An effective multi-objective approach to prioritisation of sewer pipe inspection
L. Berardi, O. Giustolisi, D. A. Savic and Z. Kapelan

ABSTRACT

The first step in the decision making process for proactive sewer rehabilitation is to assess the condition of conduits. In a risk-based decision context the set of sewers to be inspected first should be identified based on the trade-off between the risk of failures and the cost of inspections. In this paper the most effective inspection works are obtained by solving a multi-objective optimization problem where the total cost of the survey programme and the expected cost of emergency repairs subsequent to blockages and collapses are considered simultaneously. A multi-objective genetic algorithm (MOGA) is used to identify a set of Pareto-optimal inspection programmes. Regardless of the proven effectiveness of the genetic-algorithm approach, the scrutiny of MOGA-based inspection strategies shows that they can differ significantly from each other, even when having comparable costs. A post-processing of MOGA solutions is proposed herein, which allows priority to be assigned to each survey intervention. Results are of practical relevance for decision makers, as they represent the most effective sequence of inspection works to be carried out based on the available funds. The proposed approach is demonstrated on a real large sewer system in the UK.

Key words | decision support, genetic-algorithms, multi-objective optimisation, pipe inspection, prioritization, sewer

INTRODUCTION

The sewer system is one element of urban infrastructure that is expected to operate without interruptions. Condition assessment and rehabilitation of such buried systems should be performed continuously to maintain a desired level of service. A proactive approach to sewer asset management is of key importance for preventing uncontrolled deterioration and for reducing both direct and indirect costs (i.e. social, environmental and third party damage) associated with sewer failures.

Existing guidelines for condition assessment and rehabilitation of sewer assets suggest that prioritization of inspections should precede the decision-making process. Information on physical integrity and hydraulic capacity coming from direct inspections helps to select the best rehabilitation intervention options (WRc 2001; Bennis et al. 2003). A number of procedures for developing rehabilitation plans for sewer and drainage systems are available, ranging from Markov based models (Burgess 1990) to multi-objective optimization approaches (Reyna et al. 1994). However, little attention has been devoted to the development of decision support tools for planning inspections. The straightforward approach based on the condition assessment algorithm developed by WRc (2001) has become the industry standard. Two other methodologies proposed in the literature are based either on the assessment of “impact factors” (McDonald & Zhao 2001) or on the use of Bayesian belief networks (Hahn et al. 2002). They identify where the propensity and the consequences of failures are high enough to justify direct inspections. Both methodologies elicit expert knowledge of the system and use available asset data to prioritize pipe surveys.
In a risk-based decision making process for selecting the set of pipes to be inspected it is necessary to consider the trade-off between economic, technical and management criteria. Accordingly, an inspection programme could be developed using a multi-objective optimization approach where decision variables are the sewer pipes to inspect and the objectives represent distinct selection criteria.

During the last two decades, the multi-objective genetic algorithms (MOGA) have proven to be an effective search technique capable of solving large, complex, combinatorial optimization problems (Goldberg 1989). In spite of their good performance in many water system design and management applications (Halhal et al. 1997), it has been observed that MOGA generate intervention strategies which do not provide any explicit prioritization of actions that should be undertaken (Giustolisi & Berardi 2009). For example, in the case of water distribution systems, pipe replacement strategies obtained by MOGA can differ significantly from each other even when they have comparable costs. Such a lack of “contiguity” between solutions becomes more and more evident as the size of the system (i.e. the number of pipes) and the number of objective functions increases.

To make the MOGA solutions more effective for decision makers, a post-process is needed which assigns “priority” to every single pipe. Giustolisi & Berardi (2009) demonstrated the effectiveness of prioritizing pipes according to the frequency of selection among MOGA solutions. The results obtained there motivate the current work, which extends the post-processing analyses to the problem of planning inspection of sewer pipes.

In this paper the problem of selecting the most critical sewer pipes for CCTV inspection is posed. The choice of CCTV as the unique inspection technology is justified here by its applicability to most existing sewer diameters and its common use for pipe condition assessment. Nevertheless, the application of the present methodology to other real-life sewer systems might include other survey technologies. For example, different types of inspections may be better suited for large pipe diameters and/or accounting for the actual accessibility of manholes could be introduced. Although such details would help in refining the costs involved and/or make decision support more realistic, the prioritization methodology proposed herein would be the same.

**PLANNING SEWER INSPECTIONS WITH MULTI-OBJECTIVE GENETIC ALGORITHMS**

Planning sewer inspections is essentially a multi-objective optimization problem whose solution is relevant to a decision maker. In such an optimisation, after the decision-maker has defined all the objectives, he/she has to determine the multi-objective optimal zone by using the concept of Pareto dominance (Pareto 1896-7) which is depicted in Figure 1 in the case of a 3-objective minimization problem. Each subplot of Figure 1 is the projection of the 3-dimensional surface of objectives on planes $f_1-f_2$ and $f_1-f_3$ respectively. Point B is said to dominate point H because $f_j(B) \leq f_j(H)$ for all $j = 1, 2$ and 3 and $f_j(B) < f_j(H)$ for at least one objective function. Accordingly, point H is placed in the upper right region identified by the dotted lines centred on B in both subplots. All non dominated points are said to be Pareto-optimal with respect to the set of solutions considered and are reported as circled dots in Figure 1. Note that when moving from one Pareto-optimal solution to another, it is not possible to improve on one objective without making at least one of the other objectives worse. It is clear, however, that there is a need to identify as many solutions as possible within the Pareto-optimal range in order to ensure that an acceptable solution will be produced and selected by the decision-maker.

Several authors, including Goldberg (1989), showed that evolutionary algorithms and, in particular, genetic algorithms (GA) are more suitable to handling discrete and combinatorial optimization problems than classical point-by-point approaches. Genetic algorithms are adaptive search methods that emulate natural evolution on the basis of preferential survival, reproduction of the fittest members (by using “mutation” and “crossover” operators)
and maintenance of a population with diverse members. In single-objective GA, the unique objective function is also the driving criterion for selecting the most promising individuals (i.e. solutions). In multi-objective GA (Goldberg 1989) such information is based on the Pareto dominance concept and the assignment of a rank to each solution. Fonseca & Fleming (1993) proposed assigning a rank equal to \(1 + n(g)\) to each solution, where \(n(g)\) is the number of points that dominate that solution at generation \(g\). For example, in Figure 1, points A–G are all Pareto-optimal and have rank = 1; solutions H and I have rank > 1 and the shadowed regions identify the subspaces where relevant dominant solutions are located. Solution H has rank = 3 as it is dominated by B and C; solution I has rank = 4 since it is dominated by D, G and F (solution E has rank = 1 but it does not dominate I). Such an approach enables MOGA to work without the need to aggregate the individual objective functions into a single parameterized function or the need to switch between the objectives during the search phase. Moreover, it permits assigning fitness by considering the whole population rather than the individual fitness values independent of other solutions.

The algorithm used herein is called the Optimized Multi Objective Genetic Algorithm (OPTIMO GA) (Giustolisi et al. 2004). Its efficiency has been proved in benchmark tests and a wide range of applications. Important features of the OPTIMO GA algorithm are as follows: (i) the existence and maintenance of a dynamic archive of dominant individuals during the search phase, (ii) the maintenance of a variable-size population of individuals and (iii) rank-based fitness assignment as proposed by Fonseca & Fleming (1995). For further details of OPTIMO GA the reader is referred to Giustolisi et al. (2004).

**CASE STUDY AND OBJECTIVE FUNCTIONS**

The analyses reported in this paper are based on a large, real-life sewer network. The database has been confidentially provided by a UK water company and contains significant information for every single pipe, although no information on network topology or economic data is available. Pipe attributes (fields in the database) can be classified into the following categories: *asset features* (i.e. diameter, age, construction epoch, shape, material, length, gradient, cover depth, change in the angle between upstream and downstream pipes); *proximity to important locations* (i.e. straight distance from the nearest hydraulic control, building, watercourse, area of vegetation and distance from sewer experiencing historical blockages/collapses along the sewerage system); *surrounding environment* (i.e. traffic load, soil type); *service* (i.e. number of properties connected to the individual sewer and the upstream sewer); *serviceability* (i.e. condition grade predicted by the water company using a Markov chain model (ECG), historic blockages and collapses recorded during 5 years of monitoring, from 2001 to 2006); *interventions* (i.e. date of any lined sewers and length of individual sewer cleansed). As in the case of many water utilities, this large amount of information was partially corrupted by some missing entries or unreliable/inconsistent data. Information on those sewers that were rehabilitated by inserting a pipe liner was encapsulated into the age value by reducing it by 10 years (starting from the date of that action) as this is the typical guarantee of the suppliers of these products; missing ECG values were in-filled with the average ECG of sewers of the same age.

**Objective functions**

The abovementioned data have been used to develop an effective inspection programme by using OPTIMO GA first and then the prioritization strategy proposed. Without a loss of generality, only three objective functions are formulated and optimized in the present work: (1) the cost of inspection programme (investment), (2) the expected cost of emergency repairs associated with sewer blockages and (3) the expected cost of emergency repairs associated with sewer collapses.

**Cost of inspection programme (investment)**

Only CCTV inspections are considered. Costs of inspections are borrowed from the work of Zhao (1998) which report an approximate unit cost of 0.009 $/m/mm diameter (between 1.75 and 14.00 $/m). Accordingly, all costs of both inspection and repairs are expressed in Canadian dollars in the rest of the paper.
Original data included diameters from 30 to 1,850 mm; however, the following analysis refers to the range 100–1,000 mm. This is because pipes smaller than 100 mm are assumed to be recording errors, while failure models developed here might be not valid for pipes larger than 1,000 mm (see next sub-section). Moreover, inspection costs for pipes smaller than 200 mm are assumed equal to the lower bound of the cost interval (i.e. 1.75 $/m) reported in Zhao (1998). The total cost of each inspection programme is computed by Equation (1).

\[
f_1 = \sum_{p \in I} (C_{CCTV} \cdot D_p \cdot L_p)
\]

where \( C_{CCTV} \) is the assumed unit cost of CCTV inspection, \( D_p \) is pipe diameter and \( L_p \) is pipe length. The summation refers to all pipes of the inspected set \( I \). Such a function should be minimized during the search for an optimal inspection scheme.

**Expected cost of sewer blockages and collapses**

There are several rationales which might be considered in addition to \( f_1 \) to make inspections more effective. For example, they could accomplish the minimization of multiple traffic disruptions along the same street by coordinating inspections with other works on different buried utilities and/or maximizing proximity between inspected pipes. The inclusion of some objectives would require the knowledge of network topology which is not available for this case study. Nevertheless, the inclusion of preferential selection of certain pipes is quite easy to implement, as reported in Giustolisi & Berardi (2009).

Present work considers the risk of emergency repairs associated with sewer blockages and collapses only in terms of expected costs (i.e. damage) related to future failures. Zhao & Rajani (2002) report that the average unit cost of emergency repairs are 3.6 times higher than the average unit cost of non-emergency rehabilitation. The same work reports that the ratio of social to direct costs can range from 1:1 to 4:1 depending on the location of a failure. As repair costs were not available in this case study, some assumptions are made to quantify damage.

(i) Damage subsequent to sewer blockages is assumed to be the same as collapses because both type of failures lead to wastewater flooding, service interruptions and traffic disruptions for repairs.

(ii) Without loss of generality, it is assumed that the only direct cost considered is that reported by Zhao & Rajani (2002) about the cured-in-place pipes (CIPP) method for emergency intervention scenarios. The CIPP process can be considered as a renovation because it incorporates the existing pipeline fabric into the finished product to produce improved performance of the original pipeline. The assumed cost is 5 $/m/mm diameter

(iii) social and direct costs are incorporated into damage value by multiplying CIPP cost by a “damage and other cost” factor. Such a multiplier is computed for each pipe as in Equation (2).

\[
d_p = 1 + \frac{U_{sp}}{\max(U_s)} + \frac{T_{rp}}{\max(T_r)} + \frac{1}{wd_p + 1} \\
= 1 + d_{Us,p} + d_{Tr,p} + d_{wd,p}
\]

where \( U_{sp}, T_{rp} \) and \( wd_p \) are the number of properties connected upstream of the sewer \( p \), the traffic load (estimated number of vehicles) on the pipe \( p \) and the distance from the nearest watercourse respectively; \( \max(U_s) \) and \( \max(T_r) \) are the maximum values of \( U_s \) and \( T_r \) in the database. In other words, \( d_{Us,p} \) is a surrogate measure for service interruption in case of sewer failure, \( d_{Tr,p} \) accounts for traffic disruption and \( d_{wd,p} \) is linked to the possible water pollution in case of sewer flooding near a watercourse. Note that a more refined expression of \( d_p \) could be adopted if the land use above the network were known. According to Equation (2), the damage expected for a hypothetic large sewer (i.e. with a large number of properties connected upstream), buried under a high traffic road close to a watercourse is about 4 times the direct (CIPP) rehabilitation cost (Zhao & Rajani 2002).

A crucial element in defining a risk function is the failure prediction model. For this case study, both collapse and blockage models are developed from the available data and historical incident records. The Evolutionary Polynomial Regression (EPR) modelling technique (Giustolisi & Savic 2006; Giustolisi et al. 2006) and its Multi Case
Strategy variant (MCS-EPR) (Berardi & Kapelan 2007) have been used to model collapses and blockages respectively. It is worth remarking that using data-mining embodies a statistical approach for predicting failures (Kleiner & Rajani 2001), which is a cost effective way of analyzing small to medium diameter pipes only. On the contrary, a physically based approach would be adopted for large sewers as potential damage subsequent to their failure justify expensive data collection for model validation. Accordingly, both the failure prediction models and the whole methodology reported here are referred to sewer pipes from 100 to 1,000 mm diameters only (16,875 pipes in total).

In brief, what distinguishes EPR from MCS-EPR is the possibility of splitting data into subsets according to failure history (Giustolisi & Berardi 2009). In particular, MCS-EPR can be used for developing distinct models for different subsets of pipes; such models have the same mathematical structure but different parameters. A remarkable difference exists between the two models to be developed here, which is caused by the large imbalance between the number of collapses (57) and blockages (688) recorded during the 5 years of monitoring. Furthermore, only one pipe experienced multiple collapses (two), whereas there are 102 pipes that had from 2 to 5 recorded blockages in the period of observation. Thus, there are enough incident data to use MCS-EPR for blockages only, while a collapse model can be obtained from the original EPR approach (Berardi et al. 2008a). In the former case (i.e. blockages) data were first split into two subsets (datasets): the first, called the low blockage rate subset, includes sewers with null or one blockage recorded in 5 years; the second, called the high blockage rate subset, refers to those pipes with two or more blockage events. In the latter case (i.e. collapses) no division is applied to the dataset. Next, data in each dataset have been classified according to key attributes. These are the diameter \((D)\), the total length \((L)\), the total number of connected properties \((P)\) and the total number of blockages \((BL)\) or collapses \((CL)\).

Blockage models obtained by applying MCS-EPR are summarized in Equation (3).

\[
BL_{class} = a_{\text{subset}} P_{\text{class}}^{0.5} L_{\text{class}}^{0.5} D_{\text{class}}^{-1}
\]  

where subscript \(class\) emphasizes that this is an aggregate model (i.e. all quantities refer to pipe classes, each of which contain a number of pipes homogeneous for \(D,\) Era and \(gr\)). Parameter \(a_{\text{subset}}\) refers to the blockage dataset considered and can be either \(a_{\text{low}} = 0.3394\) (for low blockage rate subset) or \(a_{\text{high}} = 12.5963\) (for high blockage rate subset). It follows from Equation (3) that the number of blockages is inversely proportional to the pipe diameter and increases with the number of properties directly connected to the pipes and with the class total length. This is consistent with the common experience that smaller pipes are more prone to clog than larger ones and that a large number of direct connections leads to more frequent obstructions. Furthermore, the longer the pipe class the more likely it is to experience blockages. Interestingly, in the annual planning context, all selected variables can be considered constant over time (i.e. usually they are updated annually). This means that the blockage rate is expected to be constant over time as well.

The collapse model obtained from EPR is given in Equation (4):

\[
CL_{class} = 1.69 \times 10^{-5} \frac{P_{\text{class}} A_{\text{class}}}{H_{\text{class}}^{2.5}}
\]  

where \(H\) is the length-weighted average of cover depth values falling into the class (made up of pipes homogeneous for \(D,\) Era and \(H/D\)). Also in this case, the variables selected reflect a physical understanding of the described failure phenomenon. The presence of age \((A_{\text{class}})\) indicates that the ageing process leads to material deterioration and the lack of resistance. On the other hand model (4) shows that the higher the cover depth \((H_{\text{class}})\), the lower the direct effect of load transmission from surface. The selection of variable \(P\) indicates a surrogate measure of class extent (size), like the effect of length \(L\) in the blockage model.
Blockage and collapse models are used here to predict the number of failures for short-time planning of CCTV surveys. The failure rate (the number of incidents per year) in \( t \)-years planning horizon is reported in Equations (5) and (6).

\[
\lambda_p^{BL}(t) = \begin{cases} 
    a_{\text{low}} \cdot \frac{P_p}{L_{\text{class,0}}} \cdot \frac{L_{\text{class,0}}}{P_{\text{class,0}}} \cdot \frac{b_p}{T} \cdot B_{P,0}^{R} \leq 1 \\
    \frac{B_{P,0}^{R}}{T} \cdot B_{P,0}^{R} > 2 
\end{cases} 
\]

\[
\lambda_p^{CL}(t) = \begin{cases} 
    1.69 \times 10^{-5} \cdot \frac{P_p}{L_{\text{class,0}}} \cdot \frac{P_{\text{class,0}}}{P_{\text{class,0}}} \cdot \frac{c_p}{T} \cdot \frac{CL_{P,0}}{CL_{P,0}} = 0 \\
    0 \cdot \frac{CL_{P,0}}{CL_{P,0}} \geq 1 
\end{cases} 
\]

In Equations (5) and (6) superscript \( R \) refers to quantities recorded during the \( T \) years of monitoring, while subscript 0 means that quantities refer to the end of the monitoring period (i.e. \( t = 0 \)). The differences between the second expressions of Equations (5) and (6) are the result of the different actions undertaken after incidents are detected during the \( T \) years of monitoring. As collapsed pipes are normally just cleaned and as they are more likely to suffer further blockages due to similar hydraulic conditions their individual blockage history is used to predict future events and develop plans for inspections. Coefficients \( b_p \) and \( c_p \) are “pipe-level coefficients” that depend on the variables computed by summation and selected by EPR (Berardi et al. 2008a) (i.e. \( P \) and \( L \) for blockages and only \( P \) for collapses) as reported in Equations (7).

\[
b_p = \frac{1}{2} \left( \frac{L_p}{L_{\text{class,0}}} + \frac{P_p}{P_{\text{class,0}}} \right) \quad c_p = \frac{P_p}{P_{\text{class,0}}} 
\]

The number of blockages and collapses expected in a 1-year planning horizon are as follows:

\[
BL_p = \int_0^1 \lambda_p^{BL}(t) \, dt 
\quad \text{CL}_p = \int_0^1 \lambda_p^{CL}(t) \, dt 
\]

As a new inspection plan is needed at the end of the planning horizon, two new incident models need to be developed based on the updated asset and incident records. This allows asset changes (e.g. in terms of age, gradient, diameter and so on) which have occurred during the planning horizon, to be taken into account.

Expected cost of emergency repairs due to sewer blockages (\( f_2 \)) and collapses (\( f_3 \)) are computed as in Equations (9) and (10) respectively.

\[
f_2 = \sum_{p \in NI} d_p \cdot (C_{\text{CIPP}} \cdot D_p \cdot L_p) \cdot BL_p 
\]

\[
f_3 = \sum_{p \in NI} d_p \cdot (C_{\text{CIPP}} \cdot D_p \cdot L_p) \cdot CL_p 
\]

where summations refer to all non-inspected pipes (NI). The product in brackets is the rehabilitation costs of pipe \( p \) assuming a unit cost \( C_{\text{CIPP}} \) of 5 \$/m/mm diameter; while \( d_p \) is the multiplier as in Equation (2). In a decision support context, both types of failure models and objective functions should be updated yearly by using new data records. The implicit working hypothesis here is that condition assessment is adequate to take the right measures and avoid unexpected incidents in a one year time horizon. Also \( f_2 \) and \( f_3 \) are minimized during search and optimization.

It is worth noting that, despite of the fact that the cost data are not obtained in the UK, the resulting economic analysis is consistent as both cost of inspections (by CCTV) and repairs (as CIPP) are used from the same source (Canada). Thus, the incoherence between the place where the pipe failures occurred (UK) and the currency used for economic analysis (Canadian dollars) does not impair the consistency of the numerical analysis reported in this work.

FROM MOGA SOLUTIONS TO PRIORITISED INSPECTIONS

As mentioned above, the selection of a set of sewers to be inspected is performed by using a multi-objective genetic algorithm (OPTIMOGA). Here each inspection scheme is represented by a chromosome whose length equals the number of sewer pipes considered (16,875 corresponding to about 780 km of pipeline) and the only decision variable is ‘to inspect’ (value 1) or ‘not to inspect’ (value 0). Such an “exhaustive” coding identifies a huge global search space of \( 2^{16,875} \) solutions. In order to allow for an adequate balance between exploration and exploitation of the Pareto front, each OPTIMOGA run was performed for 500 generations.
The maximum size of the evolving population is 100 individuals, while the maximum number of elements in the archive is left undefined so that the search continues until the maximum number of generation is reached. Mutation and crossover probability are set at 0.1 and 0.4, respectively. Furthermore, the optimization was repeated 5 times to take into account the effects of different starting populations.

Scrutiny of returned replacement schemes revealed the following issues.

- Both the number of returned solutions (different inspection schemes) and pipes selected vary considerably over the 5 runs.
- Pareto solutions in the close proximity of each other in the objective space differ considerably in the decision space (i.e. the set of pipes selected for inspection are different from solution to solution). In particular, all renewal schemes falling into overlapping intervals of 1% of the total-inspection cost (i.e. investment for the whole network CCTV survey) were investigated. Figure 2 depicts the number of solutions falling into each cost interval (left) and the percentage of “common” pipes (i.e. those simultaneously selected) over all pipes in the same cost interval (right). For the sake of clarity, these figures refer to one of the 5 runs only. The horizontal axis reports the investment required for the cheapest solution in each interval. It is evident that the most populated cost intervals are those between about 30% and 65% of the complete CCTV inspection cost. However, this cost interval shows also a very low percentage of pipes “common” to neighbouring solutions. This means that, given a monetary budget for inspections, the decision manager has to choose from a number of possible “optimal” alternatives, which are substantially different from each other. Figure 2 (left) shows also that the cheapest cost intervals are as populated as the most expensive ones (on average) but the percentage of “common” pipes is very different. In particular, solutions up to 30% of the total-inspection cost (associated with the commonly available budgets) contain about 3% of common pipes on average. Also in this case the selection from these solutions is quite a hard task.
- As shown in Figure 2-right, MOGA solutions range from about 20% to 80% of the total-inspection cost, without any solutions up to 20% and between 80% and 100%.
- None of the pipes has been selected by all of the solutions returned in a single run.

These facts suggest that once a given inspection scheme is considered by the decision maker, it is impossible to move to the next inspection programme without changing most of the selected pipes. Despite the MOGA’s proven effectiveness in many other design and management applications, it should be noted that it has limitations in terms of search effectiveness and efficiency, especially when solving large optimisation problems (e.g. related to real-life networks) with a large number of objectives considered. Some of these problems arise from the heuristic nature of the GA search which allows for the rapid approach to the real Pareto front from a random starting point but gets into difficulties when converging to it. This is a well known problem of slow finishing that occurs due to the lack of selection pressure toward the end of the GA run (Goldberg 1989).

Figure 2 | Analysis of OPTIMOGA solutions. Number of solutions in each 1% cost intervals (left). Percentage of pipes simultaneously selected for inspection among all solutions within the same 1% cost intervals (right).
Although MOGA solutions should not be used as a decision support for planning inspections, they are obtained from a global exploration of the search space and could be regarded as a knowledge base for successive analysis. In this study pipes have been sorted according to the number of times they were selected from all solutions returned by 5 OPTIMOGA runs. This in turn means assigning priority to inspections based on the probability of selection during OPTIMOGA global search. Once this is done, a new set of intervention plans is created by progressively adding pipes to inspect in order of decreasing priority. In other words, the most advisable work plan can be obtained by adding the CCTV inspection costs of all pipes sorted in decreasing order of priority until the budget constraint is reached. This way, a given plan differs from its more expensive neighbour by just one pipe whose inspection is less urgent from the statistical point of view.

**Figure 3** shows the inspection schemes returned by OPTIMOGA (crosses) and those based on priority (black squares—looking like a thick black line due to the density of points). The figure depicts the projections of the objective space on the planes $f_1-f_2$ (Investment—Risk of blockages) and $f_1-f_3$ (Investment—Risk of collapses). The axes of investment and risk functions are scaled between 0 and 1.

It is evident that prioritized schemes are Pareto-dominant with respect to all OPTIMOGA solutions. In fact, when OPTIMOGA solutions and prioritized inspection schemes are compared, the former are assigned rank $>1$. Furthermore, the prioritized front shows a quick reduction in both risk functions just after 162 pipes are selected for inspection. This point is marked with a circle in **Figure 3** (left and right) and represents an inspection programme with the cost of about 1% of the total network survey cost and allows risk due to blockages and collapses (i.e. reduction in emergency repairs) to be reduced approximately by 33 and 47%, respectively.

Kapelan *et al.* (2003, 2005) compared MOGA solutions with other ranking approaches from literature on the problem of sampling design. Similarly, **Figures 3** shows the comparison with two pipe rankings obtained by using greedy algorithms. Each of them starts with an empty set of optimal solutions and adds one pipe at a time; this pipe is the one with the current highest ratio between risk reduction and investment. In the first case (i.e. Rbl/C) risk reduction refers to blockages, in the second case (i.e. Rcl/C) it refers to collapses. It is evident that each of these ranking schemes dominates the other when evaluated into the proper two-objective sub-space (e.g. Rbl/C in $f_1-f_2$ plane), while it is dominated in the opposite case (e.g. Rbl/C in $f_1-f_3$ plane). **Figure 3** shows that the proposed procedure (prioritization of OPTIMOGA solutions) represents a compromise between the two rationales in the in the area of low investment, which is the more important from a decision maker’s perspective. Indeed, the solutions obtained are generally preferable (are between Rbl/C and Rcl/C) up to 19% of total-inspection investment. Furthermore, all solutions before the inflection point approximate very well both rankings obtained with greedy algorithms, i.e. Rbl/C and Rcl/C. This is because pipes with highest risk of both blockage and collapse events are selected first.
These observations are likely to be of general validity, i.e. even when other ranking algorithms based on one objective at a time are applied.

A further analysis has been performed to verify whether the rank of all prioritized strategies is equal to 1 (i.e. whether they are Pareto efficient with respect to each other). The result shows that 178 solutions out of 16,785 are Pareto-dominated by others. However, the first dominated solution occurs after the selection of 185 sewers, hence beyond the inflection point in Figure 3. Within the range 0–30% of the complete inspection investment, just 18 (out of 5,859) prioritized solutions are sub-optimal. Remaining sub-optimal solutions are spread through the front of prioritized solutions with an increasing density towards more expensive ones. This apparent drawback can be explained by the insufficient pressure of selection in such a large search space and could be easily overcome by including additional objective(s) during the optimization process. For example, if the information on network topology was available, the adjacency between selected pipes might be used as an additional objective, similarly to Berardi et al. (2008b).

DISCUSSION AND CONCLUSIONS

This paper presents and discusses the application of a multi-objective genetic algorithm (OPTIMOGA) to the selection of optimal sewer pipe inspection schemes in a large, real-life sewer network. The analysis shown here unveils a lack of contiguity between the set of inspections obtained from the multiple OPTIMOGA runs. This makes inspection strategies less effective for decision makers who have to select from a large set of different feasible pipe combinations. A prioritization scheme is demonstrated that is able to expose the most critical pipes to satisfy a given set of objective functions simultaneously. Such a prioritization is based on the post-processing of solutions returned by the global OPTIMOGA search. Nevertheless, it could be potentially applied to solutions obtained from other multi-objective optimization techniques in order to develop the most effective supports for a decision maker. As a potential further development, pipes may be resorted during the OPTIMOGA run in order to drive the search towards those Pareto-optimal solutions which are also effective from a practical perspective.

The case study shown here considered two types of objectives: (1) the total investment required and (2) the risk of emergency repairs subsequent to sewer incidents. Sewer pipe blockages and collapses have been modelled by using the EPR and the MCS-EPR techniques. Although these techniques are not new in the field of sewer failure modelling, a novel application to predict the number of incidents for individual sewer pipes has been presented here. Some limitations of the methodology shown here arise from the lack of knowledge about the actual network topology. If available, this could be used to both improve aggregation into homogeneous pipe classes (prior to modelling failures) and to optimize the allocation of inspections (e.g. by adding further objective functions into the optimization process). Nonetheless, previous similar studies on even smaller water distribution pipe networks (Berardi et al. 2008b; Giustolisi & Berardi 2009) have proven that such further information neither reduces problem complexity nor overcomes the need for a post processing of MOGA solutions.

All solutions obtained after post-processing dominate all those returned by five runs of a multi-objective genetic algorithm. Prioritized inspection schemes where also compared with two different ranking strategies, each following a benefit/cost ratio based on one objective (i.e. type of failure) at a time. The proposed approach is demonstrated to provide preferable solutions, at least in the realistic, low-investment area. Finally, the inclusion of other objectives is suggested as the straightforward remedy to overcome the occurrence of sub-optimal solutions amongst prioritized ones and, also, to make the whole decision support tool more flexible to fit end user’s needs.

REFERENCES


Pareto, V. 1896-7 Cours d’écologie politique professée à l’Université de Lausanne, (Course of political economy at University of Lausanne) 2 vols. Lausanne.


