Using decision analysis to determine optimal experimental design for monitoring sewer exfiltration with tracers

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ABSTRACT
The tracer methods developed to assess exfiltration from sewers in the European project APUSS (Assessment of the Performance of Sewer Systems) have a high degree of freedom with regard to the choice of tracer and the dosing strategy. These can lead to very different degrees of uncertainty in the measured exfiltration ratio. In this study, we demonstrate how to select an optimal experimental design using decision analysis, which accounts for this uncertainty and its associated costs. Although the results are site-specific, we can conclude generally that, when NaCl is used as the tracer, the accuracy of the exfiltration estimate is most sensitive to the amount of tracer used and the starting time of the experiment.

KEYWORDS
QUEST; sewer leakage; experimental design; decision analysis; Monte Carlo Simulation

INTRODUCTION
We have recently proposed a number of techniques for determining exfiltration rates in sewers using tracers (Rieckermann et al., 2005a; Rieckermann et al., 2005b) that were developed within the scope of the European project APUSS (Assessment of the Performance of Sewer Systems). The application of any of these techniques requires the investigator to make a number of decisions regarding experimental design. These include the number of tracer additions to use, the mass of tracer used in each addition, the relative timing of additions, and the starting time of the experiment. These choices influence the amount of uncertainty in the final estimate of exfiltration. However, there is no universal answer to the question what is the optimal choice of options. The best experimental design depends on how much the investigator is willing to spend on the monitoring process (in terms of effort and financial resources) and how these expenditures compare with the consequences of an incorrect determination of exfiltration. The goal of this paper is to address these issues using the formal framework of decision analysis (Clemen, 1996).

Decision analysis is a method for selecting among alternatives based on formal axioms of human preference. The basic principle is that a decision-maker can state his/her preferences for the possible outcomes of a decision, expressed as the levels of a selected set of measurable attributes, as well as his/her attitude towards risk. Additionally, he/she can obtain estimates of the likelihood of all possible outcomes of each decision alternative, expressed using probability distributions of attribute levels. The decision-maker should then prefer the alternative that maximizes a mathematical combination of the stated preferences and probabilities. This approach differs from purely statistical methods such as power analysis because it accounts not only for the probabilities of making "correct" and "incorrect" decisions but also for the relative consequences of these decisions.

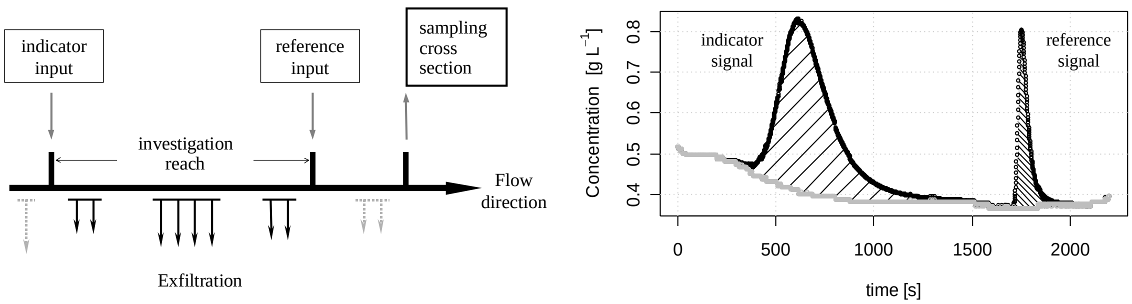

Figure 1 Left: Conceptual sketch of the experimental set-up of the QUEST method. Right: Example results of a QUEST experiment showing the concentration time series of an arbitrary tracer at the sampling cross section. Both figures taken from (Rieckermann et al. 2005b).

We demonstrate the decision analytic approach to experimental design using the QUEST method of exfiltration estimation (Rieckermann et al., 2005b), as applied to a stretch of a main sewer in Rümlang, Switzerland. For the sake of clarity, we limit our analysis to one particular variant: QUEST with NaCl as tracer.

MATERIAL AND METHODS

Exfiltration estimation using the QUEST method

The QUEST method is described in detail by Rieckermann et al. (2005b). We will only provide sufficient information here to set the context for the experimental design decisions being investigated. Briefly, the method uses two sets of pulsed tracer additions straddling the investigation reach: an upstream indicator addition and one or more downstream reference additions (Figure 1, left). Exfiltration is then estimated by performing a mass balance on the indicator addition by comparing the total mass passing the sampling cross section with the mass added. The mass lost is then a direct indication of the loss of wastewater over the investigation reach. The reference addition serves as a type of internal calibration, eliminating the effect of systematic proportional errors. This improves the accuracy of exfiltration estimates. In a typical situation, the signals of the indicator and reference additions are clearly distinguishable at the sampling cross section because of the differing degree of longitudinal dispersion caused by different travel times (Figure 1, right).

The precision of estimated exfiltration is influenced by the dosing strategy (number of pulses, timing, etc.) and could be improved through experimental design optimization. Alternately, it is possible that in some cases a less precise estimate would be appropriate, accompanied by some savings in cost and effort. In general, it would be beneficial to have a formal framework for considering the role of uncertainty in the decision process. Addressing these issues is the goal of decision analysis, as described in the next section.

Decision analysis

Reichert et al. (2005) describe a general procedure of how decision analysis techniques can be used to support environmental decisions. The procedure is divided into seven steps:

- Step 1: Definition of the decision problem
- Step 2: Identification of objectives and attributes
- Step 3: Identification and pre-selection of alternatives
- Step 4: Prediction of outcomes

Step 5: Quantification of preferences for outcomes
Step 6: Ranking of alternatives
Step 7: Assessment of results

In the following case study, we will first give a brief description of the investigated system and then develop the optimal experimental design, providing details on the seven step decision analysis procedure as we proceed.

CASE STUDY

System description

We applied our methodology at an investigation reach of 980m length on a trunk sewer between the villages of Rümlang and Oberglatt, Switzerland. The circular sewer has a diameter of 0.9m and a slope of 0.9 per mil, and the mean flow in the reach is 25 L s^{-1} with an average depth of 0.12m.

Rieckermann et al. (2005b) discuss the choice of possible tracers, suggesting the use of NaCl, as measured by conductivity, because it is the cheapest and easiest tracer to apply in comparison with fluorescent dyes and radioactive tracers. The difficulty however is that conductivity is present at non-negligible background levels in the sewer due to the presence of NaCl and other solutes. Variability in this baseline can confound accurate estimation, because peaks in the background can occur simultaneously with the passage of a tracer peak and be mistaken for part of the dosed tracer mass. Careful experimental design (such as nighttime dosing) can minimize such effects, but they can never be completely eliminated.

Preliminary field tests: As the design of the experiment depends critically on the sewer characteristics, the discharge and conductivity baseline were first monitored over several days. Dispersion in the reach determines the shape and duration of the tracer peaks at the measurement point. We assessed dispersion from preliminary tracer experiments with single indicator and reference pulses. Estimating sewer dispersion from empirical formulae is also possible (Rieckermann et al., 2004), but experiments lead to more reliable estimates of peak shapes.

Experimental design using the decision analytic framework

Step 1: Definition of the decision problem. The premise of the case study is that a decision has already been made to use QUEST to estimate exfiltration in the Rümlang reach and that the resulting estimates will be used to decide whether or not to rehabilitate the sewer. Given this situation, the investigator would like to know: “What is the best QUEST layout for this particular reach?”

We believe it is relevant to approach this question as a decision problem, rather than to perform the experiment spontaneously, because:

- Evaluation of the consequences of sewer leakage is site-specific; therefore the optimal balance of experimental cost and accuracy should be site-specific.
- Uncertainty in measurement of exfiltration is site- and method-specific, therefore it should be considered explicitly.
- The attitudes of the decision-maker toward cost and risk should be considered.

Step 2: Identification of objectives and attributes. An objective is something a decision maker would like to achieve, and attributes are measurable system properties that can be used to quantify the degree of fulfilment of the objectives. These form the basis for both the preference and likelihood evaluations.

In our case study, the objectives are relatively straightforward: The investigator would like to minimize the costs associated with an incorrect determination of exfiltration, as well as to minimize the cost of the tracer experiment itself. An incorrect determination of exfiltration may be costly for one of two reasons: either sewer rehabilitation is undertaken unnecessarily (when exfiltration is over-estimated), or sewers are allowed to continue to leak (when exfiltration is under-estimated) causing undesirable surface or ground water pollution. We define these as avoidable costs. The experimental costs include the cost of the tracer material, equipment costs, labour costs, and the added costs of working at night. Costs, in units of Euro, are the appropriate attribute for assessing each of the objectives.

Step 3: Identification and pre-selection of alternatives. The next step in applying decision theory is to select the set of alternatives to be considered. In the present context, this means choosing all the components of a dosing strategy (e.g. the time of the investigation, the number of tracer pulses, etc.). As these options imply an impracticably large number of combinations, we define some representative scenarios for further analysis, based on the peak shapes estimated from the preliminary field tests:

First, we define experiments, which indicate the different dosing strategies with respect to how many tracer pulses are dosed at what time-intervals, using the following parameters: tracer masses of reference and indicator additions (M_R and M_I in [g]), number of reference pulses per indicator peak (N_R) and three timing parameters (T_1, T_2, T_3 in [s]) (Figure 2). Second, we define *layouts*, which are composed of one or more experiments, using the starting time of the experiment (t_0 in [h]) and the total number of indicator additions (N_I).

In total, 42 different experiments were analysed by randomly sampling from a range of values for M_R [10, 2000] , M_I [100, 5000], N_R [1, 5], T_1 [50, 1000], T_2 [400, 3000], and T_3 [2, 800]. Further considering N_I to take all values from 1 to 4 and t_0 to take hourly values from 0:00 to 23:00, we obtain 4032 different layouts, which form the full set of alternatives considered.

Step 4: Prediction of outcomes. Determination of the probability distributions of each attribute for each decision alternative is the next task in the analysis. We predict the outcomes for the different QUEST layouts with a two-component model: (1) a technical sub-model

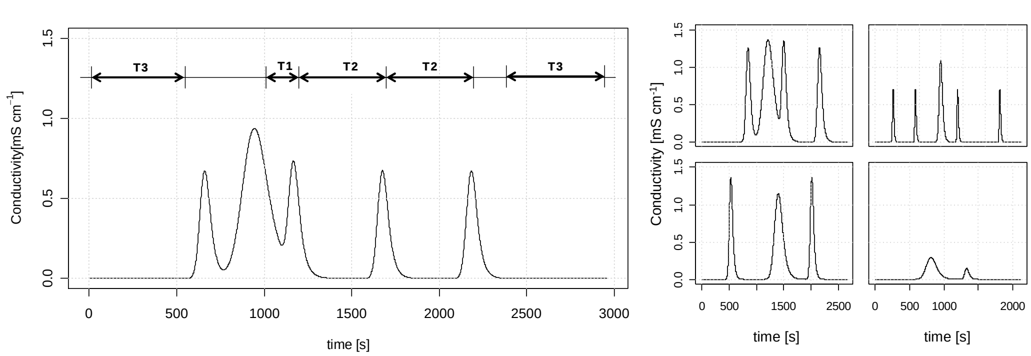

Figure 2. Left: Timing-parameters of a QUEST experiment: T1=time between indicator and first reference pulse, T2=time between reference pulses, T3=time outside peak span that is used for data analysis. Right: Examples of possible experiments indicating different combinations of T_1, T_2, T_3 and N_R, M_R, M_I.

which predicts the error in exfiltration estimates and (2) an economic sub-model that computes the experimental cost and expected pollution and rehabilitation costs for each layout.

Technical sub-model: A method for performing a full uncertainty analysis of the QUEST method is described by Rieckermann et al. (2005b). As it was found that errors from dosing, sensor calibration and discharge measurements can be practically neglected, only the error contribution from the baseline is considered. The baseline error, which does not necessarily follow a statistical probability distribution, is random and conditional on the dosing strategy. We assessed it using a bootstrap resampling approach (Efron and Tibshirani, 1993), as described by Rieckermann et al. (2005b). This was done by performing a large number of simulations for each experiment and determining the distribution for the underlying baseline error for each possible starting time. In our case the error is time-dependent and specific for each experiment. Our calculations are based on 750 bootstrap samples from two days of baseline and flow measurements. Second order sampling uncertainty was found to be negligible for sample sizes larger than 700. The errors were lumped together in bins of hourly intervals, to match the time resolution of t_0. As we are interested in the error of each layout, we use Monte Carlo Simulation to propagate the error from each experiment to the corresponding layouts. When a certain layout starts at t_0, samples from the baseline error of the underlying experiment are drawn from the bin t_0 according to the number of indicator pulses used. If multiple indicator pulses are injected, the duration of this layout might extend over n hours. In this case, the baseline error is also sampled at the following starting times t_0+1, ..., t_0+n. Finally, all samples of the baseline error are averaged to compute one error of this certain layout. In order to obtain a realistic probability distribution of the exfiltration error estimate for each alternative, this procedure is repeated 5000 times for each layout.

Economic sub-model: The determination of the cost functions is a matter of engineering economics, and we follow a rather simple approach (Table 1). The experimental cost associated with a specific layout follows directly from the layout's definition. For example, the starting time and duration of the experiment determine the labour costs. The avoidable costs are either caused by unnecessary surface or ground water pollution (underestimation of exfiltration) or unnecessary rehabilitation (overestimation of exfiltration). In the Rümlang case study, we assume a rehabilitation cost of 550 € m^{-1} (Berger et al., 2002), which leads to a rehabilitation cost for the 980m long reach of about 0.54 Mio. €. The cost of pollution (e.g. soil remediation) is assumed to be directly proportional to the percent exfiltration. For simplicity, we assume an expected long-term pollution cost of 0.2 Mio. € percent^{-1} (Figure 3, left). If we assume that the sewer operator will make an economically sensible decision when

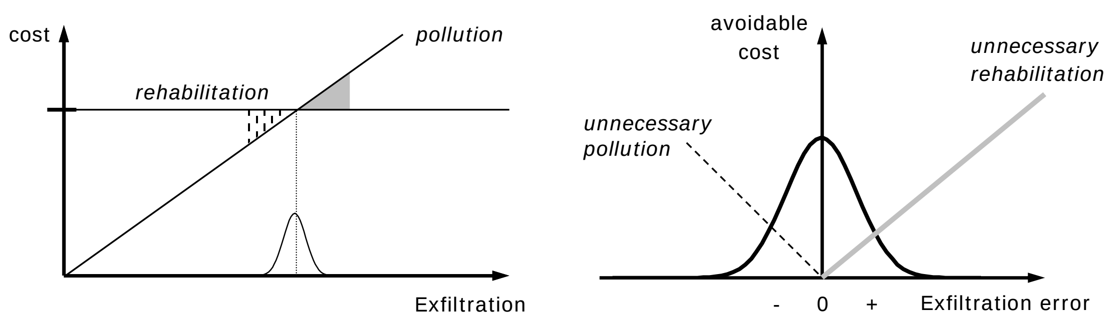

Figure 3. Left: Simplified cost functions for sewer rehabilitation (adapted from Reckhow (1994)). Right: The marginal increase in costs associated with uncertainty in the tracer method. Layouts that have a low measurement error would have lower expected cost.

Table 1. Parameter values of the cost function.

Category	Description	Value	Comments
Labour cost	Worker salary	50 € per hr	
	Engineer salary	70 € per hr	
	# of workers	2	
	Night-time supplement factor	1.33	Increase in salary from 21:00 to 05:00; Variable cost, depending on starting time of layout
Labour hours	Preparation	8 hrs	4 hrs worker, 4 hrs engineer; Fixed cost
	Execution	Dependent on duration of the layout	Variable cost
	Data analysis	4 hrs per indicator pulse	4 hrs engineer; Variable cost
	Reporting	4 hrs	2 hrs worker, 2 hrs engineer, Fixed cost
Consumables	Cost for consumables during experiment: tracer, car, tools, water, etc.	1 € per kg NaCl	Includes overhead. Retail price for NaCl is about 0.3 € per kg; Variable cost
Equipment	Flow meter	20 € per campaign	Standard ultrasonic Doppler device; Fixed cost
	Conductivity device	10 € per campaign	Fixed cost
	# of flow meters	1	Fixed cost
	# of conductivity devices	2	Fixed cost

given accurate information on exfiltration, then he/she would choose to rehabilitate the sewer when the exfiltration is known to be greater than 2.7% and would not rehabilitate when exfiltration is less than this value. When uncertainty exists, incorrect decisions are most likely to occur when exfiltration is near this breakpoint. In such a situation, the costs of errors in exfiltration are symmetric about the mean estimate, with a cost slope of 0.2 Mio. € percent^{-1} in either direction. In this way, the most uncertain estimation methods are the most penalized in terms of cost.

Step 5. Quantification of Preferences for Outcomes. The preferences of the decision-maker for the possible outcomes must next be quantified. This is done by constructing value or utility functions over the range of each attribute. Value functions describe the preference structure of the decision-maker with respect to the attribute (i.e. whether more or less of the attribute is better; whether there is decreasing, increasing, or constant marginal value associated with increases in the attribute level), while utility functions include additional information on the decision-maker's risk attitudes. Both value and utility functions are subjective entities, generally determined through the performance of elicitation interviews with the decision-maker (Clemen, 1996). When the decision-maker is assumed to have a risk-neutral, marginally-constant (i.e. linear) preference structure and all attributes can be expressed using monetary units, then preferences can be described using financial costs or benefits directly. This is the situation we assume in this case study, and thus use costs, rather than value or utility as the measure of relative preference.

Step 6: Ranking of alternatives. The technical model developed in step 4 leads to probability distributions of the error in exfiltration for each layout, based on the Monte Carlo samples. Applying the economic model then leads to an experimental cost for each layout and an avoidable cost for each value of the exfiltration error. The total expected cost for each layout is then calculated as the fixed experimental cost plus the expected value of the avoidable cost (calculated as the integrated product of the cost function and the probability distribution).

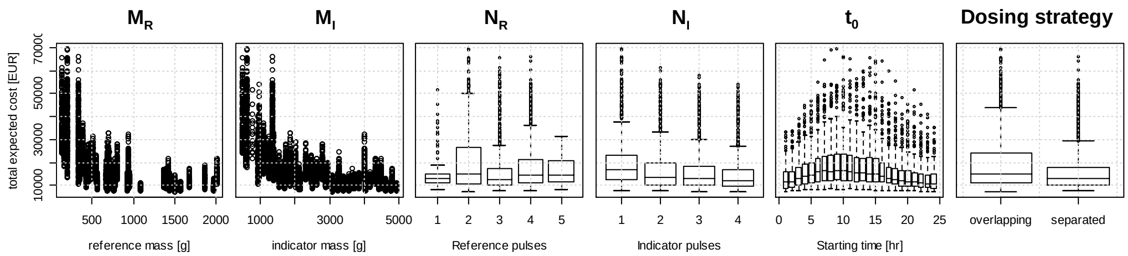

Figure 4. Influence of important layout parameters on total expected cost. Points indicate the 4032 layouts, and boxplots indicate statistical summaries in the case of discrete parameters.

Decision theory dictates that the layout with the minimal total expected cost should be preferred. In our analysis, the layout with minimal expected cost is one with a starting time of 23:00 that uses three repetitions of the indicator pulse, each with two reference pulses, and leads to an overall experimental time of approximately 2.25h. The optimal masses of NaCl for the reference and indicator additions are 1500 and 3100g, respectively. This layout leads to a total expected cost of 7262€, of which 2220€ are experimental costs for preparation, measurements, data analysis, and reporting. The remainder is the expected costs of pollution and/or unnecessary rehabilitation.

Step 7: Assessment of results. When the total expected cost for all 4032 layouts is plotted against the parameters describing the layout alternatives (Figure 4), we observe that the cost is most sensitive to the mass of added tracer (M_R and M_I). This is because increased mass generally leads to reduced uncertainty in exfiltration estimation. It is also clearly beneficial to perform the measurement campaign in the night hours 22:00-3:00 when baseline variation is low. Additionally, uncertainty decrease substantially with the dosing of several indicator pulses.

Analyzing the 100 top-ranked layouts (not shown), we found that they all start between 13:00 to 2:00, and in 96% of the cases multiple indicator pulses are dosed. Further, all the top-ranked layouts are created from only 8 different experiments (Figure 4).

DISCUSSION

The described decision analytic procedure leads to an optimal design of a QUEST experiment. However, the result is based on assumptions (e.g. details of the cost model) which may be rather simplistic. Therefore, the sensitivity of the final ranking of layouts should be analysed with respect to technical and economic model uncertainty. Although this is important to gain insight into the power of the results, we must omit it here for the sake of brevity.

Our results suggest that a separation of indicator and reference peaks would result in lower expected cost (see Figure 4, far right), due mostly to more precise exfiltration estimates. This would also lead to a simpler data analysis procedure (Rieckermann et al., 2005b). However, previous studies (Rieckermann et al., 2005b) have suggested that peak overlap is preferable. It must be noted that in the present study this issue could not be precisely addressed, as all experimental parameters were varied simultaneously, confounding the effects of peak overlap and relative timing. We plan to examine this issue in more detail in the future. During the original development of our procedure, we took the identifiability of peak parameters to be a measure for the quality of experimental design. However, we found that identifiability measures, which are often based on sensitivity functions (Brun et al., 2001), are useful tools for data analysis but are not conclusive for experimental design. Therefore, we recommend the more "holistic" decision analytic procedure described here.

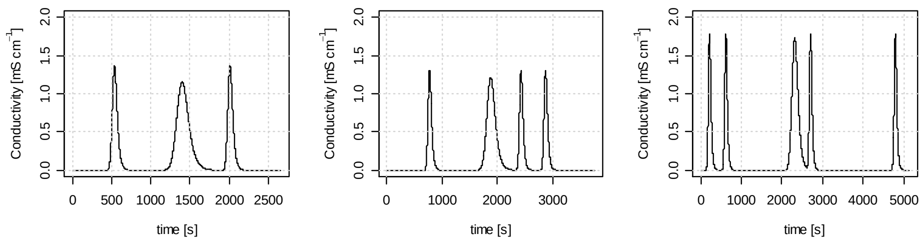

Figure 5 The three best of the top eight experiments contained in all of the top 100 layouts, ranked best to worst from left to right.

CONCLUSIONS

We have demonstrated a decision analytic method for selecting an optimal experimental design for exfiltration estimation using tracer methods, such as those developed in the APUSS project. Decision analysis accounts for uncertainty in estimation and its associated costs. Results will depend on site-specific technical and economic models, but we believe that it can generally be concluded that, when NaCl is used as the tracer, accuracy in exfiltration estimation is most sensitive to the amount of tracer used and the starting time of the experiment. Our analysis is particularly relevant for engineers who are interested in applying the tracer methods, but the decision analytic framework described here is transferable to other applications in urban hydrology as well.

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