International Journal of Industrial Engineering, 30(1), 147-165, 2023

MULTI-OBJECTIVE OPTIMIZATION MODELING OF INTEGRATED SUPPLY CHAIN FOR SOLID WASTE TREATMENT

Emad Fararah[1], Emad Abouel Nasr[1, *], and Haitham Abbas Mahmoud[1]

[1]Department of Industrial Engineering, College of Engineering
King Saud University
Riyadh, Saudi Arabia
*Corresponding author's email address: eabdelghany@ksu.edu.sa

Solid waste management (SWM) has been proven as a vital research area, as it contributes in providing a basic and renewal source of production resources like recycled raw materials, fuel and energy sources. Hence, this research investigates the SWM problem by simultaneous consideration of key environmental and economic factors. In this regard, a multi-objective mathematical model is presented for an integrated solid waste supply chain to minimize total costs and environmental impacts while maximizing the recovered energy. The designed supply chain is being modeled as a weighted goal programming (WGP) model to achieve the desired objectives, and this model is solved by applying a simplex-based solution algorithm. In addition, the model and the solution algorithm are validated through the application on real case study data. The comparisons' results show that the integrated supply chain's model attains reasonably outperforming results in terms of minimizing the average total cost and environmental impacts.

Keywords*:* Integrated Model, Solid Waste Management, Weighted Goal Programming.

(Received on October 18, 2022; Accepted on December 25, 2022)

1. INTRODUCTION

The amount of waste has been suddenly increasing due to the increasing human population and urbanization, and this rapid increase in population causes risks to both environment and human health, especially when coupled with the gradually decreasing number of disposal sites. In general, waste materials have resulted from both industrial and domestic activities. Waste management techniques (WMTs) are regularly utilized to recover beneficial resources from waste materials; basically, solid waste (SW) is a favorable source of numerous industrial resources. WMTs are directed toward dealing with solid, liquid, gaseous or radioactive substances, and each type of waste can be collected separately. Early researchers considered waste management (WM) as one of the public physical infrastructures that play major roles in providing input production resources for goods and services, and in this respect, it resembles the electricity, natural gas, and water sector. In recent years, WM services have made a concerted effort to use information technology to reduce WM costs and to identify missing/stolen waste collection bins. In this concern, to reduce the WM operation cost and to improve efficiency, intelligent systems can play a significant role in providing intelligently processed and personalized information about WM customers, WM administrators and WM services (Kwenda *et al*., 2022; Torkayesh *et al*., 2022). The main processes considered in (WMS) are:

1. Production of materials: waste sources, production rates, and waste types.
2. Collection and transportation: waste collection and transfer.
3. Treatment or reprocessing: physical reprocessing, thermal reprocessing, and biological reprocessing.
4. Final disposition: recycling and landfilling.

SW encompasses wasted durable goods, nondurable goods, containers and packaging, food scraps, yard trimmings, and miscellaneous inorganic wastes from residential, commercial, and industrial sources. Effective WM through SW composition studies is important for numerous reasons, including the need to: estimate material recovery potential, identify sources of component generation, facilitate the design of processing equipment, estimate physical, chemical, and thermal properties of the waste and maintain compliance with national law and European directives. Numerous inefficient SWM systems may create serious negative environmental impacts like infectious diseases, land and water pollution, obstruction of drains and loss of biodiversity; for that, an integrated WMS should be suitably planned for local conditions such as the SW composition and the demand in local markets for possible recycled products. Accordingly, management programs should be established to separate waste, reduce its contamination and measures to help enterprises become more viable in the market. Such programs include

DOI: 10.23055/ijietap.2023.30.1.8647 ISSN 1943-670X

coordinating waste collection in various districts to support enterprises operating on large scales and creating demand for recycled products (Chen *et al*., 2021).

Modeling SWM issues have been tackled thoroughly in previous research. The formulation procedure for SW problems is traditionally performed through many approaches, such as mathematical programming, metaheuristic algorithms, and supply chain network models. Therefore, it is crucially important to select the appropriate tool for formulating the designed SWM problem, considering all problem's constraints and boundaries. This will most likely lead to the optimal solution within an acceptable time (Shafiq and Luong, 2021). The motivation for this research is based on the aforementioned observations that show a lack of models that integrate overall economic costs and environmental impacts for SWM systems. Therefore, the review of the literature delivers motivation to develop and demonstrate a WGP model of an SWM supply chain with the aim of reducing the whole financial costs and environmental effects whereas boosting the recovered energy. This modeling process takes into account the initial selection of SW collection bins and their potential locations, the inventory level of recycled products and the amount of electricity produced in the treatment plant in each time period. In addition, a real case study will be utilized to validate the proposed model.

The remainder of this paper is organized as follows. In Section 2, an extensive literature review is presented. A multi-objective WGP model formulation is proposed in Section 3. The proposed model is validated through the application on a real case study in Section 4. In Section 5, the results are presented and compared with those of the previously developed models in the relevant literature. An extensive sensitivity analysis is conducted in Section 6 in order to investigate the effect of changed parameters on the behavior of the SWM model. Finally, a conclusion is presented that summarizes the main research findings and presents future research directions.

2. LITERATURE REVIEW

SWM problem has been attracting many researchers, and it has been studied in numerous research articles, trying to find an optimum strategy for manipulating and treating SW of different types. This problem is highly complicated, as it comprises many conflicting constraints that should be considered. Developing a supply chain model to handle the SW is a tedious research work for such a complicated combinatorial problem, thanks to its multi-objective nature and its variety of hard and soft constraints. Examples of the difficulties that exist in this problem include deciding the number of facilities to be installed on the supply chain, selecting the types of solid waste to be involved in the chain, and estimating the total investment needed for establishing and running the main facilities of the chain. Previous research has shown that the SWM problem can be solved using several multi-objective optimization techniques such as mathematical programming, metaheuristic algorithms, supply chain network models, and location-allocation problem technique. So, the remainder of this section will be divided into multiple paragraphs, and each paragraph discusses different solution techniques and listed various studies that are related to that technique.

The solutions gotten from the mathematical programming approaches are most likely being the best ones since they are considered optimal. For example, by applying a bi-level programming model, Sharif *et al.* (2018) had approved that purchasing waste with a variable price, based on the quantity and quality of separated waste, would have a significant effect on the final profit and also enhance management. It was shown that the costs of separation and the number of transfer stations can, thus, be decreased. In addition, Jammeli *et al*. (2021) suggested a hierarchical model to involve another decision variable of the vehicles routes while minimizing the collection costs and the environmental impact. Another mathematical programming model, developed by Gambella *et al*. (2019), was employed to examine the impact of stochastic waste generation on the solution of the WM problem. The stochastic methodology was compared to a deterministic formulation that resulted in an unreliable decision plan. The comparison results show that stochastic solutions attain better alternative decisions compared to deterministic solutions. On the other hand, the effect of the separation rate factor was studied by Heidari *et al*. (2019), who proved that increasing the studied factor positively affects the system performance in terms of sustainability indicators. For this purpose, a fuzzy multi-objective mathematical model was developed to introduce waste-separating units equipped with compacting technologies to an SWM system with multiple types of waste. Also, Yousefloo and Babazadeh (2020) presented a mixed integer linear programming (MILP) model to minimize the overall economic and environmental costs and approved that establishing the tabu search (TS) in the scheme decreases the transference cost but rises the total cost. By dropping the risk, the establishment of the TS shrinks the transference costs and total costs. As a result, with more risk reduction, more TS is established.

Several studies considered the SWM from the supply chain perspective and solved problems in order to get the strategic and functional decisions in waste supply chain networks, containing the coordinated operations, creation, and conveyance. Mohammadi *et al*. (2019) indicated that among the plastic, metal, glass, paper, and non-recyclable waste, plastic recycling had a significant contribution to the economy, and recycling was the most profitable waste management option. Another model was developed by Saif *et al*. (2019), who added uncertainty features to the supply chain problem and formulated deterministic and stochastic models for the supply chain problem as MILP models. The results showed that adopting a stochastic model is more advantageous for the estimation of treatment cost and for the technology capacity selection. Moreover, it has been approved that there is an increase in cost versus risk minimization. Furthermore, Abdallah *et al*. (2021) presented a systematic optimization framework that identifies the most beneficial set of waste-to-energy (WTE) management strategies through non-linear mathematical modeling. The proposed model determines the optimum allocation of the different waste streams to selected waste management facilities, including material recovery facilities (MRFs), incinerators, anaerobic digestion (AD) plants, and sanitary landfills with gas recovery. Using another approach, Gopalakrishnan *et al*. (2020) proposed a blockchain-based SWM model that can help municipalities enhance the efficiency of their WM efforts. The blockchain framework owned and controlled by a municipality is proposed in which customer companies pay to join the platform to avail services from the suppliers managed by the municipality. Further, the cost aspects associated with blockchain implementation are estimated from several use cases that are obtained from companies providing blockchain solutions.

Recently, Zaeimi and Rassafi (2021) tackled an integrated location-allocation problem to plan the operations such as collection, recycling, disposal, and transportation under uncertainty. The study aimed to minimize the total costs and the total volume of pollutant emissions simultaneously by applying a WGP method. They concluded that increasing the confidence level leads to increasing the number of objective functions in most cases. Additionally, increasing the size of the problem causes a significant growth in the problem's solution time. Alternatively, Seruga (2021) applied methods for the collection and treatment of an organic fraction of municipal solid waste (MSW) to be treated by AD technology; these methods studied the effects of selective waste collection system introduction. He found that the AD ensures energy recovery from bio-waste, which can cover facility electricity needs and material recovery and contributes to the economic balance. The model was thought to be improved by replacing costs with sales revenue. On the other hand, Mojtahedi *et al*. (2021) proposed a new coordinated framework for a practical and efficient vehicle routing problem, considering the triple bottom line of sustainability. The coordinated solid waste management (CSWM) multiple objective functions were applied in this study for the purpose of combining financial, environmental and social considerations. This approach guaranteed a sustainable vehicle routing problem with optimization goals.

Multi-objective optimization (MOO) techniques have been widely adopted in previous research; Mamashli *et al.* (2021) presented a multi-objective mathematical model to minimize total costs, environmental impacts, and transportation risks while maximizing social impacts and resilience of the logistics system. The transportation risks were calculated by adopting the fuzzy failure mode and effects analysis (FMEA) method. Also, Mayanti *et al*. (2021) presented a MOO approach for a WTE problem to realize for the problem's thermal, economic, and environmental objectives. They found that the use of MOO can improve the performance of the WTE plant, although a conflict occurs between the economic and thermal objectives. Additionally, Arbolino *et al*. (2021) executed another methodology for the determination of ventures subsidized by policy implementation and to boost the effectiveness of public asset distribution. Results delineated that, in correlation with multi-criteria methods, the proposed model permits accomplishing a superior portion of public assets in both quantitative and subjective terms. Also, Singh and Tirkey (2021) fostered a strong strategy for the demonstration and enhancement of variable air gasification boundaries by utilizing the ASPEN plus test system and response surface methodology (RSM). Then, RSM had been utilized for the multi-objective improvements of the variable gasification boundary. As a result, gasification temperature and equivalence ratio had been optimized using the response optimizer plot.

On the other hand, Sellitto *et al*. (2021) were interested to create industrial networks for economic, environmental and social benefits in order to bring together companies from all business sectors through material trading and sharing assets to add value, reduce costs and benefit the environment. This concept can be applied to involve many tasks of municipal solid waste management (MSWM), such as recycle, reuse, transportation, separation and distribution, compared with SWM. Moreover, it gives a wider view of the most probable scenarios.

With respect to the previously presented research work and which is summarized in Table 1, it can be seen that few studies utilized the WGP model to investigate optimized solutions of WM problems. Regarding WM, mathematical programming models are capable of attaining the best performance of the supply chain's network. This is realized by optimizing the location of treatment facilities and the allocation of waste types to them. Besides, the previous research work that examined the related investigate the problem from a mathematical modeling point of view seldom tended to a few vital concepts, such as maintainability and resiliency. Thus, the main contribution of this research work is to develop an appropriate mathematical model that can deal with the integrated supply chain of the SWM system. The proposed model is intended to cover the following gaps, which are extracted from the previously presented research articles:

- Few researchers developed mathematical models for determining the total number of waste collection bins required in any site, considering different environmental and economic factors.
- The relationship between the four components of the waste treatment (WT) chain (collection, transportation, treatment, and final disposition) has not yet been clarified, so it is not obvious which one is dominant in the actual supply chain.
- Limited studies were published regarding the integration of the environmental objective using goal programming in the WTE system to evaluate recovery energy, cost, and environmental impact.

From these motivations and search gaps, the research questions can be stated as follows:

- How to formulate the relationship between the four components of the WT chain?
- How to design a coordinated framework for practical and efficient vehicle routing?
- How to utilize the WGP model to investigate optimized solutions of SWM problems in order to minimize the overall costs and maximize the total recovered energy?

Table 1. Summary of Literature Review.

References	Objectives					Multi-Objective Optimization Techniques			
	Determine the number of waste bins	Selection of treatment technologies	Minimization the total cost	Maximization of the total recovery energy	Minimization of final waste disposal to the landfill	Mathematical Model	Metaheuristic Algorithms	Integrated Supply Chain Network	Location-allocation Technique
(Sharif *et al*., 2018)			√		√	√			
(Jammeli *et al.*, 2021)			√	√		√			
(Gambella *et al.*, 2019)	√	√				√			
(Heidari *et al.*, 2019)		√	√			√			
(Yousefloo and Babazadeh, 2020)			√	√	√	√	√		
(Mohammadi *et al.*, 2019)			√	√				√	
(Saif *et al.*, 2019)			√		√	√		√	
(Abdallah *et al.*, 2021)	√	√	√					√	√
(Gopalakrishnan *et al.*, 2020)			√		√		√	√	
(Zaeimi and Rassafi, 2021)			√		√				√
(Seruga, 2021)		√	√	√			√		√
(Mojtahedi *et al.*, 2021)			√	√			√		√
(Mamashli *et al.*, 2021)			√	√			√		
(Mayanti *et al.*, 2021)			√	√	√		√		
(Arbolino *et al.*, 2021)			√				√		
(Singh and Tirkey, 2021)					√			√	
(Sellitto *et al*., 2021)			√	√	√	√		√	

3. RESEARCH METHODOLOGY

The current research methodology follows the steps exhibited in Figure 1, as follows:

- Classify and compare the available solid waste treatment (SWT) technologies.
- Model the SWT supply chain considering environmental and economic factors using the appropriate modeling methodology.
- Develop a solution algorithm to solve the designed model.
- Validate the model and solution methodology by application on a real case study and real collected data.
- Compare the model results with those of models previously developed in presented in the relevant literature.

The main objective of this research is to develop an integrated supply chain model for the SWT and management problem in order to restrict the inclusive commercial expenses and environmental influences, as well as augment the recovered energy from the SWT processes.

There are seven different SWT technologies considered in the developed model, which are listed and introduced in Table 2. The guidelines for selecting the appropriate treatment techniques are illustrated in Figure 2.

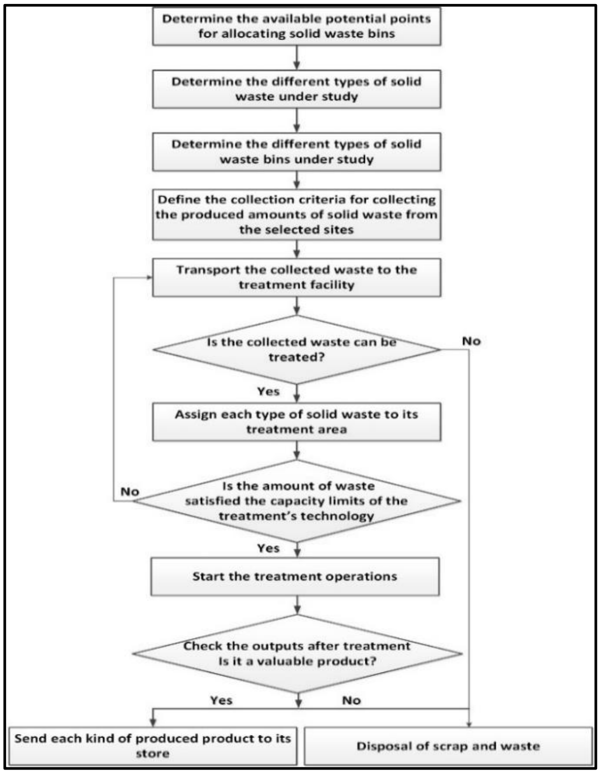

Figure 1. Flowchart of the integrated waste management chain.

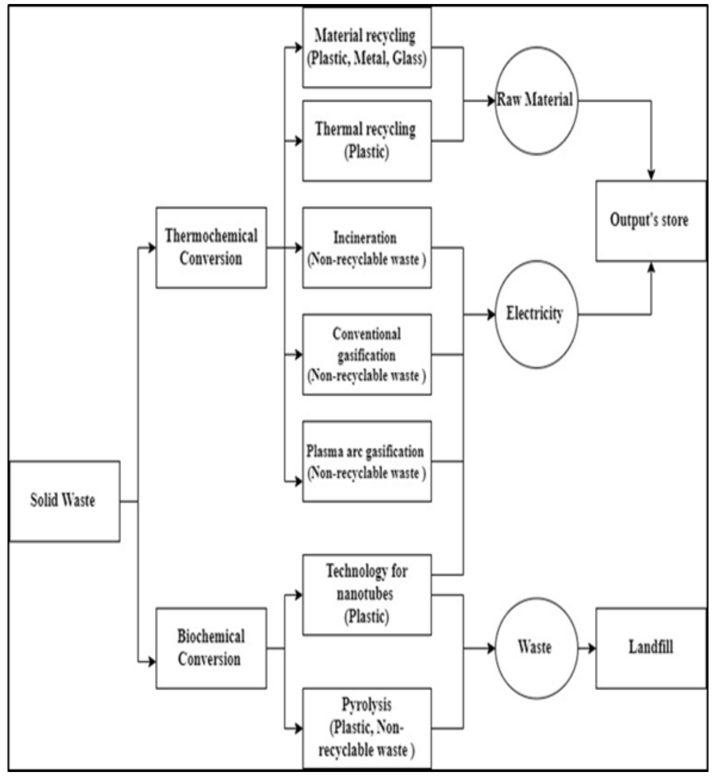

Figure 2. Flowchart for selecting the SWT technology.

3.1 Mathematical Formulation

The proposed model is a multi-objective WGP model to minimize both the total SWM supply chain's costs and environmental impacts through amplifying the total energy recovered from the SWT processes. The following subsections will present the steps and items of the model's scientific formulation.

In addition, several assumptions were associated with the model to facilitate its procedure. These assumptions are as follows:

- Labor costs, transportation within the facility, and setup cost are included in the treatment cost.
- There are no separation centers, as the splitting process will be carried out inside the facility in a special sorting unit. This, consequently, reduces the cost of the entire chain by saving the establishment and operating costs of these centers.
- The facility is established in a somewhat remote place from the city center, and this leads to an increase in the traveled distance, but it allows all the techniques included in this study to be carried out. This leads to a decrease in the costs of setting up factories for each technology separately and helps in reducing the number of vehicles required to transport waste from the sites of collection to these different facilities.

Table 2. Treatment technologies and types of selected waste.

NO.	Technology	Waste types that can be processed	Main Features
1	Technology for nanotubes	Plastic	• Nanotubes are applied in fluidic WT and energy harvesting. • Uses for removal of dyes and heavy metals from waste. (Williams and Valorization, 2021)
2	Material recycling	Plastic, Metal and Glass	• Recovery and reprocessing of waste materials for use in new products. • Recycling is a key component of modern waste reduction. • The third component of the "Reduce, Reuse, and Recycle" waste hierarchy (Nanda and Berruti, 2021).

NO.	Technology	Waste types that can be processed	Main Features
3	Thermal recycling	Plastic	• Thermal recycling converts solid waste into either electricity or steam. • Protects the environment, and it is a valuable source for generating renewable energy (Mao *et al.*, 2021).
4	Pyrolysis	Plastic and Non-recyclable waste	• Thermochemical decomposition of organic material at high temperatures and in the absence of oxygen. • The process requires an external heat source to maintain the high temperature required (Wang *et al.*, 2021).
5	Incineration	Non-recyclable waste	• Involves the combustion of organic substances contained in waste materials. • Commonly referred to WTE facilities. • Reduce the volume of un-compacted waste by more than 90 percent (Chen *et al.*, 2022).
6	Conventional gasification	Non-recyclable waste	• Converts solid waste to a usable synthesis gas, or syngas. • Breaking solid waste down into simple molecules, primarily a mixture of carbon monoxide and hydrogen (Cai *et al.*, 2021).
7	Plasma arc gasification	Non-recyclable waste	• Uses a combination of electricity and high temperatures to turn waste into usable by-products without combustion. • Converts the organic waste into a gas and converts the inorganic waste into an inert vitrified glass called slag. • Production of value-added products (metals) from slag (Chu *et al.*, 2022).

Indices and Input Parameters

- Number of sites i=1…N
- Number of types of bins j= 1…M
- Number of types of waste k= 1… W
- Number of types of vehicles v= 1… V
- Number of time`s period t=1… T
- Number of types of Technologies h= 1... H
- n^f = Number of final products of products f = 1… F.
- Number of cities covered by final products and electricity c = 1…C.
- n^e = amount of produced electricity from a ton of treated waste (kWh).
- Q_{ikt} : Average quantity of waste (of type k) generated per a period of time t at commercial places in site i.
- C_j: Capacity of type j bin.
- $Tre\_Capacity$: Capacity of the treatment facility.
- $Dis\_Capacity$: Capacity of the disposal landfill.
- $Cost_{\,j}$: Purchasing cost of type j bin.
- $Tre\_Cost_{\,kht}$: Treatment cost of waste type k processed by technology h in time period t.
- $Dis\_Cost_{\,kt}$: Disposal cost of waste type k in time period t.
- δ_{kh} : Separation factor for waste type k to be processed by technology h.
- $Space_j$: Space required by a type j bin.
- CW_{ij}: Variable cost for allocating bin j in site i.
- L_v: Capacity limit of vehicle type v.
- Vehicle $\_Cost_{\,v}$: Purchasing cost of type v vehicle.
- Veh _Var_$Cost_{\,v}$: Variable cost of type v vehicle used for transport waste to treatment facility.
- CT_{kh}^{low} : Lower capacity limit of technology h to process waste k.
- CT_{kh}^{up} : Upper capacity limit of technology h to process waste k.
- TD_i: Transportation distance from the bin site i to the collection/ treatment center.
- C_t^{store}: The unit cost of store waste per a period of time t.
- C_t^{sort}: The unit cost of sorting waste per a period of time t.

- $D_{c,t}^{n^f}$: Demand of product n^f in city c at time period t.
- $D_{c,t}^{n^e}$: Demand of electricity n^e in city c in time period t (kWh).
- S^{n^f}: Storage capacity of product n^f.
- VR: Volume reduction ratio at the treatment facility.
- RB_{kt} : revenues from biological treatment for composting waste type k at time period t, it is the compost unit price.
- RT_{kt} : revenues from thermal treatment for composting waste type k at time period t, it is the compost unit price.
- $WP_h^{n^f}$: The waste to product conversion factor for product n^f generated from technology h.
- $WP_h^{n^e}$: The waste to electricity conversion factor for electricity n^e generated from technology h.
- IU^{n^f}: Initial inventory level of product n^f stored in the plant.

Decision Variables

- X_{jk}: Number of selected bins of type j for waste type k.
- Y_{ij} = 1 if site i is selected for allocating bin j, 0 otherwise
- P_{kht} = 1 if waste type k is sent to technology type h in time period t, 0 otherwise
- QP_{kht}: Quantity of solid waste type k to be processed in the treatment center by technology h in time period t.
- $QD_{k,t}$: Quantity of solid waste type k to be disposed to the landfill in time period t.
- Z_{iv} : Number of vehicle type v required for transportation from the bin site i to collection/ treatment center.
- $qp_t^{n^f}$: Quantity of product n^f produced in treatment plant in period t.
- $qe_t^{n^e}$: Amount of electricity n^e produced in treatment plant in period t (kWh).
- $Tq_{c,t}^{n^f}$: Total quantity of product n^f shipped to city c in time period t.
- $Tq_{c,t}^{n^e}$: Total quantity of electricity n^e send to city c in a period of time t (kWh).

Output parameters

- TTC: Total Transportation cost.
- TBC: Total cost for allocating and using of different types of bins.
- $TTre\_C$: Total treatment cost.
- $TDis\_C$: Total cost of disposed waste to the landfill.
- TVC: Total cost for using of different types of vehicles.
- TCC: Total coat of the whole chain.
- C_{SS}: Total cost of sorting and storage of waste.
- $IL_t^{n^f}$: Inventory level of product n^f stored in plant in period of time t.
- BTR: Total Biological treatment revenues.
- TTR: Total Thermal treatment revenues.

Objective functions

This research is intended to develop an integrated supply chain model for the SWM problem. The model is multi-objective, as it aims at minimizing the overall costs of SWT (Equations 1) in addition to maximize the total amount of energy recovered from the SWT processes. This research work would cover the following main points:

- Determine the total number of waste collection bins required in any site and selecting the best potential sites for different types of bins.
- Optimal selection of treatment technologies for potential treated SW.
- Minimize the transportation distance between the bin locations and the collection/ treatment center, and accordingly minimize the total transportation cost.
- Minimize the fixed costs for the installation of any new facility in the chain.
- Minimize the quantity of waste disposal to the landfill.
- Maximize energy recovery that is produced from the treatment of the different types of selected waste (Equations 2).

$$Minmize: \sum_{j=1}^{M}\sum_{k=1}^{W} Cost_{\,j} \times X_{jk} + \sum_{j=1}^{M}\sum_{i=1}^{N}\sum_{k=1}^{W} CW_{ij} \times Y_{ij} \times X_{jk} + \sum_{k=1}^{W}\sum_{h=1}^{H}\sum_{t=1}^{T} QP_{kht} \times P_{kht} \times Tre_{Cost_{kht}} + \sum_{k=1}^{W}\sum_{t=1}^{T} QD_{kt} \times Dis_{Cost_{kt}} + \sum_{i=1}^{N}\sum_{v=1}^{V} \text{Vehicle}\_Cost_{\,v} \times Z_{iv} + \text{Veh}\_\text{Var}\_Cost_{\,v} \times TD_i \times Z_{iv} + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{k=1}^{W} Q_{ikt} \times C_t^{\text{store}} + Q_{ikt} \times C_t^{\text{sort}} . \quad (1)$$

In the first objective, the designed model works to optimize the total chain cost, which includes the cost of allocation of new waste bins, the cost of the treatment process for SW by the selected technologies, the cost of disposal of the unrecycled waste into landfill, the fixed and variable cost for purchasing and running different types of required vehicles, and the total cost of sort and stores the collected amount of SW inside the treatment facility.

$$Maximize : \sum_{k=1}^{W} \sum_{h=1}^{H} QP_{kht} \times WP_h^{n^e}; \quad n^e = Electricity, \forall \ t = 1 \dots T \ . \qquad (2)$$

The environmental impact of the system has been considered and evaluated on the basis of material and energy recovery, as presented on the second objective. The WGP model aims to maximize the total recovered energy (electricity) produced during the treatment processes. The total electricity can be calculated by multiplying the total amount of treated SW by the product conversion factor for electricity generated from a ton of SW using a certain treatment technology.

Constraints

The current model comprises several sets of constraints to consider the boundaries and operating conditions of the SWT supply chain and processes. Firstly, the site selection constraints for the wastes' collection bins are presented in Equations 3 and 4; their formulation has a condition that if a site i is selected; at least one bin should be established on it and the total number of waste bins will be greater than or equal the total generated amount of waste in each time period divided by bin's capacity.

$$\sum_{j=1}^{M} \sum_{k=1}^{W} Y_{ij} \times X_{jk} \geq 1 \quad ; \forall i = 1 \dots N \qquad (3)$$

$$X_{jk} \geq \frac{Q_{ikt}}{C_j} \quad ; \forall i = 1 \dots N, \\ \forall k = 1 \dots W, \forall j = 1 \dots M, \ \ \forall t = 1 \dots T \qquad (4)$$

The total quantity of waste to be processed in the treatment facility will be decided by the separation factor for waste type k to be processed by technology h multiplied by the total amount of generated SW as follows:

$$QP_{kht} = \delta_{kh} \times \sum_{i=1}^{N} Q_{ikt} \quad ; \forall k = 1 \dots W, \forall t = 1 \dots T, \forall h = 1 \dots H \qquad (5)$$

The total amount of wastes entering to a treatment plant and landfill plant in each time period should be less than or equal to their capacity, as shown in Equations 6 and 7, respectively.

$$\sum_{k=1}^{W} \sum_{h=1}^{H} QP_{kht} \leq Tre_{Capacity} \ ; \quad \forall t = 1 \dots T \qquad (6)$$

$$\sum_{k=1}^{W} QD_{k,t} \leq Dis\_Capacity \ ; \forall t = 1 \dots T \qquad (7)$$

Equation 8 enables the calculation of the number of vehicles used for the transportation of waste from the bin site to treatment plants. This number will be in the range of the total generated amount of waste in each time period divided by the capacity limit of each type of vehicle.

$$Z_{iv} - 1 \leq \frac{\sum_{k=1}^{k=W} Q_{ikt}}{L_v} \leq Z_{iv} \ ; \ \forall i = 1 \dots N, \forall v = 1 \dots V, \forall t = 1 \dots T \qquad (8)$$

As is common in standard vehicle route problem (VRP) route structuring, the following constraints ensure that each site is visited once by a compatible vehicle.

$$\sum_{v=1}^{V} \sum_{j=1}^{M} Z_{iv} * Y_{ij} = 1 \, ; \ \forall i = 1 \dots N \qquad (9)$$

The amount of waste entering the landfill, received from all separation centers, can be calculated by subtracting the total amount of SW that had been treated, using different types of treatment technologies, from the total generated amount of waste. This is formulated in Equation 10.

$$QD_{k,t} = \sum_{i=1}^{N} Q_{ikt} - \sum_{h=1}^{H} QP_{kht} \quad ; \quad \forall k = 1 \dots W, \forall t = 1 \dots T \qquad (10)$$

The collected waste in each type of bins cannot exceed the capacity of that bin; this can be satisfied using Equation 11.

$$Q_{ikt} \times Y_{ij} \leq C_j \quad ; \forall i = 1 \dots N, \quad \forall k = 1 \dots W, \forall j = 1 \dots M, \forall t = 1 \dots T \tag{11}$$

Equation 12 is used to calculate the total allocation and usage costs of the different types of bins. This comprises the purchasing cost of each type of bins and the variable cost for allocating bins in different designated sites.

$$TBC = \sum_{j=1}^{M} \sum_{i=1}^{N} \sum_{k=1}^{W} Cost_{j} \times X_{jk} + CW_{ij} \times Y_{ij} \times X_{jk} \tag{12}$$

The total cost of the waste treatment and disposal to the landfill is calculated using Equations 13 and 14, respectively. The treatment cost will equal the total amount of SW that had been treated multiplied to be the treatment cost that comprises the processing cost, setup cost for treatment technology, labor cost, and transportation cost within the facility. At the same time, the disposal cost is evaluated by multiplying the total amount of waste entering the landfill by the disposed of cost.

$$TTre\_C = \sum_{k=1}^{W} \sum_{h=1}^{H} \sum_{t=1}^{T} QP_{kht} \times P_{kht} \times Tre\_Cost_{kht} \tag{13}$$

$$TDis\_C = \sum_{k=1}^{W} \sum_{t=1}^{T} QD_{kt} \times Dis\_Cost_{kt} \tag{14}$$

Equation 15 is used to calculate the total cost of different types of vehicles; this cost includes the fixed purchasing cost of several types of vehicle plus the variable cost of each type multiplied by the distance transported from the bin sites to the treatment center.

$$TVC = \sum_{i=1}^{N} \sum_{v=1}^{V} \text{Vehicle}\_Cost_{v} \times Z_{iv} + \text{Veh}\_\text{Var}\_Cost_{v} \times TD_i \times Z_{iv} \tag{15}$$

The capacity limit constraint of waste processing technologies is formulated in Equation 16. This equation ensures that the total amount of SW that had been treated by a specific treatment technology will be greater than or equal to the lower capacity limit of the technology and less than or equal to the upper capacity limit of the technology.

$$CT_{kh}^{low} \times P_{kht} \leq QP_{kht} \leq CT_{kh}^{up} \times P_{kht} ; \quad \forall k = 1 \dots W, \forall h = 1 \dots H, \forall t = 1 \dots T \tag{16}$$

The total cost of sorting and storing waste inside the treatment facility is calculated using Equation 17; this equation directly multiplies the total amount of collected (or generated) waste by the storing and sorting costs as follows:

$$C_{SS} = \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{k=1}^{W} Q_{ikt} \times \mathrm{C}_t^{\text{store}} + Q_{ikt} \times \mathrm{C}_t^{\text{sort}} \tag{17}$$

The total cost of the whole chain for waste treatment is obtained by applying Equation 18. This cost will be the sum of the total treatment cost, total disposal cost, total allocating cost, total vehicle cost, total sorting cost, and total storing cost.

$$TCC = TTre_C + TDis_C + TBC + TVC + C_{SS} \tag{18}$$

For final products and electricity that could be produced from the treated SW, there are different demands of each product type by the several cities covered by the designed treatment facility. The distribution balance constraints of the products and electricity distributed to the cities are calculated using Equations 19 and 20. However, the demand satisfaction constraints of products and electricity are shown in Equations 21 and 22. It is assumed that the demand for every type of product will be fulfilled during each period, and no backordering (delay fulfillment) or lost sales (no fulfillment) are allowed.

$$\sum_{c=1}^{C} Tq_{c,t}^{n^f} = qp_t^{n^f} \;; \forall n^f \mid f = 1 \dots F, \forall t = 1 \dots T \tag{19}$$

$$\sum_{c=1}^{C} Tq_{c,t}^{n^e} = qe_t^{n^e} : \;; \; n^e = \text{Electricity}, \forall t = 1 \dots T \tag{20}$$

$$Tq_{c,t}^{n^f} = D_{c,t}^{n^f} \;;\;; \forall n^f \mid f = 1 \dots F, \forall t = 1 \dots T, \forall c = 1 \dots C \tag{21}$$

$$Tq_{c,t}^{n^e} = D_{c,t}^{n^e} \;; \; n^e = \text{Electricity}, \forall t = 1 \dots T, \forall c = 1 \dots C \tag{22}$$

The initial inventory level of final products, which equals the inventory level at the first time period, is given in Equation 23, and it is going to be zero. The inventory level of products at any time period ($t \geq 2$) can be calculated by Equation 24, and it is equal to the inventory level of the previous period plus the total quantity of products produced in the current time period. Moreover, the storage capacity limit constraint is indicated in Equation 25.

$$IL_t^{n^f} = IU^{n^f} \;;\;; \forall n^f \mid f = 1 \dots F, t = 1 \tag{23}$$

$$IL_t^{n^f} = IL_{t-1}^{n^f} + qp_t^{n^f} - \sum_{c=1}^{C} q_{c,t}^{n^f} \;\; ; ; \forall n^f \mid f = 1 \dots F, \;\; \forall\, t = 2 \dots T \tag{24}$$
$$IL_t^{n^f} \;\le\; S^{n^f} \,; \;\; ; \forall n^f \mid f = 1 \dots F, \forall t = 1 \dots T \tag{25}$$

The quantity of product n^f produced in a treatment plant at time period t can be calculated by multiplying the waste-to-product conversion factor by the total amount of SW that had been treated using different types of treatment technologies; this is illustrated in Equation 26. In addition, the amount of generated electricity n^e is formulated in Equation 27; it includes the direct multiplication of the total amount of SW that had been treated and the waste-to-electricity conversion factor.

$$qp_t^{n^f} = \sum_{k=1}^{W} \sum_{h=1}^{H} QP_{kht} \;\times WP_h^{n^f} \;; \forall n^f \mid f = 1 \dots F, \forall\;\; t = 1 \dots T \tag{26}$$
$$qe_t^{n^e} = \sum_{k=1}^{W} \sum_{h=1}^{H} QP_{kht} \;\times\; WP_h^{n^e};\;\; n^e = \text{ Electricity}, \forall\;\; t = 1 \dots T \tag{27}$$

To calculate the total income from the biological and thermal treatment technologies, Equations 28 and 29 are applied, respectively. The total income from the biological and thermal treatments equals the total amount of SW that had been treated using different types of treatment technologies multiplied by the volume reduction ratio at the treatment facility and the compost unit price.

$$BTR = \sum_{t=1}^{T} \sum_{h=1}^{5} \sum_{k=1}^{W} QP_{kht} \;\times (1 - VR) \times\; RB_{kt} \tag{28}$$
$$BTR = \sum_{t=1}^{T} \sum_{h=6}^{H} \sum_{k=1}^{W} QP_{kht} \;\times\; RT_{tk} \tag{29}$$

The optimization model has been solved by using LINGO solver with Excel, as well as, CPLEX solver; this allows obtaining superior solutions and comparing results with previous studies (Mohammadi *et al.*, 2019) and (Tascione *et al.*, 2021).

3.2 Simplex Algorithm

The linear solver in LINGO uses the revised simplex method with product form inverse. A barrier solver may also be obtained, as an option, for solving linear models. LINGO's nonlinear solver employs both successive linear programming (SLP) and generalized reduced gradient (GRG) algorithms. Integer models are solved using the branch-and-bound method. In linear integer models, LINGO performs considerable preprocessing (i.e., adding constraint "cuts" to restrict the non-integer feasible region). These cuts will greatly improve solution times for most integer programming models.(Banerjee *et al.*, 2021, Leyang *et al*., 2022)

The simplex algorithm moves around the exterior of the feasible region to the optimal solution, while the interior point algorithm, or barrier solver, moves through the interior of the feasible region. The simplex algorithm stops when it reaches the optimality criterion as below:

$$C_j - Z_j \;\le 0;\; for\ a\ maximum\ problem$$
$$C_j - Z_j \;\ge 0;\; for\ a\ minimum\ problem,$$

where

C_j: The coefficients of the objective function.

Z_j: The objective function value.

However, for the selected problem under this study, which includes multi-criteria situations (a combined maximum-minimum problem), there is a variety of approaches to deal with multiple criteria. One of the most appropriate approaches for such a problem is Pareto Optimal Solutions. A solution to a multi-criteria problem is said to be Pareto optimal if there is no other solution that is at least as good according to all criteria and strictly better according to at least one criterion.(Petchrompo *et al*., 2022, Salehi *et al*., 2022)

Procedure Scheme of the Simplex Algorithm(A, b, c)

(N, B, A, b, c, v) ← INITIALIZE- SIMPLEX (A, b, c)
while some index j ∈ N has $C_j > 0$
  do, choose an index ế ∈ N for which $C_{ế} > 0$
    for each index $i \in B$
      do if $a_{i,ế} > 0$
        then $\Delta_i \leftarrow b_i / a_{i,ế}$
        else $\Delta_i \leftarrow \infty$
    choose an index $l \in B$ that minimizes Δ_i
    if $\Delta_i \leftarrow \infty$
      then return "unbounded"
      else (N, B, A, b, c, v) ←PIVOT (N, B, A, b, c, v, l, ế)
for i ← 1 to n
  do if $i \in B$
    then $\bar{x}_j \leftarrow b_j$
    else $\bar{x}_j \leftarrow 0$
return the optimal solution $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$

4. CASE STUDY

In order to validate the model and solution algorithm, different data sets were utilized that were previously published by (Mohammadi *et al.*, 2019) and (Tascione *et al.*, 2021) for a case study treated in their research work; the inputs to the optimization model were the parameters obtained from the datasets. The constraints were defined based on the range of values given in the input datasets. The cost ranges were defined based on available estimates from online sources. The data values are normally distributed to cover a wide range of prices offered by different companies. In addition, the average quantity of waste collected from each site fits a Weibull distribution with the expression 0.22 + WEIB (0.131, 2.13), and the demand of product n^f in city c at time period t belongs to a Triangular distribution with the expression TRIA (10, 28.9, 60). Moreover, the demand of electricity n^e in city c in time period t fits a Beta distribution with expression 24 + 3 * BETA (0.558, 1.51), while the Erlang distribution has the least error, and it is the suitable distribution for treatment cost of waste type k processed by technology h with expression; the derived expression is 0.43 + ERLA (0.0178, 4). The initial parameters utilized for the input data set are 4 types of waste, 4 different types of waste bins, 10 different sites to allocate the selected bins, 7 treatment technologies for processing the different types of the collected waste, as previously indicated in Table 2. All specifications and information about the different waste bins and the designed treatment facility are summarized in Table 3.

Three different types of vehicles are proposed with dissimilar capacities and costs, as presented in Table 4. The model's solution is supposed to allocate the best selection of different types of bins to the appropriate sites; this will contribute to minimizing the total cost of the WT chain while smoothing the flow of waste into the treatment facility. Therefore, the current model's objectives are to optimize the selection of waste bins on the different available sites and to maximize the amount of energy recovery simultaneously. So, the overall economic costs and environmental impacts are minimized.

Moreover, inside the treatment facility, there is a separation unit assigned to isolate each type of waste and in what quantity is entering the desired treatment technology; the entering waste quantity depends on the separation factor for each type of waste, as illustrated in Table 5. On the other hand, each technology has its operation data, such as the treatment cost for each type of waste and the lower and upper bound of the waste amount that enters that technology. After finishing the treatment process of the collected waste, three different products (plastic pallets, recycled aluminum and recycled glass) in addition to energy (electricity) are being produced. Production quantities and electricity generated depend on the waste-to-product and WTE conversion factors, which are summarized in Table 6. These produced products and energy are then distributed to four different cities according to their demand patterns.

Table 3. Operation data of waste bins and the designed treatment facility

Number of types of waste	4			
Number of types of bin	4			
Number of types of technology	7			
Number of sites	10			
Number of types of vehicles	3			

Number of time periods	4			
Number of Final product	3			
Number of cities	4			
Capacity of type j bin (Ton)	10	15	20	25
Purchasing cost of type j bin ($)	150	200	220	250
Space required by a type j bin. (m2)	1.5	2	2.5	2.25
Capacity of the treatment facility (Ton/day)	100000			
Capacity of the disposal landfill (Ton)	50000			
The unit cost of store waste ($)	10			
The unit cost of sorting waste ($)	4			
Reduction Ratio at treatment facility	0.2			

Table 4. Features of different types of vehicle

Types of vehicles	Vehicle capacity limit (Ton)	Purchasing cost of vehicle ($)	Variable cost of vehicle ($/km)
Vehicle 1	5	30000	50
Vehicle 2	7	45000	120
Vehicle 3	8	70000	200

Table 5. Separation factor for types of waste processed by each technology (%)

	Plastic	Metal	Glass	Non-recyclable waste
Nanotubes	0.2	0	0	0
Material recycling	0.15	0.5	0.5	0
Thermal recycling	0.1	0.15	0.1	0
Pyrolysis	0.1	0.1	0.25	0
Incineration	0	0	0	0.25
Conventional gasification	0	0	0	0.15
Plasma arc gasification	0	0	0	0.55

Table 6. Waste to product conversion factor (ton product/ton waste; MJ Energy/ton waste)

	Plastic Pellet	Recycled Aluminum	Recycled Glass	Electricity/ Energy
Nanotubes	0.299	0	0	1.958
Material recycling	0.15	0	0.333	2.056
Thermal recycling	0.415	0	0.333	2.466
Pyrolysis	0.672	0.84	0	0.246
Incineration	0	0.84	0.432	2.938
Conventional gasification	0	1	0.446	0
Plasma arc gasification	0	1	0	0

5. RESULTS AND DISCUSSION

5.1 Weighted Goal Programming (WGP) Modeling

To achieve the problem's two objectives (those may even be in conflict), the multi-objective problem was converted into a goal programming model. Consequently, two other equations were created, Equations 30 and 30, to replace Equations 1 and 2 in the original model, respectively. In these two added equations, new deviation variables were being defined, which are the overachievement (E) and the underachievement (U). This goal programming allows users to assign some priority for their goals.

$$TCC + U_1 - E_1 = 0 \tag{30}$$

$$\left(\sum_{k=1}^{W}\sum_{h=1}^{H} QP_{kht} \times WP_h^{n^e}\right) + U_2 - E_2 = 0;\ n^e = Electricity, \forall\ t = 1 \dots T \tag{31}$$

The new objective is to minimize the penalty of not meeting the goals (minimize the overall cost and maximize the recovery energy), represented by the detrimental variables. For that reason, new objective function equation (Equation 32) was formulated.

$$Minimize\ Z = A \times\ E_1 + B\ \times\ U_2\ , \tag{32}$$

where A and B are used to assign different priority levels.

5.2 Computational results and comparisons

The results show that the designed model gives an accepted performance with a total cost of $3,496,534. The number of vehicles that are required to transport the collected waste from each site to the treatment facility is indicated in Table 7.

The model and solution algorithm was applied on the selected data sets, and the results are summarized in Table 8 and Table 9. For better results' representation, Figure 3 and Figure 4, illustrates the results in bar diagrams. Table 8 includes the quantities of different types of products produced as a result of waste treatment, as well as the amount of electricity recovered through the treatment processes. Three products are produced in the facility, which are plastic pallets, recycled aluminum and recycled glass; the study time horizon covers the four seasons per annum to cope with fluctuations in the waste amounts collected in the different time periods. On the other hand, Table 9 includes the resultant quantities of wastes to be disposed to the landfills. Comparisons were made between the results of the current model and those obtained and published from a previous study that applied the MILP approach. Figure 5 illustrates the comparison between the two modeling approaches; which elucidates that there are better results for the WGP model in terms of the average quantity of products and energy produced. Figure 4 exhibits the amounts of wastes disposed to the landfill (graphical representation of Table 9), while Figure 6 shows the comparison between these quantities attained by the WGP approach and those resulted from the MILP approach applied in (Mohammadi *et al.*, 2019). Figure 6 clarifies that the designed model gives less average quantity that had been disposed to landfill. The produced quantity can cover the demand of all cities in each period of time with the purpose of avoiding penalty payments of delay or shortage of a shipped quantity. Finally, the proposed methodology can be applied on large instance with many types of waste (k= N) and several technologies (h= M) in several time periods (t=T).

Table 7. Number of vehicles per sites

	vehicle 1	vehicle 2	vehicle 3
Site 1	2	2	2
Site 2	3	2	2
Site 3	3	2	2
Site 4	3	2	2
Site 5	2	2	2
Site 6	2	2	2
Site 7	2	2	2
Site 8	2	2	2
Site 9	2	2	2
Site 10	2	2	2

Table 8. Quantity of product produced and amount of electricity (Ton of product/ MJ of Energy)

	Plastic Pellet	Recycled Aluminum	Recycled Glass	Electricity
Winter	52.63745	83.804	48.89715	328.5577
Spring	56.72755	87.948	52.6104	360.7329
Summer	60.97695	118.692	60.0552	399.3225
Fall	65.93705	96.11	59.0208	406.0462

Table 9. Amount of solid waste to be disposed to the landfill (Ton of waste)

	Winter	**Spring**	**Summer**	**Fall**
Plastic	31.5	41.85	43.65	45.45
Metal	17.75	22.25	20.25	22.25
Glass	13.05	10.95	13.65	15
Non-recyclable waste	2.95	3.15	4.65	3.25

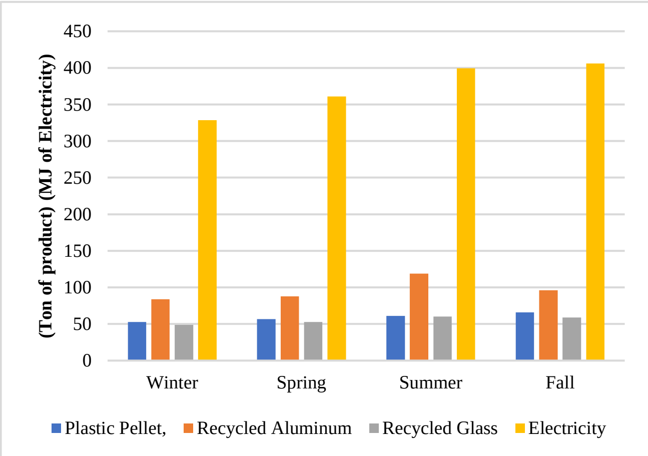

Figure 3. Quantity of products and energy produced

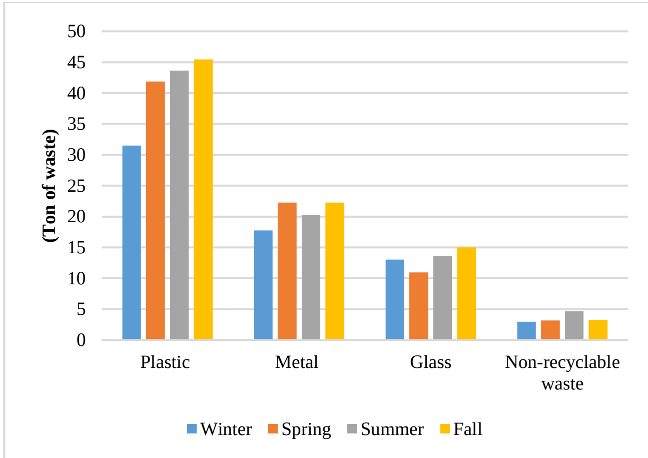

Figure 4. Amount of solid waste to be disposed to the landfill

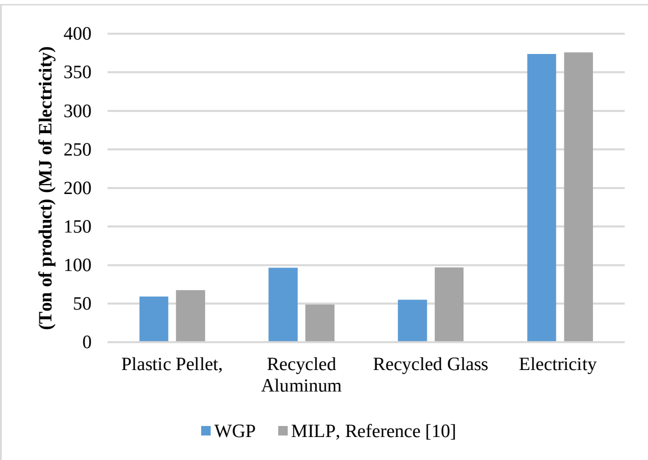

Figure 5. Comparison on the average quantity of products and energy produced

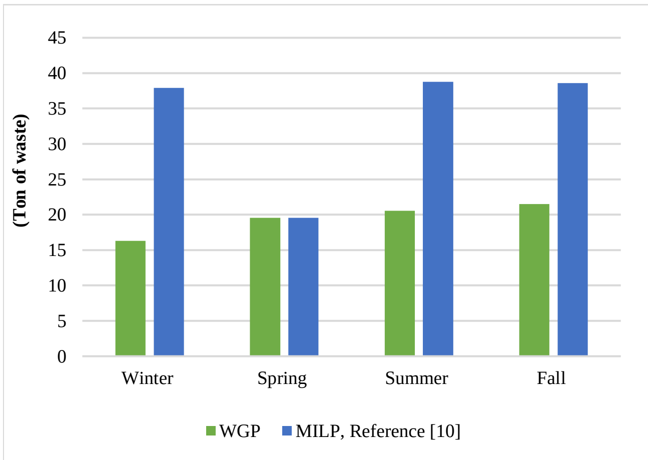

Figure 6. Comparison on the Average amount of solid waste to be disposed to the landfill

6. SENSITIVITY ANALYSIS

In this research, sensitivity analysis is performed to investigate the effect of altering the operating parameters on the WT supply chain's performance. A plan was formed to utilize key sensitivity analysis in developing WT study protocols; these plans consider a clear awareness of the limitations of the data and the nature of the problem. As clarified by (Arbolino *et al*., 2021), the use of sensitivity analysis to examine the underlying assumptions will build confidence and robustness of associations to assumptions, and it will be a crucial component of grading the strength of evidence provided by a study. As a result, in this study, the considered factors in the analysis are the reduction ratio (RR), treatment technology's boundaries, and the WTE factor affecting the supply chain's performance; Table 10 summarizes the several levels of factors that were selected in the analysis.

Table 10. Levels of different parameters that were selected to be analyzed

Parameters	Values
Reduction Ratio (RR)	(0.10, 0.15, 0.20, 0.25)
Treatment technology's lower capacity bound	(4, 5, 6, 7, 8, 9, 10, 12)
Waste to energy factor	(0.246, 0.346, 0.658, 0.927, 1.958, 2.056, 2.466, 2.938)

Sensitivity analysis was conducted in two stages; the first stage considered studying the effect of changes in the RR and treatment technology's boundaries on the total cost of the entire WT chain. Figure 7 and Figure 8 illustrate the ranges of optimality for these factors, as their fluctuation within these ranges does not change the optimality status of the final solution. Noticing Figure 7, it can be seen that the total cost decreases dramatically with the reduction in the RR with a range of (10% - 15%) and by changing its treatment technology's lower capacity bound from 4 to 6 tons of waste. This saving of treatment cost, as clarified in Figure 8, can be explained as the decline of RR will drop the amount of SW required to be processed. Thus, increasing the technology's lower capacity bound will lead to less number of setups needed for treating waste.

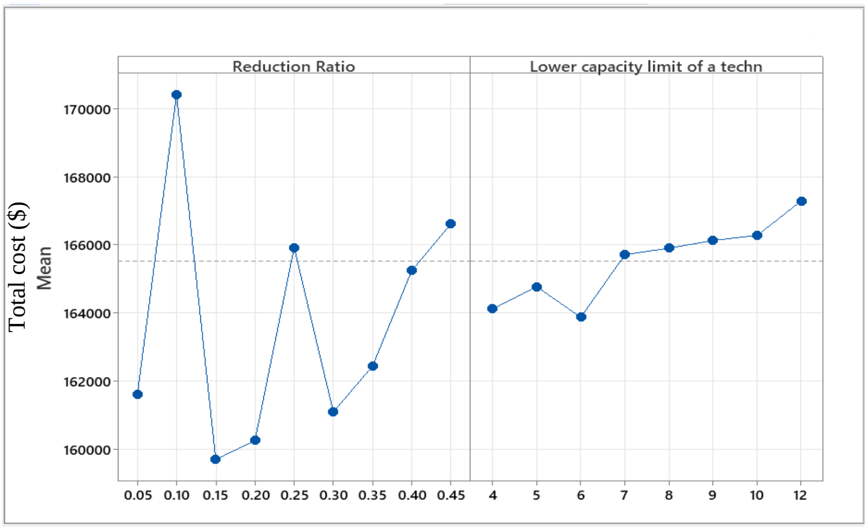

Figure 7. Main effects analysis of RR and technology's lower bound to the total cost

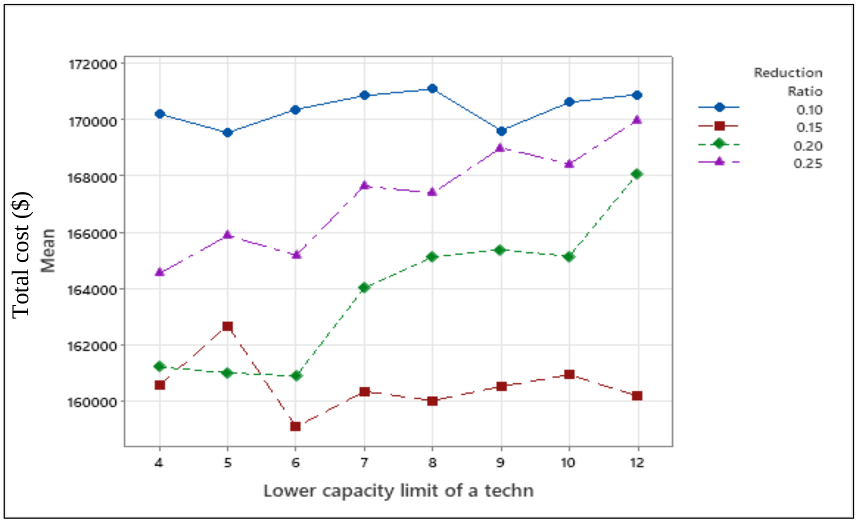

Figure 8. Two-factor interactions analysis of RR and technology's lower bound to the total cost

The second stage of the conducted sensitivity analysis was to study the impact of changing the RR and the WTE factor on the total energy recovery. As exhibited in Figure 9, results show that when the RR drops to the range of 15 to 20%, the optimal value of total recovery energy can be attained. However, it can be observed that increasing the WTE factor to the level of 2.466 % yields an optimal value of energy recovered from the treated waste. This increase in the total energy recovery, as shown in Figure 10, can be explained by the fact that growing of the WTE factor raises the energy extracted from each ton of waste.

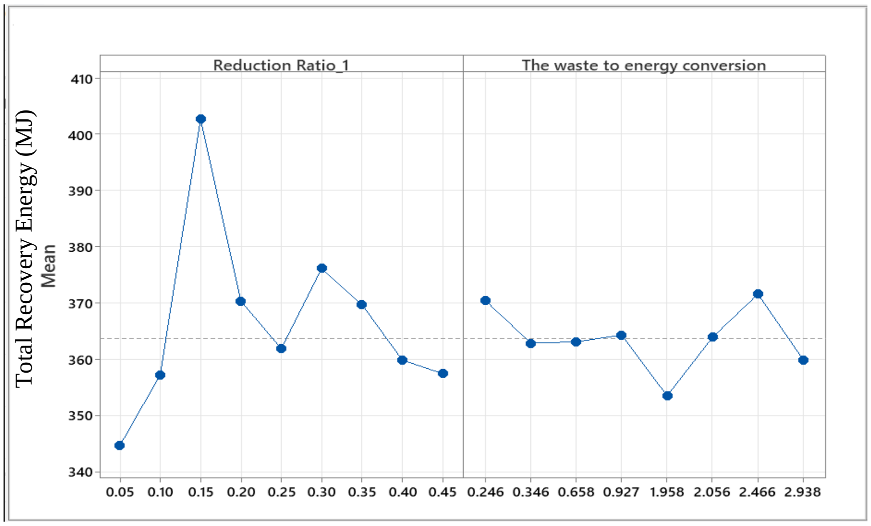

Figure 9. Main effects analysis of RR and waste to energy factor to the total energy

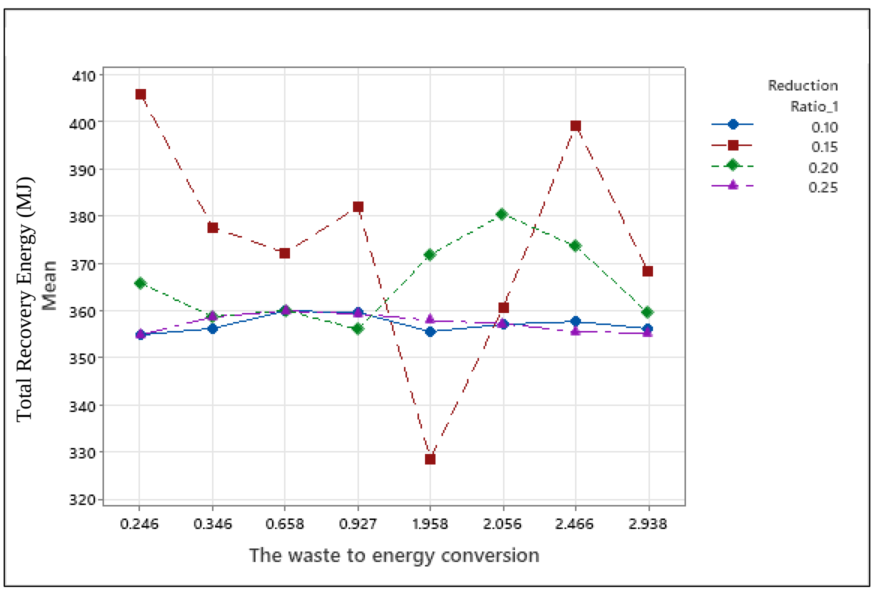

Figure 10. Two-factor interactions analysis of RR and waste to energy factor to the total energy.

7. CONCLUSION AND FINAL REMARKS

This article presents a model and a solution methodology to deal with the difficulties of designing an integrated supply chain for SWT, considering economic and environmental factors. Reducing the overall economic costs and environmental impacts were the objectives for the targeted problem to deal with joint improvement in the two cost sources. WGP has been utilized to reach the optimal solution. Firstly, four different types of waste bins were allocated in several sites, and numerous types of waste were collected from these bins. Then, the collected amounts of waste were transferred into treatment facility using special types of vehicles to be treated by seven technologies in order to produce three different products and energy. After that, the created quantity of products and energy were sent to four cities according to their demand. This model was tested by applying it to a hypothetical context based on realistic data. The model calculates the total costs to manage each waste fraction in private and outsource certain sectors of public administration completely, such as waste management, to reduce public spending. The proposed model for the integrated chain showed reasonably good results in reducing the average total cost and environmental impacts compared with the previous interested studies. Furthermore, the developed model using the adopted mathematical modeling technique (WGP) showed a better average recovered amount of energy than that obtained by the mathematical formulation utilized in the relevant previous research; this answers a part of the research questions. As well as the designed model includes the relationship among the four components of the WT chain and suggests a coordinated framework for practical and efficient vehicle routing while satisfying the main objectives (Minimize the overall costs and maximize the total recovered energy).

This study introduces serval sensitivity analysis experiments to develop the economic interpretation of altering operating parameters on the WT supply chain's performance; this would take on a new role in decision-making that goes beyond the simple allocation of waste fractions in the various destinations. In fact, these analyses could be useful for a more general strategic reorganization of the SWM of a local organization. For example, a municipality could delegate WM to another organization in case outsourcing was cheaper. Also, the decision maker can add, remove and modify any constraints to immediately check how a different optimal solution can affect the regional structure of WM.

For future research work, the current proposed model can be extended to handle other uncertainties such as variations in number of waste types and demand deviations. It is also crucial to consider optimizing the design of the WT facility; this might help in reducing operating costs through the application of motion studies and reduce the distances traveled inside the facility by labor, tools or waste.

ACKNOWLEDGEMENT

The authors extend their appreciation to King Saud University for funding this work through Researchers Supporting Project number (RSP2023R164), King Saud University, Riyadh, Saudi Arabia.

REFERENCES

Abdallah, M., Hamdan, S., and Shabib, A. (2021). A multi-objective optimization model for strategic waste management master plans. *Journal of Cleaner Production,* 284. DOI: Https://Doi.Org/10.1016/j.jclepro.2020.124714

Arbolino, R., Boffardi, R., De Simone, L., and Ioppolo, G. (2021). Multi-Objective Optimization Technique: A Novel Approach in Tourism Sustainability Planning. *Journal of Environmental Management*, 285. DOI: Https://Doi.Org/10.1016/j.jenvman.2021.112016

Banerjee, A., Shah, P., Nandani, S., Tyagi, S., Kumar, S., and Chaudhury, B. (2021). An Empirical Investigation of OpenMP Based Implementation of Simplex Algorithm. *International Workshop on OpenMP*, 12870: 96-110. DOI: Https://Doi.Org/10.1007/978-3-030-85262-7_7

Cai, X., Cai, H., Shang, C., and Du, C. (2021). Two-Stage Pyrolysis/Gasification and Plasma Conversion Technology for The Utilization of Solid Waste. *IEEE Transactions on Plasma Science*, 49(1): 191-213. DOI: Https://Doi.Org/10.1109/TPS.2020.3044534

Chen, H. L., Nath, T. K., Chong, S., Foo, V., Gibbins, C., and Lechner, A. (2021). The Plastic Waste Problem in Malaysia: Management, Recycling and Disposal of Local and Global Plastic Waste. *SN Applied Sciences*, 437: 1-15. DOI: Https://Doi.Org/10.1007/s42452-021-04234-y.

Chen, L., Wang, L., Zhang, Y., Ruan, S., Mechtcherine, V., and Tsang, D. (2022). Roles of Biochar in Cement-Based Stabilization/Solidification of Municipal Solid Waste Incineration Fly Ash. *Chemical Engineering Journal*, 430. DOI: Https://Doi.Org/10.1016/j.cej.2021.132972

Chu, C., Boré, A., Liu, X., Cui, J., Wang, P., Liu, X., Chen, G., Liu, B., Ma, W., Lou, Z., Tao, Y., and Bary, A. (2022). Modeling The Impact of Some Independent Parameters on The Syngas Characteristics During Plasma Gasification of Municipal Solid Waste Using Artificial Neural Network and Stepwise Linear Regression Methods. *Journal of Renewable and Sustainable Energy Reviews*, 157. DOI: Https://Doi.Org/10.1016/j.rser.2021.112052

Gambella, C., Maggioni, F., and Vigo, D. (2019). A Stochastic Programming Model for A Tactical Solid Waste Management Problem. *European Journal of Operational Research*, 273(2): 684-694. DOI: Https://Doi.Org/10.1016/j.ejor.2018.08.005

Gopalakrishnan, P. K., Hall, J., and Behdad, S. (2020). A Blockchain-Based Traceability System for Waste Management in Smart Cities. *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers*, 6: 6-15. DOI: Https://Doi.Org/10.1115/DETC2020-22553

Heidari, R., Yazdanparast, R., and Jabbarzadeh, A. (2019). Sustainable Design of A Municipal Solid Waste Management System Considering Waste Separators: A Real-World Application. *Journal of Sustainable Cities and Society*, 47. DOI: Https://Doi.Org/10.1016/j.scs.2019.101457

Jammeli, H., Argoubi, M., and Masri, H. (2021). A Bi-Objective Stochastic Programming Model for The Household Waste Collection and Transportation Problem: Case of The City of Sousse. *Operational Research International Journal*, 21: 1613-1639. DOI: Https://Doi.Org/10.1007/s12351-019-00538-5

Kwenda, P. R., Lagerwall, G., Eker, S., and Van Ruijven, B. (2022). Identifying The Leverage Points in The Household Solid Waste Management System for Harare, Zimbabwe, Using Network Analysis Techniques. *Journal of Sustainability* 14(19)**,** 12405. Https://Doi.Org/10.3390/su141912405

Leyang, W., Longxiang, S., and Guangyu, X. (2022). Combinations of The Simplex and Weighted Distance-Based Grey Wolf Algorithms for The Seismic Source Parameter Inversion with Gps Measurements. *Journal of Geomatics and Information Science of Wuhan University*, 0-0. DOI: Https://Doi.Org/10.13203/j.whugis20210114

Mamashli, Z., Nayeri, S., Tavakkoli-Moghaddam, R., Sazvar, Z., and Javadian, N. (2021). Designing A Sustainable–Resilient Disaster Waste Management System under Hybrid Uncertainty: A Case Study. *Journal of Engineering Applications of Artificial Intelligence*, 106. DOI: Https://Doi.Org/10.1016/j.engappai.2021.104459

Mao, L., Wang, J., Zeng, M., Zhang, W., Hu, L., and Peng, M. (2021). Temperature Dependent Reduction of Cr (Vi) to Cr (V) Aroused by Cao During Thermal Treatment of Solid Waste Containing Cr (Vi). *Journal of Chemosphere*, 262. DOI: Https://Doi.Org/10.1016/j.chemosphere.2020.127924

Mayanti, B., Songok, J., and Helo, P. (2021). Multi-Objective Optimization to Improve Energy, Economic and, Environmental Life Cycle Assessment in Waste-To-Energy Plant. *Journal of Waste Management*, 127: 147-157. DOI: Https://Doi.Org/10.1016/j.wasman.2021.04.042

Mohammadi, M., Jämsä-Jounela, S.-L., Harjunkoski, I. (2019). Optimal Planning of Municipal Solid Waste Management Systems in An Integrated Supply Chain Network. *Journal of Computers & Chemical Engineering*, 123: 155-169. DOI: Https://Doi.Org/10.1016/j.compchemeng.2018.12.022

Mojtahedi, M., Fathollahi-Fard, A. M., Tavakkoli-Moghaddam, R., and Newton, S. (2021). Sustainable Vehicle Routing Problem for Coordinated Solid Waste Management. *Journal of Industrial Information Integration*, 23. DOI: Https://Doi.Org/10.1016/j.jii.2021.100220

Nanda, S. and Berruti, F. (2021). Municipal Solid Waste Management and Landfilling Technologies: A Review. *Journal of Environmental Chemistry Letters*, 19**:** 1433-1456. Https://Doi.Org/10.1007/s10311-020-01100-y

Petchrompo, S., Wannakrairot, A., and Parlikad, A. K. (2022). Pruning Pareto Optimal Solutions for Multi-Objective Portfolio Asset Management. *European Journal of Operational Research*, 297: 203-220. DOI: Https://Doi.Org/10.1016/j.ejor.2021.04.053

Saif, Y., Rizwan, M., Almansoori, A., and Elkamel, A. (2019). Municipality Solid Waste Supply Chain Optimization to Power Production under Uncertainty. *Journal of Computers & Chemical Engineering*, 121: 338-353. DOI: Https://Doi.Org/10.1016/j.compchemeng.2018.11.003

Salehi, K., Mehrabian, A., Khalili, H. A., and Navabakhsh, M. (2022). Analysis of Specific States in Nonparametric Decision-Making Methods. *International Journal of Industrial Engineering*, 29(2): 192-205. DOI: Https://Doi.Org/10.23055/ijietap.2022.29.2.8041

Sellitto, M. A., Murakami, F. K., Butturi, M. A., Marinelli, S., Kadel Jr, N., and Rimini, B. (2021). Barriers, Drivers, and Relationships in Industrial Symbiosis of A Network of Brazilian Manufacturing Companies. *Journal of Sustainable Production and Consumption*, 26**:** 443-454. DOI: Https://Doi.Org/10.1016/j.spc.2020.09.016

Seruga, P. (2021). The Municipal Solid Waste Management System with Anaerobic Digestion. *Journal of Energies*, 14(8). DOI: Https://Doi.Org/10.3390/en14082067

Shafiq, M. and Luong, H. T. (2021). Optimal Quantity Allocation Decision in Revenue Sharing Contract. *International Journal of Industrial Engineering*, 28(6): 644-664. DOI: Https://Doi.Org/10.23055/ijietap.2021.28.6.6847

Sharif, N. S., Pishvaee, M. S., Aliahmadi, A., and Jabbarzadeh, A. (2018). A Bi-Level Programming Approach to Joint Network Design and Pricing Problem in The Municipal Solid Waste Management System: A Case Study. *Journal of Resources, Conservation and Recycling*, 131: 17-40. DOI: Https://Doi.Org/10.1016/j.resconrec.2017.12.008

Singh, D. K. and Tirkey, J. V. (2021). Modeling and Multi-Objective Optimization of Variable Air Gasification Performance Parameters Using Syzygium Cumini Biomass by Integrating Aspen Plus with Response Surface Methodology (RSM). *International Journal of Hydrogen Energy*, 46: 18816-18831. DOI: Https://Doi.Org/10.1016/j.ijhydene.2021.03.054

Tascione, V., Mosca, R., and Raggi, A. (2021). A Proposal of An Economic Optimization Model for Sustainable Waste Management. *Journal of Cleaner Production*, 279. DOI: Https://Doi.Org/10.1016/j.jclepro.2020.123581

Torkayesh, A. E., Rajaeifar, M. A., Rostom, M., Malmir, B., Yazdani, M., Suh, S., and Heidrich, O. (2022). Integrating Life Cycle Assessment and Multi Criteria Decision Making for Sustainable Waste Management: Key Issues and Recommendations for Future Studies. *Journal of Renewable and Sustainable Energy Reviews*, 168. DOI: Https://Doi.Org/10.1016/j.rser.2022.112819

Wang, J., Okopi, S. I., Ma, H., Wang, M., Chen, R., Tian, W., and Xu, F. (2021). Life Cycle Assessment of The Integration of Anaerobic Digestion and Pyrolysis for Treatment of Municipal Solid Waste. *Journal of Bioresource Technology*, 338. DOI: Https://Doi.Org/10.1016/j.biortech.2021.125486

Williams, P. T. (2021). Hydrogen and Carbon Nanotubes from Pyrolysis-Catalysis of Waste Plastics: A Review. *Journal of Waste and Biomass Valorization*, 12: 1-28. DOI: Https://Doi.Org/10.1007/s12649-020-01054-w

Yousefloo, A. and Babazadeh, R. (2020). Designing An Integrated Municipal Solid Waste Management Network: A Case Study. *Journal of Cleaner Production*, 244. DOI: Https://Doi.Org/10.1016/j.jclepro.2019.118824

Zaeimi, M. B. and Rassafi, A. A. (2021). Designing An Integrated Municipal Solid Waste Management System Using A Fuzzy Chance-Constrained Programming Model Considering Economic and Environmental Aspects under Uncertainty. *Journal of Waste Management*, 125: 268-279. DOI: Https://Doi.Org/10.1016/j.wasman.2021.02.047