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ESG Modeling and Prediction Uncertainty of Electronic Waste

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Abstract: Driven by a variety of factors, including the advent of digitalization, increasing population and urbanization, and rapid technological advancements, electronic waste (e-waste) has emerged as the fastest growing waste stream globally. Effective management of e-waste is inherently aligned with environmental, social, and governance (ESG) frameworks and is typically examined within this context. Accurate quantification of the current and future accumulation of e-waste is a key step towards ensuring its proper management. Numerous methodologies have been developed to predict e-waste generation, with the grey modeling approach receiving considerable attention due to its ability to yield meaningful results using relatively small datasets. This study aims to introduce a novel forecasting technique for predicting e-waste, particularly when limited historical data are available. The proposed approach, the non-linear grey Bernoulli model with fractional order accumulation NBGMFO(1,1) enhanced by Particle Swarm Optimization, demonstrates superior accuracy compared to alternative forecasting models. Additionally, the Fourier residual modification method is applied to enhance the precision of the forecast. To provide a practical illustration, a case study utilizing waste mobile phone data from Turkey is presented.

Keywords: electronic waste; fractional order; improved grey modeling; particle swarm optimization; environmental, social, and governance (ESG) framework

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1. Introduction

Electronic waste, also known as e-waste, is a rapidly growing environmental problem, as the amount of discarded electronic devices continues to increase at a rapid pace. In 2019, the world generated 53.6 million metric tons of e-waste, and this amount is projected to increase to 74.7 million metric tons by 2030 [1]. E-waste contains valuable materials such as metals and rare earth elements, but also hazardous substances (e.g., lead, mercury, nickel, and cadmium) that pose significant health and environmental risks if not managed properly [2].

Earlier studies also provide evidence regarding the negative social effects, such as domestic fires, child labor, and unsafe work conditions during the storage and recycling of e-waste. Soil quality is also one of the primary concerns related to electronic waste. The toxic materials can leach into the soil when electronic waste is disposed of inappropriately, potentially contaminating agricultural and livestock products. Furthermore, toxic metals can impair soil fertility and reduce crop productivity. E-waste can also have indirect impacts on food safety. Many electronic devices contain chemicals such as phthalate, esters, benzene, dioxins, polyaromatic hydrocarbons, and polyvinyl chloride that can pose health risks when they enter the environment [3]. These chemicals can bioaccumulate in the food chain, potentially leading to health problems for both animals and humans [4].

Moreover, electronic waste disposal contributes to greenhouse gas emissions, which can lead to changes in climate patterns with significant potential impacts on food production. Climate change can result in food stress in some regions by affecting crop diversity and availability. Additionally, the cost of dealing with electronic waste is significant, with estimates suggesting that it costs billions of dollars each year to manage electronic waste properly. These costs are often passed on to consumers in the form of higher prices for electronic devices. Hence, the proper management of electronic waste is critical to mitigate these risks and ensure a sustainable future for all.

While this staggering accumulation of waste makes the issue more pressing from an environmental and societal perspective [5], the accelerated growth of e-waste brings with it an opportunity allowing economies of scale to be in effect for the financially viable raw materials recovery. The precious metal content makes these end-of-life (EOL) products viable candidates for material recovery which would concurrently lead to e-waste reduction. E-waste contains approximately 60 different kinds of metal, including copper, gold, silver, palladium, and platinum. The value of raw materials in the global e-waste generated in 2019 was equal to approximately 57 billion USD, with iron, copper, and gold being the three metals that contributed most to this value [1]. Recovery of these metals from e-waste could reduce the total global demand for new metal production to some extent [6–8], making EOL processing of e-waste an integral part of environmental, social, and governance (ESG) frameworks.

The economic efficiency of EOL processing activities heavily relies on accurate predictions of e-waste, its homogeneity, and location, highlighting the importance of e-waste disclosure. Currently, of the 53.6 million tons of e-waste generated, only 17.4% is documented as processed [1,9] whereas the remaining EOL products join the accumulating stock, resale, and landfill inventories. The increasing amount of stringent environmental regulations while pawing the path for greener solutions also require that the manufacturers consider the impact of their products on the environment as early as the product design stage to consumption, reuse, remanufacturing, recycling, and proper waste disposal. The current practice, especially in developing regions, however, is that e-waste joins informal economies where waste collectors and scrap pickers dismantle EOL products for their raw materials, components, and subassemblies. This makes location, quantity, quality, and content tracing very difficult, hindering the ESG management practices and reducing the e-waste value proposition for manufacturers.

Motivated by these factors, this study elucidates upon the importance of forecasting e-waste for the betterment of ESG management practices. Such forecasting can help governments, organizations, and businesses develop effective strategies and policies to manage e-waste in a sustainable and responsible manner. By linking the forecasting of e-waste to ESG management practices, this study suggests that accurate predictions about e-waste generation can inform and improve sustainability efforts and corporate strategies. This implies that organizations that proactively address e-waste issues can enhance their ESG performance and contribute positively to environmental and social goals.

The rest of this article is organized as follows. Section 2 details the relationship between e-waste collection and ESG management. The literature review, providing information regarding the related work, is in Section 3. In this section, the focus is on previously proposed e-waste prediction techniques, along with the grey models used in this study. Section 3 also provides a detailed explanation of our research contribution, which focuses on addressing the existing research gap in the field of electronic waste prediction. Specifically, we propose a novel grey forecasting model to accurately forecast electronic waste, and this model is elaborated upon in Section 3. Section 4 outlines the research methodology and provides information on the applied model. A case study utilizing waste mobile phone data from Turkey is presented in Section 5. Conclusions and directions for future research are provided in the final section, Section 6.

2. E-Waste Collection and Environmental, Social, and Governance (ESG)

In their study, Murthy and Ramakrishna [9] stated that out of the total e-waste generated in 2019, only a small proportion of 17.4% (9.3 Mt) was gathered and recorded, while the remaining 82.6% (44.3 Mt) was uncertain and had varying effects on the environment, such as soil and water contamination and human health (e.g., skin irritations, neurological disorders, memory disorders, and cognitive debilities) in different parts of the world [3,10]. E-waste is a valuable resource that contains a range of natural and processed materials, including precious and platinum group metals, base metals, plastics, and other non-metals. The total value of these metals is estimated to be USD 57 billion, which is equivalent to the GDP of many countries [1]. However, instead of being processed at formal facilities to recover these valuable materials as secondary raw materials and extend their life, they were often disposed of openly or incinerated [9,11].

Environmental, social, and governance (ESG) management is a holistic approach that considers the sustainability and ethical impact of an organization's operations. The topic has gained increasing attention from investors, regulators, and other stakeholders in recent years, reflecting a growing awareness of the interdependence between business performance and sustainable development [12]. ESG also provides investors with a comprehensive understanding of a company's long-term financial prospects and sustainability. The relationship between electronic waste recycling and ESG management is expected to become even stronger as the pressure to address the environmental and social impacts of organizational operations increases.

E-waste often contains toxic materials and persistent organic pollutants (e.g., brominated flame retardants), which can contaminate soil, water, and air when their disposal is not managed correctly [13]. This pollution can have severe consequences for ecosystems, including the loss of biodiversity, depletion of natural resources, and the disruption of food chains. Moreover, the extraction of valuable materials, such as gold, silver, and copper, from e-waste often involves informal recycling processes that release toxic chemicals into the environment [14].

The social implications of e-waste are equally concerning and highlight the importance of integrating social factors into ESG management. In many developing countries, informal e-waste recycling is a prevalent practice, involving manual dismantling and the extraction of valuable materials from discarded electronic devices. This informal recycling often takes place in unsafe working conditions, exposing workers, including children, to hazardous substances and increasing their risk of experiencing adverse health effects, such as respiratory illnesses, skin diseases, and neurological disorders [9,15,16].

Governance plays a significant role in addressing these challenges that e-waste introduces. Implementing and enforcing regulations that promote responsible e-waste management, such as extended producer responsibility (EPR) policies to achieve a reduction in e-waste amounts, reduces the e-waste disposed of, reduces hazardous constituents in the e-waste, decreases the use of virgin materials and metals, mitigates environmental pollution, and enhances the design for the environment [16]. Implementing robust governance policies to ensure that organizational operations are compliant with national and international regulations is also proving effective in addressing the issue. To ensure the community buy-in, engaging with stakeholders that include governments, NGOs, and local communities, to promote responsible e-waste management practices and increase awareness, would potentially be impactful in sustaining these efforts. International cooperation and global partnerships are vital components of combating the illegal transboundary movement of e-waste, which often results in the transfer of e-waste in countries with ineffective environmental and health regulations [17,18].

As the awareness of environmental compliance grows among purchasing groups, there is an increasing number of organizations that use green supply chain management [19] and other ESG practices as a leverage to remain competitive. The literature indicates that regardless of the size of the organization, suppliers associate green innovation with positive returns. However, ESG with a focus on e-waste offers different challenges due to its unique characteristics. First and foremost, e-waste predictions are required to handle a great deal of uncertainty while dealing with scarce datasets. Furthermore, the ESG models that focus on e-waste should consider governmental regulations while tackling organizational responses to the changing legislations.

Focusing on supply chain alignment, Kim et al. [20] stated that sustainable supply chains require transparency, information sharing, and commitment from all supply chain entities, including upper-tier suppliers, consumers, and the reverse supply chain. Further, contributing to ESG research that focuses on e-waste, Cotta [21] emphasized the problems of access to resources and allocation of responsibilities, risks, and burdens in the global trade of e-waste. Given that ESG committees usually involve C-level decision makers, Abd-Mutalib et al. [22] looked at the issue from the lens of corporate disclosures, and investigated the extent and quality of e-waste disclosure and its variability based on the businesses and boards' characteristics. The authors indicated that the size of the corporate boards was positively correlated with the e-waste management and disclosure.

E-waste collection has been investigated by researchers under the general concept of closed loop supply chain and reverse logistics. Majority of these studies have addressed the issue from the operational point of view, namely, the reverse logistics network design using multi-criteria decision making and linear programming approaches [23–29]. However, these studies mainly focused on the economic aspect of the reverse logistics operations [30]. Closed loop supply chain and reverse logistics operations contribute to the sustainable supply chain management framework and environmental and social aspects of sustainability need to be included [31].

Due to the exclusive nature of e-waste, the triple bottom line approach, namely, economic, environmental, and social aspects of sustainability, can be integrated into the reverse logistics of e-waste. To address this issue, Bal and Satoglu [32] and Safdar et al. [30] applied goal programming and multi-objective programming methods to include the triple bottom line approach of sustainability for the reverse logistics network design of e-waste. Duman et al. [33] stated that accurate e-waste forecasts were essential in designing reverse logistics infrastructures that would ensure the proper collection, recycling, and disposal of e-waste.

In 2015, the United Nations and all member states adopted the 2030 Agenda for Sustainable Development and identified 17 Sustainable Development Goals (SDGs) [34]. The improper and unsafe treatment of e-waste and disposal through incineration or in landfill delivers significant challenges to the environment and human health, and hinders these goals. E-waste management is organically aligned with many SDGs, specifically, with SDG8 on decent work and economic growth, SDG3 on good health and well-being, SDG6 on clean waste and sanitation, and SDG14 on life below water. SDG 12 further discusses the importance of e-waste [1] and provides up-to-date data hazardous waste generated by type, including e-waste.

ESG has been heavily scrutinized in the private sector, while, compatible with the increasing consumer demand, more and more local governments are also seeking ways to qualify for ESG labels. Trying to map this trend, Shittu et al. [35] reviewed global e-waste trends and legislations. Although Europe and America have been predominantly the biggest generators of e-waste per capita [35], only 9.4% e-waste has been documented as having been collected and properly recycled in the Americas, compared to Europe's 42.5% in 2020 [9,36]. European Union directives allow consumers to return discarded electronics and related equipment free of charge. Contrary to this governance, the authors indicated that e-waste management in the USA varied between states due to a lack of federal e-waste laws and legislations. Since then, initiated by the State of California legislators in 2003, 25 states and the District of Columbia have passed legislations mandating statewide e-waste recycling [37–39]. E-waste management in these states is generally handled via municipal waste management services [40]. Among these 25 states, the state of Washington has a well-established e-waste recycling program with publicly available data to demonstrate its capabilities [38]. The state releases publicly available reports about the quantity and types of e-waste through its "e-cycle" program on an annual basis [38]. Several studies have investigated the Washington State e-cycle program [7,33,38,39,41–44], with it being one of the only available historical datasets available to researchers. Among these, Schumacher and Agbemabiese [39] noted that approximately 125 new e-waste recycling-related jobs had been created in the state of Washington, further strengthening the social impact of the ESG and Sustainable Development Goals.

3. Literature Review

The U.S. Environmental Protection Agency (EPA) conducted two studies on Electronics Waste Management [45,46] in the past decade to address this issue. The first study used electronic product sales data to predict lifespans and quantities of specific end-of-life products, while the second study utilized statistical information on electronic product sales along with the lifespan data from the first approach to estimate the quantities of end-of-life products. Both approaches employed material flow analyses (MFA) to track the sources, pathways, and destinations of materials. Similar MFA methods have been used in Japan and Chile to analyze e-waste from various electronic products [47–51]. Additionally, other methods such as the Carnegie Mellon method [52] and the Market Supply method [53] have been proposed and applied in different countries such as the United States and India to predict e-waste quantities. Various forecasting techniques, including logistic models and a range of forecasting models such as Bass, Gompertz, and ARIMA, have also been employed to estimate e-waste generation and accumulation in different regions of the world. Various forecasting methods have also been employed to estimate the generation of electronic waste. For instance, Yang and Williams [54] utilized a logistic model-based forecasting technique specifically for obsolete computers. Petridis et al. [55] employed multiple forecasting models such as Bass, Gompertz, logistic, trend model, level model, ARIMA, and exponential smoothing to estimate the accumulation of obsolete computers in different global regions. Similarly, Albuquerque et al. [56] utilized an autoregressive integrated moving average (ARIMA) technique to estimate both computer production quantities and the resulting e-waste in Brazil.

3.1. Grey Forecasting Model

After being introduced by Deng [57], the first-order grey model with one variable, GM(1,1), has gained widespread application in forecasting due to its capacity to deliver highly accurate predictions. Over the years, various adaptations of this initial forecasting model, as well as enhanced grey forecasting models, have been proposed with the aim of further improving accuracy in the field of forecasting.

As grey forecasting evolved, various models with better forecasting accuracy have also emerged. Out of these, the grey Verhulst model, GVM(1,1), is the integration of the Verhulst method into grey modeling. GVM(1,1) has the ability to deal with data series forming a sigmoid or s-curve. Another grey forecasting model, the nonlinear grey Bernoulli model, NGBM(1,1), was proposed by Chen [58] as a generalized form of the Verhulst model. In that study, the NGBM(1,1) was applied to predict the annual unemployment rate in specific countries. In another study, Chen et al. [59] utilized the NGBM(1,1) to forecast the foreign exchange rates of Taiwan's major trading partners. Wang et al. [60] developed an optimized version of the NGBM(1,1) to estimate the qualified discharge rate of industrial wastewater in China. Additionally, Pao et al. [61] applied the NGBM(1,1) to forecast carbon emissions, economic growth, and energy consumption in China.

Developed by Wu et al. [62], grey modeling with fractional order accumulation, GMFO, is another technique that aims to enhance the forecasting accuracy. Unlike the first-order accumulation used in GM(1,1), the GMFO model incorporates the fractional accumulation generating order, allowing it to handle the nonlinearity inherent in real systems [63]. Wu et al. [64] further applied GMFO to minimize errors arising from the inverse accumulated generating operator of the grey model. Several studies have employed grey modeling with fractional order in various domains [65–68].

3.2. Optimized Grey Forecasting Models

The primary objective of the aforementioned improved grey models is to achieve higher accuracy in forecasting. The literature includes a range of studies focused on optimizing the background value coefficient, which is typically set to 0.5. This coefficient helps smooth the data, reducing randomness and emphasizing the most recent data point. To determine the optimal or near-optimal background value coefficient, various heuristic methods have been integrated into both traditional and improved grey models. Examples of these methods include Genetic Algorithm [69–74], Ant Colony Algorithm [75], Ant Lion Optimizer [76], Moth-Flame Optimization [77], and Particle Swarm Optimization (PSO) [78–81]. Furthermore, recent studies in the grey modeling domain indicate that integrating a Fourier approximation method increases the forecast accuracy significantly. Jiang et al. [82] proposed an improved grey multivariable Verhulst model integrated with Fourier series to forecast China's CO_2 emissions. Hu [83] applied a fractional grey prediction model with Fourier series to forecast tourism demand in Taiwan. Hu [84] also developed a grey prediction with Fourier series using Genetic Algorithm for tourism demand forecasting. Jiang et al. [85] analyzed China's Outward Foreign Direct Investment (OFDI) using a novel multivariate grey prediction model with Fourier series. Nguyen et al. [86] employed Fourier series to improve the prediction accuracy of a univariate nonlinear grey Bernoulli model. Kiran et al. [87] proposed an improved multivariate discrete grey model combining Fourier Transform and an exponential smoothing technique that was used to forecast the in-use stock of mobile phones, televisions, and personal computers considering the Gross Domestic Product and rural and urban populations.

With this motivation, this paper proposes an improved nonlinear grey Bernoulli model with fractional order accumulation, which is further improved using Particle Swarm Optimization (PSO) in conjunction with the Fourier residual modification method. The aim of this approach is to enhance the accuracy of the forecasting process. To our knowledge, this study is the only research integrating fractional order accumulation and Fourier residual modification to NBGM(1,1) with PSO to estimate e-waste. An important contribution of this study involves the utilization of PSO to optimize all variables, for instance, the optimization of both the background value coefficient and the fractional order in the same model. Specifically, both the background value coefficient and the fractional order are optimized within the same model. This is noteworthy since the background value coefficient plays a crucial role in enhancing prediction accuracy, while the fractional order eliminates the constraint of representing the model's order solely with integer values. These combined improvements enhance the overall robustness of the model.

4. Methodology

As mentioned previously, accurate estimation of generated e-waste is crucial when planning and designing reverse logistics infrastructures and resource allocation. Early work embodies material flow analysis, life cycle analysis, and various forecasting techniques. The accuracy of these methods, however, heavily relies on the availability of large amounts of data. Given that the data collected in the e-cycle program is relatively new and small in scale, grey modeling-based forecasting methods provide more accurate results [33,41,88].

In their early work, Duman et al. [41] proposed a non-linear grey Bernoulli model, NBGM(1,1), improved by Particle Swarm Optimization (PSO). The efficiency and robustness of the proposed algorithm are depicted via a comparative analysis that included a variety of forecasting models. This novel method applied to forecast-generated e-waste in Washington State. Recent studies in the grey modeling domain indicate that integrating fractional order accumulation increases the forecast accuracy significantly.

In the following section, the multivariate grey Bernoulli model with fractional order accumulation (NBGMFO(1,1)) improved by Particle Swarm Optimization (PSO) integrated with Fourier series is detailed. The schematic representation of the research flow is provided in Figure 1.

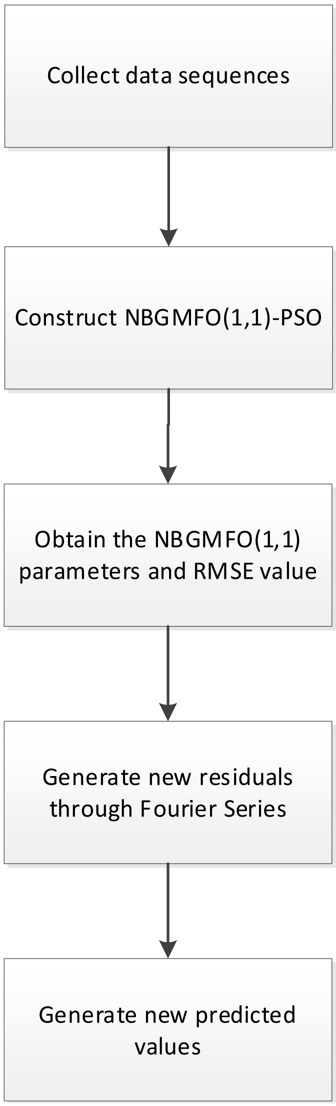

Figure 1. The schematic representation of the forecasting model flow.

The nomenclature used in this study is given in Nomenclature, and the details relating to the formulas utilized in each method are provided in the following sections.

4.1. NBGMFO(1,1)–PSO Integrated with Fourier Series

The GM(1,1) can only be used in positive data sequences and requires at least four observations [89]. An accumulation generator is applied to the data sequence and the differential equation is solved. An inverse accumulating generator is then applied to obtain the predicted values of the data sequence [90]. Deng [57] constructed the GM(1,1) as follows. Other developed models have essentially been built on the original GM(1,1) method.

Let us denote $X^{(0)}$ as the original data sequence:

$$X^{(0)} = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \tag{1}$$

The time sequence is subjected to the accumulating generation operator:

$$X^{(1)} = x^{(1)}(1),\ x^{(1)}(2), .., x^{(1)}(n), \tag{2}$$

where

$$x(k)^{(1)} = \sum_{i=1}^{n} x(i). \tag{3}$$

The background sequence values of $X^{(1)}$ is defined as $Z^{(1)}$:

$$Z^{(1)} = z(1)^{(1)}, z(2)^{(1)}, .., z(n)^{(1)}, \tag{4}$$

where

$$z(k)^{(1)} = px(k)^{(1)} + (1-p)x^{(1)}(k-1) \quad k = 2, 3, .., n \text{ and } p \in [0,\ 1]. \tag{5}$$

The background value coefficient p is commonly utilized as 0.5. However, several studies indicate that optimizing the background value coefficient improves the forecasting accuracy. Hence, various heuristic methods have been integrated into the traditional and improved grey models to obtain the optimal/near-optimal background value coefficient, for instance, Genetic Algorithm [69–74], Ant Colony Algorithm [75], Ant Lion Optimizer [76], Moth-Flame Optimization [77], and Particle Swarm Optimization (PSO) [78–81].

The basic form of GM(1,1) is:

$$x^{(0)}(k) + az^{(1)}(k) = b. \tag{6}$$

Parameters a and b are obtained via the least squares method.

$$[a, b]^T = \left(B^T B\right)^{-1} B^T Y, \tag{7}$$

where B and Y matrices are constructed as:

$$Y = \left[x^{(0)}(2),\ x^{(0)}(3), \ldots,\ x^{(0)}(n)\right]^T, \tag{8}$$

And

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ . & . \\ . & . \\ -z^{(1)}(n) & 1 \end{bmatrix}. \tag{9}$$

The whitening equation is given as:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b, \tag{10}$$

so that the predicted cumulative $\hat{x}^1(k)$ can be obtained as follows:

$$\hat{x}^{(1)}(k+1) = \left[x(1)^{(0)} - \frac{b}{a}\right]e^{-ak} + b/a. \tag{11}$$

Here, $x^{(1)}(1) = x^{(0)}(1)$ and the predicted values of the original sequence are:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k). \tag{12}$$

4.1.1. Grey Model with Fractional Order

Grey modeling with fractional order accumulation was proposed by Wu et al. [62] to improve prediction accuracy. Unlike GM(1,1), which uses first order accumulation, GMFO applies a fractional order accumulation generating approach that can handle nonlinear characteristics of real systems, as explained by Wu et al. [63]. Additionally, the authors applied GMFO to reduce errors in the inverse accumulated generating operator of grey models. Numerous studies have employed GMFO in various fields [65–67].

Let $r = p/q$ and $X^{(0)} = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)$ is the original data sequence as in Equation (1). Then, $X^{(r)} = x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)$ is called the r.th order cumulative generation sequence. Thus, $x^{(r)}(k)$ can be expressed as follows:

$$x^{(r)}(k) = \sum_{i=1}^{k} \frac{(k-i-1)(k-i+2)\ldots(k-i+r-1)}{(r-1)!} x^{(0)}(i) \quad r \in R\ ,\ k = 1,2,\ldots,n \tag{13}$$

In order to express the r.th order cumulative, the Gamma function Γ is utilized. Therefore,

$$x^{(r)}(k) = \sum_{i=1}^{k} \frac{\Gamma(k-i-1)}{\Gamma(\mathrm{r})\Gamma(\mathrm{k-i-1})} x^{(0)}(i) \quad r \in R\ ,\ k = 1,2,\ldots,n \tag{14}$$

The grey reducing generation $X^{(-r)} = x^{(-r)}(1), x^{(-r)}(2), \ldots, x^{(-r)}(n)$ corresponds to the grey accumulating generation, implying that these two operators meet the reciprocity condition.

$$x^{(-r)}(k) = \sum_{i=0}^{k-1} \frac{\Gamma(r+1)}{\Gamma(\mathrm{r+1})\Gamma(\mathrm{r-i-1})} x^{(0)}(k-i) \quad r \in R\ ,\ k = 1,2,\ldots,n \tag{15}$$

As in the original GM(1,1), the background sequence values of $X^{(r)}$ are defined as $Z^{(r)}$, where:

$$Z^{(r)} = z^{(r)}(1), z^{(r)}(2), \ldots, z(n)^{(r)}, \tag{16}$$

and

$$z(k)^{(r)} = px(k)^{(r)} + (1-p)x^{(r)}(k-1)k = 2,3,\ldots,n \ and \ p \in [0,1]. \tag{17}$$

Similarly, the basic form of GMFO is:

$$x^{(r-1)}(k) + az^{(r)}(k) = b. \tag{18}$$

Parameters a and b are obtained via the least squares method.

$$[a,b]^T = \left(B^T B\right)^{-1} B^T Y \tag{19}$$

B and Y matrices are constructed as:

$$Y = \left[x^{(r-1)}(2),\ x^{(r-1)}(3), \ldots,\ x^{(r-1)}(n)\right]^T, \tag{20}$$

and

$$B = \begin{bmatrix} -z^{(r)}(2) & 1 \\ -z^{(r)}(3) & 1 \\ . & . \\ . & . \\ -z^{(r)}(n) & 1 \end{bmatrix}. \tag{21}$$

The predicted r.th cumulative data sequence can be obtained using Equation (22):

$$\hat{x}^{(r)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + b/a \tag{22}$$

The restored value of the original data sequence is computed using Equation (23):

$$\hat{x}^{(0)}(k) = x^{(r)(-r)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(\mathrm{i+1})\Gamma(\mathrm{r-i-1})} \hat{x}^{(r)}(k-i) \tag{23}$$

4.1.2. Nonlinear Grey Bernoulli Model

Chen [58] proposed the nonlinear grey Bernoulli model, NGBM(1,1), as a generalized form of the Verhulst model. The model was applied by the author to forecast the annual unemployment rate of selected countries. Similarly, Chen et al. [91] used an improved NGBM(1,1) to predict foreign exchange rates of Taiwan's major trading partners. Wang and Li [92] developed an optimized version of NGBM(1,1) to forecast the qualified discharge rate of industrial wastewater in China. Pao et al. [61] employed NGBM(1,1) to predict carbon emissions, energy consumption, and economic growth in China.

The nonlinear grey Bernoulli model NGBM(1,1) can be formed as:

$$x^{(0)}(k) + az^{(1)}(k) = b\left(z^{(1)}(k)\right)^{m} \tag{24}$$

where

$$z(k)^{(1)} = px(k)^{(1)} + (1-p)x^{(1)}(k-1) \quad k = 2, 3, \ldots, n \; and \; p \in [0, 1]. \tag{25}$$

Similarly, to the original:

$$\text{GM} \quad [a, b]^{T} = \left(B^{T}B\right)^{-1}B^{T}Y \tag{26}$$

where B and Y matrices are constructed as:

$$Y = \left[x(2)^{(0)},\ x(3)^{(0)}, \ldots,\ x(n)^{(0)}\right]^{T} \tag{27}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & z^{(1)}(2)^{m} \\ -z^{(1)}(3) & z^{(1)}(3)^{m} \\ . & . \\ . & . \\ -z^{(1)}(n) & z^{(1)}(n)^{m} \end{bmatrix} \tag{28}$$

When m = 0, NGBM(1,1) becomes traditional GM(1,1) and when m = 2, it is the grey Verhulst model GVM(1,1). Thus, the predicted cumulative $\hat{x}^{1}(k)$ is obtained as:

$$\hat{x}^{(1)}(k+1) = \left[(x^{(0)}(1) - \frac{b}{a})e^{-a(1-m)k} + b/a\right]^{1/(1-m)} \tag{29}$$

The restored values of $X^{(0)}(k)$ are computed by:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{30}$$

4.1.3. Particle Swarm Optimization

Particle Swarm Optimization (PSO), first proposed by Eberhart and Kennedy [93], is a population-based heuristic computation technique that simulates the social behavior metaphor of the birds. In the algorithm, the population is considered as the swarm and the individuals are called the "particles". PSO performs iterative searches to obtain the optimal or near-optimal solution, where each particle changes its searching direction according to its own best previous experience and the best experience of the entire swarm.

The five basic steps of the PSO are as follows:

Step 1. Initialize randomly the position (*pBest*) and speed for each particle.

Step 2. Set *pBest* as the current position and *gBest* as the optimal particle position in initial swarm.

Step 3. Compute the RMSE of the model when the value of the variable is *pBest*.

Step 4. Compute the velocity and the position for each particle using:

$$V = w * V + c_1 * rand * (pBest - Present) + c_2 * rand * (gBest - Present), \quad (31)$$

and

$$Present = Present + V, \quad (32)$$

where V is the velocity, *rand* is the random number generator in the range [0, 1], w is the inertia factor, and c_1 and c_2 are the learning factors. If the fitness of this particle is superior to *pBest*, then *pBest* becomes the new position. If the fitness of this particle is superior to *gBest*, then *gBest* is accepted as the new position.

Step 5. Go back to Step 3 until one of the two termination criteria is met: i. obtaining sufficiently good fitness value, or ii. reaching the maximum number of iterations. In this study, PSO is utilized to find the optimal or near optimal parameters of the grey models while minimizing the calculated Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\sum_{k=1}^{n} \left(x^{(0)}(k) - \hat{x}^{(0)}(k)\right)^2 / n}\,. \quad (33)$$

4.1.4. Residual Error Modification by Fourier Series

A Fourier approximation method increases the forecast accuracy significantly. Jiang et al. [82] proposed an improved grey multivariable Verhulst model integrated with Fourier series to forecast China's CO_2 emissions. Hu [83] applied a fractional grey prediction model with Fourier series to forecast tourism demand in Taiwan. Hu [84] also developed a grey prediction with Fourier series using Genetic Algorithm for tourism demand forecasting. Jiang et al. [85] analyzed China's Outward Foreign Direct Investment (OFDI) using a novel multivariate grey prediction model with Fourier series. Nguyen et al. [86] employed Fourier series to improve the prediction accuracy of a univariate nonlinear grey Bernoulli model. Kiran et al. [87] proposed an improved multivariate discrete grey model combining Fourier Transform and an exponential smoothing technique that was used to forecast the in-use stock of mobile phones, televisions, and personal computers considering the Gross Domestic Product and rural and urban populations.

To build a residual modification model, Fourier series can be used to alter the residuals generated by the NBGMC(1,1)–PSO model, further improving prediction performance. Let $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots\ \ldots, \varepsilon_n)$ denote the sequence of residual values, where:

$$\varepsilon_k = x_k^{(0)} - \hat{x}_k^{(0)}, \quad k = 2, \ldots, n \quad (34)$$

Since any periodic function can be represented by an infinite series composed of sine and cosine functions, ε_k can be expressed through a Fourier series:

$$x_k^{(0)} = \frac{1}{2}a_0 + \sum_{i=1}^{F}\left[a_i\cos\left(\frac{2\pi i}{n-1}k\right) + b_i\sin\left(\frac{2\pi i}{n-1}k\right)\right], \quad k = 2, \ldots, n \quad (35)$$

where $F = ((n-1)/2) - 1$ is called the minimum deployment frequency of the Fourier series and takes only integer values. Therefore, the residual series can be rewritten as:

$$\varepsilon^{(0)} = PC \quad (36)$$

where

$$P = \begin{bmatrix} \frac{1}{2} & \cos\left(\frac{2\pi 1}{n-1} * 2\right) & \sin\left(\frac{2\pi 1}{n-1} * 2\right) & \ldots & \cos\left(\frac{2\pi F}{n-1} * 2\right) & \sin\left(\frac{2\pi F}{n-1} * 2\right) \\ \frac{1}{2} & \cos\left(\frac{2\pi 1}{n-1} * 3\right) & \sin\left(\frac{2\pi 1}{n-1} * 3\right) & \ldots & \cos\left(\frac{2\pi F}{n-1} * 3\right) & \sin\left(\frac{2\pi F}{n-1} * 3\right) \\ \vdots & \vdots & \vdots & \ldots & \vdots & \vdots \\ \frac{1}{2} & \cos\left(\frac{2\pi 1}{n-1} * n\right) & \sin\left(\frac{2\pi 1}{n-1} * n\right) & \ldots & \cos\left(\frac{2\pi F}{n-1} * n\right) & \sin\left(\frac{2\pi F}{n-1} * n\right) \end{bmatrix} \quad (37)$$

and

$$C = [a_1, b_1, a_2, b_2, \ldots, a_F, b_F]^T \tag{38}$$

The parameters $a_1, b_1, a_2, b_2, \ldots, a_F, b_F$ are obtained using the ordinary least squares method, resulting in the following equation:

$$C = \left(P^T P\right)^{-1} P^T \left[\varepsilon^{(0)}\right]^T \tag{39}$$

Once the parameters are calculated, the predicted residuals $\hat{\varepsilon}_k^{(0)}$ are easily obtained via Equation (40).

$$\hat{\varepsilon}_k^{(0)} = \frac{1}{2}a_0 + \sum_{i=1}^{F}\left[\hat{a}_i \cos\left(\frac{2\pi i}{n-1}k\right) + \hat{b}_i \sin\left(\frac{2\pi i}{n-1}k\right)\right], \ k = 2, \ldots, n \tag{40}$$

The new predicted values can then be calculated via Equation (30).

$$\tilde{x}_k^{(0)} = \hat{x}_k^{(0)} + \hat{\varepsilon}_k^{(0)}, \quad k = 2, \ldots, n \tag{41}$$

The proposed model highlights the nonlinear grey Bernoulli model and its enhancement with two techniques: Particle Swarm Optimization and Fourier approximation. The grey Bernoulli model is a mathematical tool for prediction and forecasting, particularly suited for nonlinear systems. To improve its accuracy, Particle Swarm Optimization optimizes model parameters, while Fourier approximation represents complex functions using simpler trigonometric functions. The combined model offers improved accuracy and reliability for predicting outcomes, especially in nonlinear scenarios, providing a robust forecasting tool across different domains. The proposed model employed in this study provides valuable insights into the e-waste prediction process. However, to gain a more comprehensive understanding, it is recommended to complement these results with a detailed case study. Furthermore, a case study could provide practical implications and recommendations for improving e-waste prediction and management strategies. In the following section, a case study utilizing waste mobile phone data is presented to illustrate the applicability of the proposed model.

5. Case Study in WMP Predictions

In their study, Ozsut Bogar and Gungor [94] employed the Distribution Delay (DD) method to calculate the waste mobile phone (WMP) quantity in Turkey between 2001 and 2020. Furthermore, the authors applied seven different time series methods (namely, simple exponential smoothing, Holt's, logistics, Gompertz, logarithmic, Bass, and ARIMA models) and calculated the MAPE and RMSE values for each method. For the given data, also provided in Table 1, Holt's method was determined to be the best method to forecast the WMP quantities for the years from 2021 to 2035.

Table 1. Waste mobile phone (WMP) data [94].

Year	WMP Quantity
2001	1,515,539
2002	1,661,498
2003	1,851,941
2004	2,127,025
2005	2,580,265
2006	3,140,099
2007	4,026,068

Table 1. *Cont.*

Year	WMP Quantity
2008	5,146,729
2009	6,097,611
2010	6,602,838
2011	7,098,585
2012	7,688,849
2013	7,919,715
2014	8,180,400
2015	8,419,223
2016	8,761,059
2017	9,024,298
2018	9,192,462
2019	9,136,731
2020	9,286,120

This study builds on Ozsut Bogar and Gungor's [94] study and proposes an optimized univariate nonlinear grey Bernoulli model with fractional order accumulation. Nonlinear grey Bernoulli models are essentially the integration of the Bernoulli distribution to traditional grey models and are generally applied to handle series with saturated regions such as the s-curve or sigmoid [60,61,95,96]. As can be observed from Table 1 and Figure 2, the actual e-waste data sequence forms a saturated distribution. Hence, the nonlinear grey Bernoulli model with fractional order accumulation is applied to obtain higher accuracy in the e-waste prediction model.

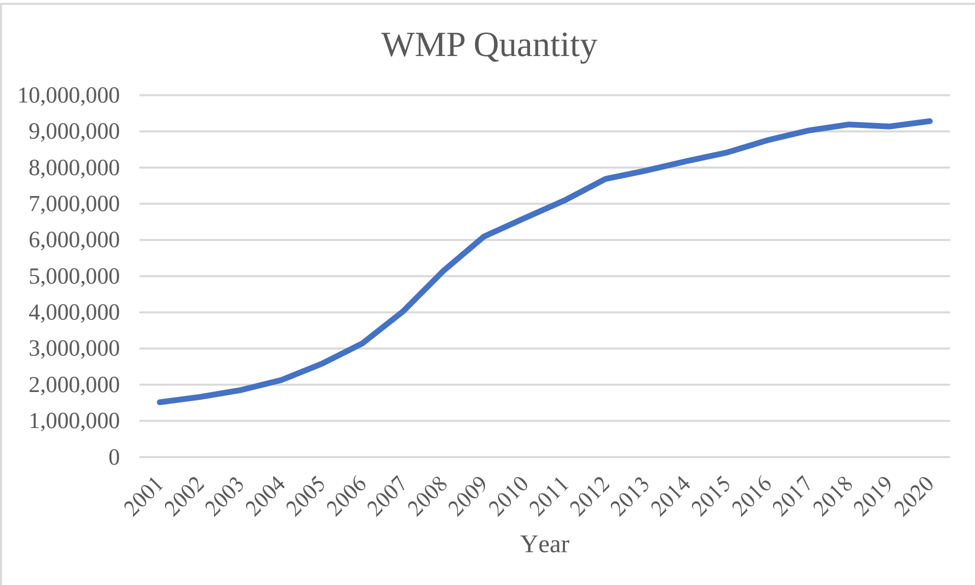

Figure 2. Waste mobile phone (WMP) data [94].

Similarly, to Ozsut Bogar and Gungor's [94] study, the data from 2001 to 2020 are employed for modeling using Equation (1) to Equation (32). The corresponding RMSEs (via Equation (33)) are then computed. The PSO configuration and the range for associated variables, i.e., background value coefficient p, exponential coefficient m, and fractional order value r, are provided in Table 2.

Table 2. PSO configuration and computed parameter values.

Population	30	Learning factor 1	1	
Maximum iteration	300	Learning factor 2	1	
Inertia value	0.8	Range for p	$(0 < p < 1)$	
Range for m	$(0 < m < 1)$	Range for r	$(0 < r < 1)$	
Results				
Method	RMSE	p	m	r
NBGMFO(1,1)	537,926.78	0.9615	0.6035	0.1047

To increase the prediction accuracy and obtain a lower RMSE value, Fourier Series were applied via utilizing Equations (34)–(41) and the obtained results, along with actual and NBGMFO(1,1)–PSO estimates, are presented in Table 3.

Table 3. Estimated values of generated e-waste via NBGMFO(1,1)–PSO and NBGMC(1,1)–PSO with Fourier Series.

Year	**NBGMFO(1,1)–PSO Estimates**	**NBGMFO(1,1)–PSO with Fourier Series Estimates**
2001	1,515,539	1,515,539
2002	1,992,497	1,644,780
2003	2,551,513	1,868,659
2004	3,140,572	2,110,307
2005	3,738,236	2,596,983
2006	4,330,556	3,123,381
2007	4,907,595	4,042,786
2008	5,462,248	5,130,011
2009	5,989,585	6,114,329
2010	6,486,393	6,586,120
2011	6,950,802	7,115,303
2012	7,381,991	7,672,131
2013	7,779,947	7,936,433
2014	8,145,260	8,163,682
2015	8,478,967	8,435,941
2016	8,782,418	8,744,341
2017	9,057,175	9,041,016
2018	9,304,931	9,175,744
2019	9,527,444	9,153,449
2020	9,726,488	9,269,402

As can be observed from Table 3, there is a significant increase in the estimation accuracy after employing the Fourier residual modification method. The obtained RMSE is 16,717.744.

In their study, Ozsut Bogar and Gungor [94] utilized various forecasting methods and compared the obtained RMSE values. Our proposed model outperforms its counterparts discussed in Ozsut Bogar and Gungor's [94] study. They provided forecasted WMP quantities for 2001–2035 using Holt's method. The forecasted WMP quantities for 2001–2035 obtained via our proposed method are presented in Figure 3. As anticipated, the generated WMP quantity will approach 11 million in 2035.

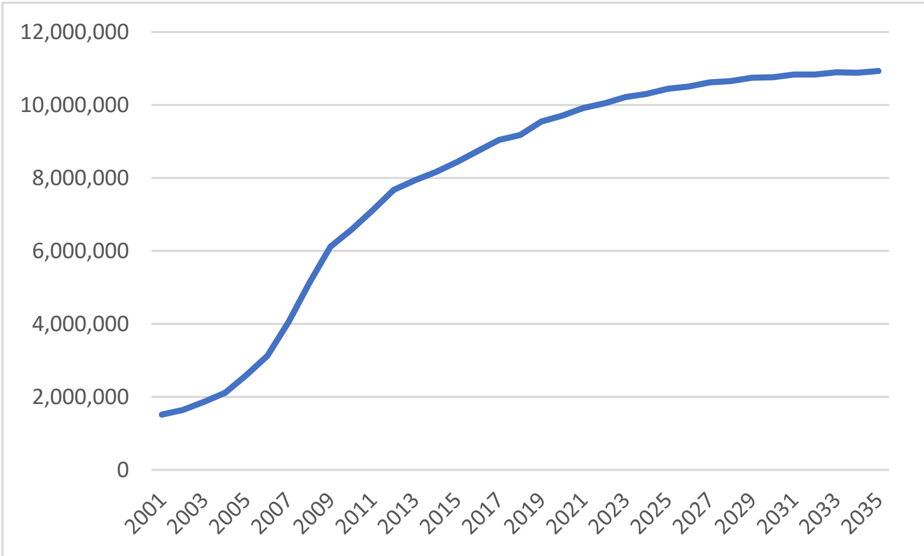

Figure 3. Estimated WMP quantities for 2001–2035 in Turkey.

6. Conclusions

Electronic waste is an emerging environmental issue, with the quantity of discarded electronics escalating rapidly year after year. This has raised concerns about the impact of electronic waste on the environment, public health, and the economy. Although there is no direct link between electronic waste and food, the environmental effects of electronic waste can have indirect impacts on food production, safety, and supply chains. This makes proper management of electronic waste critical to mitigate these risks and ensure a sustainable future for all. E-waste management also aligns with the Sustainable Development Goals adopted by the United Nations and efficient management of e-waste is crucial to achieve environmental, social, and governance goals.

Government agencies and municipalities are usually responsible for waste management in a particular region. They are tasked with planning and implementing strategies to effectively manage e-waste generated by households, businesses, and industries within their jurisdiction. They can utilize the proposed forecasting methods to plan their e-waste collection, recycling, and disposing to build and sustain green cities. Accurate e-waste predictions are crucial for formulating strategies aimed at the prevention and reduction of e-waste.

Several forecasting techniques have been proposed to predict the generated e-waste accurately. Among these techniques, grey models are known to provide reliable predictions in the presence of limited data. With this motivation, this paper utilizes the nonlinear grey Bernoulli model with fractional order accumulation improved by Particle Swarm Optimization (PSO) integrated with the Fourier residual modification method to predict waste mobile phone in Turkey. To the best of our knowledge, this study is the only research that utilizes this particular methodology to estimate waste mobile phone in Turkey. The findings indicate that the model performs superiorly to the available prediction algorithms and is especially suitable for scarce datasets, which is a common characteristic of electronic waste recovery systems. One of the limitations of this study is that the dataset does not include data for the years 2021 and 2022, which can directly affect the accuracy in forecasting for the following years. In the future, this study can be extended by multivariate grey models to increase the accuracy in forecasting.

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Nomenclature

${X_i}^{(0)}$	Original data series
${X_i}^{(1)}$	Accumulated data series
n	Total number of data series
r	Fractional order value
b_i	Model parameters
u	Grey control parameter
z_i	Background value
p	Background value coefficient
B	Input matrix
Y	Output vector
m	Exponential coefficient
RMSE	Root Mean Square Error
w	Inertia weight
V	Velocity of a particle
c_1, c_2	Learning factors
ε	Residual values
P	Input matrix in Fourier series
C	Output vector in Fourier series

References

1. Forti, V.; Balde, C.P.; Kuehr, R.; Bel, G. *The Global E-Waste Monitor 2020: Quantities, Flows and the Circular Economy Potential*; United Nations University/United Nations Institute for Training and Research: Bonn, Germany; International Telecommunication Union: Geneva, Switzerland; International Solid Waste Association: Rotterdam, The Netherlands, 2020.
2. Alshibli, M.; El Sayed, A.; Tozanli, O.; Kongar, E.; Sobh, T.M.; Gupta, S.M. A decision maker-centered end-of-life product recovery system for robot task sequencing. *J. Intell. Robot. Syst.* **2018**, *91*, 603–616. [CrossRef]
3. Saha, L.; Kumar, V.; Tiwari, J.; Rawat, S.; Singh, J.; Bauddh, K. Electronic waste and their leachates impact on human health and environment: Global ecological threat and management. *Environ. Technol. Innov.* **2021**, *24*, 102049.
4. Zhao, G.; Wang, Z.; Dong, M.H.; Rao, K.; Luo, J.; Wang, D.; Zha, J.; Huang, S.; Xu, Y.; Ma, M. PBBs, PBDEs, and PCBs levels in hair of residents around e-waste disassembly sites in Zhejiang Province, China, and their potential sources. *Sci. Total Environ.* **2008**, *397*, 46–57. [CrossRef]
5. Pietrelli, L.; Ferro, S.; Vocciante, M. Eco-friendly and cost-effective strategies for metals recovery from printed circuit boards. *Renew. Sustain. Energy Rev.* **2019**, *112*, 317–323. [CrossRef]
6. Kumar, A.; Holuszko, M.; Espinosa, D.C.R. E-waste: An overview on generation, collection, legislation and recycling practices. *Resour. Conserv. Recycl.* **2017**, *122*, 32–42. [CrossRef]
7. Namias, J. *The Future of Electronic Waste Recycling in the United States: Obstacles and Domestic Solutions*; Columbia University: New York, NY, USA, 2013.
8. Yao, P.; Gupta, S.M. Invasive Weed Optimization Algorithm for Solving Multi-Objective Sequence-Dependent U-Shaped Disassembly Line Balancing Problem. *Int. J. Res. Eng. Sci.* **2022**, *10*, 1705–1716.

9. Murthy, V.; Ramakrishna, S. A Review on Global E-Waste Management: Urban Mining towards a Sustainable Future and Circular Economy. *Sustainability* **2022**, *14*, 647. [CrossRef]
10. Robinson, B.H. E-waste: An assessment of global production and environmental impacts. *Sci. Total Environ.* **2009**, *408*, 183–191. [CrossRef]
11. Perkins, D.N.; Drisse, M.-N.B.; Nxele, T.; Sly, P.D. E-waste: A global hazard. *Ann. Glob. Health* **2014**, *80*, 286–295. [CrossRef]
12. Patil, R.A.; Ghisellini, P.; Ramakrishna, S. Towards sustainable business strategies for a circular economy: Environmental, social and governance (ESG) performance and evaluation. In *An Introduction to Circular Economy*; Springer: Singapore, 2021; pp. 527–554.
13. Lundgren, K. *The Global Impact of E-Waste: Addressing the Challenge*; International Labour Organization: Geneva, Switzerland, 2012.
14. Grant, K.; Goldizen, F.C.; Sly, P.D.; Brune, M.-N.; Neira, M.; van den Berg, M.; Norman, R.E. Health consequences of exposure to e-waste: A systematic review. *Lancet Glob. Health* **2013**, *1*, e350–e361. [CrossRef]
15. Heacock, M.; Kelly, C.B.; Asante, K.A.; Birnbaum, L.S.; Bergman, Å.L.; Bruné, M.-N.; Buka, I.; Carpenter, D.O.; Chen, A.; Huo, X. E-waste and harm to vulnerable populations: A growing global problem. *Environ. Health Perspect.* **2016**, *124*, 550–555. [CrossRef]
16. Ikhlayel, M. An integrated approach to establish e-waste management systems for developing countries. *J. Clean. Prod.* **2018**, *170*, 119–130. [CrossRef]
17. Bisschop, L. Is it all going to waste? Illegal transports of e-waste in a European trade hub. *Crime Law Soc. Chang.* **2012**, *58*, 221–249. [CrossRef]
18. Chen, Y.; Wu, T.-H. Effective E-Waste Management—The Role of International Cooperation and Fragementation. 2010. Available online: https://mpra.ub.uni-muenchen.de/25902/1/MPRA_paper_25902.pdf (accessed on 30 May 2023).
19. Erhun, F.; Kraft, T.; Wijnsma, S. Sustainable Triple—A Supply Chains. *Prod. Oper. Manag.* **2021**, *30*, 644–655. [CrossRef]
20. Kim, S.T.; Lee, H.-H.; Lim, S. The Effects of Green SCM Implementation on Business Performance in SMEs: A Longitudinal Study in Electronics Industry. *Sustainability* **2021**, *13*, 11874. [CrossRef]
21. Cotta, B. What goes around, comes around? Access and allocation problems in Global North–South waste trade. *Int. Environ. Agreem. Politics Law Econ.* **2020**, *20*, 255–269. [CrossRef]
22. Abd-Mutalib, H.; Muhammad Jamil, C.Z.; Mohamed, R.; Shafai, N.A.; Nor-Ahmad, S.N.H.J.N. Firm and Board Characteristics, and E-Waste Disclosure: A Study in the Era of Digitalisation. *Sustainability* **2021**, *13*, 10417. [CrossRef]
23. Achillas, C.; Vlachokostas, C.; Moussiopoulos, N.; Banias, G. Decision support system for the optimal location of electrical and electronic waste treatment plants: A case study in Greece. *Waste Manag.* **2010**, *30*, 870–879. [CrossRef]
24. Ayvaz, B.; Bolat, B.; Aydın, N. Stochastic reverse logistics network design for waste of electrical and electronic equipment. *Resour. Conserv. Recycl.* **2015**, *104*, 391–404. [CrossRef]
25. Gomes, M.I.; Barbosa-Povoa, A.P.; Novais, A.Q. Modelling a recovery network for WEEE: A case study in Portugal. *Waste Manag.* **2011**, *31*, 1645–1660. [CrossRef]
26. Guarnieri, P.; Sobreiro, V.A.; Nagano, M.S.; Marques Serrano, A.L. The challenge of selecting and evaluating third-party reverse logistics providers in a multicriteria perspective: A Brazilian case. *J. Clean. Prod.* **2015**, *96*, 209–219. [CrossRef]
27. Kilic, H.S.; Cebeci, U.; Ayhan, M.B. Reverse logistics system design for the waste of electrical and electronic equipment (WEEE) in Turkey. *Resour. Conserv. Recycl.* **2015**, *95*, 120–132. [CrossRef]
28. Li, R.C.; Tee, T.J.C. A Reverse Logistics Model For Recovery Options of E-waste Considering the Integration of the Formal and Informal Waste Sectors. *Procedia Soc. Behav. Sci.* **2012**, *40*, 788–816. [CrossRef]
29. Prakash, C.; Barua, M.K.; Pandya, K.V. Barriers Analysis for Reverse Logistics Implementation in Indian Electronics Industry using Fuzzy Analytic Hierarchy Process. *Procedia Soc. Behav. Sci.* **2015**, *189*, 91–102. [CrossRef]
30. Safdar, N.; Khalid, R.; Ahmed, W.; Imran, M. Reverse logistics network design of e-waste management under the triple bottom line approach. *J. Clean. Prod.* **2020**, *272*, 122662. [CrossRef]
31. Sarkis, J.; Helms, M.M.; Hervani, A.A. Reverse logistics and social sustainability. *Corp. Soc. Responsib. Environ. Manag.* **2010**, *17*, 337–354. [CrossRef]
32. Bal, A.; Satoglu, S.I. A goal programming model for sustainable reverse logistics operations planning and an application. *J. Clean. Prod.* **2018**, *201*, 1081–1091. [CrossRef]
33. Duman, G.M.; Kongar, E.; Gupta, S.M. Estimation of electronic waste using optimized multivariate grey models. *Waste Manag.* **2019**, *95*, 241–249. [CrossRef]
34. United Nations. Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: https://sdgs.un.org/2030agenda (accessed on 30 May 2023).
35. Shittu, O.S.; Williams, I.D.; Shaw, P.J. Global E-waste management: Can WEEE make a difference? A review of e-waste trends, legislation, contemporary issues and future challenges. *Waste Manag.* **2021**, *120*, 549–563. [CrossRef]
36. Forti, V.; Baldé, C.P.; Kuehr, R.; Bel, G. *The Global E-Waste Monitor 2020*; United Nations University (UNU): Bonn, Germany; International Telecommunication Union (ITU): Geneva, Switzerland; International Solid Waste Association (ISWA): Rotterdam, The Netherlands, 2020.
37. National Conference of State Legislatures. Electronic Waste Recycling. Available online: https://www.ncsl.org/research/environment-and-natural-resources/e-waste-recycling-legislation.aspx (accessed on 30 May 2023).
38. Jaunich, M.K.; DeCarolis, J.; Handfield, R.; Kemahlioglu-Ziya, E.; Ranjithan, S.R.; Moheb-Alizadeh, H. Life-cycle modeling framework for electronic waste recovery and recycling processes. *Resour. Conserv. Recycl.* **2020**, *161*, 104841. [CrossRef]

39. Schumacher, K.A.; Agbemabiese, L. Towards comprehensive e-waste legislation in the United States: Design considerations based on quantitative and qualitative assessments. *Resour. Conserv. Recycl.* **2019**, *149*, 605–621. [CrossRef]
40. Ongondo, F.O.; Williams, I.D.; Cherrett, T.J. How are WEEE doing? A global review of the management of electrical and electronic wastes. *Waste Manag.* **2011**, *31*, 714–730. [CrossRef] [PubMed]
41. Duman, G.M.; Kongar, E.; Gupta, S.M. Predictive analysis of electronic waste for reverse logistics operations: A comparison of improved univariate grey models. *Soft Comput.* **2020**, *24*, 15747–15762. [CrossRef]
42. Gui, L.; Atasu, A.; Ergun, Ö.; Toktay, L.B. Implementing extended producer responsibility legislation: A multi-stakeholder case analysis. *J. Ind. Ecol.* **2013**, *17*, 262–276. [CrossRef]
43. Noon, M.S.; Lee, S.-J.; Cooper, J.S. A life cycle assessment of end-of-life computer monitor management in the Seattle metropolitan region. *Resour. Conserv. Recycl.* **2011**, *57*, 22–29. [CrossRef]
44. Templeton, N.J. Dark Side of Recycling and Reusing Electronics: Is Washington's E-Cycle Program Adequate. *Seattle J. Soc. Just.* **2008**, *7*, 763.
45. EPA Management of Electronic Waste in the United States Approach Two. Available online: https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P100BC9O.TXT (accessed on 18 September 2018).
46. EPA Electronics Waste Management in the United States: Approach I. Available online: https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P1001FPK.TXT (accessed on 18 September 2018).
47. Brunner, P.H.; Rechberger, H. *Handbook of Material Flow Analysis: For Environmental, Resource, and Waste Engineers*; CRC Press: Boca Raton, FL, USA, 2016.
48. Lau, W.K.-Y.; Chung, S.-S.; Zhang, C. A material flow analysis on current electrical and electronic waste disposal from Hong Kong households. *Waste Manag.* **2013**, *33*, 714–721. [CrossRef] [PubMed]
49. Steubing, B.; Böni, H.; Schluep, M.; Silva, U.; Ludwig, C. Assessing computer waste generation in Chile using material flow analysis. *Waste Manag.* **2010**, *30*, 473–482. [CrossRef]
50. Oguchi, M.; Kameya, T.; Yagi, S.; Urano, K. Product flow analysis of various consumer durables in Japan. *Resour. Conserv. Recycl.* **2008**, *52*, 463–480. [CrossRef]
51. Althaf, S.; Babbitt, C.W.; Chen, R. Forecasting electronic waste flows for effective circular economy planning. *Resour. Conserv. Recycl.* **2019**, *151*, 104362. [CrossRef]
52. Matthews, H.S.; McMichael, F.C.; Hendrickson, C.T.; Hart, D.J. Disposition and end-of-life options for personal computers. In *Carnegie Mellon University Green Design Initiative Technical Report*; 1997. Available online: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=83f0ce7279333cc05eb7af08cb6c225a9e05e681 (accessed on 30 May 2023).
53. Jain, A.; Sareen, R. E-waste assessment methodology and validation in India. *J. Mater. Cycles Waste Manag.* **2006**, *8*, 40–45. [CrossRef]
54. Yang, Y.; Williams, E. Logistic model-based forecast of sales and generation of obsolete computers in the U.S. *Technol. Forecast. Soc. Chang.* **2009**, *76*, 1105–1114. [CrossRef]
55. Petridis, N.E.; Stiakakis, E.; Petridis, K.; Dey, P. Estimation of computer waste quantities using forecasting techniques. *J. Clean. Prod.* **2016**, *112*, 3072–3085. [CrossRef]
56. Albuquerque, C.; Mello, C.; Paes, V.; Balestrassi, P.; Souza, L. Electronic Junk: Best Practice of Recycling and Production Forecast Case Study in Brazil. In *New Global Perspectives on Industrial Engineering and Management*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 127–134.
57. Deng, J.L. Introduction to Grey system theory. *J. Grey Syst.* **1989**, *1*, 1–24.
58. Chen, C.I. Application of the novel nonlinear grey Bernoulli model for forecasting unemployment rate. *Chaos Solitons Fractals* **2008**, *37*, 278–287. [CrossRef]
59. Chen, C.I.; Chen, H.L.; Chen, S.-P. Forecasting of foreign exchange rates of Taiwan's major trading partners by novel nonlinear Grey Bernoulli model NGBM(1,1). *Commun. Nonlinear Sci. Numer. Simul.* **2008**, *13*, 1194–1204. [CrossRef]
60. Wang, Z.X.; Hipel, K.W.; Wang, Q.; He, S.-W. An optimized NGBM(1,1) model for forecasting the qualified discharge rate of industrial wastewater in China. *Appl. Math. Model.* **2011**, *35*, 5524–5532. [CrossRef]
61. Pao, H.-T.; Fu, H.-C.; Tseng, C.-L. Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model. *Energy* **2012**, *40*, 400–409. [CrossRef]
62. Wu, L.; Liu, S.; Yao, L.; Yan, S.; Liu, D. Grey system model with the fractional order accumulation. *Commun. Nonlinear Sci. Numer. Simul.* **2013**, *18*, 1775–1785. [CrossRef]
63. Wu, L.; Liu, S.; Fang, Z.; Xu, H. Properties of the GM(1,1) with fractional order accumulation. *Appl. Math. Comput.* **2015**, *252*, 287–293. [CrossRef]
64. Wu, L.; Liu, S.; Yao, L.; Xu, R.; Lei, X. Using fractional order accumulation to reduce errors from inverse accumulated generating operator of grey model. *Soft Comput.* **2015**, *19*, 483–488. [CrossRef]
65. Shili, F.; Lifeng, W.; Liang, Y.; Zhigeng, F. Using fractional GM(1,1) model to predict maintenance cost of weapon system. In Proceedings of the 2013 IEEE International Conference on Grey Systems and Intelligent Services (GSIS), Macao, China, 15–17 November 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 177–181.
66. Duan, H.; Lei, G.R.; Shao, K. Forecasting Crude Oil Consumption in China Using a Grey Prediction Model with an Optimal Fractional-Order Accumulating Operator. *Complexity* **2018**, *2018*, 3869619. [CrossRef]

67. Li, S.; Meng, W.; Xie, Y. Forecasting the Amount of Waste-Sewage Water Discharged into the Yangtze River Basin Based on the Optimal Fractional Order Grey Model. *Int. J. Environ. Res. Public Health* **2017**, *15*, 20. [CrossRef]
68. Wu, L.; Zhao, H. Discrete grey model with the weighted accumulation. *Soft Comput.* **2019**, *23*, 12873–12881. [CrossRef]
69. Xie, Q.; Xie, Y. Forecast of Regional Gross National Product Based on Grey Modelling Optimized by Genetic Algorithm. In Proceedings of the 2009 International Conference on E-Learning, E-Business, Enterprise Information Systems, and E-Government, Hong Kong, China, 5–6 December 2009; IEEE: Piscataway, NJ, USA, 2009; pp. 3–5.
70. Xie, Y.; Li, M. Research on gray prediction modeling optimized by genetic algorithm for energy consumption demand. In Proceedings of the 2009 International Conference on Industrial Mechatronics and Automation, Chengdu, China, 15–16 May 2009; IEEE: Piscataway, NJ, USA, 2009; pp. 289–291.
71. Wang, C.H.; Hsu, L.-C. Using genetic algorithms grey theory to forecast high technology industrial output. *Appl. Math. Comput.* **2008**, *195*, 256–263. [CrossRef]
72. Hsu, L.-C. A genetic algorithm based nonlinear grey Bernoulli model for output forecasting in integrated circuit industry. *Expert Syst. Appl.* **2010**, *37*, 4318–4323. [CrossRef]
73. Hsu, L.-C. Forecasting the output of integrated circuit industry using genetic algorithm based multivariable grey optimization models. *Expert Syst. Appl.* **2009**, *36*, 7898–7903. [CrossRef]
74. Hu, Y.-C. A multivariate grey prediction model with grey relational analysis for bankruptcy prediction problems. *Soft Comput.* **2020**, *24*, 4259–4268. [CrossRef]
75. Wang, F.X.; Zhang, L.-S. Combination Gray Forecast Model Based on the Ant Colony Algorithm. *Math. Pract. Theory* **2009**, *14*, 017.
76. Zhao, H.; Guo, S. An optimized grey model for annual power load forecasting. *Energy* **2016**, *107*, 272–286. [CrossRef]
77. Zhao, H.; Zhao, H.; Guo, S. Using GM(1,1) optimized by MFO with rolling mechanism to forecast the electricity consumption of inner mongolia. *Appl. Sci.* **2016**, *6*, 20. [CrossRef]
78. Zhou, J.; Fang, R.; Li, Y.; Zhang, Y.; Peng, B. Parameter optimization of nonlinear grey Bernoulli model using particle swarm optimization. *Appl. Math. Comput.* **2009**, *207*, 292–299. [CrossRef]
79. Li, K.; Liu, L.; Zhai, J.; Khoshgoftaar, T.M.; Li, T. The improved grey model based on particle swarm optimization algorithm for time series prediction. *Eng. Appl. Artif. Intell.* **2016**, *55*, 285–291. [CrossRef]
80. Liu, L.; Wang, Q.; Wang, J.; Liu, M. A rolling grey model optimized by particle swarm optimization in economic prediction. *Comput. Intell.* **2016**, *32*, 391–419. [CrossRef]
81. Zeng, B.; Li, C. Improved multi-variable grey forecasting model with a dynamic background-value coefficient and its application. *Comput. Ind. Eng.* **2018**, *118*, 278–290. [CrossRef]
82. Jiang, H.; Kong, P.; Hu, Y.-C.; Jiang, P. Forecasting China's CO_2 emissions by considering interaction of bilateral FDI using the improved grey multivariable Verhulst model. *Environ. Dev. Sustain.* **2021**, *23*, 225–240. [CrossRef]
83. Hu, Y.-C. Forecasting tourism demand using fractional grey prediction models with Fourier series. *Ann. Oper. Res.* **2021**, *300*, 467–491. [CrossRef]
84. Hu, Y.-C. Developing grey prediction with Fourier series using genetic algorithms for tourism demand forecasting. *Qual. Quant.* **2021**, *55*, 315–331. [CrossRef]
85. Jiang, H.; Hu, Y.-C.; Lin, J.-Y.; Jiang, P. Analyzing China's OFDI using a novel multivariate grey prediction model with Fourier series. *Int. J. Intell. Comput. Cybern.* **2019**, *12*, 352–371. [CrossRef]
86. Nguyen, N.T.; Phan, V.T.; Malara, Z. Using Fourier series to improve the prediction accuracy of nonlinear Grey Bernoulli model. In Proceedings of the ACIIDS 2019: Intelligent Information and Database Systems, Yogyakarta, Indonesia, 8–11 April 2019; Springer: Berlin/Heidelberg, Germany, 2019; pp. 363–372.
87. Kiran, M.; Shanmugam, P.V.; Mishra, A.; Mehendale, A.; Sherin, H.N. A multivariate discrete grey model for estimating the waste from mobile phones, televisions, and personal computers in India. *J. Clean. Prod.* **2021**, *293*, 126185. [CrossRef]
88. Wang, F.; Yu, L.; Wu, A. Forecasting the electronic waste quantity with a decomposition-ensemble approach. *Waste Manag.* **2021**, *120*, 828–838. [CrossRef] [PubMed]
89. Ye, J.; Dang, Y.; Yang, Y. Forecasting the multifactorial interval grey number sequences using grey relational model and GM(1,N) model based on effective information transformation. *Soft Comput.* **2019**, *24*, 5255–5269. [CrossRef]
90. Ene, S.; Öztürk, N. Grey modelling based forecasting system for return flow of end-of-life vehicles. *Technol. Forecast. Soc. Chang.* **2017**, *115*, 155–166. [CrossRef]
91. Chen, C.I.; Hsin, P.-H.; Wu, C.-S. Forecasting Taiwan's major stock indices by the Nash nonlinear grey Bernoulli model. *Expert Syst. Appl.* **2010**, *37*, 7557–7562. [CrossRef]
92. Wang, Z.-X.; Li, Q. Modelling the nonlinear relationship between CO_2 emissions and economic growth using a PSO algorithm-based grey Verhulst model. *J. Clean. Prod.* **2019**, *207*, 214–224. [CrossRef]
93. Eberhart, R.; Kennedy, J. A new optimizer using particle swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995; pp. 39–43.
94. Ozsut Bogar, Z.; Gungor, A. Forecasting Waste Mobile Phone (WMP) Quantity and Evaluating the Potential Contribution to the Circular Economy: A Case Study of Turkey. *Sustainability* **2023**, *15*, 3104. [CrossRef]

95. Wang, Z.X. An optimized Nash nonlinear grey Bernoulli model for forecasting the main economic indices of high technology enterprises in China. *Comput. Ind. Eng.* **2013**, *64*, 780–787. [CrossRef]
96. Zhang, L.; Zheng, Y.; Wang, K.; Zhang, X.; Zheng, Y. An optimized Nash nonlinear grey Bernoulli model based on particle swarm optimization and its application in prediction for the incidence of Hepatitis B in Xinjiang, China. *Comput. Biol. Med.* **2014**, *49*, 67–73. [CrossRef]