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Changing the World's Energy Future

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A decision support tool for e-waste recycling operations using the hen-and-chicks bio-inspired optimization metaheuristic

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ABSTRACT

E-waste from end-of-life electrical and electronic devices is one of the fastest growing waste streams from households and businesses. E-waste recycling yields environmental sustainability and economic benefits. Due to continuous changes in e-waste types and compositions, recycling businesses face challenges to optimize their operational configuration to achieve better economic and environmental performance. To help e-waste recyclers mitigate this problem, we have developed a modular decision support tool called the Comprehensive Manufacturing Assessment Tool (CMAT) that can simulate both e-waste recycling operations and economics. This tool can give valuable insights regarding the profitability of the entire operation and different e-waste types. In addition, a new bio-inspired metaheuristic optimization algorithm, hen-and-chicks optimization (HACO), was developed to assign manpower to different workstations to maximize operational efficiencies. According to the results of our case study, laptops, desktops, and computer peripherals are the three electronic waste products that produce the most profit. Our examination of the sensitivity of material prices shows that the price of steel has the most significant influence on total profit, because it is the most widely used material in the majority of electronic devices. We have released the decision support tool as open-source software under a general public license. It could be customized for other recycling industries beyond e-waste to achieve business sustainability by making their operations more efficient.

1. Introduction

In 2019, 53.6 million metric tons of electronic waste ("e-waste") were generated globally [1] with projections showing e-waste generation reaching ∼110 million metric tonnes by 2050 [2]. Yet, only 9.3 million metric tons of e-waste or 17.4% were recycled in 2019 [3]. E-waste is regarded as one of the fastest growing solid waste streams and developed countries have been taking steps to address waste management of this stream [2]. Addressing the e-waste stream is paramount because e-waste recycling yields environmental, health, and economic benefits [2,4]. First, e-waste contains hazardous substances, including mercury, brominated flame retardants, and chlorofluorocarbons — all of which end up in the environment if improperly disposed [4,5]. Second, these substances are subject to human exposure when e-waste is landfilled with other municipal solid waste [3]. Third, e-waste may also contain up to 60 to 69 desirable elements, including precious metals and critical raw materials, which may be recovered during the recycling process [3,6]. Additionally, they are sometimes present at concentrations higher than in the traditionally mined ore [7]. For these reasons, it is desirable to create and implement sustainable e-waste recycling processes worldwide.

At its backbone, the e-waste recycling process consists of a series of stages designed to receive, store, sort, dismantle, shred, separate, and recover materials from e-waste [8]. Within this process, various inefficiencies can pose limitations to its profitability. To combat these limitations, in the United States (U.S.), legislation exists in 25 states that pass the costs of mandated recycling to consumers or manufacturers to offset the cost of e-waste recycling [9,10]. Mandates vary by state with the two main program types being Extended Producer Responsibility (EPR) and Advanced Recovery Fee (ARF) [10]. While the responsibility of cost in the EPR is defined as a manufacturer's responsibility, the ARF system places the responsibility on the consumer. However, it should be noted that in the EPR system, the recycling cost is likely passed to the consumer in terms of higher product prices. Therefore, it can be inferred that reducing e-waste recycling costs will help reduce product prices.

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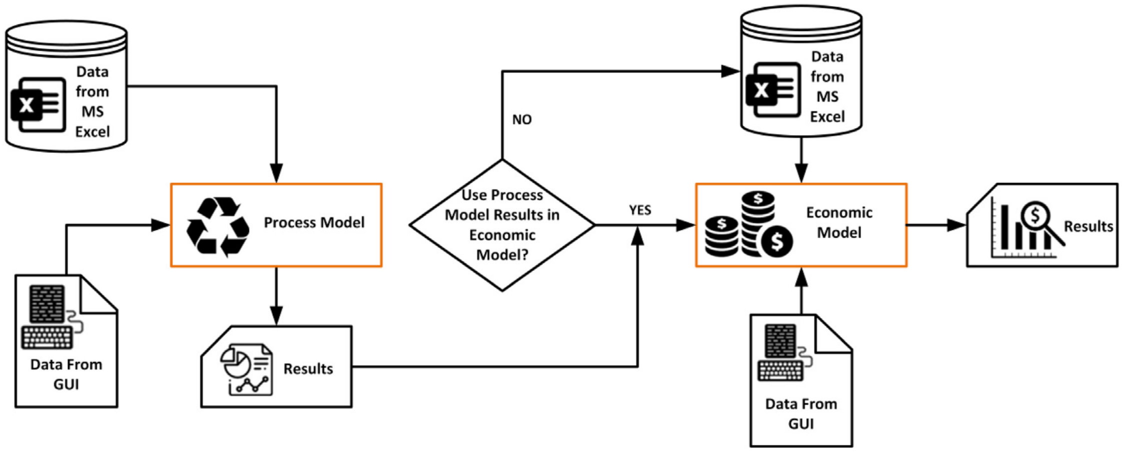

Fig. 1. High-level diagram of the architecture of the decision support tool.

There have been many past studies and models that have focused on decision support systems and decision analysis models [11–14]. In recent times, researchers have shown increased interest in machine learning-based decision support systems [15–18] and computer simulation-based decision support systems [19–23], which have gained popularity due to their effectiveness and efficiency. Narrowing down from broadscale decision support systems, many studies [24–29] have shown that data-driven decision-making to attain cost efficiency is extremely important for business sustainability during and post COVID-19 pandemic. Cost efficiency is especially important for e-waste recycling as evidenced by the varying U.S. recycling legislation required to encourage e-waste recycling. Investigation into the details of e-waste recycling costs revealed a common theme for larger impacts on recycling costs. In a survey of ten liquid crystal display (LCD) recycling companies worldwide, D'Adamo et al. found that labor has a significant weight in plant operating costs [30]. Kang and Schoenung revealed that the greatest costs in e-waste recycling were materials and labor in California in the U.S. [31]. Dias et al. showed that labor represents over 90% of the first stage (sorting, dismantling, and shredding) recycling cost in Australia [32]. With labor being identified as one of the key cost components of e-waste recycling, optimization of manpower could play an important role to reduce e-waste recycling costs.

A variety of different studies have been conducted that analyze many different aspects related to e-waste recycling spanning from material flow analysis to life cycle assessment to reverse logistics. To start, previous studies have modeled the process flow of recycling material for economic and material recovery purposes. Wolf et al. developed a network flow model to optimize the material recovery, material grade, material mass flow, and ordering of multi-stage material separation in a recycling system [33]. Ip et al. implemented a network flow model to evaluate the performance of material separation in a material recovery facility to enhance profit, efficiency, and material recovery rate [34]. Many groups have investigated e-waste reverse logistics spanning topics from e-waste reverse logistics system evaluation and framework development to e-waste reverse logistics network design decisions [35]. For instance, system evaluation and framework development included work that examined legislative requirements, cost and profitability, qualitative evaluation frameworks, and life cycle assessments [36–38]. Network design decision included work to minimize the cost of recycling and help determine optimal facility locations and material flow in the system [39–44].

The existing literature on e-waste recycling processes does not adequately address the need for a comprehensive analysis tailored to individual e-waste recyclers. While some studies have examined certain aspects of e-waste recycling, such as the environmental impact, they have not taken into account the modular process model required to optimize the process for a specific recycling operation. Additionally, the relationship between the composition of e-waste and the economics of the recycling process has not been fully explored. There is need for a decision support tool for e-waste recycling companies which is easy to use with a graphical user interface (GUI) that meets the above analytical needs. Therefore, this study aims to fill this research gap by developing a modular process model that identifies material flow bottlenecks, assesses process and economic inefficiencies, and analyzes the recycling economics of different e-waste types.

The contributions of this study can be summarized as follows. First, we developed a modular decision support tool to simulate e-waste recycling processes that can evaluate the performance of a given process layout and identify bottlenecks. Second, an economic model was integrated into the tool which can run independently or can utilize the results of the process model as input and perform profitability analysis for different streams of e-wastes. Third, we introduced a new bio-inspired optimization algorithm called hen-and-chicks optimization (HACO) and successfully employed it in the process model to automatically optimize manpower in workstations to maximize output. Fourth, we developed a no-code GUI for users without computer programming knowledge. Users with knowledge on Microsoft Excel should be able to use the tool. Finally, we released our tool as open-source software under a general public license at this repository— https://github.com/mamunur-ipe/CMAT, so that e-waste recycling companies can use it for free and developers can customize the tool, potentially, for other recycling industries to achieve business sustainability.

The remaining parts of this article are structured as follows: Section 2 explains the methodology used in this study, which involves the development of a process model, selection of an optimization algorithm, integration of an economic model with the process model, and development of a GUI for the decision support tool. In Section 3, a case study is presented which uses real data from an e-waste recycling company to demonstrate the tool's application. Section 4 discusses the results obtained from the tool for both the base case and alternative layout scenarios of our case study. In addition, this section provides the outcomes of the sensitivity analysis of various factors on profit, and concludes with a discussion of managerial implications, limitations of the study, and future research directions. Finally, Section 5 offers concluding remarks on the study.

2. Methodology

Fig. 1 shows the high-level diagram of the decision support tool. There are two primary components in the tool – (1) process model and (2) economic model. The process model simulates the shop floor of the e-waste recycling plant, and the economic model evaluates the economic performances of both processing and overall business performance. We integrated the economic model with the process model so that processing outputs can become inputs for economic calculation if the users choose this option. Otherwise, the economic model can also be run independently using the user's inputs from a Microsoft Excel file and GUI. We used the Python programming language and different Python-based libraries including SimPy [45], NumPy [43], PyQT [46], and Matplotlib [47] for the development of the decision support tool and the GUI. Detailed descriptions of the process and economic models are provided below.

2.1. Process model

We developed a discrete-event simulation tool under this process model. The tool can simulate the operations of e-waste recycling operations. There are five key attributes of the process model. First, the model can read the necessary input data from an excel file. Second, the model is modular in nature. The number of workstations and the layout of the recycling operations can be changed easily in the input excel file. Third, the model can minimize the overall processing cost by allocating manpower to different workstations. Last, the model automatically captures the relevant statistics, export results, and generate plots without additional steps or coding.

To achieve the modularity feature of our model, we followed the Object-Oriented Programming approach to create five types of classes. A brief description of the classes with initial attributes are described as follows:

Storage area: Here the collected e-waste raw materials, work in process (WIP), and finished goods are stored. Some of the attributes defined under this class include the name of the storage area, storage capacity, number of laborers, labor wage rate, labor cost, and capacity utilization.

Manual workstations: These workstations are manual labor dependent. There are three types of manual workstations— (1) sorting station where initial sorting is performed, (2) refurbishing station where functional electronic products are refurbished for resale to customers, and (3) dismantling station where electronic products are dismantled for further processing. The capacity of these workstations is defined by the processing capacities of the labor. Some of the attributes defined under this class include the name of the workstation, capacity, product processing time, input queue, output queue, busy time, idle time, capacity utilization, output, number of laborers, labor wage rate, and labor cost.

Machines: In e-waste recycling, different types of machines are used like shredder, ring mill, magnetic sorting, and so on. Some machines require operators (e.g., shredder) while others do not (e.g., ring mill). The maximum capacity is defined by its material processing capacity. Some of the attributes defined under this machine class include the name of the machine, input queue, output queue, processing capacity, cycle time, energy consumption rate, amount of energy consumed, number of operators, operator wage rate, busy time, down time, idle time, capacity utilization, labor cost, and energy cost.

Material handling equipment: To transfer material from one location to another location, different types of material handling equipment are used. Some of the common material handling equipment used in e-waste recycling plants are conveyors, trolleys, and forklifts. Some of the attributes defined under this class include loading point, unloading point, moving capacity, amount of transported materials, and capacity utilization.

Product: The e-waste collected for recycling can be categorized into nine major categories — cathode ray tube (CRT) television (TV), CRT monitor, LCD TV, LCD monitor, desktop, laptop, printer, small consumer electronics, and computer peripherals. Depending on the source, e-waste can be collected from residents or businesses. Some of the attributes defined under this class include the name of the product, collection source, product total mass, battery mass, CRT tube mass, and so on. The related product mass data of each category of e-waste come from a user-input excel file.

Fig. 2 depicts the development of the process model simulation workflow. We used Python programming language to develop the process simulation module titled 'process_model.py'. Inside this module, we created a class called 'Warehouse' where we defined different methods to perform the following four tasks:

(1) Data Query: At the beginning of the simulation, we perform the data query to collect the necessary data. The data relating to storage areas, manual workstations, machines, material handling equipment, and products come from a user-provided excel file. Only the data related to simulation time comes from the GUI.

(2) Process Model Generation*:* In this step, different classes are called under the 'buildSystem' method under the 'WareHouse' class and the necessary number of instances (simulation entities) of storage areas, manual workstations, machines, material handling equipment are created with necessary initial attributes. The connections between the simulation entities and the overall layout of the process are created by analyzing the input data.

(3) Model Simulation: We utilized the SimPy library [45], a Python programming language-based discrete-event simulation framework, to create the simulation environment. In the simulation environment, the storage areas, workstations, machines, and material handling equipment are defined as shared resources and the e-waste products are the active components that utilize the shared resources. The simulation period is defined by the user's input.

(4) Results: The process model collects necessary statistics while running the simulation. We utilized the Matplotlib library [47], a Python programming language-based data visualization program, to display the results to the users. We used the Pandas library [48], a Python-based data manipulation and analysis program, to export the summary statistics as a comma-separated values file for future uses.

2.2. Optimization of the process model

We have developed a new bio-inspired metaheuristic algorithm for optimizing the allocation of manpower in different workstations in the process model to maximize outputs and minimize processing costs. The development of the optimization algorithm used in the process model can be best described as an analogy regarding the food-searching behavior of chickens. Chickens primarily rely on visual, auditory inputs, and their sense of smell to search for food [49]. A mother hen along with her chicks search for food as a team. As soon as a team member finds food, the mother hen guides the rest of her chicks to that location and keeps exploring nearby places for new food sources. At times, some of the chicks isolate themselves from the flock temporarily and search for food randomly. Sometimes they are successful to find food and other chicks join them. A sample orientation of the hen and her chicks is illustrated in Figure S1 of the supplementary document. This flock intelligence inspired us to design a new algorithm for optimization titled "HACO". A description of the HACO algorithm can be found below.

2.2.1. Algorithm

Step 1 (Initialization of the population)

a. Initialize a population of chickens randomly based on Eq. (1) and define the associated parameters, including population size N, the maximum number of iterations k, and percentage of random chickens f, where $N, k \in Z^+$ and $f \in Q$.

$$X = LB + r * (UB - LB) \tag{1}$$

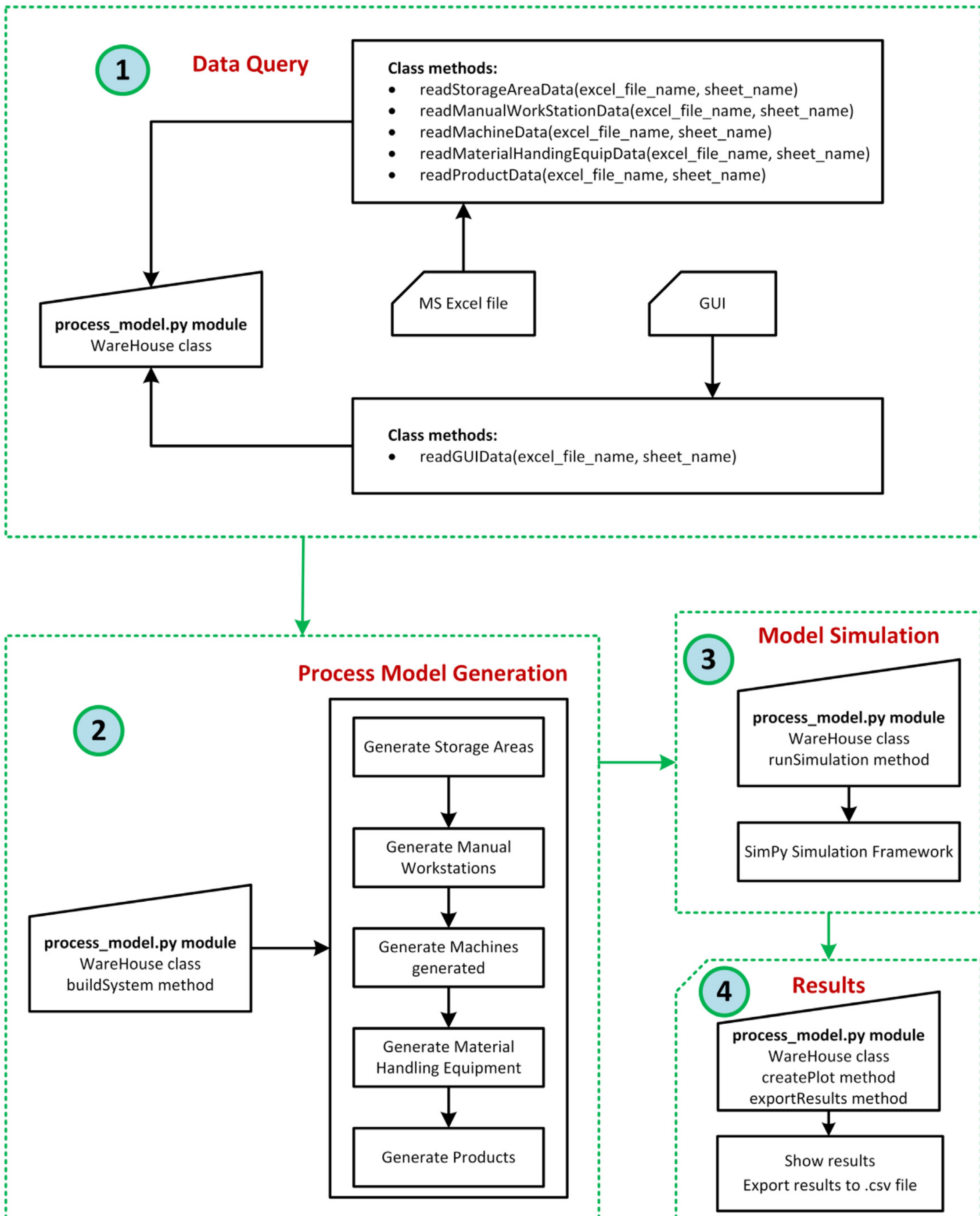

Fig. 2. Development of the process model simulation workflow.

Here X is the position of the chickens, which represents potential solutions to the optimization problem. The search space is bounded by LB and UB, which are the lower and upper bounds, respectively, of the variable values that the chickens' positions can take. These bounds help constrain the search and ensure that the solutions found are feasible. Additionally, r represents a random number where $r \in [-1, 1]$.

b. Rank the chickens based on fitness (objective function) values and find the best position (solution) X_{best} in the flock. The hen takes the best position X_{best} in the flock and guides the rest of the members to explore food.

Step 2 (Chicks are guided by the mother hen)

a. Find the new positions of the chicks based on Eq. (2)

$$X' = X + \varphi_i * r * (X_{best} - X) \tag{2}$$

Here X' is the new position of the chickens, and φ_i is the step size of the chickens during movement which is defined by

Eq. (3).

$$\varphi_i = S_{max} + \left(\frac{S_{min} - S_{max}}{k}\right) * i \tag{3}$$

Here φ_i is the step size at iteration i, S_{min} is the minimum step size, and S_{max} is the maximum step size where $S_{min}, S_{max} \in [0, 1]$ and $S_{min} < S_{max}$. As per this equation, initially, the step size is bigger, and it gradually decreases with iterations. This means that initially when a chicken finds a food source, it runs to the food very fast, and over time it reduces its speed as it gets closer to the food. It establishes an important characteristic of our algorithm. In the beginning, the algorithm hunts the search space in 'exploration' mode with larger steps and it switches to the 'exploitation' mode at the later stage of the iterations with smaller steps.

b. Make sure that the new positions of the chickens are within bounds:
   i. if $X' < LB$ then $X' \leftarrow LB$
   ii. if $X' > UB$ then $X' \leftarrow UB$
c. Perform greedy selection based on the fitness value. If the new position of a chick is not better, then go back to the previous position:
   i. For minimization problems: if $f\left(X'\right) > f(X)\, then\ X' \leftarrow X$
   ii. For maximization problems: if $f\left(X'\right) < f(X)\, then\ X' \leftarrow X$

Step 3 (Chicks are guided by their peers)

a. Chicken within flock: Update positions of the chicks based on Eq. (4)

$$X' = X + \varphi_i * r * (X_{random\_other\_chick} - X) \tag{4}$$

Here $X_{random\_other\_chick}$ is the position of a randomly selected chick in the flock.

b. Random chicken: Find new positions of the temporarily isolated random chicks from the main flock based on Eq. (5).

$$X' = LB + r * (UB - LB) \tag{5}$$

c. Make sure that the new positions are within bounds
   i. if $X' < LB$ then $X' \leftarrow LB$
   ii. if $X' > UB$ then $X' \leftarrow UB$
d. Perform greedy selection based on the fitness value. If the new position is not better, go back to the previous position
   - For minimization problems: if $f\left(X'\right) > f(X)\, then\ X' \leftarrow X$
   - For maximization problems: if $f\left(X'\right) < f(X)\, then\ X' \leftarrow X$

Step 4 (Termination)

Repeat steps 2 and 3 until the algorithm meets any of the following stopping conditions:

a. The maximum number of iterations k is complete.
b. There is no improvement of the objective function for the last m iterations where $m \in Z^+$ and $m < k$.

The performance of HACO algorithm for optimization problems compared to well-known metaheuristics such as genetic algorithm and particle swarm optimization are discussed in the supplementary document (Table S1).

2.2.2. Manpower allocation optimization

Our decision support tool offers assistance to managers of e-waste recycling facilities in optimizing their workforce allocation. This optimization aims to reduce costs and increase profits, with labor costs being a significant factor affecting the overall operational costs of U.S. recycling companies, as noted by D'Adamo et al. [30]. Managers often encounter the challenge of assigning manpower to workstations in a manner that minimizes costs while maximizing profits.

Our discrete-event process simulation model incorporates various costs associated with the processing of e-waste products, including sorting, dismantling, shredding, and CRT tube and battery processing, as well as factory overhead, as outlined in Eq. (6). The model calculates the processing cost per pound of e-waste using Eq. (7). The process simulation model effectively tracks the flow of materials between different stations and monitors all types of costs associated with the process. Upon completion of the simulation, the model generates the overall processing cost per pound of e-waste.

$$Total\ cost = C_{sort} + C_{dismatnl} + C_{shred} + C_{crt} + C_{battery} + C_{fo} \tag{6}$$

$$Processing\ cost\ per\ pound = \frac{Total\ cost}{Output\ (in\, lbs)} \tag{7}$$

Here C_{sort} is sorting cost, $C_{dismatnl}$ is dismantling cost, C_{shred} is shredding cost, C_{crt} is CRT processing cost, $C_{battery}$ is battery processing cost, and C_{fo} is factory overhead.

The optimization problem of assigning manpower on workstations can be formulated as below:

Minimize Processing cost per pound

Subject to

$$\sum_{i \in W} O_i \le N \tag{8}$$

$$O_i \le n_i \qquad \forall i \in W \tag{9}$$

$$LB_i = 0 \qquad \forall i \in W \tag{10}$$

$$UB_i = n_i \qquad \forall i \in W \tag{11}$$

$$N, n_i \in Z^+$$

Here, the decision variable O_i represents the number of operators assigned to workstation i. The set of workstations that require operators to operate is denoted as W, while n_i indicates the available number of operators to work at workstation i. N denotes the total number of available operators. Furthermore, LB_i indicates the minimum number (lower bound) of operators that can be assigned at workstation i, and UB_i indicates the maximum number (upper bound) of operators that can be assigned at workstation i. Finally, Z^+ represents the set of all positive integers. Eq. (8) guarantees that the total number of operators assigned to different workstations does not exceed the total number of available operators. Eq. (9) ensures that the number of operators assigned to a workstation does not surpass the available number of operators possessing the necessary skills to operate at the workstation. Eqs. (10) and (11) define the search space's boundaries. It can be noted that if no operator is assigned to a manual workstation, it indicates that the workstation is eliminated.

The alternative formulation of the above optimization problem is as follows:

$$\text{Minimize} \quad \text{Processing cost per pound} + P \tag{12}$$

Subject to

$$P = \begin{cases} M, & if \sum_{i \in W} O_i > N \\ 0, & otherwise \end{cases} \tag{13}$$

$$O_i \le n_i \qquad \forall i \in W \tag{14}$$

$$LB_i = 0 \qquad \forall i \in W \tag{15}$$

$$UB_i = n_i \qquad \forall i \in W \tag{16}$$

$N, n_i \in Z^+$

Here, the variable M represents a significantly large positive number. If the number of assigned operators exceeds the number of available operators, we impose a substantial penalty on the objective function. This penalty is necessary to ensure that the constraint defined in Eq. (8) is not violated in the optimal solution.

Our HACO algorithm described in Section 2.2.1 utilizes Eq. (12) as the objective function to minimize. It is important to note that the search space described in the HACO algorithm is continuous. As a result, the position of the chickens, represented by potential solutions X and X', can take fractional values. However, the manpower required cannot take fractional values. To address this, we discretized the search space, thereby restricting the chickens to take only integer values.

Furthermore, in our optimization problem, we do not need to incorporate constraints that are already taken care of by the process simulation model. For instance, the process simulation model already includes parameters such as machine capacities, storage area capacities, availability of resources such as machines and material handling equipment. These factors are integrated into the simulation model and thus do not require explicit constraint formulation in the optimization problem.

2.3. Economic model

We developed an economic model for analyzing the economic performance of the whole operating plant. Besides, the model can calculate processing costs, revenues, and profits for the individual categories of e-wastes to understand how each e-waste type contributes to the overall financial performance.

Fig. 3 displays the workflow for the development of the economic simulation model. We created a Python module titled 'economic_model.py'. Inside this module, we declared a class called 'EconomicModel'. In the data query step, the 'readData' class method imports required data from an external excel file and the GUI. Different types of costs have been considered for the calculation of processing costs. For example, the fixed manufacturing overhead includes insurance, property tax, safety and environmental cost, compliance fee, auditing fee, facility rent, housekeeping costs, and so on. The variable manufacturing cost includes labor cost, energy cost, transportation cost, CRT and battery treatment costs, etc. For the calculation of revenue, the users can input finished product (i.e., sorted — aluminum, steel, and copper) market price data using the GUI and the model will calculate the overall and category-wise revenues. The recycling companies charge environmental fees for recycling CRT tubes. These fees are considered revenues in the model.

Moreover, users can input cost data related to the freight and processing fees charged by smelters for processing shredded materials from e-waste recyclers so that the model uses these cost data while calculating the profits. In the data query step, the imported data are processed and prepared for the next step to run the simulation model. It should be noted that the user can choose the economic model to connect with the process model and use the variable cost data from the process model results. Otherwise, the user can run the economic model independently where the variable cost data comes from a user-input excel file instead of the process model results. In the second step, the 'runSimulation' class method performs all the necessary calculations to run the simulation model. First, the sorting, dismantling, and shredding — costs are combined to calculate variable costs for each category of products (Figure S2, supplementary document). The variable cost also includes CRT tube and battery processing costs which are further processed by a third party. The manufacturing overhead cost is distributed along the product categories according to the product quantity (in lbs) processed. Besides, smelters charge transportation and processing cost for recovering metals from the shreds. These three cost components are added together to calculate the category-wise processing cost. Next, category-wise revenues are calculated from the materials market price data. Recycling companies also receive battery and CRT tube recycling fees as revenues. Finally, the profit/loss is calculated for each product category from the processing cost and revenue results.

In the final step as shown in Fig. 3, the 'createPlot' class method generates necessary plots and displays the results to the users.

2.4. Development of the GUI

We used a five-step process for the development of a GUI as discussed below.

1. *Requirement Specifications:* We collected the functional and non-functional requirements of the GUI as the first step.
2. *User Analysis:* We assumed that the final users of the simulation tool are not technically savvy, and only possess the basic knowledge of computers with no programming skills. Therefore, we designed the GUI as simple as possible to avoid potential confusion.
3. *Task Analysis:* The simulation tool performs two major tasks — simulating the recycling process and analyzing the economic performance. The major tasks are divided into smaller subtasks and synchronized with each other to ensure performance, consistency, and usability.
4. *GUI Design and Implementation:* We used the PyQT [46,50] library, a Python programming language-based cross-platform GUI development toolkit, for building the GUI. Primarily, we used the QT Designer [51] program for developing the layout and designing the application widgets. The process and economic Python modules are integrated with the GUI to run simulations in the backend.
5. *Testing:* The GUI has been tested by the developers and by our industry partner in their factory operations for usability and compatibility.

Fig. 4 displays the user input window for the process simulation, allowing users to import necessary data from an MS Excel file and specify the simulation period before running it. The menu bar, located at the top left corner of the window, contains the manpower optimization option that users can select to open a new window, as depicted in Fig. 5. This window comprises the regular fields from the process simulation model input window, along with additional fields for the HACO optimization algorithm, such as population size, maximum iteration, and maximum optimization time. The economic modeling window, as illustrated in Fig. 6, is where users can input information about various cost components and the market price of recycled materials before executing the model.

3. Case study

To test the usefulness of our tool, we partnered with an electronic recycling company based in New York, USA to get their input and feedback. For data privacy, we describe the company as XYZ Recycler and use pseudo data for illustration purposes. A sample process diagram was used to simulate a base case e-waste recycling operation (Fig. 7).

The process diagram was broken into two main components: workstations and storage areas. Workstations were defined as mechanical or manual unit operations undertaken by the e-waste recycling facility to produce finished goods. Storage areas were defined as intermediary steps between specific workstations in which intermediate products were stored before passing through the next workstation. The figure shows residential first in first out (FIFO) and business FIFO storage areas where received residential and business e-wastes were stored, respectively. STD dismantling, LCD dismantling, and CRT dismantling operations were grouped as the overall dismantling station. The shredder, ring mill, and magnetic sorting workstations were grouped into the overall shredding station. Related product data including mass, collected volume, sorting time, dismantling time, and the market prices

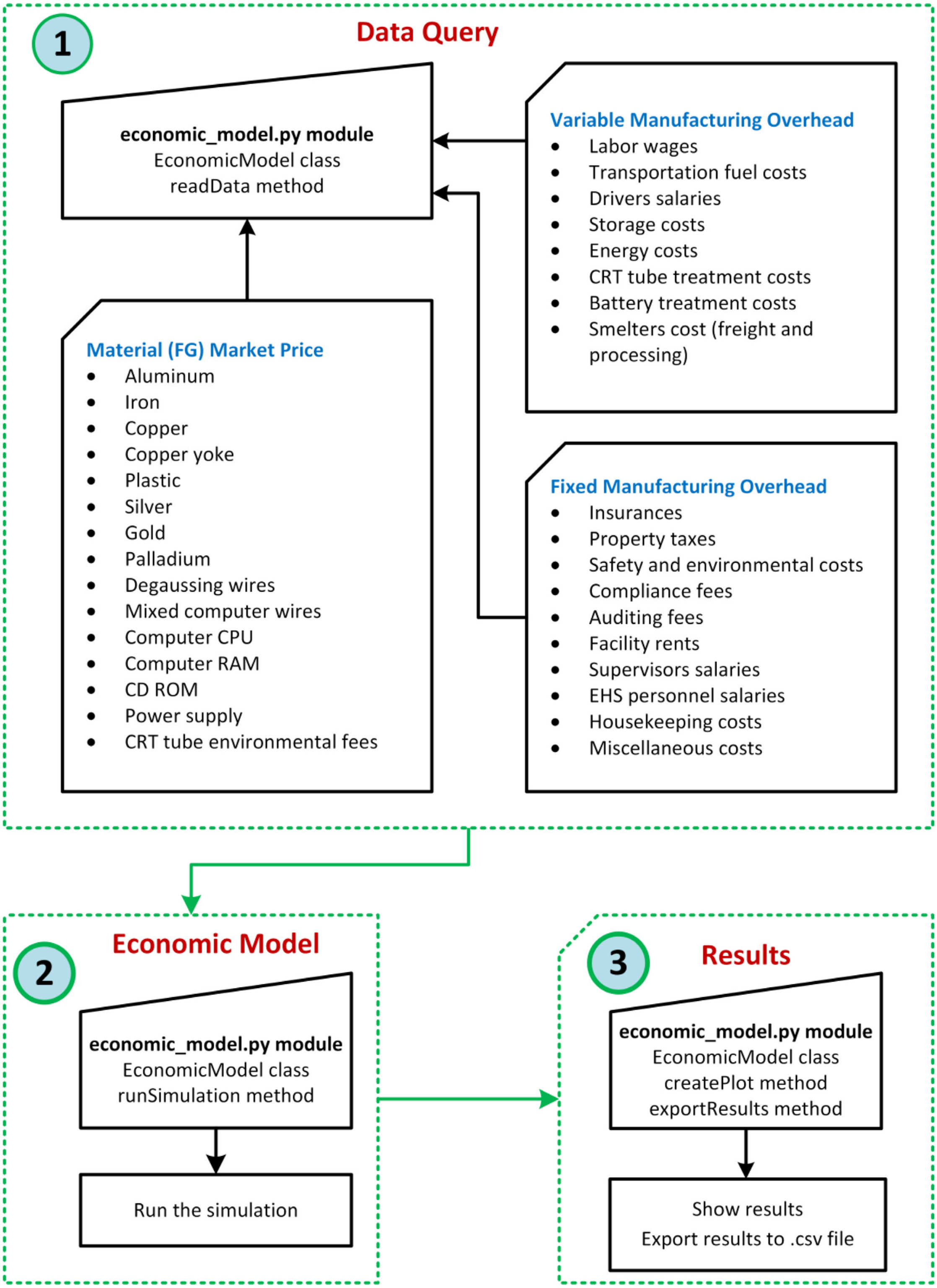

Fig. 3. Development of the economic model simulation workflow.

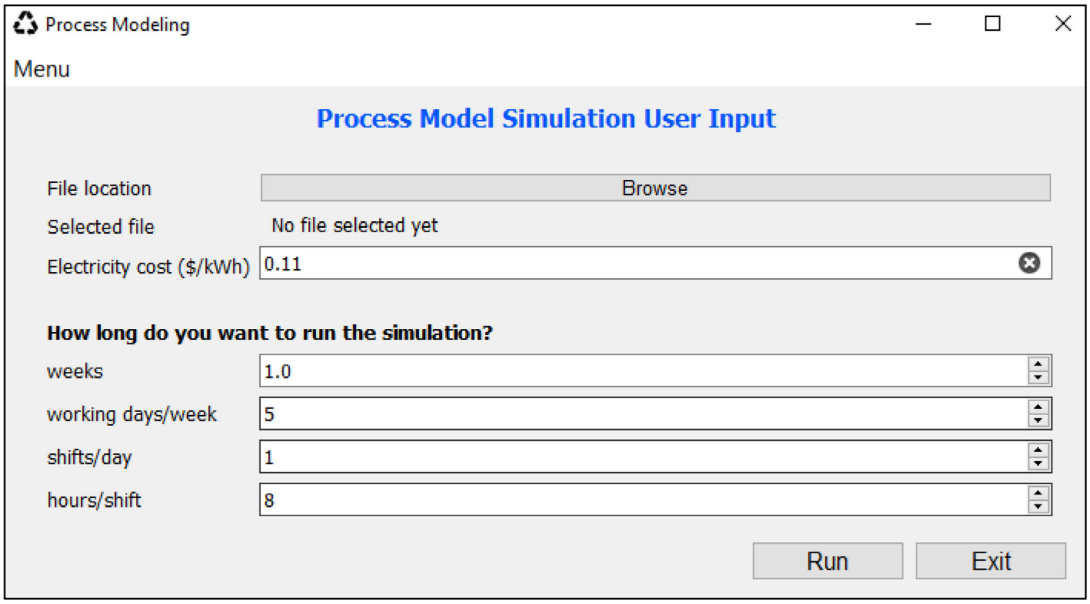

Fig. 4. A snapshot of the process modeling simulation GUI.

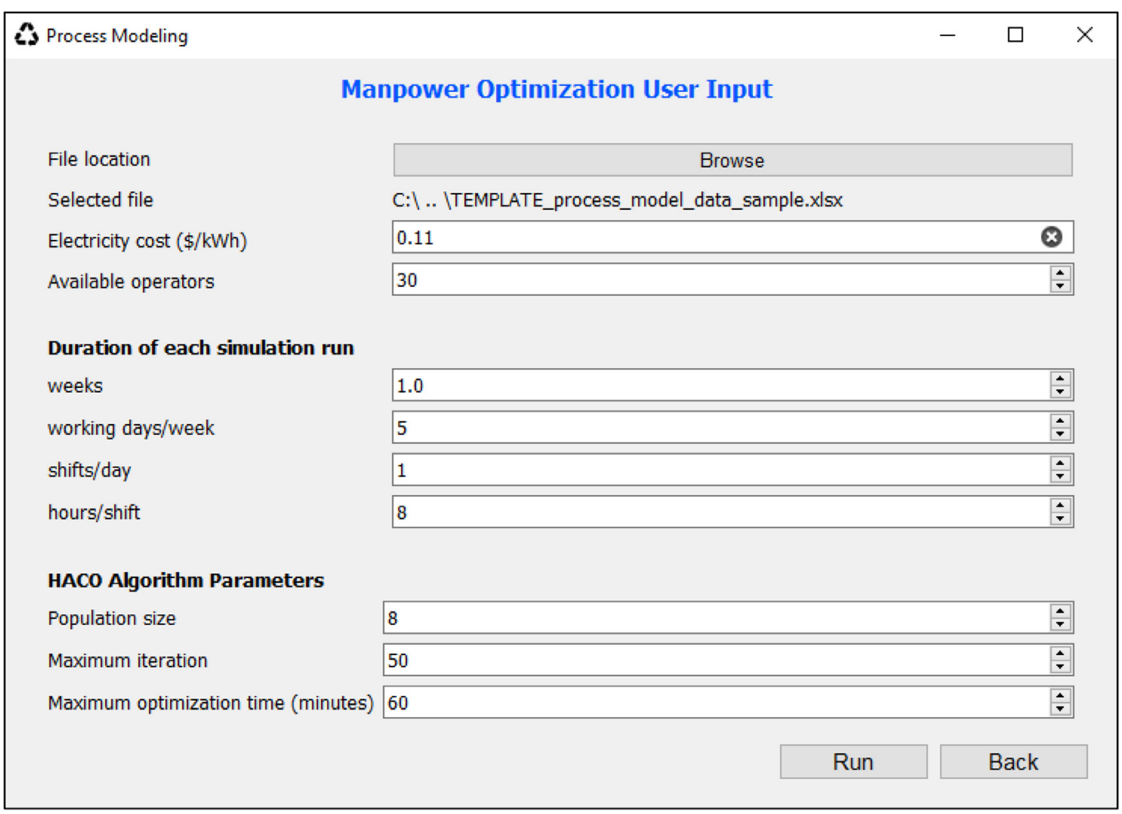

Fig. 5. A snapshot of the manpower optimization GUI.

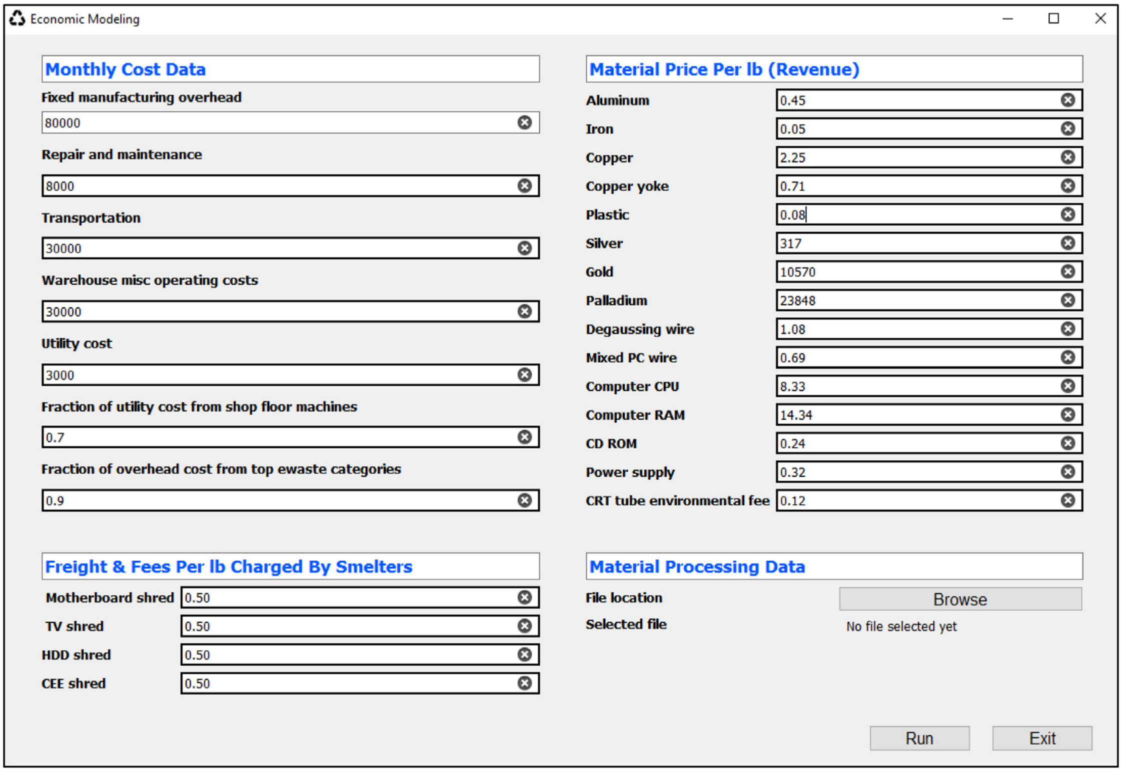

Fig. 6. A snapshot of the economic modeling GUI.

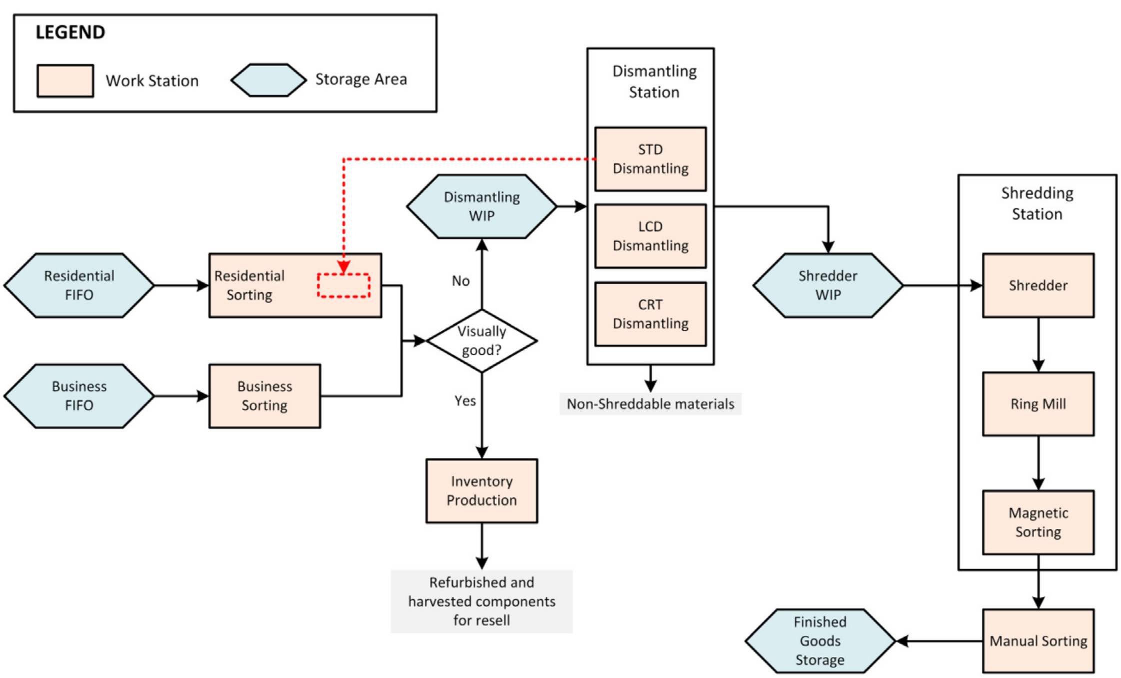

Fig. 7. Sample process diagram for the base case scenario. An alternative layout is represented by the red dotted arrow line where the standard (STD) dismantling station is moved to the Residential Sorting area.

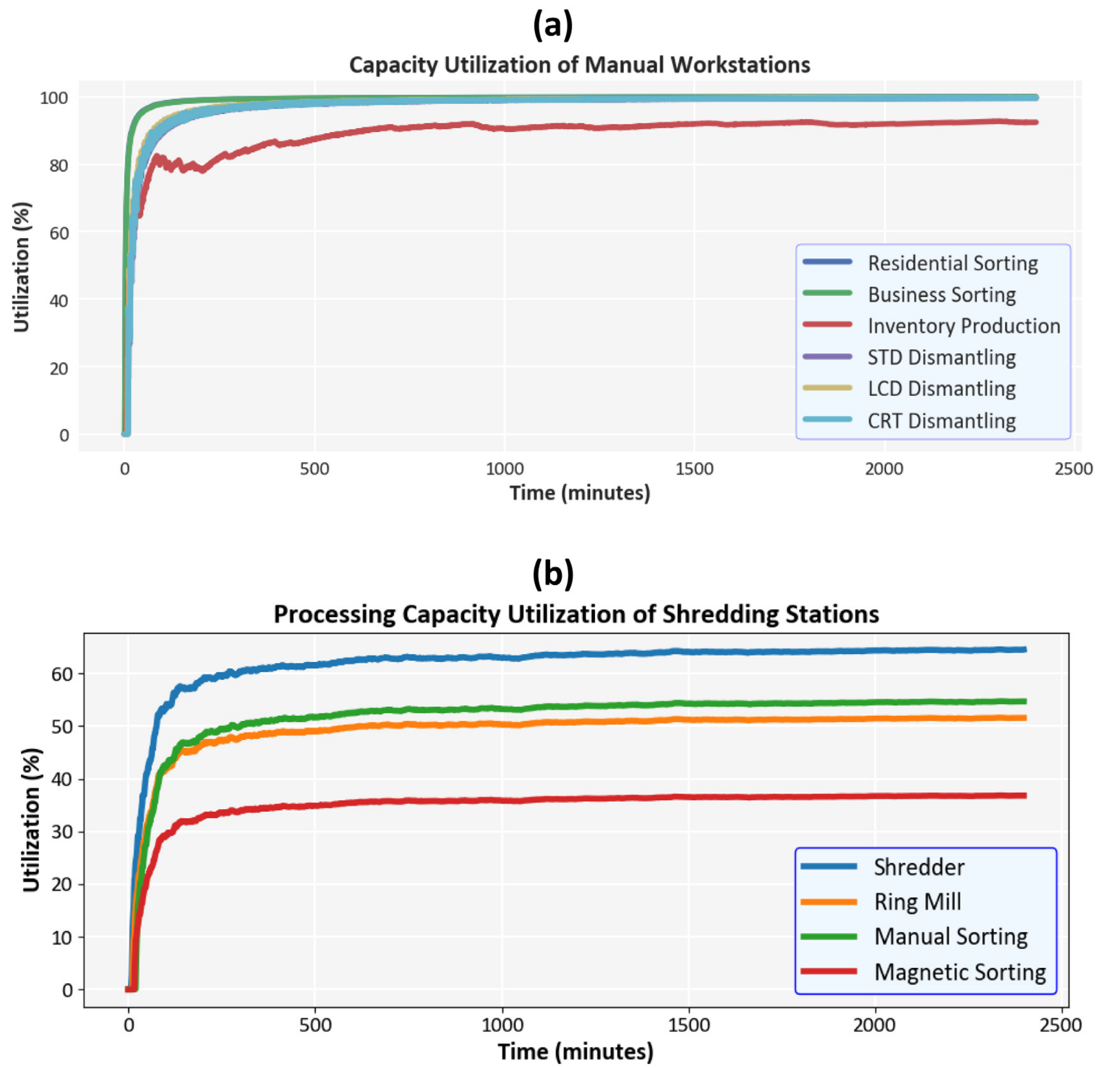

Fig. 8. (a) Manual workstation capacity utilization (%) over time, (b) Shredding workstation capacity utilization (%) over time.

of different recycled and harvested commodities are provided in the supplementary document (Tables S2, S3, and S4). CRT tube and battery treatment costs charged by the recycling company were assumed to be $0.12 and $0.10 per pound, respectively. The excel files used to input data can be accessed in this repository: https://github.com/mamunur-ipe/CMAT/tree/main/CMAT.

4. Results and discussion

4.1. Base case

The process model was simulated for 2400 min which is equivalent to one week of operation assuming five working days/week, one shift/day, and eight working hours/shift. For the case study process layout, results demonstrated the capacity utilization of both the workstations and storage areas. When starting with empty storage areas, capacity utilization of the manual workstations quickly increases until reaching a steady state by ∼500 min (∼8 h), detailed can be seen in Fig. 8(a) of the supplementary document. The shredding station capacity utilization reaches ∼500 min (∼8 h) while capacity utilization of other workstations in the shredding station achieved a steady state with the manual shred sorting achieving the highest capacity utilization (∼65%), more details in Fig. 8(b).

The total mass output of the individual workstations in the e-waste recycling system is shown in Fig. 9 for the entire simulation period. For this particular simulation run scenario, the optimization algorithm determined that increasing the outputs of sorting stations would not lead to an increase in the ultimate output of finished goods (FG) produced by the manual sorting station, which is the last operation in the process. Instead, the algorithm found that the previously accumulated work-in-progress (WIP) in the sorting stations, combined with the current production rate, was sufficient to feed the successive workstations (such as the shredder, ring mill, magnetic sorting, and manual sorting stations). As a result, even though the output from the sorting stations decreased, the overall output of FG actually increased. The algorithm was able to optimize the outputs of each station to maintain a minimum amount of WIP while maximizing the production of the end product (FG).

As discussed earlier, the economic model could extract results from the process model as inputs or the user's input using an excel file. For the figures displayed below, the base case utilized the results of the process model for the economic analysis. As seen in Fig. 10, the top three profit-generating e-waste items were laptops (1.05 USD/lb), desktops (0.46 USD/lb), and computer peripherals (0.27 USD/lb). The bottom three profit-generating items were CRT monitors (0.02 USD/lb), printers (0.03 USD/lb), and CRT TVs (0.04 USD/lb). In addition to profit, the economic model computed the overall revenue and processing cost of each category of e-wastes. The overall profit was 0.17 USD/lb after manpower optimization indicating that the base case process layout was profitable (Figure S3, supplementary document).

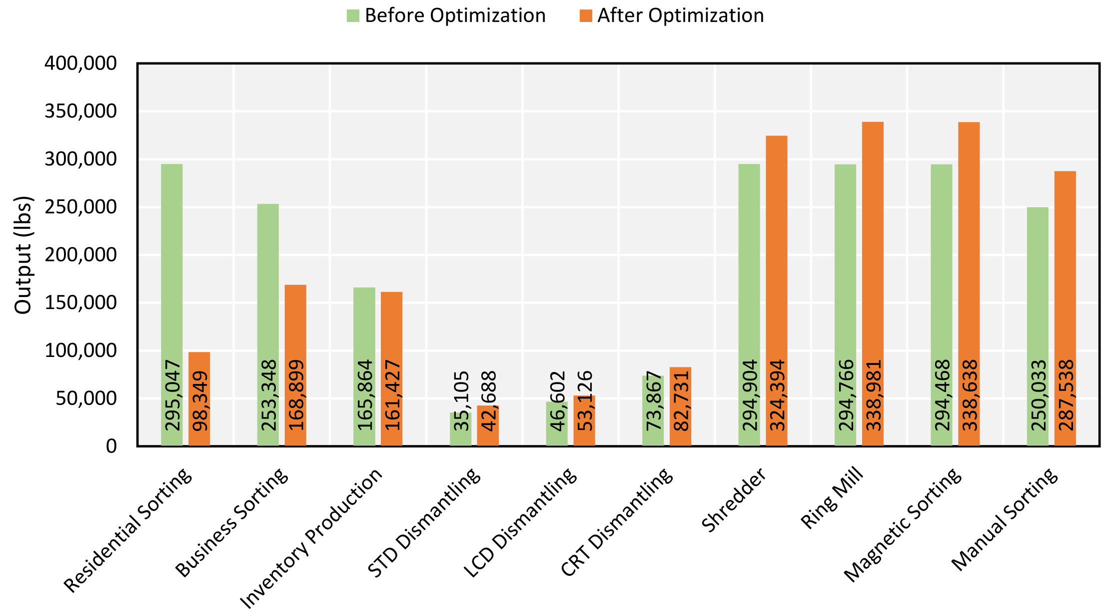

Fig. 9. Comparison of outputs from different workstations before and after manpower optimization using the HACO algorithm.

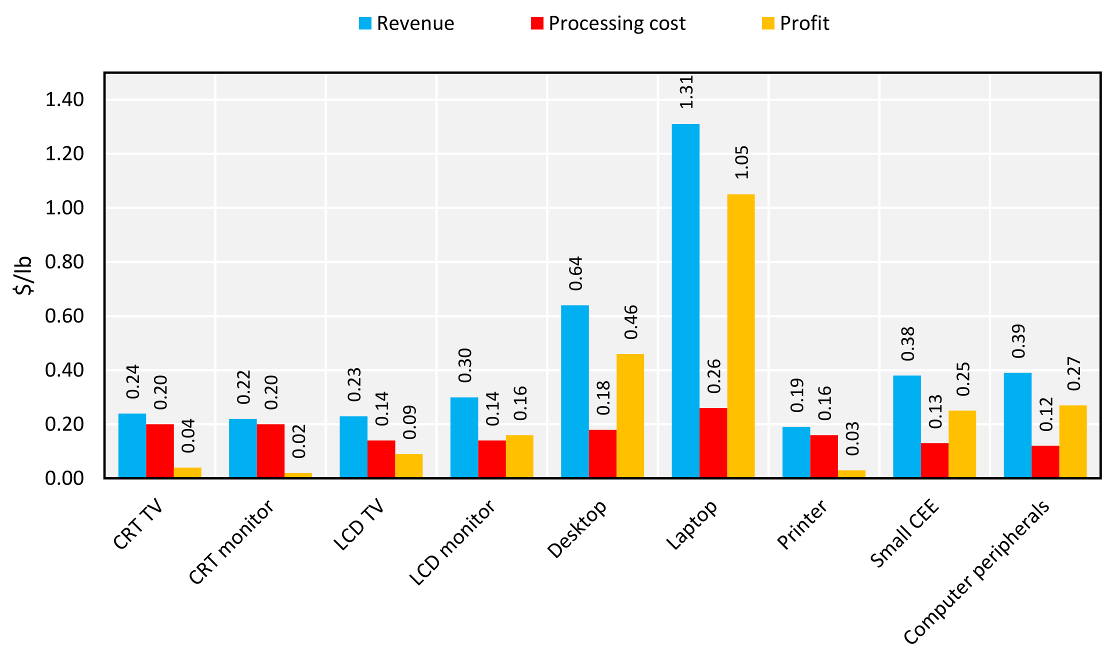

Fig. 10. Revenue, processing cost, and profit for different e-waste products.

4.2. Labor allocation to minimize processing costs

The utilization of the HACO algorithm was paramount to developing more economically viable distributions of labor at the e-waste recycling facility. There were 27 employees required at various workstations within the e-waste recycling facility. Several workstations such as the shredding stations required a fixed number of employees and therefore were not subject to optimization. The initial distribution of employees before HACO optimization was set as uniformly as possible across the varying workstations. Following HACO optimization, labor was distributed more heavily to the workstations in the dismantling station (STD, LCD, and CRT dismantling) because these stations were the bottleneck in the base layout. The actual distribution of employees at different workstations can be seen in Table S5 of the supplementary document. To achieve this optimized labor distribution, the HACO algorithm required 18 iterations to converge and yielded an overall processing cost of ~0.07 USD/lb from ~0.11 USD/lb (Figure S4, supplementary document). This processing cost does not include overhead costs and therefore, differs from the overall cost seen in Figure S3 of the supplementary document. HACO algorithm results for individual workstation outputs can also be seen in Fig. 9 where residential and business sorting saw the greatest decrease in workstation output, whereas the shredding workstations and manual sorting workstations saw the greatest increase in workstation output.

4.3. Alternative layout

One key feature of our model was its modularity in the process flow diagram. To highlight this modularity, the STD dismantling station was moved to the residential sorting location in the process flow diagram

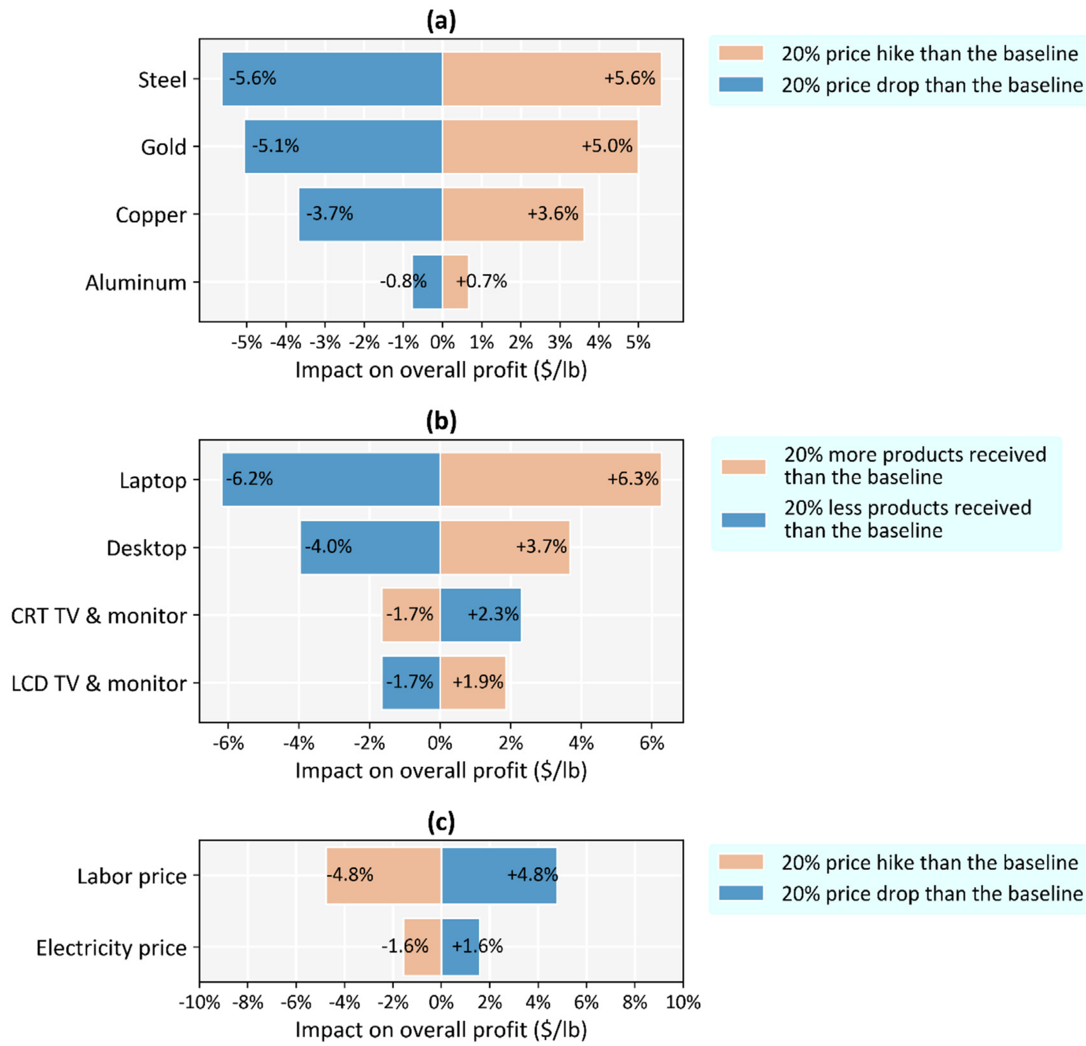

Fig. 11. Sensitivity analysis for (a) material price, (b) quantity of input product, and (c) operating costs.

(Fig. 7). The location change resulted in a 4.77% reduction in the processing cost compared to the baseline layout from 0.069 USD/lb to 0.065 USD/lb. During dismantling products like small covered electronic equipment and computer peripherals, the batteries are separated quickly and sent to the shredder WIP area. This small task can be performed right after the sorting process which results in bypassing some steps — transportation to the dismantling WIP area and waiting in the queue before entering the dismantling station. Therefore, the new layout is more efficient.

4.4. Sensitivity analysis

A sensitivity analysis was performed on several key input variables including (a) material price, (b) quantity of input product, (c) operating costs, and (d) material composition in LCD TVs. The measured output of the sensitivity analysis was overall profit. An increase and decrease of 20% were applied to the input variables for the sensitivity analyses (a)–(c) whereas two separate LCD TV compositions (Table S6, supplementary document) were used as the input in the sensitivity analysis (d). The results of the sensitivity analysis can be seen in Fig. 11.

The material price sensitivity analysis showed that steel prices had the greatest impact on overall profit (± 5.6%) due to it being the most prevalent material in most electronics. All input variables tested showed that a decrease in material price led to a corresponding decrease in overall profit. The quantity of input product sensitivity analysis showed that laptops had the largest impact on overall profit with a 20% increase in laptops in the input stream yielding a higher profit of 6.3%. However, for CRT TVs and monitors, an increase of 20% in quantity led to a decrease in profit of 1.7%. The operating costs sensitivity analysis showed that a 20% increase in labor price and electricity price resulted in a decrease in overall profit with labor price having a larger impact on overall operating costs (± 4.8%) which is consistent with the findings by D'Adamo et al. [30]. Lastly, the results of the differing LCD TV material composition sensitivity analysis showed that profitability increased with increases in steel and aluminum composition. The composition with increased steel and aluminum resulted in a profit of ~0.144 USD/lb versus the composition with less steel and aluminum with a profit of ~0.139 USD/lb.

4.5. Managerial implications

In e-waste recycling companies, layout design is an important factor that can impact the efficiency and effectiveness of the recycling process. A good layout design can improve the flow of materials, people, and information, minimize bottlenecks and reduce unnecessary movements, which can lead to higher productivity, quality, and profitability. Our decision support tool can simulate a real-life scenario in a virtual environment without impacting the actual operations. Managers can input various parameters, such as the number and capacity of workstations, number of manpower deployed at different workstations, the amount of WIP at different locations, capacity of different storage areas, and the rework rate of workstations. The simulation tool can then model the performance of the layout under different scenarios and generate various metrics, such as throughput, inventory levels, processing cost, and so on. By using the simulation capability of our tool, managers can compare multiple layout options and evaluate their performance based on the metrics generated by the tool. They can assess the strengths and weaknesses of each layout, identify potential problems, and explore different solutions. This can help managers make informed decisions on which layout design to choose, leading to better operational performance and overall efficiency of the system.

Our decision support tool can help managers in an e-waste recycling facility to optimize their allocation of workers, in order to reduce costs and maximize profits. Labor prices have a larger impact on the overall operating costs of US recycling companies [30]. Often managers face the challenge to assign manpower to workstations to minimize cost and maximize profit, which means reducing the expenses associated with operating the facility while increasing the revenue generated by recycling e-waste. The decision support tool can provide managers with data and insights on the performance of different workstations and workers, helping them to identify inefficiencies and opportunities for improvement. By optimizing the allocation of workers, managers can reduce the amount of idle time and improve the overall productivity of the facility, which can reduce costs. At the same time, by ensuring that the most profitable workstations are fully staffed and operational, managers can increase the revenue generated by the facility, maximizing profits.

The decision support tool can provide managers with valuable information on the financial performance of different categories of e-waste, helping them to identify which categories are generating the most revenue and which ones are generating the least. This information can be used to adjust the operations of the facility to maximize profitability. For example, if the economic analysis reveals that a particular category of e-waste is not generating a lot of revenue, managers may choose to cut resources to that category or focus on finding ways to improve the recycling process for that type of e-waste. On the other hand, if the analysis shows that another category is particularly profitable, managers may allocate more resources to that category in order to maximize profits.

The decision support tool is designed to be user-friendly, requiring minimal training. Basic knowledge of Microsoft Excel is sufficient to operate it, so users do not need to learn new software, programming languages, or complex commands unlike other technologies. This ease of use makes it accessible to a wider range of people, including managers without extensive technical expertise.

To summarize, the CMAT tool provides decision makers with the ability to optimize their recycling operations through various means, such as increasing output, identifying bottlenecks, allocating manpower efficiently, and providing valuable insights into the profitability of different e-waste streams. By implementing these strategies, efficient and profitable e-waste recycling can increase recycling volume, which is critical for minimizing the environmental impact of discarded electronic products. Consequently, the CMAT tool can potentially serve as an essential tool for managers who seek to achieve long-term business sustainability goals in the e-waste sector.

4.6. Limitations and future work

While our decision support tool offers valuable insights, it does have some limitations. Firstly, the tool does not provide graphical animations of the objects such as machines, people, and material handling equipment during the simulation. Including graphical animations in future versions of the tool would make it more interactive and improve user experience.

Secondly, although the tool can evaluate the performance of a given process layout, it cannot automatically optimize and recommend the best layout by altering or swapping process elements. The proposed optimization algorithm can only be applied to optimize the allocation of manpower to workstations. Incorporating automatic optimization capabilities for layout configurations would add a unique feature to the tool.

Thirdly, recent studies show that Reinforcement Learning (RL), one of the active research areas in artificial intelligence, can be deployed in solving complex problems related to manpower and resource allocation [52–55]. Performance of RL can be examined for our manpower optimization problem. Moreover, while our proposed HACO algorithm has shown promising results in solving benchmark optimization functions compared to genetic algorithms and particle swarm optimization (as presented in Table S1 in the supplementary document), the performance of these metaheuristics has not been explicitly investigated for our specific problem. Therefore, further research could be conducted to explore the effectiveness of these alternative methods.

Fourthly, the tool does not support the import of computer-aided design or picture files to populate the process layout. We plan to incorporate this capability in future versions of the tool to enable rapid modeling and enhance its usability.

Lastly, while Python is a powerful and versatile programming language, it is not the most efficient one in terms of energy consumption, time, and memory usage compared to languages like C and C++ [56,57]. As such, we plan to release the source codes for future versions of the tool in C or C++ languages.

5. Conclusion

E-waste recycling companies face challenges to optimize their process operations due to continuous changes in product configuration and compositions. These changes impact their revenues as well. In this study, we developed a decision support tool to help e-waste recycling companies evaluate the performance of their operations and conduct economic analysis. Unlike other simulation tools, this program requires zero computer programming knowledge. The modularity functionality allows users to change the layout of the processes from input excel files and compare the effectiveness among different layouts. The simulation tool has been exported as a cross-platform standalone computer program that can be run on computers without installing the Python programming language. A new bio-inspired metaheuristic optimization algorithm HACO has been introduced to optimally assign manpower to different workstations. As a case study, the performances of two alternative process layouts have been evaluated using real-world recycling business data. The economic model has been integrated well with the process model and can give valuable insights regarding the profitability of the different streams of e-wastes. A user can choose either the option to import the results of the process model into the economic model or the option to run it independently without the help of the process model. The tool has been released as open-source software under a general public license and can be customized by developers for other recycling industries in addition to e-wastes for business sustainability.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Damon Hartley and Ruby Nguyen report financial support was provided by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Advanced Manufacturing Office Award Number DE-EE0007897 awarded to the REMADE Institute, a division of the Sustainable Manufacturing Innovation Alliance Corp.

Data availability

https://github.com/mamunur-ipe/CMAT

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.dajour.2023.100216. The supplementary document contains additional results and data.

References

[1] Jonovan Van Yken, Naomi J. Boxall, Ka Yu Cheng, Aleksandar N. Nikoloski, Navid R. Moheimani, Anna H. Kaksonen, E-waste recycling and resource recovery: A review on technologies, barriers and enablers with a focus on Oceania, Metals 11 (1313) (2021).

[2] Keshav Parajuly, Ruediger Kuehr, Abhishek Kumar Awasthi, Colin Fitzpatrick, Josh Lepawsky, Elisabeth Smith, Rolf Widmer, Xianlai Zeng, Future e-waste scenarios, 2019.

[3] Vanessa Forti, Cornelis Peter Baldé, Ruediger Kuehr, Garam Bel, The global E-waste monitor 2020, 2020.

[4] Ashok Kumar Verma, E-wastes and their impact on environment and public health, Int. J. Appl. Res. (2020).

[5] M.C Vats, S.K. Singh, E-waste characteristic and its disposal, Int. J. Ecol. Sci. Environ. Eng. 1 (2014) 49–61.

[6] Amit Kumar, Maria Holuszko, Denise Crocce Romano Espinosa, E-waste: An overview on generation, collection, legislation and recycling practices, Resour. Conserv. Recy. 122 (2017) 32–42.

[7] R. Cayumil, R. Khanna, R. Rajarao, P.S. Mukherjee, V. Sahajwalla, Concentration of precious metals during their recovery from electronic waste, Waste Manage. 57 (2016) 121–130.

[8] RTS, The complete e-waste recycling process, Recycle Track Syst. (2021) https://www.rts.com/blog/the-complete-e-waste-recycling-process/.

[9] EPA, Regulations, Initiatives and Research on Electronics Stewardship, EPA, 2022, Accessed 13 June 2022. https://www.epa.gov/smm-electronics/regulations-initiatives-and-research-electronics-stewardship.

[10] ERI, State E-Waste Legislation in the U.S. - ERI, ERI, 2022, Accessed 13 Jun. 2022. https://eridirect.com/sustainability/us-legislation/.

[11] H Pouresmaeil, M.G. Faramarz, M. ZamaniKherad, M. Gheibi, A.M. Fathollahi-Fard, K. Behzadian, G. Tian, A decision support system for coagulation and flocculation processes using the adaptive neuro-fuzzy inference system, Int. J. Environ. Sci. Technol. 19 (2022) 10363–10374.

[12] Moe Mojtahedi, Amir Fathollahi-Fard, Reza Tavakkoli-Moghaddam, Sidney Newton, Sustainable vehicle routing problem for coordinated solid waste management, J. Ind. Inf. Integr. 23 (2021) 100220.

[13] Nasim Ghadami, Mohammad Gheibi, Zahra Kian, Mahdieh G. Faramarz, Reza Naghedi, Mohammad Eftekhari, Amir M. Fathollahi-Fard, Maxim A. Dulebenets, Guangdong Tian, Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods, Sustainable Cities Soc. 74 (2021) 103149.

[14] Mohammad Gheibi, Mohammad Eftekhari, Mehran Akrami, Nima Emrani, Mostafa Hajiaghaei-Keshteli, Amir M. Fathollahi-Fard, Maziar Yazdani, A sustainable decision support system for drinking water systems: Resiliency improvement against cyanide contamination, Infrastructures 7 (2022) 88.

[15] M.M Rahman, Y Ghasemi, E Suley, Y Zhou, S Wang, J. Rogers, Machine Learning Based Computer Aided Diagnosis of Breast Cancer Utilizing Anthropometric and Clinical Features, IRBM, 2020, http://dx.doi.org/10.1016/j.irbm.2020.05.005.

[16] M.M Rahman, Y Zhou, S Wang, J. Rogers, Wart treatment decision support using support vector machine, Int. J. Intell. Syst. Appl. 12 (2020) 1–11.

[17] M.M Rahman, S Wang, Y Zhou, J. Rogers, Predicting the performance of cryotherapy for wart treatment using machine learning algorithms, in: IISE Annual Conference, Institute of Industrial and Systems Engineers, Orlando, FL, 2019.

[18] M.M Rahman, T. Nguyen, Python library for vehicular emission estimation, 2021, http://dx.doi.org/10.11578/dc.20210820.4.

[19] L Lu, R Nguyen, M.M Rahman, J. Winfree, Demand shocks and supply chain resilience: An agent-based modelling approach and application to the potato supply chain, in: P. Antras, D. Zilberman (Eds.), Risks in Agricultural Supply Chains, National Bureau of Economic Research, Inc, 2021.

[20] Md.M Rahman, M.A Galvez, Y. Zhou, Evaluation of 'crowd-informing' on parking performance and environmental emissions: An agent-based simulation of an urban university campus, in: A. Ghate, K. Krishnaiyer, K. Paynaba (Eds.), IISE Annual Conference, Institute of Industrial and Systems Engineers, 2021.

[21] M.M Rahman, Y Zhou, J Rogers, V Chen, M Sattler, K. Hyun, A comparative assessment of CO2 emission between gasoline, electric, and hybrid vehicles: A well-to-wheel perspective using agent-based modeling, J. Clean Prod. 321 (2021) 128931, http://dx.doi.org/10.1016/j.jclepro.2021.128931.

[22] M.M Rahman, M.A Galvez, Y. Zhou, Evaluation of crowd-informing on parking performance and environmental emissions: An agent-based simulation of an urban university campus, in: Proceedings of the 2021 IISE Annual Conference, Institute of Industrial and Systems Engineers, 2021.

[23] M.M Rahman, R Nguyen, L. Lu, Multi-level impacts of climate change and supply disruption events on a potato supply chain: An agent-based modeling approach, Agric. Syst. 201 (2022) 103469, http://dx.doi.org/10.1016/j.agsy.2022.103469.

[24] Usama Awan, Saqib Shamim, Zaheer Khan, Najam Ul Zia, Syed Muhammad Shariq, Muhammad Naveed Khan, Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance, Technol. Forecast. Soc. Change 168 (2021) 120766.

[25] Jogendra Jangre, Kanika Prasad, Dharmendra Patel, Analysis of barriers in e-waste management in developing economy: an integrated multiple-criteria decision-making approach, Environ. Sci. Pollut. Res. 29 (2022) 72294–72308.

[26] Esrat F. Dulia, Mir S. Sabuj, Syed A.M. Shihab, Benefits of advanced air mobility for society and environment: A case study of ohio, Appl. Sci. 12 (2021) 207.

[27] Syed Mithun Ali, Sayem Ahmed, Humaira Nafisa Ahmed, Aliza Sharmin, Rafat Rahman, Reducing plastic pollutants through catalyzing consumer roles: A novel application of fuzzy total interpretive structural modeling, J. Clean. Prod. 335 (2022) 130327.

[28] Humaira Nafisa Ahmed, Sayem Ahmed, Muztoba Ahmad Khan, Syed Mithun Ali, Sustainable supply chain in emerging economies during and post COVID-19 pandemic: a systematic literature review and future research directions, Int. J. Emerg. Mark. (2022).

[29] Fariba Goodarzi, Vahid Abdollahzadeh, Masoomeh Zeinalnezhad, An integrated multi-criteria decision-making and multi-objective optimization framework for green supplier evaluation and optimal order allocation under uncertainty, Decis. Anal. J. 4 (2022) 100087.

[30] Idiano D'Adamo, Francesco Ferella, Paolo Rosa, Wasted liquid crystal displays as a source of value for e-waste treatment centers: a techno-economic analysis, Curr. Opin. Green Sustain. Chem. (2019) 19.

[31] Hai-Yong Kang, Julie M. Schoenung, Economic analysis of electronic waste recycling: Modeling the cost and revenue of a materials recovery facility in california, Environ. Sci. Technol. (2006) 40.

[32] Pablo Dias, Andréa Moura Bernardes, Nazmul Huda, Ensuring best E-waste recycling practices in developed countries: An Australian example, J. Clean. Prod. 209 (2019) 846–854.

[33] Malima Isabelle Wolf, Marcello Colledani, Stanley B. Gershwin, Timothy G. Gutowski, A network flow model for the performance evaluation and design of material separation systems for recycling, IEEE Trans. Autom. Sci. Eng. (2013) 10.

[34] Karine Ip, Mariapaola Testa, Anne Raymond, Stephen C. Graves, Timothy Gutowski, Performance evaluation of material separation in a material recovery facility using a network flow model, Resour. Conserv. Recy. (2018) 131.

[35] Zhiqin Ni, Hing Kai Chan, Zhen Tan, Systematic literature review of reverse logistics for e-waste: overview, analysis, and future research agenda, Int. J. Logist. Res. Appl. (2021) 1–29.

[36] Xin Tong, Dongyan Tao, Reid Lifset, Varieties of business models for post-consumer recycling in China, J. Clean. Prod. 170 (2018) 665–673.

[37] Luís Peres Azevedo, Fernando Gabriel da Silva Araújo, Carlos Alberto Ferreira Lagarinhos, Jorge Alberto Soares Tenório, Denise Crocce Romano Espinosa, E-waste management and sustainability: a case study in Brazil, Environ. Sci. Pollut. Res. 24 (2017) 25221–25232.

[38] Mendes Campolina, Carolina São Leandro Sigrist Juliana, Jane Maria Faulstich de Paiva, Andréa Oliveira Nunes, Virgínia Aparecida da Silva Moris, A study on the environmental aspects of WEEE plastic recycling in a Brazilian company, Int. J. Life Cycle Assess. 22 (2017) 1957–1968.

[39] Shanshan Wei, Kejing Zhang, Optimization model of e-waste reverse logistics and recycling network, in: 2008 3rd International Conference on Intelligent System and Knowledge Engineering, Vol. 143, 2008, pp. 6–42.

[40] B. Wang, H. Li, Optimization of electronic waste recycling network designing, in: 2020 5th International Conference on Electromechanical Control Technology and Transportation, ICECTT, 2020, pp. 368–371.

[41] Luu Quoc Dat, Doan Thi Truc Linh, Shuo-Yan Chou, Vincent F. Yu, Optimizing reverse logistic costs for recycling end-of-life electrical and electronic products, Expert Syst. Appl. 39 (2012) 6380–6387.
[42] Marianna Ottoni, Pablo Dias, Lúcia Helena Xavier, A circular approach to the e-waste valorization through urban mining in Rio de Janeiro, Brazil, J. Clean. Prod. 261 (2020) 120990.
[43] Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, K. Christoph Gohlke, Travis E. Oliphant, Array programming with NumPy, Nature 585 (2020) 357–362.
[44] Siqi Cao, Wenzhu Liao, Yuqi Huang, Heterogeneous fleet recyclables collection routing optimization in a two-echelon collaborative reverse logistics network from circular economic and environmental perspective, Sci. Total Environ. 758 (2021) 144062.
[45] Norm Matloff, Introduction to Discrete-Event Simulation and the Simpy Language, Vol. 2, Dept of Computer Science. University of California at Davis, 2008, pp. 1–33, Retrieved on August,
[46] Bintu M. Harwani, Qt5 Python GUI Programming Cookbook: Building Responsive and Powerful Cross-Platform Applications with PyQt, Packt Publishing Ltd, 2018.
[47] John D. Hunter, Matplotlib: A 2D graphics environment, Comput. Sci. Eng. 9 (2007) 90–95.
[48] Wes McKinney, Pandas: a foundational python library for data analysis and statistics, Python High Perform. Sci. Comput. 14 (2011) 1–9.
[49] Silke S. Steiger, Andrew E. Fidler, Mihai Valcu, Bart Kempenaers, Avian olfactory receptor gene repertoires: evidence for a well-developed sense of smell in birds? Proc. R. Soc. Lond. Ser. B 275 (2008) 2309–2317.
[50] Mark Summerfield, Rapid GUI Programming with Python and Qt: The Definitive Guide to PyQt Programming (Paperback), Pearson Education, 2007.
[51] Joshua M. Willman, Creating GUIs with Qt designer, in: Beginning PyQt, Springer, 2022.
[52] S. Zhang, B. Sun, Human resource scheduling control method based on deep reinforcement learning, in: Multimedia Technology and Enhanced Learning: 4th EAI International Conference, ICMTEL 2022, Virtual Event, April 15-16, 2022, Proceedings, Cham Springer Nature, Switzerland, 2022, pp. 368–382.
[53] Y Smit, F. den Hengst, S Bhulai, E. Mehdad, Strategic workforce planning with deep reinforcement learning.
[54] A.M Karimi-Majd, M Mahootchi, A. Zakery, A reinforcement learning methodology for a human resource planning problem considering knowledge-based promotion, Simul. Model. Pract. Theory 79 (2017) 87–99.
[55] J. Wang, J. Cao, S. Wang, Z. Yao, W. Li, IRDA: Incremental reinforcement learning for dynamic resource allocation, IEEE Trans. Big Data 8 (3) (2020) 770–783.
[56] Rui Pereira, Marco Couto, Francisco Ribeiro, Rui Rua, Jácome Cunha, João Paulo Fernandes, João Saraiva, Ranking programming languages by energy efficiency, Sci. Comput. Program. 205 (2021) 102609.
[57] Marco Couto, Rui Pereira, Francisco Ribeiro, Rui Rua, João Saraiva, Towards a green ranking for programming languages, 2017, pp. 1–8.