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Micro Genetic Algorithm Based Electrical Power Dispatch for Deregulated Electricity Market

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Abstract

The application of the genetic algorithm and micro genetic algorithm are used to solve the optimal power dispatch problem for a multi-node auction market is proposed in this paper. The optimal power dispatch problem is a non-linear optimisation problem with several constraints. The objective of the proposed algorithms is to maximise the total participants' benefit at all nodes in the system. The proposed algorithms is simple to implement and can easily incorporate additional constraints. The algorithm was tested on a 17-node, 26-line system and 14-node 20-line system . The results have shown that the proposed algorithms micro genetic algorithm takes less time than genetic algorithm and both algorithms yields good results that are consistent with typical market behaviour.

Index Terms: Multi-node auction market, Optimal power dispatch (OPD) Genetic algorithm (GA), Micro genetic algorithms(MGA), Independent system operation (ISO).

1. Introduction

The electricity industries in number of countries have recently been deregulated to introduce competition. In a centralised power industry, the planning is done to minimise the production cost. In a competitive electricity market, generation resources are, scheduled based on offers and bids of the suppliers and consumers. Many approaches have been proposed in literature to solve the optimal power dispatch problem for electricity markets [1–4].

One of the competitive electricity market models is the auction market model, in which participants place their bids to sell or buy electricity. In an electricity auction market, the two main participants are distribution companies and generation companies. These participants will submit their bids to an independent system operation (ISO) company. A supply bid is given as a cost per MW and a quantity in MW which a generation company is willing to generate in a particular period. Each generation company may place several bids. A demand bid is given as a cost per MW and a quantity in MW which a distribution company is willing to consume in a particular period. Several demand bids may be placed by each distribution company. The optimal power dispatch models proposed by several researchers [1,2,4,5] have the objective to maximise the total benefit to the participants in the multimode auction market. This paper demonstrates the application of a genetic algorithm and micro genetic algorithm to solve the optimal power dispatch problem for a multi-node auction market. The model used in this paper, like most of the models available in literature, does not directly consider the reactive power market and the transmission cost. The advantage of the proposed genetic algorithm is the simplicity of handling non-linear constraints, without having to simplify the power flow constraints. In addition, the algorithm is easy to implement and additional features such as security constraints can be easily incorporated in the algorithm.

2. Problem Description For Single Node Electricity Market

For a single node auction market, the supply and demand curves at each node can be illustrated as shown in fig. 1. The spot price at a single node is the price which matches the supply and demand bids, i.e., the point at which the supply and demand curves intersect each other. At the spot price, the benefit of participants is maximized and is illustrated by the shaded area in Fig.1.

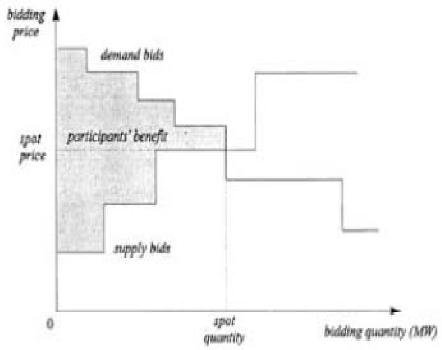


Figure 1: Example of the supply and demand curves

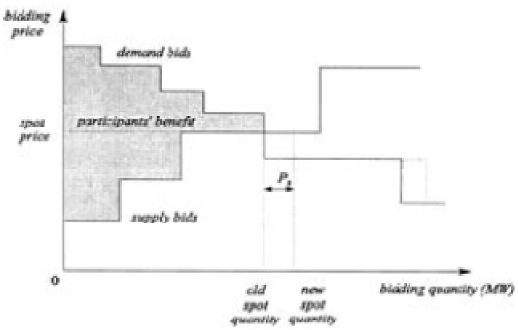


Figure 2(a) with network effects

Assuming that there are *Mk* supply bids and *Nk* demand bids at the k^{th} node. Let *Sik* be the i^{th} supply bid at node *k* and is given by *Sik* = $\{x^s_{ik}, p^s_{ik}\}$, where $x^s{}_{ik}$ is the selling price an p^s_{ik} is the selling quantity. In addition, let *Bik* be the i^{th} demand bid at node *k* and is given by *Bik* = $\{x^d_{ik}, p^d_{ik}\}$, where x^d_{ik} is the buying price and p^d_{ik} is the buying quantity. If x^ $_k$ denotes the spot price and p^$_k$ denotes the spot quantity, then the maximum participants' benefit, which is the sum of suppliers' benefit and consumers' benefit can be given as

$$B_k = \sum_{i \in M_k^s} (\hat{x}_k - x^s_{ik})\tilde{p}^s_{ik} + \sum_{j \in N_k^d} (x^d_{jk} - \hat{x}_k)\tilde{p}^d_{jk} \tag{1}$$

Where P~^{d} $_{ik}$ and P~^{s} $_{ik}$ are consumer's and supplier's dispatched quantity respectively, M^s $_k$ and N$^s{}_k$ are the sets of all dispatched suppliers and dispatched consumers respectively.

2.1 Problem Description for Multi Node Electricity Market

For a multi-node electricity market, there are transmission lines connected between bidding nodes. The connections result in real power P_k and reactive power Q_k injection to the network at each node. The real power injection to a node can be modelled as an additional demand bid (or a supply bid if the real power injection is negative) by the network for the quantity P_k at the selling (or buying) price x ^$_k$,which is equal to the spot price[1]. As an example, Fig. 2 illustrates the dispatch of the bids when the real power injection is considered. In Fig. 2(a), the injection of Pk to the node is supplied by the partly dispatched generator bid. The spot quantity has increased and the price has not changed. If the injected power is greater than the undispatched amount of the partly dispatched supply bid then the additional amount cannot be supplied at the same price. Therefore, the spot price will increase as shown in Fig. 2(b). This will result in displacing some consumers as shown by *dc* in Fig. 2(b). It can be seen in Fig. 2 that the spot price and spot quantity may be changed due to the effect of the real power injection. This may result in changing the sets B_{ik} and S_{ik} of all dispatched suppliers and dispatched consumers. Consequently, the participants' benefit at node k is now given by [1]

$$B_k^{'} = \sum_{i \in \dot{M}_k^s} (\dot{x}_k - x^s_{ik})\tilde{p}^s_{ik} + \sum_{j \in \dot{N}_k^d} (x^d_{jk} - \dot{x}_k)\tilde{p}^d_{jk} - \dot{x}_k p_k \tag{2}$$

where M^s $_k$ and N^s $_k$ are the new sets of all dispatched suppliers and dispatched consumers respectively, □□□is the new spot price and the last term is the amount paid by the transmission line. In addition, the total participants' benefit at all nodes can be expressed as

$$B_k^{'} = \sum_{k=1}^{K} \left\{ \sum_{i \in \dot{M}_k^s} (\dot{x}_k - x^s_{ik})\tilde{p}^s_{ik} + \sum_{j \in \dot{N}_k^d} (x^d_{jk} - \dot{x}_k)\tilde{p}^d_{jk} - \dot{x}_k p_k \right\} \tag{3}$$

It can be easily seen that the participants' benefit at each node($B`_k$) is a function of the real power injection. Therefore, the optimization problem of the total participants' benefit at all nodes is similar to the conventional optimal load flow problem, with the exception that the objective is to maximize the participants' benefit, rather than minimize the generation cost. This optimization problem can be described as

$$\text{Maximize} \quad \sum_{k=1}^{K}\left\{\sum_{i\in M_k^s}(\dot{x}_k - x_{ik}^s)\tilde{p}_{ik}^s + \sum_{j\in N_k^d}(x_{jk}^d - \dot{x}_k)\tilde{p}_{jk}^d - \dot{x}_k p_k\right\} \qquad (4)$$

subject to the following constraints:The capacity constraints which provide the limits on real power (p_k) and reactive power (q_k) injection to the network by any node i.e

$$\underline{p}_k \le p_k \le \overline{p}_k \qquad (5)$$

$$\underline{q}_k \le q_k \le \overline{q}_k \qquad (6)$$

Where $\underline{P}_k$,P_k and $\underline{q}_k$ q_k are the minimum and maximum real and reactive power output limits of generators associated with node *k* respectively. Power flow Constraint is given by (7)

$$|p_{kl}| \le \overline{p}_{kl} \qquad (7)$$

Where P_{kl} is the maximum power flow limit in a line *kl*. In addition, the real and reactive power injection at each node can be determined using (8),(9) These are given by

$$p_k = \sum_{\substack{l=1 \\ l\neq k}}^{K} p_{kl} \qquad (8)$$

$$q_k = \sum_{\substack{l=1 \\ l\neq k}}^{K} q_{kl} \qquad (9)$$

where p_{kl} and q_{kl} are the real power and reactive power flow along the transmission line connecting node *k* and node *l*, respectively. Furthermore, the real power and reactive power flow are given by the following equations

$$p_{kl} = G_{kl}(v_k^2 - v_k v_l \cos(\theta_k - \theta_l)) - B_{kl}(v_k v_l \sin(\theta_k - \theta_l)) \qquad (10)$$

$$q_{kl} = -B_{kl}(v_k^2 - v_k v_l \cos(\theta_k - \theta_l)) + G_{kl}(v_k v_l \sin(\theta_k - \theta_l)) \qquad (11)$$

where *Gkl* and *Bkl* are real and imaginary component of the admittance of the line connecting node *k* and node *l*, θk and θl are angles at node *k* and *l* and v*k* and v*l* are voltages at node k and node l

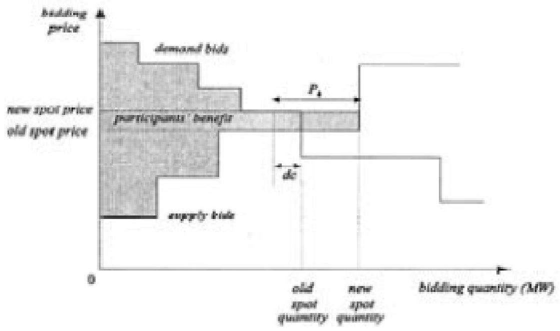


Figure 2(b). Example of the network effects

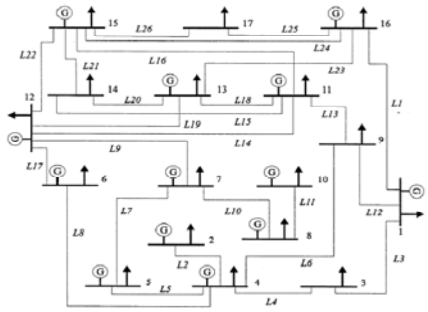


Figure 3: Online diagram of the 17-Bus test system

This optimization problem has non-linear constraints which is difficult to solve using the linear programming technique. A GA is proposed in the following section to solve the above problem. GAs are simple to implement and additional constraints can be easily incorporated into the problem.

3. Application of Genetic Algorithm (GA) and Micro Genetic Algorithm to Optimal Power Dispatch

The essential schemes need to be designed in order to apply GA to a multi-node electricity market are the encoding scheme, fitness function, crossover method and control parameters, Most GAs produces poor results when populations are small, because insufficient information is processed about the problem and, as a consequence, premature convergence to a local optimum occurs. Population size generally varies from 30 to 300 individuals. In contrast, MGAs explore the possibility to work with small populations (from five to 20 individuals usually) in order to reduce the processing time. From a genetic point of view, it is known that frequent reproductions inside a small population may disseminate hereditary diseases rarely found in large populations. On the other hand, small populations can act as natural laboratories where desirable genetic characteristics quickly can emerge. In MGAs, mutations are unnecessary because after a certain number of generations, the best chromosome is maintained and the rest are substituted by randomly generated ones. On the other hand ,it requires adoption of some preventive strategy against loss of diversity in population.By applying the both the algorithms Micro genetic algorithms are more efficient to solve this kind of problems, as they are faster and converge to better optimal solutions**.**

4. Results :

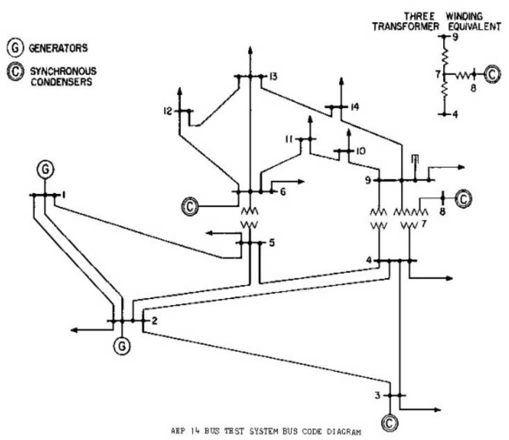
The developed GA and Micro Genetic Algorithm (MGA) have been tested on a 17-node, 26-line system (figure 3) and 14 node,20 line systems(figure 4) . The objective is to maximize the total participants' benefit at all nodes in the system, which in turn depends on the real power injection to the system. The encoding chromosome consists of 2*10*(*K*- 1) bits, ('K' is the number of nodes), in which each 10-bit binary string is used to represent a range between the maximum and minimum real power (or reactive power) limit at each node. In addition, the real power and reactive power injection at the reference node can be obtained from the load flow solution Figure 5 shows the variation of error with generations for GA and MGA algorithms.

Comparison of GA and MGA on 17 bus

Algorithm	Total benefit ($)	Execution time(sec)
GENETIC ALGORITHM	1273.88	8.610
MICRO GENETIC ALGORITHM	1271.33	1.672

Comparison of GA and MGA on 14 bus

Algorithm	Total benefit ($)	Execution time(sec)
Genetic algorithm	849.579	2.6894
Micro genetic algorithm	848.826	0.5621



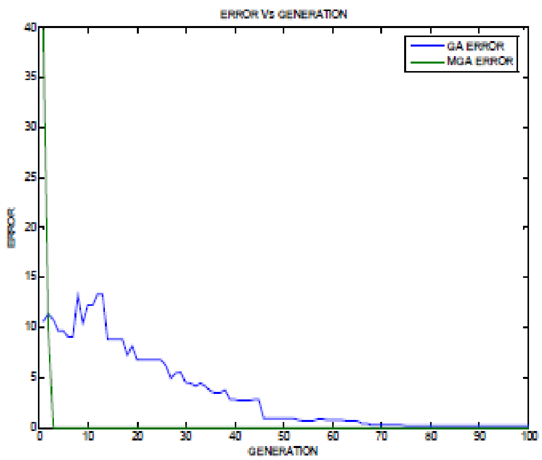


Figure 4: IEEE14-Bus system Figure 5 Graph of Error Vs Generation.

5. Conclusions

This paper presented GA and MGA approaches for solving the optimal power dispatch in a multi-node electricity market. The objective of the algorithm is to maximize the total participants' benefit at all nodes in the system. GAs are inspired by nature, and have proved themselves to be effective solutions to optimization problems. However, these techniques are not a panacea, despite their apparent robustness. Their slow convergence is a hindrance when applied to a real time system studies. Any improvement in the convergence of such algorithms is appropriate as far as the real time studies are concerned. MGAs are more efficient to solve this kind of problems, as they are faster and converge to better optimal solutions.

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