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Title page

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Abstract

This paper presents a multi-objective optimization (MOO) of waste-to-energy (WtE) to investigate optimized solutions for thermal, economic, and environmental objectives. These objectives are represented by net efficiency, total cost in treating waste, and environmental impact. Integration of the environmental objective is conducted using life cycle assessment (LCA) with endpoint single score method covering direct combustion, reagent production and infrastructure, ash management, and energy recovery. Initial net efficiency of the plant was 16.27% whereas the cost and environmental impacts were 75.63 €/ton-waste and $-1.21\text{x}10^{8}$ Pt/ton-waste, respectively. A non-dominated sorting genetic algorithm (NSGA-II) is applied to maximize efficiency, minimize cost, and minimize environmental impact. Highest improvement for single objective is about 13.4%, 10.3%, and 14.8% for thermal, economic, and environmental, respectively. These improvements cannot be made at once since the objectives are conflicting. These findings highlight the significance role of decision makers in assigning weight to each objective function to obtain the optimal solution. The study also reveals different influence among decision variable, waste input, and marginal energy sources. Finally, this paper underlines the versatility of using MOO to improve WtE performance regarding the thermal, economic, and environmental aspects without requiring additional investment.

Keywords: multi-objective optimization, life cycle assessment, life cycle costing, energy efficiency, waste-to-energy, elitist non-dominated sorting genetic algorithm

Nomenclature

APC	air pollution control
C_{el}	electricity price (€/MWh)
C_p	cost of treating the waste (€/ton-waste)
C_{labor}	total annual salaries (€/year)
DFCI	Direct fixed-capital investment
FCI	Fixed-capital investment
FEP	Fossil energy provision
FU	functional unit
h	enthalpy (kJ/kg)
HPT	high pressure turbine
IFCI	Indirect fixed-capital investment
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
LHV	lower heating value (kJ/kg)
LPT	low pressure turbine
$\dot{m}$	mass flow rate (kg/s)
MNG	maximum number generation
MOO	multi-objective optimization
nGD	normalized generational distance
nSP	normalized spread
NSGA-II	non-dominated sorting genetic algorithm
PEC	purchased-equipment cost
$\dot{Q}$	heat (kW)

r	interest rate
SEP	Sustainable energy provision
SNCR	selective non-catalytic reduction
SSDTC	steady-state detection
SSI	single score impact (Pt/ton-waste)
t_a	annual plant operation (hours)
$\dot{W}$	power (kW)
WPD	weighted percentage deviation factor
WtE	waste-to-energy
y	discount period (years)

Greek

ε_{el}	electric efficiency
η_{pb}	boiler pump isentropic efficiency
η_{pc}	condenser pump isentropic efficiency
$\eta_{T,s}$	turbine isentropic efficiency
χ	vapor quality

Subscripts

i	inlet
o	outlet

1. Introduction

Unsustainable production and consumption drive an increase in waste generation. Currently, waste-to-energy (WtE) is the most common technology to deal with a variety of municipal waste as well as part of industrial solid waste (Arena and Di Gregorio, 2013; Lausselet et al., 2016). In 2018, Europe treated approximately 70 million ton of municipal solid waste in WtE, showing a 117% increase compared to 1995, and this trend is predicted to rise (Birgen et al., 2021; Eurostat, 2019; Scarlat et al., 2019). Incineration technology in the WtE plant not only is robust, but also can significantly reduce the waste volume that goes to landfill and generate heat and electricity (Arena, 2012; Fruergaard and Astrup, 2011). However, WtE is regarded expensive since the payback period can take about 10-30 years, and the cost in treating waste per ton can range from 53-150 € (Assamoi and Lawryshyn, 2012; Fernández-González et al., 2017; Zabaniotou and Giannoulidis, 2002).

To ensure the benefit from WtE, its operation must be optimized to increase energy efficiency so that the electricity or heat obtained from the process can be maximized. In the optimization of thermal power generation, the thermo-economic objectives are combined to maximize energy efficiency and minimize the cost by applying multi-objective optimization (MOO). MOO, which can utilize different algorithms, becomes the main solution to optimize the power generation system. NSGA-II was commonly used to maximize thermal efficiency and minimize the cost of steam cycle, organic Rankine cycle, Kalina cycle in cogeneration plant, and WtE (Behzadi et al., 2018; Hajabdollahi et al., 2012; Hajabdollahi and Fu, 2017; Özahi and Tozlu, 2020). The results showed an increase in thermal efficiency and decrease in the cost rate. Optimization using other types of algorithms, such as genetic diversity evaluation method or modified differential evolution, also showed improvement of thermal efficiency and cost for different types of power generation (Baghernejad and Yaghoubi, 2011; Naserabad et al., 2018; Wang et al., 2014).

However, with growing concern about sustainability, there is still a lack of integration of environmental impact in the optimization problem of power generation. Some of existing studies integrated environmental objective into MOO on power generation as total damage cost (Mahmoodabadi et al., 2015; Sayyaadi, 2009) or CO_2 emission (Ahmadi et al., 2011; Javadi et al., 2019). Few studies applied comprehensive approach by integrating environmental objective through life cycle assessment (LCA). Gerber et al. (2010) and Nguyen et al. (2014) integrated the environmental objective to optimize biomass power generation as well as oil and gas platforms using LCA. Hence, their included a broad range of emissions and impact categories from the product's life cycle to produce comprehensive assessment, prevent burden-shifting, and identify activities that cause the highest impact.

Currently, to the authors' knowledge, there seems to have been no study regarding the integration of the environmental objective using LCA and MOO in the WtE system to evaluate energy, cost, and environmental impact. This creates a gap concerning assessment of the environmental performance of an improved WtE plant. Therefore, this paper presents the study of WtE optimization that considers energy efficiency, cost, and environmental life cycle assessment. The aim is achieved by focusing on several objectives, such as i) assessing the cost, environmental impact, and energy efficiency of the system, ii) applying NSGA-II to improve WtE performance taking environmental, thermal, and economic aspects as objective functions, iii) applying scenario and sensitivity analysis to evaluate the behavior of the model and the influence of each decision variable in the steam cycle operation.

2. Material and methods

2.1 System description

This illustrative case was a scenario built on an actual incinerator with electricity recovery. The information concerning the WtE specification and its operating condition were obtained from a company which operates a small-scale incinerator, then supplemented by Ecoinvent database.

[Fig. 1 is here]

Fig. 1. displays a scheme of the WtE with annual throughput of 36208 ton-waste. Bottom ash and fly ash are transported to the landfill and hazardous landfill, respectively, without any material recovery. The plant recovers energy in the form of electricity for self-consumption and sale, and heat for self-consumption. Energy recovery that is shown in dashed boxes can avoid conventional production of electricity and heat. The cycle in the center of **Fig. 1.** are the simplified version of steam cycle consisting of boiler, turbine, feed pump, and condenser. Heat from combusting waste is used by boiler to convert water into steam. Thermal energy in the steam is extracted by turbine to rotate generator and produce electricity. The steam outflow from turbine is then transformed back into water by the condenser and being cycled back to the boiler by using feed pump. More detail process in steam cycle is shown by **Fig. 2**.

[Fig. 2. is here]

Apparatus 1 and 2 are high-pressure turbine (HPT) and low-pressure turbine (LPT), respectively. Both will extract energy out of steam generated by boiler. However, HPT works for higher pressure steam and LPT is designed to recover exhaust energy from lower pressure steam that comes out of HPT. The symbol 'G' next to HPT and LPT are generators that convert rotary motion into electricity. Apparatus 3 and 8 are principally heat exchanger. The former is a steam condenser that recirculates water (from source 10 to sink 11) to condense the steam into water, and the latter utilizes steam to preheat the air that is used in the combustion process (apparatus 14 and 15 represent source of air and heated air, respectively). Steam (line 7), water (line 12 and 19), and make-up water (line 20) flow to the deaerator (apparatus 5). Deaerator removes dissolve gases from water to prevent corrosion in the system. The steam (line 7) will heat up the water so that the dissolved gases are released and can be vented out. Excess water is drained to sink 12, while the feedwater is being pumped and recirculated to boiler. Line 3, a steam bleed from HPT, has zero flow presently. It is illustrated in **Fig. 2.** because the WtE operator considers a possibility to reuse the steam. (e.g., supplying to other company).

2.2 Energy assessment

For the energy assessment, mass and energy balance are utilized to model the mass flow rate and energy transfer rate among unit operations using the assumption that there is no loss during the operation. The performance indicator for energy assessment is electric efficiency delivered to the grid (ε_{el}) derived from the total electricity recovered from the combusted waste subtracted by the amount for self-consumption. The formula to calculate mass and energy balance are expressed by equation (1) and (2):

$$\sum \dot{m}_i = \sum \dot{m}_o \tag{1}$$

$$\dot{\boldsymbol{Q}} - \dot{\boldsymbol{W}} = \sum \dot{m}_o \boldsymbol{h_o} - \sum \dot{m}_i \boldsymbol{h_i} \tag{2}$$

where $\dot{m}$ is the mass flow rate (kg/s), subscripts i and o indicate the incoming and outgoing stream, respectively, $\dot{Q}$, $\dot{W}$, h are heat (kW), power (kW), and enthalpy (kJ/kg), respectively.

The net energy efficiency is calculated using equation (3):

$$\varepsilon_{el} = \frac{\dot{W}_{net}}{\dot{m}_{waste}.\, LHV_{waste}} \tag{3}$$

where $\dot{m}_{waste}$, LHV_{waste}, and $\dot{W}_{net}$ are waste mass flow rate (kg/s), waste lower heating value (kJ/kg), and net power (kW), respectively. The net power is determined by using equation (4):

$$\dot{W}_{net} = (\dot{W}_{HPT} + \dot{W}_{LPT}) - (\dot{W}_{pump\ 4} + \dot{W}_{pump\ 6}) - \dot{W}_{self\ consumption} \tag{4}$$

where $\dot{W}_{HPT}$ and $\dot{W}_{LPT}$ are power generated (kW) by HPT and LPT, respectively, $\dot{W}_{pump\ 4}$ and $\dot{W}_{pump\ 6}$, are power consumed (kW) by pump 4 and pump 6, respectively, and

$\dot{W}_{self\ consumption}$ is the amount of electricity consumed by the plant (kW) that is generated by the plant. Thermal modeling is initially simulated using Cycle Tempo software which is later compared to the actual system to ensure it is correct. The model is then reconstructed using thermotables, a Ms. Excel thermodynamics add-in (University of Alabama, 2011) since the optimization was performed using an Excel-based MOO program (Sharma et al., 2012; Wong et al., 2016).

2.3 Economic assessment

The economic assessment determines the associated cost of treating the waste, C_p (€/ton-waste). The cost was calculated as the sum of annualized fixed-capital investment (FCI), insurance and maintenance, labor cost, cost of flue gas cleaning and ash disposal, and revenue from electricity sale, as shown in equation (5).

$$C_p = \sum_{t=1}^{y} \frac{r/(1-(1+r)^{-y}).FCI + C_{IM} + C_{labor} + C_{FGA} - (\varepsilon_{el}.C_{el}.t_a.\dot{m}_{waste}.LHV_{waste})}{Plant\ capacity} \quad \textbf{(5)}$$

where r and y correspond to interest rate and discount period, respectively. C_{IM} indicates the cost of insurance and maintenance, C_{labor} implies the total annual salaries of the personnel (€/year), whereas C_{FGA} refers to the cost of flue gas cleaning and ash management. The revenue is associated with net efficiency (ε_{el}), the price of selling electricity (C_{el}), annual operating hours (t_a), waste flowrate ($\dot{m}_{waste}$), and lower heating value of the waste (LHV_{waste}).

FCI consists of different cost items, including purchased-equipment cost (PEC). PEC was calculated as a function of thermodynamics, where the results will be used to estimate total investment cost. To perform the calculation of PEC, the cost coefficient was adjusted to the year 2018 using the chemical engineering plant cost index (CEPCI, 2018). A percentage of PEC was used to estimate the total investment as a sum of various cost items, such as equipment installation, piping, instrumentation, legal cost, etc. Information concerning parameters and equation used to calculate the cost is given in the Supplementary material (see Tables 2-4).

2.4 Environmental assessment

Environmental assessment was carried out using life cycle assessment (LCA). LCA is commonly used for the environmental accounting of a system or comparing the performance of two or more systems. The methodology in this study follows the procedure provided by the ISO (ISO, 2006a, 2006b). The LCA in this study is used to assess the environmental performance of WtE within the Finnish context. The functional unit (FU) is 1 ton of incoming waste treated in the WtE plant. System boundaries cover direct emission resulted from waste combustion and indirect emission from upstream and downstream activities concerning waste treatment in the WtE. Upstream activities include reagent production and WtE infrastructure, whereas downstream activities comprise ash management and electricity recovery. Other than treating waste, WtE provides a function as electricity and heat producer. This multifunctionality issue was resolved by applying system expansion, where the conventional electricity and heat production system was considered. The electricity from WtE was assumed to substitute the average electricity consumption mix whilst the heat will supersede the average heat consumption by the plant.

A WtE plant recovers energy in the form of electricity for self-consumption and sale, heat for self-consumption, while bottom ash is sent to landfill, and the APC residue is assumed to be sent to hazardous waste landfill. The waste composition for municipal solid waste in Finland was modified from Liikanen et al. (Liikanen et al., 2016) since there is a difference in waste categorization between their study and the present one. The waste composition consists of 45.9% organic waste, 16.8% plastics, 8.8% cardboard, 8% paper, 5.5% textiles, 5.4% composite waste, 3% sanitary textiles, 2% non-combustible (e.g., ceramics), 1.95% metals, 1.55% glass, 0.9% combustible (e.g., wood), and 0.2% hazardous waste.

WtE specification and waste composition were used as inputs for the analysis, and it resulted life cycle inventory (LCI). LCI was quantified using the waste incineration life cycle inventory (WILCI), a tool developed based on the incineration sector in France (Beylot et al., 2018, 2017). This tool was used because it provided a seamless way to define the input, output, as well as the management options for air pollution and ash. Moreover, the results of LCI from WILCI can be modified as an input to perform life cycle impact assessment (LCIA) in OpenLCA software. WILCI also provides results on flue gas volume, which is used to estimate the cost of APC unit.

LCIA was conducted using ReCiPe methodology for the midpoint and endpoint single score result, taking a hierarchist perspective (RIVM, 2016). Hierarchist (H) is rooted from the most common policy approach that uses medium time horizon of 100 years. In this study, the single score impact (SSI) is the indicator of environmental performance that is utilized as the environmental objective in the MOO. The optimized system has to minimize the environmental impact, or in the other words, the system needs to maximize the environmental benefit. To avoid confusion, environmental benefit here refers to the environmental impacts avoided from conventional electricity and heat production, and it was later indicated by a minus sign. Primary data from the plant was used in combination with Ecoinvent database. The temporal scope was 2018-2038, and the geographical scope was Finland.

2.5 Multi-objective optimization

This section describes the methodology for multi-objective optimization, which consists of the objective functions, decision variables, and non-dominated sorting genetic algorithm (NSGA-II).

2.5.1 Formulation of the objective functions

Three objective functions in the WtE system were considered as the optimization problem. They covered the energy, environment, and economic aspects represented by energy efficiency, LCA single score impact (SSI), and cost, respectively.

The objective function of the energy aspect represented by net efficiency (%) is displayed by equation (6):

$$Max\ \varepsilon_{el} = \frac{\dot{W}_{net}}{\dot{m}_{waste}.LHV_{waste}} \tag{6}$$

$$subject\ to\ x = 0.9\ and\ \eta_{T,s} \leq 0.9\ ;$$

where x and $\eta_{T,s}$ are steam quality in pipe 8 and isentropic efficiency for both turbines (see **Fig. 2**). The annualized cost, C_p, in treating incoming waste (€/ton-waste) is the economic objective, as shown by equation (7):

$$Min\ C_p = FCI + C_{IM} + C_{labor} + C_{FGA} - C_{sale} \tag{7}$$

in which FCI is the fixed-capital investment, C_{IM} the cost of insurance and maintenance, C_{labor} the labor cost; C_{FGA} refers to cost of flue gas cleaning and ash management, $and\ C_{sale}$ represents revenue from the sale of electricity. For the environmental aspect, SSI is the objective to minimize, as displayed by equation (8):

$$Min\ SSI = \sum_{n=1}^{n} DE_n + AM_n + RN_n - ER_n \tag{8}$$

Where SSI is the total environmental impact and subscript n indicates each of the impact categories, whilst DE_n, AM_n, RN_n, ER_n represent the environmental impacts of direct emission, ash management, reagent, and infrastructure, as well as energy recovery, respectively.

2.5.2 Decision variables

Six decision variables were selected, namely high-pressure turbine (HPT) inlet temperature, HPT inlet pressure, HPT outlet temperature, low-pressure turbine (LPT) outlet pressure, and pump isentropic efficiency. To ensure that the optimization results did not exceed a reasonable range of the typical specification of the equipment and standard steam cycle operation, a range of variables and constraints were introduced.

The actual value of the decision variables that were obtained from the WtE operator, as well as the range of design parameters used in the optimization are shown in **Table 1.** The numbers of the pipes and equipment in the table refer to **Fig. 2.** Non-dominated sorting genetic algorithm (NSGA-II)

[Table 1 is here]

NSGA-II is one of metaheuristic genetic algorithms inspired by natural selection that is used to generate solutions in the optimization problem. It employs a generating technique whereby a sequence of searching for many Pareto-optimal solutions and deciding the appropriate trade-off to select one of them is carried out (Sharma et al., 2012). NSGA-II is used because i) a crowding distance method results in diversity in the solutions, ii) a non-dominating sorting method can generate solutions that are close to pareto-optimal, iii) an elitist method preserves the best solution in the next generation (Deb et al., 2002; Subashini and Bhuvaneswari, 2012; Yusoff et al., 2011). The optimization problem was solved using an Excel-based MOO (EMOO) program following the principle of NSGA-II developed by Sharma et al. (2012) and Wong et al. (2016).

Maximum number of generations (MNG) is a common termination criterion used in MOO. The iteration has to be large enough to ensure the solutions are converged, but at the same time it should not be too large so that it will cause an excessive number of computations (Wong et al., 2016). This study used steady-state detection (SSDTC) as the termination criterion. This criterion determines convergence based on steady state detection, where it performs precisely with computational efficiency for single-objective optimization (SOO) (Rhinehart, 2014). Wong et al. (2016) developed SSDTC for MOO, which terminates reliably and produces non-dominated solutions close to MNG with quicker computational time. The crossover probability and mutation probability were set at 0.9 and 0.1, respectively, along with population size of 100.

2.6 Sensitivity analysis

Sensitivity analysis was used to investigate how results differ as an effect of a change in input. We applied perturbation analysis, which was implemented by increasing and decreasing each decision variable by 5% of its value while keeping all other variables at their baseline value. The results from perturbation analysis allows the calculation of ratio change between the initial results and perturbation results.

2.7 Scenario analysis

Scenario analysis was used to assess the model's robustness based on the change related to waste management and WtE. Three changes were applied to perform scenario analysis: i) waste composition, ii) sustainable energy provision (SEP), iii) fossil energy provision (FEP). In the first scenario, the change was applied only to organic and plastic waste since these two types of waste are typically significant in the waste composition (Martinez-Sanchez et al., 2016). The organic and plastic waste content in the baseline scenario are 45.95% and 16.8%, respectively, while in the scenario analysis they are 30.9% and 31.8%, respectively. For the two scenarios in energy provision, the change was made in the source of marginal energy. Energy source in SEP consisted of wood, wind, and nuclear whereas FEP consisted of nuclear, natural gas, and hard coal. Information about scenario analysis input is given in Supplementary material Table 5-6.

3. Results

3.1 Energy analysis

The total energy input from the waste was 12.71 MJ/kg-waste. The enthalpy of boiler, HPT, and LPT were -13763.11 kW, 1790.86 kW, and 2085.09 kW, respectively (see Supplementary material Table 7). Waste flow rate per hour was 4.6 ton, resulting total electricity of 3245.72 kW, at which 649 kW was for self-consumption. These results corresponded to 16.27% net efficiency of the system. Studies on the efficiency of WtE with electricity recovery ranging about 14-28% (Beylot et al., 2018; Martinez-Sanchez et al., 2016). The low efficiency of WtE with electricity recovery is caused by energy wasted from electricity generation through heat discharge that is not recaptured for further utilization as in a cogeneration plant (Verbruggen, 2008). The energy wasted is particularly pronounced in between source and sink 10-11 when the steam is being cooled.

3.2 Economic analysis

The economic analysis showed the average cost of treating waste per ton. It considered the fixed cost, which consists of fixed-cost investment, insurance and maintenance, labor cost, as well as cost of flue gas cleaning, ash disposal, and revenue from the sale of electricity. The remaining cost is expected to be covered by a gate fee. **Table 2** shows the results of cost items in treating the waste per ton in WtE plant. The total average cost was 75 €/ton-waste, where the major contribution was fixed cost and electricity sale. For the total fixed cost, the contribution from fixed cost equipment, insurance and maintenance, and labor cost contributed about 65.8%, 22.96%, and 11.25%, respectively to the total value of 83.63 €/ton. A similar value was reported by Martinez-Sanchez et al. (2016), where the total fixed cost for WtE with electricity recovery was 83 €/ton-waste. However, the total average cost was different due to system efficiency that caused different values in electricity generation. In this study, one ton of waste generated around 705.47 kW of electricity.

[Table 2 is here]

The difference between our results compared with other studies can be affected by different calculation methods, cost items, and assumptions used in estimating fixed cost. Investment cost can be calculated based on capacity using a formula devised by Waste to Energy International (Waste to Energy International, 2015) or using information of the known cost and capacity of other plants, and adjusting the value based on the desired capacity. In this case, we calculated the purchased equipment cost (PEC), which consists of steam cycle and air pollution control, then we used ratio of PEC adopted from Lemmens (2016) to calculate in the rest of the cost components in the FCI. Overall, the cost of this study was congruous with WtE plants that have similar capacity, as shown by ENEA (ENEA, 2007).

3.3 Environmental analysis

3.3.1 Total impact

On the midpoint level, the global warming potential from direct emission and total emission per ton waste input were 510 kg CO_2-eq and 175 kg CO_2-eq, respectively. Lower total value compared with direct emission were the results of the benefit from energy recovery. The midpoint results were converted into normalized endpoint and weighted score so that SSI can be calculated. For the endpoint, the highest impact was from global warming regarding human health with the value of 1.13×10^{-3} Pt/ton-waste, whereas the highest benefit was fossil resource scarcity at -1.20×10^{8} Pt/ton-waste. The SSI showed net benefit of -1.21×10^{8} Pt/ton-waste. The total impact of treating waste in WtE plant shows a negative environmental impact, or in other words, it provides an environmental benefit from avoided process. Hence, the benefit depends on the amount and the source of electricity being substituted. Information regarding life cycle inventory, midpoint impact, and endpoint impact is given in the Supplementary material Table 8-10.

3.3.2 Contribution analysis

Contribution of different activities to the environmental impact is shown in **Fig. 3.** Across all impact categories, energy recovery provided benefits (shown by negative impact), ranging from 27% up to 99% of the total benefits and impacts of the WtE in absolute value. This value means a proportion of energy recovery in its absolute value relative to the sum of impacts from direct emission, ash management, energy recovery (absolute value), as well as infrastructure and reagent. In 10 out of 22 impact categories, energy recovery made the highest contribution to the total impact and benefit. These impact categories were fine particulate matter formation, mineral resource scarcity, freshwater eutrophication, ionizing radiation, fossil resource scarcity, terrestrial acidification, human carcinogenic toxicity, terrestrial ecotoxicity, land use, and freshwater ecotoxicity.

[Fig. 3. is here]

Direct emission contributed around 0-72% of the total impact and benefit across the impact categories. It represented the highest contributor for 9 out of 22 impact categories, namely stratospheric ozone depletion, marine ecotoxicity, human non-carcinogenic toxicity, global warming on terrestrial ecosystem, global warming on freshwater ecosystem, ozone formation on human health, marine eutrophication, ozone formation on terrestrial ecosystem, and global warming on human health. The contribution of reagent and infrastructure ranged around 0-65% across all the impact categories. The highest contribution was found in the impact of water consumption on human health, aquatic ecosystem, and terrestrial ecosystem. Lastly, the management of bottom ash and fly ash only contributed about 0-11% across all impact categories.

3.4 Multi-objective optimization

The MOO was solved ten times using EMOO followed by computation of the true Pareto-optimal front as the outcomes is displayed by **Fig. 4**. On average, steady state detection (SSDTC) terminated the calculation in generation 141, with 29 as the standard deviation. Maximum improvement for single objective were 13.4%, 10.3%, and 14.8% for thermal, economic, and environmental, respectively. However, these improvements cannot be achieved altogether due to conflicting objectives. Higher efficiency results an increase in cost exponentially, whilst linear correlation is found between environmental impact and efficiency. Therefore weighted percentage deviation factor (WPD) was applied to determine the optimal solution as shown by equation (9) (Inghels et al., 2019).

$$WPD = \sum_{j=1}^{j} W_j \cdot \left[\frac{|f_{j,s} - f_{j,o}|}{f_{j,o}}\right] \tag{9}$$

where j and W_j indicate objective function and the weight assigned, respectively. The value of jth objective function obtained from true Pareto optimal front and best value of each objective are represented by $f_{j,s}$ and $f_{j,o}$, respectively. The lowest WPD_s is the selected solution due to its closeness to the best value for all objectives.

[Fig. 4. is here]

The outcome of single optimal solution depends on the weight assigned to each objective function by the decision makers. Different set of weight was applied to the environmental objective (W_{en}), economic objective (W_{ec}), and thermal objective (W_{th}) to show the effect of weight factor to the optimal solution. The set of weight including situation i) S1 that assigns equal weight to all objectives, ii) S2 with $W_{th}= W_{en} = 0.3, and\ W_{ec}= 0.4$, iii) S3 which assumes $W_{th}= W_{en} = 0.2, and\ W_{ec}= 0.6$, and iv) S4 with $W_{th}= W_{en} = 0.15, and\ W_{ec}= 0.7$. **Table 3** summarizes the operation configuration for different weight.

[Table 3 is here]

3.5 Sensitivity analysis

Sensitivity analysis is used to investigate the varied results due to change in the input variables. This analysis can identify the decision variables that have a significance influence on each objective. Perturbation analysis, where change applied to one variable while holding the rest to the initial value, is conducted by changing six decision variables by +5% and -5%, followed by a calculation of the ratio of change. Relationship of the ratio of change and decision variables is shown by **Fig. 5.**

[Fig.5. is here]

Similar results were found for the thermal and environmental objectives, where they are most sensitive with T1. The rest of the decision variables affected the thermal and environmental objectives by less than 1%. These similarities are expected since the MOO shows positive linear correlation between the environmental and thermal objective. Environmental benefit depends on the amount of energy recovery which is the direct definition of efficiency. However, there is a slight difference in the actual value: for example, with a reduction of 5% in T1, efficiency and environmental benefit show a change of about -6% and -6.79%, respectively. For the economic objective, the cost results are most sensitive to T2. When the variable T2 was increased and decreased by 5%, the change in cost results were about 63% and 20%, respectively. Unlike the thermal and environmental objectives, where one decision variable has a much more significant effect on the results, in the economic objective, all variables affect the cost by changing the results by at least 13.5%.

3.6 Scenario analysis

3.6.1 Modification of waste composition

A change in waste composition resulted in different outcomes compared with the baseline. The change occurred in thermal, economic, and environmental assessment. The energy balance provided higher results due to the change of waste input. Waste input in a WM scenario has higher LHV at 16.94 MJ/kg, and the system is assumed to have the same efficiency, hence the power output increased as well. The enthalpy of boiler, HPT, and LPT were -18621.85 kW, 2949.84 kW, and 2652.47 kW, respectively. The highest difference compared with baseline scenario occurred in gross energy output of the HPT, at 65%.

The overall cost in treating one ton of waste was 85.61 €, showing an increase of about 13% compared to the baseline. Higher fixed cost and higher revenue were obtained when waste input has higher LHV, with a slight decrease in the cost of flue gas cleaning and ash disposal. The SSI of waste modification scenario was -1.63x10^8 Pt/ton-waste, showing that modified waste provided higher benefit to the environment for about 35%. This is caused by the higher power output so that more electricity production can be avoided and substituted by WtE production. See Supplementary material for complete results in WM scenario (Table 11-13).

The WM model was then solved ten times using EMOO for a comparison with the baseline scenario. On average, the calculation terminated at generation 134 with a standard deviation of 32. A similar improvement can be found in baseline and WM scenarios as a result of the MOO. The maximum improvements in energy efficiency in the baseline and WM scenario were about 13% and 15%, respectively. The economic objective could be improved by around 11.5% and 12.6% at the highest in the baseline and WM, respectively. Meanwhile, the environmental objective had the highest improvement of about 13% and 14% for baseline and WM scenario, respectively.

Performance metrics (PM) were calculated to compare the performance of MOO in finding the non-dominated solutions (Sharma et al., 2017). PM are useful in measuring the performance of MOO algorithm so that they were utilized to evaluate the model when modification was made (Wong et al., 2016). Normalized spread (nSP) and generational distance (nGD) are used as performance metrics in this study. The objectives are normalized using extreme value to avoid bias (Sharma et al., 2017). The first metric, nSP, is used to identify the scope of computed Pareto-optimal fronts so that the larger value is the better one (Audet et al., 2020), whereas nGD measures the convergence performance at which the lower value indicates the closest solutions to true Pareto-optimal front (Sharma and Rangaiah, 2013).

The value of nGD for baseline and WM scenario were similar at about 0.000234 and 0.000227, respectively. Both models provide non-dominated solutions that are equally close to the value of true Pareto-optimal. For spread, the nSP results were 0.5297 and 0.4916 for baseline and WM, respectively. This shows that the baseline scenario has a wider extent of spread in a Pareto-optimal front.

3.6.2 Modification of electricity mix

The second type of scenario applied change in the source of the marginal energy mix. SEP comprised of greener energy sources compared to baseline, whereas FEP consisted of an energy mix that was less green compared with the baseline. The calculation assumed that the electricity price remained the same regardless of the source of the energy. Hence, the change in outcome was only found in the environmental benefit derived from avoided electricity production. The environmental benefit in the SEP and FEP scenario were $-2.49\text{x}10^7$ Pt/ton-waste and $-3.43\text{x}10^8$ Pt/ton-waste, respectively. SEP and FEP scenario differed by about -93% and 183% from the baseline scenario, respectively (see supplementary material Table 14).

SEP and FEP scenarios were optimized to evaluate how the model would behave with a modification. The average termination for SEP and FEP were generations 98 and 129, respectively, whereas the standard deviations were 27 and 29, respectively. The results of performance metrics nGD for baseline, SEP, and FEP were 0.000234, 0.000575, and 0.000266, respectively. FEP showed similar nGD with the baseline, which implied that the non-dominated solutions were close to the true Pareto-optimal front. Meanwhile, the value of nGD for SEP was two times higher than the baseline and FEP, indicating that the non-dominated solutions were less converged. For spread, nSP results for baseline, SEP, and FEP were 0.5297, 0.5517, and 0.7037. For these metrics, similarity was found in the baseline and SEP, where the spread of non-dominated solutions was less extensive than FEP. In both PMs, FEP scenario showed better performance.

4. Discussions

4.1 Importance of waste composition

Waste compositions affect the results of thermal, economic, and environmental assessments. It determines the LHV and chemical contents that will affect the combustion process, emission type and quantity, and the operating cost. Therefore, difference can be found in different studies regarding LCA of WtE although comparable pattern exists across different studies. Midpoint climate change (CC) impact of this study as a result of a direct emission in every ton of waste is 510 kg CO_2-eq. Similar findings were found in Beylot et al. (2018) where the value was around 400 kg CO_2-eq. Comparable results were found in studies by Astrup et al. (2009) and Damgaard et al. (2010) where direct CC impact were 347-371 kg CO_2-eq and 300 kg CO_2-eq, respectively. Within Norway context, Lausselet et al. (2016) reported the CC impact in different scenarios ranging from 265 to 637 kg CO_2-eq.

Waste composition also affects the cost in treating per ton waste in WtE plant. The baseline of this study shows that the cost in treating incoming waste is 75.63 €/ton-waste. The result increases to 85.61 €/ton-waste in scenario analysis as the waste composition is modified. Martinez-Sanchez et al. (2016) confirmed the pattern when waste input has higher LHV. The cost increased with higher LHV due to lower mass flow rate treated in the plant.

4.2 Importance of assumptions and assessment method

The assumptions, system boundary, functional unit, and methods affect the results of LCA, thermal analysis, cost calculation, and optimization problem. The average condition, common method, and FU are used to accommodate the differences among all possible value and enable comparison across studies. For the LCA, there are various impact assessment methods that include different substances, classify impact categorization differently or present the results as midpoint or endpoint result. Midpoint results are commonly used in LCA study, hence it is used as well in this study for comparison purpose. However, for the MOO, the single score method was apply. Midpoint impact can have up to 18 impact categories that will become impractical if each of them used as separate objective function. Single score can simplify the calculation while containing all different impact categories at one. This simplification comes with caveat that some information may be condensed resulting higher uncertainty (Meijer, 2014).

The choice of system boundary and economic assumption must be representative for the system being assessed and commonly used for comparison with other studies. This study covers the direct emission and indirect emission including system expansion method. This choice is made to avoid overlooking environmental benefit from energy recovery. System boundary can be defined iteratively along with inventory analysis to reassure the relevant boundaries are covered (Baumann and Tillman, 2004). Broad range of economic assumption such as discount period, discount rate, electricity price, and fixed-capital investment cost that is calculated using percentage of PEC influence the cost function. Gate fee is not included in this study as it should be decided after the cost of treating waste is known. So that the economic assessment focus on the cost in treating waste instead of the revenue from selling electricity.

The finding also highlights the role of decision makers in determining optimal solution through assigning weight to each objective function. The total of weight across different objective function must be 1, and the objective function that is considered relatively more important has to be assigned higher weight. Various factors such as stringency of environmental policy in certain region, labor wage and the price of consumables, thermodynamics characteristics of the equipment, and the sources of marginal energy may affect the way the decision makers prioritize the objective function.

4.3 MOO parameters

SSDTC terminates the computation for various scenario in generation 98-141. Other termination criteria is maximum number of generations (MNG) that is commonly used in MOO. MNG must be large enough to make sure the results are converged but not too large that it can cause unnecessary computation. It was reported by Roosen et al. (2003) that an increase in MNG from 150 to 730 resulted marginal improvement, and computation for more than 1000 generations provided negligible improvements. MNG for NSGA-II for power generation study can range from 400 to 700 (Behzadi et al., 2018; Ghasemian and Ehyaei, 2018; Hajabdollahi et al., 2012). The use of alternative termination criteria other than MNG can save computational time.

Crossover and mutation probability in NSGA can range around 0.7-0.9 and 0.01-0.2, respectively (Ghasemian and Ehyaei, 2018; Hajabdollahi et al., 2012; Mousavi-Avval et al., 2017). There is no general value to use for crossover and mutation probability, and it can be problem specific (Hassanat et al., 2019).

4.4 Sensitivity and scenario analysis

Perturbation analysis shows how sensitive the thermal and environmental model to T1, and the cost model to T2. The analysis is useful to assess the sensitivity of the model to the decisions variable so that the MOO can focus on fewer decision variables that are most sensitive with expectations of saving computational requirement for the optimization. The high sensitivity of these variables also shows that only small change is required to optimize the system without violating the range of equipment specifications shown by **Table 1.**

Scenario analysis demonstrates the importance of waste composition as discussed in section **4.1.** The change in waste composition will shift the energy balance including the power output of the system, environmental impact, and cost function. Although it should be noted that differences on the outcomes are also affected by ash management, APC technology, impact assessment methods, energy recovery as well as underlying assumptions used in the study such as electricity source being substituted (Beylot et al., 2018; Fruergaard Astrup et al., 2015; Lausselet et al., 2016; Turconi et al., 2011). Attention is required as well to the background system as the modification of the energy mix shows significant change in LCA results. It implies that the more sustainable the sources of the marginal energy, the less environmental benefit is obtained. Whereas WtE provides more environmental benefits when marginal energy sources are less sustainable. It is possible that WtE provides no benefit to the environment if the marginal energy has exceptionally sustainable source.

Scenario analysis can also be used to evaluate the EMOO by measuring nGD and nSP. The change in the foreground system, represented by waste modification, does not change the convergence of the solutions resulted by the EMOO as shown by comparable nGD, however an extent of spread for baseline is better than WM scenario. The change in the mixed of marginal energy source represents a shift in background system. SEP scenario performs worst in the convergence of non-dominated solutions while FEP performs best for the spread. The variety resulted by scenario analysis indicates that this study is contextual so that careful consideration is needed when generalizing the results of this study.

4.5 Implications and limitations

The results demonstrate that an improvement in WtE plant is possible by applying small changes in the operation configuration without requiring new investment. The relationship between the three objective functions indicated the conflict between cost and efficiency, while positive linear correlation presents the environmental impact and efficiency because the benefit from WtE is derived from the amount energy being recovered. Nevertheless, a separate environmental objective is necessary to ensure that WtE still provides environmental benefit, otherwise waste diversion for different treatment may be required. The method of the study can be implemented not only for WtE plant that is in ongoing operation, but also in the design phase. In designing new WtE plant, the decision variables can be expanded by considering different types of APC technologies and ash management.

The study covers a broad range of aspects that require large data input and various methodologies. Unavailable data were estimated, and this could lead to uncertainty. The choice of methodologies and formula affected the results of the study. Data and methodological issues are especially pronounced in economic and environmental assessment. To address this, the most common methodologies were chosen as well as the implementation of sensitivity analysis and scenario analysis to study how the model behaves and what parameters affect the model the most.

MOO calculation provides different choices for termination criteria, mutation probability, and crossover. However, we applied only one type of these aforementioned categories based on a previous study of the use of EMOO program (Wong et al., 2016). The use of different values of crossover and mutation probability can provide different results since there is no global value to use for these parameters. Our focus on using value and termination criteria that haves been tested limits the study on the effect of these parameters.

5. Conclusion

This paper has presented an MOO that integrates LCA to assess environmental objective. The integration of LCA and the use of single score endpoint allowing comprehensive assessment of the environmental objective that are commonly presented as damage cost or CO_2 emission. The use of MOO can improve the performance of WtE plant although a conflict occurs between the economic and thermal objectives, while positive linear correlation is found between the thermal and environmental objective. Each objective shows maximum improvement for about 13.4%, 10.3%, and 14.8% for thermal, economic, and environmental, respectively. These findings present an important role of decision makers to weigh the priority of each objective and generate optimal solution. The study suggests incorporating MOO not only during operational phase of WtE, but also during the planning phase of building a WtE by including more decision variables such as different type of equipment or technology to improve its design. This will provide general information about how the WtE will perform during its operational time.

The paper also demonstrates that each decision variable affects the outcomes differently. By obtaining the information about the most influential variables with regards to the optimization results, modification to the optimization problem can be applied by reducing the number of decision variables to save computational time. Furthermore, applying MOO will help the plant to continuously evaluate the environmental benefit derived from WtE. As the marginal energy sources changes, the environmental benefit will change up to the point that WtE operation is not environmentally beneficial. Knowledge about this matter can help decision makers to formulate waste management policy regarding appropriate treatment or a decision in diverting waste stream.

Overall, WtE plant can be optimized by modifying operation configuration without making new investment. Careful consideration is required when generalizing this study because i) the WtE operation is specific for plant with a certain steam cycle structure, waste composition, energy recovery, APC technologies, and ash management, ii) the assessment was carried out using the Finnish or European context, iii) the impact assessment method for the environmental objective used ReCiPe (H), and iv) the cost function depends on equipment with specific thermodynamic properties.

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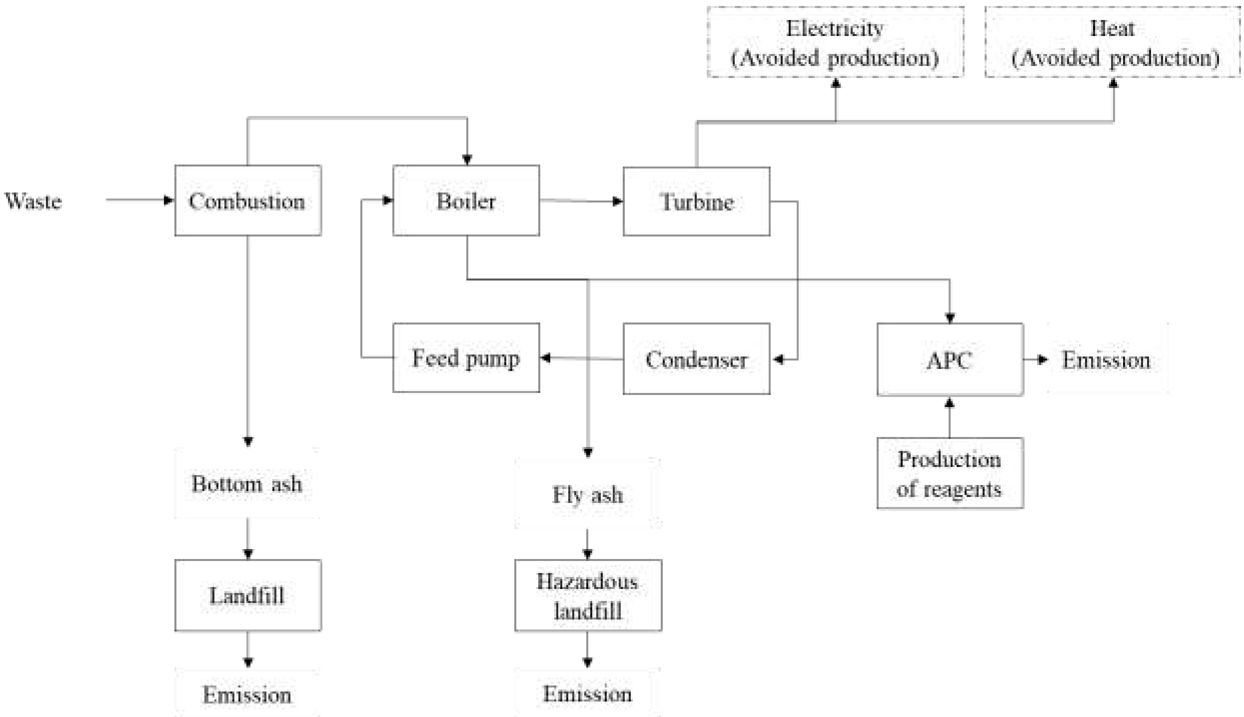


Fig. 1. System description of WtE plant.

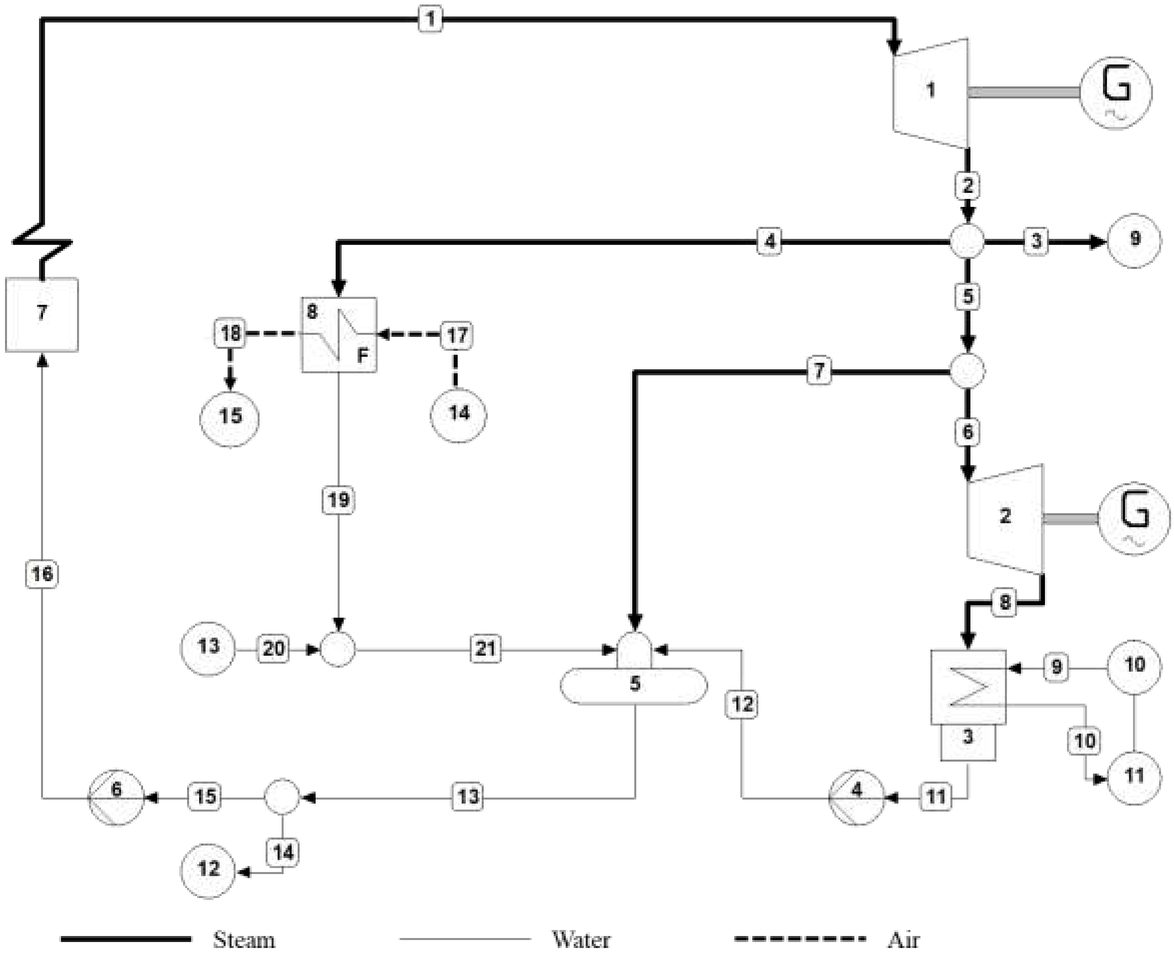


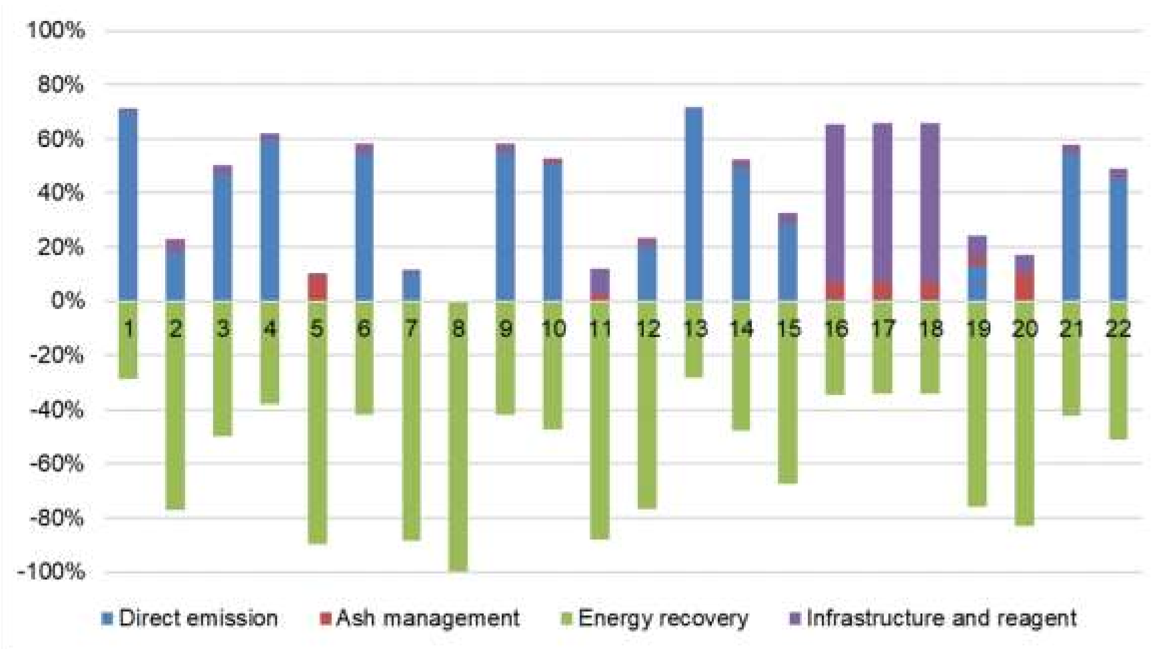
Fig. 2. Schematic of steam turbine cycle studied in this paper. The steam cycle consists of apparatus such as: high-pressure turbine (HPT) (1), low-pressure turbine (LPT) (2), steam condenser (3), condensate pump (4), deaerator (5), feedwater pump (6), boiler (7), heat exchanger (8), source (10, 13, 14), sink (9, 11, 12, 15), and generator (G).

Table 1 Decision variables and range of variation

Operation configuration	Description	Actual value	Range of optimization
T_1 (°C)	Steam temperature (pipe 1)	400	380 – 500
P_1 (kPa)	Steam pressure (pipe 1)	4100	3800 – 4500
T_2 (°C)	Steam temperature (pipe 2, 3, 4, 5, 6, 7)	198	185-210
P_7 (kPa)	Steam pressure (pipe 8, 11)	23	20 - 25.5
η_{pc}	Pump isentropic efficiency (component 4)	0.75	0.75 - 0.85
η_{pb}	Pump isentropic efficiency (component 6)	0.75	0.75 - 0.85

Table 2 Economic analysis of treating waste in WtE

Items	Cost (€/ton-waste)			
Fixed cost	83.63			
Fixed-capital investment (FCI)		55.02		
Direct fixed-capital investment (DFCI)			45.26	
- Purchased-equipment cost (PEC)				17.96
- Purchased-equipment installation				6.74
- Piping				4.49
- Instrumentation and controls				2.60
- Electrical equipment and material				2.02
- Architectural, civil, and structural work				6.06
- Service facility				5.39
Indirect fixed-capital investment (IFCI)			9.76	
- Engineering and supervision				1.64
- Construction and contractor				4.10
- Contingencies				3.30
- Legal cost				0.73
Insurance and maintenance		19.20		
Labor cost		9.41		
Flue gas cleaning and ash disposal	8.93			
Electricity sale	-16.9			
Total average cost	**75.63**			



1 Stratospheric ozone depletion; 2 Fine particulate matter formation; 3 Marine ecotoxicity; 4 Human non-carcinogenic toxicity; 5 Mineral resource scarcity; 6 Global warming, terrestrial ecosystems; 7 Freshwater eutrophication; 8 Ionizing radiation; 9 Global warming, freshwater ecosystems; 10 Ozone formation, human health; 11 Fossil resource scarcity; 12 Terrestrial acidification; 13 Marine eutrophication; 14 Ozone formation, terrestrial ecosystems; 15 Human carcinogenic toxicity; 16 Water consumption, human health; 17 Water consumption, aquatic ecosystems; 18 Water consumption, terrestrial ecosystem; 19 Terrestrial ecotoxicity; 20 Land use; 21 Global warming, human health; 22 Freshwater ecotoxicity

Fig. 3. Normalized endpoint impact of WtE.

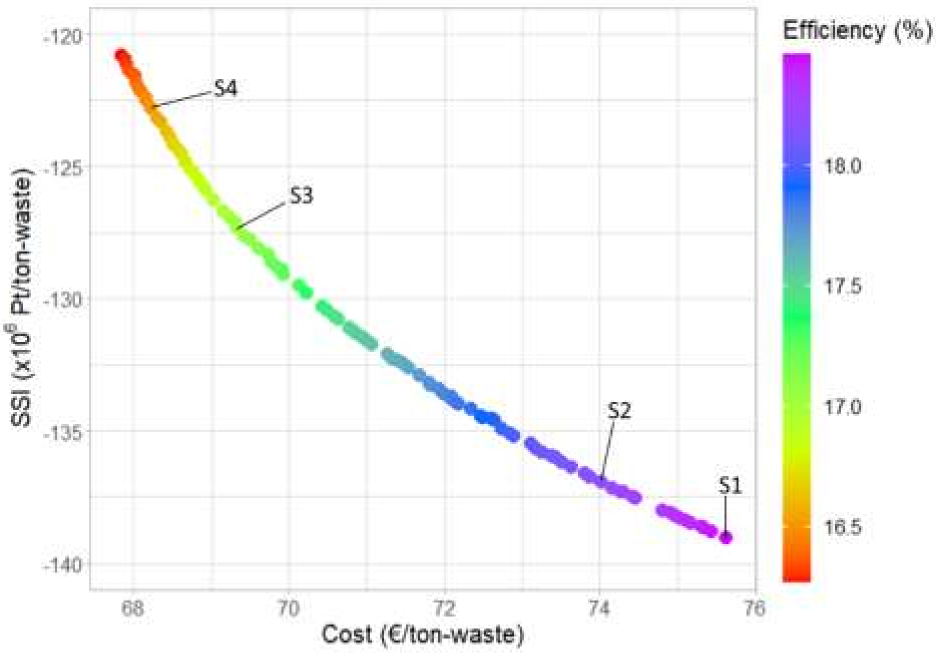


Fig. 4. True Pareto-optimal front of MOO with environmental, economic, and thermal objectives

Table 3 Operation configuration for different weighting factors

Operation configuration	Actual value	S1	S2	S3	S4
T_1 (°C)	400	446.73	440.22	414.07	402.85
P_1 (kPa)	4100	4356.80	4214.98	3803.71	3804.12
T_2 (°C)	198	189.29	187.47	185.05	185.05
P_7 (kPa)	23	20.71	20.71	20.71	20.71
η_{pc}	0.75	0.75	0.77	0.79	0.77
η_{pb}	0.75	0.75	0.75	0.75	0.75

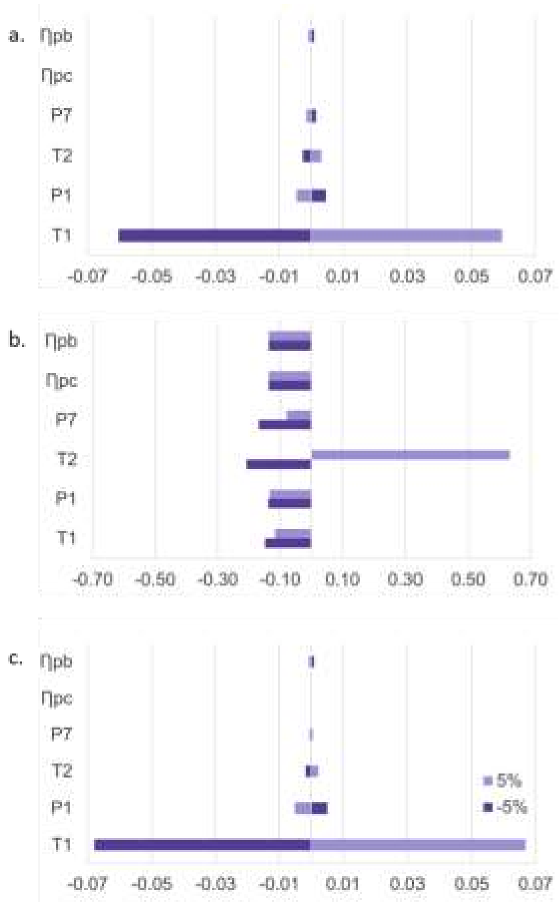


Fig. 5. Sensitivity results of (a) efficiency, (b) cost, (c) environmental impact due to variations of the decision variables