Fuzzy Clustering Based on Multiobjective Optimization Problem for Decision Support of Non Player Character in Serious Game

I.G.P. Asto Buditjahjanto [1,2] , Mochamad Hariadi [1] , Mauridhi Hery Purnomo [1]

Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia [1]
Department of Electrical Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia [2]

Summary
Decision support plays important role in decision-making, mistaken in decision-making be able to lose the competition. Decision-making is very complicated especially when the problem is in multiobjective problem. In this research, the objective is to build Non Player Character (NPC) as decision support for decision maker or player in serious game. This NPC is developed with two stages; the first stage is multiobjective optimization problem that uses NSGA2 method. This stage results some optimal solutions. The second stage is clustering to cluster optimal solutions from first stage to be a small number of solutions. In this stage, we compare two clustering methods such as FCM, and FLVQ to achieve the best method for NPC.

Key words:
Optimization, Multiobjective, NPC, Serious game, Clustering

1. Introduction

Nowadays, game development is growing rapidly. At first time the emerge of game is only for entertainment but right now game is also used to other diciplines such as educational, company, politics, militer, medical and so on. A game that designed for a primary purpose other than pure entertainment is called a serious game. A serious game is refer to products used by industries such as engineering, health care, management, defense, education, scientific exploration, city planning, politics, and religion [12,14].

A serious game can be used to help companies problems with lower budget by simulate the problems than perform in the real system. A serious game also can be used by companies to learn a decision in solve their problems. Problems in the companies are not only single objective problem but also multiobjective problems. These problems have multiobjective that must be fulfilled simultaneously. These problems become complex because each objective will conflict each other. As a result, it is needed a way to solve these problems by use best search solution. This best search solution will achieve objective that compete under different trade off scenario. Multiobjective Optimization Problems (MOP) may not have one best solution (minimum or maximum global) 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 [2].

Recently, there are some methods of MOP such as Multi-Objective Genetic Algorithm (MOGA), Strength Pareto Evolutionary Algorithm (SPEA), Nondominated Sorting Genetic Algorithm (NSGA). Each methods has capability to solve multi objective problem based on its characteristic. Power plant companies also have problem with MOP in production unit. This MOP is known as Economic and Emission Dispatch (EED) problem. The EED problems are to minimize production cost and emission level. Some researches that used MOP to solve EED problem are: Abido [1] used Non-dominated Sorting Genetic Algorithm II (NSGA2) and Zhao [18] used multiobjective particle swarm optimization (MOPSO) method.

Although some MOP methods have been developed and learned but few of them to evaluation results from MOP. This is because of choosing a solution for system implementation from the Pareto-optimal set can be a difficult task, generally because Pareto-optimal sets can be extremely large or even contain an infinite number of solutions. A practical approach is used to help in the analysis of the solution of multi-objective optimization and provide the decision-maker a workable sized set of solutions to analyze. This method is based on clustering methods [6], in which the solutions in the Pareto optimal set are clustered so that the Pareto optimal front is reduced to a set of clusters. Hariadi [9] has used clustering for NPC as decision support for MOP where the number of cluster has known previously.

A character with which the player can interact is called a Non-Player Character (NPC) [19, 20]. This research builds a NPC module for serious game in electric power production on power plant. This NPC module gives several solutions for player. These solutions are produced from MOP and clustered them into a small number of solutions based on their cluster

Manuscript received December 5, 2009
Manuscript revised December 20, 2009

center. As a result, player can choose his decision easier than before. Learning decision through playing game is more interesting than learning through decision tool. By playing game, players or decision makers can learn their decision that they have decided [3, 5, 14].

2. Principles of Multiobjective Optimization Problem

In real life, some problems need optimization simultaneously from many things that cannot be measure and usually on conflicting objectives each other. Usually, there is no single optimal solution, but some alternative of solutions. This alternative of solutions will optimal if there are no other solutions in space search and there are dominant on other solutions, when all objectives are considered. A general multiobjective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows:

$$\text{Minimize:} \quad f_i(x), \qquad i = 1, \ldots, Nobj \tag{1}$$

Subject to:

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

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

where f_i is the ith objective function, x is a decision vector that represents a solution, and $Nobj$ 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 [6].

2.1 Pareto Optimal Solution

For a multiobjective optimization problem, any two solutions x_1 and x_2 can have one of two possibilities: one dominates the other or none dominates the other. To define, 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:

$$\forall i \in \{1, 2, \ldots, Nobj\} : f_i(x_1) \le f_i(x_2), \tag{4}$$

and

$$\exists j \in \{1, 2, \ldots, Nobj\} : f_j(x_1) < f_j(x_2) \tag{5}$$

If one of condition does not achieved, 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 [2].

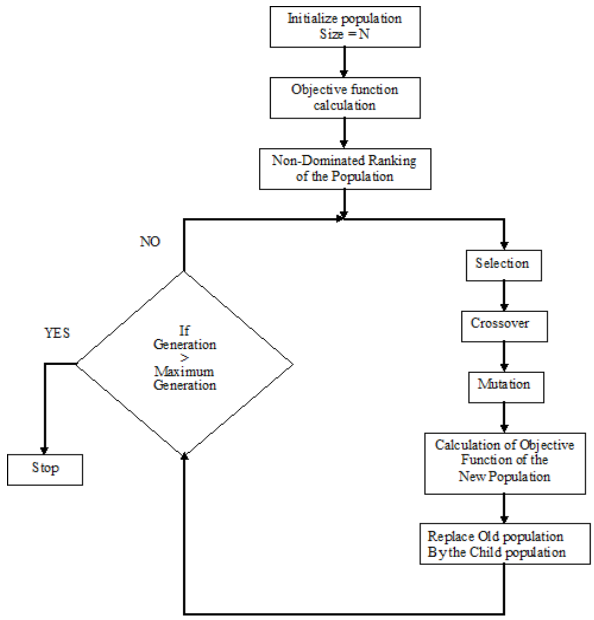

Fig. 1 Flow chart of NSGA 2

2.2 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 and developed by N. Srinivas and Kalyanmoy Deb [8]. NSGA2 Algorithm is based on some layers of individual classification. Before selection is shown, population is ranked on based non-domination. All non-dominated individual is classified in one category by a dummy fitness value that proportional with population size to provide a reproductive potency that equal for this individual.

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

NSGA2 builds a population from competed individual, ranks and selects each individual based on non-domination level. NSGA2 also applies Evolutionary Operations to create new pool from offspring and to combine parents and offspring before separation new combination into front, as seen on Figure 1.

3. Clustering

Clustering is a fundamental method in data mining and pattern recognition area. Fuzzy clustering allows natural grouping of data in large data set and provides a basis for constructing rule-based fuzzy model.

3.1 Fuzzy C Means

The well known of fuzzy clustering algorithm is Fuzzy C-Means (FCM) that introduced by Jim Bezdek [13]. FCM algorithm is to assign of data point into cluster with varied degree of membership. Exponent $m \in [1,\infty]$ is weighting factor that determine fuzzyfication of cluster. Consider the finite X set formed 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 (cluster centers) for X. The FCM algorithm can be summarized as follows [7]:

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 $v = v + 1$
   - $$u_{ij,v} = \left[\sum_{\ell=1}^{C} \left(\frac{\|x_i - v_{j,v-1}\|^2}{\|x_i - v_{\ell,v-1}\|^2} \right)^{1/(m-1)} \right]^{-1}, \text{ where}$$
     $1 \le i \le M$; $1 \le j \le C$ (6)
   - $$v_{j,v} = \frac{\sum_{i=1}^{M} (u_{ij,v})^m x_i}{\sum_{i=1}^{M} (u_{ij,v})^m}, \text{ where } 1 \le j \le C \quad (7)$$
   - $$E_v = \sum_{j=1}^{C} \|v_{j,v} - v_{j,v-1}\|^2 \quad (8)$$
4. if $v < N$ and $E_v > \varepsilon$, then go to step 3

3.2 Fuzzy LVQ

Fuzzy Learning Vector Quantization (FLVQ) is an integration 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 [7]:

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)
   - $$\alpha_{ij,v} = \left[\sum_{\ell=1}^{C} \left(\frac{\|x_i - v_{j,v-1}\|^2}{\|x_i - v_{\ell,v-1}\|^2} \right)^{1/(m-1)} \right]^{-m}, \text{ where}$$
     $1 \le i \le M$; $1 \le j \le C$ (10)
   - $$\eta_{j,v} = \left(\sum_{i=1}^{M} \alpha_{ij,v} \right)^{-1}, \text{ where } 1 \le j \le C \quad (11)$$
   - $$v_{j,v} = v_{j,v-1} + \eta_{j,v} \sum_{i=1}^{M} \alpha_{ij,v} (x_i - v_{j,v-1}), \text{ where}$$
     $1 \le j \le C$ (12)
   - $$E_v = \sum_{j=1}^{C} \|v_{j,v} - v_{j,v-1}\|^2 \quad (13)$$
5. if $v < N$ and $E_v > \varepsilon$, then go to step 3

3.3 Cluster Validity

Optimal fuzzy clustering concerns the determination of the optimal number of clusters that provides a fuzzy partition with data belonging to the same cluster are as similar as possible, and data belonging to different clusters are as dissimilar as possible. Even though FCM can detect similarities within a data set, but it cannot exhibit optimal fuzzy clustering since it assumes an a-priori knowledge of the number of clusters. As a result, optimal fuzzy clustering is a cluster validity problem.

In fuzzy clustering, a data point x_i is associated with each cluster according to a membership coefficient u_{ij}, which is defined as an element in the *C* x *M* fuzzy partition matrix *U*. Partition coefficient (PC) measures the amount of overlapping between clusters. It is defined by Bezdek [15, 17] as follows:

$$PC = \frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{C} u_{ij}^{2} \quad (14)$$

The value of *PC* is in the range of [1/C, 1].
Partition entropy (PE) measures the fuzziness of the cluster partition only, which is similar to the partition coefficient:

$$PE = -\frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{C}(u_{ij}\log_a u_{ij}) \quad (15)$$

Where $a \in (1, \infty)$ is the logarithmic base and the range of values of *PE* is $[0, \log_a C]$.

4. Design of Non Player Character

The objective of this research is to build NPC that behave as decision support for player while playing serious game on electric power production. Our NPC is developed with two stages: the first stage is Multiobjective Optimization Problem for Economic and Emission Dispatch Problems. In this stage NSGA2 method is used to results some optimal solutions. These optimal solutions are too many. Therefore, it is needed second stage namely clustering, to reduce number of some optimal solutions to be a small number of optimal solutions. The second stage consists of validity cluster and clustering. In this research, cluster validity is used in order to achieve optimal number of cluster. After knowing the optimal number of cluster then clustering method such as FCM and FLVQ is used to cluster optimal solutions from first stage to be a small number of optimal solutions. These small numbers of optimal solutions are used by NPC to offer player to choose one of the small number of optimal solutions to be his decision.

In general, module of NPC 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 on Figure 2. In NPC module, player is offered several solutions based on scenario or problem that player confront it. Player might choose one of solution to be a decision. 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 player takes into consideration with other factors such as: penalty of pollution, fulfillment of capacity production, production cost, and profitability level. Penalty is given, if these factors do not be accomplished, player scoring is reduced. Winning or losing of playing this game based on rank of player score.

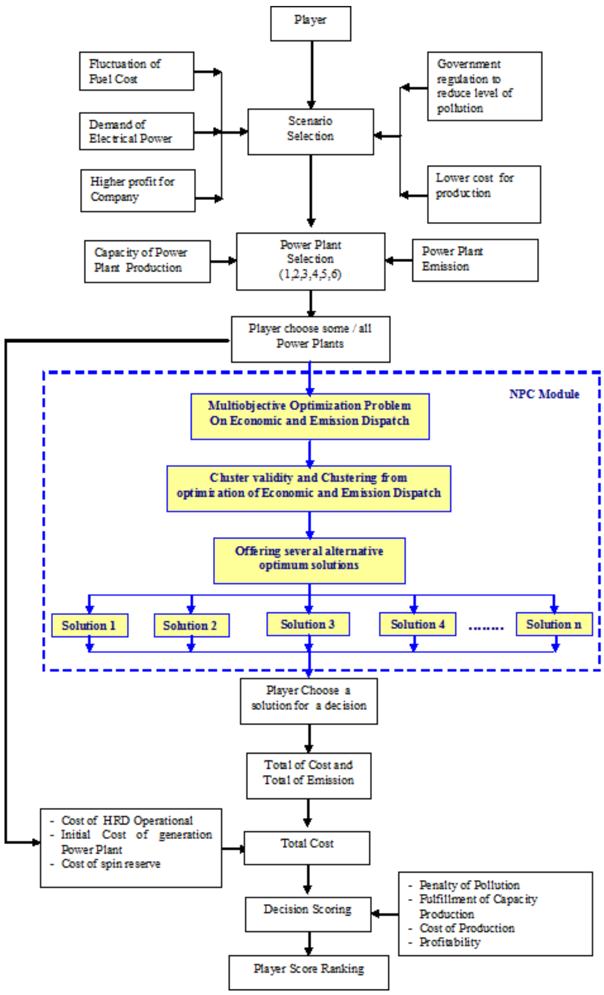

Fig. 2 Design of NPC in electric power production

5. Simulation Results

5.1 Case study

Economic and Emission Dispatch Problems are multiobjective problems. These multiobjective problems are to minimize fuel cost, emission and transmission losses that produced by power plant. 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:

$$F(P_i)=\sum_{i=1}^{N}(a_iP_i^2+b_iP_i+c_i) \tag{16}$$

where, P_i 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. Moreover, 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:

$$E(P_i)=\sum_{i=1}^{N}(d_iP_i^2+e_iP_i+f_i) \tag{17}$$

where d_i, e_i, f_i are coefficients from *i-th* generator that show us as emission characteristics. This system has constraints such as:

a. Constraint of Power Capacity
   For stable operation, real power output from each generator is limited by upper bound and lower bound, as shown below:

$$P_{min\ i} \le P_i \le P_{max\ i} \tag{18}$$

b. Constraint of Power Stability
   Total of electric power must meet with total of electric demand power P_D and P_L as a result:

$$\sum_{i=1}^{N}P_i - P_D - P_L = 0$$
(19)

where P_D is total required load (MW), and P_L, is transmission losses (MW). The transmission losses can be represented as:

$$P_L=\sum_{i=1}^{N}\sum_{j=1}^{N}P_iB_{ij}P_j$$
(20)

where B_{ij}, transmission losses coefficient.

Problem of EED can be formulated mathematically as multiobjective optimization problem as follows:

$$Minimize\ [F,\ E,\ P_L] \tag{21}$$

Simulations of this research used 6 power plants. The characteristics of each power plant is in Table 1 that consists of fuel cost function coefficients and constraint of each power plant. Table 2 lists emission data of each power plant and B - Coefficient of six unit systems can be seen on Table 3 [11].

Table 1: Power plant characteristic

No.	Fuel cost function coefficients			$P_{min\ i}$ (MW)	$P_{max\ i}$ (MW)
	a_i	b_i	c_i		
1	0.15247	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.39650	1049.9977	35	225
4	0.03546	38.30553	1243.5311	35	210
5	0.02111	36.32782	1658.5690	130	325
6	0.01799	38.27041	1356.6592	125	315

Table 2: Power plant emission

No.	Emission function coefficients		
	d_i	e_i	f_i
1	0.00419	0.32767	13.85932
2	0.00419	0.32767	13.85932
3	0.00683	- 0.54551	40.2669
4	0.00683	- 0.54551	40.2669
5	0.00461	- 0.51116	42.89553
6	0.00461	- 0.51116	42.89553

Table 3: *B*-Coefficient of six-unit system (in the order of 10^{-4}).

1.40	0.17	0.15	0.19	0.26	0.22
0.17	0.60	0.13	0.16	0.15	0.20
0.15	0.13	0.65	0.17	0.24	0.19
0.19	0.16	0.17	0.71	0.30	0.25
0.26	0.15	0.24	0.30	0.69	0.32
0.22	0.20	0.19	0.25	0.32	0.85

At the first stage, NSGA2 was used to produce some optimal solutions. In all simulations, the following parameters were used such as population at 500, generation at 100, crossover probability at 0.9 and mutation probability at 0.1. In addition, for the demand load, P_D was assumed to be 700MW.

Figure 3 shows the relationship of fuel cost, emission and transmission losses of non-dominated solutions obtained by NSGA2. The numbers of optimal solutions are too a lot (500 optimal solutions). Because Pareto optimal sets can be extremely large or even contain an -

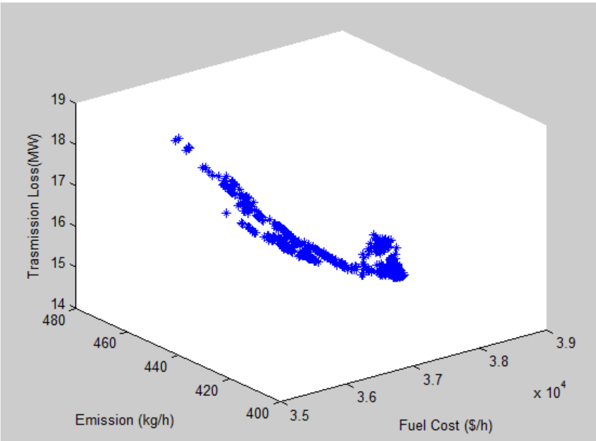

Fig. 3 Optimal solutions from NSGA2

infinite number of solutions. Therefore, it is need method that based on clustering methods, in which the solutions in the Pareto optimal set are clustered so that the Pareto optimal front is reduced to a set of clusters [6]. For that reason, it is needed subsequent stage to reduce number of optimal solution from NSGA2. The subsequent stage is clustering. This research used fuzzy clustering such as FCM and FLVQ. However before to cluster some optimal solutions, we must know the optimal number of cluster. Thus, we used cluster validity to determine the optimal number of cluster. PC and PE were used to calculate cluster validity.

Table 4: Index of cluster validity

No. of Cluster	2	3	4	5	6	7	8	9	10
PC	0.849	0.871	0.831	0.808	0.790	0.773	0.773	0.763	0.747
PE	0.107	0.096	0.135	0.161	0.182	0.200	0.200	0.216	0.234

Based on the simulation, the optimal number of cluster for cluster validity of PC and PE for clustering is 3 clusters. It can be seen on Table 4 and Figure 4, the highest PC and the lowest PE index of cluster validity is 0.871, 0.096 respectively. Thus, this stage used 3 clusters to cluster optimal solutions from NSGA2. These optimal numbers of clusters were used to set up several solutions for NPC.

Simulation results based on optimal number of clusters for FCM and FLVQ are shown in the table 5 and 6. Simulation of FCM used maximum of iteration at 10000 iterations and error tolerance (ε) at 1E-7 as stopping parameters. Simulations ran by changing weighting exponent (m) from m=1.1 until m=1.9 in order to achieve the best result of number of iteration and E_v employ Eq. (8). The weighting exponent m is analyzed, because it has significant effect on the final cluster centers.

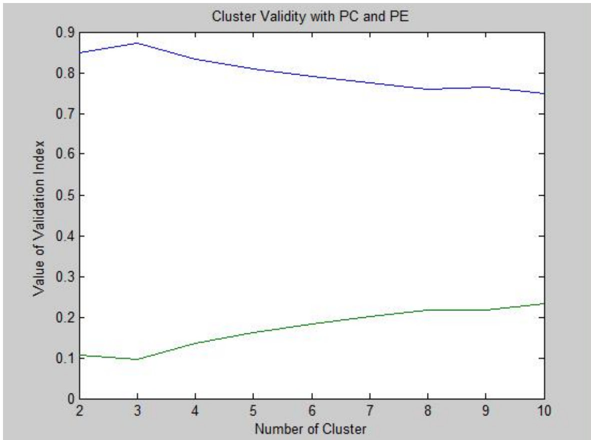

Fig. 4 Cluster validity

Table 5 lists the results of the tests with the effect of varying the weighting exponent m. It is noticed that high values of m tend to increase the number of iterations by the algorithm to find the cluster centers. Simulation results show that the best result for number of iterations and E_v for weighting exponent (m) is at 1.4, with number iteration at 49 and E_v at 7.630 E-07.

Table 5: FCM clustering performance results

Performance measure	Weighting Exponent m								
	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9
No. of iterations	40	44	47	49	49	49	51	53	53
E_v	8.408 E-07	7.563 E-07	8.155 E-07	7.630 E-07	9.179 E-07	9.313 E-07	9.252 E-07	8.595 E-07	8.816 E-07

Table 6: FLVQ clustering performance results

Performance measure	Initial Weighting Exponent m_i								
	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0
No. of iterations	41	43	45	46	48	50	51	53	54
E_v	1.278 E-07	1.394 E-07	1.297 E-07	1.126 E-07	1.620 E-07	1.256 E-07	1.623 E-07	1.234 E-07	1.557 E-07

As comparison, we also ran simulation of FLVQ that used maximum of iteration at 10000 iterations and error tolerance (ε) at 1E-7 as stopping parameters. Simulations ran by changing initial weighting exponent (m_i) from m_i=1.2 until m_i=2.0 with final weighting exponent (m_f) at 1.1 in order to obtain the best result of number of iteration and E_V using Eq. (13). In [7] the heuristic constraint $7 > m_i > m_f > 1.1$ is recommended. Table 6 lists the results of the tests with the effect of varying the initial weighting exponent m_i. Simulation results from FLVQ show that the best result for number of iterations and E_V for initial weighting exponent (m_i) is at 1.5 with number iteration at 46 and E_V at 1.126E-07.

Table 7: Comparison methods and center value

Algorithm	Value of cluster center		
	Fuel Cost ($/h)	Emission (kg/h)	Transmission Losses (MW)
FCM (m=1.4)	38392.6390 37334.2363 36368.9133	444.2445 433.6240 444.8653	14.6599 15.3603 16.7944
FLVQ (m_i=1.5)	38399.2173 37335.5627 36365.0327	444.4023 433.4185 444.9293	14.6566 15.3610 16.8039

Table 7 shows comparison aspects for the best achieved results for each method and its cluster center. FCM has the best iteration at 49 iterations and E_v at 7.630 E-07. Moreover, FLVQ has the best iteration at 46 iterations and E_v at 1.1262E-07. From this comparison based on E_v and iteration, we can conclude that FLVQ has the best result because its E_v and iteration is lower than E_v and iteration of FCM. Therefore in our NPC, values of cluster centers from FLVQ are used as alternative solutions to choose a decision for determine fuel cost, emission and transmission losses.

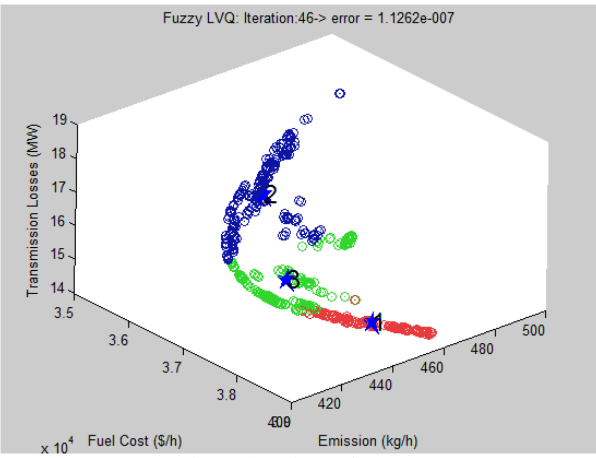

Fig. 5 Clustering with FLVQ

Figure 5 shows the result of clustering that used FLVQ clustering with different viewpoint from figure 3. It can be seen that the number of clusters are 3 based on their colors. Each of the clusters has cluster center that becomes solution for player to decide his decision to choose one of these offered solutions. Detail of each cluster center as solution can be seen at Table 8.

The cluster centers from simulation can be used by NPC as solutions for player. These solutions are offered to player when he plays serious game in production of electric power. Player can learn his decision while playing this serious game. In this simulation, cluster centers of FLVQ were used. For example, NPC offers to player with these three solutions. The decision is depended on player. If player wants low fuel cost (only concern with profit), Player will tend to choose the third solution at 36365.0327 $/h but with consequent, player has emission at 444.9293 kg/h which the highest than other solutions, from game scenario we can add that the number of this emission accumulatively can get penalty while playing this serious game. In addition, a transmission loss is at 16.8039 MW which is also the highest than other solutions.

Table 8: Center value of FLVQ as solution

Cluster Center	FLVQ		
	Fuel Cost ($/h)	Emission (kg/h)	Transmission Losses (MW)
Solution 1	38399.2173	444.4023	14.6566
Solution 2	37335.5627	433.4185	15.3610
Solution 3	36365.0327	444.9293	16.8039

In other way, If player concerns about environment, player will tend to choose the second solution with emission at 433.4185 kg/h, fuel cost at 37335.5627 $/h and transmission losses at 15.3610 MW. Otherwise, player wants to play with low transmission losses, player will tend to choose the first solution with transmission losses at 14.6566 MW, fuel cost at 38399.2173 $/h and emission at 444.4023 kg/h. Selection of a good solution for a decision will be a problem for player when the number of solutions are enormously. By using NPC, player is supplied with only several solutions. Player can choose a solution to solve a problem that given by scenario of serious game.

6. Conclusion

Clustering for MOP can be used as decision support of NPC module for playing serious game. Simulation results show that solutions from NSGA2 at 500 solutions are too large for player to decide his decision. Therefore, clustering method such as FCM and FLVQ can help player to choose his decision by reducing several solutions to be 3 solutions. Simulation results show that

FLVQ is better than FCM in clustering solutions. FLVQ has E_v at 1.1262E-07 while FCM at 7.5630E-07.

Acknowledgments

The Authors would like to thank to DP2M DIKTI (Indonesian Higher Education Directorate General) for its financial support under Competitive Research Grand for International Publication, Batch I 2009 and for Prof Hajime Miyauchi from Department of Computer Science and Electrical Engineering, Kumamoto University, Japan, in favor of his advices.

References

[1] Abido. M. A, 2006, *Multiobjective Evolutionary Algorithms for Electric Power Dispatch Problem*, IEEE Transaction On Evolutionary Computation, Vol.10, No 3, June 2006.

[2] Branke Jürgen, Kalyanmoy Deb, Kaisa Miettinen, Roman Słowi´nski, 2008, *Multiobjective Optimization Interactive and Evolutionary Approaches*, Berlin Heidelberg, Springer-Verlag.

[3] Buditjahjanto I.G.P. Asto, Fressy N, Mochammad Hariadi, Mauridhi Hery Purnomo, 2008a, *Using Business Games to Offer Life Skills for The Vocational High School Students*, VTE Research and Networking 2008, An International Conference of Senior Administrators, Policymakers, Researchers and other Practitioners ,"Nurturing Local VTE Research Efforts: A Response to Global Challenges", Bali, Indonesia, 7-8 July 2008.

[4] Buditjahjanto I.G.P. Asto, Mochammad Hariadi, Mauridhi Hery Purnomo, 2008b, *Using Simulated Annealing for Simulation Based Optimization on Power Plant Scheduling*, The 4th International Congress on Logistics and SCM Systems, Effective Supply Chain & Logistic Management for Sustainable Development, Bangkok, THAILAND 26-28 November, 2008.

[5] Clark Aldrich, 2005, *Learning by Doing: A Comprehensive Guide to Simulations, Computer Games, and Pedagogy in e-Learning and Other Educational Experiences*, John Wiley & Sons.

[6] Coello Coello. C.A., Gary B. L, David A., 2007, Evolutionary Algorithms for Solving Multi-Objective Problems, second edition, Springer Science + Business Media

[7] Karayiannis, Nicolaos, B., Bezdek, James, C., 1997, *An Integrated Approach to Fuzzy Learning Vector Quantization and Fuzzy c-Means Clustering*, IEEE Transactions on Neural Networks Vol 5 no 4.

[8] Deb, K. Agarwal, S. Pratap, Meriyan. T, 2000, *A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II*, KanGal Report Number 200001, Indian Institute of Technology, Kanpur, India.

[9] Hariadi Mochammad, I.G.P. Asto Buditjahjanto, Mauridhi Hery Purnomo, 2009, *Decision Support Based on Integration of Fuzzy Clustering and Multiobjective Optimization Problem for Non Playable Character in Business Game,* International Conference on Soft Computing and Pattern Recognition, December 4th – 7th , Malacca, Malaysia.

[10] Hideyuki Mizuta, Yoshiki Yamagata, 2002, *Transaction Cycle of Agents and Web-Based Gaming Simulation for International Emissions Trading*, Proceedings of the 2002 Winter Simulation Conference, page. 801-806.

[11] Li Xuebin, 2009, *Study of Multi-objective Optimization and Multi-attribute Decision-making for Economic and Environmental Power Dispatch,* Elsevier, Electric Power System Research, Volume 79, page 789-795.

[12] Elaine M. Raybourn, 2007, *Applying simulation experience design methods to creating serious game-based adaptive training systems*, Elsevier, Interacting with Computers, Volume 19, page 206–214.

[13] Saman K. Halgamuge, Lipo Wang, 2005, *Classification and Clustering for Knowledge Discovery*, Springer-Verlag Berlin Heidelberg 2005, Printed in The Netherlands

[14] Stapleton A., 2004, *Serious Games: Serious Opportunities.* Paper presented at the Australian Game Developers' Conference, Academic Summit, Melbourne, VIC

[15] Valente, J de Oliveira, Witold Pedrycz, 2007, *Advances in Fuzzy Clustering and its applications*, John Willy and Son Inc

[16] Woods. Allen J. and Bruce F. Wollenberg, 1996, *Power Generation, Operation and Control*, John Willy and Son Inc

[17] Xu Rui, Donald C. Wunsch II, 2009, *Clustering*, IEEE Press Series on Computational Intelligent. John Willy and Son Inc.

[18] Zhao Bo, Cao Yi-jian, 2005, *Multiple-objective particle swarm optimization technique for economic load dispatch*, Journal of Zhejiang University SCIENCE, 2005, 6A(5), page 420-427.

[19] Clayton Walnum, 2003, *Game Programming with DirectX in 21 Days*, Sams Publishing, Indiana, USA

[20] Stephanie B. Linek, Daniel Schwarz, G. Hirschberg, Michael Kickmeier, D. Albert, *Designing the Non-Player Character of an Educational Adventure-Game: The Role of Personality, Naturalism, and Color,* http://wundt.uni-graz.at/pubicdocs/pubications/Linek_NPC-paper.pdf

I Gusti Putu Asto Buditjahjanto is a Ph.D student in the department of electrical engineering, with major Game Technology at Sepuluh Nopember Institute of Technology, Surabaya, Indonesia. He received his B.Eng. from electrical engineering at Sepuluh Nopember Institute of Technology, Surabaya, Indonesia in 1998. He received his master in department of industrial engineering at Sepuluh Nopember Institute of Technology, Surabaya, Indonesia in 2003. He is a lecturer at Surabaya State University. His teaching and research interests include computer simulation, modeling, optimization and management of technology.

Mochamad Hariadi received the B.E. degree in Electrical Engineering Department of ”Sepuluh Nopember” Institute of Technology (ITS), Surabaya, Indonesia, in 1995. He received both M.Sc. and Ph.D. degrees in Graduate School of Information Science Tohoku University Japan, in 2003 and 2006 respectively. Currently, he is the staff of Electrical Engineering Deparment of Sepuluh Nopember Institute of Technology Indonesia . He is the project leader in joint research with PREDICT JICA project Japan and WINDS project Japan. His research interest is in Video and Image Processing, Data Mining and Intelligent System. He is a member of IEEE, and member of IEICE.

Mauridhi Hery Purnomo received the bachelor degree from Institute of Technology Sepuluh Nopember (ITS), Surabaya, Indonesia in 1985. He received his M.Eng., and Ph.D degrees from Osaka City University, Osaka, Japan in 1995, and 1997, respectively. He has joined ITS in 1985 and has been a Professor since 2004. His current interests include intelligent system applications an electric power systems operation, control and management. He is a Member of IEEE.