Interactive Compromise Approach with Particle Swarm Optimization for Environmental/Economic Power Dispatch

Ming-Tang Tsai, and Chih-Wei Yen

***Abstract*—**In this paper, an Interactive Compromise Approach with Particle Swarm Optimization(ICA-PSO) is presented to solve the Economic Emission Dispatch(EED) problem. The cost function and emission function are modeled as the nonsmooth functions, respectively. The bi-objective including both the minimization of cost and emission is formulated in this paper. ICA-PSO is proposed to solve EED problem for finding a better compromise solution. The solution methodology can offer a global or near-global solution for decision-making requirements. The effectiveness and efficiency of ICA-PSO are demonstrated by a sample test system. Test results can be shown that the proposed method provide a practical and flexible framework for power dispatch.

***Keywords*—**Interactive Compromise Approach, Emission Control, Economic Dispatch, Particle Swarm Optimization.

I. Introduction

THE primary objective of the economic dispatch (ED) is a scheme to minimize total fuel cost subject to several unit and system constraints. For a more effective operation, efficient strategies have been developed in [1-6]. Those strategies are mainly operated in such a way that the operating cost is minimized regardless of emissions produced. The passage of the 1990 U.S. Clean Air Act Amendments[7] has forced the utilities to modify their operating strategies to meet environmental standards set by legislation. In recent year, some operating strategies including emissions dispatch and fuel switching have been developed in[8-12]. Emissions dispatch adds a second objective to the operating problem, which can obtain both emissions reduction and minimizing power production cost. Fuel switching uses the fuel co-firing technique to reduce the emissions. These techniques not only intended to reduce emission into atmosphere but also want to minimize the operation cost.

Due to the conflicting and noncommeasurable natures of fuel cost and emission control, a single objective function seems not appropriate for this problem. Considering the emission, a trade-off between economy and environment need to be considered in the optimization process. With increased requirements for environmental protection, alternative strategies are required. It is a complicated problem, which includes two objectives. An efficient and reliable technique is needed to solve this Economic Emission Dispatch(EED) problem. Most previous studies[8-12] formulated this problem with only a single objective and emissions are treated as binding constraints. Since the emissions are important to both the power utilities and customers, it is beneficial to tackle the emissions as another objective function instead of just constraints. Various optimization techniques had been developed to solve the bi-objective problem[13-15]. The major disadvantage in solving the EED problem is that they are incapable of handing nonsmooth fuel cost and emission functions. An efficient and reliable technique is needed. This paper proposes the use of Particle Swarm Optimization(PSO) [16] to solve the nonsmooth functions. PSO searches from a population of points, not a single point. The population can move over hills and across valleys. It can search a complicated and uncertain area to find the solution. Therefore, PSO can discover a globally or near globally optimal point. Since PSO is a global searching technique, it is more capable of getting away from the local minimum to improve the quality of solution.

In this paper, an Interactive Compromise Approach[17] with Particle Swarm Optimization(ICA-PSO) is presented to solve the Economic Emission Dispatch(EED) problem. The bi-objective function considered the economy and emission level. Nonsmooth fuel cost functions, nonsmooth emission functions, and the transmission losses are taken into account. The PSO is used to seek for a global or near-global optimal solution when the ICA procedure interacted with the Decision Makers(DMs). The type of information such as trade-offs can make available to DMs in the interactive procedure. DMs also adjusted single-objective dependent upon their satisfactory strategies. By using the ICA-PSO, it easily enables the Decision Makers(DMs) to alternative a paerto-optimal solution. Effectiveness of the proposed method is demonstrated on an example system. Results show that the proposed method provides a set of flexible best selection for operation dispatch by following the instructions of DM's.

II. Problem Formulation

The bi-objective function including cost model($C(\bullet)$) and emission model($E(\bullet)$) can be formulated by

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$$Min. \quad [C(\bullet), E(\bullet)] \tag{1}$$

$$C(\bullet) = \sum_{i=1}^{N} \left(a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin\left(f_i \left(P_{i,\min} - P_i\right)\right)\right| \right)$$

$$E(\bullet) = \sum_{i=1}^{N} \left(\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \eta_i \times \exp(\delta_i \times P_i) \right)$$

Subject to

1. Power balance constraints

$$\sum_{i=1}^{N} P_i - P_L - P_D = 0 \tag{2}$$

2. Generating capability constraints

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{3}$$

Where a_i, b_i, c_i are the fuel cost coefficients of the $i-th$ unit, and e_i, f_i are the fuel cost coefficients with valve-point effects. $\alpha_i, \beta_i, \gamma_i, \eta_i, \delta_i$ are the emission coefficients of the $i-th$ unit, P_i is the real power of the $i-th$ unit(MW). P_D is defined as the total load demand(MW). $P_{i,\min}$ and $P_{i,\max}$ are lower and upper limits of the real power of the $i-th$ unit(MW). N is the number of generation unit. P_L is the total power losses, which are approximated on terms of B-coefficients as shown in Equation (4).

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} \left(P_i B_{ij} P_j\right) \tag{4}$$

III. Brief of Particle Swarm Optimization

When birds forage, they exchange information to find targets. Individuals provide messages to the population, thus influence the group behavior, which is a normal social phenomenon in nature. If the message provided by an individual is regarded as a local solution, the foraging process could be regarded as problem solving.

PSO is a random search method, but it does not contain complicated mechanisms such as crossover or mutation. PSO generates a set of initial solution through the initialization mechanism, known as particles and searches the optimal value through iterative evolution. More importantly, every particle has a memory capacity, and can provide one-way message to the population. Thus, the search process of PSO is the process of following current optimal solution. For example, if food distance is known to the population but location is unknown, the simplest way to find the food is to search the peripheral regions of the birds that are closest to the food. The solution program first sets the end condition (number of iterations or error tolerance), and obtains the optimal solution lastly.

PSO can have several solutions at the same time, each solution is called a particle, and particles have a cooperative relationship for sharing messages. Through specific equations, each particle adjusts its position and determines the search direction according to its search memory and those of others. In other words, it tries to reach compatibility between local search and global search. The search memory of a particle is the objective function and the optimum position found by the particle.

In the search space, the velocity and position influence the search behavior of PSO. The number of particles are numbered as $i = 1,2,\ldots,PS$, where PS (Population Size) is the total number of particles, and each particle is assumed to have N dimensions. Particle i is defined by its position that

$$X_i = [x_{i1}, x_{i2}, \ldots, x_{1N}] \tag{5}$$

The current optimal position of each particle is defined by

$$Pbest_i = [pbest_{i1}, pbest_{i2}, \ldots, pbest_{1N}] \tag{6}$$

The current global optimal position of the particle among all particles in the population is defined by:

$$Gbest_g = [gbest_{g1}, gbest_{g2}, \ldots, gbest_{gN}] \tag{7}$$

The velocity of each particle is defined by

$$V_i = [v_{i1}, v_{i2}, \ldots, v_{1N}] \tag{8}$$

Each particle updates its velocity and position as expressed in Equation(9) and Equation(10).

$$\begin{aligned} V_i^{l+1} = W \cdot V_i^l + C_1 \cdot Rand(0,1) \cdot (Pbest_i - X_i^l) + \\ C_2 \cdot Rand(0,1) \cdot (Gbest_g - X_i^l) \end{aligned} \tag{9}$$

$$X_i^{l+1} = X_i^l + V_i^{l+1} \tag{10}$$

where V_i^l is the speed of particle i of the current l generation. V_i^{l+1} is the speed of the next l+1 generation of particle i. $Rand(0,1)$ is a random number between 0 and 1. C_1 and C_2 are learning constants which influence the forward speed of the particle. In this paper, C_1 and C_2 are 2.05. W is the speed weight of current generation, small W means a small variance when the particle changes the position, otherwise the variance is large.

Fig. 1 is the search mechanism of PSO. Each particle moves from the current position to the next one according to the present fitness function values. Generally, the fitness function is same the objective functions. The local best of other particles in the population should be changed if the present fitness function value is better than the previous. Repeat the new searching points until the maximum number of generations reached. 100 generations are set in this paper as the stopping criteria.

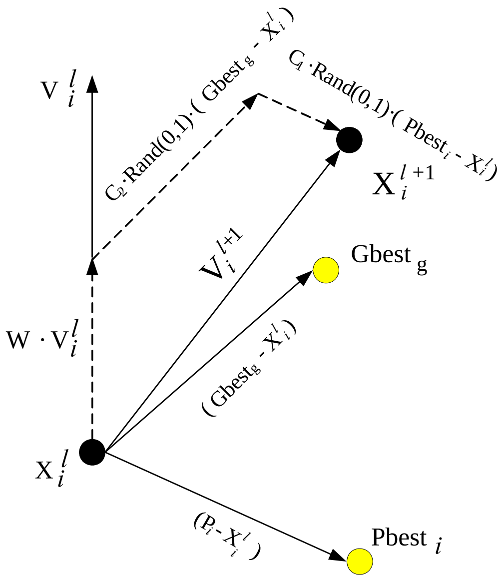

Fig. 1 The Search Mechanism of PSO

IV. Solution Methodology and Implement

The objective function shown in Equation(1) is a bi-objective function. The improvement of one objective can be only reached by retarding the other. The ICA approach is developed to deal with the dilemma by using PSO.

A. Initial Ideal and Non-ideal Solution

In Equation (1), we first solve the single goal problem by using PSO procedure. The detailed PSO procedure is shown in Section III. The optimization can provide the best solution and then the worst solution of E(・) and C(・). The best solutions of C(・) and E(・) are defined as "Cost_ideal" and "Emission_ideal", and the worst solutions of C(・) and E(・) are defined as "Cost_nonideal" and "Emission_nonideal".

The Best Solution

$$Min.\quad Cost = Cost\_ideal$$
$$Min.\quad Emission = Emission\_ideal$$

The Worst Solution

$$Max.\quad Cost = Cost\_nonideal$$
$$Max.\quad Emission = Emission\_nonideal$$

B. A Minimum Least Square Error Approach

The minimum least square approach is defined by:

$$Min\ T(X_i) = \left[\left(\frac{C(X_i) - Cost\_ideal}{Cost\_nonideal - Cost\_ideal}\right)^2 + \left(\frac{E(X_i) - Emission\_ideal}{Emission\_nonideal - Emission\_ideal}\right)^2\right]^{1/2} \quad (11)$$

$$Subject\ to: \begin{cases} Equation\,(2) \sim (3) \\ Cost\_ideal \le C(X_i) \le Cost\_nonideal \\ Emission\_ideal \le E(X_i) \le Emission\_nonideal \end{cases}$$

X_i is a particle as defined in PSO. If the minimization of $T(X_i)$ occurs in $X_{i,\min}$, $X_{i\ min}$ will be an ICA-PSO solution with

$$\begin{cases} Cost = C(X_{i\ min}) \\ Emission = E(X_{i\ min}) \end{cases} \quad (12)$$

C. Satisfaction Factor

An ICA-PSO solution($X_{i\ min}$) may not fit company police. To choose a desirable solution, $X_{i\ min}$ should be judged by the DMs. A satisfaction factor is defined for DMs in Equation (13).

$$SR\_Cost = \frac{|Cost\_nonideal - Cost|}{|Cost\_nonideal - Cost\_ideal|} \times 100\%$$
$$SR\_Emi = \frac{|Emission\_nonideal - Emission|}{|Emission\_nonideal - Emission\_ideal|} \times 100\% \quad (13)$$

D. Alternation of Decision Region

For cases that $C(X_i)$ needs further reduction, $E(X_i)$ will be chosen as the compromised term and the parameters $Cost\_nonideal$ and $Emission\_ideal$ will be adjusted by

$$IF\quad C(\bullet)\quad THEN\quad \begin{cases} Cost\_nonideal = Cost \\ Emission\_ideal = Emission \end{cases} \quad (14)$$

Conversely,

$$IF\quad E(\bullet)\quad THEN\quad \begin{cases} Cost\_ideal = Cost \\ Emission\_ideal = Emission \end{cases} \quad (15)$$

F. Definition of Goal Index

Following the above steps, the decision region will become smaller and smaller with the DMs' an important decision factor. A goal index defined in Equation (16) could provide the information of the maximal improvement which the next search can attain. The DMs will then decide if further searching should continue or not. Fig. 2 shows the flowchart of the ICA-PSO approach.

$$Dis\_Cost = |Cost\_nonideal - Cost\_ideal|$$
$$Dis\_Emission = |Emission\_nonideal - Emission\_ideal| \quad (16)$$

Fig. 2 shows the flowchart of the ICA-PSO approach.

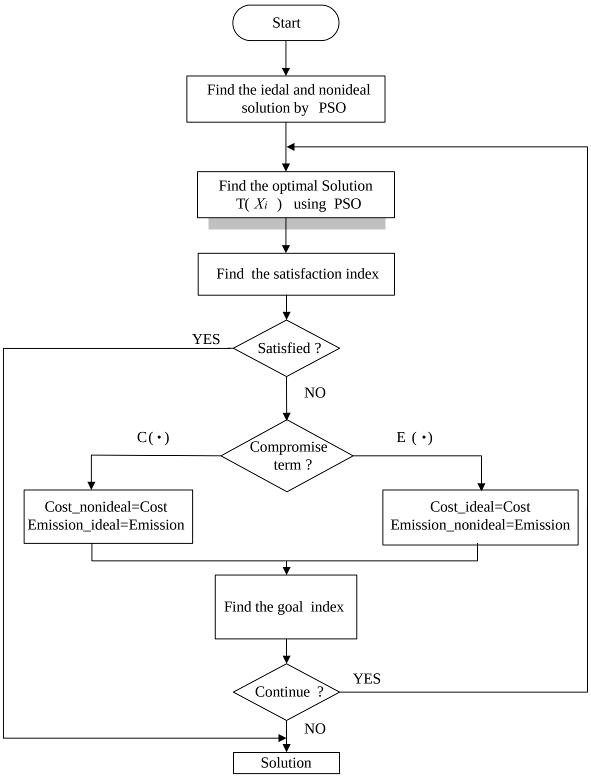

Fig. 2 The Flowchart of the ICA-PSO Approach

V. Case Study

The proposed algorithm is tested on a 10-unit system. The associated coefficients for units are listed in Table I and Table II [18]. Table III shows the results of minimizing cost and minimizing emission by PSO. In the Table III, if the total cost achieves the best, the emission required is the largest.

TABLE II
THE ASSOCIATED COEFFICIENTS FOR EMISSION FUNCTIONS

Generator	α (lb/h)	β (lb/MWh)	γ $(lb/(MW)^2h)$	η (lb/h)	δ (1/MW)
1	360.0012	-3.9864	0.04702	0.25475	0.01234
2	350.0056	-3.9524	0.04652	0.25475	0.01234
3	330.0056	-3.9023	0.04652	0.25163	0.01215
4	330.0056	-3.9023	0.04652	0.25163	0.01215
5	13.8593	0.3277	0.00420	0.24970	0.01200
6	13.8593	0.3277	0.00420	0.24970	0.01200
7	40.2669	-0.5455	0.00680	0.24800	0.01290
8	40.2669	-0.5455	0.00680	0.24990	0.01203
9	42.8955	-0.5112	0.00460	0.25470	0.01234
10	42.8955	-0.5112	0.00460	0.25470	0.01234

TABLE III
THE RESULTS OF SINGLE-OBJECTIVE PROGRAMMING

	Minimal Cost $C(\cdot)$		Minimal Emission $E(\cdot)$	
	Cost ($/h)	Emission(lb/h)	Cost ($/h)	Emission(lb/h)
P1	3631.8691	283.2018	3639.9064	283.3732
P2	4831.8592	331.9080	4816.4782	330.9727
P3	6222.9289	441.8854	4692.0231	319.5801
P4	5844.9768	393.5508	4793.0090	318.0850
P5	4922.4355	69.1040	10853.9355	175.4702
P6	4786.7750	67.0031	17633.6546	338.8449
P7	15932.1932	500.2547	15514.8099	474.8169
P8	18030.8124	655.5568	15400.7342	478.9648
P9	23447.5099	902.2280	19338.4030	592.9174
P10	23347.9568	902.0944	19320.1188	593.8536
Total	110999.3168	4546.7869	116003.0726	3906.8788

Table IV and Table V show the interactive compromised procedure. In Table IV, it is shown that SR_Emi degraded from 70.33% to 0% when SR_Cost improved from 37.58% to 100%. If the DMs find the result not to be suitable for the police of utilities, further compromise can be made according to the direction dictated by DMs. Similarly, if the DMs want to reduce the emission, the operation cost will be selected a compromised term as shown in Table V.

Fig. 3 shows the relationship between operation cost and satisfied factor. It provides the utility planners a wider range of alternatives showing the various feasible regions. Instead of using maximal allowable limits for emissions as constraints, an appropriate operating strategy can be chosen to meet the desired level of emission or cost. Two curves are intersected on 57.16% and 57.99% for SR_Cost and SR_Emi, respectively. The intersection of two curves may be a suitable dispatch strategy for DMs.

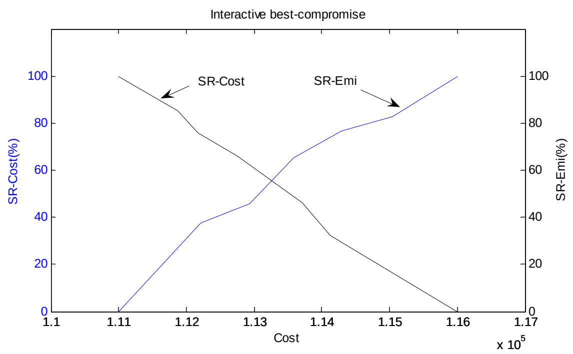

Fig. 3 The Relationship between Operation Cost and Satisfied Factor

TABLE I
THE ASSOCIATED COEFFICIENTS FOR FUEL COST FUNCTIONS

Gnerator	P_{min} (MW)	P_{max} (MW)	a ($/h)	b ($/MWh)	c ($/(MW)^{2}h)	e ($/h)	f (rad/MW)
1	10	55	1000.403	40.5407	0.12951	33	0.0174
2	20	80	950.606	39.5804	0.10908	25	0.0178
3	47	120	900.705	36.5104	0.12511	32	0.0162
4	20	130	800.705	39.5104	0.12111	30	0.0168
5	50	160	756.799	38.5390	0.15247	30	0.0148
6	70	240	451.325	46.1592	0.10587	20	0.0163
7	60	300	1243.531	38.3055	0.03546	20	0.0152
8	70	340	1049.998	40.3965	0.02803	30	0.0128
9	135	470	1658.569	36.3278	0.02111	60	0.0136
10	150	470	1356.659	38.2704	0.01799	40	0.0141

TABLE IV
THE INTERACTIVE COMPROMISED PROCEDURE FOR COST

	Interactive Cost ($C(\bullet)$)					
Cost ($/h)	114122.86	113712.86	112745.10	112169.93	111866.95	110999.32
Emission(***lb/h***)	4096.76	4159.69	4217.48	4339.04	4390.39	4546.79
SR_Cost (%)	37.58	45.77	65.11	76.61	82.66	100
SR_Emi (%)	70.33	60.49	51.46	32.47	24.44	0

TABLE V
THE INTERACTIVE COMPROMISED PROCEDURE FOR EMISSION

	Interactive Emission ($E(\bullet)$)					
Cost ($/h)	112212.23	112937.26	113581.26	114294.74	115044.48	116003.07
Emission(***lb/h***)	4339.31	4250.68	4124.87	4060.23	4002.53	3906.88
SR_Cost (%)	75.76	61.27	48.40	34.14	19.16	0
SR_Emi (%)	32.42	46.27	65.93	76.03	85.05	100

Fig. 4 shows the convergent characteristics(Min $T(X_i)$) for cost compromise and emission compromise. Algorithm was implemented in the programming language Matlab 7.0 on a PIV-2.6GHZ computer with 512MB RAM.

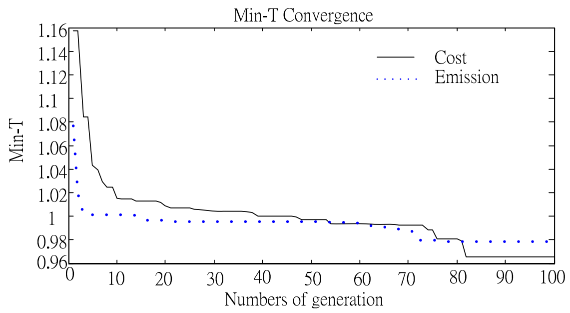

Fig. 4 The Convergent Characteristics(Min $T(X_i)$) of Cost compromise and Emission compromise

VI. CONCLUSION

A bi-objective function including cost and emissions is formulated for the economic emission dispatch. An ICA combined with PSO is used to solve the bi-objective problem while meeting the requirements of unit's capacity and power balance. This approach was tested on a 10-units system. Results provide a practical and flexible framework for evaluating the emission strategies. The optimization generates trade-off's process between cost and emission based on economic dispatch. With the introduction of this approach, it can support the DMs to know better where to look for improved solutions and how to recognize a final solution upon interactive procedure.

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