

Techno-economical optimization of a solid waste management system using evolutionary algorithms

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Abstract—Renewable energy technologies are becoming popular due to higher depletion rate of fossil fuel resources. In such circumstances conversion of municipal solid waste into energy is helpful in many ways. However, it is difficult to come up with an optimum conversion technique which depends on number of techno-economical factors. There are number of difficulties in using classical optimization to optimize solid waste management systems.

This research paper introduces a novel optimization algorithm based on evolutionary algorithms to conduct the optimization. The novel optimization algorithm is having the capability to conduct Pareto multi objective optimization considering constraints in both objective and decision spaces. Life cycle cost, net energy produced and landfilling capacity were taken as objective functions in the multi objective optimization. Finally, a brief discussion is presented based on the results obtained.

Keywords—Waste Management, Waste to Energy Network, Multi Objective Optimization and Evolutionary Algorithm

I. INTRODUCTION

Renewable energy systems are getting popular due to higher depletion of fossil fuel resources and global concern on Green House Gases (GHG) emission. However, converting existing energy systems in to 100% renewable is a difficult task due to seasonal variation of renewable energy sources such as wind and solar energy. In such circumstances, Waste to Energy (WTE) can be used as a dispatchable energy source which can absorb the fluctuation of renewable energy sources and replace fossil fuels in Combined Heat and Power (CHP) generation [1]. Moreover, it can address number of issues which arise in Municipal Solid Waste (MSW) Management.

Conversion of MSW into energy depends upon number of factors such as chemical and physical properties of waste, limitations of waste processing techniques, impact of moisture content on combustion technique, economy of scale etc. Optimum conversion technique selected for a particular application may change when moving to another case. This makes it essential to come up with a method to optimize Waste to Energy Network (WTEN) considering multiple objectives. Several methods have been proposed to come up with best strategy to handle the issue. Most of the recent research work have been focused on uncertainty in decision making when coming up with optimum system design [2]–[7]. Several groups have focused on using stochastic methods to come up with optimum management plan [8]. Multi criterion decision making has also been used recently [9], [10]. However, most of these techniques have been based on linear programming techniques. Moreover, scale of the waste flow

and, chemical and physical characteristics of MSW were not taken into consideration when coming up with the optimum management system. It is essential to move from classical linear programming methods when deriving optimum MSW management systems in order to overcome these limitations.

Evolutionary algorithms are getting popular to conduct Pareto multi objective optimization for complex engineering problems where classical gradient based method and linear programming techniques cannot be used. This research paper introduces a novel optimization algorithm based on evolutionary computation to optimize WTEN which is an extension to the previous work presented in Ref. [11]. In this research, Pareto multi-Objective optimizations were conducted considering conflicting objectives such as Life cycle cost(LCC)-landfilling capacity and LCC-net power generation. This research paper present the computational tool developed to come up with optimum set of solutions considering LCC and Net Energy produced and landfilling capacity. A concise description about the mathematical model is presented in Section II. A detailed description about the evolutionary algorithm including operators used, formulation of the objective functions and optimization algorithm is presented in Section III. Results obtained through the multi objective optimization algorithm is presented in Section IV.

II. ENERGY, MATERIAL AND CASH FLOW MODELING

WTEN consist of Direct Thermal Conversion (DTC) of waste into energy, Thermal Conversion after producing Refused Derived Fuel (RDF), and landfilling are taken into consideration in the mathematical model (Fig. 1). Fourteen different RDF production techniques were taken into consideration and both Thermal Conversion of RDF (TCR) and RDF selling were taken as options. Grate firing of waste for electricity production and heating were considered as the options for DTC. Grate firing, Circulating Fluidized bed and CHP generation were taken as the options for TCR. Finally, open landfilling was taken in order to match with the present Sri Lankan Context.

Energy flow model is capable of producing the annual power generation based on waste flow. Total Energy output is computed using Eq. 1 where $\eta_{M,i}$ denotes the mass conversion efficiencies of the selected technique, $\eta_{E/H,i}$ denotes efficiency of heat/power generation, LHV denotes lower heat value solid waste/ RDF and $w_{i,j}$ denotes the daily waste flow. Detailed description about the Energy flow model can be found in Ref. [11].

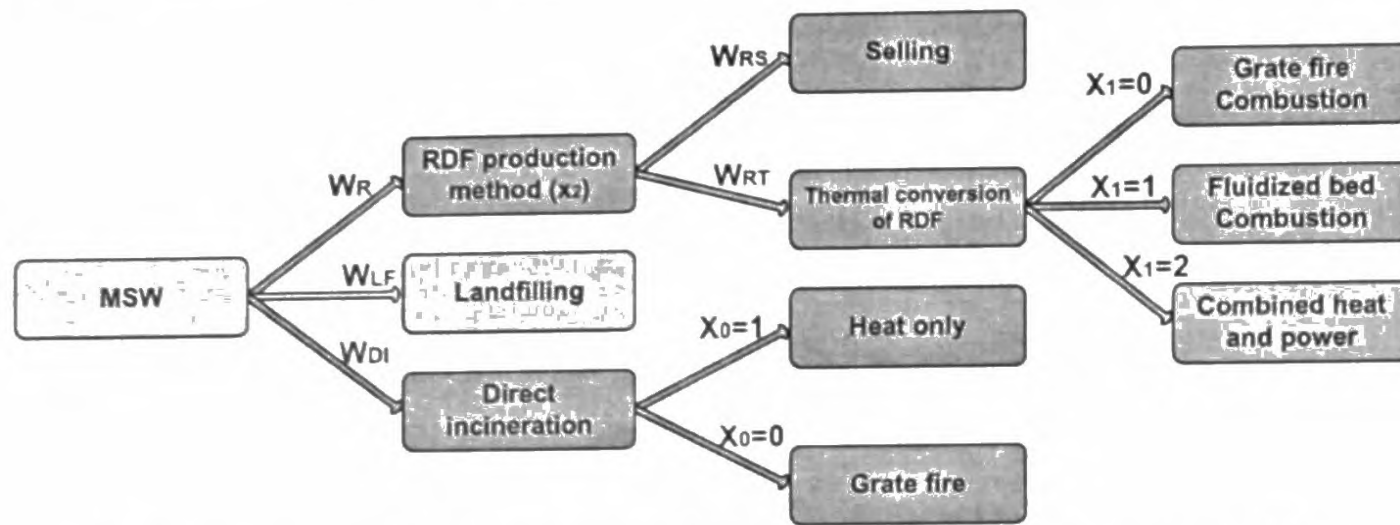


Fig.1. Alternative paths of waste management system and decision space of the optimization problem

$$P_{net} = \sum_{j=1}^{20} \sum_{i=1}^{265} w_{ij} LHV_k \eta_{E/H} \eta_{M,I} \quad (1)$$

Fourteen different production line configurations were taken into consideration, which consist unit operations such as ballistic classifying (BC), drying (D), densifying (DE), eddy current separating (ECS), hand sorting (HS), milling (M), magnetic separator (MS), preliminary trommel screening (PT), shredding (S) and trommel screen (T) [12], [13]. Mass conversion efficiency and LHV varies with the line configuration. Therefore, $\eta_{M,I}$ and LHV for each method are taken from Ref. [12], [13] and tabulated in Table 1. At the same time, $\eta_{M,I}$ and $\eta_{E/H}$ varies with the scale of the power plant. These parameters were taken as a function of the plant capacity according to Table 2.

Similar to energy flow model, cash flow model consists of Initial Capital Investment (ICI) and annual Operation and Maintenance (OM) cost of the entire WTEN (Table 3). Income through the power generation and RDF selling were also considered. Net present value of the entire cash flows for a period of 20 years (taken as the life times) were taken and based on that levelized processing cost per year was computed.

$$LCC = ICC + FOM \times CRF + \sum_{k=0}^{20} p^k \cdot VOM_k \quad (2)$$

In Eq. 2, CRF denotes capital recovery factor, FOM denotes fixed OM and VOM denotes variable OM costs. Income through electricity production and RDF selling is taken under OM.

III. MULTI OBJECTIVE OPTIMIZATION OF WASTE FLOW

A. Pareto Multi Objective Optimization

Most of the engineering problems need con-current optimization of more than one objective, which are conflicting from each other. Two approaches have been used in this regard to arrive at the optimum solution/s [14]. Among them, optimization of a weighted objective function amalgamating all the objectives, is taken as the first method. The relative importance of each objective is represented through the weight and decision makers need to come-up with the weight matrix before conducting the optimization. Weight matrix convert the multi objective optimization problem into a mono-objective optimization problem which is easy to be solved. However, it is a challenging task to obtain the weight matrix without a detailed analysis on the objective space.

The second approach is to use Pareto multi objective optimization where Pareto set of solutions are derived considering conflicting objectives. Pareto optimum set

includes non-dominant solutions with respect to each other. When moving from one solution to the other, there is an increase in at-least in one objective in order to attain gain in one or more objectives (Fig. 2). Pareto set portrays a much better picture of the objective space which support the decision makers to arrive at the optimum solution. Nonetheless, arriving at the Pareto front is a challenging task compared to weighted multi objective optimization. Furthermore, decision support system is essential to be combined with the multi objective optimization algorithm in order to select the final solution from the Pareto front [15]–[17].

TABLE 1: VARIATION OF MASS CONVERSION EFFICIENCY AND LHV OF RDF WITH PROCESS PATH [12], [13]

Line No	Line configuration	η_M (%)	LHV _{RDF}
1	PT-HS-MS-S-T-M-T	18.3	14538
2	T-HS-MS-S-T-M-T	24.9	14161
3	T-HS-MS-S-T-MS-M-T	24.3	14224
4	T-HS-MS-S-T-MS-M-T-MS	23.8	14237
5	T-HS-MS-S-T-ECS-M-T	24.1	14354
6	T-HS-ECS-S-T-ECS-M-T	24.0	14370
7	T-HS-MS-S-T-S-T-M-T	20.9	14822
8	T-HS-MS-S-T-MS-S-T-M-T	20.5	14876
9	T-HS-MS-S-T-ECS-S-T-M-T	20.3	15006
10	S-T-MS-M-T	30.7	13175
11	S-T-MS-S-T-M-T	24.7	14249
12	S-T-MS-S-T-MS-M-T	24.1	14312
13	S-T-ECS-S-T-MS-M-T	23.7	14579
14	S-T-ECS-S-T-ECS-M-T	23.6	14604

TABLE 2: $\eta_{E,DI}$, $\eta_{M,DI}$ VALUES FOR THERMAL CONVERSION PROCESSES

Thermal conversion method	$\eta_{M,DI}$	$\eta_{E,DI}$
Fluidized bed combustion	0.77	0.29
Grate fire combustion	0.77	0.29
Integrated gasification combined cycle	0.87	$0.054 \ln(P) + 0.20$
Co-firing natural gas power plant with gasification	0.8	0.50
Combined heat and power	0.6	$0.022 \ln(P) + 0.206$

TABLE 3:
OPERATION STRATEGY OF THE SYSTEM

Thermal conversion method	η_{M-DI}	η_{E-DI}	ICI (\$ 10 ⁶ /MW)	OM (% of ICI)	Scale (MW)
Fluidized bed	0.77	0.016 ln(P) + 0.270	-0.561ln(P) + 4.77	4	50-1000
Gratefire	0.77	0.29	-0.624ln(P) + 5.297	4	50-1000
Heat only	0.83	0.8 (Heat)	-0.006ln(P) + 0.622	6	1-20
CHP	0.6	0.022 ln(P) + 0.206 + 0.4 (Heat)	-0.105ln(P) + 0.677	4	10-200

Objective 1

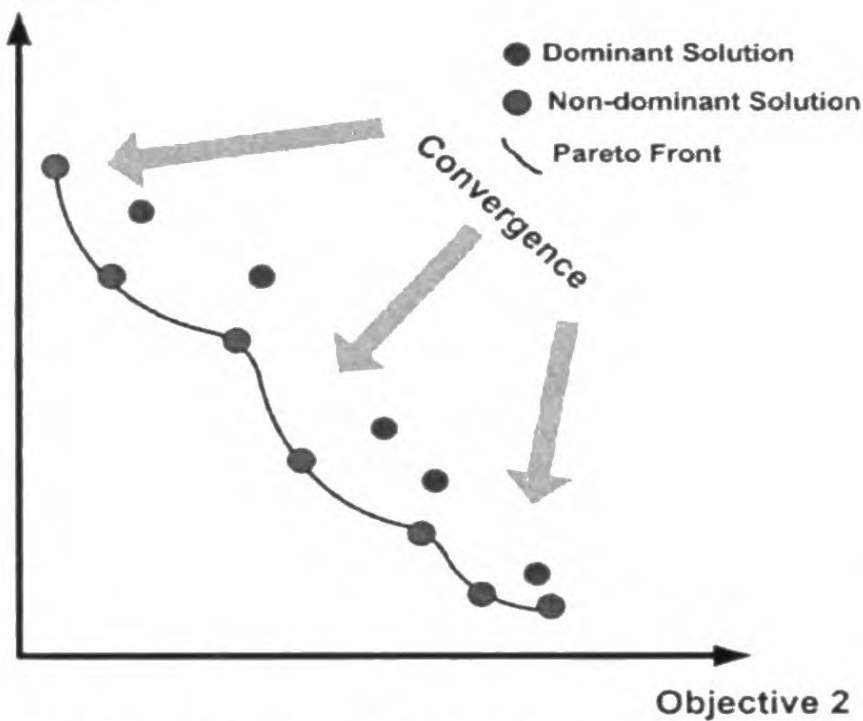


Fig 2 Pareto front of a multi objective optimization problem

B. Optimization Algorithm

Multi objective optimization of a WTEN is a lengthy process, which needs to go through the modeling and simulation initially. Hierarchical decision tree was developed to support decision making while considering waste flow towards landfilling, DTC and TCR as decision space variables initially. Waste flow through RDF is further divided into two. Energy, cash and material flow through the basic system components, need to be modeled, and subsequently simulated throughout the life cycle. Values of the Objective functions were computed based on the simulation results. These results were combined with the optimization algorithm as shown in Fig. 4. Limitations in the conversion processes were taken as constraints. Finally Optimization algorithm was adopted to conducted constraint multi objective optimization.

Selection of the optimization technique depend upon the complexity of decision space variables and the nature of objective functions. When it comes to multi objective optimization of a solid waste management system, objective functions are neither linear nor analytical. Decision space is mapped to the objective space through a life cycle simulation as shown in Fig. 3 which makes the process more complex. furthermore, both process and flow need to be optimized simultaneously. Therefore, it is essential to move towards heuristic methods to overcome these difficulties.

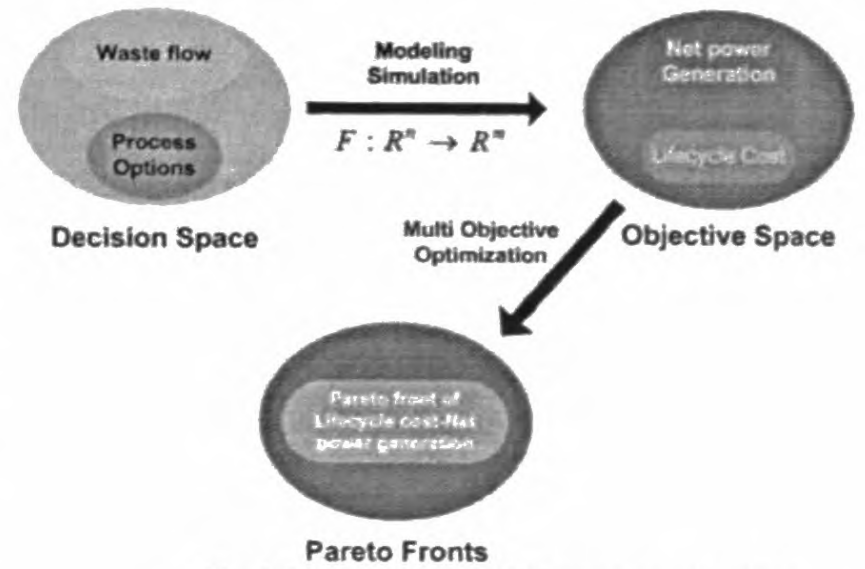


Fig. 3 Optimization of MSW management system

TABLE 4:
RANGE OF THE DECISION SPACE VARIABLES

Parameter	Minimum	Maximum
W_R	0	1
W_{DI}	0	1
W_{RS}	0	1
X_0 (Integer)	0	2
X_1 (Integer)	0	3

Steady ϵ -state evolutionary algorithm [18], which is based on ϵ -dominance method [19], was used in this study in order to perform multi objective optimization. At the beginning, initial population is randomly generated and objective function values of those functions and constraint violation is subsequently computed after simulating those randomly generated population. Based on that, non-dominant set of solution is selected considering the constraint violation (constraint tournament method) and ϵ -dominance method. After coming up with the initial archive and population crossover operator and mutation operators were used to reproduce population and archive. This routine is taken place until the termination of main loop, which take place when desired generations were achieved (Fig. 3). Upper bound and lower bound of those variables were selected according to Table 4.

C. Operators Used for the Optimization Algorithm

Simulated Binary Crossover (SBC) operator [20] and Polynomial Mutation Operator (PMO) [21] were used along with constraint tournament [21] method to come up with the Pareto fronts.

Simulated Binary Crossover operator

SBC operator is a real parameter operator. SBC works with two parent solutions and produce off springs symmetric about the parent solution using a probability distribution. Random number u_i [0,1] need to be chosen in order to come up with the two offspring, which can be used to calculate β_{qi} using Eq. 3, Finally offspring are computed using Eq 4, 5.

$$\beta_{qi} = \begin{cases} (2u_i)^{\frac{1}{1+n_c}}, & \text{if } u_i \leq 0.5; \\ \left(\frac{1}{2(1-u_i)}\right)^{\frac{1}{1+n_c}}, & \text{otherwise} \end{cases}$$

$$x_i^{(1,t+1)} = 0.5 [(1 + \beta_{qi})x_i^{(1,t)} + (1 - \beta_{qi})x_i^{(2,t)}] \quad (4)$$

$$x_i^{(2,t+1)} = 0.5 [(1 - \beta_{qi})x_i^{(1,t)} + (1 + \beta_{qi})x_i^{(2,t)}] \quad (5)$$

where $x_i^{(1,t+1)}$, $x_i^{(2,t+1)}$ denotes off spring and $x_i^{(1,t)}$, $x_i^{(2,t)}$ parents which represent the decision space variables.

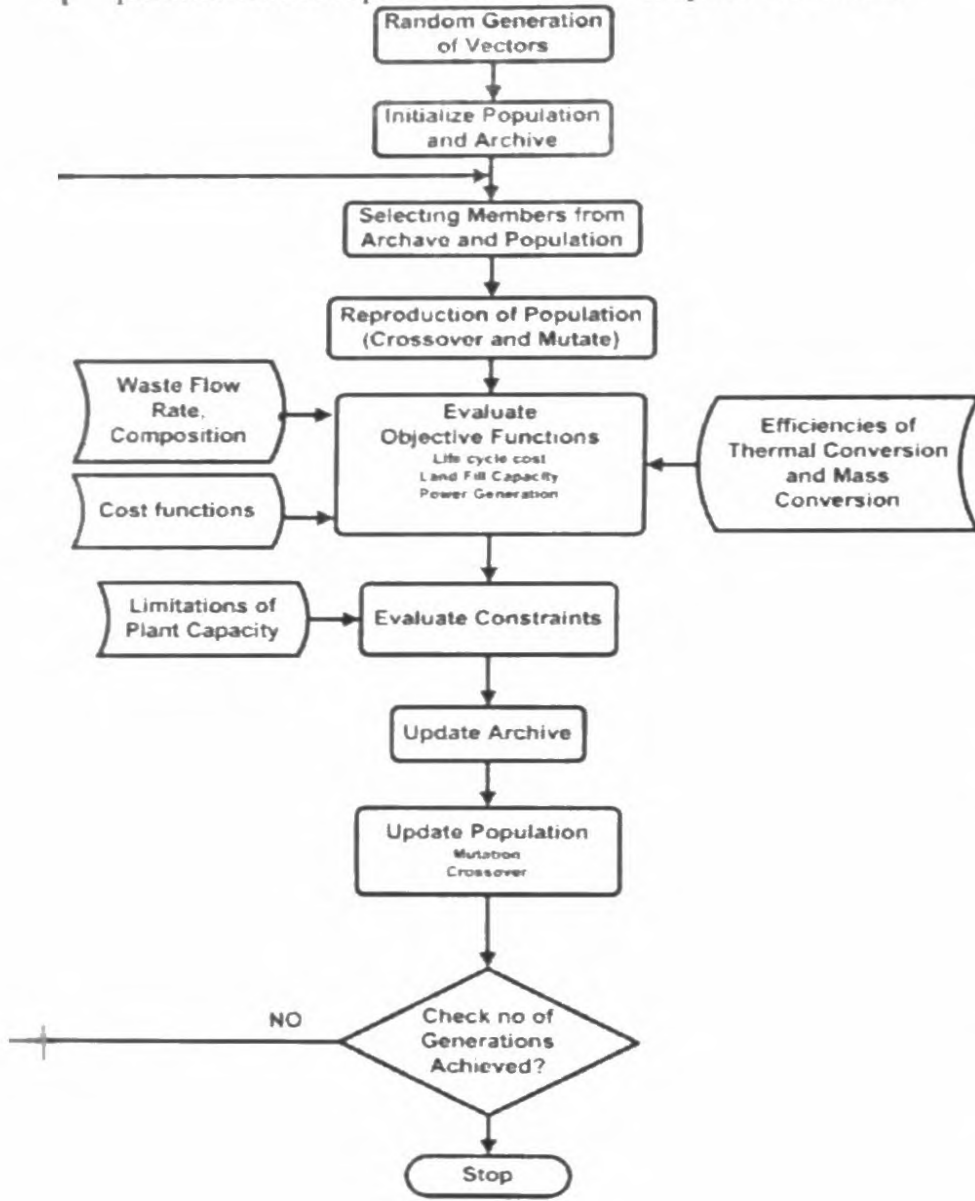


Fig. 4 Optimization Algorithm

Polynomial Mutation Operator

PMO is also a real parameter operator. A random number was chosen initially which is used to calculate $\bar{\delta}_i$ according Eq. 6. Finally, children can be computed using Eq. 7

$$\bar{\delta}_i = \begin{cases} (2r_i)^{\frac{1}{1-p_m}} - 1, & \text{if } r_i \leq 0.5; \\ 1 - (2(1 - r_i))^{\frac{1}{1-p_m}}, & \text{otherwise} \end{cases} \quad (6)$$

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + (x_i^u - x_i^l)\bar{\delta}_i \quad (7)$$

where $y_i^{(1,t+1)}$, denotes child, $x_i^{(1,t+1)}$ parent and x_i^u , denotes upper and lower limit of the decision space variable (Table 4).

Constraint Tournament Method

When it comes to applications with complex objective functions it is quite difficult to come up with penalty functions. Optimal solutions depend of penalty function and usually end up with local minima. Therefore, in order to avoid

these limitations, constraint tournament method was used in this study.

In constraint tournament method update process of Archive and Population (illustrated in next section) is taken place based on following four rules.

Rule 1: Both solutions are taken between two feasible non-dominant solutions

Rule 2: Non-dominant solution is taken over dominant solution when both are feasible

Rule 3: Any feasible solution is preferred over infeasible solution

Rule 4: When both solutions are infeasible, solution is selected similar to rule one and two.

IV. SCENARIO ANALYSIS: MEETHOTAMULLA, COLOMBO SRI LANKA

The proposed MSW management system is having a capacity of 700 MT per day. The composition of the collected waste was found based on field tests carried out. LHV of solid waste was computed based on the composition. Since land filling is the present practice, Pareto front of LCC and land filling fraction were taken into consideration. In order to evaluate the sensitivity of Purchase Price of Electricity Unit (PPEU), Pareto fronts were obtained for PPEU of 15.6, 19.5 and 23.4 LKR (Fig. 5). Furthermore, Selected solutions from the Pareto front of the PPEU with LKR 15.6 is given in Table 5. Similarly, Pareto front of LCC-net energy produced is presented in Fig. 6. In Fig. 6 a sensitivity analysis is also presented considering the increase of waste flow.

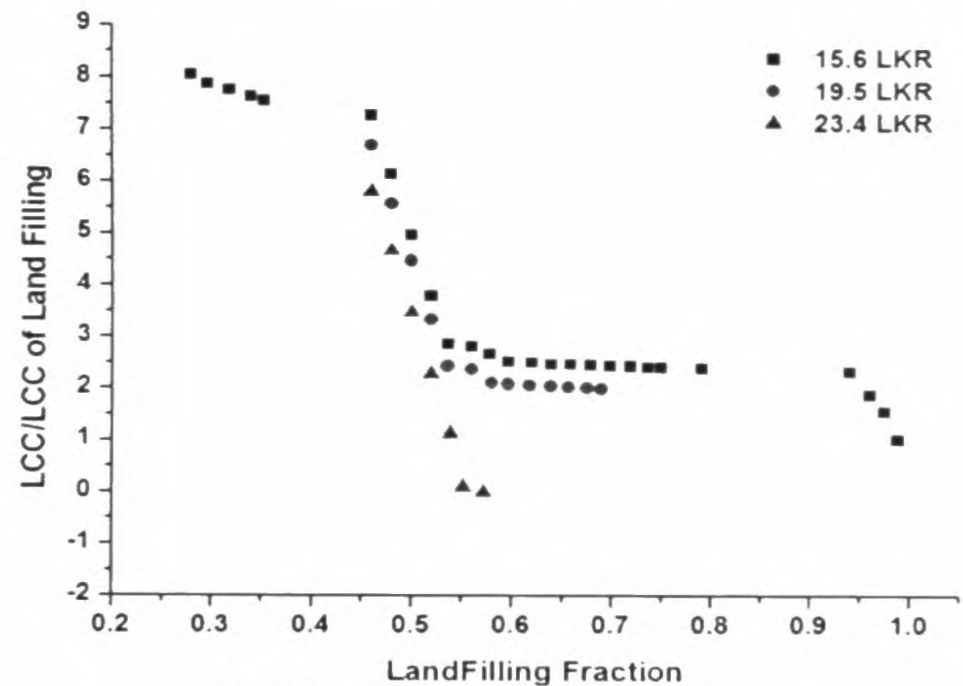


Fig. 5: Pareto front of cost-landfilling capacity

When analyzing the Pareto fronts it is clear that when PPEU is 15.6 and 19.5 LKR land filling is economical compared to power generation. However, when PPEU is 23.4 LKR power generation becomes economical compared to direct land filling. However, when analyzing the decision space vector it was found that optimum waste to energy path is through RDF production and direct combustion of waste is still not economically viable. Combined heat and power generation is the optimum power generation technique that need to be adopted. With the increase of PPEU it is encouraging to venture on waste to energy.

TABLE 5
OPERATION STRATEGY OF THE SYSTEM

RDF Fraction	DI Fraction	Direct LF Fraction	RDF Conversion technique	DI Method	RDF-Thermal conversion method	LCC/LCC(land filling)	Land filling fraction
0.0000	0.9891	0.0109	5	GF	CHP	8.0363	0.2799
0.0099	0.9307	0.0594	14	GF	GF	7.7415	0.3182
0.0098	0.8824	0.1078	14	GF	GF	7.5386	0.3534
0.7752	0.2171	0.0078	9	Heat Only	CHP	6.1339	0.4791
0.9346	0.0561	0.0093	9	Heat Only	CHP	3.7791	0.5198
0.9216	0.0098	0.0686	9	Heat Only	CHP	2.7994	0.5597
0.9406	0.0099	0.0495	5	Heat Only	CHP	2.5117	0.5969
0.8416	0.0099	0.1485	5	Heat Only	CHP	2.4663	0.6395
0.7500	0.0096	0.2404	5	Heat Only	CHP	2.4376	0.6791
0.6614	0.0079	0.3307	5	Heat Only	CHP	2.4190	0.7185
0.5842	0.0099	0.4059	5	Heat Only	CHP	2.3872	0.7502
0.0096	0.0769	0.9135	14	Heat Only	GF	2.3058	0.9399
0.0096	0.0288	0.9615	14	Heat Only	GF	1.5355	0.9749

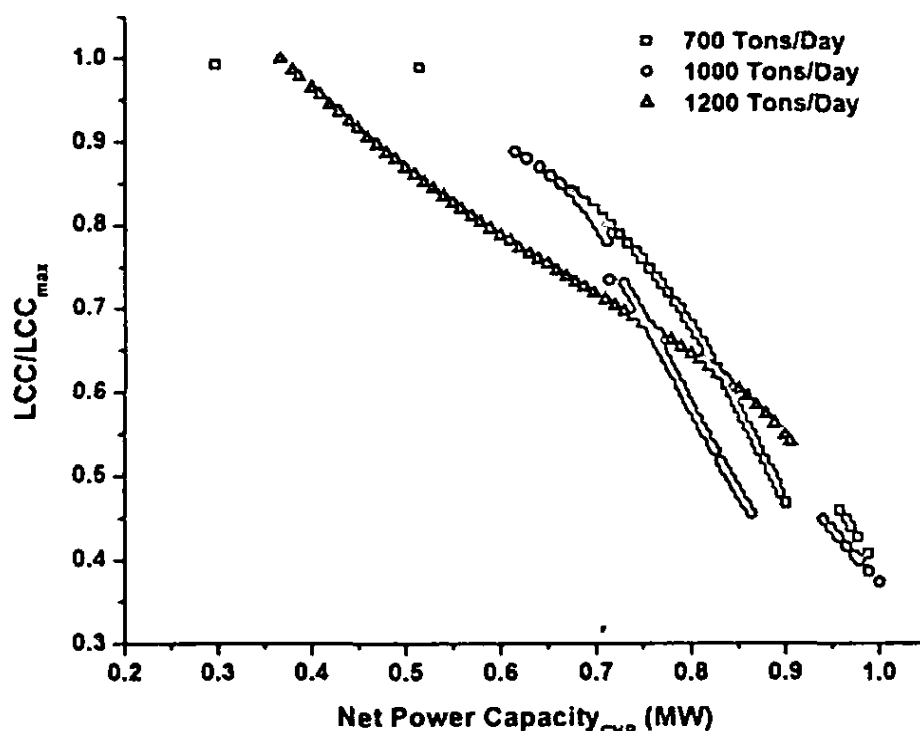


Fig. 6: Pareto front of cost-landfilling capacity

V. CONCLUSIONS

Modelling and optimization of WTEN can be helpful in many ways in the decision making process. Pareto front obtained through the multi objective optimization algorithm can be coupled with a decision support system in order to come up with final system design [22].

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