System representation of dependencies when developing intervention programs on infrastructure networks

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Summary
Considering dependencies between the assets of an infrastructure network when developing intervention programs can increase the resilience of the infrastructure. Existing literature lacks in a structured way how all the different dependencies and their effect on the costs of an intervention program are considered. In this work, a system representation is proposed that enables to represent the dependencies between candidate interventions and between the candidate interventions and the effect of the interventions on the provided service during the execution of the interventions when developing intervention programs on infrastructure networks. The representation using graphs enables the straightforward formulation of mathematical optimisation models that can be solved using global optimisation techniques. The use of a general intervention classification scheme and the definition of dependency rules between these categories allow the representation to be used for a combination of different types of assets, for different interventions and for different network topologies.

Keywords
Complex Systems, Dependencies, Intervention Programs, Network model, Infrastructure Management

Introduction
Resilient infrastructure requires an optimal intervention planning, where one major task is to decide which interventions, i.e. maintenance and renewal, to execute on which assets within an upcoming planning period and with which condition they are executed, i.e. during a complete shutdown of the system, during short shutdown periods, or under operation. These decisions are defined in intervention programs, whose determination requires to consider the dependencies between the interventions and between the interventions and the service provided in order to develop optimal intervention program. For the development of intervention programs, economical, structural, topological and resource dependencies are to be considered (Burkhalter & Adey, 2018; Dekker et al., 1997; Olde Keizer et al., 2017; Thomas, 1986). Thereby, economical dependencies refer to situations where the cost of executing multiple interventions differs from the sum of the execution cost for individual interventions. Structural dependencies refer to the situation where an intervention on one asset either implies or prohibit an intervention on another asset. Topological dependencies refer to the relations between the assets functionality and the system functionality. Resource dependencies refer to the limitations of resources that are shared among the interventions executed in an intervention program. In respect with intervention programs, the structural and resource dependencies constrain the possible combination of interventions selected. The economical and topological dependencies affect the costs of an intervention program, where economical dependencies have an effect on the costs on the asset level, i.e. the intervention costs, while the topological dependencies have an effect on the costs on the network level, i.e. the costs due to disturbed service, e.g. additional travel time in a transportation network. These two dependencies lead to non-linear cost functions on the asset and network level of an intervention program.

The existing literature in the field of optimising intervention programs use simple grouping (Furuya & Madanat, 2013; Van Horenbeek & Pintelon, 2013), graph theory (Hajdin & Lindenmann, 2007; Lethanh et al., 2018), two-step optimisation (Fecarotti & Andrews, 2018; Hankach et al., 2019; Kerwin & Adey, 2020), and use bi-level optimisation models (Lu et al., 2016; Ng et al., 2009; Zhang & Alipour, 2019) to consider some of the dependencies. The first three groups simplify the problem by considering simplified dependencies between the interventions and the effects on the service provided and by reducing the number of possible combinations for grouping interventions. The bi-level optimisation models are capable to consider detailed dependencies between the decisions on the interventions and the effect on the service provided. They cannot use global optimisation techniques and require heuristic optimisation models to optimise the intervention program. None of these approaches, however, has a clear and consistent structure how the different dependencies and their effects on the costs can be represented enabling to build straightforward optimisation models. Another group of research use reliability block diagrams, which are the most common and standardised representation of dependencies between assets functionality and the system functionality (Burkhalter et al., 2018; Pargar et al., 2017; Van Horenbeek et al., 2010). They are limited in considering economical dependencies in the asset level costs and in determining the combined network level costs of multiple interventions with different execution durations within the planning period.

In this work, a system representation is presented that models the dependencies between candidate interventions of an intervention program in respect to the costs of the intervention program. This enables the quantification of the costs of an intervention program during its execution and can be transformed into straightforward mathematical optimisation model.

System representation

The system representation considers the candidate interventions, i.e. the interventions that could potentially be executed within the intervention program, and their dependencies. The representation formulates a mathematical graph with two levels, i.e. the asset level and the network level, representing the effect of the dependencies on the two levels. The asset level is used to consider asset level costs when selecting the interventions of an intervention program, while the network level is used to quantify how the network operation is disturbed due to the intervention program and for how long it is disturbed. Figure 1 illustrates the concept of the representation with nine candidate interventions X_1 to X_9.

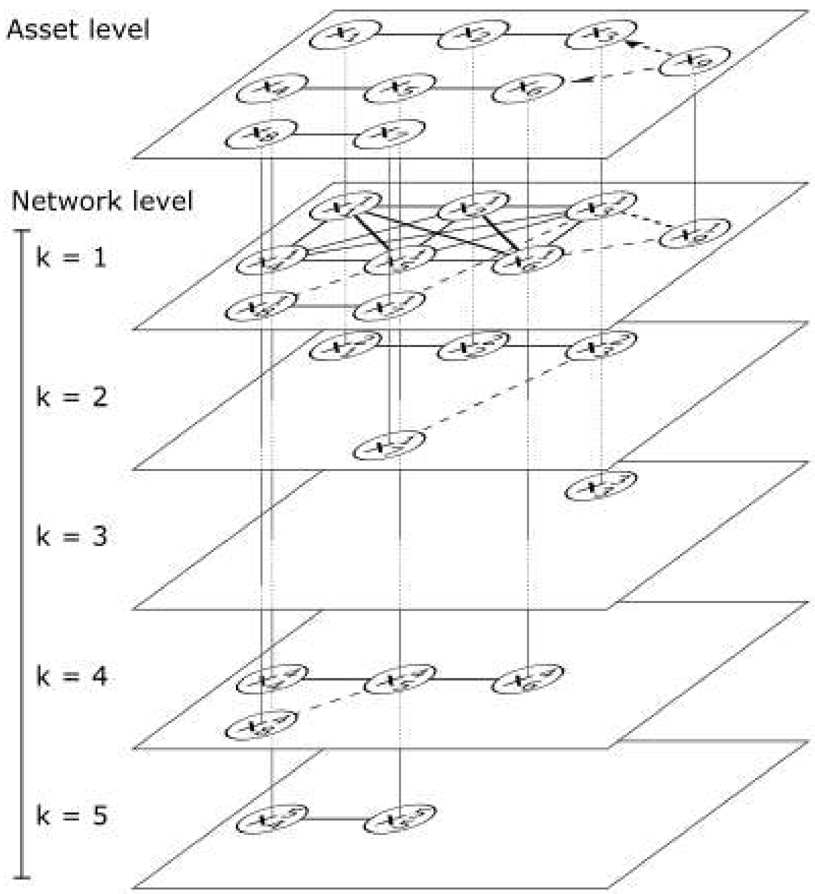

Figure 1. Level interaction

The asset level considers the candidate interventions and their structural and economical dependencies. It is represented by a graph $\mathcal{F} = (V, E)$ with the set of nodes V and the set of edges E. Each node $v \in V$ represents a candidate intervention $x \in X$. Each undirected edge $e^{ED} = (u, v) \in E^{ED} \subseteq E$ represents an economical dependency between two candidate interventions x_i and x_j represented by nodes u and v (sold lines in Figure 1). Each directed edge $e^{SD} = (u, v) \in E^{SD} \subseteq E$ represents a structural dependency between two candidate interventions x_i and x_j (dashed arrows in Figure 1). In the example in Figure 1, X_9 is structural dependent on X_3, while X_3 is economical dependent with X_2.

The network level is represented by a multi-layer graph $\mathcal{H} = (V, E, K)$. Each layer $k \in K$ represents a network state, which each defines a specific configuration of the service provided by the infrastructure. For example, a network state of a railway infrastructure could be the operation of a railway network with a single track closure on the double track line. A node $v^k \in V$ represents a candidate intervention x_i executed with network state k, i.e. x_i^k. An edge $e = (u^k, v^k)$ represents the requirement for sequential execution of two candidate interventions x_i^k and x_j^k represented by nodes u^k and v^k. For example, candidate interventions X_1 and X_2 have to be executed in sequence in network state 2.

The inter-level edges L ensure that the duration of each selected intervention is assigned to a network state with which it can be executed. An edge $e_i^k = (v_i, v_i^k)$ connects the candidate intervention node of the asset level v_i with its execution node in network state k of the network level v_i^k. The inter-level edges are illustrated in Figure 1 by the vertical edges from the asset level to the different traffic state layers in the network level. For example, the inter-level edge (X_1, X_1^2) relates the selection of candidate intervention X_1 with the execution of the intervention with network state 2 X_1^2.

Intervention categorisation

The system representation can be constructed for different situations, i.e. different asset types, intervention types and network topologies, using a structured and orthogonal categorisation of all candidate interventions and a set of rules regarding the dependencies between interventions of different categories. This categorisation requires considering the effect of an intervention on the systems functionality and the effect for other interventions. Table 2 shows the categorisation used for a railway network with intervention types I to V.

Table 2: Intervention categories

Category	Description	Example
I	Interventions executed continuously along the network, disturb the service provided, and hinder other interventions at the same location.	The renewal of a railway track executed with maintenance trains along the track.
II	Interventions on local assets disturbing the service provided within the proximity of the service provided, which hinders other interventions to be executed at the same location.	The replacement of a bridge in a road network.
III	Interventions outside of the proximity of the service that disturb the service provided.	Renewal of the controlling equipment on railway networks, which does not allow safe traffic operation.
IV	Local interventions in the proximity of the service without disturbing the service provided.	Filling cracks under operation of the road.
V	Interventions outside of the proximity of the service that do not disturb the service provided.	Vegetation management alongside the network.

Optimisation

The system representation presented enables to apply analytical and global optimisation techniques when optimising the intervention programs considering the dependencies between the interventions and between the costs of the interventions. The asset level can be transformed into a circular min-cost problem by introducing edges from a source node to all nodes of the asset level and from all nodes on the asset level back to the source node. The inter-layer relation can be modelled as an assignment problem dependant on the selection on the asset level. The network level can be transformed into a scheduling problem given the assignment of the selected interventions, where interventions connected by an edge within a network state can be seen as tasks that have to be executed in sequence without a specific order. In Burkhalter & Adey (2018), a constrained network flow model is proposed to combine these three problems into a single network flow problem that can be solved by common mixed integer linear programming, which is illustrated in Figure 2.

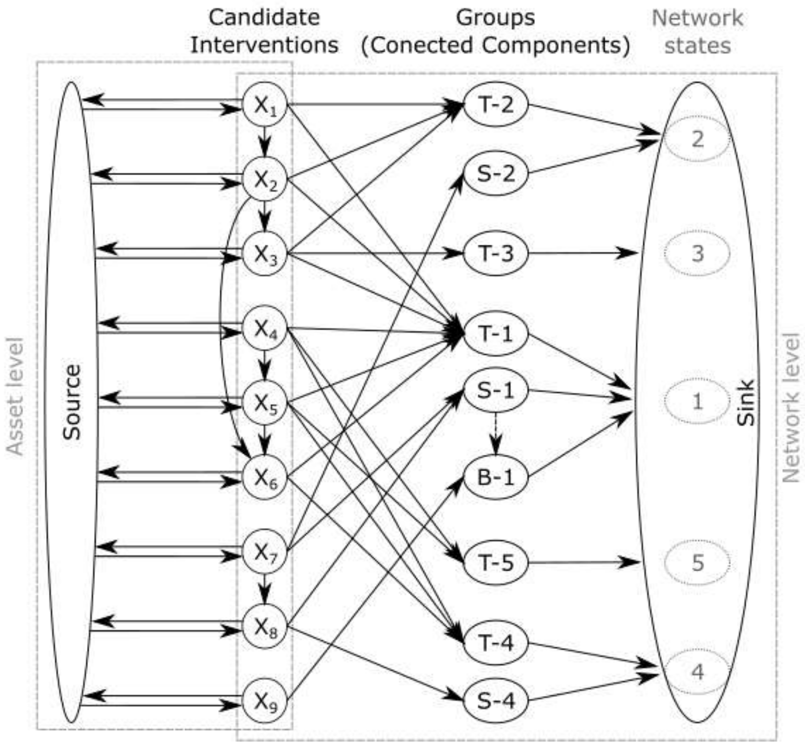

Figure 2. Network flow model as proposed in Burkhalter & Adey (2018)

Conclusion

The representation proposed in this work enables to represent the dependencies between the candidate interventions and the dependencies between the candidate interventions and the costs on the asset and network level when developing intervention programs. This representation allows formulating efficient optimisation models using network optimisation technics and integer linear programming. The use rules for the construction of the representation based on a general intervention categorisation enables the representation to be used for a combination of different types of assets and for different interventions.

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