Sustainable Optimization of Waste Management Network to Energy Products over Extended Planning Time Horizon

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Abstract:

This study proposes a multiperiod mixed integer linear programming model for the management of a single municipal solid waste (MSW) treatment plant with sustainability as the objective. Discrete and continuous variables define the capacity selections for diverse MSW technologies, and the operation of the MSW network, respectively. The economic target is considered to maximize the net present value. The environmental impact is the minimization of a normalized environmental objective function (NEOF). The social target is the maximization of jobs. An interesting feature about the research work is the requirement of biodrying technologies for MSW moisture content control. Due to the conflicted nature among the sustainability components, a multi-objective optimization (MO) is carried out to find the Pareto optimal solutions. The MO results show that the Pareto optimal solutions vary around profit range of

US$ 4.9-8.5 billion, NEOF impact range of 3.2-3.6 units, and social benefit range of 2700-4828 jobs.

KEYWORDS: Sustainability, MSW treatment design, Mixed Integer Programming, Multiobjective optimization, Cyclic economy.

1. INTRODUCTION

World population estimation was 7.6 billion with 1.2% growth rate in 2018.[1,2] This rapid increase in population normally will lead to expansion of industries, urbanization, and economic growth which are key factors for municipal solid waste (MSW) generation growth. Solid waste generation was 2.01billion ton in 2016 and it is expected to increase to 3.4 billion ton in 2050.[3] The MSW generation rate and its associated composition depends on economic, environmental, and social factors for any given country.[4] Developing countries still lack appropriate MSW management to deal with the negative impacts of current MSW practices (e.g. open burning and dumping sites). These practices contribute to global warming, human health hazards, and damage of ecosystems.[5] Therefore, decision support models are needed to aid policymakers for efficient MSW management practices development.

MSW management follows several hierarchical steps in order to bring values from the MSW constituents. First step involves collection and followed by segregation processes. After the segregation step, the treatment of the MSW components can be carried out either separately or collectively. Eventually, it is expected to reach final valuable products, and side-wastes which require final treatment. In general, the recyclable material can be treated separately and the non-recyclable parts can be treated jointly.[6] The non-recyclable MSW can be transformed to other products such as electricity or biofuels.[7-9]

Existing MSW management studies were focused on several assessment criterions such as economic, environmental, and efficiencies of technologies. Decision support models were developed in the past based on several mathematical programming formulations which include linear programming (LP) and mixed integer linear programming (MILP), nonlinear programming (NLP), mixed integer nonlinear programming (MINLP), stochastic programming, and hybrid models, for the assessment of optimal MSW management.[10] Other studies also applied the life cycle assessment tools for the MSW management.[11,12] The MSW optimization studies covered in the following literature review are focused on centralized and decentralized mathematical programming based models for the MSW management under deterministic and stochastic model parameters.

Centralized MSW management has received research attention to examine different MSW management issues. Single site optimization of MSW management was addressed to assess optimal processing pathways of MSW under deterministic conditions.[13] The optimization framework was based on superstructure optimization to extract the best optimal economic structure for processing MSW constituents. A multi-objective optimization model (MO) was later examined the tradeoff between the economic and environmental objective functions.[14,15] These studies considered the transformation of recyclable wastes, and nonrecyclable waste to electricity and biofuels. Another study considered the tradeoff between the economic and risk objective functions while optimizing the MSW network.[16] Single site optimization of organic MSW treatment was examined by multiperiod NLP model with only incineration technology for integrated heat and power production.[17] The selection of optimal processing technologies for the transformation of organic MSW to power production was addressed under uncertainties of economic and technical parameters through Monte Carlo simulation over long time planning horizon.[18]

Decentralized MSW management addressed many issues which include the effect of transportation through distributed sites. A multi-objective (MO) MILP formulation was developed to maximize the profit from MSW treatment network while maximizing the conversion of MSW constituents.[19] Another superstructure optimization study addressed the sustainable utilization of MSW in Malaysia with four treatment technologies (e.g., composting, material recycling facility, incineration, landfill gas recovery system).[20] An MILP model is also developed for Hong Kong situation to assess the feasibility of incineration technology.[21] Other studies considered supply-demand and power price uncertainties effects on the MSW supply chain configuration to obtain power from the organic MSW part, and general MSW supply chain management in Mexico.[22-24]

MSW generation normally varies over time with general increasing trend. The MSW treatment network capacity should cope with the increasing flow of MSW over time. It was clearly emphasized that MSW projects face unfavorable difficulties of high cost requirements, fund arrangement, environmental impacts, and public acceptance.[7,25] Thus, optimal cash flow, MSW treatment technology selection, and MSW treatment network impact should be addressed simultaneously over time to find optimal MSW treatment network. The optimal solution for MSW management also should address the environmental impact and social responsibilities. To the best of our knowledge, a capacity expansion of MSW treatment network is not addressed yet in the literature to simultaneously examine the previously mentioned issues. In this research study, a capacity expansion planning model is presented as a multiperiod MILP model for the treatment of MSW on a single site. The model examines the optimal selection of treatment capacities for several MSW treatment technologies (e.g., biological, and thermal technologies). Furthermore, the study explores the tradeoff between the conflicted objective functions (e.g., economic, environmental, and social) through ε-constraint approach in order to find efficient Pareto optimal solutions. Pretreatment of MSW is an important step prior to energy extraction by the thermal MSW treatment technologies.[7,26-28] The aim from the pretreatment step (e.g., moisture content control prior to the thermal treatment technologies) is to find suitable input flow of material with acceptable moisture content, and to enhance the thermal technologies operation. This specific issue was overlooked in the literature for the optimization studies addressing optimal MSW management. The case study for Abu Dhabi city will be examined during the time period of 2025-2055 to show the optimization model application.

The following section describes the MSW treatment network and the research objectives. In section 3, an MILP model will be developed for the capacity expansion of MSW treatment, and MO optimization approach description. In section 4, Abu Dhabi city will be considered as a case study for the proposed model. Finally, we provide research conclusions and future research directions in section 5.

2. RESEARCH OBJECTIVES

2.1 Overview

MSW generation volume and composition vary significantly around the world. These variations can be attributed to different factors such as socioeconomic profile, climatic conditions of a given geographical region, extent of recycling, waste collection efficiency.[29] In addition, the MSW generation volume varies over time which imposes optimal strategic and tactical planning. It is an important task to know the volume, the characteristics (e.g., moisture content, calorific value), and composition of a given MSW in order to design an effective MSW treatment facility.[30] There are many potential technologies for the treatment of MSW[7], however, a legitimate question remains about which technology or combination of technologies that will serve positive economic, environmental, and social impacts over time. These treatment technologies normally present different capital and operation cost, environmental impact, technical constraints, and social impact. Therefore, it is essential to build a systematic decision framework to evaluate these technologies simultaneously. In this research, we base our analysis of MSW management on network optimization which helps in developing a decision based optimization model as will be explained in the following sections.

2.2 Network Representation

Graph theory has been a useful tool to represent material flow through networks for a single site or multiple distributed sites with various engineering applications.[31,32] These networks can be assembled by certain sets of nodes and arcs. It is assumed that the modeler has economic data, technical efficiency for technologies, technology operation restrictions, emissions and environmental data, and social data. The modeler can set up a network which includes large design alternatives that should be evaluated according to a given criterion. Usually, the modeler specifies certain connectivity between the nodes by arcs within the network in order to obtain large number of design alternatives. Our objective is first to give a treatment network representation for the MSW treatment. It is assumed that a set of nodes and another set of arcs are given. It is desired to construct an MSW treatment network based on given information about a set of technologies (tc). These technologies are further decomposed to a set of pretreatment technologies and another set of treatment technologies. Figure 1 depicts an MSW treatment network with consecutive stages starting from a starting node of an MSW source to final nodes of valuable desired products (p).

The figure shows that a single mixed MSW stream represents an input to the MSW network. The MSW is assumed to be with known flowrate and characteristics (e.g., composition, moisture content, etc). After the collection step, the mixed MSW stream is segregated into its corresponding components. A secondary step involves mixing of MSW constituents according to a designer prejudgment in order to insure suitability of predefined mixed constituents with respect to the MSW treatment technologies. In the pretreatment section, the mixed constituents undergoes pretreatment to achieve certain predefined characteristics in order to improve the operation of downstream MSW treatment technologies (e.g., moisture content). The final step involves the transformation of several mixed MSW constituents in the treatment section to final desired end products. Also, it can be noticed that there are some MSW constituents which bypass the treatment technologies. These streams represent recyclable materials which flow through material recycling facilities (MRF) to deliver final recycled products. In addition, side-solid waste generation (SSWG) (e.g., bottom and fly ash) can be generated during the MSW processing and requires final treatment. In this study, we assume SSWG is an inert material and can be disposed in landfills. Therefore, the MSW treatment network represents different alternatives of MSW management which requires simultaneous evaluation to achieve desired goals set by the designer. The following section describes the research problem statement.

2.3 Problem Structure

The proposed research methodology for the optimal MSW management on a single site passes through different hierarchical stages which comprise data collection, MSW system identification, model development, generation of results, analysis of the results, and final recommendations. These steps will be explained briefly in this section. It is assumed that a given region or a city facing growth of population and MSW generation over time. It is desired from a public authority or private investors to evaluate potential benefits from the treatment of MSW. Obviously direct MSW dumping in landfills is not an acceptable solution and the sustainable utilization of MSW is an ultimate target. Therefore, it is assumed that the following is given:

- A planning time horizon (t) that involve yearly time increments.
- Projection of MSW generation and its characteristics over the planning time horizon.
- Set of treatment technologies (tc) with economic and technical data.
- Set of desired products that should bring benefits.

It is desired to identify;

- The optimal MSW treatment network from Figure 1.

- Projection of the capacity expansion of the selected treatment technology over time.
- Assessments of the operational and environmental impact for the selected technologies.
- Evaluation for the tradeoff between the economic, environmental, and social impacts.
- Recommendations from the obtained results.

The following section provides details for the proposed mathematical programming formulation.

3. MILP MODEL

In this section, the MILP capacity expansion model is explained. Section 3.1 covers the design constraints and section 3.2 presents the operation constraints. Section 3 presents the objective functions covered in this study, and section 4 shows the MO optimization approach for the MSW constrained problem.

3.1 Design Constraints

The MILP model describes capacity expansion of MSW network by discrete and continuous variables. Capacity expansion models require selection of efficient technologies among a set of available technologies for the MSW treatment over the planning time horizon.[33-35] The selected optimal values will affect eventually the economic, environmental, and social impacts for the MSW treatment facility. Technology selection is described by a binary variables (y), and the required capacity installation at a given time period (t) is given by a continuous variable (ex). Furthermore, the accumulative capacity of a given technology at a given time period is described by a continuous variable (ac).

$$ex^{UP} y_{tc,t} \leq ex_{tc,t} \geq ex^{LO} y_{tc,t} \; \forall tc, t \tag{1}$$

$$ac_{tc,t} = ac_{tc,t-1} + ex_{tc,t} \; \forall tc, t \tag{2}$$

Eq. (1) states that the expansion of a treatment technology is constrained by an upper (ex^{UP}) and lower (ex^{LO}) bounds of a desired capacity available in the market. It is also implies that a given technology will have zero capacity if it is not selected (e.g., the value for the binary variable y is zero). In addition, Eq. (2) describes the accumulative capacity of a given technology over time.

3.2 Operation Constraints

3.2.1 Material Flow Constraints

The network depicted by Figure 1 shows material flow from an MSW node source to final terminal nodes that provide saleable products. The model represents any stream within the network with total waste flow ($f^{¿}$), and an individual MSW component flow (f_{sw}). For any given node, it is required to conserve material flow balance. The network shows several mixer (mn) and splitter (sn) nodes. Therefore, total and individual material flow can be conserved for the mixer nodes, and splitter nodes. Eqs. (3) and (4) conserve the total material flow, and individual MSW constituent flow balance requirements for a splitter node, respectively. Similar equations can be set easily for the mixer nodes following the same concept. Eq. (5) states that a product flow (f_{pr}) from a given technology is related to the input flow through a conversion factor. Furthermore, the input flow to a given technology should not exceed the available capacity as described by Eq. (6)

$$f_{sn,t} = \sum_{mn} f_{mn,sn,t} \; \forall sn,t \quad (3)$$

$$f_{sn,sw,t} = \sum_{mn} f_{mn,sn,sw,t} \; \forall sn,sw,t \quad (4)$$

$$f_{pr,tc,t} = \alpha_{tc} f_{tc,t} \; \forall tc,t \quad (5)$$

$$f_{tc,t} \leq ac_{tc,t} \; \forall tc,t \quad (6)$$

3.2.2 Environmental and Social Impact Constraints

Processing MSW stream results with gas emissions emitted into the environment. There are large number of critical emissions contributing to the global warming potential (GWP), acidification potential (AP), and human toxicity by furan and dioxin potential (FDP). Regarding GWP, nonbiogenic carbon dioxide, methane (CH_4), and nitrous oxides (N_2O) are considered to be the most contributing components to the GWP. It should be noted the calculation for nonbiogenic carbon dioxide follows the IPCC guidelines.[36] Other chemicals such as Sulphur hexafluoride (SF6), Perfluorocarbons (PFCs) and HydroFluoroCarbons (HFCs) do contribute to global warming, however, their emission factors are limited in the literature.[37] GWP is expressed as carbon dioxide equivalent and it is given by Eq. (7). β represents the emission factor for a given pollutant (e.g., CO_2, CH_4, N_2O) from a given technology. g represents the global warming ratio for a given pollutant (e.g., CH_4, N_2O) with respect to CO_2.

$$GWP = \sum_{tc,t} \beta_{tc}^{CO2} f_{tc,t} + \beta_{tc}^{CH4} g^{CH4} f_{tc,t} + \beta_{tc}^{N2O} g^{N2O} f_{tc,t} \quad (7)$$

AP is considered as equivalent of sulfur dioxide (SO_2) impact, and it is attributed to sulfur dioxide (SO_2), hydrogen chloride (HCl), and ammonia (NH_3). The AP is expressed by Eq.(8). In this equation, β represents the emission factor for a given pollutant (e.g., SO_2, HCl, NH_3), and s represents the acidification ratio for a given pollutant (e.g., HCl, NH_3) with respect to SO_2. Other toxic organic pollutants consist of dioxins and furans and referred to as PCDDs/PCDFs (polychlorinated dibenzodioxins/dibenzofurans). FDP is expressed by Eq. (9) with respect to dioxins and furans emissions with similar terminology for the parameters given by Eq. (8). In addition, SSWG can be formulated with similar concept given by Eq. (9). Eq. (10) expresses the job creation (Jobs) by every technology as a function of constant parameter (η), and the expansion capacity of the MSW technologies. It is also worth mentioning that other sections in the treatment network (e.g., segregation and pretreatment sections) may generate jobs. However, these sections have limited information in the literature regarding jobs creation.

$$AP=\sum_{tc,t} \beta_{tc}^{SO2} f_{tc,t} + \beta_{tc}^{HCl} s^{HCl} f_{tc,t} + \beta_{tc}^{NH3} s^{NH3} f_{tc,t} \quad (8)$$

$$FDP=\sum_{tc,t} \beta_{tc}^{PCDDs/PCDFs} f_{tc,t} \quad (9)$$

$$Jobs=\sum_{tc,t} \eta_{tc} ex_{tc,t} \quad (10)$$

3.2.2 Carbon Avoidance Constraints

Diversion of MSW flow from direct landfilling should bring positive economic, environmental, and social impacts. In general, construction of MSW treatment plants leads to generation of carbon credits as recommended by United Nations through the clean development mechanism. In order to give an estimate for the carbon avoidance ($f_{\square}^{ca}$), the global warming potential ($GWP_{\square}^{LF}$) from direct disposing of MSW mass in landfills is needed. We follow the IPCC guidelines for this estimation.[38] The carbon avoidance by adopting the MSW treatment network is expressed by Eq. (11).

$$f_{\square}^{ca} = GWP_{\square}^{LF} - GWP \tag{11}$$

3.2.3 Biodrying Technology Constraints

MSW encompasses several fractions of MSW with different physical and chemical properties. The moisture content of the MSW fractions affects negatively the extractable energy from these fractions. The MSW high moisture content might lower the overall efficiency of the plant, and rise the operating cost of combustion.[27,28,39] It is assumed that a biodrying process exits before the thermal MSW treatment technologies to reduce the moisture content to an acceptable level if it is necessary. This condition imposes additional modelling constraints.

We assume that several MSW constituents are allowed to pass through the biodrying process. An overall material balance is carried out for every MSW constituent around the biodrying process, and it is given by Eq. (12). fin and fout represent the input and output material flow for a given MSW constituent, respectively. Orgloss and MSfout are continuous variables that describe the organic material loss, and the moisture drying output from MSW constituents as a result of the biodrying process operation. The organic material loss from these fractions is proportional to the input flow by a factor (e.g., $OF\%¿$ as given by Eq.(13). Also, there is need for moisture content balance around the biodrying process, and it is given by Eq. (14). inmo, and outmo are parameters which provide the input and output moisture content, respectively. In addition, Eq. (15) represents moisture content requirement for a given MSW thermal treatment technology. mo is a parameter which gives the maximum allowable moisture content for the inlet feed to a given thermal MSW treatment technology. This equation states that the moisture content for the feed prior to a given thermal treatment technology should be lower than the moisture content for the biodrying process exit stream. In the supplementary section, the biodrying parameters are provided.

$$fout_{sw,tc,t} + Orgloss_{sw,tc,t} + MSfout_{sw,tc,t} = fin_{sw,tc,t} \; \forall sw, tc, t \tag{12}$$

$$Orgloss_{sw,tc,t} = OF\%_{sw} fin_{sw,tc,t} \; \forall sw, tc, t \tag{13}$$

$$inmo_{sw} fin_{sw,tc,t} = outmo_{sw} fout_{sw,tc,t} + MSfout_{sw,tc,t} \; \forall sw, tc, t \tag{14}$$

$$\sum_{sw} outmo_{sw} fout_{sw,tc,t} \leq mo_{tc} f^{¿}_{tc,t} \; \forall tc, t \tag{15}$$

3.3 Objective Functions

The cost associated with the MSW network comprises capital cost, operation cost, and profit generated from the desired products, carbon credit, and tipping fees. These elements (e.g., cost and benefits) are optimized over the planning time horizon taking into consideration an annual interest rate (i). The net present value (NPV) is maximized in case the objective is with an economic target. The NPV involves several terms as given by Eq.(16). The profit is generated from selling a set of products (p), carbon credit, and tipping fee on the MSW treatment as given by Eq.(17). The capital cost and operation cost are given by Eqs. (18,19).

$$NPV = Profit - (Capital + Operation) \tag{16}$$

$$Profit = \sum_{p,t} \frac{c_p f_{p,t}}{(1+i)^t} + \frac{c_{ca} f_t^{ca}}{(1+i)^t} + \frac{c_{tip} f_t^{¿,MSW}}{(1+i)^t} \tag{17}$$

$$Capital = \sum_{tc,t} \frac{c_{tc}^{capital} ex_{tc,t}}{(1+i)^t} \tag{18}$$

$$Operation = \sum_{tc,t} \frac{c_{tc}^{operation} f_{tc,t}^{¿,MSW}}{(1+i)^t} \tag{19}$$

Another objective function considered in this study is to minimize the environmental impact of the treatment network. We described previously that the environmental impact is due to GWP, AP, FDP, and SSWG. Although it is possible to minimize all these contributors to the environmental impact, the computational requirements for the ε-constraint method which will be described later becomes demanding. To circumvent this issue, we define an aggregate normalized environmental objective function (NEOF) that should be minimized. Eq. (20) describe the NEOF which includes mainly four parts reflecting the GWP, AP, FDP, SSWG. NF_1, NF_2,NF_3, and NF_4 are normalized constant factors for the GWP, AP, FDP, SSWG. These constants are the optimal solutions for the GWP, AP, DFP, and SSWG when we carry out the analysis under economic target (e.g., by considering only maximization of Eq. (19)). Therefore, the optimal results by minimizing Eq. (20) shows how relatively the NEOF of the MSW treatment can be minimized with respect to the solutions from the economic target. The social objective function is to simply maximize Eq. (10).

$$NEOF = \frac{GWP}{NF_1} + \frac{AP}{NF_2} + \frac{FDP}{NF_3} + \frac{SSWG}{NF_4} \tag{20}$$

The economic, NEOF, and social objective functions normally show conflicted results when these functions are treated in an isolated fashion. The decision makers may be interested in a compromised solution among several optimal solutions. The following section describes the MO approach adopted in this study.

3.4 MO Optimization

MO optimization methods can be classified in general as Pareto and scalar weighted methods.[40] Pareto based MO optimization approach showed several advantages over the weighting approach.[41,42] Therefore, we adopt the augmented ε-constraint method, and it is shown to be effective in identifying the Pareto optimal solutions with an effective solution algorithm.[41,42] To explain this method, first let’s consider the mathematical programming model below as MP1. For the sake of simplicity, we assume that we consider p objective functions that should be maximized subject to the feasible set of solutions S. These functions are defined over the decision variables x. In addition, we assume that the objective functions pose conflicted results.

$$\left.\begin{array}{l} max\left(of_1, of_2, \ldots, of_p\right) \text{¿¿} X \in S \text{¿¿} \\ \quad subject \\ \quad \text{¿} \end{array}\right\} MP1$$

In order to apply the method, the ranges for the considered objective functions have to be determined. This is an essential step to carry out the method for finding the efficient Pareto optimal solutions. A common approach to identify these ranges is through the construction of payoff table or lexicographic optimization. To construct the payoff table, one can treat the MO problem with a single objective function as a first step. Then, in a second step, an upper bound is added for the first objective function since we have maximization, and the second objective function is optimized. Afterwards, bounds on the first and the second objective functions are added and the third one is optimized. This procedure continues for other objective functions under consideration. From this procedure, it is guaranteed that the obtained ranges for the considered objective functions confine the Pareto optimal solutions, and further discussions and theoretical background can be found elsewhere.[41,42]

Another phase for the augmented ε-constraint method is to divide the ranges of the considered p-1 objective functions from the previous step into several grid points. Then, the last objective function can be optimized over all the given obtained grid points to find the efficient Pareto optimal solutions. The mathematical programming model given by MP1 can be transformed to MP2 in order to carry out the augmented ε-constraint method. In MP2 formulation, we assume that we have three objective functions (e.g., economic, environmental, and social functions). Two objective functions are treated as constraints, and the third one is optimized. Furthermore, we assume that the environmental (f_2), and social (f_3) objective functions are treated as constraints, and the economic one (f_1¿ is the focus of the optimization by MP2.

$$\left.\begin{array}{l} \underset{\text{subject } ¿}{max} \, o f_1 + eps\left(\frac{s_2}{r_2}+\frac{s_3}{r_3}\right) ¿ o f_2 - s_2 = e_2 ¿ o f_3 - s_3 = e_3 ¿ X \in S ¿¿ \end{array}\right\} MP2$$

This formulation is an attractive one since the constraints for p-1 objective functions are binding at the optimal solution for the optimized target objective function. e_2 and $e_3$are parameters which define a grid point, and s_2 and s_3 are slack positive variables. eps is a small number (e.g., 10^{-6}).[41] In addition, r_2 and r_3 are values to normalize the slack variables which can be chosen as explained before by Eq. (20) in the previous section. It should be pointed out that MP2 is not always feasible for all the grid points.[41] The algorithm starts from the relaxed bounds of the environmental and social objective functions (e.g., grid points with the relaxed bounds), and the economic objective can be solved. Then, the bounds move to restricted regions in order to explore all chosen grid points. The algorithm declares Pareto optimal solution if model MP2 is feasible, otherwise Pareto optimal solutions do not exist if model MP2 is infeasible. Interested readers can cover the research work and algorithm development for further details about the ε-constraint method.[41,42] The following section presents the result for Abu Dhabi city MSW treatment network.

4. CASE STUDY

4.1 Overview

The United Arab Emirates (UAE) is a federation of seven emirates, and Abu Dhabi city is the capital of the country. The per capita MSW generation rate in UAE is between 1.76 and 2.3 kg/d which is reasonably higher and comparable to average American citizen with about 2.1 kg of waste/day.[43,44] In UAE, Abu Dhabi Emirate is the largest emirate by area and has population of approximately 2.8 million.[45] MSW generation in the Emirate is approximately 1.3-1.7 million tons every year.[46] Most of the MSW is disposed in the dumpsites, which is not a sustainable MSW practice. Only 20% of the waste is recycled in year 2015.[46] Figure 2 shows the expected growth of MSW for Abu Dhabi city during the considered planning time horizon[18], and Table 1 shows the composition of the MSW components. From the given MSW estimate, it is clear that the MSW management should be revised to identify potential sustainable utilization of the MSW constituents, and bring values for the Emirate.

4.2 Abu Dhabi Emirate Initiatives

The center for waste management was setup in February 2008 by the government of Abu Dhabi to manage and coordinate waste management responsibilities. There are interests in landfills with energy recovery, incineration, biofuels, and compositing facilities. Masdar Institute carried out research in the application of MSW dark fermentation to produce biodiesel. The outputs from the research suggested that the produced biogas could generate 18 MW/y for Abu Dhabi.[47] Other research projects are in progress which include for example the production of biodiesel from waste restaurant oils. TAQA, an international energy company based in Abu Dhabi, is adopting the waste to energy initiatives in Abu Dhabi by considering an incineration plant.[48] TAQA plans to construct two waste to energy plants, and the company plans to convert one million ton/year of waste to power.[49] The plant is projected to eliminate the discharge of more than one million ton of CO_2 per year.

4.3 Case Study Structure

The case study covers the MSW sustainable management for Abu Dhabi city during the time frame of 2025-2055. The starting year is chosen to be 2025 because normally MSW construction projects may take up to five years due to preliminary design, procurement, installation, and commissioning activities.[50] In addition, any further capacity expansions during the planning time horizon is only allowed for every five consecutive years. Several biological technologies such as landfill gas with energy recovery (LFGE), composting, and anaerobic digestion (AD) are considered. Thermal treatment technologies are represented by incineration and pyrolysis, and material recycling facility (MRF) are for recycling the recyclable material. Further description of these technologies is given in the supplementary section with technical, economic, environmental, and social data. The assignment of wastes to the treatment technologies is listed in Table 2. The proposed model was coded in the General Algebraic Modelling System (GAMS) and solved by Cplex solver. This model involves 7,957 equations, 7,594 continuous variables, and 63 binary variables. The execution time takes around 0.18 CPU seconds.

Several conditions will be analyzed in the following sections. These conditions describe the following:

- The first one shows that the decision makers focus primarily on the economic impact.
- Under the second condition, the interest of decision makers is to examine the possibilities of reducing the environmental impact from the MSW treatment network over time.
- The third condition examines enhancing the social impact of the MSW treatment network.
- The fourth condition explores the tradeoff between the economic, environmental, and the social objectives.

4.4 Results and Discussion

4.4.1 Economic Objective Condition

The NPV is around US$ 8.67 billion as given in Figure 3, and the selected treatment technologies are LFGE, composting, AD, and pyrolysis for the treatment of nonrecycable MSW constituents. MRF is the accumulated treatment capacity for recycling the glass, and metals as given in Figure 4. LF without energy recovery is the ultimate disposable of SSWG from the treatment technologies. In Figure 3, the generated profit arises mainly from selling the compost and generating CO_2 credit, followed by the tipping fee, MRF sale, and power sale. The digestate represents minor profit which is around 0.14% from the generated profit. In addition, the capital and operation cost is relatively smaller than the generated profit. In Figure 4, it can be noticed that heavy installment capacities of the treatment technologies occur in early years of the planning time horizon, and followed by smaller expansion of capacities over time due to the time value of money (e.g., the interest rate is assumed to be 8%). Also, it can be noticed that the biological treatment technologies are the dominant technologies which represent 91% of the total accumulated treatment capacity, followed by the pyrolysis technology.

Figure 5 depicts the share of MSW components by the selected MSW technologies over the planning time horizon. The MSW treatment operation for the selected technologies are affected by the optimization model restrictions (e.g., the existing capacities, MSW moisture content, economic). The biological technologies are less sensitive with respect to the inlet feed moisture content compared with the thermal technologies. In general, the biodrying process leads to material loss, and moisture content reduction. The optimizer under the given condition seeks maximum utilization of material in order to gain more profit. Furthermore, biological treatment technologies are less expensive compared with the thermal technologies. These factors (e.g., economic and MSW moisture content) leads to the given distribution of subwastes. Composting technology receives organic and paper components with high moisture content. This affects the economic to great extent since the majority of profit arises from compost sales. Similar observation can be stated for subwastes diversion to the AD and LFGE technologies. The optimal solution diverts these MSW components from pyrolysis to avoid high mass loss by the biodrying technology (see Table S11 in the supplementary section), and to enhance the material utilization. The total amount of MSW treatment is around 1.52 billion ton over the planning time horizon. Around 92% of this flow is treated by the biological technologies, and the rest is treated by the pyrolysis technology.

The environmental and social impacts are given in Figure 6. In this figure, the MRF environmental and social impacts are excluded from the presentation since the technology shows fixed amount of environmental and social impacts over all the given conditions under this study which will be covered in the following sections. The GWP and AP for the selected technologies in Figure 6 are 16.4 Million ton of CO_2 equivalent, and 1.2 Million ton of SO_2 equivalent, respectively. The FDP and SSWG are 635 grams, and 77.2 million ton, respectively. LFGE and composting technologies contribute around 52.8%, and 34.7% to the GWP, whereas AD and pyrolysis technologies contribute only 7.2%, and 5.3% to the GWP, respectively. The AP potential is affected mainly by the composting technology with 84.1% impact. Other technologies shares the rest of the AP. In terms of FDP, the LDGE contributes the major part with a value around 99.3%. Thus, LFGE and composting technology are the major contributors to the overall environmental impact. The social impact shows an overall generation of 1249 jobs over the planning time horizon, and 999 jobs are generated for the selected technologies in Figure 6. This social impact is affected mainly by the pyrolysis and composting technologies with values around 50% and 31% of the total generated jobs, respectively. In the following section, the environmental impact is considered as a driving objective for the decision makers.

4.4.2 Environmental Objective Condition

Under the given condition, the NEOF reflecting the GWP, AP, FDP, and SSDG is minimized. The normalized values for the environmental objective contributors are based on the values obtained from the previous section results. The NEOF optimal value is 2.9, thus, the NEOF reduction is around 28%. AD and pyrolysis are the only selected technologies. Figure 7 shows the distribution of the environmental and social impacts among the treatment technologies. Again, the MRF results are excluded from the presentation similar to the reasoning given in the previous section. The GWP and AP over the planning time horizon are 10.9 Million ton CO_2 equivalent, and 0.32 Million ton SO_2 equivalent, respectively. Thus, reductions of 33% of GWP, and 73% of AP can be achieved under the given condition. In addition, the SSWG and FDP optimal values are around 93.5 Million ton, and 25.7 grams, respectively. Under the given condition, the results indicate an increase of SSWG by 21%, and a reduction of FDP by 96% in comparison with the previous condition. Furthermore, the given condition shows positive social impact with 2675 job creation.

The economic distribution and capacity expansion projection for the treatment technologies over time are given in the supplementary section. The NPV is estimated around US$ 3.95 billion, which shows negative economic impact by 54% compared with the previous condition. The major profit contribution arises from CO_2 credit generation which represents almost 69.6% of the generated profit. Other profit are distributed among MRF sale, power sale, tipping fee, and digestate profit. AD is the major MSW treatment technology with total capacity around 4404 ton/day, whereas the installed capacity of pyrolysis technology is around 2118 kg/day over the planning time horizon. In addition, the utilization of MSW components by the treatment technologies is given in the supplementary section. Similar to the previous condition, the AD biological technology processes MSW constituents with high moisture content, and high material loss potential by the biodrying technology, whereas the pyrolysis technology processes MSW components with low moisture content and low material loss potential. The following section examines the social impact as an objective for the decision makers.

4.4.3 Social Objective Condition

The optimal solution under the given condition gives 5359 jobs over the planning time horizon. Clearly there is great improvement for the social indicator by 329% compared with the economic objective condition. However, the NPV degrades by 54% compared with the economic condition. Pyrolysis and composting are the selected technologies under the given condition. In addition, MRF and LF exist in the treatment network for recycling glass and metal, and disposal of SSWG. In terms of the environmental impact, the NEOF shows improvement by 9.8% compared with the economic condition. The NPV distribution, capacity expansion for the selected technologies, material utilization, and environmental and social impacts can be found in the supplementary section. In general, one can conclude from the previous results that enhancement of the environmental and social indicators leads to degradation of the economic indicator by roughly 54%.

The given results for the sustainability indicators show completely different selection of treatment technologies. The capacities are normally chosen with relatively high values at early time periods for better economics. Furthermore, the economics, environmental, and social impacts are different under the given conditions. Consequently, improper decisions at the early planning stages will affect the future sustainability impacts. In addition, there is clear tradeoff among the sustainability indicators. The decision makers may need to look at compromised solutions which give tradeoff between these indicators. Therefore, carrying out MO analysis is necessary to identify efficient non-dominant optimal solutions.

4.4. MO Optimization

In order to properly apply the augmented ε–constraint method, one must have the range of at least two objective functions (e.g., the range between the maximum and minimum values for the NEOF and social objective function). Then, the economic objective function can be optimized over the obtained ranges for the normalized environmental and social objective functions. In order to apply the method, the payoff table should be constructed by the lexicographic optimization. The results of the lexicographic optimization is given in Table 3. Within these ranges of the objective functions, the Pareto optimal solutions exit. However, it is not guaranteed to find optimal values for all grid points within these ranges since infeasibilities may exist.[41,42]

Five grid points were chosen for every range of the objective functions. Figure 8 shows the NPV variation with the social indicator under different values of the NEOF. It can be noticed in this figure that the NPV values do not exist below 3.2 for the NEOF values since the optimization solver declares infeasibilities. Furthermore, infeasibilities do exist for job values higher than 4200 with some NEOF values (e.g., under social impact of creating jobs higher than 4200 job is not feasible with reduced environmental impact below 3.3). It can be stated clearly from the obtained results that the range of the Pareto optimal solutions greatly reduced as compared with the results given in Table 3 (e.g., the tradeoff between the objective functions exists within 3.2-3.6 range of the NEOF, and within 2700-4800 jobs for the social impact). This may imply for the decision makers that the environmental impact is minor within the Pareto optimal solutions compared with the values for the social impact (e.g., the environmental impact changes within 0.4 units, while the social impact range changes within 2100 jobs). Furthermore, the results in Figure 8 show reduced economic gain trend with reduced environmental impact and increased social impact. For example, the lowest economic gain is around US$ 4.9 billion for the grid point representing 3.3 value for the NEOF and 4297 job creation, whereas the maximum economic gain is around US$ 8.52 billion under the relaxed environmental and social impacts (e.g., the NEOF is around 3.6 units and the social objective function is around 2700 jobs).

It is also worth examining the selected capacities for the MSW treatment technologies within the Pareto optimal solutions. Figure 9 shows the capacities for the selected treatment technologies under different environmental and social impacts. A quick observation from the figure reveals that pyrolysis technology shows an increasing trend of capacities as a function of jobs creation, and the capacity selection is insensitive with respect to the environmental impact. In addition, the contribution of pyrolysis technology capacity is higher than the capacities of biological technologies. Thus, if one assumes that the decision makers are neutral about the environmental impact generated by the pyrolysis technology (e.g., previous results showed that the overall NEOF changes by 0.4 units within the environmental objective function range), then this technology is an attractive option from sustainability point of view.

The biological technologies show decreasing trend of capacity expansion as a function of the social impact. In addition, the selected biological technologies are sensitive with respect to the environmental impact metric. LFGE technology is not attractive option within low desired environmental impact. Although LFGE is a cheaper technology compared with MSW treatment technology, LDFGE technology is less attractive technology compared with the selected technologies due to relatively its negative environmental and social impacts. In Figure 9, the selected capacities for AD and composting shows opposite trend with respect to each other under the considered ranges of environmental and social indicators. Under low environmental impact, the results show that AD technology is more preferred than the composting technology, whereas the composting technology is more preferred under loose environmental impact compared with AD technology.

The results in this section show that the optimal selection of MSW treatment technologies are different than the results when the optimization model is treated under single objective function target. Considering MO optimization bring useful insights about the tradeoff existing among these objective functions. Clearly the decision makers may impose their interests within the considered domains of the objective functions. Under the assumption of less interest being paid by the decision makers toward the environmental impact (e.g., the NEOF changes within 3.2-3.6 units) and more emphasis is given for the economic target, a compromised solution can be found in Figure 8. This solution shows that considering environmental impact value with 3.5 units gives economic impact around US$ 8.27 billion, and social impact around 3765 jobs. Comparing this solution with possible ranges for the objective functions shows minor deterioration in the environmental impact by 9% compared with the best environmental value (e.g., the results show that the best environmental impact value is around 3.2 units as given in Figure 8). Furthermore, the economic indicator shows negative impact of around 3% loss of profit compared with the best economic value in Figure 8. The social impact shows negative loss of jobs by approximately 22% compared with best social impact value in Figure 8. For the given solution, the selected technologies are composting, AD, and pyrolysis. It is worth mentioning that incineration technology does not appear as a promising sustainable technology under the given examined conditions in this research study.

5. CONCLUSIONS

In this study, sustainable utilization of MSW constituents are presented through an MILP model. The model addressed the capacity expansion and selection of several biological and thermal treatment technologies over an extended planning time horizon. The model also examined sustainability of the MSW treatment network by considering the economic target maximization, environmental impact minimization, and social impact maximization. Due to the conflicted nature between the sustainability indicators, the augmented ε–constraint method is proposed to find the Pareto optimal solutions. Additional feature of the optimization model is the consideration of the biodrying technology prior to the thermal treatment technologies.

The optimization model is applied for Abu Dhabi city in UAE for the time periods of 2025-2055. The case study is analyzed preliminary under single objective functions which include economic, environmental, and social impacts. The NPF under the economic target showed net profit around US$ 8.67 billion, whereas significant economic deterioration appeared under the environmental and social targets roughly by 54%. The environmental target showed that the optimal value for the NEOF is 2.9 units which is lower than the environmental impact under the economic target by 28%. In addition, the social target optimal result provides around 5359 jobs which is higher than the economic target by 329%. The selected treatment technologies vary significantly under the economic, environmental, and social conditions.

The results for the MO optimization showed that the Pareto optimal solutions possibly vary around profit range of US$ 4.9-8.5 billion, NEOF range of 3.2-3.6, and social benefit range of 2700-4828 jobs. The general trend for the results showed that there is profit loss under strict environmental requirements, and high social impact. The selected technologies are LFGE, AD, composting, and pyrolysis within the Pareto optimal solutions. In addition, the biological technologies showed decreasing capacity trend with high social responsibilities, whereas pyrolysis technology showed opposite trend. Under the assumption of low interest for the decision makers toward the environmental impact and high interest toward economics, a compromised solution is proposed. This solution provides profit around US$ 8.27 billion, 3.5 units of NEOF, and 3765 jobs. The current study treated the model parameters at their averaged values, however, these parameters may be uncertain. Therefore, our future aim is to carry out the modelling and analysis for the MSW treatment network under uncertainty.

NOMENCLATURE

Abbreviations

AD	Anaerobic digestion
AP	Acidification potential
CWM	Center of waste management
FDA	Furan and dioxin potential
GWP	Global warming potential
LFGE	Landfill gas with energy recovery
LP	Linear programming
MILP	mixed integer linear programming
MINLP	Mixed integer nonlinear programming
MO	Multi-objective optimization
MRF	Material recycling facility
MSW	Municipal solid waste
NEOF	Normalized environmental objective function
NLP	Nonlinear programming
NPV	Net present value
SSWG	Side solid waste generation
UAE	United Arab emirates

Sets

mn	Set of mixer nodes in the MSW network
p	products
sn	Set of the splitter nodes in the MSW network
sw	MSW constituents
t	Years for the planning time horizon
tc	MSW treatment technologies

Variables

ac	Accumulated capacity for a treatment technology
AP	Acidification potential
Capital	Capital cost for the treatment technology
ex	Expansion capacity for the treatment technologies
f	Mass flow in the network
FDB	Furan and dioxin potential
fin	Input flow for an MSW constituent to biodrying technology
fout	Output flow for an MSW constituent to biodrying technology
GWP	Global warming potential
Jobs	Number of jobs created by the MSW treatment technologies
MSfout	Moisture loss as a result of biodrying technology

NEOF	Normalized environmental objective function
NPV	Net present value
of	It represents one of the objective functions
Operation	Operation cost for the treatment technology
Orgloss	Organic loss in the biodrying technology
Profit	Profit generation from selling the product
s	Slack variables as defined by MP2
SSWG	Side solid waste generation
y	Binary variable for the expansion of a treatment technology
Parameters	
α	Efficiency of a treatment technology
e	Grid point value as defined by MP2
eps	Small number
r	Normalization factor as defined by MP2
NF	Normalized environmental factor as defined by Eq. (20)
c_{tip}	Tipping fee constant
c_p	Sale coefficient for a given product
i	Interest rate
c_{ca}	Carbon credit constant
$c_{tc}^{operation}$	Operation cost coefficient for a treatment technology
outmo	Outlet moisture content for an MSW constituent
mo	Inlet moisture content for an MSW treatment technology
inmo	Inlet moisture content for an MSW constituent
$c_{tc}^{capital}$	Capital cost for a treatment technology
OF %	Percentage of organic loss from an MSW constituent
η	Ratio for job creation by a treatment technology
β	Emission factor
g	Global warming ratio for a given pollutant
s	Acidification ratio for a pollutant
Superscripts	
ca	It designate the carbon avoidance
LF	It designate the landfilling without energy recovery
LO	A lower bound for a decision variable
to	Designation of a stream total flow within the network
UP	An upper bound for a decision variable

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