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ORIGINAL ARTICLES

A Hybrid Intelligent System for Decision Making

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ABSTRACT

In this paper we design a hybrid intelligent system to help decision maker to make a good decision in economic and emission dispatch (EED) problem. The EED problem is in multiobjective form. The objectives are to minimize fuel cost and to minimize emission. The proposed approach consists of four stages such as multiobjective optimization problem, clustering, fuzzy inference system and decision making. In the first stage NSGA2 method is used to solve EED problem with some optimal solutions, in the second stage FCM is used to cluster those optimal solutions then in the third stage Mamdani FIS is used to build rule bases and the last stage a decision is selected by decision maker. To learn EED problem three scenarios are given. Those scenarios are profit oriented, environment oriented and profit and environment oriented. Decision maker must select the best solution as a decision where the decision is based on the scenario. Then decision maker's decision is used to calculate decision score. The higher decision score is the better decision.

Key words: Fuzzy C Mean, Fuzzy Inference System, Decision Making, Intelligent System.

Introduction

In modern era, decision making plays important role in the people's life. Almost every day people must decide a decision to solve their problem, mistaken in decision making is able to lose in a competition. Therefore it is needed an instrument that can help people in decision making. One of the instruments is an intelligent system that based on Soft Computing (SC). As we know that SC consists of several computing paradigms, including fuzzy logic, neural networks, and genetic algorithms, which can be used to build powerful hybrid intelligent systems. Combining SC techniques, we can create powerful hybrid intelligent systems that can use the advantages that each technique offers (Patricia Melin, 2005). A proper combination of these methodologies will result in a hybrid intelligent system that will solve efficiently and accurately a specific decision making problem.

In this paper the proposed approach is to build a hybrid intelligent system that can be used as decision tool to help Decision Maker (DM) to make and learn a decision. Our hybrid intelligent system consists of four stages such as multiobjective optimization problem, clustering, fuzzy inference system and decision making. In our model system, DM makes a decision in Economic and Emission Dispatch (EED) problem.

EED problem is Multiobjective Optimization Problems (MOP). The objective of EED problem is to minimize fuel cost and emission. These multiobjective problems must be fulfilled at the same time. These problems become complex because each objective will conflict each other. As a result, it is needed a method to solve these problems by use best search solution. This best search solution will achieve objective that compete under different trade off scenario (Branke Jürgen, 2008). MOP may not have one best solution on all objectives, but group of solutions that superior at end of solution from search space when all objectives are considered. But inferior at other solutions on search space on one objective or more (Coello Coello, 2007). There are some methods of MOP such as Multi-Objective Genetic Algorithm (MOGA), Strength Pareto

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Evolutionary Algorithm (SPEA) and Non-dominated Sorting Genetic Algorithm II (NSGA2). Some researches (Abido, 2006; Basu, 2008) use NSGA2 to solve EED problem.

Materials and Methods

Multiobjective optimization problem:

A multiobjective optimization problem consists of a number of objectives to be optimized instantaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows:
Minimize:

$$f_i(x), \quad i = 1, \ldots, N_{obj} \tag{1}$$

Subject to:

$$g_j(x) = 0, j = 1,...,L \tag{2}$$

$$h_k(x) \le 0, k = 1,...,K \tag{3}$$

where f_i is the ith objective function, x is a decision vector that represents a solution, and N_{obj} is the number of objectives.

The purpose of solving and arranging from multiobjective optimization problem is to find a solution for each objective that has been optimized and quantized, how superior its solution if compare with other solution (Coello Coello, 2007).

Pareto Optimal Solution:

A multiobjective optimization problem that has two solutions x_1 and x_2 can have one of two possibilities, namely one dominates the other or none dominates the other. To describe, it can be shown on minimizing problem of two solutions x_1, x_2 where x_1, to said dominated x_2 if the following two conditions are satisfied:

$$\forall i \in \{1, 2, ..., N_{obj}\} : f_i(x_1) \le f_i(x_2), \tag{4}$$

and

$$\exists j \in \{1, 2, ..., N_{obj}\} : f_j(x_1) < f_j(x_2) \tag{5}$$

If one of condition does not reached, solution x_1 will not dominate solution x_2. Moreover, if solution x_1 dominates solution x_2, x_1 is called non dominated solution with group $\{x_1, x_2\}$. Solution in non-dominated with all search space is known as Pareto optimal and form Pareto Optimal Set or Pareto Optimal Front (Coello Coello, 2007; Branke Jürgen, 2008).

Non-dominated Sorting Genetic Algorithm 2:

One of type of Multiobjective Genetic Algorithm (MOGA) is non-dominated Sorting Genetic Algorithm (NSGA2) that is modification from ranking procedure (Deb, 2000). NSGA2 Algorithm is based on some layers of individual classification. Before selection is shown, population is ranked on based non-domination. Each of non-dominated individual is classified in one category by a dummy fitness value that proportional with population size to present a reproductive potency that equal for this individual.

To maintain variety of population, this classified individual is divided by their dummy fitness value. After that this group of classified individual is ignored and other layers from non-dominated individual are deliberated. The process continues until all individuals on population are classified. Because individuals on first front have maximum fitness value, they always have duplication that better than remain population. It allows to a better searching on Pareto Front and results convergence from population to its domain.

NSGA2 builds a population from competed individual, ranks and chooses each individual based on non-domination level. NSGA2 also employs evolutionary operations to produce new pool from offspring and to combine parents and offspring before separation new combination into front. Flow diagram of NSGA2 can be seen on Figure 1.

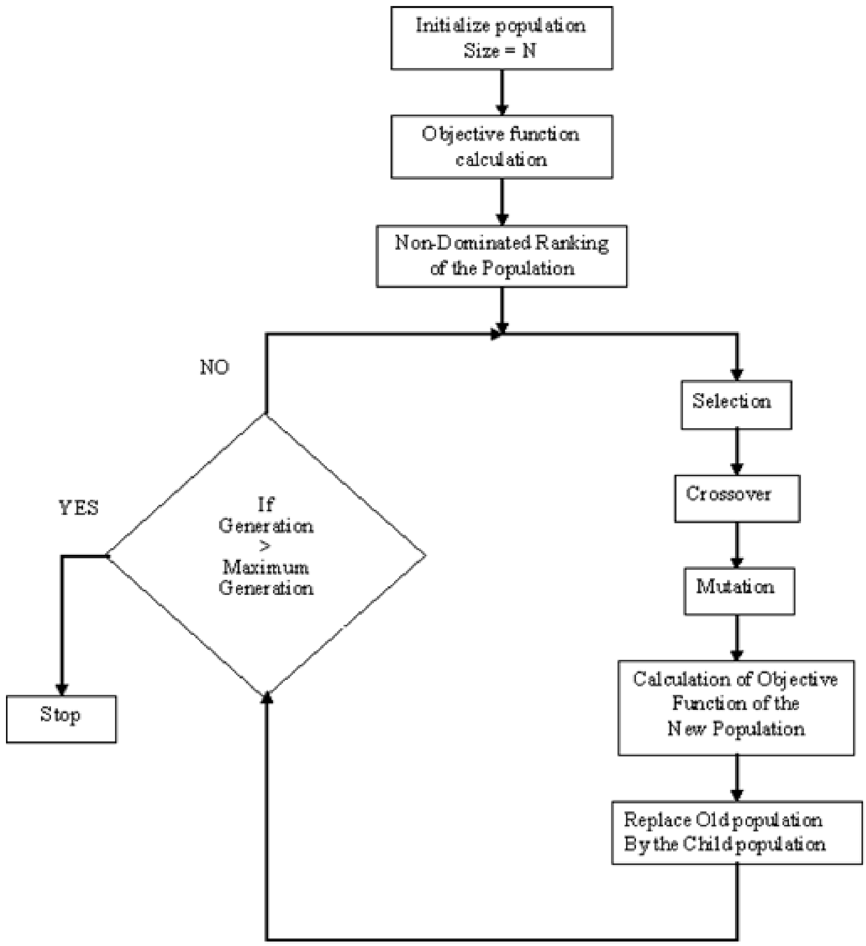

Fig. 1: Flow Diagram of NSGA 2.

Fuzzy C Means:

Clustering is a process of grouping a set of object into classes of similar objects. Fuzzy C-Means (FCM) clustering that is one of data mining technique is used to cluster data to improve accuracy and efficiency (Ahmad Shahi, 2009). FCM algorithm is to give of data point into cluster with various degree of membership. Exponent $m \in [1,\infty]$ is weighting factor that determine fuzzy membership of cluster. Consider the finite X set constructed by M feature vectors; that is, $X = \{x_1, x_2, \ldots x_M\}$, $x_i \in \Re^n$, $1 \le i \le M$. Let, $V = \{v_1, v_2, \ldots, v_C\}$, $v_j \in \Re^n$, $1 \le j \le C$ be a set of C point prototypes or cluster centers for X. The FCM algorithm can be summarized as follows (Xu Rui, 2009; Valente, 2007):

Select number of cluster *C*, weighting exponent *m*, and a small positive number (error tolerance) *e*; maximum number of iterations *N* ; set $v = 0$;
Generate an initial set of prototypes $V_0 = \{v_{1,0}, v_{2,0}, \ldots, v_{C,0}\}$;
Set $v = v + 1$

$$u_{ij,v} = \left[\sum_{\ell=1}^{C} \left(\frac{\left\| x_i - v_{j,v-1} \right\|^2}{\left\| x_i - v_{\ell,v-1} \right\|^2} \right)^{1/(m-1)} \right]^{-1} \quad \text{, where}$$

$1 \le i \le M$; $1 \le j \le C$ (6)

$$v_{j,v} = \frac{\sum_{i=1}^{M} (u_{ij,v})^m x_i}{\sum_{i=1}^{M} (u_{ij,v})^m} \quad \text{, where}$$

$$1 \le j \le C \tag{7}$$

$$E_v = \sum_{j=1}^{C} \left\| v_{j,v} - v_{j,v-1} \right\|^2 \tag{8}$$

if $v < N$ and $E_v > e$, then go to step 3

Linguistic Variables:

In the process of decision making, making an exact evaluation and conveying the feeling and identification of objects for decision makers is relatively complicated, as is providing precise numerical values for the criteria. This is because of the vagueness of human feeling and identification, like "moderately", "equally", "strongly", "very strongly" and "extremely". Moreover, it is also recognized that human judgment on qualitative attributes is always subjective and imprecise. Therefore, fuzzy set theory can play a significant role in decisions of this kind (Jiang-Jiang Wang, 2008).

Fuzzy set theory is suitable for dealing with the uncertainty and imprecision associated with information concerning various parameters. In a universal set of discourse X, a fuzzy subset Z of X is defined by a membership function $f_Z(x)$, where $f_Z(x)$, "$x \in X$, indicates the degree of x in Z. The degree of an element is defined by a value between 0 and 1. If x belongs to Z, then $f_Z(x) = 1$ and if clearly not, $f_Z(x) = 0$. The higher $f_Z(x)$ then the greater is the grade of membership for x in Z.

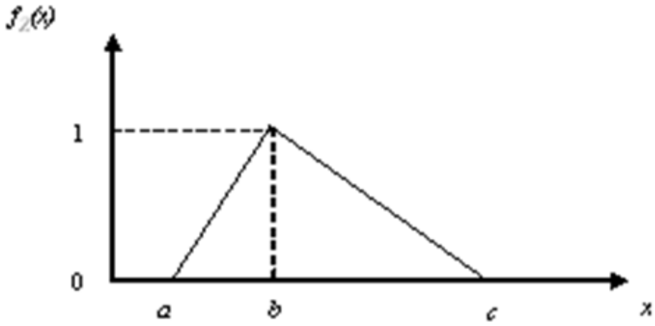

Fig. 2: Membership functions of triangular fuzzy number Z.

Figure 2 shows a triangular fuzzy number Z. It is a fuzzy number with piecewise linear membership function $f_Z(x)$ defined by linear membership function $f_Z(x)$ defined by:

$$f_Z(x) = \begin{cases} 1, & x = b \\ (x-a)/(b-a), & a \le x < b \\ (c-x)/(c-b), & b < x \le c \\ 0, & otherwise \end{cases} \tag{9}$$

Fuzzy Inference Rules:

The FIS has been used successfully in a wide variety of fields, including automatic control, data classification, decision analysis, expert systems, time series prediction, robotics and pattern recognition. It is based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. The structure of a FIS (Jang, 1997) consists of three parts: a rule base, a database for membership functions and a reasoning mechanism. There are two types of FIS: the Mamdani type and the Sugeno type. In the Mamdani type, both the input and output of the IF–THEN rules consist only of fuzzy sets.

Economic and Emission Dispatch:

The objective of EED Problem is to minimize fuel cost and emission. Fuel cost of system can be related as an important criterion for economic feasibility. Curve of fuel cost is assumed for prediction with quadratic function from real power output generator as (Gong, 2009; Abido, 2006):

$$FC(\vec{P}_G) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{10}$$

where, P_{Gi} is real power output from *i-th* generator; N is sum of total generator; a_i, b_i, c_i, are coefficients of fuel cost curve from *i-th* generator simultaneously. In addition, emission that produces from this generator is Nitrogen Oxide (No_x) emission type. This emission is given as a function from generator output that is sum of quadratic and function of exponential as shown below (Gong, 2009; Abido, 2006):

$$EM(\vec{P}_G) = \sum_{i=1}^{N} 10^{-2}\left(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2\right) + \zeta_i \exp(\lambda_i P_{Gi}) \tag{11}$$

where $\alpha_i, \beta_i, \gamma_i$ are coefficients from *i-th* generator that show us as emission characteristics. This system has constraints such as:

Constraint of Power Capacity

For stable operation, real power output from each generator is limited by upper bound and lower bound, as shown below:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \quad , i = 1,2,\ldots,N \tag{12}$$

Constraint of Power Stability

Total of electric power must meet with total of electric demand power P_D and P_L as a result:

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \tag{13}$$

where P_D is total required load (per unit - p.u), and P_L, is transmission losses (p.u). Problem of EED can be formulated mathematically as multiobjective optimization problem as follows (Gong, 2009):

Minimize [FC, EM] (14)

Proposed Hybrid Method:

The objective of this proposed approach is to build a Hybrid Intelligent System to help Decision Maker (DM) to make a decision in EED problem. The framework of Hybrid Intelligent System is shown in Figure 3. This Hybrid Intelligent System is consisted of four stages such as MOP, Clustering, Mamdani FIS and Decision Making.

In the stage 1, NSGA2 is used to produce some optimal solutions for EED problem. In the stage 2, FCM is used to cluster the optimal solutions from NSGA2 result. In this paper, we use three clusters to group these optimal solutions. In the stage 3, Mamdani FIS is used to form rule bases where the inputs come from the level of fuel cost and emission and the output comes from satisfaction rate (SR). Satisfaction rate represents the level of satisfaction within the attainable search region. The satisfaction rate uses the following formula (Cheng Chien Kuo, 2010):

$$Satisfaction\ Rate = \frac{\max\left\{\frac{E}{F}\right\} - \left\{\frac{E}{F}\right\}}{\max\left\{\frac{E}{F}\right\} - \min\left\{\frac{E}{F}\right\}} \quad (15)$$

Equation (15) shows that *E* is the emission and *F* is the fuel cost that comes from NSGA2 results (first stage). The satisfaction rate value ranges from 0 to 1. In the stage 4, DM decides a solution for EED problem. EED problem is consisted of three scenarios such as profit oriented, environment oriented and profit and environment oriented. Profit oriented scenario is based on profit with less concern with environment, environment oriented scenario is based on low pollution of emission and profit and environment oriented scenario is based on balancing of profit and emission. A penalty will be given if the numbers of emission exceed a rule for example government regulation. This penalty will reduce DM's decision score. On the other side, if the numbers of emission do not exceed a government regulation. An incentive will be given to this selection. Therefore DM's decision score will increase. Where decision score is:

$$\text{Decision score} = \text{Profit} + \text{Incentive} - \text{Penalty} \quad (16)$$

The proposed HIS helps DM by giving a recommendation when decide a solution. HIS's recommendation is a value of SR where the numeric value from SR is converted to a linguistic variable. The linguistic variable for SR is *Very Bad*, *Bad*, *Fair*, *Good* and *Very Good*. For example, if a set of optimal solutions are given (in this paper we use five solutions) and then DM must select the best solution as a decision where the decision is based on the scenario. Decision score is used to calculate score between profit and penalty. The higher decision score is the better decision.

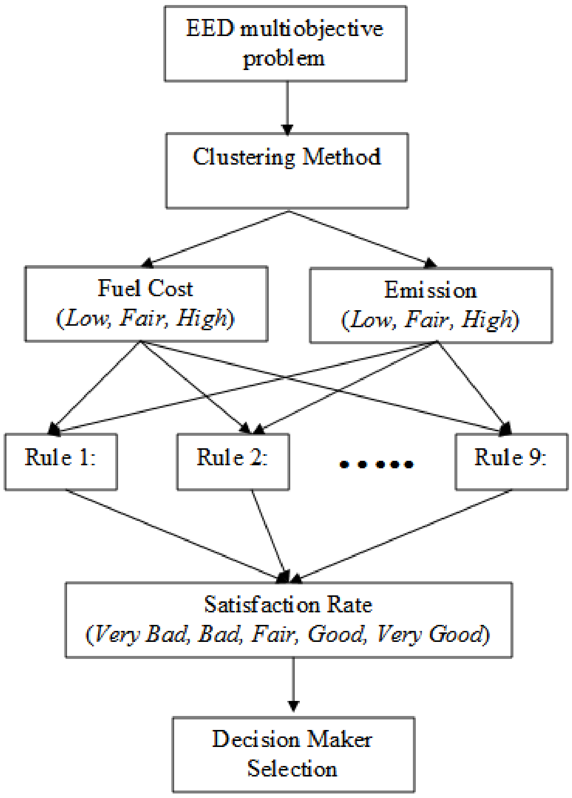

Fig. 3: Framework of a hybrid intelligent system for decision making.

RESULTS

EED multiobjective problem is used in this simulation. This multiobjective problem has two objectives to be minimized such as fuel cost and emission. Simulations of this research used 6 power plants. The characteristics of each power plant are in Table 1 and Table 2 (Gong, 2009; Abido, 2006). Table 1 consists of fuel cost coefficient and generating limits of six generating unit system. Table 2 consists of emission coefficient of six generating unit system.

Table 1: Fuel cost coefficient and generation limits of six generating unit system

No.	P_{Gi}^{min} (p.u)	P_{Gi}^{max} (p.u)	*ai*	*bi*	*ci*
1	0.05	0.5	10	200	100
2	0.05	0.6	10	150	120
3	0.05	1.0	20	180	40
4	0.05	1.2	10	100	60
5	0.05	1.0	20	180	40
6	0.05	0.6	10	150	100

In this simulation, transmission losses are ignored. Therefore, total electric power demand is equal to the generated power. The power demand (P_D) for this simulation was 2.834 p.u. In the first stage, the parameters for NSGA2 were set in the following way: population = 200, generation = 1000, crossover probability = 0.9 and mutation = 0.1. Figure 4 shows the tradeoff between fuel cost and emissions of non-dominated solutions obtained by NSGA2. By using these parameters, we obtained 200 optimal solutions.

Table 2: Emission coefficient of six generating unit system

No.	*a*	*b*	*g*	*z*	*l*
1	4.091	-5.554	6.490	2.0e-4	2.857
2	2.543	-6.047	5.638	5.0e-4	3.333
3	4.258	-5.094	4.586	1.0e-6	8.000
4	5.326	-3.550	3.380	2.0e-3	2.000
5	4.258	-5.094	4.586	1.0e-6	8.000
6	6.131	-5.555	5.151	1.0e-5	6.667

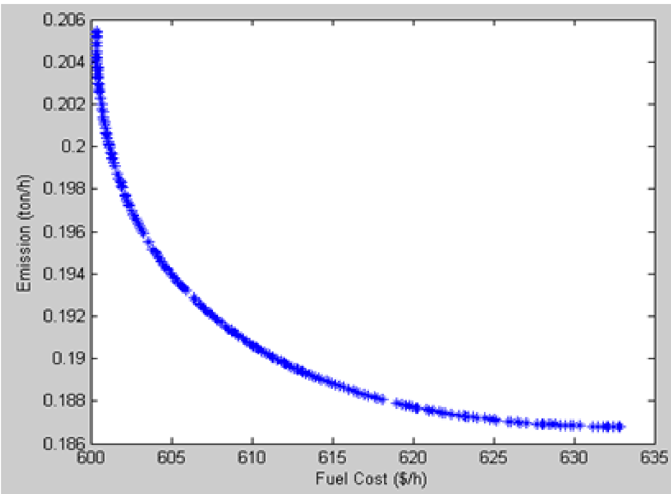

Fig. 4: Simulation result of NSGA2

Next stage, FCM method was used to cluster the Pareto optimal set. In this stage we used three clusters. Therefore we must know the optimal number of weighting exponent (*m*). The parameters of FCM were set in the following way: the maximum of iteration = 1000 iterations, error tolerance (*e*) = 1E-7 as stopping parameter. Table 3 shows us the performance of FCM for three clusters. As seen in Table 3 the optimal *m* is 1.2 for three clusters. Then the clusters are used to form qualitative based on their cluster centers as inputs for Mamdani FIS.

Table 4 shows simulation results of cluster centers for fuel cost and emission; the maximum value of fuel cost is 624.9217 and the minimum value of fuel cost is 602.4634. In addition, the maximum value for emission is 0.1982 and the minimum value of emission is 0.1872.

The triangular function as in Equation (9) is used to form membership of fuel cost and emission based on their cluster center's value. The results of the membership function are then converted to linguistic variables, such as *High, Fair* and *Low*.

Table 3: Performance of FCM for three clusters

Weighting exponent (*m*)	Number of iteration	Error
1.1	50	8.0313E-08
1.2	48	7.3404E-08
1.3	41	9.2352E-08
1.4	47	7.4974E-08
1.5	43	9.3529E-08
1.6	44	8.2591E-08
1.7	42	7.4005E-08
1.8	42	7.3792E-08
1.9	44	7.6409E-08
2.0	46	7.4992E-08

Table 4: Cluster center of FCM

No.	Cluster center of fuel cost	Cluster center of emission
1	624.9217	0.1872
2	612.7183	0.1896
3	602.4634	0.1982

Table 5 shows the linguistic representation of cluster centers, such as *High, Fair* and *Low*. The DM can use these linguistic variables as input for their linguistic preference for the level of fuel cost and the level of emission. These level combinations of fuel cost and emission make it easier for decision makers to select their preference than to choose from 200 optimal solutions at stage 1.

Table 5: Linguistic representation of cluster center

	Converting value of cluster center to fuzzy degree		
Cluster center of fuel cost	Fuzzy Degree	Cluster center of emission	Fuzzy Degree
624.9217	*High*	0.1872	*Low*
612.7183	*Fair*	0.1896	*Fair*
602.4634	*Low*	0.1982	*High*

Figure 5 shows the membership function for fuel cost. These membership functions consist of three degree such as *High, Fair* and *Low*. Each cluster centers becomes the peak of the membership function. For example, for the membership function of *Low*, the peak is = 602.4634, as seen in Table 5.

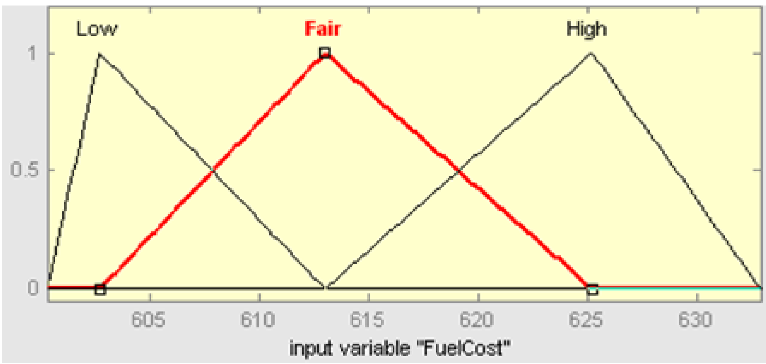

Fig. 5: The membership degree of fuel cost

The membership functions of emission also consist of three degree such as *High, Fair* and *Low,* as shown in Figure 6. Each cluster centers becomes a peak of the membership function. For example, the peak is 0.1982 for membership in *High*, as seen in Table 5.

After the calculation of satisfaction rate, we can use the values of the satisfaction rate to form a membership function of satisfaction rate as the output for rule bases. We use the triangular form in Eq. (9) to calculate the membership function of satisfaction rate. Figure 7 shows the membership functions of satisfaction rate. These satisfaction rates have five levels of membership: *Very Bad, Bad, Fair, Good* and *Very Good*. The maximum value of the satisfaction rate is 1 and the minimum value of satisfaction rate is 0.

After that, we can build the FIS, where fuel cost and emission are the antecedent and the satisfaction rate as the consequent. The Mamdani type is used to build rule bases in the following way:

R1: If the Fuel Cost = *High* and the Emission = *High* then the Satisfaction Rate = *Fair*
R2: If the Fuel Cost = *Low* and the Emission = *High* then the Satisfaction Rate = *Bad*
R3: If the Fuel Cost = *Low* and the Emission = *High* then the Satisfaction Rate = *Very Bad*
R4: If the Fuel Cost = *High* and the Emission = *Fair* then the Satisfaction Rate = *Very Good*

R5: If the Fuel Cost = *Fair* and the Emission = *Fair* then the Satisfaction Rate = *Good*
R6: If the Fuel Cost = *Low* and the Emission = *Fair* then the Satisfaction Rate = *Fair*
R7: If the Fuel Cost = *High* and the Emission = *Low* then Satisfaction Rate = *Very Good*
R8: If the Fuel Cost = *Fair* and the Emission = *Low* then Satisfaction Rate = *Good*
R9: If the Fuel Cost = *Low* and the Emission = *Low* then Satisfaction Rate = *Fair*
We run some simulations to test the output with some combinations of the inputs. The inputs are randomly selected from NSGA2 outputs as seen in Table 6. Figure 8 shows simulation with combination of fuel cost = 600.8119 \$/h (*Low*) and emission = 0.2011 ton/h (*High*), then the satisfaction rate is 0.1670 (*Very Bad*).

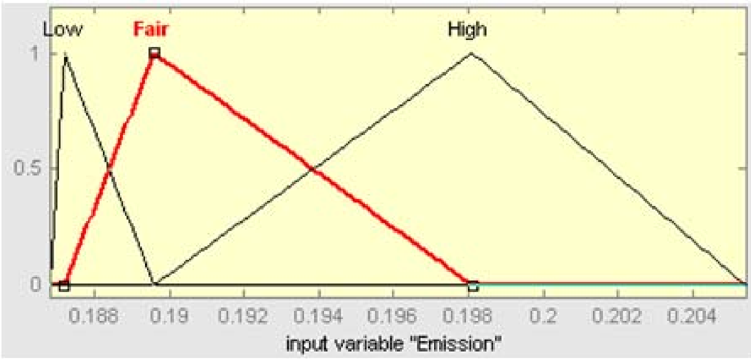

Fig. 6: The membership degree of emission

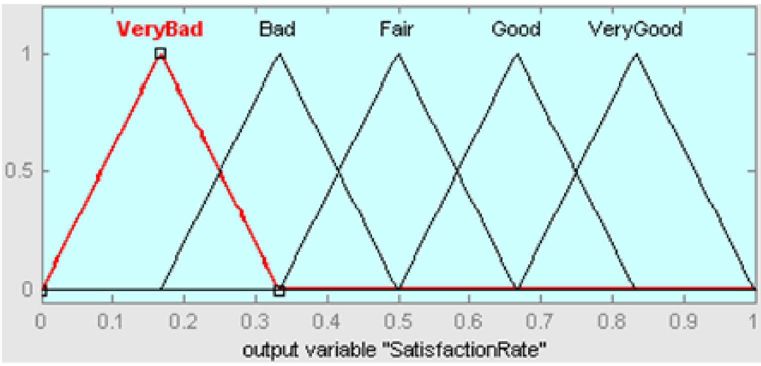

Fig. 7: The membership degree of satisfaction rate

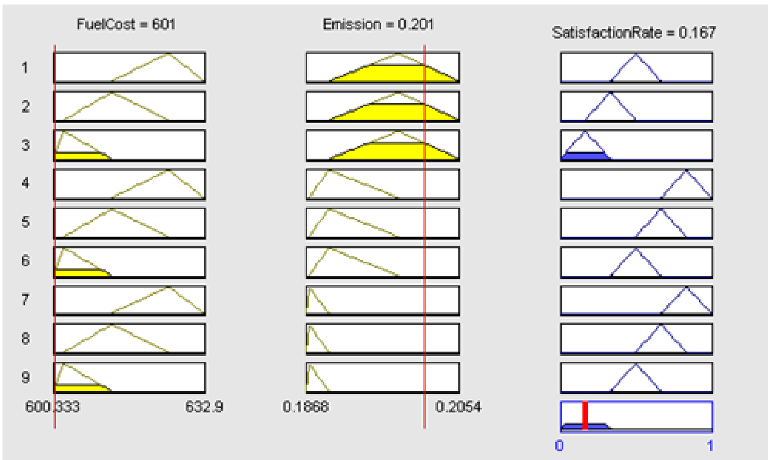

Fig. 8: The Decision Maker's decision for fuel cost = Low and emission = High then SR = Very Bad.

Figure 9 shows simulation with combination of fuel cost = 608.0621 \$/h (*Low*) and emission = 0.1916 ton/h (*Fair*), then the satisfaction rate is 0.4730 (*Fair*).

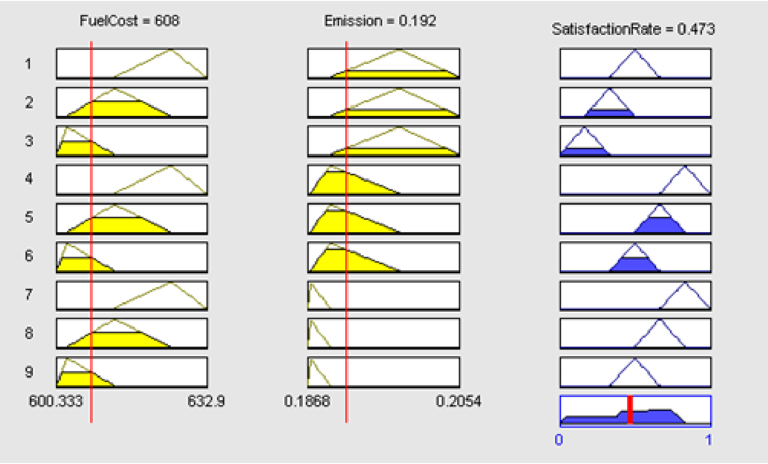

Fig. 9: The Decision Maker's decision for fuel cost = Low and emission = Fair then SR= Fair.

Figure 10 shows simulation with combination of fuel cost = 619.5581 \$/h (*High*) and emission = 0.1877 ton/h (*Low*), then the satisfaction rate is 0.7550 (*Very Good*).

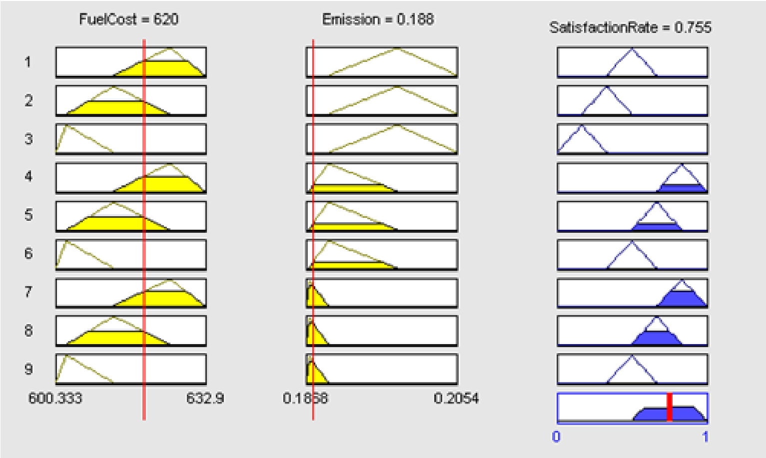

Fig. 10: The Decision Maker's decision for fuel cost = High and emission = Low then SR = Very Good.

Figure 11 shows simulation with combination of fuel cost = 610.9894 \$/h (*Fair*) and emission = 0.1902 ton/h (*Fair*), then the satisfaction rate is 0.5780 (*Good*).

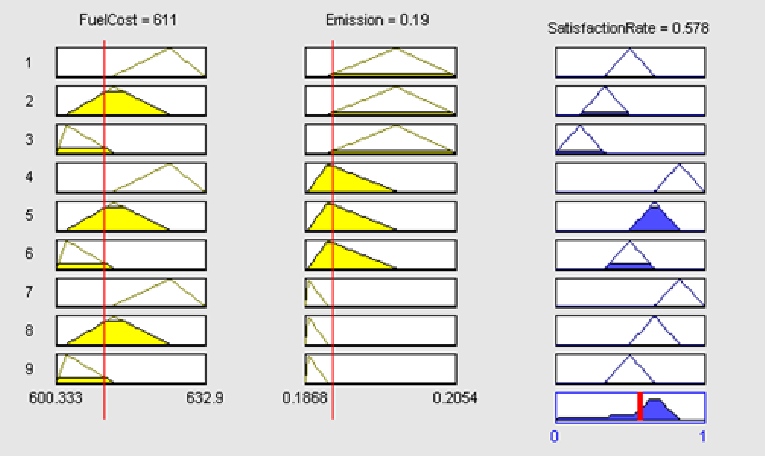

Fig. 11: The Decision Maker's decision for fuel cost = Fair and emission = Fair then SR = Good.

Figure 12 shows simulation with combination of fuel cost = 602.6209 $/h (*Low*) and emission = 0.1968 ton/h (*High*), then the satisfaction rate is 0.2760 (*Bad*).

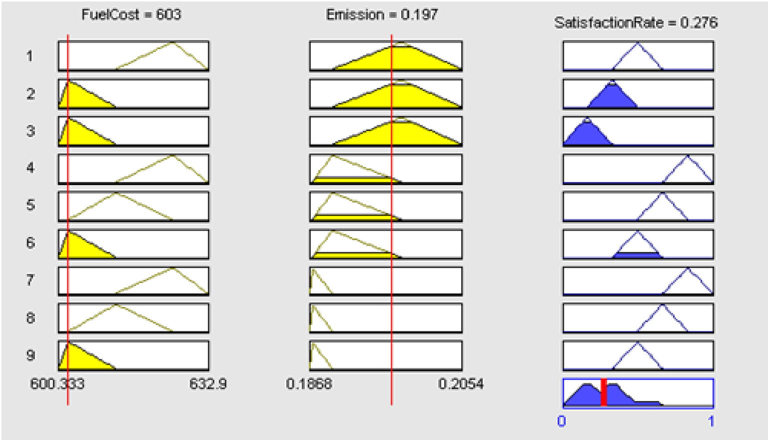

Fig. 12: The Decision Maker's decision for fuel cost = Fair and emission = High then SR= Bad.

Table 6 shows the input combinations of fuel cost and emission with their output. The outputs are in numeric value and in qualitative value. The numeric value is calculated from Eq. (15) and qualitative value is form from Eq. (9).

Table 7 shows the input combinations of fuel cost and emission with their outputs. The outputs are in numeric value and in qualitative value. The numeric value and qualitative value is calculated from Mamdani FIS. Table 6 and Table 7 show simulation results from five combinations of fuel cost and emission from calculation and FIS simulation, respectively. Simulation results show that the qualitative outputs of SR from Table 6 and Table 7 are similar. Although there are some different output results between SR calculation and Mamdani FIS simulation in numeric value.

Table 6: Qualitative value of satisfaction rate

No.	Fuel cost ($/h)	Emission (ton/h)	Satisfaction Rate	Qualitative
1	600.8119	0.2011	0.1562	*Very Bad*
2	602.6209	0.1968	0.3305	*Bad*
3	608.0621	0.1916	0.5730	*Fair*
4	610.9894	0.1902	0.6570	*Good*
5	619.5581	0.1877	0.8313	*Very Good*

These simulation results can be used to learn a decision making when confront with a scenario. For example if EED problem scenario is profit oriented then an appropriate qualitative value for SR is *Very Bad* (solution number 1) or *Bad* (solution number 2). Because the number of fuel cost for this solution is lower than others. It means that power plants can produce electrical energy with low cost that will increase the profit. Consequently, if power plants produce more emission and the numbers of emission is over the limit from the government regulation, a penalty will be given. As a result the profit will decrease.

Table 7: Qualitative value of Mamdani FIS

No	Fuel cost ($/h)	Emission (ton/h)	Mamdani FIS	Qualitative
1	600.8119	0.2011	0.1670	*Very Bad*
2	602.6209	0.1968	0.2760	*Bad*
3	608.0621	0.1916	0.4730	*Fair*
4	610.9894	0.1902	0.5780	*Good*
5	619.5581	0.1877	0.7550	*Very Good*

When EED problem scenario is environment oriented, therefore a suitable qualitative value for SR is *Very Good* (solution number 5) or *Good* (solution number 4). Because the number of emission is lower than others. It means that power plants can produce electrical energy with low of emission but with higher cost. If the number of emission is not over the limit from the government regulation, an incentive will be given. As a result the profit will increase.

Another EED problem scenario is profit and environment oriented. The best selection for an appropriate qualitative value for SR is *Fair* (solution number 3). Because power plants can produce electrical energy with the number of fuel cost and the number of emission is in balance. Therefore DM must select a good decision for this scenario.

Conclusion:

The proposed approach consists of MOP, FCM, Mamdani FIS and Decision Making. It can be used as decision tool to help DM to learn and make a decision in EED Problem.

NSGA2 is used to produce some optimal solutions from EED problem, and then FCM is used to cluster those solutions. Then these clusters are used by Mamdani FIS to build rule bases. The output in qualitative value is used to determine the solution.

Five optimal solutions from NSGA2 are offered to DM to select a decision when confront with a scenario of EED problem such as profit oriented, environment oriented and profit and environment oriented. Simulation shows that proposed hybrid intelligent system can help DM easier to make a decision.

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