A scalable optimization approach to the intervention planning of complex interconnected infrastructures

Kammouh, Omar; Fecarotti, Claudia; Marandi, Ahmadreza

DOI
10.1016/j.ress.2024.110281

Publication date
2024

Document Version
Final published version

Published in
Reliability Engineering and System Safety

Reliability Engineering and System Safety 250 (2024) 110281

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

A scalable optimization approach to the intervention planning of complex interconnected infrastructures

Omar Kammouh [a,*], Claudia Fecarotti [b], Ahmadreza Marandi [b]

[a] Department of Multi-Actor Systems, Delft University of Technology, the Netherlands
[b] Department of Industrial Engineering and Innovation Sciences, Eindhoven University of Technology, Eindhoven, the Netherlands

A R T I C L E I N F O

Keywords:
Interconnected infrastructure
Intervention planning
Maintenance
Optimization
Grouping

A B S T R A C T

The functioning of infrastructure networks is vital for modern communities. Maintenance should be planned to ensure infrastructure's functionality and safety at the lowest cost. Interconnected infrastructure networks can affect each other's functionality, and maintenance on one network can impact the serviceability of others. Planned intervention grouping across infrastructures reduces set-up costs and service interruption, improving infrastructure availability and serviceability at lower costs.

Finding the best grouping strategy is a known NP-hard problem, with several optimization strategies have been proposed, mainly based on nonlinear models which are computationally expensive and do not guarantee scalability. Furthermore, infrastructure intervention planning models mostly focus on grouping of interventions which are considered as given. In this paper, we propose a new efficient optimization model to optimize intervention grouping for interconnected infrastructure networks. We develop a scalable two-step optimization model where we first plan each individual intervention type based on a preventive maintenance policy accounting for the degradation behavior of objects, then group interventions to minimize the net costs, considering dependencies within and accross infrastructure networks.

We formulate the grouping problem as an Integer Linear Program, which can be solved *exactly* with standard solvers. The model accounts for interactions between infrastructure networks and considers the impact on all stakeholders. It also accommodates various intervention types like maintenance, removal, and upgrading.

Using a demonstrative application, we show that our model significantly reduces net costs and outperforms alternative nonlinear formulations and related heuristics in terms of both solution quality and computation performance. Additionally, the optimal intervention plan shows repetitive patterns, which suggests that a rolling horizon strategy could be used where the optimization problem is solved for shorter time horizons, leading to significant computational benefits.

Nomenclature

- $C_{j,k}^{prev} \in \mathbb{R}^+$: preventive intervention cost of object j within intervention type k
- $\boldsymbol{C}_{1\times K}^{prev}$: vector of preventive intervention costs whose k^{th} component $C_k^{prev} \in \mathbb{R}^+$ indicates the cost of preventive intervention k, which is equivalent to the summation of the preventive intervention costs of all objects within intervention type k
- $C_j^{corr} \in \mathbb{R}^+$: cost of a corrective repair of object j
- $\boldsymbol{C}_{1\times N}^{shut}$: vector of service interruption costs whose j^{th} component $C_j^{shut} \in \mathbb{R}^+$ indicates the cost of suspending the j^{th} object
- $\boldsymbol{C}_{1\times E}^{setup}$: vector of set-up costs whose e^{th} component $C_e^{setup} \in \mathbb{R}^+$ indicates the set-up cost of the e^{th} intervention group
- $C_{tot}^{prev} \in \mathbb{R}^+$: total costs of preventive interventions

(*continued on next column*)

(*continued*)

- $E \in \mathbb{N}$: number of intervention groups
- $\boldsymbol{G}_{E\times K}$: matrix whose component $G_{e,k} \in \{0,1\}$ indicates if intervention type k belongs to intervention group e
- $\boldsymbol{I}_{N\times N}$: matrix whose component $I_{i,j} \in [0,1]$ indicates the degree of interdependency between object i and object j
- J_k: set of objects j targeted by intervention k
- $K \in \mathbb{N}$: number of intervention types
- $\boldsymbol{M}_{K\times T}$: matrix whose components $M_{k,t} \in \{0,1\}$ indicates whether intervention type k is executed at time step t.
- $N \in \mathbb{N}$: number of objects
- $\boldsymbol{R}_{N\times K}$: relation matrix whose component $R_{j,k} \in \{0,1\}$ indicates if intervention type k intervenes on object j

(*continued on next page*)

* Corresponding author.
E-mail address: o.kammouh@tudelft.nl (O. Kammouh).

https://doi.org/10.1016/j.ress.2024.110281
Received 15 May 2023; Received in revised form 4 May 2024; Accepted 11 June 2024
Available online 14 June 2024

(*continued*)

$S_{tot} \in \mathbb{R}^+$: total set-up costs
$T_{min,k} \in \mathbb{N}$: minimum time steps between any two interventions of type k
$T_{max,k} \in \mathbb{N}$: maximum time steps between any two interventions of type k
$T \in \mathbb{N}$: number of time steps considered
$T^{opt}_{j,k} \in \mathbb{N}$: the optimal interval for preventive intervention type k on object j
$T_{opt,k} \in \mathbb{N}$: optimal interval for preventive intervention type k, which is the minimum value of $T^{opt}_{j,k}$ across all objects targeted by intervention k
$U_{tot} \in \mathbb{R}^+$: total service interruption costs caused by the interventions
$\boldsymbol{U}_{N\times T}$: matrix whose components $U_{i,t} \in \{0,1\}$ indicates if object j is directly or indirectly affected by at least one intervention activity at time step t
$\boldsymbol{V}_{E\times T}$: : matrix whose component $V_{e,t} \in \{0,1\}$ indicates if intervention group e contains at least one intervention activity executed at time step t
$\alpha_j \in \mathbb{R}^+$: scale parameter of the Weibull distribution of an object j
$\beta_j \in \mathbb{R}^+$: shape parameter of the Weibull distribution of an object j
$\delta(.)$: Kronecker delta function
$\lambda_j(t)$: the failure rate of an object j at time t
χ^2: Chi square-error

Notes: Bold characters refer to matrices and vectors (e.g., $\boldsymbol{A}_{B\times C}$ is a matrix with B rows and C columns and $\boldsymbol{A}_{1\times C}$ denotes a Vector with C columns). Non-bold characters refer to scalar values.

1. Introduction

Infrastructure networks continuously degrade over time due to age and wear. Degradation ultimately leads to failures which affects the service quality and causes safety issues and physical damages. Interventions are executed to ensure the continuous fulfillment of the infrastructure's functional goals and quality of service (e.g., water protection, traffic flow, etc.). To increase infrastructure availability while minimizing intervention costs, a shift from a corrective to a preventive approach is needed [1]. Unlike corrective interventions, preventive maintenance allows activities to be adequately planned in advance, thus facilitating their grouping which can be highly beneficial as it enables intervention and disruption costs to be reduced by taking advantage of the economy of scale. The execution of maintenance activities causes service interruption to the network targeted by the intervention as well as to other networks which are at spatial proximity or have a topological or functional connection with the infrastructure object(s) being maintained.

Grouping of interventions enables set-up costs to be shared and service interruptions to be reduced. To achieve the maximum benefit, grouping should not be limited to objects within the same network (e.g. only water pipes or only road sections), but also across interconnected infrastructure networks. In addition, grouping should be optimized not only based on the spatial proximity, topological, and functional connection between assets, but also based on the time at which each asset will need maintenance depending on their degradation and failure processes. If preventive thresholds for objects replacement are not optimized and taken into account in the grouping strategy, there can be negative economic consequences due to either the increased frequency of some activities and the waste of remaining useful life for early replacement, or an increased risk of failure if maintenance is not executed on time [2,3].

1.1. Literature review

The existing literature on maintenance optimization for multi-item systems has shown a growing interest in opportunistic maintenance policies and grouping strategies as the two main approaches to address the simultaneous maintenance of multiple components to further minimize maintenance costs. The former approach mainly focuses on the optimization of thresholds-based rules which trigger maintenance of components if an opportunity arises due to a preventive or, more often, a corrective replacement of another component. The latter usually focuses on the clustering of interventions to be executed at either predetermined or optimized moments. Recent contributions on opportunistic maintenance models are [4–6]. In [6] a system of multiple machines in series is considered; the opportunistic thresholds are determined for each machine via Genetic Algorithm, while a search method is developed to determine the optimal schedule for the entire system. In [4,5], with particular focus on economic and structural dependencies, the inspection interval and the preventive and opportunistic thresholds are determined by first calculating the long-run maintenance cost rate via Montecarlo simulation and then by optimizing via Particle Swarm Optimization. In [7] the authors develop a nonlinear optimization model solved via Genetic Algorithm to determine the number of inspections and the preventive and opportunistic thresholds which minimize the total maintenance costs for a multi-component repairable system over a finite planning horizon. In that work, only economic dependencies are considered. The optimization of opportunistic maintenance policies for multi-component systems are very challenging to solve exactly, thus simulation and heuristics are often implemented.

Grouping was addressed early in 1991 by Dekkert et al. [8] who developed a set partitioning optimization model to combine maintenance activities at an operational level with the aim to minimize maintenance costs for multi-component systems. Later on in [9], the same authors proposed a dynamic grouping algorithm to minimize intervention cost and introduced an optimization approach that can help set up an elicitation procedure which is especially useful when deterioration modeling is based on expert judgment rather than statistical data analysis. Wildeman et al. [10] developed a dynamic grouping policy based on a rolling horizon approach which take a long-term (stationary) tentative planning per component and then deviate from it at system level to group activities.

Grouping strategies for complex systems whose components are arranged into series and parallel configurations are developed and optimized with respect to maintenance costs by [11,12] in stationary contexts, and by [13–16] in a dynamic contexts using a rolling horizon approach and solved via Genetic algorithm. Dynamic grouping is also addressed in [12], where two optimization approaches are proposed to solve the grouping problem: Particle Swarm Optimization which is applicable only to small-medium size systems, and a constrained clustering approach formulated as a mathematical programming model more suitable for larger systems and solved via a dedicated simulator.

Similarly, Chalabi et al. [17] implement Particle Swarm Optimization to group preventive maintenance interventions for series production systems with the aim to minimize the cost of the preventive intervention schedule while maximizing the system's availability. Moinian et al. [3] developed a genetic algorithm to solve the grouping problem for multi-component systems with application to gas turbines, to find the optimal balance between the maintenance costs and system unavailability. More recently, grouping has been considered in [18] for a series system of eight components. First the optimal maintenance period for each individual component is determined, then the optimal group structure is optimized in a rolling horizon setting by implementing a heuristic which imposes that each group includes only a sequence of consecutive activities within a given shorter horizon for which dynamic programming is implemented. Mathematical programming is adopted in [19], where a mixed integer linear program is proposed to determine groups of interventions for a single multi-component machine; the aim is to minimize the number of stoppages based on a given predefined schedule of individual activities and time windows tolerances within which interventions can be shifted. However, dependencies between components are not explicitly modeled, and groups of interventions which can be possibly clustered are input to the model. The model is solved exactly via standard solvers, which makes it accessible for real applications. The abovementioned papers focus on generic multi-component systems and are not specifically developed for application to infrastructure systems and their peculiarities. Because of the complexity of the resulting optimization problems, heuristic and meta-heuristic approaches are used rather than exact solution algorithms. The combinatorial explosion of grouping optimization problem is even more relevant when grouping is considered in the context of infrastructure networks, where one usually deals with large scale systems with dependencies across objects.

With specific focus on papers targeting intervention planning for infrastructure networks, most contributions deal with single networks while much less research has been devoted to grouping and intervention programs optimization for multiple interconnected infrastructures as pointed out in [20,21]. In the terminology used in the field of infrastructure asset management, the problem of grouping optimization is often referred to as work zone(s) optimization, where work zones correspond to groups of infrastructure objects which are maintained simultaneously. The problem of grouping road sections into work zones for road infrastructures is addressed in [22] where an integer linear program is developed and solved via an ad hoc heuristic based on enumeration. Grouping into work zones is optimized on net benefit accounting for both infrastructure owner and users costs; dependencies across objects, however, are not modeled and the feasibility of groups is based on the maximum length that a work zone can reach and the minimum distance between different work zones. In [2], the optimization of repair and grouping policies for road pavement systems is addressed, where both spatial proximity and temporal aspects related to the deterioration of individual pavement sections are considered. The authors develop a dynamic programming approach to solve the problem exactly for small systems, and a rule-based heuristic for larger scale systems. A maintenance grouping and prioritization method for networks of bridges is presented in [23]. Bridges' criticality is evaluated based on complex networks centrality measures and used to prioritize maintenance, while grouping is contemplated at bridge level to combine maintenance of bridge's components. A penalty cost for shifting activities is associated to grouping, which is performed only if the benefit of shared set-up costs and reduced operational disruption exceeds the penalty cost.

The authors in [20,24] address the optimization of work programs by grouping maintenance activities for multiple interconnected networks. In [20], two grouping methodologies are proposed for multiple infrastructure networks, one static based on spatial proximity only, and the other one dynamic based also on topological connections between objects and their failure probability. Based on some predefined thresholds imposed by the infrastructure operators, objects are classified into two levels of urgency depending on whether they are in an unacceptable state and an intervention is justified on its own (level 1), or they are not yet in need of maintenance but an intervention will be needed in the near future (level 2). Level 2 objects can be grouped with level 1 objects which trigger an intervention. Groups are then ranked based on the consequences that execution of the interventions has on service interruption. Temporal factors related to the scheduling of interventions are not considered by the authors. A Genetic Algorithm is developed in [24] where objects are first grouped into an intervention program, and then the related costs and service disruption are calculated. A decision support tool which employs a Genetic Algorithm to plan intervention programs for water distribution and sewer networks is developed also in [25]. Predefined groups of objects (e.g., all pipes in a street) rather than individual objects are considered as replacement units, and coordination of interventions between groups which can be performed simultaneously is optimized via a Genetic Algorithms procedure based on different parameters reflecting replacement priority, intervention costs, the length of the street affected by the intervention. An integer nonlinear optimization model is developed in [26,27] to group intervention activities for multiple interconnected infrastructures. Based on an initial predefined schedule which is given as input, interventions are grouped to minimize service disruption. Due to the model complexity, a genetic algorithm procedure is implemented to obtain an approximate solution. Only the direct cost of interventions are minimized while set-up costs are not explicitly considered.

The optimization approaches and methods mentioned above are mainly based on nonlinear models which are computationally expensive and do not guarantee scalability. Moreover, most of these approaches are project-based and focus on single infrastructures rather than multiple interconnected networks. Little effort has been devoted so far to the optimization of intervention programs for interconnected infrastructure networks, where interventions targeting one network may impact the functionality of the other networks too. When planning interventions for multiple interconnected infrastructures, not only one has to account for those dependencies across the assets which determine the cascading effects of failures and interventions across the system, but also for the role played by multiple stakeholders involved in the decision process. In the available literature however, the complex dependencies across multiple infrastructures and the perspective of multiple stakeholders are not adequately tackled. Furthermore, in the literature on infrastructure intervention planning there is a lack of exact methods to determine long-term grouping (or work zones) policies which incorporate both the economies of scale to save costs, and the deterioration processes of the objects. Most of the times grouping is based on a predefined set of interventions to be executed within a given time window and which can be rearranged to be grouped. The formulation of the grouping problem is often such that heuristic approaches are implemented to find approximate solutions which often lack a quality check with respect to optimality.

1.2. *Contribution of the paper*

This paper contributes to the scientific literature on intervention planning and grouping optimization for multiple interconnected infrastructures. We cover some of the shortcomings in the existing scientific literature discussed above by introducing a scalable optimization approach for grouping interventions in such a way to minimize direct intervention costs, set-up costs, and service interruptions. Grouping feasibility is formulated based on spatial proximity and functional and topological dependencies between infrastructure objects, which are modeled via adjacency matrices, but also on temporal aspects related to the degradation and failure processes of the infrastructure objects. We develop a two-stage approach where we first determine the optimal planning for each intervention type based on the object's failure probability and then use these as tentative plannings based on which grouping is optimized, taking advantage of time window tolerances, which is an approach commonly used in practice [19]. The grouping problem is formulated as a nonlinear integer problem, which we then linearize and solve exactly. As computational complexity is a notorious feature of combinatorial problems and often a barrier towards model scalability, we conduct an extensive numerical analysis to investigate how computation time changes with the number of objects, interventions, and the length of the planning horizon. We also compare our results in terms of solution performance and computational efficiency with the ones obtained (1) with an alternative model where optimal intervention timing based on failure and degradation modeling is not considered and a nonlinear formulation of the grouping problem is solved via Genetic Algorithm, and (2) when coordination between interventions is disregarded. The main contributions of the paper are summarized as follows:

1. We propose an efficient and effective approach to modeling interconnected infrastructures, including both the interdependencies within a single infrastructure network and those across multiple infrastructure networks.
2. We develop a two-step linear optimization model for the grouping problem that is computationally inexpensive and ensures scalability.

3. We formulate the grouping problem as an Integer Linear Program, enabling exact and rapid solutions using standard solvers.
4. We integrate infrastructure degradation into the first step of the optimization problem to optimize the preliminary intervention program of each object. The initial intervention program serves as the starting point for the second stage of the optimization.

The rest of the paper is organized as follows. Section 2 presents the problem description and the developed intervention planning approach. Section 3 introduces the multi-system optimization model. Section 4 presents an example to illustrate the proposed optimization model. Finally, conclusions and future work are drawn in Section 5.

2. Problem description and system modelling

In this paper, we consider a system of multiple interconnected infrastructure networks (e.g. railroad, water distribution, highway). Each network consists of multiple objects; for example, the railroad network consists of multiple track sections while the water distribution network consists of multiple pipe sections. Infrastructure operators can be responsible for managing intervention plannings for one or multiple networks. Different types of dependencies (economic, physical, geographical, functional [28]) exist between objects within the same network and/or across different networks. Interventions can be of different types, from routine maintenance to replacing and upgrading. The same intervention type can target one or more objects of the same type simultaneously (e.g. multiple road sections or multiple pipe sections). Intervention types can be classified into two macro-categories: central and non-central interventions. The former must occur at pre-established time moments that cannot be re-scheduled. The latter instead can be re-scheduled if a suitable opportunity arises to be combined with a central intervention. Based on a preliminary schedule of both central and non-central interventions, we pursue an optimal grouping of these activities to minimize the total net costs while respecting necessary constraints related to the timing of interventions and their "compatibility" based on objects interdependencies.

Grouping intervention activities results in broad economic and societal benefits. Three elements contribute to the net cost of an intervention plan: (1) direct preventive intervention cost, which constitutes all costs that are directly linked to the intervention activity (e.g., replacement parts, specialized crew, etc.), (2) Set-up cost, which constitutes generic costs needed to execute an intervention but can be shared by several intervention activities (e.g., cost of crew traveling, excavation, scaffolding, etc.), and (3) system interruption cost, due to objects (i.e., component of a network) unavailability while under maintenance (e.g., extra travel time due to road disruption, low water pressure, etc.). It is not unusual that the direct intervention costs may increase in the optimal intervention plan due to the higher frequency of some activities based on the optimal grouping. However, in this case, the global benefits achieved by the intervention grouping will be due to less system interruption and set-up costs. The interruption cost of the service must be monetized to be able to combine it with the intervention cost into one utility function. Several methods to monetize the impact of service interruption have been recently developed [1,29,30].

2.1. System modelling

We model the system as a set of objects $N := \{j : j = 1,\ 2,\ \dots,\ |N|\}$, subject to a set of intervention types $K := \{k : k = 1,\ 2,\ \dots,\ |K|\}$. We assume that objects are subject to wear and aging and thus they exhibit an increasing failure rate; we therefore adopt a Weibull distribution to model the reliability behavior of the objects. The flexibility of the Weibull distribution which, by suitably varying the values of the shape and scale parameters, can cover a wide variety of lifetime behaviors for components subject to wear and age over time. Its generalizations and modifications allow for a wide range of applications, including lifetime behavior. For this reason the Weibull distribution is widely and commonly used for similar applications in the scientific literature [31,32] as well as in practice. In this paper, we use the Weibull distribution to describe the failure behavior of an object j, with corresponding failure rate function given by $\lambda_j(t) = \frac{\beta_j}{\alpha_j}\cdot\left(\frac{t}{\alpha_j}\right)^{\beta_j-1}$, where $\alpha_j > 0$ and $\beta_j > 1$ are the scale and shape parameters respectively. An intervention type k in K can target one or more objects in N. We discretize the planning horizon into a finite number of time steps of equal length, which we consider as the time unit in our analysis. The length of the planning horizon $T \in \mathbb{N}$ is therefore equal to the total number of time steps considered. We define $T_{max,k}$ as the maximum interval between two consecutive interventions of type k. The failure risk of an object increases as the time from the last intervention increases [33,34]. Various methods can be used to compute $T_{max,k}$, such as block replacement models [35], delay-time models [36], and degradation models [37–39]. Here, we adopt a block replacement policy with minimal repair. Block replacement policy with minimal repair is a strategy used to manage the maintenance of a system that can fail. It aims to minimize repair costs while maintaining system reliability. The system/component is brought to as-good-as-new condition at predetermined intervals, regardless of its current condition. This ensures the system/component is less likely to fail before the next maintenance. If the system/component fails before the scheduled maintenance, a minimal repair is performed instead. This minimal repair restores the system/component to working condition, but it does not necessarily address the underlying cause of the failure. The key benefit of this policy is reducing unnecessary costs since minimal repairs are often cheaper and faster than full repairs.

In this paper, we use block replacement policy with minimal repair and determine $T_{max,k}$ accordingly (See Section 3.1 for more details). While the interval for central interventions remains fixed, non-central interventions can be rescheduled to allow grouping. Therefore, for non-central interventions we assign a minimum interval $T_{min,k}$ in addition to $T_{max,k}$, to ensure that an intervention is not performed too frequently (which can be unfeasible for various reasons). The time interval for a non-central intervention can therefore vary between $T_{min,k}$ and $T_{max,k}$ to enable grouping with central interventions.

Similarly to [40–42], we use adjacency matrices to model dependencies. The matrix allows for modeling dependencies among components within and across multiple systems, and for any number of components. Additionally, it can represent both direct and indirect interactions among these components. In our work, the dependencies between the objects are represented by interaction matrix $\boldsymbol{I}_{N\times N}$ where the interaction coefficients $I_{i,j} \in [0,1]$ indicates the level at which an intervention executed on object j affects functionality of object i. Interactions between any number of objects can be modeled. The interaction between objects is not necessarily binary, because an intervention on object j can also only partially affect object i. This is captured by setting the value of the interaction coefficients between 0 (no interaction) and 1 (full interaction). The diagonal terms are all equal to 1. $\boldsymbol{I}_{N\times N}$ can be asymmetric due to the non-reciprocal interaction behavior among the objects. The values of the interaction coefficients can be obtained from experts judgment [41,42]. Along with the dependencies between objects, we also model dependencies between interventions and objects by defining matrix $\boldsymbol{R}_{N\times K}$ to indicate which objects are directly subject to which intervention type. Its components $R_{j,k} \in \{0,\ 1\}$ are binary and indicate whether intervention k is executed on object j (1) or not (0). Some intervention types can be grouped and executed together to share set-up costs which are therefore only incurred once. We, therefore, define groups of interventions that can potentially be clustered together, and collect these groups in set $E = \{e = 1,\ 2,\ \dots,\ |E|\}$. We then introduce matrix $\boldsymbol{G}_{E\times K}$ whose components $G_{e,k} \in \{0,1\}$ takes the value 1 if intervention type k belongs to group e, and 0 otherwise.

3. Mathematical formulation of the intervention grouping optimization problem

This section presents the mathematical formulation of the proposed intervention optimization model. We adopt a bottom-up approach where we first (stage 1) determine tentative planning for each individual intervention type k separately based on a block replacement policy with minimal repair. Then (stage 2), based on these tentative plannings, we optimize the intervention program for the entire network by grouping interventions to minimize the total net cost.

3.1. Stage 1: tentative planning for individual intervention type

An intervention k can target one or multiple objects of the same type. We indicate as J_k the set of objects j targeted by intervention k. We adopt a block replacement policy with minimal repair according to which all objects subject to intervention k are preventively maintained simultaneously at a fixed interval. This maintenance policy is designed to restore the objects to a state as close to new as possible. If an object fails between two scheduled maintenance intervals, it is repaired to a state comparable to its condition immediately prior to the failure, known as "as bad as old" conditions. We first determine the optimal preventive maintenance interval for each object j targeted by intervention k independently, by minimizing the long-run expected maintenance cost.

Let $C_{j,k}^{prev}$ denote the cost of preventive intervention k for object j, C_j^{corr} the cost of a corrective repair of object j. According to the block replacement policy with minimal repair [16], the expected intervention cost during time interval [0,t] if preventive intervention k is performed at time t is givcentralen by:

$$E\left[C_{j,k}(t)\right] = C_{j,k}^{prev} + C_j^{corr}\cdot \int_0^t \lambda_j(t)dt = C_{j,k}^{prev} + C_j^{corr}\cdot\left(\frac{t}{\alpha_j}\right)^{\beta_j}, \tag{1}$$

where the second term in the sum denotes the expected cost of minimal repair during time interval [0,t], namely between two consecutive preventive interventions. By taking the first derivative of the expected cost per time unit and imposing it equal to zero, we obtain the optimal interval for preventive intervention k on object j which minimize the expected maintenance cost per unit time:

$$T_{j,k}^{opt} = \alpha_j\cdot \sqrt[\beta_j]{\frac{C_{j,k}^{prev}}{C_j^{corr}\cdot(\beta_j - 1)}}. \tag{2}$$

At this point, we need to determine the interval for preventive intervention k. As indicated before, an intervention k targets the set of objects J_k . However, each of the objects in J_k has a different optimal intervention interval. Therefore, we consider the interval for preventive intervention k to be equal to that of the component with the shortest optimal interval. Though considered conservative, a larger interval would exceed the allowable failure probability of the critical object with the shortest optimal interval. This, in turn, would lead to more corrective interventions, ultimately increasing net costs. We, therefore, take as an interval for preventive intervention k, the minimum value of $T_{j,k}^{opt}$ across all objects targeted by intervention k:

$$T_{opt,k} = \min_{j\in J_k}\left\{T_{j,k}^{opt}\right\}. \tag{3}$$

3.2. Stage 2: final grouping intervention scheduling for the global system

The global optimization problem introduced in this section aims at grouping interventions in such a way to minimize the net cost which includes the direct intervention costs, set-up costs, and the compound costs of service interruption. The grouping of interventions implies rescheduling of (some of) the non-central interventions with respect to the tentative planning obtained in stage 1. The decision is whether to perform intervention k at time step t or not; we therefore introduce decision variables $M_{k,t}\in\{0,1\}$ which takes value 1 if intervention k is performed at time step t, and 0 otherwise. We collect all decision variables in matrix $M_{K\times T}$. The objective is to minimize the net cost:

$$\min_{M_{K\times T}}\left(C_{tot}^{prev} + U_{tot} + S_{tot}\right), \tag{4}$$

where C_{tot}^{prev}, U_{tot} and S_{tot} are the total preventive cost, the total service interruption cost, and the total set-up cost, respectively. In the following we define each cost function separately.

The preventive cost C_{tot}^{prev} is given by:

$$C_{tot}^{prev} = \sum_{t=1}^{T}\mathbf{C}_{1\times K}^{prev}\times \mathrm{M}_{K\times T}^{t}, \tag{5}$$

where $\boldsymbol{C}_{1\times K}^{prev}$ is the vector of preventive intervention costs whose k^{th} component C_k^{prev} indicates the cost of performing preventive intervention type k, and $\boldsymbol{M}_{K\times T}^{t}$ is the t^{th} column of the matrix $\boldsymbol{M}_{K\times T}$. It is assumed that every intervention activity is performed within a single time interval.

The total service interruption cost U_{tot}, caused by the interventions, is:

$$U_{tot} = \sum_{t=1}^{T}\boldsymbol{C}_{1\times N}^{shut}\times\overline{\delta}\left(\boldsymbol{I}_{N\times N}\times\boldsymbol{R}_{N\times K}\times\boldsymbol{M}_{K\times T}^{t}\right), \tag{6}$$

where $\boldsymbol{C}_{1\times N}^{shut}$ is the vector of service interruption costs whose j^{th} component C_j^{shut} indicates the service cost due to unavailability of object j, $\overline{\delta}(.)$ represents the Kronecker delta function, which is applied to each component of the vector. By using the Kronecker delta function, we can avoid double-counting the service cost associated with the unavailability of an object that is affected by multiple interventions scheduled at the same time step. The Kronecker delta function is defined as follows:

$$\delta(x) = \begin{cases} 0 \; if x = 0 \\ 1 \; if x \neq 0 \end{cases}. \tag{7}$$

Finally, the total set-up costs of the interventions S_{tot} is:

$$S_{tot} = \sum_{t=1}^{T}\mathbf{C}_{1\times E}^{setup}\times\delta\left(\mathrm{G}_{E\times K}\times\mathrm{M}_{K\times T}^{t}\right), \tag{8}$$

where $\boldsymbol{C}_{1\times E}^{setup}$ is vector of set-up costs whose e^{th} component C_e^{setup} is the set-up cost associated to group e in set E.

The minimization of the net cost is subject to the following constraints:

$$0 \le \sum_{t}^{t+T_{\min,k}-1} M_{k,t} \le 1 for \forall k = 1,2,...,K, \forall t = 1,2,...,T - T_{\min,k} + 1, \tag{9}$$

$$\sum_{t}^{t+T_{opt,k}-1} M_{k,t} \ge 1 for \forall k = 1,2,...,K, \forall t = 1,2,...,T - T_{opt,k} + 1. \tag{10}$$

Constraint (9) and (10) ensure that the time interval between any two successive interventions of the same type k is no less than a minimum value $T_{min,k}$ and no larger than a maximum value $T_{opt,k}$, respectively. $T_{opt,k}$ is the optimal interval obtained for each intervention type in stage 1 of the optimization procedure while $T_{min,k}$is an externally imposed parameter.

The use of the Kronecker delta function makes the set-up cost and service interruption cost functions nonlinear. The resulting optimization problem is therefore a nonlinear integer programming model, and as such, computational complexity can virtually increase with the size of the problem instance.

3.3. Solution approach: linearization of original problem

One of the paper's objectives is to propose a scalable optimization model. The non-linear model in Section 3.2 is computationally expensive and does not guarantee scalability (and so are several existing intervention optimization models the literature). Here, we propose a linearization approach that enables us to transform a nonlinear problem into a linear one without any loss of generality. Because of this, we could employ a solution algorithm which solves the optimization problem to optimality.

To guarantee the scalability of the optimization problem, we reformulate the nonlinear model as a binary linear programming model as follows. We introduce two new sets of decision variables based on which we reformulate the expression of the service interruption and set-up costs. Decision variables $U_{i,t} \in \{0,1\}$ collected in matrix $\boldsymbol{U}_{N\times T}$, take value 1 if object i is affected (directly or indirectly) by at least one intervention executed at time t, and 0 otherwise. The service interruption cost U_{tot} is reformulated as:

$$U_{tot} = \sum_{t=1}^{T} \boldsymbol{C}_{1\times N}^{shut} \times \boldsymbol{U}_{N\times T}^{t}, \tag{11}$$

where $\boldsymbol{U}_{N\times T}^{t}$ is the t^{th} column of the matrix $\boldsymbol{U}_{N\times T}$.

We further define decision variables $V_{e,t} \in \{0,1\}$, which indicates whether at least one intervention in group e is executed at time step t ($V_{e,t} = 1$) or not ($V_{e,t} = 0$), and collect them in matrix $\boldsymbol{V}_{E\times T}$. The total set-up cost S_{tot} can be rewritten now as:

$$S_{tot} = \sum_{t=1}^{T} \boldsymbol{C}_{1\times E}^{setup} \times \boldsymbol{V}_{E\times T}^{t}\ , \tag{12}$$

where $\boldsymbol{V}_{E\times T}^{t}$ is the t^{th} column of the matrix $\boldsymbol{V}_{E\times T}$.

We add the following constraints:

$$\sum_{j=1}^{N}\sum_{k=1}^{K} I_{i,j}\ R_{j,k}\ M_{k,t} \le \delta_1 \times U_{i,t}\ \ for\ \forall i = 1,2,\dots,N,\ \forall t = 1,2,\dots,T, \tag{13}$$

$$\sum_{k=1}^{K} G_{e,k}\ M_{k,t} \le \delta_2 \times V_{e,t}\ \ for\ \forall e = 1,2,\dots,E,\ \forall t = 1,2,\dots,T, \tag{14}$$

Constraint (13) helps avoid double-counting of interruption costs. That is, if an object is directly or indirectly affected by more than one intervention activity, its service interruption cost will only be considered once. Constraint (14) helps avoid double-counting of set-up costs. That is, if two or more intervention activities belonging to a specific group are executed at the same time step, the corresponding set-up cost will only be considered once. Parameters δ_1 and δ_2 are two integer numbers whose value is set equal to $N \times K$ and K, respectively. The formulation of the total preventive cost C_{tot}^{prev} in Eq. (5) and the constraints (9) and (10) defined in the previous section, remain unchanged.

4. Numerical example: application to an infrastructure network

In this section, we demonstrate the applicability of the proposed intervention planning model with an illustrative example of an infrastructure network.

4.1. Case description

For the sake of comparison and to show the benefits of our proposed approach with respect to computational efficiency and performance of the solutions obtained, we use the system depicted in Fig. 1 as a test instance, and compare our results with the ones obtained with the model presented in [26]. The latter does not account for the deterioration and failure process of objects in the optimization and does not explicitly minimize set-up costs (which can affect the grouping substantially). In addition, its nonlinear formulation and solution procedure does not enable finding an optimal solution given its heuristic nature. We also investigate the performance of the solution obtained by implementing our grouping model with respect to a standard approach where interventions are planned for each network separately, thus overlooking the possibility to share set-up costs and the cascading effect of service interruptions. We refer to this standard approach as "individual intervention program", and the interval between interventions of the same type k is simply given by $T_{opt,k}$ (Table 2). This is a common approach to

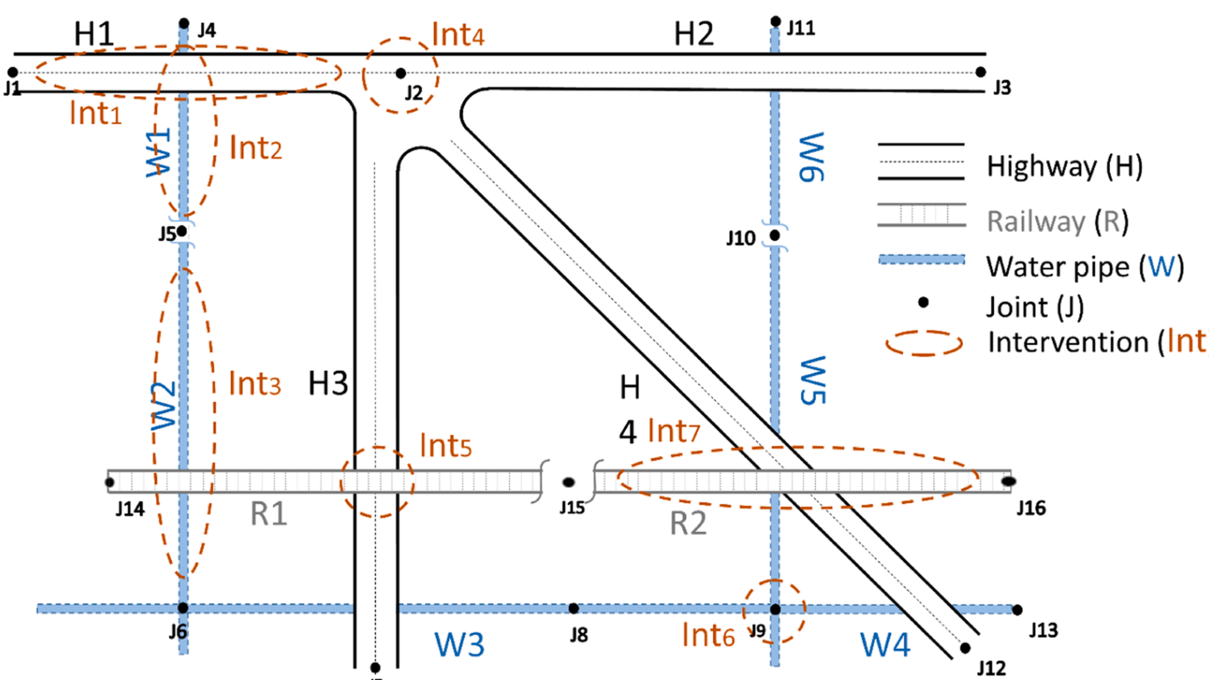

Fig. 1. Infrastructure networks with preventive interventions to be planned.

interventions planning in real life [1] because there is usually minimal or no coordination between the operators of different networks.

The system considered in our numerical analysis consists of three individual infrastructure networks: a water network, a highway network, and a railway network (Fig. 1). The original data for this example were obtained from experts in the NGInfra organization (Next Generation Infrastructure, which brings together representatives of all major infrastructure operators in the Netherlands). However, to protect data sensitivity, the data has been translated for demonstrative purposes while maintaining realistic proportions and relationships. While the translated data used in this example does not directly relate specific units (euros, months, etc.), it reflects reality and serves well for the objective of this example. This approach allows us to focus on the core relationships and trends relevant to the example.

In this example, each network is managed by an independent operator which we refer to as W for the water network, H for the highway network, and R for the railway network. There are in total seven intervention types to be planned. The objects intersect each other at different locations. This determines interdependencies between objects such that an intervention on one object could disrupt the intersecting objects.

The service disruption costs incurred by each object j, C_j^{shut}, are listed in Table 1. Service interruption costs are assumed to be significantly larger than the intervention cost based on [43–45]. The relations among the objects which are needed to feed the interaction matrix $\boldsymbol{I}$, are listed in Table 1. The service interruption cost occurs every time an object is directly or indirectly affected by one of the interventions. For example, Int2 is performed on water pipe W1 and requires the excavation (and therefore closure) of highway H1 as well as the closure of water pipe W2 which is an extension object of W1. In this case, W1 is assumed to be directly affected by Int2, while H1 and W2 are indirectly affected. The service interruption costs of W1, W2, and H1 are thus applied. The interaction matrix for the system is given by Eq. (15):

$$\mathrm{I}_{N\times N} = [I_{ij}] = \left[\begin{array}{lcccccccccccc} & W1 & W2 & W3 & W4 & W5 & W6 & H1 & H2 & H3 & H4 & R1 & R2 \\ W1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ W2 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ W3 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ W4 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ W5 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ W6 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ H1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ H2 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ H3 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ H4 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ R1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ R2 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{array}\right]. \tag{15}$$

The intervention types are listed in Table 2, along with the minimum ($T_{\min,k}$) and maximum ($T_{opt,k}$) time intervals between two consecutive interventions of the same type k. $T_{\min,k}$ is a given parameter set to avoid unnecessarily frequent interventions; without loss of generality it is assumed to be equal to one time step for all intervention types. $T_{opt,k}$ is optimized in stage 1 of the proposed approach (see Section 3.1) based on the deterioration parameters (Table 2) of the targeted objects, to minimize the risk of unexpected failures. Intervention type Int3 is a central intervention which is executed every 5 time steps. Column 8 shows the cost of executing the intervention types, C_k^{prev}, which includes direct costs such as replacement parts, mobilizing resources, etc. Table 2 also contains a list of objects targeted by each intervention. For example, the crossing joint of highway H3 and railway R1 are both targeted by Int5. In this case, two operators (i.e., operators H and R) are responsible for the costs of the shared intervention. The relations between the objects and the intervention types, are modelled with the relation matrix $\mathrm{R}_{N\times K}$ in Eq. (16), which indicates upon which object j each intervention type k intervenes.

$$\mathrm{R}_{N\times K} = [r_{j,k}] = \left[\begin{array}{lccccccc} & Int1 & Int2 & Int3 & Int4 & Int5 & Int6 & Int7 \\ W1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ W2 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ W3 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W4 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W5 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ W6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ H1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ H2 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ H3 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ H4 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ R1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ R2 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right]. \tag{16}$$

Finally, Table 3 indicates feasible groups of intervention types and corresponding shared the set-up cost. The relations between the interventions and the groups, derived from Table 3, are represented by the relation matrix $\mathrm{G}_{E\times K}$ in Eq. (17), which indicates the intervention groups to which the intervention types belong.

$$\mathrm{G}_{E\times K} = [G_{e,k}] = \left[\begin{array}{lccccccc} & Int1 & Int2 & Int3 & Int4 & Int5 & Int6 & Int7 \\ G1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ G2 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ G3 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ G4 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{array}\right]. \tag{17}$$

4.2. Results

The optimal intervention program is obtained by solving the optimization problem described in Section 3. The optimization problem has been solved using the CPLEX Mixed Integer Linear programming solver

Table 1
Data of the analyzed objects.

Object	Index (j)	Service interruption cost of object j, C_j^{shut} (monetary unit) $\times 10^3$	Deterioration parameters α_j, β_j	Interaction with other objects (j)	Start joint	End joint
W1	1	15	4.3, 2	2 (W2), 7 (H1)	J4	J5
W2	2	7,5	4.8, 2.2	1 (W1), 11 (R1)	J5	J6
W3	3	12	4.1, 1.9	9 (H3)	J6	J8
W4	4	13.5	4.4, 2.1	10 (H4)	J8	J13
W5	5	9	4.2, 1.9	6 (W6), 10 (H4), 12 (R2)	J9	J10
W6	6	16.5	3.6, 2.1	5 (W5), 8 (H2)	J10	J11
H1	7	9	3.5, 2	-	J1	J2
H2	8	15	2.7, 1.9	-	J2	J3
H3	9	7,5	2.8, 2.1	11 (R1)	J2	J7
H4	10	12	3.2, 2.2	12 (R2)	J2	J12
R1	11	13,5	2.6, 2.2	9 (H3), 12 (R2)	J13	J15
R2	12	9	2.7, 1.9	10 (H4), 11 (R1)	J15	J16

Table 2
Description of the intervention types.

Intervention type	Index (k)	Description on	Objects directly affected (j)	$T_{min,k}$ (time steps)	$T_{opt,k}$ (time steps)	Intervention cost per time unit C_k^{prev} (monetary unit) $\times 10^3$	Operator responsible (W,H,R)
Int1 (1)	1	Intervention on highway H1	7	1	4	5	H
Int2 (2)	2	Intervention on water pipe W1	1	1	6	2,5	W
Int3 (3)	3	Intervention on water pipe W2	2	1	5	4	W
Int4 (4)	4	Intervention on the highway intersection J2	7, 8, 9, 10	1	4	4,5	H
Int5 (5)	5	Intervention on crossing joint of the highway H3 and railway R1	9, 11	1	3	3	H&R
Int6 (6)	6	Intervention on water joint J9	3, 4, 5	1	6	5,5	W
Int7 (7)	7	Intervention on the railway R2	12	1	4	3	R

Table 3
Intervention groups and set-up costs.

Intervention group	Index (e)	Intervention types included in the group	Shared set-up cost C_e^{setup} (monetary unit) $\times 10^2$
G1	1	Int2, Int3	7
G 2	2	Int1, Int4	5.5
G 3	3	Int5, Int7	8
G 4	4	Int6	6.4

in Matlab© [46]. The optimization problem was solved on a mobile workstation with the following specifications: Windows 10, Intel Core i7-9750H CPU @2.60 GHz, and installed memory (RAM) of 16 GB. The results of the optimization problem are presented below.

4.2.1. Optimal intervention program

Fig. 2 shows the optimal intervention program obtained for a period of 60 time steps obtained by implementing our proposed model and the approach in [26], respectively. The vertical axis on the left indicates the cumulative net cost, and the vertical axis on the right shows the different intervention types to be planned. Every row on the graph (i.e., a set of bars with the same color) represents the schedule of one intervention type. Every bar is an execution of an intervention type. As can be observed, the intervention frequencies obtained in stage 1 of our methodology and reported in Table 2, which are optimal for the individual interventions, are not necessarily optimal when the entire system is considered due to dependencies across objects. This demonstrates that finding the optimal intervention plan is not intuitive, and decision tools are needed especially when large networks are involved. The implementation of our model results in a program where patterns with intervals of fixed length can be observed for all intervention types. These patterns, or cycles, repeat themselves every 30 timesteps. This indicates that the optimization can be run for just one cycle regardless of the length of the planning horizon, with consequent computation advantages. The interval for intervention type $k = 5$ remains the same as it is the smallest among all $T_{opt,k}$. Intervention types $k = 1$, 4 and 7 are grouped with intervention type 5, while intervention type 3 is shifted to be grouped with intervention type 2. Intervention type 6 cannot be grouped with any other intervention. Fig. 3 shows the intervention program obtained by implementing the approach in [26] for 30 time steps; here no clear pattern can be recognized and the interval for the same intervention type can vary within the time horizon.

Along with the optimal intervention program, the cumulative direct

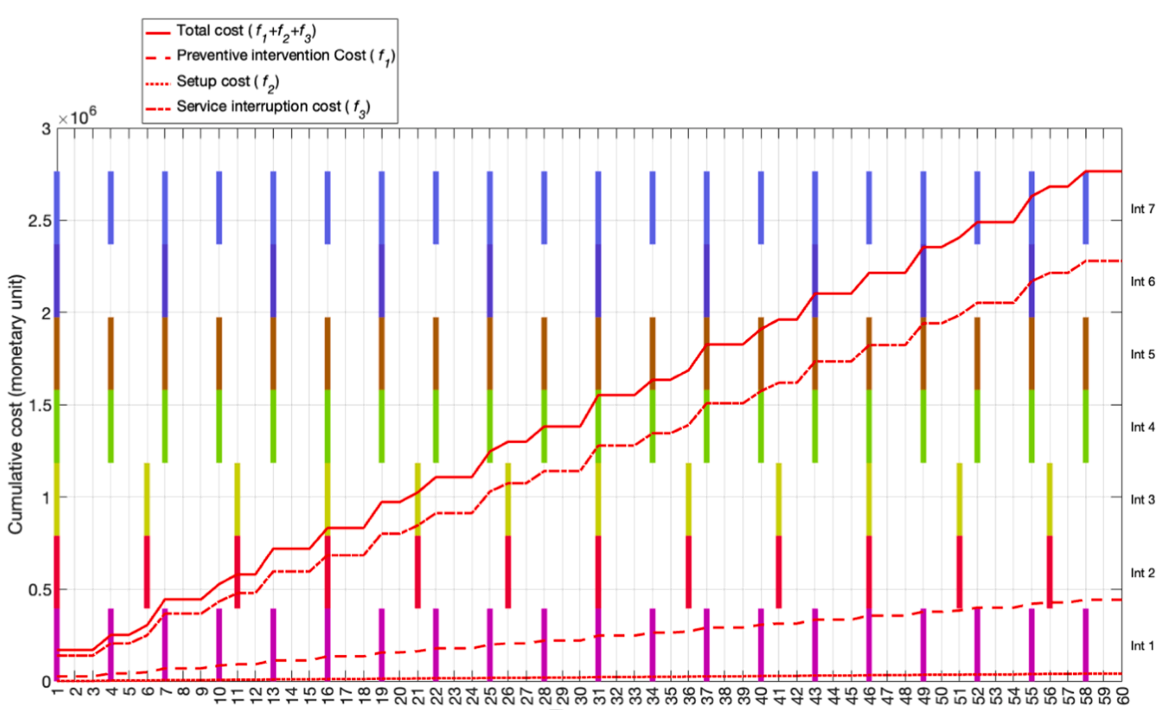

Fig. 2. Optimal intervention program with the corresponding cumulative cost for T = 60 time steps.

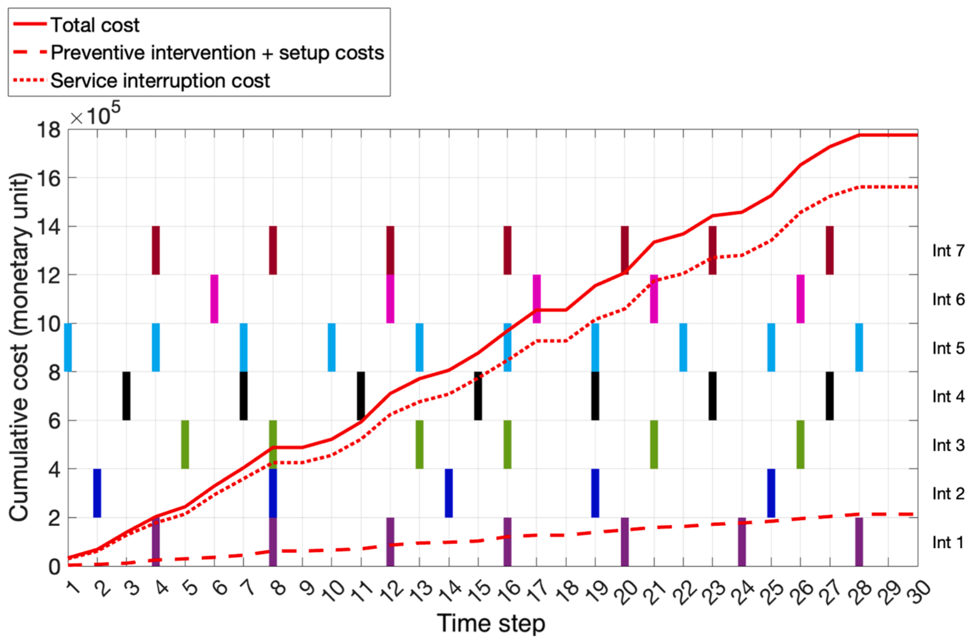

Fig. 3. Near-optimal intervention program and corresponding cumulative cost for T = 30 time steps, obtained from the model in [26].

costs of preventive interventions f_1, the cumulative set-up cost f_2 and the cumulative cost of service interruption f_3, are plotted. It can be observed that our proposed model yields lower total costs than the model in [26]; we can also observe that, while the cost of interventions (direct and set-up costs) are similar, the service interruption cost resulting from our proposed model is much lower. This means that our grouping strategy enables interventions to be rearranged in such a way to reduce the total frequency of interventions, thus resulting in less service interruptions. In general, however, the service interruption cost makes up for most of the total costs. If we want to further decrease the impact on service, then a penalty factor could be added to U_{tot} in objective function (7).

A comparison of Figs. 2 and 3 reveals that our model facilitates a reduction in total costs compared to the model in [26] despite considering the set-up cost. Therefore, the solution obtained by [44] is far from optimal. This comparison focuses on the initial 30 time steps, corresponding to the time horizon depicted in Fig. 3. A longer time horizon could not be considered for that model due to computational limitations, as the model utilizes Genetic Algorithm (GA) for optimization. At the

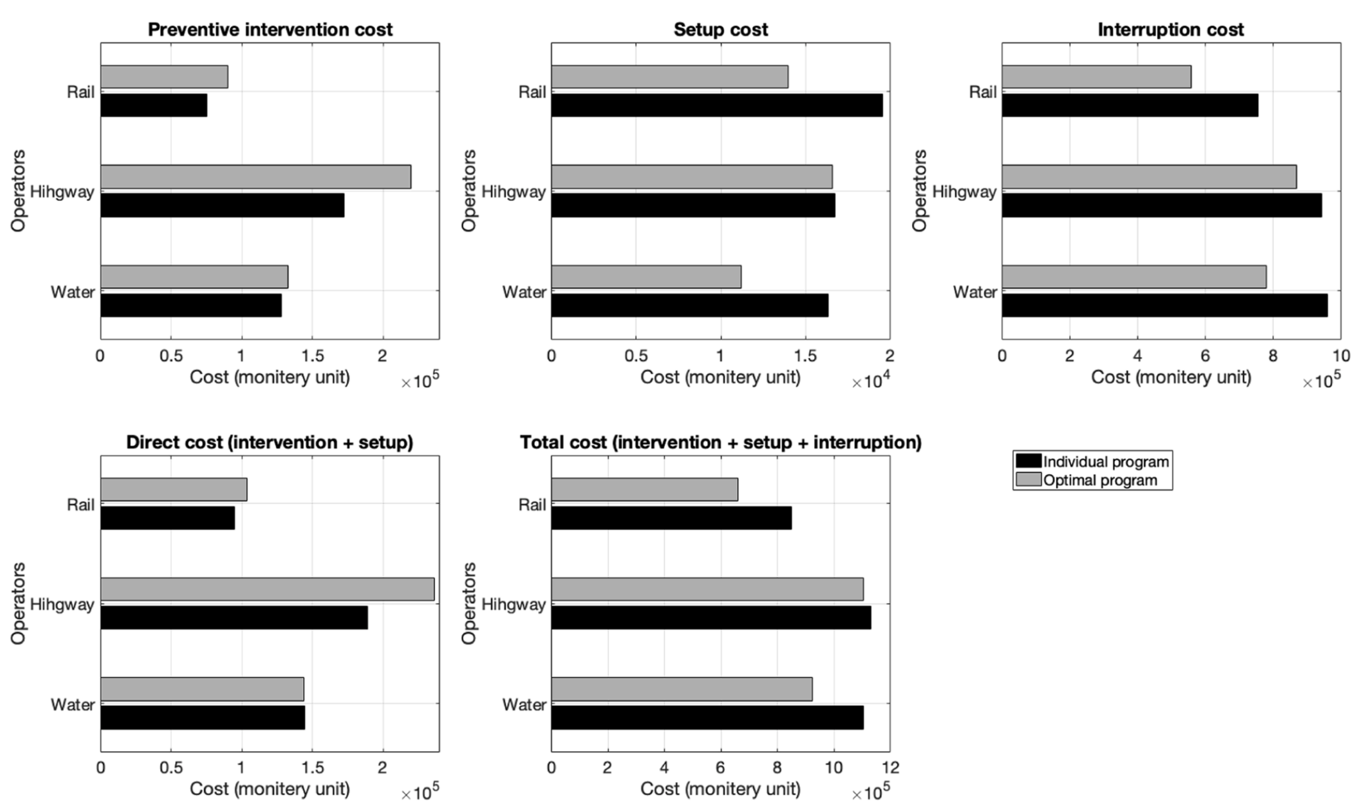

Fig. 4. Stakeholder cost analysis: comparison between the individual and the optimal intervention programs for the three operators.

30th time step, the total cost associated with the optimal program derived from our approach (Fig. 2) amounts to 1.41×10^6, whereas the near-optimal program from [26] has a total cost of 1.79×10^6. This represents a 21% reduction in cost.

4.2.2. Multistakeholder analysis

Fig. 4 illustrates the cost distribution among the three operators for both the individual and optimal programs, which is attributed to the increased frequency of executing preventive interventions.

In terms of preventive intervention costs, all three operators are expected to incur higher expenses in the optimal plan compared to the individual plan. Conversely, the setup costs for all operators are projected to be lower in the optimal program, as grouping intervention activities allows for shared setup costs. Likewise, all three operators would experience reduced interruption costs in the optimal program compared to the individual program.

Considering direct costs, which encompass preventive intervention and setup costs, all three operators are anticipated to have to pay more in the optimal program relative to the individual program. This is because the optimal plan typically requires most operators to increase the frequency of their interventions, leading them to perform more interventions than usual and consequently placing them at a disadvantage. Several strategies can be employed to alleviate the extra costs borne by the operators. One approach involves selecting a sub-optimal intervention program that ensures an equitable distribution of additional costs among all operators. However, this method results in a potential loss of net benefit. An alternative strategy entails distributing the extra costs across all operators proportionally to the amount they would pay if they planned their intervention programs individually.

Also, it appears that there is a negative relationship between the direct (intervention + setup) and indirect costs (interruption). The two bottom subplots show that the higher the costs that the operators stand, the lower the costs for the users.

Ultimately, the optimal plan proves more favorable in terms of total cost. As the total cost is primarily influenced by interruption costs, it exhibits similar behavior.

4.2.3. Computation performance of the proposed model

To verify the scalability characteristics of our optimization model, we analyze how the computation time varies with the size of the problem instance, and compare it with the computational performance of the grouping approach proposed in [26]. Specifically, we study the effects on computation time of the length of the planning horizon T (and therefore the number of time steps), the number of intervention types $|K|$ and the number of objects $|N|$. We run three numerical experiments where we vary T, $|K|$ and $|N|$ one at a time. Fig. 5 shows a linear trend between computation time for our model and the length of the time horizon T (number of time steps), while the number of intervention types and number of objects are fixed. Computation time remains below 90 seconds when T is increased up to 2900 time steps. Similarly, in Fig. 6, the computation time for the model in [26] is depicted as a function of T, showing a strongly nonlinear behavior and an increase up to 12×10^4 seconds when T is increased up to 300.

Similarly, Fig. 7 shows a linear trend between the computation time and the number of intervention types while Fig. 8 exhibits a strong exponential behavior.

Figs. 9 and 10 depict the relationship between the computation time and the number of objects for the proposed model and the model in [26], respectively. For the proposed model, results show that the number of objects has little effect on the computational complexity. This is an expected result because in our model there is no direct one-to-one correspondence between on object and a decision variable. Instead, decision variables are linked to interventions, and each intervention is linked to multiple objects, thus leading to reduced model complexity and a better representation of reality. This also constitutes one advantage of the proposed model compared to the more common assumption made in other models in the literature where an intervention activity can only target one object at a time.

4.2.4. Rolling horizon for long term planning

From Fig. 2, it can be observed that altering the time horizon (i.e., the number of time steps in a single optimization run) does not significantly impact the intervention program patterns. In fact, the interval for each individual intervention type remains consistent regardless of the time steps. If this holds true, the analysis can be performed over a shorter time horizon and the results can be replicated across a longer horizon, resulting in substantial computational advantages. In this section, we examine the effects of time horizon length on the structure of the optimal intervention program. To achieve this, we compare the outcomes of 19 optimization runs, each featuring different time horizons ranging from 12 to 120 time steps, with increments of 6 time steps. We evaluate the optimization runs in pairs by calculating the Chi-square error between the intervention programs of the two optimization runs corresponding to pairs of time horizons $T_i,\ T_j \in \{12,\ 18,\ 24,\ \ldots,\ 120\}$, as follows:

$$\chi^2 = \sum_{k=1}^{k=|K|} \sum_{t=1}^{\min(T_j,T_j)} \frac{\left(M_{k,t}^{T_i} - M_{k,t}^{T_j}\right)^2}{2} \times \frac{1}{\min(T_i,T_j)} \times 100\ \forall\ T_i,\ T_i \in \{12,\ 18,\ 24,\ \ldots,\ 120\} \tag{18}$$

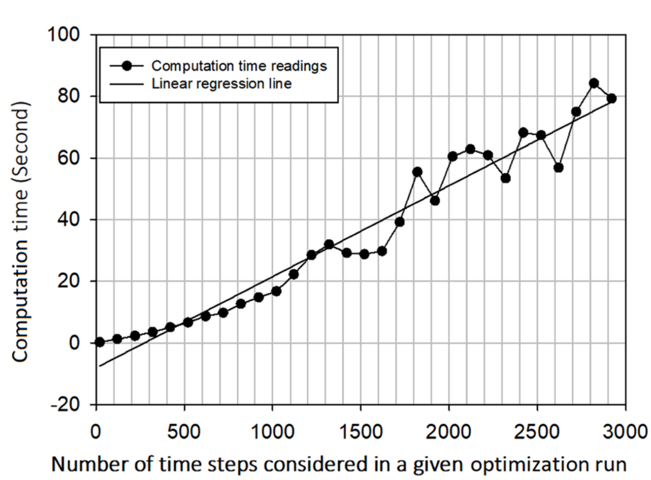

Fig. 5. Computation time as function of the number of time steps T resulting from our model.

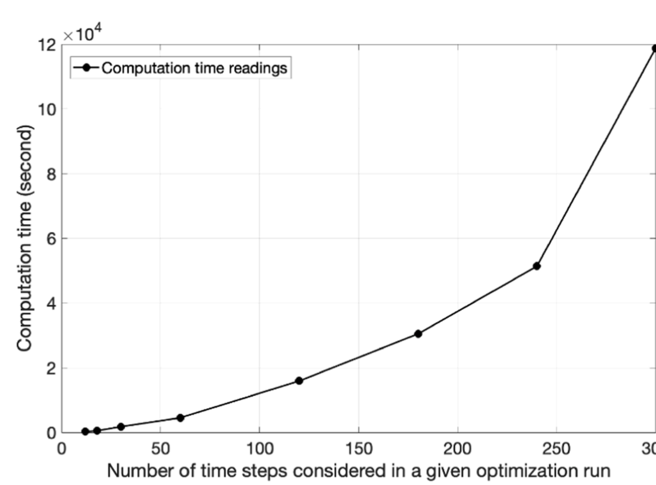

Fig. 6. Computation time as function of the number of time steps T obtained from implementation of model in [26].

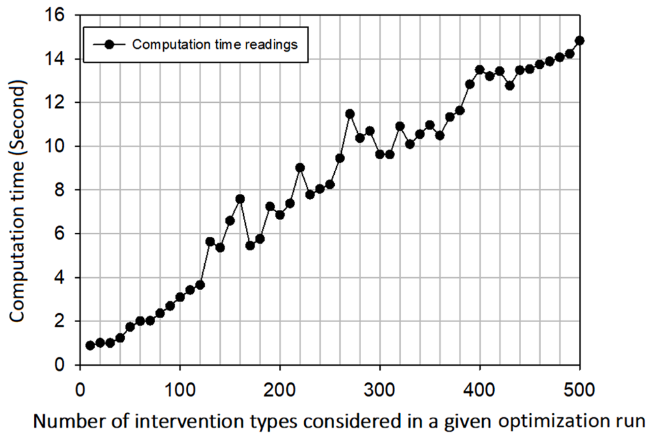

Fig. 7. Computation time of different optimization runs with varying number of intervention types (obtained from the proposed optimization problem).

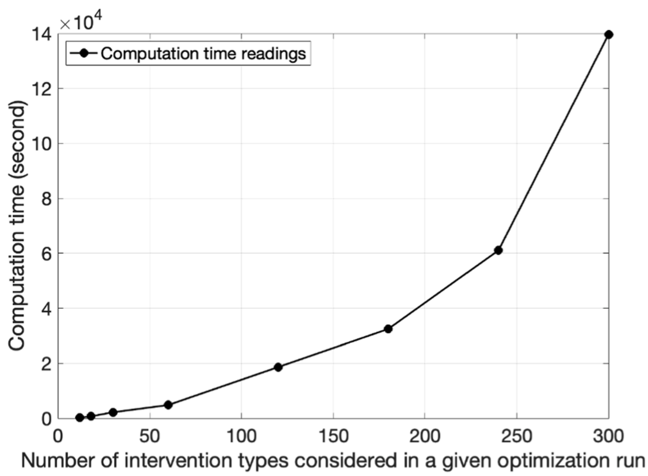

Fig. 8. Computation time of different optimization runs with varying number of intervention types obtained from implementation of model in [26].

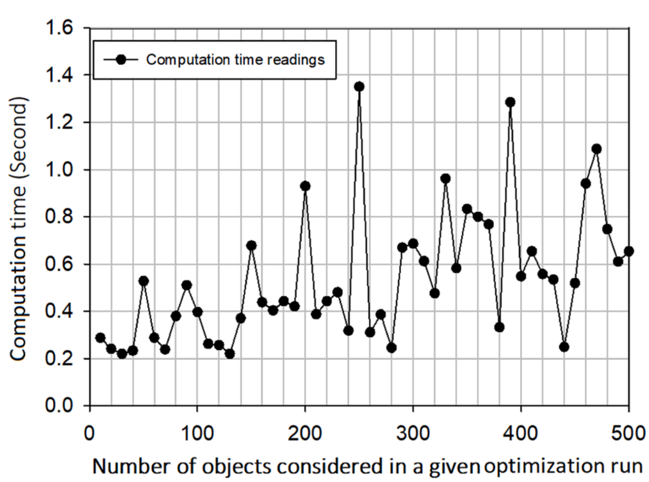

Fig. 9. Computation time of different optimization runs with varying number of objects (obtained from the proposed optimization problem).

where$M_{k,t}^{T(.)}$ indicates whether intervention type k is executed at time step t in the intervention program with time horizon $T_{(.)}$. As we use the chi-square error method to compare intervention programs, the term "error"

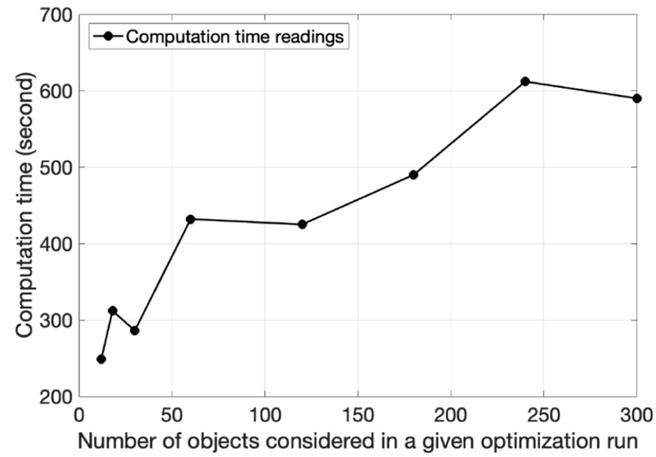

Fig. 10. Computation time of different optimization runs with varying number of objects obtained from implementation of model in [26].

is replaced from now on by "difference" which is more appropriate for our case.

Fig. 11 presents the results of the analysis. Each circle symbolizes the percentage difference between two intervention programs optimized over distinct time horizons. The figure can be interpreted as a symmetrical matrix with a zero diagonal, as an intervention program should exhibit no difference when compared to itself.

To illustrate the results, consider the node at the intersection of coordinates $T_1 = 24$ and $T_2 = 30$. The difference between the two intervention programs is 1 %, indicating that these programs are nearly identical for the initial 24 time steps, which corresponds to the smaller time horizon.

Apart from the first row and first column, the percentage differences are negligible, with a maximum of only 6 %. This indicates that if a long time horizon is desired, the analysis can be conducted over a shorter time horizon, and the resulting program can then be replicated (or rolled) across the extended horizon. This approach offers considerable computational benefits while maintaining the effectiveness of the intervention program.

Regarding the first row and first column, it becomes evident that 12 time steps are inadequate for the program to develop a discernible pattern. Consequently, it is advisable to select a sufficiently large base time horizon to ensure the program's effectiveness and reliability. In this particular instance, a base time horizon of 18 time steps is recommended.

A comparable analysis was conducted to assess costs associated with the intervention programs. The objective was to determine whether altering the time horizon would have a significant impact on cost outcomes. Interestingly, this cost comparison also produced similar results to the previous analysis. The consistency in cost patterns across varying time horizons further reinforced the observation that the structure of optimal intervention programs remains largely unaffected by the length of the time horizon. This consistency provides an opportunity for researchers and decision-makers to conduct analyses over shorter time horizons, replicate the results over longer horizons, and achieve substantial computational advantages without compromising the quality and effectiveness of the intervention programs.

5. Conclusions and remarks

Dependencies among interconnected infrastructure networks imply that interventions performed on objects of one network can directly or indirectly affect the functionality of (part of) other networks. Although in the current practice these dependencies are not considered and interventions are planned for each network individually, it is widely recognized that there is a need for coordinating interventions across

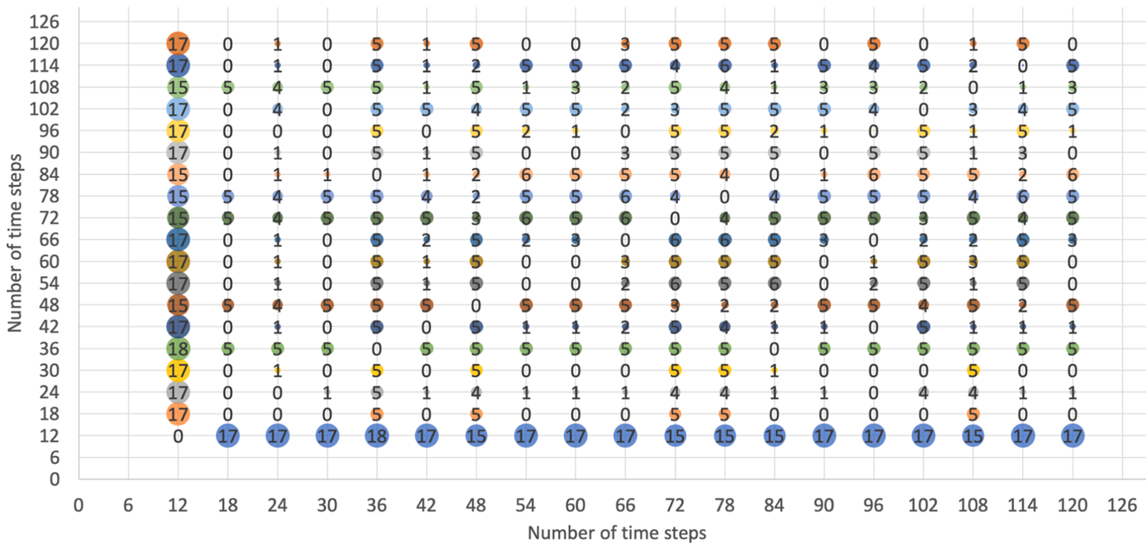

Fig. 11. Difference between intervention programs with different time horizons.

different networks within interconnected systems to reduce net costs. However, this is a challenging task that calls for tools to support a systematic and collaborative approach to intervention planning.

To address this challenge, we have proposed a novel two-stage optimization model for planning interventions for systems of multiple interconnected networks. Starting from an optimal plan for individual intervention types, grouping of interventions is based on the dependencies between the different networks and is optimized against the total net cost which includes the direct intervention costs incurred by different infrastructure operators and service disruption costs. Through application to a representative system, we have shown that the optimal arrangement of interventions may significantly reduce the net costs mainly due to the shared set-up costs as well as shared maintenance windows, which lead to a reduction in service interruptions. The scalability of our model is demonstrated empirically by showing that the computation time is roughly proportional to the number of decision variables rather than growing exponentially as in most of the existing models. This is a significant advantage from a modeling perspective which is reflected in a more practical implementation of our model to large-scale systems. Moreover, the analysis of the optimization results conducted for a range of different planning horizons has shown that repetitive patterns can be identified in the planning. These patterns can be exploited to reduce computation time as the intervention plan can be optimized simply over the pattern length.

It should be noted that while this paper focuses on minimizing net costs, additional factors such as environmental impact and noise pollution can be incorporated into the objective function. This makes the problem a multi-objective optimization problem. The customary way to solve such problems is the weighted sum of the objectives, where everything is translated again into a single objective optimization problem.

Also, the proposed model optimizes decisions at the tactical level by determining groups of interventions that can be performed together. The results of the model can then inform decisions to be further optimized at the operational level, where more detailed consideration of the maintenance duration can be considered to guide the execution of activities.

One of the main observations is that there exists a negative relationship between direct costs incurred by operators (i.e., intervention and setup costs) and indirect costs incurred by users (i.e., service interruptions). This conflict makes it challenging to adopt the optimal solution that minimizes net costs. However, it is important to note that operators are not solely concerned with direct costs, as service availability is a crucial factor indicating the quality of their service. This highlights the need for proper coordination when planning interventions. Infrastructure managers should prioritize clear communication, as coordination based on grouping would significantly benefit all stakeholders.

We aim to further extend our work by (1) accounting for a more complex structure of dependencies among infrastructure objects (e.g. stochastic dependencies), (2) including the uncertainty of interventions occurrence, and (3) by relaxing the assumption that an intervention is completed during a single time interval and considering duration of interventions. The last point would most likely lead to additional constraints to the model to account for maintenance duration when interventions are grouped.

CRediT authorship contribution statement

Omar Kammouh: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Claudia Fecarotti:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition. **Ahmadreza Marandi:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data used are present in the article.

Acknowledgments

This research was made possible thanks to the funding of the 4TU. HTSF DeSIRE program of the four universities of technology in the Netherlands.

References

[1] Adey B, Burkhalter M, Martani C. Defining road service to facilitate road infrastructure asset management. Infrastruct Asset Manag 2020;7(4):240–55. https://doi.org/10.1680/jinam.18.00045.

[2] Mizutani D, Nakazato Y, Lee J. Network-level synchronized pavement repair and work zone policies: optimal solution and rule-based approximation. Transp Res Part C: Emerg Technol 2020;120:102797. https://doi.org/10.1016/j.trc.2020.102797.

[3] Moinian F, Sabouhi H, Hushmand J, Hallaj A, Khaledi H, Mohammadpour M. Gas turbine preventive maintenance optimization using genetic algorithm. Int J Syst Assur Eng 2017;8(3):594–601.

[4] Dinh DH, Do P, Iung B. Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts. Reliab Eng Syst Saf 2022;217:108055. https://doi.org/10.1016/j.ress.2021.108055.

[5] Dinh DH, Do P, Iung B, Nguyen PTN. Reliability modeling and opportunistic maintenance optimization for a multicomponent system with structural dependence. Reliab Eng Syst Saf 2024;241:109708. https://doi.org/10.1016/j.ress.2023.109708.

[6] Shi H, Zhang J, Zio E, Zhao X. Opportunistic maintenance policies for multi-machine production systems with quality and availability improvement. Reliab Eng Syst Saf 2023;234:109183. https://doi.org/10.1016/j.ress.2023.109183.

[7] Zhang W, Zhang X, He S, Zhao X, He Z. Optimal condition-based maintenance policy for multi-component repairable systems with economic dependence in a finite-horizon. Reliab Eng Syst Saf 2024;241:109612. https://doi.org/10.1016/j.ress.2023.109612.

[8] Dekkert R, Smit A, Losekoot J. Combining maintenance activities in an operational planning phase: a set-partitioning approach. IMA J Manag Math 1991;3(4):315–31.

[9] Dekker RH. Integrating optimisation, priority setting, planning and combining of maintenance activities. Eur J Oper Res 1995;82(2):225–40.

[10] Wildeman R, Dekker R, Smit ACJM. A dynamic policy for grouping maintenance activities. Eur J Oper Res 1997;99(3):530–51. https://doi.org/10.1016/s0377-2217(97)00319-6.

[11] Do P, Vu HC, Barros A, Bérenguer C. Maintenance grouping for multi-component systems with availability constraints and limited maintenance teams. Reliab Eng Syst Saf 2015;142:56–67.

[12] Hanini M, Khebbache S, Bouillaut L, Hadji M. Dynamic and adaptive grouping maintenance strategies: new scalable optimization algorithms. Proc Inst Mech Eng Part O 2021. https://doi.org/10.1177/1748006X211049924. *Journal of Risk and Reliability*, 1748006×211049924.

[13] Bouvard K, Artus S, Bérenguer C, Cocquempot V. Condition-based dynamic maintenance operations planning & grouping. Application to commercial heavy vehicles. Reliab Eng Syst Saf 2011;96(6):601–10. https://doi.org/10.1016/j.ress.2010.11.009.

[14] Do Van P, Barros A, Bérenguer C, Bouvard K, Brissaud F. Dynamic grouping maintenance with time limited opportunities. Reliab Eng Syst Saf 2013;120:51–9. https://doi.org/10.1016/j.ress.2013.03.016.

[15] Vu HC, Do P, Barros A. A study on the impacts of maintenance duration on dynamic grouping modeling and optimization of multicomponent systems. IEEE Trans Reliab 2018;67(3):1377–92. https://doi.org/10.1109/TR.2018.2827926.

[16] Vu HC, Do P, Barros A, Bérenguer C. Maintenance grouping strategy for multi-component systems with dynamic contexts. Reliab Eng Syst Saf 2014;132:233–49. https://doi.org/10.1016/j.ress.2014.08.002.

[17] Chalabi N, Dahane M, Beldjilali B, Neki A. Optimisation of preventive maintenance grouping strategy for multi-component series systems: particle swarm based approach. Comput Ind Eng 2016;102:440–51.

[18] Wu T, Yang L, Ma X, Zhang Z, Zhao Y. Dynamic maintenance strategy with iteratively updated group information. Reliab Eng Syst Saf 2020;197:106820. https://doi.org/10.1016/j.ress.2020.106820.

[19] Mena R, Viveros P, Zio E, Campos S. An optimization framework for opportunistic planning of preventive maintenance activities. Reliab Eng Syst Saf 2021;215:107801. https://doi.org/10.1016/j.ress.2021.107801.

[20] Kielhauser C, Adey BT, Lethanh N. Investigation of a static and a dynamic neighbourhood methodology to develop work programs for multiple close municipal infrastructure networks. Struct Infrastruct Eng 2017;13(3):361–89. https://doi.org/10.1080/15732479.2016.1162818.

[21] Liang Z, Parlikad AK. Predictive group maintenance for multi-system multi-component networks. Reliab Eng Syst Saf 2020;195:106704. https://doi.org/10.1016/j.ress.2019.106704.

[22] Lethanh N, Adey BT, Burkhalter M. Determining an optimal set of work zones on large infrastructure networks in a GIS framework. J Infrastruct Syst 2018;24(1):04017048. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000410.

[23] Hadjidemetriou GM, Herrera M, Parlikad AK. Condition and criticality-based predictive maintenance prioritisation for networks of bridges. Struct Infrastruct Eng 2022;18(8):1207–21. https://doi.org/10.1080/15732479.2021.1897146.

[24] Kielhauser C, Adey BT. Determination of intervention programs for multiple municipal infrastructure networks: considering network operator and service costs. Sustain Resilient Infrastruct 2020;5(1-2):49–61. https://doi.org/10.1080/23789689.2018.1497879.

[25] Ramos-Salgado C, Muñuzuri J, Aparicio-Ruiz P, Onieva L. A decision support system to design water supply and sewer pipes replacement intervention programs. Reliab Eng Syst Saf 2021;216:107967. https://doi.org/10.1016/j.ress.2021.107967.

[26] Kammouh, O., Nogal, M., Binnekamp, R., & Wolfert, A. R. M. R. (2021). Multi-system intervention optimization for interdependent infrastructure. *Autom Constr*, 127, 103698. 10.1016/j.autcon.2021.103698.

[27] Kammouh O, Nogal M, Bruijne MD, Binnekamp R, Wolfert ARM. Interdependent infrastructure interventions optimization: an integrative systems thinking approach [Conference Paper]. In: Proceedings of the 30th European safety and reliability conference, ESREL 2020 and 15th probabilistic safety assessment and management conference. PSAM; 2020. 2020, https://www.scopus.com/inward/record.uri. ?eid=2-s2.0-85110397703&partnerID=40&md5=1111be9d7d495891fa9c5fd240dcded5.

[28] Rinaldi SM, Peerenboom JP, Kelly TK. Identifying, understanding, and analyzing critical infrastructure interdependencies. IEEE Control Syst Mag 2001;21(6):11–25. https://doi.org/10.1109/37.969131.

[29] Kerwin S, Adey BT. Optimal intervention planning: a bottom-up approach to renewing aging water infrastructure. J Water Resour Plan Manag 2020;146(7):04020044. https://doi.org/10.1061/(asce)wr.1943-5452.0001217.

[30] Papathanasiou N, Adey BT. Usefulness of quantifying effects on rail service when comparing intervention strategies. Infrastruct Asset Manag 2020;7(3):167–89. https://doi.org/10.1680/jinam.19.00071.

[31] Idoniboyeobu DC, Wokoma B, Ibanibo VC. Preventive maintenance for substation with aging equipment using Weibull distribution. Am J Eng Res 2018;7:95–101.

[32] Pascale E, Freneaux T, Sista R, Sannino P, Marmo P, Bouillaut L. Application of the Weibull distribution for the optimization of maintenance policies of an electronic railway signaling system. In: Proceedings of the ESREL 2017, European safety and reliability conference; 2017.

[33] Adey BT, Martani C, Papathanasiou N, Burkhalter M. Estimating and communicating the risk of neglecting maintenance. Infrastruct Asset Manag 2019;6(2):109–28. https://doi.org/10.1680/jinam.18.00027.

[34] Burkhalter M, Martani C, Adey BT. Determination of risk-reducing intervention programs for railway lines and the significance of simplifications. J Infrastruct Syst 2018;24(1):04017038. https://doi.org/10.1061/(asce)is.1943-555x.0000401.

[35] Barlow RE, Proschan F. Mathematical theory of reliability, Vol. 17. Siam; 1996.

[36] Christer A, Waller W. Delay time models of industrial inspection maintenance problems. J Oper Res Soc 1984;35(5):401–6. https://doi.org/10.2307/2581368.

[37] Baraldi P, Balestrero A, Compare M, Benetrix L, Despujols A, Zio E. A modeling framework for maintenance optimization of electrical components based on fuzzy logic and effective age. Qual Reliab Eng Int 2013;29(3):385–405. https://doi.org/10.1002/qre.1388.

[38] Papathanasiou N, Adey BT, Burkhalter M. Defining and quantifying railway service to plan infrastructure interventions. Infrastruct Asset Manag 2020;7(3):146–66. https://doi.org/10.1680/jinam.18.00044.

[39] Yuan XX. Principles and guidelines of deterioration modelling for water and waste water assets. Infrastruct Asset Manag 2017;4(1):19–35. https://doi.org/10.1680/jinam.16.00017.

[40] Cimellaro GP, Zamani-Noori A, Kammouh O, Terzic V, Mahin SA. Resilience of critical structures, infrastructure, and communities. P. E. E. R. C. (PEER); 2016.

[41] Kammouh O, Cimellaro GP. PEOPLES: a tool to measure community resilience. In: Proceedings of the structures congress (SEI2018); 2018. April 19–21, 2018.

[42] Kammouh O, Noori AZ, Taurino V, Mahin SA, Cimellaro GP. Deterministic and fuzzy-based methods to evaluate community resilience [journal article] Earthq Eng Eng Vibration 2018;17(2):261–75. https://doi.org/10.1007/s11803-018-0440-2.

[43] Dekker R, van Rijn C. PROMPT, a decision support system for opportunity-based preventive maintenance. Reliability and maintenance of complex systems, 154. Springer; 1996. p. 530–49. https://doi.org/10.1007/978-3-662-03274-9_27.

[44] Edwards DJ, Holt GD, Harris FC. Predicting downtime costs of tracked hydraulic excavators operating in the UK opencast mining industry. J Construct Manag Econ 2002;20(7):581–91. https://doi.org/10.1080/01446190210163552.

[45] Geraerds, W. (1985). The cost of downtime for maintenance: preliminary considerations. *Maint Manage Int*, 5(1), 13-21. https://pure.tue.nl/ws/files/4237068/30830.pdf.

[46] Lofberg J. YALMIP : a toolbox for modeling and optimization in MATLAB. In: Proceedings of the IEEE international conference on robotics and automation (IEEE Cat. No.04CH37508); 2004.