CHEMICAL ENGINEERING TRANSACTIONS

VOL. 97, 2022

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Jeng Shiun Lim, Nor Alafiza Yunus, Jiří Jaromír Klemeš

ISBN 978-88-95608-96-9; **ISSN** 2283-9216

DOI: 10.3303/CET2297067

Socio-economic Correlation Analysis of E-waste and Prediction of E-waste Generation via Back-propagation Neural Network

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With the rapid electronics production in China, the lack of proper collection and disposal mechanisms of e-waste is a growing concern. Accurate predictions of e-waste can help improve the efficiency of e-waste collection and disposal. As China's capital city with a high gross domestic product, studying the e-waste generation in Beijing could provide an example for other province-level administrations. Analysing the correlation between e-waste generation with their socio-economic factors (e.g., gross domestic product, unemployment rate, educational level) is vital in revealing their influential critical factors. This study analyses Beijing's socio-economic correlation with e-waste using Pearson correlation analysis and develops a Back-propagation Neural Network to predict e-waste generation. The major socio-economic factors influencing e-waste generation are municipal solid waste generation, population, gross domestic product, and carbon dioxide emissions. The Back-propagation Neural Network prediction shows the air-conditioner type e-waste with the greatest growth rate, 40.24 % from 2019 to 2025, while the washing machine type achieves the least. Through this study, the identified correlated socio-economic factors and the predictive model could provide e-waste growth rate and socio-economic influencing factors of e-waste to Beijing's government in planning a more sustainable e-waste management system.

1. Introduction

With the rapid development of global electronic technology, e-waste is increasing along with people's demand for electronic products. Globally, e-waste generated is estimated to exceed 5×10^7 t in 2019, of which 2.49×10^7 t were generated in the Asia-Pacific region (Perkins et al., 2014). Among the Asian countries, China is one of the major electronic and electrical equipment producers. Currently, 1.01×10^7 t of e-waste was produced in China in 2019 (Andeobu et al., 2021). As China's capital city, Beijing is estimated to generate 2.82×10^6 units by 2020 (Liu et al., 2006). Based on the calculation of 9.95 kg/unit for e-waste (Alavi et al., 2015), Beijing accounts for 0.27 % of China's e-waste, exceeding the average e-waste generation of 663 cities in China. In China, the E-waste Treatment List identified five categories of e-waste: television (TV), refrigerator (RE), washing machine (WM), air conditioner (AC), and personal computer (PC). Before 2017, AC, monitor, PC, and TV accounted for 71 % of the total e-waste by weight (Awasthi and Li, 2017). E-waste must be appropriately treated as bio-accumulative toxic substances in the raw materials of electronic devices harm human health and the environment (Woon and Lo, 2016). Precious metals could also be recovered by effective e-waste collection (Trucillo et al., 2021).

Paper Received: 14 June 2022; Revised: 10 July 2022; Accepted: 18 July 2022
Please cite this article as: Tian R., Hoy Z.X., Woon K.S., Hanafiah M.M., Liew P.Y., 2022, Socio-economic Correlation Analysis of E-waste and Prediction of E-waste Generation via Back-propagation Neural Network, Chemical Engineering Transactions, 97, 397-402 DOI:10.3303/CET2297067

To reduce the threat of e-waste, the Chinese government has taken a series of targeted policies. Circular Economy Promotion Law is formulated to reduce e-waste pollution and the Extended Producer Responsibility system to effectively track e-waste managers (Yu et al., 2010). In 2020, Beijing adopted the "Decision on Revising the Regulations of Beijing Municipal Household Waste Management" (Beijing Municipal Public Complaints Office, 2019). In 2021, Beijing's government issued the "Implementation Plan of Beijing on The Construction of a Modern Environmental Governance System" to strengthen household waste management and promote the capital's sustainable economic and social development (The State Council, 2021a).
As e-waste generation is highly driven by social and economic standards, studying the socio-economic correlation of e-waste could reveal the relationship between socio-economic factors and e-waste generation for effective e-waste management (Kumar et al., 2017). Awasthi et al. (2018) applied correlation analysis to reveal a robust linear relationship between global e-waste generation and GDP. Boubellouta and Kusch-Brandt (2021) demonstrated an increasing e-waste trend with GDP until a certain level; then, it decreases with further increment in GDP in 30 European countries. These studies only studied the relationship between economic growth and e-waste generation, neglecting its possible correlation with social parameters. The future predictions of e-waste can also resolve data scarcity and assist the e-waste management by improving the estimates of their resource potential and providing a reference for e-waste recovery (Mao et al., 2020). Machine learning models such as the Back-propagation Neural Network (BPNN) have been growing in popularity due to their non-parametric property and ability to reveal the internal relationship of the data sample (e.g., temporal fluctuations and data uncertainty) (Galang and Ballesteros, 2018). Since each e-waste type grow at a different rate and pattern, the BPNN could be applied to resolve the trend complexity.
This study expands the scope of socio-economic factors by revealing more socio-economic relationships between Beijing's e-waste generation. The BPNN is applied to predict Beijing's e-waste generation. The correlated socio-economic factors and effective prediction of e-waste could help the Beijing government establish effective e-waste management to reduce environmental pollution, ultimately achieving SDG 3 (Good Health and Well-being) and SDG 12 (Sustainable Consumption and Production).

2. Methods

2.1 Data collection

Possession of 5 types of electronics (i.e., TV, RE, WA, AC, and PC) in Beijing is collected as shown in Table 1. TV possession data is separated into TV (colour) and TV (DC) to represent colour TV and direct current TV (black and white TV). Several key socio-economic parameters for solid waste management highlighted in Lakioti et al. (2017) are considered in the correlation analysis, including gross domestic product (GDP), unemployment rate (UR), population, municipal solid waste (MSW) generation, age frame, educational level (EL), and CO_2 emissions are collected from the government statistics and database.

Table 1: Data source for correlation analysis and prediction of e-waste

Phase	E-waste type	Data source
Phase 2a: Correlation analysis	GDP	NBS (2022)
	UR	MOHRSS (2021)
	Population	NBS (2022)
	MSW	MOHURD (2021)
	Age frame	NBS (2022)
	Educational level	NBS (2022)
	CO_2 emissions	Carbon Emission Accounts & Datasets (2022)
Phase 2b: Prediction of e-waste	TV (colour) possession	NBS (2022)
	TV (DC) possession[1]	
	WM possession	
	AC possession	
	RE possession	
	PC possession	
	Obsolete Year	Oguchi et al. (2006)

2.2 Methodology Flow Chart

Figure 1 shows the overall methodology flow of research. Phase 1 estimates the e-waste data using the electronics possession data and obsolete parameters. Phase 2a involves the correlation analysis between e-waste and each socio-economic factor. Phase 2b predicts the e-waste generation via BPNN and evaluates the prediction accuracy based on the R-squared value (R^2).

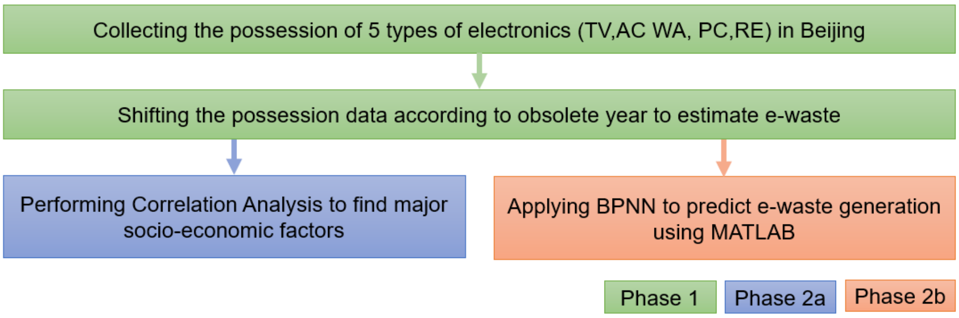

Figure 1: Overall methodology flow of research

2.2.1 E-waste generation estimation (Phase 1)

The e-waste generation is estimated based on the electronic possession and their lifespan. The electronics possession data is assumed based on the electronic sales amount, while the obsolete ratio and collection rate are assumed to be constant within 10 years according to Duan et al. (2016). After collecting possession data of e-waste, the obsolete year of electronics was determined using Weibull distribution, as shown in Eq (1):

$$f(t) = 1 - exp\left\{-\left(\frac{t}{t_0}\right)^{\mu} \cdot \left[\Gamma\left(1+\frac{1}{\mu}\right)\right]^{\mu}\right\} \qquad (1)$$

where, t is the lifetime of each electronic; t_0 is the average lifespan of the electronic; μ is a parameter of Weibull distribution, ranging from 1.7 to 3.3 for electronic devices; Γ is the gamma function.

2.2.2 Pearson correlation analysis (Phase 2a)

Pearson correlation coefficient, R, is a quotient to measure the covariance and standard deviation between two variables. The closer to +1 the R was, the stronger the positive correlation was; the closer to -1 the R was, the stronger the negative correlation was; and the closer to 0 the R was, the weaker the correlation was. As shown in Eq (2), x_i represents e-waste amount, z_i represents socio-economic factors.

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(z_i-\bar{z})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(z_i-\bar{z})^2}} \qquad (2)$$

2.2.3 Back-Propagation Neural Network (BPNN) (Phase 2b)

BPNN was constructed using MATLAB and developed separately to predict each e-waste type up to 2025. BPNN predicted e-waste generation in t year based on e-waste generation in the t-1 and t-2 years. For example, WM type e-waste generation in 2015 are predicted based on e-waste generation in 2013 and 2014. The R^2 value was used as the evaluation index of the prediction accuracy BPNN. It indicates how well a model predicts new observations. The BPNN continuously adjusts the weights and thresholds of network nodes by learning input and output mode mappings and using the activation function $f(x) = \tanh(x)$ for error back propagation in the hidden layer to determine bias, b, and (Pan et al., 2020). The structure of the developed BPNN is 2:4:1, as shown in Figure 2. The mapping between input x (estimated e-waste in t-1 and t-2 years) and output y (predicted e-waste in t year) of the BPNN (w is the weight and φ is the mapping relation) is as Eq (3):

$$y = \varphi(x, w) + b \qquad (3)$$

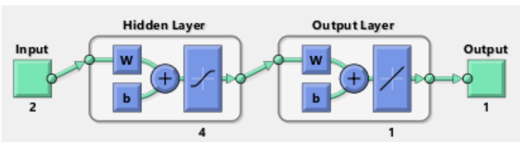

Figure 2: Structure of the developed BPNN

3. Results and discussion

3.1 Pearson correlation analysis of socio-economic factors and e-waste

The absolute value of a correlation coefficient larger than 0.8 can be regarded as a strong correlation coefficient between the two factors. As shown in Figure 3, the more yellow colour, the e-waste more strongly correlates with MSW, population, GDP growth, and CO_2 emissions. TV DC shows the opposite correlation trend with the other four factors. This is because the usage rate of TV DC decreases year by year, which leads to the elimination of TV DC from the market, showing a negative trend with the increasing social-related factors. The e-waste growth in Beijing is not as strongly correlated to the UR, educational level, and age structure.

		Socio-economic factors											
		UR	MSW	Population	EL:primary	EL:middle	EL:senior	EL:>senior	age:0-14	age:15-64	age:>65	GDP	CO2
E-waste Category	WM	0.054	0.864	0.924	-0.715	-0.715	-0.715	-0.714	-0.714	-0.715	-0.714	0.934	-0.893
	TV colour	0.293	0.977	0.857	-0.522	-0.522	-0.522	-0.522	-0.522	-0.522	-0.522	0.988	-0.919
	TV DC	-0.056	-0.851	-0.968	0.657	0.657	0.657	0.656	0.656	0.657	0.656	-0.907	0.878
	AC	0.333	0.992	0.827	-0.060	-0.074	-0.057	-0.028	-0.039	-0.052	-0.027	0.997	-0.890
	RE	0.178	0.851	0.977	-0.743	-0.744	-0.743	-0.742	-0.743	-0.743	-0.742	0.905	-0.933
	PC	0.288	0.979	0.893	-0.491	-0.491	-0.491	-0.490	-0.490	-0.491	-0.490	0.984	-0.891

-1 0 1

Figure 3: Socio-economic correlation coefficient

The positive correlation between the growth of e-waste and GDP (0.891-0.934) comes from the fact the growth of GDP relates to higher living standards. The GDP growth reflects residents' consumption ability and promotes the demand for electronic products, increasing the e-waste generation potential (Kumar et al., 2017). The strong correlation between e-waste and MSW (0.851-0.992) reflects the people's ability to produce waste. This may have resulted from the same driving force of GDP (Ding et al., 2021). Kumar et al. (2017) observed that there is no apparent influence of population growth on e-waste growth globally, but China shows the outlier. In this study, a positive and strong correlation with the population (0.827-0.977) further reveals a similar relationship. This may relate to an increased resident's absolute demand due to the population boost in China. The results also clearly show that the growth of e-waste negatively correlates with CO_2 emissions. The CO_2 emissions reflect industrial production's activity (Gu et al., 2020). While Beijing's industrial production has not decreased, Beijing's government enacted a policy of "Beijing studying and formulating an action plan for carbon neutrality" (The State Council, 2021b). This policy aims to protect the environment through greening and industrial CO_2 emission absorption to gradually cause Beijing's CO_2 emissions to decrease over the years. The relationship between the decrease in CO_2 emissions and the increase in e-waste generation explains their strong negative correlation.

The correlation results show that the generation of e-waste in Beijing strongly correlates to the GDP, population, and MSW. With the continual increase in population and GDP in China, it is expected that the e-waste generation in Beijing will follow the increasing trend, urging the need to improve Beijing's e-waste disposal and collection system.

3.2 Prediction of e-waste using BPNN

Figure 4 shows the prediction of the six types of e-waste up to 2025.

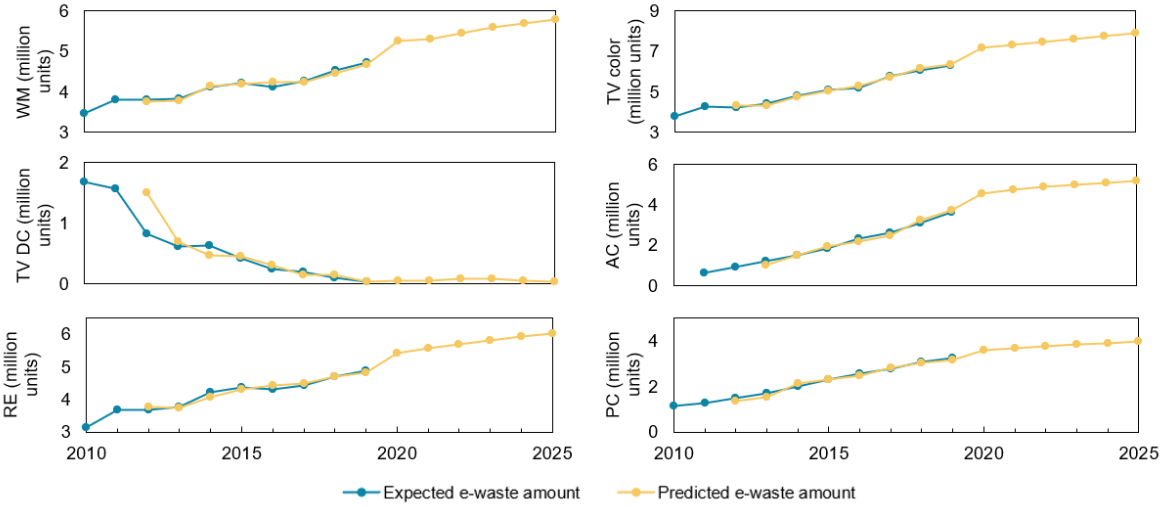

Figure 4: Different e-waste type predictions using BPNN

As shown in Table 2, only the TV DC type e-waste shows a decreasing trend. As the utilization rate of TV DC is decreasing annually, it gradually leads to its elimination from the market, which explains its continuous decreasing trend. The remaining five types of e-waste show steady growth rates. The AC type e-waste shows the most significant growth rate from 2019 to 2025 (40.24 %), while the WM type shows the least significant growth rate (24.00 %). This is due to the increased use of AC to replace electric fans to regulate the room temperature in the residential, commercial, and industrial areas. WM is a daily necessity with a limited demand within the residential area. PC shows the second-largest growth rate of 25.62 % due to the high development of information technology. TV colour type e-waste shows the third-largest growth rate of 24.88 %, contributed by its active replacement of the use of TV DC. As identified in the correlation analysis, GDP and population are strongly correlated to e-waste generation. The overall increasing e-waste trend is consistent with the economic and population growth.
Table 2 shows that the R^2 between expected and predicted e-waste amount is greater than 0.95, except for the TV DC type e-waste. This might be due to TV DC type e-waste being the only e-waste type with a drastic decreasing trend, most noticeable in the early 2010s, while the other types of e-waste show steady growth rates. As the years go by, the decreasing rate of TV DC type e-waste also decreases and approaches zero due to its elimination from the electronics market, resulting in the low fitting accuracy.

Table 2: Summary table of the e-waste prediction using BPNN

	WM	TV colour	TV DC	AC	RE	PC
R^2 between expected and predicted amount	0.965	0.991	0.799	0.986	0.954	0.981
Growth rate from 2019-2025 (%)	24.00	24.88	-6.63	40.24	24.98	25.62

The high prediction accuracy of e-waste generation shows the possibility to apply the proposed method in regions with similar e-waste driving forces to analyse their e-waste issues. While this research attempts to perform future e-waste predictions as a measure to overcome the data shortage issue, the lack of actual historical e-waste data still acts as a limitation of the study. Existing researches mostly rely on electronics possession data to estimate the e-waste amount, but there will be data uncertainty (Duan et al., 2016). Improvement of e-waste management and implementation of relevant policies may cause underestimation in the electronics possession data. The possession data from electronic sales may also neglect electronics entering into possession without involving the market. Developing a robust e-waste data inventory in China is urgently needed for a more effective e-waste management system.

4. Conclusions

This study has identified the major socio-economic factors influencing e-waste generation using Pearson correlation analysis. E-waste generation in Beijing has a strong positive correlation with GDP growth, population, MSW, and a strong negative correlation with CO_2 emission. A BPNN model is developed to predict e-waste generation in Beijing. The developed BPNN model predicted WM, TV colour, TV DC, AC, RE, and PC type e-waste growth rate from 2019-2025 with 24.00%, 24.88%, -6.63%, 40.24%, 24.98%, and 25.62%. The predicted increasing e-waste amount is consistent with the population and economic growth, as indicated in the correlation analysis. The identified correlated socio-economic factors and the predicted e-waste generation in Beijing could provide insights to Beijing's government in understanding the e-waste system for the future allocation of e-waste treatment capacity resources and becoming a prominent example for e-waste management among the provinces in China.

Acknowledgments

This work was supported by the Ministry of Higher Education Malaysia through the Fundamental Research Grant Scheme [FRGS/1/2020/TK0/XMU/02/2].

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