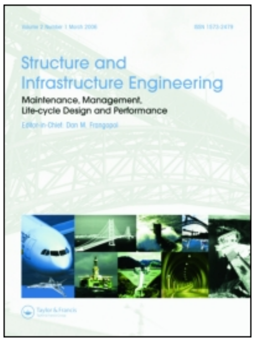

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Structure and Infrastructure Engineering

Maintenance, Management, Life-Cycle Design and Performance

ISSN: 1573-2479 (Print) 1744-8980 (Online) Journal homepage: https://www.tandfonline.com/loi/nsie20

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STRUCTURE AND INFRASTRUCTURE ENGINEERING, 2017
VOL. 13, NO. 3, 361–389
http://dx.doi.org/10.1080/15732479.2016.1162818

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Investigation of a static and a dynamic neighbourhood methodology to develop work programs for multiple close municipal infrastructure networks

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ABSTRACT

Interventions on infrastructure networks in cities cause disruptions to the services provided by those but also to other networks that have to be at least partially shut down for the interventions executed. Due to these effects, there is substantial benefit to be obtained by grouping interventions on networks that are spatially close to one another. This benefit is principally due to reduced costs of intervention and reduced service disruption. In this paper, two intervention grouping methodologies to develop work programs for infrastructure networks are investigated. The first is based on static, the second is based on dynamic grouping. The two methodologies are investigated by developing work programs on multiple infrastructure networks in an urban area and compared against the same methodologies, albeit without coordination. In the example, interventions on the objects of five different infrastructure networks are grouped based on failure probability of the objects and their closeness. It is found that the dynamic grouping methodology results in work programs that result in a better consideration and prioritisation of objects that are in urgent need for an interventi, while accounting for the synergies that can be created due to efficient coordination. The advantages, disadvantages and future research directions are discussed.

ARTICLE HISTORY
Received 06 July 2015
Revised 20 January 2016
Accepted 12 February 2016
Published online 13 April 2016

KEYWORDS
Infrastructure; maintenance; civil engineering; sewers & drains; pipes & pipelines

1. Introduction

Municipalities often manage multiple infrastructure networks such as electricity, gas, road, sewer and water distribution and road networks. These networks are some of the main assets of the municipalities but also some of the main cost drivers. In order to obtain maximum net benefit from these networks, they need to be well managed. One part of that task is to plan interventions to be executed on the infrastructure in a way to minimise the costs of intervention and the disruption in service, i.e. to determine optimal work programs (OWPs). The grouping of interventions in WPs can lead to reductions in both (Arthur, Crow, Pedezert, & Karikas, 2009; Morcous & Lounis, 2005; Tscheikner-Gratl, Sitzenfrei, Rauch, & Kleidorfer, 2016; Zayed & Mohamed, 2013). This is true for single networks, and for multiple proximate networks, i.e. multiple networks that are physically close to one another. The latter is tackled in this paper.

A traditional methodology to the development of work programs on proximate infrastructure networks, is herein, considered to be one where managers, armed with information related to the individual objects within the network they are managing, such as age, condition and level of service to be provided, generate, for a small number of time intervals in the near future, a list of interventions that they would like to execute, and then discuss these lists with those responsible for the other objects within the same network, and then with those responsible for the objects in the other networks. Through these discussions, possible reductions in costs and in service interruptions are taken into consideration and a final work program for the interrelated infrastructure networks is generated. It is expected that this methodology, although an improvement on one where no coordination occurs, could be improved further and that this improvement can come through the exploitation of operations research methods and GIS software. Some challenges, however, need to be overcome.

One of the challenges of determining OWPs for proximate networks is that they are structurally and functionally different. They are structurally different in that they are comprised of different numbers, sizes and types of objects, e.g. electricity networks tend to be split into a large number of small objects, whereas sewer networks consist of objects with a length in the range of tens to hundreds of metres. They are functionally different in that they provide service in different ways, e.g. the objects in an electricity network are normally considered to either work or not work, and the objects in sewer networks, are considered to provide service levels associated, in general, with possible condition states. In addition to these two differences, they are also monitored in different ways, for example, some objects in some networks are monitored in a way that allows a manager only to know if the object is working or not, e.g. a cable in an electricity distribution network, and others are monitored in ways so that their deterioration over time can be followed, e.g. a section of a road network. This difference is due to the ability of managers to evaluate the progress of processes that will result in an inadequate level of service.

In this paper, two grouping methodologies are presented. Both are based on spatial analysis, which serves to group the interventions. Additionally, both methodologies are flexible enough to allow the incorporation of other decision-making tools. One methodology is based on the spatial relationship

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between objects alone. The other is based on both the spatial relationships and the topological structure of the infrastructure networks. Both methodologies allow for consideration of the spatial proximity of the objects within the infrastructure networks and for different methods to be used to prioritise objects for intervention.

The two methodologies are referred to as the static neighbourhood methodology and the dynamic neighbourhood methodology. In the former, each infrastructure object in each network is associated to a predefined square grid cell[1] and the proximity of the infrastructure objects is then determined by determining the proximity of the grid cells. In the latter, the proximity of the infrastructure objects is determined by investigating the network topology, for objects in the same network, and calculating Voronoi cells (Lejeune Dirichlet, 1850) for objects from different networks. Both of these methodologies can be used to take into consideration the structural and functional differences, as well as the different ways that the networks are typically monitored, which is represented by the way the condition is recorded (two-state/multiple discrete states/continuous). They are explained in detail in Section 3. In Section 4, they are both used to develop work programs for five proximate infrastructure networks in a municipality with approximately 30,000 inhabitants. The WPs are developed for the case where it is possible to execute an unlimited number of interventions and when there are restrictions placed on the number of interventions that can be executed. The resulting work programs are compared with the work programs that would result if WPs were developed for each infrastructure network separately.

2. Literature review

There has been substantial research over the last 40 years in the determination of OWPs for single objects, e.g. Liu and Frangopol (2004) and an increasing amount of research in the last 10 years on the determination of OWPs for infrastructure networks e.g. Arthur et al. (2009), Cardoso, Coelho, Matos, and Alegre (2004), Coelho (1997), Hajdin and Lindenmann (2007), Jeong, Abraham, and Baik (2005), Morcous and Lounis (2005), Zayed and Mohamed (2013). There has, however, been little to no research on the determination of OWPs for interrelated infrastructure networks, i.e. where events on one network affect other networks, by physical (an output from a system is required as an input to another system and vice versa), cyber (the state of a system is dependent on information transmitted through an information infrastructure), geographic (two or more systems can be affected by the same local event, i.e. they are spatially proximate) or logical (includes all other types of interdependencies, e.g. related to human behaviour) interaction (Rinaldi, Peerenboom, & Kelly, 2001). An idea of the state of the art in the determination of work programs for each of the networks is given in the following sections.

2.1. Electricity networks

Electricity networks are characterised by their binary state objects (working/not-working) with limited inspection possibilities. Therefore, intervention planning is based on the probability of failure of the objects. Stillman (2003) proposed to classify interventions on electricity network objects in two classes: (1) Emergency interventions, where upon failure the object is brought back as quickly as possible to a 'before failure' state, and (2) preventive interventions, where an object is replaced at a prearranged point in time. Combining costs for both types of interventions and service interruptions, as well as a safety constraint (maximum allowed risk of failure, disregarding a cost minimum), an optimal time interval for replacement is found according to his methodology. Work in the area of intervention planning reported on in literature has been basically focused more on the accurate estimation of the underlying statistical processes for failures and the resulting intervention intervals (Louit, Pascual, & Banjevic, 2009). Only recently, has Dehghanian, Fotuhi-Firuzabad, Aminifar, and Billinton (2013) defined a practical methodology making use of reliability centred maintenance techniques to determine work programs for electricity networks. The proposed methodology consists of three stages. In the first stage, the model to be used in the methodology is set up, including a check for data availability, system boundaries and system goals. In the second stage, the objects in the network most in need of an intervention are identified by means of reliability analysis. In the third stage, work programs are created that fit the reliability boundary conditions. These work programs are then ranked by their benefit-cost ratio, to find the OWP.

2.2. Gas networks

Gas networks, as electricity networks, are characterised by their binary state objects with limited inspection possibilities, and, therefore, intervention planning is also centred on the probability of failure of the objects. When this is the case, the development of work programs is essentially the same as that proposed by Dehghanian et al. (2013) as described in the previous section. To improve upon the limited inspection possibilities, however, Pandey (1998), proposed a probabilistic model for gas and oil pipelines, that uses magnetic–flux–leakage[2] sensors to update the failure probability by locating irregularities in the pipeline wall, such as corrosion or mechanical dents. The defects were to be ranked by the maximum allowed operating pressure (MAOP). If the defect was expected to cause the pipe section to fail at a pressure of 1.3 MAOP or below, an immediate intervention was required, if not the failure probability curve parameters of that object were adjusted to fit the observations which results in a different failure probability over time. This leads to a work program that consists of (1) immediate interventions, which must be executed, and (2) a list of candidate interventions which will either be included or not in the work program depending on how much their inclusion in the work program will reduce the overall failure probability and the available resources. The OWP is the one that results in the lowest overall failure probability, which was calculated using Monte Carlo simulations.

2.3. Road networks

Road networks are to some extent different from other infrastructure networks, including electricity and gas, but also sewer and water distribution networks. Road objects are much more unique, in a sense that every bridge, underpass or tunnel is adapted to its surroundings, using different construction techniques and materials according to the local properties, etc., thus being far less standardised than objects on other networks. Due to this uniqueness, intervention strategies and work programs are often made for single objects in road networks first and this information is then aggregated to a higher level (Lee & Madanat, 2015; Sathaye & Madanat, 2012), whereas in other networks there is more a tendency to start at a high level and work down. In other words, there is more a tendency for a bottom-up approach with roads whereas it is top down with other networks.

On object level, Miyamoto, Kawamura, and Nakamura (2000) presented a model for rating concrete bridges using a step model. The first step consisted of performing bridge inspections. The second step consisted of the evaluation of the inspection results taking into consideration the technical specifications. Third step consisted of ranking the results using a scale of 0 to 100. Based on the rating, the present deterioration could be characterised and the remaining life of the bridge estimated. Combining the cost and effects of both repair interventions and strengthening interventions with the prediction curve of the object deterioration, it was possible to determine both the quality and costs related to the candidate work programs. Miyamoto et al. (2000) then used genetic algorithms (GAs) to determine the best work program of the possible work programs by applying a multi-objective optimisation in two steps. In the first step, the minimal cost solution is found, which gives information about the quality achieved at minimal costs. This is then evaluated incrementally in the sense of an incremental cost-benefit analysis, giving the maintenance intervention strategy that yields the highest quality increase per additionally spent monetary unit compared to the minimal cost solution. Frangopol, Kong, and Gharaibeh (2001) proposed a way to determine OWPs for bridges based on how the reliability of the bridges were deteriorating over time, instead of the how the physical condition was changing over time.

On a network level, Hajdin and Adey (2006), Hajdin and Lindenmann (2007) proposed a model to be used to group interventions on multiple objects into work zones. In these models, the problem is modelled as a directed graph, with the nodes being the possible places where work zones can start and end, and the arcs are used to represent the costs. This translates the optimisation problem into a shortest-path problem with multiple sources and multiple sinks. Two other examples on the network level are the work by Mathew and Isaac (2013) and Lethanhm, Adey, and Sigrist (2014). Mathew and Isaac (2013) used genetic algorithms to determine the OWPs for a rural road network in Kerala, India. Lethanh et al. (2014) used a mixed integer linear model for determining OWPs taking into consideration the spatial distribution of objects in the network and the reductions in costs that were possible by combining interventions.

2.4. Sewer networks

Sewer networks are similar to roads in that different condition states exist, and that object condition is monitored over time albeit to a lesser extent than roads, due to the difficulty of access. A lot of research has been done on determining work programs for sewer networks, although the majority of managers of sewer systems, appear to ignore the results of this research and develop work programs using a traditional approach (Fenner, 2000). This is partly due to the lack of available information and partly due to the inability to use this information even if it existed. To overcome these problems, Fenner, Sweeting, and Marriott (2000) proposed a GIS-based model to calculate 'critical grid squares' where algorithms were developed to predict the likelihood of sewer failure in each square. This allowed the determination of geographical 'hotspots', as well as, finding grids that have the best cost-benefit ratio if the sewers requiring intervention in this grid were repaired or replaced. In this methodology, it is possible, when, enough information is available, to use advanced models,[3] as described in Fenner (2000). Use of more sophisticated models (especially risk-based models), however, is a complicated process and requires large amounts of information to calibrate the models in general (Ahmadi et al., 2014) but if available would result in the development of work programs over multiple time intervals. Such models will, however, undoubtedly become more important in the future, taking into consideration the increasing availability of data, which is coupled with the movement from manual to automated inspections, e.g. automated CCTV inspection (Kirstein, Müller, Walecki-Mingers, & Deserno, 2012) and the quickening development and use of integrated decision support systems. The most advanced of these systems for sewer management, for example, now use spatial information to detect 'similar' sewage infrastructure objects that can be combined into groups upon which interventions can be simultaneously executed, taking into account different intervention methods and time periods (Halfawy, Dridi, & Baker, 2008).

2.5. Water distribution networks

Water distribution networks are like gas and electricity networks, with respect to their network characteristics. A lot of research has been done with respect to the development of work programs based on the probability of failure of water pipes. Due to inspection difficulties much research has been focused on how to accurately calculate the failure probabilities, such as the work conducted by Kleiner, Adams, and Rogers (1998), Shamir and Howard (1979), Walski and Pelliccia (1982), Wang, Moselhi, and Zayed (2009). In the development of work programs, recently, Zayed and Mohamed (2013) presented a method to determine work programs, using a simulation-based priority index derived from an integrated hierarchy process/multi-attribute utility theory (AHP/MAUT) model, using a technique developed by Saaty (1996). The interventions selected for each pipe section included in the work program were done taking into consideration the condition of the pipe sections and the costs of the intervention. The OWP was determined using proprietary optimisation software.

2.6. Two relevant grouping methods that can be used to determine OWPs

In addition to the work that has been specifically done to determine work programs for infrastructure, there has also been work done recently to better define network relations and data mining. Three papers that are worth particular mention are the papers of Garland, Flintsch, Garvin, and Sotelino (2009), Jiang and Claramunt (2004) on network relations from a topological point of view and the paper of Fung (2001), that focuses on clustering. They are particularly important because their work can be integrated into methodologies to improve how work programs for multiple proximate infrastructure networks can be generated. Garland et al. 2009, Jiang and Claramunt (2004) proposed to use topological measures to be able to better support decision making involving network-like assets. Their work is useful in determining the closeness of objects in network infrastructure, or in other words, defining a topology-based neighbourhood. A disadvantage, however, with respect to the determination of OWPs for multiple networks is that there is no connection to other networks, even though they may be spatially close.

Clustering is the act of grouping things together. The objects grouped together are then called clusters. According to Witten and Frank (2005), '... these clusters should reflect some mechanism at work in the domain from which instances or data points are drawn, a mechanism that causes some instances to bear a stronger resemblance to one another than they do to the remaining instances'. When thinking of constructing work programs the spatial location of the interventions can be thought of as the domain, the interventions the instances and the resemblance as location. This means that the construction of work programs, which involves the grouping of interventions can be seen as a spatial clustering problem. In the case of infrastructure, however, one additional constraint has to be imposed: in traditional clustering, the goal is to 'partition all instances X into k clusters $C_1 \cdots C_k$ such that every data that belong to the same group [=cluster] are more "alike" than data in different groups [=clusters]' (Fung, 2001). As in the determination of OWPs, some interventions will not be able to be put in clusters because they are too far away from other interventions, it is necessary to have a clustering algorithm, that can also handle this situation. One family of such algorithms is the DBSCAN family. It was originally presented in Ester, Kriegel, Sander, and Xu (1996) and allows the spatial clustering of large (i.e. with numerous objects) spatial object sets while including 'noise' which has an interpretation as remotely located non-groupable objects. In other words, with algorithms from this family it is possible to group interventions that are close enough (with the possibility to define closeness by a number of different metrics), while being able to identify interventions that cannot be grouped because of their remote location. Several modifications exist. For example, Birant and Kut (2007), Liu, Zhou, and Wu (2007), Ram, Jalal, Jalal, and Kumar (2010) Xu, Ester, Kriegel, and Sander (1998), proposed modifications that allow for better cluster detection depending on the specific data properties or spatial-temporal cluster generation. For work programs containing multiple time steps, this is of particular benefit, as this algorithm is capable of not only grouping interventions within one time step but also moving the interventions from one time step to optimise grouping, e.g. postponing an intervention if there are other close interventions, over multiple time steps.

2.7. Summary

All the presented literature shows that there are advances in each of the single networks that allow generation and optimisation of work programs (albeit being developed differently for different systems with a recent trend to move from object oriented to network oriented). However, a combination of those to a work program encompassing multiple networks is still missing, although literature states a demand Dueñas-Osorio, Craig, Goodno, and Bostrom (2007): 'To better understand network failure mechanisms it is necessary to further analyse these multiple infrastructure systems as a single interacting entity'. Bobylev (2009): 'Including [the interrelation of urban infrastructure networks] in a general urban infrastructure maintenance plan will advance the efficiency of urban infrastructure network maintenance'. Additionally, although some grouping approaches are being made, an overall grouping methodology that can handle multiple networks with multiple object types and groups is still missing.

3. Methodologies

In this section, the two investigated methodologies are described. The first is the static neighbourhood methodology (SNM), which is so named because the objects of different infrastructure networks within a predefined (i.e. static) rectangular grid are considered for intervention as a group. The second is the dynamic neighbourhood methodology (DNM), which is so named because the neighbourhood and the grouping are calculated dynamically within the methodology. Both methodologies will be investigated in four scenarios each, (1) without budget constraint/with consideration of other networks, (2) with budget constraint/with consideration of other networks, (3) without budget constraint/without consideration of other networks and (4) with budget constraint/without consideration of other networks. To facilitate naming, the naming convention from Table 1 will be used.

In both methodologies, the criteria used to determine whether or not an object is a candidate for intervention is its probability of failure to provide an adequate level of service,[4] i.e. an object must have a probability of failure to provide an adequate level of service exceeding a specified threshold to be considered as a candidate for intervention. Whether or not each object is included in the work program then depends on agency rules, e.g. if object 1 is to have an intervention and object 2 is close to needing an intervention, execute interventions on both objects. The created work programs will be designated by the respective methodology/scenario abbreviations, e.g. WP_{DNMc} for a work program created by the dynamic neighbourhood methodology in the constrained-budget scenario with consideration of other networks. The basic steps in both methodologies are shown in Figure 1, which was drawn using BPMN 2.0, which is a standard for drawing process flow charts. An introduction into BPMN 2.0 can be found in Allweyer (2010). The differences between the methodologies occur in the subprocesses 'Calculate Neighbourhood', and 'Group objects'. Therefore, those subprocesses as well as all other subprocesses will be shown and explained in detail.

3.1. Determine level 1 objects

In this process, objects with high priority (Level 1 objects) are determined. In this paper, level 1 objects are defined as follows:

> Level 1 objects are objects, which are in such a state (defined using trigger values e.g. failure probability, age, level of service) that an

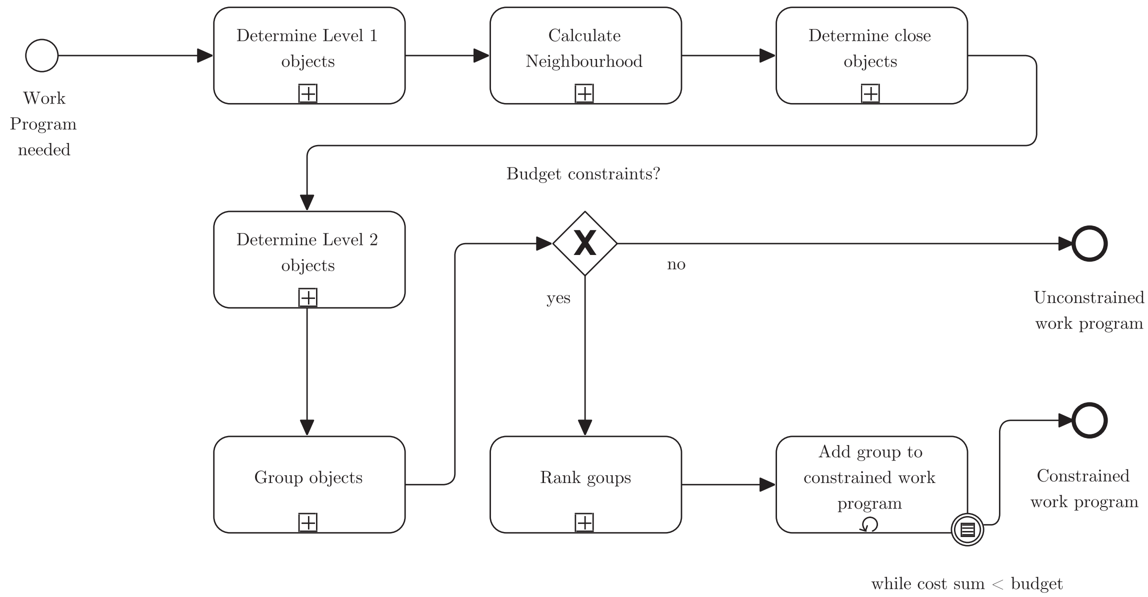


Figure 1. Common steps.

intervention on this object is justified on its own, i.e. the decision to do an intervention is independent from other objects.

In other words, level 1 objects are objects, that are in an unacceptable state and therefore need an intervention. In the first step, of this subprocess, triggers for selecting an object as a level 1 object are defined. These triggers are thresholds of one value or a combination of values of the object attributes. The attribute can be of the object itself, which is denoted as ζ_n^I with the subscript n ($n = 1 \dots N$) representing the object ID, and/or of the network ξ_m^I with the subscript m ($m = 1 \dots M$) representing the network ID and the superscript ^{I} denoting the level 1 objects. An example of the former is object condition. An example of the latter is the change in network reliability. For example, if an area is served by two objects with a significantly high (but still below the trigger value) failure probability, the combined failure probability (which is equivalent to 1 reliability) for the served area might still be over an acceptable level and thus justify an intervention on one or both objects.

In the next step, objects are compared with the triggers. The function used to determine if an object qualifies for an intervention is referred to as a selector function f_I. It is defined as a logical function, with $f_I = 1$ (true) when an object is selected, and 0 otherwise. A set of objects $o_{n,m}$ is determined based on the boundaries of the physical area to be analysed and the jurisdiction of the manager. Objects that are either outside the area to be analysed, or are the responsibility of another manager, are excluded. Each object in each network is characterised by certain attributes, which are related to the amount of time required before a corrective intervention would need to be executed, e.g. failure probability, or condition state. The set of all objects considered is denoted by the object vector $\vec{o}_{n,m}$ consisting of all objects $o_{n,m}$: $\vec{o}_{n,m} = (o_{1,1}, o_{2,1}, \dots, o_{N,1}, o_{1,2}, \dots, o_{N,2}, \dots, o_{N,M})$. This selector function is applied to $\vec{o}_{n,m}$ in order to obtain the logical selection vector for the level 1 objects $\vec{\delta}^I_{n,m}$:

$$\vec{\delta}^I_{n,m} = f_I\left(\vec{o}_{n,m}, \zeta_n^I, \xi_m^I\right) \tag{1}$$

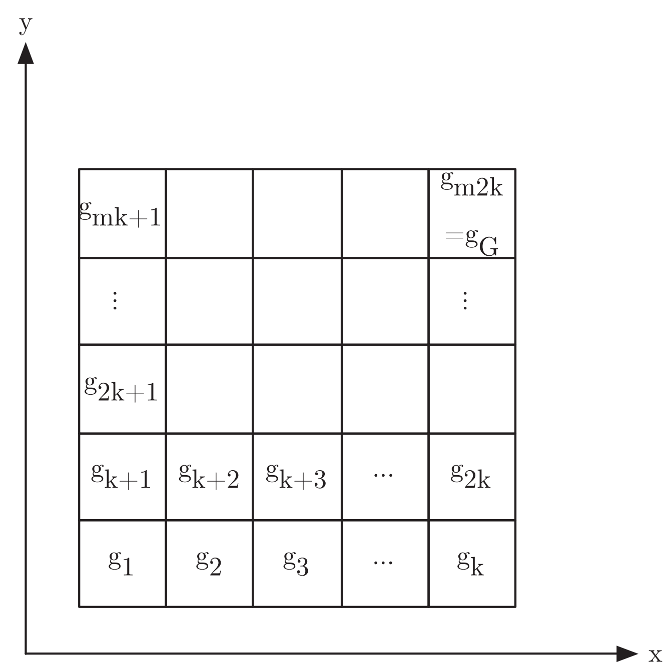


Figure 2. Definition of grid cells.

To avoid confusion, the following notation will be used: $\vec{\delta}^I{}_{n,m}$ refers to the selection vector, whereas $\delta^I_{n,m}$ refers to an element of this vector. In the last step, this logical selection vector is stored to be used for further computations.

3.2. Calculate neighbourhood

In this subprocess, the neighbourhood is calculated. The neighbourhood of object a is defined as the region around object a, where object b would be considered close if it lies within that region.

3.2.1. Static neighbourhood calculation

The SNM is based on the classification of all objects in all networks within predefined regular polygon area tessellations, e.g. equally sized quadratic grid cells, as proposed by Fenner et al. (2000). In the first step, the predefined (i.e. object-independent and thus static) grid cells are fetched from the database. The definition of the grid cells (tessellation tiles) and their numbering are given in Figure 2. The vector representing all grid cells is denoted as $\vec{g}_i$ with $i = 1 \ldots G$. In the next step, the neighbourhood matrix $\mathbf{N}_S$ (with the subscript $_S$ denoting the static neighbourhood methodology) is calculated:

$$\mathbf{N}_S = \vec{g}_i \prod \vec{o}_{n,m} \tag{2}$$

with $\vec{g}_i \ldots$ grid-cell vector and $\vec{g}_i \prod \vec{o}_{n,m} \ldots$ the dyadic geometric intersection between $\vec{g}_i$ and $\vec{o}_{n,m}$. The definition of $\vec{g}_i \prod \vec{o}_{n,m}$ is as follows: with the abbreviation of $g_i \between o_{n,m}$ for 'at least one point of the object $o_{n,m}$ lies within the grid cell g_i', $\vec{g}_i \prod \vec{o}_{n,m}$ is defined as:

$$\vec{g}_i \prod \vec{o}_{n,m} = \begin{pmatrix} g_1 \between o_{1,1} & g_1 \between o_{2,1} & \cdots & g_1 \between o_{N,M} \\ g_2 \between o_{1,1} & g_2 \between o_{2,1} & & \\ \vdots & & \ddots & \\ g_i \between o_{1,1} & & & g_i \between o_{N,M} \end{pmatrix} \tag{3}$$

If an object lies in more than one grid cell (i.e. if an object's physical volume crosses a grid boundary), the dyadic geometric intersection yields a 'true' ($= 1$) value for both grid cells. In the last step, the cells containing level 1 objects can be calculated:

$$\vec{\Delta}_i = H\left(\left(\mathbf{N}_S \otimes \left(\vec{\delta}^{I}_{n,m}\right)^{\top}\right) \cdot \vec{1}\right) \tag{4}$$

with $H(x) \ldots$ Heaviside function[5], $\vec{1} \cdots \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix}$ and $\vec{\Delta}_i \ldots$ selection variable vector for grid cell g_i. All grid cells where $\Delta_i = 1$ form the static neighbourhood. Per definition, the neighbourhood consists only of grid cells, that have level 1 objects in them.

3.2.2. Dynamic neighbourhood calculation

The dynamic neighbourhood methodology is based on a wider definition of neighbourhood. This subprocess is shown in Figure 3. The process is used to determine the neighbourhood of all level 1 objects being investigated. This is done by determining the topological neighbourhood, the distance neighbourhood and the Voronoi neighbourhood. The first two of these neighbourhoods consist of all objects that are in the neighbourhood of the level 1 object and are in the same network. The last consists of all objects that are in the neighbourhood of the level 1 objects but are in different networks than the level 1 object. To better explain the three different neighbourhoods, Figure 4 shows a sample network with seven objects. Logical nodes are denoted with • and geometric nodes are denoted with ∘. Logical nodes are nodes that signify a join between two or more objects. Geometric nodes are nodes that are used to model the shape of an object. Lines with the same number are used to denote one object. Geometric nodes are used to detail the object shape in between the endpoints (logical nodes).

3.2.2.1. Topological neighbourhood. The topological neighbourhood of an object is based on the topological distance along the network. This distance is defined by the number of objects between two logical nodes. In that sense, two objects are neighbours if the network distance between their closest logical nodes is below a certain threshold. For example, the distance between object 1 and 6 is 1, because only object 5 has to be crossed to get from object 1 to object 6. In that sense, objects which share one logical node, for example, objects 2 and 4, have a

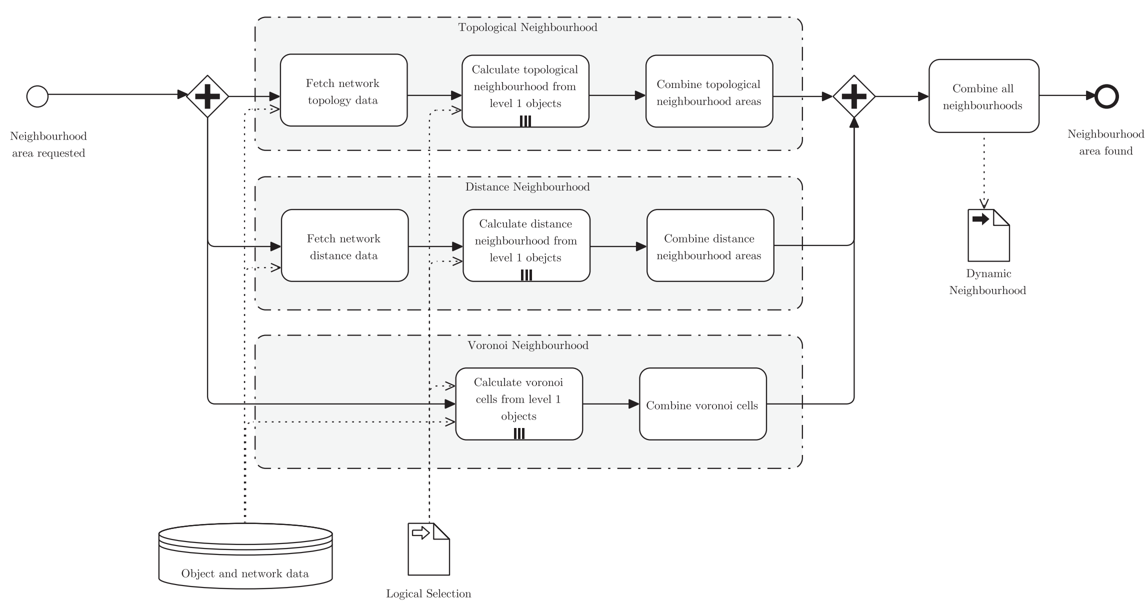


Figure 3. Subprocess 'dynamic neighbourhood calculation'.

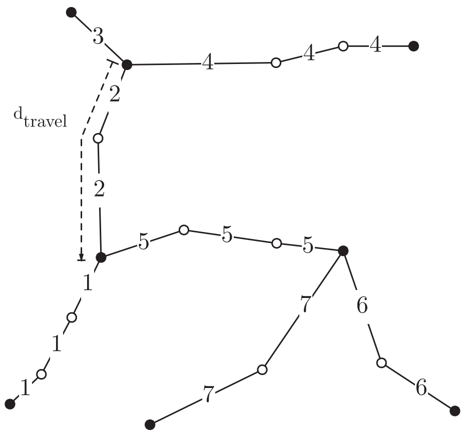


Figure 4. Example network with objects 1–7.

network distance of 0. If the focus is on object 6 and the distance threshold is 1, then objects 1, 2, 5 and 7 can be considered to be in the same neighbourhood, as at most 1 object (namely 5) has to be crossed to reach it. Mathematically, objects that are close (i.e. within a certain neighbourhood threshold) can be found as follows: first, the incidence matrix $\mathbf{C}_m$ (i.e. a matrix describing which edges are connected to which nodes) is converted to an adjacency matrix $\mathbf{L}_m$, which is just another way to describe a network:

$$\mathbf{L}_m = \mathbf{C}_m^\top \cdot \mathbf{C}_m - diag\left(\mathbf{C}_m^\top \cdot \vec{1}\right) \tag{5}$$

with $\boldsymbol{L}_m \ldots$ Adjacency matrix of network m, $\boldsymbol{C}_m \ldots$ Incidence matrix of network m. This corresponds to the flowchart activity 'Fetch network topology data' in Figure 3. From there, all nodes reachable in a distance k can be calculated by

$$\boldsymbol{K}_m = sgn\left(\sum_{x=0}^{k} \boldsymbol{L}_m^x\right) \tag{6}$$

with $\boldsymbol{K}_m \ldots$ Reachability matrix of network m for k steps and $sgn(x)$ representing the sign function[6]. Each element from $\boldsymbol{K}_m = \left[k_{m,i,j}\right]$ shows if a node is reachable from another node with a maximum of k steps. Combining those reachability matrices to a grand matrix, gives the neighbourhood matrix $\mathbf{N}_T$:

$$\mathbf{N}_T = \begin{bmatrix} \mathbf{K}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{K}_2 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{K}_M \end{bmatrix} \tag{7}$$

Note that this matrix has to be filled with 0 matrices because objects in different networks, at least in our example, are not connected in a topological sense. This matrix is almost identical to the neighbourhood matrix from the grid-cell methodology, only with the difference that both rows and columns represent individual objects.

3.2.2.2. Distance neighbourhood. As the sizes of network objects can differ by orders of magnitudes (e.g. compare one valve with a 300-m stretch of straight pipe), neighbourhoods can also be defined by distance along the network. This is an alternative neighbourhood definition which takes into account only the physical distance from each other along the network. For this, an object is defined as a neighbour, if it can be reached within a certain distance along the network. For example, objects 3 and 5 are within a distance d_{travel} of each other, as shown in Figure 4, as their closest nodes are within a distance of d_{travel}. Mathematically, the shortest path between all logical nodes q of all objects has to be calculated (or loaded from the database if available). This corresponds to the flowchart activity 'Fetch network distance data' in Figure 3.

$$\mathbf{D}_{m,q} = APSP_m(m, q) \tag{8}$$

with $\mathbf{D}_{m,q} \ldots$ All logical node pairs distance matrix for network m, $APSP_m \ldots$ All node pairs shortest path algorithm for networks as described in Johnson (1977). The minimal distance between all object pairs is then the minimum of the minimal distances between each objects' logical nodes.

$$\mathbf{D}_m = \min\left(dist\left(\mathbf{D}_{m,q}, \mathbf{D}_{m,q}\right) | q_m \in n_m\right) \tag{9}$$

With $\mathbf{D}_m \ldots$ minimal distance matrix for all objects in network m, $q_m \ldots$ logical nodes of network m and $n_m \ldots$ objects of network m. Comparing this minimal distance matrix with a distance threshold $d_{lim,m}$ for each network m gives the neighbourhood matrix $\mathbf{D}_{d,m}$:

$$\mathbf{D}_{d,m} \coloneqq \mathbf{D}_m \leq d_{lim,m} \tag{10}$$

Combining those distance matrices into a grand matrix, gives the neighbourhood matrix $\mathbf{N}_N$:

$$\mathbf{N}_N = \begin{bmatrix} \mathbf{D}_{d,1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{D}_{d,2} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{D}_{d,M} \end{bmatrix} \tag{11}$$

3.2.2.3. Voronoi neighbourhood. Both, topological and distance neighbourhood definitions have the prerequisite that all objects have to belong to the same network. To overcome this limitation, the neighbourhood can also be defined by Voronoi cells. Figure 5(a) shows a Voronoi tessellation of that example network. Starting from a given set of points p_i (in this case: all network nodes, both logical and geometric), Voronoi cells V_v consist of every point whose distance to p_k is less or equal to any other point $p_{j \neq k}$. A Voronoi region R_i for one object is then the set of all Voronoi cells emanating from the nodes of that object (see Figure 5(b) or (c)). Combining those regions gives the set of all Voronoi regions $\vec{R}_{n,m}$ for all objects $o_{n,m}$. This can be used to define the neighbourhood as follows: objects A and B are neighbouring, if object B touches object A's Voronoi region. The neighbourhood can then be defined as:

$$\mathbf{N}_V = \vec{R}_{n,m} \prod \vec{o}_{n,m} \tag{12}$$

with $\vec{R}_{n,m} \ldots$ Voronoi regions of objects $\vec{o}_{n,m}$, and $\mathbf{N}_V \ldots$ neighbourhood matrix for Voronoi methodology.

3.2.2.4. Neighbourhood combination. In the last activity of the dynamic neighbourhood, all neighbourhoods are combined to a grand neighbourhood, by combining all neighbourhood matrices to the dynamic neighbourhood matrix $\mathbf{N}_D$:

$$\mathbf{N}_D = \left(\mathbf{N}_T \vee \mathbf{N}_N\right) \vee \mathbf{N}_V \tag{13}$$

with the symbol $\vee$ denoting the logical 'or', which is an operator that returns a value of '1' if at least one input is '1', i.e. '1' and '0' or '0' and '1' or '1' and '1'. In words, two objects are neighbours if they are either topological, distance or Voronoi neighbours.

3.3. Determine close objects

In the next step in both methodologies, the so-called close objects are determined. Those objects are objects that are located in the neighbourhood, which is defined either by the static neighbourhood matrix $\mathbf{N}_S$ or the dynamic neighbourhood matrix $\mathbf{N}_D$. This process ensures that only close objects, i.e. objects that are sufficiently near to level 1 objects are screened for being potential level 2 objects in the next step. Mathematically, the whole process can be expressed in one equation for the SNM and another equation for the dynamic neighbourhood methodology. For the SNM:

$$\vec{\delta}^{C,S}_{n,m} = \left(\left(\mathbf{N}_S \otimes \vec{\Delta}_i\right)^\top \cdot \vec{1}\right) \nrightarrow \vec{\delta}^{I}_{n,m} \tag{14}$$

with $\vec{\delta}^{C,S}_{n,m}$ ... binary variable vector indicating if object $o_{n,m}$ is part of the close object set. The superscript ^{C} denotes the close objects, the superscript ^{S} denotes the SNM and the symbol $\nrightarrow$ denotes the material non-implication. This operator only returns a value of '1' if the first input is '1' and the second input is '0'. In this case: an object is only a close object for the SNM ($\delta^{C,S}_{n,m} = 1$) if the object is within the same cell as a level 1 object $(((\mathbf{N}_{T,k} \otimes \vec{\delta}^{I}_{n,m})^\top \cdot \vec{1}) = 1)$ but has not been already selected as an initial intervention ($\delta^{I}_{n,m} = 0$). For the DNM:

$$\vec{\delta}^{C,D}_{n,m} = \left(\left(\mathbf{N}_D \otimes \vec{\delta}^{I}_{n,m}\right)^\top \cdot \vec{1}\right) \nrightarrow \vec{\delta}^{I}_{n,m} \tag{15}$$

with $\vec{\delta}^{C,D}_{n,m}$ ... binary variable vector indicating if object $o_{n,m}$ is part of close object set, and the superscript ^{D} denoting the dynamic neighbourhood methodology. In the last activity, the selection vector is stored for further use.

3.4. Determine level 2 objects

In this subprocess, objects with lesser priority (Level 2 objects) are determined. In this paper, level 2 objects are defined as follows:

> Level 2 objects are objects, which are in such a state (defined using trigger values e.g. failure probability, age, level of service) that an intervention on this object is not justified on its own but the synergies created by doing a combined intervention with a level 1 object justify an intervention, i.e. the decision to do an intervention is dependent from other proximate objects.

In other words, level 2 objects are objects, that are not yet in an unacceptable state that needs an intervention, but will be in the near future, what justifies their inclusion in a work program. In the first activity of this subprocess, triggers for selecting an object as a level 2 object are defined. These triggers are thresholds of one value or a combination of values of the object attributes, which if passed mean that an intervention should be executed. The attribute can be of the object itself, which is denoted as ζ^{II}_n and/or of the network ξ^{II}_m with the superscript ^{II} denoting the level 2 objects. In the next activity of the flowchart, objects are compared with the triggers. Similar to level 1, the function used to determine if an object qualifies for an intervention is referred to as a selector function f_{II}. This selector function is applied to $\vec{o}_{n,m}$ multiplied with the close objects selector $\vec{\delta}^{C,S}_{n,m}$ or $\vec{\delta}^{C,D}_{n,m}$ (depending on the methodology used) in order to obtain the level 2 objects logical selection vector $\vec{\delta}^{II}_{n,m}$:

$$\vec{\delta}^{II}_{n,m} = f_{II}\left(\left(\vec{o}_{n,m} \cdot \vec{\delta}^{C,S}_{n,m}\right), \zeta^{II}_n, \xi^{II}_m\right) \quad \text{or}$$
$$\vec{\delta}^{II}_{n,m} = f_{II}\left(\left(\vec{o}_{n,m} \cdot \vec{\delta}^{C,D}_{n,m}\right), \zeta^{II}_n, \xi^{II}_m\right) \tag{16}$$

In the last activity, this logical selection vector is stored into a variable to be used for further computations.

3.5. Group objects

In this subprocess, the level 1 and level 2 objects, which have been identified in the previous steps, are combined into intervention groups, i.e. sets of interventions that are executed together.

3.5.1. Static neighbourhood grouping

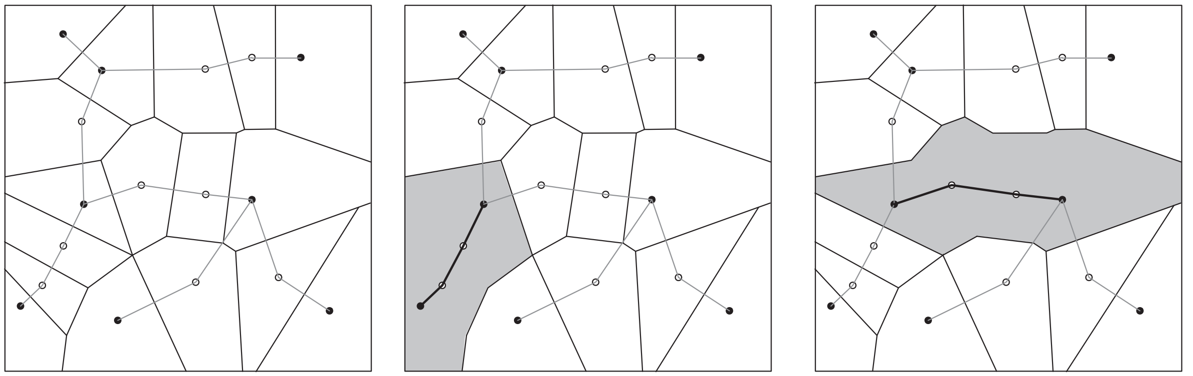
For static neighbourhood grouping, the interventions on level 1 objects and level 2 objects within a cell are combined into a group (To discern between SNM and DNM, combinations of objects made by the SNM will be referred to as groups, whereas combinations of objects from the DNM will be referred to as clusters). One intervention group equals one grid cell, i.e. all interventions in one grid cell are executed in the same time interval. All interventions together can be represented by an intervention matrix $\mathbf{I}_S$, where rows represent each grid cell and columns represent each object. Therefore, each row represents one intervention group:

$$\mathbf{I}_S = \mathbf{N}_S \otimes \left(\vec{\delta}^{I}_{n,m} \vee \vec{\delta}^{II}_{n,m}\right)^\top \tag{17}$$

The intervention matrix $\mathbf{I}_S$ has entries for all objects, but '1' values are only in cells representing objects that are neighbouring (represented by $\mathbf{N}_S$) and are either selected as level 1 objects ($\delta^{I}_{n,m} = 1$) or level 2 objects ($\delta^{II}_{n,m} = 1$). The cost of each group is then calculated as the sum of the set-up cost for executing all interventions in grid cell g_i (c_i) and the unit costs without set-up costs for each object of each network ($c_{n,m}$) multiplied with its size ($u_{n,m}$). As there are only costs, if an intervention is executed, the terms are multiplied by the respective binary selection variable (Δ_i).

$$C_i = \Delta_i \cdot c_i + \left(\left(\left(\mathbf{I}_S \otimes \left(c_{n,m}\right)^\top\right) \otimes \left(u_{n,m}\right)^\top\right) \cdot \vec{1}\right) \tag{18}$$

with C_i ... vector of intervention costs in all cells g_i. If there are no interventions in a cell, the cost value for that cell equals to 0. WP_{SNM} is simply the whole set of intervention groups, i.e. all rows of $\mathbf{I}_S$. The total costs are then the sum of the cost vector C_i.



(a) Voronoi cells for network nodes (b) Voronoi region for network element 1 (c) Voronoi region for network element 5

Figure 5. Network definitions.

$$C_{WP_{SNM}} = \sum_{i=1}^{G} C_i \tag{19}$$

This would be the final work program, if the static neighbourhood method is used, and no constraints exist. It is important here to reiterate that once the groups are formed they are no longer to be broken up, for example, in the case of budget constraints.

3.5.2. Dynamic neighbourhood grouping

Section 3.2.2 calculates the neighbourhood from the level 1 objects, i.e. defines a subset of all objects from all networks, that is close to the level 1 objects. This, however produces objects that could either be level 2 or objects that do not need an intervention. Therefore, these objects not in need of an intervention are separated in Section 3.4 and thus removed from the subset. With a change in the subset elements, there is a certain possibility that the grouping is not valid any more. Therefore, the intervention objects (both levels 1 and 2) need to be regrouped. For dynamic neighbourhood grouping, this is done using the DBSCAN algorithm as described in Ester et al. (1996). This algorithm takes the centroid point coordinates of the objects requiring intervention and two values as inputs:

Eps: the distance, that defines a neighbourhood, in this case, the maximum distance in which two interventions should be grouped into one intervention group

MinPts: the number of interventions, that form the smallest group size. For most practical contexts, this will be ‘2’

Then, the points are classified as either belonging to a group (in DBSCAN terminology: a cluster) or being single objects (in DBSCAN terminology: noise). If they belong to a group, then the interventions are included in the work program as a group, otherwise it has to be discerned between level 1 and level 2 objects. Level 1 single objects are also included in the work program as intervention, although they could not be grouped, because per definition level 1 signifies that an intervention is justified even without grouping. Level 2 objects belonging to no group however, will be discarded. The subprocess is shown in Figure 6. Mathematically:

$$\mathbf{I}_D = DBSCAN\left(\vec{\delta}^{I}_{n,m} \wedge \vec{\delta}^{II}_{n,m}, Eps, MinPts\right) \tag{20}$$

with $\mathbf{I}_D$ . . . intervention group matrix for the DBSCAN clusters. The cost of each group is the sum of the set-up cost for executing all interventions in group s_j (c_j) and the unit costs without set-up costs for each intervention on each object of each network ($c_{n,m}$) multiplied by its size ($u_{n,m}$).

$$C_j = c_j + \left(\left(\left(\mathbf{I}_D \otimes \left(c_{n,m}\right)^{\top}\right) \otimes \left(u_{n,m}\right)^{\top}\right) \cdot \vec{1}\right) \tag{21}$$

with C_j . . . cost vector of intervention in all groups s_j. WP_{DNM} is simply the whole set of intervention groups, i.e. all rows of $\mathbf{I}_D$. The total costs is then simply the sum of the cost vector C_j.

$$C_{WP_{DNM}} = \sum_{j=1}^{J} C_j \tag{22}$$

3.6. Rank groups

If there are constraints (which are in most cases budget constraints) and not all intervention groups can be executed, a priority is calculated so that the groups with the highest priority can be included in the work program. A flowchart for the ranking process is given in Figure 7. The priority of a group is related to the consequences that will be incurred due to service interruption when an intervention is executed. It is in this methodology based on two components: (a) the object priority value, which relates to the object itself and its role in the network, e.g. for a sewer network object how many upstream objects will also be blocked if this object has to be blocked for maintenance, and (b) a multiplicative factor related to the location, e.g. population density of the area with service interruption. Although this is multiplicatively connected with the object priority value, it is kept separately because the population density, for example, is not network dependent, whereas the object priority value is. Mathematically:

$$\vec{W}_i = \left(\left(\mathbf{I}_S \otimes \left(\lambda_{n,m}\right)^{\top}\right) \cdot \vec{1}\right) \circ \vec{\lambda}_i \text{ or } \vec{W}_i = \left(\left(\mathbf{I}_D \otimes \left(\lambda_{n,m}\right)^{\top}\right) \cdot \vec{1}\right) \circ \vec{\lambda}_i \tag{23}$$

with W_i . . . priority vector of group s_i, $\vec{\lambda}_{n,m}$ . . . object priority vector based on object n and network m, $\vec{\lambda}_i$ . . . group priority vector based on group location, and $\circ$ representing the element-wise multiplication of vectors[7]. From there, the rank r_i of a group can be calculated:

$$r_i = rank\left(sort\left(W_i \mid desc.\right)\right) \tag{24}$$

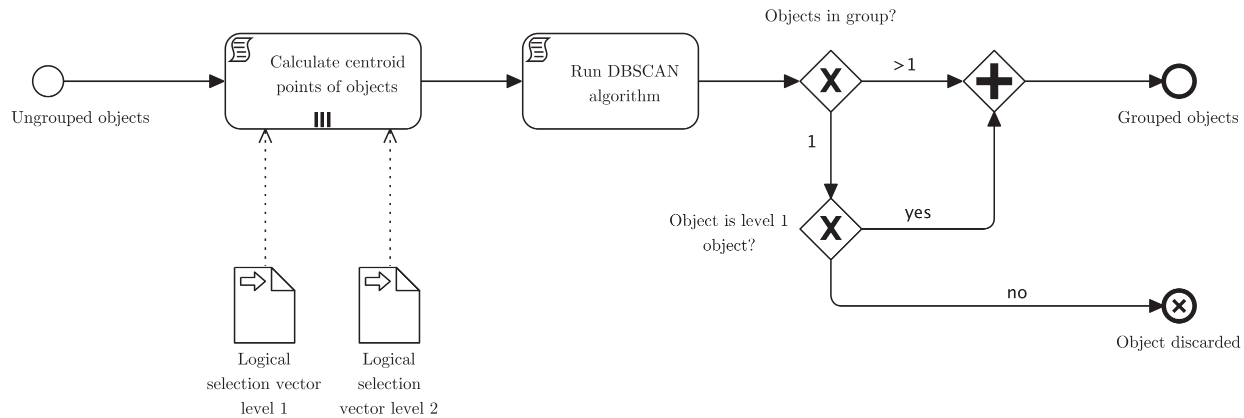


Figure 6. Subprocess 'Group objects' with dynamic neighbourhood grouping.

This results in the group with the highest priority W_g having the lowest rank r_i.

3.7. Add group to constrained work program

The work programs with constraints (WP_{SNMc} and WP_{DNMc}) are constructed out of WP_{SNMc} or WP_{DNMc}: The groups are added one at a time to the constrained work program (i.e. a selection variable Δ_g^c is changed from 0 to 1) starting with the group with the highest priority (i.e. where $r_i = 1$, then where $r_i = 2, 3, \ldots$ etc.) and then the budget is checked. If the budget is not exceeded the group is kept in WP_{SNMc}/WP_{DNMc} and the group with the next highest priority is tried. This process is repeated until the sum of the costs of the groups in the work program reaches the budget limit C_{lim}:

$$\Delta_g^c = \begin{cases} 1 & \text{for } \sum_{g_i(r_i=1)}^{g_i(r_i=N)} \left(C_i\right) \leq C_{lim} \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

with $\Delta_g^c \ldots$ binary vector indicating inclusion in WP_{DNMc} (1 = yes, 0 = no), $C_{\text{lim}} \ldots$ Budget limit. WP_{SNMc}/WP_{DNMc} is the whole set of intervention groups $\mathbf{I}_S$ or $\mathbf{I}_D$ subsetted by the inclusion variable Δ_g^c:

$$\mathbf{I}_S^c = \left(\mathbf{I}_S \otimes \Delta_g^c\right) \text{ or } \mathbf{I}_D^c = \left(\mathbf{I}_D \otimes \Delta_g^c\right) \tag{26}$$

The total cost is the sum of the cost vector C_i times the inclusion vector.

$$C_{WP_{DNMc}} = \sum_{g=1}^{G} \left(C_i \circ \Delta_g^c\right) \tag{27}$$

4. Case study

The methodologies described in Section 3 were used to determine work programs for five proximate municipal infrastructure networks. These work programs were then compared with the work programs generated by the two methodologies, albeit without consideration of the other infrastructure networks, which serves as a reference scenario that is assuming that no coordination takes place and every infrastructure manager plans his work programs on his own. All methodologies will be compared for two cases: (1) where there is no budget constraint, and (2) where a budget constraint is in place. To facilitate naming, the naming convention from Table 1 will be used.

4.1. Overview

The infrastructure networks (electricity, gas, roads, sewage and water) used in this case study belong to a city with a population of approx. 30,000 and a population density of approx. 1,000 people per sq. km. As can be seen in the overlay of all networks (Figure 8(a)), the city is grouped into one densely populated core and two satellites (upper left and upper right). The single network maps are shown in Figure 8(b)–(f). Table 2 gives an overview about the network characteristics at the time of investigation, as received from the city. It was chosen to keep the received data in the original format, i.e. preserving the different types of condition state recording. The electricity network (Figure 8(b)) is a large network with a high number of objects and multiple redundancies. The condition of this network is recorded in a binary state (1 = in operation, 5 = defunct). The gas network (Figure 8(c)), consisting of three subnetworks which are not connected to each other, also has the condition state recorded as binary values, like the electricity network. The road network (Figure 8(d)) has a continuous condition state recording, with values between 0 (as new) and 5 (defunct). The sewer network (Figure 8(e)) is one connected network with the endpoint located at the left side (the wastewater treatment plant, marked with a black dot), with the condition being recorded in five discrete condition states. The water distribution network (Figure 8(f)) consists of two non-connected parts that both have their origin in the same water plant. The condition is recorded binary, like the electricity and gas network. These different recording types also reflect the city's ability to inspect each.

As the population density differs over the city and at some location objects with higher need for a functioning infrastructure (e.g. hospitals, schools, government buildings) are scattered around the city, importance zones can be defined by the city

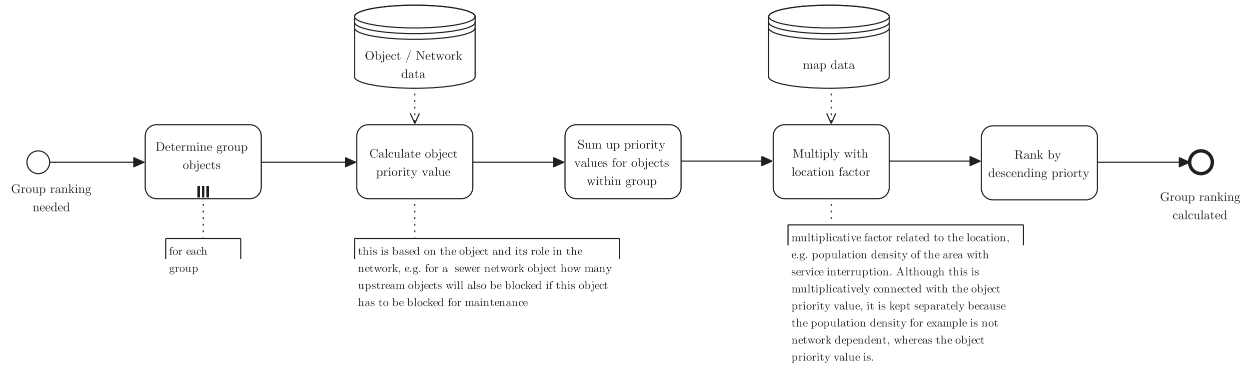


Figure 7. Flowchart for process 'Rank groups'.

Table 1. Methodology/scenario abbreviations.

Methodology	Scenario	Consideration of other networks	Without consideration of other networks
Static	No budget constraint	SNM	SWC
	Budget constraint	SNMc	SWCc
Dynamic	No budget constraint	DNM	DWC
	Budget constraint	DNMc	DWCc

Table 2. Network characteristics at the time of investigation.

		Electricity	Gas	Water	Sewer			Road
Length	[km]	328.0	102.1	146.7	116.5			141.9
Objects	[–]	35,073	5725	4209	4282			1905
Avg. object length	[m]	9.4	17.8	34.9	27.2			74.5
Type of condition state		Binary	Binary	Binary	Discrete			Continuous
No of condition state		2	2	2	5			0–5
Condition state	1(as new)	100%	100%	100%	93.2%	Cond. state range	0–1	4.7%
	2	–	–	–	6.2%		1–2	24.7%
	3	–	–	–	.5%		2–3	48.5%
	4	–	–	–	.1%		3–4	19.6%
	5 (defunct)	0%	0%	0%	0%		4–5	2.5%

government to reflect the relative priority of an area in relation to each other. Figure 9 shows the spatial distribution of these (fictive[8]) priority zones, with their assigned importance factor λ_i (see Equation (23)). This is an additional factor to help take into consideration the consequences of the loss of service that may happen during the execution of an intervention or due to a failure and the follow up intervention.

4.2. Indicators for interventions

To be able to decide if an object should be included in a work program, an indicator is chosen that defines the boundary between intervention and non-intervention. For the networks whose objects can only be in one of two condition states, the selection is based on a threshold failure probability, i.e. the probability of being in condition state 5, which may be thought of as failure to provide an adequate level of service. Selecting an appropriate threshold probability is a management decision, which depends on several inputs, such as the amount of risk the infrastructure manager is willing to take, available resources, knowledge of the manager about his asset stock and others. Therefore, the determination of these appropriate thresholds is beyond the scope of this work. Once determined the basic intervention strategy is then:

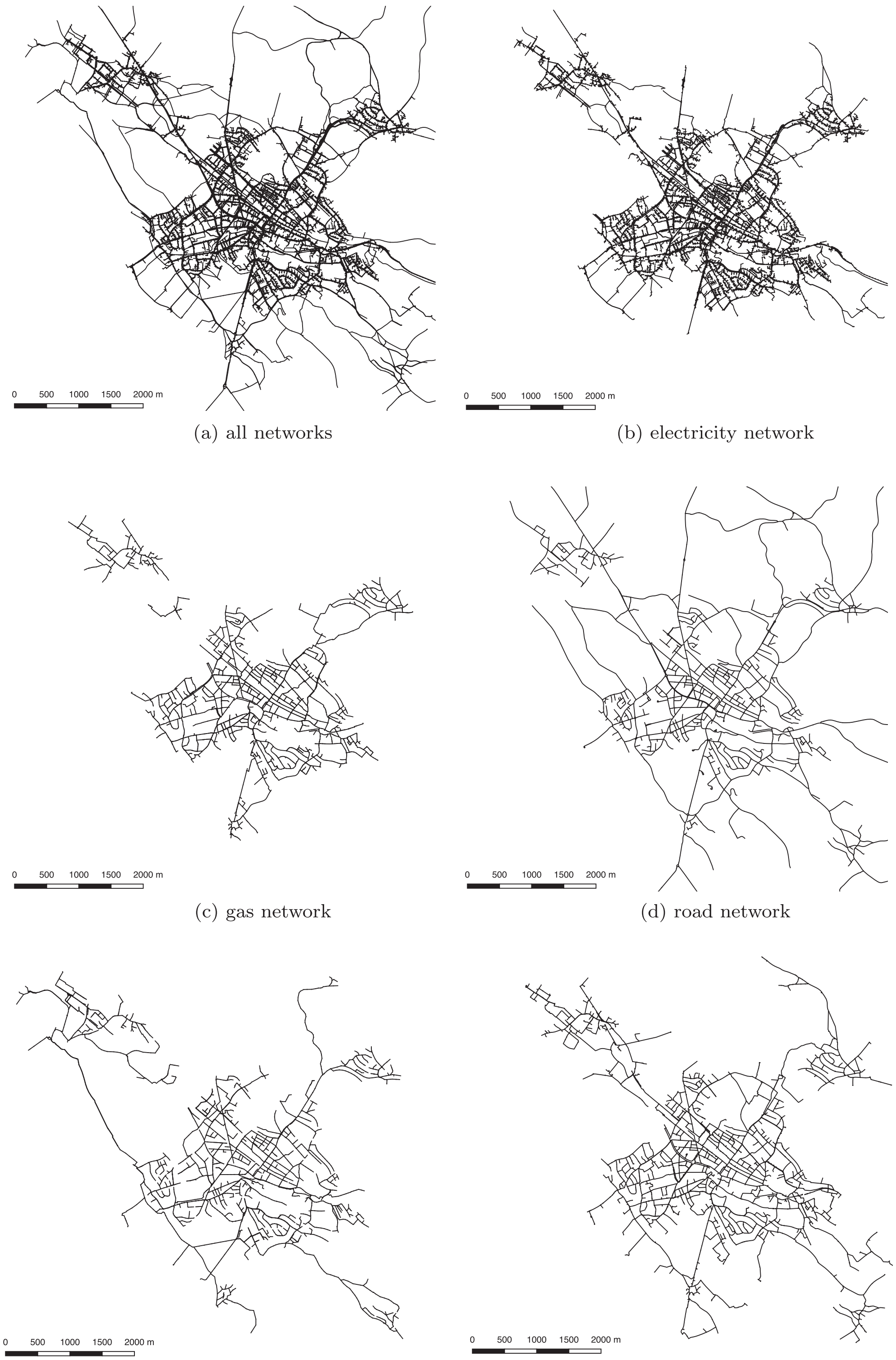
$$\forall o_{n,m} \begin{cases} P_{n,m}(t) \geq \overline{P}_{n,m} & \text{Level 1 object} \\ P_{n,m}(t) < \overline{P}_{n,m} & \text{no Level 1 object} \end{cases} \tag{28}$$

with t ... age, $o_{n,m}$ ... all objects, $P_{n,m}(t)$ ... failure probability for object n from network m at age t, and $\overline{P}_{n,m}$ ... threshold failure probability of object $o_{n,m}$. The level 1 objects are then determined by

$$f_I(o_{n,m}, \zeta_n, \xi_m) = H\left(P_{n,m}\left(t\right) - \overline{P}_{n,m}\right) \tag{29}$$

Here, the failure probability $P_{n,m}$ at each time t for each object n is calculated and compared against the threshold probability $\overline{P}_{n,m}$ for level 1 objects. If the failure probability of an object exceeds this threshold probability, this object is selected as level 1 object. For sewer objects, which can be in one of more than two condition states, the selection is based on the transition probability of an object from any condition state 1–4 (providing adequate level of service) to state 5 (providing inadequate level of service).

$$\forall o_{n,sewer} \begin{cases} \Theta^{\rightarrow 5}_{n,sewer}(t) \geq \overline{\Theta}^{\rightarrow 5}_{n,sewer} & \text{Level 1 object} \\ \Theta^{\rightarrow 5}_{n,sewer}(t) < \overline{\Theta}^{\rightarrow 5}_{n,sewer} & \text{no Level 1 object} \end{cases} \tag{30}$$



(a) all networks (b) electricity network

(c) gas network (d) road network

(e) sewer network (f) water network

Figure 8. Network maps.

with $\Theta_{n,sewer}^{\rightarrow 5}(t) \ldots$ transition probability for sewer object n from $CS < 5$ to CS 5 at time t, and $\overline{\Theta}_{n,sewer}^{\rightarrow 5} \ldots$ threshold transition probability of sewer object n. The level 1 objects are then determined by

$$f_{I,sewer}(o_n, \zeta_n, \xi_{sewer}) = H\left(\Theta_{n,sewer}^{\rightarrow 5}(t) - \overline{\Theta}_{n,sewer}^{\rightarrow 5}\right) \qquad (31)$$

For road objects, which also can be in one of more than two condition states, the selection is based on a threshold condition state, which is associated with a failure to provide an adequate level of service. Again the condition state to trigger an intervention is a management decision and is beyond the scope of this work. This gives the basic intervention strategy as:

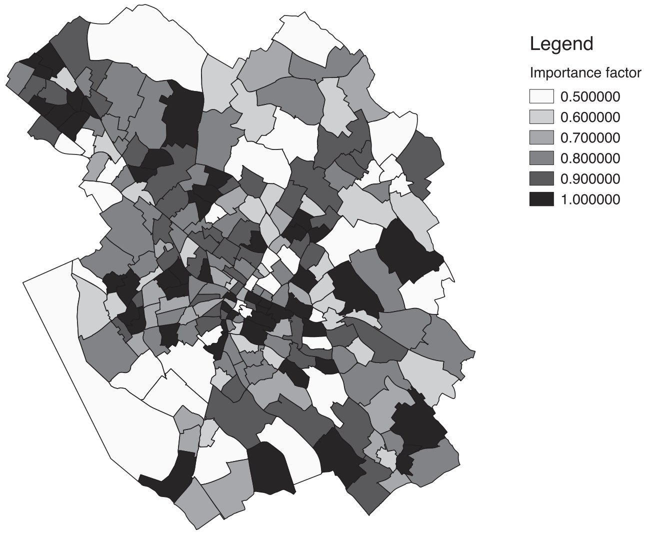


Figure 9. Location priority.

$$\forall o_{n,roads} \begin{cases} CS_{n,}(t) \geq \overline{CS}_n & \text{Level 1 object} \\ CS_n(t) < \overline{CS}_n & \text{no Level 1 object} \end{cases} \quad (32)$$

with $CS_n\left(t\right)\ldots$ condition state of road object n at age t, and $\overline{CS}_n\ldots$ threshold condition state of object n. Therefore, the selector function for level 1 road objects is:

$$f_{I,roads}(o_n, \zeta_n, \xi_{roads}) = H\left(CS_n\left(t\right) - \overline{CS}_n\right) \quad (33)$$

Likewise, for level 2 objects, a second threshold probability/condition state is chosen. In this case, the respective threshold probabilities will of course be lower/the condition state will be better than those used to trigger interventions on level 1 objects. For binary-state networks, this probability reflects also a probability to be in condition state 5, but a lower one. This means that a level 2 object has a probability of failure that is too low to justify an intervention on its own but high enough to be combined with a close level 1 object. The same is true for the multiple-state networks, but instead of failure probability, the probability of being in an inadequate state is used. Table 3 lists the chosen probabilities/condition state. This table shows, that for electricity and gas networks, objects are classified as level 1 if their failure probability exceeds .025 and as level 2 if their failure probability exceeds .013, for the water distribution network the failure probabilities are .020 and .005, respectively. For roads, the threshold condition states are 3.67 and 3.10, and for sewer, the transition probabilities are .020 and .005.

4.3. Interventions

Only one type of intervention per object was considered. This was done to help ensure an understandable example. There is no particular hindrance to taking into consideration interventions of multiple types. The interventions and their respective unit costs are listed in Table 4. This table also lists set-up costs per intervention set-up. For this example, it was assumed that the set-up costs are independent from the network type and group size. As before, there is no particular hindrance to taking into consideration network and group size independent set-up costs.

4.4. Constraints and assumptions

The work programs were developed assuming no budget constraint and assuming there was a budget limit C_{lim}, which was set to 4 million monetary units (mu) for both methodologies. This allows to show a wide range of possible budget situations, i.e. networks where the constrained budget is enough to do all interventions but also networks where only a fraction of the interventions can be done. As for the non-coordination case, no coordination in any form is postulated, the budget was assumed to be evenly distributed among the networks, thus making it 800,000 mu per network. The work programs were developed for one time interval. For the object importance factor $\lambda_{n,m}$ the rule is postulated, that only level 1 objects have non-zero values. This ensures that the ranking of the groups under constraints is not skewed by groups with many level 2 objects, but few level 1 objects, and only level 1 objects are in a state that needs an intervention, and thus should be the basis for the ranking.

4.5. Results

4.5.1. SNM without coordination

Table 5 shows the detailed results of the SWC and the SWCc. It can be seen that the SWC selects 2534 objects and the SWCc 858 objects to be included in the work program. A total amount of 43,024 and 20,401 m, respectively. In the case of an unlimited budget, the total cost is 11,908,691 mu. In the case of a constrained budget with only 4,000,000 mu available, the total cost is 3,350,911 mu, which is 84% of the total. It can be seen that in the SWCc, only 47% of the SWC objects (measured in object length) are selected. The percentage of $\frac{units\ \mathrm{SWCc}}{units\ \mathrm{SWC}}$ varies strongly across the networks (sewer and gas: 100%, electricity: 49%, water: 38%, roads: 13%). Reasons for this will be discussed in Section 5.

4.5.2. SNM with coordination

Table 6 shows the detailed results of the SNM and SNMc. It can be seen that the SNM selects 3957 objects and the SNMc 1006 objects to be included in the work program. A total amount of 66,849 and 16,322 m, respectively. In the case of an unlimited budget, the total cost is 13,299,795 mu. In the case of a constrained budget with only 4,000,000 mu available, the total cost is 3,323,546 mu, which is 83% of the total. It can be seen that in the SNMc, only 24% of the SNM objects (measured in object length) are selected. The percentage of $\frac{units\ \mathrm{SNMc}}{units\mathrm{SNM}}$ varies across the networks (sewer: 42%, water: 38%, gas: 32%, electricity: 21%, roads: 14%), although not so widely as in the SWC/SWCc. Reasons for this will be discussed in Section 5.

4.5.3. Dynamic neighbourhood without coordination

Table 7 shows the detailed results of the DWC and DWCc. This table shows that the the DWC selects 1977 objects for a work program and the DWCc 1024 objects. A total amount of 41,467 and 16,332 km, respectively, will be renewed. In the case of an unlimited budget, the total cost is 8,834,067 mu. In the case of a constrained budget with only 4,000,000 mu available, the total cost is 2,937,748 mu, which means a budget utilisation of 73%. It can be seen that in the DWCc, only 39% of the SNM objects (measured in object length) are selected. The percentage of $\frac{units\mathrm{DWCc}}{units\ \mathrm{DWC}}$ varies strongly across the networks (sewer and gas:

Table 3. Maximum acceptable failure probability/transition probability/CS.

Network	Type	Level 1	Level 2
Electricity	Failure probability	.025	.013
Gas	Failure probability	.025	.013
Roads	Condition state	3.67	3.10
Sewer	Transition probability	.020	.005
Water	Failure probability	.020	.005

Table 4. Intervention types and costs.

Network	Type	Effect	Value	Unit
Sewer	Replacement	As-new condition	250	(mu/m)
Electricity	Replacement	As-new condition	100	(mu/m)
Gas	Replacement	As-new condition	150	(mu/m)
Roads	Replacement	As-new condition	350	(mu/m)
Water	Replacement	As-new condition	300	(mu/m)
Set-up cost	Cost per intervention set-up		1500	(mu/set-up)

Table 5. SWC/SWCc: detailed results.

	No. of objects		Amount				Cost (mu)	
Network	SWC	SWCc	SWC	SWCc	Units	$\frac{units\ \text{SWCc}}{units\ \text{SWC}}$	SWC	SWCc
Sewer	48	48	1058	1058	m	100%	370,915	370,915
Electricity	1987	473	25,280	12,331	m	49%	3,934,478	732,748
Gas	304	304	4472	4472	m	100%	785,866	785,866
Roads	113	8	8190	1025	m	13%	5,859,777	679,865
Water	82	25	4024	1515	m	38%	957,655	781,517
Sum	2534	858	43,024	20,401	m	47%	11,908,691	3,350,911

Table 6. SNM/SNMc: detailed results.

	No. of objects		Amount				Cost (mu)	
Network	*SNM*	*SNMc*	*SNM*	*SNMc*	Units	$\frac{units\ \text{SNMc}}{units\ \text{SNM}}$	SNM	SNMc
Set-up cost			638	115	Cells	18%	957,000	172,500
Sewer	308	131	6392	2692	m	42%	1,653,692	622,031
Electricity	2816	614	33, 733	6984	m	21%	3,373,394	698,451
Gas	537	191	8942	2884	m	32%	1,341,343	432,661
Roads	171	24	12, 268	1687	m	14%	4,293,836	590,718
Water	125	46	5512	2073	m	38%	1,680,530	807,185
Sum	3957	1006	66, 849	16, 322	m	24%	13,299,795	3,323,546

100%, water: 59%, electricity: 38%, roads: 11%). Reasons for this will as well be discussed in Section 5.

4.5.4. Dynamic neighbourhood methodology with coordination

Table 8 shows the detailed results of the DNM for the non-constraint (DNM) and constraint (DNMc) case. Table 8 shows that the DNM selects 2143 objects for a work program and the DNMc 1370 objects. A total amount of 46,787 and 21,791 m, respectively, will be renewed. In the case of an unlimited budget, the total cost is 9,912,505 mu. In the case of a constrained budget with only 4,000,000 mu available, the total cost is 3,944,940 mu, which means a budget utilisation of 99.9%. It can be seen that in the DNMc, only 47% of the DNM objects (measured in object length) are selected. The percentage of $\frac{units\ \text{DNMc}}{units\ \text{DNM}}$ varies across the networks (gas: 80%, sewer: 79%, electricity: 50%, water: 43%, roads: 24%), although not so widely as in the DWC/DWCc. Reasons for this will also be discussed in Section 5.

4.6. Comparison

In this section, the results are compared. This is done by first illustrating how each methodology includes interventions in work programs, and then by comparing (1) the work programs when there are no budget constraints and (2) the work programs when there are budget constraints. The comparisons are done using two indicators; the cost per improved condition state and the reduction in the probability of failure beyond an acceptable level.

4.6.1. Constructed work programs

It can be seen by comparing the four methodologies, that there is a difference between the numbers of interventions proposed (SWC: 2534, SNM: 3957, DWC: 1977, DNM: 2143) when no budget constraint is imposed and (SWCc: 858, SNMc: 1006, DWCc: 1024, DNMc: 1370) when budget constraints are imposed. This is due to the definition of closeness that is used. In the SWC and SNM, closeness is defined solely by the grid cell,

Table 7. DWC/DWCc: detailed results.

	No. of objects		Amount				Cost (mu)	
Network	DWC	DWCc	DWC	DWCc	Units	$\frac{\textit{units}\ \text{DWCc}}{\textit{units}\ \text{DWC}}$	DWC	DWCc
Sewer	40	40	1037	1037	m	100%	272,964	272,964
Electricity	1434	648	20,081	7626	m	38%	2,168,695	785,171
Gas	262	262	3771	3771	m	100%	603,244	603,244
Roads	157	7	12,277	1372	m	11%	4,451,576	489,245
Water	84	67	4298	2523	m	59%	1,337,588	787,122
Sum	1977	1024	41,467	16,332	m	39%	8,834,067	2,937,748

Table 8. DNM/DNMc: detailed results.

	No. of objects		Amount				Cost (mu)	
Network	DNM	DNMc	DNM	DNMc	Units	$\frac{\textit{units}\ \text{DNMc}}{\textit{units}\ \text{DNM}}$	DNM	DNMc
Set-up cost			184	30	*Clusters*	16%	276,000	45,000
Sewer	71	60	2237	1772	m	79%	559,282	443,124
Electricity	1515	956	21,144	10,635	m	50%	2,114,426	1,063,510
Gas	292	241	4880	3911	m	80%	731,970	586,649
Roads	172	60	13,464	3290	m	24%	4,712,368	1,151,627
Water	93	53	5062	2183	m	43%	1,518,456	655,028
Sum	2143	1370	46,787	21,791	m	47%	9,912,505	3,944,940

whereas in the DWC and DNM a dynamic calculation is used. Figures 10, 11, 12, 13, 14, 15, 16, 17 show a graphical representation of the generated work programs with the intervention zones marked in grey.

The difference between the static and the dynamic methodologies is directly visible. In the SWC/SWCc/SNM/SNMc all work programs are grid-cell based, thus leading to a 'pixelated' appearance of the work programs (see Figures 10,11,14,15). When the dynamic methodologies (DWC/DWCc/DNM/DNMc) are used, some clusters have an area-like appearance, and some others have a linear appearance (see Figures 12,13,16,17). This is due to the different object groups included in the work programs. As all clusters stem from convex polygons around the selected object groups, widespread groups (which can be seen, for example, in the city centre) form area-like clusters, and linear objects or linear adjacent objects are or appear to be linear, as can be seen at the city peripherals.

When looking at the number of objects included in the work program, it can be noted that the methodologies without coordination select in both the constrained and unconstrained case fewer objects than the methodologies with coordination. This is expected, as without these methodologies only look at their own objects when looking for possible level 2 objects to include in the groups. This can be seen clearly in the part of the city shown in Figure 18. Figure 19 shows the level 1 objects in part of the city, that serve as starting points of the work program generation. Figure 20 shows the generated SNM/SWC work program. The grid cells are shown in grey, level 1 objects are marked with solid lines and additionally selected level 2 objects are marked with dashed lines. Note that the grid cells and objects are the same for both methodologies in this region, except, that all grid cells have to be visited multiple times, as the level 1 objects belong to different networks. It can be seen, that almost the whole area is selected, although the amount of level 1 objects is rather small. Additionally, it can be seen that a level 2 object (dashed line) also crosses an area without an intervention. Reasons and implications will be discussed in Section 5.

Figure 21 shows the generated DWC work program. Clusters are shown in grey, level 1 objects are marked with solid lines and additionally selected level 2 objects are marked with dashed lines. It can be seen that four clusters are selected. The two large clusters are obvious, the third cluster is situated on the top, between the two big clusters and the fourth one is the line protruding from the left big cluster at the lower right. Each cluster originates from a different network. In comparison to that, Figure 22 shows the same area, but with the work program calculated by the DNM. Like before, clusters are shown in grey, level 1 objects as solid lines and additionally selected level 2 objects as dashed lines. It can be seen, that only one big cluster is formed, that encircles all the smaller clusters. Additionally, there are more selected level 2 objects, especially around the smaller clusters from Figure 21. This shows the advantage of the consideration of multiple networks. The additionally selected level 2 objects belong to different networks than the corresponding level 1 objects, but are selected because they are spatially close. Summarising, it can be said, that the selected methodology influences the work programs, as can be seen in Figures 10–22. However, this qualitative comparison is not able to quantify the observed differences, wherefore an additional comparison is necessary. This comparison will be done for both the constrained and unconstrained cases.

4.6.2. Work programs with no budget constraints

The work programs with no budget constraints are evaluated in terms of the improvement they bring to the network per monetary unit spent. This is measured using the following indicator of cost effectiveness:

$$B = \sum_{n=1}^{N} \sum_{m=1}^{M} \left(\frac{mu_{n,m}}{\Delta^{a}_{n,m} \cdot u_{n,m}} \right) \tag{34}$$

Figure 10. SWC.

where $B\ldots$ is the number of monetary units spent divided by the number of years removed age per object $\Delta^a_{n,m}$, multiplied by extent of the object $u_{n,m}$. When insufficient money is available all interventions can be executed that have a probability of failure above the acceptable threshold, and, therefore, the methodology that produces the best work program is the one that has the largest network improvement per monetary unit spent, i.e. the lowest B value. The risk of failure associated with each work program is in this case 0 because interventions are executed on all level 1 objects, and therefore there are no objects with unacceptable levels of risk.

Network improvement is measured as the improvement in the collective condition of the objects of the networks. Age is used as a proxy for condition, e.g. when a gas pipe is 70 years old and is replaced with a new identical pipe, it is considered to have improved the condition of the infrastructure by 70 years. The collective condition of the objects of the networks is used as a proxy for improvement in the level of service provided. The improvement in condition is weighted by object type to take into consideration the fact that although it may be easier to improve the condition of the objects on one network than another, it is not better to only spend money on improving the condition of the objects on the easier to improve network than on other networks. For example, if it is easier to improve the condition state of a metre of pipe than a square metre of road, it does not mean that all money should be spent on fixing pipes and letting the roads become unusable. For this example, it is assumed that the reduction in the age of 1 m of pipe by one

Figure 11. SWCc.

year for all networks is equal to the improvement of 1 year of a m^2 of road. The determination of the appropriate weighting factors to be used is beyond the scope of this work. Keeping this in mind, the results are shown in Table 9. It can be seen that the work program produced using the DNM is the most cost-effective $\left(1.48\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$, with the work programs produced by the DWC being second $\left(1.61\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$, by the SNM being third $\left(1.67\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$ and by the SWC being last $\left(1.77\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$.

4.6.3. Work programs with budget constraints

The work programs with budget constraints are also evaluated in terms of the improvement they bring to the network per monetary unit spent. The results are shown in Table 10. It can be seen that the work program produced using the DNMc is the most cost-effective $\left(2.08\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$, with the work programs produced by the DWCc being second $\left(2.85\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$, by the SNM being third $\left(3.42\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$ and by the SWC being last $\left(3.43\ \frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$. Two additional interesting things that can be seen are, that (1) the ratios *B* of the constrained work programs (Table 10) are higher (i.e. less cost efficient) than the ratios of the unconstrained work programs (Figure 17) and (2) the methodologies with coordination perform better than the methodologies without coordination, which is consistent with the assumption that coordination of work programs improves cost efficiency.

When budget constraints exist it is, however, no longer sufficient to use this indicator of cost-effectiveness alone. If there is not enough money available to execute interventions on all level 1 objects, then the OWP becomes the one where there is

Figure 12. DWC.

Table 9. Network improvement and cost of unconstrained work programs.

	SWC	SNM	DWC	DNM
Cost (mu)	11,908,691	13,299,795	8,834,067	9,912,505
Removed age units · length (m · t)	6,717,337	7,974,484	5,490,717	6,678,985
$B\left(\frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$	1.77	1.67	1.61	1.48

a trade-off between network improvement per unit of money spent and the amount of risk above the acceptable level. The proxy to measure the amount of risk associated with each work program used here is the number of removed failure units on level 1 objects as shown in Equation (35). Level 2 objects have a probability of failure below an acceptable threshold and, therefore, have no risk associated with them.

$$\mathrm{RFU} = \sum_{n=1}^{N} \sum_{m=1}^{M} \left(\Delta_{\mathrm{age},L1,n,m} \cdot \frac{u_{n,m}}{\sum_{n=1}^{N} \left(u_{n,m}\right)} \cdot \frac{\chi_{n,m}}{\chi_{\max,m}} \right) \quad (35)$$

with RFU ... removed failure units, $\Delta_{\mathrm{age},L1,n,m}$ ... object age at time of intervention with only level 1 objects counted, $\chi_{n,m}$ ... importance factor of object $o_{n,m}$, $\chi_{\max,m}$ ... maximum impor-

Figure 13. DWCc.

Table 10. Network improvement and cost of constrained work programs.

	SWCc	SNMc	DWCc	DNMc
Cost (mu)	3,350,911	3,323,546	2,937,748	3,944,940
Removed age units · length (m · t)	977,432	972,628	1,030,239	1,898,911
$B\left(\frac{\text{mu}}{\text{m}\cdot\text{t}}\right)$	3.43	3.42	2.85	2.08

tance factor of network m. The extent of the object is used to take into consideration that there are, normally, larger consequences associated with the failure of larger objects, than with smaller objects. The extent of the object is normalised with respect to the extent of the network, which reflects the assumption that the consequences of failure on one network are identical to the consequences of a similar failure on another network. The last term in Equation (35) represents the relative importance of an individual object in the network. For the sewer and water network, this indicator is calculated by the topological distance to the wastewater treatment plant/freshwater plant, according to the practices and data given by the city. For the road, electricity and gas network, the situation is different. These networks exhibit a 'net-like' structure, with a lot of interconnections and loops. Therefore, the indicator is calculated by the so-called 'edge betweenness', which is a value that counts the number of

Figure 14. SNM.

shortest paths between all possible network objects, that cross the particular object in question. The more shortest paths that cross the object in question, the more important it is.

Table 11 shows the calculated RFU indicator for all constrained methodologies When looking at the total sum, it can be seen that the RFUs increase from left to right with 154.4, 157.9, 166.6 and 166.6, and that with this indicator, DWCc and DNMc have both the same and the highest score. When looking at the individual networks, it can be seen that the RFU for the sewer network is exactly the same for all methodologies. This is due to the fact that for all methodologies, the same level 1 objects are selected. It can be seen that the dynamic methodologies are better than the static methodologies, in terms of the number of RFUs that they remove, i.e. they allow a greater reduction in risk,[9] regardless of the network.

It can also be seen that by constructing work programs in different ways that increasing the risk associated with one network can result in the reduction of risk overall. For example, using the SNMc instead of the SWCc, there is an increase in risk associated with the electricity network (the RFUs removed are reduced from 1.54 to .22) but the overall risk is decreased (the RFUs overall are increased from 154.41 to 157.95). This happens because the reallocation of the resources means that more RFUs can be removed from the gas network (3.12 instead of 1.30). Although there is no difference between the risks associated with the DWCc and the DNMc it can be seen that there are changes

Figure 15. SNMc.

in the risks associated with the individual networks. Switching from the DWCc to the DNMc results in an increase in risk on the water and gas networks (137.95→135.28/6.34→4.69) but a decrease in risk on the electricity and roads network (1.69→1.73/4.31→8.57).

5. Discussion

5.1. Methodologies

The results shown in Tables 5–11 show, that the presented methodologies can be used to systematically group interventions on infrastructure networks. All methodologies are able to select additional interventions, once initial objects in need of intervention are identified. The selection methods are, however, different, which can be seen in Figures 10–22. The SWC/SNM rely on an equally spaced grid cells, whereas DNM/DWC use the topological and geometric properties of the network itself. All four methodologies not only show specific strengths but also specific weaknesses. These will be discussed in the following sections, grouped into methodology-specific and case-study-specific discussion as well as possible perspectives thereof.

5.1.1. Methodology-specific

The SNM/SWC relies on an arbitrarily predefined grid, which could lead to situations where two objects could actually be side by side but would not be seen as close, as they lie in different grid cells. Additionally, the treatment of objects that exceed the cell boundaries is a problem, as can be seen in Figure 20. An additional weakness of these methodologies is the challenge

Figure 16. DNM.

Table 11. RFU in the constrained case.

Network	SWCc	SNMc	DWCc	DNMc
Sewer	16.33	16.33	16.33	16.33
Electricity	1.54	.22	1.69	1.73
Gas	1.30	3.12	6.34	4.69
Roads	3.27	3.27	4.31	8.57
Water	131.98	135.01	137.95	135.28
Sum	154.41	157.95	166.62	166.62

of determining the optimal grid-cell size, which depends on multiple criteria such as city layout, maximum worksite size or network layout. An advantage, here, however, is that if a suitable grid size is found, the SNM has a low computational cost (i.e. a short runtime) which is favourable for iterative tasks.

The DNM uses dynamically calculated neighbourhoods, which rely on a suitable definition of closeness. For the closeness within one network, the closeness definition of distance along the network and the number of crossed logical nodes is intuitive and straightforward. The Voronoi cell-based closeness defini-

Figure 17. DNMc.

tion might be less intuitive, but using the geometric definition of Voronoi cells[10] is possible. A weakness, albeit small, of the DNM is that the computational cost is higher than for the SNM, which leads to higher requirements to appropriate programming to amend this weakness or a prolonged calculation runtime. The DWC uses the same dynamic neighbourhood approach as the DNM, without the use of Voronoi cells. This makes the DWC straightforward to understand, but at the same time it neglects the benefits of combining interventions across different networks. In terms of runtime, the DWC lies in between the DNM and the SNM, as although a dynamic calculation is necessary, the computationally expensive Voronoi cell calculation is not necessary.

5.1.2. Case-study-specific

When comparing the $\frac{\textit{units}\ \text{constrained}}{\textit{units}\ \text{unconstrained}}$ ratios in Tables 5–8, it can be seen that the variations of the values within one methodology are strongly linked to the element of coordination (e.g. Table 6: 14–38%) or non-coordination (e.g. Table 7: 11–100%), whereas the differences in variation between the static or dynamic properties of the methodology are of lesser influence. This is expected, as for the methodologies without coordination the budget was assumed to be split evenly among all networks. This assumption is reasonable, because if the postulated non-coordination is interpreted in a strict way, the network managers do not have any information on the other networks, which makes a budget splitting based on network properties (e.g. network length) impossible.

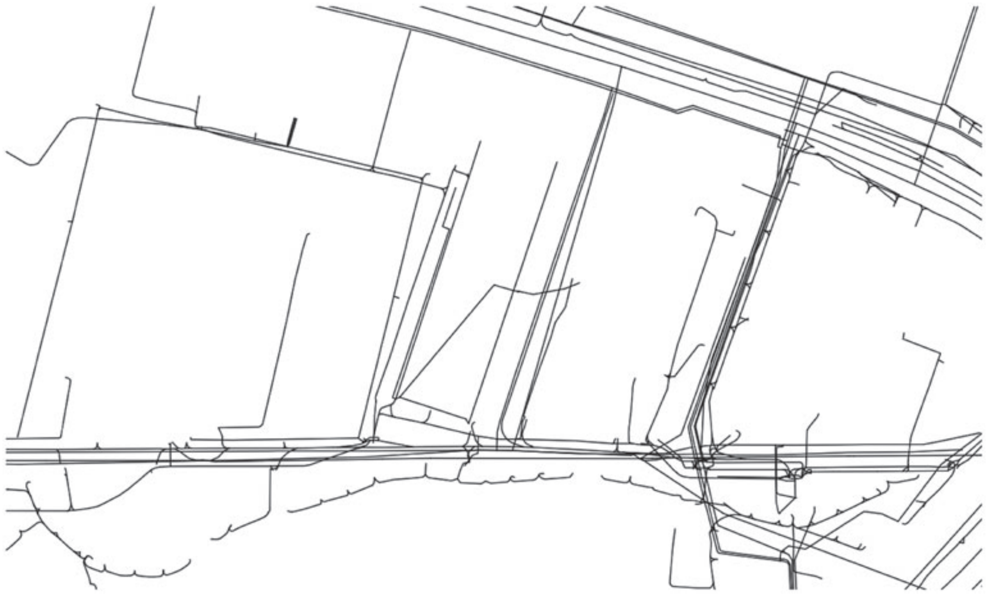


Figure 18. Part of city network.

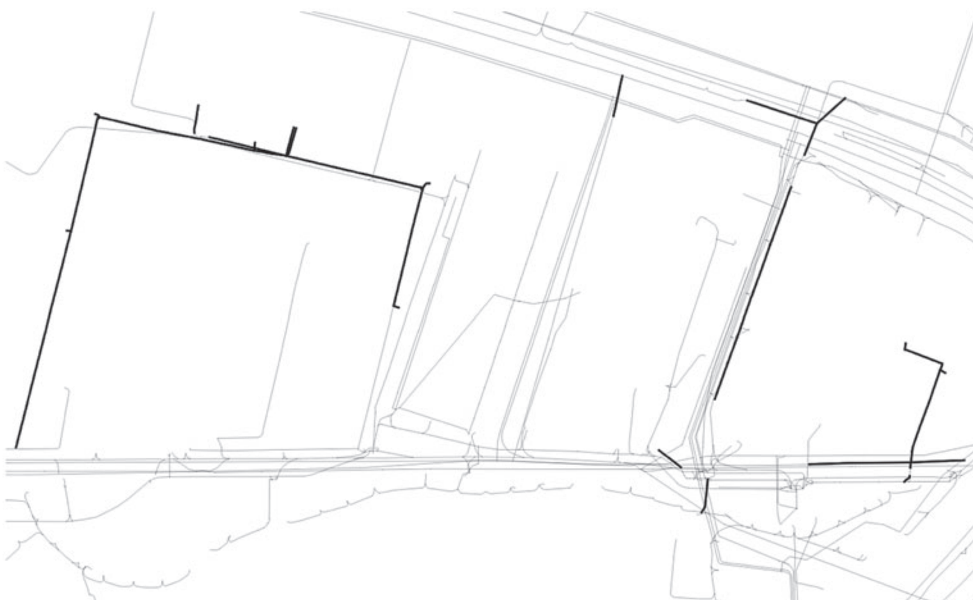


Figure 19. Level 1 objects.

With that, the differences can be explained by the fact that the unused budgets are not re-allocated to the other networks when there is no coordination. This happens with the sewer and gas networks in Tables 5 and 7, where 100% of the interventions can be executed. These unused financial resources should be reallocated to the networks where there is no enough available to execute all interventions, e.g. the Road network in Tables 5 and 7, where only 13% respective 11% of the interventions can be executed.

When comparing the budget versus the objects in the SWC resp. SWCc, it is noticeable that the SWCc budget is approx. 1/3 of the SWC budget, but 47% of the objects are chosen for an intervention. This is due to the fact that in this city, the number of level 1 objects in the predefined static cells varies a lot. The algorithm therefore selects the cells with more level 1 objects first, as these cells get higher priority. This also means, that the set-up cost can virtually be divided among the number of objects. The non-selected cells in the SWCc are cells, that contain only few, mostly only one level 1 object, which means that the set-up costs have to be paid for every cell but can only assigned to one object.

What can also be seen is, that the costs between the methodologies vary to a significant extent. This is owed to several facts: (1) the scenarios without coordination assume, that every network manager acts on his own, without coordination. That means, if there are five interventions at one place, each from a different network, the set-up cost has to be paid five times, instead of only one time in the coordinated scenario. (2) The unused budget in the uncoordinated scenario leads to lower total costs in summation of all networks, as allocated money is

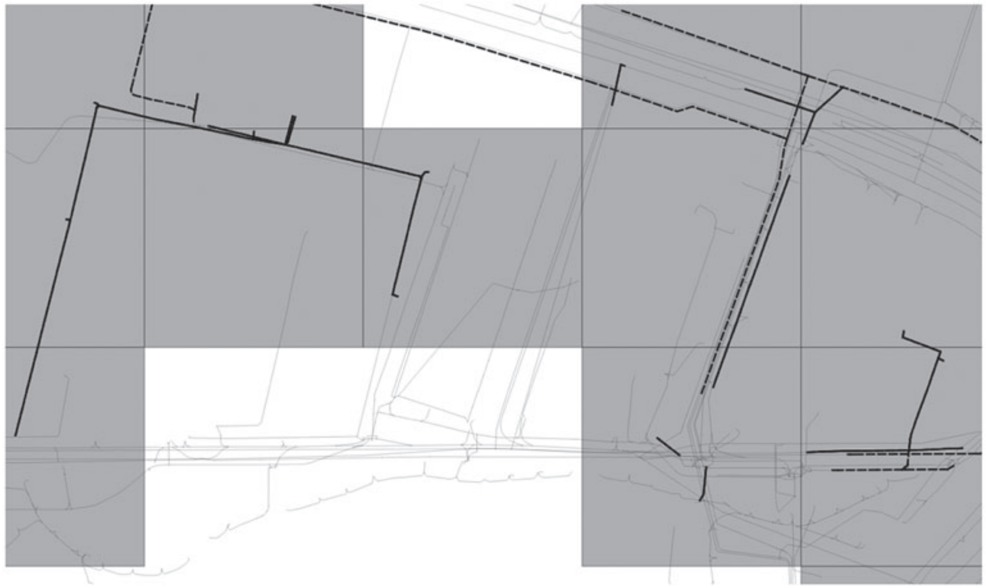


Figure 20. SNM/SWC.

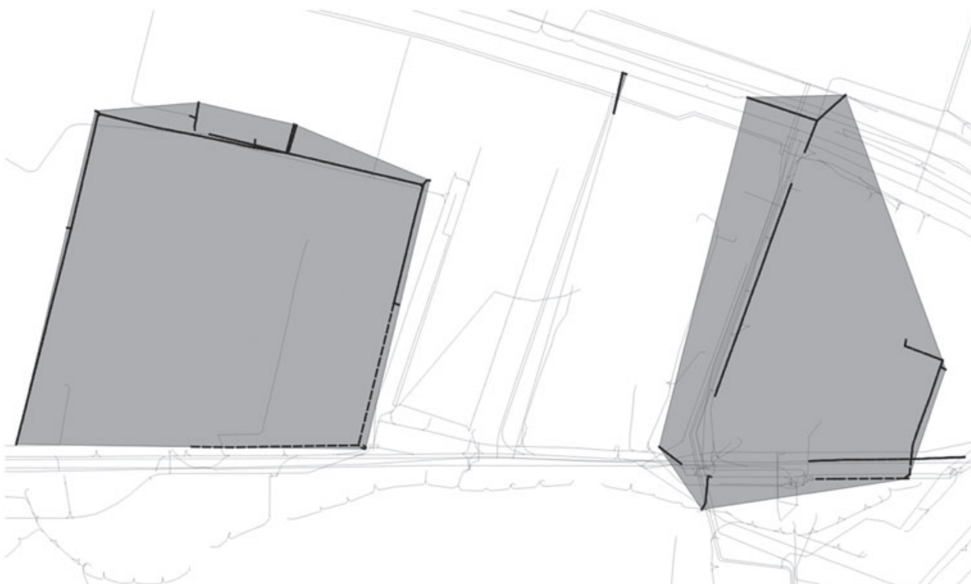


Figure 21. DWC.

simply not spent. (3) The incorporation of other networks in the unconstrained coordinated scenario adds level 2 objects from other networks to level 1 objects if they are close. This increases the total cost, as additional objects are added in comparison to the unconstrained uncoordinated scenario.

5.1.3. Perspectives

As mentioned in Section 5.1.1, both methodologies have certain cases, where the automated spatial grouping could lead to unwanted results. In the SNM/SWC for objects exceeding the grid-cell boundaries, there are different ways of treating these objects, which all have different implications. One possibility would be to cut the objects to grid-cell size, so that no object crosses any grid boundaries. From a computational point of view, this would be reasonable, but from a practical point of view, it would pose a problem: the grid-cell layout now dictates the object size, and not the actual network geometry nor commercially available pipe lengths. In reality, this is nonsensical. Another possibility is to include all grid cells that touch the object in question. This, however, would lead to cascading effects (i.e. one object touches a second cell, in which another object lies that also touches a fourth, and fifth cell, and so on) that would basically make a large portion of the network a single cell(-group). To limit this cascading effect in this paper, the methodology in this paper only accounts for one cascading step (i.e. selecting all cells that are touched by the level 1 object, and then selecting all objects that touch these cells). This cascading effect in general is seen as a weakness of this methodology. For the DNM/DWC, it may be the case, however, that two object should not being include in the same work site even if they are in the same Voronoi cell as defined here, e.g. two pipes are within the same voronoi cell but separated by a railway track. To counteract this problem, dummy objects, which work as a 'barrier' could be implemented.

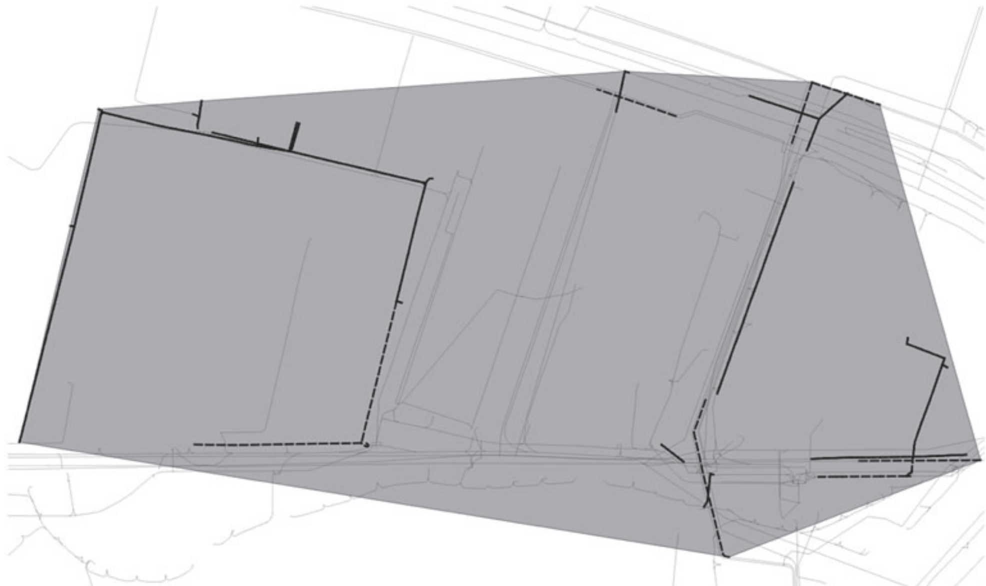


Figure 22. DNM.

In this paper, the methodologies without coordination were used as a sort of base scenario to try to emulate the range of possible used methodologies. The DWC is based on assuming that the network managers use an advanced, dynamic work program planning algorithm, but do not coordinate their work (This would be the case for a situation, where each network is owned by a separate company that uses in-house optimisation processes to create their work programs, but do not communicate with the other network operators). The SWC is based on the assumption, that no dynamic work program planning algorithm is used, but the network is managed by experienced personnel, that is aware of the 'hotspots' (i.e. grid cells) that need special attention (replicated by adjusting the respective grid cell importance factor). In reality, there is probably a deviation from both assumptions. Not all network managers will use dynamic work program planning algorithms or only employ experienced personnel (which have to retire at some point of time and be replaced by personnel with less experience). This means, that actual work programs would most likely be different than those shown here, but the ones generated here are sufficient for the illustration of the differences between the investigated methodologies.

5.2. Assumed values

In this paper, the assumption was made that the set-up costs for interventions are equal for all types of interventions. This assumption may be a simplification but still shows, that by efficient grouping, savings are possible and also non-negligible. To improve accuracy, the methodology is easily expandable to account for network combination and group size-dependent set-up costs. Additionally, only one type of intervention per object was considered. This was done to help ensure an understandable example. There is no particular hindrance to taking into consideration interventions of multiple types with different costs and different effectiveness in improving the object's condition state.

In this paper, only one time step was investigated in the case study. Therefore, the assumption of the threshold not changing within the investigated timestep seems reasonable. Priority zones were used as a proxy to location-based consequences of failure. For this paper, factors such as population density and closeness to important city locations like hospitals and government buildings were used. Both seem to be reasonably positively linked to consequences of failure and thus be usable as a proxy. If more information about the consequences of failure is available, hazard and risk maps can be used instead to improve the accuracy. However, it is still seen as difficult to obtain these informations (Le Gauffre et al., 2007).

Lastly, it was assumed, that the budget is distributed evenly if there is no coordination. This assumption depends on the negotiating skills of the respective network managers, when applying for their budget proportion. Although an even split might not always be the case, this example should only show the ways the proposed methodologies handle a limited budget in comparison to an unlimited budget.

5.3. Indicators

The indicator B seems to be a good measure the network improvement per monetary unit spent as it captures the idea that a manager should be trying to obtain the most improvement for the money spent. The assumption that that all networks have the same importance per unit is one that can be relaxed when better approximations are available. This indicator could be improved to take into consideration other stakeholders, different costs and the expected costs of failure. The number of RFUs removed seems to be a good indicator of the amount of risk reduction due to the execution of a work program. In this paper, only the RFUs related to level 1 objects was used, using the object age as a proxy for the failure probability, the relative size of the object in the network and the relative importance. This is consistent with the idea that the manager initially would like to execute interventions on all level 1 objects and there should be some sort of penalty related to not exe cuting them in exchange for increased savings by including level 2 objects in the work program. It would also be possible to include the numbers of RFUs for level 2 objects of desired.

The object age seems a reasonable proxy, as age is related to the failure probability. This assumption, however, causes a linear relation between age and RFU, which can be only an approximation. This approximation was used, as actual failure probability was not available for all networks. This can easily be improved, if estimates of the failure probabilities are available. Additionally, if more information were available, cohorts of different build types with different deterioration behaviour could be accounted for easily. The relative size of an object in the network, expressed as the ratio of object size to network size, seems a reasonable partial proxy for consequences of failure.

The relative importance of an object, normalised to be between 0 and 1 seem, in addition to the relative size, a reasonable partial proxy for consequences of failure. The values of the importance factor for tree-like networks was based on the topological distance to the root node, as in the original data delivered by the participating city, which serves as a proxy for the total flow in this object, as the closer an object is to the root node, the higher the flow is. This, however disregards cases, where a small subtree branches off close to the root node by giving them higher weight. The estimation of the values can however be improved, if the actual consumption values of each leaf node (i.e. the single households at the end of the networks), and with that the real network flow, are known. The values of the importance factor for grid-like networks (i.e. the road, gas and electricity network) was based on edge betweenness, which counts the number of shortest paths between all pairs of network nodes, that lead through the object in question. This assumption is equal to the statement, that in these network, the flow between two nodes only happens along the shortest path but seems reasonable. The estimation of the values can be improved if the consumption and input data are available. For road networks, the estimation of the values could be improved if traffic flow models were used.

An additional adjustment to the RFUs that one might want to make is that they are weighted by network to take into consideration that there are higher consequences related to the failure of one network than another, e.g. the failure of a gas pipe, which might lead to an explosion compared to the failure of a road section. Additionally, a direct minimisation is not visible. However, the minimisation of cost is addressed in the RFU, but in an inverse way, i.e. by maximising the output per monetary unit by choosing those clusters with the highest output among the possible ones. Both indicators have been calculated for one timestep only to demonstrate the properties of the methodologies. To incorporate the benefits of grouping not only locally but also time-wise, i.e. to account for antedating or postponing interventions, however, a multi-timestep calculation is necessary. The presented methodology is able to incorporate this with only minor changes. The reduction of service disruption is best accounted for in a multi-timestep methodology, as the reduction in not 'revisiting' the same places in consecutive or close time steps.

6. Conclusions

In this paper, two methodologies (static, dynamic) in four scenarios each (without and with budget constraint resp. with and without coordination) to determine work programs for municipalities possessing multiple infrastructure networks were investigated and compared with each other. In the investigated example, the methodologies were used to determine work programs for five infrastructure networks in a city with a population of ca. 30,000. It was found that the dynamic methodologies for grouping objects in need of intervention within a network and on multiple networks leads to improvements over the static methodologies. This demonstrated that the explicit consideration of the proximity of objects within multiple networks should be systematically done.

It was found, in the example that the dynamic methodologies lead to work programs that incorporate more RFUs and generate lower per unit improvement costs than the static methodologies. This is because the SNM/SWC rely on predefined grid cells while the DNM/DWC dynamically calculate those from the network data. In general, the dynamic methodologies showed high potential to be extended.

In summary, all of the presented methodologies can be used to group of interventions when there are large numbers of possible groupings (in this example 51,194 objects with possible interventions, making $2^{51\,194} \approx 8 \times 10^{15\,410}$ theoretically possible groupings), that the dynamic calculation of the work programs results in better work programs than the static calculation of work programs (Tables 9, 10 and 11), and that methodologies with coordination are better than methodologies without coordination. Of the methodologies investigated, the DNM and DWC have the greatest potential to be used in practice.

Future research in this direction should include

- the enhancement of the dynamic methodologies to determine work programs using more direct consideration of the costs of service interruption,
- the extension of the dynamic methodologies to determine work programs over multiple time periods, including time-dependent formulation of trigger thresholds,
- the adaptation of the dynamic methodologies to take into consideration functional relationships between the objects within one network and within multiple networks, e.g. the effect of reduced water flow(or even no flow in separated sewer/stormwater systems) in sewers due to interventions on the freshwater network which opens possibilities for interventions on the sewer network,
- the enhancement of the dynamic methodologies to better take into consideration real-world costs, i.e. more accurate representations of the variant and invariant costs involved with intervening on one or more networks, and on one or more objects,
- comparison of the dynamic methodologies with a real-world situation (i.e. with a partial manual coordination) to investigate the potential advantages and disadvantages of its use in practice.

Notes

1. Theoretically, all regular area tessellations (triangles, squares or hexagons) are possible.
2. A powerful magnet is used to magnetise the steel walls. At areas where there is corrosion or deformed metal, the magnetic field 'leaks' from the steel. By interpreting the magnetic leakage field, it is possible to identify damaged areas and estimate the depth of metal loss.
3. i.e. models that allow for better condition development predictions.
4. For objects that are only described by two states (in operation/ defunct), this is directly the failure probability. For objects with multiple condition states, this is the probability of not providing the requested service, which can be the case in more than one condition state.
5. $H\left(x \leq 0\right) = 0$ and $H\left(x > 0\right) = 1$.
6. The sign function is defined as follows: $sgn(x) = \begin{cases} x < 0: & -1 \\ x = 0: & 0 \\ x > 0: & 1 \end{cases}$.
7. e.g. $\begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \circ \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} a_1 \cdot b_1 \\ a_2 \cdot b_2 \end{bmatrix}$.
8. The spatial distribution has been slightly altered due to security concerns of the participating city.
9. In this case study, risk was proxied by the product of age (proxying failure probability) and importance factor (proxying consequences). A detailed discussion can be found in Sections 5.2 and 5.3.
10. Simplified: A Voronoi cell defines the region around an object, where no other object is closer.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Ahmadi, M., Cherqui, F., de Massiac, J.-C., Werey, C., Lagoutte, S. A., & Le Gauffre, P. (2014). Condition grading for dysfunction indicators in sewer asset management. *Structure and Infrastructure Engineering, 10*, 346–358.

Allweyer, T. (2010). *BPMN 2.0: Introduction to the standard for business process modeling*. Norderstedt: BoD-Books on Demand.

Arthur, S., Crow, H., Pedezert, L., & Karikas, N. (2009). The holistic prioritisation of proactive sewer maintenance. *Water Science and Technology, 59*, 1385–1396.

Birant, D., & Kut, A. (2007). St-dbscan: An algorithm for clustering spatial-temporal data. *Data & Knowledge Engineering*, *60*, 208–221.

Bobylev, N. (2009). Mainstreaming sustainable development into a city's master plan: A case of urban underground space use. *Land Use Policy, 26*, 1128–1137.

Cardoso, M., Coelho, S., Matos, R., & Alegre, H. (2004). Performance assessment of water supply and wastewater systems. *Urban Water Journal, 1*, 55–67.

Coelho, S. T. (1997). *Performance in water distribution: A systems approach*. New York, NY: Research Studies Press.

Dehghanian, P., Fotuhi-Firuzabad, M., Aminifar, F., & Billinton, R. (2013). A comprehensive scheme for reliability centered maintenance in power distribution systems – Part I: Methodology. *IEEE Transactions on Power Delivery, 28*, 761–770.

Dueñas-Osorio, L., Craig, J. I., Goodno, B. J., & Bostrom, A. (2007). Interdependent response of networked systems. *Journal of Infrastructure Systems*, *13*, 185–194.

Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of 2nd international conference on knowledge discovery and data mining (KDD-96)*. Portland, Oregon, USA.

Fenner, R. A. (2000). Approaches to sewer maintenance: A review. *Urban Water, 2*, 343–356.

Fenner, R. A., Sweeting, L., & Marriott, M. (2000). A new approach for directing proactive sewer maintenance. *Proceedings of the ICE – Water and Maritime Engineering*, *142*, 67–77.

Frangopol, D. M., Kong, J. S., & Gharaibeh, E. S. (2001). Reliability-based life-cycle management of highway bridges. *Journal of Computing in Civil Engineering*, *15*, 27–34.

Fung, G. (2001). A comprehensive overview of basic clustering algorithms. *Google Code*,

Garland, A., Flintsch, G., Garvin, M. J., & Sotelino, E. (2009). Characterization of network topology to support infrastructure asset management. *Public Works Management & Policy, 14*, 81–101.

Hajdin, R., & Adey, B. T. (2006). Optimal worksites on highway networks subject to constraints. In *International forum on rngineering decision making*. Lake Louise, Canada.

Hajdin, R., & Lindenmann, H.-P. (2007). Algorithm for the planning of optimum highway work zones. *Journal of Infrastructure Systems, 13*, 202–214.

Halfawy, M. R., Dridi, L., & Baker, S. (2008). Integrated decision support system for optimal renewal planning of sewer networks. *Journal of Computing in Civil Engineering*, 22, 360–372.

Jeong, H. S., Abraham, D.M., & Baik, H.S. (2005). *An ordered probit model approach for developing Markov Chain based deterioration model for wastewater infrastructure systems* (pp. 649–661). Houston, TX: American Society of Civil Engineers.

Jiang, B., & Claramunt, C. (2004). Topological analysis of urban street networks. *Environment and Planning B: Planning and Design, 31*, 151–162.

Johnson, D. B. (1977). Efficient algorithms for shortest paths in sparse networks. *Journal of ACM, 24*(1), 1–13.

Kirstein, S., Müller, K., Walecki-Mingers, M., & Deserno, T. M. (2012). Robust adaptive flow line detection in sewer pipes. *Automation in Construction, 21*, 24–31.

Kleiner, Y., Adams, B. J., & Rogers, J. S. (1998). Selection and scheduling of rehabilitation alternatives for water distribution systems. *Water Resources Research, 34*, 2053–2061.

Le Gauffre, P., Joannis, C., Vasconcelos, E., Breysse, D., Gibello, C. & Desmulliez, J. (2007). Performance indicators and multicriteria decision support for sewer asset management. *Journal of Infrastructure Systems*, *13*, 105–114.

Lee, J., & Madanat, S. (2015). A joint bottom-up solution methodology for system-level pavement rehabilitation and reconstruction. *Transportation Research Part B: Methodological, 78*, 106–122.

Lejeune Dirichlet, G. (1850). Über die Reduction der positiven quadratischen Formen mit drei unbestimmten ganzen Zahlen [About the reduction of positive quadratic forms with three unknown integers]. *Journal für die reine und angewandte Mathematik, 40*, 209–227.

Lethanh, N., Adey, B. T., & Sigrist, M. (2014). A mixed-integer linear model for determining optimal work zones on a road network. In *Proceeding of the international conference on engineering and applied sciences optimization*, KOS Island.

Liu, M., & Frangopol, D. M. (2004). Optimal bridge maintenance planning based on probabilistic performance prediction. *Engineering Structures, 26*, 991–1002.

Liu, P., Zhou, D., & Wu, N. (2007). Vdbscan: Varied density based spatial clustering of applications with noise. In *2007 International conference on service systems and service management* (pp. 1–4). Chengdu, China.

Louit, D., Pascual, R., & Banjevic, D. (2009). Optimal interval for major maintenance actions in electricity distribution networks. *International Journal of Electrical Power & Energy Systems, 31*, 396–401.

Mathew, B. S., & Isaac, K. P. (2013). Optimisation of maintenance strategy for rural road network using genetic algorithm. *International Journal of Pavement Engineering*, *15*, 352–360.

Miyamoto, A., Kawamura, K., & Nakamura, H. (2000). Bridge management system and maintenance optimization for existing bridges. *Computer-Aided Civil and Infrastructure Engineering*, *15*, 45–55.

Morcous, G., & Lounis, Z. (2005). Maintenance optimization of infrastructure networks using genetic algorithms. *Automation in Construction, 14*, 129–142.

Pandey, M. D. (1998). Probabilistic models for condition assessment of oil and gas pipelines. *NDT & E International, 31*, 349–358.
Ram, A., Jalal, S., Jalal, A. S., & Kumar, M. (2010). A density based algorithm for discovering density varied clusters in large spatial databases. *International Journal of Computer Applications, 3*(6), 1–4.
Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *Control Systems, IEEE, 21*, 11–25.
Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytic network process* (Vol. 17). Pittsburgh, PA: RWS Publications.
Sathaye, N., & Madanat, S. (2012). A bottom-up optimal pavement resurfacing solution approach for large-scale networks. *Transportation Research Part B: Methodological, 46*, 520–528.
Shamir, U., & Howard, C. D. D. (1979). An analytic approach to scheduling pipe replacement. *Journal – American Water Works Association, 71*, 248–258.
Stillman, R. H. (2003). Power line maintenance with minimal repair and replacement. In *Reliability and Maintainability Symposium, 2003. Annual* (pp. 541–545). Tampa, Florida, USA.
Tscheikner-Gratl, F., Sitzenfrei, R., Rauch, W., & Kleidorfer, M. (2016). Integrated rehabilitation planning of urban infrastructure systems using a street section priority model. *Urban Water Journal*, *13*, 28–40.
Walski, T. M., & Pelliccia, A. (1982). Economic analysis of water main breaks. *Journal – American Water Works Association, 74*, 140–147.
Wang, Y., Moselhi, O., & Zayed, T. (2009). Study of the suitability of existing deterioration models for water mains. *Journal of Performance of Constructed Facilities, 23*, 47–54.
Witten, I. H., & Frank, E. (2005). *Data mining: Practical machine learning tools and techniques*. San Francisco, CA: Morgan Kaufmann.
Xu, X., Ester, M., Kriegel, H. P., & Sander, J. (1998). A distribution-based clustering algorithm for mining in large spatial databases. In *14th International conference on data engineering, 1998. Proceedings* (pp. 324–331). Orlando, Florida, USA.
Zayed, T., & Mohamed, E. (2013). Budget allocation and rehabilitation plans for water systems using simulation approach. *Tunnelling and Underground Space Technology, 36*, 34–45.