A Fast Algorithm for Reactive Power Market Management Using Artificial Neural Networks

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Abstract

This paper presents a novel algorithm to find optimal reactive power market schedule in deregulated electricity markets. There are many factors which can impact on optimal system operating point. Furthermore, the number of control and decision variables in an optimization problem in a general power system is very large. Therefore, finding the optimal reactive power market schedule may be very time consuming. In order to overcome this deficiency, the proposed algorithm suggests using Artificial Neural Networks (AANs) to speed up the market clearing process. In this algorithm, at first, many different samples should be produced by traditional market clearing process. Then, using these samples an ANN will be trained to fined optimal reactive power market schedule. The proposed algorithm is tested on IEEE 24-bus test system with satisfactory results.

Keywords: Deregulated electricity market, reactive power market, optimal system operating point, artificial neural network.

1. Introduction

In deregulated electricity markets, ancillary services are among the most important issues which have vital role in power system operation and security (Shahidehpour, Yamin, & Li, 2002)(Raoofat & Kargarian, 2009). According to FERC Order No.888, there are six different ancillary services (FERC Staff Report, 2005). In almost all electricity markets, system operators are responsible for providing these services for the system. Reactive power provision is one important ancillary service which has significant impact on power system stability and security (Kargarian, Raoofat, 2011). In a typical market, the system operator should provide adequate reactive power to ensure system security. For example, the lack of reactive power can cause voltage drop in some buses and consequently it may result in system voltage instability (P. Kundur, 1994).

Different electricity markets around the world use different methods for reactive power market clearing (Kargarian, Raoofat, & Mohammadi, 2011). As an example, the New York ISO (NYISO) uses an embedded cost to pay generators for their reactive power services. If any generator needs to reduce its active power in order to increase its reactive power generation, the NYISO should pay a lost opportunity cost to the generator (New York Independent System Operator, 2008). In California market, the generators do not receive any payments for reactive power provision when they are working in the range of 0.9 lagging to 0.95 leading power factors. To procure a reactive power beyond these limits, the California ISO (CAISO) should pay off the generators for their reactive power including lost opportunity cost (California Independent System Operator Corporation, 2000).

In almost all electricity markets, the system operators try provide adequate reactive power with the minimum payment considering system constraints. Different optimization problems are proposed in literature which most of them define the total reactive power payment as an important object of the optimization (Bhattacharya, & Zhong, 2001)(Hao, 2003)(Hasanpour, Ghazi, & Javidi, 2009).

If the operator only seeks to minimize cost of reactive power provision, it will contract with providers which offer the minimum prices. But, it may result in increasing transmission energy loss and consequently increasing total system payment. Therefore, cost of both reactive power provision and transmission energy loss should be considered in the stage of reactive power market clearing (Hao, 2003). In order to find the best reactive power market schedule, the system operator should solve an optimization problem. The objective function of the optimization is minimization of reactive power provision cost and transmission loss payment. There are many constraints which should be satisfied during market clearing, for example, bus voltage limits and load flow equations (Kargarian, Raoofat, & Mohammadi, 2011).

As it is clear, in a typical power system, there are a large number of constraints which should be regarded in the time of reactive power market clearing. Also, most of these constraints are nonlinear. Therefore, to find the best reactive power market schedule, a nonlinear constrained optimization problem should be solved. This process is a time consuming process and the required time increases with increasing the size of power system and so the optimization problem.On the other hand, in electricity markets, the time is very important and has significant impact on the decisions of market participants and consequently on the benefit of theses participants (Shahidehpour, Yamin, & Li, 2002)(Raoofat & Kargarian, 2009). Therefore, if the operator could make the fast decisions, the market proficiency will be improved. For example, it can reduce the probability of market power.

This paper presents a novel fast reactive power market clearing algorithm for forward ancillary services market. The proposed algorithm is an Optimal Power Flow (OPF) formulation. The object of the algorithm is minimization of reactive power provision cost as well as transmission loss payment. In the typical power system with large number of buses and generators, it takes too m any time to find the optimal reactive power market schedule. In order to overcome this deficiency, in this paper, it is proposed to employ Artificial Neural Networks (ANNs) to speed up the market clearing process. Using this algorithm, the operator can schedule reactive power market very fast and so it will improve the proficiency market. The algorithm accurately considers variations of power demand of each bus, reactive power provision cost and active power schedule in time of ANN training. The proposed algorithm is applied on IEEE 24-bus test system. The results show the suitability of the algorithm.

2. Reactive power provision cost

According to NERC operation policy 10, only reactive power produced by synchronous generators has been considered as ancillary service and is eligible for financial compensation (North Amer. Elect. Reliability Council, 2001). Some references deem it is necessary to pay the other reactive power providers such as capacitor banks, synchronous condensers and FACTS devices (FERC Staff Report, 2005). In Australia both synchronous generators and synchronous condensers receive payments for reactive power provision (National Electricity Market Management Company, 2001). In this paper, reactive power provided by synchronous generators, condensers and capacitor banks are assumed as ancillary service which should be compensated by the system operator.

2.1 Cost of generator's reactive power

Different reactive power payment structures can be used for synchronous generators (Bhattacharya, & Zhong, 2001)(Hao, 2003)(Hasanpour, Ghazi & Javidi, 2009). In (Hasanpour, Ghazi & Javidi, 2009) a quadratic reactive power cost curve has been proposed for a typical synchronous generator. This cost curve models the investment cost, operational cost and also lost opportunity cost of a synchronous generator accurately. It has been defined as follows:

$$Cos(Q_{gi}) = a_{q,i}Q_{gi}^{\ 2} + b_{q,i}Q_{gi} + c_{q,i} \tag{1}$$

Where Qgi is reactive power output of ith generator; and aq, bq and cq are constant coefficients. As it is described in (Hasanpour, Ghazi & Javidi, 2009), knowing active power cost curve of a generator, its capability curve and maximum amount of active and reactive power of that generator, these constant coefficients can be estimated accurately using a suitable interpolation technique. This equation can provide accurate results in reactive power market while it is very simple for implementation.

2.2 Cost of condenser's reactive power

Synchronous condenser is a synchronous machine without any prime mover which can provide only reactive power. The reactive power cost curve of a condenser consists of the investment cost and operating cost. The operating cost of a synchronous condenser includes running cost and investment cost. The running cost contains the cost of energy consumed to overcome the mechanical friction and electrical loss, and the maintenance cost. Consequently, the reactive power cost curve of a synchronous condenser can be formulated by (2) (Dai et al, 2003):

$$Cost(Q_{ci}) = (\beta_{ci} + \sigma_{ci})Q_{ci} \tag{2}$$

Where Qci is the reactive power output of condenser, σ ($/Mvar-h) is the operating cost of condenser and βci ($/Mvar-h) which is formulated by (3) models the investment cost.

$$\beta_{ci} = \frac{Capital\ investment\ cost}{8760 \times lifespan \times average\ usage\ ret} \tag{3}$$

2.3 Cost of capacitor's reactive power

The charge for using capacitors is similar to synchronous condensers and can be expressed by (2). The capacitors have little operating cost and their reactive power production costs have been considered to be calculated based on their capital investment costs (Dai et al, 2003). Hence, for the capacitors, in equation (2) the parameter σ should be set to be zero.

3. The proposed algorithm

As previously discussed, solving an optimization problem especially in large power systems is a time consuming process. If the system operator reduces the time of decision making in the market, it can improve the market proficiency. In this section, based on using artificial neural networks, a novel fast reactive power market clearing algorithm is proposed. This algorithm seeks to rapidly find the optimal reactive power market schedule while its objective function minimization of reactive power provision cost in addition to transmission loss payment. The algorithm includes three steps, data generation, ANN training and ANN testing. These steps are described in the following subsections.

3.1. Step 1: data generation

As the first step, many different data should be generated. To generate data, the reactive power market is cleared using sequential quadratic programming which is among conventional nonlinear optimization programming. The object of the optimization is minimization of Market Payment (MP) which is summation reactive power provision cost and also transmission loss payment. The problem formulation is as follow:

$$Min. \quad MP = \sum_{i \in providers} Cost(Q_i) + \lambda Pl_{oss} \tag{4}$$

Subject to:

$$P_{Gi} - P_{Di} = \sum_{j=1}^{n} V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) \; \forall i \tag{5}$$

$$Q_{Gi} + Q_{Ci} - Q_{Di} = -\sum_{j=1}^{n} V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) \; \forall i \tag{6}$$

$$Q_{G\min,i} \le Q_{Gi} \le Q_{G\max,i} \quad \forall i \in SM \tag{7}$$

$$Q_{C\min,i} \le Q_{Ci} \le Q_{C\max,i} \quad \forall i \in SC \tag{8}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall i \tag{9}$$

$$\left| S_{ij}(V,\delta) \right| \le S_{ij}^{\max} \quad \forall ij \tag{10}$$

Where:

n: Number of buses
λ: Market energy price
SM: Set of synchronous machines
SC: Set of capacitors
PG_i: Active power generated at ith bus
QG_i: Reactive power generated at ith bus
PD_i: Active power demand at ith bus
QD_i: Reactive power demand at ith bus
QC_i: Capacitors generated reactive power at ith bus
V_i: Voltage magnitude of bus i
δ_i: Voltage angle of bus i
$Y_{ij}\angle\theta_{ij}$: The ijth element of admittance matrix
S_{ij}: MVA of line between bus i and j

In the above OPF formulation, (5) and (6) are the nodal active and reactive power flow equations. The constraints of provision of reactive power by generators, condensers and existing capacitors are considered by (7) and (8), respectively. Limits of all bus voltages and transmission line power flows are imposed by (9) and (10). To generate the training samples, this optimization has been solved under different market conditions.

It is notable that reactive power cost curve of each provider, market energy price (λ), active power schedule in energy market and power demand of each bus are different in different the samples.

3.2. Step 2: ANN training

Neural network is a powerful tool for solving complicated and nonlinear mathematical problems and has been successfully applied to a wide variety of real world problems. An artificial neural network has three parts; input layer, hidden layers and output layer. The first layer is named input layer, the last layer is output layer and the layers that are between them are hidden layer. Each layer is built of several nodes. Signals enter to input layer and cross all hidden layers respectively until arrive to output layer. Number of nodes in the input layer is equal to system's inputs and number of nodes in the output layer is equal to system's outputs. Number of hidden layers and nodes that each of them requires, depend on the complexity of solution process (Wasserman, 1993). The Multi Layer Perceptron (MLP) neural network is used in this paper. Fig. 1 shows a typical MLP structure which has one hidden layer.

Insert figure (1) about here

In this step of the algorithm, using the samples generated in the first step, an ANN is trained to find the optimal reactive power market schedule. It is notable that in this paper the MLP structure is used. Also, resilient backpropagation algorithm (RPROP) is used with logarithmic sigmoid transfer function (logsig) for hidden layers in this paper. However, other neural network structures can also be used instead of in this step of the algorithm.

3.3. Step 3: ANN testing

After training the ANN, it should be evaluated. In the last step of the proposed algorithm, using a set of data which are generated in step one, the ANN is evaluated. If the ANN has acceptable error so it will pass this step, but if not, it has to be trained again. This procedure will be repeated until the ANN passes the test step.

4. Numerical results

In this section, in order to show the suitability and effectiveness of the proposed reactive power market clearing algorithm, it is applied on IEEE 24-bus test system (Reliability Test System Task Force of the Application of Probability Methods Subcommittee, 1999). As depicted in Fig. 2, the system consists of ten generators, one synchronous condenser and seventeen load points. Table 1 shows the maximum and minimum limits of market participants for producing active and reactive power.

Insert figure (2) about here

Insert table (1) about here

At first, many different samples should be generated to train an ANN. The Monte Carlo simulation method is used to produce random load demand pattern, active power output of generators and reactive power cost curve. After generating the samples, an ANN is trained for reactive power market clearing.

Here, one of the tasting samples is presented to how the proficiency of the proposed algorithm. The active power cost curve of each generator is shown in Table 2. The parameter λ (market clearing price) and the ramp of cost curve of the condenser (β+σ) are equal to 100 $/MW and one $/Mvar-h, respectively. System loading condition is according to Table 3.

Insert table (2) about here

Insert table (3) about here

To compare the results, the reactive power market is cleared and the results are depicted in Table 4. In this table, both accurate (without using ANN) and estimated (the proposed algorithm) results can be seen.

Insert table (4) about here

The error of the proposed reactive power market clearing algorithm is shown in Fig. 3.

Insert figure (3) about here

As it can be seen from Fig. 3, the maximum amount of error is 0.006 (G_3) which is negligible. Therefore, the proposed algorithm is a fast method that can be used for reactive power market clearing with very good accuracy.

5. Conclusion

While the time plays and an important role in deregulated open access environments, many market clearing and programming in electricity market are time consuming. If the system operator can make the fast decisions in the market, it can improve the market efficiency. This paper proposes a novel algorithm which can find the optimal reactive power market schedule rapidly. This algorithm uses artificial neural networks to accelerate the market clearing process. As the objective function, the algorithm seeks to minimize summation of reactive power provision cost in addition to transmission loss payment. The proposed algorithm is tested on IEEE 24-bus network and the numerical results show the suitability of the algorithm

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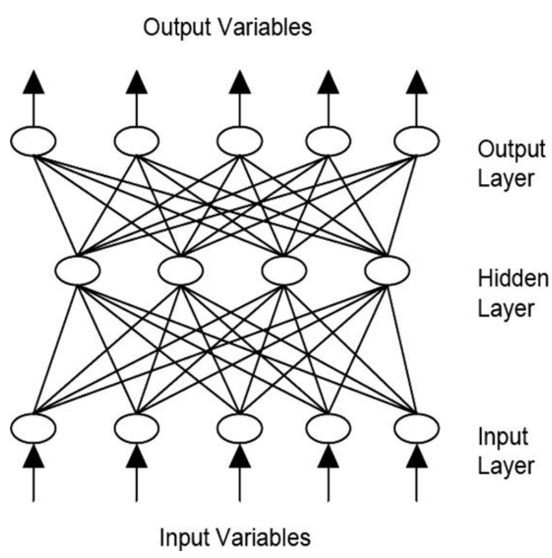

Figure 1. A typical structure of MLP neural network

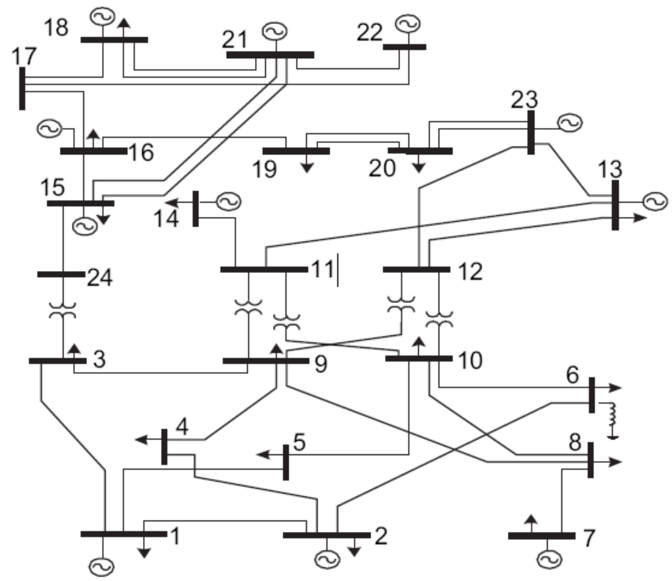

Figure 2. IEEE 24-bus test system

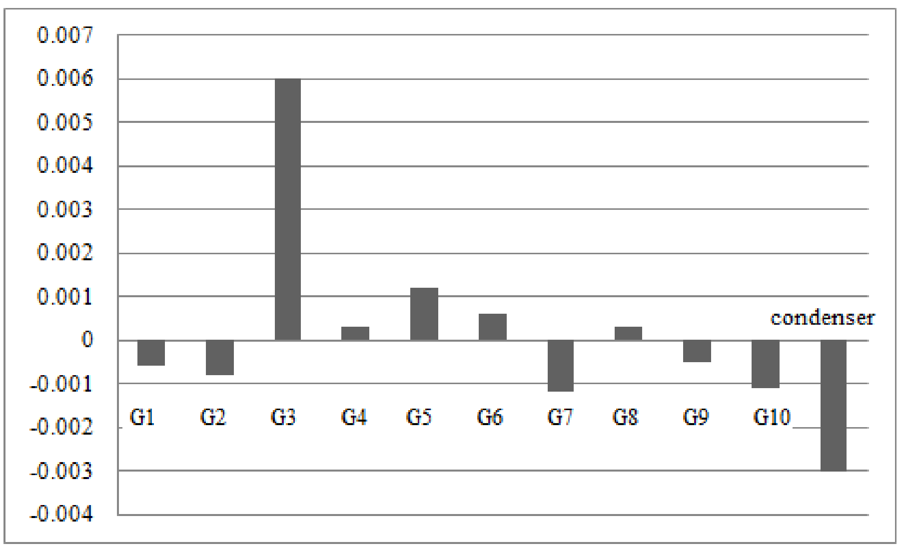

Figure 3. Error between accurate and estimated results (pu)

Table 1. Market participants' parameters (S_{base}=100MVA)

Provider	P_{min} (pu)	P_{max} (pu)	Q_{min} (pu)	Q_{max} (pu)
G1	0	2.00	-0.50	1.20
G2	0	1.92	-0.50	1.00
G3	0	3.00	0	1.20
G4	0	5.91	0	2.40
G5	0	2.15	-0.50	1.20
G6	0	1.55	-0.50	0.80
G7	0	4.00	-0.50	2.00
G8	0	4.00	-0.50	2.00
G9	0	3.00	-0.60	0.96
G10	0	6.60	-1.25	3.10
Condenser	0	0	-0.50	2.00

Table 2. Active power cost curve of generators

Provider	ap*	bp*	cp*
G1	0.0200	2.50	160
G2	0.0284	2.90	250
G3	0.0310	2.98	205
G4	0.0312	3.23	310
G5	0.0296	2.99	285
G6	0.0309	315	295
G7	0.0299	3.21	410
G8	0.0300	3.04	344
G9	0.0288	2.92	296
G10	0.0300	2.89	190

Table 3. Power demand and active power generation for all buses

Bus	Pd (pu)	Qd (pu)	Pg (pu)	Bus	Pd (pu)	Qd (pu)	Pg (pu)
1	1.10	0.25	1.30	13	2.75	0.62	4.14
2	1.08	0.30	1.40	14	2.10	0.45	0
3	2.03	0.50	0	15	3.35	0.70	2.15
4	0.84	1.41	0	16	1.15	0.34	1.55
5	0.81	0.30	0	17	0	0	0
6	1.46	0.40	0	18	3.46	0.75	4.00
7	1.37	0.60	2.60	19	1.95	0.45	0
8	1.85	0.40	0	20	1.48	0.37	0
9	1.87	0.46	0	21	0	0	4.00
10	2.09	0.44	0	22	0	0	3.00
11	0	0	0	23	0	0	6.60
12	0	0	0	24	0	0	0

Table 4. Reactive power market schedule

Providers	Accurate results	Estimated results
G1	0.9306	0.9312
G2	0.9325	0.9333
G3	0.9350	0.9290
G4	1.1518	1.1515
G5	1.0475	1.0463
G6	0.1245	0.1239
G7	0.6044	0.6056
G8	0.5642	0.5639
G9	-0.2524	-0.2519
G10	0.9401	0.9412
Condenser	1.8340	1.8370
MP($)	6147	6140