Economic Dispatch with Linear Decreasing and Staircase Incremental Cost Functions by Micro Genetic Algorithms

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ABSTRACT- In this paper, a Micro Genetic Algorithm (MGA) to solving the economic dispatch (ED) problem with linear decreasing and staircase incremental cost (IC) functions for combined cycle (CC) units is proposed. To demonstrate its advantage, the proposed MGA methods with two different encoding schemes are tested and compared to the unconstrained Brute Force (BF), Simple Genetic algorithm (SGA), Merit Order Loading (MOL), and equal-lambda based Newton methods on five combined cycle units. As the ramp rate constraints are taken in account, the proposed MGA solutions are ensured to be feasible. Test results indicate that the solutions are found to be close to the optimal solution of the unconstrained BF method and its total fuel costs are lower than those of the SGA, MOL, and Newton methods.

KEYWORDS: Micro Genetic Algorithm (MGA), Economic Dispatch (ED), Brute Force (BF), Simple Genetic Algorithm (SGA), Merit Order Loading (MOL), Newton Method.

บทคัดย่อ บทความนี้นำเสนอไมโครจินิติก อัลกอริธึมในการแก้ปัญหาการ Dispatch หน่วยผลิตไฟฟ้าอย่างประหยัดสำหรับหน่วยผลิตพลังความร้อนร่วมที่มีสมการ Incremental Cost ที่มีความชันเป็นลบ และ ที่เป็นขั้นบันได เราทดสอบ ไมโครจินิติกอัลกอริธึม และ เปรียบเทียบผลกับวิธี Brute Force ที่ไม่คิดขีดจำกัดอัตราการเพิ่มกำลังการผลิต, วิธีจินิติกอัลกอริธึมอย่างง่าย, วิธี Merit Order Loading (MOL), และ วิธีนิวตัน บนระบบไฟฟ้ากำลังที่มีหน่วยผลิตพลังความร้อนร่วมจำนวน 5 หน่วยเพื่อที่จะแสดงถึงประโยชน์ของอัลกอริธึม ผลที่ได้จากการทดสอบมีความเป็นไปได้ในการ Dispatch เนื่องจากเราพิจารณาอัตราการเพิ่มกำลังการผลิตในการคำนวณ ผลการทดสอบให้ต้นทุนการผลิตรวมใกล้เคียงกับต้นทุนการผลิตรวมต่ำสุด และ ต้นทุนการผลิตรวมที่ได้ต่ำกว่า ผลที่ได้จากวิธีจินิติกแบบธรรมดา, วิธี MOL, และ วิธีนิวตัน

คำสำคัญ : ไมโครจินิติกอัลกอริธึม, การ dispatch หน่วยผลิตไฟฟ้าแบบประหยัด, Brute Force, จินิติกอัลกอริธึมแบบธรรมดา, Merit Order Loading, วิธีนิวตัน

1. Introduction

Economic dispatch (ED) is used to determine the optimal schedule of on-line generating outputs so as to meet the load demand at the minimum operating cost. The existing ED program, a standard function of the Energy Management System (EMS), National Control Center (NCC), Electricity Generating Authority of Thailand (EGAT), is applicable only for monotonically increasing incremental cost (IC) functions which is limited in flexibility. Neither linear decreasing IC functions nor staircase IC functions can be handled by the program [1].

At present, combined cycle (CC) units of EGAT system are always scheduled to serve the base load. However, during light load periods when there are no other generating units that can further reduce their outputs, there is a need to vary the CC units in an economical and smooth manner instead of a zero-one discrete basis. Therefore, if the linear decreasing IC and decreasing staircase IC functions (or non-convex and non-smooth input-output functions) of the CC units are included in the database, the conventional ED program based on the equal lambda methodology cannot determine the optimal solution [2].

Ongsakul [1,2] proposed the Merit Order Loading (MOL) method based on the unit lambda values at the highest operating outputs to solving the ED problem with linear decreasing IC and decreasing staircase IC of CC units. It was shown that the proposed MOL solution was close to the optimal solution and the real time implementation was valid on the existing EMS of EGAT without violating the ramp rate constraints. However, the monthly fuel costs of CC units of EGAT are in the order of several billion Thai baht, a few percent improvement of the existing ED program for CC units can lead to substantial fuel cost savings. Accordingly, this paper will investigate a Micro Genetic algorithm (MGA) to solving the ED with linear decreasing IC and decreasing staircase IC which are non-monotonically increasing functions.

Bakirtzis et al [3] proposed the Genetic algorithm to solving ED problem without convexity restrictions on the generator cost functions with valve point loading. The proposed method outperformed the dynamic programming in terms of computing times for the generating units ranging from 9 to 72. But the success rate to the optimal solution was still only 40% for the 72 generating unit system.

Wong et al [4] proposed the Genetic/Simulated-annealing approaches to ED problem. The algorithm was developed based on the combination of the incremental genetic-algorithm approach and the simulated-annealing technique. It was shown to be computationally faster than the earlier simulated annealing based method on a 13 generator practical system.

Sheble et al [5,6] proposed the Genetic algorithm (GA) and refined Genetic algorithm (RGA) to solving ED with valve point loading. Several techniques were explored to enhance the efficiency and accuracy such as mutation prediction, elitism, interval approximation and penalty factors. Test results however were shown on a very small size three-bus system.

Chen et al [7] proposed the large-scale ED by genetic algorithm with a normalized lambda encoding method. The network losses, ramp rate constraints, and prohibited zone were also taken into account. The proposed GA was tested on the system sizes ranging from 5 to 40 units. Even though this encoding scheme is practical for large scale implementation, its application is restricted to monotonically increasing IC functions only.

In this paper, a Micro Genetic algorithm (MGA) to solving the ED with linear decreasing IC and decreasing staircase IC functions of CC units is proposed. The ramp rate constraints are also taken into account to insure the feasibility of solutions. Two different encoding methods including concatenated and embedded methods are investigated. The MGA is tested and compared to Simple Genetic algorithm (SGA), MOL, Newton and unconstrained BF on a five CC unit system.

Two types of cost functions used for CC generating units at EGAT can be summarized as follows [1].
Second order polynomial cost function for a CC unit: One combined cycle unit consists of a series of single-cycle gas turbines in conjunction with a heat-recovery steam generator (HRSG). In a closed cycle operation mode, a cost function is obtained by curve-fitting among at least three test points using the least squares method. In fact, the second order polynomial cost function for a CC unit is estimated by $a + bP + cP^2$, where the coefficient $c < 0$, and IC is a linear decreasing function ($b+2cP$). This phenomenon is explained by the characteristics of a CC unit in such a way that the higher the output is, the better the efficiency will be.

Piecewise linear cost functions for a CC unit: To obtain extreme accuracy, instead of using only one quadratic equation to represent the cost function of a CC unit, several piecewise linear functions are employed to represent cost functions for each mode of the closed cycle operation. The piecewise linear cost functions and their decreasing staircase IC functions of one of the closed cycle modes are as follows.

$$C_i(P_i) = a_{i1} + b_{i1} P_i, \quad P_{i,min} \le P_i < P_{i,int}, \tag{1a}$$
$$= a_{i2} + b_{i2} P_i, \quad P_{i,int} \le P_i \le P_{i,max}, \tag{1b}$$
$$IC_i(P_i) = b_{i1}, \quad P_{i,min} \le P_i < P_{i,int}, \tag{2a}$$
$$= b_{i2}, \quad P_{i,int} \le P_i \le P_{i,max}, \tag{2b}$$

where $b_{i1} > b_{i2} > 0$.

The organization of the paper is as follows. The ED problem formulation is introduced in Section 2. Section 3 describes the SGA and MGA. The experimental results on a five unit system are given in Section 4. Conclusion is given in the last section.

2. Economic Dispatch Formulation

2.1 Basic Economic Dispatch Formulation

The conventional ED problem is to minimize the total cost function. The problem is formulated as:

$$\text{Minimize } C_T = \sum_{i=1}^{N} C_i\,(P_i), \tag{3}$$

subject to a power balance constraint:

$$\sum_{i=1}^{N} P_i = P_D + P_L(P_1, \ldots, P_N), \tag{4}$$

and operating limit constraints:

$$P_{i,min} \leq P_i \leq P_{i,max}, \qquad i = 1, \ldots, N, \tag{5}$$

where,
C_T = total fuel cost (baht/hr),
$C_i(P_i)$ = cost of the ith generating unit (baht/hr),
P_i = real power output of the ith generating unit (MW),
P_D = total load demand (MW),
$P_L(P_1,\ldots,P_N)$ = total transmission line loss (MW),
N = total number of on-line units to be dispatched,
$P_{i,min}$ = minimum power output of the ith unit (MW),
$P_{i,max}$ = maximum power output of the ith unit (MW).

2.2 Economic Dispatch Formulation with Ramp Rate Limits

Ramp rate of generating units are due to the fact that CC generating outputs can be not adjusted instantaneously. Therefore, to reflect the actual operating process, ED problem should include the ramp rate limits to ensure the feasibility of the solutions.

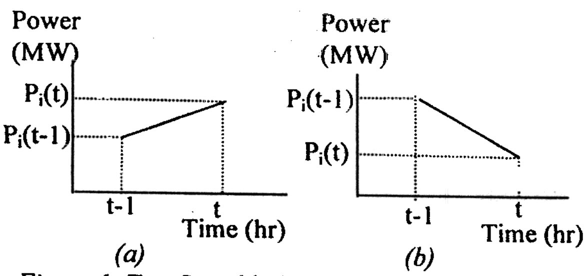

Figure 1. Two Possible Situations of On-line ith Unit

As shown in Figure 1, the inequality constraints of ramp rate limits are given as:

1. if the ith generation unit output increases (see Figure 1a)
$$P_i(t) - P_i(t-1) \leq UR_i \tag{6}$$
2. if the ith generation unit output decreases (see Figure 1b)
$$P_i(t-1) - P_i(t) \leq DR_i \tag{7}$$

Where UR_i and DR_i are up ramp and down ramp limits of the ith unit which are in the units of MW/hr. In practice, DR_i is greater than UR_i. Combining equations (3), (4), (5), (6) and (7), the constrained ED problem formulation becomes:

$$\left[\begin{array}{l} \text{Minimize } C_T = \sum_{i=1}^{N} C_i\,(P_i(t)), \\ \text{Subject to: } \sum_{i=1}^{N} P_i(t) = P_D(t) + P_L(P_1(t), \ldots, P_N(t)), \\ \qquad P_{i,low}(t) \leq P_i(t) \leq P_{i,high}(t),\ i = 1, \ldots, N. \end{array}\right. \tag{8}$$

Where,
$_{i,low}(t)$ = the possible lowest power output of the ith unit at time t $(Max(P_{i,min}, P_i(t-1) - DR_i))$,
$P_{i,high}(t)$= the possible highest power output of the ith unit at time t $(Min(P_{i,max}, P_i(t-1) + UR_i))$,

In this paper, the total power loss is neglected, thus $P_L(P_1,(t)\ldots,P_N(t)) = 0$.

3. Genetic Algorithms

Genetic algorithm (GA) is essentially a searching method based on the concept of natural selection and natural genetics. GA searches on encoded bit strings (usually binary representations) called individuals rather than the real data points in solution space. GA has the ability to solve non-smooth, non-continuous, and non-differentiable cost functions which is not possible to obtain the optimal solution by a classical Lagrange method. GA uses the objective function to evaluate the performance, not its derivatives or auxiliary equations; and it has ability to exploit prior knowledge from previous solution guess to increase the performance of future solutions. Furthermore, GA exploits probability transition rules rather than deterministic rules [8].

3.1 Simple Genetic Algorithm

In this paper, we shall use the Simple Genetic algorithm (SGA) developed by Goldberg [8] to solve the ED problem for comparison. The outputs of the N generating units have to satisfy the power balance constraint, operating limit constraints, and ramp rate constraints. For arbitrary free unit outputs P_i, $P_{i,low}(t) \leq P_i(t) \leq P_{i,high}(t)$, $i = 1,\ldots,N-1$, it is assumed that the Nth reference unit power output is

$$P_N(t) = P_D(t) - \sum_{i=1}^{N-1} P_i(t) \tag{9}$$

constrained by the power balance equation as:

3.1.1 Encoding and Decoding

In this paper, concatenated and embedded encoding methods are explored.

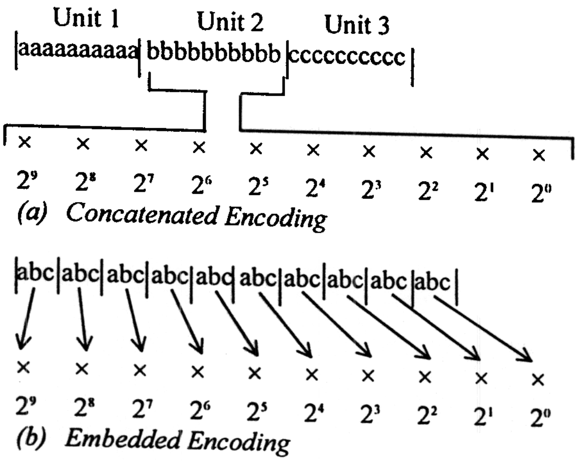

Figure 2. Two Different Encoding Schemes

As shown in Figure 2, each unit output of N-1 free units is encoded in a binary based string normalized over its operating range. The concatenated encoding method stacks each unit's normalized string in series with each other to constitute the string individual. Each unit's string structure is assigned by the same number of n bits. On the other hand, the embedded encoding method employs the same binary system and encoding as the concatenated one. The only difference is that the assigned bit structures of each unit string are embedded within each other throughout the individual. Each individual consists of a series of smaller string structures (3 instead of 10). For both methods, a string individual has $n(N-1)$ bits.

For a concatenated encoding example, three generating unit power outputs are encoded in a 30 bit string individual as:

0111111101 1011011011 0100011011

To obtain the actual generating power output of each unit for fitness function evaluation to be discussed, we need to decode each of 10 bit string to the decimal value by,

$$P_i(t)= P_{i,low}(t)+ [B_i* (P_{i,high}(t)- P_{i,low}(t))/(2^n - 1)] \quad (10)$$

Where,

B_i = decimal integer value of converted binary string of the ith unit,

= number of bits representing each unit output.

For example, the first generating unit power output, encoded by the first ten bits of the binary string individual, has UR_1 and DR_1 as 50 and 80 MW/hr respectively and suppose $P_1(t-1)$ is 230 MW, $P_{1,min}$ =100, and $P_{1,max}$ = 250. Then

$$P_{1,low}(t) = Max(100,230\text{-}80) = 150\ MW,$$
$$P_{1,high}(t) = Min(250,230+50) = 250\ MW,$$
$$B_1 = (2^9*0)+ (2^8*1)+ (2^7*1)+ (2^6*1)+ (2^5*1)+ (2^4*1)+ (2^3*1)+ (2^2*1)+ (2^1*0)+ (2^0*1) = 509.$$

Therefore, $P_1(t) = 150 + [509*(250 - 150)/(2^{10} - 1)] = 199.76$ MW. In this paper, each free unit is represented by 15 bits. The more the number of bits, the higher the resolution.

SGA randomly generates initial NP (a specified population size) string individuals. For each generation (or iteration), SGA performs four basic operations: fitness function evaluation, reproduction, crossover, and mutation.

3.1.2 Fitness Function Evaluation

The performance in finding optimum solution of SGA is mainly related to the highest single fitness value. The fitness function including the power balance constraint of the jth individual is:

$$f_j = 0.5/Cst_j + 0.5/Pow_j,\ j=1,...,NP \quad (11)$$

Where,

Pow_j $= 1+ (\Sigma_{i=1,N} P_i^j(t) - P_D(t))^2/P_D(t)$,

Cst_j $= 1+ k*(C_T(P_1^j(t),..,P_N^j(t)) - Cost_{min})^2$,

$P_i^j(t)$ = real power output of the ith unit of the jth individual at time t,

$Cost_{min}$ = minimum total fuel cost at $P_{i,min}$, $i=1,..,N$ (baht),

k = a constant value.

The fitness function evaluates a power balance difference and a total fuel cost difference. By experiment, k = 0.001 is used to scale down the total fuel cost difference squared component. Otherwise, the cost difference squared component will dominate the power balance difference squared over the total load demand component. After decoding the jth individual to $[P_1^j(t),...,P_{N-1}^j(t)]$ and substituting in Eq. (9),

if $P_N^j(t) < P_{N,low}(t)$, $P_N^j(t)=P_{N,low}(t)$, and

if $P_N^j(t) > P_{N,high}(t)$, $P_N^j(t)=P_{N,high}(t)$.

We use $[P_1^j(t),..,P_N^j(t)]$ to evaluate the fitness value in Eq. (11) even though the power balance may not be satisfied. By using Eq. (11), the fitness value is ensured to be in the range of 0 to 1.

3.1.3 Reproduction

This reproduction method is based on the biased roulette wheel or "survival of the fittest" aspect [8]. The bigger the string individual fitness value, the higher the probability to have copies of them in the mating pool. For a population size NP, a reproduction probability and cumulative reproduction probability of the ith string individual with fitness value f_i, are

$$p_{rep,j} = \frac{f_j}{\sum_{j=1}^{NP} f_j}; Cumulative\ p_{rep,j} = \sum_{k=1}^{j} p_{rep,k}. \tag{12}$$

Where $j = 1,..,NP$. The selected parents' string individuals to be copied to the mating pool are those having cumulative $p_{rep,j}$ just above the real number randomized between 0 and 1.

3.1.4 Crossover

Crossover is a process of exchanging bits between two string individuals. In particular, two individuals from the mating pool are randomly selected as parent individuals based on the biased roulette wheel. Then arbitrary positions on both individuals are chosen for crossing locations, where the exchanges of bits take place. A crossing mask is employed to determine the crossing locations. Two parent individuals will exchange their bits at every location where the corresponding position in the mask is one. As an example, it is assumed that two 30 bit string parent individuals are selected for two-point and uniform crossover as follows:

```
Position     1234567890 1234567890 1234567890
Parent1:     0111111101 1011011011 0100011011
Parent2:     1011110010 1111001100 1010011001
```

For the two-point crossover, the mask comprises one set of 1's bits surrounded by two sets of 0's bits [9]. Two crossing locations are arbitrarily selected from bit positions 2 to 30. If the crossing locations are 5 and 23, we will have

```
Position:    1234567890 1234567890 1234567890
Mask:        0000111111 1111111111 1110000000
Offspring1:  0111110010 1111001100 1010011011
Offspring2:  1011111101 1011011011 0100011001
```

For the uniform crossover, the mask comprises a string of 1's and 0's bit randomly distributed along its length [10]. The number of exchanged bits depends on the number of 1's bits in the mask varying from 0% to 50% of the total number of bits in a mask.

```
Position:   1234567890 1234567890 1234567890
Mask:       0100110111 0011101000 1001010010
Offspring1: 0011111010 1011011011 1100011001
Offspring2: 1111110101 1111001100 0010011011
```

The uniform crossover generates new offspring individuals to participate in genetic process. Without crossover, the fittest individual is obtained from the initial random population. However, were every individual to cross with another one after reproduction (crossover probability = 1.0), then we might lose many superior individuals. It has been shown in [10] that the convergence rate of uniform crossover is faster than the two-point crossover. Hence, the uniform crossover is used in this paper.

3.1.5 Mutation

Mutation is a process of flipping bits in a randomly chosen offspring string individual at random positions after performing crossover. In other words, it is a toggle from 0 to 1 or vice versa in a binary based system. Mutation is designed to give the offspring individual characteristics which do not exist in parent individuals. The rate of mutation is much lower than that of crossover since it is considered to be a secondary role. It is about 0.001 to 0.01 depending upon the types of applications. For instance, if we have offspring individual bits mutated at positions 2,15, and 21, then

```
Position:   1234567890 1234567890 1234567890
Mask:       0100000000 0000100000 1000000000
Offspring1:0111110010 1111001100 1010011011
             ↓              ↓     ↓
Offspring1:0011110010 1111101100 0010011011
```

Note the mutation should be employed with caution since the high mutation rate will deteriorate the search performance.

3.2 Micro Genetic Algorithm

Micro GA, one of the variation of the conventional SGA, was originally proposed by Krishnakumar [11]. In addition to performing four basic operations, MGA uses the elitism principle and checks the convergence of population at the end of each generation. Since any of the four basic operations do not guarantee that the new population string individuals are always better. Elitism guarantees that the best string individual survives. If the best individual in the current generation is worse

Table 1. Input-Output Characteristic of Rayong CC Units

RY unit no.	P_{min} (MW)	P_{max} (MW)	Fuel cost (baht/Gcal)	Input-output coefficient (GCal/hr)			Ramp rate (MW/hr)	
				A_i	B_i	C_i	UR_i	DR_i
1	100	300	273.8	-123.26930	3.1770742	-0.00275183	50	80
2	100	300	273.8	-127.79030	3.2410401	-0.00310412	40	70
3	100	150	273.8	-30.27881	2.2650570	-0.00092385	40	60
4	100	300	273.8	-127.79030	3.2410401	-0.00310412	40	70

Table 2. Input-Output Characteristic of Khanom CC Units

KN unit no.	P_{min} (MW)	P_{int} (MW)	P_{max} (MW)	Fuel cost (baht/Mbtu)	Input-output coefficient (Mbtu/hr)			Ramp rate (MW/hr)	
					A_i	B_i	C_i	UR_i	DR_i
1.1	376	495	-	79.413	450.5580	7.3659	-	40	50
1.2	-	495	678	79.413	820.2499	6.6173	-	40	50

than the previous generation, the best individual of previous generation will be randomly replaced to any individual of the current generation that would be parent individuals of the next generation. Consequently, MGA with elitism guarantees that at least the best individual exists until the last generation.

MGA checks the convergence after applying elitism. If the best string individual at each generation, which has the highest fitness value, has the total number of bit difference from the other individuals less than 5% of the total number of bits in the population size ($n\times(N-1)\times NP$), that population is converged. Then MGA needs to copy the best individual to the next generation whereas the other individuals are all re-initialized [11].

In general, MGA performs well on a very small size of population. By experiment, the mutation and uniform crossover probability are 0.00 and 0.50 respectively. The attractive aspect of MGA is that it requires a relatively smaller population size than the SGA which results in less computation time. Moreover, once the population is converged, MGA tries to explore another set of solutions which would result in a higher chance to bail the solutions out of the local optimal solutions.

4. Experimental Results

For cost functions data, four units of Rayong (RY) CC and one unit of Khanom (KN) CC power plants [2] are used as benchmark data because their IC functions are linear decreasing and decreasing staircase functions, respectively. The low and high operating limits, coefficients of input-output functions, ramp rates, as well as the gas fuel costs of RY and KN units are shown in Tables 1 and 2, respectively. It is noted that an input-output function is given as $A_i + B_iP_i + C_iP_i^2$ and the cost function is calculated by multiplying the input-output function by the fuel cost.

Table 3. Parameter Selection of SGA and MGA

Method	Pop. size	Crossover prob.	Mutation prob.	Maximum gen. limit
SGA with concatenated (SGAC)	90	0.5	0.02	1500
SGA with embedded (SGAE)	55	0.45	0.01	1500
MGA with concatenated (MGAC)	5	0.5	0	500
MGA with embedded (MGAE)	5	0.5	0	500

According to our experiments, the parameters selection which are suitable for our ED problem are shown in Table 3. These parameters include the population size, crossover probability, mutation probability, and maximum generation limits. SGA and MGA with concatenated and embedded encoding methods are investigated and compared. Note SGA retains the best individual for each generation and its solution is selected from the best individuals of all generations.

Computer programs for the SGA and MGA were developed in Pascal programming language. The experimental results obtained for increasing load demands from 776 to 1728 MW are compared to the unconstrained BF, MOL, and equal-lambda based Newton results. The load demand step is 10 MW. The ramp rate constraints in MW/hr are taken into account for each step.

Table 4. Comparisons of Total Fuel Costs

Method	Total fuel costs (baht)	Total cost difference from BF (baht)	% total cost difference
BF	68,364,198	0	0
MGAC	68,484,219	120,021	0.1756
MGAE	68,489,662	125,464	0.1835
SGAC	68,521,126	156,928	0.2295
SGAE	68,521,520	157,322	0.2301
MOL Pmin	68,665,609	301,411	0.4409
MOL Pmax	68,750,475	386,277	0.5650
Newton	70,366,638	2,002,440	2.9291

As shown in Table 4, the percentage of total fuel cost difference of all load demand steps of MGA with concatenated and embedded encoding methods are 0.1756% and 0.1835% higher than the unconstrained BF whereas SGA with concatenated and embedded encoding methods are 0.2295% and 0.2301% higher. MGA with concatenated encoding method has a lower fuel cost than the MOL based on the unit lambda values at P_{min} and P_{max} results in [2] by 0.2653% and 0.3894%, respectively. This improvement of ED program would therefore result in substantial fuel cost savings.

We measure the performance of MGAC and MGAE by the total cost difference from the unconstrained BF. Therefore, it is difficult to determine the success rate if it is defined by how many times that we achieve the optimal solution from a certain number of runs. However, from 20 runs of MGAC and MGAE without ramp rate limits, the percentage average total cost difference from BF is 0.0993%, where its minimum and maximum total cost difference are 0.03% and 0.1631% respectively.

MGA average computing time is 2.42 seconds compared to 40 seconds of SGA on a Pentium 166 PC platform. This is because MGA requires a smaller size of population (5) than SGA (55 and 90). Moreover, the number of maximum generation limit of MGA (500) is smaller than SGA (1500) as the iteration processes of both methods continue until they reach their maximum generation limits. It should be observed that the unconstrained BF does not take the ramp rate constraints into account, thereby its solution is not guaranteed to be feasible. But we use its results for benchmarking. Note the equal-lambda based Newton has the highest fuel cost since the equal lambda principle is not applicable for linear decreasing and staircase IC functions [2].

5. Conclusions

A Micro Genetic algorithm (MGA) method to solving the ramp rate constrained economic dispatch problem with linear decreasing IC and staircase IC functions is proposed. The MGA outperforms SGA in terms of lower total fuel costs and faster computing times since it has a higher chance to obtain the optimal solution with a relatively smaller size of population. It is shown that the total fuel cost of MGA is less than MOL, leading to substantial fuel cost savings. Real-time implementation of ED for EGAT CC units with linear decreasing and staircase IC functions by MGA is potentially viable.

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