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Research article

Exploring the industrial solid wastes management system: Empirical analysis of forecasting and safeguard mechanisms

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ABSTRACT

Industrial solid wastes (ISWs) not only destroys the ecological environment, but also seriously affects human health, which is one of the main obstacles to sustainable development. Consequently, Effective management of ISWs is essential to support efforts to achieve cleaner production and ecological upgrading of industrial structure. In this study, metabolic grey model (MGM (1,1)) is adopted to forecasting the ISWs generation and treatment in China. Meanwhile, we develop an ISWs management system involving its safeguard mechanisms. Forecasting results show that China's ISWs generated have been a slowly increasing trend from 2018 to 2025, which will be controlled between 389819 million tons and 488002 million tons, and the utilization, disposal and storage of ISWs have a significant upward trend. However, the ratio of ISWs utilized will eventually remain at around 50% in the future. According to the prediction results, the application of this ISWs management system can increase the efficiency of waste recycling and reuse, and make ISWs become renewable resources. Research results also illustrate that the safeguard mechanisms, including government policy tools, collaborative agents of the industry-university, green technology innovation, and circulation of green products, have ensured a highly efficient recycling and beneficial waste management to create more added values for the ISWs materials.

1. Introduction

In recent years, environmental problems have become increasingly critical, as both developed and developing countries are facing serious waste discharge and disposal issues created by industrialization, rapid economic development and growing population, among others (Sandberg et al., 2019). Environmental protection and sustainable development have received more attention as a result of growing governments worldwide awareness of environmental pollution and resource shortage (Tang et al., 2016). To achieve that ambitious goal, countries around the world strengthen cooperation by formulating international regulations and laws, for example, the Kyoto Protocol is now replaced by the Paris Agreement, which is of great importance to not only address carbon emissions but also sustainable growth of the ecological economy (Ameyaw et al., 2019; Du et al., 2016). As a result, countries have designed their environmental policies according to their actual conditions, such as the plan of greenhouse gas emissions in Turkey and strict environmental regulations from China's 13th five-year plan (Li et al., 2020; Şahin, 2019).

Over the past decades, China's industrialization has made great economic and social development. However, experience from China's industrial production has caused some serious environmental pollution, such as waste pollution, dust pollution, and water pollution (Ding et al., 2017a; Yang and Li, 2018). Especially excessive generations of industrial solid wastes (ISWs) have become a significant cause of environmental pollution in China (Liu et al., 2016). To accommodate the need for modern industrial development, as well as dispose of the increasing industrial solid wastes, the Chinese government integrated the concept of green economic growth in designing solid wastes management and recycling framework (Qu et al., 2020; Sun et al., 2018). From the perspective of sustainable development, forecasting the generation and treatment of ISWs plays an important role in formulating the ISWs management system and protecting the international agreement to combat environmental pollution (Lertpocasombut and Sriploy, 2017; Song et al., 2017). Therefore, accurate prediction of ISWs production and disposal status is one of the major problems in the goal of environmental protection.

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Prevention and Control of Solid Waste Pollution, ISWs can be categorized into genreal industrial solid wastes (GISWs) and hazardous industrial solid wastes (HISWs) (Geng et al., 2007). GISWs mainly include smelting waste residue, fly ash, slag, coal gangue, chemical waste residue, tailings, radioactive waste residue and other solid waste; and HISWs either have explosive, flammable, oxidizable, toxic, corrosive, or may cause infectious diseases (Tang et al., 2020). In the process of recycling and utilization of ISWs, the disposal of GISWs and HISWs are significantly different because of their differences in generated materials (Guan et al., 2019). Through raw material recovery, conversion and utilization, and waste exchange, the GISWs can be extracted and converted into available resources, renewable and sustainable energy sources, and cheap raw materials (Tang et al., 2020). The methods of ISWs treatment have four types, including landfill, incineration, thermophilic composting and comprehensive utilization (Zhang et al., 2016). Compared with GISWs, HISWs have the characteristics of toxicity, flammability and corrosiveness. Therefore, the most common treatment methods for HISWs are landfill, chemical treatment, solidification, biological treatment, and marine disposal, which can be changed the physical, chemical and biological properties of these materials, thereby reducing or even eliminating the hazard of wastes (Kavouras et al., 2003; Krishna et al., 2020).

Previous studies in solid waste management and recycling have focused on the development of management models, include in 3Rs (reduce, reuse, recycle) (Seyoum and Adeloju, 2008), cradle-to-grave (the management of all stages of the life cycle for solid waste) (Salihoglu, 2010), and integrated waste management system (Cobo et al., 2018). However, many scholars are adding new dimensions in paying attention to the research of ISWs management and recycling, pointing out problems, and providing ideal methods and tools to address these issues. For example, (Chandra Manna et al., 2018; Zamorano et al., 2011) considered that significant weaknesses of ISWs management are the lack of environmental awareness among the public and training and certifying for ISWs management personnel. (Zhang et al., 2016) concluded that the non-hazardous industrial solid waste manifest system is an effective tool for analyzing ISWs characteristics and determining links between waste handlers to establish a waste recycling industry chain. (Nouri et al., 2018) used the analytic hierarchical process and analytic network process to assess the four appropriate disposal scenarios according to the quality of the produced solid wastes and ultimately select the fourth scenario to achieve proper management of generated ISWs. (Das et al., 2019) described the waste management scenarios of different countries to study feasible approaches for sustainable recycling and treatment of solid wastes by life cycle assessment (LCA) and other tools. (Krishna et al., 2020) pointed out that the application of green technology in the construction industry can promote cleaner production and sustainable development by effective utilization of solid waste.

Growing population coupled with rapid industrialization and urbanization has caused tremendous ISWs production (Ezeudu and Ezeudu, 2019; Li et al., 2020). To achieve ISWs recycling and optimized management, accurate forecasting of ISWs generation and treatment status is an essential part of a sustainable management system (Abbasi and El Hanandeh, 2016; Asante-Darko et al., 2017). Currently, solid wastes management, especially ISWs management have aroused much attention, while the research about forecasting solid waste has become one of the most significant international study problems. (Dyson and Chang, 2005) used the system dynamics simulation tool to forecast various trends of solid waste generation associated with five different models by a case study in the city of San Antonio, Texas (USA). (Intharathirat et al., 2015) forecasted the municipal solid waste quantity in a developing country; and they showed that the municipal solid waste quantity would increase 1.40% per year from 43,435–44,994 tons per day in 2013 to 55,177–56,735 tons per day in 2030. (Yang et al., 2016) used a systematic approach to forecast the industrial solid waste generation by the industrial sector in Shanghai; and they found that the total ISW generation will be 20630, 20340, and 22590 million tons in 2010, 2015, and 2020, respectively. (Duman et al., 2019) developed a novel forecasting technique based on a grey model to predict the electronic waste generation forms a saturated distribution in Washington State from 2018 to 2030; the results showed that population density has a major impact on the generated e-waste followed by household income level. (Hoque and Rahman, 2020) forecasted solid waste collected from 2012 to 2016 at landfill site of Dhaka South City Corporation using an Artificial Neural Network (ANN); and they found that the landfill authority can save the valuable urban landfill area requirement up to 28.6%.

One of the forecasting methods of ISWs is a grey prediction model (GM), firstly proposed by (Deng, 1982). Compared with other forecasting techniques, the grey prediction model can not only solve numerous problems with small sample sizes but also can establish a first-order differential equation to indicate the unknown evolution law (Huang et al., 1997; Kahraman et al., 2010). Thereinto, GM (1,1) model is a basic grey prediction model, which provides short-term predictions from sample sequences with little data and poor information (Cui et al., 2013; Wang et al., 2010). With the development of grey prediction theory, GM (1,1) model has been widely applied in forecasting electricity demand, energy forecasting consumption, forecasting CO2 emissions, forecasting the production and sales of new energy vehicles and other fields (Ding et al., 2017b; He et al., 2020; Lee et al., 2011; Ma and Liu, 2016; Zhou et al., 2006). However, the GM (1,1) model does not always fit the actual data very well; therefore, the improved GM (1,1) model can be used (Akay and Atak, 2007; Şahin, 2019).

In the traditional GM (1,1) modeling, the original data from the real-time $t = n$ is used (Pao and Tsai, 2011). However, over time, the grey system will generate some random disturbance factors, which will affect the prediction results (Wang et al., 2020). To make full use of the existing information and improve the prediction accuracy of the GM (1, 1) model, the method of “metabolism” is using to improve the grey prediction model (Şahin, 2019; Wang et al., 2018). The basic advantage of the metabolic grey model (MGM (1,1)) is based on metabolic steps that adopt recent data by eliminating old data for each cycle (Chang et al., 2005; Chen et al., 2016). Many applications of MGM (1,1) model, including prediction of iron ore import and consumption in China, prediction of lithium-ion battery capacity and forecasting of Turkey's CO2 emissions, have more accuracy than the GM (1,1) model (Ayvaz et al., 2017; Chen et al., 2016; Ma et al., 2013). Simultaneously, the accuracy of grey prediction models is measured by using mean absolute percentage error (MAPE), and when the MAPE is less than 10% is believed as highly accurate forecasting (Cui et al., 2015; Lewis, 1982). Thereinto, the results of (Zhao et al., 2016) show that the MAPE value of the MGM(1,1) and GM(1,1) is 9.55% and 25.01% by predicting the electricity consumption. According to the results of (Akay and Atak, 2007), the MAPE value is below 5% when they use the MGM(1,1) model to forecast total and industrial electricity consumption in Turkey. In addition, (Boran, 2015) has forecasted the natural gas consumption from 1995 to 2012 in Turkey based on MGM (1,1) model; they found that the prediction accuracy of this model is 93.5%.

In this study, we collected annual data on ISWs generated, utilized, disposed and stored in China for 2006–2017 from the China Statistical Yearbook (http://www.stats.gov.cn/tjsj/ndsj/). As mentioned above, forecasting of generation and treatment for ISWs plays an important role for decision-makers of governments worldwide to design their ISWs management and recycling frameworks. because of sustainable development has become the consensus of all countries. Although the GM (1,1) can predict many problems with small sample sizes, the MGM (1,1) has more accuracy than the GM (1,1). Therefore, based on the MGM (1,1) model, we adopt recent data by eliminating old data for each loop to forecast the generation and treatment status of ISWs in China. The objective of this study are as follows:

(1) In order to forecast the generation and treatment of ISWs in China, the metabolic grey model is proposed, which can obtain the capacity of providing high-precision predictions in the case of having chaotic data.
(2) From the theoretical modeling aspect, we contribute to the literature by developing the MGM (1,1) model that considers prediction error and applying it to predict the generation and treatment of ISWs. And the paper is one of the few that focuses on forecasting of ISWs to achieve ISWs recycling and management.
(3) Considering that the environmental goal of China's 13th five-year plan (2016–2020) in the current and China's 14th five-year plan (2021–2025) in the future, our results can help decision-makers in setting strategic plans for manage and use of ISWs in China and selecting suitable ISWs management and recycling benchmarks.

2. Methodology

2.1. The modeling algorithm of GM (1,1)

In this study, GM (1,1) model is used to forecast the generation and treatment status of industrial solid wastes in China. Some basic steps of GM (1,1) related to the paper are outlined as follows:

Step 1. The original input data is computed by$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$. And a cumulative series of accumulated generation operators (AGO) is defined as Eq. (1).

$$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdot \cdot \cdot, x^{(1)}(n)\right) \tag{1}$$

where, $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, \cdots, n.$

Step 2. The mean series $x^{(1)}(k)$is denoted$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1),\ \ k = 2, 3, \cdots n$, and the grey differential equation of GM (1,1) is established by Eq. (2).

$$x^{(0)}(k) + az^{(1)}k = b \tag{2}$$

Based on Eq. (2)., the albinism differential equation is defined as

$$\frac{dx^{(1)}(t)}{d(t)} + ax^{(1)}t = b \tag{3}$$

Where t represents the time and a represents the development coefficient of GM (1,1), and b denotes the endogenous control greyscale.

Step 3. Using the least-squares regression to estimate the parameters of GM (1,1). The least-squares regression is calculated by Eq. (4).

$$\widehat{u} = \left(\widehat{a}, \widehat{b}\right)^{T} = \left(B^{T}, B\right)^{-1} B^{T} Y \tag{4}$$

Where u represents the parameter vector and B represents the accumulated matrix, namely$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix}$; and Y denotes the constant vector, namely $Y = (x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n))^{T}$.

Step 4. Predictive values of GM (1,1) are computed by Eq. 5

$$\widehat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \ \ t = 0, 1, \cdots, n-1, \cdots \tag{5}$$

Step 5. The predictive value of the sequence $x^{(0)}$ can be used to obtain by a single regressive inverse operation is defined as Eq. (6).

$$\widehat{x}^{(0)}(t+1) = \widehat{x}^{(1)}(t+1) - \widehat{x}^{(1)}(t), \ \ t = 1, 2, \cdots, n-1, \cdots \tag{6}$$

2.2. The metabolic grey model

According to the GM (1,1) model constructed with 2006–2017 data as the original sequence. we adopt recent data by eliminating old data for each loop to forecast the generation and treatment status of industrial solid wastes in China. Some modeling algorithms of the metabolic grey model (MGM (1,1)) related to this paper are given as follows.

In the original sequence$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$, the latest data$x^{(0)}(n+1)$ is placed and the oldest data $x^{(0)}(1)$is removed. Then, a new data sequence is defined as Eq. (7).

$$x^{(0)} = \left(x^{(0)}(2), x^{(0)}(3), \cdot \cdot \cdot, x^{(0)}(n+1)\right) \tag{7}$$

Using Eq. (7) as the original sequence, the metabolic grey model can be obtained by Eq. (8).

$$x^{(0)}(k) + az^{(1)}k = b \tag{8}$$

Simultaneously, the accumulated matrix B and the constant vector Y are obtained by Eq. (9) and Eq. (10), respectively.

$$B = \begin{bmatrix} -\frac{1}{2}\left(x^{(1)}(2) + x^{(1)}(3)\right) & 1 \\ -\frac{1}{2}\left(x^{(1)}(3) + x^{(1)}(4)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(x^{(1)}(n) + x^{(1)}(n+1)\right) & 1 \end{bmatrix} \tag{9}$$

$$Y = \begin{bmatrix} x^{(0)}(3) \\ x^{(0)}(4) \\ \vdots \\ x^{(0)}(n+1) \end{bmatrix} \tag{10}$$

Baes on the research of (Li et al., 2018; Ma et al., 2018; Şahin, 2019), in MGM (1,1) process, the oldest data$x^{(0)}(1)$ is removed and new data $(x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), \cdots x^{(0)}(n+1))$ is used by the MGM(1,1) to predict the value of next data at the first metabolic stage. After the oldest data$x^{(0)}(2)$ is removed and new data $(x^{(0)}(3), x^{(0)}(4), x^{(0)}(5), \cdots x^{(0)}(n+2))$ is set to predict the value of the next data. It repeats this process until the prediction is completed.

In this study, the prediction processes of MGM (1,1) are outlined as follows: The first sequence is established based on the actual data from 2006 to 2010 to predict the data in 2011. The second sequence, the oldest data is removed and the new actual data, which is come from 2011, is to predict the value of data in 2012. In order to complete the prediction process of 2006–2017, the above prediction process is continued until the last data of 2017 is predicted. Then, the predicted data is compared with the actual data to measure the accuracy of the MGM (1,1) model. Finally enter the prediction stage, we remove the oldest data from the sequence and add the forecasted value as the latest data to the sequence; and we repeat this cycle until the last data in 2025 is predicted. In this way, the forecasting process will include data from 2018 to 2025.

2.3. The accuracy measurement

To verify the generalization ability of the MGM (1,1), the accurate measurement of this model should be evaluated. In this study, the mean absolute percentage error (MAPE) and the absolute percentage error (APE) can be adopted to test the accuracy measurement of MGM (1,1). The standard of APE and MAPE are defined by Eq. (11) and Eq. (12), respectively (He et al., 2020; Xu et al., 2019).

$$APE(\%) = \left|\frac{x(t) - \widehat{x}(t)}{x(t)}\right| \times 100 \tag{11}$$

$$MAPE(\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x(t) - \widehat{x}(t)}{x(t)}\right| \times 100 \tag{12}$$

Where$x(t)$represents actual data and $\widehat{x}(t)$ denotes forecast data. MAPE standards for accurate measurement of the model are listed in Table 1.

3. Results and discussions

Data for ISWs generation and treatment in the range 2006–2017 is shown in Fig. 1. According to the results, the ISWs generated from China have been an increasing trend in the range 2006–2017 with the rapid development of industry. Although there has no significant increase since 2011, the total amount of ISWs generated has been maintained at around 300000 million tons. However, with dramatically increase of ISWs generated, the curve of ISWs utilized remains stable and has a downward trend. At the same time, the disposal and storage of ISWs were basically the same in 2006–2017. This implies that China's industrialization process continues to accelerate, but its huge ISWs generated are in contrast to the low comprehensive utilization in China. Therefore, in addition to ISWs generated, the utilization, disposal and storage of ISWs are also predicted and forecasted in the paper.

3.1. The result of correlation test

In order to make the model obtain a better prediction effect, the result of correlation test for original data is analysed in this study, including the relative residual and class ratio dispersion. (Bezuglov and Comert, 2016) pointed out that the relative residual and class ratio dispersion are used to measure the deviation and error of the fitted data and the actual data. The smaller the values of relative residual and class ratio dispersion, the better the accuracy of the grey prediction model to describe the original sequence (Lin and Yang, 2003). In this study, the relative residual and class ratio dispersion can be adopted to test the validity of the model. The standards of relative residual and class ratio dispersion are defined by Eq. (13) and Eq. (14), respectively (Kumar and Jain, 2010; Lin and Yang, 2003).

$$\varepsilon(k) = \frac{x^{(0)}(k) - \widehat{x}^{(0)}(k)}{x^{(0)}(k)}, \quad k = 1, 2, \cdots, n \tag{13}$$

$$\rho(k) = 1 - \left(\frac{1 - 0.5a}{1 + 0.5a}\right)\lambda(k), \quad k = 1, 2, \cdots, n \tag{14}$$

Where $\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k = 1, 2, \cdots, n$. At the same time, when $\varepsilon(k) < 0.2$ and $\rho(k) < 0.2$, the model has passed the test and has good predictive ability, and when $\varepsilon(k) < 0.1$ and $\rho(k) < 0.1$, the model has passed the test and has high predictive ability (Lin et al., 2001).

Fig. 2 shows the test of relative residual and class ratio dispersion for the four types of ISWs. In the study, the relative residual and class ratio dispersion are less than 0.2 imply that the model exhibit a good predictive capability. In addition to Fig. 2 (d). the relative residual and class ratio dispersion in Fig. 2 are all lower than 0.2, which indicat that the model show a good predictive capability for ISWs. Although the relative residual and class ratio dispersion of ISWs stored with exponential trend are greatly higher than the other three types of ISWs, the model still has a good predictive effect. It indicat that the MGM (1,1) model has exhibited a good predictive capability among those conforming to the data for ISWs generation and treatment.

Table 1
MAPE standards for accurate measurement of the model (Lewis, 1982).

MAPE (%)	Forecasting ability	MAPE (%)	Forecasting ability
<10	Highly accurate forecasting	20–50	Reasonable forecasting
10–20	Good forecasting	>50	Weak forecasting

3.2. Prediction of ISWs generation and treatment

China's ISWs generated are predicted using the GM (1,1) and the MGM (1,1) over the period 2006–2017. Predicted and APE values of China's ISWs generated for two prediction models are shown in Table 2. Table 2 shows the MAPE value of the GM (1,1) model is 11.78% and the maximum APE value is 20.85%. However, MGM (1,1) model has the lowest MAPE value that is 1.51% and the maximum APE value is 4.62%. By comparing the MAPE values, the metabolic grey model has more accurate results than the traditional grey model.

In the same way, the prediction performances of the GM (1,1) and the MGM (1,1) for ISWs treatment from the year 2006–2017 are given in Table 3, Table 4 and Table 5 respectively. According to the results, for the utilization, disposal and storage of ISWs, the MAPE values are calculated as 2.99%, 6.69%, 15.31% in the MGM (1,1), which are lower than the MAPE values in the GM (1,1). At the same time, MGM (1,1) model has the maximum APE values are 4.83%, 14.68% and 28.16% respectively, which are lower than the maximum APE values for the GM (1,1). Thus, it is obvious that the MGM (1,1) provides the most accurate prediction compared with the GM (1,1) in this study.

After comparing the prediction model with the actual data, China's ISWs generated are forecast from the year 2018–2025. Fig. 3 shows the prediction results of the MGM (1,1) model. The left-hand side of the dotted line is a fitting area, which indicates that the fitted performance verification of this model is very well. And the right-hand side is a prediction area, which has been an increasing trend in the total ISWs generated. According to the prediction results of MGM (1,1), China's ISWs generated is forecasted as 389819 million tons in 2018 and 488002 million tons of ISWs generated in 2025. The increase of ISWs generated from 2018 to 2025 is found as 98183 million tons, and the growth rate of China's ISWs generated is 25.19%. Although the slow growth of ISWs generated, it can be seen that the base of ISWs is huge after a certain period of time.

The forecasting of China's ISWs treatment from 2018 to 2025 is shown in Fig. 4. Forecast results show that the curve of China's ISWs utilized increases at an insignificant increase trend. At the same time, the utilization, disposal and storage of ISWs have a significant upward trend. Additionally, the ratios of ISWs utilized are calculated as 57.6%, 56.5% and 55.3% from 2018 to 2020 (China's 13th five-year plan), and are predicted as 54.4%, 53.6%, 52.4%, 51.4% and 50.6% from 2021 to 2025 (China's 14th five-year plan). By comparing the ratios of disposal and storage for ISWs, we find that the ratios of ISWs utilized in different periods are the highest. Therefore, although comprehensive utilization is an important way to dispose of industrial solid wastes, the ratios of ISWs utilized will also decline with the generation of industrial solid wastes decreases.

4. Discussions

ISWs are growing environmental concern in China requiring and proper solid waste management system for achieveing efficient recycling. With the motivation, this study utilizes grey prediction model improved to predict China's ISWs. The data set for the utilization, disposal and storage of ISWs is run to analyze the prediction capability of the MGM (1,1) model by comparative analysis. Due to the characteristics of the data set, the MGM (1,1) model outperforms the GM (1,1) model. In the MGM (1,1), the MAPE values are lowest for all the data set of ISWs. This means that the MGM (1,1) has better performance than the GM (1,1). As also stated in recently published studies (Chen et al., 2016; Wang and Song, 2019), the MGM (1,1) model enhanced the prediction accuracy significantly. Although the relative residual and class ratio dispersion are both less than 0.2, the MGM (1,1) could also be applied for achieving accurate prediction of China's ISWs. As also stated in recently published studies, the metabolic grey model has a practicality and higher performance of the capacity prediction except for short-term predictions. This result is also consistent with the other studies about

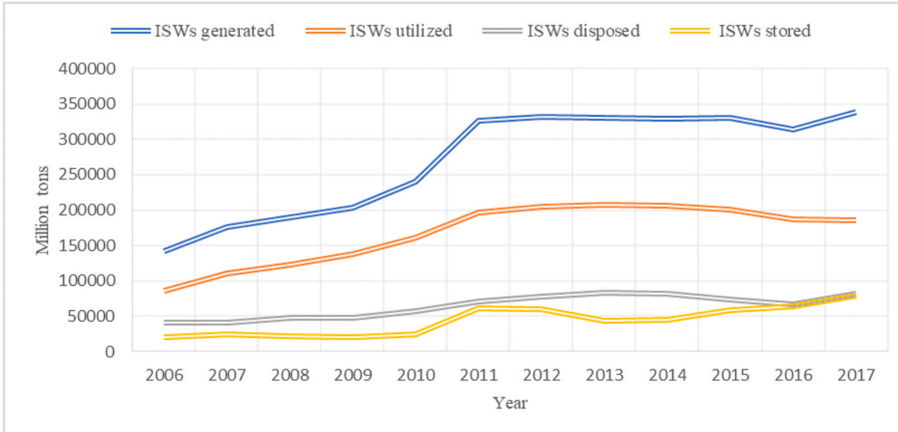


Fig. 1. The generation and treatment status of ISWs in China (2006–2017).

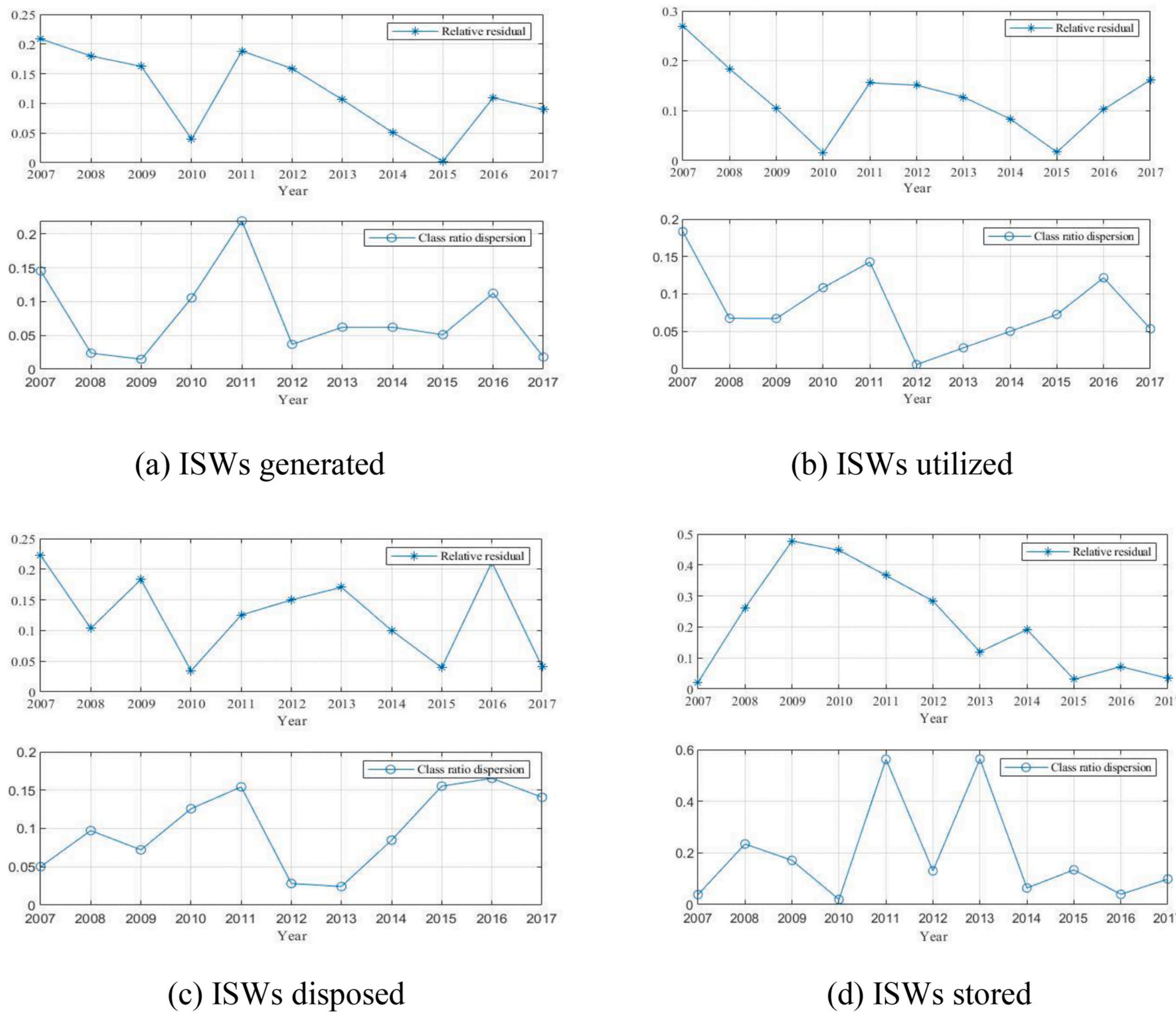


Fig. 2. The test of relative residual and class ratio dispersion.

Table 2
Predicted and APE values of China's ISWs generated.

Year	Actual	GM (1,1)		MGM (1,1)	
		Predicted	APE (%)	Predicted	APE (%)
2006	142053				
2007	175632	212249.1	20.85		
2008	190127	224309.4	17.98		
2009	203943	237054.9	16.24		
2010	240944	250524.8	3.98		
2011	326204	264759.9	18.84	328860.0	0.81
2012	332510	279803.9	15.85	328905.7	1.08
2013	330859	295702.8	10.63	328951.4	0.58
2014	329254	312505.0	5.09	328997.1	0.08
2015	331067	330261.9	0.24	329042.8	0.61
2016	314557	349027.9	10.96	329088.6	4.62
2017	338529	368860.2	8.96	329134.3	2.78
MAPE			**11.78**		**1.51**

Table 3
Predicted and APE values of China's ISWs utilized.

Year	Actual	GM (1,1)		MGM (1,1)	
		Predicted	APE (%)	Predicted	APE (%)
2006	142053				
2007	175632	140043.1	26.95		
2008	190127	146186.8	18.39		
2009	203943	152600.0	10.43		
2010	240944	159294.6	1.53		
2011	326204	166282.9	15.59	206500.7	4.83
2012	332510	173577.7	15.11	203723.5	0.36
2013	330859	181192.6	12.73	200983.8	3.19
2014	329254	189141.5	8.36	198280.8	3.93
2015	331067	197439.2	1.70	195614.3	2.61
2016	314557	206100.9	10.26	192983.5	3.24
2017	338529	215142.5	16.15	190388.2	2.78
MAPE			**12.47**		**2.99**

Table 4
Predicted and APE values of China's ISWs disposed.

Year	Actual	GM (1,1)		MGM (1,1)	
		Predicted	APE (%)	Predicted	APE (%)
2006	41190				
2007	41350	50554.7	22.26		
2008	48291	53296.1	10.36		
2009	47488	56186.2	18.32		
2010	57264	59232.9	3.44		
2011	71382	62444.9	12.52	76489.0	7.15
2012	77443	65831.1	14.99	76587.7	1.10
2013	83671	69400.9	17.06	76686.4	8.35
2014	81317	73164.3	10.03	76785.3	5.57
2015	74208	77131.7	3.94	76884.3	3.61
2016	67128	81314.3	21.13	76983.5	14.68
2017	82350	85723.7	4.09	77082.7	6.39
MAPE			**12.56**		**6.69**

prediction of Turkey's greenhouse gas emissions (Şahin, 2019) and forecasting of South Africa's coal consumption (Ma et al., 2018).

Furthermore, China's ISWs generated have been a slowly increasing trend from 2018 to 2025, which will be controlled between 389819 million tons and 488002 million tons. These forecasts are higher than those obtained by (Yang et al., 2016), who used a systematic approach involving a regional input-output analysis for the forecasting of ISWs generation and found the total ISWs generation in 2020 will be 425900 million tons. In addition, (Guo et al., 2018; Li et al., 2020) showed that China's ISWs generated will still increase slightly, but will be controlled at about 350000–470000 million tons with the transformation and upgrading of Chinese industry in the future. At the same time, with the increase of ISWs generated, the utilization, disposal and storage of ISWs have a significant upward trend. The ISWs utilized as a kind of most important treatment method for Chinese enterprises to make solid waste become a renewable resource. However, the ratio of ISWs utilized will eventually remain at around 50% in the future. This implies that the widespread industrial overcapacity has caused higher ISWs generated and put pressure on the comprehensive utilization of ISWs in the long term. Our results are similar with this of (Tang et al., 2020) study, which believed that the treatment efficiency of industrial solid waste is relatively low in China, and only Zhejiang, Hainan, Shanghai, Beijing, Fujian, Shandong, Guangdong, Tianjin, Shanxi, Hebei, Hunan and Liaoning, the ratio of ISWs utilized have >50%. However, A study by (Guan et al., 2019) found that the ratio of ISWs utilized is expected to increase from 30%-50% to 50%–80% by using clean production technologies. These discussions can help decision makers plan for more effective industrial solid wastes management system that would ensure collection, transportation, utilization and disposal of ISWs in a sustainable way.

Table 5
Predicted and APE values of China's ISWs stored.

Year	Actual	GM (1,1)		MGM (1,1)	
		Predicted	APE (%)	Predicted	APE (%)
2006	20698				
2007	24119	24648.9	2.19		
2008	21883	27606.4	26.15		
2009	20929	30918.8	47.73		
2010	23918	34628.6	44.78		
2011	61200	38783.5	36.63	50077.2	18.17
2012	60633	43436.9	28.36	52770.1	12.98
2013	43445	48648.8	11.98	76686.4	8.35
2014	45724	54485.9	19.16	55607.9	27.99
2015	59175	61023.4	3.12	58598.3	28.16
2016	63757	68345.4	7.19	65070.2	2.06
2017	79268	76545.8	3.43	68569.4	13.49
MAPE			**20.98**		**15.31**

According to the forecast of this paper, it is clear that the total ISWs generation has been an increasing trend, however, the comprehensive utilization of ISWs is relatively low among the three treatment states. At present, the major challenges of ISWs management are large waste production and inadequate waste treatment in China (Guo et al., 2018; Tang et al., 2020). To achieve the goal of environmental protection the ambitious target of cutting ISWs generated and improving the efficiency of ISWs recycle and reuse, the priority of management, and use ISWs should towards proper waste management systems that improve waste utilization (Das et al., 2019). Lack of environmental awareness and clean production technologies and infrastructures are major factors leading to the growth of ISWs generated at an unexpectedly rapid rate (Geng et al., 2007). In the future, ISWs generated will reach critical proportions in China with the development of the economy. Simultaneously, the ISWs management, including raw material recovery, processing, and reuse, conversion and utilization and waste exchange, has always been of the utmost importance in waste treatment status (Luo et al., 2020; Xiao and Zhou, 2020; Yang et al., 2016). Therefore, the sustainable way for ISWs reduction must be to strengthen the environmental responsibility of enterprises, to carry out green technology innovation, and also to improve ISWs recycling to reduce the total waste load.

5. Proposed framework for ISWs management

To make ISWs become a renewable resource, it is necessary to develop a framework for ISWs management and recycling (Guan et al., 2019; Tang et al., 2020). As shown in Fig. 5, this paper designs a ISWs management system to effective solid waste management. The priority of the framework is to shift from traditional waste landfill and incineration that are cost-intensive and harmful to the ecological environment towards an sustainable ISWs management system that promote the

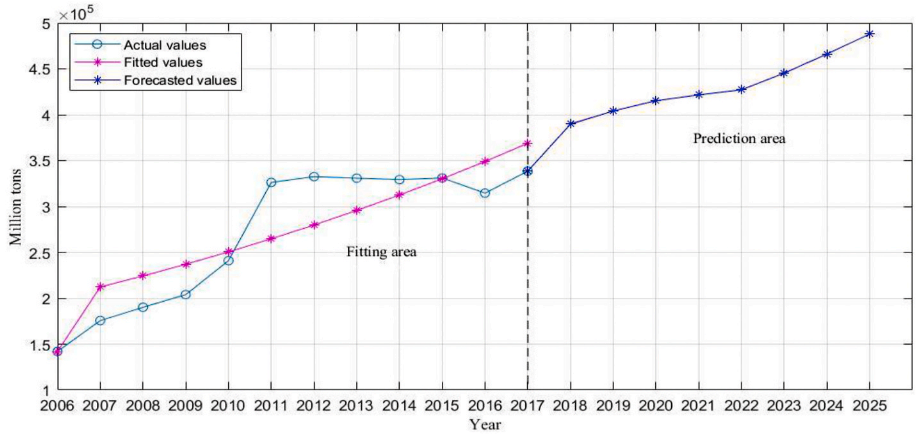


Fig. 3. The prediction results of China's ISWs generated from 2018 to 2025 using the MGM (1,1).

recycling of the waste within the industrial development (Salihoglu, 2010; Zhang et al., 2016). Below is a list of the main contents associated with the ISWs management system.

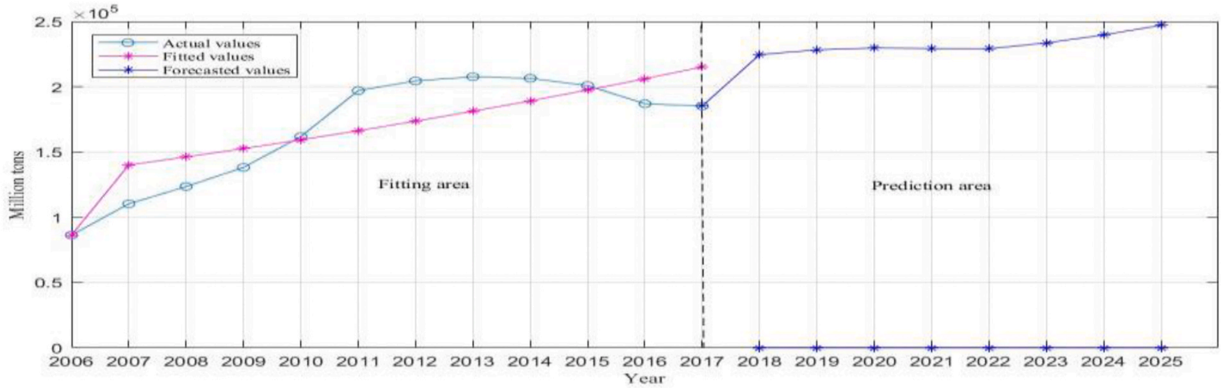
(a) Internal management and recycling of ISWs: Firstly, by adopting safe, clean and efficient green production technology with higher utilization efficiency and lower solid wastes generation, timely improving outdated technology and equipment that dispose of huge ISWs generated, developing key technologies for resource conservation and recycling, and establishing technical systems such as recycling of renewable resources. Secondly, the enterprises are focused on the classification and reuse obtained from industrial waste products. Through waste recycling and disposal within the waste generator, waste products can be sold and reused in the market. This process is an environmentally friendly and economic benefit, as it realizes the recycling of ISWs. Finally, the internal management and recycling of ISWs were designed such that the number of hazardous wastes and other wastes are minimized to ensure that maximum utilization is achieved.
(b) External management and recycling of ISWs: For enterprises with imperfect waste disposal infrastructure, the external management and recycling of ISWs can effectively promote the recycling and waste-to-energy of hazardous wastes and other wastes. Firstly, hazardous wastes and other wastes are then stored, collected, transported, and disposed of by waste receiving enterprises that are the final utilization and disposal facility. Secondly, through the harmless and stable treatment of wastes, the toxicity, and composition of hazardous waste and other waste can be degraded. This process can be achieved the reuse and valorization of these wastes using environmentally friendly workflows. Finally, when wastes that cannot be solidified and stabilized are concerned, it should be stored centrally to avoid the discharge and disposal of these wastes.

The ISWs management and recycling based on industrialization and circular economy is a top priority for the Chinese government (Guerrero et al., 2013). In China, factors like supply-side structural reform, cleaner production, and environmental quality fuel sustainable ISWs management (Jin et al., 2017; Zhang et al., 2016). The current environmental pollution has shed light on the necessity for linking the ISWs management system from government policy, industry-university cooperative innovation, and green finance (Huang et al., 2020; Yao and Zhang, 2018). Therefore, the application of safeguard mechanisms plays a pivotal role in sustainably ensuring ISWs management and recycling by multi-sectoral cooperation. The safeguard mechanism of the ISWs management system is shown in Fig. 6.

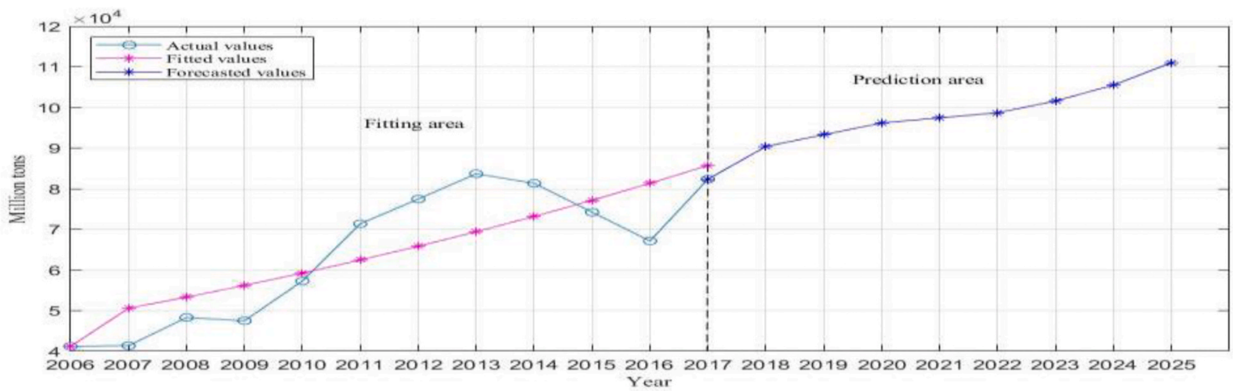
As it shows, firstly, the forecasting of China's ISWs reveals which the stage generates what quantities of solid waste, and in what the effect of treatment. On the one hand, these prediction results will be widely used for the evaluation of various environmental regulatory policies related to ISWs management. On the other hand, the results may also provide decision support for government policymakers to improve ISWs management programs to establish ISWs recycling systems and prevent environmental risks. Secondly, China should strengthen environmental constraints to resolve industrial overcapacity and promote the mechanism of the heavy pollution production capacity withdrawal and excess capacity resolution. All levels of the government should strictly implement environmental regulatory policies from the central government, and incorporate the management and recycling of ISWs into the performance appraisal system of local officials. Moreover, a well-functioning waste management system allows the media and public to supervise the clean production activities of enterprises and the enforcement of environmental regulations by local governments. Simultaneously, the media serves a vital function in conveying green consumption to the public. Next, collaborative agents of the industry-university have shared risks and benefits in the process of green technology innovation, including academic resources, personnel training, green technology R&D and transfer, and green technology application, and so on. And the collaborative of industry-university can actively improve the comprehensive utilization of ISWs with the help of green technology innovation. Another significant aspect of the safeguard mechanism is to promote the development of green finance. Financial support is the key factor to maintain the operation of ISWs management. The government should actively encourage and guide the flow of social and private capital to the field of ISWs management and recycling, such as implementing environmental subsidies and credit concessions for ISWs recycling projects, setting up special investment funds for ISWs management and supporting the transformation and upgrading of waste recycling equipment. Finally, by improving the government's green procurement system and promoting the evaluation and certification of green technologies, the sales of green products can be expanded. Further, the enterprises should focus on making it easier for consumers to make purchasing decisions by providing good quality green products in the ISWs recycling.

6. Conclusion

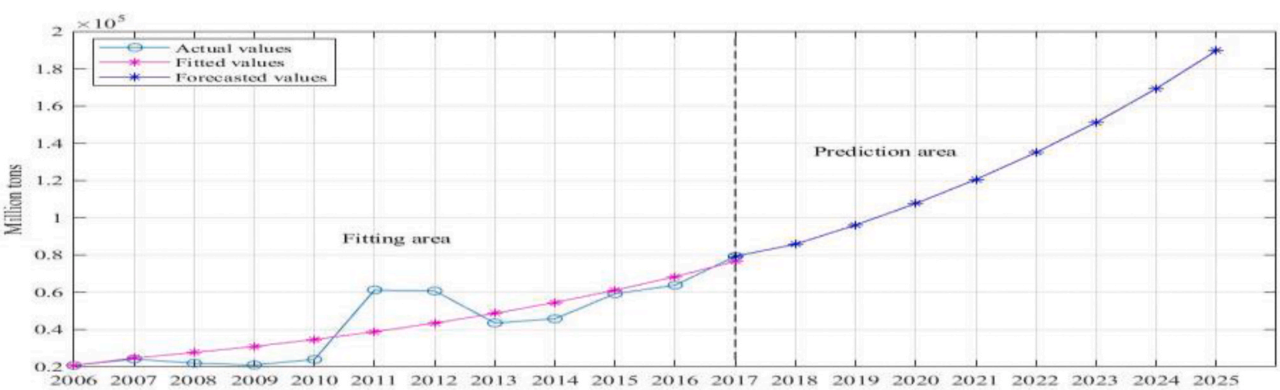
Considering that the MGM (1,1) model has the lowest MAPE value compared with the GM (1,1) model, the paper has forecasted the generation and treatment of ISWs from 2018 to 2025 in China based on MGM (1,1) model. Furthermore, the proposed prediction model can be applied as a guideline for a variety of future ISWs management and recycling in China. Our conclusion is that although China has benefitted from fast industrialization, the total amount of China's ISWs generated is



(a) ISWs utilized



(b) ISWs disposed



(c) ISWs stored

Fig. 4. The prediction results of China's ISWs treatment from 2018 to 2024 using the MGM (1,1).

large and the comprehensive utilization of ISWs is still far from optimal, and the establishment of an ISWs management and recycling framework is particularly important. In this paper, the main research conclusions are as follows: (1) China's ISWs generated have been a slowly increasing trend from 2018 to 2025, which will be controlled between 389819 million tons and 488002 million tons. (2) The utilization, disposal and storage of ISW have a significant upward trend. And the ratio of ISWs utilized will eventually remain at around 50% in the future (3) The tasks of industrialization, urbanization, and agricultural modernization in China have not yet been completed, and ecological and environmental protection are still facing great pressure; therefore, we develop an ISWs management system involving its safeguard mechanisms. Within the context of sustainable development, the Chinese government has incorporated environmental protection into corporate responsibility through environmental regulation policies. In the future, we need to take effective policies and measures to reduce China's ISWs generated and improve the efficiency of ISWs recycle while maintaining ISWs management in a sustainable way.

At the same time, this study has several potential limitations: (1) Although the MAPE of the MGM (1,1) model is less than 10% is believed

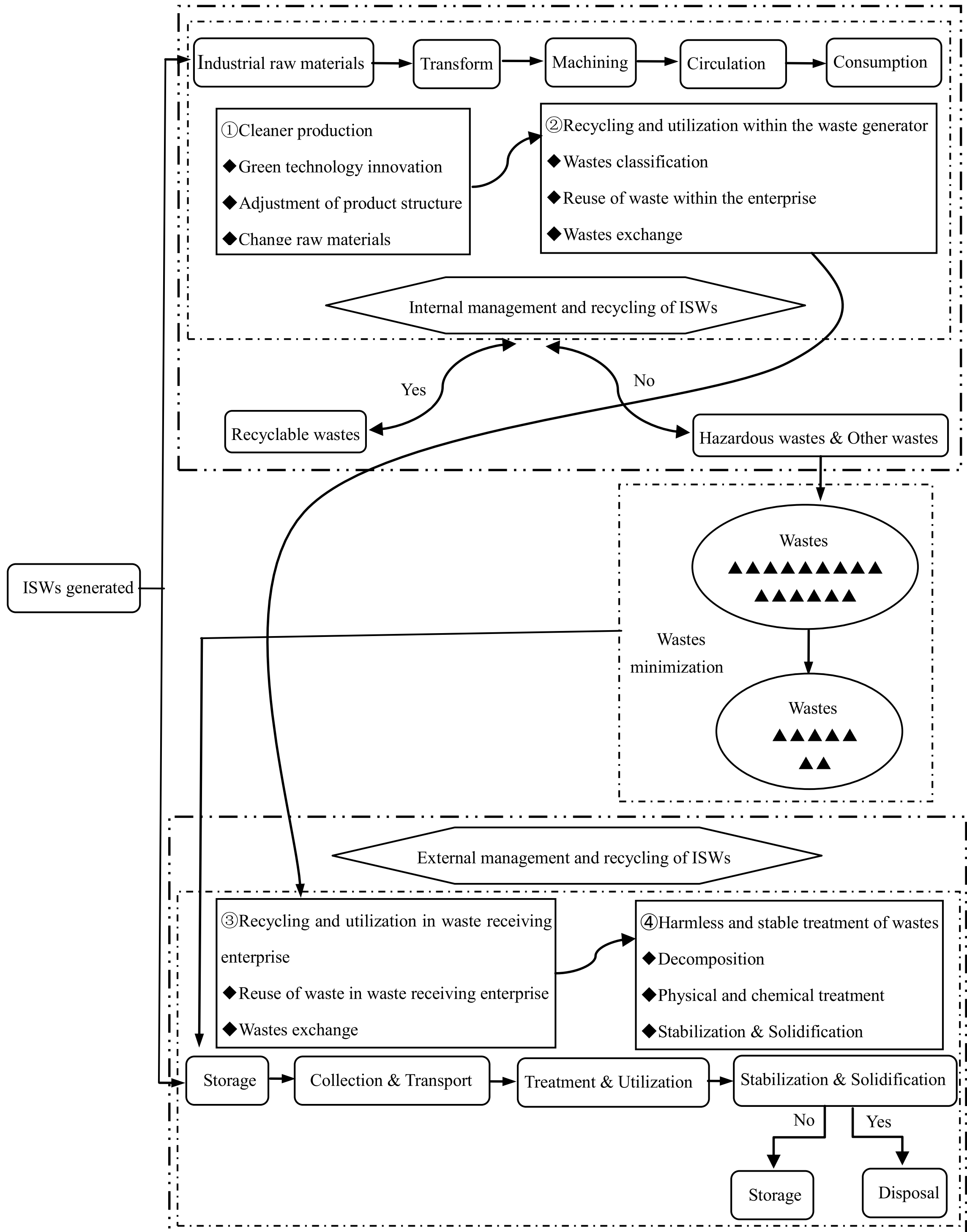


Fig. 5. The ISWs management system.

as highly accurate forecasting, the relative residual and class ratio dispersion are still relatively high and the model not be applied for a long-term period. For further studies, the prediction of ISWs may be correlated with including environmental policies and socio-economic factors. (2) The applicability of this ISWs management system to cleaner production and solid waste management based on different situations needs to be verified or improved in future studies. In addition, to improve the prediction ability of the MGM (1,1), the other optimization techniques, including the Genetic Algorithm (GM), Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO), should be employed to optimize the parameters of the prediction model. These models can be widely used to the prediction of ISWs generated, utilized, stored, disposed, and discharged. Future research should aim to expand on this study by these predictions to the most appropriate scenarios for ISWs management and recycling.

Credit author statement

Zhi Yang: Data curation, Writing - original draft. Heng Chen: Conceptualization, Methodology. Lei Du: Visualization, Formal analysis.

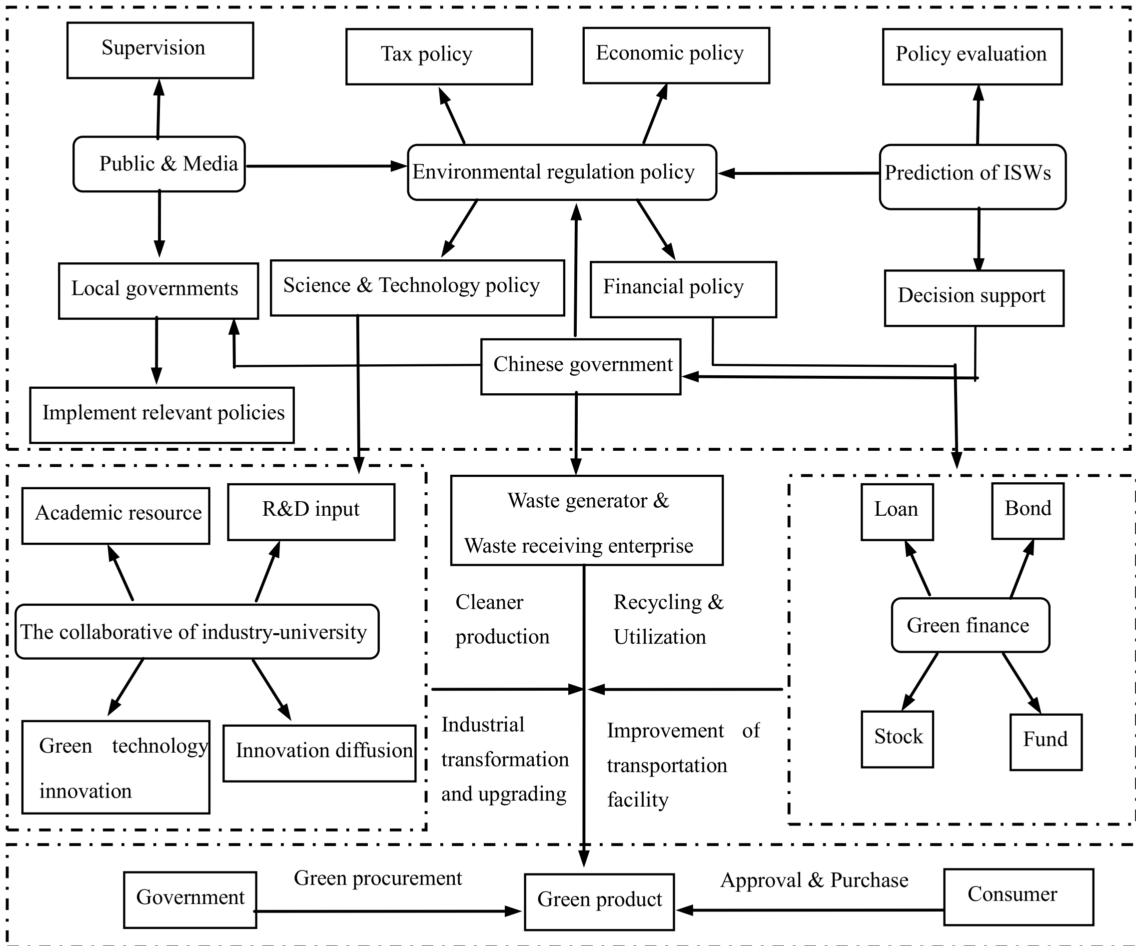


Fig. 6. The safeguard mechanism of the ISWs management system.

Wei Lu: Software, Validation. Kai Qi: Writing - review & editing.

Declaration of competing interest

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

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