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Stochastic Multi-objective Generation Dispatch by Search Methods

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Abstract: This stidy explores the use of genetic algorithm and Hooke-Jeeves search methods to search for the optimum active power generation schedule of thermal power systems, so as to obtain the best compromised solution, in the multi-objective framework. The multi-objective problem is formulated to minimize non-commensurable objectives viz. operating cost, NO_x emission and variance of active power generation with explicit recognition of statistical uncertainties in the thermal power generation cost coefficients, emission coefficients, power demands and hence power generations and bus voltages, which are considered random variables. Inequality constraint to maintain security of transmission lines with respect to active power flow and equality constraint of active power balance are considered in the form of objective functions to be optimized. The objectives are quantified by defining their membership functions using fuzzy set theory. The solution set of such formulated problems is non-inferior due to contradictions among the objectives taken. Active power generations are searched by genetic algorithm and Hooke-Jeeves search methods in the non-inferior domain. Among the generated set of non-inferior solutions of power generation schedules, system operator chooses the set that provides maximum satisfaction level of the most under achieved objective in terms of membership function and is termed as fitness function. The validity of the proposed methods is demonstrated and results are compared for an IEEE system comprising of 25-nodes, 35-lines and 5-generators.

Key words: Stochastic multi-objective optimization, Genetic Algorithm(GA), fuzzy goals, membership function, Hooke-Jeeves(HJ) method

INTRODUCTION

The optimal economic emission dispatch problem is a major topic of interest and need in electric power and energy systems. The problem is not only to reduce the cost or emission but other objectives also play vital role in the overall performance of the power system. Various authors have contributed a number of research papers in which the overall performance of the power system is improved. A security constrained economic dispatch problem was solved by Arya *et al.*[1] using Davidon-Fletcher-Powell's optimization method. Line flow constraints were taken into account by exterior penalty function method. Environmental/economic dispatch using fuzzy logic controlled GA was presented by Song *et al.*[2]. Two objectives economy and emission were optimized. Two fuzzy controllers for control of crossover and mutation operators were used based upon some heuristics. Hota *et al*,[3]. have solved a multi-objective problem through an interactive fuzzy satisfying method[3] and simulated annealing technique using goal attainment method[4]. Objectives taken were economy, emission and line security. Abido[5] used a Tabu search based approach to solve the optimal power flow problem. An attempt has been made to minimize cost, squared deviations of; real and reactive power generations and voltages, from the violated limits, etc. by combining them into an augmented objective function. A multi-objective secure EELD problem has been by using evolutionary algorithms[6]. Economic dispatch and unit commitment problems have been solved by genetic algorithm based search by Chen and Chang[7]. Xu *et al.*[8] have solved the global optimization problem of constrained muti-objective longitudinal interconnected power system using genetic algorithm.

While solving such multi-objective optimization problems, generally the trend is to assume the system data to be deterministic i.e. certain without any variation. Only in a few research papers, the stochastic nature of system parameters has been taken into account. Hawary

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and Mbamalu[9] solved a stochastic optimal load flow problem using Newton Raphson iterative technique. Total fuel cost to be minimized was the only objective. Active and reactive powers and voltages were considered stochastic in nature. In the same direction, another study has been presented by Dhillon *et al.*[10], three objectives considered for minimization were fuel cost, NO_x emission and expected real power deviations. Lagrangian function was defined and minimized, using Newton Raphson algorithm. Fuzzy set theory was used to decide the optimal solution out of a number of feasible non-inferior solutions. Chang and Fu[11] presented a stochastic multi-objective generation dispatch of combined heat and power systems. Both the power and heat demands were treated as random variables. The three conflicting objective functions to be minimized were; total generation cost, the expected power generation deviation and the expected heat generation deviation. The goal-attainment method was used to solve the optimization problem. Bath *et al.*[12] solved a stochastic multi-objective problem of generation scheduling by taking cost, emission, variance of active power and variance of reactive power as the conflicting objectives to be optimized. To solve the problem, scalar lagrangian function was formed and solved by Newton-Raphson technique. Genetic algorithm based evolutionary search method and fuzzy set theory was used to search the most suitable weight combination.

Stochastic means variation or randomness due to uncertainty and inaccuracy in measurement, assessment and forecasting of various system parameters. Due to randomness, the optimal solution found out using deterministic data, may not be the true optimal solution. So in this study, an attempt has been made to form and to solve a stochastic multi-objective optimization problem. Variations in system parameters and variables are modeled mathematically using their variance and covariance. Evolutionary search based genetic algorithm and Hooke-Jeeves search methods are used to select the active power generations of individual generators within their minimum and maximum capacity limits and to generate non-inferior solutions among which the best solution is selected. Genetic Algorithm (GA) is a global optimization technique and uses stochastic operators instead of deterministic rules to search for a solution. GA hops randomly from point to point thus skipping from local optimum in which other algorithms might land. Another attractive property of GA is that it searches for many optimum points in parallel. GA has been successfully applied in various areas[2,6-8,11,12]. Being imprecise nature of the Decision Maker's (DM's) judgment, it is assumed that the DM has fuzzy goals and can be defined by their membership functions. Min-max technique has been used to select solution from a number of non-inferior solutions, which selects the maximum value among the most underachieved membership function values of the participating objectives. There is no need to evaluate derivatives of any objective function for solving the minimization problem by GA and by Hooke-Jeeves method.

STOCHASTIC MULTI-OBJECTIVE PROBLEM FORMULATION

The multiple objectives with equality and inequality constraints pertaining to the power system optimization problem and taken into account are; minimization of expected values of; (i) fuel cost, (ii) polluting gaseous emission, (iii) variance of active power generation, and equality constraint of (iv) active power mismatch with its load demand plus losses and inequality constraint of (v) security of transmission lines due to active power flow. The stochastic economic-emission formulation is adopted, considering fuel cost coefficients, emission coefficients, active power injections and bus voltages as random variables. The stochastic models are converted into their deterministic equivalents by taking their expected values, with the assumption that all the random variables are normally distributed and statistically dependent on each other. Randomness of parameters is represented by variance and covariance, which in turn are defined as:

$$\mathrm{var}(x) = C^2(x)\,\bar{x}^2 \qquad (1)$$

$$\mathrm{cov}(x,y) = R(x,y)\,C(x)\,C(y)\,\bar{x}\,\bar{y} \qquad (2)$$

Expected fuel cost: The fuel cost curve is approximated by a quadratic function[10] of the generator's real power output, P_{Gi}

$$F_1 = \sum_{i=1}^{?G} \left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i \right) \ \mathrm{Rs/h} \qquad (3)$$

A stochastic model of F_1 is formulated by considering the cost coefficients and active power demand and hence the active power generations as random. The expected value of the fuel cost function is obtained by expanding the function, employing Taylor's series, about the mean.

$$\bar{F}_1 = \sum_{i=1}^{NG} \left[\begin{array}{l} \bar{a}_i \bar{P}_{Gi}^2 + \bar{b}_i \bar{P}_{Gi} + \bar{c}_i + \bar{a}_i \,\mathrm{var}(P_{Gi}) + \\ 2\bar{P}_{Gi}\,\mathrm{cov}(a_i, P_{Gi}) + \mathrm{cov}(b_i, P_{Gi}) \end{array} \right] \qquad (4)$$

Expected emission: The emission curve can be directly related to the cost curve through the emission rate per Mbtu (1 Btu = 1055.06 J), which is a constant factor for a given type or grade of fuel. Therefore, the amount of gaseous pollutant emission is given as a quadratic function of generator output P_{Gi}[10].

$$F_2 = \sum_{i=1}^{NG} \left(d_i P_{Gi}^2 + e_i P_{Gi} + f_i \right) \quad \text{kg h}^{-1} \tag{5}$$

A stochastic model is formulated by considering the emission coefficients and active power demand and hence generations as random. The expected pollutant emission is obtained as:

$$\bar{F}_2 = \sum_{i=1}^{NG} \begin{bmatrix} (\bar{d}_i \bar{P}_{Gi}^2 + \bar{e}_i \bar{P}_{Gi} + \bar{f}_i + \bar{d}_i \, var(P_{Gi}) \\ +2\,\bar{P}_{Gi} \, cov(d_i, P_{Gi}) + cov(e_i, P_{Gi}) \end{bmatrix} \tag{6}$$

Expected deviations: Generator outputs; P_{Gi} are treated as random variables. There will be deviation in total active power generation from the deterministic value. This expected deviation is considered as objective to be minimized and is represented as[10]:

$$\bar{F}_3 = \sum_{i=1}^{NG} var(P_{Gi}) + \sum_{i=1}^{NG} \sum_{\substack{j=1 \\ j \neq i}}^{NG} cov(P_{Gi}, P_{Gj}) \tag{7}$$

Expected transmission loss: The active power transmission loss; P_L is calculated by using loss coefficients[10]. The expected transmission losses, using Taylor's series expansion are represented as:

$$\bar{P}_L = \sum_{i=1}^{NB} \sum_{j=1}^{NB} \left[\bar{a}_{ij} (\bar{P}_i \bar{P}_j + \bar{Q}_i \bar{Q}_j) + \bar{ß}_{ij} \, (\bar{Q}_i \bar{P}_j - \bar{P}_i \bar{Q}_j) \right]$$
$$+ \sum_{i=1}^{NG} \bar{a}_{ii} \left[var(P_{Gi}) + var(Q_{Gi}) \right]$$
$$+ \sum_{i=1}^{NG} \sum_{\substack{j=1 \\ j \neq i}}^{NG} \bar{\alpha}_{ij} \left[cov(P_{Gi}, P_{Gj}) + cov(Q_{Gi}, Q_{Gj}) \right]$$
$$+ \sum_{i=1}^{NG} \sum_{\substack{j=1 \\ j \neq i}}^{NG} (\bar{ß}_{ji} - \bar{ß}_{ij}) \, cov(P_{Gi}, Q_{Gj}) \tag{8}$$

where

$$\bar{P}_i = \bar{P}_{Gi} - \bar{P}_{di} \tag{9a}$$

$$\bar{Q}_i = \bar{Q}_{Gi} - \bar{Q}_{di} \tag{9b}$$

$$\bar{a}_{ij} = \frac{t_{ij} R_{ij}}{\bar{V}_i \bar{V}_j} \cos(\bar{d}_i - \bar{d}_j) \tag{9c}$$

$$\bar{\beta}_{ij} = \frac{t_{ij} R_{ij}}{\bar{V}_i \bar{V}_j} \sin(\bar{d}_i - \bar{d}_j) \tag{9d}$$

$$t_{ij} = \begin{cases} 1.0 + 6.0 \dfrac{var(|V_i|)}{|\bar{V}_i|^2} & ;\text{if } i=j \\ 1.0 + \dfrac{var(|V_i|)}{|\bar{V}_i|^2} + \dfrac{var(|V_j|)}{|\bar{V}_j|^2} + \dfrac{cov(|V_i|,|V_j|)}{|\bar{V}_i||\bar{V}_j|} & \\ -\dfrac{var(d_i) + var(d_j)}{2.0} - cov(d_i, d_j) & ;\text{if } i \neq j \end{cases}$$

Expected power flow on transmission lines: Real power flow on m[th] transmission line, connected from bus j to k, is given by:

$$P_{Tm} = g_m |V_j|^2 - |V_j||V_k| \left(g_m \cos(\delta_j - \delta_k) + b_m \sin(\delta_j - \delta_k) \right) \tag{10}$$

Expected value of real power flow on mth transmission line connected from bus j to k, is given by:

$$\bar{P}_{Tm} = g_m \left(1 + C^2(V_j) \right) |\bar{V}_j|^2 - |\bar{V}_j||\bar{V}_k|$$
$$\left(g_m \cos(\bar{\delta}_j - \bar{\delta}_k) + b_m \sin(\bar{\delta}_j - \bar{\delta}_k) \right) \lambda_{jk} \tag{11}$$

where

$$\lambda_{jk} = \begin{bmatrix} 1.0 - 0.5 * \left(var(\delta_j) + var(\delta_k) \right) + \\ cov(\delta_j \delta_k) + R(V_j, V_k) C(V_j) C(V_k) \end{bmatrix}$$

Membership function of objectives: The fuzzy sets are defined by equations called membership functions. These functions represent the degree of membership in certain fuzzy sets using values from 0 to 1[10]. The value of the membership function indicates up to which degree a solution is satisfying the F_i objective. Here $\mu(F_i)$ is assumed to be strictly monotonically decreasing and continuous function, defined as:

$$\mu(\bar{F}_i) = \begin{cases} 1 & ;\bar{F}_i \leq \bar{F}_i^{min} \\ \dfrac{\bar{F}_i^{max} - \bar{F}_i}{\bar{F}_i^{max} - \bar{F}_i^{min}} & ;\bar{F}_i^{min} \leq \bar{F}_i \leq \bar{F}_i^{max} \\ 0 & ;\bar{F}_i \geq \bar{F}_i^{max} \end{cases} \quad ;I = 1,2,...,4 \tag{12}$$

Aggregating the above equations, the deterministic equivalent of stochastic multi-objective problem is defined as to search optimal active power generation so as to

$$\text{Maximize} \quad \left[\mu\left(\bar{F}_1\right), \mu\left(\bar{F}_2\right), \mu\left(\bar{F}_3\right) \right]^T \tag{13a}$$

Subject to equality and inequality constraints, such as:

$$\sum_{i=1}^{NB}\bar{P}_{di} - \sum_{i=1}^{NG}\bar{P}_{Gi} + \bar{P}_{L} = 0 \quad (13b)$$

$$\bar{P}_{Gi}^{min} \le \bar{P}_{Gi} \le \bar{P}_{Gi}^{max} \quad ;i = 1,2,...,NG \quad (13c)$$

$$\bar{P}_{Tm} \le P_{TR_m} \quad ;m = 1,2,...,NL \quad (13d)$$

Equality constraint defined by Eq 13b is considered in the form of additional objective to be minimized.

$$\bar{F}_4 = \left|\sum_{i=1}^{NB}\bar{P}_{di} - \sum_{i=1}^{NG}\bar{P}_{Gi} + \bar{P}_{L}\right| \quad \left(\bar{F}_4\right) \quad (14)$$

Membership function $\mu(\bar{F}_4)$ is calculated using Eq 12. Higher the satisfaction value better is the convergence. $\bar{F}_4^{min}$ is the convergence to be achieved and $\bar{F}_4^{max}$ gives the range of feasibility of solution. Inequality constraint of Eq 13c is taken care of while searching the active power generations. Membership function $\mu(P_{Tm})$ for active power flow on m^{th} line is defined as follows:-

$$\mu(\bar{P}_{Tm}) = \begin{cases} 1 & ;|\bar{P}_{Tm}| \le \sigma_1 P_{TR_m} \\ \dfrac{\sigma_2 P_{TR_m} - |\bar{P}_{Tm}|}{\sigma_2 P_{TR_m} - \sigma_1 P_{TR_m}} & ;\sigma_1 P_{TR_m} \le |\bar{P}_{Tm}| \le \sigma_2 P_{TR_m} \\ 0 & ;|\bar{P}_{Tm}| \ge \sigma_2 P_{TR_m} \end{cases} \quad ;m=1,...,NL \quad (15)$$

Where σ_1 and σ_2 are factors taken to decide tolerable minimum and maximum limits of active power flow on transmission lines. Inequality constraint of Eq 13d is defined in the form of membership function as given below:

$$\mu(\bar{F}_5) = \min\left[\mu\left(\bar{P}_{Tm}\right); \quad m = 1,2,...,NL\right] \quad (16)$$

So the active power optimization is redefined to search the active power generation schedule subject to constraints (13c), so as to

$$\text{Maximize}\left[\mu\left(\bar{F}_1\right), \mu\left(\bar{F}_2\right), \mu\left(\bar{F}_3\right), \mu\left(\bar{F}_4\right), \mu\left(\bar{F}_5\right)\right]^T \quad (17)$$

Evolutionary search based GA and Hooke-Jeeves pattern search methods are used to generate the set of non-inferior solutions. The optimum solution is selected using min-max technique. Convergence of the method is based on the satisfaction of $\mu(\bar{F}_4)$ and $\mu(\bar{F}_5)$ objectives.

SEARCH BASED OPTIMIZATION METHODS

Search based optimization techniques are generally divided into categories like conventional and non-conventional methods. In conventional method the search is guided and follow some logical criteria whereas non-conventional techniques are stochastic and follow selection criterion based on principles of natural phenomenon such as some physical process e.g. simulated annealing[4] or biological process e.g. genetic algorithm. Conventional method used in this study is Hooke-Jeeves (HJ) search method and non-conventional method used is Genetic Algorithm (GA).

Genetic algorithm based active power generation search: GA operates on string structures. A finite length of binary numbers, which is concatenated by sub-strings, is used to represent the coding of the search parameters (active power generations in the present study). A binary string is decoded into an unsigned integer for the GA implementation. The inequality constraint is performed in such a way that the individual string is normalized over the operating region. The higher precision of the generations can be obtained by defining longer binary strings. A decoding method is formulated in following equation.

$$y_i^j = \sum_{k=0}^{x_i-1} bit_k 2^k \quad ;I = 1,2,...,NG, j = 1,2,...,S \quad (18)$$

where x_i is length of sub-string, bit_k is k^{th} binary coefficient and S is the population size. If the parameter belongs to P_{gi}^{min} and P_{gi}^{max}, the decoded value of parameter can be computed.

$$P_{Gi}^j = P_{Gi}^{min} + \frac{y_i^j * (P_{Gi}^{max} - P_{Gi}^{min})}{2^{x_i-1}} \quad ; i = 1,2,...,NG, j = 1,2,...,S \quad (19)$$

Genetic Algorithm: To implement the genetic algorithm to search for the active power generation schedule a stepwise procedure is outlined below:

- Input the data; such as number of objectives NOB, population size S, chromosome length l, length of sub-string x_i, maximum number of generations K^{max}, crossover probability p_c, mutation probability p_m and minimum and maximum limits of active power generations.
- Find the minimum and maximum values of the objectives, F_i^{min} and F_i^{max}; i = 1,2,...,NOB.
- Generate the initial population of generation schedule randomly. Decode each individual string of population using Eq 18 and normalize it using Eq 19.
- Evaluate objectives, membership functions and fitness value corresponding to each string using sub-algorithm 3.3
- Initialize generation counter, K=0.
- Select the string having maximum fitness, γ^{pre}.
- Increment the generation counter, K=K+1.
- If ($K>K^{max}$) then GO TO 17.

- Select the most-fit strings from old population by stochastic remainder roulette wheel selection, for crossover.
- Select the crossover site by flipping the coin with crossover probability. Perform single point crossover and mutation to get the new population.
- Decode the string using Eq.18 and normalize it fornew generated strings using Eq.19.
- Evaluate different objectives, their membership functions and fitness value of each power generation set of population using sub-algorithm 3.3.
- Select the string having maximum fitness in the new population, γ^{max}.
- If $(\gamma^{max}-\gamma^{pre}) \le \epsilon$ then GO TO 17.
- Update the value of population fitness.

$$\gamma^{pre} = \begin{cases} \gamma^{pre} & ;\gamma^{pre} > \gamma^{max} \\ \gamma^{max} & ;\gamma^{max} > \gamma^{pre} \end{cases}$$

- GO TO 7 and repeat.
- Stop.

Hooke-Jeeves search based generation optimization: In the Hooke-Jeeves method[13], a combination of exploratory move and pattern move is made iteratively to search out the optimum solution for the problem. In the exploratory move, the current point is perturbed in positive and negative directions along each variable (generation here) one at a time and the best point is recorded. The current point is changed to the best point at the end of each variable perturbation. The exploratory move is a success if the perturbed point is different from the starting point, otherwise the exploratory move is a failure. In case, the exploratory move fails, then perturbation factor is reduced to continue the process. If the exploratory move is a success, then two successive best points are used to perform the pattern move. In case of better results, pattern move is repeated. This process is repeated till some termination criterion is met.

Hooke-jeeves Algorithm: Active power generation is searched as follows:

Step 1. Select the minimum and maximum values of the objectives, F_i^{min} and F_i^{max}; i = 1,2,...,NOB, a small step factor Δ, a step reduction factor α>1 and a termination parameter, ϵ.

Step 2. Calculate the initial generation schedule, neglecting power losses, P_{gi}^0; i =1,2,...,NG. Calculate objectives, membership functions and fitness value γ using sub algorithm 3.3 and set $?^{(c)}_{max} = ?\left(P^0_{G1}, P^0_{G2}, ..., P^0_{GNG}\right)$

Step 3. Set iteration counter k=0. Let $P_{gi}^{(c)}$; i =1,2,...,NG. Set $\gamma_{max}^{(k)}$ and $\gamma_{max}^{(c)}$.

Step 4. Set j =2 and perform an exploratory move as follows:

4.1 Set P_{Gi}; i =1,2,...,NG.

4.2 Find out function outcomes, using sub algorithm 3.3 and set:

$$\gamma = \gamma(P_{G1},.,P_{Gj},.,P_{GNG}) \quad \gamma^+ = \gamma(P_{G1},.,P_{Gj}+\Delta,.,P_{GNG})$$
$$\gamma^- = \gamma(P_{G1},.,P_{Gj}-\Delta,.,P_{GNG})$$

4.3 Find $\gamma_{max} = \max(\gamma, \gamma^+, \gamma^-)$. If $\gamma_{max} > \gamma^{(c)}{}_{max}$ $\gamma^{(c)}{}_{max} = \gamma_{max}$ and $P_{Gj}^{(c)}$ corresponding to γ_{max}.

4.4 If j < NG, update j = j + 1 and GO TO 4.1

4.5 If $\gamma^{(c)}{}_{max} \le \gamma^{(k)}{}_{max}$ GO TO Step 6.

Step 5. Else set $\gamma^{(k+1)}{}_{max} = \gamma^{(c)}{}_{max}$ $P^{(k+1)}{}_{Gi} = P^{(c)}{}_{Gi}$;i = 1,2,...,NG and GO TO Step 7;

Step 6. If $\|\Delta\| < \epsilon$, Then GO TO 11; Else set $\Delta = \Delta / \alpha$ and GO TO Step 4.

Step 7. Set k = k+1 and perform the pattern move as follows:

$$P_{Gi}^{(k+1)} = P_{Gi}^{k} + (P_{Gi}^{k} - P_{Gi}^{(k-1)}) \quad ;I=1,2,...,NG$$

Step 8. Calculate membership functions using sub algorithm 3.3 and find out

$$?^{(k+1)}_{max} = \text{Min}\left\{\mu\left(F_j\right); j = 1,2,...NOB\right\}$$

Step 9. If $\gamma_{max}^{(k+1)} > \gamma_{max}^{(k)}$, then "pattern move is a success"; GO TO 7.

Step 10. Else set $P_{gi}^{(c)} = P_{gi}^{(k)}$; i = 1,2,...,NG and GO TO Step 6.

Step 11. Stop.

Sub-algorithm:

Step 1: Run decoupled load flow.

Step 2: Compute power loss using eq 8. and active power line flows using Eq 11.

Step 3: Evaluate objectives $\overline{F_i}; i = 1,2,\ldots,4$ using Eq 4, 6, 7 and 14, respectively.

Step 4: Evaluate the membership functions $\mu\left(\overline{F}_i\right); i = 1,2,\ldots,4$ by using Eq. 12 and $\mu\left(\overline{F}_5\right)$ by Eq 15.

Step 5: Then fitness value γ is selected as given below:

$$? = \min\left\{ \mu(F_j) \quad ; j = 1,2,...,NOB \right\}$$

Test system and results: The validity of the proposed method is demonstrated on an IEEE 5-generators, 25-bus, 35-lines, power system[1,3]. The non-inferior solutions for different generation combinations are searched, using GA based search method and Hooke-Jeeves pattern search method, considering all the objectives simultaneously. The preferred solutions are selected using min-max technique, for the following cases.

Case 1: All the coefficients of variance and covariance are considered as zero.

Case 2: $C(V_i) = 0.05$; $C(\delta_i) = 0.10$; $i = 1,2,\ldots,NB$
$R(V_i,V_j) = R(\delta_i,\delta_j) = 1.0; i = 1,2,\ldots,NB; j = 1,2,\ldots,NB$

Case 3:

$$C(a_i) = C(b_i) = C(d_i) = C(e_i) = 0.10;\ C(P_{Gi}) = 0.10$$

$$R(a_i,P_{Gi}) = R(b_i,P_{Gi}) = R(d_i,P_{Gi}) = R(e_i,P_{Gi}) = 1.0 \quad I = 1,2,\ldots,NG \quad i = 1,2,\ldots,NG$$

$$R(P_i,P_j) = 1.0 \quad ;I = 1,2,\ldots,NB;\ j = 1,2,\ldots,NB$$

Case 4:

$$C(a_i) = C(b_i) = C(d_i) = C(e_i) = 0.10;$$

$$; i = 1,2,\ldots,NG$$

$$R(a_i,P_{Gi}) = R(b_i,P_{Gi}) = R(d_i,P_{Gi}) = R(e_i,P_{Gi}) = 1.0$$

$$; i = 1,2,\ldots,NG$$

$$R(P_i,P_j) = 1.0$$

$$;i = 1,2,\ldots,NB;\ j = 1,2,\ldots,NB$$

Case 5:

$$C(P_{Gi}) = 0.10,\ C(V_i) = 0.05,\ C(\delta_i) = 0.10,$$

$$;I = 1,2,\ldots,NG$$

$$C(V_i) = 0.05\ \ C(P_{Gi}) = 0.10\ C(\delta_i) = 0.10$$

$$;i = 1,2,\ldots,NG$$

$$R(a_i,P_{Gi}) = R(b_i,P_{Gi}) = R(d_i,P_{Gi}) = R(e_i,P_{Gi}) = 1.0$$

$$;I = 1,2,\ldots,NG$$

$$R(P_i,P_j) = R(V_i,V_j) = R(\delta_i,\delta_j) = 1.0$$

$$;I = 1,2,\ldots,NB;\ j = 1,2,\ldots,NB$$

Generations P_{Gi}, i=1,2,...,NG are searched between minimum and maximum capacity limits of generators and necessary input data are assumed. Factors σ_1, σ_2 for line flows are taken as 0.5 and 1.5 respectively. For search by GA, size of population S is 25, total length of string, 171, length of each sub-string x_i is 35, 34, 34, 33 and 35 respectively, crossover probability, p_c varies from 0.5 to 0.8 for different cases, mutation probability, p_m is 0.01 and maximum number of generations, K^{max} is 25. For search by HJ method, step factor Δ and step reduction factor α have been taken as 0.3 and 2.0, respectively.

RESULTS AND DISCUSSION

Different case has been formed by taking diverse combination of variations of various random parameters. Genetic algorithm based on evolutionary search technique and Hooke-Jeeves pattern search techniques have been used to solve the stochastic multi-objective optimization problem. Evolutionary computing is an adaptive search technique based on the principles of genetics and natural selection. Genetic algorithms search for many points in the search space at once, and yet continually narrow the focus of the search to the areas of the observed best performance.

Table 1 shows the cost and emission coefficients of generators. Table 2 shows the optimum generation schedules obtained by the two search methods for all the five cases. It is clear from the table that optimum schedule is different for different combinations. Therefore optimum solution obtained for deterministic case will not remain optimum if any or some of the system parameters are varied. So there is a need to reschedule the active power generation. Objective function values and membership function values (Table 3 and 4). Table 5 shows that all the active power line flows are well below their respective power flow ratings i.e. line security is fully maintained while scheduling the active power generations of generators. Table 6 shows the bus voltages for Case-1 and Case-5.

Both the methods used here are search methods; therefore no derivatives of any objective function are required to be evaluated for minimizing them. From Table 3 and 4 it is observed that no method can be said to be superior to the other one in terms of objective function values.

Table 1: Cost curve coefficients and emission curve coefficients

Gen. No.	a_i (Rs/h)/MW^2	b_i (Rs/h) MW^{-1}	c_i Rs h^{-1}	d_i (Kg/h)/MW^2	e_i (Kg/h) MW^{-1}	f_i Kgh^{-1}
1	15.0	180.0	40.0	120.0	-55.5	30.0
2	30.0	180.0	60.0	150.0	-55.5	50.0
3	12.0	210.0	100.0	105.0	-135.5	60.0
4	80.0	200.0	25.0	180.0	-80.5	80.0
5	10.0	200.0	120.0	80.0	-60.0	45.0

Table 2: Generation schedules corresponding to optimum solutions for different cases

Case No.	Searchmethod	P_{G1}, (pu)	P_{G2}, (pu)	P_{G3}, (pu)	P_{G4}, (pu)	P_{G5}, (pu)
1	GA	2.475076	0.898906	1.642670	0.680522	1.739848
	HJ	2.461355	0.807719	1.583164	0.657045	1.931457
2	GA	2.475077	0.898906	1.642670	0.680522	1.739848
	HJ	2.457163	0.833353	1.597227	0.644740	1.909485
3	GA	2.441334	0.907675	1.642541	0.690836	1.756214
	HJ	2.419284	0.923442	1.625351	0.621303	1.857923
4	GA	2.469561	0.963452	1.550374	0.682056	1.772649
	HJ	2.362998	0.838900	1.657217	0.655336	1.933889
5	GA	2.484206	0.963461	1.532099	0.680689	1.776775
	HJ	2.441326	0.873451	1.639561	0.746875	1.732298
$\overline{P}_{Gi}^{min}$		0.5	0.2	0.3	0.1	0.4
$\overline{P}_{Gi}^{max}$		3.0	1.25	1.75	0.75	2.5

Table 3: Objective function values

Case No.	Searchmethod	Cost F_1 Rs h^{-1}	Emission F_2 Kg h^{-1}	Power, Variance F_3 (Pu)^2	Power Mismatch F_4 (Pu)	Execution- Time (Sec)
1	GA	1997.182	1161.168	0.0	0.000004	36.36
	HJ	1995.963	1164.444	0.0	0.000001	10.27
2	GA	1997.183	11.61.169	0.0	0.002606	36.53
	HJ	1995.285	1162.555	0.0	0.002671	10.44
3	GA	2007.562	1165.645	0.138332	0.000325	36.30
	HJ	2004.162	1166.366	0.138656	0.000345	13.12
4	GA	2017.122	1199.853	0.553252	0.001288	36.14
	HJ	2017.493	1171.938	0.554778	0.001381	11.64
5	GA	2016.889	1205.133	0.553124	0.003910	37.57
	HJ	2021.927	1185.057	0.552571	0.003844	17.63
$\overline{F}_i^{min}$		1980.0	1040.0	0.01	0.0001	
$\overline{F}_i^{max}$		2100.0	1300.0	0.8	1.0	

Table 4: Membership function values

Case No.	Searchmethod	$\mu(\overline{F}_1)$	$\mu(\overline{F}_2)$	$\mu(\overline{F}_3)$	$\mu(\overline{F}_4)$	$\mu(\overline{F}_5)$	Fitness, γ
1	GA	0.856813	0.533967	1.0	1.0	0.519647	0.519647
	HJ	0.866975	0.521369	1.0	1.0	0.521403	0.521369
2	GA	0.856812	0.533967	1.0	0.997494	0.517168	0.517168
	HJ	0.872626	0.528634	1.0	0.997429	0.528567	0.528567
3	GA	0.770320	0.516750	0.837554	0.999775	0.513728	0.513728
	HJ	0.798646	0.513978	0.837145	0.999755	0.513854	0.513854
4	GA	0.690654	0.385180	0.312339	0.998812	0.524580	0.312339
	HJ	0.687555	0.492545	0.310408	0.998719	0.504051	0.310408
5	GA	0.692589	0.364874	0.312501	0.996189	0.525170	0.312501
	HJ	0.650611	0.442088	0.313201	0.996256	0.500089	0.313201

In case of GA length of sub-strings have to be calculated depending upon the accuracy of search required. Also crossover probability has to be varied for different cases of variations of parameters and variables to satisfy the constraint of line power flow security. For solving the problem by HJ method, proper initial guess is required for starting base case and for step factor. It is done by having some initial trial runs of the program. It is observed from Table 3 that the execution time required by GA is 2-3 times that required by HJ method with a CPU clock frequency of 200 MHz.

CONCLUSIONS

Power system generation is subjected to various changes due to uncertainties and inaccuracies in the measurement and forecasting of various parameters of the network. There may be changes in active power load demands or variations in characteristic coefficients of generators and hence deviations in the generator power outputs, variation of cost coefficients and gaseous emission coefficients; variation in bus voltages etc. To take these variations into

Table 5: Line flows and line flow ratings [1], for 25-bus system

Line	Case-1		Case-2		Case-3		Case-4		Case-5		Rating
No.	GA	HJ	GA	HJ	GA	HJ	GA	HJ	GA	HJ	(pu)
1	0.428	0.388	0.429	0.401	0.432	0.432	0.396	0.437	0.387	0.424	0.460
2	0.383	0.399	0.384	0.395	0.381	0.381	0.396	0.379	0.401	0.386	0.490
3	0.074	0.111	0.074	0.109	0.087	0.115	0.102	0.129	0.102	0.079	0.170
4	0.007	0.014	0.007	0.009	0.002	0.002	0.007	0.021	0.007	0.012	0.080
5	0.262	0.256	0.263	0.259	0.259	0.262	0.258	0.254	0.258	0.254	0.360
6	0.325	0.320	0.326	0.323	0.322	0.325	0.321	0.318	0.322	0.318	0.420
7	0.152	0.152	0.152	0.156	0.158	0.175	0.196	0.152	0.200	0.148	0.300
8	0.325	0.281	0.326	0.293	0.326	0.326	0.335	0.297	0.334	0.316	0.390
9	0.322	0.274	0.323	0.287	0.323	0.322	0.332	0.290	0.331	0.312	0.380
10	0.255	0.254	0.256	0.252	0.248	0.231	0.211	0.255	0.208	0.260	0.260
11	0.447	0.430	0.449	0.436	0.449	0.449	0.433	0.452	0.430	0.446	0.490
12	0.266	0.300	0.266	0.309	0.262	0.325	0.273	0.306	0.275	0.217	0.430
13	0.398	0.403	0.399	0.402	0.401	0.398	0.402	0.405	0.403	0.407	0.440
14	0.249	0.254	0.249	0.253	0.252	0.249	0.253	0.256	0.253	0.258	0.260
15	0.297	0.332	0.298	0.326	0.299	0.308	0.298	0.327	0.300	0.302	0.370
16	0.737	0.837	0.739	0.824	0.746	0.786	0.752	0.835	0.756	0.747	1.030
17	0.456	0.513	0.457	0.513	0.461	0.513	0.473	0.522	0.475	0.437	0.530
18	0.000	0.001	0.000	0.004	0.007	0.023	0.044	0.000	0.047	0.004	0.100
19	0.058	0.043	0.058	0.047	0.058	0.057	0.061	0.048	0.060	0.055	0.075
20	0.112	0.084	0.112	0.091	0.113	0.113	0.119	0.095	0.118	0.105	0.150
21	0.071	0.046	0.071	0.051	0.071	0.066	0.073	0.051	0.073	0.067	0.075
22	0.053	0.017	0.053	0.027	0.055	0.057	0.063	0.032	0.062	0.044	0.080
23	0.079	0.105	0.079	0.100	0.080	0.084	0.077	0.099	0.078	0.084	0.110
24	0.063	0.071	0.064	0.070	0.065	0.069	0.066	0.072	0.066	0.064	0.080
25	0.013	0.020	0.013	0.020	0.014	0.019	0.016	0.021	0.016	0.013	0.025
26	0.011	0.016	0.011	0.009	0.012	0.013	0.018	0.006	0.017	0.004	0.026
27	0.225	0.209	0.226	0.214	0.227	0.227	0.212	0.229	0.209	0.224	0.230
28	0.076	0.092	0.077	0.088	0.075	0.075	0.089	0.073	0.093	0.079	0.130
29	0.129	0.134	0.129	0.137	0.129	0.147	0.134	0.139	0.135	0.116	0.200
30	0.023	0.018	0.023	0.015	0.022	0.005	0.017	0.013	0.017	0.035	0.050
31	0.142	0.147	0.142	0.145	0.145	0.142	0.146	0.149	0.146	0.150	0.150
32	0.183	0.193	0.183	0.190	0.189	0.183	0.191	0.197	0.191	0.199	0.200
33	0.102	0.097	0.103	0.100	0.100	0.102	0.098	0.095	0.099	0.095	0.160
34	0.084	0.089	0.084	0.087	0.087	0.084	0.088	0.091	0.088	0.092	0.095
35	0.067	0.062	0.067	0.064	0.064	0.066	0.063	0.060	0.063	0.059	0.105

Table 6: Voltage profile at the buses

Bus	Case-1. ||(pu)		Case-5. ||(pu)		Load Demand (pu)	
No.	GA search	HJ Search	GA search	HJ Search	P_{di}	Q_{di}
1	1.03000	1.03000	1.03000	1.03000	2.00	0.65
2	1.00200	1.00200	1.00200	1.00200	0.10	0.03
3	1.05000	1.05000	1.05000	1.05000	0.50	0.17
4	1.01500	1.01500	1.01500	1.01500	0.30	0.10
5	1.00700	1.00700	1.00700	1.00700	0.25	0.08
6	1.00596	1.00596	1.00668	1.00588	0.15	0.05
7	0.98794	0.98846	0.98788	0.98806	0.15	0.05
8	0.98821	0.98880	0.98814	0.98834	0.25	0.00
9	0.97994	0.97990	0.97993	0.97995	0.15	0.05
10	0.99119	0.99143	0.99122	0.99123	0.15	0.05
11	0.99219	0.99244	0.99225	0.99222	0.05	0.00
12	0.98998	0.99046	0.98998	0.99007	0.10	0.00
13	1.01196	1.01197	1.01250	1.01190	0.25	0.08
14	0.98029	0.98086	0.98090	0.98037	0.20	0.07
15	0.97707	0.97756	0.97760	0.97713	0.30	0.10
16	0.98830	0.98873	0.98875	0.98836	0.30	0.10
17	0.99484	0.99515	0.99494	0.99486	0.60	0.20
18	0.99044	0.99045	0.99043	0.99056	0.15	0.05
19	1.00807	1.00777	1.00798	1.00820	0.15	0.05
20	0.99327	0.99324	0.99325	0.99322	0.25	0.08
21	0.98358	0.98356	0.98356	0.98354	0.20	0.07
22	0.97480	0.97486	0.97485	0.97489	0.20	0.07
23	0.99779	0.99779	0.99779	0.99779	0.15	0.05
24	0.97201	0.97200	0.97200	0.97198	0.15	0.05
25	0.97980	0.97979	0.97980	0.97979	0.25	0.08

account, a stochastic multi-objective problem has been formed and random nature of various parameters has been considered by coefficients of variance and covariance. The expected values of various objective functions are calculated instead of deterministic ones. It is clear from the results that generations need rescheduling if system parameters are varied. Genetic algorithm and Hooke-Jeeves search methods have been used to search the optimum active power generation schedules to solve the stochastic multi-objective problem. Constraints are taken as the additional objectives to be optimized. The solution procedure is very simple in the sense that no derivative of any function, neither of first order nor of second order is required to be evaluated. Therefore no function discontinuities are involved. Convergence of solution is ensured. To obtain the optimum solution while maintaining the security of all the transmission lines, methods are sensitive to the range of minimum and maximum limits of objective function values taken.

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