Optimal power flow based congestion management using enhanced genetic algorithms

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Article Info

ABSTRACT

Congestion management (CM) in the deregulated power systems is germane and of central importance to the power industry. In this paper, an optimal power flow (OPF) based CM approach is proposed whose objective is to minimize the absolute MW of rescheduling. The proposed optimization problem is solved with the objectives of total generation cost minimization and the total congestion cost minimization. In the centralized market clearing model, the sellers (i.e., the competitive generators) submit their incremental and decremental bid prices in a real-time balancing market. These can then be incorporated in the OPF problem to yield the incremental/ decremental change in the generator outputs. In the bilateral market model, every transaction contract will include a compensation price that the buyer-seller pair is willing to accept for its transaction to be curtailed. The modeling of bilateral transactions are equivalent to the modifying the power injections at seller and buyer buses. The proposed CM approach is solved by using the evolutionary based Enhanced Genetic Algorithms (EGA). IEEE 30 bus system is considered to show the effectiveness of proposed CM approach.

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NOMENCLATURE

C_i^+	Incremental cost coefficients of ith generating unit.
C_i^-	Decremental cost coefficients of ith generating unit.
$\Delta P_i^+, \Delta P_i^-$	Rescheduled power outputs from preferred schedule in positive or negative side of ith generator.
P_{Gi}	Amount of power injections added at i^{th} seller bus.
$P_{Gi}^{min}, P_{Gi}^{max}$	Lower and upper bounds for active power outputs of ith generator.
P_{Dj}	Amount of power taken at j^{th} buyer bus.
S_L^{max}	Line flow capacity/thermal limit of Lth transmission line.
Q_{Gi}, Q_{Di}	Reactive power generation and demand at i^{th} bus.
$Q_{Gi}^{min}, Q_{Gi}^{max}$	Lower and upper bounds for reactive power outputs of ith generating unit.
V_i^{min}, V_i^{max}	Lower and upper bounds of voltages at i^{th} bus.

1. INTRODUCTION

With the increasing demand for electric power all around the globe, electric utilities have been forced to meet the same by increasing their power generation. However, the electric power that can be transmitted between two locations on a transmission network is limited by several transfer 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. Ensuring that the power system operates within its limits is vital to maintain power system security, failing which can result in widespread blackouts with potentially severe economical and social consequences.

Background: The deregulated electrical power market tries to make the full utilization of electric network with high economical benefits and also maintains the security of power system. Congestion management (CM) re-dispatches the generation and load levels, to establish a system state without the violations of system constraints. The CM problem can be solved by using the sensitivity factors based methods, pricing based methods, auction based methods, and re-dispatch and willingness to pay methods. The methods generally adopted to manage congestion by including the rescheduling of generator power outputs, supplying reactive power support or physically curtailing the transactions. Generally, the Independent System Operators (ISOs) use the first option as much as possible and the last option as the last resort.

In Reference [1], a literature review work has been carried out to unite all the publications in the CM area of research. Reference [2] presents a modified OPF approach whose objective is to minimize the absolute MW of rescheduling. The dispatch problem has been formulated with two different objective functions: cost minimization and minimization of transaction deviations. A generalized and flexible economic modeling framework based on a decomposed inter-temporal equilibrium model by including the generation, transmission, as well as their inter-linkages is proposed in [3]. Reference [4] proposes a CM approach based on an ac power flow method with the help of Flexible AC Transmission System (FACTS) devices in the power system. A detailed review on CM, by considering the conventional methods of CM and the important discussions on each topic are presented in [5]. Reference [6] proposes a single and multi-objective optimization approaches for optimal choice, location and size of FACTS controllers in deregulated power system to minimize congestion, improve voltage stability and reduce the transmission line losses. A new method to determine the optimum locations and capacity of FACTS devices in a power system using a multi-objective optimization function is proposed in [7]. A new hybrid fish bee swarm optimization algorithm is proposed in [8] to determine the types of FACTS devices and its optimal location in a power system without violating the thermal and voltage limits.

A new CM approach by using the generation rescheduling and load shedding, with the realistic voltage-dependent load modeling is proposed in [9]. Reference [10] proposes a new CM approach to relieve congestion and to improve the voltage profile in a system with FACTS controllers in the restructured power system. Reference [11] proposes a multi-objective technique for achieving the optimal capacities of distributed generators such as wind, solar and biomass in order to relieve congestion in the transmission lines. Reference [12] proposes a simple transmission congestion pricing scheme based on tracing principle by considering the generator fixed cost, cost for incurring loss and transmission congestion cost. An energy management approach to remove the congestion on transmission lines by rescheduling the generators with the objective of minimizing energy rescheduling cost on day-ahead and hour-ahead basis is proposed in [13]. An approach to manage congestion in deregulated environment using the particle swarm optimization (PSO) algorithm with improved time-varying acceleration coefficients is proposed in [14]. Reference [15] proposes an economical and secure CM approach, in hybrid power system; by considering the linear piece-wise hydro model and probabilistic wind generation model. An Improved Differential Evolution based approach to release congestion in transmission lines by generator rescheduling and the installation of new wind farms is proposed in [16].

The Problem: From the above literature review on the CM methods, it can be observed that there is no suitable CM approach which can be applicable for the centralized market, and the bilateral and multi-lateral transactions. This paper uses the OPF as a tool for solving the CM problem. Usually, the OPF address the optimal control problem. OPF utilizes all control variables to optimize the costs of power system operation. It also yields valuable economic information and insight into the power system. Therefore, OPF very adeptly addresses both the control and economic problems. After developing the OPF model, it will produce a feasible solution by removing the congestion in the system (here the congestion has been created by adding the bilateral and multi-lateral transactions between the buyer and seller nodes). After that, the congestion has been alleviated by using the rescheduling the generation of each generating station. In the proposed approach, each generating unit submits it's incremental and decremental bidding cost to the ISO. This bidding information is useful to calculate the minimum cost necessary to remove the congestion, and this rescheduling cost is called as the congestion cost.

The Proposed Solution: In this paper, the proposed CM approach has been solved using the evolutionary based algorithm. The evolutionary algorithms differ from classical search and optimization algorithm in many ways. Classical search techniques use a single solution updates in every iteration and mainly use some deterministic transition rules for approaching the optimal solution. Such algorithms start

from a random guess solution and based on some pre-specified transition rule, the algorithm suggests a search direction which is arrived at by considering local information. A unidirectional search is performed along the search direction, to find a best solution. The best solution becomes the new solution and the search is continued for a number of times. Evolutionary algorithms have many advantages over classical approaches. Evolutionary algorithms search a population of points in parallel and not a single point. They don't require derivative information or other auxiliary knowledge. The objective function and fitness values alone influence the direction of search. They use probabilistic transition rules and not deterministic ones. They are more straightforward to apply. They provide a number of potential solutions to a given problem.

2. CONGESTION MANAGEMENT (CM): PROBLEM FORMULATION

In the restructured power system, the role of independent system operator (ISO) is to maintain the system security and reliability while making the economical decisions on market participants. In the present paper, the active power outputs of generating units are rescheduled to relieve the congestion in the system [17], [18]. This CM problem is formulated as the minimization of congestion cost. Mathematically it is formulated as,
minimize,

$$J = \left[\sum_{i=1}^{N_G} C_i^+(\Delta P_i^+)\right] - \left[\sum_{i=1}^{N_G} C_i^-(\Delta P_i^-)\right] \tag{1}$$

The ISO always ensures the system security by making this type of rescheduling operations. This problem is solved subjected to various constraints mentioned below:

2.1. Equality/power balance constraints

The equality constraints reflect the physics of power system. These constraints can be enforced through the power flow equations which require that the net injection of active and reactive power at each bus is equal to zero [19], and they are represented as,

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{n} V_j \left(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}\right) = 0 \tag{2}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{n} V_j \left(G_{ij}sin\delta_{ij} - B_{ij}cos\delta_{ij}\right) = 0 \tag{3}$$

In the above equations, i=1,2,3,...,n. Where n is the number of buses in the system. G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively. Inequality constraints represent system operating limits and they are presented next:

2.2. Generator constraints

The output power of each generating unit has a lower and upper bound, and this constraint is expressed by using,

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{4}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \tag{5}$$

2.3. Voltage constraints

The voltage magnitudes at each bus are bounded by,

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{6}$$

2.4. Bilateral transaction constraint

The power transactions in the restructured power market are modeled as either bilateral transaction between two buses or multi-lateral transactions between many seller and buyer buses considering the system power balance conditions. The bilateral transaction between a pair of buyer bus 'j' and seller bus 'i' can be modeled using [2], [20], [21],

$$P_{Gi} - P_{Di} = 0 \ (7) \tag{7}$$

2.5. Multi-lateral transaction constraint

The constraint on multi-lateral transaction can be modeled using,

$$\sum P_{Gi} - \sum P_{Di} = 0 \tag{8}$$

These transactions by various buyer and seller buses are submitted to the ISO for checking the feasibility without any violations on network constraints. If any violation occurs, then the CM approach should be applied to make the system operation in the secure mode.

2.6 Line flow/thermal constraints

The line flows of all transmission lines must be within their line capacity (MVA) limits, and they are

expressed as,

$$S_L \leq S_L^{max} \tag{9}$$

3.   ENHANCED GENETIC ALGORITHMS (EGA)

References [22], [23] propose the Enhanced Genetic Algorithms to solve the OPF problem. In EGA, after the application of simple genetic operators (i.e., elitism, crossover and mutation), the advanced and problem specific operators are used. Traditional GA is capable of locating near optimal solutions but requires a large number of generations to converge. This problem becomes more intense for large scale optimization problems with difficult search spaces and lengthy chromosomes. Here, the chances of traditional GA getting trapped in local minima are more and the convergence becomes slower. At this point, the application of advanced and problem specific operators, which are derived from the nature of the problem, will enhance the performance of search technique [24]. The brief description of advanced problem specific operators are presented next:

a) Gene Swap Operator (GSO): This operator randomly selects two genes from the chromosomes and swaps their values. This operator swaps genes between variables of similar type. However, the swapping between two different variables is not permitted. Figure 1 depicts the principle of operation of GSO.
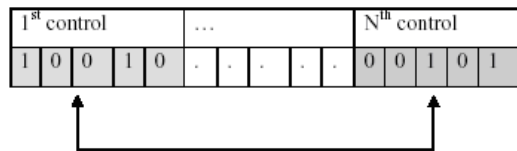

Figure 1. Operation of gene swap operator (GSO)

b) Gene Cross-swap operator (GCSO): This operator is a variant of GSO. It randomly selects two chromosomes and two genes, one from each selected chromosome and swaps their genetic material. While the crossover operator exchanges information between high fit chromosomes, the GCSO searches for alternative alleles, exploiting information stored even in low fit strings. Figure 2 depicts the operation of Gene Cross Swap operator (GCSO) [23].
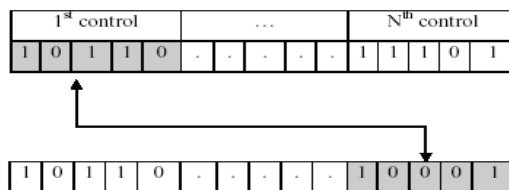

Figure 2. Operation of Gene Cross Swap Operator (GCSO)

c) Gene Copy Operator (GCO): In this operation, a gene is randomly selected in a chromosome and with equal probability its value is copied to its predecessor or the successor gene of the same control type in the same chromosome. This operator causes consecutive controls to operate at same output level. Figure 3 depicts the operation of Gene Copy Operator (GCO).
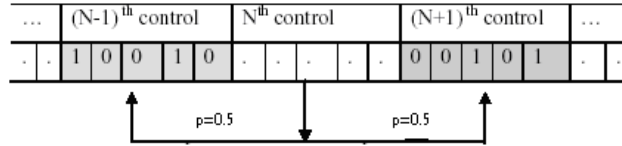

Figure 3. Operation of gene copy operator (GCO)

d) Gene Inverse Operator (GIO): This operator acts like a sophisticated mutation operator. It randomly selects one gene from a chromosome and inverses its bits from 0 to 1, and vice versa for the selected n^{th} control. GIO searches for new areas of search space far away from the current solution, and retains the diversity in population. Figure 4 depicts the operation GIO. It may be noted that n^{th} control variable genes would act as mask for uniform crossover approach.
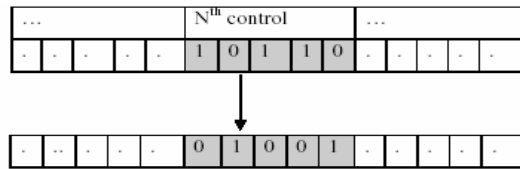

Figure 4. Operation of gene inverse operator (GIO)

e) Gene Max-Min operator: This operator selects a gene in a chromosome randomly and tries to identify the binding control variable lower or upper limits. With equal probability, fills its area with 0's or 1's. Figure 5 depicts the operation of Gene Max-Min operator.
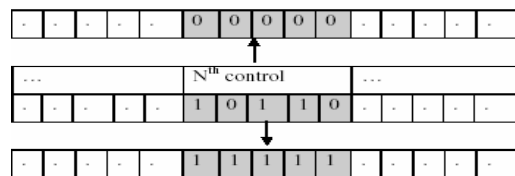

Figure 5. Operation of gene max-min operator

EGA starts with a random initial population. The population members are evaluated and assigned fitness. The condition for convergence is checked and if the problem is not converged simple genetic operators are applied. After the application of basic operators, advanced and problem specific operators are used. Based on the population statistics, the crossover and mutation probabilities are changed [25]. This process is repeated until the number of generations is less than or equal to maximum number of generations.

Infeasible solutions are penalized by applying a constant penalty to those solutions, which violate feasibility in any way. The penalized objective function would then be the unpenalized objective function 'J' plus a penalty (for a minimization problem) [26]. The violated functional operating constraints are incorporated as penalties in objective function. Therefore, the augmented objective function is represented by,

$$J_{aug} = J + \lambda_P\left(P_{G1} - P_{G1}^{limit}\right)^2 + \lambda_V \sum_{i=1}^{N_D}\left(V_{Di} - V_{Di}^{limit}\right)^2 + \lambda_Q \sum_{i=1}^{N_G}\left(Q_{Gi} - Q_{Gi}^{limit}\right)^2 + \lambda_L \sum_{i=1}^{N_L}\left(S_{Li} - S_{Li}^{limit}\right)^2 \qquad (10)$$

$$x^{limit} = \begin{cases} x^{max} & x > x^{max} \\ x^{min} & x < x^{min} \end{cases} \qquad (11)$$

Where x can be PGi, VDi, QGi or SLi of Equation 10. In this equation, the operating constraint limits are set according to Equation 11. 'λ' in Equation 10 indicates the penalty weight for the violated constraint. Initial values of penalty weights and their modifications during the solution run depend largely on the power system [22], [23].

4.   SIMULATION RESULTS AND DISCUSSION

As mentioned earlier, in this paper the standard IEEE 30 bus test system is considered to perform the proposed CM approach. The IEEE 30-bus system has 41-branches. The network parameters of the system are taken from [27]. The network consists of 6 generator buses, 21 load buses and 41 branches, of which 4 branches are tap setting transformer branches. The EGA works on the similar lines as the traditional GA. The population is initialized with random chromosomes. In EGA, after the application of basic genetic operators (i.e., parent selection, crossover and mutation) the problem specific operators like Gene Swap operator, Gene cross swap operator, Gene copy operator, Gene Inverse Operator, Gene Max-Min operator are applied to enhance the performance of traditional GA.

In this paper, the considered Population size is 60, the maximum number of generations/iterations are 200, uniform crossover is applied with the probability of 0.95. The considered mutation probability is 0.001 and the elitism probability is 0.15. Roulette wheel parent selection technique is used. In addition to the basic genetic operators, problem specific operators are applied with a probability of 0.5. The algorithm is stopped when all chromosomes assume similar fitness values. In this paper, two case studies are performed, and they are described next:

4.1. Case 1: Optimum generation scheduling under normal operating conditions

This Case refers to the Base Case, i.e., normal operating conditions are considered here. Table 1 presents the optimum generation schedules and optimum cost for Case 1. The total generation required in this case is 292.155MW and the total transmission losses obtained is 8.755MW. The optimum cost obtained is 799.56$/hr.

Table 1. Optimum Generation Schedules and Cost for Case 1

Optimum Generation Schedules	Case 1
P_{G1} (MW)	177.285
P_{G2} (MW)	48.93
P_{G5} (MW)	21.29
P_{G8} (MW)	20.49
P_{G11} (MW)	11.93
P_{G13} (MW)	12.23
Total Generation (MW)	292.155
System Losses (MW)	8.755
Optimum Cost ($/hr)	799.56

4.2. Case 2: CM using optimum generation rescheduling considering bilateral and multi-lateral transactions

The bilateral and multilateral transactions took place over and above the base case between the seller and buyer while the both parties are willing to pay the congestion rental. The wheeling transactions are added to the system. The details of bilateral and multi-lateral transactions added are presented in Table 2. The incremental and decremental costs of generators (i.e., the bidding price of generators) in the market are presented in Table 3.

With the addition of the transactions that are reported in Table 2, over the base case, results an overloading on the transmission lines 10 and 32. Table 4 presents the line flow comparisons of over loaded lines before and after the CM using the generation rescheduling. From Table 4, it can be observed that the line 10 which has the loading limit of 32 MVA, but it is overloaded to 36.432 MVA. Similarly, line 32 has the maximum limit of 16 MVA, but it is overloaded to 18.865 MVA. Now, the proposed CM algorithm is applied to find the change in power generation that is necessary to remove the congestion in the system. After applying the proposed CM approach, the line flows of over loaded lines are within their limits and this can be seen in Table 4.

Table 2. Details of Bilateral and Multi-lateral Transactions for Case 2

Bilateral Transactions		
From Bus	To Bus	Transaction Power (MW)
14	22	20
16	8	15
17	24	15
27	5	15
Total power		65
Multi-lateral Transactions		
From Bus	Transaction Power (MW)	To Bus	Transaction Power (MW)
18	20	8	15
21	12	12	15
3	26	25	10
Total Power	58	20	20
		Total	60

Table 3. Bidding Price of Generators

Generator Number	Incremental Cost	Decremental Cost
1	45	40
2	40	28
5	45	32
8	40	38
11	42	40
13	48	25

Table 4. Over Loaded Line Flows Before and After the CM

Line Number	Line Limits (MVA)	Before the CM	After the CM
10	32	35.0045	31.9999
23	16	18.5525	15.5631

Table 5 presents the optimum generation schedules, and congestion cost after the generation rescheduling. In this Case, the optimum congestion cost obtained is 208.53$, and the total generation cost is 307.70MW.

Table 5. Over Loaded Line Flows before and after the CM

Optimum Generation Schedules	Case 2
P_{G1} (MW)	176.324
P_{G2} (MW)	48.860
P_{G5} (MW)	21.251
P_{G8} (MW)	23.896
P_{G11} (MW)	13.537
P_{G13} (MW)	12.000
Total Generation (MW)	307.70
System Losses (MW)	11.831
Optimum Congestion Cost ($)	208.53

Suppose, if we do not consider the bids and offer submitted by the generator and customer, but if we add the bilateral and multi-lateral transaction over and above the base case system. And, now if we try to alleviate the congestion in the system, then the cost associated to eliminate congestion become high which the ISO would not allow. The cost obtained in this case is 1032.45$. But, in Case 2, the cost associated with the removal of congestion is 208.53$.

From the above simulation results, it can be observed that the EGA has been applied successfully to manage congestion in the system and to reduce the total congestion cost and transmission losses.

5. CONCLUSIONS

This paper has presented the congestion management (CM) approach within an optimal power flow (OPF) framework in the restructured electricity market scenario. The conventional OPF problem is modified to create a mechanism that enables the market players to compete and trade and simultaneously ensures that the system operation stays within security constraints. The centralized and bilateral dispatch functions of an ISO are presented in this paper. The enhanced genetic algorithms (EGA) is selected to solve the proposed

CM problem. The effectiveness of the proposed approach has been tested on standard IEEE 30 bus system. From the simulation results, it can be observed that the EGA is applied successfully to manage the congestion in the system, and to reduce the total congestion cost and transmission losses.

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