was done using the condition of the protective barriers (1) is shown in Table 80, where

- The indicator was first assumed to have its worst possible value (0) and the likely intervention costs and reductions in service (€54.8 million) that would follow the occurrence of the reference landslide were estimated (listed as the maximum values for the intervention costs (€9.4 million), and the reductions in service (€2.3 million - travel time, €42 million - safety, and €1 million – socio-economic).
- The cost of improving the value of the indicator by one unit and the expected benefit in terms of avoided intervention costs, and reductions in service, were then estimated, incrementally, assuming the indicator had the value of 1, 2, 3, 4 and 5. For example, the cost of moving the value of the condition of the protective barriers indicator from

1 to 2 was estimated in €5 million and the expected avoided intervention costs and reductions in service in €11 million, yielding a net benefit of €14 million and a B/C of 2.19, which indicates that the target should be moved to 2 from 1. The costs of improvement of the value of this indicator were assumed to increase non-linearly, while the reductions in service were assumed to increase linearly.

- The target for the indicator was selected as the last value before the incremental net-benefit becomes negative or the highest value possible, which in this case is 5, and 5 is above the legal requirement of 2.

Following this logic targets were set for 31 resilience indicators out of the 42 presented in Table 73-78, i.e. 11 of the 42 indicators of the transport system have no targets. This is because they refer to situations that cannot be modified by the infrastructure manager (e.g. hazard zone) and therefore no target can be set on these. The targets for all 31 indicators are given in Table 81.

Table 80. Setting targets based on net-benefit for the condition state of the protective barriers

Possible values	Costs (10^3€)	Target	Max/ per value	Measures of resilience (10^3€)							Net benefit (10^3€)
				Avoided interven-tion costs	Avoided reductions in service				B/C		
					Travel time	Safety	Socio-econ.	Total			
		5	*Max*	*9'391*	*2'317*	*42'120*	*983*	*54'811*	*N/A*		N/A
0	0		0	0	0	0	0	0	0.00		0
1	3'000		1	1'878	463	8'424	197	10'962	3.65		7'962
2	5'000		2	1'878	463	8'424	197	10'962	2.19		5'962
3	5'000		3	1'878	463	8'424	197	10'962	2.19		5'962
4	7'000		4	1'878	463	8'424	197	10'962	1.57		3'962
5	10'000		5	1'878	463	8'424	197	10'962	1.10		962

Table 81. Targets proposed for the 31 resilience indicators considered to be in the control of the infrastructure manager. (part 1)

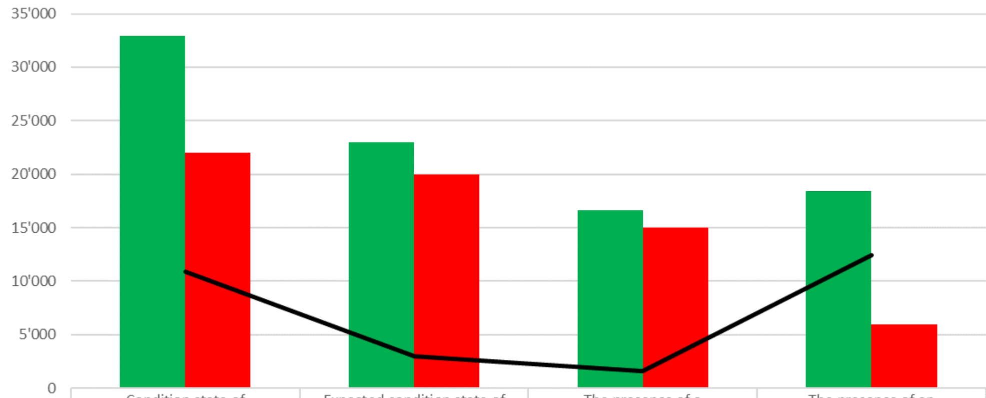
ID	Indicator	Scale	Actual value	Target value	Costs to reach target	Benefit of reaching target	B/C	Net benefit of reaching
					10^3€	10^3€		(10^3€)
1.1.1	The possibility of building a temporary alternative route for vehicles	2	0	**0**	0	0	0.00	0
1.1.2	The possibility of using another means to satisfy transport demand	2	1	**1**	1'200	1'481	1.23	281
1.1.3	The number of possible existing alternative ways to deviate vehicles	1	1	**0**	0	0	0.00	0
1.1.4	The presence of a warning system	2	2	**2**	2'500	3'046	1.02	546
1.1.5	The presence of a safe shutdown system	1	0	**0**	0	0	0.00	0
1.1.6	The presence of emergency / evacuation paths	2	1	**1**	0	0	0.00	0

Table 81. Targets proposed for the 31 resilience indicators considered to be in the control of the infrastructure manager. (part 2)

ID	Indicator	Scale	Actual value	Target value	Costs to reach target 10^3€	Benefit of reaching target 10^3€	B/C	Net benefit of reaching (10^3€)
1.1.7	The presence of special measures to help evacuate persons	2	0	**0**	0	0	0.00	0
1.2.1	Compliance with the current slope stability design code	2	2	**1**	0	0	0.00	0
1.2.2	Presence of protection barriers	1	1	**0**	0	0	0.00	0
1.2.3	Adequate protection barriers	1	1	**1**	2'000	43'567	21.78	41'567
1.3.1	Age / Age of replacement of the warning system	3	2	**0**	0	0	0.00	0
1.3.2	Condition of infrastructure	5	4	**3**	0	0	0.00	0
1.3.3	Condition of protective barriers	5	***2***	**5**	30'000	54'811	1.10	24'811
1.3.4	Condition of assistance alert systems	5	2	**1**	2'500	2'557	1.02	57
1.3.5	Expected condition of infrastructure	3	***1***	**2**	35'000	45'910	1.15	10'910
1.3.6	Expected condition of protective barriers	3	2	**0**	0	0	0.00	0
1.3.7	Expected condition of assistance alert systems	2	2	**0**	0	0	0.00	0
2.1.12	Extent of vegetation cover	3	1	**0**	0	0	0.00	0
2.1.13	Traffic	3	2	**0**	0	0	0.00	0
2.1.14	Hazards goods traffic	2	1	**0**	0	0	0.00	0
2.1.15	Flammable goods traffic	1	1	**0**	0	0	0.00	0
2.2.1	Budget availability	2	2	**1**	20'000	20'027	1.00	27
3.1.1	The presence of a monitoring strategy	2	1	**0**	0	0	0.00	0
3.1.2	The presence of an maintenance strategy	2	***1***	**2**	25'000	33'193	1.11	8'193
3.1.3	The extent of interventions executed prior to the event	2	1	**1**	20'000	28'287	1.41	8'287
3.2.1	The presence of an emergency plan	2	***1***	**2**	9'000	36'912	3.08	27'912
3.2.2	Practice of the emergency plan	4	2	**1**	3'000	3'021	1.01	21
3.2.3	Review/update of the emergency plan	2	1	**1**	5'000	9'268	1.85	4'268
3.2.4	Expected time for tendering	3	2	**2**	14'000	23'175	1.05	9'175
3.2.5	Expected time for demolition	3	3	**3**	520	2'929	4.58	3'773
3.2.6	Expected time for construction	3	2	**1**	10'000	14'177	1.42	4'177

* The grey shaded actual values highlight the ones that are below the target.

In Table 81 it can be seen that only 4 indicators have actual values below the target values, i.e. the condition state of protective barriers indicator (1.3.3), the expected condition state of infrastructure indicator (1.3.5), the presence of a maintenance strategy indicator (3.1.2), and the presence of an emergency plan indicator (3.2.1). Of these 4 indicators (Figure 49), it seems that the greatest net-benefit (€12.5 million) would be developing and improving the operative emergency plan, i.e. replacing the current generic emergency plan with one where specific tasks, resources and responsibilities are defined; the second best would be improving the condition state of the protective barriers (€10.9 million), i.e. replacing the deteriorated nets and piles; the third would be achieved by improving the expected condition of the infrastructure following the occurrence of the reference landslide event(€3 million), i.e. reinforcing the pillars and girders of the bridges that are currently expected to have significant damage when affected by the reference landslide (e.g. as the bridge that was moved away by the landslide of the 7th of March, 2005); and the fourth would be improving the maintenance strategy (€1.6 million) to ensure a solid preventive maintenance throughout the whole infrastructure. This means that if only one thing can be done developing an operative emergency plan should be prioritized, requiring €6 million. If all are to be done approximately €63 million would be required.



	Condition state of protective barriers	Expected condition state of infrastructure	The presence of a maintenance strategy	The presence of an emergency plan
Total benefit	32'886	22'955	16'597	18'456
Total costs	22'000	20'000	15'000	6'000
Net benefit	10'886	2'955	1'597	12'456

Figure 49. Total benefit, total costs and net benefit to align the current four indicators out of target to their targets

6.3.8.2 Summary

The targets have been set for 31 out of the 42 resilience indicators, while for the 11 indicators that the infrastructure manager has no power to modify, no target have been set. Out of the 31 targets set, only 4 indicators currently have a value that is below the target value: the condition state of protective barriers indicator, the expected condition state of infrastructure indicator, the presence of a maintenance strategy indicator, and the presence of an emergency plan indicator. Moving these indicators from their current values to the targets is expected to provide a relatively large total benefit (indicated here to be in the order of €91 million) and is expected to cost in the order of €63 million. Although, more exact numbers would require more detailed analysis, these give a good idea that it is worthwhile to undertake the efforts, i.e. reinforce the bridges that are currently expected to have significant damages when affected by the reference landslide, replace the deteriorated protection barriers, develop maintenance strategies for all assets on the highway, and develop an operative emergency plan to be followed in the case of a landslide.

6.3.9 Conclusion

In this paper, it is shown that the FORESEE guidelines (Adey et al., 2020) provide a systematic way for infrastructure managers to obtain an idea of the resilience of their transport systems, and an idea of how to set resilience targets, when infrastructure managers want to assess resilience, but do not yet know where to concentrate their efforts. It is also shown that for some resilience enhancing actions, these initial results are perhaps sufficient to take action, whereas others point to where more investigation is required, which is part of the iterative process that all infrastructure managers should following in risk assessment (Adey et al., 2016).

The use of the guideline helps ensure that infrastructure managers define service and resilience clearly and consistently, and that they are systematically considered when evaluating the resilience of the transport system, as well as obtaining an idea of how to improve resilience. The example shows that this is possible, with relatively little input and effort. Of course, if the results of such an analysis are not sufficient to plan risk-reducing interventions, they can also be used to focus more detailed future analysis.

Future work should be focused on developing more examples with different types of infrastructure, different types of hazards and different organisations. This work could lead to organisations to develop more specific guidelines as to how they would like to measure service and resilience to enable them to make the best decisions possible. It may also lead to the development of country or region specific guidelines that would allow the fair comparison of the resilience of multiple transport systems, which would aid to the efficient distribution of limited resources. Additionally, future work should focus on investigating the accuracy of using resilience indicators when compared to results that come from detailed analysis. It is anticipated that in the framework of the FORESEE project simulations using real data will be run to demonstrate the applicability of the guidelines.

6.3.10 Acknowledgements

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6.3.11 Disclaimer:

The work presented in this article is a mere exercise, for which the vast majority of inputs have been set based on authors' assumptions, i.e. the inputs are realistic, but fictive and as such does not reflect the current situation of the highway chosen for the present application. Therefore the results cannot be in any way connected to the actual resilience of the real transport infrastructure. For a real assessment of the resilience of the infrastructure, the current inputs should be replaced with the actual data on the highway and relevant indicators considered. It is expected to conduct such simulation in the framework of the FORESEE project to demonstrate the applicability of the guidelines

6.3.12 References

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