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Forecasting of municipal solid waste quantity in a developing country using multivariate grey models

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ABSTRACT

In order to plan, manage and use municipal solid waste (MSW) in a sustainable way, accurate forecasting of MSW generation and composition plays a key role. It is difficult to carry out the reliable estimates using the existing models due to the limited data available in the developing countries. This study aims to forecast MSW collected in Thailand with prediction interval in long term period by using the optimized multivariate grey model which is the mathematical approach. For multivariate models, the representative factors of residential and commercial sectors affecting waste collected are identified, classified and quantified based on statistics and mathematics of grey system theory. Results show that GMC (1, 5), the grey model with convolution integral, is the most accurate with the least error of 1.16% MAPE. MSW collected would increase 1.40% per year from 43,435–44,994 tonnes per day in 2013 to 55,177–56,735 tonnes per day in 2030. This model also illustrates that population density is the most important factor affecting MSW collected, followed by urbanization, proportion employment and household size, respectively. These mean that the representative factors of commercial sector may affect more MSW collected than that of residential sector. Results can help decision makers to develop the measures and policies of waste management in long term period.

1. Introduction

To plan, manage and use municipal solid waste (MSW) in a sustainable way, accurate forecasting of MSW generation and composition plays a key role (Batinic et al., 2011; Beigl et al., 2008; Cherian and Jacob, 2012; Kumar et al., 2011). However, due to lack of sufficient reliable historical data of MSW characteristics, particularly in developing countries, it is difficult to develop accurate forecasting models (Rimaityte et al., 2011). Failure of accurate forecasting and assessment may lead to several problems in the environment and waste management systems, such as increased environmental impacts and over-or under-estimated capacity of MSW treatment facilities as well as irrelevant policies. In the context of MSW management, it is also necessary to understand how influencing factors (e.g. socio-economic and demographic factors) affect MSW generation.

Beigl et al. (2008) reviewed 45 methods, used for forecasting MSW quantities, which could be categorised into seven groups, such as correlation analysis, group comparison, single regression analysis, multiple regression analysis, time-series analysis, input–output analysis, and system dynamics. Among these methods, regression analysis is widely used to forecast MSW generation due to its mature theory and simple algorithms (Xu et al., 2013). However, regression analysis neither can learn from new data nor can adapt to new situations, and its precision is poor when inaccurate data are used (Ordonez-Ponce et al., 2004; Thanh et al., 2010). Regression analysis does not also consider all factors affecting waste generation (Noori et al., 2009b).

Several literature have shown better results using time-series analysis which appears to be the most appropriate forecasting method considering seasonal impacts (Chung, 2010; Rimaityte et al., 2011). However, this requires a large number of data to provide accurate forecasting in short term period (Beigl et al., 2008; Xu et al., 2013). In waste management perspective, time-series analysis leads to lack of power of generalization and intellectual values, while factor analysis can explain the changes of MSW characteristics associated with influencing variables (Beigl et al., 2008; Chung, 2010).

Recently, Artificial Neural Network (ANN) has been shown to provide more accurate results compared to regression analysis and traditional time series analysis because of the ANN's ability

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to learn and construct a complex nonlinear system through a set of input/output examples (Ali Abdoli et al., 2012; Batinic et al., 2011; Jalili Ghazi Zade and Noori, 2008; Kumar et al., 2011; Noori et al., 2009a; Ordonez-Ponce et al., 2004; Patel and Meka, 2013; Roy et al., 2013; Shahabi et al., 2012). However, it needs a large number of historical data and has some disadvantages, such as over-fitting training, difficulty in the determination of network architecture, local minimum, and poor generalizing performance remain unsolved and limit the application of ANN approach into practice (Abbasi et al., 2014).

To overcome the lack of data for modeling and the complexity of the forecasting model, Grey model (GM) has been implemented successfully to forecast for long-term periods with higher accuracy than conventional time series analyses and ANN (Pai et al., 2008; Srivastava and Nema, 2006; Xu et al., 2013). It is usually represented as GM (m, n) for dealing with m, the order of the differential equation and using n variables (Hsu and Wang, 2009).

Grey system theory which consists of grey relational analysis (GRA), grey generating space, grey forecasting, grey decision making, grey control, grey mathematics and grey theory was initially pioneered by Deng (1989) in 1982. For grey forecasting, GM (1, 1), an univariate model, conforms to the grey exponential law (Tien, 2012) and is the most widely used in MSW forecasting and other applications, with higher accuracy (Chen and Chang, 2000; Guo, 2009; Liu and Yu, 2007; Srivastava and Nema, 2006; Untong, 2012; Xiang and Daoliang, 2007; Xu et al., 2013; Ying et al., 2011). In addition, GM (1, 1)-α, i.e., applying GM (1, 1) with adaptive levels of α, has also been used in a tourism field (Huang, 2012), however, it has not been applied in MSW management.

Nevertheless, forecasting of MSW generation by univariate model is not satisfactory because solid waste is heterogeneous and can be affected by numerous factors (Ali Abdoli et al., 2012; Chen, 2010). Therefore, GM (1, n), a multivariate model, which was also pioneered by Deng (Deng, 1988 cited from Tien, 2012) has been implemented for MSW forecasting (Wang et al., 2012; Zhang, 2013) and other applications (Hsu and Wang, 2009; Pai et al., 2008, 2007). For the multivariate grey model, GRA was used to investigate the relationship between MSW generation and other factors affecting amount of waste (Liu and Yu, 2007; Wang et al., 2012). However, in view of provision of supplementary information, the prediction accuracy of GM (1, n) should be higher than that of GM (1, 1). The solution of the whitening differential equation of GM (1, n) can be mostly inaccurate and may thereby producing significant practical forecasting errors (Tien, 2012). According to Tien (2012), the GM (1, n), as $n \geqslant 2$, can only be used for relational analysis of the system's factors but cannot be used for prediction.

Grey model with convolution integral GMC (1, n) was proposed by Tien (2005) to derive a more accurate trend by adding a grey control parameter u, like GM (1, 1) besides the same terms of the GM (1, n) model. Thus, the GMC (1, n) can degenerate to be GM (1, 1) for the special case $n = 1$ and becomes the linear differential equation (Tien, 2005). GMC (1, n) model has been applied in only few studies such as internet access population forecast (Wu and Chen, 2005) and the indirect measurement of tensile strength forecast (Tien, 2012). However, its application of MSW management has not been found.

A few literature identified and quantified the influencing factors affecting MSW quantities in residential and commercial sectors using regression analysis and geographical information system (GIS) approaches (Buenrostro et al., 2001; Lebersorger and Beigl, 2011; Purcell and Magette, 2009). Several studies forecasted MSW quantity in Thailand using regression and time-series analyses associated with few influencing factors, such as population, GDP and expenditure (DEDE, 2009; Luanratana, 2003; Mongkoldhumrongkul and Thanarak, 2012; TGO, 2010; Vanapruk, 2012). These results might be inaccurate due to insufficient number of data. Also, a study investigated the factors affecting MSW generation by comparing standardize coefficient at a city level (Sukholthaman and Chanvarasuth, 2013). However, the model providing explanatory factors affecting residential and commercial wastes has not been found.

This study attempts to identify, quantify and select suitable factors affecting the MSW collected. For policy and planning of waste management, these factors represent the influence of residential and commercial sectors. Especially, the study aims to develop the alternative models (i.e. GM (1, 1), GM (1, 1)-α, GM (1, n) and GMC (1, n)) and select the most accurate to forecast MSW collected with the uncertainty forecasting, prediction interval (PI) approach.

The information related to Thailand and the data collection used in this study is given in Section 2. The methodology and the literature review of the hypothesis of influencing factors and MSW forecasting models are described in Section 3. The results are illustrated and discussed in Section 4. Finally, Section 5 concludes the key findings and provides recommendations for further research.

2. Background of study area and data

Thailand located in Southeast Asia has total area of approximately 513,000 km^2 and has population of 64.6 million in 2012. As one of the rapidly increasing income and urbanization country, MSW generation in Thailand increased by 3.34% during the four years, i.e., from 23.93 million tonnes (Mt) in 2008 to 24.73 Mt in 2012 (PCD, 2013). The highest amount of MSW generation was 25.35 Mt in 2011 due to the huge flood. In 2012, about 13.62 Mt or 55% of MSW generated was disposed through open dumping or burning sites and left within the township (PCD, 2013). In early 2014, a fire broke out at several dump sites and caused two hundred residents to move away due to the release of poisonous gases (Fredrickson, 2014). Hence a critical problem facing Thailand is also a serious issue of managing the huge amount of MSW generated associated with environmental impacts. Ineffective policies is another vital problem of MSW management. In the Tenth National Economic and Social Development Plan (NESDP: 2007–2011), Thailand could not achieve both targets as part of MSW management strategies i.e., 30% of waste generation recovered by 3R and waste-to-energy (WTE) (about 26% of such was achieved) and 40% of waste generation disposed properly (approximately 38% of such could be obtained) (Vanapruk, 2012).

As waste generation cannot be measured directly in developing countries, the amount waste reported in a country level is normally obtained from municipalities measuring from the estimation of vehicles capacity and/or weight at the dump sites. The quantities of MSW was reported by the Pollution Control Department (PCD) in the country level, as called MSW collected in this study, including the amount of residential and commercial wastes (PCD, 2001-2013, 2011). The time series of the amount of MSW collected and influencing factors were accessed from PCD, the National Statistical Office (NSO) (NSO, 2013), the Bank of Thailand (BOT) (BOT, 2014), the Bureau of Registration Administration (BORA) (BORA, 2014) and the Bureau of Epidemiology (BOE) (BOE, 2014). These time series data during 2000–2012, totally 13 data, were used to develop models. Ten data, i.e. during 2000–2009, were used in building the alternative models, while the remaining data; i.e., three data during 2010–2012, were used for verification by the calculation of the error measure (mean absolute percentage error: MAPE).

3. Methodology

As shown in Fig. 1, the study could be distinguished as having four main steps for forecasting the MSW collected, i.e. (i) identifying and selecting the influencing factors, (ii) developing

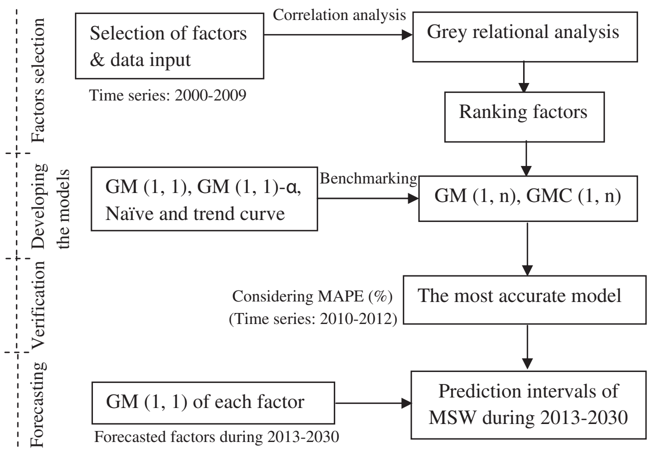

Fig. 1. Procedure for forecasting MSW quantity collected.

the alternative models, (iii) verifying the models, and (iv) forecasting amount of MSW collected at country level with prediction interval (PI).

3.1. Identification and selection of factors

This section consists of two steps i.e., (i) identifying the influencing factors based on literature review and (ii) selecting the suitable factors based on statistics and mathematical approaches.

3.1.1. Identification of the factors

Table 1 presents the most important influencing factors affecting MSW quantities based on study of 50 literature considering different levels, household, city and country. According to Buenrostro et al. (2001), Lebersorger and Beigl (2011) and Purcell and Magette (2009), these factors can be categorised into two groups, based on six criteria such as the frequency of use, the effect of the factor on waste generation, redundancy of factors, the applicability with the models, the similar studied area with Thailand (i.e. developing country, middle income, Asian country) and relation and availability in Thailand in order to aid understanding of waste generation patterns beyond, referring to waste generated by residential and commercial sectors. Based on characteristics of the factors, they can also be grouped in two categories i.e., socio-economic and demographic factors as presented in Fig. 2 and described below.

Socio-economic factors consist of income, gross domestic product (GDP), expenditure, tax, employment, unemployment, number of overnight stays per habitant of tourists and business travelers, energy consumption, etc. Among these, income is the most widely and significantly hypothesized factor in MSW forecasting, followed by GDP, expenditure and employment, respectively.

In order to investigate the relationship between MSW generation and socio-economic factors at household level, questionnaires survey has effectively been used for data collection (Beigl et al., 2008). Income is widely utilized to forecast MSW quantity at household and city levels. Higher income represents higher potential consumption and more waste generated. However, income is not only a function as daily life consumption, but also a function as investment in edible goods and paying debt. Therefore, some literature found that income affected MSW generation insignificantly (Mohd.Yosof et al., 2002; Skovgaard et al., 2005). Liu and Yu (2007) also found that income was the least (among seven factors) factor affecting waste quantity.

GDP represents the situation of a country's economy while GDP per capita represents power of pay per capita. The increase of GDP leads to increase the waste generation because high prosperity increases consumer activities and business expansion (Mazars, 2003 cited from Purcell and Magette, 2009). Despite GDP not being a measure of living standard, it has been hypothesized in MSW forecasting at city and country level because it is often measured consistently, frequently, and is widely available (Ahmad, 2012; Kumar et al., 2011; Liu and Wu, 2010; Sjöström and Östblom, 2010). However, Sokka et al. (2007) and Liu and Wu (2010) did not find the clear-cut relationship between GDP and the quantity of wastes in Finland and China, respectively. There seems to believe that improved policy measures contributed the reduction of MSW and a decoupling of MSW generation and GDP (Sokka et al., 2007). Liu and Wu (2010) also found that the annual growth rate of GDP, a factor that is often used for analyses did not match the MSW quantity.

From Table 1, though consumption expenditure is observed to be a factor less important than the GDP, the proportion of significantly to insignificantly hypothesis is higher than that of GDP. Several studies also found that consumption expenditure are connected more closely with MSW generation than GDP (Liu and Wu, 2010; Liu and Yu, 2007; Weng, 2009). Therefore, individual consumption expenditure were reasonably and significantly hypothesized as a driving force of MSW generation and composition (Skovgaard et al., 2005; Weng, 2009).

Proportion of employment represents the wage and purchasing power of the citizen at city and country levels. Higher the proportion of employees to total citizens in any area, the more MSW is generated due to economic prosperity (Bandara et al., 2007; Batinic et al., 2011; Rimaityte et al., 2011).

Demographic factors comprise population, population density, number of households, urbanization, household size, age of people, education and attitude, number of rooms of a habitant, infant mortality rate, life expectancy at birth, etc. Population-related factors (population, population density and number of household) are the most widely and significantly hypothesized to forecast MSW generation, followed by household size, urbanization, education, and age-related factors, respectively. Social characteristics and demographic factors were identified as the most significant factors to explain the variation of MSW generation than economic ones (Chen, 2010). A number of previous research studies have significantly hypothesized population-related factors affecting MSW quantities positively. The number of households or size of population was closer correlated with MSW quantities than the level of private consumption (Skovgaard et al., 2005). This means that higher population generated larger quantities of MSW (Chen, 2010). This has been shown to be the best factor for explaining the increasing of MSW (Skovgaard et al., 2005). Johnstone and Labonne (2004) selected population density instead of total population in order to avoid the redundancy of factors (with urbanization as described below).

Household size or family size has widely been hypothesized at household level. It should be noted that the literature reviewed can be categorized in two groups. First, the literature which surveyed the data of influencing factors using questionnaires and investigated MSW characteristics at households; household size affected MSW quantities significantly and positively. This means that single family generated MSW lower than multi-family dwelling (Beigl et al., 2008). Second, literature that surveyed using questionnaires for data collection of the factors at household level but carried out MSW characteristics at municipal level or from statistical data; household size factors affected waste quantities significantly and negatively. This means that average household size decreased and where there has been an increase in apartment type dwelling, MSW has increased (Purcell and Magette, 2009).

As industrialization and urbanization changed people's lifestyle, this phenomenon has been brought as 'mass production, mass

Table 1
MSW forecasting models and the hypothesis of influencing factors.

Models	Methods used	No. of data	No. of regions	Type of data	Period forecasted	Level of data collection	Influencing factors considered											Remarks	References
							GDP	Income	Expense	Employment	Urbanization	Family size	Age	Population	Education	Waste generated rate	Other factors		
Thailand																			
Regression	MRA	9	1	Y-TS	S	CO$^{\blacktriangledown}$			+●$^{(1)}$					+●$^{(2)}$					Vanapruk (2012)
	MRA	10	1	Y-TS	L	CI$^{\blacktriangledown}$	+●^{1}							+●					Mongkoldhumrongkul and Thanarak (2012)
	SRA	60	1	M-TS	L	CI$^{\blacktriangledown}$	+●^{1}									+●			Luanratana (2003)
	SRA	12	1	Y-TS	L	CO$^{\blacktriangledown}$													DEDE (2009)
	MRA	96	1	M-TS	–	CI$^{\blacktriangledown}$	●$^{(1)}$	●$^{(1)}$				●$^{(2)}$		●$^{(2)}$			No. of household$^{(2)}$, CPI$^{(1)}$	Standardize coefficient compared	Sukholthaman and Chanvarasuth (2013)
Time series	TSA	16	1	Y-TS	L	CO$^{\blacktriangledown}$	+●							+●		+●		Extrapolation	TGO (2010)
Other countries																			
Statistics data analysis	CA	110	$1^{CI}/4^{*}$	CD	–	HH▽		+●$^{(4)}$		+●$^{(3)}$		+●$^{(1)}$	○		+●$^{(5)}$		(+) No. of rooms$^{(2)}$, marital status area of urban construction, area of paved roads, area of urban garden, No. of large cities, energy consumption		Sankoh et al. (2012)
	PCA, CTA	21	1	Y-TS	–	CO$^{\blacktriangledown}$	○	○	○		○							Among 3 groups, economic and urbanization is the most important.	Liu and Wu (2010)
	ANOVA	125	1^{CI}	CD	-	HH$^{\blacktriangledown}$		●				●			●				Ojeda-Benítez et al. (2008)
Regression	CA, MRA	100	1^{CI}	CD	–	HH$^{\blacktriangledown}$		+●$^{(3)}$				–●$^{(2)}$		+●$^{2(1)}$					Thanh et al. (2010)
	CA, MRA	400	6^{CO}	CD	–	HH$^{\blacktriangledown}$		–●		+○		+○			–●		No. of room		Monavari et al. (2011)
	MRA	7 each	5^{CO}	Y-TS	L	CO▽,$^{\blacktriangledown}$	●				●			●	●^{3}				Khajuria et al. (2010)
	MRA	243	1^{CI}	CD	–	HH$^{\blacktriangledown}$		+●$^{(1)}$		○		+●$^{(2)}$	○		○		No. of working date, area of facilities, working hours per day	Studying on non-and-residential waste	Buenrostro et al. (2001)
	MRA	542	1^{ST}	CD	–	CI▲				○		–●$^{(2)}$	○	○^{4,5}			(–) heat$^{(1)}$,(–) tax$^{(3)}$, over night stay, percentage of building/area		Lebersorger and Beigl (2011)
	MRA	422	1^{CI}	CD	–	HH$^{\blacktriangledown}$		+●		+●		–●					Tax, No. of vehicles in household		Bandara et al. (2007)
	MRA	550	1^{CI}	CD	–	HH$^{\blacktriangledown}$		+●$^{(2)}$				–●$^{(1)}$			○		(–) tipping fee per household$^{(3)}$		Abuhress (2013)
	MRA	100	1^{CI}	CD	–	HH$^{\blacktriangledown}$		○				+●$^{(1)}$	○		○		(–) dining out$^{(2)}$, home cooking rate, marital status, religion, sex, race, house category, ownership status, unit types, home cooking	Data collection at household level, conclusion at city level	Mohd.Yosof et al. (2002)
	SRA	14, 34	2^{CO}	Y-TS	–	CO▲	●		●					●				The EU countries and the US	Daskalopoulos et al. (1998)
	MRA	10	1	Y-TS	L	CI$^{\blacktriangledown}$			+●$^{(2)}$		+●$^{(1)}$								Yuan et al. (2012)
	MRA	NA	1	NA	NA	CO$^{\blacktriangledown}$	●				●								Wang and Nie (2001)
	MRA, CA, PCA, OLS	86	55^{CI}, 32^{CO}	PD, Y-TS	–	CI, CO▲	+●$^{(4)}$					–●$^{(1)}$	+●$^{7(3)}$				Unemployment rate, (–) infant mortality rate$^{(5)}$, over night stay, (+) life expectancy at birth$^{(2)}$	Three prosperities were studied	Beigl et al. (2004)

Table 1 (*continued*)

Models	Methods used	No. of data	No. of regions	Type of data	Period forecasted	Level of data collection	Influencing factors considered: GDP	Income	Expense	Employment	Urbanization	Family size	Age	Population	Education	Waste generated rate	Other factors	Remarks	References
Regression	FGLS	156	30^{CO}	PD	–	HH▲			+●$^{(3)}$		+●$^{(2)}$			+●$^{2(4)}$			(−) percentage of children$^{(1)}$		Johnstone and Labonne (2004)
	SVM, PLS-SVM	144	1	PD, W-TS	–	CI▼		●											Abbasi et al. (2013)
	SVM, WT-SVM	>240	2	W-TS	–	CI▼		●											Abbasi et al. (2014)
Time series & combined model	TSA	1–12 each	15^{CO}	PD	L	CO▲	●		●			●		●			No. of household, Gross value added	Individual forecasting of the EU countries.	Skovgaard et al. (2005)
	MRA,TSA (ARIMA, SES)	87, 384	1	PD, W-TS	L	CI▲	○			●		●	●				Infant mortality rate, life expectancy,% of labour force		Rimaityte et al. (2011)
	TSA (ARIMA), FA	29	1	Y-TS	L	CI▲	●$^{(2)}$							●$^{(3)}$			(−) No. of housing estates participated$^{(1)}$		Chung (2010)
	TA (SARIMA), GM (1, 1)	120, 10	1	M-TS	S, L	CI▼													Xu et al. (2013)
Grey models	GFM (1,1)	10	1	Y-TS	-	CI▼													Xiang and Daoliang (2007)
	GM (1,1),, GFM (1,1)	14	1	Y-TS	S	CI▼													Chen and Chang (2000)
	GM (1,1)	10	1	Y-TS	L	CI▼													Guo (2009)
	GM (1,1),GFM, GRA, GRNN	13	1	Y-TS	S	CI▼	●$^{(3)}$	●$^{(2)}$						●$^{(1)}$					Srivastava and Nema (2006)
	GRA, GM (1,1), GIM (1), GPPM (1), GLPM (1)	13	1	Y-TS	L	CI▼	●$^{(4)}$	●$^{(7)}$						●$^{(6)}$			Consumption of gas$^{(1)}$, water$^{(2)}$, and consumption of electricity$^{(3)}$, total retail sales $^{(5)}$		Liu and Yu (2007)
	MRA, GM	14	1	Y-TS	S	CI▼											No detail of factors of MRA and GM		Ying et al. (2011)
	GRA,GM(1,5)	10	1	Y-TS	L	CI▼	●$^{(4)}$		●$^{(2)}$		●$^{12(1)}$						Sales of consumer goods$^{(3)}$		Wang et al. (2012)
	GM (1,5)	9	1	Y-TS	S	CI▼	●$^{(4)}$		●$^{(3)}$					●$^{(1)}$			Retail sales$^{(2)}$		Zhang (2013)
Kuznets curve	EKC	275	25^{CO}	PD, Y-TS	–	CO▲	○		○		○	○	○	+●$^{2(1)}$			Policies, (−) share of manufacturing$^{(2)}$	EU25 countries case	Mazzanti and Zoboli (2008)
	MRA, EKC	11 each	6^{CI}	Y-TS	–	CI▼		●$^{(6)}$		−●$^{6(2)}$			-●$^{(3)}$	●$^{2(5)}$	●$^{(4)}$		(+) policy$^{(1)}$		Chen (2010)
Artificial Neural Network	OLS, ANN	120	1	M-TS	L	CI▼		+●$^{(3)}$						+●$^{(1)}$			(+) maximum temperature$^{(2)}$		Ali Abdoli et al. (2012)
	MRA, ANN	342	1	Y-TS	–	CO▲		−●$^{8(3)}$			+●$^{(4)}$			+●$^{(1)}$	+●$^{(5)}$		(+) No.of libraries$^{(2)}$		Ordonez-Ponce et al. (2004)
	ANN, PCA-MRA	158	1	W-TS	S	CI▼										●	No. of trucks		Noori et al. (2009a)
	ANN	144	1	W-TS	S	CI▼										●	No. of trucks		Jalili Ghazi Zade and Noori (2008)
	ANN	54	1 ^{CO}	CD, W-TS	L	CI▼		●		●			●		●		Housing condition		Batinic et al. (2011)
	ANN	40	1	Y-TS	L	CI▼	●				●			●		●			Kumar et al. (2011)
	ANN	144	1	W-TS	–	CI▼										●	No. of trucks		Shahabi et al. (2012)
	ANN	384	1	W-TS	–	CI▼													Roy et al. (2013)
	ANN	98	1ST	CD	L	CI▼								●		●	Total received as tax, latitude, longitude		Patel and Meka (2013)
	WT-ANFIS, WT-ANN	240	1	W-TS	–	CI▼													Noori et al. (2009b)

(*continued on next page*)

Table 1 (*continued*)

Models	Methods used	No. of data	No. of regions	Type of data	Period forecasted	Level of data collection	Influencing factors considered: GDP	Income	Expense	Employment	Urbanization	Family size	Age	Population	Education	Waste generated rate	Other factors	Remarks	References
Econometric	OLS, LES, MNL, SESY	25	1[ST]	Y-TS	L	CI[▼]	●		●	○		○	○	○			Unemployment, policies, saving rate, No. of household, ratio of family, Gini coefficient, Engel ratio		Weng (2009)
	SEM, OLS	NA	5[ST]	Y-TS	–	CI[▼]											Urban road lighting[(1)], community health center visits[(2)], accommodation enterprises[(3)], passenger traffic volume[(4)], investment enterprises profit rate[(5)]	All factors affected to MSW positively	Yu et al. (2014)

Remarks: ○ denotes as insignificant factor, ● denotes as significant factor (as concluded in the literature reviewed).
[(1), (2),…, (n)] denotes the order of significant factors from the most important variables to the least one.
[CI] City region, [CO] Country region, [ST] State region, *Constituency region.
ANFIS – Adaptive Neuro-Fuzzy Inference System; ANN – Artificial Neural Network; ANOVA – Analysis of Variance; ARIMA – Autoregressive Integrated Moving Average; CA – Correlation analysis; CTA – Cluster Analysis; EKC – Environmental Kuznets Curve Hypothesis; FA – Factor analysis; FGLS – Feasible General Least Square; GFM – Grey fuzzy dynamic model; GIM – Grey index model; GLPM – Grey logarithm power model; GM – Grey model; GPPM – Grey parabola power model; GRA – Grey relational analysis; GRNN – General regression neural network; LES – Linear Expenditure System; MRA – Multiple regression analysis; MNL – Multinomial Logit; OLS – Ordinary Least Square; PCA – Principal Component Analysis; PLS-SVM – Hybrid Partial Least Square and Support Vector Machine; SARIMA – Seasonal Autoregressive Integrated Moving Average; SEM – Spatial error model; WT-SVM – Hybrid Wavelet Transform-Support Vector Machine; SES – Seasonal exponential smoothing; SESY – Simultaneous Equation System; SRA – Single regression analysis; TSA – Time-series analysis.
PD – Panel data, the term of data refers to multi-dimensional data frequently involving measurements over time; CD – Cross-sectional data, data collected by observing many subjects at the same point of time or without regard to differences in time; W-TS – Weekly time-series; M-TS – Monthly time-series; Y-TS – Yearly time-series.
S – Short term period (⩽5 years); L – Long term period (>5 years).
CO – Country level; CI – City level; HH – Household level; ▽ low income country; [▼]middle income country; ▲ high income country; NA – Not available.
[1] Gross Provincial Production or GPP; [2] population and population density; [3] illiteracy rate; [4] population and population density; [5] percentage of population in each ranked age and percentage of immigrants; [6] unemployment rate; [7] percentage of population aged 15–59 years; [8] indigents; [9] consumption of gas, [10] consumption of water, [11] consumption of electricity; [12] No. of urban non-agriculture population.

consumption, mass waste discard' (Weng, 2009). The proportion of population in urban areas significantly and positively affected MSW generation. Also, the total amount of MSW has been affected by the growth of urbanization, rather than by GDP (Rimaityte et al., 2011).

Several studies included age as an influencing factor in the different models at various levels. Elderly couples generated lower MSW quantities than that of households with infants and schoolchildren (Beigl et al., 2008). However, most of such literature concluded that age affected quantity of waste insignificantly. In addition, education or attitudes factors which were primarily used in many literature to explain the changes of MSW generation at the household level but were not considered significant for MSW modeling at municipality level (Lebersorger and Beigl, 2011).

3.1.2. Quantification and selection of influencing factors

To develop the multivariate grey models, the influencing factors are essentially ranked and shown that the highest grey relational grade (nearby 1.0) is the most important factor affecting MSW quantity. The aim of this step is to quantify and select the factors proposed from the previous section. Based on statistics, Pearson correlation coefficient was firstly used to ensure that the proposed factors are related to MSW collected, and then grey relational analysis, the mathematics-based, is used to rank these factors based on the sequences of importance.

3.1.2.1. Grey relational analysis (GRA). GRA is utilized to determine the relationship between reference series and compared series, which are denoted as $x_0 = (x_0(1), x_0(2), x_0(3), \ldots, x_0(k))$ and $x_i = (x_i(1), x_i(2), \ldots, x_i(k)),\ (i = 1, 2, \ldots, n)$, respectively. The grey relational coefficient can be obtained from Eq. (1) while Eq. (2) provides grey relational grade (Hsu and Wang, 2009; Liu and Yu, 2007).

$$\gamma(y_0(k), y_i(k)) = \frac{\min_i \min_k |y_0(k) - y_i(k)| + \rho \max_i \max_k |y_0(k) - y_i(k)|}{|y_0(k) - y_i(k)| + \rho \max_i \max_k |y_0(k) - y_i(k)|} \quad (1)$$

$$\gamma(y_0, y_i) = \frac{1}{m}\sum_{k=1}^{m} \gamma(y_0(k), y_i(k)), \quad i = 1, 2, \ldots, n, \quad k = 1, 2, \ldots, m \quad (2)$$

where, $\rho \in (0, 1)$, generally taken as 0.5, which is the distinguishing coefficient used to diminish the effect of a large absolute error.

3.2. Developing the alternative models

The annual time series MSW collected from 2000 to 2009 were used to develop the alternative models including five univariate models (Naïve, trend curve analysis, GM (1, 1), GM (1, 1)-α = 0.1 and GM (1, 1)-α = 1.0) and ten multivariate models (GM (1, 2)–GM (1, 6) and GMC (1, 2)–GMC (1, 6)). For multivariate models, the time series of ranked influencing factors from Section 3.1.2 were input into these ten models. In this section, three steps were involved in developing the model. First, assuming an initial series of MSW collected and influencing factors as $x_1^{(0)}$ and $x_2^{(0)}$ to $x_n^{(0)}$, respectively. The accumulated generating operation (AGO) of these series was then applied for both the reference series (MSW collected) and compared series (influencing factors) as defined $x_1^{(1)}$ and $x_2^{(1)}$ to $x_n^{(1)}$, respectively. Second, the unknown variables of the first order differential equation built using the AGO series were determined by the ordinary least square method (OLS). Third, the results from the previous step were input in the forecasting equation of the various grey models as discussed further.

The Naïve method states that the value of the period to be forecasted equals the value of the last period for which data is available: $F_k = A_{k-1}$ (Hsu and Wang, 2009). Trend curve analysis is a simplest method which can also be used to forecast amount of waste in this study by $\widetilde{F}_k = 9.3582 \times k^3 - 56272.2433 \times k^2 +$

$112791308.9809 \times k - 75359185666.6011$ at time k (estimated by the author).

In grey model, the first index stands for first order derivative of I-AGO (accumulated generating operation) series of second index. The procedures of grey models are investigated by assuming an initial series as: $x_i^{(0)} = \{x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(k)\}$, $i = 1, 2, \ldots, n$, $k = 1, 2, \ldots, m$ which is non-negative series. Based on the initial series, AGO is defined as $x_i^{(1)} = \{x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(k)\}$, where $x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j)$.

3.2.1. GM (1, 1) and GM (1, 1)-α models

The GM (1, 1) and GM (1, 1)-α models represent the first-order and one-variable grey differential equation model without considering influencing factors (Huang, 2012; Xu et al., 2013). The first order differential equation of GM (1, 1) and GM (1, 1)-α is $\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = u$, where a is a developing coefficient, and u is a control parameter. These variables can be determined by ordinary least square method (OLS) as (Hsu and Wang, 2009; Huang, 2012; Liu and Yu, 2007; Xu et al., 2013):

$$[a \quad u]^T = (B^T B)^{-1} B^T Y_n, \text{where}$$

$$B = \begin{pmatrix} -[\alpha x_1(1) + (1-\alpha)x_1(2)] & 1 \\ -[\alpha x_1(2) + (1-\alpha)x_1(3)] & 1 \\ \vdots & \vdots \\ -[\alpha x_1(m-1) + (1-\alpha)x_1(m)] & 1 \end{pmatrix} \text{ and } Y_n = \begin{pmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{pmatrix}, \tag{3}$$

where α is in the range of [0, 1]. When α is close to 0 (zero), it means that the old data is more important to the system. Conversely, if α is close to 1.0, the latest data is very important. If $\alpha = 0.5$, GM (1, 1)-α will be the GM (1, 1). The forecasting function of GM (1, 1) and GM (1, 1)-α is re-written as:

$$x_1^{(1)}(k) = \left[x_1^{(0)}(1) - \frac{u}{a}\right]e^{-a(k-1)} + \frac{u}{a} \text{ and } x_1^{(0)}(k) = x_1^{(1)}(k) - x_1^{(1)}(k-1) \text{or} \tag{4}$$

$$x_1^{(0)}(k) = \left[x_1^{(0)}(1) - \frac{u}{a}\right](1 - e^a)e^{-a(k-1)}, \quad k = 2, 3, \ldots, m \tag{5}$$

3.2.2. GM (1, n) model

In order to forecast MSW collected associated with $n-1$ number of influencing factors, these factors are input in the discrete equation of GM (1, n) which is $x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=2}^{n} b_i x_i^{(1)}(k)$, where $k \geqslant 2$ and z is a back ground value, $z_1^{(1)}(k) = 0.5x_1^{(1)}(k) + 0.5x_1^{(1)}(k-1)$. These parameters can also be estimated by OLS as (Hsu and Wang, 2009):

$$[a \quad b_2 \quad \cdots \quad b_n]^T = (D^T D)^{-1} D^T Y_n, \tag{6}$$

where

$$D = \begin{pmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_n^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_n^{(1)}(3) \\ \vdots & \vdots & \vdots & \\ -z_1^{(1)}(m) & x_2^{(1)}(m) & \cdots & x_n^{(1)}(m) \end{pmatrix} \text{ and } Y_n = \begin{pmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{pmatrix}.$$

The forecasting equation of GM (1, n) is denoted as (Hsu and Wang, 2009; Zhang, 2013)

$$x_1^{(1)}(\tilde{k}) = \sum_{l=2}^{n} \beta_l x_l^{(1)}(k) - \alpha x_l^{(1)}(\tilde{k} - 1), \tilde{k} = 2, 3, \ldots, m, \tag{7}$$

where $\alpha = \frac{a}{1+0.5a}, \beta_l = \frac{b_l}{1+0.5a}, l = 2, 3, \ldots, n$.

3.2.3. GMC (1, n) model

Almost all algorithms of the convolution integral GMC (1, n) model are similar to GM (1, n). While GMC (1, n) is added with the grey control parameter u, as in GM (1, 1), besides the same terms of the GM (1, n) model (Tien, 2012). The grey control parameter u is introduced into the GMC (1, n) model so that GMC (1, n) can degenerate to be GM (1, 1) for the special case $n = 1$. Thus, the representation for GMC (1, n) becomes the linear differential equation as written as $x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=2}^{n} b_i x_i^{(1)}(k) + u$ where, a is the grey control parameter and b_i are the associated coefficients corresponding to the associated series $x_i^{(0)}$, $i = 2, 3, \ldots, n$, respectively. These modeling parameters of GMC (1, n) can also be determined by OLS (Tien, 2005, 2012; Wu and Chen, 2005) as:

$$[a \quad b_2 \quad \cdots \quad b_n \quad u]^T = (E^T E)^{-1} E^T Y_n \tag{8}$$

$$\text{where } E = \begin{pmatrix} -z_1^{(1)}(2) & z_2^{(1)}(2) & \cdots & z_n^{(1)}(2) & 1 \\ -z_1^{(1)}(3) & z_2^{(1)}(3) & \cdots & z_n^{(1)}(3) & 1 \\ \vdots & \vdots & & \vdots & \\ -z_1^{(1)}(m) & z_2^{(1)}(m) & \cdots & z_n^{(1)}(m) & 1 \end{pmatrix}, \quad Y_n = \begin{pmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{pmatrix}, \text{ and} \tag{9}$$

$$f(k) = b_2 x_2^{(1)}(k) + b_3 x_3^{(1)}(k) + \ldots + b_n x_n^{(1)}(k) + u, k = 2, 3, \ldots, m \tag{10}$$

The estimated value can be obtained from

$$x_1^{(1)}(k) = x_1^{(0)}(1) \times e^{-a(k-1)} + \frac{1}{2} \times e^{-a(k-1)} \times f(1) + \sum_{\tau=2}^{k-1}[e^{-a(k-\tau)} \times f(\tau)] + \frac{1}{2} \times f(k), \quad k = 2, 3, \ldots, m, \tag{11}$$

$$x_1^{(0)}(k) = x_1^{(1)}(k) - x_1^{(1)}(k-1), \quad k = 2, 3, \ldots, m, \tag{12}$$

where $x_1^{(1)}(k) = e^{-a(k)}$ is the unit impulse response function $h(t)$ of the model $x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=2}^{n} b_i x_i^{(1)}(k) + u$.

3.3. Verification of the models

The mean absolute percentage error (MAPE, %) which is a sensitive measure as defined as $MAPE(\%) = (\sum_{k=1}^{m} |(A_k - \widetilde{F}_k)/A_k|/m) \times 100$, where A_k denotes actual observations, and $\widetilde{F}_k$ denotes the forecasted value, is used to evaluate the performance of the alternative models (Hsu and Wang, 2009; Pai et al., 2007; Xu et al., 2013).

This study forecasts MSW collected using ex-ante forecast and validates the models by using ex-post forecast. The MAPE of the models are carried out using three years of data, during 2010–2012 on the average, and compared to select the most accurate model. The performance of the forecasting models can be categorized into four categories as listed in Table 2 (Lewis, 1982).

3.4. Forecasting of MSW collected with PI

Literature often forecast MSW generation as single numbers or point forecasts which gave no guidance as to their likely accuracy. Prediction intervals (PI) presents an important part of the forecasting process intended to indicate the likely uncertainty in the point forecasts and the different planning strategies for the range of possible outcomes. PI comprises an upper and a lower limit between which the future value is expected to lie with a prescribed

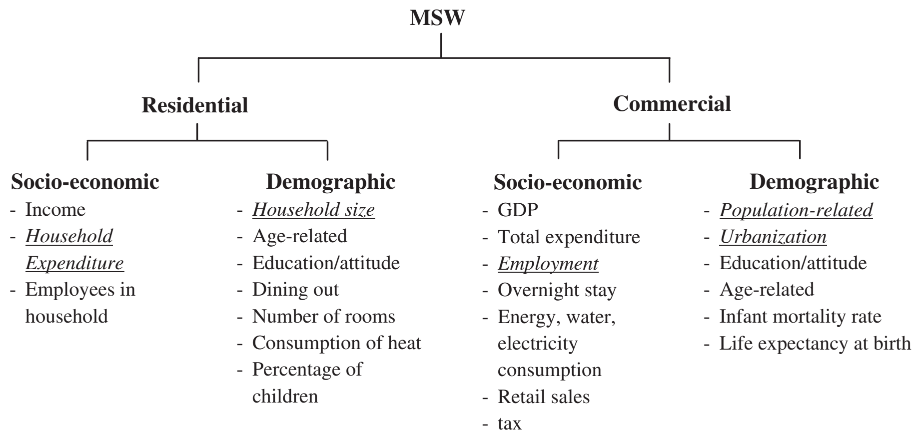

Fig. 2. List of important factors affecting MSW generated in residential and commercial sectors. (Note: the underlined factors are the most important representative factors of each sector as discussed further in Section 4.1).

Table 2
Range of MAPE. Source: Lewis (1982).

MAPE (%)	Forecasting performance
<10	Excellent
10–20	Good
20–50	Reasonable
>50	Incorrect

probability (Armstrong, 2002). In this study, each influencing factors from Section 3.1.2 was firstly forecasted by using GM (1, 1) due to its mature implementation. The most accurate model from Section 3.3 was then utilized to forecast MSW collected with PI (95% confidence intervals) during 2013–2030. If the forecast errors are normally distributed, the equation of prediction intervals for a $100(1-\alpha)\%PI$ is $\widetilde{F}_k(h) \pm z_{\alpha/2}\sqrt{Var[e_k(h)]}$, where $\widetilde{F}_k(h)$ defines as the point forecast of the value at time h, the time steps ahead, $z_{\alpha/2}$ denotes as the appropriate (two-tailed) percentage point of a standard normal distribution, $e_k(h)$ denotes forecast error which equal $A_{k-}\widetilde{F}_k(h)$ (Armstrong, 2002).

4. Results and discussion

4.1. Influencing factors

Based on the influencing factors described in Section 3.1.1 and given in Table 1, five representative factors from two groups, namely, two factors of household or residential sector (i.e., household consumption expenditure and household size) and three factors of commercial sector (i.e., employment, population density and urbanization) as described in Fig. 2 (the italics underlined) have been identified. The descriptions and statistics of these factors and MSW collected are presented in Tables 3 and 4. Since the inflation causes the change in the cost of goods and services, the household consumption expenditure as collected from NSO (2013) has been adjusted by inflation rate (or Consumer Price Index (CPI) in this study) collected from BOT (2014).

Since time series data was used in this study, stationary of such data is one of the features to be tested before being used in the statistical analysis in order to ensure that the series can strongly influence its behavior and properties. Data which is trending over time or non-stationary data can give misleading parameters estimates of the relationships between variables (Mahadeva and Robinson, 2004). The results show that all series are stationary at different levels as shown in Table 4. Therefore, stationary data must be strongly concerned before using time series in a statistics-based, e.g. correlation analysis in this study.

To ensure that five influencing factors from Section 3.1.1 are related to MSW collected, Pearson correlation coefficients were then determined. Results illustrated that these factors correlates with MSW collected because their coefficients are higher than 0.7 (Streiner and Norman, 1995 cited from Hsu and Wang, 2009) as presented in Table 4. Therefore, this study utilized all proposed influencing factors, such as household consumption expenditure, household size, employment, population density and urbanization, into GRA.

In GRA, the series of MSW collected and the proposed factors must be firstly normalized to be the same order because inaccurate grey relational grade will be induced by the order variation of the data characterizing the factors (Hsu and Wang, 2009). Mean value is used to normalize the original data in this study due to the normal distribution of data as $y_0 = \frac{x_0(k)}{\frac{1}{m}\sum_{k=1}^{m} x_0(k)}$, $y_i = \frac{x_i(k)}{\frac{1}{m}\sum_{k=1}^{m} x_i(k)}$, $i = 1, 2, \ldots, n$, $k = 1, 2, \ldots, m$. Grey relational grade of each factor was

Table 3
Definitions and sources of variables.

Variables	Description	Unit	Accessed sources
MSW collected	Waste collected by municipality, typically comprises household waste and commercial wastes, excluding hazardous waste and industrial waste	Tonnes/day	PCD (2001–2013)
Consumption expenditure (AdCONEXP)	Consumption expenditure per household adjusted by Consumer Price Index (CPI) based on the bench marking in year 2011	Bath/month	NSO (2013) and BOT (2014)
Household size (HHSIZE)	Number of members in a household	Capita	NSO (2013)
Proportion employment (EMPLOY)	Number of employed person/ total population	None	BORA (2014), NSO (2013) and BOE (2014)
Population density (POPDEN)	Population in Thailand/Area	Capita/km^2	BORA (2014), NSO (2013) and BOE (2014)
Urbanization (URBAN)	Proportion of number of population stay in urban area of municipality to total population	None	BORA (2014), NSO (2013) and BOE (2014)

Table 4
Statistics and mathematical approaches of variables.

Variables	MSW collected (tonnes/day)	AdCONEXP (THB/month)	HHSIZE (capita)	EMPLOY	POPDEN (capita/m^2)	URBAN
Mean	39,727	9616.042	3.39	0.5386	122.25	0.2987
Median	39,598	9183.750	3.32	0.5626	122.47	0.3011
Maximum	41,410	13843.71	3.80	0.5936	123.80	0.3328
Minimum	38,170	6375.730	3.18	0.3499	120.59	0.2669
Std. Dev.	1025.468	2690.103	0.197	0.070	1.102	0.024
Skewness	0.216	0.330	0.965	−2.153	−0.186	−0.006
Kurtosis	2.099	1.751	2.869	6.532	1.818	1.577
Jarque–Bera	0.416	0.831	1.560	12.926	0.640	0.844
Probability	0.812	0.660	0.458	0.002	0.726	0.656
Stationary at	1st difference	1st difference	Level	Level	1st difference	1st difference
Pearson correlation	–	0.940**	−0.887**	0.754*	0.761*	0.935**
Sig.	–	0.000	0.001	0.012	0.011	0.000
Grey relational grade	–	0.5404	0.7996	0.8295	0.9479	0.8310

1 USD = 31 THB.
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

obtained and presented that population density is the largest factor (0.9479), followed by urbanization (0.8310) and proportion employment (0.8295). Household size is the fourth (0.7996) and household consumption expenditure is the fifth (0.5404) as illustrated in Table 4. Despite no separate information of MSW generated from residential and commercial sectors in Thailand, this study expects that the representative factors of commercial sector affect more MSW collected than that of residential sector.

It is no surprise that population density contributes the largest MSW collected because higher population generated larger quantities of MSW. In spite of population being the most important driving factor, other factors also affect MSW collected. For the last 13 years, population in Thailand increased 4.17% from 2000 to 2012 while waste collected rapidly rose by 13.83%. MSW quantity typically also increases with the improvement of living standards.

In Thailand, urbanization rapidly increased in last decade. The number of municipalities which are classified as cities increased from 1131 in 2000 to 2272 in 2012 and urbanization doubled during this period. Therefore, urbanization is the second important factor contributing MSW collected because as urbanization increases, life style, consumption style and living conditions change, and more MSW is generated. In fact, the inner disparities of the lifestyle and the consumer behavior may exist between the urban and rural regions (Weng et al., 2011). In urban area, the actual population in the cities is larger than the official statistics, as many people live in the city and produce waste but are not registered as citizens (Wang and Nie, 2001). The employment which represents the wage and purchasing power increased by 79.88%, from 22 million persons in 2000 to 39 million persons in 2012. This factor also affects waste quantities due to economic prosperity related GDP which rose 3.98% annually from 2000 to 2012 (NESDB, 2014). At country level, it means that MSW generated not only from individual's consumption, but also from activities of services because large amount of food wastes discarded from hotels, super markets, institutes and so on. In this study, it can be concluded that commercial sector plays a crucial role on MSW collected.

In the context of residential sector, household size is the most important factor, followed by household consumption expenditure. This means that demographic factors significantly affect more MSW collected than that of socio-economic factors. However, in this study, household size slightly affected MSW collected negatively because household size slowly decreased from 3.80 capita per household in 2000 to 3.04 capita per household in 2012. Individual's consumption expenditure has been considered as one important factor to produce MSW due to its preferences of the changes in lifestyle (Weng et al., 2011; Yuan et al., 2012). However, in most countries, the size of population or the number of households is closer correlated with MSW quantities than the level of private consumption (Skovgaard et al., 2005). In this study, household consumption expenditure is the least factor affecting MSW collected because the correlation degree of GRA is required to be greater than 0.6 (Hui et al., 2013). Hence, at country level, the representative factors of residential sector affected less MSW collected than that of commercial sector.

4.2. The forecast of MSW collected

This study simulated 15 alternative models which comprise five univariate models and ten multivariate models as presented in Table 5. Results show that all models reveal high performance for MSW forecasting with excellent accuracy. Considering the univariate models, Naïve analysis can be used to forecast amount of waste for short term period only. In long term period, the univariate grey models i.e., GM (1, 1), GM (1, 1)-$\alpha = 0.1$ and GM (1, 1)-$\alpha = 1.0$ show higher accuracy than the traditional model, trend curve analysis.

Comparing the two main types of models, it can be observed that the multivariate models not only provide higher performance or more accuracy than that of univariate models, but also present the factors affecting waste quantities. Among these, multivariate grey models, GMC (1, 5) gives the best representation of MSW collected forecast with least error of 1.16% MAPE. It demonstrates that GMC (1, 5) is a robust forecasting model to forecast MSW collected

Table 5
Performance comparison of the alternative models.

	Models	MAPE (%)	Accuracy
Univariate	*Traditional models*		
	Naïve	2.06	Excellent
	Trend curve analysis	2.98	Excellent
	Grey models		
	GM (1, 1)	2.51	Excellent
	GM (1, 1)-$\alpha_{=0.1}$	2.84	Excellent
	GM (1, 1)-$\alpha_{=1.0}$	2.32	Excellent
Multivariate	GM (1, 2)	5.57	Excellent
	GM (1, 3)	2.68	Excellent
	GM (1, 4)	2.28	Excellent
	GM (1, 5)	2.90	Excellent
	GM (1, 6)	3.89	Excellent
	GMC (1, 2)	2.73	Excellent
	GMC (1, 3)	1.88	Excellent
	GMC (1, 4)	1.18	Excellent
	GMC (1, 5)	**1.16**	**Excellent**
	GMC (1, 6)	7.74	Excellent

The bold value is selected as the best fit model.

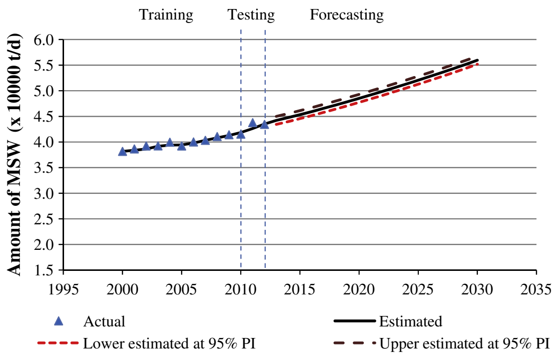

Fig. 3. Forecasting of MSW collected using GMC (1, 5) model during 2013–2030 with 95% PI.

from 2013 to 2030. This illustrates that the decrease of household size, the increase of population density, urbanization and proportion employment result in the increase of MSW collected.

To forecast MSW collected by using GMC (1, 5), it is necessary to estimate the annual values of each influencing factors from 2013 to 2030. Due to maturity of GM (1, 1) model, this study uses ex-post forecast by using twelve time series data (from Tables 3 and 4) during 2000–2011 as inputs for training models and used one data in 2012 for validation. Results show the excellent accuracy of influencing factors forecast by 0.69%, 1.20%, 1.80% and 1.06% MAPE for population density, urbanization, proportion of employment and household size, respectively. Therefore, population density would increase from 125.07 capita per km^2 in 2013 to 130.64 capita per km^2 in 2030. Urbanization and proportion employment would also increase from 0.3676 and 0.6238 in 2013 to 0.5617 and 0.7901 in 2030, respectively while household size would decrease from 2.96 persons per household in 2013 to 2.30 persons per household in 2030.

As shown in Fig. 3, the GMC (1, 5) model provides good fitness of MSW data collected, correlating closely with actual data and the forecasted curve trends in the extrapolated forecasting phrase. In this study, MSW collected increases with the average annual growth rate of 1.40%. The uncertainty of MSW forecast was carried out by using the prediction interval (PI) technique. The results show that the PI of MSW collected rate per day is expected to increase from 43,435–44,994 tonnes in 2013 to 47,735–49,293 tonnes in 2020, and to 55,177–56,735 tonnes in 2030 as presented in Table 6. These forecasts are similar to those obtained by the Thailand Greenhouse Gas Management Organization (TGO, 2010), who used GDP and population as influencing factors in extrapolation method and found that MSW increased at 1.08% annually from 43,751 tonnes per day (t/d) in 2013, to 47,112 t/d in 2020 and to 52,560 t/d in 2030. Besides, the Department of Alternative Energy Development and Efficiency (DEDE, 2009) forecasted MSW collected rate by using single linear regression analysis, and concluded that it would be 42,667 t/d in 2013 and 45,146 t/d in 2020 with 0.80% annually average growth rate. MSW forecasted in this study is slightly higher than that of TGO (2010). In addition, it can be concluded that DEDE (2009) underestimated MSW collected (40,896–42,313 t/d) comparing with the actual data (41,064–43,448 t/d) during 2008–2012.

Table 6
Forecast interval of MSW collected rate (tonnes per day).

Year	2013	2015	2020	2025	2030
GMC (1, 5)	44,214	45,336	48,514	52,061	55,956
Lower estimated at 95% PI	43,435	44,556	47,735	51,281	55,177
Upper estimated at 95% PI	44,994	46,115	49,293	52,840	56,735

Continuous data is required for using the grey model. A single or a few outliers can be accepted; this is one advantage of the grey model over that of statistical regression analysis. If frequent outliers occur, the grey model is not an appropriate choice (Liu and Yu, 2007). The models have been validated by using 2012 data alone and both 2011 & 2012 data. Results indicate that an outlier cannot be included in GM (1, n) and GMC (1, n) models. Therefore, the time series data used is required to support and improve the reliability of grey model. In order to develop the accurate model associated with influencing factors, not only the selection of suitable factors, but also the accurate forecasts of influencing factors play the important role for MSW forecasting.

MSW forecast by GMC (1, 5) model comprising three representative factors and one representative factor affecting waste generated from commercial and residential sectors, respectively. This is expected to provide the policy makers an understanding of waste quantity patterns beyond. The influencing factors of commercial sector affect the amount MSW collected rather than residential sectors. A study by Manomaivibool (2012) showed that hotels in Chiang Saen And Chiang Khong district, Chiang Rai generated solid wastes of about 3.15 kg/capita/day which was higher than that from guest houses, 2.3 kg/capita/day. This shows that more commercial activities produce more wastes because hotels offer services, and more food is produced and more waste is discarded. The main sources of commercial sector wastes include hotels, supermarkets, restaurants, hospitals, institutes and public areas. They not only generate more wastes, but also make for easier implementation of waste management programs than residential sector. In order to achieve the government's targets as described in Section 2, specific strategies of 3R, WTE, and regulation for commercial and residential sectors; enhancement of 3R strategy in the main sources such as hotels, supermarkets, restaurants and institutes; sufficient economic philosophy for decreasing human activities; and control the increase of population density and urbanization should be strongly focused and implemented. However, segregated information/data of waste generated from residential and commercial sectors will be needed.

5. Conclusion

To forecast MSW collected associated with influencing factors based on the limited data available, 15 alternative models including two traditional models, three univariate grey models and ten multivariate grey models were simulated in this study. For multivariate models, the influencing factors of residential and commercial sectors affecting waste collected were identified, classified and quantified using correlation analysis and GRA. The most accurate model is used to forecast waste collected in long term period for Thailand with the uncertainty forecast, prediction interval technique.

Among these models, the grey model with convolution integral GMC (1, 5) is the best representative model to forecast MSW collected with the least error of 1.16% MAPE. This model indicates that the amount of MSW collected would increase by 1.40% per year which is in the range from 43,435–44,994 t/d in 2013 to 47,735–49,293 t/d in 2020, and to 55,177–56,735 t/d in 2030. The increase of MSW collected may be affected due to the representative factors of commercial sector (i.e., population density, urbanization and proportion employment) rather than that of residential sector (i.e., household size). It was also observed that demographic factors are more important than socio-economic factors. In long term period, these results can help decision makers to develop the measures and policies for waste management, e.g., the implementation and development of the new targets for 3R and WTE strategies in commercial and residential sectors; strong enhancement of 3R strategy in the main sources such as hotels, supermarkets, restaurants and institutes; focus on sufficient economic philosophy to decrease human activities; and control the increase of population density and urbanization. However, future research on estimating MSW quantities in spatial distributions in the residential and commercial sectors is needed.

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