

Re-Scheduling the Unit Commitment Problem in Fuzzy Environment

Bo Wang

The Graduate School of
Information, Production and Systems,
Waseda University,
Kitakyushu 808-0135, Japan
Email: bwangips@gmail.com

You Li

The Graduate School of
Information, Production and Systems,
Waseda University,
Kitakyushu 808-0135, Japan
Email: rubyli@toki.waseda.jp

Junzo Watada

The Graduate School of
Information, Production and Systems,
Waseda University,
Kitakyushu 808-0135, Japan
Email: junzow@osb.att.ne.jp

Abstract—The conventional prediction of future power demands are always made based on the historical data. However, the real power demands are affected by many other factors as weather, temperature and unexpected emergencies. The use of historical information alone cannot well predict real future demands. In this study, the experts' opinions from related fields are taken into consideration. To deal the uncertainty of historical data and imprecise experts' opinions, we employ fuzzy variables to better characterize the forecasted future power loads. The conventional unit commitment problem (UCP) is updated here by considering the spinning reserve costs in a fuzzy environment. As the solution, we proposed a heuristic algorithm called local convergence averse binary particle swarm optimization (LCA-PSO) to solve the UCP. The proposed model and algorithm are used to analyze several test systems. The comparisons between the proposed algorithm and the conventional approaches show that the LCA-PSO performs better in finding the optimal solutions.

Index Terms—Power supply reliability, Fuzzy set theory, Unit commitment problem, Fuzzy Value-at-Risk, Local convergence averse binary particle swarm optimization, Test systems.

I. INTRODUCTION

Most previous studies have evaluated power loads forecasted using sufficient historical data. Nevertheless, these studies have the disadvantage that: there are many factors that must be simulated or determined in order to find which factors will affect the real power loads. For example, weather, temperature and unexpected emergencies influence power consumption. As a result, the power systems are suffering from the uncertainty associated with the fact that the real power demands always deviate from forecasts [1]. Consequently, the use of historical information alone cannot predict real future demands.

In this study, the conventional methods are improved to mitigate the above shortcoming. The experts' opinions from related fields are taken into consideration to better describe the future power loads. To handle the uncertainty that arises from the use of historical data and expert opinions, it is better to treat the forecasted power loads as variables with imprecise distributions, i.e., fuzzy variables.

In actuality, fuzzy set theory is a fundamental mathematical system that describes uncertainty, and various researchers have applied it to solve power system problems. To minimize real power losses and improve the voltage profile of a given system, Rahman [4] mathematically formulated an optimal reactive

power control problem in which the objective function and constraints are expressed by fuzzy sets when modeled. In Khare's paper [5], fuzzy set theory was used to capture the subjective preferences of human operators in order to model their decision-making and generate a prioritized list of emergency problems that is more acceptable to the operator. Using a multi-objective fuzzy linear programming technique, Abou El-Ela [6] proposed a multi-stage procedure that lessens the influence of different emergency conditions. The results of their experiments showed that the proposed fuzzy procedure can reduce the influence of different emergency conditions.

Employing fuzzy set theory, we take the forecasted loads as fuzzy variables. The conventional unit commitment problem (UCP) which has been commonly formulated as a complex, nonlinear, mixed-integer optimization problem [1], [2], [3] is improved here to take the spinning reserve costs in a fuzzy environment into consideration. To handle this improved UCP, we propose a local convergence averse binary particle swarm optimization (LCA-PSO), which outperforms existing algorithms.

The remainder of this paper is organized as follows: in Section 2, we briefly review previous fuzzy power system problems and introduce some basic background regarding fuzzy variables; Section 3 illustrates the improved UCP; then, Section 4 provides the LCA-PSO as the solution; the model and algorithm are exemplified by some test systems in Section 5; finally, Section 6 summarizes the conclusions.

II. PRELIMINARIES

In this section, we preliminarily provide some basic concepts and features of fuzzy variables.

Suppose ξ is a fuzzy variable whose membership function is μ_ξ , and r is a real number. Then, the possibility, necessity and credibility of event $\xi \leq r$ are expressed, respectively, as follows:

$$\text{Pos}\{\xi \leq r\} = \sup_{t \leq r} \mu_\xi(t), \quad (1)$$

$$\text{Nec}\{\xi \leq r\} = 1 - \sup_{t > r} \mu_\xi(t), \quad (2)$$

$$\text{Cr}\{\xi \leq r\} = \frac{1}{2} [\text{Pos}\{\xi \leq r\} + \text{Nec}\{\xi \leq r\}]. \quad (3)$$

The credibility measure is formed on the basis of the possibility and necessity measures, and in the simplest case, it is taken as their average. The credibility measure is a self-dual set function [7], *i.e.* $\text{Cr}\{\xi \leq r\} = 1 - \text{Cr}\{\xi > r\}$. Equation (3) also results in the following:

$$\text{Cr}\{\xi \leq r\} = \frac{1}{2} \left[\sup_{t \leq r} \mu_{\xi}(t) + 1 - \sup_{t > r} \mu_{\xi}(t) \right]. \quad (4)$$

For further information on fuzzy variables, one may refer to [7], [8] and [9].

According to [10], the VaR of an investment can be considered as the greatest value under a given confidence level. Following [11], if $\tilde{L}_t$ denotes the fuzzy power demand of period t , in a fuzzy environment, the VaR of L_t with a confidence of $(1 - \beta)$ can be written as:

$$\text{VaR}_{1-\beta} = \sup\{\lambda | \text{Cr}(\tilde{L}_t \geq \lambda) \geq \beta\}, \quad (5)$$

where $\beta \in (0, 1)$.

Equation (5) tells us that the greatest value of $\tilde{L}_t$ under confidence level $(1 - \beta)$ is the largest λ .

The following numerical example illustrates the calculation of the VaR.

Example 1. Supposing fuzzy variable $\tilde{L} = FN(1.0, 2.0)$, its membership function is normally distributed as $\mu_{\tilde{L}}(r) = \text{Exp}\{-(r - 1.0)/2\}^2$, then let us calculate $\text{VaR}_{0.9}$.

At first, we need to calculate the credibility function of $\tilde{L} \geq r$. From Equation (1) and (2), we can compute the possibility and the necessity of $\tilde{L} \geq r$ in the following:

$$\begin{aligned} \text{Pos}\{\tilde{L} \geq r\} &= \begin{cases} 1 & r \leq 1.0 \\ \text{Exp}\{-(r - 1.0)/2\}^2 & r > 1.0 \end{cases} \\ \text{Nec}\{\tilde{L} \geq r\} &= \begin{cases} 1 - \text{Exp}\{-(r - 1.0)/2\}^2 & r \leq 1.0 \\ 0 & r > 1.0. \end{cases} \end{aligned} \quad (6)$$

Hence, according to Equation (3), the credibility of $\tilde{L} \geq r$ is written as:

$$\text{Cr}\{\tilde{L} \geq r\} = \begin{cases} 1 - \frac{1}{2} \text{Exp}\{-(r - 1.0)/2\}^2 & r \leq 1.0 \\ \frac{1}{2} \text{Exp}\{-(r - 1.0)/2\}^2 & r > 1.0. \end{cases} \quad (7)$$

Therefore, making use of Equation (5), we have,

$$\text{VaR}_{0.9} = \sup\{\lambda | \text{Cr}(\tilde{L} \geq \lambda) \geq 0.1\} = 2.91.$$

Recently, the measure of Value-at-Risk has been applied to many engineering problems to build fuzzy optimization models [11], [12], [13], [14], [15].

III. MODELING

From the literatures, with the purpose of providing sufficient electricity and reducing the generation cost, the UCP is solved by determining the power generation unit schedule. It is necessary to provide sufficient real power and spinning reserve in each period. However, in a market environment, the profit is also important. Therefore, the majority of the previous studies summarized the UCP as minimizing the cost function without violating the constraints.

A. The conventional UCP

1) Objective function:

$$\min F = \sum_{t=1}^T \sum_{i=1}^N u_i^t \cdot [f_i(P_i^t) + S C_i(1 - u_i^{t-1})]. \quad (8)$$

Respectively, F denotes the total cost of the power plant over the scheduling periods; T and N denote the number of considered system periods and the number of generation units, P_i^t is the power generation of unit i at time t ; $S C_i$ is the start cost of unit i ; u_i^t denotes the status of unit i at time t . $f_i(P_i^t)$ is the cost function of unit i at time t , which is normally expressed by the following equation:

$$f_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2, \quad (9)$$

where, a_i , b_i and c_i are the coefficients determined by the attributes of each generation unit.

B. The improved UCP

1) Objective function: This study takes the spinning reserve cost into consideration. Then, in a fuzzy environment, the objective function is modified as follows:

$$\begin{aligned} \min F &= \sum_{t=1}^T \sum_{i=1}^N u_i^t \cdot \{[1 - \text{Pos}(Q_t > P_t)] f_i(P_i^t) \\ &\quad + \text{Pos}(Q_t > P_t) f_i(P_i^t + R_i^t) + S C_i(1 - u_i^{t-1})\}. \end{aligned} \quad (10)$$

P_t is the forecasted power demand of period t . If we assign a suitable value to the confidence level β , then, P_t can be calculated by Equation (5). Q_t is the real load in period t , $\text{Pos}(Q_t \geq P_t)$ is the possibility that the real demand is larger than the forecasted value P_t , R_i^t is the spinning reserve of unit i at time t , and $\sum_{i=1}^N R_i^t = R_t$, respectively.

Remarks:

□ Supposing $\Delta P = Q_t - P_t$, if and only if $\Delta P > 0$ (that is to say the real load is larger than the forecasted value), the reserve is considered to be called (even though the ΔP is sufficiently small).

□ In an uncertain environment, the power loads are fuzzy variables, and subsequently, the possibility theory can be applied to measure the chance that the spinning reserve will be called:

$$\text{Pos}\{Q_t > P_t\} = \sup_{t > P_t} \mu_{\tilde{L}_t}(t). \quad (11)$$

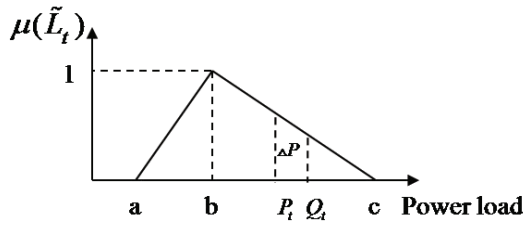


Fig. 1. The situation that spinning reserve is called

2) *Constraints*: The constraints are forwarded on the basis of system objective environmental demands. From the literature, they can be summarized as follows:

a). Power demand balance

$$\sum_{i=1}^N P_i^t u_i^t = P_t, \quad (12)$$

where P_t is the total power demand in period t .

b). Spinning reserve balance

$$\sum_{i=1}^N P_{max}^t u_i^t \geq P_t + R_t, \quad (13)$$

where R_t is the spinning reserve in period t .

c). Interval of each generation unit

$$P_{min}^i \leq P_i^t \leq P_{max}^i, \quad (14)$$

where P_{max}^i and P_{min}^i are the maximum and minimum generation capacity of unit i , respectively.

d). Unit on/off limitations

Usually, the unit state should be kept on for certain hours before it can be changed.

$$\begin{cases} T_{i,on}^t \geq T_{i,up} \\ T_{i,off}^t \geq T_{i,down} \end{cases} \quad (15)$$

where, respectively, $T_{i,on}^t$ and $T_{i,off}^t$ are the time periods that unit i has been turned on or off. $T_{i,up}$ and $T_{i,down}$ are the minimum unit on time and maximum off time which are determined by the property of each unit.

e). Initial status of each unit

Before arranging the schedule, the unit initial status needs to be taken into consideration. That is, it is necessary to decide how many hours each unit has been committed or de-committed.

IV. THE SOLUTION

In this section, we provide the solution for the improved UCP in fuzzy environment.

UCP has been solved using various kinds of heuristic algorithm, such as genetic algorithm (GA) [16], evolutionary programming (EP) [17] and lagrangian relaxation based PSO (LRPSO) [18]. Based on these methods, Yuan [3] proposed an

improved binary PSO (IPSO) algorithm, which has proven to be more effective than other approaches.

In this research, based on original PSO [19], an LCA-PSO is proposed to better solve the problem. The following is a preliminary explanation of the proposed method.

A. The fitness function of the improved UCP

Considering the spinning reserve cost and fuzzy power load, the objective function is updated as Equation (10), which is considered as the fitness function of LCA-PSO.

B. The equations update particle's position and velocity

The equations proposed in classic binary PSO [20] are employed here. The particle position is updated by the following equations:

$$v_i = \omega \cdot v_i + c_1 \cdot rand() \cdot (P_{best,i} - x_i) + c_2 \cdot rand() \cdot (G_{best} - x_i),$$

$$x_i = x_i + v_i, \quad (16)$$

where, v_i is the velocity of i , ω is the inertia weight, c_1 and c_2 are the learning rates generated in the interval $[0, 4]$. $rand()$ is a random number distributed in the interval $[0, 1]$. $P_{best,i}$ and G_{best} are the personal and global best among the iterations of particles, respectively. Subsequently, the position of particle i is updated by Equation (16).

Finally, the particles 0/1 states are determined by a sigmoid function $S(x)$:

$$S(x) = \frac{1}{1 + e^{-x_i}}. \quad (17)$$

C. The local convergence of PSO

It is well known that the PSO algorithm can find the optimal solution in fewer iterations than other algorithms, but may suffer from the local convergence problem. In particular, when the selection problem contains a large number of objectives, this defect of the PSO becomes more obvious. To solve this problem, Yuan [3] performed 10 trials from different initial populations and selected the smallest cost as the result. Lee [21] proposed a mutation-based PSO (MPSO) where mutations occur with given possibility. In this paper, we design the LCA-PSO by employing the escape speed (ES) and velocity modification (VM).

Escape speed: If the optimal solution cannot be updated after a specified number of time iterations, it will be considered as having fallen into local convergence. Then, each particle speed will be modified by the escape speed. The value of ES should be determined by the experiments' performances: on one hand, if the escape speed is sufficiently large, all of the particles can jump out of the current loop and resume searching in different areas; on the other hand, if the escape speed is smaller, the new optimal solution can be obtained more quickly.

Velocity modification: After the above step, each particle's velocity has been modified to an opposite direction with a random value. This is inappropriate for the future search.

Therefore, the VM is used to modify the velocity to a suitable value and in direction. In this case, a potential global optimal solution will be found.

We use the following two-dimensional Figure 2 to approximate the LCA-PSO.

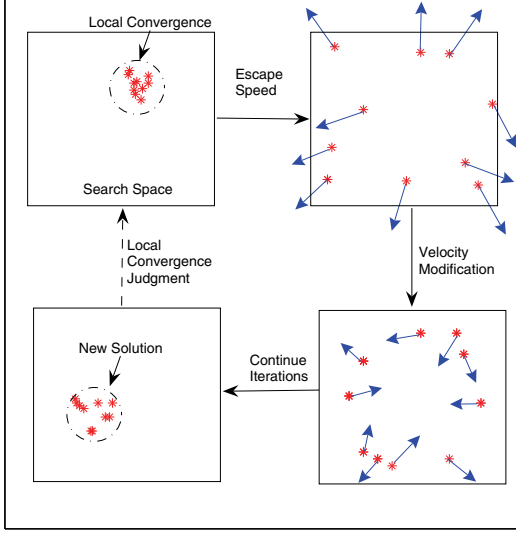


Fig. 2. Local convergence averse BPSO

Based on the above analysis, we summarize the LCA-PSO algorithm as follows:

[Step 1]. Initialize particles: Each particle contains $T \times N$ generator states, as:

$$x_i = \begin{bmatrix} u_1^1 & u_1^2 & \cdots & u_1^T \\ u_2^1 & u_2^2 & \cdots & u_2^T \\ \vdots & \vdots & \ddots & \vdots \\ u_N^1 & u_N^2 & \cdots & u_N^T \end{bmatrix}.$$

[Step 2]. Check the constraints of UCP, as mentioned in Subsection 3.2.2, part B.

[Step 3]. Solve the economic load dispatch (ELD) problem and update gray zone states for start-up cost. The concepts of ELD and gray zone have been well described in previous studies. One may refer to [3] and [22] for further information regarding these topics.

[Step 4]. Initialize personal best and global best: The personal best and global best are determined by the fitness function (10).

[Step 5]. Particle iterations: The particle positions are updated by Equation (16), and Step 2 is repeated to modify the unit states, then, new P_{best} and G_{best} are calculated.

[Step 6]. Solve the local convergence problem: If the global best cannot be improved in a given number of iterations, we consider the program to have fallen into the local convergence. Then, the aforementioned approach is used to cause the particles to jump out of current loop and to revise the particle's velocity.

[Step 7]. Following the completion of all iterations, the final global best is returned as the optimal result.

V. EXEMPLIFICATION USING TEST SYSTEMS

A. The performances of the proposed model and LCA-PSO

In this section, the proposed model and algorithm are exemplified using test systems. The 24-hour power loads are fuzzy variables evaluated from previous data and experts' opinions, as listed in Table 1. (a, b, c) denotes the triangular fuzzy variable, and $FN(a, \sigma^2)$ represents a normally distributed fuzzy variable. The power demand here are measured in megawatt (MW).

TABLE I
24 HOURS FORECASTED FUZZY POWER DEMANDS

Period	Power Demands	Period	Power Demands
1	(650, 700, 750)	13	(1350, 1400, 1450)
2	(700, 750, 800)	14	(1250, 1300, 1350)
3	(800, 850, 900)	15	(1150, 1200, 1250)
4	(900, 950, 1000)	16	(1000, 1050, 1100)
5	(950, 1000, 1050)	17	FN(1000, 400)
6	(1050, 1100, 1150)	18	FN(1100, 410)
7	(1100, 1150, 1200)	19	FN(1200, 410)
8	FN(1200, 440)	20	FN(1400, 430)
9	FN(1300, 420)	21	FN(1300, 400)
10	FN(1400, 400)	22	(1050, 1100, 1150)
11	FN(1450, 400)	23	(850, 900, 950)
12	FN(1500, 390)	24	(750, 800, 850)

Supposedly, the lowest and highest confidence levels provided by the grid company of VaR is 80% and 95%, respectively. Then, using Equation(5), we get the demands and reserves in real values, as listed in the following Table 2.

TABLE II
24 HOURS EVALUATED POWER DEMANDS AND RESERVES

Period	Demands	Reserves	Period	Demands	Reserves
1	730.0	15.0	13	1430.0	15.0
2	780.0	15.0	14	1330.0	15.0
3	880.0	15.0	15	1230.0	15.0
4	980.0	15.0	16	1080.0	15.0
5	1030.0	15.0	17	1019.1	11.2
6	1130.0	15.0	18	1119.4	11.3
7	1180.0	15.0	19	1219.4	11.3
8	1220.1	11.7	20	1419.4	12.1
9	1319.6	11.5	21	1319.1	11.2
10	1419.1	11.2	22	1130.0	15.0
11	1469.1	11.2	23	930.0	15.0
12	1518.9	11.1	24	830.0	15.0

Based on the above analysis, the proposed LCA-PSO is evaluated through the use of different-sized test systems (10, 20, 40, 60, 80 and 100 units), which are expanded from a 10-unit based system [17]. All of the experiments are implemented on a Dell E8500 3.16 GHz CPU with 2.96 GB of RAM.

We first tested the LCA-PSO in different systems of various unit sizes. The parameters were selected as follows: 20 particles, 500 iterations, $c_1 = 2.8$, $c_2 = 1.2$, $\omega = 1$, a maximum speed of 4.0 and a minimum speed of -7.0. For LCA-PSO, the given time iteration mentioned in Section IV was set at 20,

and this was used to evaluate whether the local convergence occurs.

Table 3 illustrates the performance of LCA-PSO by comparing the initial cost and the cost after 1000 iterations in different-sized systems. The savings are calculated as $(InitialCost - FinalCost)/InitialCost * 100\%$.

TABLE III
THE PERFORMANCE OF LCA-PSO

Unit No.	Initial Cost	Final Cost	Savings
10	602,270	570,006	5.36%
20	1,208,507	1,139,005	5.75%
40	2,420,321	2,277,396	5.91%
60	3,625,509	3,420,438	5.67%
80	4,827,049	4,554,346	5.65%
100	6,036,371	5,706,201	5.46%

From Table 3, we can find that, the LCA-PSO could result in a cost-saving of more than 5.3% amongst all of the test systems.

In Tables 4 and 5, we show an example of initial and final schedules as found by the LCA-PSO for the 10-unit test model. This illustrates the number of start-up and shut-down decisions made through the LCA-PSO optimization process.

TABLE IV
THE INITIAL SOLUTION OF LCA-PSO (cost: 602,270)

Unit No.	0	1	2	3	4	5	6	7	8	9
1	1	1	1	1	1	0	0	1	1	0
2	1	1	1	1	1	0	0	0	0	1
3	1	1	1	1	1	0	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	0	0	0
6	1	1	1	1	1	1	1	0	0	0
7	1	1	1	1	1	0	1	1	0	0
8	1	1	1	1	1	0	1	0	0	1
9	1	1	1	1	1	0	1	0	1	1
10	1	1	1	1	1	1	1	0	0	0
11	1	1	1	1	1	1	1	0	1	0
12	1	1	1	1	1	1	1	0	0	1
13	1	1	1	1	1	1	1	0	0	0
14	1	1	1	1	1	1	1	1	1	0
15	1	1	1	1	1	1	1	0	1	1
16	1	1	1	1	1	1	1	1	1	0
17	1	1	1	1	1	1	1	0	1	1
18	1	1	1	1	1	1	1	0	0	1
19	1	1	1	1	1	1	1	0	0	1
20	1	1	1	1	1	1	1	0	0	1
21	1	1	1	1	1	1	0	1	0	1
22	1	1	1	1	1	1	0	0	0	0
23	1	1	1	1	1	0	0	0	1	0
24	1	1	1	1	1	0	0	0	0	0

B. Comparisons between LCA-PSO and other improved PSO algorithms

In this subsection, we compare the LCA-PSO with IPSO (the best result of 10 trails was selected) [3] and MPSO [21]. For MPSO, the mutation probability was 0.1. After 1000 iterations, the total costs and CPU time of each algorithm are listed in Tables 6 and 7.

TABLE V
THE OPTIMIZED SOLUTION OF LCA-PSO (cost: 570,006)

Unit No.	0	1	2	3	4	5	6	7	8	9
1	1	1	0	0	1	0	0	0	0	0
2	1	1	0	0	1	0	0	0	0	0
3	1	1	0	0	1	0	0	0	0	0
4	1	1	0	0	1	0	0	0	0	0
5	1	1	0	0	1	0	0	0	0	0
6	1	1	0	1	1	0	0	0	0	0
7	1	1	0	1	1	0	0	0	0	0
8	1	1	1	1	1	0	0	0	0	0
9	1	1	1	1	1	0	0	0	0	0
10	1	1	1	1	1	1	1	0	0	0
11	1	1	1	1	1	1	1	0	0	0
12	1	1	1	1	1	1	1	1	0	0
13	1	1	1	1	1	1	1	0	0	0
14	1	1	1	1	1	1	0	0	0	0
15	1	1	1	1	1	0	0	0	0	0
16	1	1	1	1	1	0	0	0	0	0
17	1	1	1	1	1	0	0	0	0	0
18	1	1	1	1	1	0	0	0	0	0
19	1	1	1	1	1	0	0	0	0	0
20	1	1	1	1	1	1	0	1	0	0
21	1	1	1	1	1	1	0	0	0	0
22	1	1	0	0	1	1	0	0	0	0
23	1	1	0	0	1	0	0	0	0	0
24	1	1	0	0	1	0	0	0	0	0

TABLE VI
OPTIMAL RESULTS OF DIFFERENT ALGORITHMS

Unit No.	LCA-PSO	MPSO	IPSO
10	570,006	574,905	599,782
20	1,139,005	1,152,966	1,196,029
40	2,277,396	2,323,435	2,401,728
60	3,420,438	3,451,762	3,592,585
80	4,554,346	4,691,481	4,798,427
100	5,706,201	5,864,719	5,988,264

We found that, in most of the test systems, the LCA-PSO was able to obtain better optimal solutions with less runtime cost than other approaches.

Nevertheless, compared with the CPU time used in prior work, more computation time is required to reach the final optimal solutions in this study. The reason for this could be that the objective function here is modified from Equations (8) to (10). Therefore, during each iteration, the cost was computed with respect to two options: 1. The reserve was not called (as in the conventional UC models); 2. The reserve was called. We must re-arrange different unit on/off schedules for each situation. Therefore, more time was required to obtain the optimal result.

To prove the effectiveness of LCA-PSO, we employed a 100-units test system, and Figure 3 shows the performance of each method during the 1000 iterations.

Finally, in Figure 3, it should be noted that, in the 100 units test system, the IPSO and MPSO are suffering from the local convergence problem. However, the proposed LCA-PSO could overcome the local convergence effectively, the ES and VM were quite effective in solving such unit commitment

TABLE VII
COMPARISONS OF CPU TIME (s)

Unit No.	Methods	LCA-PSO	MPSO	IPSO
10		18.34	15.73	14.48
20		57.32	65.87	60.65
40		274.67	317.29	316.86
60		572.30	673.46	744.19
80		1068.58	1284.01	1439.51
100		1734.67	2122.44	2503.78

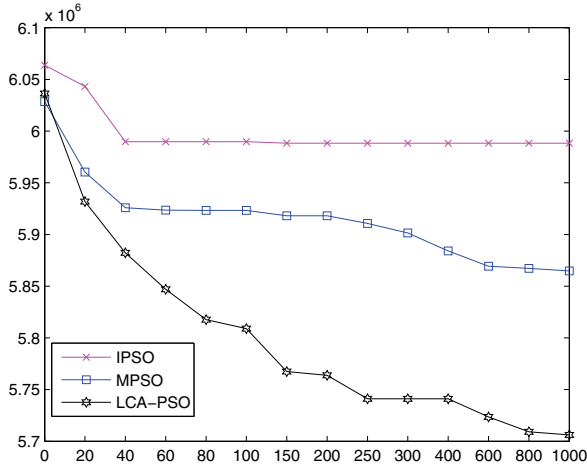


Fig. 3. Performances in a 100 unit test system

optimization problem.

VI. CONCLUSION

In this study, the fuzzy variable is used to more accurately describe the future power load while the fuzzy Value-at-Risk is employed as a technique to evaluate the power demand and reserve for each period. The conventional unit commitment model is improved by considering the possibility that the reserve is called in uncertain environment. This model can minimize the system cost by considering various constraints. To solve the problem, we proposed an LCA-PSO as the solution that has been proved to be most useful and effective by the test systems. Furthermore, comparisons with existing algorithms show that the LCA-PSO has higher performance. In addition, the proposed model can be applied to various engineering reliability control problems.

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