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Energy use and environmental emissions of integrated waste management system in Tehran municipality

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Abstract

The aim of this study was to evaluate energy use, environmental emissions, recycled materials quantity, and environmental pollutants in Tehran Municipality's integrated waste management (IWM) system. The system consists of six subsystems: transportation, processing and separation, aerobic digestion, anaerobic digestion, incineration, and landfill. Data was obtained from the Waste Management Organization of Tehran Municipality. The analysis indicated that energy consumption for transportation, processing, and recycling was approximately 227.02 and 271.21 GJ per 8500 tons of municipal solid waste (MSW), respectively. Various environmental impact indicators were studied using the LCA method to assess environmental emissions in Tehran's MSW recycling system, including AD, AC, EP, GWP, OLD, HT, FE, ME, TE, and PO. The results of the LCA revealed transportation as a significant hotspot in MSW recycling, with recycling paper demonstrating a decrease in adverse environmental effects. The rate of TE release was calculated at -10.55 kg 1,4-DB eq., mainly attributed to paper recycling efforts.

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Introduction

The exponential growth of technology and human population since the industrial revolution has led to a significant increase in waste production. The environmental issues associated with the indiscriminate production of various types of waste have become more pressing than ever. Municipal Solid Waste (MSW), which includes household, garden, and institutional waste, is projected to double in the next decade due to factors such as population growth, urbanization, and the social and economic development of low- and middle-income countries (Rajaeifar et al., 2019). In the urbanizing world, a significant issue is the management of MSW in countries, particularly in developing nations where economic growth and urban expansion have led to a substantial increase in MSW generation. The volume of MSW generated in Iran has surged in recent years, with Tehran Metropolis currently being the country's primary contributor to MSW. In 2015, Tehran Metropolis produced 8500 tons (approximately 1.1 kg per capita) of MSW daily. MSW accounts for over 97% of solid waste in Tehran, while the remaining three categories - hospital waste (1.0%), industrial waste (0.6%), and construction waste (0.5%) - make up less than 3% collectively. Household solid waste contributes around 62.5% to the total MSW output (Chen et al., 2016).

This requires the implementation of strategies to reduce emissions. Municipal activities are a major source of global waste generation, prompting various initiatives to tackle these challenges. One such initiative is municipal waste recycling, which can recover valuable materials and lessen environmental harm. Energy consumption plays a vital role in sustainable economic development during the recycling process. Environmental experts highlight energy consumption as a key factor in carbon dioxide emissions, a major contributor to greenhouse gas emissions, global warming, and climate change (Rasapoor et al., 2016). Life cycle assessment (LCA) is utilized to evaluate the environmental impact of MSW recycling, offering a comprehensive approach to identifying effective waste management solutions. LCA is a widely used method for assessing the environmental impacts of products throughout their lifecycle (Khandelwal et al., 2019). The study addresses the challenges and opportunities of municipal solid waste management, focusing on the city of Tehran. It introduces a comprehensive model that takes into account various factors such as costs, air pollution, and waste volume, and evaluates the effectiveness of different waste management technologies. The analysis highlights the importance of recycling and composting in waste management, with incineration and anaerobic digestion identified as suitable technologies for managing specific waste fractions. The study also proposes capacities for energy generation systems based on different technologies, emphasizing the need for sustainable waste management practices to mitigate pollution and maximize resource recovery (Hosseinalizadeh et al., 2021).

LCA is commonly utilized in various studies as a valuable tool for efficient MSW management. It aids in conducting environmental assessments of different waste management systems and identifying areas that may benefit from enhancements (Erses Yay, 2015). Several recent studies have applied this tool to evaluate various municipal waste management scenarios, focusing on outlining alternative waste management strategies for recyclable materials and residual mixed waste. Many of these studies have highlighted the role of LCA in guiding decision-making towards the most environmentally sound waste management practices (Tonini and Astrup, 2012). Additionally, Artificial Neural Networks (ANN) are computational tools used in various fields for solving complex problems like estimating non-linear functions, pattern recognition, clustering, simulation, and optimization. ANN models have been employed in predicting energy consumption and pollutant emissions in different research studies. Furthermore, research utilizing Artificial Intelligence (AI) to forecast waste production has shown promising results, validating the effectiveness of AI methods in modeling various processes (Kaab et al., 2019). Although energy is crucial, there has been a lack of comprehensive research on energy analysis and modeling in relation to energy output and environmental indicators compared to energy consumption in the recycling of MSW in Tehran, Iran. Given the significant economic value, growing export rates, and absence of energetic and LCA studies in MSW recycling, this study aimed to assess and contrast the energy consumption and environmental effects of the recycling process waste. Additionally, it sought to develop a detailed Artificial Neural Network (ANN) model for predicting the quantity of recycled materials and the environmental impact categories of MSW on a daily basis.

One novelty about the energy use and environmental emissions of the integrated waste management (IWM) system in Tehran Municipality of Iran is the implementation of advanced technologies and practices to minimize the environmental impact of waste management activities. This includes the use of energy-efficient equipment, such as waste-to-energy plants and landfill gas capture systems, to reduce greenhouse gas emissions and improve air quality. Additionally, Tehran Municipality has been actively promoting recycling and composting programs to divert waste from landfills and reduce the overall energy consumption associated with waste disposal. By implementing these sustainable waste management practices, the municipality is working towards achieving its environmental goals and contributing to a cleaner and healthier environment for its residents. Overall, the integration of innovative technologies and sustainable practices in the waste management system of Tehran Municipality sets a positive example for other cities in Iran and around the world to follow in order to reduce energy use and environmental emissions associated with waste management activities.

Materials and methods

Background information about the case study

The capital of Iran, Tehran, a city with more than 220 years of age, is situated on the southern foothills of the Alborz Mountains. It is centrally located in the between latitude 35° 34′ – 35° 50′ North and longitude 51° 08′ – 51° 37′ East. The city's altitude ranges from 1700 m in the North to 1200 m in the center and 1100 m in the South. Tehran experiences a hot and dry climate, with a mean air temperature of 18°C. The average maximum and minimum temperatures are 38.7 and -7.4°C, respectively, with an annual precipitation of 245–316 mm. The city spans an area of 664 km^2, consisting of 22 urban regions. Tehran has two waste collection sites, namely Abali and Kahrizak. The Abali site is situated 17 km east of Tehran and 4 km west of the Judgerood River, while the Kahrizak site is approximately 35 km south of Tehran. Both sites receive various types of waste according to the Waste Management Organization of Tehran Municipality.

To gain a comprehensive understanding of solid waste management in Tehran, data pertaining to various aspects were gathered and examined. This included details on MSW generation (both quantity and quality), on-site management, storage, processing, collection systems, transfer logistics (including transfer stations), as well as the prevailing recycling and processing methods within regional municipalities.

Energy flow

Assessing and examining the flow of energy and modeling energy consumption in a production system requires the calculation of input-output energies. To achieve this, energy coefficients are utilized to convert all inputs to their energy equivalent during the waste management recycling process. Data was collected for 8500 tons (the daily production of MSW in Tehran) and converted into energy units using embodied energy equivalents for each input and output energy type, expressed in GJ (8500 ton MSW)$^{-1}$. The energy coefficients, as shown in Table 1, were utilized to determine the energy equivalent by multiplying the consumption of inputs and production of outputs with the equal energy content. In the recycling process, inputs such as fossil fuels (diesel and natural gas), electricity, human labor, transportation, and water were considered, while recycled materials were classified as outputs.

Table 1. Energy equivalent of inputs and output in waste management systems.

Items	Unit	Energy equivalent (MJ unit^{-1})	Reference
A. Inputs			
1. Human labor	h	1.96	(Nabavi-Pelesaraei et al., 2018)
2. Diesel fuel	L	56.31	(Taherzadeh-Shalmaei et al., 2023)
3. Transportation	ton.km	4.5	(Ghasemi-Mobtaker et al., 2020)
4. Natural gas	L	49.5	(Molaee Jafrodi et al., 2022)
5. Electricity	kWh	11.93	(Azizpanah et al., 2023)
6. Water	L	2.96	(Kazemi et al., 2023)
B. Output			
1. Recycled materials	kg	16.43	(Nabavi-Pelesaraei et al., 2017)

Energy indices such as energy use efficiency, energy productivity, specific energy, and net energy were calculated for the processing and recycling scenario of solid waste management. These energy indices are presented as described by (Kaab et al., 2023).

$$\text{Energy use efficiency} = \frac{\text{Output energy (GJ (8500 ton MSW)}^{-1})}{\text{Total input energy (GJ (8500 ton MSW)}^{-1})} \tag{1}$$

$$\text{Energy productivity} = \frac{\text{Recycled materials (ton (8500 ton MSW)}^{-1})}{\text{Total input energy (GJ (8500 ton MSW)}^{-1})} \tag{2}$$

$$\text{Specific energy} = \frac{\text{Total input energy (GJ (8500 ton MSW)}^{-1})}{\text{Recycled materials (ton (8500 ton MSW)}^{-1})} \tag{3}$$

$$\text{Net energy} = \text{Output energy (GJ (8500 ton MSW)}^{-1}) - \text{Total input energy (GJ (8500 ton MSW)}^{-1}) \tag{4}$$

LCA methodology

LCA methodology is a systematic approach to evaluate the environmental impacts of a product, process, or service throughout its entire life cycle, from raw material extraction to end-of-life disposal. It involves quantifying the resource use, energy consumption, emissions, and waste generation associated with each stage of the life cycle to identify opportunities for improvement and optimization. The LCA methodology typically consists of four main steps (Mälkki and Alanne, 2017):

Goal and scope definition

The objective of this research was to evaluate the environmental recycling of MSW from a life cycle perspective. The study focused on a functional unit (FU) of 8500 tons of MSW produced daily in Tehran. The FU is crucial in LCA as it serves as a reference unit for normalized inventory data. Consequential LCA was utilized to determine the system boundary, as it examines how environmental flows may change in response to different decisions.

As illustrated in Figure 1, the system boundary of the study encompasses waste transport, MSW material processing, and recovery. The boundaries included all inputs from the cradle to the processing and recycling of waste site. This border system covered transportation operations (from the MSW collection center to recycling sites and within the site), processing, and recovery in the recycling of waste site.

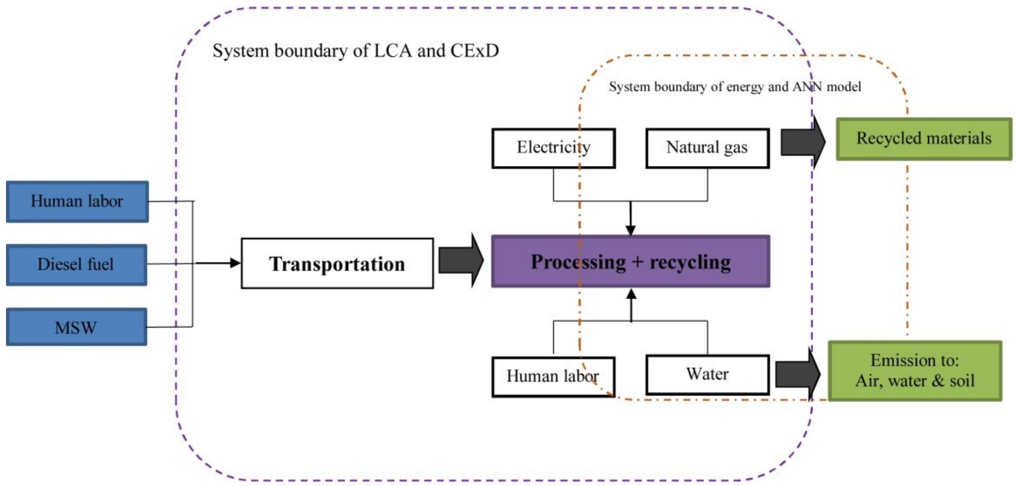

Figure 1. System boundaries of processing and recycle scenario of MSW management.

Life cycle inventory
The life cycle inventory (LCI) is focused on identifying and quantifying the environmental impacts associated with a system, resulting in a compilation of environmental inputs and outputs (Chen et al., 2020). The LCI process is particularly demanding as it involves creating a flow diagram of processes, planning and collecting data, and computing LCI results (Altun-Çiftçioğlu et al., 2016). There is limited public data available on MSW management systems. Obtaining sufficient LCI data for our study proved to be challenging, as is often the case. The data utilized in this research were sourced from the waste management organization of Tehran Municipality and the EcoInvent 2.2 database.

Transportation
Road transportation plays a role in the environmental impact caused by the use of vehicles for collecting and transporting waste to processing and recycling facilities. The distance covered between waste collection points and recycling sites in Tehran typically ranged from 20 to 40 km. Although some recycling facilities may be located further away, a standard distance of 20 to 40 km was considered for waste transportation. The transportation process was modeled using the "Transport, freight, lorry > 32t" unit process from the Ecoinvent database in SimaPro. Additionally, there are internal transportation steps within the recycling site, which involve moving materials from the point of waste entry to various stages of the recycling process.

Electricity
The LCI data for electricity production in Iran was unavailable, so the necessary information was sourced from the EcoInvent database regarding the production and consumption of electricity. It is crucial to identify the specific fuel types utilized in power plants as the combustion of different fuels can result in varying environmental impacts. With the majority of electricity in Iran being generated from natural gas (71.8%), followed by oil (15.6%) and diesel fuel (12.6%) (Ministry of Jihad-e-Agriculture of Iran, 2021), natural gas was chosen for power generation in this study.

Diesel fuel
Lorries primarily used diesel fuel to transport waste from collection points to the recycling center. In certain production systems for LCA of production, the term diesel consumption was replaced with the term traction, which encompasses total diesel fuel consumption and is measured in MJ. LCIs for traction are suggested by (Nemecek et al., 2007) and Nielsen et al. (Guinée et al., 2010), as shown in Table 2.

Table 2. Life cycle inventory data for 1 MJ burning in Ecoinvent database.

Emissions	Amount (g MJ^{-1} diesel)
Carbon dioxide (CO_2)	74.5
Sulfur dioxide (SO_2)	2.41E-02
Methane (CH_4)	3.08E-03
Benzene	2.39E-07
Cadmium (Cd)	1.19E-06
Chromium (Cr)	1.19E-06
Copper (Cu)	4.06E-05
Dinitrogen monoxide (N_2O)	2.86E-03
Nickel (Ni)	1.67E-06
Zink (Zn)	2.39E-05
Benzo (a) pyrene	7.16E-07
Ammonia (NH_3)	4.77E-04
Selenium (Se)	2.39E-07
PAH (polycyclic hydrocarbons)	7.85E-05
Hydro carbons (HC, as NMVOC)	6.80E-02
Nitrogen oxides (NO_x)	1.06
Carbon monoxide (CO)	1.50E-01
Particulates (b2.5 μm)	1.07E-01

Material recovery

The MSW that is collected will undergo separation at a sorting plant. Recyclable materials like metal, glass, paper, and plastics will be recycled at a 40% rate in accordance with relevant regulations. Due to losses in the recycling process, one ton of waste material will not perfectly replace one ton of material not used. Specifically, paper, plastic, and metal are recycled with rates of 17%, 28%, and 5% loss, respectively. Glass, on the other hand, will be recovered without any loss of material (Erses Yay, 2015). The information regarding these materials and the recycling procedures was sourced from the EcoInvent 2.2 database.

Life cycle impact assessment

In the impact assessment phase, the potential environmental impacts were evaluated using the inventory analysis data. In this phase, the inventory data was associated with impact categories and indicators (ISO, 2006). In this study, ten impact categories included in the CML method (It is an update from the CML 2 baseline 2000 method) were investigated: abiotic depletion (AD), acidification (AC), eutrophication (EP), global warming potential (GWP) for time horizon of 100 years, ozone layer depletion (OLD), human toxicity (HT), freshwater aquatic ecotoxicity (FE), marine aquatic ecotoxicity (MAE), terrestrial ecotoxicity (TE) and photochemical oxidation (PO).

Cumulative Exergy Demand (CExD)

Managing waste has become a significant challenge in modern society, with environmental and energy issues at stake. Exergy measures are traditionally used to assess energy efficiency and losses in process systems. These measures consider the quality of resources and the exergy contained within them. By evaluating the resources needed and the total exergy extracted from nature to produce a product, exergy measures provide valuable insights (Bösch et al., 2007). The CExD method for LCA was developed based on a method from the Ecoinvent center, with additional data obtained from their databases. This method aims to quantify primary energy consumption throughout the life cycle of a product or service, including both renewable and non-renewable energy sources. The method does not account for waste used for energy purposes. CExD is structured into five impact categories: non-renewable (fossil), renewable (potential), renewable (water), non-renewable (metals), and non-renewable (minerals) (Hischier et al., 2015).

Artificial neural networks

ANNs are computational techniques inspired by the human nervous system, consisting of interconnected neurons. While the human brain processes data using neurons, ANNs use a mathematical processor. ANNs typically have input, hidden, and output layers, each containing multiple neurons. One key feature of ANNs is their ability to learn, similar to the human brain. In this study, a feed-forward back-propagation (BP) ANN model with Levenberg-Marquardt (LM) training algorithm was utilized. LM training algorithm is commonly used for network training. The network was trained with five inputs (human labor, water, electricity, natural gas, and transportation) and 11 outputs (ten environmental impact categories and recycled materials). Various network structures were evaluated and trained using experimental data to achieve the most accurate predictions.

In this study, performance of the developed ANN model was evaluated by comparing the obtained prediction results from the converged/combined neural network and the measured data. Error function in the neural network was calculated using the following equation (Houshyar et al., 2010):

$$E = \frac{1}{p}\sum_{p}\sum_{k}\left(t_{pk} - z_{pk}\right)^2 \quad (5)$$

Where 'p' is the index of the p training pairs of vectors, 'k' is the index of element in the output vector, 'z_{pk}' the kth element of the output vector when pattern p is presented as input to the network and 't_{pk}' is the kth element of the pth desired pattern vector.

To assess the performance of the developed ANN model for estimating the desired output in production, some statistical quality parameters including root mean square error (RMSE), coefficient of determination (R^2) and mean absolute percentage error (MAPE) were employed as follows (Khoshnevisan et al., 2017):

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i}^{n}\left(t_i - z_i\right)^2} \quad (6)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \quad (7)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{\left|(t_i - z_i)\right|}{z_i} \times 100\right) \quad (8)$$

Where 't_i' and 'z_i' are the predicted and actual output and 'n' is the number of points in the data set.

Also, using the sensitivity analysis of selected ANN, the main input variables were selected and ranked. Sensitivity analysis with partial differentiation is based on the calculation of the inputs, weight and output variables of the ANN results. The equations related to sensitivity analysis are presented in the following equations (Kaab et al., 2019):

$$S = \frac{\partial O}{\partial I} = O'\left(\sum_{J=1}^{J} w_{ij}^{1} H' w_{ij}^{2}\right) \quad (9)$$

$$S = \frac{\partial f(O)}{\partial X}\left(\sum_{J=1}^{J} w_{ij}^{1} \frac{\partial f(H)}{\partial X} w_{ij}^{2}\right) \quad (10)$$

Where *'O'* is the output, *'I'* is the input, *'H'* is hidden node that has to be differentiated, *'X'* is the output value from hidden layer nodes, 'w_{ij}^{1}' is the weight vector between input and hidden layers and 'w_{ij}^{2}' is the weight vector between hidden and output layers. This kind of analysis is of great significance and importance to select the parameters that should be considered as the most significant and least significant ones during the creation of the satisfactory model. Excel 2013 spreadsheets were utilized for examining energy consumption patterns and conducting energy analysis. SimaPro software, a widely used tool for LCA analysis, was employed to assess environmental impacts throughout the life cycle. Matlab software was used to input basic data on inputs and outputs for ANN analysis on a personal computer.

Results and Discussion

Input– output energy flow

The detailed breakdown of inputs and outputs per 8500 tons of MSW in the study area is outlined in Table 3. The inputs were examined in two distinct categories: transportation and processing/recycling. The transportation segment encompassed aspects such as human labor, diesel fuel, and transportation. Meanwhile, the processing and recycling phase involved human labor, natural gas, electricity, water, and transportation.

Table 3. Amounts of inputs and output in processing and recycle scenario of waste management for 8500 ton MSW.

Items	Unit	Processing and recycle system	
		Transformation	Processing + recycling
A. Inputs			
1. Human labor	h	98.91	8221.36
2. Diesel fuel	L	1866.45	-
3. Transportation	ton.km	27050	21002.57
4. Natural gas	L	-	891.96
5. Electricity	kWh	-	9013.40
6. Water	L	-	3009.12
B. Output			
1. Recycled materials	kg	-	1998891.44

Table 4 shows the energy consumption for transportation, processing, and recycling. The results indicate that the average energy input values were 498.23 GJ (8500 ton MSW)$^{-1}$, with 227.02 GJ (8500 ton MSW)$^{-1}$ attributed to transportation and 271.21 GJ (8500 ton MSW)$^{-1}$ to processing and recycling. The average output energy values in this study were calculated as 32841.79 GJ (8500 ton MSW)$^{-1}$.

Table 4. Amounts of energy inputs and output in processing and recycle scenario of waste management for 8500 ton MSW.

Items	Processing and recycle system	
	Transformation (GJ)	Processing + recycling (GJ)
A. Inputs		
1. Human labor	0.19	16.11
2. Diesel fuel	105.10	-
3. Transportation	121.73	94.51
4. Natural gas	-	44.15
5. Electricity	-	107.53
6. Water	-	8.91
Total energy input	227.02	271.21
B. Output		
1. Recycled materials	-	32841.79

Additionally, Figure 2 illustrates the distribution of each input's contribution to overall energy usage in the processing and recycling scenario. The findings from Figure 2 reveal that electricity accounted for the largest portion of energy consumption, representing 39.65% during the processing and recycling stages. Following electricity, transportation accounted for approximately 34.85% of the total energy consumption, while natural gas held a share of 16.28%, placing it in the third position.

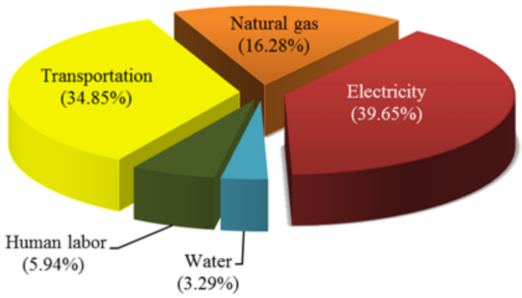

Figure 2. The share of energy input for processing and recycle scenario of MSW management.

The findings indicated that transportation played a crucial role in energy consumption during waste recycling. It is essential to focus on minimizing energy consumption during transportation by utilizing trucks with low fuel consumption and selecting routes that are shortest to the recycling site, especially during peak urban traffic hours. Additionally, factors such as energy use efficiency, energy productivity, specific energy, net energy, and energy intensiveness are detailed in Table 5. The study revealed an energy use efficiency of 121.56, highlighting the potential for waste recycling to not only address environmental concerns but also generate significant energy. Furthermore, the energy productivity was calculated at 7.40 (ton GJ^{-1}), indicating that 7.40 tons of recycled materials were produced per 1 GJ of energy consumed.

Table 5. Energy indices of processing and recycle scenario of waste management in Tehran municipality, Iran.

Items	Unit	Processing and recycle system
Energy use efficiency	-	121.56
Energy productivity	ton GJ^{-1}	7.40
Specific energy	GJ ton^{-1}	0.14
Net energy gain	GJ	32570.57

Interpretation of LCA results

Table 6 illustrates the impact category values for a solid waste management recycling system based on 8500 tons of MSW. Additionally, Figure 3 displays the percentage contributions of inputs and production processes utilized in the processing and recycling scenario to selected impact categories for MSW. The key aspect in this processing and recycling system is the mitigation of environmental pollutant emissions through recycling and reusing materials such as metal, glass, paper, and plastic. By separating and reusing these materials or incorporating them as raw materials into the production cycle, a significant reduction in emissions from their production cycle is achieved. This practice is known as emission avoidance in LCA studies. As indicated in Table 6 and Figure 3, the impact of recycling these wastes is reflected in negative numbers, highlighting the effective role of recycling in reducing environmental pollution.

The study explores the challenges posed by increasing urban population and waste generation in municipal solid waste management (MSWM). It emphasizes the adoption of Integrated Solid Waste Management (ISWM) strategies like anaerobic digestion (AD), composting, and landfill usage to address environmental and economic challenges. The focus is on optimizing solid waste management in Tehran through LCA to minimize carbon dioxide emissions and energy consumption while considering economic factors. Two scenarios are compared: current waste management practices in Tehran versus incorporating advanced technologies like AD and landfill gas recovery. Results from the study demonstrate that the second scenario, which involves newer technologies, not only reduces costs but also significantly decreases CO2 emissions and energy consumption compared to the first scenario (Pourreza Movahed et al., 2020).

Table 6. Values of the environmental impact of processing and recycle scenario per 8500 ton of daily MSW.

Impact categories	Measurement units	Values	SD
AD	kg Sb $_{eq.}$	90.48	8.30
AC	kg $SO_{2\,eq.}$	14.61	1.34
EP	kg $PO^{-3}{}_{4\,eq.}$	37.74	3.46
GWP	kg $CO_{2\,eq.}$	8678.65	796.16
OLD	kg CFC11 $_{eq.}$	0.00084	0.00008
HT	kg 1,4-DB $_{eq.}$	1384.61	127.02
FE	kg 1,4-DB $_{eq.}$	98.88	9.07
ME	kg 1,4-DB $_{eq.}$	1197775.59	109881.63
TE	kg 1,4-DB $_{eq.}$	-10.55	0.97
PO	kg $C_2H_{4\,eq.}$	0.14	0.01

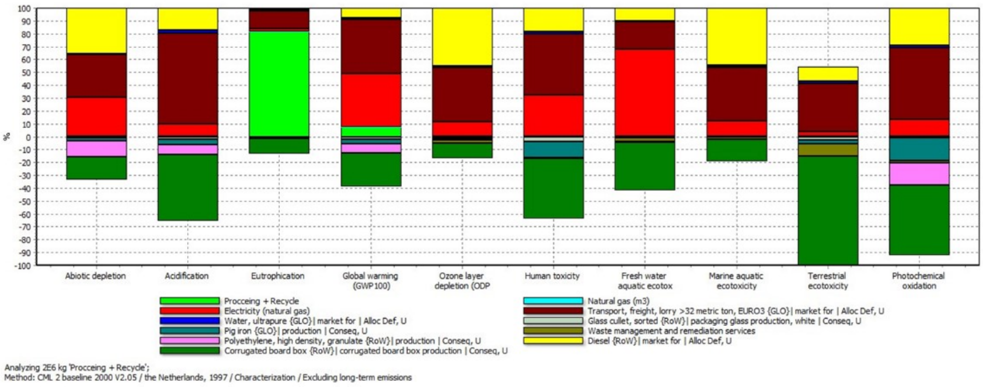

Figure 3. Contribution of inputs to environmental impact categories based on processing and recycle scenario of MSW management in Tehran Municipality, Iran

The Global Warming Potential (GWP) represents the relative contribution of a specific material to the greenhouse effect (Ghannadzadeh and Meymivand, 2019). According to Table 6, the GWP values for processing and recycling scenarios per 8500 tons of MSW per day from 'cradle to gate' were estimated to be approximately 8678.65 kg CO^2 equivalent per 8500 tons of MSW. In Figure 3, it is evident that transportation and electricity play a significant role in the generation of GWP during the recycling process, each contributing around 40%. However, the recycling process led to a 40% reduction in GWP for recycled paper, plastic, metal, and glass, with the majority of the decrease attributed to paper recycling. Additionally, Liang et al. (2023) demonstrated that the recycling system exhibited the lowest greenhouse gas emissions compared to other systems such as bioethanol production and incineration for paper recycling. In Denmark, the recovery system showed increased benefits (negative impacts) on GWP, particularly in metal recovery, mainly due to significant savings from recycling aluminum scrap, which accounted for over 50% of the total net impact (Timonen et al., 2019).

Regarding Acidification Potential (AC), sulfur dioxide (SO_2) is a key contributor. Other materials associated with acidification include nitrogen oxides and ammonium. The impact of sulfur oxides (SO_x) is comparable to that of SO_2 (Toma et al., 2018). As indicated in Table 6, the AC values for MSW recycling were 14.61 kg SO^2 equivalent per 8500 tons of MSW. In the processing and recycling scenario of

MSW, transportation of MSW played a significant role in AC production, contributing approximately 70%, while recycling paper led to a reduction of about 50% in the release of this environmental indicator.

In Figure 5, diesel fuel emerged as the primary concern in the impact of ozone layer depletion (OLD) during MSW recycling. OLD, predominantly caused by hydrocarbons like Carbon, Chlorine, and fluorine (CFC), was highlighted by PRe Consultants in 2015. Diesel fuel contributed around 45% to the overall OLD impact category in MSW recycling, with transportation ranking second. This underscores the significance of using biofuels and avoiding old vehicles to prevent irreversible harm to the ozone layer. Recycling less than 20% of MSW, mainly paper, led to a decrease in the index.

The "toxicity" impact category assesses the effects of toxic substances on humans and ecosystems (Brentrup et al., 2004). In Table 6, MAE had the most significant impact related to toxicity, followed by HT, FE, and TE. Transportation was a key hotspot in toxicity impacts, but recycling notably reduced emissions, especially in the TE category, showing a negative rate of release (-10.55 kg 1,4-DB eq.) due to paper recycling. Thus, recycling paper not only generates income but also reduces the environmental impact in terms of toxicity. The Environmental Potential (EP) indicates the amount of nutrients washed from the environment due to input use (Zangina et al., 2023). Figure 3 highlights that processing and recycling of MSW were major hotspots in the EP impact category, each sharing about 80%. These activities also had minimal positive impacts (less than 15%). For Antimony (AD) at 90.48 kg Sb eq. and Ethylene (PO) at 0.14 kg C_2H_4 eq., transportation and paper recycling played significant roles in reducing emissions in both categories, especially in PO. In MSW recycling, transportation, electricity, and diesel fuel were key hotspots in various impact categories, while paper, metal, plastic, and glass recycling led to harmful environmental emissions. Efficient energy use in recycling not only reduces consumption but also prevents the release of inappropriate environmental factors, promoting environmental sustainability. The energy analysis in Table 7, based on CExD, shows that 116.24 GJ (8500 tons of MSW) $^{-1}$ fossil energy was consumed during the MSW recycling process, mainly due to diesel fuel and transportation. Transportation and electricity were major energy consumers in the recycling process, with paper recycling playing a significant role in energy conservation.

The research conducted aimed to assess the waste management situation in Ahvaz and its environmental consequences. It included an evaluation of different scenarios using LCA to quantify potential environmental impacts. The scenarios examined various methods such as landfilling with and without biogas collection, composting, recycling, incineration, and anaerobic digestion. Emissions were analyzed through the IWM model, considering factors like resource consumption, global warming, acidification potential, photochemical oxidation, and eco-toxicity. Among the scenarios, it was found that scenario 3, involving composting and landfilling without biogas collection, performed poorly in terms of resource consumption and non-renewable resource depletion due to the absence of recycling and energy recovery. Scenarios 1 and 2, which involved landfilling without and with biogas collection, respectively, showed higher greenhouse gas emissions leading to increased global warming impact. However, implementing landfill gas and energy recovery methods reduced the global warming impact by 12% compared to non-recovery methods. Scenarios that focused on energy production from waste demonstrated more positive outcomes regarding greenhouse gas emissions and their impact on global warming (Zarea et al., 2019).

Table 7. The results of energy forms calculated by CExD method of LCA.

Items	Measurement units	Values	SD
1. Non-renewable, fossil	GJ	114.96	10.55
2. Renewable, potential	GJ	0.02	0.001
3. Renewable, water	GJ	0.86	0.08
4. Non-renewable, metals	GJ	-0.27	0.02
5. Non-renewable, minerals	GJ	0.04	0.003

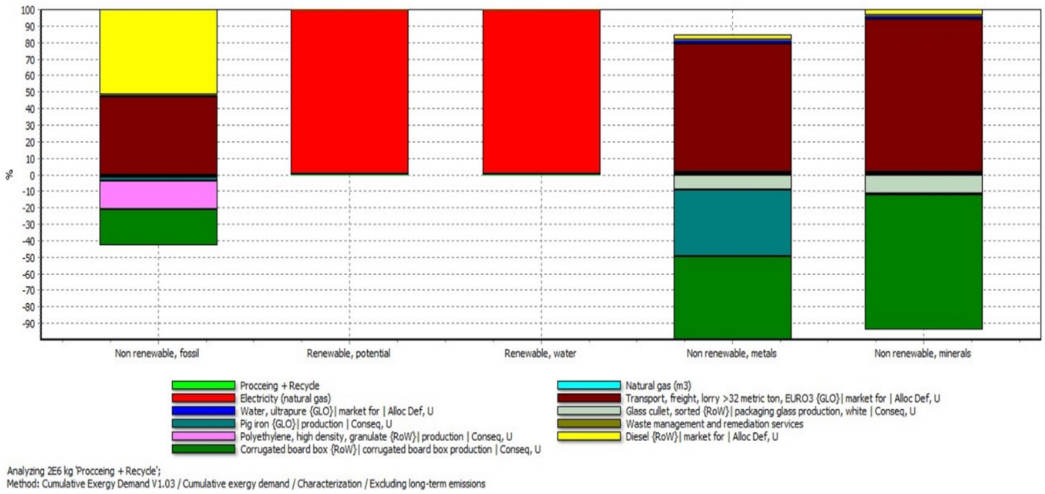

Figure 4. Contribution of inputs to consumption of energy forms in processing and recycle scenario based on CExD

Since other waste disposal methods are utilized, it is crucial for LCA methods and comparisons to be conducted until a suitable model is established to mitigate negative environmental impacts and decrease energy consumption related to waste management in the area under study, while considering project costs.

Evaluation of artificial neural networks

In this research, a series of neural networks were trained and developed using MATLAB software to accurately predict the recycled materials and various environmental impact categories. These neural networks had different configurations in terms of hidden layers, number of neurons, and activation functions. A feed-forward back-propagation neural network utilizing the Levenberg-Marquardt training algorithm was utilized. The best-performing network employed tangent sigmoid and linear activation functions for the hidden layers and output layer, respectively.

The outcomes of the different network models are summarized in Table 8. The optimal network was chosen based on having the highest R^2 value, as well as the lowest RMSE and MAEP values. The most effective network structure identified was 5-7-7-11, as shown in the first row of Table 8. The results showed that the R^2 values ranged from 0.926 to 0.978 for the training set, 0.935 to 0.983 for the testing set, and 0.934 to 0.971 for the validation set.

Table 8. The results of different arrangement of models.

Topologies	Items	Statistics indices	RM	AD	AC	EP	GWP	OLD	HT	FE	ME	TE	PO
5-7-7-11	Train	R^2	0.976	0.945	0.973	0.976	0.952	0.969	0.978	0.948	0.926	0.951	0.965
		RMSE	0.089	0.082	0.125	0.063	0.120	0.113	0.098	0.142	0.096	0.094	0.084
		MAPE	0.002	0.009	0.009	0.008	0.002	0.002	0.003	0.002	0.009	0.003	0.001
	Test	R^2	0.937	0.973	0.935	0.943	0.980	0.954	0.958	0.940	0.961	0.955	0.983
		RMSE	0.128	0.111	0.100	0.132	0.079	0.108	0.093	0.122	0.076	0.141	0.097
		MAPE	0.005	0.009	0.007	0.005	0.005	0.005	0.007	0.007	0.004	0.007	0.002
	Validation	R^2	0.968	0.934	0.956	0.954	0.942	0.971	0.955	0.955	0.952	0.945	0.954
		RMSE	0.125	0.143	0.079	0.113	0.095	0.149	0.106	0.067	0.123	0.117	0.086
		MAPE	0.001	0.001	0.001	0.008	0.007	0.008	0.009	0.008	0.007	0.007	0.009
5-6-6-11	Train	R^2	0.897	0.855	0.893	0.843	0.862	0.855	0.799	0.806	0.777	0.783	0.800
		RMSE	0.219	0.147	0.154	0.158	0.153	0.155	0.171	0.157	0.166	0.229	0.202
		MAPE	0.013	0.014	0.013	0.010	0.011	0.020	0.016	0.009	0.009	0.016	0.013
	Test	R^2	0.868	0.783	0.887	0.856	0.772	0.809	0.849	0.904	0.899	0.772	0.801
		RMSE	0.130	0.200	0.133	0.159	0.169	0.191	0.173	0.205	0.149	0.118	0.109
		MAPE	0.019	0.013	0.021	0.013	0.011	0.015	0.017	0.020	0.011	0.012	0.014
	Validation	R^2	0.880	0.905	0.830	0.778	0.905	0.800	0.786	0.872	0.811	0.848	0.830
		RMSE	0.204	0.205	0.238	0.185	0.197	0.219	0.225	0.153	0.233	0.141	0.224
		MAPE	0.018	0.012	0.009	0.020	0.014	0.018	0.019	0.012	0.013	0.017	0.015
5-8-11	Train	R^2	0.892	0.796	0.785	0.787	0.857	0.832	0.798	0.900	0.893	0.869	0.886
		RMSE	0.102	0.115	0.097	0.164	0.245	0.185	0.191	0.211	0.212	0.196	0.226
		MAPE	0.018	0.020	0.016	0.013	0.019	0.014	0.018	0.016	0.015	0.012	0.011
	Test	R^2	0.800	0.813	0.876	0.843	0.782	0.855	0.815	0.889	0.783	0.823	0.820
		RMSE	0.206	0.104	0.200	0.125	0.171	0.199	0.141	0.187	0.145	0.207	0.174
		MAPE	0.019	0.009	0.014	0.011	0.017	0.009	0.009	0.019	0.012	0.014	0.018
	Validation	R^2	0.779	0.895	0.796	0.817	0.875	0.861	0.872	0.850	0.795	0.775	0.891
		RMSE	0.237	0.164	0.163	0.194	0.187	0.179	0.239	0.091	0.193	0.222	0.132
		MAPE	0.016	0.013	0.014	0.015	0.010	0.017	0.015	0.013	0.017	0.019	0.019
5-5-5-11	Train	R^2	0.779	0.812	0.887	0.841	0.900	0.876	0.899	0.874	0.817	0.887	0.818
		RMSE	0.089	0.116	0.205	0.096	0.111	0.176	0.140	0.124	0.093	0.093	0.208
		MAPE	0.011	0.021	0.015	0.012	0.009	0.018	0.009	0.014	0.009	0.020	0.017
	Test	R^2	0.794	0.820	0.793	0.772	0.892	0.888	0.821	0.795	0.790	0.820	0.812

		RMSE	0.198	0.172	0.145	0.161	0.128	0.190	0.198	0.110	0.213	0.098	0.180
		MAPE	0.017	0.011	0.010	0.013	0.016	0.009	0.009	0.015	0.017	0.013	0.020
	Validation	R^2	0.848	0.808	0.839	0.884	0.796	0.826	0.808	0.857	0.826	0.800	0.810
		RMSE	0.126	0.144	0.085	0.244	0.109	0.221	0.232	0.153	0.122	0.180	0.125
		MAPE	0.018	0.017	0.013	0.016	0.017	0.017	0.017	0.014	0.011	0.013	0.014
5-10-11	Train	R^2	0.828	0.881	0.811	0.896	0.895	0.848	0.904	0.774	0.792	0.793	0.830
		RMSE	0.158	0.177	0.107	0.129	0.199	0.214	0.090	0.235	0.154	0.138	0.207
		MAPE	0.012	0.019	0.020	0.017	0.019	0.010	0.011	0.015	0.018	0.012	0.016
	Test	R^2	0.791	0.817	0.815	0.822	0.889	0.899	0.862	0.854	0.835	0.787	0.828
		RMSE	0.120	0.144	0.125	0.232	0.223	0.248	0.140	0.165	0.168	0.165	0.138
		MAPE	0.021	0.010	0.009	0.019	0.013	0.013	0.018	0.015	0.021	0.014	0.020
	Validation	R^2	0.844	0.895	0.794	0.790	0.815	0.867	0.796	0.869	0.849	0.809	0.805
		RMSE	0.107	0.111	0.145	0.133	0.134	0.203	0.181	0.121	0.141	0.235	0.095
		MAPE	0.021	0.011	0.018	0.013	0.014	0.017	0.021	0.013	0.018	0.016	0.014

In a study conducted by (Henchion et al., 2017) on the prediction of industrial solid waste (ISW) amounts in Durg-Bhilai, India from 2010 to 2026 using ANN and ANFIS models, it was found that the ANFIS model had lower uncertainty levels. Another study in Tehran focused on modeling and forecasting production waste (WG) using Wavelet-ANFIS and Wavelet-ANN, with the WT-ANFIS model showing superior predictive capabilities compared to WT-ANN (Nabavi-Pelesaraei et al., 2017). The advantages, disadvantages, and future prospects of determining the most suitable neural network structure were also discussed in this study. Overall, the use of ANN for prediction and modeling in waste management has shown promising results in various studies.

Conclusions

This research investigated the energy usage and environmental effects of the waste recycling system in Tehran, Iran. With a focus on waste transportation and processing, the study calculated that 227.02 and 271.21 GJ of energy were consumed in handling 8500 tons of municipal solid waste (MSW). The highest energy consumption occurred during processing and transportation, particularly in the use of electricity. Despite this, the energy use efficiency was found to be 121.56, indicating that recycling indeed generates a significant amount of energy. LCA results demonstrated that recycling paper, plastic, and metal can help reduce pollution by diminishing landfill waste and litter, which emit methane gas and contribute to air pollution. Moreover, recycling decreases the reliance on new resources, which can also lead to pollution. The study highlighted transportation as a key factor impacting various aspects of recycling and energy consumption, suggesting the use of fuel-efficient trucks and optimal transport routes to recycling facilities. The study also investigated the use of ANN models to predict recycled materials and environmental indicators within recycling systems, showing promising accuracy. It recommended the development of advanced models, potentially using Data Envelopment Analysis (DEA) or Genetic Algorithms (GA), to optimize input usage, especially in transportation, and enhance the sustainability of recycling practices in Tehran.

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