Economic Load Dispatch of Power System Using Genetic Algorithm with Valve Point Effect

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Abstract. This paper presents the solution of economic load dispatch problem using quadratic cost functions with valve point effect by means of Genetic Algorithm (GA). GA technique is particularly useful for optimization problems with non-convex, discontinuous and non-differentiable solution. In this paper, three methods of GA are used: namely the Micro Genetic Algorithm (MGA), Classical Genetic Algorithm (GA) and Multipopulation (MPGA). The three methods were tested and validated on the Nigerian Grid system made of four thermal power plants and three hydro power stations. The simulation results with and without losses considered are compared. It is shown that the MPGA gives better results in term of minimized production cost than both MGA and GA. However, the MGA is faster in finding a quick feasible solution as a result of its small population size. The results demonstrate the applicability of the three techniques for solving economic load dispatch problem in power system operations.

Keywords: Genetic algorithm · Economic load dispatch · Micro genetic algorithm · Quadratic cost function · Valve point effect

1 Introduction

Economic load dispatch (ELD) is an important task in power systems operations. The aim of ELD is to allocate power generation to match load demand at minimal possible cost while satisfying all the power units and system operation constraints of the different generation resources [1]. Therefore, the ELD problem is a large scale constrained non-linear optimization problem.

For the purpose of economic dispatch studies, online generators are represented by functions that relate their production cost to their power output [2]. For simplicity, the generator cost function is mostly approximated by a single quadratic function. However, because the cost curve of a fossil fired plant is highly non-linear, containing discontinuities owing to valve point loading [3], the fuel cost function is more realistically denoted as a recurring rectified sinusoidal function [4] rather than a single quadratic cost function. The ELD problem is traditionally solved using conventional mathematical techniques such as lambda iteration and gradient schemes. These approaches require that fuel cost curves be increased monotonically to obtain the global optimal solution. Conversely, the units have naturally highly non-linear input-output properties due to valve point effect

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[5]. Also, different approaches such as linear programming and nonlinear programming have been applied to economic load dispatch problem. The main drawback of linear programming methods is that they are associated with the piecewise linear cost approximation although they are fast and reliable and the nonlinear programming approaches are complex [6].

However, with the advent of evolutionary algorithms such as Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Artificial Bee Colony (ABC) etc. which are stochastic based optimization techniques that search for the solution of problems using a simplified model of the evolutionary process found in nature, ELD problems can be solved easily. The success of Evolutionary Algorithms (EAs) is partly due to their inherent capability of processing a population of potential solutions simultaneously, which allows them to perform an extensive exploration of the search space [7]. Although the heuristic methods provide fast and reasonable solutions, they do not always guarantee globally optimal solutions in finite time [6].

Genetic Algorithm methods have been employed successfully to solve complex optimization problems, In this paper, three methods of GA are applied to solve economic load dispatch problem with valve point effect; namely, the Micro Genetic Algorithm (MGA), Classical Genetic Algorithm (GA) and Multipopulation Genetic Algorithm. The simulation results with and without transmission losses are considered in this paper. The performances of these methods are validated using the Nigerian grid system.

2 Problem Formulation

Consider an interconnected power system consisting of n thermal power stations as shown in Fig.1, the ELD problem seeks to find the optimal combination of thermal power plants that minimizes the total cost while satisfying the total demand and system constraints [8].

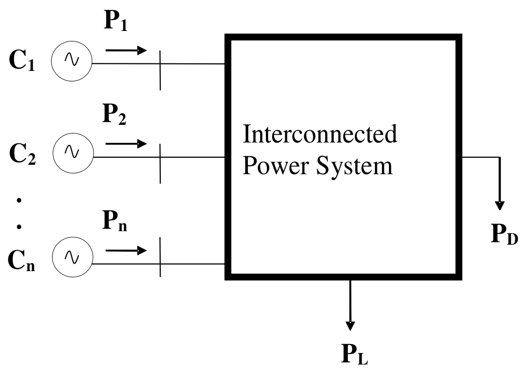

Fig. 1. Interconnected power system

The ELD problem is formulated as follows:

$$\text{Min} \quad C_T = \sum_{i=1}^{n} C_i(P_i) \tag{1}$$

where C_T is the total generation cost .and

$$C_i\,(P_i) = \alpha_i + \beta_i P + \gamma_i P^2 \tag{2}$$

is a quadratic cost function of the i^{th} unit, α_i, β_i, and γ_i are cost coefficient of the i^{th} generator, which are found from the input-output curves of the generators and are dependent on the particular type of fuel used. P_i is the power output of i^{th} unit of thermal plants.

Note that, when the thermal generating unit changes its output, there is a nonlinear cost variation due to valve point effect. Typically, the valve point effect arises because of the ripple like effect of the valve point as each steam begins to open. This is illustrated in Fig. 2 [9]. The fuel cost of a thermal generation unit considering nonlinear effect of valve will be a nonlinear function as given in (3):

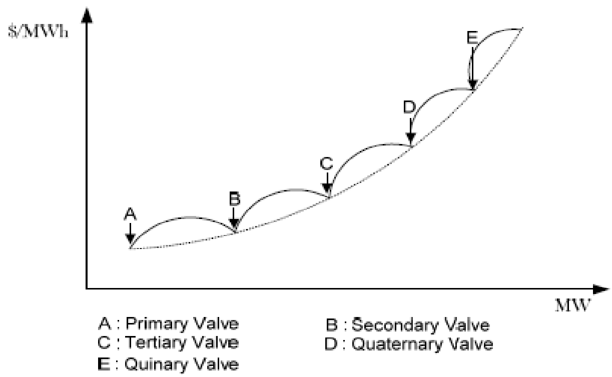

Fig. 2. Valve Point Effect

$$C_i\,(P_i) = \propto_i + \beta_i P_i + \gamma_i P_i^2 \mid e_1 * \sin\,(f_1 * (P_i^{min} - Pi)) \mid \tag{3}$$

where e_i and f_i are cost coefficients of the i^{th} generator.
The minimization is subject to the following constraints:

2.1 Power Balance

The total power generated must to be equal to the sum of load demand and transmission losses as given in eqn. (4):

$$P_D + P_L - \sum_{i=1}^{n} P_i = 0 \tag{4}$$

where:

P_D = the power demand
P_L = the transmission loss

The transmission losses can be represented by the B-coefficient method as shown in eqn. (5):

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \quad (5)$$

where B_{ij} is the transmission loss coefficient.

2.2 Maximum and Minimum Power Limits

The power generated by each generator has some limits and can be expressed as:

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

$P_i^{\min}$ = the minimum power output
$P_i^{\max}$ = the maximum power output

3 Overview of Genetic Algorithm

Genetic Algorithm searches a solution space for optimal solutions to a problem. The key characteristic of GA is how the searching is done. The algorithm creates a "population" of possible solutions to the problem and lets them "evolve" over multiple generations to find better and better solutions. The following steps were used to solve a problem using GA:

1. Create a population of random candidate solution named *pop*.
2. Until the algorithm termination conditions are met, do the following (each iteration is called a generation):
    a. Create an empty population named *new-pop*.
    b. While *new-pop* is not full, do the following:
        i. Select two individuals at random from *pop* so that individuals who are more fit are more likely to be selected.
        ii. Cross-over the two individuals to produce two new individuals.
    c. Let each individual in *new-pop* have a random chance to mutate.
    d. Replace *pop* with *new-pop*.
3. Select the individual from *pop* with the highest fitness as the solution to the problem.

The population is a collection of candidate solutions that are considered during the course of the algorithm. Over the generations of the algorithm, new and often "good" members are “born” into the population, while older and “bad” members “die” out of the population. A single solution in the population is referred to as an individual. The fitness of an individual is a measure of how “good” the solution represented by the individuals. The selection process is analogous to the survival of the fittest in the natural world. Individuals are selected for cross-over based upon their fitness value. The fitter the individual the more likely the individual will be able to reproduce and survive to the next generation. The cross-over occur by mingling the solutions together to produce two new individuals. During each generation there is a small chance for each individual to mutate, which will change the individual in some small ways.

3.1 Micro Genetic Algorithm

When dealing with high dimensionality problem, it may be difficult or too time consuming for all the model parameters to converge within a given margin of error. In particular, as the number of model parameters increases, so does the required population size. Also, large population sizes imply large numbers of cost-function evaluations. An alternative is the use of micro-genetic algorithms, which evolves very small populations that are very efficient in locating promising areas of the search space. But, the small populations are unable to maintain diversity for many generations. Therefore, whenever diversity is lost the algorithm is restarted while keeping only the very best fit individuals (usually we keep the best one that is elitism of one individual). Restarting the population several times during the run of the genetic algorithms has the added benefit of preventing further exploration of the search space and so may make the program converge to a local minimum. Also, since we are not evolving large populations, convergence can be achieved more quickly and less memory is required to store the population.

In principle, micro genetic algorithms are similar to the classical genetic algorithm in the sense that they share the same evolution parameters and similar features except that new genetic material is introduced in to the population every time the algorithm restarted. This is an important distinction: since without the restarting, the algorithm will lose its exploitation capability. It was also found out that the algorithm is much less sensitive to the choice of evolution parameters.

3.2 Multipopulation Genetic Algorithm

In GA, individuals are selected according to their fitness for the production of offspring. Parents are recombined to produce offspring. All offspring will be mutated with certain probability. The fitness of the offspring is then computed. The offspring are inserted into the population replacing the parents, producing a new generation. This circle is performed until the optimization criteria are reached. Such a single population genetic algorithm is powerful and performs well on a broad class of problems. However, better results can be obtained by introducing many populations called subpopulation. Every subpopulation evolves for a few generations isolated (like the single population genetic algorithm) before one or more individuals are exchanged between the subpopulations. The multipopulation genetic algorithm models the evolution of a species in a way more similar to nature than the single population genetic algorithm

4 Nigerian Grid System

The Nigerian national grid belongs to rapidly growing power systems faced with complex operational challenges at different operating regimes. Indeed, it suffers from inadequate reactive power compensation leading to wide spread voltage fluctuations coupled with high technical losses and component overloads during heavy system loading mode. The standardized 1999 model of the Nigerian network comprises 7 generators, out of which 3 are hydro whilst the remaining generators are thermal, 28 bulk load buses and 33 extra high voltage (EHV) lines. The typical power demand is 2,830.1MW and with technical power network loss of about 39.85MW. The single line diagram of the 330kV Nigerian grid system is shown in Fig.3.

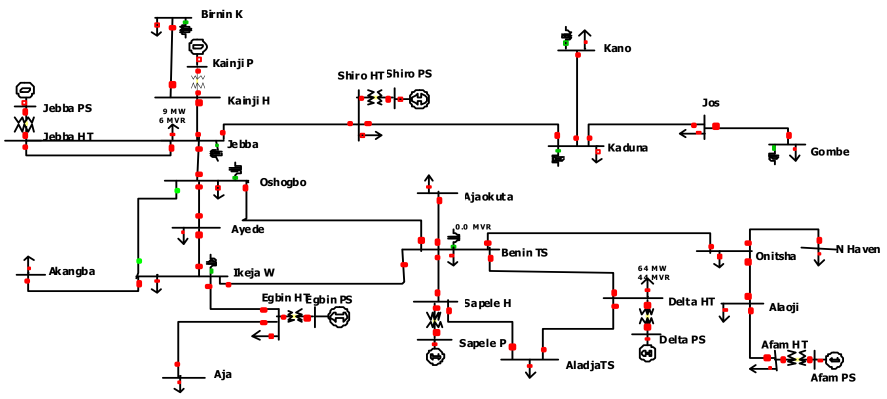

Fig. 3. Single line diagram of Nigerian 330kV 31-bus grid systems

The Nigerian thermal power plants characteristics are shown in Table 1 with each plants cost coefficients and their corresponding minimum and maximum power outputs.

Table 1. Nigerian thermal power plants characteristics

Units	α	β	γ	e	f	P_i^{min}	P_i^{max}
Sapele	6929	7.84	0.13	600	0.052	137.5	550
Delta	525.74	6.13	1.2	260	0.028	75	300
Afam	1998	56	0.092	450	0.048	135	540
Egbin	12787	13.1	0.031	850	0.094	275	1100

5 Discussion of Results

In this work, the ELD is applied to the four thermal plants of Egbin, Sapele, Delta and Afam. The results of the ELD with and without losses considered are shown in Table 2 and Table 3, respectively. With a total power generating capacity of 2823.1MW, the contribution of each thermal power plant to the total power generated and the cost of generation using the GA methods are shown in Table 2 and Table 3, respectively.

Table 2. ELD without losses

	MGA	GA	MPGA
Egbin (MW)	1070.71	937.5	942.8
Sapele (MW)	179.81	227.88	233.6
Delta (MW)	80.59	81.03	90.2
Afam (MW)	201.99	289.68	266.5
Shiroro (MW)	490	490	490
Kainji (MW)	350	350	350
Jebba (MW)	450	450	450
P_G (MW)	2823.1	2823.1	2823.1
P_D (MW)	2823.1	2823.1	2823.1
Cost ₦/hr	101203	99712	97832

Table 3. ELD with losses

	MGA	GA	MPGA
Egbin (MW)	838.39	814.56	817.47
Sapele (MW)	345.46	457.79	451.13
Delta (MW)	88.48	89.51	89.82
Afam (MW)	300.46	212.82	215.62
Shiroro (MW)	490	490	490
Kainji (MW)	350	350	350
Jebba (MW)	450	450	450
P_G (MW)	2862.79	2862.68	2864.04
P_D (MW)	2823.1	2823.1	2823.1
P_L (MW)	39.69	41.58	40.94
Cost ₦/hr	113410	112736	110324

The ELD was implemented on MATLAB 2012 platform. The contributions of the hydro power plants to the load demand were fixed, while the least cost schedule of the thermal power plants were determined. The minimum cost of production without losses given by MPGA is 97832$/hr compared to 101203$/hr for MGA and 99712$/hr for GA as shown in Table 2. With losses considered in Table 3, MPGA gives the least cost of production of $110324/hr and MGA gives lowest transmission losses of 39.69MW compared to 41.58MW of GA and 40.94MW of MPGA. The generators schedule reflects the best possible contribution of the individual generators based on the demand. From these results, it can be seen that the MPGA gives the lowest total cost of production compare to the other two algorithms.

6 Conclusion

In this paper, MGA, GA and MPGA methods have been applied to schedule generators of the Nigerian thermal power plants. The results show that these methods are capable of being applied successfully to the economic dispatch problem of larger thermal power plants. However, MPGA is shown to give the best cost minimization as a result of many populations called subpopulation used in the optimization process. Therefore, these methods can be applied to solve economic load dispatch of larger power system in future for economic operations and planning purposes.

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