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Journal of Management Science & Engineering Research
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Companies' E-waste Estimation Based on General Equilibrium Theory Context and Random Forest Regression Algorithm in Cameroon: Case Study of SMEs Implementing ISO 14001:2015

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ABSTRACT

Given the challenge of estimating or calculating quantities of waste electrical and electronic equipment (WEEE) in developing countries, this article focuses on predicting the WEEE generated by Cameroonian small and medium enterprises (SMEs) that are engaged in ISO 14001:2015 initiatives and consume electrical and electronic equipment (EEE) to enhance their performance and profitability. The methodology employed an exploratory approach involving the application of general equilibrium theory (GET) to contextualize the study and generate relevant parameters for deploying the random forest regression learning algorithm for predictions. Machine learning was applied to 80% of the samples for training, while simulation was conducted on the remaining 20% of samples based on quantities of EEE utilized over a specific period, utilization rates, repair rates, and average lifespans. The results demonstrate that the model's predicted values are significantly close to the actual quantities of generated WEEE, and the model's performance was evaluated using the mean squared error (MSE) and yielding satisfactory results. Based on this model, both companies and stakeholders can set realistic objectives for managing companies' WEEE, fostering sustainable socio-environmental practices.

Keywords: Electrical and electronic equipment (EEE); Waste from electrical and electronic equipment (WEEE); General equilibrium theory; Random forest regression algorithm; Decision-making; Cameroon

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ARTICLE INFO
Received: 29 July 2023 | Revised: 24 August 2023 | Accepted: 25 August 2023 | Published Online: 27 September 2023
DOI: https://doi.org/10.30564/jmser.v6i2.5862

CITATION
Djoukoue, G.T., Teledjieu, I.D., Bai, S.J., 2023. Companies' E-waste Estimation Based on General Equilibrium Theory Context and Random Forest Regression Algorithm in Cameroon: Case Study of SMEs Implementing ISO 14001:2015. Journal of Management Science & Engineering Research. 6(2): 60-81. DOI: https://doi.org/10.30564/jmser.v6i2.5862

1. Introduction

The best living conditions and guaranteed survival depend on a healthy environment. International policies are becoming increasingly responsible and protective of this environment. However, even if good living conditions are supported by the consumption of electrical and electronic equipment (EEE), WEEE creates a retarding effect to these efforts through its exponential growth, estimated at more than 1,400,000 Mega tons by 2023 [1], and its poorly controlled management in most developing countries.

African developing countries, in their race towards a numerical balance [2], are becoming WEEE dumping grounds as a result of cross-border movements combated by the Basel Convention [3]. The fight against WEEE is thus becoming an uphill battle, as second-hand or end-of-life EEE is easier to access. As the lifespan of these EEEs is almost over, they very quickly become WEEE and are abandoned in the environment to the benefit of informal recyclers. Through their dismantling and open-air incineration activities, informal recyclers become catalysts for environmental pollution [4].

The hazardous nature of WEEE no longer needs to be demonstrated, either for the environment or for health. The incineration of WEEE also causes air pollution and greenhouse gas emissions [5]. Incineration ash has a high concentration of metals such as Cu > Pb > Zn > Mn > Ni > Sb > Cr > Cd and contaminates between 10 and 30 cm of the earth's crust [6]. Rahul Rautela [7] emphasizes the polluting properties of informal recycling activities on soil, air, and water.

On the human side, some of the substances resulting from incineration such as PBDD/Fs (polybrominated dibenzo-p-dioxins) are lipophilic and can bioaccumulate through the food web in the human body [8]. Many studies also found connections with elevated rates of spontaneous abortions, premature births, and reduced birth weights due to backyard WEEE recycling [7].

On the economic and social front, there has been a strong expansion of informal recycling trades employing mainly young people; this means the creation of between 4,000 and 6,000 direct jobs [9] in sub-Saharan Africa with rudimentary remuneration [10]. Conversely, the treatment of e-waste allows for entrepreneurship, job creation, reuse, and refurbishment for the sale of cheap electronics, less waste, and the recovery of metals [9].

In Cameroon, like everywhere else, companies consume common EEE to support their core business, and for reasons of social responsibility and contribution to sustainable development are called upon to play their part in the production of WEEE. An EEE is defined as equipment operating using electric currents or electromagnetic fields, as well as the production, transfer, and measurement of these currents and fields, designed to be used at a voltage not exceeding 1000 volts in alternating current and 1500 volts in direct current [11], A waste is economically conceptualized as a product whose physical and financial flow have the same direction [12], it is defined as any residue from a production, transformation or use process; any substance or material produced; or, more generally, any movable or immovable property abandoned or intended for abandonment [13]. A joint order in Article 2 distinguishes waste electrical and household electronic appliances (WEHEA) from professional waste electrical and electronic equipment (PWEEE) [11]. National waste management policy is oriented towards municipal solid waste collection, transport, and landfill [14].

Several research studies interested in understanding the growth of WEEE have proposed methods for estimating and calculating the amount of WEEE generated at national, regional, and international levels. However, it is difficult to approve calculation methods and Vanessa Froti and all [15] think that determining the quantities of global WEEE is difficult due to a lack of harmonization on the definition of WEEE, the difficulty of measuring the flows of legal or illegal cross-border movements; elimination of WEEE in ordinary garbage cans and informal collection and recycling practices. Research studies attempting to estimate the quantities of WEEE in developing countries, especially in Africa, have always deplored the lack of a historical database. This is due to the lack of control over EEE imports, which is a legacy of cross-border movements [16,3], and the limited data available held by agencies and organizations [17].

As WEEE production is the result of EEE consumption, it would be interesting to start estimating or calculating the quantities of WEEE generated by these economic agents. Companies in developing countries are not insignificant when it comes to WEEE production. They use EEE to provide saleable products and services for profit. The question arises regarding how to estimate or calculate the WEEE companies produce.

Trying to answer this question, we're going to analyze the use made of EEE in companies, to understand the path it takes. This step is important if we are to understand the stages undergone by an item of EEE before it becomes WEEE. Since we're talking about companies, the consumption of EEE is objectified, i.e., their consumption patterns are not necessarily similar to those of households. With this in mind, we propose a set of contextual hypotheses based on general equilibrium theory (GET). This theory is widely used in economics to analyze the behavior of economic agents and to understand and anticipate certain economic phenomena and interactions at both macro and micro levels. Adapting this economic theory to our phenomenon will enable us to propose a model for calculating WEEE quantities that is close to the realities of business.

This paper proposes a model for calculating the amount of WEEE produced by companies, taking into account the economic context of the company and its performance objectives. Assumptions derived from Walrasian equilibrium by adaptation simplify the calculation context of WEEE and the random forest regression learning algorithm will be deployed for prediction. The method we use will be both qualitative and quantitative. Qualitative in order to determine the stages in the EEE's journey until it becomes WEEE, and quantitative for reasons of manipulation of the numerical data collected to quantify the WEEE produced.

This article will be structured as follows: Section 2 will present the state of the art in WEEE estimation and calculation, the applications of GET to WEEE management, and the random forest regression algorithm; Section 3 will present the methodology used in this research, which is a mixture of qualitative and quantitative approaches; Section 4 will present the results of applying the model; Section 5 will be devoted to discussions and recommendations; and Section 6 will provide a conclusion to this research.

2. Literature work

The existence of WEEE and its inordinate growth rate is a fact. Given the harmful nature of this type of waste, we're seeing a great deal of progress in WEEE research. Many researchers have focused on the hazardous components of WEEE, such as PVC in wire coatings and cables, di (2-ethylhexyl) phthalate (DEHP), diisononyl phthalate (DINP), butylbenzyl phthalate (BBP), diisodecyl phthalate (DIDP) and dibutyl phthalate (DBP) [18]. Informal recycling activities expose nature and life to substances such as PCBs and chlorinated materials [19]; chlorobenzenes [20], triphenyl phosphates (TPPs), cadmium sulphide [21]; mercury, chromium, beryllium [22].

Other research has highlighted environmental impacts such as high concentrations of heavy metals in soils [23] and vegetation [24]. Concentrations of manganese, nickel, and bismuth were respectively up to 4, 11, and 53 times higher in e-waste soils than in reference soils [25]; high concentrations of Cu, Pb, Zn, and Cr in some soil samples in Yaoundé, exceeding recommended thresholds [26].

Research has focused on human and socio-economic impacts. Toxins released into the environment accumulate in human tissues [27]; they have been found in e-waste workers [28], surrounding populations [29] and represent environmental risks [10]. Informal e-waste recycling is a major source of income for many poor urban communities [30]. E-waste management has economic benefits such as financial stability, job creation, and community cohesion [31]. These impacts, requiring an effective response, have led to the application of concepts such as reverse logistics and the circular economy.

More recent articles look at reverse logistics and the circular economy as tools for sustainable WEEE management. The concept of circular economy and its link with trade and highlighting their different interactions are presented [32]. 110,000 tons of e-waste were collected, of which 80% were recycled into useful materials and 17% were recovered energetically through the circular economy in Holland in 2016 [33]. The circular economy deployment model adopted by China and the challenges facing the country are highlighted [34]. A mathematical model for managing end-of-life electronics, considering multiple manufacturers and retailers for reverse logistics [35]. A focus on approaches such as recycling, the adoption of circular economy concepts, the formulation of appropriate policies, and the use of advanced computational techniques are discussed as effective ways of managing e-waste, with the possibility of recovering valuable and critical materials, as well as the use of machine learning for monitoring and processing such waste [36]. These techniques for clean, sustainable management of WEEE contribute to the SDGs, but will only be fully appreciated once the quantities of WEEE produced have been brought under control.

With regard to estimating or calculating WEEE, a number of research projects have been carried out at both national and regional levels, using different methods depending on data availability and the type of EEE. The table below summarizes the state of the art in this field.

This state-of-the-art estimation or calculation of WEEE (**Table 1**) indicates that calculation methods differ based on the approaches and available data for certain EEE. These methods possess the distinct feature of being grounded in mathematical techniques and tools of varying complexity, which might not be readily understandable for common readers or users. Furthermore, these studies are focused on the quantities of WEEE at national or regional scales. Engaging with scales of this nature might appear relevant due to the requirements and achieved outcomes. However, discrepancies between the predicted results and actual reality can be notable.

This article adopts a "reverse" approach as it focuses on the consumption of EEE to propose a calculation method. The main producers of WEEE are economic agents such as households and businesses. SMEs use EEE to improve their activities and ultimately generate WEEE. In order to remain profitable and address environmental challenges, businesses need to manage EEE in a particular way, leading to potentially unique approaches to managing WEEE. Considering its economic specificity, we propose a calculation model for WEEE specific to the business context, drawing inspiration from general equilibrium theory (GET).

General equilibrium is an economic concept introduced by Léon Walras in his 1874 work, "Elements of Pure Economics or the Theory of Social Wealth". It aims to explain how prices are formed in markets by reducing the economic system to a model.

GET relies on three main characteristics [56]. Firstly, it is based on a system of interdependent variables representing quantities supplied and demanded in markets under certain price conditions. Secondly, it refers to the individual behaviors of economic agents. Rational individual choices are taken into account in the analysis, considering the constraints perceived by agents. The third characteristic of general equilibrium is that it relies on coordination through prices. Economic agents primarily coordinate through a system of prices that can be flexible, fixed, or partially fixed.

Any general equilibrium analysis explicitly or implicitly refers to these characteristics and takes a stance on each of them. Some research may emphasize certain characteristics, neglect them, or reserve them for other studies. The formalisms used to study general equilibrium are generally not directly transferable to other disciplines. However, the general idea of general equilibrium can be adapted to other fields of study by translating the characteristics according to the specific needs of each object of study in accordance with its extension principle.

The extension of GET to various research domains has allowed its application to the environment,

Table 1. Overview of existing methods for estimating or calculating WEEE.

Authors	**Methods**																		**Country/region**
	DRA	**TSA**	**FM**	**EA**	**IOA**	**Methods**										**GM**	**SD**	**MM**	
					TS	**MSM**					**SBM**		**MFA**	**PBM**	**SSLM**				
						SD	**DD**	**SM**	**CM**	**A2**	**SLM**	**C&U**							
Zeng et al. [37]													x						China
Duman et al. [38]																x			Washington
Islam and Huda [39]							x												Australia
Ravindra and Mor [40]												x							Chandigarh e India
Awasthi et al. [41]				x															European Countries
Tran et al. [42]											x								Vietnam
Pengwei et al. [43]							x												China
Babayemi et al. [44]													x						Nigeria
Guo and Yan [45]														X					China
Gomes et al. [46]	x																		Brazil
Kumar et al. [47]				x															Global
Kusch and Hills [48]				x															European Countries
Parajuly et al. [49]							x												Denmark
Dasgupta et al. [50]																	x		India
Hamouda et al. [51]											x								Algeria
Ikhlayel [52]					x	x	x			x		x							Jordan
Petridis et al. [53]							x		x										Global
Cao et al. [54]						x		x				x							China
Neto et al. [55]		x					x												Brazil

Note: Method (group): DRA—Disposal Related Analysis; TSA—Time Series Analysis; FM—Factor Model; EA—Econometric Analysis; IOA—Input-Output Analysis; IOA methods: TS—Time Step method; MSM—Market supply method; SM—Simple Delay; DD—Distribution Delay; SM—Stanford Method; CM—Carnegie Mellon Method; A2—Approximation 2 method; SBM—Stock-Based Model; SLM—Stock Lifespan Model; C & U—Consumption and Use method; MFA—Material Flow Analysis; PBM—Population Balance model; SSLM—Sales stocks and lifetime model; GM—Grey Model; SD—System Dynamics; MM—Mathematical Model.

specifically in the management of WEEE. Plambeck and Wang [57] highlight the importance of striking a balance between WEEE reduction and promoting sustainability in the electronics industry through regulations based on "purchase tax" and "disposal tax" and their impacts. Wakolbinger et al. [58] examine the influence of technical, commercial, and legislative factors on WEEE management and demonstrate the importance of the interaction between the supply and demand of precious materials in policy decisions.

Authors have focused on the WEEE supply chain and recycling, leading to the formulation of a variational inequality model used to obtain material flows and prices in a multi-level electric bicycle network, along with an algorithm for analyzing qualitative properties of the equilibrium model [59]. Another model analyzes a Cournot pricing game between manufacturers and consumer markets, offering interesting perspectives [60].

Research has examined the impact of government subsidies on recycled material flows in a decentralized reverse supply chain through an equilibrium model, revealing that the optimal allocation of subsidies to laptop collectors significantly increases the total quantity of recycled materials collected [61]. The allocation to transformers has a significant impact on equilibrium quantities and subsidy efficiency [62].

One study proposes an advanced computable general equilibrium analysis at the country level to assess the impacts and adaptations related to climate change. It focuses on Egypt and simulates the effects of climate change on consumption, investment, and income until 2050. The results indicate that, in the absence of adaptation investments, Egypt's real GDP could decrease by 6.5% by 2050, but adaptation measures could reduce this loss to around 2.6% [63].

GET is widely used to analyze the impacts of parameter variations on certain phenomena. However, few authors have drawn inspiration from General Equilibrium Theory to estimate the quantities of waste generated. Yuzuru Miyata [64] is one such author who constructed a computable general equilibrium (CGE) model to analyze the interaction between waste disposal/treatment and the economy in the city of Hokkaido in 1985. The model incorporates waste production and treatment for both businesses and households. The effects of waste pricing, promotion of recycling, and other factors on the economy, including income, prices, and well-being, are examined by applying the model [64].

Given that our study focuses on a specific economic agent, namely the enterprise, it is highly appropriate to provide context for this research. The challenges faced by businesses are certainly different from those of other EEE consumers. They need to optimize their investment returns and exhibit rational behavior. Thus, GET serves as the theoretical foundation that aligns with our research objectives.

The main objective of this article is to estimate or predict the quantities of WEEE. After simplifying our study context using GET, we will apply our data to a learning process. Our approach involves using a machine learning algorithm to estimate WEEE production.

Machine learning and its ability to solve problems in various domains have made it increasingly popular through its algorithmic solutions [65]. There are several learning algorithms available, including linear regression, support vector machines, decision tree classifiers, random forest regression, and neural networks [66]. In line with our need to quantify WEEE, the random forest regression algorithm will be our estimation algorithm.

Indeed, there are several regression methods such as linear regression, decision tree regression, gradient boosting regression, and random forest regression. Our choice is oriented toward Random Forest Regression due to its effectiveness in ensemble learning, where multiple decision trees are combined to make predictions [67]. This method has gained popularity owing to its ability to handle both categorical and numerical features, effectively capturing complex patterns and interactions. The algorithm offers the following key advantages:

1) Versatility: Random forest regression can accommodate various types of data, making it suitable for datasets with a mixture of feature types. And doesn't mean that the more trees, the better the pre-

diction.

2) Non-linear relationships: It has the capability to capture non-linear relationships between variables, allowing it to model complex data patterns effectively.

3) Robustness: Random forest regression addresses the issue of overfitting by aggregating predictions from multiple decision trees, thereby reducing individual tree biases.

These characteristics make random forest regression a suitable choice for estimating the amount of electronic waste generated by SMEs in developing countries. By considering the diverse nature of the data and capturing complex relationships, this method can provide reliable and accurate estimates for waste management planning and policy-making.

What makes this article innovative is its approach of moving from the specific to the general. In other words, it proposes a calculation model that is applicable to individual economic agents and can be generalized to multiple enterprises. From another perspective, this study takes into account the realities of the economic agents under investigation, in the truest sense of the term, and closely relates to the life cycle of EEE within enterprises. Lastly, the main innovation lies in the fact that the random forest regression algorithm is deployed for the calculation of the quantities of generated WEEE will be based on relevant parameters of EEE usage.

3. Research methodology

3.1 Area of study

In this study, the city of Douala in Cameroon was chosen as the place of study. It is located on the edge of the Atlantic Ocean, at the bottom of the Gulf of Guinea, and at the mouth of the Wouri River [68]. Given its openness to sea lanes for both Cameroon and countries of the Central African sub-region, it constitutes a geographically strategic location for the establishment of businesses. According to the National Institute of Statistics of Cameroon [69], this justifies the presence of 41.4% of modern enterprises (in the formal sector and producing a DSF) installed in the city of Douala in 2018. Our study was carried out in Cameroon, by its recognized status as a developing country and, more specifically, with ISO 14001: 2015-certified small and medium-sized companies in the economic capital Douala.

3.2 Data collection tools

In the first part of our structured interview guide, we were only able to obtain limited data, such as those necessary for calculating the rates related to the maintenance of EEE. The most significant rates included their repair rate, utilization rate, and average lifespan of the EEE.

The main input data for the model, specifically the quantities of available EEE within the company, were obtained through the review of the financial statements for the year 2021. The EEE selected for our analysis is based on their significance as support for the company's core activities and their representation across various industry sectors. These include "Phones", "Laptops", "Desktops" and "Air conditioners".

3.3 Sampling

For the sake of representativeness, our sample consisted of specific organizations based in the city of Douala. This choice was made due to Douala being Cameroon's economic pool. Companies are more diverse there than in other cities in the country. Our sampling technique was theoretical, as it selects participants according to a rationale based on the concepts that emerge during a study. The relevance of our sample stems from the fact that the people with whom we spoke were authorized managers and responsible for strategic or operational IT maintenance. Given that our study was carried out during the COVID-19 period, the accessibility and administration of an interview guide to collect qualitative and quantitative data proved to be more complicated in companies; hence, we eventually obtained a reduced number of samples.

The guide was drawn up in a detailed manner, in order to not deviate from the orientations that we have given ourselves around the following themes: general information about the company, general information on EEE and WEEE, company culture in WEEE material, and their EA (Environmental Aspects), regulatory and normative knowledge in terms of WEEEM (WEEE Management), controls and measures to prevent and fight against WEEE, and potential difficulties related to WEEEM.

3.4 Contextual hypothesis

1) The market for Electrical and Electronic Equipment (EEE) remains unsaturated, allowing for continued access to new EEE. The EEE available in the market is in excellent condition without any defects.

2) Equilibrium is achieved when the total quantity of EEE within the company is equal to the quantity of WEEE generated by the company. Factors such as utilization rate, lifespan, and repair rate contribute to the transformation of EEE into WEEE.

3) The company adopts a rational approach and optimizes the performance of its EEE. The decision to purchase EEE is based on forecasts of the generated WEEE. Emphasis is placed on the utilization rate, maintenance, and lifespan of the equipment to maximize efficiency.

- Utilization rate represents the actual usage of the devices relative to the predicted usage, indicating how the devices are used in practice.

- Lifespan refers to the average operational lifetime of the EEE, with average values considered for each type of equipment.

- Maintenance encompasses the maintainability of the EEE, focusing on actions such as repair, leading to the repair rate.

4) The company is environmentally conscious and aligns with the sustainable development goals (SDGs). It adheres to environmental laws and regulations by implementing appropriate practices for the management of its WEEE. The company actively contributes to sustainable development and environmental preservation.

3.5 Data analysis tools

Our analysis of the data for this initial survey category was conducted in two stages. The data were categorized into two groups based on their nature. Qualitative data was identified as relevant parameters impacting the life of Electrical and Electronic Equipment (EEE) in a business context. Quantitative data was utilized to construct data tables for each company.

The development of a machine learning algorithm using the Python programming language, based on the random forest regression method, enabled us to estimate the quantities of Waste Electrical and Electronic Equipment (WEEE) that could be generated over a one-year period.

3.6 Preliminary data processing

To begin with, we needed to simplify the expressions of relevant parameters influencing the life cycle of EEE in the business context.

The first parameter is the lifespan of the EEE. In this research, we have adopted the average lifespan of EEE based on existing studies, as in reality, these values are relatively consistent.

The second parameter is the utilization rate of the EEE. This is a performance indicator used by our sample companies. It is calculated by dividing the total duration of EEE usage by its maximum intended usage duration.

The third parameter is the repair rate of the EEE. All the companies in our sample prioritize the repair of EEE experiencing failures, which is also a performance indicator. It is highly regarded by our sample companies and is calculated as the ratio of the total duration of EEE interruption due to failures to the total number of interruptions for failure-related reasons (see **Table 2**).

3.7 WEEE estimation algorithm

To estimate the quantities of WEEE that can be generated over a one-year period, we developed an estimation algorithm based on the random forest

Table 2. Formula of parameters calculation.

Parameters	**Mathematical expression**	**Observations**
Lifespan (L)	L = Literature review average lifespan for each device	/
Using rate (U)	$U = (\sum u_i / u_{max}) \times 100$ UI = using time, u_{max} = maximum using time,	Rates are determined annually for each type of EEE by the company
Repair rate (R)	$R = (\sum r_i / N_i) \times 100$ r_i = interruption duration, N_i = number of failures	

regression method implemented in the Python programming language.

Here is an overview of the steps involved in the algorithm:

Step 1. Data collection: We gathered relevant data, including qualitative parameters impacting the life of EEE in the company and quantitative data used to construct data tables for each company.

Step 2. Data preprocessing: We simplified the expressions of the relevant parameters influencing the EEE lifecycle in the business context, such as the lifespan of EEE, utilization rate, and repair rate. This involved normalizing and transforming the data to ensure compatibility.

Step 3. Setting program: 1-Input Data

Let Dn = ((Ei, Xi), ..., (En, Xn)) be the training set, where Ei is an input vector representing parameters such as the quantity ofWEEE, utilization rate (U), repair rate (R), mean lifespan (L), and Xi is the corresponding amount of generated WEEE over a given period (see **Table 3**).

2-Random forest training: To train the random forest regression model, we follow the following steps:

- Tree construction: We create a set of M random regression trees, where M is the number of trees in the forest (we can let M approach infinity for better performance).

- Resampling: Before constructing each tree, we resample the training set D_n using a random variable Θ to obtain a new data sample D_n^(Θj) for each tree Θj.

- Node splitting: At each node of the tree, we randomly select m_tree directions from the input parameters E to perform a split according to the CART (Classification and Regression Trees) criterion.

- Tree Construction: We build the tree by performing successive splits until each cell (node) contains fewer data points than node size (see **Figure 1**).

Step 4. Model Training: Using the random forest regression method, we trained the algorithm on the preprocessed data. Random forest regression is a machine learning technique that constructs an ensemble of decision trees and combines their predictions to generate accurate estimates.

Step 5. Feature importance analysis: We performed a feature importance analysis to identify the parameters that have the most significant impact on the quantities of generated WEEE. This analysis helps in understanding the key factors driving WEEE

Table 3. Tabular representation of data organization.

	Company ($C_{1,\dots,8}$)			
	Phones	Desktops	Laptops	Air conditioners
EEE quantity (E^n)	$E_{1,1}^{\ n}$; … ; $E_{1,8}^{\ n}$	$E_{2,1}^{\ n}$; … ; $E_{2,8}^{\ n}$	$E_{3,1}^{\ n}$; … ; $E_{3,8}^{\ n}$	$E_{4,1}^{\ n}$; … ; $E_{4,8}^{\ n}$
Using rate (U)	$U_{1,1}^{\ n}$; … ; $U_{1,8}^{\ n}$	$U_{2,1}^{\ n}$; … ; $U_{2,8}^{\ n}$	$U_{3,1}^{\ n}$; … ; $U_{3,8}^{\ n}$	$U_{4,1}^{\ n}$; … ; $U_{4,8}^{\ n}$
Repair rate (R)	$R_{1,1}^{\ n}$; … ; $R_{1,8}^{\ n}$	$R_{2,1}^{\ n}$; … ; $R_{2,8}^{\ n}$	$R_{3,1}^{\ n}$; … ; $R_{3,8}^{\ n}$	$R_{4,1}^{\ n}$; … ; $R_{4,8}^{\ n}$
Lifespan (L)	L_1	L_2	L_3	L_4
WEEE generated quantities $^{(n+1)}$	$X_{1,1}^{\ n+1}$; … ; $X_{1,8}^{\ n+1}$	$X_{2,1}^{\ n+1}$; … ; $X_{2,8}^{\ n+1}$	$X_{3,1}^{\ n+1}$; … ; $X_{3,8}^{\ n+1}$	$X_{4,1}^{\ n+1}$; … ; $X_{4,8}^{\ n+1}$

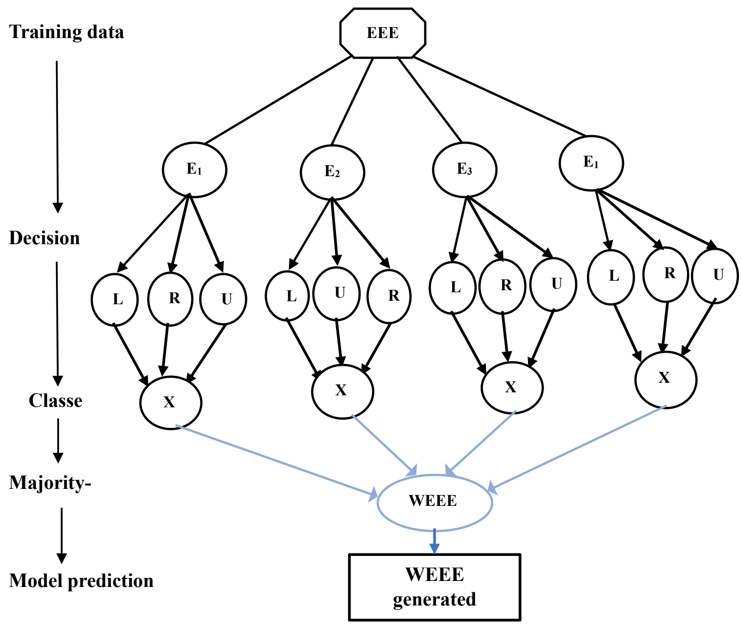

Figure 1. Random forest trees for an SME.

generation.

Step 6. Estimation of generated WEEE quantity: Once we have trained the ensemble of M trees, we can use the model to estimate the quantity of WEEE generated for new input data Xi, i.e., for new combinations of input parameters. The estimation of the generated WEEE quantity for an input vector Ei is given by:

m_(M,n) (Ei;Θ1,…,Θ_M,Dn) = 1/M ∑_(j=1)^M (1_(Ei∈An (Ei;Θj,Dn)) Xi)/(Nn (Ei;Θj,Dn));

where An (Ei; Θj, Dn) is the cell containing the input vector Ei in tree Θj, and Nn (Ei; Θj, Dn) is the number of data points (parameters) previously selected and falling into that cell.

-Final Prediction:

To predict the quantity of WEEE generated over a given period for a company, we take the average of the estimations for each input vector Ei:

m_ (∞,n) (Ei;Dn) = E_Θ [m_(M,n) (Ei;Θ, Dn)];

where E_Θ represents the expectation with respect to the random parameter Θ, conditioned on Dn. This represents the final prediction of the quantity of WEEE generated for a given company using the random forest regression model.

By using the trained algorithm, we applied it to the input data, which includes the quantities of EEE available in the company. The algorithm utilizes the identified parameters and their relationships to generate estimates of WEEE quantities for a one-year period. This was made possible by training on 80% of the data and using the remaining 20% for simulation purposes.

Step 7. Evaluation and validation: We assessed the accuracy and reliability of the generated estimates by comparing them to real data or conducting validation experiments. The mean squared error (MSE) was the most suitable scientific tool for this procedure as it is highly recommended for regression programs. This step ensured the effectiveness of the estimation algorithm.

4. Result analysis

This research follows a quantitative paradigm primarily because it utilizes quantitative data obtained from literature reviews, documentary research, and observations conducted on our samples. The definition of the study context using GET and the algorithmic programming of an estimation model through the Python programming language has led us to results that closely approximate reality.

The methodological result of our scientific approach is shown in **Figure 2** below.

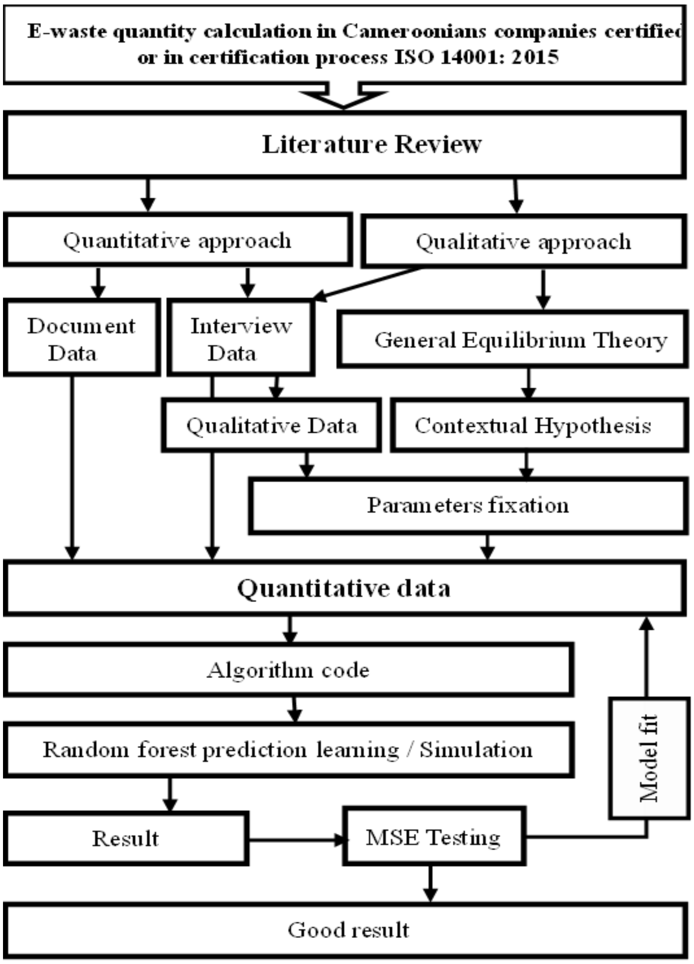

Figure 2. Research flowchart.

4.1 Qualitative results

The qualitative results of this approach allow us to identify the relevant parameters that describe the lifecycle of an EEE within companies. It emerges that, in the majority of cases, EEE devices have a certain average lifespan that is more or less known. The manner in which they are utilized significantly influences their fate, thus necessitating consideration of their utilization rate. Typically, before being permanently taken out of service, they undergo several repairs aimed at maintaining their operational status, which justifies the relevance of the repair rate. **Figure 3** represents the EEE using process. Furthermore, the relevance of the selected parameters is based on the fact that our sample SMEs have identified these three parameters as their main indicators for assessing and evaluating their EEE.

4.2 Quantitative results

As mentioned in our methodological approach, a crucial step was to develop and deploy the machine learning code that would correspond to our prediction problem, namely the random forest regression algorithm. The learning phase was conducted using 80% of the data, representing N = 8 companies from our sample. The remaining 20% served as a performance test for the regression model.

The training data used are summarized in **Table 4** below:

After machine learning by the algorithm, we proceeded to analyze the performance of our prediction. The performance of a regression model generally expresses the reliability of its application in terms of the quality of its prediction results. A good prediction should provide values close to reality. Our chosen performance indicator for this model was the mean

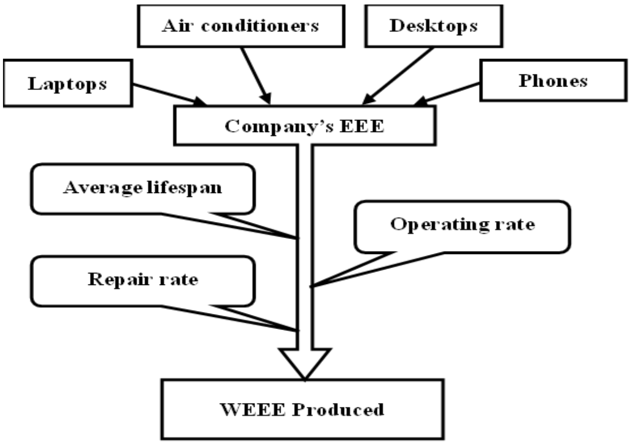

Figure 3. Flowchart of EEE using process.

Table 4. Tabular representation of data organization.

	Company ($C_{1,2,3,4,5,6,7,8}$)			
	Phones	**Desktops**	**Laptops**	**Air conditioners**
EEE quantity (E^{2020})	10, 15, 10, 21, 43, 12, 13, 4	13, 15, 8, 27, 11, 10, 10, 0	6, 8, 8, 12, 22, 2, 2, 4	8, 5, 4, 15, 9, 31, 32, 1
Using rate (U)	0.9, 0.9, 0.8, 0.7, 0.55, 0.7, 0.7, 0.6	0.9, 0.92, 0.9, 0.8, 0.7, 0.95, 0.95, 0.0	0.9, 0.89, 0.8, 0.75, 0.85, 0.7, 0.7, 0.7	0.8, 0.6, 0.7, 0.8, 0.9, 0.9, 0.6, 0.85
Repair rate (R)	0.0, 0.3, 0.35, 0.2, 0.2, 0.1, 0.15, 0.2	0.6, 0.7, 0.6, 0.6, 0.6, 0.15, 0.15, 0.0	0.7, 0.6, 0.4, 0.4, 0.5, 0.2, 0.25, 0.4	0.8, 0.8, 0.8, 0.8, 0.85, 0.1, 0.1, 0.23
Lifespan (L)	3	10.36	5.066	12.3
WEEE generated quantities $^{(2021)}$	4, 3, 2, 6, 8, 3, 1, 1	3, 2, 2, 3, 2, 1, 0, 0	1, 1, 1, 2, 3, 0, 0, 0	1, 1, 0, 3, 1, 0, 1, 0

squared error (MSE). Its application to our study yielded an MSE ranging from 0 to 0.9 for each of the studied EEE. **Figure 4** below provides a graphical representation of this performance evaluation.

This figure highlights the MSE as a measure of error evaluating the performance of our model. The values range from 0.3 to 0.8, indicating a discrepancy between the predictions and the actual data. This discrepancy, for us, is an area for improvement, but it remains close to the reality of our sample companies. Improving this performance would likely involve a much larger dataset, which would facilitate the algorithm's learning process and bring the predicted results even closer to reality.

The simulation of our model was conducted using data obtained from two explored companies. The results of the simulation are as follows:

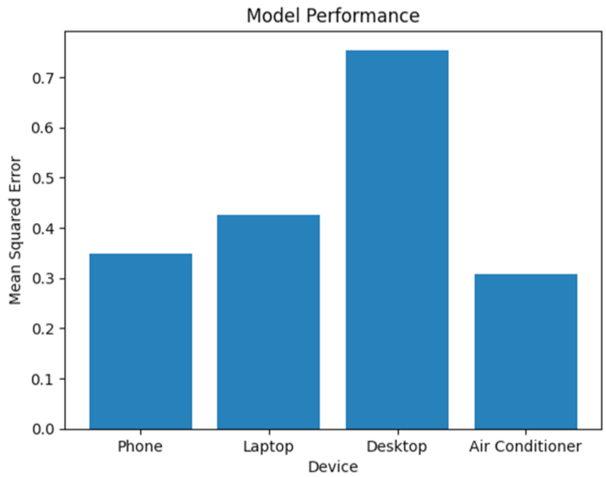

Figure 4. Graph of predicting performance.

Tables 5 and 6 allow us to formulate the following interpretation: For each of the companies, the deployed algorithmic model can predict the quantities of WEEE they are likely to generate. Based on the EEE used by these companies during the year 2020, along with their respective utilization rates, repair rates, and average lifespan of the studied EEE, the algorithm provided us with quantities of WEEE produced in 2021 that are very close to the actual values, with decimal differences. For example, in company 9, the algorithm estimated 3.59 waste phones, and the actual number was 4 waste phones. In companies 9 and 10, we observed 2 and 3 desktops, respectively, as waste produced in 2021, and the model predicted 3.59 and 3.55 desktops as waste for the same year.

A graphical representation of the prediction results (**Figure 5**) clearly reveals the proximity between the actual quantities of WEEE generated by types of EEE in 2021 and the predicted quantities of WEEE for the same year.

A graphical synthesis of both prediction results and reality provides a better understanding of the discrepancies between them.

Figure 6 clearly suggests some confusion between the units of predicted quantities of WEEE

Table 5. Predicted E-waste quantities from Company 9.

	Company (C_9)			
	Phones	Desktops	Laptops	Air conditioners
EEE quantity (E^{2020})	16	10	6	3
Using rate (U)	0,7	0,8	0,75	0,85
Repair rate (R)	0,22	0,6	0,4	0,8
Lifespan (L)	3	10,36	5,066	12,3
WEEE generated quantities $^{(2021)}$	4	2	1	1
WEEE predicted quantities $^{(2021)}$	3.59	2.21	0.92	0.74

Table 6. Predicted E-waste quantities from Company 10.

	Company (C_{10})			
	Phones	Desktops	Laptops	Air conditioners
EEE quantity (E^{2020})	22	17	5	7
Using rate (U)	0,8	0,9	0,8	0,75
Repair rate (R)	0,3	0,5	0,4	0,6
Lifespan (L)	3	10,36	5,066	12,3
WEEE generated quantities $^{(2021)}$	4	3	1	1
WEEE predicted quantities $^{(2021)}$	3.55	2.51	0.91	0.81

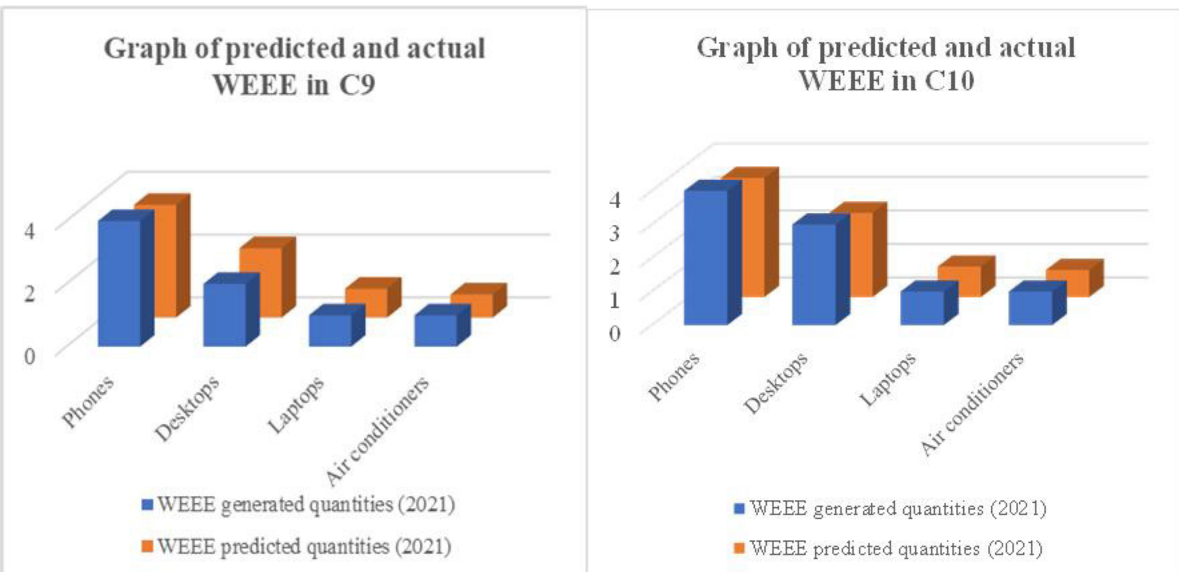

Figure 5. Graph of predicted and actual WEEE.

and the actual quantities produced for each of the studied EEE. This, in turn, confirms the performance of the prediction model. The visible prediction errors underscore the need for a larger dataset to refine the algorithm's learning process and, consequently, enhance its precision.

We can have an idea of the quantities of WEEE for the year 2022 if we obtain data regarding the quantities of EEE used by these organizations in 2021, as well as the parameter values related to factors such as lifespan, utilization rate, and repair rate for that specific year.

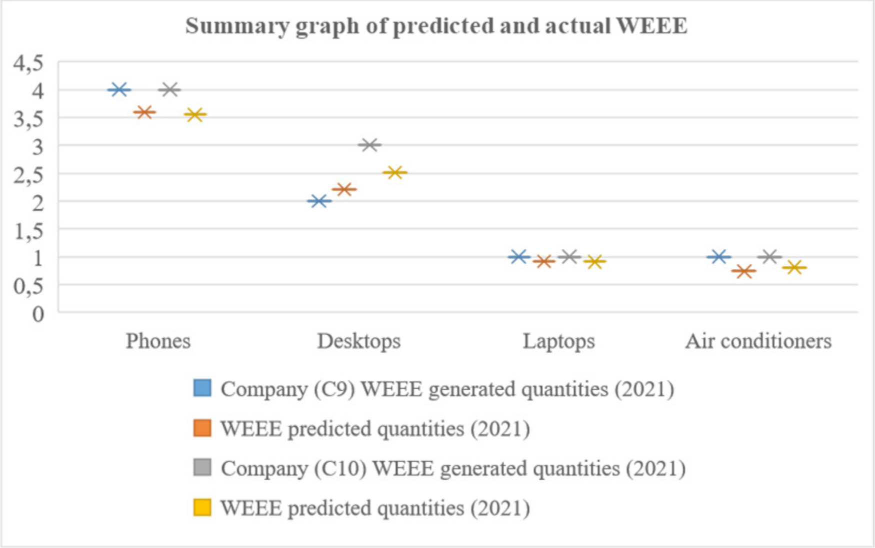

Figure 6. Synthetic graph of predicted and actual WEEE.

5. Discussion

This study allowed us to delve into the behavior of a specific type of economic agent, namely businesses, in Cameroon (a developing country). More specifically, we analyzed and highlighted the trajectory of EEE within the context of SMEs. The results led us to understand that the transformation of EEE into WEEE is influenced not only by its lifespan but also by its utilization rate and repair rate.

The method of calculating or estimating the quantities of generated WEEE appears better suited through the automated algorithmic learning technique based on random forest regression, provided accurate data is available. Given that businesses operate continuously, no organizational year goes by without the production of WEEE.

In comparison to existing works, conducting a direct comparative study is challenging due to the fact that the pre-existing works do not adhere to the same ideological approach as ours. Our approach quantifies WEEE among end consumers and aims to generalize it to find aggregated values over a specific period. The advantage of this approach lies in the fact that end consumers almost always have data on the EEE in use or consumed, and the main difficulty could be accessing this data. Conversely, other prediction approaches require considerable amounts of data, which might not always be available or need to be constructed.

Moreover, this study's strength lies in describing the journey of EEE in its context and considering the factors influencing their transformation into WEEE. This seems rare since existing works that share similar perspectives mainly consider the lifespan of EEE and/or planned obsolescence.

Regarding the calculation method, existing works propose statistical techniques and tools of varying complexity, which might not be easily reproducible for common users. In contrast, in our case, once the algorithm is available and well-trained, having input data is sufficient to generate results. The proposed prediction method is practical, accessible, and does not require statistical prerequisites from users.

One common aspect shared with other research might be that the method's performance is better demonstrated with larger datasets. However, considering the performance results of our method, having a large dataset might be necessary but not sufficient.

In conclusion, this discussion of the results highlights the practical, reproducible, and performance-driven nature of the proposed method.

5.1 Recommendations

It is no longer necessary to provide a historical overview of estimation methods used by researchers to calculate the quantities of WEEE. This research proposes a new approach to estimation methods that can be generalized to consumers of the same nature. Furthermore, the application of this method can be extended to any type of EEE consumer, provided that the specificity of parameters related to their transformation into WEEE is taken into account. In the past, calculation methods appeared complex, and data availability was limited. With this approach, the only remaining challenge lies in the availability of data.

5.2 Managerial implication

In practice, managing without measurement is merely blind action and management entails forecasting, organizing, directing, and controlling. This research proposes a tool for predicting the quantities of WEEE that will be produced by companies. It would serve the organization itself in assessing and revising its WEEE management strategy, setting reasonable targets to minimize its environmental footprint.

The potential benefits of this research for businesses are as follows:

- Informed decision-making: With a reliable model for estimating WEEE, businesses will be able to make more informed decisions regarding their electronic waste management policies. This may include waste reduction strategies, choices of recycling or revalorization options, and more relevant investments in sustainable WEEE management.

- Financial planning: By having a more accurate estimation of generated electronic waste, businesses can better plan for waste management costs and forecast future expenses. Considering that Cameroonian law on hazardous waste from businesses (referred to as PWEEE) places the responsibility for their evacuation, treatment, and disposal on the users and mandates that it must be done by approved service providers, this can lead to improved financial management and more efficient resource utilization in the near future.

- Compliance with regulations: Electronic waste management is subject to strict environmental laws in many countries. In the Cameroonian context, though the legislative framework for WEEE exists, its implementation suffers from infrastructure and rigorous monitoring insufficiencies. A reliable estimation model can help businesses comply with legal requirements regarding WEEE management.

- Social responsibility and brand image: Implementing responsible WEEE management can enhance a company's brand image by demonstrating its commitment to sustainability and the environment. This demonstration becomes more significant when backed by quantifiable forecasted objectives. A WEEE prediction model provides a forecast basis for the quantities of WEEE against which quantified and budgeted management practices and objectives can be aligned.

This research can bring significant advantages to businesses by improving their WEEE management. It can enable better financial planning, compliance with environmental regulations, and enhance their social responsibility and brand image. These improvements can contribute to the overall sustainability of businesses and their positive impact on the environment.

The potential benefits of this research at the governmental level are as follows:

- Waste management policies: By providing reliable estimates of the quantity of WEEE generated by businesses, this research can assist governments in developing more targeted and effective waste management policies. These policies may include incentives to encourage WEEE recycling and revalorization, as well as regulations to control and reduce electronic waste.

- Planning and resource allocation: Accurate estimates of WEEE produced by businesses will enable governments to better plan and allocate their resources for waste management. This may involve establishing collection infrastructures, recycling centers, and appropriate disposal sites.

- Monitoring environmental compliance: With a WEEE estimation model, governments can better monitor and assess businesses' compliance with environmental regulations regarding electronic waste management. This will allow corrective actions to be taken in case of non-compliance and ensure responsible WEEE management.

- Business and public awareness: The results of this research can be used to raise awareness among businesses and the public about issues related to electronic waste and the importance of proper management. Increased awareness can lead to more active participation by businesses and citizens in WEEE management.

- Collaboration with businesses: Accurate estimates of WEEE produced by businesses can facilitate collaboration between governments and companies to find effective and sustainable solutions for electronic waste management. Public-private partnerships can be encouraged to promote responsible WEEE management.

Overall, this research can have significant implications for governmental waste management strategies, resource planning, environmental compliance monitoring, awareness campaigns, and collaborative efforts with businesses to address the challenges posed by electronic waste.

By this research, governments would have a means to predict the quantities of WEEE generated by companies, contributing to the development of an effective national strategy for short, medium, and long-term WEEE management. It also serves as a control tool for monitoring the fate of WEEE.

The environmental, health, and social impacts of the rapid growth of WEEE in developing countries are undeniable. This research provides a quantified barometer for awareness programs emphasizing the importance of implementing responsible WEEE management practices to minimize their environmental impacts.

From the perspective of environmental regulations, this work offers targeted guidance on environmental objectives regarding WEEE production by companies. The choices and adoption of rules can be realistic and context-appropriate.

Additionally, a precise estimation of the quantities of generated WEEE serves as a data source for business opportunity analysis and can facilitate the commitment to invest in the eco-friendly treatment industry of WEEE.

5.3 Research limits

This study has certain limitations that should be taken into account. Firstly, the accurate estimation of WEEE produced by companies can be challenging due to the accessibility of reliable data. Companies have the particularity that all inputs are recorded in their financial documents, but they may not be readily available to the public.

This research may not have considered certain aspects related to EEE, such as their nature at the time of purchase, as companies may acquire second-hand EEE. An approach that incorporates cost-based estimation, such as the costs of purchasing EEE, maintenance costs, and/or EEE productivity, could have been included in the predictive analysis. The redefinition of WEEE, where declared WEEE may still be usable for another entity, could also influence the prediction results.

This work was conducted with a small sample size, totalling 10 companies, which may be considered less statistically significant for some researchers. Thus, there is room for further research that provides sufficient data to refine the trend of WEEE quantities produced.

Another limitation of this article is that the predictions are only feasible in the short term (1 year). It would be possible to make estimations for the medium and long term by aggregating predictions over multiple years. Additionally, it could be proposed for the algorithm to learn and make predictions for the medium and long term by incorporating parameter values corresponding to these time periods.

6. Conclusions

The field of management remains a complex area of study as it typically involves multiple disciplines. Our endeavor was to calculate or estimate the quantities of WEEE produced by companies. A review of the literature presented several studies with a similar objective. Each study distinguished itself by the chosen estimation method based on data availability and size. These studies primarily focused on larger scales of analysis. In contrast, our study concentrated on the sources of WEEE production and conducted research on the consumption of EEE by ISO 14001:2015 certified SMEs in the economic capital of Cameroon. It was found that the transformation of EEE into WEEE is influenced during consumption by parameters such as average lifespan, utilization rate, and maintenance, often expressed through repair rates. General Equilibrium Theory enabled us to contextualize and simplify this qualitative analysis while adhering to the paradigm of our population.

We needed to adopt an estimation method that was user-friendly, efficient, and up-to-date. Hence, our choice fell on the random forest regression machine learning algorithm. After developing the code using the Python programming language, data deployment was carried out through machine learning. 80% of our collected data was used for the algorithm to learn and generate predictive values of WEEE for one year. The remaining 20% of our collected data, representing data from two companies, served as a simulation, and the discrepancies were found to be insignificant. The performance test of our algorithmic model using the MSE method yielded values ranging from 0.3 to 0.8, indicating promising performance.

The significant contribution of this research lies in its hybrid methodology. Our study combined classical research methods with artificial intelligence through a learning algorithm to estimate the quantities of WEEE produced. Moreover, the application of GET established the foundation of this research and simplified the research context without losing sight of the fundamental objectives of our study population. The relevance of this research is that it provides the scientific community with an easy method for calculating or estimating WEEE, thereby resolving difficulties associated with calculation methods and shifting focus to data availability and accessibility issues.

This work represents a relevant management tool for organizations and institutions. By applying this method, organizations and companies have a kind of barometer that allows them to anticipate the quantities of WEEE they may produce in a given year and plan for their EEE needs accordingly. Given their environmental orientations, they have the opportunity to set realistic targets and define appropriate policies to reduce their environmental footprint and contribute to sustainable development goals. Institutions, on the other hand, have a concrete tool to anticipate the annual size of WEEE, which would enable them to develop a national policy and plan for managing business WEEE. It will now be possible to monitor the quantities of WEEE and their fate.

However, there are limitations to this research. The size of our sample could have been larger, but data collection was heavily disrupted by the COVID-19 pandemic. Health restrictions and the imposition of new habits significantly limited our contact with the study population. We do not claim to have considered all the aspects influencing the transformation of EEE into WEEE in companies. The prediction period in this research may seem short to some researchers, and future studies could explore medium or long-term predictions. Another limitation is that the model's performance evaluation could be questioned by employing an indicator other than MSE.

Future research should aim to improve the model by incorporating more real-world data collected in the field, enabling the algorithmic model to learn more and refine predictions, thus reducing the MSE values closer to zero. Consequently, the management of WEEE and the race toward contributing to sustainable development will also involve developing countries.

Author Contributions

Each author has made significant contributions to this manuscript, with roles as follows:

- Gilson Tekendo Djoukoue: Conception/design, Data collection, qualitative analysis and results interpretation.

- Idriss Djiofack Teledjieu: Development of a machine learning algorithm for prediction.

- Sijun Bai: Supervision, Review, and Validation of the final version for submission and publication.

Conflict of Interest

We declare that there are no conflicts of interest related to this research. None of the authors have any financial or professional relationships that could inappropriately influence the results or interpretations presented in this article.

Funding

This research received no external funding.

Acknowledgement

We, the authors of this paper, extend our sincere thanks to the various organizations that contributed to this study despite the difficult conditions due to COVID-19. We express our gratitude to the staff who have devoted themselves to the cause of this research work.

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