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A multi-objective evolutionary approach for generator scheduling

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ABSTRACT

This paper presents a novel, two-phase approach for optimal generation scheduling, taking into account the environmental issue of emission allowance trading in addition to the economic issue of operation cost. In the first phase, hourly-optimal scheduling is done to simultaneously minimize operation cost, emission, and transmission loss, while satisfying constraints such as power balance, spinning reserve and power generation limits. In the second phase, the minimum up/down time and ramp up/down rate constraints are considered, and a set of 24-h optimal schedules is obtained using the outputs of the first phase. Simulation results indicate effectiveness of the proposed approach.

1. Introduction

OPTIMAL generation scheduling is done to minimize certain objective functions, while satisfying various system and operating constraints. The objective functions may include economic costs, system security, or other costs (Saadat, 2002). When the only objective involved is the operating cost, the optimal generation scheduling problem is identical to the well-known unit commitment problem. Various optimization techniques have been developed to address it, including priority list methods, dynamic programming, integer and linear programming, branch-and-bound methods, Lagrangian relaxation methods and artificial intelligence techniques (Padhy, 2004).

Although green energy is receiving increasing attention, fossil fuel power plants burning coal, oil and natural gas still produce a large share of electricity supply, releasing carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x). While CO_2 contributes to global warming, SO_2 and NO_x are responsible for acid rain. Emissions rates can be adjusted according to the levels of pollution control, the characteristics of the fuels combusted, power plant efficiency and emission dispatching. Emission dispatching is an effective strategy as a short-term alternative to achieve the emission targets without investment for new pollutant cleaning equipment.

Energy loss occurs during transmission due to line resistance. The total loss in the transmission network can be approximated by the B-matrix loss formula. The system operator is encumbered with the task of delivering power from the generators with high efficiency.

Appropriate coordination between the operation cost, emission and transmission losses can result not only significant cost savings but also compliance with the emission caps. The operation cost has been minimized with the emission as a constraint (Granelli, Montagna, Pasini, & Marannino, 1992; Wong & Yuryevich, 1998; Shahidehpour, Yamin, & Li, 2002). Elsewhere, the emission cost is included as a separate objective (Yokoyama, Bae, Morita, & Sasaki, 1988; Song, Wang, Wang, & Johns, 1997; Abido, 2003). However, in the reported research, neither have the transmission losses been treated as an objective for minimization, nor have the minimum up/down and ramp up/down constraints been taken into account, although these are critical factors for optimal generation scheduling for 24 h periods.

Multi-objective evolutionary optimization is very useful in power systems. Power dispatch problems that simultaneously consider environmental and economic objectives have successfully applied these approaches (Das & Panigrahi, 2008; Ah King, Rughooputh, & Deb, 2005; Ah King, Rughooputh, & Deb, 2006; Srinivas, Patvardhan, & Bhagwan Das, 2007; Victoire & Suganthan, 2007; Wang & Singh, 2007; Deb, 2008). An algorithm for the unit commitment problem has been suggested recently (Georgopoulou & Giannakoglou, 2009). NSGA-II is one of the most effective algorithms for multi-objective optimization and has been successfully applied to problems in power systems (Deb, Pratap, Agarwal, & Meyarivan, 2002; Milosevic & Begovic, 2003; Favuzza, Ippolito, & Sanseverino, 2006; Mendoza, Bernal-Agustin, & Dominguez Navarro, 2006; Xiao & McCalley, 2009; Kannan, Baskar, McCalley, & Murugan, 2009; Maghouli, Hosseini, Buygi, & Shahidehpour, 2009; Yang & Chang, 2009).

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Nomenclature

$\alpha_i,\beta_i,\gamma_i,\varsigma_i,\tau_i$	characteristic coefficients of unit i's emission
a_i,b_i,c_i	characteristic coefficients of unit i's fuel cost
g	iteration number of HSGA/DSGA.
h_{it}^{off}	number of continuous time intervals that a unit i has remained OFF before current period t
h_{it}^{on}	number of continuous time intervals that a unit i has remained ON before current period t
i,j,k	index of units
$npop$	population size of HSGA
t	index of time period
λ	market price for the emission allowance
CSC_i	cold start cost of unit i
CSH_i	cold start hours of unit i
D_t	system load demand in period t
E	total emission produced by all units in Thours
$Ecap$	emission cap of all units in Thours
E_t	emission produced by all units in period t
F	total operation cost in Thours, considering emission allowance trading
FC_{it}	fuel cost of unit i in period t
F_e	emission cost caused by purchasing or selling additional emission allowance
F_0	total operation cost in Thours without emission allowance trading
F_{0t}	operation cost of all units in period t
HSC_i	hot start cost of unit i
MD_i	minimum down time of unit i
MU_i	minimum up time of unit i
NG	number of units
P_{it}	power output in period t
P_i^{max}	maximum generation limit of unit i
P_i^{min}	minimum generation limit of unit i
P_g	population of parent solutions in iteration g
Q_g	population of offspring solutions in iteration g
R_g	merged population
R_t	reserve requirement in period t
RD_i	ramp-down limit of unit i
RU_i	ramp-up limit of unit i
SDC_i	shutdown cost of unit i in period t
STC_i	startup cost of unit i in period t
$S0$	set of off-line units
$S1$	set of on-line units
T	entire time interval, in this paper, 24 h
U_{it}	0/1 variable which states OFF/ON status of unit i in period t

A novel approach is proposed for multi-objective optimal dispatch. The proposed algorithm is applied to three test systems. At first, for the two objective problem, with both operation cost and emission as objectives, a 10-unit system is used to analyze the algorithm's performance. An IEEE 118-bus system is tested to analyze the effect of emission allowance trading scheme. Finally, with the transmission losses included in the model, a 6-unit system is used to test the performance of the algorithm with three-objectives.

2. Emission cap and trade

One of the most important hazards of $NO_x$is that it results in ground-level ozone responsible for respiratory ailments. To help the Northeast and mid-Atlantic regions reduce harmful ground-level ozone, in 1990 the U.S. Congress established the Ozone Transport Commission (OTC) under the Clean Air Act Amendments. NO_x also contributes to regional haze, eutrophication of water bodies, etc. Utility companies have been reducing the atmospheric emissions of the thermal power plants by various strategies (El-Keib, Ma, & Hart, 1994; Talaq, El-Hawary, & El-Hawary, 1994). With the aim to reduce summertime NO_x emissions, the OTC NO_x Budget Program was implemented from 1999 to 2002, and has since been replaced by the NO_x Budget Trading Program under "NO_x State Implementation Plan (SIP) Call", a broader federal program issued by the U.S. Environmental Protection Agency, involving 22 eastern states and the District of Columbia. The OTC NO_x Budget Program has generally been viewed as a success to achieve NO_x reductions using a "cap-and-trade" policy. The apportionment of total budget allowances among the OTC states, or the establishment of the state caps, was accomplished in a uniform manner based on heat input. However, methods to allocate allowances to regulated sources, i.e. electricity generating units, were determined by each state individually. For example, some states such as Delaware, New Hampshire, New York, Pennsylvania, and the District of Columbia had fixed allocations from 1999 to 2002, while some other states such as Connecticut, Maryland, and New Jersey adjusted their allocations periodically based on various factors (Beamon et al.).

After receiving marketable emission permits (allowances), power plant operators are allowed to either cover their own emissions by their allowance, or to make profit by selling them to others. One benefit of the "cap-and-trade" program is that if the allowance market is well-designed, those with the lowest cost emission reduction opportunities would sell the unwanted allocated allowances to make profit. Meanwhile, because some other plants' emission reduction opportunities are costly, they may purchase additional allowances to cover emission excess. Finally it is expected that all the power plants acquire the necessary allowance they need, while the net emission comply with the emission caps at the lowest possible cost (Yokoyama, Bae, Morita, & Sasaki, 1988). In general the annual allocation of allowances to each utility does not change over time, and utilities need to measure and report emissions to the regulatory agency regularly to balance the emissions with the allowances they have. Each day if the operators have a set of different schedules, which are trade-off between operation cost and emission, they will have a good understanding of the environmental performance of the power plants on a daily basis, thus have the flexibility to adopt different daily schedule to comply with their standards.

3. Problem formulation

3.1. Objective Functions

(1) Operation cost, including fuel costs, startup costs, and shutdown costs for the entire period is given by:

$$F_0 = \sum_{t=1}^{T}\sum_{i=1}^{NG}[FC_{it} + STC_{it} + SDC_{it}] \tag{1}$$

$$FC_{it} = \left(a_i + b_iP_{it} + c_iP_{it}^2\right)U_{it} \tag{2}$$

$$STC_{it} = ST_{it}(1 - U_{i(t-1)})U_{it} \tag{3}$$

$$SDC_{it} = SD_{it}(1 - U_{it})U_{i(t-1)} \tag{4}$$

$$ST_{it} = \begin{cases} HSC_i & if\ h_{it}^{off} \leqslant CSH_i + MD_i \\ CSC_i & if\ h_{it}^{off} > CSH_i + MD_i \end{cases} \tag{5}$$

When the emission allowances are enforced, the operators have the option to buy the deficit from the market or sell the excess to the market, resulting in an additional emission cost:

$$F_e = (E - Ecap)\lambda. \tag{6}$$

When F_e is negative the plant operator benefits from selling the excess emission allowance to others, thus curtailing the total operation cost. It is assumed that the plant operator can sell the unwanted allowance successfully by all means. Accordingly, the revised operation cost can be represented by:

$$F = F_e + F_0 \tag{7}$$

(2) The NO_x emission function model depends on the parameter estimating techniques used to approximate the amount of NO_x emission (Srinivas et al., 2007; Deb, 2008; Georgopoulou & Giannakoglou, 2009). However polynomial and exponential functions produced average emission rates for the systems (Section 4) too far away from the real-world rates (Deb et al., 2002). A combination of polynomial and sinusoidal terms is more appropriate here (Srinivas et al., 2007). Hence,

$$E = \sum_{t=1}^{T}\sum_{i=1}^{NG}\left\{\left[\alpha_i + \beta_i P_{it} + \gamma_i P_{it}^2 + \varphi_i \sin(\tau_i P_{it})\right]U_{it}\right\} \tag{8}$$

(3) The transmission losses can be expressed as a function of unit power outputs using the $\boldsymbol{B}$ matrix loss formula:

$$P_{loss} = \sum_{t=1}^{T}\left(\sum_{i=1}^{NG}\sum_{j=1}^{NG} P_{it}B_{ij}P_{jt} + \sum_{i=1}^{NG} B_{0i}P_{it} + B_{00}\right) \tag{9}$$

3.2. Constraints

(1) Power balance:
If the transmission losses are not considered, then

$$\sum_{i=1}^{NG} P_{it} = D_t \tag{10}$$

If the transmission losses are considered, then

$$\sum_{i=1}^{NG} P_{it} = D_t + P_{loss,t} \tag{11}$$

(2) Spinning reserve:

$$\sum_{i=1}^{NG} P_i^{max} U_{it} \geqslant D_t + R_t \tag{12}$$

(3) Power generation limits:

$$P_i^{min} U_{it} \leqslant P_{it} \leqslant P_i^{max} U_{it} \tag{13}$$

(4) Minimum up/down time:

$$\left(h_{i(t-1)}^{on} - MU_i\right)(U_{i(t-1)} - U_{it}) \geqslant 0 \tag{14}$$

$$\left(h_{i(t-1)}^{off} - MD_i\right)(U_{it} - U_{i(t-1)}) \geqslant 0 \tag{15}$$

(5) Ramp up/down rate:

$$P_{it} - P_{i(t-1)} \leqslant [1 - U_{it}(1 - U_{i(t-1)})]RU_i + U_{it}(1 - U_{i(t-1)}P_i^{min}) \tag{16}$$

$$P_{i(t-1)} - P_{it} \leqslant [1 - U_{i(t-1)}(1 - U_{it})]RD_i + U_{i(t-1)}(1 - U_{it}P_i^{min}) \tag{17}$$

4. Proposed approach

In the first phase, the optimal dispatch problem is formulated as a constrained multi-objective optimization problem that obtains optimal solutions independently for each hour. It applies the proposed hourly schedule genetic algorithm (HSGA), which uses several features of NSGA-II. In the second phase, the hourly-optimal solutions from the first phase are evolved using the proposed daily schedule genetic algorithm (DSGA), which is also based on NSGA-II, to obtain the optimal solutions for the entire period T. The minimum up/down and ramp up/down rate constraints are considered during this second phase. Details of the proposed method are discussed below.

4.1. Hourly schedule genetic algorithm (HSGA)

The hourly dispatch problem, which is addressed in the first phase, is formulated as follows:

Minimize F_{0t}, E_t, $P_{loss,t}$ where,

$$F_{0t} = \sum_{i=1}^{NG}[FC_{it} + STC_{it} + SDC_{it}] \tag{18}$$

$$E_t = \sum_{i=1}^{NG}\left\{\left[\alpha_i + \beta_i P_{it} + \gamma_i P_{it}^2 + \varphi_i \sin(\tau_i P_{it})\right]U_{it}\right\} \tag{19}$$

$$P_{loss,t} = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_{it}B_{ij}P_{jt} + \sum_{i=1}^{NG} B_{0i}P_{it} + B_{00} \tag{20}$$

Subject to power balance (10) or (11), spinning reserve (12) and power generation limits (13).

In this phase, HSGA is applied separately T times, once for each hourly time interval $t = 1, 2, \ldots, T$. Although earlier genetic algorithm based approaches for unit commitment have typically used binary coding schemes (to denote the OFF or ON state of each unit), our method explicitly determines the power output of each unit. Therefore we use real valued representation instead. Each solution in our method in this phase is a row vector of length NG, whose ith entry corresponds to the output of unit i during the time interval t under consideration. There will be $npop$ such solutions in the population at any given time.

At the beginning of the first phase, the output of each unit i is generated from randomly generated numbers following the uniform distribution from 0 to$P_i^{\max}$. Simulated binary crossover (SBX) and polynomial mutation are used (Kazarlis, Bakirtzis, & Petridis, 1996; Ting, Rao, & Loo, 2006; Deb & Goyal, 1996).

Occasionally, the initial randomly generated solutions, as well as those created by HSGA through crossover and mutation, are infeasible because of the presence of generation limits and load balance constraints. A repair procedure that ensures solution feasibility has been devised and incorporated within HSGA to rectify this situation. This procedure includes two major schemes: generation limits repair scheme and load balance repair scheme. The generation limits repair scheme addresses three possible ways in which generation limits can be violated. When a unit has its power output beyond the maximum limit $P_i^{\max}$, it is lowered to $P_i^{\max}$. Likewise, a unit whose power output exceeds a threshold, $\theta P_i^{\min}$ is increased to the minimum allowable value, $P_i^{\min}$, whereθ is a constant, that is set to 0.5 throughout this paper. On the other hand, if the solution allocates a power output below $\theta P_i^{\min}$ to the unit, then this output is simply reset to zero.

The load balance repair procedure is executed following the generation limits repair scheme. If the transmission losses are not considered, the total generation needs to equal the load, as shown in Eq. (10). If the total power output of all the units is greater than the load demand, we decrease the output of one of the units randomly selected from the on-line units to maintain balance between generation and load. If this balance is not possible with one unit, additional units are selected at random to make further adjustments. Likewise, if the total power output of all units is less than the load demand, two cases arise. First, if the total sum of the maximum output limits of all the on-line units is greater than the load demand, the repair scheme increases the outputs of the online units to maintain load balance in a manner similar to that discussed above. The other case occurs when in spite of all the on-line units having reached their maximum output limits, the total power output is insufficient. Under this circumstance the repair mechanism turns on some off-line units and increases their outputs until the requirements are met. This is repeated iteratively until all units' outputs are either within their limits or zero.

When the transmission losses are included in the power balance equation (Eq. (11)), the following method adopted.

The transmission losses can be rewritten as Wong and Fung (1993):

$$P_{loss,t} = \mathbf{P}'B\mathbf{P} + \mathrm{P}'B_0 + B_{00} \tag{21}$$

where $\mathbf{P}'$ is the transpose of vector $\mathbf{P}$, which is a column vector of all generator outputs at hour t,B is a $NG \times NG$ matrix, and B_0 is a NG column vector.

$$\mathbf{P} = \begin{bmatrix} P_{1t} \\ P_{2t} \\ \vdots \\ P_{NGt} \end{bmatrix} \tag{22}$$

$$B = \begin{bmatrix} B_{11} & \cdots & B_{1NG} \\ \vdots & \ddots & \vdots \\ B_{NG1} & \cdots & B_{NGNG} \end{bmatrix} \tag{23}$$

$$B_0 = \begin{bmatrix} B_{01} \\ B_{02} \\ \vdots \\ B_{0NG} \end{bmatrix} \tag{24}$$

Rearrangement of Eq. (21) gives:

$$P_{loss,t} = [\mathbf{P}'_a|P_{rt}] \begin{bmatrix} \boldsymbol{B}_{aa}|B_{ar} \\ B_{ra}|B_{rr} \end{bmatrix} \begin{bmatrix} \mathbf{P}_a \\ P_{rt} \end{bmatrix} + [\mathbf{P}'_a|P_{rt}] \begin{bmatrix} B_{0a} \\ B_{0r} \end{bmatrix} + B_{00} \tag{25}$$

where $\mathbf{P}'_a$ is the transpose of the vector $\mathbf{P}_a$, which is a column vector of the (NG-1) generators' outputs at hour t, excluding the unit r. P_{rt} is a scalar value representing the generation output of unit r at hour t. B_{aa} is a (NG-1) $\times$ (NG-1) matrix, B_{ar} and B_{0a} are (NG-1) column vectors and B_{ra} is a (NG-1) row vector. B_{rr},B_{0r} and B_{00} are scalars.

Eq. (25) can be expressed by a quadratic function in the form of Eq. (26).

$$P_{loss,t} = k_2 P_{rt}^2 + k_1 P_{rt} + k_0 \tag{26}$$

where,

$$k_2 = B_{rr} \tag{27}$$

$$k_1 = B_{ra}\mathbf{P_a} + \mathbf{P'_a}B_{0r} + B_{ar} \tag{28}$$

$$k_0 = \mathbf{P'_a}\boldsymbol{B}_{\mathbf{aa}}\mathbf{P}_a + \mathbf{P'_a}B_{0a} + B_{00} \tag{29}$$

It is also known that,

$$P_{rt} = D_t - \sum_{\substack{i=1 \\ i \neq r}}^{NG} P_{it} + P_{loss,t} \tag{30}$$

After all the generators' outputs are determined by using load balance repair scheme without considering transmission losses as described in the previous section, an online generator r is randomly chosen from those online generators to pick up the transmission losses. From Eqs. (26) and (30), the new output of generator r is calculated by solving the quadratic equation below (Deb, 2008):

$$k_2 P_{rt}^2 + (k_1 - 1)P_{rt} + \left(k_0 + D_t - \sum_{\substack{i=1 \\ i \neq r}}^{NG} P_{it} \right) = 0 \tag{31}$$

Selecting one of the two roots P_{rt} in the new generation is done in the following manner. If both roots are within generation limits, we randomly choose one root. If only one is within the generation limits then it is chosen. If both are not within the limits, the one have a smaller violation is chosen. The violation is calculated as the absolute value of the difference between the root and its closest boundary limit. In case the new generation output of generator r still exceeds its limits, the generation limit repair scheme is invoked.

4.2. Daily schedule genetic algorithm (DSGA)

In the second phase, the overall optimal schedule consisting of T = 24 separate periods can be obtained by assembling all the hourly-optimal solutions from the first phase. The mathematical formulation of the overall dispatch problem is:

Minimize: operation cost (7), emission (8) and transmission losses (9).

Subject to minimum up/down time (14) and (15) and ramp up/down rate (16) and (17).

Note that λ = 0 indicates that the emission allowance trading is not considered in this phase.

The generation schedule for the entire period T is represented by a vector of size T. The hth element ($1 \leqslant h \leqslant T$) in this vector lies between 1 and $npop$ and is the index of a solution in the hth hourly non-dominated front obtained from the first phase. For example, if the vector [12 31 … 77] were to represent the generation schedule for the entire T periods, it would include the 12th solution obtained during the first phase for the first hour, the 31st solution for the second hour, and the 77th solution for the last hour. Fig. 1 illustrates this scheme. Here, hourly solutions of the form [P_{1h} P_{2h} …P_{NGh}] are shown as circles. Non-dominated fronts of each of the T separate periods are grouped together using dotted lines. The second phase solution shown is made up of indexes to these hourly solutions. The initial vectors are generated randomly by picking indexes between 1 and $npop$ for each hour.

Two-point crossover and Gaussian mutation are adopted in DSGA for this second phase. Two-point crossover is applied to two parent vectors to yield two offspring vectors. Two crossover points of the parent vectors are selected randomly, and all the elements between them are swapped between the parents to produce offspring.

Gaussian mutation is applied element-wise to each vector, the probability of mutation being p_m, the mutation rate. As mutation is applied sparingly, p_m is a very small quantity. A random number that follows Gaussian distribution with zero mean and standard deviation σ is added to each such element, which is then rounded off to the nearest integer value. A correction is applied to elements that are below 1 or above $npop$, following mutation, by replacing them with 1 and $npop$ respectively. In this manner, each mutated element is now associated with another solution from the phase-1 non-dominated front. Since best results were obtained when

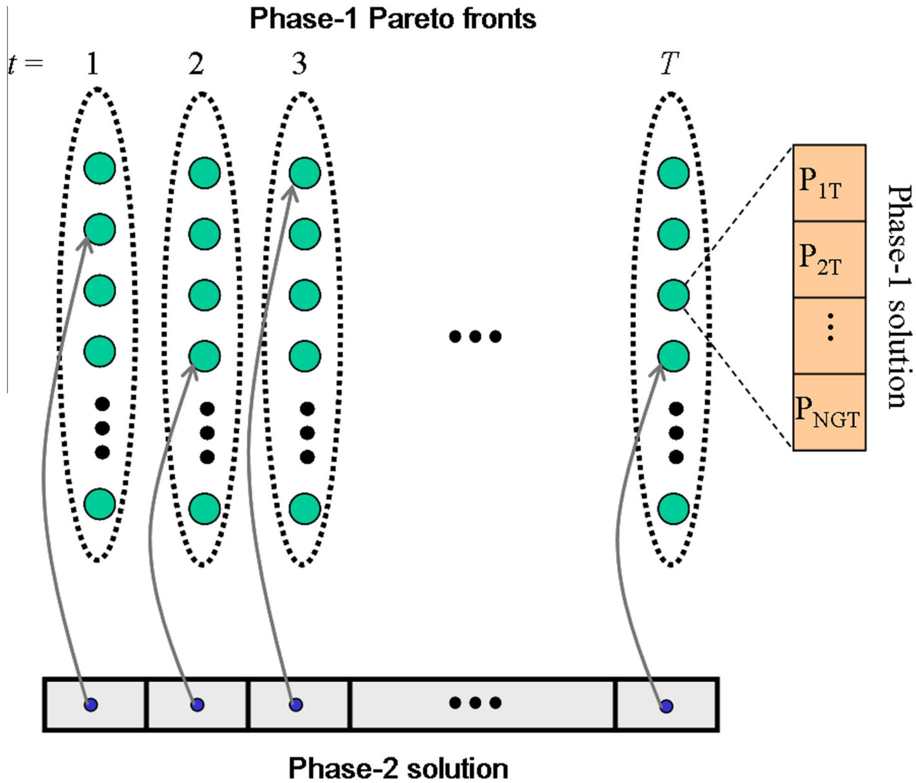

Fig. 1. Solution encoding scheme during the second phase.

the level of mutation was higher during the initial stages of the algorithm, the standard deviation σ of the Gaussian mutation was set to σ = max ($npop \times r^{-g}$, 30), where r is a number slightly greater than 1. For our experiments,r was chosen to be 1.007.

In the following argument, we will call those solutions in the non-dominated front, which are minimum along any one objective as *extreme* solutions. As both phases are bi-objective, any non-dominated front will contain only two extreme solutions (indexed as 1 and *npop*). As neither the minimum up/down times nor the ramp up/down rates are considered when obtaining the hourly solutions in the first phase, attempting to produce extreme solutions for the T = 24 h period by simply concatenating the extreme solutions for each hour might be invalid in terms of any of these constraints. Thus, the extreme solutions of the non-dominated front in the second phase might include as indexes, non-extreme, first phase solutions.

As one of the goals of multi-objective optimization is to increase the spread of the non-dominated front, the second phase includes a separate scheme to increase the spread by making further improvements to the extreme solutions. The extreme solutions of the second phase are examined to see if they contain hourly solutions that are far away from their own hourly non-dominated fronts. When the distance between any such hourly solution and the extreme of its own front exceeds a certain threshold, HSGA of the first phase is re-invoked to generate a few additional solutions, while simultaneously imposing the minimum up/down time as well as the ramp up/down rate constraints. Initial simulations not reported in this paper, showed that this improvement, although invoked rarely, helped improve the front.

5. Numerical simulations

To investigate the performance of the proposed method, the two-phase method using HSGA and DSGA was implemented in MATLAB on a 10-unit system, the IEEE 118-bus system and a 15-unit system. A total of 20 independent runs were carried out on each system, which is also used to compare the performance of the proposed method with a well known multi-objective evolutionary algorithm (SPEA-2), as well as recent multi-objective simulated annealing algorithm, (AMOSA), where only the hourly performances are investigated (Bandyopadhyay, Saha, Maulik, & Deb, 2008).

In the first phase, the population size (*npop*) was 200. HSGA was executed for a total of 200 iterations. The percentage of solutions in the population subject to crossover was 90%. The probability of mutation of each entry of the solution vectors was 10%. The crossover and mutation distribution indexes were 10 and 20 (see Kazarlis et al., 1996; Ting et al., 2006 for details).

The population size in the second phase was kept at 300 and 500 iterations of DSGA were allowed. The mutation rate was lowered slightly to 5% while the crossover rate was 80%.

5.1. Comparison of HSGA with SPEA-2 and AMOSA on 10-unit system

In this case, without considering transmission losses and the emission allowance trading ($\lambda = 0$), the 10-unit system is studied. The system data are based on U.S. Environmental Protection Agency (2008). For comparison, the spinning reserve at each hour was kept at 10% of the load demand and the shutdown cost for each unit was neglected (U.S. Environmental Protection Agency, 2008).

In SPEA-2 the number of iterations and the population and archive sizes were kept at the same values as HSGA. Additionally, the crossover and mutation operators were identical to the latter. In AMOSA, which uses no crossover, only the mutation operator was used. The lower bound on the archive size was equal to HSGA's population size, while the upper bound, adjusted for best performance, was 350. It was run for an equal number of function evaluations as HSGA.

Fig. 2 show the hourly non-dominated fronts for minimum (700 MW, hour 1), medium (1100 MW, hour 6) and maximum (1500 MW, hour 12) load conditions obtained by the three algorithms, based on the results from one sample run.

In HSGA and SPEA-2, it is obvious that the non-dominated front becomes more convex with increase in load. The reason is that increasing load needs more units to meet the load balance resulting in more plausible combinations of these units, yielding a more evenly distributed front.

From the figure, clearly both HSGA and SPEA-2 outperform AMOSA. Closer examination of the fronts also shows that HSGA performs better than SPEA-2. For high load conditions, HSGA performed somewhat better than SPEA-2. From all runs, HSGA's solutions dominated 35.7% of those of SPEA-2, whereas SPEA-2 dominated over 31.9% of HSGA's solutions in the front. For medium and smaller loads, the differences were clearer, with HSGA's solutions dominating over those of SPEA-2 39.6% and 41.1% of the time respectively, the corresponding figures for SPEA-2 being only 26.2% and 17.8%. Additionally, from visual inspection, HSGA's solutions were more uniformly distributed over the front in all cases than those of SPEA-2.

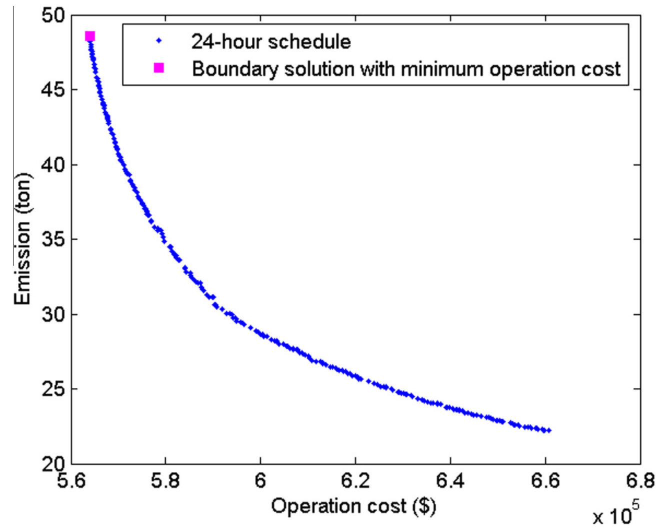

Fig. 3. 24-h Pareto front for the 2-objetive model. The system data are the same as used in Ting et al. (2006).

5.2. DSGA on 10-unit system

A sample non-dominated front with 300 solutions for 24-h scheduling obtained from a sample run is shown in Fig. 3. We can see the total operation cost of 24 h has a wide range from \$563,943 to \$660,813, corresponding to the emission's range from 48.61 to 22.19 ton offering great flexibility to the operator. The solution with minimum operation cost of \$563,943 is shown in Table 1. The average emission rate 1.7936 kg/MWh is little higher than the national NO_x average emission rate of 1.66 kg/MWh in USA and lower than 1.83 kg/MWh in Mexico in 2002 (Deb & Agrawal, 1995). By comparison, the rate decreases up to 0.8188 kg/MWh with maximum operation cost of \$660,813. In Table 2, the solution with the minimum operation cost is compared with outputs of other unit commitment techniques. It is clear that our approach produces almost the best one with the cost of \$563,943, (merely \$1 more than the best outcome) (MPI, 2008). It should be noted that in Gaing (2003), the best operation cost calculated by the unit output power is \$563,977 instead of \$563,865 as reported.

Table 3 shows the minimum, maximum and median values of each objective obtained by merging all solutions of 20 runs. The small range indicates the robustness of the approach.

Comparing the performances of DSGA with that of the other algorithms is not necessary as DSGA uses solutions produced by HSGA. Using inferior solutions obtained from AMOSA or SPEA-2 produced significant deterioration in the fronts in the second phase.

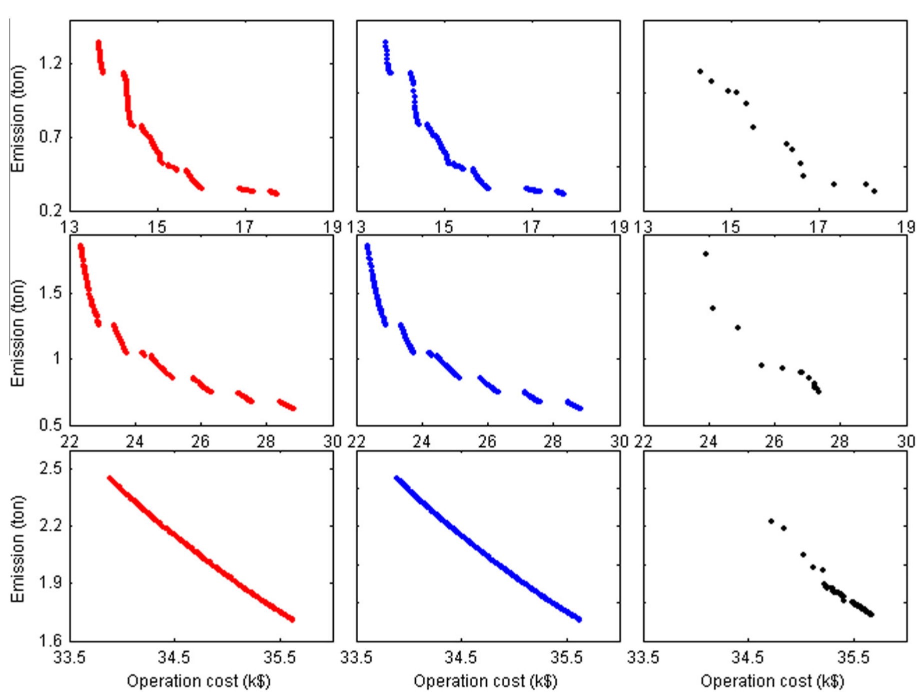

Fig. 2. Performances of HSGA (left), SPEA-2 (middle) and AMOSA (right) for low (top), medium (middle), and high (bottom) load conditions.

Table 1
Boundary solution with minimum operation cost on the 24-h non-dominated front.

Hour	Fuel cost ($)	Startup cost ($)	Emission (ton)	Emission Rate (kg/MWh)	Generation Schedule (MW)									
1	13,683	0	1.3481	1.9258	455	245	0	0	0	0	0	0	0	0
2	14,554	0	1.4694	1.9592	455	295	0	0	0	0	0	0	0	0
3	16,809	900	1.738	2.0447	455	370	0	0	25	0	0	0	0	0
4	18,598	0	2.0792	2.1886	455	455	0	0	40	0	0	0	0	0
5	20,020	560	1.8772	1.8772	455	390	0	130	25	0	0	0	0	0
6	22,387	1100	1.8246	1.6587	455	360	130	130	25	0	0	0	0	0
7	23,262	0	2.0121	1.7497	455	410	130	130	25	0	0	0	0	0
8	24,154	0	2.1961	1.83	455	453.56	129.99	130	31.451	0	0	0	0	0
9	27,253	860	2.2898	1.7614	455	454.5	130	130	85.409	20.088	25	0	0	0
10	30,058	60	2.3659	1.6899	455	455	130	130	162	33	25	10	0	0
11	31,916	60	2.4138	1.6647	455	455	130	130	161.99	73.014	25	10	10	0
12	33,890	60	2.4511	1.6341	455	455	130	130	162	80	25	43.001	10	10
13	30,058	0	2.3659	1.6899	455	455	130	130	162	33	25	10	0	0
14	27,251	0	2.2919	1.763	455	455	130	130	85	20	25	0	0	0
15	24,150	0	2.2029	1.8357	455	455	130	130	30	0	0	0	0	0
16	21,514	0	1.6658	1.5865	455	310	130	130	25	0	0	0	0	0
17	20,642	0	1.5361	1.5361	455	260	130	130	25	0	0	0	0	0
18	22,387	0	1.8246	1.6587	455	360	130	130	25	0	0	0	0	0
19	24,150	0	2.2029	1.8357	455	455	130	130	30	0	0	0	0	0
20	30,058	490	2.3659	1.6899	455	455	130	130	162	33.002	25	10	0	0
21	27,251	0	2.2915	1.7627	455	454.91	130	130	85.095	20.001	25.005	0	0	0
22	22,736	0	2.2028	2.0026	455	455	0	0	145	20	25	0	0	0
23	17,645	0	1.9714	2.1905	455	425	0	0	0	20	0	0	0	0
24	15,427	0	1.6193	2.0241	455	345	0	0	0	0	0	0	0	0
Total/Average	559,853 + 4090 = 563,943		48.6061	1.7936										

Table 2
Minimum operation cost comparison of different techniques.

Method	SPL (Senjyu et al., 2003)	EP (Srinivasan & Chazelas, 2004)	EPL (Zhao et al., 2006)	PLEA (Cheng et al., 2000)	PSO (Ongsakul & Petcharaks, 2004)	IPSO (Ongsakul & Petcharaks, 2004)	HPSO (MPI, 2008)	LRGA (Damousis et al., 2004)	ELR (Senjyu et al.)	GA (U.S. Environmental Protection Agency, 2008)	LR (U.S. Environmental Protection Agency, 2008)
operating cost $	564,950	565,352	563,977	563,977	564,212	563,954	563,942	564,800	563,977	565,825	565,825
Method	ICGA (Sum-im & Ongsakul)	UCCGA (Victoire & Jeyakumar, 2005)	ACSA (Valenzuela & Smith, 2002)	DP (U.S. Environmental Protection Agency, 2008)	DPLR (Senjyu et al.)	TS-RP (Sun et al., 2006)	TS-IRP (Sun et al., 2006)	MA (Hosseini et al., 2007)	MRCGA (Wong & Fung, 1993)	SF (Gaing, 2003)	HSGA/DSGA
operating cost $	566,404	563,977	564,049	565,825	564,049	564,551	563,937	565,827	564,244	563,977	563,943

Table 3
Performance of the proposed approach for the 10-unit system (20 run average).

	Operation cost ($)			Emission (ton)		
	Min	Max	Median	Min	Max	Median
Best operation cost	563,943	563,952	563,949	48.59	48.61	48.60
Best emission	658,374	660,813	659,345	22.19	22.32	22.28

5.3. Test with IEEE 118-bus system

To study the effect of the emission allowance trading, standard IEEE 118-bus 54-unit system is tested. All parameters are as before, except the population size and iterations: 500 and 600 (HSGA); 800 and 1500 (DSGA).

The base study without considering the allowance trading shows the boundary solutions with maximum emission *Emax* of 205.8 tons (corresponding to the minimum cost of \$1,645,374) and minimum emission *Emin* of 147.93 tons (corresponding to the maximum cost of \$1,701,868), as shown in Fig. 4. Next the allowance trading is considered. The emission cap is $Emin + \rho(Emax\text{-}Emin)$, with $\rho = 0$.

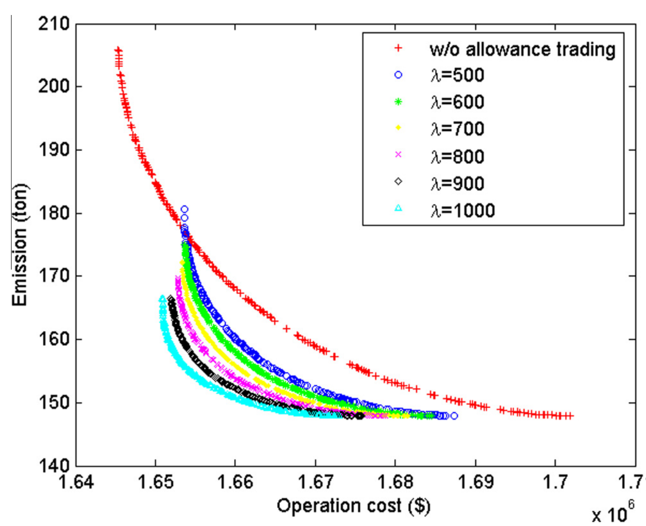

Fig. 4. Pareto fronts for different emission allowance prices with $\rho = 0.5$.

In 2007, NO_x allowance market spot price began the year around \$900/ton, fluctuating between \$500/ton and \$1000/ton

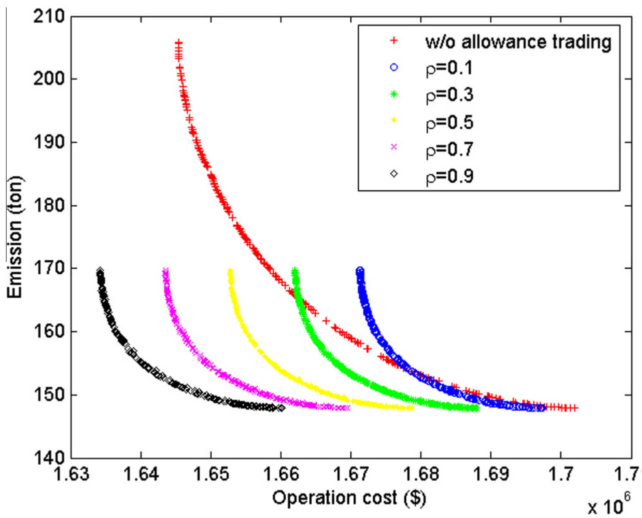

Fig. 5. Pareto fronts for different emission caps with $\lambda = 800$.

throughout the year, ended up to a year-end closing price of \$825/ton (Senjyu, Miyagi, Saber, Urasaki, & Funabashi, 2006; Juste, Kitu, Tunaka, & Hasegawa, 1999). Accordingly, the market price for emission allowance is set to $\lambda = 500$, 600, 700, 800, 900 and 1000 \$/ton. Then for each λ, we run DSGA in the second phase to get the non-dominated solutions shown in Fig. 5. With increasing of λ, the front converges to a narrower range.

Fig. 5 shows obtained Pareto fronts for emission caps $\rho = 0.1$, 0.3, 0.5, 0.7, 0.9 and $\lambda = 800$ \$/ton. Although the emission caps vary here, the optimal emissions corresponding to the minimum operation costs are almost all around 170 tons and the minimum emissions in each is around 148 tons.

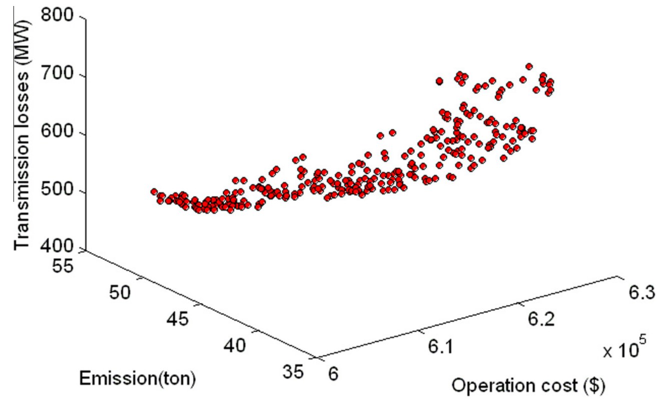

Fig. 7. 24-h Pareto front obtained by DSGA for 3-objective model.

5.4. Test with 15-unit system

With the transmission losses as the third objective, the model was studies on a 15-unit system (Gaing, 2003). Fig. 6 show the hourly non-dominated fronts for minimum (1050 MW, hour 1), medium (1800 MW, hour 6) and maximum (2630 MW, hour 12) load conditions obtained by the three algorithms from a sample run. Clearly HSGA and SPEA-2 outperform AMOSA. Closer examination shows that HSGA performs better than SPEA-2. For high load conditions, HSGA performed better than SPEA-2. Combining all independent runs, HSGA's solutions dominated 38% of those of SPEA-2, whereas SPEA-2 only dominated over 10% of HSGA's solutions in the front. For medium and smaller loads, the differences were also clear, although not as much, with HSGA's solutions dominating over those of SPEA-2 17.8% and 11% of the time respectively, the corresponding figures for SPEA-2 being only 11.7% and 5%. Additionally, from visual inspection, HSGA's solutions were more uniformly distributed over the front in all cases than those of SPEA-2.

Fig. 7 shows the 24-h Pareto front obtained by DSGA.

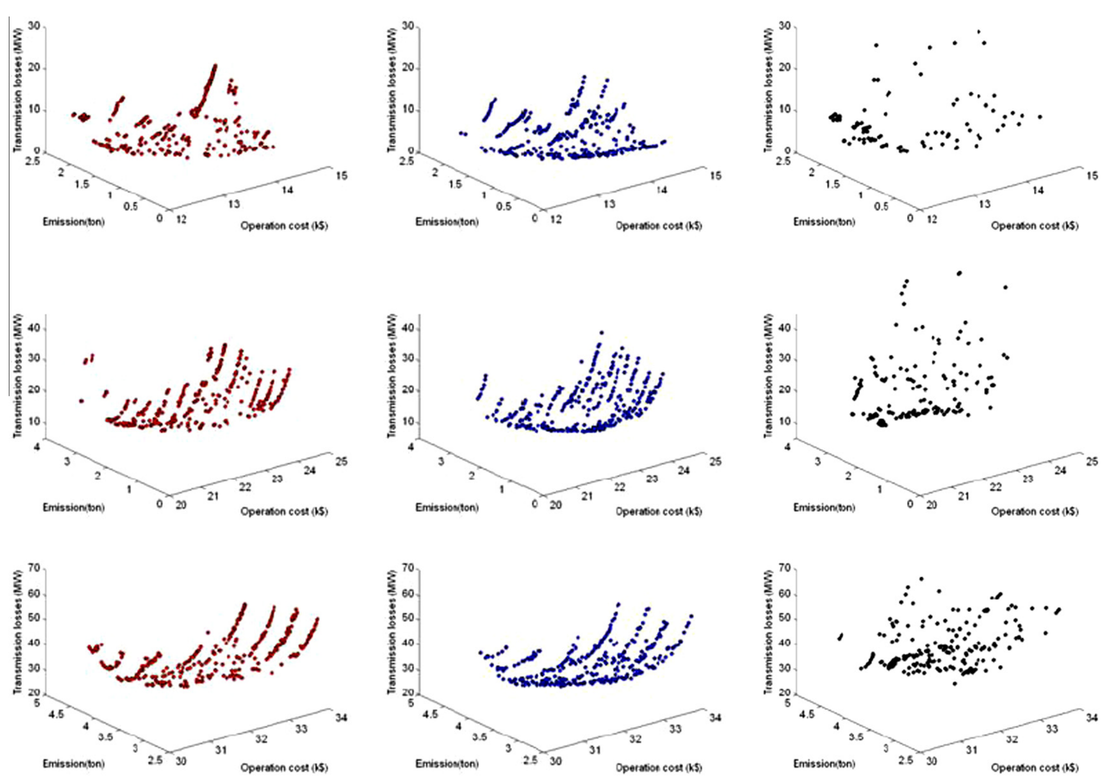

Fig. 6. Performances of HSGA (left), SPEA-2 (middle), AMOSA (right).

6. Conclusion

In this paper, a novel two-phase multi-objective evolutionary approach to solve optimal dispatch problem is proposed. The results show that the approach is for the multi-objective dispatch problem, obtaining a set of optimal solutions, that allow greater flexibility in decision making.

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