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Multiarea Environmental Dispatch with Emission Constraints using Hybrid Intelligence Algorithm

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Abstract:- This paper presents the combination of Gravitational search Algorithm and Sequential Quadratic Programming based optimization (GSA-SQP) algorithm to solve complex economic emission load dispatch (EELD) problems of thermal generators of power systems. EELD is an important optimization task in fossil fuel fired power plant operation for allocating generation among the committed units such that fuel cost and emission level are optimized simultaneously while satisfying all operational constraints. It is a highly constrained multiobjective optimization problem involving conflicting objectives with both equality and inequality constraints. In this paper, multi-objective hybrid GSA method has been proposed to solve EELD problem. Numerical results of three test systems demonstrate the capabilities of the proposed approach. Results obtained from the proposed approach have been compared to those obtained from non dominated sorting genetic algorithm-II and strength pareto evolutionary algorithm 2.

Keywords:- Economic Emission Load Dispatch, GSA, SQP and Valve Point Loading.

I. INTRODUCTION

The multiobjective generation dispatch in electric power system generally treats economy and emission impact as competing objectives which requires some form of conflict resolution to arrive at a solution. The optimization of nonlinear multiobjective economic emission load dispatch is to generate optimal amount of generating power from the fossil fuel based generating units in the system by minimizing the fuel cost and emission level simultaneously by satisfying all constraints. The increased concern over environmental protection and the passage of the U.S. Clean Air Act amendments of 1990 forced the utilities to modify their operation strategies for generation of electrical power not only at minimum generation cost but also at minimum pollution level [1-3]. However, the objective of minimum cost of generation will not provide minimum pollution level and objective of minimum emission does not provide minimum cost of generation.

The major parts of electric power generation are fossil-fired plants, which use coal, oil, gas or combinations thereof as the primary energy resource and produce atmospheric emissions whose nature depend on the type of fuel and its quality. Coal produces particulate matter such as ash and gaseous pollutants such as carbon dioxide (CO_2), sulfur dioxide (SO_2) and oxides of nitrogen (NO_x). It causes damage to materials by reducing visibility as well as causing global warming. The emission dispatching option is an attractive alternative in which both fuel cost and emission is to be minimized [4-8].

This article proposed the hybridization of Gravitational search and SQP based methods which are robust and reliable algorithms for solution of the economic and emission load dispatch (EELD) problems. This approach is applied to six unit thermal power system to obtain the best compromising solution. The results confirm the potential and effectiveness of the promising proposed algorithm compared to other intelligent method like NSGA II and SPEA 2 [9-13] methods.

The present formulation treats Economic Environmental Dispatch (EED) problem as a multi-objective mathematical programming problem, which attempts to minimize both cost and emission simultaneously while satisfying equality and inequality constraints.

II. PROBLEM STATEMENT

Economic: The fuel cost function of each generating unit considering valve-point effects [14] is expressed as the sum of a quadratic and a sinusoidal function. The total fuel cost in terms of real power output can be expressed as:

$$f_{1i}\left(P_{gi}\right)=\sum_{m=1}^{M}\sum_{i=1}^{N}\left[a_i+b_iP_{im}+c_iP_{im}^2+\left|d_i\sin\left\{e_i\left(P_i^{\min}-P_i\right)\right\}\right|\right] \quad (1)$$

where *ai* , *bi* , *ci* , *di* , *ei* are the cost curve coefficients of *i*th unit, *Pim* is the output power of *i*th unit at time *m*, $P_i^{\min}$ is the lower generation limits for i^{th} unit, *N* is number of generating units, *M* is the number of hours in the time horizon.

***Emission*:** Thermal power stations are major causes of atmospheric pollution because of high concentration of pollutant they cause. In this study, nitrogen oxides (NOx) emission is taken as the selected index from the viewpoint of environment conservation. The amount of emission from each generator is given as a function of its real power output [14], which is the sum of a quadratic and an exponential function. The total emission in the system can be expressed as:

$$f_{2i}\left(P_{gi}\right)=\sum_{m=1}^{M}\sum_{i=1}^{N}\left[\alpha_i+\beta_iP_{im}+\gamma_iP_{im}^2+\eta_i\exp\left(\delta_iP_{im}\right)\right] \quad (2)$$

where $\alpha_i,\beta_i,\gamma_i,\eta_i,\delta_i$ are emission curve coefficients of i^{th} generator.

A. Constraints

- ***Real Power Balance Constraints:*** The total real power generation must balance the predicted power demand plus the real power losses in the transmission lines at each time interval over the scheduling horizon.

$$\sum_{i=1}^{N}P_{im}-P_{Dm}-P_{Lm}=0 \qquad m\in M \quad (3)$$

- ***Real Power Operating Limits***

$$P_i^{\min}<P_{im}<P_i^{\max} \qquad i\in N \qquad m\in M \quad (4)$$

B. Determination of Generation Levels

In this approach, the power loadings of first (*N* − 1) generators are specified. From the equality constraints in Eq. (3) the power level of the N^{th} generator (i.e., the remaining generator) is given by the following expression:

$$P_{Nm}=P_{Dm}+P_{Lm}-\sum_{i=1}^{N-1}P_{im} \qquad m\in M \quad (5)$$

The transmission loss P_{Lm} is a function of all the generators including that of the dependent generator and it is given by:

$$P_{Lm}=\sum_{i=1}^{N-1}\sum_{i=1}^{N-1}P_{im}B_{ij}P_{jm}+2P_{Nm}\left(\sum_{i=1}^{N-1}B_{Ni}P_{im}\right)+B_{NN}P_{Nm}^2 \qquad m\in M \quad (6)$$

Expanding and rearranging, Eq. 6 becomes

$$B_{NN}P_{Nm}^2+\left(2\sum_{i=1}^{N-1}B_{Ni}P_{im}-1\right)P_{Nm}+\left(P_{Dm}+\sum_{i=1}^{N-1}\sum_{i=1}^{N-1}P_{im}B_{ij}P_{jm}-\sum_{i=1}^{N-1}P_{im}\right)=0 \qquad m\in M \quad (7)$$

III. PRINCIPLE OF MULTI-OBJECTIVE OPTIMIZATION

Many real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable and often competing and conflicting objectives. Multi-objective optimization with such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as Pareto-optimal solutions. The multiobjective constrained nonlinear optimization problem can be mathematically formulated as:

Minimize: $T(P_{gi})$

Subject to: $g(P_i) = 0$, $h(P_{gi}) \leq 0$

where, g is the equality constraint representing the power balance and h is the inequality constraint representing the generation capacity and power emission constraints.

IV. GRAVITATIONAL SEARCH ALGORITHM

Gravitational Search Algorithm (GSA) is a recently developed, new heuristic search algorithm proposed by Rashedi et al. It is a stochastic optimization population based search algorithm motivated by Newton's law of gravity and mass interaction. According to the proposed algorithm, agents are assumed to be objects that their performances are measured by means of masses. The whole agents pull each other by the gravitational attraction force and this force induces the movement of the agents globally towards the agents with heavier masses. In GSA, each mass has four particulars: its position, its inertial mass, its active gravitational mass and passive gravitational mass. The position of the mass equaled to a solution of the problem and its gravitational and inertial masses are specified using a fitness function. This method has been successfully applied in solving various non-linear functions. The obtained results confirm the high performance and efficiency of proposed method in these problems. GSA has a flexible and well-balanced mechanism to enhance exploration and exploitation abilities.

V. SEQUENTIAL QUADRATIC PROGRAMMING

Sequential quadratic programming (SQP) [7] is widely used to solve practical optimization problems. It outperforms every other nonlinear programming method in terms of efficiency, accuracy and percentage of successful solutions. The method closely mimics Newton's method for constrained optimization just as is done for unconstrained optimization. At each major iteration, an approximation is made of the Hessian of the Lagrange function using Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton updating method. As the objective function to be minimized is nonconvex, SQP requires a local minimum for an initial solution. In this paper, SQP is used as a local optimizer for fine-tuning of the better region explored by AI. For each iteration, a QP is solved to obtain the search direction which is used to update the control variables. QP problem can be described as follows:

$$\nabla F(\mathrm{P}_k)^{\mathrm{T}} d_k + \frac{1}{2} d_k^{\mathrm{T}} \mathrm{H}_K d_k$$

subject to the following constraints: $g_i(\mathrm{P}_k) + [\nabla g(\mathrm{P}_k)]^{\mathrm{T}} d_k = 0$ $\quad i = 1,...., m_e$

$g_i(\mathrm{P}_k) + [\nabla g(\mathrm{P}_k)]^{\mathrm{T}} d_k \leq 0$ $\quad i = m_e + 1,..., m$

where

H_k : the Hessian matrix of the Lagrangian function at the k th iteration

d_k : the search direction at the k th iteration, P_k : the real power vector at the k th iteration

m_e : number of equality constraints; m : number of constraints

$$L(\mathrm{P}, \lambda) = F(\mathrm{P}) + g(\mathrm{P})^{\mathrm{T}} \lambda \quad ,$$

where λ is the vector of Lagrangian multiplier.

H_k is calculated using quasi-Newton formula given by the following expression:

$$\mathrm{H}_{k+1} = \mathrm{H}_k + \frac{q_k q_k^{\mathrm{T}}}{q_k^{\mathrm{T}} S_k} - \frac{\mathrm{H}_k^{\mathrm{T}} S_k^{\mathrm{T}} S_k \mathrm{H}_k}{S_k^{\mathrm{T}} \mathrm{H}_k S_k}$$

where,

$$S_k = \mathrm{P}_{k+1} - \mathrm{P}_k$$

$$q_k = \nabla L(\mathrm{P}_{k+1}, \lambda_{k+1}) - \nabla L(\mathrm{P}_k, \lambda_{k+1})$$

For each iteration of the QP sub-problem the direction d_k is calculated using the objective function. The solution obtained forms a new iterate given by the following expression:

$$P_{k+1} = P_k + \alpha_k d_k$$

VI. PROPOSED HYBRID APPROACH

The proposed hybrid method uses the property of the GSA, which can give a good solution even when the problem has many local optimum solutions at the beginning and at last SQP, which has a local search property that is used to obtain the final solution.

Step 1: Initialization

When it is assumed that there is a system with N (dimension of the search space) masses, position of the i^{th} mass is described as follows. At first, the positions of masses are fixed randomly.

$$X_i = (x_i^1, \ldots\ldots x_i^d, \ldots. x_i^n) \qquad \text{for, i=1,2,......,N} \tag{10}$$

Where, x_i^d is the position of the i^{th} mass in d^{th} dimension.

Step 2: Fitness Evaluation of all agents

In this step, to execute for all agents at each iteration and best and worst fitness are computed at each iteration as follows:

$$best(t) = \min_{j \in \{1,......,N\}} fit_j(t) \tag{11}$$

$$worst(t) = \max_{j \in \{1,.,....N\}} fit_j(t) \tag{12}$$

Where $fit_j(t)$ is the fitness of the j^{th} agent of iteration t, $best(t)$ and $worst(t)$ are best (minimum) and worst (maximum) fitness of all agents.

Step 3: Compute the Gravitational Constant (G (t))

In this step, the gravitational constant at iteration t (G (t)) is computed as follows:

$$G(t) = G_0 \exp(-\alpha \frac{t}{T}) \tag{13}$$

Step 4: Update the Gravitational and Inertial Masses

The gravitational and inertial masses are updated for each iteration as follows:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \qquad \text{i=1,2..........,N} \tag{14}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{15}$$

where $fit_i(t)$ is the fitness of the i^{th} agent at iteration t.

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{16}$$

where M_{ai} is the active gravitational mass of the i^{th} agent, M_{pi} is the passive gravitational mass of the i^{th} agent, M_{ii} is the inertia mass of the i^{th} agent, Mi(t) is the mass of the i^{th} agent at iteration t.

Step 5: Calculate the Total Force

In this step, the total force acting on the i^{th} agent $(F_i^d(t))$ is calculated as follows:

$$F_i^d(t) = \sum_{j \in kbest j \neq i} rand_j F_{ij}^d(t) \tag{17}$$

where $rand_j$ is a random number between interval [0,1] and *kbest* is the set of first K agents with the best fitness value and biggest mass. The force acting on the i^{th} mass from the j^{th} mass at the specific iteration t is described according to the gravitational theory as follows:

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{18}$$

where $R_{ij}(t)$ is the Euclidean distance between i^{th} and j^{th} agents $(\| X_i(t), X_j(t) \|_2)$ and ε is the small constant.

Step 6: Calculation the Acceleration and Velocity

In this step, the acceleration and $(a_i^d(t))$ and velocity $(v_i^d(t))$ of the i[th] agent at iteration t in d[th] dimension are calculated through law of gravity and law of motion as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{19}$$

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$$

where $rand_i$ is the random number between interval [0,1].

Step 7: Update the Position of Agents

In this step the next position of the i[th] agents in d[th] $(x_i^d(t+1))$ dimension are updated as follows:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{20}$$

Step 8: Repeat

In this step, steps from 2 to 7 are repeated until the iterations reach the stopping criteria.This value is the global solution of the optimization problem. Solution of EED problem is used again in SQP method to get the fine tune of optimal solution.

VII. SIMULATION AND RESULTS

The proposed algorithm has been applied to a test system with two hydro plants and four thermal plants whose characteristics and load demand are given in the reference no. [15]. Transmission loss formula coefficients are also given in the [15]. In the search process, water availability constraint of each generator and power balance constraints are satisfied. All the algorithms have been implemented in MATLAB 7 on a PC (Pentium-IV, 80 GB, 3.0 GHz).

At first fuel cost and emission objectives are minimized individually, usually GSA is used to explore the extreme points of the tradeoff surface. In GSA, parameters are set for simulation: G0= 0.10; $\alpha = 100$,Maximum Iteration =200 and No.of agent= 100 respectively for this system. Table 1 and Table 2 show the results corresponding to minimum cost and minimum emission respectively using HGSA. In order to show the effectiveness of the proposed HGSA, NSGA-II [15] and SPEA2 [16] have been applied to solve this problem. In NSGA-II and SPEA2, the population size, maximum number of generations, crossover and mutation probabilities have been selected as 50, 20, 0.9 and 0.2 respectively. Results obtained from proposed HGSA are compared with those obtained from NSGA-II and SPEA2 which are shown in Table 4 and Table 5 respectively.

Table I: Results obtained from minimum cost dispatch using HGSA

Subin-terval	P_{h1} (MW)	P_{h2} (MW)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	Cost ($\times 10^5$ $)	Emission (ton)	CPU time (second)
1	203.9308	390.2665	20.3598	116.9936	118.6575	69.8771	1.0405	30.1132	69.2969
2	214.8976	367.1722	99.2748	163.2068	199.7235	83.0383			
3	233.8747	342.5052	120.5530	149.4603	123.9475	52.5581			
4	225.9710	485.4104	120.3860	172.8833	222.0177	112.4474			

Table II: Results obtained from minimum Emission dispatch using HGSA

Subin-terval	P_{h1} (MW)	P_{h2} (MW)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	Cost ($\times 10^5$ \$)	Emission (ton)	CPU time (second)
1	225.8448	346.4268	59.1227	80.6248	94.4369	112.6025	1.7578	13.5006	212.4844
2	204.2791	415.1411	99.4410	109.8165	100.6414	198.2062			
3	206.3630	379.1909	75.3078	103.1934	84.7221	174.1563			
4	241.8294	448.1700	124.2912	136.5360	119.8365	267.0817			

Table III: Results obtained from minimum Economic Emission dispatch using HGSA

Subin-terval	P_{h1} (MW)	P_{h2} (MW)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	Cost ($\times 10^5$ \$)	Emission (ton)	CPU time (second)
1	208.6984	342.1106	21.6420	84.1885	133.7850	128.6318	1.4510	15.5302	70.78
2	208.2955	340.9764	124.9017	162.2047	123.9135	165.8642			
3	222.8391	440.9762	23.3726	131.3734	110.5003	95.8262			
4	238.7053	461.0389	119.5286	142.6768	151.5517	224.5035			

Table IV: Results obtained from NSGA II

Subin-terval (MW)	P_{h1} (MW)	P_{h2} (MW)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4}	Cost ($\times 10^5$ \$)	Emission (ton)	CPU time (second)
1	222.7854	363.6666	68.8587	81.5098	97.2670	84.9300	1.5154	15.31	65.42
2	224.5925	355.8079	114.2571	144.9426	119.5392	167.0913			
3	216.5599	426.5156	61.2768	78.4991	113.9784	126.9349			
4	214.3244	442.2844	105.1776	161.8825	166.4349	246.9871			

Table V: Results obtained from SPEA 2

Subin-terval	P_{h1} (MW)	P_{h2} (MW)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	Cost ($\times 10^5$ $)	Emission (ton)	CPU time (second)
1	220.0141	373.6812	55.9314	106.6907	93.5193	69.1633	1.4470	16.847	74.82
2	224.2143	369.3395	96.1524	142.6874	124.6655	169.1103			
3	219.3209	408.6647	90.3732	66.4857	111.9016	126.1977			
4	214.1066	437.4369	119.2218	150.8741	188.4459	226.5423			

VIII. CONCLUSIONS

In this paper, economic environmental dispatch problem has been formulated as multi-objective optimization problem with competing fuel cost and emission objectives. Results obtained from the proposed approach have been compared with those obtained from strength pareto evolutionary algorithm 2 and nondominated sorting genetic algorithm-II. It is seen from the comparison that the proposed approach provides a competitive performance in terms of solution as well as computation time. The proposed multi-objective GSA is simple, robust and efficient. It does not impose any limitation on the number of objectives and can be extended to include more objectives.

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