E-Waste Conversion Efficiency Tracking System for Landfill Creation to Optimize Resource Allocation for Recycling

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I. Introduction

In the past few decades, the development of relatively affordable, useful electronic devices has increased their usage manifold all across the globe. This extensive usage has led to a surge in the production of electronic waste (eWaste). Such waste has deleterious effects on neighboring areas due to the extremely high concentrations of Mercury, Lead, and Cadmium. According to the United Nations Environment Programme, less than 20% of eWaste is recycled formally. A large chunk of this waste is dumped in landfills, which are increasing in number by the day. Due to the stringent environmental regulations, the cost of recycling eWaste exceeds the revenue generated. A more meticulous approach is needed to transform this into a viable industry. The distribution of such waste differs from region to region based on a plethora of factors, including geography, demographics, and economy. Simply trying to extract useful components in a desultory fashion is a long-drawn and futile effort. It is imperative that we discern which landfills contain the largest amount of "useful" eWaste and allocate resources to extract the maximum amount of resources from those wastelands. To determine how to channel resources optimally, we develop a technique to monitor and eventually, over time, predict which regions are likely to produce and, thus, which landfills are more likely to have a large proportion of eWaste. If this can be achieved, we can prevent not only land pollution but also air pollution caused due to the incineration of such materials. We discuss our method to obtain the best distribution below.

II. Method

We need to account for the following factors whilst attempting to prepare a model to quantify the useful materials extracted from a landfill and decide on the future allocation of resources to recover material from a given landfill:
1] Mean cost of a given weight and volume of waste analyzed per day 2] Distance and transportation costs to and from the landfill per day 3] Mean daily revenue from plastic and metals recovered 4] Mean daily revenue from precious metals recovered 5] Cost recovery from arrangements with governments or conglomerates
Let the above parameters be modelled by $c_w,\ c_t,\ c_p,\ c_{pm},\ c_g$. d is the distance between the plant and the landfill. The net revenue per day can be obtained from a linear combination of the above parameters. Thus, we define

$$c_{net} = w_1 c_w + w_2 c_t + w_3 c_p + w_4 c_{pm} + w_5 c_g$$

$$= w_1 c_w + w_2 f_1(c_w,\ d) + w_3 f_2(c_w) + w_4 f_3(c_w) + w_5 f_4(c_w) + cross\ terms$$

This is the expression of net revenue per day from a particular landfill. w_1 and w_2 are negative vacuously. Subject to these constraints, we use the following Multi-Level Perceptron Model to simulate the situation. Let $\mathbf{c} \in \mathbb{R}^5$ and $c_{net} \in \mathbb{R}$. Define an $m \times 5$ weight matrix $\mathbf{W_1}$. Let

$$\mathbf{y} = \mathbf{W_1 c}$$

On applying a sigmoid activation function $g(a) = \frac{1}{1+e^{-a}}$, we get

$$\mathbf{z} = g(\mathbf{W_1 c})$$

such that the function g applies on each entry individually. Now, define a $1 \times m$ weight matrix $\mathbf{W_2}$. Our prediction

$$\hat{c}_{net} = \mathbf{W_2 z}$$

We now define a loss function

$$\mathcal{L} = \sum_{k=1}^{n} (\hat{c}_{net,\ k} - c_{net,\ k})^2$$

where n is the number of data points already available. We apply stochastic gradient descent to find the entries of the matrices $\mathbf{W_1}$ and $\mathbf{W_2}$ with step size η, until $|L^{(t)} - L^{(t+1)}| < \epsilon$. Here, we already know the functions $f_1, \cdots, f_4$ since these more or less remain the same as long as the method of recovering materials from waste is the same. However, w_1 through to w_4 and then the coefficients for the $(m-4)$ cross terms need to be determined. These are nothing but the entries of $\mathbf{W_1}$. We use $\mathbf{W_2}$ to account for various demographic factors such as the population, access to modern technology, and per capita income of the region to determine how likely it is that a landfill near that region will contain a certain amount of eWaste. This varies from place to place based on the factors mentioned previously. Thus, based on the data available, we determine the above weights. Now, we have a model to predict that, given a new landfill, will the revenue generated be sufficient to justify collecting and recycling eWaste from it.

We define the efficiency with respect to a given landfill $\eta = \frac{c_{net}}{c_w + c_t}$ The overall procedure now works as follows:

1) Transportation costs are affine functions of distance and are least for road transport until some distance between the landfill and the plant (say, D_1). From D_1 to a distance D_2, rail is the cheapest mode, and beyond that, inland water transport is the way to go. Based on the availability of these modes, we have $f_1(c_w, d)$.
2) Analysis cost depends on the extraction process. First, we use a VCG 19 model as shown in [2] or [5] to categorize waste as electronic and non-electronic and then use robots to separate waste into these two categories. This involves mechanical separation- disassembly of electronic products (for which companies like Apple already have robots), followed by shredding and pulverization. Finally, a cascade of liquid-based sorting, electrostatic and magnetic separation is used. Now, pyrometallurgy and electrorefining are used to extract metals and precious metals. Smelting may be done within the same plant or be outsourced. The cost of this entire process is c_w.
   We try to localize the model used by [4] Thus, we have
   $$EL_X = \frac{(c_d + c_r)E_X}{P_X} = \frac{(c_w)E_X}{P_X}$$
   Where EL_X is the environmental load per capita for that given region and P_X is the population for that region.
3) Here, plastic and metals can be recovered directly and sold, or they can be directly converted to self-powered portable electronics as depicted in [3] either within the same plant (thus, it'll be subsumed in $f_2(c_w)$) or in association with another plant where it'll be included in $f_4(c_w)$. The percentages of non-precious metals recovered can be found in Table 1. (taken from [6]). Furthermore, we can categorize whether certain items contain a particular type of eWaste (say, a PCB of a specific category) by using a matrix:
   $$\mathbf{M} = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_k \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ m_{k1} & m_{k2} & \cdots & m_{kn} \end{bmatrix}$$
   where M_1 through to M_k are the various metals and m_{ij} denotes a product containing metal i.
4) The percentage of precious metals contained in eWaste can be found in Table 2. (taken from [6]). From this, we can determine $f_3(c_w)$. PCBs contain a majority of the precious metals in eWaste and are thus used to depict the relations we wish to establish.
5) In terms of the eWaste recycled, collaborations between the recycling firms and the government, including contracts with certain sustainability goals, can work as great incentives for these firms. Furthermore, deals with private corporations who produce goods containing possible eWaste could be struck. They can then reuse the recycled goods obtained from their own products, which will help create a circular economy. We model the revenue from such deals by $f_4(c_w)$. This varies from company to company and will thus help generalize our model even better.

PCB Cat.	Metal Content		
	Tin	Nickel	Copper
1	1.49%	0.07%	13%
2	2.70%	0.11%	11%
3	0.69%	1.13%	20%
4	0.73%	0.26%	17.25%

TABLE I
METAL CONTENT IN DIFFERENT PCB CATEGORIES

PCB Cat.	Precious Metal Content		
	Silver	Gold	Palladium
1	0.01%	0.003%	0.003%
2	0.02%	0.002%	0.001%
3	0.17%	0.04%	0.01%
4	0.08%	0.01%	0.002%

TABLE II
PRECIOUS METAL CONTENT IN DIFFERENT PCB CATEGORIES

III. CONCLUSION

On being able to effectively train our model, we can determine, with a high degree of certainty, where a new landfill should be created, given we know the location of the eWaste processing plant. Not only this, we will be able to possibly remove certain landfills from which eWaste is recovered, if the efficiency is too low, and find out newer landfill locations for the corresponding representative population. As we attempt to edge towards a more sustainable and circular economy, the method proposed contributes to the global eWaste dilemma, which has progressively gotten worse, especially over recent years. The model parameters can be continuously fine-tuned with the incorporation of real-time data. This effort should go a long way in finally attaining a sustainable eWaste Management system which leads to holistic societal development and provides benefits to various factions of society.

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