Sensitivity analysis on the pollutant trapping efficiencies of a novel sewerage overflow screening device

M. A. Aziz, M. A. Imteaz, H. M. Rasel and M. Samsuzzoha

ABSTRACT

A novel 'Comb Separator' was developed and tested with the aim of improving sewer solids capture efficiency and reducing blockages on the screen. Experimental results were compared against the industry standard 'Hydro-Jet™' screen. Analysing the parameter sensitivity of a hydraulic screen is a standard practice to get better understanding of the device performance. In order to understand the uncertainties of the Comb Separator's input parameters, it is necessary to undertake sensitivity analysis; this will assist in making informed decisions regarding the use of this device. Such analysis will validate the device's performance in urban sewerage overflow scenarios. The methodology includes multiple linear regression and sampling using the standard Latin hypercube sampling technique to perform sensitivity analysis on different experimental parameters, such as flowrate, effective comb spacing, device runtime, weir opening and comb layers. The input parameters 'weir opening' and 'comb layers' have an insignificant influence on capture efficiency; hence, they were omitted from further analysis. Among the input parameters, 'effective spacing' was the most influential, followed by 'inflow' and 'runtime'. These analyses provide better insights about the sensitivities of the parameters for practical application. This will assist device managers and operators to make informed decisions.

Key words | capture efficiency, comb separator, effective spacing, sensitivity analysis, sewage overflow

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INTRODUCTION

During continuous downpours of rain, existing urban sewer systems are not able to carry the excess water. This results in this excess water, which carries significant amounts of sewer solids, flowing into the open creek system. The sewer solids are inevitably dispersed, suspended or washed into the rivers, where they settle, creating odours and a toxic/corrosive environment in the mud deposits at the bottom. Furthermore, these solids create unaesthetic situations either by their general appearance (increasing dirtiness) or through the actual presence of specific, objectionable items, such as floating debris, sanitary discards/faecal matter, scum, or even parts of car tyres. To overcome such challenges, options include the development of wet detention ponds (Dan'azumi *et al.* 2013), wet temporary holding tanks at sewerage treatment plants, real-time control of sewer systems, enlarged upstream sewers to provide transient storage, separation of storm and sewage flows, and various screening devices in combined sewer overflow (CSO) chambers. In most cases, screening is the only economically viable method adopted in the hydraulic system (Faram *et al.* 2001). The hydraulic design of an efficient sewer network is of pivotal importance (Duque *et al.* 2016). A deterioration model could provide insight for prioritising inspection of existing sewer overflow sites (Rokstad & Ugarelli 2015).

Analysing the parameter sensitivity of a hydraulic device such as a Comb Separator has been a standard

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practice of hydraulic engineers for many years (Johnson 1996; Jetmarova *et al.* 2015). It is essential to generate an accurate simulation of the input models (Méndez *et al.* 2013) in sensitivity testing. Such analysis qualitatively or quantitatively explains the sources of variation (Saltelli 2004). A comprehensive review of the application of sensitivity analysis in environmental models is presented by Hamby (1995). Sensitivity analysis of the input parameters of the Comb Separator device provides a better understanding of them. This includes their influence on the outcome capture efficiency, identifying which parameter is the most important, the relative importance of each input parameter, and identification of those parameters requiring further research.

One of the most frequently used devices is the rotary screen proposed by Moffa (1997). This consists of a large rotating drum that is slightly angled to maximise dewatering. The angle of the drum ensures effective dewatering, as the screenings travel up the drum, where they are removed from the unit. Metcalf & Eddy (1991) proposed a centrifugal screen, with a series of screens attached to a cage that rotates around a vertical axis. The sewage overflow enters from the bottom and travels upward to a deflection plate at the top of the unit, and sewage solids are collected from outside the cage. In addition to these, Faram *et al.* (2001) tested the Hydro-Jet™ device that has been installed in the USA, Australia and mainland Europe. A detailed review of different types of screens can be found in the work of Saul (2008) and Madhani & Brown (2011) have provided a recent update of this literature.

The literature suggests that screens need to be 'self-cleansing' mechanisms; otherwise they are subject to blinding when placed in remote unmanned sewer environments (Aziz *et al.* 2013). Most 'conventional' screening systems utilise electro-mechanical components to facilitate such a process. However, given the harsh unmanned remote environment of sewer overflow device locations, this is clearly not ideal. Blocking and seizure of moving parts, as well as electrical failure, are common maintenance problems, which in many cases lead to an onerous maintenance commitment (Aziz *et al.* 2014). To overcome these drawbacks, a new overflow screening device, known as the 'Comb Separator', was proposed and tested at Swinburne University of Technology. The new device is self-cleansing and low maintenance, with fewer operating costs. A detailed description of this device can be found in the work of Aziz *et al.* (2014, 2015).

Another thoroughly investigated research screening device is the Hydro-Jet. This device has a self-cleansing mechanism, and its suggested use is in CSOs that utilise a purely hydraulic cyclic backwashing mechanism. The National Rivers Authority (1993) in the UK set the standard for intermittent wet weather discharge and removal of pollutants. The most stringent condition requires the segregation of solids greater than 6 mm diameter in any two dimensions. The Hydro-Jet was subjected to a rigorous evaluation process (Andoh *et al.* 1999; Andoh & Saul 2000; Faram & Andoh 2000). After assessing the available documentation on the evaluation process of the Hydro-Jet, the current research considers this is the benchmark device to consider in a comparative analysis of the proposed research screening system. The methodology adopted for this research is shown in the flowchart (see Figure 1). Both the Comb Separator and the Hydro Jet were developed with the aim of improving sewer solids capture efficiency and functional effectiveness of the screening device, and with lower maintenance costs. The capture efficiency of the Comb Separator varies more than that of the Hydro-Jet. To gain a better understanding of the fluctuating capture efficiency, it is important to perform a thorough sensitivity analysis of the input parameters of the Comb Separator.

The sensitivity of input parameters is of paramount importance for the Comb Separator, as this device will be located in remote, unstaffed locations. Moreover, sensitivity analysis will help to answer the following questions:

- What is the input parameter that most influences sewer solids capture efficiency?
- Which parameters are insignificant to model output, and thus can be omitted from further analysis?
- How is it determined whether a model maintains the underlying input–output relationship when expanding the dataset using a sampling technique?
- Which, if any, input parameters interact with each other?

Uncertainty analysis does not provide any meaningful results that assist in designing input variables (Hall *et al.*

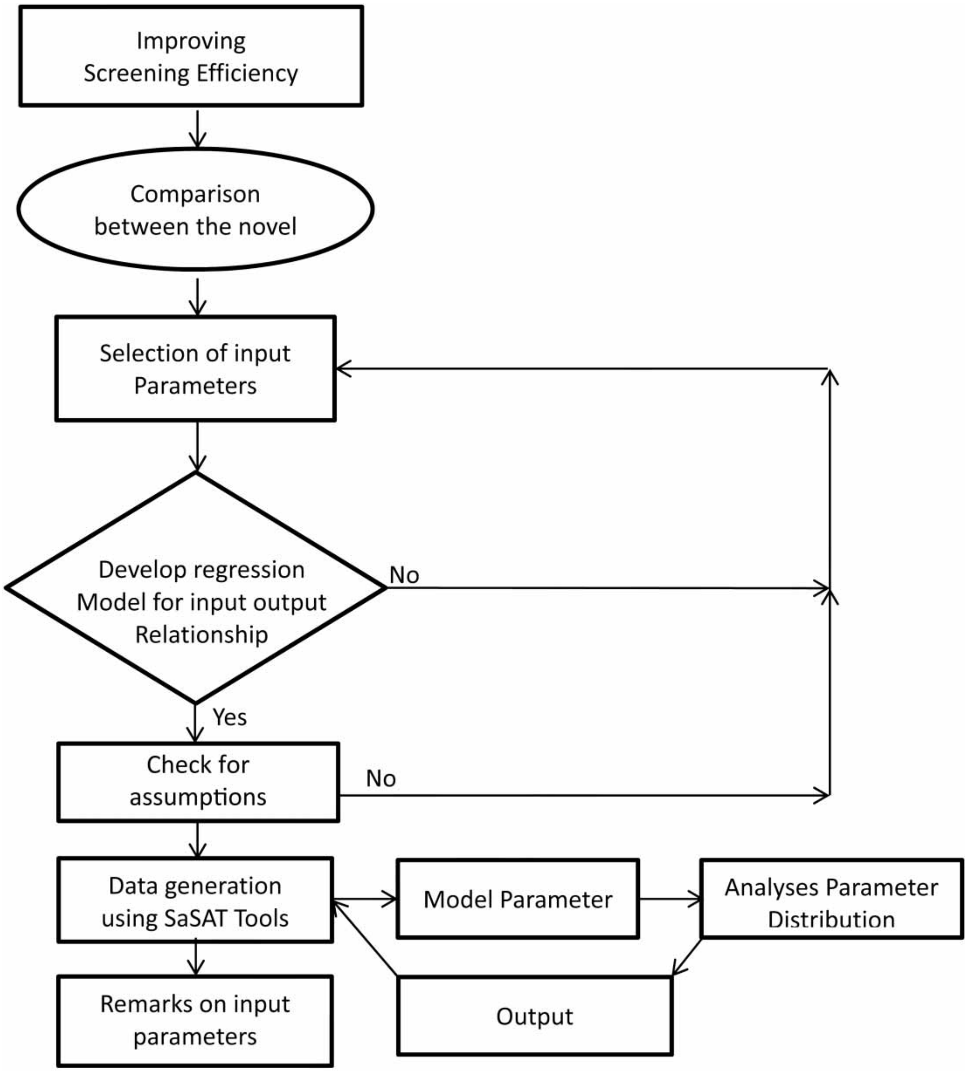

Figure 1 | Flow chart of the methodology adopted in sensitivity analysis.

2009). Hence, the focus of this paper is limited to sensitivity analysis. The key objectives of the sensitivity analyses of the Comb Separator device are listed as follows:

- To develop a robust understanding of the meaningful input parameters.
- To undertake a performance comparison of the proposed Comb Separator with a standard Hydro-Jet device under low flow (up to 60 L/s) conditions.
- To comprehend the impact of experimental design parameters (runtime, flow discharge, effective comb spacing, weir opening and comb layers) on sewer solids capture efficiency.
- To understand the relative significance of the input parameters, and to identify which parameter is the most influential in the development of output results.

This paper continues on to discuss the screening mechanism of the Comb Separator device, followed by sensitivity analysis and a review of the results.

SCREENING MECHANISM OF THE COMB SEPARATOR

The Comb Separator was connected to an inlet pump and inlet pipe. Two outlets were mounted on the device: one

Figure 2 | Set up of the Comb Separator.

to convey overflow water away, and the other to drain the sewage water remaining in the storage chamber. A series of combs to segregate sewage solids from the sewage overflow were mounted next to the sharp crested weir (see Figure 2). The separator of sewer solids is explained in Phase 1 and Phase 2 below.

Phase 1: After the precipitation overflow starts, the storage chamber fills with sewage. A floating ball at the bottom of the sewage solids holding chamber closes at this point, as shown in Figure 3 (top). As the overflow continues, the storage chamber overflows above the sharp crested weir. The captured sewage solids are intercepted by the parallel combs, and fall into the holding chamber (pollutant capture chamber).

Phase 2: After the cessation of precipitation, the water level within the storage chamber falls below the valve level. The low pressure of the liquid in the sewage solids holding chamber allows the ball to drop, flushing all the captured sewage solids back into the storage chamber (shown in Figure 3 (bottom)). The experimental conditions were varied by changing the critical experimental set-ups such as flow discharge, weir opening, comb spacing and comb layers. (The schematic diagram of the experimental set-up is provided in Figure 3 (bottom).) The aim was to achieve higher capture efficiency – at or above 80% – with minimal blockage on the combs, and testing on a one-in-one-year overflow for sewer solids less than 10 mm, such as cigarette butts. (For a concept diagram, refer to Figure 4.) Flow discharge (Q) is presented on the X axis as follows:

$Q1 = 1$ sewer overflow occurring in 1 year
$Q1/2 = 2$ sewer overflow occurring in 1 year
$Q1/4 = 4$ sewer overflow occurring in 1 year

The captured sewer solids are presented as a percentage on the Y axis. The capture efficiency of sewer solids is calculated according to the total number of sewer solids retained in the Comb Separator versus the total number of solids tested in the inflow. Therefore Equation (1) of capture efficiency would be as follows:

$$\text{Capture efficiency} = \frac{\text{Total number of sewage solids retained}}{\text{Total number of sewage solids with inflow}} \times 100 \quad (1)$$

The robustness of the optimum experimental conditions was validated by repeating the experiment several times to ensure reasonable consistency of results (Aziz et al. 2015).

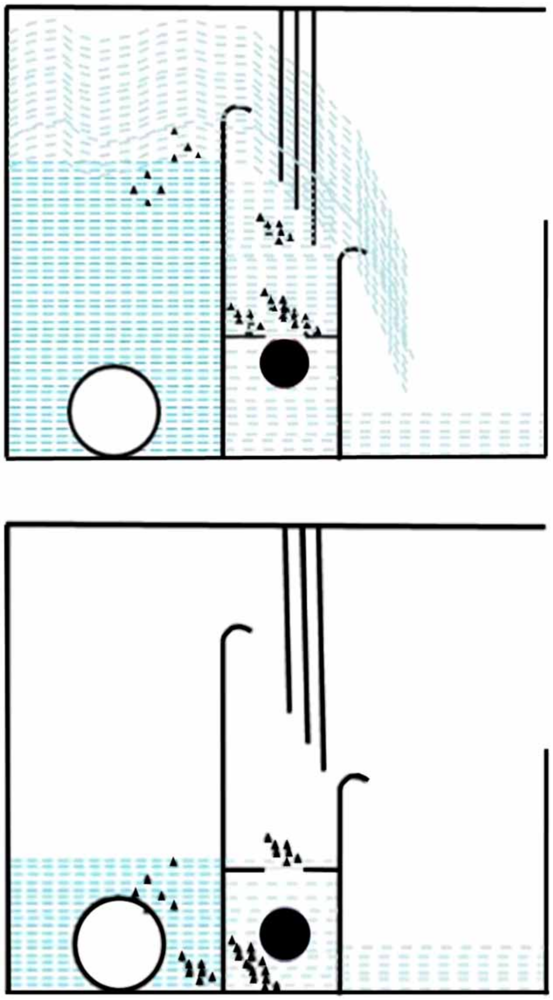

Figure 3 | Operation of the Comb Separator Phase 1 (top) and Phase 2 (bottom).

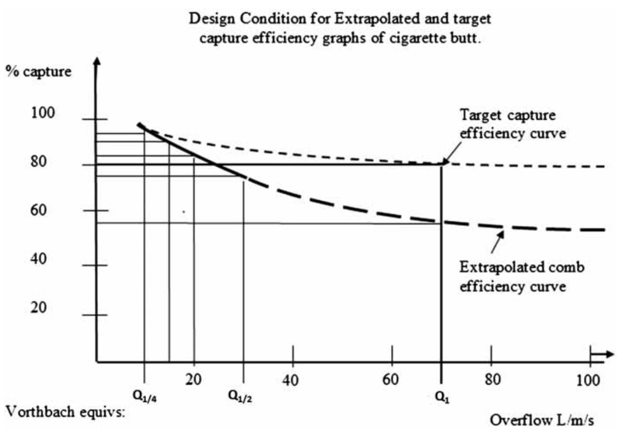

Figure 4 | Concept diagram of target capture efficiency curve.

SENSITIVITY ANALYSIS

Data-driven models such as an artificial neural network and machine learning are complex to understand and execute, so the focus in this research is to adopt a methodology that is fit for the purposes of sensitivity analysis. It is complex to understand model sensitivity where there is more than one input parameter as these input parameters could influence one another. All model input parameters for this model should be defined in such a way that each input parameter has an approximate probability density function associated with it which is similar to the multiple linear regression (MLR) model dataset. The next step would be to simulate by sampling a single value from each parameter's distribution. The sample and sensitivity analysis tool (SaSAT) was used in the model (Hoare *et al.* 2008). SaSAT produces input parameter samples for an external model. These samples, in conjunction with outputs (responses) created from the outer model (for example, regression model), perform the sensitivity analysis. The data generation process using SaSAT is shown in Figure 5.

In the current investigation, 42 sets of experimental data were collected for the Comb Separator at five different experimental conditions to develop a MLR model. The statistical properties of data collection are summarised in Table 1. SPSS Version 22 (IBM Corp. 2013) was used as a tool for analysing MLR modelling. The MLR model shows the relation of the input parameters to output capture efficiency. However, experimental investigations are limited by the physical challenges of generating a massive experimental dataset. This is an inherent limitation in visualising a range of experimental conditions. To overcome this limitation, a sampling technique was used that allows for expansion of the data series without compromising the relationship between input and output model parameters. The standard Latin hypercube sampling (LHS) technique (Iman & Helton 1981) was used to generate 10,000 sets of data without compromising the relationship between the input–output parameters. SaSAT tools were used (see Table 2).

Key considerations for developing the methodology are listed below:

- Develop meaningful and simplified inputs for the model considering the key input parameters' influence on the output capture efficiency.

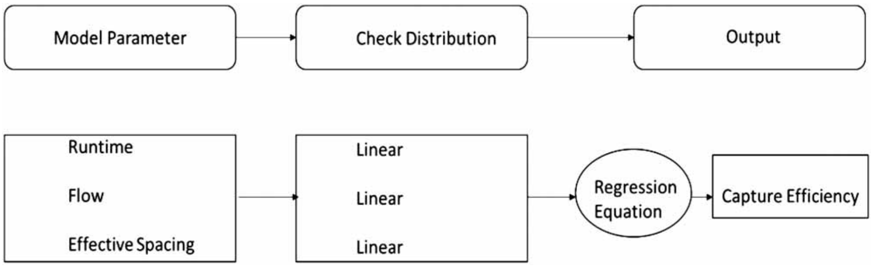

Figure 5 | Schematic diagram of SaSAT data generation.

Table 1 | Statistical properties of input data

Input parameter	Units	Minimum	Maximum	Average	Standard deviation
Runtime	min	6	27	17.04	7.05
Flow	m/s	20	67	43.51	15.65
Effective spacing	mm	1.5	4.8	3.05	1.31
Weir opening	mm	470	970	765.45	251.62
Layers of combs	No.	2	3	2.6	0.49

- Develop a MLR model and check for the necessary assumptions for validation of the model.
- To gain a better understanding of the input–output relationship through expanding the dataset without compromising the input–output relationship (Aziz *et al.* 2015). The LHS technique is highly recommended in the scientific literature for parameter sampling (Loh 1995; Keramat & Kielbasa 1997; Chrisman 2014).
- The sampling dataset was allowed to generate 10,000 sample data, some noise data also eliminated based on unrealistic input spacing, flow discharge, runtime and capture efficiency.

Further details of data expansion are provided in the following sections.

DEVELOPMENT OF MLR MODEL

MLR is a statistical technique that uses several explanatory (independent) variables to predict the outcome of a response (dependent) variable. The goal of MLR is to model the relationship between independent (input or predictor variables) and dependent variables.

The MLR model can be expressed using the following equation:

$$Y_i = (b_0 + b_1X_{1i} + b_2X_{2i} + \ldots\ldots\ldots\ldots.. + b_nX_{ni}) + \varepsilon \tag{2}$$

where Y_i is the outcome (dependent) variable, b_0 is the constant, b_1 is the coefficient of the first predictor (input) X_{1i}, b_2 is the coefficient of the second predictor (input) X_{2i}, b_n is the coefficient of the nth predictor (X_{ni}), and ε is the difference between the predictor and the observed value of Y for the i^{th} participant. In the case studied

Table 2 | Comparison between initial and final model results

Predictors	R	R square	Adjusted R	Change statistics: R square change	F change	df1	df2	Sig. F change
Model 1: Considering five parameters								
Layers of combs, runtime, flow, weir opening, effective spacing	0.753	0.567	0.507	0.567	9.438	5	36	0
Model 2: Considering three parameters								
Runtime, flow, effective spacing	0.741	0.549	0.513	0.549	15.419	3	38	0

here, the model becomes

$$\begin{aligned}(\text{Capture Efficiency})_i = b_0 + b_1(\text{Runtime})_i + b_2(\text{Flow})_i \\ + b_3(\text{Effective Spacing})_i \\ + b_4(\text{WeirOpening})_i \\ + b_5(\text{CombLayers})_i + \varepsilon\end{aligned} \quad (3)$$

The proposed model includes a b-value for both predictors and the constant. If the b-values are calculated, predictions can be made of the capture efficiencies using all five input (predictor) variables. Efficient design of the model input (predictors) parameters is important, because the values of the regression coefficient depend upon the variables in the model. Predictors (or inputs) variables should be selected based on past research to make sure all the key input variables are included in the model generation.

VALIDITY OF MODEL ASSUMPTIONS

According to Berry (1993), there are a few criteria that need to be satisfied to use MLR model:

- Variable type: It should be ensured that all input parameters (predictor variables) used in the experimental data are quantitative or categorical, and the output parameter (outcome variable) is quantitative and continuous.
- Non-zero variance: The experimental data suggest that all the input parameters are non-zero values, so the predictor variables satisfy this criterion.
- No perfect multicollinearity: Of the three key input parameters (predictors) selected for the model, there should not be a perfect linear relationship between two or more. Data were checked for multicollinearity, and it was found that no linear relationship exists between any two input parameters.
- Predictors are uncorrelated with 'external variables': This criterion means that weir opening and comb layers should not correlate with runtime, flow and effective spacing predictors; nor should they influence capture efficiency. Neither weir opening nor comb layers influenced the other predictor variables or outcome variable; hence this criterion was satisfied.
- Homoscedasticity: The data should not show any homoscedasticity. The scatter plot of the regression standardised residual against the regression standardised predicted values looks like a random array of dots evenly dispersed around zero, which confirms there is no homoscedasticity in the dataset used.
- Normally distributed errors: The residuals in the model are random and normally distributed with a mean of zero. This criterion assumes that the residuals/errors are frequently zero, or very close to zero, and only occasionally are there differences much greater than zero. The histogram and normal probability plot are used to assess this criterion.

RESULTS AND DISCUSSION

Comb Separator performed better than Hydro-Jet at low flows

The comparative analysis with the Comb Separator and the Hydro-Jet can be analysed based on spacing, average sewer flow and capture efficiency. The results suggest that at different average flow, the average capture efficiency of sewer solids of the Comb Separator is better than those of the Hydro-Jet. Average capture efficiency is plotted on the Y-axis, whereas average flow is on the X-axis (see Figure 6). In Figure 7, spacing is provided on the X-axis, whereas sewer solids capture efficiencies are plotted on the Y-axis. When the spacing between the two combs is compared with the spacing of the Hydro-Jet, the capture efficiency of the Comb Separator is found to be somewhat higher; however, the variation of capture efficiency by the Comb Separator is higher, at around 57% compared with 43% for the Hydro-Jet (see

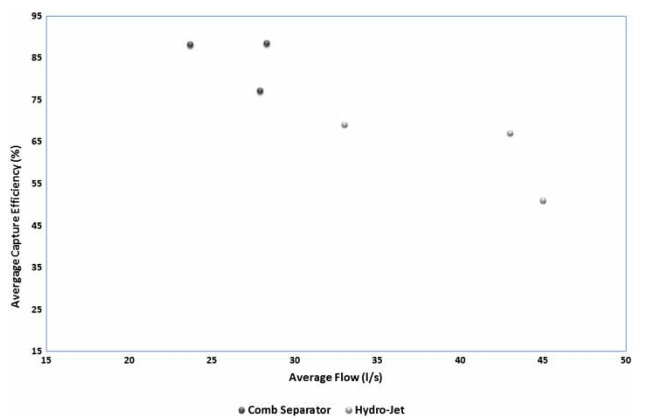

Figure 6 | Variation of average capture efficiency (%) against different average flow (L/s).

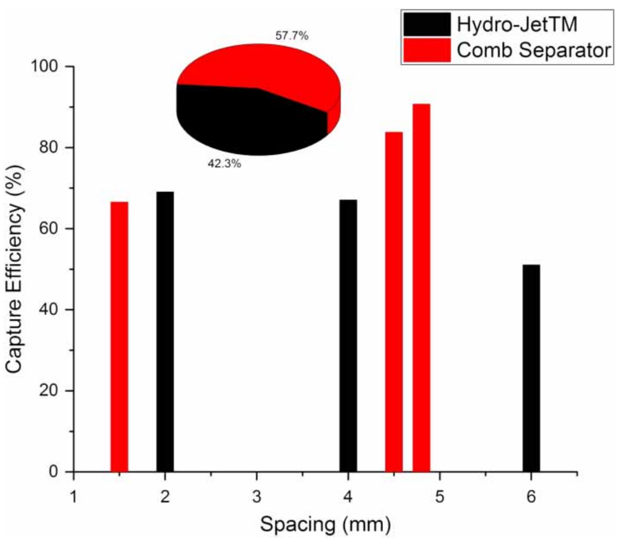

Figure 7 | Variation of average capture efficiency against different spacing.

Figure 7). The results from Figures 6 and 7 suggest that the Comb Separator can produce better screening efficiency in capturing sewer solids at low flows. There was hardly any blinding effect on the Comb Separator, which is a key improvement on the other device.

Input parameters are almost identical using MLR and LHS

The regression equation for the experimental dataset is given below:

$$\begin{aligned}\text{Capture Efficiency} = {} & 59.312 + 0.69(\text{Runtime}) \\ & - 0.339(\text{Flow}) \\ & + 5.3\,(\text{Effective Spacing})\end{aligned} \tag{4}$$

The final regression model equation after expanding the dataset to 10,000 using the LHS method shows:

$$\begin{aligned}\text{Capture Efficiency} = {} & 59.442 + 0.702(\text{Runtime}) \\ & - 0.341(\text{Flow}) \\ & + 5.317(\text{Effective Spacing})\end{aligned} \tag{5}$$

It is important to note that Equations (4) and (5) are almost identical, which ensures that the model does not compromise its underlying input–output relationship, while expanding the range of datasets from 42 to 10,000 using the LHS technique (Hoare *et al.* 2008).

Pearson's correlation coefficient suggests that effective spacing has a large positive correlation ($r = 0.68$) with the outcome, capture efficiency. Flow discharge has a negative correlation ($r = -0.53$) with capture efficiency, and runtime has a positive correlation ($r = 0.49$). All these results are statistically significant with $P < 0.001$ (see Table 3).

Effective spacing, flow discharge and runtime are the key input parameters for the Comb Separator

The initial input parameter design considers all 16 input parameters that could influence pollutant capture efficiency (Aziz *et al.* 2013). Out of these 16 input parameters, physical analysis of the experimental data highlights that only five key input parameters have major influences on capture efficiency (Aziz *et al.* 2015). Further analysis on sensitivity testing only considers five input parameters, including runtime (min), flow discharge (L/s),

Table 3 | Results using the LHS method for 10,000 data

	Correlations				
		Capture efficiency (%)	**Runtime (min)**	**Flow (L/s)**	**Effective spacing (mm)**
Pearson correlation	Capture efficiency (%)	1.00	0.49	– 0.53	0.68
	Runtime (min)	0.49	1.00	0.01	0.01
	Flow (L/s)	– 0.53	0.01	1.00	0.01
	Effective spacing (mm)	0.68	0.01	0.01	1.00
Sig. (1-tailed)	Capture efficiency (%)		0.00	0.00	0.00
	Runtime (min)	0.02		0.12	0.31
	Flow (L/s)	0.00	0.12		0.18
	Effective spacing (mm)	0.00	0.31	0.18	

weir opening (mm), effective spacing (mm) and layers of combs (number).

In the current research, forced entry (or Enter as it is known in SPSS (Statistical Package for the Social Science)) was used as the method by which all predictors are forced into the model simultaneously. Unlike the hierarchical method, the forced entry method makes no decisions about the order in which variables are entered. Table 2 shows the results for two MLR models, with five and three input parameters. In developing the MLR model initially, all input parameters that could have any influence on the output capture efficiency were considered. Trials were done in the MLR analysis, in which all predictors were entered into the model and outputs were examined to see which predictors contributed substantially to the model's ability to predict capture efficiency. In the initial model, all five input parameters – being runtime (min), flow discharge (L/s), weir opening (mm), effective spacing (mm) and layers of combs (number) – were considered. After a few different trials with the input parameters, it was found that the weir opening and comb layers were insignificant input (predictor) parameters, as they had little influence on the output sewage solid capture efficiency. The regression correlation coefficient R defines the correlation coefficients between the predictors and the outcome. R values vary from 0.753 to 0.741, from the first model to the second model, which is an insignificant difference between the two datasets. For the first model, R^2 had a value of 0.567, which means that the five input parameters' combined prediction accuracy on capture efficiency is 56.7%. However, in the second model with three parameters, the R^2 value is 0.549, which means the three input parameters' combined prediction accuracy on capture efficiency is 54.9%. Therefore two input parameters – weir opening and comb layers – account for only 1.8% influence on output predicting capture efficiency.

The final MLR considered three input parameters: runtime (min), flow (L/s) and effective spacing (mm), and excluded comb layers (number) and weir opening (mm). The adjusted R^2 provides some idea of how well our model generalises; ideally, we would have liked its value to be the same, or very close to, the value of R^2. In this case the difference of R^2 between the final model and the initial model was small $(0.549 - 0.513 = 0.036)$. This shrinkage means that if the model were derived from the population rather than from a sample, it would account for approximately 3.6% less variance in the outcome (see Table 2).

Effective spacing has a positive co-relation with capture efficiency

Effective spacing was the most significant predictor (input parameter) to influence capture efficiency. If the spacing is less, sewer solid capture efficiency is increased; however, blockage on the screen could increase if effective spacing is reduced less than 1.5 mm. The physical laboratory experiments could test up to 1.5 mm effective spacing. The effective spacing is measured in millimetres, whereas capture efficiency is measured in percentages. Therefore a 1 mm increase in effective spacing will increase to 5.32% of sewer solids captured by the screen. This relation of effective spacing with capture efficiency is valid from 1 mm to 6 mm, and also when runtime and flow are constant. A linear regression line is plotted in Figure 8. There was little noise in the simulated data, which were cleaned to reflect that there is no negative effective spacing or capture efficiency of more than 100% (see Figure 8).

Increasing flow discharge reduces capture efficiency

Flow discharge is one of the key issues to understand in the sewer overflow screening device, as the flow increases in the device (with fixed weir openings); the flow velocity also increases, which leads to a higher velocity of the sewage solids. Faster movement of sewage solids near the Comb

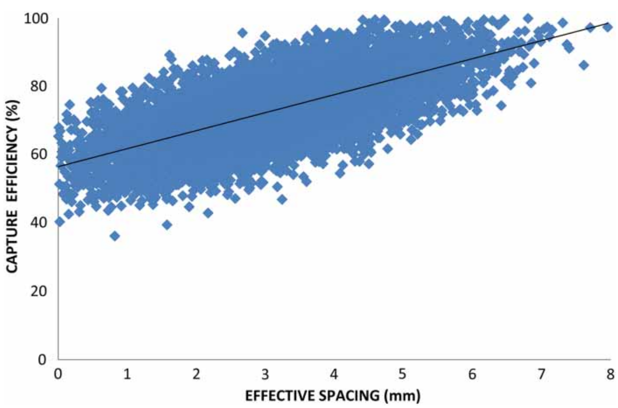

Figure 8 | Relationship between effective spacing (mm) and capture efficiency (%).

Separator is likely to reduce trapping efficiency. The existing facility at Swinburne University could allow the generation of a flow up to 70 L/s, so the simulated dataset was set to 80 L/s. An increase in flow by 1 L/s causes a reduction in capture efficiency by 0.341%, while the other two parameters – runtime and effective spacing – are kept constant. The simulated data were made noise free, with no flow less than 0 L/s. A linear regression line is plotted in Figure 9.

Overflow event duration increases sewage capture efficiency

If the sewerage overflow occurs for a longer time, this will generate more sewer solids. To overcome this issue, the device needs to perform well during longer-lasting events. In the experimental laboratory, the test ran for up to 40 minutes, and still the performance of capture efficiency was increasing. It was found that if the device runtime increases by one unit, the capture efficiency increases by 0.702%. For example, if the device runs for 30 minutes instead of 20 minutes, during the additional 10 minutes, 7.02% more sewer solids are likely to be trapped. A linear regression line was added to the figure to show the positive correlation between runtime and sewer solids capture efficiency. This relation of device runtime (minutes) is valid only in experimental cases where sewer solids are present in the flow, while effective spacing (mm) and flowrate (L/s) are kept constant (see Figure 10).

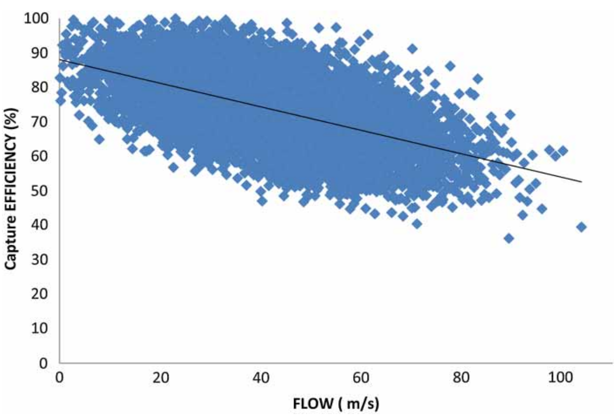

Figure 9 | Relationship between the flow (L/s) and capture efficiency (%).

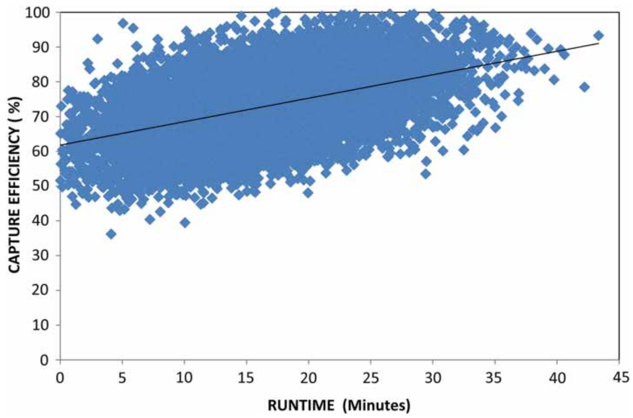

Figure 10 | Relation between runtime (minutes) and capture efficiency (%).

CONCLUSION

A series of laboratory trials with different runtimes, flow, effective spacing, layers of combs and weir openings were tested. Sensitivity analyses of these input parameters were performed to identify their influences on sewage overflow capture efficiency. The sensitivity analysis was aimed at developing a robust understanding of the relationships between the input (predictors) and output (outcome) variables. The MLR model was initially considered, using five input parameters. After significant trial and error, it was found that the two input parameters – weir opening and comb layers – could be excluded, because these two parameters only contribute to 1.8% of prediction accuracy.

The MLR model (Equation (4)) and the LHS sampling technique (Equation (5)) are almost identical. This ensured that the model retained the underlying input and output relationship when expanding the dataset from 42 sets to 10,000 sets. Sensitivity analysis delivered a cleaner understanding of the relative importance (rank) of the input parameters. It was found that effective spacing (mm) is the most influential parameter, followed by flowrate (L/s) and runtime (min). The sampling technique also provides better understanding of the input–output relations; for example, 1 unit (mm) increase in effective spacing is likely to increase output capture efficiency by 5.32%.

These sensitivity analysis results will be immensely valuable in developing a practice manual for the proposed device. This sensitivity analysis of input parameters is relatively easy to understand and explain compared with other data-driven models. Further attempts to understand the performance of the proposed Comb Separator could focus mainly on three parameters: effective spacing (mm), flow (L/s) and runtime (min). These sensitivity analysis results will help device operators and managers to make informed decisions in the management of different sewerage overflow events. The hydraulic experiments suggest good application potential for the proposed device in the urban sewer system. Further experiments are recommended to improve the understanding of the input parameters in high flows.

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