The S-curve for forecasting waste generation in construction projects

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Abstract

Forecasting construction waste generation is the yardstick of any effort by policy-makers, researchers, practitioners and the like to manage construction and demolition (C&D) waste. This paper develops and tests an S-curve model to indicate accumulative waste generation as a project progresses. Using 37,148 disposal records generated from 138 building projects in Hong Kong in four consecutive years from Jan 2011 to June 2015, a wide range of potential S-curve models are examined, and as a result, the formula that best fits the historical data set is found. The S-curve model is then further linked to project characteristics using artificial neural networks (ANNs) so that it can be used to forecast waste generation in future construction projects. It was found that, amongst the S-curve models, cumulative logistic distribution is the best formula to fit the historical data. Meanwhile, contract sum, location, public-private nature, and duration can be used to forecast construction waste generation. The study provides contractors with not only an S-curve model to forecast overall waste generation before a project commences, but also with a detailed baseline to benchmark and manage waste during the course of construction. The major contribution of this paper is to the body of knowledge in the field of construction waste generation forecasting. By examining it with an S-curve model, the study elevates construction waste management to a level equivalent to project cost management where the model has already been readily accepted as a standard tool.

Keywords: Construction waste management; Waste generation quantification; Forecast; S-curve; Curve fitting;

Introduction

Construction and demolition (C&D) waste, sometimes simply referred to construction waste, constitutes approximately 20%-30% of all waste worldwide (Srinivas, 2003). Without proper management of C&D waste can result in severe degradation of the environment (Lu and Tam, 2013; Boiral and Henri, 2012; Coelho and de Brito, 2012). Construction projects, particularly sizable ones, generate a continuous stream of waste that needs to be systematically planned and managed. This is increasingly becoming a normative feature. For example, de Guzmán Báez et al. (2012) reported the Spanish Government's 105/2008 Royal Decree (Ministry of the Presidency, 2008), within which the obligation to develop a waste management plan (WMP) in advance of each construction project is of special interest. The WMP for a project site provides an overall framework for waste management and reduction, and contains key types of waste to be reduced, waste reduction targets, waste reduction programmes, waste disposal procedures, and monitoring and audit (HKEPD, 2009). A WMP is also mandated in economies such as the UK (Brian, 2008) and Hong Kong (HKDB, 2000) for public works projects; failing to consider or comply with it as a legal duty means the commitment of an offense that is punishable by law.

In major economies, based on the polluter pays principle, different C&D waste disposal charging schemes have been enacted, whereby contractors are charged with a levy for every ton of waste they dispose of, e.g. in landfills. Nowadays, it is not uncommon for contractors to put the levy in their bids so that part of the extra cost will eventually be transferred to the client. Hence, it is critical that both client and contractors have a relatively symmetric access to the waste generation information to allow the contract to be fairly awarded. During the course of construction, contractors need the information, e.g. to define the size of roll-off containers, the best form of external and internal transport, and all the waste logistics (Nagalli, 2013). Contractors also need to benchmark actual waste generation against the WMP periodically so that appropriate interventions will be introduced when necessary. In short, forecasting the construction waste generation stream as a project progresses is pivotal in any effort to manage C&D waste.

Owing to its immediate material implications to construction waste management (CWM), forecasting the generation of construction waste has become a hot research topic, often under the umbrella of 'quantifying waste generation'. Bergsdal et al. (2007), Lu et al. (2015) and Lu et al. (2016) reported that forecasting C&D waste generation could be at a project level, a regional level, and a national level. The research reported in this paper is focused at the project level, although it could be used for estimation at a regional level, e.g. by aggregating all the construction projects in the region. Wu et al. (2014) reviewed C&D waste quantifying methods from the perspectives of waste generation activity, estimation level, and quantification methodology, and classified them into the following six types: site visit method, waste generation rate method, lifetime analysis method, classification accumulation method, variables modeling method, and other particular methods. Quantifying construction waste generation can be conducted as a post-mortem of completed or ongoing projects, e.g. by conducting on-site investigation (Lu et al., 2011), analysing waste disposal records (Poon et al., 2004) or material flow (Cochran and Townsend, 2010; Li et al., 2013), but its main thrust is to provide decision-making information for the future.

To provide this decision-making information, it is highly desirable to have a model that can forecast waste generation as the project progresses, or even before the project commences. Notably, de Guzmán Báez et al. (2012) used a linear model to forecast the waste generation stream of Spanish railway projects determined by a few project characteristics, such as length of the railway, and numbers of intersections and underpasses. Cheng and Ma (2013) and Li et al. (2016) analysed waste generation by investigating detailed design and construction units, e.g. work breakdown structure and bills of quantities. Sáez et al. (2014) described the relationship between accumulation of CDW in terms of weight or volume and durations with linear regression with seven residential building projects. While the foregoing studies sensibly emphasize the importance of investigating detailed units, they fall short of providing a reliable waste generation rate (WGR), wastage levels, or conversion ratios of materials to target products. Readers are thus encouraged to refer to the body of references on WGR, which according to Lu et al. (2011) lies at the core of many efforts for understanding waste management in the construction sector. Katz and Baum (2011) developed a novel methodology to predict the accumulation of construction waste based on field observations. According to Katz and Baum (2011), waste "accumulates in an exponential manner". This is clearly a very rough approximation of the real situation, where the amount of waste tends to decrease towards the end of projects as the finishing trades take over – suggesting a sigmoidal or S-curve to be more appropriate. However, no previous research has attempted to articulate the waste stream in this way.

The Project Management Institute (PMI) (2013) defines an S-curve as a graphic display of cumulative costs, labour hours, percentage of work, or other quantities, plotted against time. The name derives from the S-like shape of the curve (flatter at the beginning and end, and steeper in the middle) produced on a project that starts slowly, accelerates, and then tails off. The S-curve is particularly useful in project cost management. For a project of n activities, the cost accruing at time point t is C_t, and the accumulative cost $\sum_{t=1}^{n} C_t$ for a regular project follows an S-curve as the project progresses. Intuitively, the accumulative waste generated from the project should also follow an S-curve. Once the curve is substantiated, it can be used to estimate the total amount of construction waste generation, even during the preconstruction phase. This information is very useful when contractors place the waste levy in their bids. The S-curve can indicate specific accumulative waste generation at time point t and the information is particularly useful for producing the WMP, e.g., in planning the site area for temporarily storing the waste without conflicting with other trades, or planning the transport for waste disposal. During the construction process, it can be used as a baseline against which actual waste generation can be compared and interventions introduced as necessary.

S-curve is a good tool to describe the accumulation of construction activities against time. However, few studies, if not none, have used this tool to describe construction waste generation. Therefore, construction waste management usually lacks effective planning tools. The primary aim of this paper is to propose and test an S-curve for forecasting construction waste generation by taking advantage of a big data set formed by over five million waste disposal records generated from 9,850 projects in Hong Kong from Jan 2011 to June 2015. It tends to provide contractors with not only an S-curve model to forecast overall waste generation before a project commences, but also with a detailed baseline to benchmark and manage waste during the course of construction. The remainder of this paper is structured into five sections. Subsequent to this first introductory section, the second section provides a literature review of previous studies on the S-curve; the third section provides a detailed description of the methodology, at the core of which is curve fitting by trial and error applied to big data and artificial neural networks (ANNs); the fourth section presents the results and findings; the fifth section discusses the results and findings; and the sixth and final section draws a conclusion and makes suggestions for further related research.

2. The S-curve in project management

The S-curve is a graphic display of cumulative costs, labour hours, percentage of work, or other quantities, plotted against time in a project (PMI, 2013). The shape of the S-curve, normally with a smaller slope at the beginning and near the end and a larger slope in the middle, indicates that progress is slower in initiation and closure of resources but faster when the main work takes place. It is able to reveal the overall project progress in single numbers. Early research works suggested the use of cumulative plots of cost versus time and cumulative value versus time for project control, and emphasized its role in facilitating senior managers to clearly understand the overall financial situation. Cash flow forecasting based on S-curves was further developed with more appreciation of financial management in construction in the early 1970s (e.g. Hardy, 1970; Bromilow and Henderson, 1974; Balkau, 1975). Since then, the use of S-curves has been an enduring research topic for project planning and control, in forecasting cash flows in the preconstruction phase, and as targets to assess the delay of actual progress in the construction stage (Chao and Chien, 2009).

There are some risks in using S-curves to establish the progress target for project control. For example, under the threat of penalty for not meeting forecast values, contractors may speed up non-urgent activities at the expense of critical activities needed to achieve the targets (e.g. Jepson, 1969; Kim and Ballard, 2000). However, it should be noted that S-curves provide a simple and handy tool with which project managers can control projects; and the risks of misusing S-curves can be mitigated to a certain extent by integrating them with other project management approaches, such as milestone planning.

There are two approaches to generating S-curves for new projects considering the information available for analysis. One is the schedule-based analysis that accumulates the planned activity times and progress as shown by the formula in the first row of Table 1, which is a brief summary of important mathematical formulas adopted to estimate S-curves. The S-curves developed using this approach are usually uneven due to irregular real-life data series (Chao and Chien, 2009). This approach is only possible when the design and detailed project information is largely settled in advance. The other approach is the historical-data-based estimation. As its name indicates, S-curves developed in this way use data from completed construction projects. The approach can be further divided into two types depending on whether it has specific mathematic formulas. Type one is called envelop curves without specific mathematical formula; curves are used to show the lower, mean, and upper limits of cumulative project progress over time established according to a sample of completed projects. The limited is pre-set by the planner (Kaka, 1999). Type two approach is to characterize the relationship between progress and time with specific mathematical formula. Different mathematical formulas are usually used to estimate the progress along with time-based historical data. Since this study aims to forecast

S-curve of construction waste generation, type two approach using progress versus time relation is adopted in the following investigations.

Table 1 Summary of modelling for estimating S-curves

Type	Sub-type	Formula	Remarks	References
Schedule-based	S1	$P_t = \sum_{i=1}^{n} w_i \times p_{ti}$	Design and detailed project information is available	Chao and Chien (2009)
Historical data and empirical method	H1	Envelop curves without specific mathematical formula	Curves are used to show the lower, mean and upper limits of cumulative project progress over time established according to a sample of completed projects. The limited is pre-set by the planner	Kaka (1999)
Progress versus-time relation	P1	$y = x + ax^2 - ax - (6x^3 - 9x^2 + 3x)/b$	a, b can be evaluated using the Weibull function according to the contract value	Hudson, 1978; Tucker,1988
	P2	$\ln[y/(1-y)] = a + b\{\ln[x/(1-x)]\}$	a, b can be obtained through a linear regression analysis with transformed data set. The first 10% and final 10% of progress data from the set should be excluded for analysis.	Kenley and Wilson (1989)
	P3	$y = [1 + a(1-x)(x-b)]x$	a, b for given project progress data can be obtained through trial-and-error method by matching the right-hand and left-hand sides	Berny and Howes, 1982
	P4	$y = ax^3 + bx^2 + (1-a-b)x$	a, b can be obtained through the least-squared error method with the historical data, which can further be forecast by contract amount, duration, type of work, and location using neural networks.	Chao and Chien (2009)
	P5	$y = \mathrm{erf}\,(\frac{x-a}{b})$	Cumulative normal distribution	Skitmore (1998)
	P6	$y = \frac{e^{a+b^x}}{1+e^{a+b^x}}$	Cumulative logistic distribution	Skitmore (1998)
	P7	$y = \mathrm{erf}\,(\frac{lnx-a}{b})$	Cumulative lognormal distribution	Skitmore (1998)

where w_i=percent weight of activity i in the project; pti=percent complete of activity i at t. x is the standardized time range between 0 and 1, y is the standardized cost/progress range between

0 and 1. erf is the cumulative normal probability function.

Two estimation methods can be used in the historical-data-based approach with mathematic formulas. One is the nomothetic estimation, which generates a standard S-curve as the basis for predicting the S-curve of a new project that can be classified in the same category. Nomothetic estimation is based on nomothetic philosophy, which tries to derive general laws and principles across categorized or non-categorized groups of construction projects (Kenley and Wilson, 1989). Based on previous studies (e.g. Hardy, 1970; Balkau, 1975; Bromilow and Henderson, 1977; Drake, 1978; Hudson, 1978; Oliver, 1984; Singh and Woon, 1984; Miskawi, 1989; Khosrowshahi, 1991), the typical analysis process of nomothetic estimation can be summarized in the following steps: (1) collecting sufficient historical data of project progress such as cost, value, relevant time, and general characteristics of the projects; (2) classifying the projects into different groups according to their general characteristics, e.g. through ANOVA analyses; (3) for each group, identifying the best form of S-curve to fit the historical data of the individual projects; (4) generating a standard S-curve for each project group, the parameters of which is the average value of parameters of all the individual projects in the project group; (5) identifying the best formula, i.e. the one that produces the smallest means square error (MSE) when used for forecasting the historical project data, as different standard S-curves can be generated from different selected formulae; and (6) using the standard S-curve as the basis for prediction of a future project classified in that category.

The other method is the idiographic estimation, which produces an S-curve for a specific project without generalizing it to other projects. Idiographic estimation is based on the idiographic philosophy, which is devoted to understanding the meaning of contingent, unique, and subjective phenomena (Thomae, 1999). The typical analysis process of idiographic estimation can be summarized in the following steps: (1) collecting sufficient historical data of project progress (cost/value), relevant time, and general characteristics from existing projects; (2) identifying the best form of S-curve to estimate the individual project; and (3) identifying the best formula, i.e. the one that produces the smallest MSE when used for forecasting a future project.

Despite the difference in philosophy, there are some commonalities in the two methods. Firstly, they both use curve fitting to identify the best formula among available S-curve formulas to fit actual historical data (e.g. Skitmore, 1992). Secondly, they use MSE as the criterion in identifying the best formula (e.g. Oliver, 1984; Singh and Woon, 1984; Kenley and Wilson, 1989; Miskawi, 1989; Khosrowshahi, 1991; Chao and Chien, 2009). However, researchers have questioned the nomothetic estimation, as it is unreasonable to conduct a scientific investigation into an individual and unique phenomenon (in social science) with the nomothetic approach in natural science (De Groot, 1969; Runyan, 1983). As building projects are usually complex and unique, it is often questionable to use a single and standard S-curve to represent a certain type of project (Hudson and Maunick, 1974; Hudson, 1978). Therefore, idiographic estimation has been increasingly emphasized as it can better reflect historical data but its problem is the lack of the capability to predict cost or waste for new projects (e.g. Thomae, 1999; Chao and Chien, 2009).

Researchers have further developed models to link S-curves (the parameter values of determined S-curve formula) and project characteristics (e.g. contract sum, project type) based on historical data by introducing methods such as artificial neural networks (ANN) (e.g. Chao and Chien, 2009). ANNs are a family of models inspired by biological neural networks (the central nervous systems of animals, the brain in particular) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Researchers such as Chao and Skibniewski (1994), Boussabaine (1996), and Boussabaine and Kaka (1998), pointed out that the capability of ANN to perform nonlinear mapping of output from multiple inputs makes them suitable for handling estimation problems in construction that typically involve complex input-output relations. This study follows this line of inquiry to identify the link between the S-curve of construction waste generation and project characteristics using the idiographic method and ANN.

3. Research methodology

After a detailed review of the literature on the S-curves, the methodology for identifying the S-curve for forecasting construction waste generation (CWG) was developed. The analytical process is illustrated in Figure 1.

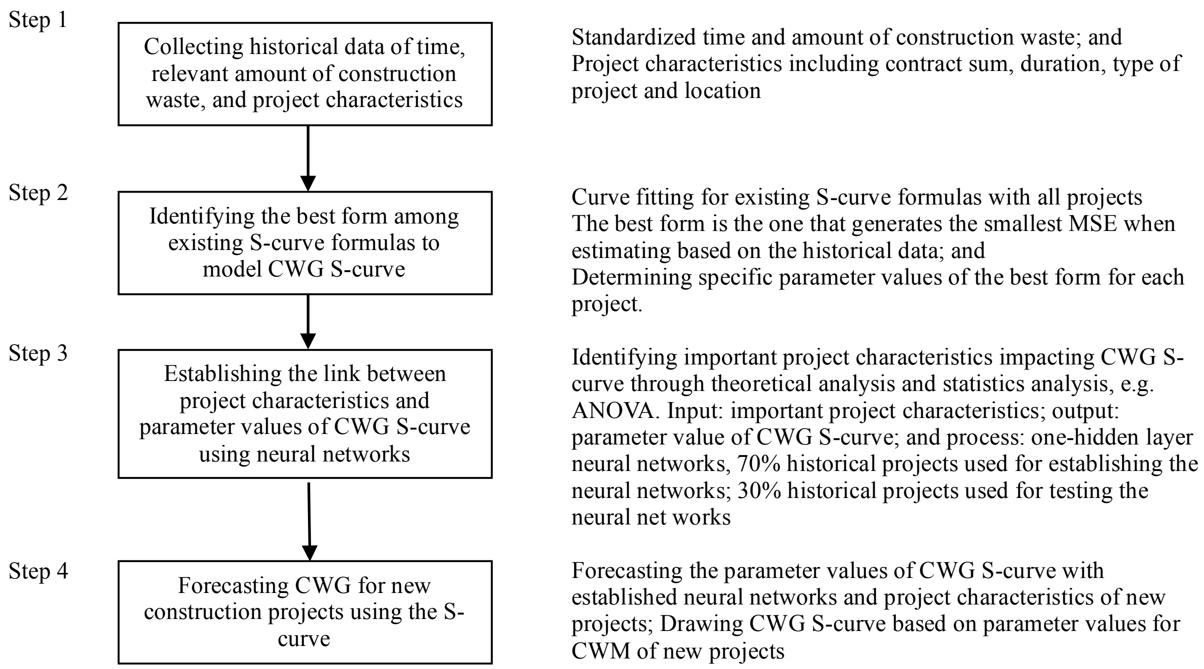


Figure 1 The research methodology for deriving construction waste generation S-curves

Step 1: Collecting historical data of time, relevant amount of construction waste, and project characteristics

In this step, historical data of CWG and relevant project characteristics is collected from completed projects. Construction waste disposal is used as a proxy of CWG, as it is usually difficult to obtain on-site waste generation statistics every day but comparatively feasible to access records of construction waste disposed at various facilities such as landfills, as public departments in charge of these waste disposal facilities normally maintain such records. For construction waste disposal, the time point can be days, weeks or months, which may vary from one region's practice to another. Supposing the total number of projects under investigation is *J*, as a result of this step, two sets of data of the *j*th project are collected as shown in Equations (1) and (2):

$T_j = \{1,2,3,\dots,L_j\}$ Equation (1)

$A_j = \{A_{1j}, A_{2j}, A_{3j}, \dots, A_{Lj}\}$ Equation (2)

where T_j is the time point set of the *j*th project, 1 is first time point of the *j*th project, L_j is the total duration and also implies the number of data points of the *j*th project, A_j is the data set of the construction waste disposal amounts by the *j*th project, A_{1j} is the amount of construction waste disposal by the *j*th project at the first time point, and A_{Lj} is the amount of construction waste disposal by the *j*th project at L_j.

As an S-curve concerns cumulative progress at a specific time point, the data set A_j should be further transformed to AC_j as shown in Equation (3):

$AC_j = \{AC_{1j}, AC_{2j}, AC_{3j}, \dots, AC_{Lj}\} = \{A_{1j}, \sum_{i=1}^{i=2} A_{ij}, \sum_{i=1}^{i=3} A_{ij}, \dots, \sum_{i=1}^{i=L} A_{ij}\}$ Equation (3)

where AC_j stands for the data set of cumulative amount of construction waste disposal by the *j*th project, AC_{1j} is the cumulative amount of construction waste disposal of the *j*th project at the first time point, and AC_{Lj} is the cumulative amount of construction waste disposal of the *j*th project at L_j.

It stands to reason that large-scale projects (e.g. construction volume, or longer duration) will normally generate more construction waste than small-scale counterparts. In order to reduce the impact of project scale, the original data set is standardized for further analyses. To this end, Equations (1) and (3) are standardized in the form of Equations (4) and (5) respectively:

$TS_j = \{TS_1, TS_2, TS_3, \dots, TS_{Lj}\} = \{\frac{1}{L_j}, \frac{2}{L_j}, \frac{3}{L_j}, \dots, 1\}$Equation (4)

$ACS_j = \{ACS_1, ACS_2, ACS_3, \ldots, ACS_{Lj}\} = \{\frac{AC_{1j}}{AC_{Lj}}, \frac{AC_{2j}}{AC_{Lj}}, \frac{AC_{3j}}{AC_{Lj}}, \ldots, 1\}$Equation (5)

where TS_j denotes the data set of standardized time of the *j*th project, and ACS_j denotes the data set of standardized cumulative amount of construction waste generation of the *j*th project.

Apart from the time points and construction waste disposal amounts, the characteristics of the project are also collected. According to existing studies of CWM and S-curves (e.g. Lu and Yuan, 2010; Wang et al., 2010; Chao and Chien, 2009), project characteristics such as duration, contract sum, location, project type, and client type (e.g. private or public) are important in influencing CWG. To identify the full list of project characteristics that has significant influences on CWG would deserve another research paper(s). A wealth of research has been produced while it is still largely inconclusive. This study roots itself in existing studies to identify the project characteristics that matter. Another important consideration is the data availability.

Step 2: Identifying the best form of S-curve to model CWG

This step identifies an S-curve formula that best describes the data sets as shown in Equations (4) and (5). Numerous S-curve models of cost and value have been developed by previous studies. This study borrows such models to model a CWG S-curve. A unique feature of this study is that a wide range of S-curves is examined in order to find the one that best fits the data sets. This is possible given the computational power available today. Software programs are designed in *Matlab* (MathWorks, 2012) to conduct curve fitting so as to select the best-fit S-curve formulas from the options as listed in Table 1.

Least-squares curve fitting analysis (LSCFA) is used to evaluate the fit of an S-curve to the data of a specific project (Lu et al., 2013). The mean-square error (MSE) is usually the specific indicator for the LSCFA, with:

$$MSE_{kj} = \frac{\sum_{i=1}^{i=L}(ACS_{ij} - ACS_{ij}^{k})^2}{L_j} \qquad \text{Equation (6)}$$

where MSE_{kj} denotes the MSE for the *j*th project when adopting the *k*th S-curve formula for curve fitting, L_j is the number of data points of the *j*th project, ACS_{ij} is the real standardized cumulative amount of CWG of the *j*th project at the *i*th time point, ACS_{ij}^{k} is the standardized cumulative amount of construction waste generation of the *j*th project agreeing with the *k*th S-curve formula at the *i*th time point.

Based on Equation (6), the average MSE (AMSE) for all available projects when adopting a specific S-curve formula is:

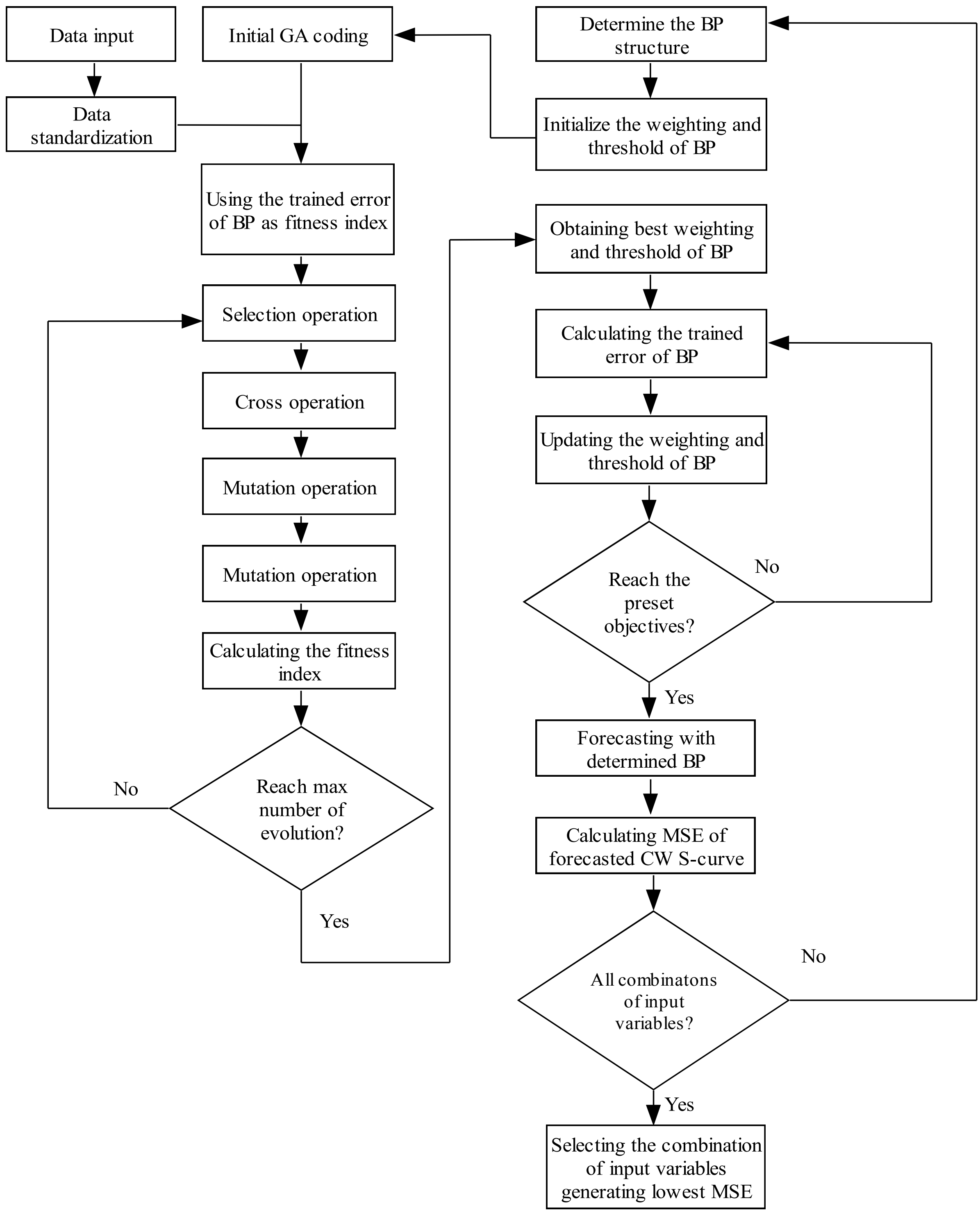
$$AMSE_k = \frac{\sum_{j=1}^{j=J} MSE_{kj}}{J} \qquad \text{Equation (7)}$$

where $AMSE_k$ is the AMSE for all available projects when adopting the *k*th S-curve formula, and J is the number of projects under consideration. The best S-curve formula used to model the S-curve of CWG is the one that generates the minimal AMSE.

Step 3: Establishing the link between project characteristics and parameter values of CWG S-curve using ANN

As a single and standard S-curve is insufficient to forecast CWG in different projects with different characteristics, a specific CWG S-curve needs to be developed by linking the standard CWG curve with the project characteristics. No previous research has been conducted to explore this link. Neither is it clear whether the link is linear or not. Nevertheless, existing studies have demonstrated that there is a complex and non-linear relationship between the cost S-curve and project characteristics (e.g. Chao and Chien, 2009). ANNs are capable of investigating complex, non-linear, or even unknown effects of inputs on outputs. They have also proved to be useful in determining a specific cost S-curve in construction projects and are therefore adopted in this study.

An ANN takes the link between inputs and outputs as a black box, while relying on training data to find the connection structure and weights that best reflect the nexus between inputs and outputs. With real input data (project characteristics in this case) and output data (parameter values of CWG S-curve of existing projects), a feed-forward multilayer network and a supervised learning technique, such as the gradient descent back-propagation (BP) algorithm, are usually adopted for training. The genetic algorithm (GA) performs better in determining the weighting and threshold of ANN models and is therefore combined with BP to develop this study's ANN model. No previous understanding has been gained on the project characteristics that impact a CWG S-curve and therefore an explorative study is used to examine the different combinations of project characteristics as the input variables. The ANN model based on the combination of characteristics that generates the lowest MSE finally determines the ANN model for future forecasting. The detailed algorithm of the ANN model development for this study is illustrated in Figure 2 by referring to Chinese Matlab Forum (2010).



Two-thirds of the real-life data collected is randomly selected for training the model. In order to avoid overtraining, the available training data is further randomly divided into two groups (Chao and Chien, 2009). Training terminates when the MSE of the real-life data and forecast data reach the preset criteria, such as 5%. In addition, one-third of remaining real-life data is randomly divided into two groups to test the performance of the trained model. Such division is a preferred approach to test the suitability of the trained model by avoiding over-fitting problem, which is widely existed in ANN (Chao and Chien, 2009). As shown in Figure 3, the ANN model is determined by its weights, which are adjusted during the training process until the pre-set criteria are satisfied.

After this step, an ANN model that describes the link between project characteristics and parameter values of the CWG S-curve is developed. The ANN model is then used for forecasting the CWG S-curve of a new project in the next step.

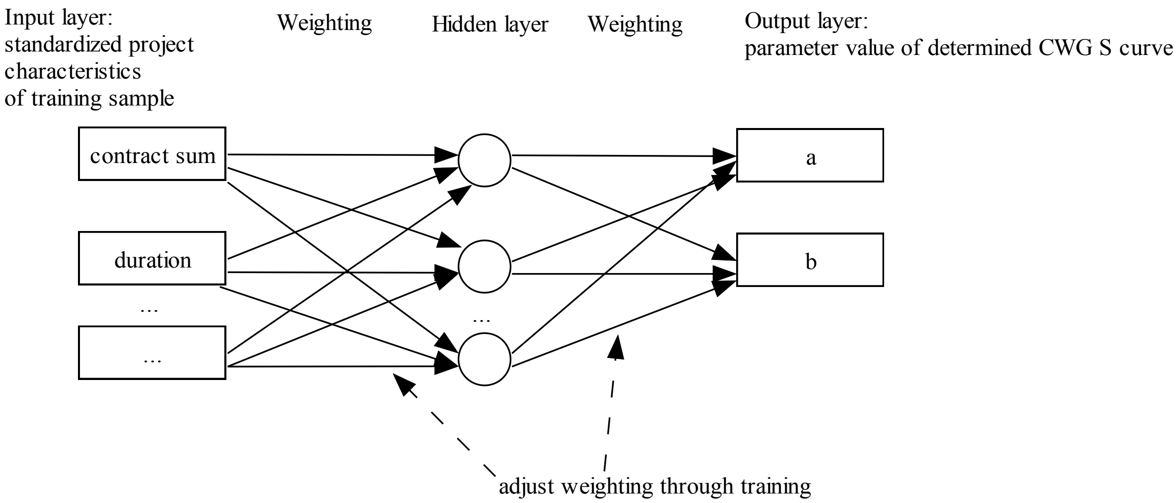


Figure 3 Structure of the ANN model

Step 4: Forecasting CWG by applying the S-curve to new projects with different characteristics

With the developed model in this study, CWG S-curve of new projects can be forecast at the preconstruction phase when the characteristics information of the projects is largely ready. The project characteristics of the new projects can be determined by the contractor reasonable estimation. With the input of project characteristics, the neural network developed in Step 3 can determine the value of parameters of the identified S-curve formula. Finally, CWG S-curve of new projects can be drawn with the parameter value and identified S-curve formula.

4. Data analyses and results

The S-curve for forecasting the waste generation from construction projects is contextualised in Hong Kong. The Construction Waste Disposal Charging Scheme has been enacted to effectively manage C&D waste in Hong Kong since 2006. This involves construction contractors disposing of construction waste in designated facilities such as landfills or public fill, with a waste disposal charging fee being applied for the waste delivered to the facilities. The Hong Kong Environment Protection Department (HKEPD) manages the facilities and also maintains the record of every truckload of construction waste received at a designated facility. The scheme led to the creation of a big data set containing 5,631,539 disposal records generated from 9,850 projects from January 2011 to June 2015. Figure 4 is a screenshot of some typical records included in the big data. Every waste disposal record contains the date of a transaction, the vehicle number, the amount of the construction waste (weight-in, weight-out and net weight), time-in and time-out, and the account number of the corresponding construction project. Using the account numbers, the disposal records are linked to another relational database where project information is stored, such as contract sum, construction type, site address, and client type (see Figure 5).

1	Facility	Transaction Ref No	Vehicle No.	Time-in	Weight-in	Time-ou	Weight-out	Net weight	Account No.	Chit No.	Date of transaction	Waste depth
2	TM38--SF	130000258	KK2684	16:47	7.44	16:51	5.6	1.84	7000205	9787125	1/2/2013	1.17
3	TKO137SF	130000873	KK2684	13:11	7.21	13:23	5.38	1.83	7000205	9787126	1/4/2013	0.82
4	TM38--SF	130000753	KK2684	19:45	6.95	19:50	5.35	1.6	7000205	9787127	1/5/2013	0.61
5	TM38--SF	130000993	KK2684	15:21	7.14	15:25	5.06	2.08	7000205	9787128	1/7/2013	0.59
6	TM38--SF	130001029	KK2684	17:54	6.88	17:58	5.3	1.58	7000205	9787129	1/7/2013	0.43
7	WENT	2091708	KK2684	19:02	6.57	19:14	5.23	1.34	7000205	9787130	1/8/2013	1.09
8	TKO137SF	130002496	KK2684	10:28	7.5	10:40	5.09	2.41	7000205	9787131	1/9/2013	1
9	TM38--FB	130007662	KK2684	14:28	7.28	14:38	5.09	2.19	7000205	9787132	1/9/2013	0
10	TKO137SF	130002851	KK2684	11:02	6.84	11:13	5.29	1.55	7000205	9787133	1/10/2013	1.03
11	TKO137SF	130003792	KK2684	16:24	6.98	16:34	5.32	1.66	7000205	9787134	1/12/2013	0.83
12	TM38--SF	130002190	KK2684	18:32	7.26	18:37	5.3	1.96	7000205	9787135	1/15/2013	1
13	TM38--SF	130002300	KK2684	15:44	7.74	15:49	5.05	2.69	7000205	9787136	1/16/2013	0.74
14	TM38--SF	130002331	KK2684	18:06	7.1	18:10	5.06	2.04	7000205	9787137	1/16/2013	0.75
15	SENT	10504231	KK2684	11:41	6.55	11:49	5.22	1.33	7000205	9787138	1/17/2013	0.71
16	TKO137SF	130006472	KK2684	12:53	7.27	13:04	5.33	1.94	7000205	9787139	1/21/2013	1.23
17	TKO137SF	130007275	KK2684	14:44	7.56	14:56	5.13	2.43	7000205	9787140	1/23/2013	1.28

Figure 4 Screenshot of some typical transaction records in the set of 'big data'

Account	Contract name	Contract sum	Site address	Department	Type of construction work	Detail of construction work
5000241	RENOVATION WORKS TO I	1897881.9	2 MOUNT BUTLER DRIV	---	Renovation	---
5000242	TERM CONTRACT FOR TH	27000000	SHEK LEI (I) ESTATE	HKHA	Others	BUILDING MAINTENANCE & VAC
5000243	ESTATE TERM CONTRACT	25000000	IN YIU (I) & (II) ESTATE	HKHA	Others	BUILDING MAINTENANCE & VAC
5000244	DISTRICT TERM CONTRA	94000000	, TSUEN WAN AND ISL	HKHA	Others	BUILDING MAINTENANCE & VAC
5000245	DEMOLITION WORKS - BL	1680000	EGE PREPARATORY S	---	Demolition	---
5000246	PROPOSED BLOCK E, ST.	3630000	COLLEGE PREPARAT	---	Building	---
5000247	SWIMMING POOL & CLUBH	66861223	TUNG CHUNG	---	Building	---
5000248	ST.GEORGE'S BUILDINGEL	6300000	LDING, 2 ICE HOUSE S	---	Others	CHILLER PLANT REPLACEMENT
5000249	HOS DEVELOPMENT AT E	806350000	ASTERN HARBOUR CR	---	Building	---
5000250	MANAGEMENT, OPERATIO	120000000	1471, OI LAI STREET, S	HyD	Others	ELECTRICAL INSTALLATIONS

Figure 5 Screenshot of 'account details' of projects disposing of construction waste

This big data is expected to allow a CWG S-curve model to be trained and tested so that the model is able to provide adequate forecasts of the progressive waste generation of new construction projects. Since the study aims at discovering underlying patterns in the cumulative amount of construction waste disposal (AC_{Lj}) changes over time for waste disposal (L_j) of construction work, an S-curve describing the change of AC_{Lj} with L_j is drawn for each project by identifying the best form among existing S-curve formulas. Various construction types, such as buildings, demolition, substructures and civil projects are involved in the four years' construction waste disposal transactions. Building projects, which are the most typical construction type in the data set, are selected to develop the S-curve model.

Furthermore, some of the outliers are eliminated before model development. The building projects should comply with the following criteria:

(1) To stay within the scope of the data, the projects should start to generate waste between 31 Jan 2011 and 30 June 2014;

(2) To avoid non-typical projects (e.g. minor maintenance works), the construction waste disposal activities should last more than 30 days; and
(3) To provide a sufficient number of data points for fitting the S-curve, the construction waste should be produced on at least 20 single days.

These resulted in 138 building projects with 37,148 disposal records meeting the criteria. By following Steps 1 and 3, the nine analytical S-curve models listed in Table 1 are used to fit the data of the 138 projects. Table 2 summarizes the results, which show that P6, a cumulative logistic distribution developed by Skitmore (1998), generates the smallest average MSE (see Equation 7 and Table 2). Therefore, the best S-curve form used for fitting the CWG S-curve is:

$$y = \frac{e^{a+b^{x}}}{1+e^{a+b^{x}}}$$ Equation (8)

where x is the standardized time and y is the standardized amount of generated construction waste.

Table 2 Statistical summary of the MSE

Statistics of MSE	P1	P2	P3	P4	P5	P6	P7
Mean	0.0121	0.1221	0.008	0.0049	0.0077	0.0043	0.0339
Median	0.0096	0.1121	0.0041	0.0034	0.0063	0.0032	0.0284
Standard Deviation (SD)	0.0105	0.0634	0.0111	0.006	0.0058	0.0037	0.0478

Taking one of the projects (Project no. 7018343) as an example, when using P6 to fit the CWG S-curve, the fitting form is:

$$y = \frac{e^{-3.3548+11.5191^{x}}}{1+e^{-3.3548+11.5191^{x}}}$$ Equation (9)

The MSE of this fitting is 0.17%. Figure 6 is an illustration of the real-life data and fitted curve.

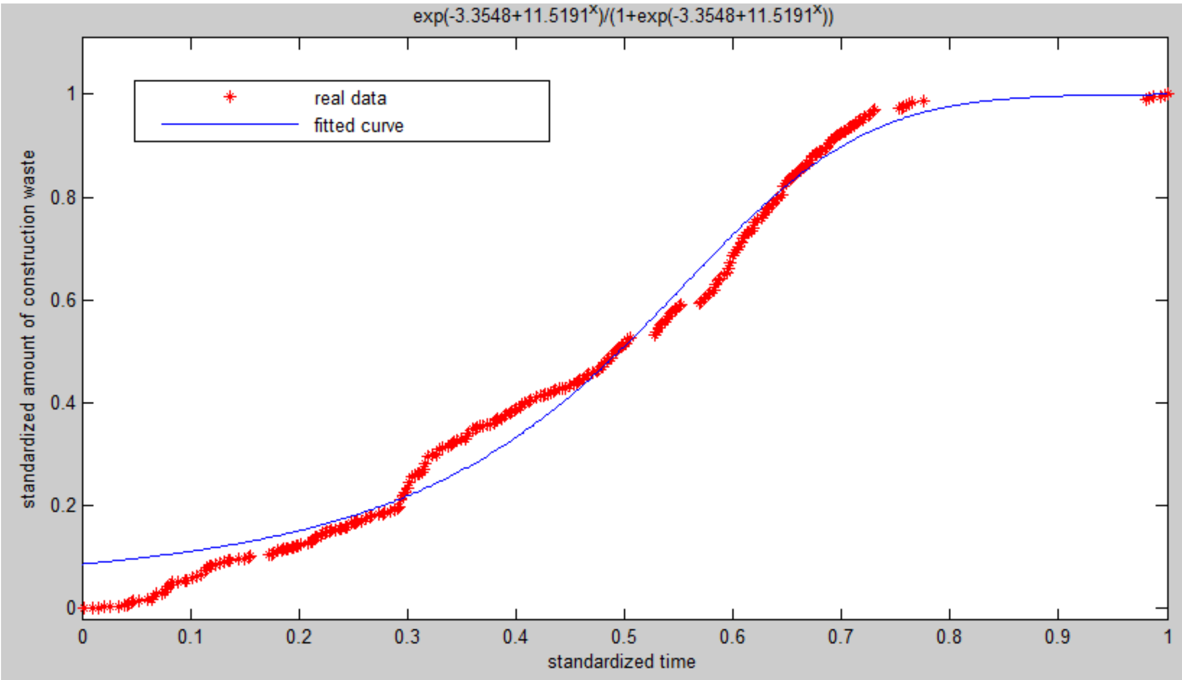


Figure 6 Comparison of the real data and fitted curve when using P6 to fit one of the project data

After the best S-curve formula to fit the CWG S-curve is determined, ANN is used to link the project characteristics and the parameter values, i.e. *a* and *b* in Equation (8). Unlike Equation (8) for a very specific project, the *a* and *b* in Equation (8) should fit a group of projects. Table 3 is a statistical summary of the project characteristics and parameter values.

Table 3 Statistical summary of the project characteristics and parameter values

Group number (location)	Number of projects	Mean value of contract sum (HKD)	Mean value of duration (days)	Mean value of project type(1=public, 0=private)	Mean value of parameter a	Mean value of parameter b
1(NT)	43	284104398.91	713.40	0.12	-3.1931	65.8094
2 (KL)	51	210461785.11	747.72	0.14	-2.9052	42.9622
3(HK)	44	242472233.72	788.93	0.02	-3.0683	17.3411

NT=New Territories, KL=Kowloon, and HK=Hong Kong Island

The data points from 100 of the projects are used in ANN model development through training and the remaining 38 used for model test. In order to reduce data bias, two sets (designated as Modeling Samples 1 and 2, each with 50 projects in it) while two testing groups (designated as

Testing Samples 1 and 2, each with 19 projects) are randomly picked from the 138 projects (Chao and Chien, 2009). Moreover, in order to alleviate potential data distortion, this study standardized the value of original contract sum and duration to be between 0 and 1 according to respective maximum value (Chao and Chien, 2009).

Firstly, an initial configuration is chosen of neural networks of four input nodes, which is the number of input project characteristics, ten nodes in one hidden layer, two output nodes in the output layer, a learning rate of 0.1, and the log-sigmoid transfer function according to Chao and Chien (2009). For parameter setting of GA, the cross probability is 0.4, the mutation probability is 0.2, the size of the population is 20, and the maximum generation (maximum number of iterations of the GA process) is 200. The initial configuration of GA and the operation program is based on Chinese Matlab Forum (2010). Each network's performance is then evaluated by the AMSE as specified in Equation (7). According to Chao and Chien (2009), a few adjustments and trials were made and the final configuration was revised to learning rate of 0.7 and seven nodes in the hidden layer in order to improve the performance of ANN. Using the ANN model, different combinations of project characteristics are tried. In the experimental study, four project characteristics, namely duration, public-private nature, location, and contract sum are available. In order to have a good explanation, at least three project characteristics should be considered, which means there are five combinations as shown in Table 4. After selecting the combinations of project characteristics, the ANN model would be rerun according to the steps as mentioned above.

As specified in Step 3, one set of fifty projects was randomly selected in training samples 1 and 2 while another set of nineteen projects was randomly selected in testing samples 1 and 2 in order to avoid the overtraining problem existed in ANN. Table 4 is a statistical summary of the MSE of the ANN model. For example, the mean MSE of fifty projects in training sample 1 is 4.55%, based on the input of ANN model as project characteristics combination of contract sum, location, public-private nature, and duration. If the input of the ANN model is a combination of project characteristics such as contract sum, public-private nature, and duration, the mean MSE of fifty projects in training sample 1 is 9.61%. It can be found that a combination of contract sum, location, public-private nature, and duration generates the lowest MSE for all samples. Therefore, the combination of contract sum, location, public-private nature, and duration is finally selected as the input of the ANN model for further analysis. For the combination of contract sum, location, public-private nature, and duration, it is found that the mean MSE of training samples 1 and 2 and testing samples 1 and 2 are different. Such difference demonstrates that the ANN model has different explanation for different samples. If training samples 1 and 2 are combined for training the model while testing samples 1 and 2 are combined for testing the model, the mean MSE of the training sample and testing sample would be lowered due to overtraining and over-fitting (Chao and Chien, 2009). Therefore, the results would be twisted without such divisions; it is thus a sensible strategy to divide training samples and testing samples if the sample is sufficient.

Table 4 Statistical summary of MSE of the ANN model (%)

Project characteristics	ANN Sample	Mean	SD	Median
Contract sum, location, public-private nature and duration	Modeling sample 1	4.55	3.73	3.35
	Modeling sample 2	4.88	3.79	3.98
	Testing sample 1	4.68	4.46	2.99
	Testing sample 2	5.00	4.95	3.88
Contract sum, public-private nature and-duration	Modeling sample 1	9.61	7.45	7.60
	Modeling sample 2	7.85	6.41	5.60
	Testing sample 1	9.92	6.75	9.51
	Testing sample 2	9.35	6.12	10.06
Contract sum, location and duration	Modeling sample 1	8.87	8.59	5.62
	Modeling sample 2	8.26	9.04	5.20
	Testing sample 1	9.37	8.74	6.31
	Testing sample 2	8.56	7.66	7.30
Location, public-private nature and duration	Modeling sample 1	8.67	8.30	5.76
	Modeling sample 2	9.63	8.49	6.96
	Testing sample 1	8.89	9.27	4.42
	Testing sample 2	10.59	10.62	5.55
Contract sum, location and public-private nature	Modeling sample 1	9.09	7.17	7.71
	Modeling sample 2	8.43	7.35	6.98
	Testing sample 1	9.44	9.88	5.75
	Testing sample 2	9.83	11.00	5.55

Under the best combination of project characteristics, the mean value of MSE of all samples is below 5% while the median value of MSE of all samples is below 3.98. The statistical results demonstrate that the forecast of CWG S-curve through the ANN model is acceptable. One of the projects in testing sample 1 is used for illustration. Equation (10) illustrates the CWG S-curve, the parameters of which were obtained from the ANN model. The MSE of this forecast is 0.23%. Figure 7 compares the real-life data and CWG S-curve forecast by the ANN model for this project (Project no. 7018343).

$$y = \frac{e^{-3.2560+10.1916^{x}}}{1+e^{-3.2560+10.1916^{x}}} \qquad \text{Equation (10)}$$

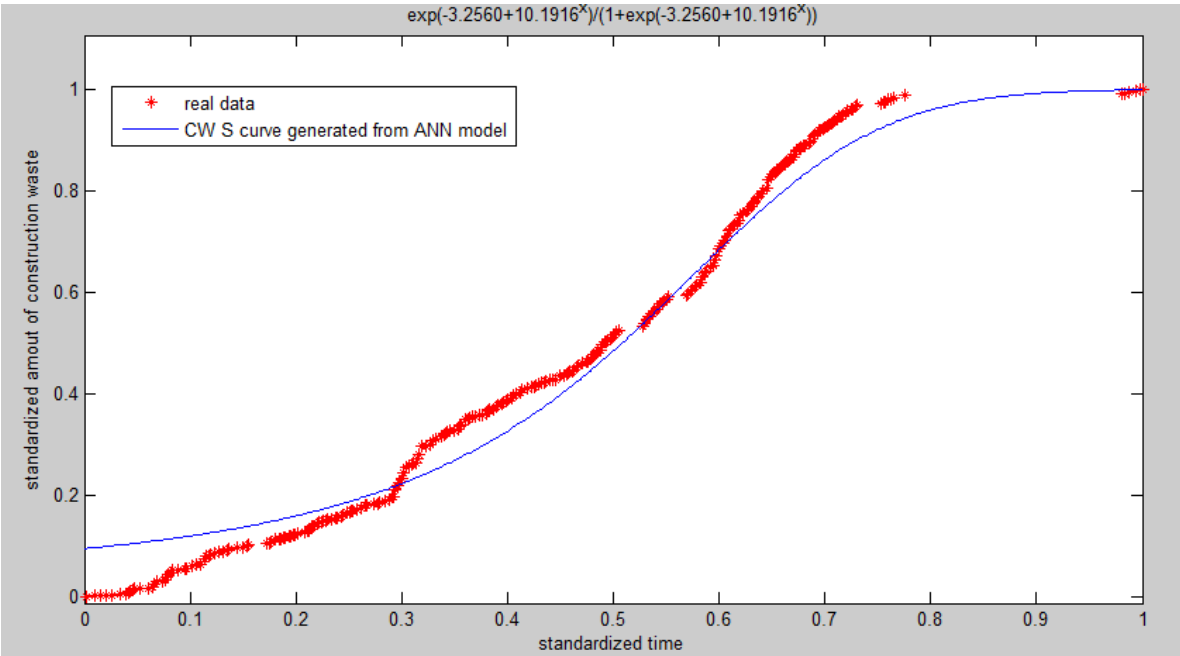


Figure 7 Comparison of real data and CWG S-curve forecast by the ANN model for Project no. 7018343

5. Discussion

This research provides useful references for both industry practitioners and academic researchers in exploring construction waste management.

5.1 Relevance to industry practitioners

As this research relies on detailed project information mined from real-scenario 'big data', the methodology, using the cumulative logistic distribution for progress generalization and ANN model, provides an ideal schedule-based progress estimate for construction control and gives early estimates for decision-makers (i.e. estimators or project managers). In project management schemes, project characteristics are normally stated before the commencement of a construction project. With the input of characteristics including estimated contract sum, site location, and estimated construction duration, the methodology is a potentially useful tool for forecasting the waste generation amount and progress of building projects, thereby bringing various benefits to multiple parties involved in CWM. The S-curve can indicate specific accumulative waste generation at a concerned time point and the information is particularly useful for producing the WMP, e.g., in planning the site area for temporarily storing the waste without conflicting with other trades, or planning the transport for waste disposal. During the construction process, it can be used as a baseline against which actual waste generation can be compared and interventions introduced as necessary. These benefits are as follows:

(1) For project contractors/managers, the model can predict a baseline S-curve to be used for estimating the waste management requirements, such as disposal amount, vehicle amount, piling space, and duty scheduling during construction progress.

(2) At the project planning stage, the CWG S-curve based on the model not only provides consultants with the predicted total waste generation amount, but also indicates construction progress through estimating waste generation progress, so that contractors can estimate financing requirements and personnel demand at different construction stages. For example, by estimating the construction peak of a project from the duration when waste amount soars in the forecast curve, a contractor may allocate more human and financial resources at the peak.
(3) As it is developed from previous building cases, the model can provide decision-makers, such as public policy-makers and building project contractors, with a baseline to benchmark waste generation amounts for future construction works.
(4) Stakeholders in CWM as a whole may utilize this model as a reference to develop a standard and handy tool to be accepted by the construction industry for predicting CWG progress.

5.2 Challenges in applying the CWG S-curve model

Compared with existing studies, the S-curve model provides a simple and handy tool with which project managers can conduct construction waste management. However, this model should be integrated with other construction waste management tools like field investigation to deal with the possible variations between the forecast and real-life waste generation amounts. It should be noticed that the results from this study have certain limitations in application to other projects and areas. The constraints of generation include unforeseen changes in construction projects, other project characteristics affecting CWG, city location of projects, and differences of construction waste management schemes.

Inherently, the accuracy of forecasting the future is open to question, even though the model developed from this study fits the historical data and the case study shows its robustness. Unforeseen changes of construction projects occur frequently, for instance, the emergence of a new construction technology that can systematically reduce CWG across the whole industry, the utilization of new light materials that can bring down the weight of construction waste by a large margin, or the wide adoption of prefabricated members that can sharply mitigate waste generation on site. All these changes will have significant impacts on CWG, hence deviating the estimated S-curve in reality. This study only identifies four project characteristics, namely, contract sum, location, public-private nature, and duration as the determinants of CWG. They are used for deriving parameters of S-curves from the ANN model. Other project characteristics when they are reported as impactful and their data is available, should be considered to develop the S-curve formula and ANN model for the purpose of developing more accurate CWG S-curves.

The CWG S-curve is developed in the context of Hong Kong, which is a small but highly condensed territory having a multitude of high-rise buildings with many standard repetitive floors. It is, therefore, reasonable to predict the total waste amount generated from building projects constructed in highly condensed and well-developed regions that predominantly use steel and concrete composite structure. However, this model should be treated with caution when applied to other scenarios, e.g. villas or low-rise building projects, which are commonly seen in countries with small populations but relatively large territories. As the quantity and quality of materials (e.g. rebar, concrete, bricks, stone) used in low-rise and high-rise structures are greatly different, the waste material amount and type will likely be different for developing the CWG S-curve.

Even in New York, London, Singapore, Tokyo and other places with a large volume of high-rise buildings with similar characteristics to Hong Kong, sufficient caution should be given before predicting waste generation. The differences of construction management schemes (e.g. major structural or finishes materials, or schedule of construction stages) should be considered when forecasting waste generation. For example, the S-curve may also 'twist' with the volume of the on-site buffer for construction waste and the construction progress schedules, which may vary with construction management regulations of specific economies. Although there are certain risks associated with using the S-curve formula and ANN model developed in this study to calculate progress S-curves for cases and jurisdictions that are not similar to those in this study, the research logic is replicable, and is hopefully replicated for developing CWG S-curves in future studies.

6. Conclusions and future studies

Forecasting construction waste generation as the project proceeds is the cornerstone of any effort to manage C&D waste, e.g. pricing construction waste disposal in bidding, benchmarking actual waste generation, introducing construction waste management interventions, and planning external and internal transport and all the waste logistics during the course of construction. This research contributes to previous studies relating to the forecasting of construction waste generation, by offering and testing an S-curve to indicate accumulative waste generation as a project progresses. Benefiting from good data availability, and using curve fitting and artificial neural networks (ANNs), this research found the existence of such an S-curve. By inputting information relating the four project characteristics of contract sum, location, public-private nature, and duration, the S-curve model can satisfactorily forecast waste generation in new construction projects. The S-curve, therefore, provides more scientific evidence for construction waste management.

However, the specific S-curve function identified in this study might not stand in contexts other than the one in which it was developed, i.e. high-rise buildings in Hong Kong predominantly adopting a steel-concrete composite structure. Nevertheless, this study provides an undeniably robust methodology to develop CWG S-curves so that researchers can replicate it and develop CWG S-curves suitable for their own context. It would also be meaningful to investigate CWG

S-curves by considering more project characteristics, such as building height. Furthermore, it is recommended to develop an overall S-curve formula and ANN model for other types of projects (e.g. civil, demolition, foundation, maintenance, and renovation). By following the same methodology, future studies are also recommended to consider unforeseen changes such as new building technologies, new materials, or adoption of prefabricated members, with a view to developing a more accurate estimation of waste generation in construction projects.

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Abbreviations list

C&D waste: construction and demolition (C&D) waste
ANNs: artificial neural networks
WMP: waste management plan
CWM: construction waste management
WGR: waste generation rate
MSE: means square error
CWG: construction waste generation
AMSE: average MSE
BP: back-propagation
GA: genetic algorithm

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