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Reliability analysis for multiple-stage solid waste management systems

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ABSTRACT

Solid waste management (SWM) is a key issue for sustainable development and environment protection, and waste collection and transportation (WCT) is one of the most important steps in managing solid waste. A well-designed SWM system with optimised location and capacity of waste transfer stations (WTSs) and final disposal facilities (FDFs) plays a critical role in waste management. However, uncertainties are inevitable in a general SWM system, which could involve in any stage of the waste management. In this paper, we propose to use the reliability analysis method to manage the uncertainties for the multiple-stage SWM system. Furthermore, an optimisation model is developed to maximise the reliability of SWM systems by optimising the allocation of waste treatment demand between facilities. We also generated an event-tree to analyse the failure mode of the whole system. Finally, a case study was undertaken in Hong Kong to demonstrate the effectiveness of the methodology. The case study results indicate that the proposed method can: (i) estate the risk level of a SWM system, (ii) provide a solution to improve the system reliability or reduce the risk level, (iii) analyse the potential contributions of different policies on the reliability index, (iv) identify the critical facilities in a SWM system.

1. Introduction

Generation rates of solid waste are rising around the world. There were 2.01 billion tonnes of solid waste generated throughout the world in 2016. With rapid population growth and urbanization, annual waste generation is expected to increase by 70% from 2016 levels to 3.40 billion tonnes in 2050 (Kaza et al., 2018). Managing waste properly is essential for building sustainable and liveable cities, which remains a big challenge for many countries and cities. Effective waste management is expensive, often comprising 20%–50% of municipal budgets (Bharadwaj et al., 2020; Kaza et al., 2018). Operating this essential municipal service requires integrated SWM systems that are efficient, sustainable, and socially supported.

However, a typical SWM system involves uncertainties that could be associated with waste generation, collection and transport, treatment, and the capacities of facilities in the system (Biswas and De, 2016; Liu et al., 2013; Srivastava and Nema, 2012). For example, the amount of waste generated in an area is affected by many different factors, such as population density, urbanisation level, and environmental regulations. The capacity of involved facilities are influenced by waste composition, the facility's operation time and waste collection and transportation condition, and they may show random and vague patterns (Liu et al., 2013). Uncertainties cannot be neglected when one is dealing with model applications or validations since models are used as tools in the decision-making process (Mailhot and Villeneuve, 2003). The reliability analysis (RA) is a method to quantify uncertainties and risks involved in a system (Cheng et al., 2018). It can provide valuable information for decision-makers such as the risk level and critical components of the system.

In this paper, we will apply RA on the management of uncertainties for municipal solid waste (MSW), which is important for decision-makers to understand the risk level of a SWM system and decide the location and capacity of facilities involved in the system. The proposed method has the following contributions: (i) quantify the risk level in a MSW management system, (ii) propose possible strategies to increase the reliability of the system, (iii) analysis the impacts of different policies on the overall reliability of the system, (iv) identify the critical facilities in the system which has the highest possible to cause the failure of the whole system.

Abbreviations: SWM, Solid Waste Management; WCT, Waste Collection and Transportation; WTS, Waste Transfer Station; FDF, Final Disposal Facility; RA, Reliability Analysis; MSW, Municipal Solid Waste; FOSM, First-Order Second Moment; PEM, Point Estimate Methods; FORM, First Order Reliability Method; GA, Genetic Algorithm.

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The remainder of this paper is structured as follows. Section 2 presents a literature review. Section 3 describes the methodology of reliability analysis of solid waste management systems the optimization model for system reliability maximization. In Section 4, we conduct a case study in Hong Kong to demonstrate the methodology. Then, Section 5 analyses the results of the case study and Section 6 provide the discussions. Finally, the conclusions, limitations of the proposed method, and the future research perspectives are provided in Section 5.

2. Literature review

2.1. Modelling MSW management under uncertainties

Uncertainties are widely considered in optimisation models for SWM (Saif et al., 2017). In general, uncertainty problems in waste management were addressed by using different inexact programming methods such as interval programming, minimax regret optimisation, inexact semi-infinite programming, and fuzzy parametric programming (Singh, 2019). In interval programming, the uncertainties can be expressed as discrete values at certain intervals instead of probability distribution functions (Cheng et al., 2003). Minimax regret optimization technique in which the problem with uncertainty is reduced into a number of certain sub-problems. And these sub-problems are focused on a calculation where the regret of not getting the goal is minimized (Averbakh, 2000). The inexact semi-infinite programming method considers input parameters as the functions of time in given intervals to represent the uncertain feature of the inputs (Guo et al., 2008). In fuzzy parametric programming, interval numbers of fuzzy membership functions are used to represent the input variables (Cheng et al., 2017; Nie et al., 2007). All these methods provide solutions for optimization problems involved in uncertainties. However, they don't have the capability to quantify the uncertainties or help to reduce the risk caused by the uncertainties.

2.2. Reliability analysis

RA is a necessary part of quantitative risk and uncertainties (Portielje et al., 2000). It cannot be neglected when dealing with model applications or validations since models are used as tools in the decision-making process (Mailhot and Villeneuve, 2003). In general, uncertainty is caused by the inherent randomness of physical processes that cannot be eliminated and should be analysed (Bogárdi and Kundzewicz, 2002). The goal of RA is to identify the uncertainty features of the system outputs, which act as a function of uncertainties in both the system model itself and the related stochastic variables. Thus, a formal and systematic framework for quantifying the uncertainty associated with the system outputs is provided (Mirakbari and Ganji, 2010). Additionally, the decision-maker can observe the contribution of each stochastic variable to the overall uncertainty of the system outputs (Ganji and Jowkarshorijeh, 2012).

Traditionally, RA is used in structural projects regarding resistance and loading (Haldar and Mahadevan, 2000). However, it has also been applied in other areas such as water quality modelling (Mailhot and Villeneuve, 2003), water distribution networks (Liu et al., 2015), the failure probability of rock slope (Zhou et al., 2017). The method has also been applied in the waste management area. (Cheng et al.) 2018 developed a model applying FORM in a disaster waste management system considering the uncertainties of disaster waste generation, and landfill capacity. The results show that the model has the capability of maximising the reliability and minimising the total clean-up costs. Cheng et al. (2019) presented a framework to estimate the overall reliability of a disaster waste management system considering the reliability of each route involved in the road network, which provides information to decision-makers regarding the priority of the routes in the system. Nevertheless, to the best of our knowledge, there is no research applied to the RA method in peace-time municipal SWM systems, usually involved with multiple stages of waste management facilities such as waste transfer stations (WTSs) and final disposal facilities (FDFs).

2.3. Reliability analysis methods

Current RA methods have been classified into three categories, namely exact methods, first-order second moment (FOSM) methods and point estimate methods (PEM) (Harr, 1987). Inexact methods (for example, Monte Carlo Simulation), probability distributions are used for comprehensive analysis (Adarsh and Reddy, 2013). In FOSM methods, the functional relationship between independent and dependent variables are simplified by a truncated Taylor series expansion. The inputs and outputs of these processes are expressed as expected values and standard deviations (Madsen et al., 2006). In the cases where the limit state function is either a graph or a chart, or a finite element solution, PEMs are useful (Harr, 1987).

To summary, the objective of this paper is to apply the RA method in a multiple-stage solid waste management system to estimate the reliability of the system and the contribution of uncertain variables involved in the system. Furthermore, we also propose an optimization model to improve the reliability of solid waste collection systems by reallocating the distribution of waste demand between facilities without decrease the waste generation or raise the waste management facilities' capacity. Moreover, we conduct sensitivity analysis to understand the contributions of different policies and event-tree analysis to identify critical facilities in the system.

3. Methodology

3.1. Problem description

Although SWM systems are different from one country to another, the major components of the systems are similar. The common task performed in all SWM systems is the collection of waste from residential areas to FDFs such as recovery plants, composting plants, landfill areas, and incinerators. When the FDFs are located far away from the waste generation area to protect the environment and maintain a reasonable service for the public, an efficient way of performing the waste collection activities is to employ WTSs (Habibi et al., 2017; Kirca and Erkip, 1988). WTSs serve as a link between communities and FDFs with a designated receiving area where waste collection vehicles discharge their loads. The waste is often compacted, then loaded into larger vehicles for long-haul shipment to an FDF (Christensen, 2010).

Normally, a SWM system with WTSs is a two-stage system. In the first stage, waste is collected from the waste generation source to WTSs. In the second stage, waste is transport from WTSs to FDFs. However, depending on the distance between waste generation sources and the FDFs, there can be several levels of transfer stations, which can lead to a three or more stages system. For example, Chongqing city has implemented two-level waste transfer stations, which leads to a three-stage waste collection system (GU, 2019). Recently, there is an increase in the number of WTSs within municipal SWM systems, which will likely continue in the future (Washburn, 2012). For example, in China, two-stage or three-stage waste collection systems has already been widely applied in many cities such as Beijing, Guangzhou, and Shenzhen

(Lu et al., 2015). Therefore, in this paper we will propose a general method to apply RA for a multi-stage SW management system considered the uncertainties in the waste management demand and capacity of facilities in the system.

3.2. Overall reliability of a general solid waste management system

Reliability is defined to measure the possibility whether a system meets certain standards, which can be described as a problem of load and resistance (Melchers and Beck, 2018). In an MSW management system, the capacity (resistance) of each facility should meet the waste management demand (load) of the facility. The reliability index (β) is a commonly used dimensionless indicator to compute the failure probability of a system (Bensoussan, 2005). The higher the reliability index, the safer the system. The reliability of the overall SWM system depends on the reliability of waste management facilities. We assume that there are enough vehicles for solid waste collection and transportation between waste generation origins and FDFs. Fig. 1 shows the reliability of a schematic diagram of a general SWM system, which can have multiple stages in waste collection and transportation (WCT). In the figure, β_{ji}^{WCT} notates the reliability of the i^{th} WTS in the j^{th} stage of waste collection and β_i^{FDF} represents the reliability of the i^{th} FDF which can be a landfill site, an incinerator, or a recycling factory.

The overall reliability of the SWM system can be estimated in three steps. In the first step, we calculate the reliability of each facility in the solid waste management system using the First Order Reliability Method (FORM), which has been applied to analyse the reliability of disaster waste management systems (Cheng et al. 2019; Cheng et al. 2018). The assumption we need to make for the FORM is that both the demand and capacity of each facility in the waste management system follow the normal distribution. Thus, the reliability of the i^{th} transfer station in the j^{th} stage of WCT, which has a capacity C_{ji}^{WCT} $(\mu_{ji}^{WCT_C}, \sigma_{ji}^{WCT_C})$ and a demand D_{ji}^{WCT} $(\mu_{ji}^{WCT_D}, \sigma_{ji}^{WCT_D})$, can be estimated according to Equation (1). Equation (2) can be used to calculate the reliability of the i^{th} FDF, which has capacity C_i^{FDF} $(\mu_i^{FDF_C}, \sigma_i^{FDF_C})$ and demand D_i^{FDF} $(\mu_i^{FDF_D}, \sigma_i^{FDF_D})$.

$$\beta_{ji}^{WCT} = \frac{\mu_{ji}^{WCT_C} - \mu_{ji}^{WCT_D}}{\sqrt{{\sigma_{ji}^{WCT_C}}^2 + {\sigma_{ji}^{WCT_D}}^2}} \tag{1}$$

$$\beta_i^{FDF} = \frac{\mu_i^{FDF_C} - \mu_i^{FDF_D}}{\sqrt{{\sigma_i^{FDF_C}}^2 + {\sigma_i^{FDF_D}}^2}} \tag{2}$$

In the second step, the reliability of the WCT stage and the FDF systems are calculated based on the network reliability theory using Ditlevsen bounds (Ditlevsen, 1979). System reliability is developed to access the reliability index of a system, which has multiple elements (Melchers and Beck, 2018). For example, in the MSW management system, there can be multiple WTSs in each stage of the waste transfer WTS stage, or more than one FDF for final waste disposal. Equations (1) to (3) can estimate the reliability index for a single facility, however the entire reliability of each WTS stage or final waste disposal need to be estimated by system reliability methods. Ditlevsen bound is a method that is developed to estimate system reliability by estimating narrow reliability bounds for a system. The failure probability is calculated as the average of the upper ($p_{j,upper}^{WCT}$ or p_{upper}^{FDF}) and lower probability bounds ($p_{j,lower}^{WCT}$ or p_{lower}^{FDF}) (Ditlevsen, 1979). Equations (3)–(6) are the estimation method for WCT stage j. F^l and F^u are functions for calculating the lower bound and upper bound of the probability of failure of a parallel system, which is described in detailed in (Ditlevsen, 1979). The same theory can be applied to calculate the reliability of the FDFs (Equations (7) to (10)). In the last step, we calculate the overall reliability of the system based on Equation (11).

$$\beta_j^{WCT} = -\phi^{-1}(1 - p_j^{WCT}) \tag{3}$$

$$p_j^{WCT} = \frac{1}{2} * (p_{j,lower}^{WCT} + p_{j,upper}^{WCT}) \tag{4}$$

$$p_{j,lower}^{WCT} = F^l(\bar{\boldsymbol{\beta}}_{\boldsymbol{j}}^{\boldsymbol{WCT}}, \bar{\boldsymbol{\mu}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}, \bar{\boldsymbol{\sigma}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}) \tag{5}$$

$$p_{j,upper}^{WCT} = F^u(\bar{\boldsymbol{\beta}}_{\boldsymbol{j}}^{\boldsymbol{WCT}}, \bar{\boldsymbol{\mu}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}, \bar{\boldsymbol{\sigma}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}) \tag{6}$$

Where $\bar{\boldsymbol{\beta}}_{\boldsymbol{j}}^{\boldsymbol{WCT}}$ is the vector of the reliability of facilities in WCT at stage j;

$\bar{\boldsymbol{\mu}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}$ is the vector of the capacity mean of facilities in WCT at stage j;

$\bar{\boldsymbol{\sigma}}_{\boldsymbol{j}}^{\boldsymbol{WCT_C}}$ is the vector of the capacity standard deviation of facilities in WCT at stage j.

$$\beta^{FDF} = -\phi^{-1}(1 - p^{FDF}) \tag{7}$$

$$p^{W\ \ FDF} = \frac{1}{2} * (p_{lower}^{FDF} + p_{upper}^{FDF}) \tag{8}$$

$$p_{lower}^{FDF} = F^l(\bar{\boldsymbol{\beta}}^{\boldsymbol{FDF}}, \bar{\boldsymbol{\mu}}^{\boldsymbol{FDF_C}}, \bar{\boldsymbol{\sigma}}^{\boldsymbol{FDF_C}}) \tag{9}$$

$$p_{upper}^{FDF} = F^u(\bar{\boldsymbol{\beta}}^{\boldsymbol{FDF}}, \bar{\boldsymbol{\mu}}^{\boldsymbol{FDF_C}}, \bar{\boldsymbol{\sigma}}^{\boldsymbol{FDF_C}}) \tag{10}$$

Where $\bar{\boldsymbol{\beta}}^{\boldsymbol{FDF}}$ is the vector of the reliability of FDFs;

$\bar{\boldsymbol{\mu}}^{\boldsymbol{FDF_C}}$ is the vector of the capacity mean of FDFs;

$\bar{\boldsymbol{\sigma}}^{\boldsymbol{FDF_C}}$ is the vector of the capacity standard deviation of FDFs.

$$\beta = -\phi^{-1}(1 - \phi(\beta_1^{WCT}) * \phi(\beta_j^{WCT}) * \cdots * \phi(\beta^{FDF})) \tag{11}$$

3.3. Optimization of solid waste collection and transportation systems

Many strategies can be implemented to improve the reliability of a solid waste management system. For example, we can build more transfer stations and landfills to increase the capacity of waste management facilities or by using reduce, reuse, and recycle technologies to decrease the generation of solid waste (Chung and Yeung, 2019). We can also achieve a more reliable system by optimizing the demand of the facilities in the system without building new facilities or implementing new policies. For example, consider a simple waste management system which has three landfill sites (L1, L2, L3), with a total waste demand of 90 t and the capacity of each landfill (C1, C2, C3) of 50 t with a standard deviation equal to 5 t. Based on the aforementioned reliability estimation method, the reliability of the system can be improved from 0.7 to 2.1 by optimizing the demand between landfills (D1, D2, D3) (Fig. 2). An optimization model is established to maximize the reliability of a solid waste management system for each WCT stage or FDFs.

Input parameters:

$\boldsymbol{D_j^{WCT}}$**:** Total demand of WCT stage j

$\boldsymbol{D^{FDF}}$**:** Total demand of FDFs

Decision variables:

$\bar{\boldsymbol{d}}_{\boldsymbol{j}}^{\boldsymbol{WCT}}$**:** The vector of demand of facilities in WCT stage j

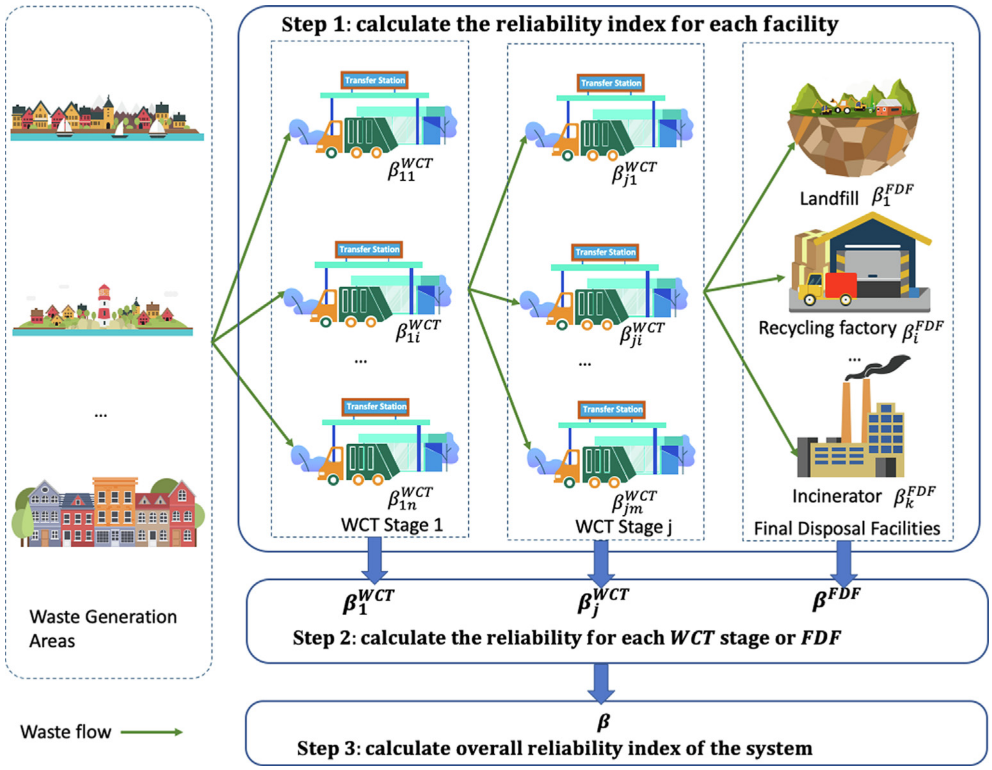

Fig. 1. Schematic diagram showing the reliability of a solid waste collection system (β: the reliability of the overall solid waste management system; β_j^{WCT}: the reliability of waste collection and transportation (WCT) stage j; β^{FDF}: the reliability of final disposal facilities (FDFs)).

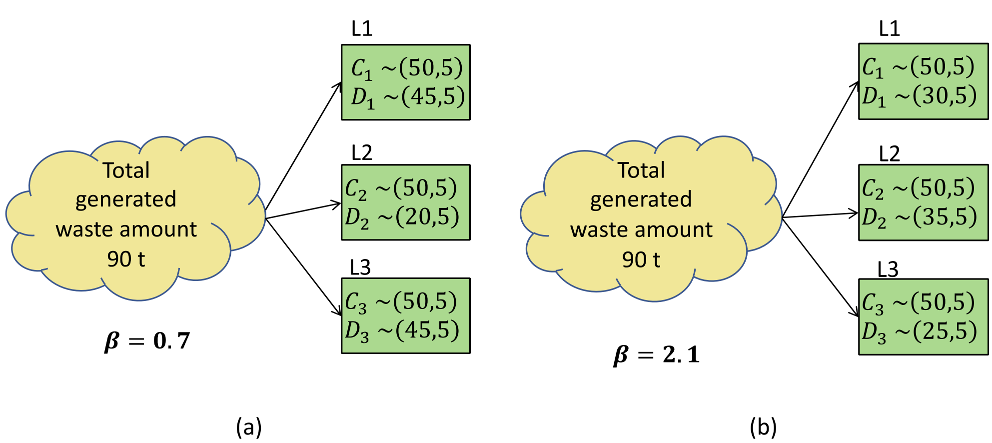

Fig. 2. Reliability of a simple waste management system (a) before and (b) after optimization of the waste arrangement between facilities.

$\bar{d}^{FDF}$: The vector of demand of FDFs

$$\max \beta \tag{12}$$

$$\min\left(\bar{d}_j^{WCT} - \bar{\mu}_j^{WCT_c}\right) \le 0 \tag{13}$$

$$\min\left(\bar{d}^{FDF} - \bar{\mu}^{FDF_c}\right) \le 0 \tag{14}$$

$$\sum \bar{d}_j^{WCT} = D_j^{WCT} \tag{15}$$

$$\sum \bar{d}^{FDF} = D^{FDF} \tag{16}$$

The objective of the model is to maximize the reliability (β) of the system. In the optimization model, constrains (13) and (14) are capacity constrains to avoid overloading the solid waste management facilities. Constraints (15) and (16) aim to ensure all the waste should be processed or disposed in every stage of the system.

The problem is a non-linear model that cannot be solved straightforwardly. Therefore, we developed a genetic algorithm (GA) to solve it. The input variables of the algorithm are shown below. The pseudocode is provided in Algorithm 1. Lines 1 to 12 generate the first generation, which satisfies the constraints mentioned in the model. In lines 13 to 15, the decimal demand values are transferred to binary to generate the coded population in line 16. Lines 18 to 30 describe the general selection, crossover, mutation, and evolution of the generations. The fitness value is the reliability index in this case. Finally, the best population in the last generation is selected as the final result. The GA process is conducted in every WCT stage and FDFs to find the optimized results for the whole solid waste management system.

Variables	Description
C:	Set of the capacity of facilities
F:	Set of facilities
l:	Length of the binary number of the demand
D:	Total demand
n:	Number population in each generation
m:	Number of generations
α:	Crossover rate
γ:	Mutation rate

Algorithm 1: Genetic Algorithm

```
Input: (C, F, I, D, n, m, α, γ)
i = 1
while i ≤ m do
for j ∈ F/|F| do
d_j = round(rand(0,1)C_j)
end
if 0 ≤ D − ∑_{i∈F/|F|} d_i ≤ C_|F| then
for j ∈ F/|F| do
f10_j(i,1) = d_j
end
i = i + 1
end
end
for j ∈ F/|F| do
f2_j = dec2Bin(f10_j, l)
end
P_0 = [f2_1; f2_2; ⋯; f2_{|F|−1}]
k = 0
while k ≤ n do
(Evaluate)
[fitnessVal, selectionProb] = fitnessFun(P_k)
P_k = rank(P_k)accordingtofitnessVal
k = k + 1
P_k = P_{k−1}(1 : m)
for i = 1 : m/2 do
[P_s(1), P_s(2)] = selection(P_k, selectionProb)
(Crossover)
r_c = rand(0,1)
if r_c ≤ α then
[t_1, t_2] = selection(P_s(1), P_s(2))
P_k = [P_k; t_1; t_2]
end
(Mutation)
r_m = rand(0,1)
if r_m ≤ γ then
t_j = mutation(P_k))
P_k = [P_k; t_j]
end
end
end
bestParent = P_k(argmax{fitnessVal(i)|i ∈ P_k})
bestFit = max{fitnessVal}
return bestParent, bestFit
```

3.4. Failure event-tree analysis

An event tree is a graphical representation of the possible outcomes of an incident that results from a selected initiating event (Crawley, 2020). The failure, which means out of function, of one of the facilities in a WCT or an FDF in a SWM system can lead to the reassignment of solid waste treatment demand in the rest of the facilities, which will affect the reliability of the entire system. An event-tree approach can be used to analyze the progressive failure condition for the solid waste management system. To conduct the event-tree analysis, the assumption we make is that when a WCT facility in stage j failed, the demand of this facility will be equally assigned to the other facilities in stage$j$. The same rule also applies to FDFs. This calculation can be iterated until the failure of the last facility in each WCT stage and FDFs. Theoretically, there would be a maximum of $n_1^{WCT}! \cdot n_j^{WCT}! \cdot \cdots \cdot n^{FDF}!$ (n_j^{WCT} is the number of facilities in WCT stage j, n^{FDF} is the number of FDFs) possible failure modes for a solid waste management system. Fig. 3 shows an example of a two-stage solid waste management system with three WCT facilities and two FDFs, which has twelve failure modes. Each failure modes represents the facility failure order. For instance, in FM_1, the WCT_{11} will fail first, then WCT_{12} and following by WCT_{13}, and in the FDF, FDF_2 will fail after FDF_1. The occurrence probability of ther^{th} failure mode FM_r can be calculated using Equation (12), which is an example of calculating the reliability of FM_1 in Fig. 3. The occurrence probability ($\beta_{FM_i}^{WCT}, \beta_{FM_i}^{FDF}$) can also be estimated using Ditlevsen (Ditlevsen, 1979; Yan and Chang, 2009). The event-tree approach can identify the most likely failure mode of the system, which has the lowest reliability and provides decision-makers with useful information in terms of the importance of each facility in the system. For example, if β_{FM_1} is the lowest one among all the failure mode, it means that FM_1 is the most possible failure mode and special attention must be paid on WCT_{11} and FDF_1.

$$\beta_{FM_1} = -\phi^{-1}(1 - \phi(\beta_{FM_1}^{WCT}) * \phi(\beta_{FM_1}^{FDF}) \quad (17)$$

4. Case study

4.1. Case study area

In this section, we use the solid waste management system in Hong Kong to demonstrate the methodology presented in Section 2. The waste management problem in Hong Kong is serious because the three landfills are almost full (Lee et al., 2016). The population of Hong Kong is 7.45 Million in 2018, which generated about 6 million tonnes of waste in the same year. The waste management system in Hong Kong is a typical two-stage waste management system, which includes WTSs to facilitate waste collection and transportation (Lee et al., 2016). The case study in Hong Kong can provide a good representation of the proposed methodology.

Hong Kong generates several different types of waste, such as municipal solid waste (MSW), construction and demolition waste (C&D waste), and hazardous waste. Each type of waste has its own requirements for handling. Here, we consider only MSW and C&D waste, which contributes more than 95% of the total waste generation according to the waste statistic data collected from the Environmental Protection Department of Hong Kong[1]. In Hong Kong's two-stage waste management system, waste is first collected and sent to seven WTSs, which are located in different districts in Hong Kong. Then, they are compacted and containerized in purposely built containers for onward transportation to three strategic

[1] https://www.wastereduction.gov.hk/en/assistancewizard/waste_red_sat.htm

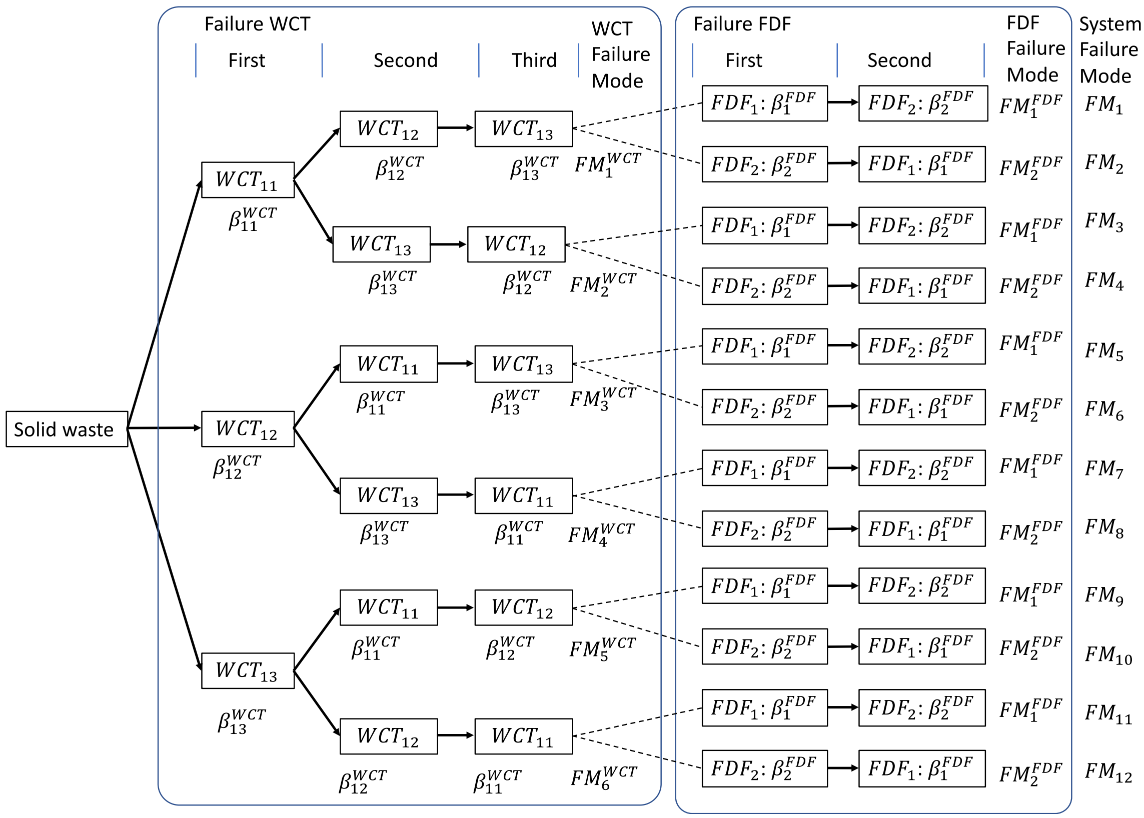

Fig. 3. An example of the failure event-tree for a waste management system with three transfer stations and two final disposal facilities.

landfills. In this case, the seven WTSs are WCT facilities mentioned in Section 2 and the strategic landfills are FDFs. Fig. 4 shows the location of the WTSs and landfills. In Hong Kong, waste is first collected from the source generation area to WTSs (green diamonds in Fig. 4), then the waste is transported to landfills (orange triangles in Fig. 4) after compression.

4.2. Data collection

We collected waste collection and transportation data from the Environmental Protection Department of Hong Kong, which provides the average daily throughout (demand) and the capacity

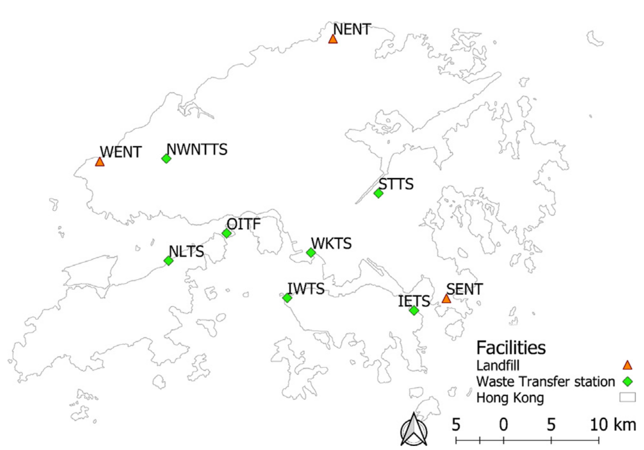

Fig. 4. Location of Transfer stations and landfills in Hong Kong (IETS: Island East Transfer Station, IWTS: Island West Transfer Station, STTS: Shatin Transfer Station, NLTS: North Lantau Transfer Station, OITF: Outlying Islands Transfer Facilities, WKTS: West Kowloon Transfer Station, NWNTTS: North West New Territories Transfer Station, NENT: North East New Territories Landfill, SENT: South East New Territories Landfill, WENT: West New Territories Landfill).

of the 7 WTSs and the 3 landfills in Hong Kong from 2014 to 2018. We also make a simple prediction of the demand from 2019 to 2023 based on the average increase rates from 2014 to 2018 for each WTS and landfill site without considering the policies the government implemented or will implement to reduce the demand. The standard deviation of both the demand and the capacity of each facility is calculated using the Monto Carlo simulation by assuming a 10% randomness in demand and 5% randomness in the capacity of each facility involved in the waste collection and the transportation system in Hong Kong. The uncertainty level in demand and capacity can be obtained from the daily waste treatment data, which is, unfortunately, not available to us. Thus, the proposed randomness level is derived from literature (Srivastava and Nema, 2012). Table 1 shows the summary of the data used for the case study.

5. Results analysis

5.1. Reliability of solid waste collection and the transportation system

In this section, we calculated the reliability of WTSs, FDFs, and the entire waste collection and transportation system in Hong Kong. Fig. 5 shows the reliability indexes from 2014 to 2023 for the original scenario (base case) presented in Table 1 and the results after optimizing the distribution of solid waste collection and transportation using the method proposed in Section 2.3. Fig. 5 presents that the curve of the original reliability index has a slight increase from 2014 to 2015, followed by a continuous decrease till 2020 and the trend continues in the future, which leads to a negative infinite reliability index in the three years.

The results indicate that if the Hong Kong government does not implement any measures to reduce the demand or increase the capacity of the solid waste management system, the system will definitely out of function from 2020. To avoid the failure of the sys-

Table 1
Capacity and demand of waste management facilities in Hong Kong.

Solid waste management facilities		Waste Transfer Stations (tonnes per day)							Landfills (tonnes per day)		
		IETS	STTS	IWTS	WKTS	OITS	NLTS	NWNTS	WENT	SENT	NENT
Capacity		**1200**	**1200**	**1000**	**2500**	**611**	**1200**	**1320**	**8800**	**5000**	**4020**
Read demand	2014	829	1096	599	3023	129	198	1081	7254	4510	3094
	2015	897	1168	859	2786	140	364	1118	7585	4098	3419
	2016	1175	1369	1111	3036	134	635	1165	8814	2500	4019
	2017	1194	1503	1161	3152	137	636	1211	8726	2300	4490
	2018	1225	1655	1153	3199	140	660	1260	8909	2140	5046
Estimated demand	2019	1358	1836	1374	3251	143	928	1309	9396	1802	5704
	2020	1505	2036	1637	3303	146	1304	1360	9910	1518	6448
	2021	1669	2259	1950	3356	149	1833	1413	10,451	1279	7288
	2022	1850	2505	2323	3410	153	2576	1469	11,023	1077	8239
	2023	2050	2779	2768	3465	156	3621	1526	11,625	907	9313
Average increase rate		11%	11%	19%	2%	2%	41%	4%	5%	−16%	13%

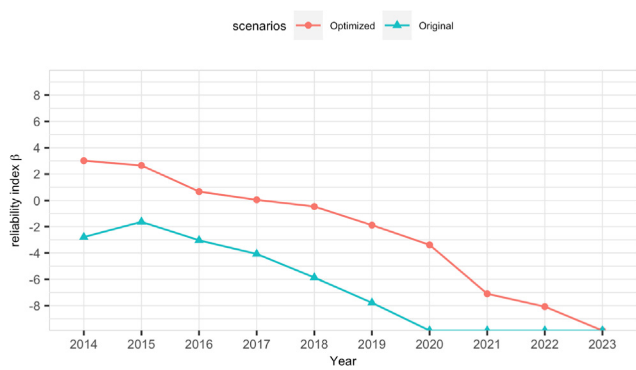

Fig. 5. Comparison between the optimized results and the original reliability index.

tem, the Hong Kong government has implemented several policies or plans. For example, in 2014, a food waste plan to reduce food waste landfill demand by 40% in 2022 (HKEB, 2014). They also built community recycling centers near residential areas to increase the recycling rate. Furthermore, the government proposed to charge for waste disposal (Chung and Yeung, 2019). On the capacity side, extend landfill capacity and the develop a new incinerator are proposed solutions (Chung and Yeung, 2019). However, aforementioned methods are either expensive or take time to play a role. Applying the optimization method proposed in Section 2.3, the reliability index of the waste management system can be improved without additional demand decrease or capacity increase policies.

In order to determine the value of input parameters for the genetic algorithm, we have conducted preliminary testing for the algorithm. The combination of the parameters n = 200 (generation number), m = 1000 (individual number in each generation), α = 0.99 (crossover rate), γ = 0.2 (mutation rate) achieves the best results. In comparison, the optimized reliability indexes are higher reliabilities than the original indexes even though both curves experience a drop-off trend because of the larger volume of the waste. For example, the reliability index increases from about -3 to 2.5 in the year 2014. The results indicate that the optimization of waste distribution between facilities can be used as an efficient policy to improve the performance or reduce the risk in a waste management system in the short-term. However, in the long-term, if waste generation keeps growing and facility capacity stays the same, the system reliability will still decrease with time. Nevertheless, the optimisation method can provide a buffer for decision-makers to develop more effective policies.

5.2. Sensitivity analysis

In this section, a sensitivity analysis is conducted to investigate the impacts of the capacity and demand on the reliability index. Six scenarios are proposed with the same baseline achieved from the optimized results in Fig. 5. In scenarios 1 to 3, the demand of each facility in the waste collection and transportation system remains the same, while the capacity of each facility increases by 10%, 20%, and 50%, respectively. In scenarios 4 to 6, the demand of each facility drops off by 10%, 20%, and 50% with the same capacity as the baseline. The results of the sensitivity analysis are presented in Fig. 6. The results illustrate that small changes (10%) of the capacity and demand has similar and limited impacts on the reliability index of the overall system. However, when the change of demand and capacity increases to 20% or 50%, the impacts of demand become more significant than capacity. Especially, reducing 50% of the demand (scenario 6) has a better performance than increasing 50% of the capacity (scenario 3), which maintains the highest reliability withβ = 10 between 2014 and 2019, notably higher than the second-highest index.

5.3. Event-tree analysis

To evaluate the robustness of the system, the study further investigates the reliability of survival facilities influenced by various failure conditions of WCTs and FDTs. This is achieved by making the damage event-tree analysis, which calculates the reliability indexes sequentially with several hierarchical stages. Then the failure mode for the overall system is calculated based on the method introduced in Section 2.4, which contains $7! \times 3! = 302407$ failure modes. To demonstrate the methodology, Fig. 7 shows the reliability indexes of a part of the event-tree, which includes the top 12 failure modes with the smallest reliability index. It indicates that failure modes (WKTS → STTS → IETS → IWTS → OITS → NLTS → NWNTTS) → (SENT → WENT → NENT) is the failure mode with the lowest reliability, meaning it has the highest failure likelihood. The event-tree analysis can also reveal that the failure of the WCT part will start with facility WKTS, which suggests that the priority is to increase the capacity of WKTS or send less waste to WKTS. On the FDF side, SENT is the most critical one. Thus, if the decision-makers decide to extend the capacity of landfills, then better start with SENT. If the decision-makers plan to build new facilities such as incinerator to share the burden of landfills, a better strategy is to take more share from SENT.

6. Discussions

Based on the results we obtained from the case study, the reliability of the solid waste collection and transportation system is rather low especially in the recent five years in Hong Kong. The optimization of the allocation of waste demand between facilities can improve the reliability of the system in a short-term, which can provide a buff for decision-makers to develop long-term plans to main-

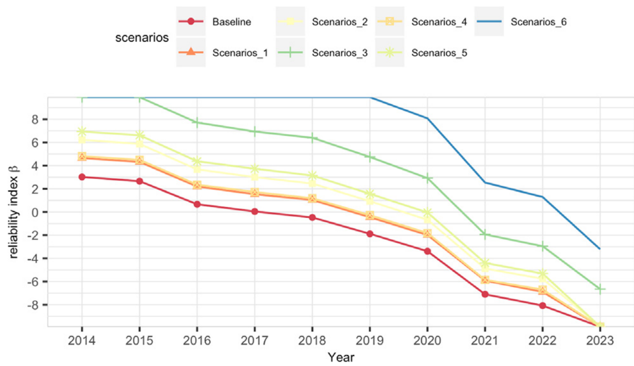

Fig. 6. Analysis of the impacts of facility capacity and recycling rate on the reliability index (Scenario_1: increase capacity by 10%, Scenario_2: increase capacity by 20%, Scenario_3: increase capacity by 50%, Scenario_4: decrease demand by 10%, Scenario_5: decrease demand by 20%, Scenario_6: decrease demand by 50%).

tain the system at a higher reliable level. On one hand, it is necessary for the government to increase the capacities of waste management facilities by either extending original facilities or building new facilities. On the other hand, policies to reduce the generation at source such as the food waste plan already implemented in Hong Kong or increase reuse and recycling are more critical for the system. The event-tree analysis identified the most critical facilities, which are WKTS and SENT in the case study area. They should have priority in future waste management plans in Hong Kong.

This study proposed the reliability analysis method to quantify the risk level of a general SWM system, which is a theorical framework that can be applied in other cities. It is the first attempt to use the reliability index to quantitatively analyse the uncertainties and suggest the risk level of the SWM system. Conventional solution needs to build new facilities or reduce waste generation to improve reliability of a SWM system (Chung and Yeung, 2019; Singh et al., 2019), which is a challenge for cities since urban area is limited and precious, such as Hong Kong. In comparison, with an optimized waste collection and transportation network, our study does not need the implementation of new facilities to improve the reliability of the system instantly, which shows its advance in practical implication for the SWM.

Our study helps to build a robust SWM system. Critical facilities have the highest possibility of causing the failure of the whole system. Previous studies lack the capability of identifying the critical facilities even though they have considered the uncertainties of the SWM (Chen et al., 2017). The event-tree analysis proposed in our study can determine critical facilities accurately, which is a crucial stage to reinforce weak nodes and to achieve a reliable SWM.

Additionally, our study implies policy making. Firstly, results derived from the sensitivity analysis indicate that reducing the food-waste landfill amount and increasing the recycling rate are more efficient than increasing the landfill capacity and building new incinerators. Secondly, the results provide another supportive evidence for using 3R (i.e., Reduce, Reuse, and Recycling) technologies in waste management, which proved to be more environmental friendly (Zan et al., 2020).

7. Conclusions

This paper presents a framework to estimate the reliability of a multiple-stage solid waste collection and transportation systems with transfer stations. The framework consists of three hierarchical components. Firstly, the reliability of the system is calculated using the first-order reliability method and Ditlevsen bounds, considering facilities involved in both waste collection and transportation stages and the final disposal stage. Secondly, to maximize the reliability index of the system without increasing the capacity or reduce the demand of the facilities, we proposed a genetic algorithm to optimize the allocation of waste demand between facilities in different stages. Finally, we applied an event-tree approach to analyse the failure modes of the system. The methodology is demonstrated by investigating the solid waste collection system in Hong Kong, which is a two-stage waste collection system with 7 waste transfer stations and 3 landfills.

While the obtained results are specific to the case study and dependent on the input data collected in Hong Kong, the framework developed in this study can help decision-makers in the following aspects: first, the RA method can quantify the reliability index or risk level of the SWM system; second, the optimisation model provide a solution to improve the system reliability, which can extend the life of a SWM system without additional cost to

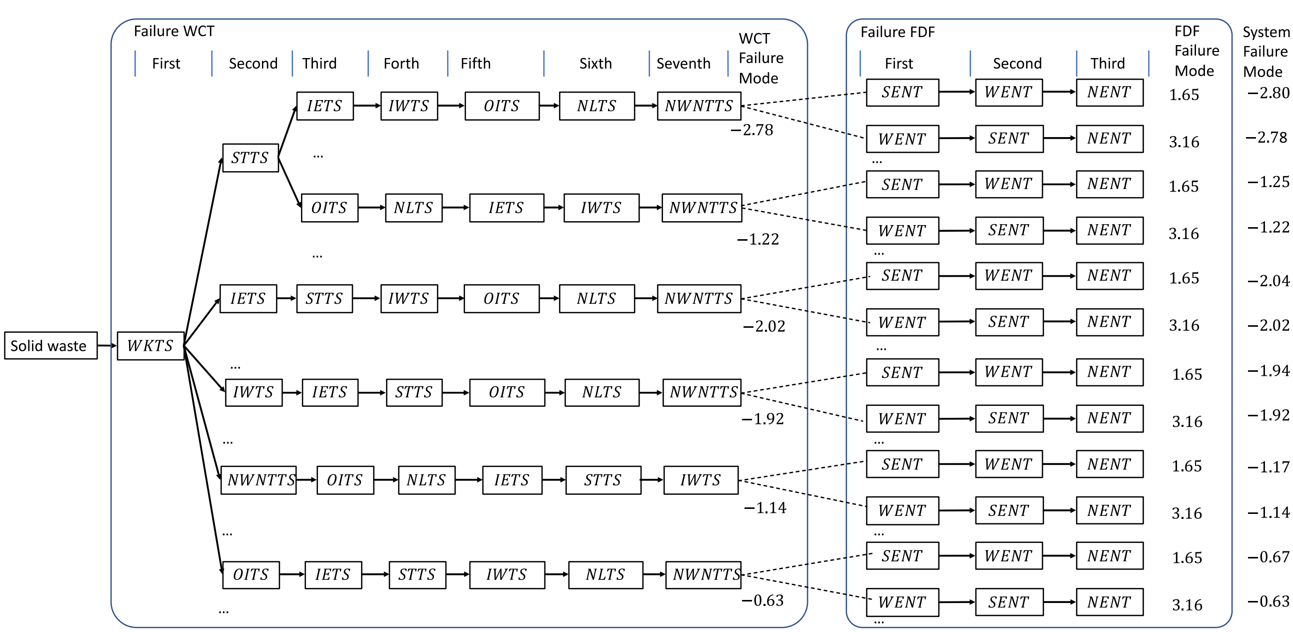

Fig. 7. Selected results of event-tree analysis (top 12 failure modes with the smallest reliability index) in 2014 based on optimized demand distribution results.

reduce waste demand or build new facilities; thirdly, the sensitivity analysis has the ability to analyses the potential contributions of different policies on the SWM system; last but not least, the event-tree analysis identifies the critical facilities in the system, which are important in the waste management plan development. Nevertheless, it should be mentioned that the versatility of the framework needs to be further investigated by involving more case studies. In addition, the route choice of waste collection and transportation, transportation cost, operation cost, and environmental impacts are not considered in the reliability analysis in this study, which could be explored in future work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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