Risk Driven Analysis of Maintenance for a Large-scale Drainage System

Yujie Chen[1], Fiona Polack[1], Peter Cowling[1], Philip Mourdjis[1] and Stephen Remde[2]
[1]*YCCSA, Computer Science Department, University of York, York, U.K.*
[2]*Gaist Solutions Limited, Lancaster, U.K.*

Keywords: Simulation, Maintenance, Risk Management.

Abstract: Gully pots or storm drains are located at the side of roads to provide drainage for surface water. We consider gully pot maintenance as a risk-driven maintenance problem. Our simulation considers the risk impact of gully pot failure and its failure behaviour. In this paper, we focus on two factors, the issue of parked cars and up-to-date gully pots status information, that may affect the scheduling of maintenance actions. The aim is to discover potential investment directions and management policies that will improve the efficiency of maintenance. We find that the "untimely system status information" is a dominant factor that weakens the current maintenance. Low-cost sensor technique could be a good development.

1 INTRODUCTION

Gully pots are designed to prevent solids and sediment from flushing into sewers and causing blockages in the underground system (Butler et al. (1995)). Regular cleaning is required for gully pots to function effectively (Karlsson and Viklander (2008); Scott (2012)). Usually, gully pots in a city are cleaned once or twice a year. Partial or complete blockages of the gully pots increases the likelihood of surface water flooding. In extreme situations such as intensive rainfall, a clogged drainage system may cause serious property loss (i.e. BBC (2011, 2012); Shieldsgazette (2012); Leylandguardian (2015)).

Our gully pot maintenance problem is based on Blackpool, UK. Blackpool's gully pot maintenance system records 28,149 gullies in an area of about 36.1 km^2. On any day, the maintenance team either carries out the normal cleaning action, categorised as the preventative maintenance, or responds to emerging events such as gully broken and blockage reports (i.e. the corrective maintenance). Depending on the local risk, these emerging events should be scheduled 5 to 20 days from when they are recorded. For broken gully pots, a different vehicle equipped with a specialist machine is required. Due to limited human resource, only one vehicle works each day.

Each day there is a schedule of gully pots to visit, starting and ending at the depot. The maintenance vehicle departs the depot at 09:00 and returns no later than 17:00. During servicing, some gully pots are inaccessible due to parked vehicles. Historical maintenance records show that this is a striking issue: about 8.3% of gully pots are not serviced each year because of parked cars.

Apart from the parking issue, we also notice another weakness of current maintenance scheduling strategy – untimely system status information. Currently, all the broken or blocked gully pots are either reported by local residents or found through preventative maintenance. Historically, the records show that reporting of gully pot issues by local residents is highest in autumn, when leaf-fall and higher rain causes many blockages; and lowest in winter, when short daylight and cold weather reduce footfall. This passive situation potentially leads to uncontrolled surface water flooding.

In order to discover techniques or policy that could improve current gully pot maintenance, this paper considers the gully pot maintenance as a risk-driven problem. In our analysis, we take account of each gully pot's failure behaviour and the risk impact of its failure, which varies across the city. The current widely used maintenance strategy, including both preventative and corrective actions, is evaluated by our risk model across various scenarios.

The remainder of this paper is organized as follows. Section 2 reviews maintenance techniques and concept. We then introduce our simulation in Section 3. Section 4 shows our results and conclusions. A summary of investment suggestions based on our simulation is provided in Section 5.

Chen, Y., Polack, F., Cowling, P., Mourdjis, P. and Remde, S.
Risk Driven Analysis of Maintenance for a Large-scale Drainage System.
DOI: 10.5220/0005749102960303
In *Proceedings of 5th the International Conference on Operations Research and Enterprise Systems (ICORES 2016)*, pages 296-303
ISBN: 978-989-758-171-7

2 RELATED WORKS

Maintenance is generally categorised into corrective and preventative maintenance (Duffuaa et al. (2001); Ahmad and Kamaruddin (2012)). Corrective maintenance (CM) usually happens after failures occur. It includes actions such as repair and replacement. Preventative maintenance (PM) is an alternative strategy. In industry, preventative maintenance typically takes place at regular time interval, based on experience.

Operational research on PM introduces decision making, based on data analysis, with techniques such as time-based (TBM) (e.g. Scarf and Cavalcante (2010); Wu et al. (2010)) and condition-based maintenance (CBM) (e.g. Carnero Moya (2004); Campos (2009)). TBM can be applied when the failure rate is predictable, whilst CBM is employed where conditions are continuously monitored by sensors or any appropriate indicators. A similar approach, tracking real-time operation information, is also applied in dynamic scheduling (e.g. Cowling and Johansson (2002)). There is a little research combining PM and CM strategies: Kenne and Nkeungoue (2008) introduce a PM/CM rate control strategy, obtaining a near-optimal maintenance policy for a manufacturing system.

For TBM, the accurate prediction of the current and future condition of a system is crucial for developing appropriate maintenance schedules. Damage, deterioration and degradation are important notions in asset life cycle management. Literature shows that related research has been done in bridge, pavement and water pipe systems (Madanat and Ibrahim (1995); Morcous et al. (2002); Baik et al. (2006)). Two techniques are normally applied: first, functional based models like exponential (Shamir and Howard (1978)) and time-powered models (Kleiner and Rajani (2001)) have been used to determine the optimal timing of water pipe inspection and replacement; time-dependent Poisson (Constantine et al. (1996)) and the accelerated Weibull hazard models (Le Gat and Eisenbeis (2000)) are also widely used. Second, Markov chain-based deterioration models have been well studied and applied in a number of real-world applications (e.g. Madanat and Ibrahim (1995); Morcous et al. (2002); Baik et al. (2006)). Different from the functional based models, Markov chain-based models focus on the transition probabilities between different grades, which also implies our conditions are evaluated discretely. The advantage of discrete methods is that clear management policies can be addressed based on the corresponding states.

This problem is also related to the periodic vehicle routing problem (PVRP) (Christofides and Beasley (1984)), which is widely used in geographically distributed maintenance and on-site service applications (e.g. Shih and Chang (2001); Gaur and Fisher (2004); Claassen and Hendriks (2007); An et al. (2012)). Different from research in the above maintenance concept, PVRP is based on the assumption that the optimal maintenance frequency and pattern for each object is known. The aim is to produce efficient schedule and daily routes that satisfy maintenance frequency and pattern constraints in a given period.

3 SIMULATION

3.1 Model for Schedule Strategy in the Real World

Due to the large-scale of the problems and gully pot condition changing over time, the schedule plan is normally provided for the near future (e.g. one week or one month). Therefore, during the planning period, not all gully pots can be serviced.

In order to discover any methodology or policy that could improve the current gully pot maintenance, we would like to simulate the actual scheduling strategy that is widely applied across local authorities. We summarise the procedure as follows.

1. Construct efficient preventative maintenance routes. In our model, This sub-problem is considered as a vehicle routing problem (VRP). The objective is building daily cleaning routes that minimize the total travelling distance, with constraints including: 1) all gully pots in the system should be visited at least once; 2) all routes should start and end at the depot; 3) no route travelling time should exceed the working hours constraint. A variable neighbourhood search (Hansen et al. (2010)) is applied. A similar solver is also described by Chen et al. (2014).
2. Collect recent information on emerging broken/blocked gully pots.
3. Generate schedule for the near future (e.g. one week or one month plan). Priority is given to broken and blockage reports. When all the reported problematic gully pots are serviced, the crew comes back to preventative maintenance. To schedule the preventative actions, we give priority to the routes with the highest risk estimates (described in the following section, function 1) that have not been scheduled in the last year.

3.2 Evaluation

In order to evaluate the performance of a maintenance schedule, we propose a risk-driven model. Each day, the risk of surface water flooding due to blocked/broken gully pots is evaluated by function 1:

$$\sum_{i=1}^{N} r_i P_i(d) \tag{1}$$

Where N is the total number of gully pots in the drainage system, r_i is the risk impact of gully pot i estimated by its surrounding environment, and $P_i(d)$ is the probability that gully pot i is failed on day d.

3.2.1 The Risk Impact Per Gully Pot (r_i)

A hazard (i.e. surface water flooding) could potentially be exacerbated by social-related factors, which are usually influenced by economic, demographic and building types (Cutter et al. (2003)). A higher risk impact here implies that if a particular gully pot is blocked and floods happen, it results in relatively larger economic and social losses. Co-operating with Blackpool local council, we firstly decide a list of social concerns with awareness of their economic and population influence. Then, each gully pot is evaluated by its location and the related social concerns.

Here, social concerns are classified in to three groups: 1) residential property; 2) commercial and industrial areas including local and district centres, business zones, and employment sites; 3) public services including schools, hospitals, doctors and public transport routes. In table 1, the estimated value of the item in group 1 is the average residential house price in Blackpool (UK GOV (2015)). Group 2 takes account of the footfall and critical building prices for each item. The estimated value of items in group 3 is based on average daily operation costs.

Flooding impact analysis involves large uncertainties. We do not expect a precise assessment of impact. Instead, we aim to find values that are able to guide gully pot maintenance actions in decision making. Here, we mainly focus on direct economic losses using a damage function which relates to property type and water level. Thieken et al. (2008) propose the impact from a range of flood water levels on different building types. After consulting the UK Environment Agency and Blackpool Council, we decide to focus on the impact of flood water levels of less than 21 cm. This gives the value-loss figures shown in table 1. For public transport we focus on bus routes, estimating the cost of road section closure due to surface water flooding.

By analysing Blackpool's historic flooding frequency (Blackpool (2009)), the probability of flooding events is used to map the flooding value loss to the daily risk impact per gully pot according to its location (last column of Table 1). We assume that gullies in the same section of a street evenly share the responsibility for the risk impact evaluated in that area. Figure 1 illustrates the geographic distribution of gully pot risk impact in Blackpool.

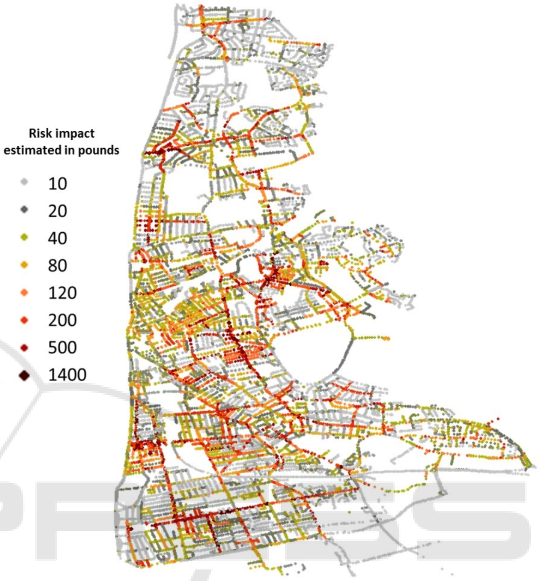


Figure 1: Gully pot risk impact in Blackpool.

3.2.2 Estimating the Process of a Gully Pot Blocking

Ahmad and Kamaruddin (2012) suggest that time-based maintenance is the normal strategy in situations where equipment has a fixed lifespan or predictable failure behaviour. After analysis of historic gully pot records, we model the gully pot blocking process using the Weibull distribution model (Weibull (1951); Ebeling (2004)), from reliability theory. The parameters of this form of Weibull distribution are the scale parameter λ, and the shape parameter k. In our study, all values applied are based on our statistical analysis of the Blackpool data. We first define $k = 6$, which captures a realistically increasing blocking rate over time. The scale parameter λ, capturing lifetime behaviour, is affected by location and seasonal factors, according to a simple linear function:

$$\lambda = \begin{cases} 10 & \text{... if gully pot recorded as broken} \\ E_{calling} & \text{... a calling event} \\ max(90, E - \sum_{f \in F} n_f * s_f) & \text{... normal state} \end{cases}$$

$E_{calling}$ represents the expected number of days

Table 1: Social factor evaluation.

Group	**Social Concerns**	**Estimated value**	**Value loss from flooding**	**Risk impact**
1	Residential	£113,000	3%	£34
2	Local center	£1,130,000	5%	£580
	District center	£1,695,000	5%	£870
	Business area	£565,000	5%	£290
	Employment sites	£226,000	5%	£116
3	School	£5,168	4%	£71
	Large hospital	£917,808	4%	£377
	Doctors	£9,178	4%	£73
	Bus route	£220	100%	£37

from a report on a gully pot to its servicing. E is the expected number of days that it would take a normal gully pot to become blocked since its last services. Here, $E = 10.3$ years. F is a set of factors that may affect gully pot lifetime, such as street type, number of trees nearby, and blown sand effect: n_f represents the effect level from a specific factor $f \in F$ to a gully pot; s_f adjusts the effect from factor f according to seasonal information. For example, if a gully pot is on a street with five deciduous trees nearby, then $n_f = 5$ with $s_f = 93, 1, 389, 433$ in spring, summer, autumn and winter respectively. If a gully pot location is not affected by factor f, we simply assign $n_f = 0$. Fig. 2 illustrates one example of a gully pot lifetime estimation taking account of the surrounding environment.

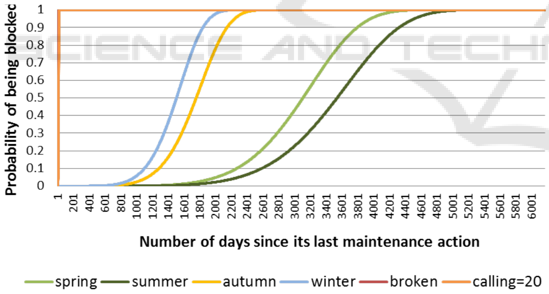


Figure 2: Probability of being blocked since last maintenance action (Example of a gully pot lifetime with 5 tree nearby at different seasons).

4 EXPERIMENT

In this section, we firstly summarise the background of our problem and simulation. All simulations were implemented in C# and executed on a cluster composed of 8 Windows computers, each with 8 cores, Intel Xeon E3-1230 CPU and 16GB RAM.

Simulation Settings

1. Total number of gully pots in the system: 28,149.
2. Broken events: Blackpool council estimates about 1.1% of gully pots are broken every year. This is represented by each gully pot becoming broken randomly with probability 0.00003 per day in our simulation.
3. Blocking probability: a gully pot lifetime is estimated by a Weibull distribution described in Section 3.2.2. Every day, each gully pot has a probability of becoming blocked according to its failure rate function $h_i(d) = \frac{R_i(d-1)-R_i(d)}{R_i(d-1)}$, where $R_i(d) = 1 - F_i(d)$ is the reliability function.
4. Seasonal factors F: the Blackpool data only allows us to include trees and leaf-fall in our simulation. Seasonal factors related to the number of trees nearby highly affect the lifetime of gully pots, and on average, each gully pot is affected by 0.4 trees in Blackpool.
5. Resident calling behaviour: about 1700 calls are received every year by the Blackpool gully maintenance team, and most of the calls concern blocked or damaged gully pots. Over 50% of all calls occur during the autumn, as shown in Figure 3. Our statistical analysis determined that, to match the resident calling behaviour in our simulation, on any given day, the probability of receiving a call if a gully pot is already broken or blocked is $p_{calls}(i) = \{0.0033, 0.005, 0.0056, 0.002\}$ for spring through winter, respectively. If a gully pot is not broken, there is still a small chance that a call is received, related to its current condition. The simulation probability is $p_{calls}(i) = P_i(d) * \gamma$, where $\gamma = 10.62$ has been measured experimentally to adjust the calling probability to match the real data.

Simulation Assumption

1. Planning horizon: In the real world, maintenance schedules are generated at varying levels of granularity, from long term (yearly) to short term (weekly). Here, we only consider the procedure

described in Section 3.1, where the maintenance schedule is updated every week according to the most recent system status reports.

2. Parking issues: inaccessibility during maintenance due to parking usually appears in preventative maintenance. For corrective actions, including servicing for both resident reports and broken gully pots, we assume the team always has access in our simulation.
3. Others: as well as broken gullies reported by residents, damage is also found during preventative maintenance. In this case, the simulation registers the broken gully and schedules it on a later day.

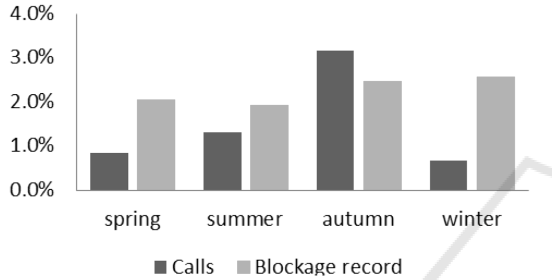


Figure 3: Seasonal calls and blockages as a percentage of the total number of gully pots in Blackpool.

These parameters and assumption have been discussed with Gaist Solutions Ltd. and agreed to be a realistic representation of gully-pot behaviour in Blackpool.

4.1 The Impact of Parking Issues

According to the maintenance records, the parking issue has been identified as a major problem that decreases the maintenance working efficiency, especially in the old town, where no extra space was designed for parked cars. The number of parked private vehicle also increases significantly. Our simulation helps us to understand the impact of parking on gully-pot maintenance performance. Therefore, potential strategies can be proposed such as banning parking when a maintenance visit for a certain street is scheduled.

In simulation, we can test the effect of inaccessible gully pots using a parameter, x, to represent the percentage of gully pots that cannot be accessed during preventative maintenance each year. The values of x are 0, 5, 8.3 (the actual value), 10 and 15 percent. Each parameter setting is run over 4 simulated years, with corresponding seasonal factors and residential report behaviours.

The results of simulation are shown in Figure 4. There is an increase in flooding risk as the percentage of inaccessible drains increases. This suggests that a policy of suspending parking on streets to be serviced might improve maintenance efficiency by 8%, which translates to about £1,400 risk decrease every day. If a "suspending parking" policy only partially decreases the number of parked cars (to 5%), little difference can be observed in risk. When the impact of parking increases up to 15%, the surface flooding risk increase significantly by 12%.

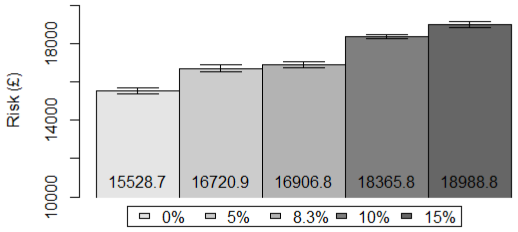


Figure 4: The average daily risk of applying maintenance schedule described in Section 3.1, with different accessibility settings during preventative maintenance. The bar with the setting of 8.3% is the current real-world situation. Error bars show 95% confidence interval.

4.2 What if we Could do Condition-based Maintenance (CBM)?

Aside from parking issues, seasonal changes and untimely system status information are identified as other factors that affect the efficiency of drainage system maintenance. Seasonal change is an uncontrollable factor. On the other hand, improving low-cost sensor techniques make it potentially feasible to continuously monitor gully-pot condition. This would allow our schedule strategies to be combined with CBM, discussed in Section 2. Currently, we only find out that a gully pot is blocked or broken either during preventative maintenance or if it is reported; because of this incomplete system information, it is difficult to produce any optimal schedules.

In simulation, we can test the importance of real time failure monitoring by varying the proportion of gully pot failures that are known immediately, as if the gully pot had a real-time sensor. As shown in Table 2, we use two parameters, "since last maintenance action θ" and "percentage of broken gully pots" to control the system's initial state. The stable state assumes that the entire system is well maintained and the number of days since the last maintenance action for each gully is uniformly distributed across 1.1 years. Furthermore, there are about 0.4% broken gullies in the system when it is in the stable situation. The other two scenarios assume that the system is recovering from a natural disaster such that a large number of gullies are broken or blocked initially regardless of prior maintenance. Both a well maintained gully-pot system (see Figure 2, recover-1) and a system that has had bad maintenance (see Figure 2, recover-2) are tested.

Table 2: “since last maintenance” and “percentage of broken gully pots” set the system’s initial state: for all gully pots, the days since their last service are evenly distributed in θ years. We randomly assign a percentage of gully pots to be in the broken state.

	Stable	**Recover 1**	**Recover 2**
Since last maintenance θ	1.1	1.1	3
Initial broken gully pots	0.4%	2%	2%

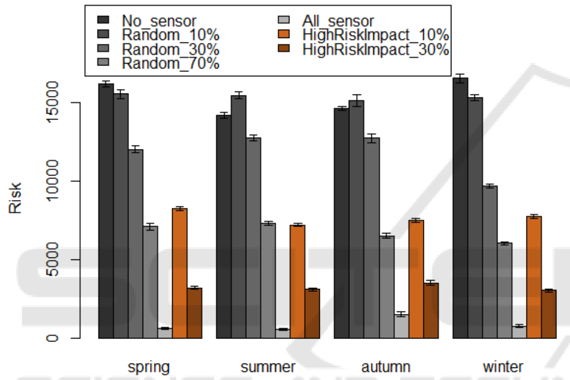


Figure 5: Performance of maintenance in stable with sensors of different install capacity. Error bars show 95% confidence intervals.

Figure 5 presents the average daily risk in four seasons over a set of four-year simulations. In comparison to the simulation of current blockage reporting, the instant information simulation shows a reduction in risk of about 92%. For the case where all gully pots have instant (sensor) information, the results clearly show the impact of seasonal factors: falling leaves in autumn increase risk by about two times compared to other seasons. Interestingly, we can not observe the clear risk difference between seasons when no sensors are installed. This is because the different residents’ reporting behaviour strongly affects the responding time of broken/blocked gullies. The dependence on local residents’ reports bury big hidden dangers for the entire system.

To provide further insight into how the availability of information on gully pots affects flooding risk, we adapt the simulation to provide instant information from only some locations, simulating the localised installation of sensors. Setting 10% of gullies to have sensors, allows us to compare an even distribution of sensors to the results when sensors are focused on critical areas of the city. We find that focusing on high risk areas reduces the daily risk, on average, by about 28%. When monitoring is increased to cover 30% gullies, the comparable saving is a 75% risk decrease.

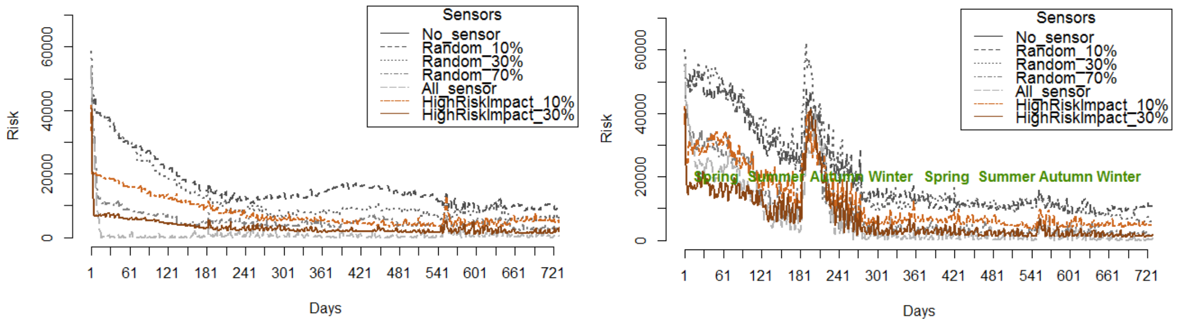
Figure 6 illustrates the daily risk change over two years in recovery states. In scenario recovery-1, the system with full sensoring performs the best in terms of recovering speed, followed by 30% high-risk-impact and 70% random strategies. The faster recovery also implies lower total surface water flooding risk through the recovery period. In scenario recovery-2, due to the previous poor system maintenance, the recovery period is significantly longer in all cases compared to scenario 1. Also, the peak point uncovers the vulnerability of a badly maintained system during the high-risk season. However, the sensoring still helps the maintenance team to produce a more informed schedule, which results in less total risk during the recovery period.

4.2.1 Discussion

The above simulations show the contribution of timely information to improving the gully-pot system maintenance quality. However, the proposed sensor system also increases the management complexity, where extra cost and manpower are needed to ensure that the system is always working correctly. Furthermore, we assume in our simulation that instant gully-pot condition information can be received with no errors, which is hypothetical. In practice, current sensor techniques can achieve up to 85% reliability (See et al. (2012)). More research is needed into both the hardware aspect and the optimization of scheduling strategies.

Another issue that has been noted is the communication performance of sensors, which decreases in weather condition such as rain or snow (See et al. (2012)). Therefore, the gully-pot system maintenance should combine a risk estimation approach (i.e. Section 3.2) with sensors to deliver optimized scheduling.

Our simulation shows large advantages when sensors are installed in high-risk areas. However, since sensors must be close enough to communicate wirelessly with each other, the network topology must be considered (Yick et al. (2008); See et al. (2012)). In order to successfully integrate sensors into the current gully-pot system, further analysis is needed into the technical feasibility and the balance between costs and benefits (i.e. surface water flooding risk decreasing) to determine if the installation and maintenance costs of the sensors are worthwhile.



(a) Daily risk tracking of scenario recovery-1.

(b) Daily risk tracking of scenario recovery-2.

Figure 6: Performance of maintenance in recovery state with sensors of different install capacity.

5 CONCLUSION

This paper considers a real-world drainage system maintenance problem. A risk-driven analysis approach is proposed to evaluate the performance of maintenance actions. We focus on the "parking issues" and "untimely system status information" that are identified as potential weaknesses of the current maintenance approach (see Section 3.1).

To summarise, "banning parking" could improve gully pot maintenance to some extent. However, this policy increases management complexity and residents' complaints. The "untimely system status information" is the dominant factor that weakens the efficiency of current maintenance. Our preliminary simulation shows promise in sensor informed maintenance. Low-cost wireless sensor techniques could be a good investment to help produce an informed maintenance schedule and lower risk. Further work is needed to form a cost/benefit analysis to discover the optimal quantity of sensors to deploy, their locations and network topology. The technical feasibility of sensors' topology should also be considered. Further work is also needed to discover the potential decrease in maintenance scheduling efficiency due to false alarms caused by the "sensor technique". New scheduling approaches may be required to make best use of the potentially large amount of data generated by the sensors.

In practice, due to the immaturity of sensor technology, we suggest that the combination of time-based preventative maintenance (with risk estimation) and condition-based corrective maintenance (with sensors) is an optimal approach.

ACKNOWLEDGEMENTS

The authors would like to thank Gaist Solutions Ltd. for providing data and domain knowledge. This research is part of the LSCITS project funded by the Engineering and physical sciences research council (EPSRC).

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