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Economic Load Dispatch of Thermal Power Plants Using Particle Swarm Optimization Technique

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ABSTRACT

The unit commitment is one of the key functions of modern energy management system and this problem is formulated as a non-linear, mixed integer constrained optimization problem with the objective of generation allocation to the power generators to minimize the total fuel cost of the power generators while satisfying all operating constraints. Unit commitment (UC) in a power system involves determining a start-up and shutdown schedule of units to meet the forecasted demand, over a short-term period. In solving the unit commitment problem, generally two basic decisions are involved, namely the "unit commitment" decision and "economic dispatch" decision. The "unit commitment" decision involves determination of the generating units to be running each hour, considering system capacity requirement, including the reserve, and constraints on the start-up and shutdown of the units. The "economic dispatch" decision involves the allocation of system demand and spinning reserve capacity among the operating units during each specific hour of operation. In this work an integer programming based optimization technique is proposed for solving unit commitment problem of thermal generating units.

INTRODUCTION

In a vertically integrated system, the primary objective of power system operation is to ensure that users demand is met at the lowest cost. This objective explicitly specifies an optimization problem with a cost function to be minimized and a variety of constraints describing the operating limits to be satisfied. Meeting this objective by properly controlling the individual components of the power system is a complex task. One of the difficulties associated with power planning is the physical size of the system. The network may have several thousands nodes (buses), lines and the generation mix may include a large number of hydro-plants, thermal plants and renewable energy based plants (wind, solar, biomass and tidal). Another major difficulty in dealing with electrical power systems is the vast range of time intervals over which various processes need to be controlled.

Unit commitment (UC) in a power system involves determining a start-up and shutdown schedule of units to meet the forecasted demand, over a short-term period. In solving the unit commitment problem, generally two basic decisions are involved, namely the "unit commitment" decision and "economic dispatch" decision. The "unit commitment" decision involves determination of the generating units to be running each hour, considering system capacity requirement, including the reserve, and constraints on the start-up and shutdown of the units. The "economic dispatch" decision involves the allocation of system demand and spinning reserve capacity among the operating units during each specific hour of operation.

With the increase in fuel prices, environmental concerns, and reduction in wind-turbine generating system, the integration of wind power generation in the power system having conventional power generators is increasing. Due to intermittency and unpredictable nature of wind, the wind power generation is not reliable and also it creates difficulty in the control of frequency and scheduling of generation.

Other issues such as voltage disturbance ride-through capability will affect opportunities for wind generation. Therefore, the determination of optimal wind power generation, which can be integrated in to the emerging power system is very important. Electricity generated from wind power can be highly variable at several different timescales: from hour to hour, daily, and seasonally. Annual variation also exists, but is not as significant. Because of instantaneous electrical generation and consumption must remain in balance to maintain grid stability, this variability presents substantial challenge to incorporating large amounts of wind power into a grid system.

State of the art

UC problem has commonly been formulated as a nonlinear large scale, mixed-integer combinatorial optimization problem with constraints. The exact solution to the problem can be obtained only by complete enumeration, often at the cost of prohibitively computation time requirement for realistic power systems. Research endeavors, therefore, have been focused on, efficient, near-optimal UC algorithms which can be applied to large scale power systems and have reasonable storage and computation time requirements. A survey of literature on UC methods reveals that various numerical optimization techniques have been employed to approach the UC problems. Specifically, there are priority list methods , integer programming. dynamic programming , branch and bound methods , mixed-integer programming , and lagrangian relaxation methods. Among these methods, the priority list method is simple and faster but the quality of final solution is approximate. Dynamic programming methods, which are based on priority lists, are flexible but computationally expensive. Branch and bound adopts a linear function to represent the fuel consumption and time dependent start cost, and obtains the required lower and upper bounds. The shortcoming of branch and bound is exponential growth in the execution time with the size of the UC problem. The integer and mixed integer methods adopt a linear programming technique to solve and check for integer solution.

These methods have only been applied to small UC problem and have required major assumptions, which limit the solution space. The lagrangian relaxation method provides a fast solution but it may suffer from numerical convergence and solution quality problems.

Optimization (PSO) techniques are proposed to solve the UC problem of thermal generating units. Many of the PSO based methods reported in the literature use penalty function based methods to satisfying equality constraints but the main disadvantage of using this method is, when the problem is highly constrained, the search space reduces and algorithm will spend a lot of time to find feasible solutions. Here, a new pseudo code based algorithm is proposed to satisfy the equality constraints.

UNIT COMMITMENT OFTHERMAL GENERATING UNITS

Introduction

The unit commitment is one of the key functions of modern energy management system and this problem is formulated as a non-linear, mixed integer constrained optimization problem with the objective of generation allocation to the power generators to minimize the total fuel cost of the power generators while satisfying all operating constraints. Conventional methods usually assume the input-output characteristics of power generators, known as cost curves, to be quadratic or piecewise quadratic, monotonically increasing functions. But the modern generating units have a variety of non-linearity in their cost curves due to valve point loading and other effects, which make this assumption inaccurate and resulting approximate solutions which cause a lot of revenue loss overtime. On the other hand, evolutionary methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are free from convexity assumptions and perform better due to their excellent parallel search capability. Hence, they are particularly popular for solving such nonlinear, non-convex, discontinuous optimization problems.

Several solution strategies have been proposed to provide quality solutions to the Unit Commitment (UC) problem and increase the potential savings of the power system operator. These include deterministic and stochastic search approaches. Deterministic approaches include the priority list method, dynamic programming , Lagrangian relaxation and the branch and bound

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methods . Although these methods are simple and fast, but they suffer from numerical convergence and solution quality problems. The stochastic search algorithms such as particle swarm optimization , genetic algorithms, evolutionary programming , simulated annealing , ant colony optimization and tabu search are able to overcome the shortcomings of traditional optimization techniques. This chapter focuses on unit commitment of thermal generating units using PSO based methods.

Problem Formulation

The objective of the UC problem is to minimize the total operating costs subjected to a set of system and unit constraints over the scheduling horizon. It is assumed that the production cost, $F_i(P_i(t))$ for unit i at any given time interval t, is a quadratic function of the generator power output, P_i

$$F_i(P_i(t)) = a_i P_i^2 + b_i P_i + c_i \qquad (2.1)$$

Each generator cost function establishes the relationship between the power injected to the system by the generator and the incurred costs to load the machine to that capacity as shown in Fig. 2.1. Typically, generators are modeled by smooth quadratic function such as to simplify the optimization problem and facilitate the application of classical techniques.

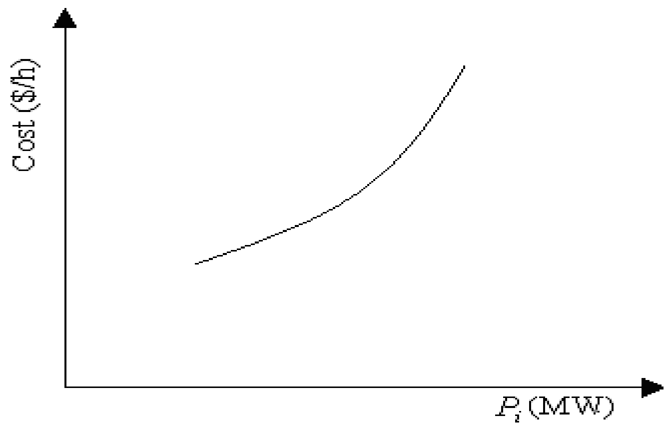

Fig.1: Typical Fuel cost function of a thermal generation unit

The total operating cost, F_T for scheduled period T is the sum of the production costs and the start-up costs. The objective function can written as

$$Minimize \quad F_T = \sum_{t=1}^{T}\sum_{i=1}^{NT}[I_i(t)\times F_i(P_i(t)) + I_i(t)\times(1-I_i(t-1))\times STC_i]$$

Constraints

Equality constraints

The power balance equation is an equality constraint that reduces the power system to a basic principle of equilibrium between total system generation and total system load. Equilibrium is met only when total system generation is equal to the total system load plus system losses. In this work, system losses are ignored. Thus,

$$\sum_{i=1}^{NT} I_i(t)\times P_i(t) = P_L(t)$$

PARTICLE SWARM OPTIMIZATIO TECHINQUES

Introduction

Evolutionary algorithms are optimization techniques that solve the problems using a simplified model of the evolutionary process. These algorithms are based on the concept of individuals that evolve and improve their fitness through probabilistic operators like recombination and mutation. These individuals are evaluated and those that perform better are selected to compose the population in the next generation. After several generations, these individual should improve their fitness as they explore the solution space for the optimal value.

The field of evolutionary computation has experienced significant growth in the optimization due to the recent advances in computation. These algorithms are capable of solving complex optimization problems such as those with a non-continuous, non-convex and highly nonlinear solution space. In addition, these can solve problems having discrete or binary variables.

Particle swarm optimization

Particle Swarm Optimization (PSO) refers to a relatively new family of algorithms that may be used to find optimal solutions to numerical and qualitative problems.

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PSO was introduced by Russell Eberhart and James Kennedy in 1995 [30] inspired by social behavior of birds flocking or fish schooling. It is easily implemented in most programming languages and has proven to be both very fast and effective when applied to a diverse set of optimization problem.

In PSO, the particles are "flown" through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has memory, which allows it to remember the best position on the feasible search space that has ever visited. This value is commonly called $Pbest$. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called $Gbest$. The basic concept behind the PSO technique consists of change in the velocity (or accelerating) of each particle toward its $Pbest$ and $Gbest$ positions at each time step. This means that each particle tries to modify its current position and velocity according to the distance between its current position and $Pbest$, and the distance between its current position and $Gbest$. The position and velocity vectors of the i^{th} particle of a d-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, ... x_{id})$ and $V_i = (v_{i1}, v_{i2}, ... v_{id})$ respectively.

On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $Pbest_i = (P_{i1}, P_{i2}, ... P_{id})$. If the g^{th} particle is the best among all particles in the group so far, it is represented as $Gbest = Pbest_g = (P_{g1}, P_{g2}, .. P_{gd})$.

The particle tries to modify its position using the current velocity and the distance from $Pbest$ and $Gbest$. The modified velocity and position of each particle for fitness evaluation in the next iteration are calculated using the following equations.

$$v_{id}^{k+1`} = w \times v_{id}^{k`} + c_1 \times rand_1 \times (Pbest_{id} - x_{id}^k) + c_2 \times rand_2 \times (Gbest_{gd} - x_{id}^k) \quad (3.1)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1`}$$

Here w is the inertia weight parameter, which controls the global and local exploration capabilities of the particle. c_1, c_2 are cognitive and social coefficients, $rand_1$ and $rand_2$ are random numbers between 0 and 1. For the proposed method, $c_1 = 2, c_2 = 2$. A large inertia weight factor is used during initial exploration and its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight (TVIM) is given by.

$$w = (w_{max} - w_{min}) \times \frac{iter_{max} - iter}{iter_{max}} + w_{min}$$

$$w_{max} = 0.9; w_{min} = 0.4$$

Where, $iter_{max}$ is the maximum number of iterations.

$$iter_{max} = 100.$$

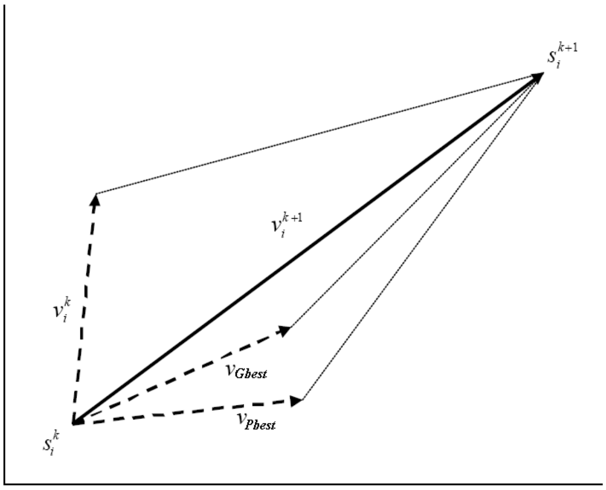

Fig 2: Concept of modification of searching point

Solution of UC problem using New PSO (NWPSO)

The solution of the complex UC problem with ramp rate limits using NWPSO is given in Fig. 3.5. Here cognitive component was split into two different components, $Pbest$ and $Pworst$ i.e., the particle is made to

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remember not only its previous best position but also its previous worst position, while calculating its new velocity. The knowledge about the worst position helps the particle in avoiding its worst position. Its implementation consists of the following steps: *Initialization of the swarm:* For a population size PS, the particles are randomly generated and normalized between the maximum and the minimum operating limits of the generators. If there are NT units, the i^{th} particle is represented as $P_i = (P_{i1}, P_{i2}, ...P_{iNT})$. The j^{th} dimension if the i^{th} particle is allocated a value of $P_{i.j}$, it has to satisfy the following constraint. $P_{i.j} = P_{j\min} + r \times (P_{j\max} - P_{j\min})$

where r is a random number between 0 and 1.

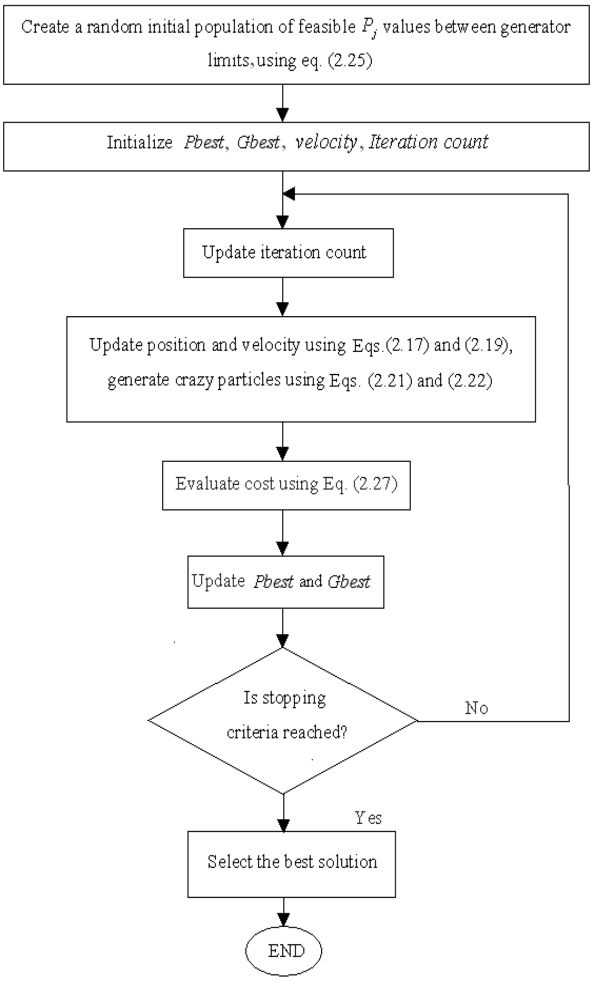

Fig. 3: Flow chart of thermal UC solution using CPSO method

RESULTS

Simulation Results

Four different PSO methods, Normal PSO (PSO), PSO with constriction factor (PSOC), PSO with crazy particles (CPSO) and new PSO (NWPSO) have been used to solve the UC problem of thermal generating units. To examine the effectiveness of the proposed method, a ten-thermal unit test system is considered. The system unit data and load demand are given in Table-4.1 and Table-4.2

A. Two different studies are conducted as follows:

Study-1: Ramp rate of thermal units and spinning reserves of system are not considered.

Study-2: Ramp rate of thermal units and spinning reserves of system are considered.

Study-1

The problem formulated in section 2.2 has been solved with four modified version of PSO. In this studied case, the ramp rate constraints of the generating units are not taken into account and the spinning reserve requirements of the system are also neglected for comparison purpose. Table-4.3 shows the determined commitment schedule of thermal generating units and Table-4.4 gives dispatch power of each unit for 24 hours. The commitment schedule and dispatch schedule is the same for different PSO methods. The cost obtained by proposed PSO methods is also same and it is $78895.5. Table-4.5 depicts the comparison of results of the proposed methods. Among the proposed versions of PSO, the simulation time is less for crazy PSO.

Table 1: Ten unit thermal system data

Unit No	$P_{i,r}^{max}$, MW	$P_{i,r}^{min}$, MW	a_i $/MW²	b_i $/MW	c_i $	STC_i $	$T_{ON,i}$ h	$T_{OFF,i}$ h	Initial Status,h	Initial Power, $/MW
1	60	10	0.0051	2.2034	15	10	3	2	-20	0
2	80	20	0.0040	1.9161	25	12	3	5	-20	0
3	100	30	0.0039	1.8518	40	12	2	2	-10	0
4	120	25	0.0038	1.6966	32	13	3	2	10	80
5	150	50	0.0021	1.8015	29	11	3	2	10	100
6	280	75	0.0026	1.5354	72	18	6	6	10	120
7	320	120	0.0029	1.2643	49	13	8	2	10	300
8	445	125	0.0015	1.2163	82	15	10	5	20	400
9	520	250	0.0013	1.1954	105	14	12	7	20	500
10	550	250	0.0014	1.1285	100	20	12	3	20	500

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Table 2: Load demand for 24 hours

Hour	Load, MW	Hour	Load, MW
1	2000	13	1200
2	1980	14	1160
3	1940	15	1140
4	1900	16	1160
5	1840	17	1260
6	1870	18	1380
7	1820	19	1560
8	1700	20	1700
9	1510	21	1820
10	1410	22	1900
11	1320	23	1950
12	1260	24	1990

Study-2

In this studied case, the ramp rate constraints of the generating units are taken in to account and the spinning reserve requirements of the system were also considered. Table-4.6 shows the determined commitment schedule of thermal generating units and Table-4.7 gives dispatch power of each unit for 24 hours. The commitment schedule and dispatch schedule is the same for all the PSO methods. The cost obtained by proposed PSO methods is also same and it is $78899.

The cost reported in the literature for hybrid dynamic programming (HDP) method is $78911. Table-4.8 depicts the comparison of results of the proposed methods. Among the proposed versions of PSO, the simulation time is less for crazy PSO.

Table 3: Unit commitment schedule for study-1

Unit No.	Hour (1 to 24)
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4	1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
5	1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1
6	1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Convergence characteristics

For study-2, the convergence behavior of different PSO methods was tested using the same fitness function for same number of iterations. The results are shown in Fig. 2.8. It can be concluded from the figure that all the four PSO based methods converged to the global solution, however, among all, CPSO converged quickly to the global solution

Table 4: Convergence characteristics of different PSO methods

Unit No.	Hour (1 to 24)
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4	1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
5	1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1
6	1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

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Table 4: Convergence characteristics of different PSO methods

Algorithm	Total cost in $	Simulation time in Sec
NPSO	78895.5	1.3
PSOC	78895.5	0.75
CPSO	78895.5	0.734
NWPSO	78895.5	1.15

Table 5: Comparison of results for study-2

Algorithm	Total cost in $	Simulation time in Sec
NPSO	78899	1.65
PSOC	78899	1.11
CPSO	78899	1.08
NWPSO	78899	1.42
HDP	78911	1.7

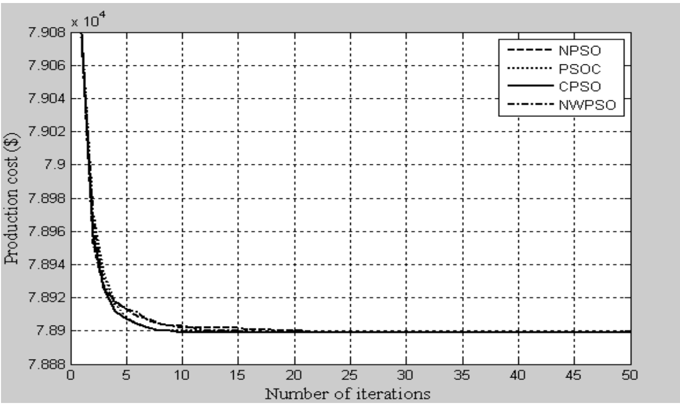

Fig. 4: Convergence characteristics of different PSO methods

Conclusion

This project presents four modified versions of particle swarm optimization (PSO) techniques to solve the unit commitment problem of thermal generating units by considering ramp rate limits and minimum up and down time constraints. A new pseudo code based algorithm is developed for handling equality constraints. A ten-unit test system is simulated to demonstrate the effectiveness of the proposed methods. From the numerical results, it is found that the proposed PSO methods provide a better cost and take less simulation time compared to other conventional methods. Moreover, the crazy PSO gives better results in cost and time compared to the other versions of PSO tested in this project.

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