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Evolutionary Algorithm Based Centralized Congestion Management for Multilateral Transactions

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***Abstract*—**This work presents an approach for AC load flow based centralized model for congestion management in the forward markets. In this model, transaction maximizes its profit under the limits of transmission line capacities allocated by Independent System Operator (ISO). The voltage and reactive power impact of the system are also incorporated in this model. Genetic algorithm is used to solve centralized congestion management problem for multilateral transactions. Results obtained for centralized model using genetic algorithm is compared with Sequential Quadratic Programming (SQP) technique. The statistical performances of various algorithms such as best, worst, mean and standard deviations of social welfare are given. Simulation results clearly demonstrate the better performance of genetic algorithm over SQP.

***Keywords*—**Congestion management, Genetic algorithm, Sequential quadratic programming.

I. Introduction

ELECTRICITY markets have been developing rapidly in many parts of the world. However, the perfect design of power markets is still under investigation for various reasons. The commodity of electricity should be transferred through the network and the transmission line capacity limit should be considered at all times.

Electric power systems, around the world, have been forced to operate to almost their full capacities due to the environmental or economic constraints to build new generating plants and transmission lines. However, the electric power that can be transmitted between two locations on a transmission network is limited by several limits such as thermal limits, voltage limits and stability limits with the most restrictive applying at a given time. When such a limit is reached, the system is said to be congested [1].

Congestion in a power system is a consequence of network constraints characterizing a finite network capacity that limits the simultaneous transfer of power from all required transactions. The complicated issues of congestion management are market economic efficiency and system operation security [2].

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Congestion or overloading in one or more transmission lines may occur due to the lack of coordination between generation and transmission utilities, it also occurs as a result of unexpected contingencies such as transmission line outages, generator outages, changes in energy demand or failure of equipments.

Congestion management problem can be generally considered as a Centralized Optimal Power Flow (COPF) problem with the objective of maximizing social welfare with load flow and operation limit constraints. However, the COPF approach has some drawbacks in market environment. COPF requires the submission of detailed private information of market participants to the Independent System Operator (ISO) that may include their benefit/cost functions. In the market environment, such sensitive information is a commercial secret that market participants are unwilling to disclose to the ISO. The COPF by the ISO lacks transparency to market participants, since the congestion price is likely to be set by the ISO, but not discovered through market mechanisms. Moreover, for the congestion management of inter-regional trades, this can share common resources (generation units, transmission lines and so on) across regions efficiently and increase the scale of economy [3], [4].

The proposed approach presents AC load flow-based centralized congestion management for de-regulated power market using Sequential Quadratic Programming (SQP) and Genetic Algorithm (GA).The optimal social welfare is computed with smooth fuel cost functions. Voltage and reactive power impacts are included in the model, which insures the stability of the system. The test results on IEEE 30 bus system clearly show the effectiveness of the proposed approach.

The calculation of Power Transfer Distribution Factors (PTDF) and available transfer capacity is also proposed. For solving the smooth optimization problems many stochastic algorithms are used. Nowadays, genetic algorithm (GA) is becoming very popular for solving such issues in various engineering applications [5], [6].

II. Problem Formulation

There are two models in congestion management namely COPF and Decentralized Optimal Power Flow (DOPF). In COPF model, there is a lack of transparency to market participants, since congestion cost is set by ISO and not through market mechanism. As a centralized authority, the ISO has ‘super power’, which is inconsistent with the principles of competitive markets. In DOPF model, the ISO does not involve in the sensitive information like cost/benefit functions [7].

A. COPF Model in Deregulated Power Market

It mainly focuses on forward contract market for real power and voltage impacts, where AC load flow is used. The PTDF values are available to the market participants (transactions).In the perfect competitive market, the ISO adjusts the contracts (generation and demand) to maximize the social welfare to achieve efficient operation with all constraints satisfied [8]. The COPF model equations are given below:

$$\sum_{k\in T}\sum_{j\in E^{(k)}} B_j^{(k)}(D_j^{(k)}) - \sum_{k\in T}\sum_{i\in G^{(k)}} C_i^{(k)}(P_i^{(k)}) \quad (1)$$

Subject to the following constraints

$$\sum_{j\in E^{(k)}} D_j^{(k)} - \sum_{i\in G^{(k)}} P_i^{(k)} = 0 \quad (k \in T) \quad (2)$$

$$P_{i,min}^{(k)} \le P_i^{(k)} \le P_{i.max}^{(k)}(i \in G^{(k)}, k \in T) \quad (3)$$

$$Q_{i,min}^{(k)} \le Q_i^{(k)} \le Q_{i,max}^{(k)}(i \in G^{(k)}, k \in T) \quad (4)$$

$$V_{i,min}^{(k)} \le V_i^{(k)} \le V_{i,max}^{(k)}(i \in G^{(k)}, k \in T) \quad (5)$$

$$V_{j,min}^{(k)} \le V_j^{(k)} \le V_{j,max}^{(k)}(j \in E^{(k)}, k \in T) \quad (6)$$

$$D_{j,min}^{(k)} \le D_j^{(k)} \le D_{j,max}^{(k)}(j \in E^{(k)}, k \in T) \quad (7)$$

$$\sum_{k\in T} l_k^{(m)}(P_k, D_k) \le L_{max}^{(m)} \quad (m \in I) \quad (8)$$

where T is the set of transactions in the market

T= {1,2,…,K};

k is the index of each transaction, for all $k \in T$;
I is the set of transmission lines involved in congestion management

I=b{1,2,…,M};

m is the index of transmission lines involved in congestion management, for all $m \in I$;
$G^{(k)}$ is the set of generators in transactions k, for all $k \in T$;
$E^{(k)}$ is the set of consumers in transaction k, for all $k \in T$;
$P_i^{(k)}$ is the real power output of generator I of transaction k, also an element of generator output vector P_k of transaction k, for all $I \in G^{(k)}$ and $k \in T$;
$Q_i^{(k)}$ is the reactive power output of generator I of transaction k;
$Q_j^{(k)}$ is the reactive power output of demand of consumer j of transaction k;
$V_i^{(k)}$ is the voltage at generator i of transaction k;
$V_j^{(k)}$ is the voltage at consumer j of transaction k, $D_j^{(k)}$ is the real power demand of consumer j of transaction k, an element of demand vector D_k of transaction k,for all $j \in E^{(k)}$ and $k \in T$;
$l_k^{(m)}$ is the load flow caused by transaction k on line m,in which PTDFs are used, for $k \in T$ and $m \in I$;
$L_{max}^{(m)}$ maximum transfer limit of line m in MW, for all $m \in I$

III. Genetic Algorithm

Genetic Algorithms (GA) are direct, parallel, stochastic method of global search and optimization, which describes the evolution of the living beings, described by Charles Darwin. GA are part of the group of Evolutionary Algorithms (EA).The evolutionary algorithms use the three main principles of the natural evolution: reproduction, selection and diversity of the species, maintained by the differences of each generation with the previous.

Genetic Algorithms work with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the optimum solution. The best-suited individuals create the next generation.

The detailed genetic algorithm is explained in following steps:

Step 1. Generate initial population – The first generation is randomly generated, by selecting the genes of the chromosomes with lower (X_l) and upper (X_u) bound information on generation and demand for the transaction.

Step 2. Calculation of the values of the function that we want to maximize the social welfare.

Step 3. Check for termination of the algorithm – In the most optimization algorithms, it is possible to stop the genetic optimization by:

i) Value of the objective function – the value of the objective function of the best individual is within defined range around a set value. It is not recommended to use this criterion alone, because of the stochastic element in the search the procedure, the optimization might not finish within sensible time;
ii) Maximal number of iterations – this is the most widely used stopping criteria .It guarantees that the algorithms will give some results within sometime, whenever it has reached the best solution or not;
iii) Stall generation – if within initially set number of iterations (generations) there is no improvement of the value of the objective function of the best variables the algorithm stops.

Step 4. Selection – between all variables in the current population are chose those, who will continue and by means of crossover and mutation will produce offspring population. At this stage elitism could be used – the best *n* variables are directly transferred to the next generation. The elitism guarantees, that the value of the optimization function cannot get worst (once the best solution is reached it would be kept).

Step 5. Crossover – the variables chosen by selection recombine with each other and new variables will be created. The aim is to get offspring individuals that inherit the best possible combination of the characteristics (genes) of their parents.

Step 6. Mutation – by means of random change of some of the genes, it is guaranteed that even if none of the individuals contain the necessary gene value for the best solution, it is still possible to reach the best result.

Step 7. New generation – the variables chosen from the selection are combined with those who passed the crossover and mutation, and form the next generation.

IV. Centralized Congestion Management Using Genetic Algorithm

In the proposed improved mathematical model, the general scheme for AC load flow based centralized congestion management for forward market is discussed. Based on the initial contracts of all the transactions, congested transmission lines and load flow caused by each transaction on the congested lines are determined by ISO, using PTDF values. Here PTDF values are calculated using Newton Raphson Load Flow method [9].Based on the load flow results, ISO determine the initial contracts of generation and demand.

Using this initial value of generation and demand, two transactions optimizes its generation and demand using genetic algorithm. For an n-transactions system, genetic algorithm is applied n-times sequentially and updated generation and demand of (n-1) transactions. The step by step genetic algorithm implementation procedure of a transaction is given below

Step 4.1. The generation is randomly generated, by selecting the genes of the chromosomes with lower (X_l) and upper (X_u) bound information on generation and demand for the transaction.

Step 4.2. Calculate the value of the fitness function that we want to maximize the social welfare.

Step 4.3. In selection process, the best solution will kept once it reached. Then the Offspring population is generated by means of crossover and mutation.

Step 4.4. Crossover will determine the offspring individuals i.e. (generation and demand) that inherit the best possible combination of the characteristics (genes) of their parents.

Step 4.5. During mutation, random change of some of the genes, guarantees that none of the individuals contains necessary genes it is still possible to reach the best solution.

Step 4.6. Steps 4.1-4.5 are repeated until a maximum number of function evaluations or tolerance of variables and objective function are reached. Generation and demand of the transaction is updated using the optimized results.

For the two transactions, steps 4.1 to 4.7 are repeated until the optimum generation and demand are obtained. The flow diagram of genetic algorithms is shown in Fig. 1.

V. Simulation Results

The IEEE 30 bus test systems are considered for testing. Testing has been performed on a Core 2 duo PC operating @ 2.93 GHz with the series computation using MATLAB software.

A. *IEEE 30 Bus System*

The IEEE 30 bus test system has considered, there are two multilateral transactions (T1,T2) and each has four participants of one generator and three consumers. The single line diagram of IEEE 30 bus system is shown in Fig. 2. Table I [10] shows initial contract details of the two transactions. The cost function of generators and benefit function of consumers are listed in Table II. Coefficients of non-smooth generator cost function presented in [11] are used here.

TABLE I
Initial Contract in MW(IEEE 30 Bus)

Transaction 1		Transaction 2	
P(MW)	D(MW)	P(MW)	D(MW)
	2.4		11.2
32.8	7.6	28.4	8.2
	23.8		9

Transmission line 28-27 is involved in the congestion management. By reducing the capacity of transmission line 28-27 from 65MW to 8MW congestion is created.

TABLE II
Cost and Benefit Function of Test Case (IEEE 30 Bus)

Transactions	Generator Bus	Generator Cost Function in $/Hr	Consumer Bus	Consumer Benefit Function in $/hr
1	5	$45P+0.01P^2$	3	$47.8D-0.03D^2$
			4	$47.8D-0.05D^2$
			7	$47.8D-0.02D^2$
2	13	$48P+0.01P^2$	12	$49.0D-0.04D^2$
			15	$48.5D-0.02D^2$
			17	$49.7D-0.02D^2$

.SQP solution is obtained by using the 'fmincon' function of MATLAB. After number of trials, it is observed that only after 50,000 function evaluations results are obtained with constraints satisfaction in SQP. For GA, population size and maximum function evaluations are fixed at 100 and 20,000 respectively. Tolerance values for fitness function (TolFun) and coordinates (TolX) are assumed as $1E^{-5}$ and $1E^{-5}$, respectively, for GA and SQP algorithms. The results of GA are compared with SQP to ensure the performance of the algorithms. Due to the randomness of the considered algorithms, their performance cannot be judged by the results of single run. An algorithm is said to be robust, if it gives almost consistent results during the independent trials. Hence in this paper, best, worst. Mean and standard deviation of social welfare obtained in 20 independent trials. These are mainly used to compare the performance of the algorithms [12].

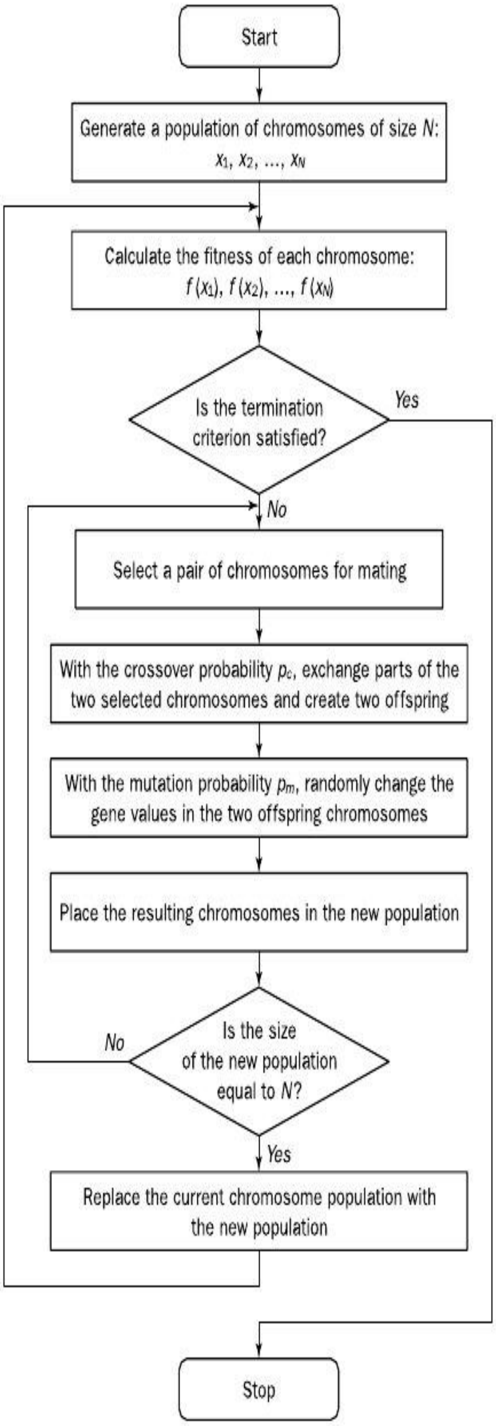

Fig. 1 Flowchart of GA

The single line diagram of IEEE 30 bus is shown below:

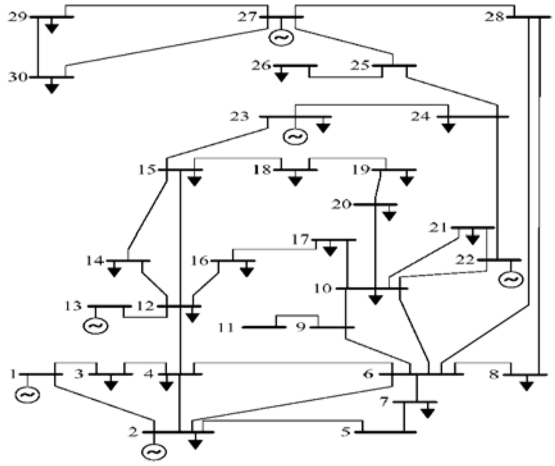

Fig. 2 Single line diagram of IEEE 30 bus system

B. Simulation Results with Smooth Cost Function

Tables III and IV compare the statistical performance of SQP and GA algorithms. The statistical results of social welfare show the better performance of GA for COPF. In Table IV, Standard deviation of GA is lesser than algorithms and it shows the consistency of GA. The closeness of the best social welfare obtained in COPF model confirms the validity of the proposed improved COPF model. The load flow caused by two transactions on line 28-27 for their best contract is also given and it shows that congestion is relieved.

The best adjusted contract of two transactions using SQP and GA for allocated capacity of the line 28-27 is shown in Table V. Table VI compares the average CPU time required to converge to the optimal solution for SQP and GA.GA gives better social welfare than SQP at comparatively lesser CPU time. If high performance computers are used, there is much room for reducing the total CPU time of proposed improved COPF model.

TABLE III
RESULTS OF COPF WITH SMOOTH COST FUNCTION FOR SQP (IEEE 30 BUS)

Method used	Capacity of Transmission Line 28-27 used by Transactions in (MW)	Total Capacity used in (MW)	Best Profit in $/hr
SQP	8.00000	8.00000	300.86

TABLE IV
RESULTS OF COPF WITH SMOOTH COST FUNCTION FOR GA (IEEE 30 BUS)

Method used	Capacity of Transmission Line 28-27 used by Transactions in (MW)	Total Capacity used in (MW)	Total Profit in ($/hr)			
			Best	Worst	Mean	SD
GA	8.0000	7.9996	301	292	296	2.61

TABLE V
ADJUSTED CONTRACTS IN MW- SMOOTH COST FUNCTION (IEEE 30 BUS)

Transactions	Transaction 1		Transaction 2	
	Power in (MW)	Demand in (MW)	Power in (MW)	Demand in (MW)
1	32.60	2.64	27.25	10.48
		7.79		7.55
		22.17		9.22
2	33.15	2.58	27.25	10.68
		7.88		7.71
		22.69		9.36

TABLE VI
COMPARISON OF AVERAGE CPU TIME

Test System	Objective Function	Model	Methods used	
			SQP in secs	GA in secs
IEEE 30	Smooth	COPF	650.40	220.77

VI. CONCLUSION

The capacity of congested line is optimally allocated to individual transactions for maximizing the social welfare using SQP and GA algorithms. Testing on IEEE 30 bus shows this centralized model and solution algorithms are effective without sacrificing the market efficiency. Simulation results has obtained for SQP and GA. Genetic algorithm gives better social welfare than SQP at comparatively lesser CPU time. Further work will be conducted for non-smooth cost function in decentralized model, the evolutionary algorithm will give better results.

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