Particle Swarm algorithm with Fuzzy decision making for a multi-objective economic and environmental optimization of design of a thermal system

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Abstract: Multi-Objective optimization for designing of a benchmark cogeneration system known as CGAM cogeneration system has been performed. In optimization approach, the thermoeconomic and Environmental aspects have been considered, simultaneously. The environmental objective function has been defined and expressed in cost terms. One of the most suitable optimization techniques developed using a particular class of search algorithms known as; Multi-Objective Particle Swarm Optimization (MOPSO) algorithm has been used here. This approach has been applied to find the set of Pareto optimal solutions with respect to the aforementioned objective functions. An example of fuzzy decision-making with the aid of Bellman-Zadeh approach has been presented and a final optimal solution has been introduced.

Keywords: Cogeneration, Environmental aspects, Thermoeconomics, Multi-Objective Particle Swarm Optimization, Fuzzy decision making, Bellman-Zadeh approach.

1. Introduction

The supply of our world with useful energy occurs through energy conversion processes. In order to minimize the environmental impact from energy supply, a primary target is to increase the efficiency of energy conversion processes and, thus, decrease the amount of fuel and the related overall environmental impact, especially the release of carbon dioxide, and NOx which are two of the main components of greenhouse gases. Cogeneration or CHP (Combined Heat and Power) continues to gain importance in Power Production because of its high efficiency, environmental friendliness, and flexibility. It is important for numerous reasons. The first is that capturing the waste heat from power generation can result in an increase in efficiency. This offers significant potential savings in energy costs. Moreover higher stack temperature means a higher energy loss from stack and more air pollution; with applying a cogeneration system these affects will be limited, hence, Cogeneration is more advantageous in terms of energy savings and environmental considerations.

Cogeneration is also more environmentally friendly than traditional fossil fuel power plants. First, CHP is more efficient, reducing total fossil fuel consumption and thereby reducing emissions to the atmosphere. Second, natural gas (a clean burning fossil fuel) is often used in cogeneration with steam injection to minimize emissions.

There are numerous requirements and objectives for design of an energy system. The system should for instance be efficient, have a low or no negative environmental impact, be safe, have high controllability, be easy to maintain and be profitable from an economic perspective, so the term Optimization in thermal systems is one of the most important subjects in the energy engineering field.

In general, objectives involved in the design optimization process are [1]: thermodynamic (e.g., maximum efficiency, minimum fuel consumption, minimum irreversibility and so on), economic (e.g., minimum cost per unit of time, maximum profit per unit of production) and environmental (e.g., limited emissions, minimum environmental impact). It is clear that improving a system thermodynamically without considering economics and environment is misleading. Hence, in design of thermal systems an integrated procedure should be performed to consider all these aspects. Many researchers have started to develop links between exergy and economics. As a result, a new area called thermoeconomics or exergoeconomics has been formed . The aim of the thermoeconomic analysis is to calculate the cost of each product of the systems and investigate the cost formation process in the systems. A simple cogeneration system (CGAM) serves as an example to illustrate the application of thermoeconomic methods for evaluating and optimizing complex energy systems. In all primary works, mathematical approaches were used for optimization process. When multi-modal fitness landscapes are involved, evolutionary algorithms are more suitable than conventional approaches for both single- and (in particular) multi-objective optimization problems.

Application of multi-objective optimization method in thermal systems is not very old. In 2002, Toffolo et al [3], considered two-objective, energetic and economic, in optimization of CGAM problem. They used evolutionary algorithms (MOEAs) with a MATLAB Simulink model and presented a Pareto optimum frontier instead of the single optimum solution of the conventional single objective optimization. They improved their work by adding the environmental impact and introduced a three objectives optimization problem [4].

However their work still suffers from some shortcoming arose from the simplification in selecting decision variable and constraint. To reduce the number of non-feasible solutions that their optimization algorithm may be faced during the optimization procedure, variable ε_{ap} was preferred to the exit temperature on the air side of the Air-Preheater T_3 (the variable used in the original CGAM problem). Furthermore during the optimization process among the five decision variables in original CGAM problem, they chose three of them ($r_{cp}, T_4, \varepsilon_{ap}$) inconstant while the other two were held constant.

In 2008,Sayyaadi [5], used a more suitable method for economic modeling of the CGAM problem (TRR method). He added the environment with cost and introduced a Thermoenvironomic objective and utilized it with exergetic objective function in multi-objective optimization approach.

In this paper we consider two objective functions: thermoeconomic and environmental aspects. In comparison with previous studies in this field ([3, 4, and 5]), this work utilizes the faster and more confidant algorithm in optimization procedure (MOPSO) without any simplifications with five decisions variables. This algorithm can overcome the problem of non feasible solution which has been faced in previous studies. No decision variables are changed or fixed, and all variables and constraints are in accordance with the original CGAM problem. These improvements lead to results that have a more general validity than the corresponding results obtained before. Additionally In application of multi-objective optimization for CGAM problem, after introducing the Pareto front in previous works, there was not a systematic approach to decision making process for selecting one point as the final optimal solution. Here, after suggesting the Pareto front, Bellman-Zadeh approach is employed for decision making process and an example of fuzzy decision making is presented and discussed.

2. Particle Swarm Optimization

It is common when working with design of energy systems to have situations with more than one objective. These problems are referred to as multi objective Mathematical programming problems. Equation (1) shows how a multi objective optimization problem can be formulated mathematically:

$$\min F_j(X) \; \forall j \in \{1,2,3,....k\} \; subject\ to\ X \in L \qquad (1)$$

Where we have $k \geq 2$ objective functions.

In this work we develop a Multi-Objective Particle Swarm Optimizer with a dynamic fitness inheritance technique [6] to decrease the computational cost dealing with some Multi-objective optimization test problems taken from literature. An external archive is used in this method to store the non-dominated solutions

which are found along the process of optimization. The leaders of other particles that guide them to the Pareto-front are selected from the top portion of this archive in each iteration. Moreover, the concept of non-dominated sorting and crowding distance is applied as NSPSO approach [7] to improve the convergence and diversity of the Pareto-optimal solutions. The comparison among the particles and their pbests is based on fully connected approach [8] to increase the selection pressure toward the true Pareto-front. In order to reduce the cost of computation during the process, we use a dynamic fitness inheritance technique which is proposed in [9]. The following formula calculates the new position of a particle in the objective space using fitness inheritance technique:

$$F_i(t) = F_i(t-1) + VF_i(t) \tag{2}$$

$$VF_i(t) = c_1 r_1 (F_{pbest-i}(t-1) - F_i(t)) + c_2 r_2 (F_{gbest-i}(t-1) - F_i(t))$$

Where $F_i(t)$, $F_{pbest-i}$ and $F_{gbest-i}$ are $i-th$ objective function value for the current particle, and its pbest and gbest objective function values, respectively. The parameter p_i , called inheritance or approximation proportion, indicates the proportion of particles that their objective function values must be inherited or approximated instead of evaluation in each iteration. As the Pareto-optimal solutions at the end of the optimization process must be true values of the objective functions, no inherited objective values can enter into the final external archive. To determine the amount of p_i , following nonlinear function is used:

$$p_i = f(x) = x^2 \ ; \ x = \frac{gen}{Gen} \tag{3}$$

Where gen is the number of current iteration and Gen is the total number of iterations.

3. Bellman-Zadeh approach

When using the Bellman–Zadeh approach[10], each $F_j(X)$ of (1) is replaced by a fuzzy objective function or a fuzzy set:

$$A_j = \{X, \mu_{A_j}(X)\} \qquad X \in L, j = 1,2,....k \tag{4}$$

Where $\mu_{A_j}(X)$ is a membership function of A_j . A final decision is defined by the Bellman and Zadeh model as the intersection of all fuzzy criteria and constraints and is represented by its membership function.

$$\mu_D(X) = \cap_{j=1}^{k} \mu_{A_j}(x) = \min_{j=1,....,k} \mu_{A_j}(x) \tag{5}$$

$$X \in L$$

Using (5), it is possible to obtain the solution proving the maximum degree:

$$\max \mu_D(X) = \max_{X \in L} \min_{j=1,...,k} \mu_{A_j}(x) \tag{6}$$

Of belonging to D and problem (6) is reduced to

$$X^0 = \arg\max_{X \in L} \min_{j=1,...,k} \mu_{A_j}(x) \tag{7}$$

To obtain (7), it is necessary to build membership functions $\mu_{A_j(X)}$, j = 1, ..., k reflecting a degree of achieving "own" optimas by the corresponding $F_j(X), X \in L$, j = 1, . . . , k. This is satisfied by the use of the membership functions. The membership function of the objectives and constraints, linear or nonlinear, can be chosen depending on the context of problem. One of possible fuzzy convolution schemes is presented below. [11]

- Initial approximation X-vector is chosen. Maximum (minimum) values for each criterion $F_j(X)$ are established via scalar maximization (minimization). Results are denoted as ''ideal'' points $\{X_j^0, j = 1,...,m\}$.
- The matrix table {T}, where the diagonal elements are ''ideal'' points, is defined as follows:

$$\{T\} = \begin{bmatrix} F_1(X_1^0) & F_2(X_1^0)... & F_n(X_1^0) \\ F_1(X_2^0) & F_2(X_2^0)... & F_n(X_2^0) \\ . & & \\ . & & \\ . & & \\ F_1(X_n^0) & F_2(X_n^0)... & F_n(X_n^0) \end{bmatrix} \tag{8}$$

- Maximum and minimum bounds for the criteria are defined:

$$F_i^{\min} = \min_j F_j(X_j^0) \ , \ i = 1,....,n \tag{9}$$

$$F_i^{\max} = \max_j F_j(X_j^0) \ , \ i = 1,....,n$$

- The membership functions are assumed for all fuzzy goals as follows.

$$\mu_{Fi}(X)=\begin{cases}0 & if \quad F_i(x)>F_i^{\max}\ , \\ \dfrac{F_i^{\max}-F_i}{F_i^{\max}-F_i^{\min}} & if \quad F_i^{\min}<F_i\le F_i^{\max}\ , \\ 1 & if \quad F_i(x)\le F_i^{\min}\end{cases} \tag{10}$$

- Fuzzy constraints are formulated:

$$\mu_{Gi}(X)=\begin{cases}0 & if \quad G_i(x)>G_i^{\max} \\ 1-\dfrac{G_j(x)-G_j^{\max}}{d_j} & if \quad G_i^{\max}<G_i(X)\le G_i^{\max}+d_j \\ 1 & if \quad G_i(x)\le G_i^{\max}\end{cases} \tag{10}$$

Where d_j is a subjective parameter that denotes a distance of admissible displacement for the bound $G_j^{\max}$ j of the j-constraint. Corresponding membership functions are defined in following manner:

$$G_j(X)\le G_j^{\max}+d_j,\quad j=1,2,....,k \tag{11}$$

- A final decision is determined as the intersection of all fuzzy criteria and constraints represented by its membership functions. This problem is reduced to the standard nonlinear programming problems: to find the such values of X and k that maximize k subject to

$$\lambda\le\mu_{F_i},\quad i=1,2,....,n \tag{12}$$

$$\lambda\le\mu_{G_j},\quad j=1,2,....,k$$

The solution of the multi-criteria problem discloses the meaning of the optimality operator and depends on the decision-maker's experience and problem understanding

4. Application of algorithm to CGAM problem

4.1. Definition

A simple cogeneration system serves as an example to illustrate the application of thermoeconomic methods for evaluating and optimizing complex energy systems. The foremost professors and/or researchers of the thermoeconomic field discussed their approaches through this problem. It assumes ideal gas behavior and constant heat capacities. The CGAM Problem designs a cogeneration plant which delivers 30 MW of electricity and 14 kg/s of saturated steam at 20 bars. The installation consists of an air compressor (AC), air preheater (APH), combustion chamber (CC), gas turbine (GT), and HRSG. The structure of the cogeneration plant is shown in Figure 1. The HRSG is composed of an economizer (EC) section where the feed water is heated and an evaporator (EV) section where the heated water is vaporized into steam. Other specifications and operating condition of the CGAM problem for the base case design are [1]:

T1=298.15K, P1=1.01325bar; T8=298.15K, P8=20bar; T10=298.15K, P10=12bar; T3=850K; T4=1520K; P2/P1=10; ηsc=0.86; ηst=0.86

4.2. The thermodynamic model

The utilized thermodynamic model is developed based on the following basic assumptions [1, 3, and 4]:

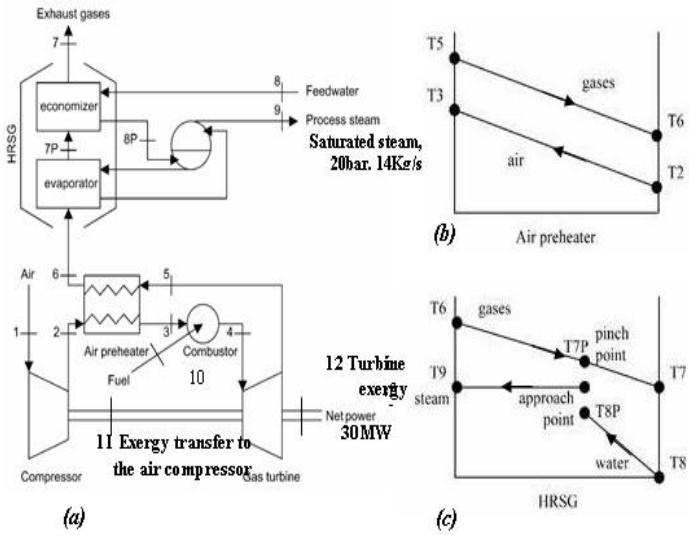

Fig. 1.Schematic flow diagram of the CGAM [1, 3].

- All processes are steady state.
- The principle of ideal-gas mixture is applied for the air and the combustion products.
- The fuel is natural gas and it is assumed to be 100% methane. The methane is an ideal gas.
- Heat loss from the combustion chamber is considered to be 2% of the fuel lower heating value. All other components are considered adiabatic.
- Constant pressure loss ratios are considered in the components.
- The restricted dead state is P0=1.013 bar and T0=25°C.

- 3% and 5% pressure losses are assumed for the air and gases in the air preheater, respectively.
- 5% pressure losses are assumed for the gases in HRSG and combustion chamber.

4.3. The thermoeconomic model

The economic model takes into account the cost of the components, including amortization and maintenance, and the cost of fuel consumption. In order to define a cost function which depends on the optimization parameters of interest, component costs have to be expressed as functions of thermodynamic variables [1and 2]. In the CGAM problem, the purchase cost functions for each plant component are already supplied. In this research, these equations with their related constants have been considered in accordance with [1 and 2].

The governing equation of thermoeconomic model for the cost balancing of a component of an energy system is as follow [1]:

$$\sum_{j=1}^{n}(c_j\dot{E}_j)_{k,in}+\dot{Z}_k^{CI}+\dot{Z}_k^{OM}=\sum_{j=1}^{m}(c_j\dot{E}_j)_{k,o} \quad (13)$$

Where cj is the unit cost of exergy for the jth stream to/from the component, $\dot{E}_j$ is exergy flow for the jth stream to/from the component and $\dot{Z}_k^{CI}$ and $\dot{Z}_k^{OM}$ are the related cost of capital investment and operating and maintenance for the component kth. Developing Eq. (13) for each component of CGAM problem along with auxiliary costing equations (according to P and F rules, see [1]) leads to the following system of equations:

$$\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0\\
0 & 1 & -1 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & \frac{1}{\dot{E}_5} & \frac{-1}{\dot{E}_6} & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0\\
0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & -1 & -1\\
0 & 0 & 0 & \frac{1}{\dot{E}_4} & \frac{-1}{\dot{E}_5} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\dot{E}_{11}} & \frac{-1}{\dot{E}_{12}}\\
0 & 0 & 0 & 0 & 0 & 1 & -1 & 1 & -1 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & \frac{1}{\dot{E}_6} & \frac{-1}{\dot{E}_7} & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}\dot{C}_1\\ \dot{C}_2\\ \dot{C}_3\\ \dot{C}_4\\ \dot{C}_5\\ \dot{C}_6\\ \dot{C}_7\\ \dot{C}_8\\ \dot{C}_9\\ \dot{C}_{10}\\ \dot{C}_{11}\\ \dot{C}_{12}\end{bmatrix}
=
\begin{bmatrix}0\\ -\dot{Z}_{AC}\\ -\dot{Z}_{APH}\\ 0\\ -\dot{Z}_{CC}\\ \frac{FC_L}{\tau}\\ -\dot{Z}_{GT}\\ 0\\ 0\\ -\dot{Z}_{HRSG}\\ 0\\ 0\end{bmatrix} \quad (14)$$

The system of 12 equations and 12 unknowns as indicated by Eq. 9 is solved to obtain the cost of streams 1 to 12 for CGAM problem.

4.4. The combustion pollutants

The original CGAM problem does not perform calculations on the formation of pollutants within the combustion chamber. A simple model, based on semi-analytical correlations [12], is added here to determine pollutant emissions.

The adiabatic flame temperature in the primary zone of the combustion chamber is derived from the expression by Gulder [13]:

$$T_{pz}=A\sigma^{\alpha}\exp(\beta(\sigma+\lambda)^2)\pi^x\theta^y\psi^z \quad (15)$$

where π is a dimensionless pressure p/pref (p being the combustion pressure p3, and pref = 101325 Pa); θ is a dimensionless temperature T/Tref (T being the inlet temperature T3, and Tref = 300 K); ψ is the H/C atomic ratio ($\psi=4$, the fuel being pure methane); $\sigma=\phi$ for $\phi\le 1$(ϕ being the fuel to air equivalence ratio) and $\sigma=\phi-0.7$ for $\phi>1$. φ is equivalent fuel to air ratio that is considered equal 0.64 in this work[4]. x, y and z are quadratic functions of σ in accordance with the following equations [13]:

$$x=a_1+b_1\sigma+c_1\sigma^2 \quad (16)$$

$$y=a_2+b_2\sigma+c_2\sigma^2 \quad (17)$$

$$z=a_3+b_3\sigma+c_3\sigma^2 \quad (18)$$

In Eq. (15) to (18) parameters denoted as A, α, β, λ, a_i, b_i and c_i are constants presented in [13]. In order to have an accurate prediction, four sets of constants have been determined for the following ranges [12]:

$$\begin{aligned}
&0.3\le\phi\le 1.0 \text{ and } 0.92\le\theta<2.0\\
&0.3\le\phi\le 1.0 \text{ and } 2.0\le\theta\le 3.2\\
&1.0<\phi\le 1.6 \text{ and } 0.92\le\theta<2.0\\
&1.0<\phi\le 1.6 \text{ and } 2.0\le\theta\le 3.2
\end{aligned} \quad (19)$$

The values of constants for each range classification are listed in [12].

The adiabatic flame temperature is used in the semi-analytical correlations proposed by Rizk and Mongia [12] to determine the pollutant emissions in grams per kilogram of fuel. With applying these assumptions the following equations for NOx emission and CO2 emission will be obtained and use for environmental pollutant modelling:

$$NO_x = \frac{0.15E16\tau^{0.5}\exp(-71100/T_{pz})}{p_3^{0.05}(\Delta p_3/p_3)^{0.5}} \quad (20)$$

$$CO = \frac{0.179E9\exp(7800/T_{pz})}{p_3^2\tau(\Delta p_3/p_3)^{0.5}} \quad (21)$$

Where τ is the residence time in the combustion zone (τ is assumed constant and is equal to 0.002 s); Tpz is the primary zone combustion temperature; p3 is the combustor inlet pressure; Δp3/p3 is the non-dimensional pressure drop in the combustor (Δp3/p3 = 0.05 as in the CGAM problem [2]).

Note that the primary zone temperature is used in the NOx correlation instead of the stochiometric temperature, since the maximum attainable temperature in premixed flames is Tpz, as pointed out by Lefebvre [13].

5. Optimization process

5.1. Definition of objective functions

The two objective functions are the "total exergetic cost rate of products" and the ''environmental impact''. The second objective function expresses the environmental impact as the total pollution damage cost ($/s) due to CO2 and NOx emissions by multiplying their respective flow rates by their corresponding unit damage cost [14] (c_{CO_2} and c_{NO_x} are equal to 0.02086 $/kgCO2 and 6.853 $/kgNOx, respectively [4]). The mathematical formulation of objective functions is as following;

Thermoeconomic:

$$\dot{C}_{P,tot} = \dot{C}_{F,tot} + \dot{Z}_{tot}^{CI} + \dot{Z}_{tot}^{OM} \quad (22)$$

Environmental [4]:

$$\dot{C}_{env} = c_{CO2}\dot{m}_{CO_2} + c_{NO_x}\dot{m}_{NO_x} \quad (23)$$

5.2. Decision variables

With employing this algorithm there is no need to change of the decision variables for overcoming the occurrence of non feasible solutions, as previous works do.

Decision variables are:

- The compressor pressure ratio p2/p1.
- Isentropic efficiency of the compressor ηsc.
- Isentropic efficiency of the turbine ηst.
- Temperature of the air entering the combustion chamber T3.
- Temperature of the combustion products entering the gas turbine T4.

5.3. Constraints

Although the decision variables may be varied in optimization procedure, each decision variable is normally required to be within a given range as follow:

$$6 \le p_2/p_1 \le 16 \quad (24)$$

$$0.6 \le \eta_{sc} \le 0.9 \quad (25)$$

$$0.6 \le \eta_{st} \le 0.92 \quad (26)$$

$$700 \le T_3 \le 1000K \quad (27)$$

$$1200 \le T_4 \le 1550K \quad (28)$$

Air preheater:

T5 > T3 (29)

T6 > T2 (30)

HRSG:

ΔTP= T7P - T9 > 0 (31)

T6 ≥ T9+ ΔTP (32)

T7 ≥ T8+ ΔTP (33)

T7P > T8P (34)

T7 ≥ 378.15K (35)

The last constraint is an additional constraint with respect to the original CGAM problem imposed on the exhaust gases temperature. This limitation is considered to prevent the condensation of the water vapour exist in the combustion products at the outlet section of economizer.

6. Results and Discussion

MOPSO is used for the thermoeconomic and environmental design optimization of CGAM problems. Fig. 2 presents the Pareto optimum solutions for CGAM problem with the objective function indicated in Eq. (22) and (23) and constraints represented in Eq. (24) to (35).

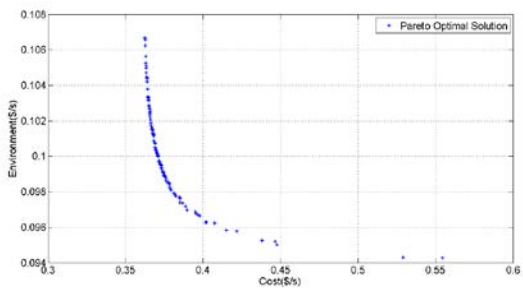

Fig. 2. The set of Pareto optimal solutions.

As shown in this figure, while the total cost rate of the plant is increased to about 0.55$/s the total cost rate of environmental damages decrease very slightly. Increasing of the total cost rate of product form 0.36$/s to 0.55$/s is corresponding to the moderate decrease in the cost rate of environmental aspect. The left most point of diagram has the minimum cost rate equal to 0.362 $/s and it is in accordance with the optimal solution found in the original CGAM problem [2]. This point corresponds to highest environmental damage cost with the value of 0.107 $/s, on the other hand, while the thermoeconomic objective rises to 0.554 $/s environment reach to its minimum on 0.0943$/s.

Table 1.Comparison of results

Objective function, decision variables, costing and operating parameters	Conventional optimization approaches presented in [2]	Left most point of Pareto front via MOPSO Algorithms presented in this work
Product Cost Rate ($/s)	0.362009	0.362489
$T_3(K)$	914.28	835.20
$T_4(K)$	1492.63	1487.53
η_{sc}	0.8468	0.8748
η_{st}	0.8786	0. 9004
p_2 / p_1	8.52	11.88

In order to evaluate advantages and robustness of the MOPSO optimization approach, the minimum cost point compared to the original CGAM problem [2] solved using conventional mathematical optimization approach.

By using fuzzy decision maker which regards the restraints of design and manufacturing processes, one can choose the best solutions along the Pareto optimal fronts to optimize cost and environment. To visualize decision making process, the intersection point which is maintained by the concept of previous section is shown in Fig. 2 by red point. This point is the best among the possible optimal trade offs according to the parameters implemented (by someone) in the fuzzy decision maker.

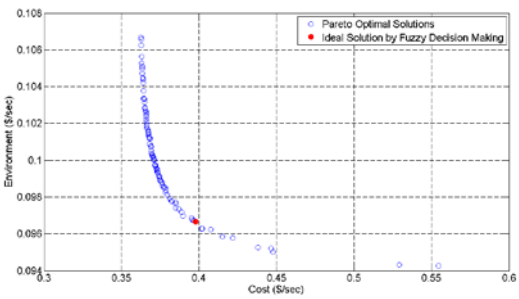

Fig. 3. The set of Pareto optimal solutions and ideal solution by fuzzy decision making

Information related to this point is summarized in table below:

Table 2.selected point among the Pareto front by Fuzzy decision making method

Selected point via fuzzy decision making information	Values
T3(k)	815.18
T4(k)	1465.2
η_{ac}	0.88057
η_{gt}	0.90743
P2/P1	11.572
Product cost rate($/s)	0.39788
Environmental damage cost rate	0.0 96661

The environmental damage cost related to cost optimum in original CGAM problem, is near to 0.11, as can be seen by using fuzzy decision making a point with more reasonable values in both environmental and thermoeconomic cost will be selected.

Conclusion

This work considered environmental aspects with thermoeconomic objective function simultaneously and introduced a fuzzy decision making. After detailed thermodynamic and thermoeconimic modeling, environmental

objective function was introduced and with employing a powerful and fast algorithm (MOPSO) the Pareto front is introduced. Finally the capability of Bellman-Zadeh approach in fuzzy decision making was shown.

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