On the preventive management of sediment-related sewer blockages: a combined maintenance and routing optimization approach

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ABSTRACT

In this work we tackle the problem of planning and scheduling preventive maintenance (PM) of sediment-related sewer blockages in a set of geographically distributed sites that are subject to non-deterministic failures. To solve the problem, we extend a combined maintenance and routing (CMR) optimization approach which is a procedure based on two components: (a) first a maintenance model is used to determine the optimal time to perform PM operations for each site and second (b) a mixed integer program-based split procedure is proposed to route a set of crews (e.g., sewer cleaners, vehicles equipped with winches or rods and dump trucks) in order to perform PM operations at a near-optimal minimum expected cost. We applied the proposed CMR optimization approach to two (out of five) operative zones in the city of Bogotá (Colombia), where more than 100 maintenance operations per zone must be scheduled on a weekly basis. Comparing the CMR against the current maintenance plan, we obtained more than 50% of cost savings in 90% of the sites.

Key words | non-deterministic failures, sediment-related sewer blockages, sewer system maintenance planning, vehicle routing

INTRODUCTION

Maintenance operations have an important role for the reliability improvement in industrial facilities and infrastructure systems (Remy et al. 2013; López-Santana et al. 2016). The purpose of preventive maintenance (PM) operations is to extend the lifetime (or the time to the next failure) of equipment or infrastructures, taking into account that replacement or reparation might be more expensive. It is expected that effective maintenance policies reduce the frequency of service disruptions and their undesirable consequences (Endrenyi et al. 2001). A well-defined plan for maintenance includes a set of tasks, time intervals, and resources that are required to perform a series of maintenance operations (Duffuaa 2000). In practice, some companies and utilities delegate PM planning to experienced employees. Based on their intuition and knowledge of the system, employees determine schedules of maintenance operations; however, an employee only considers a limited number of possibilities in the time available for such planning (López-Santana et al. 2016).

Particularly, urban water utilities are responsible for complex infrastructure systems and equipment. These systems are subject to non-deterministic failures and require maintenance. When equipment or infrastructure fails, different side effects such as service disruptions, bad publicity, public health issues, or unsafe conditions for users (among others) might arise (Korving et al. 2006; Rodríguez et al. 2012; Hickcox 2015). Although these undesired situations can be mitigated through corrective maintenance (CM) operations, costs and challenges involved are the main concerns for utilities.

Planning maintenance operations for water utilities involves an additional hurdle due to the underground nature of the system: system elements are difficult to observe and therefore to maintain (Yang & Su 2007). In this sense, sewer system sediment-related blockages are one of the main challenges faced by these utilities (Arthur et al. 2009). It is well known that this type of failures can cause flooding and sewer overflows (Korving et al. 2006) and it
is also known that such side effects can be avoided by planning PM operations (Zaman et al. 2015), for example, by using tipping flush gates (Bong et al. 2015). Nevertheless, for example, UK experiences flooding incidents that are related to blockages 78% of the time (based on data from 2006) (Arthur et al. 2009). In Australia, blockages affect at least 70,000 properties each year, while in the United States they consume between 93.5 and 126.5 million dollars to be managed (Chung et al. 2006; Marlow et al. 2011). Under this context, it is common practice that water utilities follow a corrective approach (Abraham et al. 1998); i.e., they perform maintenance operations as failures are observed and reported, which is generally perceived as more expensive than preventive interventions. Maintenance planning is essentially heuristic and subjective because those operations, in general, are documented in guidelines or manuals (Halfawy et al. 2008). Seeking to reduce risks and costs, water utilities have an increasing interest in implementing systematic, proactive, and optimized maintenance or renewal strategies (Abraham et al. 1998; Halfawy et al. 2008). These strategies involve two fundamental tasks: first, defining how the sewer system deteriorates; and second, determining the optimal maintenance planning based on a deterioration pattern. Hydraulic deterioration models of sewer systems can be classified into two main groups: (a) physically based models and (b) statistical models (including artificial intelligence-oriented approaches). Due to limitations in understanding the process and data scarcity, most deterioration models are of the statistical type (e.g., Fenner & Sweeting 1999; Fenner et al. 2000; Savic et al. 2006; Ugarelli et al. 2009; Tran et al. 2010; Zaman et al. 2015).

To tackle the problem of planning and scheduling preventive sewer maintenance operations, we extend a combined maintenance and routing (CMR) optimization approach proposed by López-Santana et al. (2016). To do so, we consider a set of geographically distributed sites subject to non-deterministic failures. Based on a statistical failure data analysis presented in Rodríguez et al. (2012), we determine the probability density function of the time between failures of each site. These probability functions are the input of a maintenance model (MM) that determines the optimal time in which a maintenance operation should take place and its corresponding frequency along the planning horizon. Given this planning, a routing model (RM) is proposed to schedule a set of crews (e.g., sewer cleaners, vehicles equipped with winches or rods, and dump trucks) that will perform the maintenance operations. To solve the routing problem, we implement a split-based procedure (Beasley 1985; Prins 2004; Prins et al. 2014) that embeds a mixed integer program (MIP). The objective is to determine a near-minimum expected cost plan to execute all the required maintenance operations.

**METHODOLOGY**

Bogotá’s water utility (Empresa de Acueducto, Alcantarillado y Aseo de Bogotá (EAB)) has an exceptionally long and spatially detailed sewer failure database that is fed from a dedicated platform for collecting and handling user complaints. After field verification, a reported complaint is classified as effective or ineffective. If effective, the failure type and corrective action are reported. It is worth noting that nearly 45% of the sediment-related reports are either ineffective, repeated, or wrongly classified. As the verified user complaints are generally not associated with a particular component of the sewer system (i.e., a pipe, manhole, or gully pot) but to the nearby address where the failure is reported, in this work we represent the sewer system a grid of equally-sized cells. Each cell has a size of 170 × 170 m that covers nearly a one to two-street block. In our analysis each site subject to non-deterministic failures becomes a cell of the grid. To plan every maintenance operation for all the cells (\(V_i\)) subject to failures, we extend and modify the CMR optimization approach by López-Santana et al. (2016). The model to support proactive management of sediment-related sewer blockages proposed by Rodríguez et al. (2012) is applied to estimate the probability distribution function (pdf) of time between failures for each cell. The statistical analysis is based on the failure intensity behaviour over time. If the failure intensity varies over time (either improving or deteriorating), the stochastic process of failures is modelled as a non-homogeneous Poisson process (NHPP) (i.e., Crow’s or Cox-Lewis models). On the other hand, if the failure intensity remains steady, the stochastic process is modelled as a homogeneous Poisson process (HPP) (modelled by an exponential distribution) or as a renewal process (RP) (modelled either by a Weibull or Gamma distribution). Rodríguez et al. (2012) concluded that NHPP models are not frequently required to represent time between failures in the case of Bogotá, thus in this work we only considered either HPP or RP models.

Once the pdf of time between failures for each cell is estimated, a routing heuristic is used in order to schedule a set of crews that are available to perform maintenance operations. The MM is used to determine the optimal time to perform a PM on each site. The MM has the
following assumptions: (1) each cell starts as new at the beginning of the planning horizon and after a maintenance operation; (2) CM costs and run times are higher with regard to PM; (3) grid cells have identical maintenance costs and times; and (4) failure processes are independent between cells. The MM is a convex non-linear function \( C(\delta) \) that denotes the maintenance cost per time unit, where \( \delta \) is the time to perform a maintenance operation. The MM is evaluated for each cell \( i \in V_s \), and is modelled by the probability function that describes the time between failures at the cell. To find the cost-optimal time to perform a maintenance operation, we use an implementation of the quasi-Newton method (see Edgar et al. 1989). The optimal time \( (\delta^*) \) is then calculated from the expected cost non-linear convex function in Equation (1) (see Figure 1), where \( \delta \) denotes time; \( CPM \), the cost of preventive maintenance; \( CCM \), the cost of corrective maintenance; \( CW \), the cost of delay; \( TPM \), the time of preventive maintenance; \( TCM \), the time of corrective maintenance; \( F(\delta) \), the cumulative probability in \( \delta \); and \( M(\delta) \), the expected time of failure before \( \delta \); and \( w \), the expected delay to perform the maintenance operation; where \( w = \delta - M(\delta) \). Given the optimal maintenance time \( (\delta^*) \) and the planning horizon \( (T) \), we calculated the frequency of these preventive operations \( (\eta_l) \) for each cell \( i \in V_s \). With these results, there is a set of maintenance operations for each site \( (\eta_l = \{\eta_1, \eta_2, \ldots, \eta_n\}) \) that is arranged along the planning horizon.

\[
C(\delta) = \frac{CPM(1 - F(\delta)) + (CCM + CW(\delta - M(\delta)))F(\delta)}{(TPM + \delta)(1 - F(\delta)) + (TCM + \delta)F(\delta)}
\]  

With the output of the MM, a directed graph \( G = (V_M, A_M) \) is built, where \( V_M \) denotes all the maintenance operations to be scheduled and \( A_M \) denotes all possible connections between the maintenance operations in time and space. Each maintenance operation is considered as a customer of a vehicle routing problem where a RM is implemented to find the routes and the time at which each site should be maintained. We implement a split heuristic procedure (see Beasley 1985; Prins 2004; Prins et al. 2014) that finds the best set of routes given a single tour that visits every customer (i.e., a travelling salesman problem – TSP – tour). Several routes are evaluated using a MIP accounting for the cost and feasibility of each route. The cost of each route corresponds to the sum of the non-linear functions \( C(\delta) \) of the sites in the route, and is computed in the MIP using a piecewise linear approximation. The previous procedure is executed several times varying the TSP tour entered as input. As a result, after a pool of routes is obtained, another optimization model selects the routes that exhibit a near-optimal minimum cost while satisfying that every maintenance operation in \( V_M \) is served.

**CASE STUDY**

The proposed method was applied to the sewer system of Bogotá (Colombia). Bogotá has roughly eight million inhabitants, settled in an urban area of about 400 km². The local water utility currently operates about 8,000 km of sewer pipes (including stormwater, foul, and combined systems). Bogotá’s sewer system is divided into five operational zones for the purpose of management. The operational zones are independently managed: maintenance operations are scheduled according to the management policies, personnel, and equipment for each zone. For our analysis we selected two zones (zones 2 and 5); see Figure 2 and Table 1. Both zones have similar characteristics in terms of area, number of maintenance operations, and pipe diameter and slope. However, zone 2 is primarily residential with both combined and separate sewer systems. On the other hand, land use within zone 5 is mixed (residential and commercial) and is drained by a separate sewer system. These two cases allow for model evaluation under different operational conditions.

The local water utility (EAB) provided preventive and corrective maintenance costs, and CM service time. We used normalized values for the CM cost. Values for the PM and waiting costs were set as a percentage of the corrective cost (i.e., 80% and 10%, respectively). We assumed PM service time to be lower than CM service time. Thus, \( T_{CM} = 0.024 \) days (0.58 hours) and we set \( T_{PM} \) as 80% of \( T_{CM} \), i.e., \( T_{PM} = 0.8T_{CM} = 0.019 \) days (0.46 hours). We established the planning horizon as \( T = 112 \) days in order to...
ensure that at least one maintenance operation is performed at each site.

RESULTS

Time between failures

We first analyzed time between failure records in zones 2 and 5. Figure 3(a) shows that most of the cells are well described by either Weibull or Gamma models in both zones. However, Crow’s or Cox-Lewis models are more frequently needed in zone 5 in comparison to zone 2. The latter means that in zone 5, it is likely that failure intensity is changing over time due to constructions that temporarily alter sediment loads into the sewer system. In addition, in order to better understand the importance of using complete or partial failure databases for estimating time between failure pdfs, we compared different period lengths of historical failure data in zone 2 (i.e., last 2, 4, and 6 years of the historical records). Figure 3(b) shows that the shorter the period the harder it is to identify changing failure intensities. Therefore, HPP and RP models are sufficient for most of the cases when databases are partially used.

Benchmark

Maintenance operations are currently scheduled by the local water utility based on a reliability measure, that is, those sites with lower reliability values are prioritized (benchmark procedure). The reliability measure is defined as the probability that a site does not fail before a time $t$. To build the schedule, we define $t = 28$ days (i.e., 4 weeks), which is the current planning horizon used by the local water utility to schedule the maintenance operations. We then calculate the reliability for each site and sort them in ascending order. Sites are assigned one at a time to each of the five routes (zones 2 and 5 have five sewer cleaners each). We enforce that sites are attended within the work shifts and following the order in which they were assigned to each route. To this end, we take into account maintenance time at a site and travel time from one site to another. The starting time of the maintenance operation is computed assuming that crews follow the sequence without waiting at any site. Finally, the expected maintenance cost is calculated for each site. Note that under this procedure there is one maintenance operation per site within the 4 weeks of their planning horizon.

Table 1 | Main characteristics of sewer system operational zones 2 and 5 in Bogotá

<table>
<thead>
<tr>
<th>Zone</th>
<th>Combined sewer pipe length (km)</th>
<th>Separate sewer pipe length (km)*</th>
<th>Average pipe slope (m/m)</th>
<th>Average sewer pipe diameter (m)</th>
<th>Main land uses</th>
<th>Area (km²)</th>
<th>Number of grid cells</th>
<th>Average weekly maintenance operations**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z2</td>
<td>441</td>
<td>1280</td>
<td>0.012</td>
<td>0.36</td>
<td>Residential</td>
<td>76.7</td>
<td>2540</td>
<td>107</td>
</tr>
<tr>
<td>Z5</td>
<td>0</td>
<td>1531</td>
<td>0.009</td>
<td>0.33</td>
<td>Residential and commercial</td>
<td>71.8</td>
<td>2397</td>
<td>116</td>
</tr>
</tbody>
</table>

*Includes both sanitary and stormwater sewer systems.
**Based on historical records from 2007 to 2009.
Both the benchmark procedure and the proposed CMR procedure are compared in terms of the relative gap between the maintenance costs per site (see Equation (2)), where $C_{BM}$ stands for the expected maintenance cost under the benchmark procedure and $C_{CMR}$ stands for the expected maintenance cost according to CMR. This relative gap is a proxy of the cost savings that the utility might gain by using the CMR approach. Figure 4 presents the results for zones 2 and 5: (a) number of cells in which cost saving is within a certain percentage range; and (b) cumulative percentage of cells with cost savings within a certain percentage range or more. Figures 4(a)–4(c) compare the effect of using different failure database periods in zone 2, i.e.,
In this work we extended and modified the CMR model proposed by López-Santana et al. (2016). The main changes are related to the cost function of the MM and the optimization model developed for the routing stage. With our implementation of the RM, we were able to solve large-scale instances with more than 100 maintenance operations on a weekly basis. The optimization phase that schedules all the maintenance operations is based on a split procedure which embeds a MIP to account for feasibility and costs.

After adjustments and the extension of the CMR method, we applied it to the sewer system maintenance problem of Bogotá (Colombia). The quality of the solution was measured as the relative gap between the total expected cost obtained in the MM (best possible solution) and the total cost provided by the RM (a solution that accounts for resource constraints). Cost savings of more than 50% in 90% of the sites were obtained when comparing the CMR against the current maintenance planning protocol of the water utility (benchmark). The average computational time to solve a weekly schedule with about 100 maintenance operations ranges from 1.71 to 3.11 hours. Future work includes: considering different cells sizes for representing the sewer system, applying the CMR to all operational zones simultaneously, and analyzing failures that follow a NHPP. Furthermore, for the MM we have assumed the following (among others): each cell starts as new at the beginning of the planning horizon and after a maintenance operation; grid cells have identical maintenance costs and times; and failure processes are independent between cells. All the previous assumptions have to be revised to better represent the reality of sediment-blockage processes.

CONCLUSIONS

In this work we extended and modified the CMR model performed better: about 60%, 68%, and 90% of sites have at least 50% of cost savings if using the CMR is able to outperform the benchmark in all cases. Moreover, using long time frames allows the CMR model to perform better: about 60%, 68%, and 90% of sites have at least 50% of cost savings if using the CMR against the current maintenance planning protocol of the water utility (benchmark). The average half-way, 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 (6), 360–372.


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