Optimal Generation Schedule of Power System Considering Nuclear Power Plant with Application of Genetic Algorithms

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ABSTRACT

Power system generation scheduling is an important issue from technical, economic and environmental safety viewpoints. It involves multiple, sometimes conflicting optimization criteria for which no unique optimal solution with respect to all criteria can be determined. Nuclear safety is one of the key parameters for power systems, which include nuclear power plants.

The expected results indicate how the nuclear power plant should operate and how the other power plants in the system should operate in order that the overall production costs and emission of pollutants are minimized.

1. INTRODUCTION

Economic dispatch (ED) is one of the most important tasks to solve in power system operation and planning [1]. The purpose of the ED is to schedule the outputs of all available generation units in the power system in order to minimize the fuel cost while satisfying all unit and system equality and inequality constraints. Except minimization of operational cost also, minimization of the emission of gaseous pollutants is considered. The latter is known as environmental dispatching (EMD) [3]. Solving both, ED and EMD optimization problems simultaneously, makes this problem a multi-objective optimization problem [4].

Various methods and algorithms have been developed so far to solve the economic-environmental power dispatch problem. The main feature of such methods is that they all convert the multi-objective optimization problem into a single-objective optimization problem [5]. Some methods involve the use of the genetic algorithm [6], particle swarm optimization [7], simulated annealing [8], and Hopfield neural network [3].

The objective of this study is to minimize simultaneously both the fuel cost and the emission cost, as well as to examine the effect that the nuclear power plant (NPP) will have on the power system. A genetic algorithm (GA) approach is used in this study to solve the
problem. To satisfy all unit and system equality and inequality constraints a penalization method based on fuzzy logic is introduced.

In this study an example power system consisting of thermal power plants (including one nuclear power plant) as well as hydro power plants was considered. It is considered that each of the plants can be consisted from one or more generating units. The mathematical model used is presented as well as the fuzzy penalization (FP) method. Two case studies are performed, each of them presenting an optimal generation schedule solution which depends on the operation of the nuclear power plant included in the system. The obtained solutions are presented in figures.

2. PROBLEM FORMULATION

Thermal generation costs consist of the generation costs associated with the operation of both fossil-fuel units (FFUs) and NPPs. In this study, they were analysed separately due to the large differences between them [9]. It was considered that hydro generating units have negligible costs.

2.1. Fuel cost function

The fuel cost for each thermal generating unit (including FFUs and NPP) in the system is determined by a second order function of the active power generation:

\[ f_c = \sum_{i=1}^{T} \sum_{j=1}^{I} (a_i + b_i P_{G_{ij}} + c_i P_{G_{ij}}^2) \Delta t_t \]  

(1)

where \(a_i\) ($/h), \(b_i\) ($/MWh), and \(c_i\) ($/MW^2h) are constants which are unique for each generating unit; \(P_{G_{jt}}\) is the power output of the \(j\)th thermal unit at time interval \(t\); \(T\) is the number of considered time intervals under study, \(I\) is the number of thermal units; \(\Delta t_t\) is the duration of each time interval.

2.2. Emission function

The total emission of atmospheric pollutants from all FFUs in the system during the studied time period is determined as follows:

\[ f_e = \sum_{i=1}^{T} \sum_{j=1}^{I} (a_i + \beta_i P_{G_{ij}} + \gamma_i P_{G_{ij}}^2 + \eta_i \exp(\lambda_i P_{G_{ij}})) \Delta t_t \]

(2)

where \(\alpha_i\) (t/h), \(\beta_i\) (t/MWh), \(\gamma_i\) (t/MW^2h), \(\eta_i\) (t/h), and \(\lambda_i\) (1/MW) are constants which are unique for each FFU. It was considered that the coefficients \(\alpha_i, \beta_i, \gamma_i, \eta_i, \text{ and } \lambda_i\) are equal to zero for NPP.

2.3. Constraints

a) Power balance constraint

The power balance equations constraint means that the sum of output powers of all generating units must be equal to the total load demand at each time interval, and it is expressed as follows:

\[ \sum_{i=1}^{I} P_{G_{it}} + \sum_{j=1}^{J} P_{H_{jt}} = P_{Lt} \quad t = 1, 2, \ldots, T \]

(3)
where $J$ is the number of reservoirs; $P_{H_{j,t}}$ is the water-to-power conversion function of the power plant associated with reservoir $j$.

b) Generator capacity constraints

The generator capacity constraints are expressed as follows:

$$P_{G_{i,t}}^{\text{min}} \leq P_{G_{i,t}} \leq P_{G_{i,t}}^{\text{max}}; \quad P_{H_{i,t}}^{\text{min}} \leq P_{H_{i,t}} \leq P_{H_{i,t}}^{\text{max}}$$ (4)

where $P_{G_{i,t}}^{\text{min}}$ and $P_{G_{i,t}}^{\text{max}}$ are the minimum and maximum power outputs for the $i$th thermal unit respectively; $P_{H_{i,t}}^{\text{min}}$ and $P_{H_{i,t}}^{\text{max}}$ are the minimum and maximum power outputs for the $j$th hydro unit respectively.

The power produced by each thermal unit is bounded by its ramping response rate limits as follows:

$$-MI_{i} \leq P_{G_{i,t}} - P_{G_{i,t-1}} \leq MD_{i}$$ (5)

where $MI_{i}$ and $MD_{i}$ are the maximum increase and the maximum decrease in the output of the $i$th thermal unit over one time interval.

c) Hydraulic constraints

Water volume in each reservoir $j$ at each time interval $t$ is determined as follows:

$$V_{j,t+1} = V_{j,t} - X_{j,t} + I_{j,t}, \quad t = 0,1,2, \ldots, T-1$$ (6)

where $I_{j,t}$ is the inflow volume in the $j$th reservoir during time interval $t$.

Physical volume limitations of each reservoir in storage are expressed as follows:

$$V_{j}^{\text{min}} \leq V_{j,t} \leq V_{j}^{\text{max}}; \quad X_{j}^{\text{min}} \leq X_{j,t} \leq X_{j}^{\text{max}}$$ (7)

where $V_{j}^{\text{min}}$ and $V_{j}^{\text{max}}$ are the minimum and maximum water volumes for the $j$th reservoir respectively; $X_{j}^{\text{min}}$ and $X_{j}^{\text{max}}$ are the minimum and maximum water discharge volumes from the $j$th reservoir respectively.

The initial and final reservoir storage volumes are expressed as follows:

$$V_{j,t}^{\text{start}} = V_{j}^{\text{begin}}, \quad V_{j,t}^{\text{end}} = V_{j}^{\text{end}}$$ (8)

where $V_{j}^{\text{begin}}$ and $V_{j}^{\text{end}}$ are the initial and final water volumes in the $j$th reservoir.

2.4. Objective function

Functions $f_{C}$ and $f_{E}$ represented by Eq. (1) and Eq. (2) respectively, are the objective functions i.e. the functions that are to be minimized. Aggregating the objectives and constraints, the economic-environmental power dispatch optimization problem can be mathematically formulated as a nonlinear, constrained, multi-objective optimization problem as follows:

$$\text{Minimize } [f_{C}(P_{G_{i,t}}), f_{E}(P_{G_{i,t}})]$$ (9)
subject to:
\[ g(x) = 0; \quad h(x) \leq 0 \]  
(10)

where \( g(x) \) and \( h(x) \) are the equality and inequality problem constraints, respectively; \( x \) is decision vector that represents possible solution.

3. PROBLEM SOLUTION

3.1. Multi objective optimization

The multi-objective, economic-environmental power dispatch optimization problem described with (9) is transformed into single-objective optimization problem as follows:

\[ \text{Minimize } f = w f_c + (1 - w) \sigma f_e \]  
(11)

where \( \sigma \) is scaling factor and \( w \) is weighting factor which is varied.

The scaling factor is applied to approximately equalize the values of the cost function \( f_c \) and the emission function \( f_e \), giving them equal chances to be minimized.

3.2. Application of genetic algorithm

GA is an evolutionary searching technic based on the mechanics of natural selection and natural genetics. GA is an attractive alternative to other optimization approaches because of its robustness. The main GA operators are initial population, selection, crossover and mutation.

The method for solving economic-environmental power dispatch optimization problem based on GA and FP is discussed in detail in this section.

a) Initial population

The GA begins with an initial population of \( N_p \) chromosomes being defined. All variables from each chromosome in the initial population are randomly determined using a uniform probability distribution, covering the entire search space uniformly. Each chromosome from the initial population is represented by a matrix of \( N_{l+1} \times N_r \) random values as follows:

\[ C_k = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,\tau} \\ \vdots & \ddots & \vdots & \vdots \\ P_{l,1} & P_{l,2} & \cdots & P_{l,\tau} \\ X_{1,1} & X_{1,2} & \cdots & X_{1,\tau} \\ \vdots & \ddots & \vdots & \vdots \\ X_{l,1} & X_{l,2} & \cdots & X_{l,\tau} \end{bmatrix} \quad k = 1, 2, \ldots, p \]  
(12)

Using the hydro discharges from Eq. (12), the water volumes at different intervals for each of the reservoirs are determined and hydro generations are calculated. Due to the possible violation in constraints, penalty functions are used. Therefore, the fitness function from (11) is upgraded as follows:

\[ \Phi = f + \Phi_{\text{pen}} \]  
(13)
where

\[ \Phi_{pen} = \sum_{m=1}^{N_1} \delta_m \cdot VIO_L \]  \hspace{1cm} (14) \]

where \( N_1 \) is the number of constraints; \( \delta_m \) is the penalty factor and \( VIO_L \) is the constraint violation. The penalty functions are discussed in details later in this section.

\( b) \) Selection

When the initial population is determined it is time to decide which chromosomes in the initial population are fit enough to survive and possibly reproduce offspring in the next generation. Thus, the fitness function is evaluated for each of the chromosomes in the population and associated chromosomes are ranked from the lowest value to the highest value [10]. Then, only the best are selected to continue, while the rest are deleted. The chromosomes that survive are then selected to reproduce. The method that is used in this study is the well-known roulette wheel method.

\( c) \) Crossover

The crossover operator is used for the creation of one or more offspring from the parents selected during the selection process. Some variables are chosen in each of the parents and swapped with each other [10]. The most common form of crossover involves one point, two points and uniform crossover. In this study uniform crossover was used.

\( d) \) Mutation

Most of the optimized functions often have many local minima and the GA can be caught in one of them. To avoid this problem, the GA is forced to explore other areas of the cost surface by randomly introducing changes/mutations [10].

3.3. Fuzzy penalization

When GA algorithms are used for constrained optimization problems, it is common to handle constraints using concepts of penalty functions, which penalize unfeasible solutions, i.e. one attempt to solve an unconstrained problem is to use a modified fitness function (13).

In this paper a new penalty method, based on fuzzy logic, is proposed. Each of the constraints which are initially not included in the initial population, are described by unique membership functions [11]. Therefore, the following membership functions are constructed:

\( a) \) Membership function for the power balance constraint

The power balance constraint requires that the sum of the generation from all generating units \( (P_g) \) at each time interval \( (\bar{t}) \) must be equal to the load demand \( (P_L) \). Because the probability that these values will differ from each other, the difference in percent \( (\Delta P_L) \) is calculated and is covered by the membership function \( \mu_{\bar{t}} \) as shown on Figure 1 a). The membership value is 1 when \( \Delta P_L = 0 \) and smaller than 1 when \( \Delta P_L \) is greater than 0. The membership function is expressed as follows:

\[ \mu_{\bar{t}} = \frac{1}{1 + \eta (\Delta P_L)^2} \]  \hspace{1cm} (15) \]

where
\[
\Delta P_{lt} = \frac{P_{lt}^s - P_{lt}^t}{P_{lt}^t} \times 100\%
\]  

(16)

\(\eta_P\) the shape parameter.

The overall violation of power balance constraint is determined as

\[VIOL_P = \sum_{t=1}^{T}(1 - \mu_{P_t}).\]

b) Membership function for the water balance at each time interval constraint

The water balance at each time interval constraint requires that water volume \(V_j\) in each reservoir \(j\) must be within the reservoir limits at each time interval \(t\). Because the probability that these values will differ from each other, the difference in percent \(\Delta V_{jt}\) is calculated and is covered by the membership function \(\mu_V\) as shown on Figure 1 b). The membership function is expressed as follows:

\[
\mu_{V_{jt}, V_j} = \begin{cases} 
1 & V_{jt} < V_j^{\min} \\
\frac{1}{1 + \eta_V (V_j^{\min} - V_{jt})^2} & V_j^{\min} \leq V_{jt} \leq V_j^{\max} \\
1 & V_{jt} > V_j^{\max}
\end{cases}
\]  

(17)

where

\[
\Delta V_{jt}^- = \frac{V_j^{\min} - V_{jt}}{V_j^{\min}} \times 100\%; \quad \Delta V_{jt}^+ = \frac{V_{jt} - V_j^{\max}}{V_j^{\max}} \times 100\%
\]  

(18)

\(\eta_V\) is the shape parameter.

The overall violation of water balance at each time interval constraint is determined as

\[VIOL_V = \sum_{j=1}^{J} \sum_{t=1}^{T}(1 - \mu_{V_{jt}, V_j}).\]

Figure 1: Membership function for the: a) power balance constraint and b) water balance at each time interval constraint

Basically, all equality and inequality constraints can be solved using the above described concept.
4. RESULTS

The example system comprises six thermal units (five FFUs and one NPP) and four hydro units. The thermal and hydro unit data used for the example system is according to reference [11]. For this study, crossover and mutation ratios were taken to be 0.85 and 0.001 respectively and population size of 80 chromosomes was used. The number of time intervals is 24 and each time interval is equal to 1 hour.

The optimal fuel cost for the example system for case 1 is 422.23 K$ and the total emission of sulphur oxides ($SO_x$) and nitrogen oxides ($NO_y$) is 164.62 t. Figure 2 shows that the sum of the total thermal generation and the total hydro generation meet the load demands.

![Figure 2: Hourly thermal and hydro generations for case 1](image)

In case 2, FFU number 4, FFU number 5, and FFU number 6 were replaced with the NPP. The optimal fuel cost for the example system for case 2 is 329.82 K$ and the total emission of sulphur oxides ($SO_x$) and nitrogen oxides ($NO_y$) is 103.91 t. From the results shown in Figure 3 it can be seen that the NPP is running on almost maximum power with very low power variations.

![Figure 3: Hourly thermal and hydro generations for case 2](image)

5. CONCLUSION

Approach based on GA and FP was presented for solving the economic-environmental power dispatch optimization problem considering nuclear power plants. The generation scheduling problem was converted into a numerical formulation and then the GA and FP
based approach was used to solve the problem. Using the proposed approach, fuel cost and emission cost were minimized. To allow the option for the nuclear power plant to follow the load, minimum power output was set to be at 80%.

Comparing the results from both of the case studies it can be seen that the cost and the air pollutants emission are significantly decreased when the NPP is considered in the system. Also, NPP is running on almost maximum power with very low power variations.

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