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FUZZY CLUSTERING BASED ON MULTI-OBJECTIVE OPTIMIZATION PROBLEM FOR DESIGN AN INTELLIGENT AGENT IN SERIOUS GAME

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ABSTRACT

Decision-making plays important role for people. Almost every day they must decide a decision to solve their problems. Mistaken in selection a decision makes happen to lose in the competition. When the problem is in multi-objective problem, decision-making becomes very complicated. In this paper, the objective is to build an intelligent agent to help the decision maker or the player with a decision support while playing a serious game in economic and emission dispatch problem. This intelligent agent is constructed by two stages; the initial stage is multi-objective optimization problem that uses NSGA2 method. In this stage, NSGA2 results some optimal solutions. The next stage is clustering to cluster optimal solutions from first stage to be a small number of solutions. In this stage, we evaluate two clustering methods such as FCM, and FLVQ to accomplish the best method for build an intelligent agent which can offer several optimal solutions to the decision maker or the player.

Keywords: *Fuzzy Clustering; Intelligent Agent; Multi-objective Optimization; Serious Game*

1. INTRODUCTION

The development of game is growing rapidly, recently. At the beginning of the development of game is only for amusement but today game is also used to other disciplines such as education, company, politics, militaries, medicals and so on. A game that designed for a primary purpose other than pure entertainment is called a serious game [1], [2]. A serious game can be used to help the decision maker when face with company's problem by simulating the problems. A serious game is more beneficial because it has lower cost and lower risk than implement the problems in the real system. A serious game also can be used by the decision maker to learn and select the best decision to solve the problems. Currently, the problems in the companies are not only single objective problem but also multi-objective problems. These multi-objective 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. Multi-objective Optimization Problems (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 [3].

There are some methods of MOP such as Multi-Objective Genetic Algorithm (MOGA), Strength Pareto Evolutionary Algorithm (SPEA), Non-dominated Sorting Genetic Algorithm (NSGA). Each of the methods has a capability to solve the multi-objective problem. Power plant companies also have some problems with MOP in a production unit. This MOP is known as Economic and Emission Dispatch (EED) problems. The EED problems are to minimize fuel cost and emission level. Some researches have used MOP to solve EED problems are: [4] and [5] used Non-dominated Sorting Genetic Algorithm II (NSGA2) and [6] used multi-objective particle swarm optimization (MOPSO) method.

Although some MOP methods have been developed but few of them are used to evaluate the results from MOP. Generally this is because of choosing a solution for system implementation from the Pareto-optimal sets (MOP results) can be a difficult task, because Pareto-optimal sets can be extremely large number of solutions. Therefore it is needed a method that is used to help in the analysis of the solution of MOP and provide the decision maker with several solutions. This method is based on clustering methods [7], [8], in which the solutions in the Pareto optimal sets are clustered to be a small number of clusters.

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Functions of intelligent agent in computer field have been used for many things. One of the function intelligent agents is to find a way to achieve the goal [9]. In the other side, game has many scenarios or problems to solve in order to achieve the goal. Therefore, intelligent agent has been also used in gaming simulation. Reference [10] has used intelligent agent for emission trade with human player. This intelligent agent can make offer and bidding for emission trade. An intelligent agent that refers to a game is also known as a Non-Player Character (NPC). NPC is a character with which the player can interact [11], [12]. In this paper we build an intelligent agent to help the decision maker to select the best decision. The intelligent agent will give a small number of solutions to the decision maker. The small number of solutions that are offered by the intelligent agent is easier for the decision maker to select than to select them from Pareto optimal sets which have a lot of solutions. Learning decision through playing game is more interesting than learning through a decision tool. By playing a game, the players or the decision makers can learn their decision that they have decided [13], [14], [15].

2. 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:

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

Subject to:

$$g_j(x) = 0,\ j = 1,\ldots,L \qquad (2)$$

$$h_k(x) \le 0,\ k = 1,\ldots,K \qquad (3)$$

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 [5].

2.1 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:

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

and

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

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 [3, 7].

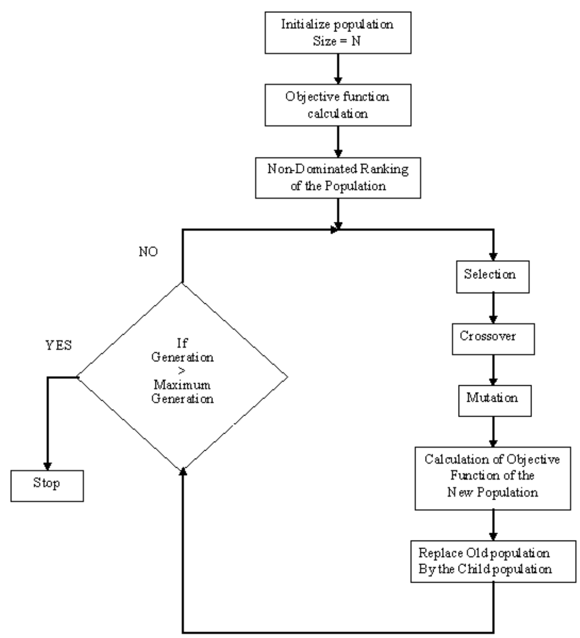

Figure 1. Flow Diagram of NSGA 2

2.2 Non-dominated Sorting Genetic Algorithm2

One of type of Multiobjective Genetic Algorithm (MOGA) is non-dominated Sorting Genetic Algorithm (NSGA2) that is modification from ranking procedure [5, 16]. NSGA2 Algorithm is

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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.

3. FUZZY CLUSTERING

3.1 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 [17, 18]. 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 [19]:

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

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

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

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

$1 \le j \le C$ (7)

- $$E_v = \sum_{j=1}^{C} \|v_{j,v} - v_{j,v-1}\|^2 \qquad (8)$$

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

3.2 Fuzzy LVQ

Fuzzy Learning Vector Quantization (FLVQ) is an combination method of Learning Vector Quantization (LVQ) and Fuzzy C-Means (FCM). FCM is a clustering method from fuzzy. While LVQ is a learning method from neural network with objective to clustering training data vector M to become C groups, in detail vector quantization (VQ) is the representation of M labeled or unlabeled feature vectors $x \in \Re^n$ by a set of C prototypes $V = \{v_1, v_2, \ldots, v_C\} \subset \Re^n$ where C is usually much less than M. This method is an improvement of FCM on calculating center of cluster. FLVQ Algorithm can be summarized as follows [19]:

1. Select number of cluster C, initial weighting exponent m_i, final weighting exponent m_f and a small positive number (error tolerance) ε; maximum number of iterations N; set $v = 0$;
2. Generate an initial set of prototypes $V_0 = \{v_{1,0}, v_{2,0}, \ldots, v_{C,0}\}$;
3. Set $v = v + 1$;
4. Calculate $m = m_i + v[(m_f - m_i)/N]$ (9)

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

where $1 \le i \le M$; $1 \le j \le C$ (10)

- $$\eta_{j,v} = \left(\sum_{i=1}^{M} \alpha_{ij,v} \right)^{-1}$$, where $1 \le j \le C$ (11)

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- $$v_{j,v} = v_{j,v-1} + \eta_{j,v} \sum_{i=1}^{M} \alpha_{ij,v}(x_i - v_{j,v-1}),$$

where $1 \le j \le C$ (12)

- $$E_v = \sum_{j=1}^{C} \left\| v_{j,v} - v_{j,v-1} \right\|^2 \quad (13)$$

if v < N *and* $E_v > \varepsilon$, *then go to step 3*

4. ECONOMIC 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 [4], [20]:

$$FC(\vec{P}_G) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (14)$$

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 [4], [20]:

$$EM(\vec{P}_G) = \sum_{i=1}^{N} 10^{-2}\left(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2\right) + \zeta_i \exp(\lambda_i P_{Gi}) \quad (15)$$

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:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max},\ i = 1,2,\ldots,N \quad (16)$$

- Constraint of Power Stability

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

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \quad (17)$$

where P_D is total required load (per unit - p.u), and P_L, is transmission losses (p.u). The transmission losses can be represented as:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{M} B_{0i} P_{Gi} + B_{00} \quad (18)$$

where B_{ij}, transmission losses coefficient. *B*-coefficients are shown as follow [20]:

B = [0.1382 -0.0299 0.0044 -0.0022 -0.0010 -0.0008
- 0.0299 0.0487 -0.0025 0.0004 0.0016 0.0041
0.0044 -0.0025 0.0182 -0.0070 -0.0066 -0.0066
- 0.0022 0.0004 -0.0070 0.0137 0.0050 0.0033
- 0.0010 0.0016 -0.0066 0.0050 0.0109 0.0005
- 0.0008 0.0041 -0.0066 0.0033 0.0005 0.0244]

Bo=[-0.0107 0.0060 -0.0017 0.0009 0.0002 0.0030]
Boo=9.8573e-4

Problem of EED can be formulated mathematically as multi-objective optimization problem as follows [21]:

Minimize [FC, EM, P_L] (19)

5. DESIGN OF AN INTELLIGENT AGENT

The objective of this paper is to build an intelligent agent with task to help a player to select a decision by offering several optimal solutions. Our intelligent agent is developed with two stages: the first stage is Multi-objective Optimization Problem for Economic and Emission Dispatch Problems. In this stage NSGA2 method is used to produce some optimal solutions. These optimal solutions are too a lot. Therefore, it is needed second stage such as clustering method. Therefore in this stage clustering method is used to reduce number of some optimal solutions to be a small number of optimal solutions. Then these small numbers of optimal solutions are used by the intelligent agent. The intelligent agent will offer those solutions to the player. Then the player will choose one of those solutions to be his decision.

In general, module of this intelligent agent is part of framework of serious game in production of electric power. Framework of this serious game consists of some factors such as fluctuation of fuel cost, number of electric power demand, higher profit for company, lower cost production, and government regulation to reduce level of pollution, as seen in Figure 2. In the intelligent agent module, the player is offered by the intellligent agent with several

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solutions based on scenario or problem that player confront it. The player might choose one of the solutions to be his decision. Then the player's decision is counted with other costs such as: initial cost of generation power plant an cost of spin reverse as a total cost. After that, decision scoring of the player takes into consideration with other factors such as: a penalty of pollution, fulfillment of capacity production, production cost, and profitability level. The penalty will be given, if the player can not fulfill those factors, then player's score is reduced. Winning or losing of playing this game is based on rank of player's score.

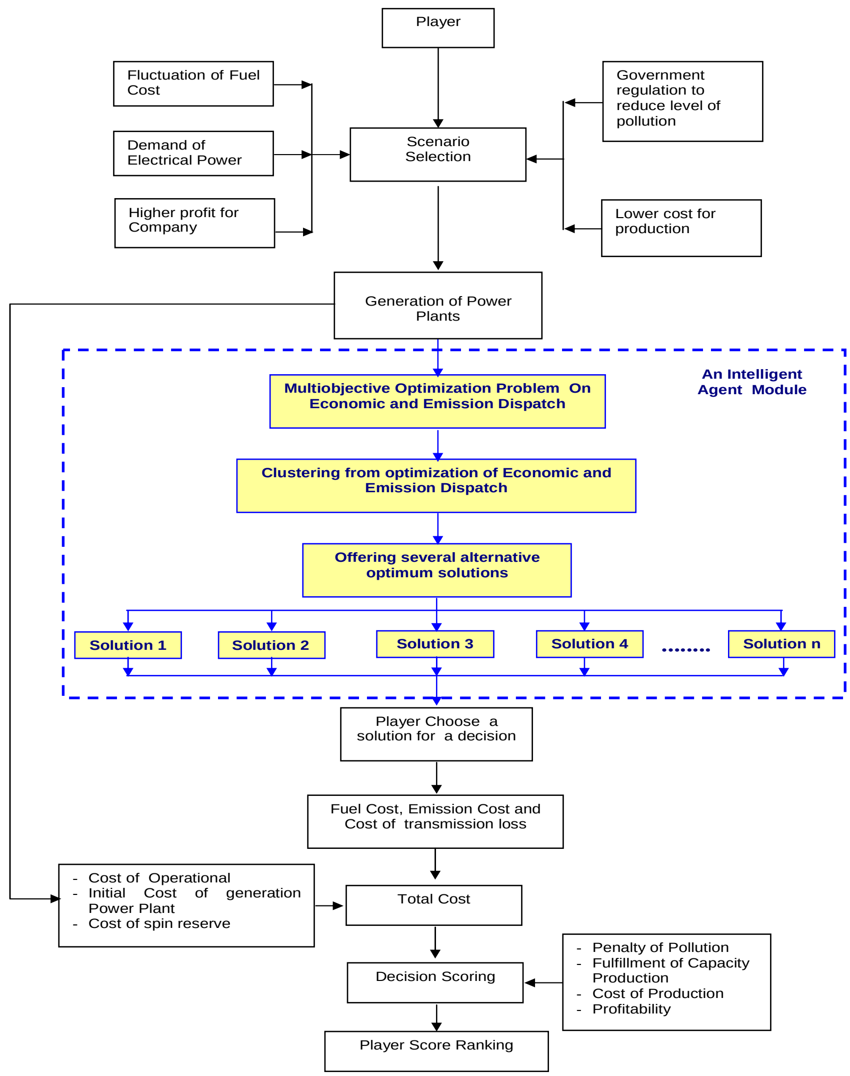

Figure 2. Design of an intelligent agent in electric power production

6. SIMULATION RESULTS

6.1 Study Case

In this paper, we use EED problem in electric power production. This EED problem has 3 objectives such as fuel cost, emission and transmission loss as seen in equation (19). Six power plants are used for simulation of this paper. The characteristics of each power plant can be seen in Table 1 and Table 2 that consist of fuel cost, emission and constraint of each power plant [4], [20], [22].

At the first stage, NSGA2 was used to produce some optimal solutions. The following parameters were used for simulation such as population = 200, generation = 1000, crossover probability = 0.9 and mutation probability = 0.1. In addition, for the demand load, P_D was assumed to be 2.834 p.u. Simulation result shows that NSGA2 produce a lot of numbers of optimal solutions at 200 optimal

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solutions. Figure 3 shows the relationship of fuel cost, emission and transmission losses of non-dominated solutions from NSGA2.

In the first stage, the optimal solutions from NSGA2 are too a lot for decision maker to choose one of the solutions. As known that Pareto optimal sets can be extremely large or even contain an infinite number of solutions. Therefore it is needed a method that based on clustering methods, in which the solutions in the Pareto optimal sets are clustered so that the Pareto optimal sets are reduced to a set of clusters [7]. For that reason, it is needed subsequent stage to reduce number of optimal solution from NSGA2. The subsequent stage is clustering method. In this stage, we used fuzzy clustering such as FCM and FLVQ. However before clustering some optimal solutions, we must know the optimal number of cluster. Therefore, we used some trial simulations by changing number of cluster to find the smallest of error.

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

No.	P_{Gi}^{min} (p.u)	P_{Gi}^{max} (p.u)	a_i	b_i	c_i
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

Table 2. Emission coefficient of six generating unit system

No.	α	β	γ	ζ	λ
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

For fuzzy clustering, we used FCM method to run the simulation. The parameters of FCM were in the following way: the maximum of iteration =10000 iterations, error tolerance (ε) = 1 e-07 as stopping parameter and weighting exponent (m) = 1.1. Simulations were run by changing the number of cluster from 2 until 10 in order to achieve the least of Ev refer to equation (8). Simulation results from FCM show that the least of number E_v for the number of clustering is at 3, with number iteration = 40 and E_v = 5.7566 e-08. Detail of simulation results can be seen in Table 3 that shows the results of the simulation with the effect of varying the number of cluster and fixed parameter of weighting exponent (m) at 1.1.

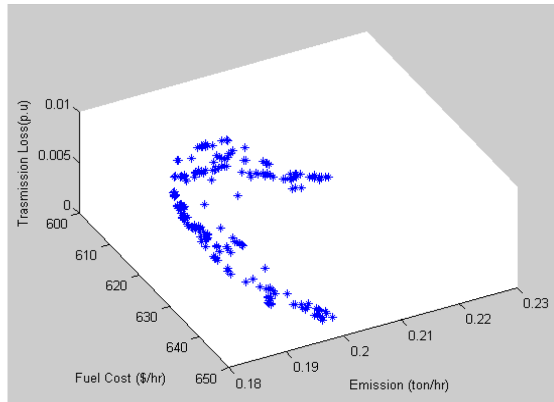

Figure 3. Simulation result from NSGA2

Next, as comparison, we also ran simulation of FLVQ method that used parameters in the following way: the maximum of iteration =10000 iterations, error tolerance (ε) = 1 e-07 as stopping parameters. The heuristic constraint for initial weighting exponent (m_i) and final weighting exponent (m_f) at range $7 > m_i > m_f > 1.1$ is recommended [19]. Therefore, in our simulation we used initial weighting exponent (m_i) = 1.5 and final weighting exponent (m_f) = 1.1. Simulations were run by changing the number of cluster from 2 until 10 in order to obtain the least of E_v refer to equation (13). Simulation results showed that the least number of E_v for the number of clustering was at 3, with number iteration = 22 and E_v = 2.8515 e-08. From simulation results, the optimal number of cluster is 3 based on the least number of errors as seen in Table 4. Consequently, this stage used 3 clusters to cluster optimal solutions from NSGA2.

Table 3. Performance results of FCM

Performance of FCM						
Number of Cluster	2	3	4	5	6	7
Iteration	23	40	92	34	40	87
Error	7.3993 e-08	5.7566 e-08	9.1355 e-08	8.8522 e-08	6.5255 e-08	8.0184 e-08

Table 4. Performance results of FLVQ

Performance of FLVQ						
Number of Cluster	2	3	4	5	6	7
Iteration	16	22	57	31	48	118
Error	5.8665 e-08	2.8515 e-08	8.0146 e-08	5.5412 e-08	2.4732 e-08	9.5717 e-08

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Table 5. Comparison methods and center value

Method	Value of cluster center		
	Fuel Cost ($/h)	Emission (ton/h)	Transmission Losses (p.u)
FCM (m =1.1)	639.3530	0.1942	0.0016
	622.5000	0.1896	0.0038
	606.0115	0.2041	0.0022
FLVQ (m_f=1.1)	639.3531	0.1942	0.0016
	622.5002	0.1896	0.0038
	606.0115	0.2041	0.0022

Table 5 shows comparison aspects for the best achieved results for each method and its cluster center. FCM has the best iteration = 40 and E_v = 5.7566 e-08. Moreover, FLVQ has the best iteration = 22 and E_v = 2.8515 e-08. From this comparison based on E_v and the number of iterations, we can conclude that FLVQ has the best result because it has the lowest E_v and the number of iteration compare with FCM. Therefore in our intelligent agent, values of cluster centers from FLVQ are used as alternative solutions to choose a decision for determine fuel cost, emission and transmission losses.

Figure 4 shows the result of clustering with FLVQ method. Three stars represent cluster centers of clustering method as seen in Figure 4. In this stage, the player is offered by an intelligent agent with a small number of decisions (three solutions). One of the cluster centers can be selected by the player as a solution. As a result, the player can choose a solution more easily than at first stage. Detail of each cluster centers can be seen in Table 6.

As mentioned before that the cluster centers from simulation can be used by the intelligent agent as solutions. These solutions are offered to the player when he plays serious game in production of electric power. Therefore the player can learn his decision through playing a serious game. For example, while playing a serious game, the intelligent agent offers to the player with these solutions. The selection of a solution is depended on the player's preference. If the player wants low fuel cost, then player will tend to choose the third solution at 606.0115 $/h but with consequent, the player's selection has emission at 0.2041 ton/h which the highest number than other solutions. In addition, a transmission loss is at 0.0022 p.u. In a game scenario we can add rule if the number of emission accumulatively is higher that emission limitation rule then the player can get penalty by reducing his score while playing this serious game.

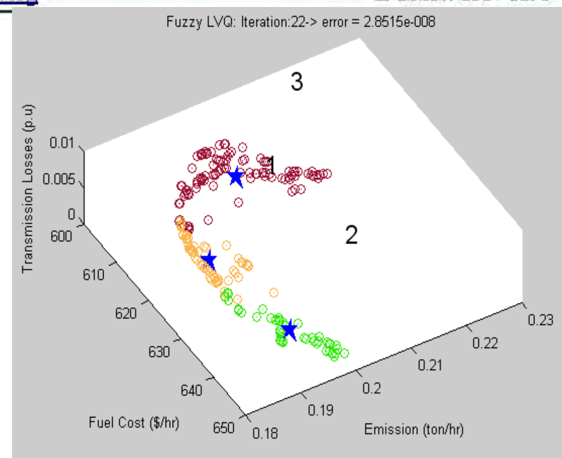

Figure 4. Clustering with FLVQ

Table 6. Center values of FLVQ as a solution

Cluster Center	FLVQ		
	Fuel Cost ($/h)	Emission (ton/h)	Transmission Losses (p.u)
Solution 1	639.3531	0.1942	0.0016
Solution 2	622.5002	0.1896	0.0038
Solution 3	606.0115	0.2041	0.0022

In other way, If the player concerns about environment, the player will tend to choose the second solution with the lowest emission at 0.1896 ton/h, but with the highest of transmission losses at 0.0038 p.u and fuel cost at 622.5002 $/h. If, the player wants to play with the lowest transmission losses, the player will tend to choose the first solution with transmission losses at 0.0016 p.u, emission at 0.1942 ton/h but with the highest fuel cost at 639.3531 $/h. Selection of a good solution for a decision will be a problem for the player when the number of solutions are enormously. By using the intelligent agent, the player is supplied with a small number of solutions, therefore it makes easier for the player to decide which one of the solutions to be his decision.

7. CONCLUSION

Clustering based on MOP can be used by the intelligent agent as decision support for the player while playing serious game. Simulation results show that solutions from NSGA2 at 200 solutions are too large for the player to decide his decision. Therefore, clustering method such as FCM and FLVQ can help the player to choose his decision by reducing the number of optimal solution to be three solutions. Simulation results show that FLVQ is better than FCM in clustering solutions. FLVQ has

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some superiority than FCM such as error and number of iterations. FLVQ has E_v = 2.8515 e-08 and number of iterations = 22 while FCM has E_v = 5.7566 e-08 and number of iterations =40. Therefore we can use the simulation results of FLVQ as solutions that offering by the intelligent agent to decision makers.

For future research, we can use this system to make a real application to help decision makers to solve their problem in EED. In addition, the problem will be complicated by combining EED with scheduling of generating of electrical power in a real system.

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