

An Improved Differential Evolution Scheme for the Solution of Large-Scale Unit Commitment Problems

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Abstract. This paper presents an improved differential evolution (IDE) method for the solution of large-scale unit commitment (UC) problems. The objective of the proposed scheme is to determine the generation schedule which minimizes the total operating cost over a given time horizon subject to a variety of constraints. Through its use of enhanced acceleration and migration processes, the IDE method limits the population size required in the search procedure and is therefore an ideal candidate for the solution of large-scale combinatorial optimization problems. The effectiveness of the proposed approach is verified by performing a series of simulations based upon the practical Tai-Power System (TPS) and various other power systems presented in the literature. In general, the results show that the IDE scheme outperforms existing deterministic and stochastic optimization methods both in terms of the quality of the solutions obtained and the computational cost. Furthermore, it is found that the magnitude of the cost savings achieved by the IDE scheme compared to that obtained by the other optimization techniques increases as the number of generating units within the power system increases. Therefore, the proposed scheme represents a particularly effective technique for the solution of large-scale UC problems.

Keywords: unit commitment, differential evolution, improved differential evolution.

1. Introduction

As the start-up and operating costs of power stations continue to soar, energy planners are placing an increasing emphasis upon the need to optimize the operating costs of existing plants. Essentially, this requires power provider enterprises (PPEs) to limit their fuel costs by deliberately restricting the time for which each generating unit within the power system is on-line. However, while seeking to minimize production costs, PPEs must nevertheless ensure that the power system is capable of satisfying the time-varying energy demands imposed upon it at all times. In practice, therefore, PPEs must achieve a satisfactory compromise between production costs, which are directly related to the number of generating units on-line at any time, and the risk of unplanned power outages. The resulting unit commitment (UC) problem, in which the aim is to identify suitable on/off states of each generating unit at each time index over the specified time horizon

such that the overall operating cost is minimized subject to certain constraints, is a complex optimization problem (Wood and Wollenberg, 1996). The optimal solution of the UC problem can only be obtained by performing a complete enumeration of all the feasible combinations of generating units within the network. In practice, this is a massive task since modern power systems typically comprise many different generating units of different types. As a result, the UC problem is most commonly formulated as a nonlinear, large-scale, mixed-integer combinational optimization problem.

Several solution techniques have been applied to solve the UC problem. These include deterministic, meta-heuristic, and hybrid approaches. Deterministic approaches include priority list (Sheble, 1990), mixed-integer programming (MIP; Mohan *et al.*, 1992), dynamic programming (DP; Padhy, 2000), branch-and-bound (BB; Chen and Wang, 1993) and Lagrangian relaxation (LR; Ngundam *et al.*, 2002). Although these methods are simple and fast, they suffer from numerical convergence and solution quality problems. They are hard to solve the real-sized problem because of computational efficient and/or solution accuracy. Recently, meta-heuristic approaches became popular in the application to overcome shortcomings of traditional optimization techniques (Misevičius and Rubliauskas, 2009). Techniques such as simulated annealing (SA; Zhuang and Galiana, 1990), genetic algorithms (GA; Kazarlis *et al.*, 1996; Padhy, 2000), evolutionary programming (EP; Yang *et al.*, 1996), Tabu search (TS; Mantawy *et al.*, 1998), ant colony optimization (Sisworahardjo and El-Kaib, 2002) and particle swarm optimization (Ting *et al.*, 2003) have been widely applied to solve the UC problem. These methods can accommodate more complicated constraints and are claimed to produce solutions of improved quality. Of the two optimization approaches presented above, the latter group appears to have the greatest potential for the solution of UC problems. The GA, EP, TS and swarm intelligence (SI) optimization algorithms are based on natural biological mechanisms (Dzemyda and Sakalauskas, 2009), whereas SA is derived from the principles of material science. However, regardless of their respective origins, these methods all provide a suitable means of solving combinatorial-type problems in a variety of decision-making arenas. Furthermore, these methods are subject to constant review and improvement with the aim of further enhancing their performance and applicability.

The differential evolution (DE) scheme developed by Storn and Price (1996, 1997, 1999) has emerged as one of the most powerful evolution algorithms (EAs). DE is a simple method based on stochastic search routines, in which the optimization function parameters are encoded as floating-point variables. However, although DE provides a convenient means of solving real-valued optimization problems, it has a tendency to converge prematurely to a local, sub-optimal solution. While this problem can be overcome to a certain extent by increasing the size of the searched population, this inevitably increases the computational time and expense. To resolve this problem, Chiou and Wang (1998) proposed a hybrid version of DE (designated as HDE), in which two additional operations, namely acceleration and migration, were introduced to improve both the speed and the thoroughness with which the solution space was searched. It was shown that these operations increased the likelihood of the scheme finding a global optimal solution. However, it was also found that the fitness characteristics of the best solutions in each

generation did not converge smoothly from one generation to the next. Accordingly, Lin *et al.* (1999) proposed an enhanced acceleration operation designed specifically to improve the fitness evolution of the best candidates during the iterative solution of mixed-integer nonlinear optimization problems. The DE family of optimization schemes has been successfully applied to the solution of many real-world problems and has a proven ability to determine global optimal solutions. However, the UC problem considered in the present study includes both continuous and discrete variables and has the form of a joint combinatorial optimization and nonlinear optimization problem. Accordingly, an improved differential evolution (IDE) method is proposed to solve the problem in a rapid and efficient manner.

The remainder of this paper is organized as follows. Section 2 reviews the general UC problem and develops its mathematical formulation. Section 3 introduces the IDE scheme developed in this study to solve the UC problem. Section 4 verifies the performance of the proposed scheme by performing a series of numerical simulations based upon a variety of power systems of different scales and benchmarking the results against those obtained from conventional deterministic and stochastic optimization schemes. Finally, Section 5 provides some brief concluding remarks.

2. Problem Description and Formulation

The principal objective of the unit commitment (UC) of power systems is to schedule the generation units in order to serve the load demand at the minimum operating cost while meeting all system constraints (Wood and Wollenberg, 1996). Generation scheduling involves the determination of the start up-time and shut down-time points and the generation levels for each unit over a given scheduling period. The schedule is subject to a number of system and unit constraints. And some major constraints that must be taken into account include: (1) The total power output must meet the load demand plus system losses. (2) There must be enough spinning reserve to cover any shortfall in generation. (3) The generation of each unit must be within its minimum and maximum allowable power output range. (4) The minimum up- and down-times of thermal generation units must be considered. (5) Ramp rates limits for thermal generation units must not be violated.

In this study, the objective of the UC problem is to establish the generating unit schedule which minimizes the total operating cost over a specified time horizon subject to various constraints. In a power system, the operating cost consists primarily of the fuel costs incurred by the committed units (thermal or nuclear) and can be expressed in the following quadratic form:

$$FC_i(P_{ih}) = a_i P_{ih}^2 + b_i P_{ih} + c_i, \quad (1)$$

where a_i, b_i, c_i cost function coefficients of unit i (\$/MW²h, \$/MWh, \$/h); $FC_i(P_{ih})$ production cost of unit i at time h (\$/h); P_{ih} output power from unit i at time h (MW).

2.1. Objective Function

As stated above, the objective of the UC problem is to minimize the total production cost over the scheduling horizon. Therefore, the objective function can be expressed as the sum of the fuel costs and the start-up costs of the individual generating units in the power system, i.e.,

$$\Phi(X, P) = \sum_{i=1}^N \sum_{h=1}^H [FC_i(P_{ih}) + STC_i(1 - X_{i(h-1)})] * X_{ih}, \quad (2)$$

where $\Phi(\cdot)$ function of total production costs; N number of generating units; H number of hours; P_{ih} generation output of unit i at time h ; X_{ih} ON/OFF status of unit i at time h ; where $X_{ih} = 1(0)$ when unit is ON (OFF); P generation matrix with elements P_{ih} , $i = 1, \dots, N$; $h = 1, \dots, H$; X schedule matrix with elements X_{ih} , $i = 1, \dots, N$; $h = 1, \dots, H$; STC_i start-up cost of unit i .

2.2. Constraints

Depending on the nature of the power system under review, the UC optimization problem is subject to various constraints, the main being those relating to the load balance and the spinning reserve, respectively, and the remainder relating to thermal constraints, fuel constraints, security constraints, and so forth (Wood and Wollenberg, 1996).

1) *Load balance constraint.* The total generated power must be sufficient to meet the load demand at all times, i.e.,

$$\sum_{i=1}^N P_{ih} X_{ih} \geq D_h, \quad (3)$$

where D_h is the load demand at time h .

2) *Spinning reserve constraint.* The spinning reserve is defined as the total amount of power generated by all of the synchronized units minus the present load plus any losses. In solving the UC problem, the value of the spinning reserve is either assigned a pre-determined value or is defined as a given percentage of the forecast peak demand. Clearly, the reserve must be sufficient to cover the loss of the most heavily loaded unit in the system. In other words, the spinning reserve constraint can be formulated as

$$\sum_{i=1}^N X_{ih} * P_i(\max) \geq D_h + R_h, \quad (4)$$

where $P_i(\max)$ maximum generation limit of unit i ; R_h spinning reserve at time h .

3) *Generation limit constraint.* The generation of each unit must satisfy the following condition:

$$P_i(\min) \leq P_{ih} \leq P_i(\max), \quad (5)$$

where $P_i(\min)$ minimum generation limit of unit i .

4) *Thermal constraints*. The temperature and pressure conditions of the different thermal units vary slightly and therefore the units must be synchronized before they are brought online. The thermal constraints are related primarily to the minimum uptime of each generating unit, the minimum downtime of each unit, and maintenance crew availability, respectively.

- a) *Minimum uptime*. Once the unit is commissioned there is a minimum time before it can be decommissioned (i.e., a unit must be ON for a certain number of hours before it can be shut off).
- b) *Minimum downtime*. Once the unit is de-committed there is a minimum time before it can be re-commissioned (i.e., a unit must be OFF for a certain number of hours before it can be brought online).
- c) *Maintenance crew availability*. Since power plants have only limited maintenance crew resources, the simultaneous start-up and/or shutdown of two or more units is generally not possible. In solving the UC optimization problem, the effect of this resource constraint is modeled by specifying appropriate values for the times required to bring each unit online and to shut it down, respectively.

3. Improved Differential Evolution (IDE) Method for Unit Commitment Problem

In solving the UC problem, two types of variables must be considered, namely the units' status variables X , which are integer variables, and the units' output power variables P , which are continuous variables. The problem can therefore be decomposed into two separate sub-problems, i.e., a combinatorial problem in X and a nonlinear optimization problem in P . In previous studies, the DE scheme was successfully applied to solve optimization problems (e.g., Storn and Price, 1996; Price, 1997), while the HDE method was used to solve both optimal control problems (e.g., Chiou and Wang, 1998) and nonlinear optimization problems (e.g., Lin *et al.*, 1999). The current study develops an improved differential evolution (IDE) method in which the migration and acceleration operations of the original DE and HDE schemes are enhanced in order to restrict the size of the searched population. As a result, the proposed IDE scheme is particularly suited to the solution of large-scale combinatorial optimization problems such as that considered in the present study. The basic operations of the DE, HDE and IDE schemes are summarized in Table 1.

The details of the IDE method are presented in the sections below.

3.1. Representation of Individual

When applying the IDE method to solve a combinatorial optimization problem, the first step is to generate an initial population of candidate solutions, in which each candidate is defined in terms of the decision variables of the problem. The most simple and direct method for generating the initial population of solutions is to employ the UC reservation

Table 1
Basic operations of DE, HDE and IDE schemes

DE	HDE	IDE
1. Initialization	1. Initialization	1. Initialization
2. Mutation	2. Migration operation (if necessary)	2. Mutation
3. Crossover	3. Mutation	3. Crossover
4. Estimation and selection	4. Crossover	4. Estimation and selection
5. Repeat Steps 2 to 4	5. Estimation and selection	5. Accelerated operation (if necessary)
	6. Repeat Steps 2 to 5	6. Migration operation (if necessary)
		7. Repeat Steps 2 to 6

decision matrix shown in Fig. 1. As shown, the elements of this matrix represent the status variables of the various units, i.e., X_{ih} , where $X_{ih} = 1$ indicates that unit i is ON at time h , while $X_{ih} = 0$ indicates that unit i is OFF at time h . Furthermore, N corresponds to the total number of generating units in the system, while H indicates the total number of hours in the scheduling time frame. However, as described in Section 2, each generating unit is subject to certain minimum uptime and downtime constraints, i.e., T_i^{up} and T_i^{down} , respectively, and clearly these constraints must be satisfied when populating the initial search space. Consequently, the candidate solutions are defined in the form of the UC decision matrix presented in Fig. 2.

In Fig. 2, each row describes the status transitions of a particular generating unit and indicates the number of hours for which the unit remains in each state. As shown, the entries in each row are divided into a series of sub-strings, i.e., $Y_{i1}, Y_{i2}, Y_{i3}, Y_{i4}$, and so forth. Each sub-string defines the ON or OFF status of a unit for a particular number of hours in the scheduling horizon. Therefore, taken sequentially, the sub-strings describe the alternation of the unit between the ON and OFF states over the entire scheduling time frame. As shown, each sub-string comprises four bits. The first bit represents the ON/OFF status of the unit (where 1 is ON and 0 is OFF), while the following three bits indicate the duration in hours for which the unit remains in the state specified by the leading

		Time (h)									
		1	2	j	H-1	H	
Unit	1	1	0	1	0	1			
	:	:	:		:		:	:			
	:	:	:		:		:	:			
	i	1	1	0	1	1			
	:	:	:		:		:	:			
	:	:	:		:		:	:			
	N	0	1	1	1	0			

Fig. 1. Unit commitment reservation decision matrix.

		Y_{i1}				Y_{i2}				Y_{i3}				Y_{i4}				...
1		0	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	..
:	:					:					:					:		
i		1	1	0	1	1	0	1	1	0	0	1	1	1	0	1	0	..
:	:					:					:					:		
N		0	0	1	1	1	1	0	1	1	0	1	0	1	1	0	1	..

Fig. 2. Unit commitment decision matrix.

bit. The total duration for which the state of the unit remains unchanged is based upon the specified values of the minimum uptime and downtime constraints. For example, if $T_i^{up} = 2$ and $T_i^{down} = 3$, the sub-string $Y_{i2} = 1|011$ indicates that unit i is continuously ON for 5 hours, while sub-string $Y_{i3} = 0|011$ indicates that unit i is continuously OFF for 6 hours.

3.2. Fitness Function

In the IDE method, the suitability of each UC decision matrix as a candidate solution for the UC problem is evaluated using a fitness function of the form

$$f_{p_j} = \frac{1}{\Phi_{p_j} \sum_{h=1}^H \lambda_h * pf}, \tag{6}$$

where Φ_{p_i} is the production cost function associated with p_i ; h is the time index; H is the total number of hours in the UC scheduling horizon; λ_h is the constraint constant and has a value of 1 if the constraints are not satisfied and a value of 0 otherwise; and pf is the penalty factor. The penalty factor is provided for the identification of the individual p_i on the constraint is satisfied or dissatisfied.

In practice, the value of the fitness function is normalized between 0 and 1, i.e.,

$$\Gamma_{p_i} = \frac{1}{1 + K \left(\frac{f_{max}}{f_{p_i}} - 1 \right)}, \tag{7}$$

where K is a scaling coefficient and f_{max} is the maximum value of f_{p_i} within the current population.

3.3. Main Operations in IDE Solution of UC Problem

The general DE algorithm is described in Storn and Price (1996), Price (1997), Storn (1999), while the HDE scheme is well documented in Chiou and Wang (1998). Hence, the details of these two schemes are omitted here. The IDE method proposed in

the present study employs a population S_p of size NP composed of floating point-encoded individuals which converge over G generations towards the optimal solution, $S_p^{(G)} = [\bar{P}_1^{(G)}, \bar{P}_2^{(G)}, \dots, \bar{P}_{NP}^{(G)}]$, in which each \bar{P}_i is a vector containing as many parameters as there are decision variables D in the problem, i.e., $N * H$ (see Fig. 2) and $\bar{P}_i^{(G)} = [P_{1,i}^{(G)}, P_{2,i}^{(G)}, \dots, P_{D,i}^{(G)}]^T$, $i = 1, 2, \dots, NP$. Note that the population size parameter, NP , is specified by the user and remains constant throughout the optimization process. As described in the following, the IDE algorithm contains seven major operations.

1) *Initialization*. An initial population of NP vectors is created for the algorithm starts. In order to obtain a uniform coverage of the entire parameter space, the random variables are assumed to conform to a uniform probability distribution, i.e.,

$$P_{j,i}^{(0)} = P_j^{\min} + \mu(P_j^{\max} - P_j^{\min}), \quad (8)$$

where $i = 1, 2, \dots, NP$ and $j = 1, 2, \dots, D$; P_j^{\min} and P_j^{\max} are the lower and upper bounds of the j th decision parameter; and $u \in [0, 1]$ is randomly selected from a uniform distribution and is generated afresh for each value of j .

2) *Mutation*. The mutation operation creates mutant vectors (\bar{P}_i^M) by perturbing a randomly selected vector (\bar{P}_α) with the difference between two other randomly selected vectors (\bar{P}_β and \bar{P}_γ), i.e.,

$$\bar{P}_i^{M(G)} = \bar{P}_\alpha^{(G)} + F(\bar{P}_\beta^{(G)} - \bar{P}_\gamma^{(G)}), \quad (9)$$

where \bar{P}_α , \bar{P}_β and \bar{P}_γ are randomly chosen vectors with $\alpha \neq \beta \neq \gamma \neq i$ and are selected afresh for each parent vector. The mutation scaling factor ($F \in (0, 2]$) is used to adjust the perturbation size in the mutation operation in order to improve the convergence of the search procedure. In general, the DE family of optimization schemes offers several variants or strategies for the solution of practical optimization problems. These strategies can be annotated as DE/ $x/y/z$, where x refers to the vector used to generate the mutant vectors, y is the number of difference vectors used in the mutation process, and z is the scheme applied to perform the crossover operation. The most commonly employed DE strategy for global optimization problems is the DE/best/2/bin variant, which perturbs the best solution found to date with two difference vectors in accordance with a binomial distribution crossover scheme, i.e.,

$$\bar{P}_i^{M(G)} = \bar{P}_{\text{best}} + F(\bar{P}_a^{(G)} - \bar{P}_b^{(G)} + \bar{P}_c^{(G)} - \bar{P}_d^{(G)}), \quad (10)$$

where \bar{P}_{best} is the best solution found to date in the optimization process and \bar{P}_a , \bar{P}_b , \bar{P}_c and \bar{P}_d are randomly chosen vectors with $a \neq b \neq c \neq d \neq i$ and are selected anew for each parent vector.

3) *Crossover*. The crossover operation generates trial vectors (\bar{P}_i^C) by mixing the parameters of the mutant vectors (\bar{P}_i^M) produced in Step 2 above with the target vec-

tors (\bar{P}_i) in accordance with a specified probability distribution, i.e.,

$$\bar{P}_{j,i}^{C(G)} = \begin{cases} \bar{P}_{j,i}^{M(G)}, & \text{if } \mu_c \leq C_r \text{ or } j = k, \\ \bar{P}_{j,i}^{(G)}, & \text{otherwise.} \end{cases} \quad (11)$$

where $i = 1, 2, \dots, NP$ and $j = 1, 2, \dots, D$; k is a randomly chosen index which guarantees that the trial vector receives at least one parameter from the mutant vector; and $\mu_c \in [0, 1)$ is a uniformly distributed random number generated afresh for each value of j . The crossover constant, i.e., $C_r \in [0, 1]$, controls the diversity of the population and prevents the algorithm from converging prematurely to local optima. Finally, $\bar{P}_{j,i}^{(G)}$, $\bar{P}_{j,i}^{M(G)}$ and $\bar{P}_{j,i}^{C(G)}$ are the j th parameters of the i th target vector, the mutant vector, and the trial vector, respectively, in the G th generation.

4) *Estimation and selection.* During the IDE iterative procedure, the parents are replaced by their offspring if the fitness (i.e., the total production cost in the current problem) of the offspring exceeds that of its parents. Conversely, if the parents have a better fitness than their offspring, they are retained within the next generation, and the offspring is rejected. This procedure can be formulated as

$$\bar{P}_i^{(G+1)} = \begin{cases} \bar{P}_i^{M(G)}, & \text{if } \Phi(\bar{P}_i^{M(G)}) \leq \Phi(\bar{P}_i^{(G)}), \\ \bar{P}_i^{(G)}, & \text{otherwise,} \end{cases} \quad i = 1, 2, \dots, NP. \quad (12)$$

5) *Acceleration operation* (if required). If the best fitness of the solutions in the present generation is not improved by the mutation and crossover operations, the best of the present individuals is artificially pushed toward a better point in accordance with

$$\bar{P}_{\text{best}}^{(G+1)} = \begin{cases} \bar{P}_{\text{best}}^{(G+1)}, & \text{if } \Phi(\bar{P}_{\text{best}}^{(G+1)}) < \Phi(\bar{P}_{\text{best}}^{(N)}), \\ \bar{P}_{\text{best}}^{(G+1)} - d_z \nabla P \Phi(\bar{P})|_{\bar{P}_{\text{best}}^{(G+1)}}, & \text{otherwise,} \end{cases} \quad (13)$$

where $\bar{P}_{\text{best}}^{(G+1)}$ represents the new best solution. Note that the gradient of the objective function $\nabla P \Phi(\bar{P})$ in Eq. (13) can be calculated with finite variation. Furthermore, the step size $d_z \in [0, 1]$ is determined according to the descent property. If the descent property is satisfied, and if $\Phi(\bar{P}_{\text{best}}^{(N)})$ is less than $\Phi(\bar{P}_{\text{best}}^{(G+1)})$, then $\bar{P}_{\text{best}}^{(N)}$ is transcribed directed into the next generation in place of the weakest individual in the current generation..

6) *Migration operation* (if required). If the best fitness of the solutions in the present generation is not improved by acceleration operations, the migration operation is performed to regenerate a newly diverse population of individuals in order to enhance the thoroughness with which the solution space is searched and therefore to make possible the use of a smaller population size than that used in the conventional DE and HDE schemes. The new population is based on the best individual $\bar{P}_{\text{best}}^{(G+1)}$, with the h th gene

of the i th individual given by

$$P_{h,i}^{(G+1)} = \begin{cases} P_{h,i}^{(G+1)} + \rho_1(P_{h,\min} - P_{h,\text{best}}^{(G+1)}), & \text{if } \rho_2 < \frac{P_{h,i}^{(G+1)} - P_{h,\min}}{P_{h,\max} - P_{h,\min}}, \\ P_{h,i}^{(G+1)} + \rho_1(P_{h,\max} - P_{h,\text{best}}^{(G+1)}), & \text{otherwise,} \end{cases} \quad (14)$$

where $P_{h,\min}$ and $P_{h,\max}$ are the minimum and maximum individuals at time h , respectively; $P_{h,\text{best}}^{(G+1)}$ is the best individual of the new generation at time h ; and ρ_1 and ρ_2 are randomly generated numbers uniformly distributed in the range $[0,1]$.

7) *Termination criterion.* The iterative IDE solution procedure terminates if either the number of iterations performed since the best solution last changed exceeds a specified value or if the maximum specified number of iterations have been completed. If the termination criteria are not satisfied, the solution procedure returns to Step 2 and the processing steps described above are repeated.

4. Performance Evaluation Results

In this study, the performance of the IDE scheme is demonstrated using the Tai-Power System (TPS) for illustration purposes. The basic parameters of this system are summarized in Table 2. Overall, TPS includes 305 buses, 506 lines, 62 generators, 151 transformers, and 40 thermal generating units.

In solving the current UC problem, the scheduling horizon is assumed to be 24 h. The minimum and maximum permissible power generation limits of each unit are summarized in Table 2 together with the corresponding cost function parameters. The minimum up-time and down-time constraints of each unit are also shown. In general, the aim of the IDE scheme is to determine the status of each unit i at each time index h such that the total operating cost of TPS is minimized over the scheduling horizon while simultaneously satisfying the power generation limits and up-time/down-time constraints specified in Table 2. In the current study, the IDE scheme is implemented using C++ (Press and Teuko, 2002) and the UC solution procedure is executed on a personal computer (PCD32m-PentiumIV-2.4G). The IDE simulation parameters are summarized in Table 3. The IDE results for the TPS UC problem are summarized in Table 4.

4.1. Performance Tests

Having demonstrated the ability of the IDE method to solve the complex, large-scale TPS UC problem, its potential for solving general UC-type problems was evaluated by benchmarking its performance against that of other optimization schemes presented in the literature, including the DP and BB deterministic approaches and the SA and GA meta-heuristic approaches, respectively. Tables 5 and 6 present typical examples of the benchmarking results. Table 5 shows the case where the IDE scheme and the DP scheme are applied to solve the UC problem for a power system comprising ten generating units.

Table 2
Unit data of Tai-Power System (TPS)

Unit	P_i (max) (MW)	P_i (min) (MW)	Cost function coefficients			STC_i	T_i^{up} (h)	T_i^{down} (h)
			c_i (\$/MW ² h)	b_i (\$/MW ² h)	a_i (\$/h)			
1	80	40	170.4	8.336	0.0307	247.396	2	3
2	120	60	309.5	7.0706	0.0202	248.107	2	3
3	190	80	369.0	8.1817	0.0094	245.837	2	3
4	42	24	135.4	6.9467	0.0848	246.244	2	3
5	42	26	135.1	6.5595	0.0969	231.796	2	3
6	140	68	222.3	8.0543	0.0114	267.588	2	3
7	300	110	28737	8.0323	0.0035	267.007	2	3
8	300	135	391.9	6.999	0.0049	326.660	2	3
9	300	135	455.7	6.602	0.0057	267.629	2	3
10	300	130	722.8	12.908	0.0060	376.284	2	3
11	375	94	635.2	12.986	0.0051	383.911	2	3
12	375	94	654.6	12.796	0.0056	384.018	2	3
13	500	125	913.4	12.501	0.0042	384.024	2	3
14	500	125	1760	8.8412	0.0075	380.379	2	3
15	500	125	1728	9.1575	0.0070	386.993	2	3
16	500	125	1728	9.1575	0.0070	380.003	2	3
17	500	125	1728	9.1575	0.0070	247.396	2	3
18	500	220	647.8	7.9691	0.0031	248.107	2	3
19	500	220	649.6	7.9550	0.0031	245.837	2	3
20	550	242	647.8	7.9691	0.0031	246.244	2	3
21	550	242	647.8	7.9691	0.0031	231.796	2	3
22	550	254	758.9	6.6313	0.0029	267.588	2	3
23	550	254	758.9	6.6313	0.0029	267.007	2	3
24	550	254	794.5	6.6611	0.0028	326.660	2	3
25	550	254	794.5	6.6611	0.0028	267.269	2	3
26	550	254	801.3	7.1032	0.0027	376.284	2	3
27	550	254	801.3	7.1032	0.0027	383.911	2	3
28	150	10	1055	3.3353	0.5212	384.018	2	3
29	150	10	1055	3.3353	0.5212	384.024	2	3
30	150	10	1055	3.3353	0.5212	380.379	2	3
31	70	20	1207	13.052	0.2509	386.993	2	3
32	70	20	810.7	21.887	0.1676	380.003	2	3
33	70	20	1247	10.244	0.2635	267.629	2	3
34	70	20	1219	8.3707	0.3057	376.284	2	3
35	60	18	641.4	26.258	0.1836	383.911	2	3
36	60	18	1112	9.6956	0.3256	384.018	2	3
37	60	20	1044	7.1633	0.3372	384.024	2	3
38	60	25	832.2	16.339	0.2391	380.379	2	3
39	60	25	834.2	16.339	0.2391	386.993	2	3
40	60	25	1035	16.339	0.2391	380.003	2	3

Table 3
Simulation parameters used in IDE solution procedure

Parameters	Symbols	Value
Decision variables	$D(N * H)$	40 * 24
Scaling coefficient	K	1000
Population size	NP	80
Mutation scaling factor	$F \in (0, 2]$	1.2
Crossover constant	$C_r \in [0, 1]$	0.5
Accelerated step size	$d_z \in [0, 1]$	0.2
Migration coefficient	$\rho_1 \in [0, 1]$	0.1
	$\rho_2 \in [0, 1]$	0.1
Maximum generations	G_{\max}	120

It is observed that the total operating cost obtained by the IDE scheme is lower than that obtained by the DP scheme; hence confirming the effectiveness of the proposed approach. Table 6 presents the total costs obtained by the IDE scheme and the BB method for power systems with 10 and 20 generating units over a scheduling horizon of 24 hours and 36 hours, respectively. In both cases, it can be seen that the IDE scheme achieves a lower operating cost.

In meta-heuristic approaches, SA is a general-purpose stochastic optimization technique which theoretically converges asymptotically to a global optimum solution with a probability of 1. GAs are a general-purpose stochastic, parallel search method based on the “survival-of-the-fittest” mechanisms inherent in biological evolutionary processes which have the ability to obtain near-global optimal solutions to complex optimization problems with various conflicting objectives within a reasonably short processing time. Therefore, the performance of the IDE scheme in solving the TPS UC problem was compared with that of the stochastic SA and GA schemes in terms of: (1) the solution quality, i.e., the total production cost; (2) the convergence speed, i.e., the CPU time required to complete 120 generations; and (3) the stability, i.e., the number of best solutions from 100 test runs. The corresponding results are presented in Table 7. (Note that the same set of random initial solutions and the same population size were used in all three schemes).

It is clear from Table 7 that the proposed IDE yields a better solution than the SA and GA schemes in the best, average and worst costs. The computational time for the proposed IDE is lower than the time for the SA and GA approaches, and the IDE has a better stability than the GA. From the comparing, it is obvious that the IDE is a reliable algorithm, resulting in a cheaper computational cost and faster speed of convergence.

4.2. Scalability of IDE Scheme

The performance of the IDE scheme was further analyzed by comparing its total cost solutions for power systems comprising 10, 20, 40, 60 and 80 generating units, respectively, over a 24 hour horizon with those computed by Kazarlis *et al.* (1996) using a GA. The corresponding results are presented in Table 8.

Table 4
IDE solutions for TPS UC problem

Unit	H																									
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
3	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1
4	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
6	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1
7	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	1	0	1	1	1	1	1	1	1
14	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
15	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
16	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1
17	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
24	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
25	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
26	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	1	1	1	1	0	0
27	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0
31	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
32	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
33	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1
34	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
35	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
36	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0
37	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5
Performance of IDE and DP schemes in solving UC problem for power system presented in Snyder *et al.* (1987)

Method	IDE	DP
Total cost (\$) of 10-unit system over 24 H	562,921	565,125

Table 6

Performance of IDE and BB schemes in solving UC problem for power systems presented in Chen and Wang (1993)

Method	IDE	BB
Total cost (\$) of 10-unit system over 24 H	78,020	78,907
Total cost (\$) of 20-unit system over 36 H	987,612	1,006,875

Table 7

Performance comparison between IDE, SA and GA schemes when applied to TPS UC problem

Method		IDE	SA	GA
Total cost (\$)	Best	2,165,082	2,266,657	2,398,513
	Average	2,169,950	2,271,886	2,401,426
	Worst	2,177,062	2,278,938	2,416,727
CPU time (sec)		161	237	167
Stability		0.99	0.99	0.98

Table 8

Performance of IDE and GA schemes in solving UC problem for systems presented in Kazarlis *et al.* (1996)

Method	IDE	GA
Total cost (\$) of 10-unit system over 24 H	562,921	563,825
Total cost (\$) of 20-unit system over 24 H	1,125,546	1,129,555
Total cost (\$) of 40-unit system over 24 H	2,247,570	2,256,501
Total cost (\$) of 60-unit system over 24 H	3,365,125	3,392,065
Total cost (\$) of 80-unit system over 24 H	4,486,010	4,524,011

From inspection, it is clear that the IDE scheme consistently produces lower total cost solutions than the GA method. Furthermore, it is apparent that the cost savings achieved by the IDE scheme increase as the size of the power system increases. In other words, the IDE approach represents a particularly suitable technique for the solution of large-scale UC problems.

5. Conclusion

In general, the overriding objective of PPEs is to meet the time-varying power demands placed upon them while simultaneously minimizing their production costs. Satisfying this objective requires the solution of a highly complex unit commitment (UC) problem. To assist PPEs in performing this task, the current study has presented an improved differ-

ential evolution (IDE) scheme designed to solve large-scale UC problems in a rapid and cost-effective manner. The performance of the proposed scheme has been benchmarked against that of other deterministic and stochastic optimization methods presented in the literature using the practical Tai-Power System (TPS) and various power systems of different scales for illustration purposes. The results have indicated that despite the comparatively small population size used in the proposed IDE scheme, the solutions obtained for the total operating costs of the various power systems are consistently better (i.e., lower) than those obtained by the other methods. Furthermore, the IDE scheme also outperforms the other schemes in terms of the CPU time required to complete the optimization procedure and the stability of the solutions, respectively. Finally, the results have indicated that the magnitude of the cost savings achieved by the IDE scheme increases as the number of generating units within the power system increases. In other words, the proposed scheme represents a particularly effective technique for the solution of large-scale UC problems.

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Pagerinta diferencialinės evoliucijos schema didelio matavimo blokų perjungimo problemoms spręsti

Chen-Sung CHANG

Šiame straipsnyje pateikiamas pagerintas diferencialinės evoliucijos (PDE) metodas didelio matavimo blokų perjungimo problemoms spręsti. Nagrinėjamoje schemoje tikslo funkcija yra skirta sudaryti generavimo tvarkaraštį, minimizuojantį bendrus aptarnavimo kaštus per duotą laiką esant duotai ribojimų aibei. Pritaikant patobulintus akseleracijos ir migracijos procesus, PDE metodas riboja populiacijos dydį, naudojamą paieškos procedūroje, ir todėl idealiai tinka spręsti didelio matavimo kombinatorinėms problemoms. Sukurto metodo efektyvumas patikrintas imitavimo būdu pasinaudojant praktinės Tai energetinės sistemos ir kitų energetinių sistemų, žinomų literatūroje, duomenimis. Bendru atveju, gauti rezultatai leidžia tvirtinti, jog PDE schema yra pranašesnė už žinomus deterministinio ir stochastinio optimizavimo metodus gauto sprendinio kokybės ir skaičiavimo sąnaudų požiūriu. Dar daugiau, taikant šią schemą kaštų sumažėjimas, pasiektas dėka PDE schemos, didėja didėjant generavimo blokų, įjungtų į energetinę sistemą, skaičiui. Tokiu būdu, pasūlyta schema pateikia ypač efektyvų būdą didelio matavimo blokų perjungimo uždaviniams spręsti.