Determining an Optimal Set of Work Zones on Large Infrastructure Networks in a GIS Framework

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Abstract: A road network consists of multiple objects that deteriorate over time with different speeds of deterioration. In order to provide an adequate level of service over time, these objects will eventually require interventions. As road managers are trying, in general, to maximize the benefit obtained from the road network, it is in their interest to determine intervention programs, which consist of the grouping of interventions in work zones. The determination of optimal intervention programs is relatively complicated when considering single objects, but it becomes even more so when considering multiple objects embedded within a network. The objects to be included in the work zones at each time interval depend on many factors, such as the interventions to be executed on the objects, the maximum allowable length of the work zones, the traffic configurations to be used in the work zones and the available financial resources. Although some initial research in this area has been conducted, none has determined the optimal set of work zones on large infrastructure networks in a geographical information system (GIS) framework, which is necessary in the world of modern infrastructure management. In the work presented in this paper, a GIS-based program was developed to determine optimal intervention programs for large infrastructure networks using a linear optimization model, which can be linked directly to a GIS. The model includes constraints on the amount of available resources, on the length of the work zone, and on the distance between two work zones. A constraint-constructing algorithm is used in order to set up the latter two constraints. The program is illustrated by determining the optimal set of work zones for an example road network similar to the one in the canton of Wallis, Switzerland, including more than 2,000 bridges, tunnels, and road sections. **DOI: 10.1061/(ASCE)IS.1943-555X.0000410.** *© 2017 American Society of Civil Engineers.*

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Introduction

Road infrastructure networks comprise different types of objects, such as road sections, bridges, and tunnels. Due to the deterioration of these objects, interventions (e.g., repair, rehabilitation, replacement) need to be executed at appropriate times to ensure that they continue to provide an adequate level of service (LOS). When an intervention is executed on an object, a work zone has to be set up to ensure that the intervention can be executed. If there is more than one object on which interventions should be executed, there is the possibility of executing interventions on multiple objects within one work zone. Whether or not the interventions can be grouped together in a work zone, or whether the required interventions can be executed at all, depends on multiple characteristics of the objects, e.g., distance between them, and external constraints, e.g., budget. The distance between two objects is important, because while grouping interventions in a single work zone can reduce installation costs, it also creates a longer work zone, which can lead to increased accident costs. Two common constraints on work zones, in addition to budget constraints, are constraints on the maximum length of a work zone and constraints on the minimum distance between two work zones. In the end, infrastructure managers are interested in finding the sets of work zones that comprise the intervention program that yields the highest total benefit considering all those constraints. A set of work zones can either be a single work zone or a group of multiple work zones. All interventions included in an intervention program are assigned to work zones.

The problem of determining optimal sets of work zones is challenging. It is especially challenging when (1) there are many possibilities, such as on a network comprised of hundreds or thousands of objects; (2) the objects are a mix of many different types of objects, which have different rates of deterioration; and (3) the possible interventions belong to many different types of interventions, each with one or more possible associated traffic configurations.

Recent research focused on solving this problem includes that by Hajdin and Adey (2006) and Hajdin and Lindenmann (2007), who developed linear optimization models to determine optimal intervention programs with single work zones for small networks. Lethanh et al. (2014) extended these optimization models so that intervention programs with multiple work zones for small networks could be determined. Although interesting, one hindrance to the extrapolation of this work to real-world networks was the fact that the models needed to be set up manually. This problem was initially addressed in the work conducted by Eicher et al. (2015), who developed an algorithm to write the constraints of the optimization model based on the network structure.

The goal of the work presented in this paper was to extend the previous works and develop a GIS-based program to determine

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optimal intervention programs for large infrastructure networks using an algorithm based on the work of Eicher et al. (2015). The proposed program includes (1) a linear optimization model with its objective function to maximize benefits incurred by stakeholders when a set of interventions is executed in a time period and (2) a set of constraints on the length of the work zone, the distance between two work zones, and on the amount of available resources. The program has been developed with its ability to access directly relational data tables supported by a geographical information system (GIS) to retrieve all required input information, such as the geospatial data to build the logical physical network model, the maximum work zone lengths, minimum distances between two adjacent work zones, and data on impacts.

The remainder of the paper is set up as follows. After literature review and background to position the contribution of this work in the context of infrastructure management is given in the next section, the proposed linear optimization model to determine the optimal set of work zones, the constraints, the algorithm, and the process to determine optimal intervention programs are explained in the following three sections. Particularly, the formation of an algorithm used to build distance constraints is illustratively presented using a small network of 45 objects. In a further section, the applicability of the program is demonstrated with an example road network similar to the one in the canton of Wallis, Switzerland, including more than 2,000 bridges, tunnels, and road sections. It is only similar, as fictive condition states of the objects and roughly estimated costs and benefits were used. A summary of the work and suggestions for future work in this area are given in the last section.

Literature Review

The determination of optimal intervention programs for transportation networks has been the focus of a substantial amount of research over the last few decades. For example, in pavement management, Ferreira et al. (2002a, b) developed segment-linked optimization models for determining optimal intervention programs for road networks using genetic algorithms. Later Bonyuet et al. (2002), Ouyang and Madanat (2004, 2006), and Abaza and Ashur (2009) proposed mixed-integer nonlinear optimization models for determining the optimal schedules of rehabilitation activities, i.e., intervention programs, for multiple pavement facilities. Sathaye and Madanat (2011) proposed a methodology to determine optimal ways to resurface pavement for multiple facilities, derived from the condition of the pavement sections and the strategies to be followed for each of them. Similar models are used in many state-of-the-art pavement and bridge management systems. These works, in general, consist of models to estimate the evolution of the state of the objects of the network over time using a set of deterioration functions and intervention strategies that are used to say under what conditions interventions are to be executed. Optimal intervention programs are then determined to minimize costs while taking constraints into consideration. The programs are, however, determined without considering explicitly the spatial proximity of the objects and whether or not they can be combined into single work zones to reduce costs (Mirzaei and Adey 2015). This has the disadvantage that possible reductions in costs and traffic disruptions due to grouping interventions in work zones are difficult to take into consideration (Adey et al. 2014).

The intervention programs are also determined without explicit consideration of the temporal proximity of interventions. This means that undesirable results can occur, such as having two adjacent road sections selected for interventions in two consecutive years.

In many cases, due to the computational complexity of the problem even when the spatial and temporal proximity of the objects to each other is ignored, the optimal intervention programs are determined using heuristic methods (Farid et al. 1994). Although these models provide road network managers with a way to come up with intervention programs, they do not result in optimal intervention programs.

Some recent work has been focused on considering the network behavior if single objects do not provide an adequate level of service, such as that done by Bocchini and Frangopol (2011, 2013). They proposed multiobjective optimization models to determine the optimal intervention programs for bridges within road networks, taking into consideration the reliability and connectivity of the network if one of the objects did not provide an adequate LOS, i.e., if the object failed and required a corrective intervention. Synergies related to grouping interventions in the construction of optimal intervention programs were not considered.

Further, multiple research efforts were concentrated on the effects of interventions on the traffic (Chang et al. 2000; Chen et al. 2005; Chien and Schonfeld 2001; Martinelli and Xu 1996; Racha et al. 2008; Winfield 2014). These efforts included traffic simulation models, either static or dynamic, so that the optimal intervention programs could be determined while taking into consideration the traffic flow on the network. They also all examined the estimation of the costs related to the interventions being conducted within single work zones.

The first research on determining optimal intervention programs made up of optimal sets of work zones, where reductions in both intervention costs and costs due to perturbations of traffic as a result of executing multiple interventions simultaneously are explicitly considered, was conducted by Hajdin and Adey (2006) and Hajdin and Lindenmann (2007). They developed integer linear optimization models to determine the optimal single work zone in a road network. Graph theory was used to represent scenarios of different traffic configurations and intervention on a highway network and to map both the physical network and the possible combinations of intervention and traffic configurations on objects of the network. They used a static traffic model in order to generate a simple integer linear model.

Ng et al. (2009) developed a mixed-integer bilevel model to develop intervention programs, which included a dynamic traffic model. They used a state-of-the-art traffic model in the estimation of user costs during the execution of multiple interventions on the network. Their model was not demonstrated on a large network.

Lethanh et al. (2014) proposed a mixed-integer linear optimization model to determine the optimal set of work zones with a maximum work zone length constraint and a minimum distance between work zones constraint, in addition to the budget and integrity constraints used in the previous works. The maximum work zone length constraint was used to force the selection of each and every work zone with length not exceeding the maximum allowed length of a work zone. The minimum distance between work zones constraint ensured that there was an adequate distance between work zones to give drivers adequate time to recover from the other work zone before they enter a new one. A difficult task in setting up the optimization models was in constructing all the single constraints based on the two distance constraints, which together define all possible combinations of work zones. This was done manually by Hajdin and Adey (2006), Hajdin and Lindenmann (2007) and Lethanh et al. (2014), and presumably by Ng et al. (2009), which was possible as the networks were small (i.e., less than

100 objects). This becomes increasingly difficult with increasingly large networks and it is even more so when the networks obtain loops, which most real-world networks do. Eicher et al. (2015) developed an algorithm to write the constraints for the model of Lethanh et al. (2014) automatically.

None of the research done to date could be used directly to determine optimal intervention programs for large infrastructure networks in a GIS framework. However, GIS-based programs for the determination of a management plan have been used considerably in other fields of science such as environmental engineering (Convertino and Valverde 2013; Greene et al. 2011) and geospatial analysis (Aerts et al. 2005; Bateman et al. 2013).

Model

The optimization model is an integer linear program consisting of an objective function, continuity constraint, budget constraint, maximum work zone length constraint, and minimum distance between work zones constraint. The general objective function is

$$\text{Maximize } Z = \sum_{n=1}^{N}\sum_{k=1}^{K}\delta_{n,k} \times (B_{n,k} - C_{n,k}) \quad (1)$$

where $\delta_{n,k}$ = binary variable, which has a value of 1 if an intervention of type k is executed on object n and 0 otherwise; $B_{n,k}$ and $C_{n,k}$ = long-term benefits and costs of executing an intervention of type k on object n, respectively.

The general formulation of the continuity constraints, which force the model to select only one intervention on each object at each unit of time, is

$$\sum_{k=1}^{K}\delta_{n,k} = 1 \quad \forall\ n \quad (2)$$

The general formulation of the budget constraint, which forces the model to select no more interventions than those for which funding is available, i.e., the total cost of all interventions on the network cannot exceed a certain threshold Ω for the investigated time period, is

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\delta_{n,k} \times C_{n,k}^{\text{owner}} \leq \Omega \quad (3)$$

where Ω = maximum budget that can be spent for the interventions and $C_{n,k}^{\text{owner}}$ = intervention costs for intervention k on object n.

The maximum work zone length constraints force the model to select interventions to be included in work zones that do not exceed the maximum allowable work zone length

$$\sum_{n=a_n^w}^{e_n^w}\lambda_n \leq \Lambda^{MAX} \quad \forall\ w \quad (4)$$

where λ_n = length of the object n; a_n^w = first object in the work zone $w = (1, \ldots, W)$; object e_n^w = last object in the work zone w; and Λ^{MAX} = maximum length of the work zone.

The minimum distance constraints force the model to select interventions in such a way that there is a minimum distance between adjacent work zones

$$\sum_{n=a_n^d}^{e_n^d}\lambda_n \geq \Lambda^{MIN} \quad \forall\ d \quad (5)$$

where a_n^d = first object after the work zone and it belongs to one of the default paths d; e_n^d = last object of the path d; and Λ^{MIN} = minimum distance between the two work zones.

Algorithm to Construct Maximum Work Zone Length and Minimum Distance between Work Zone Constraints

The establishment of the maximum work zone length and minimum distance between work zone constraints is challenging in large networks with loops. It is almost impossible manually. It can, however, be done with the algorithm described in this section based on the work of Eicher et al. (2015). The algorithm is described using a network comprised of 45 objects and 31 nodes with an equal length of 5 km per object (Fig. 1). The maximum length of each work zone and the minimum distance between two adjacent work zones are both set to 15 km in this explanation.

Calculate the Lengths of All Paths from Object n Satisfying the Maximum Length Constraints

This part of the algorithm calculates all paths along the physical network, starting at object n, that satisfy the maximum length constraints (max-paths). The lengths of these paths are defined as the sum of the lengths of the objects within the path. Once calculated, the objects associated with each possible path are stored in matrix format. For example, with Object 1, there are in total six paths that can be formed (solid thick lines in Fig. 2 and combination of objects in Table 1).

Calculate All Paths from Object n That Do Not Satisfy the Minimum Distance between Two Work Zones Constraints

This part of the algorithm calculates, for object n, all paths starting with a neighboring object of object n that is within the minimal allowable distance between work zones (min-paths). Object n is assumed to be the last object within a work zone. Objects are added to a min-path as long as the length of the min-path is smaller than the minimum allowed distance between work zones. The length of a min-path is defined as the sum of the lengths of its objects. Fig. 3 and Table 2 illustrate the matrix formation for the minimum distance constraint.

Determine Impossible Object Combinations

After all max-paths and min-paths emanating from all objects in the network have been identified, the algorithm searches for the set of impossible object combinations. Impossible object combinations are pairs of objects that violate either the maximum work zone length constraint or the minimum distance between two work zones if they have interventions simultaneously. For example, if Object 1 is part of a work zone, impossible object combinations are objects that are too far away to be part of the same work zone as Object 1, but too close to be part of an adjacent work zone. Table 3 marks them with an X (Objects 8, 11, 12, 15, and 18). The objects that are part of at least one min-path of object n but do not show up in any max-path of object n give an impossible object's combination when paired with object n.

Establish Impossible Object Combination Constraint

The impossible object combinations are written in the combination matrix. It is an m-by-n matrix where m is the number of

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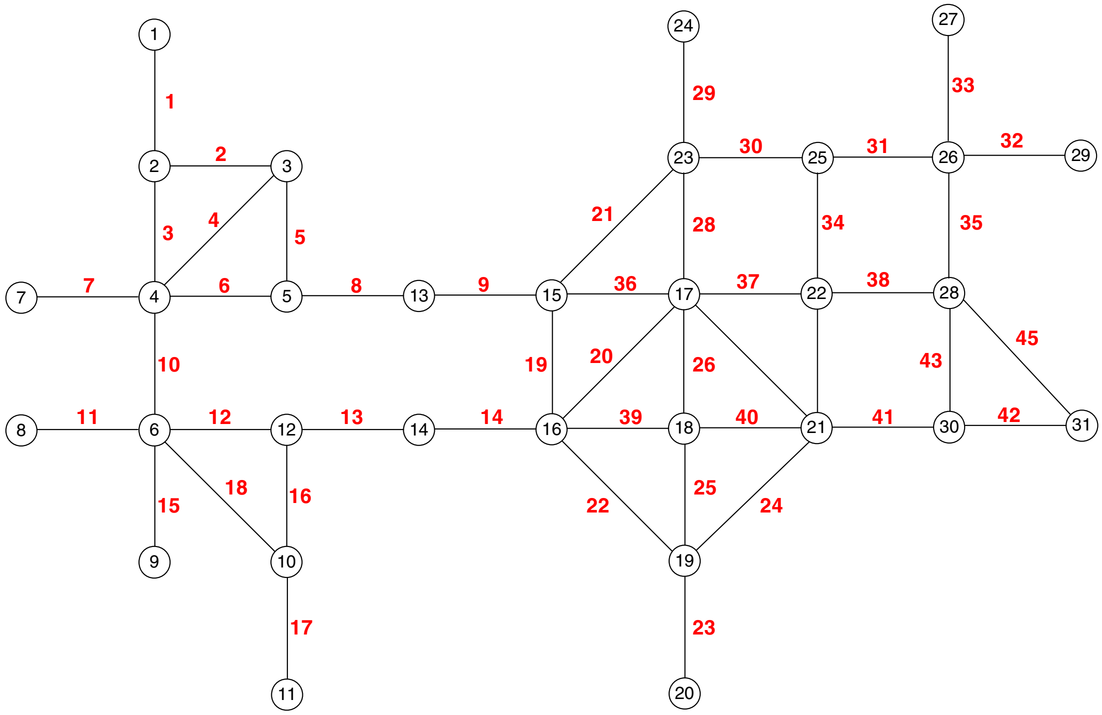

Fig. 1. A simple road network of 45 objects

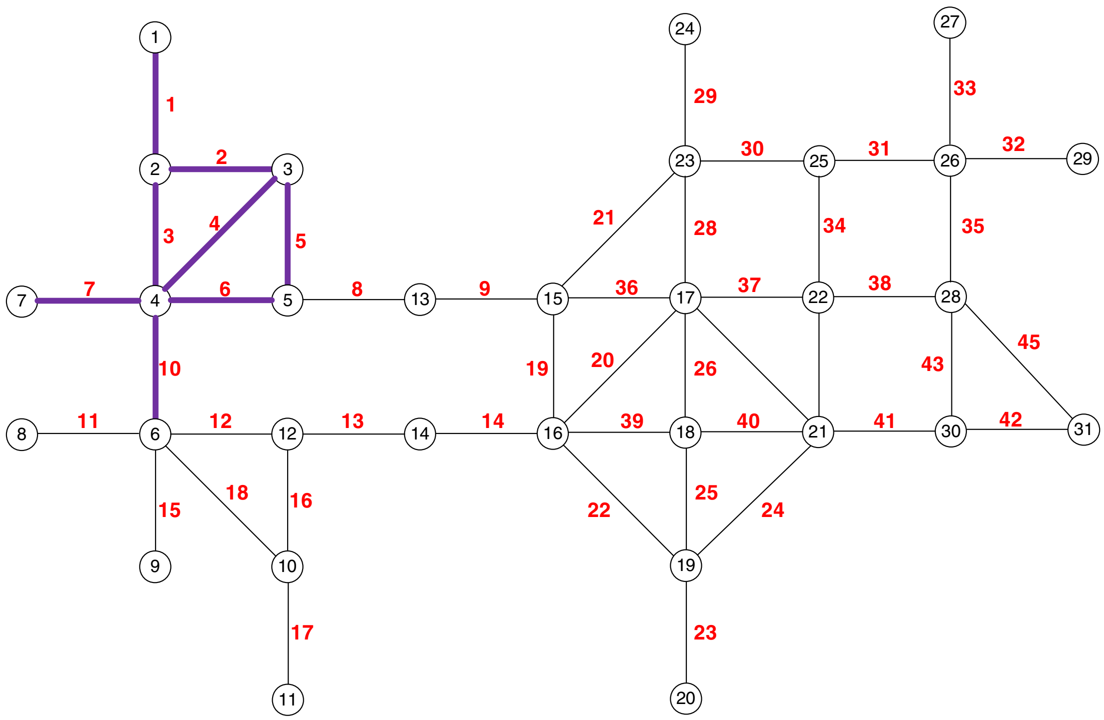

Fig. 2. All paths starting from Object 1

constraints and n is the sum-product of all the objects in the network and the number of interventions. Each row holds one impossible combination of two objects. The number of impossible object combinations, and thus the number of constraints, depends on the difference between the thresholds for the minimum distance between work zones and the maximum work zone length constraints. With increasing differences between these two thresholds, the number of impossible object combinations grows greatly with the number of constraints. The following is an example of the formulation of linear constraints for the impossible combinations with respect to Object 1 (Table 4).

Table 1. Possible Paths Starting from Object 1 Satisfying the Maximum Length Constraints (= 15 km)

Properties	Paths					
	P_1	P_2	P_3	P_4	P_5	P_6
Objects in the path	1	1	1	1	1	1
	2	2	3	3	3	3
	4	5	4	6	7	10
Total length (km)	15	15	15	15	15	15

The header of Table 4 indicates the objects and the related possible interventions. There are two types of interventions for Objects 1, and 2, denoted I_0 and I_1, and three types of intervention for Objects 3–12, denoted I_0, I_1, and I_2. Interventions denoted as I_0 are the do-nothing interventions where no physical intervention is executed and where no change to the traffic configuration occurs. Interventions denoted I_1 and I_2 are combinations of a physical intervention type and a traffic configuration. If intervention I_1 or intervention I_2 is selected, then the object is included in a work

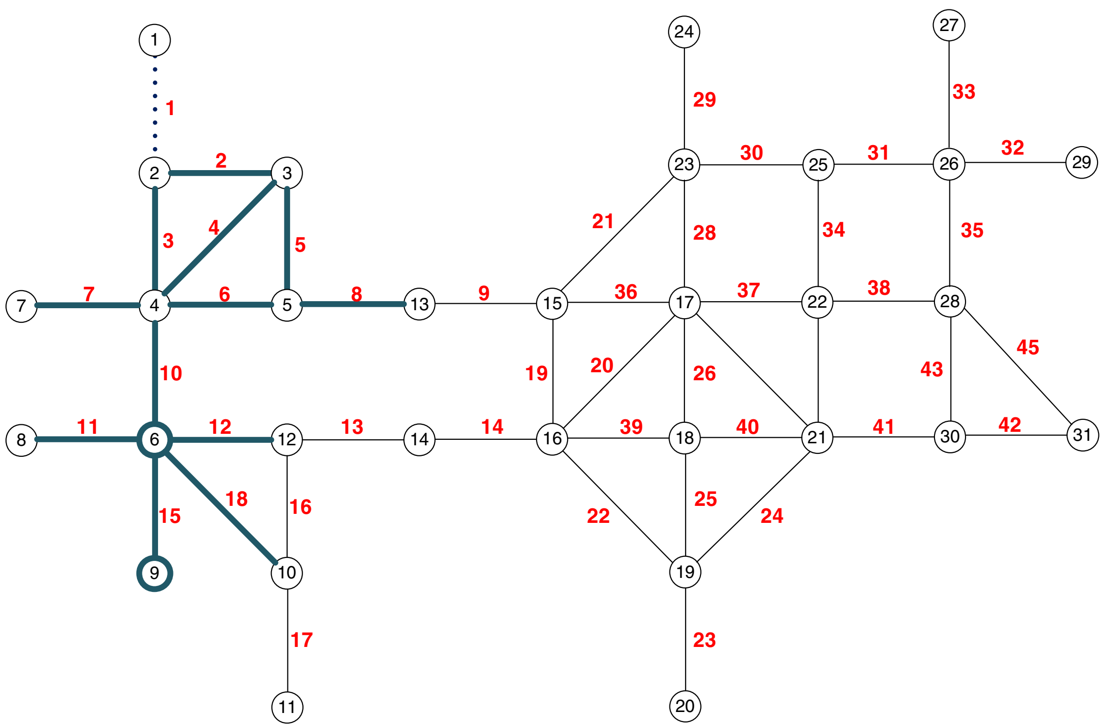

Fig. 3. All paths starting after Object 1

Table 2. Possible Min-Paths Starting after Object 1 (Last Object of a Work Zone)

Properties	Paths														
	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
Objects in the path	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3
	4	4	4	4	5	5	4	4	6	6	7	10	10	10	10
	3	6	7	10	6	8	2	5	5	8	0	11	12	15	18
Total length (km)	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15

Table 3. Impossible Object Combinations Starting from Object 1

Constraints	Objects												
	1	2	3	4	5	6	7	8	10	11	12	15	18
Maximum length	X	X	X	X	X	X	X	—	X	—	—	—	—
Minimum distance	X	X	X	X	X	X	X	X	X	X	X	X	X
Invalid combination	—	—	—	—	—	—	—	**X**	—	**X**	**X**	**X**	**X**

Note: X = object fulfils the constraints and **X** = object builds an invalid combination.

Table 4. Combination Matrix Starting from Object

Work zones	Object 1		Object 2		Object 3				Object 7			Object 8			Object 9			Object 10			Object 11			Object 11		
	I_0	I_1	I_0	I_1	I_0	I_1	I_2	…	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2
1–8	0	1	0	0	0	0	0		0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
1–11	0	1	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
1–12	0	1	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
…													…													

Note: I_i represents the ith possible intervention on the corresponding object.

Table 5. Continuity Matrix

Objects	Object 1		Object 2		Object 3			Object 4			Object 5			Object 6			Object 7			Object 8			Object 9			
	I_0	I_1	I_0	I_1	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	I_0	I_1	I_2	…
1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	…
2	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
3	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	
…													…													

Note: I_i represents the ith possible intervention on the corresponding object.

zone. Otherwise it is not. The binary values appearing in the combination matrix become 1 when it is impossible to form two work zones adjacent to each other. The sum-product of this binary value with the binary decision variables has to be 0.

Establish Continuity Constraint

The continuity constraint from Eq. (2) is written in a so-called continuity matrix (Table 5), which ensures that exactly one intervention is selected for every object in the network. The continuity matrix is a p-by-n matrix where p is the number of objects in the network and n is the sum-product of all the objects in the network and the number of interventions. The right-hand side of the continuity matrix shows the number of connections for every object. For example, Object 1 is connected to two adjacent objects and Object 2 is connected to four adjacent objects.

Process

The process to be used to determine optimal intervention programs in a GIS framework is shown in Fig. 4 at the highest level. The GIS stores not only spatial and temporal input/output data of every individual infrastructure object in its database but also serves as an interactive environment for human users or other computer programs or systems. This interaction is illustrated in the figure, where three main modules of a computer system (input, process, and output) are connected and interact with one GIS database. All the information is stored in the GIS database, from which the optimization program obtains all needed information. This program converts the input data into the form required to determine the optimal set of work zones. In the last step, the result is stored in the GIS database. This way, the results and the input data are connected with each other, which would be advantageous for the analysis of multiple time periods because the input in the next time period depends on the executed interventions. Further, the GIS enables a user-friendly representation of the whole network and the optimal solution.

Access Input

In this task all information about the objects in the network is obtained from the GIS database. The database consists of a large number of relational tables and holds the geographical information of every object in the network using coordinates (e.g., X- and Y-coordinates of a point or a series of points forming a road section) and other attributes of objects (e.g., width, length, materials, slopes); time-series information of each object (e.g., values of performance indicators, types of interventions executed, traffic volume); a set of structure query language (SQL) codes to automate the process of data filtering and data creation (e.g., creating a new table with the results from a query); and defined processes and models to be used to update information or to predict the values of performance indicators in the future of individual objects. Even though road managers may not have all the necessary information these days, they will have more and more in the future because of the increasing professionalization in the field of

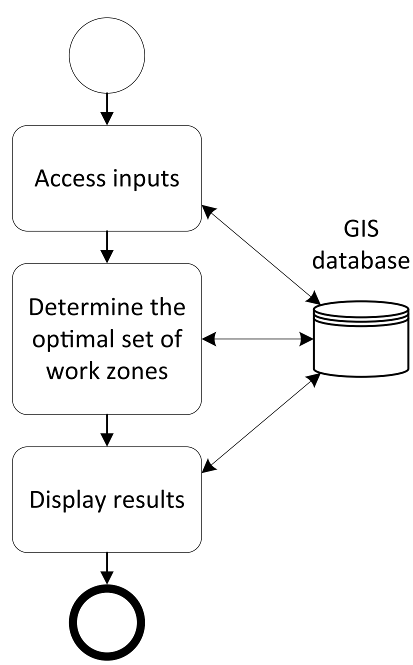

Fig. 4. Basic process

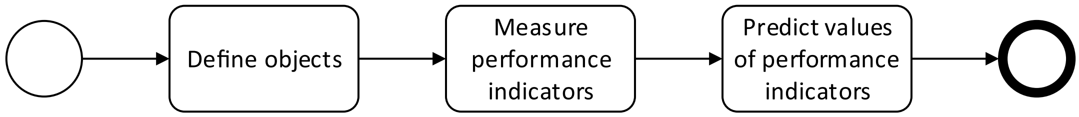

Fig. 5. Input module

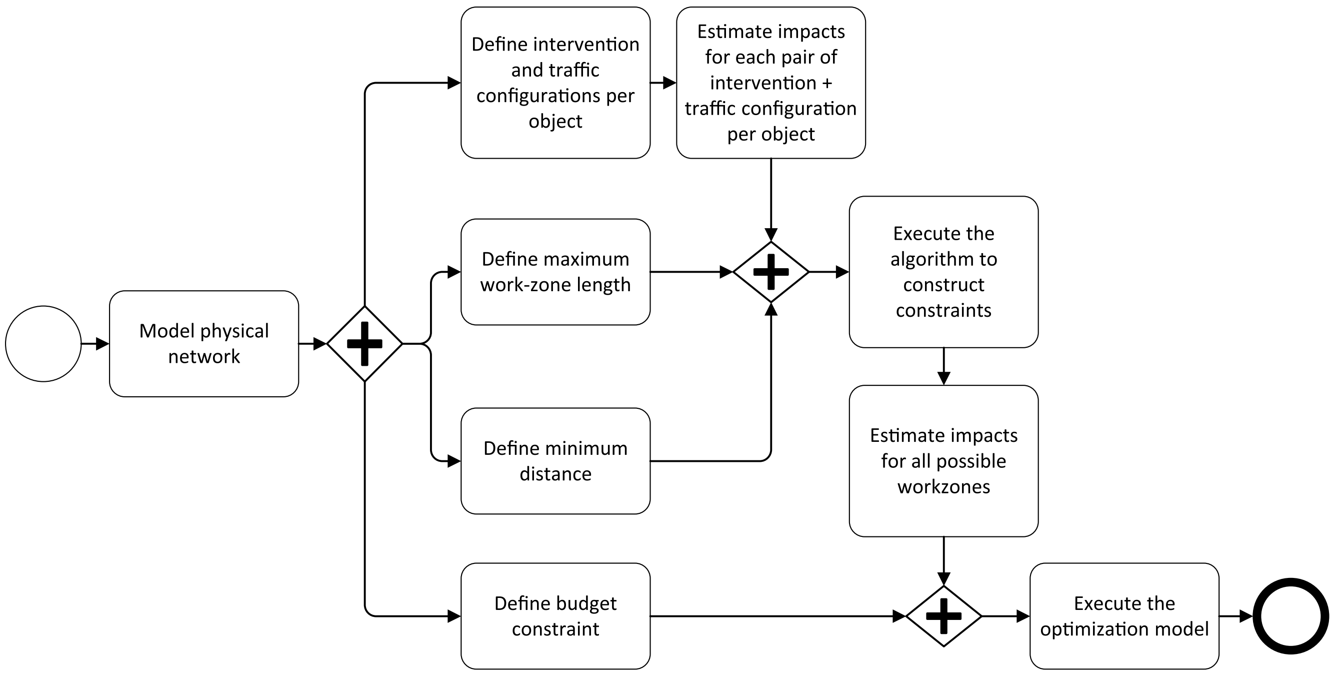

Fig. 6. Process module

infrastructure management and the rolling out of ISO 55000 (ISO 2014). This process shows them which input data they should focus on acquiring and how to store everything within a relational database.

The access input task includes three subtasks as shown in Fig. 5: (1) define objects, i.e., define the objects and the extent of the objects (e.g., length); (2) measure performance indicators, i.e., execute monitoring activities so that the values of the performance indicators for each object are determined; (3) predict values of performance indicators over the period of time to be investigated.

Determine an Optimal Set of Work Zones

The process to be used to build the appropriate optimization model from the data generated in the access inputs module and to determine the optimal intervention program is shown in Fig. 6.

Model Physical Network

The first task is to create a model of the physical network where the nodes and links are defined using the topological function of the *pgRouting* algorithm (pgRouting Contributors 2015). This algorithm is used to determine how each object is connected within the network (Obe and Hsu 2015). This topological function can be implemented in many GISs (e.g., *PostgreSQL*). An example in Table 6 illustrates this for 10 objects of the network shown in Fig. 1.

The topological function of the pgRouting algorithm automatically creates integer values for the source and target (Table 6). The words *source* and *target* have no reference to direction within the graph. They have been used to mean from a start point to an end point. Once the table is generated it is easy to construct the figure shown in Fig. 1.

Define Intervention Types and Traffic Configuration per Object

After the physical network is created in the GIS, the types of interventions that are possible for each object are defined. Example intervention types for road sections are doing nothing, resurfacing the asphalt layer and crack sealing, and reconstructing. Once the intervention types are defined, the possible traffic configurations associated with each are identified. For example, to execute a

Table 6. Example Network Model Created Using the pgRouting Algorithm

Link number	Source node	Target node
1	1	2
2	2	3
3	2	4
4	3	4
5	3	5
6	4	6
7	4	7
8	5	13
9	13	15
10	4	6

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resurfacing intervention on a four-lane highway with traffic flow in both directions, one possible traffic configuration is to close two lanes on one side of the highway and reroute the traffic on the other side so that there are two narrow lanes in both directions.

Estimate Costs Associated with Each Combination of Intervention Type and Traffic Configuration per Object

Once an intervention type and traffic configuration are defined for an object, the costs can be estimated. For example, intervention costs can be calculated as the sum of the quantity of materials, labor, and equipment (fixed and variable costs) and travel time costs, which can be estimated using a suitable traffic model.

Define Maximum Work Zone Lengths

In order to ensure that users do not have excessive stress while driving on highways, some road authorities impose maximum work zone lengths. For example, a work zone cannot be longer than 15 km. These maximum work zone length constraints are defined in this task.

Define Minimum Distances between Work Zones

Also to ensure that users do not have excessive stress while driving on highways, some road authorities impose minimum distances between work zones. For example, there must be a minimum of 50 km between work zones. These minimum distance between work zones constraints are defined in this task.

Execute the Algorithm to Construct Constraints

In this task, given the maximum work zone lengths and the minimal distances between work zones, all possible work zones are determined. This is done by executing the constraint algorithm to construct the combination matrix and continuity matrix. This determines all possible work zones.

Estimate Impacts for All Possible Work Zones

Impacts are estimated for all possible work zones, with explicit consideration of the interventions to be executed on each of the objects in the work zone and the selected traffic configurations. Using the impacts associated with each combination of intervention type and traffic configuration estimated previously, SQL codes are used to estimate the impacts that would be incurred by each stakeholder if each possible work zone was constructed. Table 7 shows all stakeholders for public roads used in this paper. An in-depth analysis of possible stakeholders and impacts on them has been carried out by Adey et al. (2012).

Define Budget Constraints

In this task, the budget constraints are defined. If the budget is equal to or greater than the costs occurring for the infrastructure owner due to the execution of the interventions within the determined work zones, the budget is considered to be unlimited. If the budget is lower, the budget is considered to be limited.

Table 7. Stakeholder Groups

Stakeholder group	Definition	Examples
Owner	Persons who are responsible for decisions with respect to physically modifying the infrastructure	Federal road authority
Users	Persons who are using the roads	Driver and passengers of a vehicle on a road
Public	Persons who are affected by the road but are not using it	Persons affected by a changing climate due to the emissions produced by vehicles driving on the road

Execute Optimization Model

In this task, the optimization model is run. It yields the values of the binary variables [refer to δ in Eqs. (1)–(3)] that, when read together, define the optimal set of work zones, including the types of interventions and the traffic configurations to be used for all objects, and, therefore, the optimal intervention program. The values of the binary variables are transformed into a set holding the selected intervention for each object, which then is automatically added to the corresponding object in the GIS database. There the optimal intervention program can be called for graphical or tabular representing.

Display Results

The output module displays the results of the analysis. These include the value of the objective function, i.e., the long-term benefit that has been maximized through the optimization process [value of Eq. (1)] and the selected intervention of each object together with the adjusted traffic configuration graphically in the GIS surrounding.

Example

To demonstrate the process, the optimal set of work zones for a road network similar to the one in the canton of Wallis in Switzerland was determined. The information was extracted from a freely distributed Internet source provided by the Federal Office of Topography (Federal Office of Topography Swisstopo 2015). It is only similar, as fictive condition states of the objects and fictive, but reasonably estimated, costs and benefits were used. The optimal set of work zones, based on the fix defined input values, were determined for four scenarios to demonstrate the models ability to take into consideration changes in budget, maximum work zone lengths, and minimum distances between work zones. The complete road network in the canton of Wallis, Switzerland is 1,352 km long and consists of nearly 35,000 objects on national highways, cantonal roads, rural mountain roads, and jogging paths (Fig. 7). The considered network in this case study consists of the highways and cantonal roads which contain 1,959 objects, including 1,637 road sections, 244 bridges, and 78 tunnels (Fig. 8). A reduced network was used as the development of intervention programs for highways and

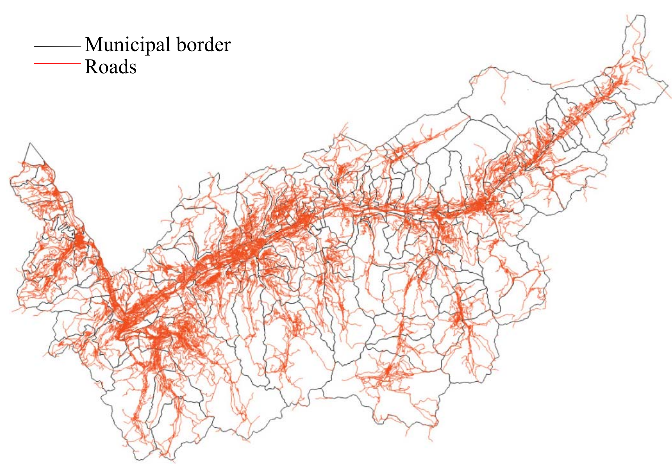

Fig. 7. Road network in the canton of Wallis, Switzerland

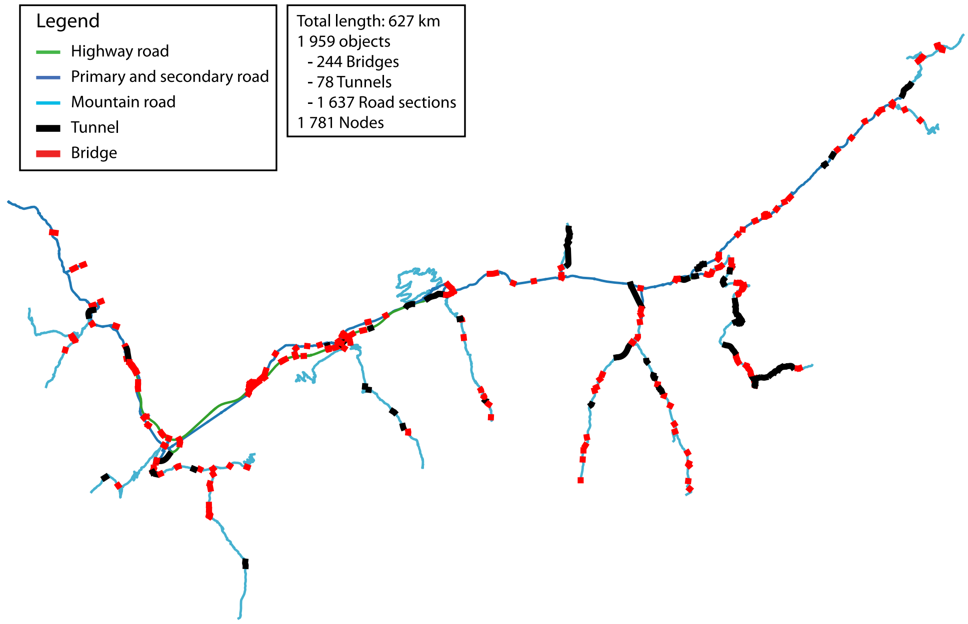

Fig. 8. Road network modeled in the example

cantonal roads is normally done separately from the rural roads and jogging paths. The entire program and data used in this example are available on Github for use by other researchers (Lethanh 2015).

Access Input

The input was accessed from the set of tables in the GIS. The *PostgreSQL* was used because it is considered one of the most advanced open-source database server systems. Within the *PostgreSQL* server, the pgRouting algorithm (pgRouting Contributors 2015) and the *PostGIS*, which is a supporting program for the *PostgreSQL* aiming to create spatial and geographic objects, were installed as *PostgreSQL*'s extensions, which were required to interact with the geospatial data (Obe and Hsu 2015). Data can be sorted, filtered, updated, and manipulated in the *PostgreSQL* using third-party software, such as pgAdmin. All tasks in the access input module were executed via a set of SQL codes to form the data set to be used by the optimization model and the constraint-constructing algorithm. The data included the infrastructure objects and their corresponding condition states. The condition of each object was defined using discrete states on a scale from 1 to 5, where objects in States 1 and 2 were considered to provide an adequate LOS and, therefore, do not require an intervention. They provide an inadequate LOS in States 3, 4, and 5, and, therefore, do require an intervention in those states. This information is summarized in Table 8. The states of each object used in this example were generated randomly and do not reflect the real states of the objects in the canton of Wallis at any time.

Table 8. Condition States and Level of Services

State	Description	Provide adequate LOS?	Require intervention?
1	Like new	Yes	No
2	Good	Yes	No
3	Moderate	No	Yes
4	Bad	No	Yes
5	Worst	No	Yes

Determine the Optimal Set of Work Zones

The code used in the process to determine the optimal set of work zones was programmed in *MATLAB*. The optimization model was developed via a built-in function *intlinprog* in *MATLAB*'s toolbox. This is a function for integer-linear programs and enables *MATLAB* to interface with its ability to feed the optimization model to the mixed-integer-linear-program (MILP) solver Gurobi (Wisconsin Institutes for Discovery 2015), which is based on branch and bound and simplex, and which finds the optimal solution by running once. Although the optimization model was written in *MATLAB* in this work, it can be written in any programming language (e.g., R, Python) that includes a linear optimization solver (e.g., Gurobi, CPLEX, MINTO) and has the capability to retrieve data from a GIS database.

Model the Physical Network

The physical network model of the road network was developed as described in the process section. Links were made of each bridge, tunnel, and road section, and nodes were the interfaces between them.

Define Interventions and Traffic Configuration per Object

It was assumed that the possible interventions to be executed on objects of each type, i.e., road sections, bridges, and tunnels, could be classified as (1) do nothing, (2) maintenance interventions, (3) rehabilitation interventions, or (4) renovation interventions. They are, however, different with respect to individual objects, e.g., a maintenance intervention on a road section is different from a maintenance intervention on a bridge or on a tunnel. The possible traffic configurations (TCs) for each type of object are shown in Figs. 9 and 10. The description of each is given in Table 9.

Estimate Costs for Each Combination of Intervention and Traffic Configuration per Object

The costs considered are the intervention costs, which are attributed to the owner; the travel time costs, accident costs, and vehicle operating costs, which are attributed to the user; and the emission costs, which are attributed to the public [Eq. (6)]. The costs are

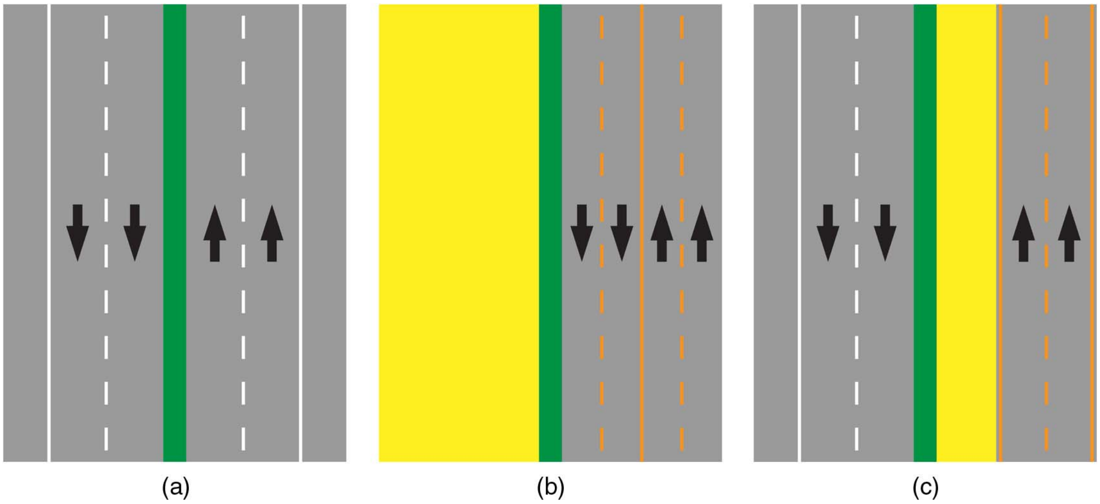

Fig. 9. Traffic configurations on four-lane highways: (a) TC0-normal flow; (b) TC1-(4-0); (c) TC2-(H2-N2)

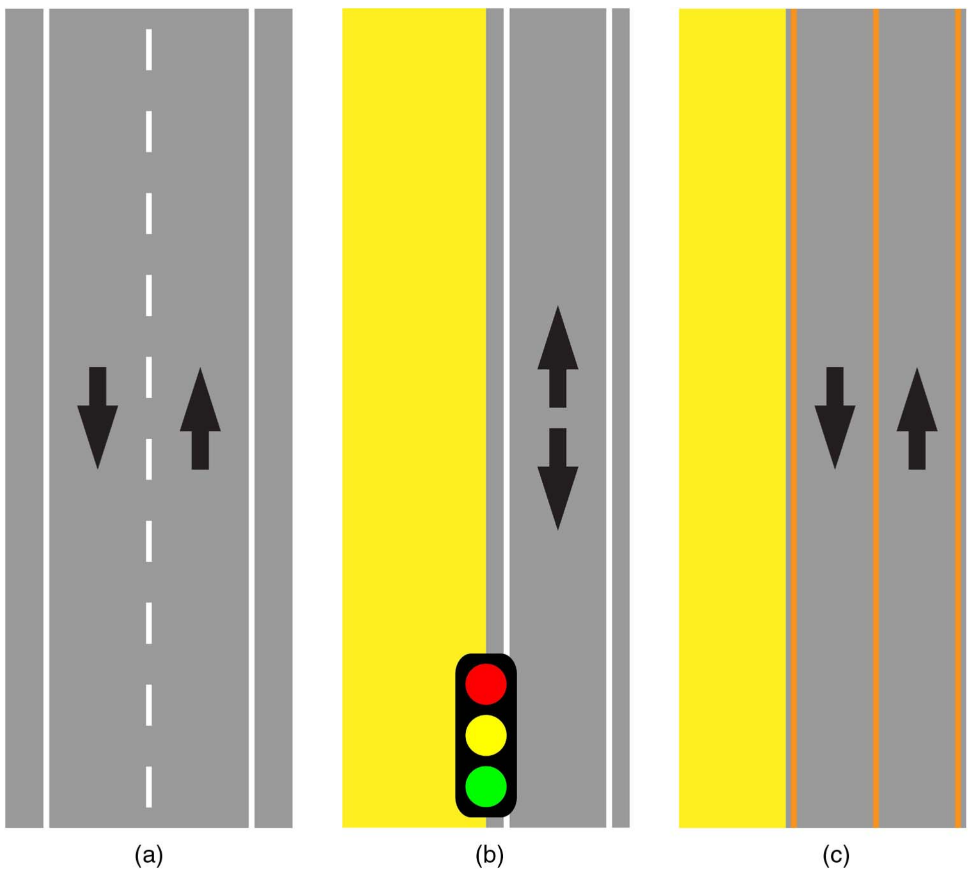

Fig. 10. Traffic configurations on two-lane roads: (a) TC0-normal flow; (b) TC1-(1-0); (c) TC2-(N2)

given in monetary units (mus) instead of a real currency to keep attention focused on the process and not the values

$$C_{n,k} = C_{n,k}^{\text{owner}} + C_{n,k}^{\text{user}} + C_{n,k}^{\text{public}} \tag{6}$$

Owner Costs. Intervention costs are directly linked to the intervention and traffic configuration combination for each object. They were calculated using the following equations:

$$C^{\text{owner}} \leq \alpha + \beta + \eta \tag{7}$$

In this equation, n and k used in Eq. (6) are omitted for the sake of readability. The total intervention costs were considered to be the summation of the fixed costs to execute the intervention α (e.g., costs not related to the length or width of each object); the variable costs to execute the intervention β (e.g., cost that vary due to the actual length and width of each object); and the fixed costs

Table 9. Description of Traffic Configurations

Traffic configurations	Four-lane objects in highways and primary roads	Two-lane objects in cantonal and rural roads
TC_0	Both sides open Two lanes in both directions Free traffic flow	Both sides open One lane in both directions Free traffic flow
TC_1	(4-0) One side is completely closed Two lanes in both directions All lanes have speed restrictions	(1-0) One side is completely closed Traffic flow in both directions is run on one lane, controlled by traffic light
TC_2	(H2-N2) Both sides open Two lanes in both directions One direction has no speed restriction The other direction has a speed restriction	(N2) Both sides open One lane in both directions Speed restrictions in both directions

related to the traffic configuration η (e.g., costs spent on setting up and regulating traffic when an intervention is executed on an object). The costs for each of the intervention types for road sections, bridges, and tunnels are given in Tables 10–12, respectively. The cost values are approximated based on historical data and Swiss norms (ASTRA 2008).

The costs related to the traffic configurations were calculated in two cases: (1) 20% of the total fixed costs are added if the work is executed under traffic. This is the case for TC2 in a four-lane road as well as for TC1 and TC2 in a two-lane road. (2) An additional fixed cost is added for the installation and operation of a traffic light for TC1 on a two-lane road.

User Costs. The costs attributed to the user (C^{users}) include travel time (Γ), accident (Δ), and vehicle operation cost (Θ)

$$C^{\text{users}} \leq \Gamma + \Delta + \Theta \tag{8}$$

Travel Time. Travel time costs are estimated as the increased amount of time that users spend traveling. This cost is linked

Table 10. Road Sections: Intervention Types and Costs

States	Intervention types	Fixed costs (mus)	Variable costs (mus/m^2)
3	Maintenance	3,500	8.00
4	Rehabilitation	4,100	52.00
5	Renovation	9,600	108.80

Table 11. Bridges: Intervention Types and Costs

States	Intervention types	Fixed costs (mus)	Variable costs (mus/m^2)
3	Maintenance	20,000	2,100
4	Rehabilitation	30,000	2,800
5	Renovation	40,000	3,500

Table 12. Tunnels: Intervention Types and Costs

States	Intervention types	Fixed costs (mus)	Variable costs (mus/m^2)
3	Maintenance	100,000	20,000
4	Rehabilitation	150,000	35,000
5	Renovation	200,000	50,000

directly to the traffic configuration for each object in a work zone. It is calculated based on speed limit (v, v_0), length of time the traffic configuration is in place (t), length of object (l), daily traffic volume (d), and the value of travel time savings (s). The following equation can be used to estimate the loss in travel time:

$$\Gamma = t^* \left[\frac{l}{v} - \frac{l}{v_0}\right] \times \sum_{i=1}^{I} d_i \times s_i \tag{9}$$

In the equation, v and v_0 represent speed limits when there is non-normal traffic flow and normal traffic flow, respectively, with t the duration in days and l the object length in kilometers. Index i represents the type of vehicle and I is the total number of vehicle types. In this example, only two types of vehicles were considered, cars and trucks. The values of s for cars and trucks were 18.1 and 132.5 mus/h, respectively. Those values were used based on the work of De Jong (2007).

Accidents. The costs incurred due to potential accidents can be calculated through the following equation:

$$\Delta = t \times l \times a \times \sum_{i=1}^{I} d_i \tag{10}$$

where a = monetary units for accidents per vehicle kilometer. When there is normal traffic flow, the value can be set to 0.23 mus/km (Bakaba et al. 2012). According to the research of Bakaba et al. (2012), additional costs of 56% are incurred (0.13 mus/km) if the traffic configuration is changed.

Vehicle Operation. Vehicle operation costs are incurred as users have to pay for fuel consumption and maintenance of vehicles. They were estimated as the sum of operation costs for all vehicle types as shown in

$$\Theta = t \times l \times p \times \sum_{i=1}^{I} d_i \times \bar{F}_i \tag{11}$$

where p = mean fuel price (1.88 mus/L) and $\bar{F}_i$ = mean fuel consumption of vehicle type i (6.7 L and 33 L per 100 km for cars and trucks, respectively) (Bakaba et al. 2012).

Public Costs. The costs incurred by the public are the emission costs (Λ), i.e., the emission produced by traveling vehicles, including carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxide (NO_x), volatile organic compounds (VOC), and particulate matter (PM)

Table 13. Emissions

Emissions	Composition (%) Car	Truck	Quantity w (g/veh · km) Car	Truck	Cost (mus/ton)
CO_2	20	20	164.8	811.7	22.05
CO	0.258	0.025	1.807	1.015	10,669.35
NO_x	0.020	0.061	0.221	2.476	3,200.81
VOC	0.018	0.005	0.007	0.203	34.85
PM	0.000	0.005	0.131	0.203	9,033.39

Table 14. Scenarios

Scenarios	Budget (mus)	Maximum work zone length (m)	Minimum distance (m)
1	Unlimited	2,000	3,000
2	**20 millions**	2,000	3,000
3	Unlimited	**1,000**	3,000
4	Unlimited	2,000	**2,000**

Note: Bold indicates the changed constraints in the scenarios in reference to the reference scenario.

$$C^{\text{users}} = \Lambda \qquad (12)$$

Table 13 shows the composition of the exhaust fumes for cars and trucks. Additionally it shows the quantity w of emissions by cars and trucks in grams per vehicle kilometer and the approximate cost associated with each emission type (Geringer et al. 2004).

The emission costs were estimated using the following equation:

$$\Lambda = t \times l \times 10^{-6} \times (1 + \bar{f}) \times (1 + \hat{f}) \times \sum_{i=1}^{I} \sum_{j=1}^{J} d_i \times e_j \times w_j \qquad (13)$$

where e_j and ω_j = quantity and cost per ton of the emission type j discharged; $\hat{f}$ and $\bar{f}$ = coefficients related to the increased disturbance due to the road characteristics (mountain) and the current condition state of the road. In this example, it was assumed that when objects were in States 3, 4, and 5, the corresponding values of $\bar{f}$ were 0.05, 0.12, and 0.20, respectively. The value of $\hat{f}$ was 0 when objects were not in the mountains and 0.18 when they were in the mountains. This value was chosen to represent the fact that, in general, vehicles consume more gasoline when traveling on mountain roads than on nonmountain roads. It was chosen to be 0.18 for demonstration purposes only. The objects in the mountains and not in the mountains can be seen in Fig. 8.

Benefit Estimation for Each Intervention and Traffic Configuration per Object

The long-term benefit of executing an intervention on an object consists of the reduced user and public costs over a defined time period (T). The benefits were estimated as follows:

$$B = \sum_{t=1}^{T} [(C_0^{\text{user}}(t) - C^{\text{user}}(t)) + (C_0^{\text{public}}(t) - C^{\text{public}}(t))] \qquad (14)$$

In this equation, n and k used in Eq. (1) are omitted for the sake of readability. The benefit is the sum of the yearly benefits in each year of the investigated time period T, where the benefits are measured as the difference between the costs that would be incurred by the user or the public if no intervention was executed and the costs incurred if the intervention is executed, e.g., the additional travel time due to slower possible vehicle speeds due to poor road conditions.

Define Constraints

All three constraints, the budget, the maximum work zone length, and the minimum distance between two work zones, are defined in Table 14. A base scenario was established (Scenario 1) from which only one constraint differs in each of the other scenarios (Scenarios 2–4).

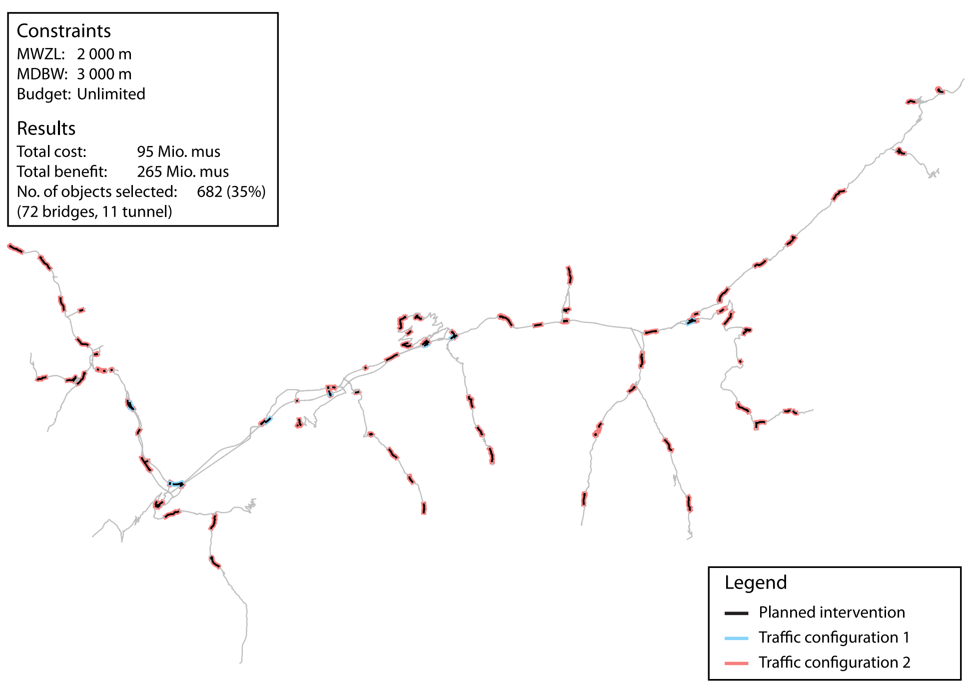

Fig. 11. Scenario 1—interventions and traffic configurations

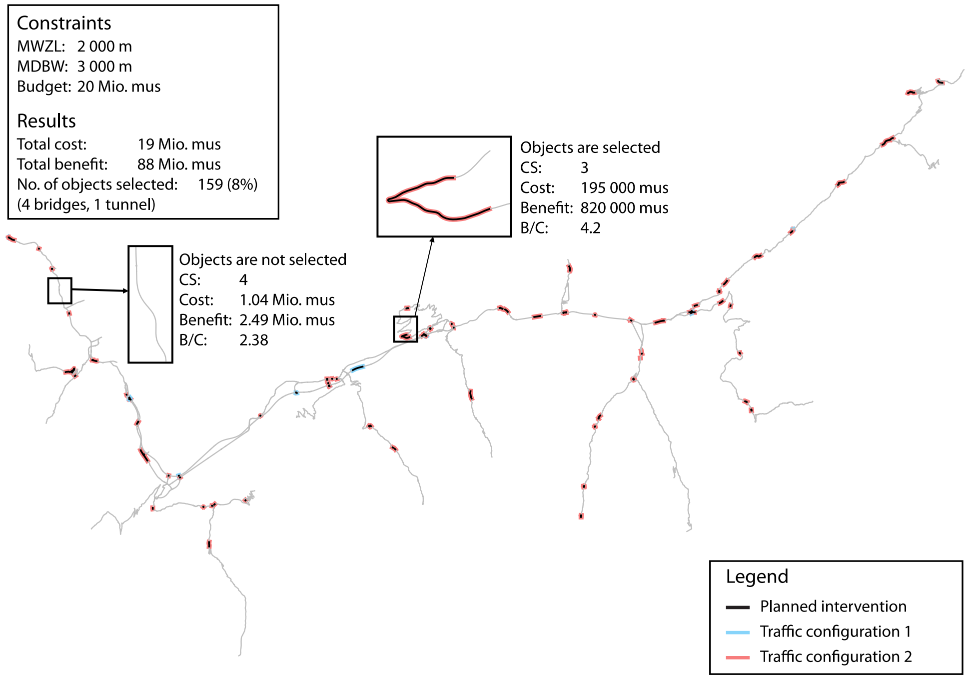

Fig. 12. Scenario 2—interventions and traffic configurations

Execute the Algorithm to Construct the Constraints

The algorithm described in the algorithm section was executed to establish the constraints for each scenario in the form of a matrix.

Estimate the Impacts for All Possible Work Zones

Costs associated with each work zone were estimated for each possible combination of intervention type and traffic configuration.

Display Results

The work zones determined for all scenarios are displayed visually (Figs. 11–14), and summary information is given in tabular form (Table 15). The figures used here show the location of the interventions to be executed (black), as well as the traffic configurations to be used (light blue and light red). The work zones are the areas where there is interrupted traffic flow. In the interest of space, the tables are not shown.

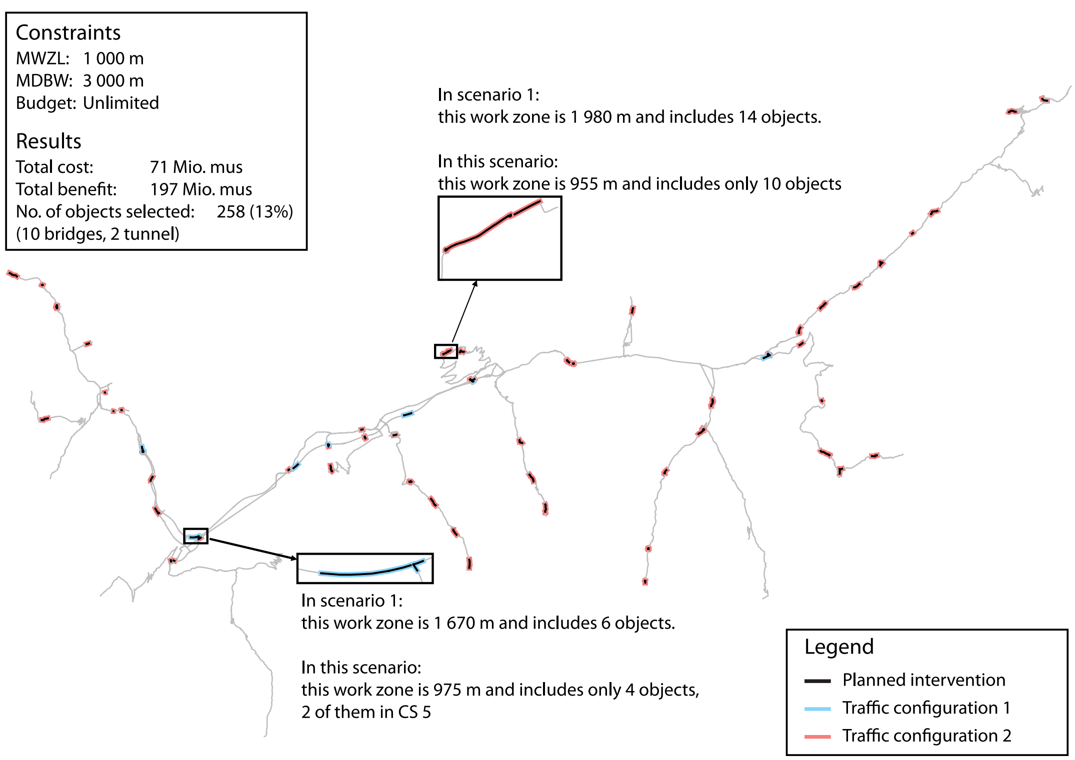

Fig. 13. Scenario 3—interventions and traffic configurations

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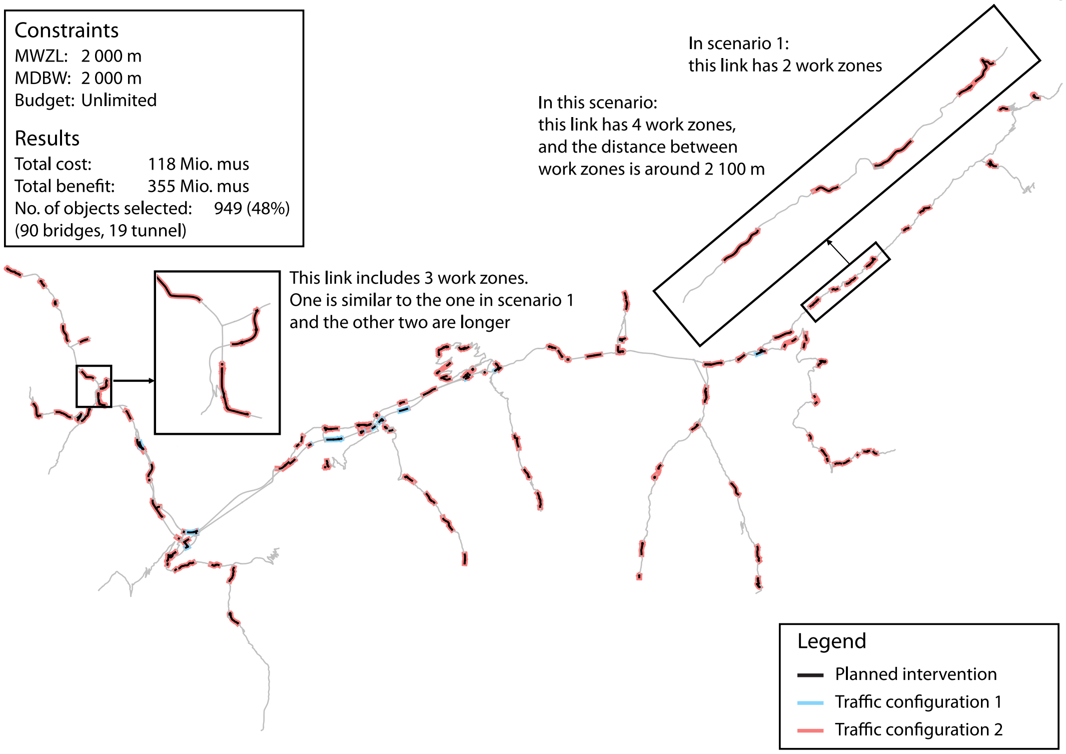

Fig. 14. Scenario 4—interventions and traffic configurations

Table 15. Summary Information

	Number of selected objects					Cost		Benefit		
Scenarios	Total	Bridge	Tunnel	Road	Mean CS	(10^6 mus)	Percent of Scenario 1	(10^6 mus)	Percent of Scenario 1	B/C ratio
1	682	72	11	599	3.2	95	—	265	—	2.8
2	159	4	1	154	3.6	19	19.6	88	33.2	4.7
3	258	10	2	246	3.7	71	74.9	197	74.2	2.8
4	949	90	19	840	3.2	118	123.8	355	134.1	3.0

Table 15 contains summary information for each scenario, including the number of objects included in a work zone (i.e., the objects to be included in the intervention program and the objects that will have a modified traffic configuration because they are between two objects included in the intervention program); the average condition state of all objects after an intervention program is executed; the costs and benefits of each intervention program; and the benefit-cost ratios. For example, Scenario 1 includes 682 objects in work zones, of which 599 are road sections, 72 are bridges, and 11 are tunnels. The average weighted condition state of all objects upon completion of the intervention program is 3.2. It is expected to cost 95×10^6 mus but yield a benefit of 265×10^6 mus.

By displaying the information in this way, differences between scenarios can be clearly seen. For example, the reduction of the budget from unlimited to 20 million mus (Scenario 2) significantly reduced the number of objects from 682 to 159, and the number of road sections, bridges, and tunnels from 599 to 154, 72 to 4, and 11 to 1, respectively. The restriction of the maximum length of a work zone from 2,000 to 1,000 m (Scenario 3) reduced the number of objects from 682 to 258, and the number of road sections, bridges, and tunnels from 599 to 246, 72 to 10, and 11 to 2, respectively. The reduction of the minimum distance between work zones from 3,000 to 2,000 m (Scenario 4) augmented the number of objects from 682 to 949, and the number of road sections, bridges, and tunnels, from 599 to 840, 72 to 90, and 11 to 19, respectively. Additionally, the table expresses the costs and benefits in percentage of the ones from Scenario 1. For example, Scenario 2 costs only 19.6% of Scenario 1, while the benefit reaches 33.2% of the one in Scenario 1.

The differences in mean condition states, costs, and benefits can be seen in similar ways. The benefit-cost ratio could be used in arguments to select a specific scenario. Graphically, the differences can be clearly seen in Figs. 12–14. The circles in these figures highlight some important differences among scenarios. Such figures help to make clear the consequences of changing the maximum lengths of work zones, the minimum distance between adjacent work zones, and the amount of money available to execute interventions.

Conclusion

A process was developed to determine optimal intervention programs for large infrastructure networks in a GIS framework. The optimization model includes constraints on the length of the work zone, the distance between two work zones, and the amount of available resources. Both the optimization model and the constraint-constructing algorithm directly access the GIS-supporting relational data tables. In the model, the intervention costs are attributed directly to the objects included in the work zones and the user costs are attributed directly to the work zones. The process was illustrated by determining the optimal set of work zones for an example road network similar to the one in the canton of Wallis, Switzerland, including more than 2,000 bridges, tunnels, and road sections. The model was found to be relatively efficient, taking only 8 h to run on a normal desktop computer.

The proposed process is usable for the determination of optimal intervention programs on real-world networks, because

- All types of objects, interventions, and traffic configurations can be considered, for example, objects of different physical nature, e.g., bridges and road sections, on which different types of interventions can be executed, e.g., rehabilitation and replacement, and for which different traffic configurations are required during the execution of the interventions, e.g., reduction of width of traffic lanes and closure of two traffic lanes;
- The process can be used for large networks as user costs were estimated using a static traffic model, and a mixed-integer linear program is used;
- The constraint-writing algorithm enables all necessary data to be read automatically out of the GIS; and
- The final displays of the intervention programs in the GIS can be easily interpreted by infrastructure managers.

Although the program can be run on a large-scale network, taking into consideration various practical constraints (distance and budget), intervention types, and traffic configurations for individual objects and work zones, it still has a number of limitations that need to be solved in future research:

- The use of dynamic traffic flow models instead of static models.
- The use of multiple time steps in the optimization instead of an optimization done on a year-by-year basis. This will require significant modeling efforts, for example, to use mixed-integer nonlinear models instead of mixed-integer linear models.
- Conducting a global sensitivity analysis to investigate the correlations between the input and output variables and their influence on overall results. This work is to be conducted once there is sufficient data on all of the input variables.
- Exploring faster algorithms than the one used in this research, to improve run time.
- Adapting the process for other types of infrastructure networks, e.g., railway networks and water distribution networks.

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