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OPF FRAMEWORK FOR CONGESTION MANAGEMENT IN DEREGULATED ENVIRONMENTS USING DIFFERENTIAL EVOLUTION

Alfredo A. Cuello-Reyna and José R. Cedeño-Maldonado
Electrical & Computer Engineering Department
University of Puerto Rico, Mayagüez Campus
PO Box 9042, Mayagüez, PR 00681
alfredo.cuello@ece.uprm.edu and jcedeno@ece.uprm.edu

ABSTRACT

One of the most challenging operational aspects in restructured systems with open transmission access is the congestion management of the grid. With the trend of an increasing number of bilateral and multilateral contracts submitted to the Independent System Operator (ISO), the possibility of insufficient resources in the transmission system may be unavoidable. In this work, we use an evolutionary computation technique known as Differential Evolution (DE), as an optimization tool for solving various congested scenarios, including pool, bilateral and multilateral transactions; as well as to estimate how the optimization process is affected by the economic valuation of those transactions. A 6-bus system and a modified IEEE 14-bus test system were used to demonstrate the effectiveness of the proposed framework.

KEY WORDS

Congestion management, deregulated environment, electricity markets, evolutionary computation techniques, open transmission access, optimal power flow.

1. Introduction

When producers and consumers of electric energy desire to produce and consume in amounts that would cause the transmission system to operate at or beyond one or more transfer limits, the system is said to be congested [1].

In early statements, congestion was discussed in terms of steady state security, and the basic objective was to control generator outputs so that the system remained secure (no limit violations) at the lowest cost. The optimal power flow routine was the most significant tool for obtaining minimum cost of generation with existing transmission and operational constraints.

In deregulated power systems, with open transmission access, congestion management is one of the most challenging operational problems. With the trend of an increasing number of bilateral and multilateral contracts submitted for electricity market trades, the possibility of insufficient resources in the transmission system may be unavoidable [2].

Under this new scenario, the role of the transmission system operator is to create a set of rules that ensure sufficient control over producers and consumers to maintain an acceptable level of power system security and reliability in the short- and long-term operation.

An optimal power flow function, with the objective of minimizing the amount of the transactions rescheduled, could be developed to solve the congestion problem. In this case, traditional optimization techniques such quadratic programming, interior point methods, and Newton-based methods, have been proposed by researches for solving this problem [1]–[7].

Evolutionary Algorithms (EA) are modern optimization techniques based on the principles of evolutionary theory. The field of investigation that covers these algorithms is known as Evolutionary Computation (EC). These algorithms simulate the evolution of individual structures in order to find optimal solutions. Some of the most popular EC techniques currently being used are genetic algorithms, evolutionary programming, evolution strategies, scatter search, ant colony search, particle swarm, cultural algorithms and differential evolution.

Differential evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution. DE uses a population of floating point encoded individuals and the operators of mutation, crossover and selection to explore the solution space in search of global optima. Each individual, or candidate solution, is a vector that contains as many parameters as the problem dimension [10]. As a robust optimization routine, it can be used in the solution of various optimization problems in power systems, including OPF formulations.

In this work we use DE for solving various congested scenarios that include pool, bilateral and multilateral transaction, and to estimate the way that the economic valuation of those transactions affects the optimization process.

2. Congestion Management in Open Access Transmission System

Open access transmission systems have led an evolution in the power markets organizational structures. This approach implies opening to competition those tasks that were, in vertically integrated structures, coordinated jointly with the objective of minimizing the total cost of operation of the utility [1].

In that scenario, congestion management was discussed in terms of steady state security and the basic objective was to control generator outputs so that the systems remained secure at the lowest cost [2].

In the new deregulated environment, whenever there are overloaded transmission branches, the system is considered to have a congestion problem, and hence operational and price signals are generated to ensure operational feasibility for the transaction proposed [3]. These price signals (increased marginal price of electricity) can be used to reschedule the generation or for planning purposes.

In competitive markets scenarios, transactions among participants (Generation Companies – GENCOs, Distribution Companies – DISCOs, and third parties with no intervention of the Independent System Operator – ISO) comprise the main system decision variables.

The role for the transmission system operator is to create a set of rules that ensure sufficient control over producers and consumers to maintain an acceptable level of power system security and reliability in the short- and long-term operation [4].

3. Optimal Transmission Dispatch Formulation

A. Pool Dispatch Formulation

In the pool market structure, the purpose of the transmission dispatch problem is to minimize the difference between generator's cost and demand's bids. Neglecting the effect of zonal price elasticities, the dispatch formulation may be stated as follows:

$$\min_{P_{Pi}, D_{Pj}} \sum_{\substack{i=1 \\ i \neq skack}}^{I} C_i(P_{Pi}) - \sum_{j=1}^{J} B_j(D_{Pj}) \qquad (1)$$

subject to

$$\begin{aligned} \mathbf{g}(\mathbf{x},\mathbf{u}) &= 0 \\ \mathbf{h}(\mathbf{x},\mathbf{u}) &\leq 0 \end{aligned} \qquad (2)$$

where

$\mathbf{g}, \mathbf{h}$ = the set of systems operation constraints, including system power flow equations, line flow limits and power balance constraints

$\mathbf{u}$ = the set of control variables, i.e., active power at generator and load buses

$\mathbf{x}$ = the set of dependent variables

I, J = the set of generators and load

$C_i(P_{Pi})$ = the pool generation cost at bus i

$B_j(D_{Pj})$ = the bid price for pool demand at bus j

B. Bilateral and Multilateral Dispatch Formulation

In bilateral/multilateral market structures, the purpose of transmission dispatch problem is to minimize the amount of the transactions requested by participants.

The objective of an open access transmission system is to make possible all transactions without curtailment arising from physical and operational constraints [5]. One of the most logical ways of rescheduling the transactions is to do it on the basis of rationing of transmission access, which could be modeled as extra charges paid by the participants to avoid curtailment of the transactions requested.

The mathematical formulation of the bilateral/multilateral dispatch problem can be expressed as [6]:

$$\text{Min } f(\mathbf{u},\mathbf{x}) = [(\mathbf{u} - \mathbf{u}^0)^T \ \mathbf{A}] \ \mathbf{w} \ [(\mathbf{u} - \mathbf{u}^0)^T \ \mathbf{A}]^T \qquad (3)$$

subject to

$$\begin{aligned} \mathbf{g}(\mathbf{x},\mathbf{u}) &= 0 \\ \mathbf{h}(\mathbf{x},\mathbf{u}) &\leq 0 \end{aligned} \qquad (4)$$

where

$\mathbf{w}$ = a diagonal matrix whose elements are the "willingness to pay" charges to avoid curtailment

$\mathbf{u}$ = the set of control variables. The proposed control variables are active power injected or extracted at generator buses and load buses, respectively

$\mathbf{u^0}$ = the desired value of $\mathbf{u}$

$\mathbf{x}$ = the set of dependent variables

$\mathbf{A}$ = a constant matrix reflecting curtailment strategies used by market participants

$\mathbf{g}, \mathbf{h}$ = the set of equality and inequality constraints equations for the power system

C. Power Balance Constraint

In general the power injected/extracted at a specific bus is given by:

$$P_i = P_{PL,i} + \sum_{k \in K} P_{T_K,i} + \sum_{k \in K} P_{LT_K,i} \qquad i \in I_G \qquad (5)$$

$$D_j = D_{PL,j} + \sum_{k \in K} D_{T_K,j} \qquad j \in J_D \qquad (6)$$

where

I_G = set of generator buses

J_D = set of load buses

P_i = active power at generator bus i

D_j = active power at load bus j

K = total number of bilateral/multilateral transactions

T_K = the *k-th* bilateral/multilateral transaction

$P_{PL,i}$ = pool power injected at bus i

$D_{PL,j}$ = power taken at bus j from the pool

$P_{TK,i}$ = power injected at bus i under transaction T_K

$D_{TK,j}$ = power extracted at bus j under transaction T_K

$P_{LT_K,j}$ = power loss compensation at bus i by bilateral/multilateral participants.

The power balance equation for bilateral contracts is:

$P_{Bij} = D_{Bji}$ *for i = 1, 2, …, m (i ≠ slack) and for j = m+1, …, n* (7)

For multilateral contracts the power balance constraint could be stated as follows:

$$\sum P_{Mik} = \sum D_{Mjk} \quad \textit{for } k = 1, 2, \ldots, K \qquad (8)$$

In this optimal power flow problem the control variables can be either P_{Bij} or D_{Bji} for bilateral contracts, and a certain number of variables from the set $\{P_{Mik}, D_{Mjk}; i = 1, 2, \ldots, m; j = m+1, \ldots, n; k = 1, 2, \ldots, K\}$.

The total power injected at a generator bus consists of power sold by the pool, injection for bilateral and multilateral contracts, and injection for loss compensation.

Some schemes are developed for loss compensation, but in this work we assume that the ISO is required to provide all loss compensation services without cost to the participants. Other schemes of loss compensation based on participation factors are addressed in [7].

D. Curtailment Strategies

As proposed in [6] and [11], four basic types of strategies implemented by the ISO in collaboration with market participants are the basis of the proposed transmission dispatch model.

1. *Pool Curtailment:* In congested scenarios, a third term is added to the pool objective function. The purpose is to minimize the deviation of the transactions from the desired values. The curtailment strategy for pool transactions can be stated as follows:

$$\text{Min } f_1(\mathbf{u},\mathbf{x}) = \sum_{j=1}^{J} w_{PLj}(P_{Dj} - P_{Dj}^0)^2 \qquad (9)$$

where

w_{PLj} = willingness to pay factor to avoid curtailment for the pool contract.

$P_{Dj}{}^0$ = the preferred schedule for pool demand at bus j

2. *Point to Point Curtailment:* This strategy concerns to bilateral contracts. As we suggested before, in an individual contract the curtailment of P_{Bij} must be the same of the curtailment of D_{Bji}. The objective function of the optimal dispatch model is:

$$\text{Min } f_2(\mathbf{u},\mathbf{x}) = \sum_{\substack{i=1 \\ i=slack}}^{m} \sum_{j=m+1}^{n} [w_{Bij}\ (P_{Bij} - P_{Bij}^0)^2] \qquad (10)$$

where

w_{Bij} = willingness to pay factor to avoid curtailment of individual contract $\{P_{Bij}, D_{Bji}\}$

P_{Bij}^0 = desired value of P_{Bij}

3. *Group Curtailment:* This is one of the two basic strategies of curtailment for multilateral (group based) transfers. The concern is to make possible a group transfer without curtailment, even if an individual generator within the group or utility has to be rescheduled. The objective function of the optimal dispatch model is:

$$\text{Min } f_3(\mathbf{u},\mathbf{x}) = \sum_{k=1}^{K} [w_{Mk}\ (\sum_{\substack{i=1 \\ i\neq slack}}^{n} P_{Mik} - \sum_{\substack{i=1 \\ i\neq slack}}^{n} P_{Mik}^0)^2] \qquad (11)$$

where

w_{Mk} = willingness to pay factor to avoid curtailment of the *kth* multilateral contract.

P_{Mik}^0 = desired value of P_{Mik}

Various forms exist to spread the curtailment of power generated by GENCOs to loads. One of the most widely used is to curtail the desired value of power demanded by the same percentage of the curtailed values of power generated by GENCOs. That is:

$$D_{Mjk} = D_{Mjk}^0 .(\sum_{k=1}^{K} P_{Mik} / \sum_{k=1}^{K} P_{Mik}^0) \qquad (12)$$

4. *Separate Curtailment:* The objective of this strategy is to minimize the change of the real power injected or extracted power block at a specific generator or load bus of a multilateral contract based on a willingness to pay factor while (8) and (12) are also satisfied. The objective function of the optimal dispatch model is:

$$\text{Min } f_4(\mathbf{u},\mathbf{x}) = \sum_{k=1}^{K} \sum_{\substack{i=1 \\ i\neq slack}}^{m} [w_{Mik} .(P_{Mik} - P_{Mik}^0)^2] \qquad (13)$$

where

w_{Mik} is the willingness to pay factor to avoid curtailment of injected power block P_{Mik}

E. Pool, Bilateral and Multilateral Dispatch Procedure

In this optimal transmission dispatch problem all power transfers are required to be as close as possible to the initial desired power transfers and curtailment decisions are based on markets participants' willingness to pay to avoid curtailment, their preferred curtailment strategies and on system security constraints [6].

The transmission dispatch procedure may be stated as follows:

Step 1: Pool, bilateral and multilateral structures submit their desired transactions to the ISO.

Step 2: If all equality and inequality constraints are satisfied go to step 4. Otherwise go to the next step.

Step 3: Use the optimal dispatch procedure model to curtail the requested power transfer. The process continues until all equality and inequality constraints are satisfied.

Step 4: When all constraints are satisfied, the generation at slack bus (loss compensation) must be spread among all participants.

Step 5: Stop.

4. Differential Evolution

DE is an extreme powerful optimization algorithm that solves real-valued problems based on the principles of natural evolution. As other evolutionary computation techniques, DE uses a population of floating point encoded individuals and mutation, crossover and selection operators to explore the solution space in search of global optima [9].

At every iteration a population ($P^{(G)}$) of N_P vectors candidates solution, must be maintained:

$$P^{(G)} = \left[X_1^{(G)}, \cdots, X_{N_P}^{(G)} \right] \quad (14)$$

where G denotes the iteration number and $X_i^{(G)}$ is the vector of state variables to be optimized

$$X_i^{(G)} = \left[X_{1,i}^{(G)}, \cdots, X_{n,i}^{(G)} \right]^T \quad (15)$$

and $i=1,\ldots,N_P$. N_P represents the population size and n represents the number of objective function parameters.

In order to begin the optimization process, the population must be initialized. An initial population of 10 times of the state variables of the problem is a common practice.

Typically, each decision parameter in every vector of initial population is assigned a randomly chosen value within the corresponding feasible bounds:

$$X_{j,i}^{(0)} = X_j^{\min} + \eta_j (X_j^{\max} - X_j^{\min}) \quad \forall i, j \quad (16)$$

η_j is an uniformly distributed random number between [0, 1] generated for each decision parameter. X_j^{min} and X_j^{max} represent the lower and upper boundary constraints, respectively.

The population of the next generation is created by applying first the mutation, then the crossover, and finally the selection operators. At every generation, each parameter vector becomes a target vector. The mutation operation is applied to each target vector in order to generate new parameter vectors called mutant vectors, $X_i'^{(G)}$. These mutant vectors are created according to:

$$X_i'^{(G)} = X_a^{(G)} + F(X_b^{(G)} - X_c^{(G)}) \quad \forall i \quad (17)$$

In this expression, a, b, and c are randomly selected indices, such that a, b, c $\in\{1,\ldots,N_P\}$ and $a \neq b \neq c \neq i$. New random values for a, b, and c have to be chosen for each value of i. F, the scaling mutation factor, is a user defined constant, typically chosen within the range (0, 2] [9] – [10].

The next step is to apply the crossover operation in order to generate trial vectors, $X_i''^{(G)}$. This is done by mixing parameters from the original population, or target vectors, and the mutant vectors. The following expression describes the crossover process:

$$X_{j,i}''^{(G)} = \begin{cases} X_{j,i}'^{(G)} & \text{if } \eta_j' \le C_R \text{ or } j = q \\ X_{j,i}^{(G)} & \text{otherwise} \end{cases} \quad \forall i, j \quad (18)$$

where η_j' is a uniformly distributed random value within the range [0,1).

C_R is a user defined parameter known as the crossover constant that controls the probability that a trial vector parameter will come from the mutant vector instead of the target vector, while q is a random parameter index that is chosen once for each i. This random parameter index, q, eliminates the possibility that the trial vector will be the same as the target vector by making sure that at least one parameter will come from the mutant vector.

Finally, the selection process decides whether or not the trial vector will be part of the next generation. This is accomplished by comparing the fitness values of the trial vectors to those of their corresponding target vectors. The following expression represents the selection operator:

$$X_i^{(G+1)} = \begin{cases} X_i''^{(G)} & \text{if } f\left(X_i''^{(G)}\right) \le f\left(X_i^{(G)}\right) \\ X_i^{(G)} & \text{otherwise} \end{cases} \quad (19)$$

where $f(x)$ represents the fitness value of vector x. The selection process makes sure that all individuals in the next generation are as good as or better than the individuals in the current population [10].

Proposed DE Framework for the Optimal Transmission Dispatch Problem

As an optimization tool, the DE algorithm can be used for solving various congested scenarios, including pool, bilateral and multilateral contracts.

The following procedure could be addressed in the implementation of the DE algorithm:

1. The first step is to select the state variables for the optimization process. Depending on the type of transaction involved in the studied scenario the set of state variable may be:
   a. P_{Pi} and D_{Pj} for pool transactions.
   b. P_{Bij} or D_{Bji} for bilateral contracts (one of them).
   c. A certain number of variables from the set $\{ P_{Mik}, D_{Mjk}\ ;\ i = 1, 2, \ldots, m;\ j = m+1, \ldots, n;\ k = 1, 2, \ldots, K\}$.
2. The next step is to initialize the population. Restrictions in the minimum power generated/demanded at a certain seller or buyer and preferred values of transaction can be used as boundary constraints for the case. The population size is selected depending on the state variables of the problem, as we discuss previously.
3. The next step is to apply the processes of mutation and recombination to all individuals of the population. These processes were detailed discussed in early statements of this work.
4. The selection process compare the fitness of the trial and the target vector in order to decide which vector could pass to the following generation. This fitness function could be the equation (1), (9), (10), (11) or (13) or a combination of them depends on the case. The fitness function could be modified, adding penalties factors when equality and inequality constraints are not satisfied.
5. The process continues until the algorithm reaches a certain criterion of convergence.

5. Case Studies

The proposed framework is applied to a six bus system test case and to the modified IEEE 14–bus test system.

1. Six bus system test case

A six - bus system shown in figure 1 is used to demonstrate the effectiveness of the algorithm solving congested scenarios. In this system three types of transactions (pool, bilateral and multilateral) were considered. Separate curtailment strategy was selected to curtail the load, if is necessary, in multilateral contracts.

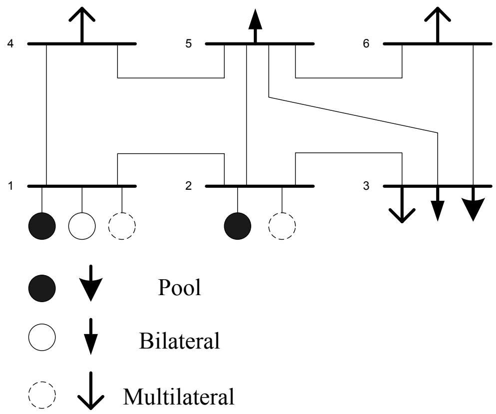

Figure 1: Six Bus System Test Case

Tables 1 – 4 provide the system data and the pool, bilateral and multilateral transactions and its preferred schedules. In those tables G, D, Types, Min, Max, a, b, Prefer and *W* refer to generation, load, types of generation, minimum value, maximum value, non linear and linear coefficient for the bid price, preferred values and willingness to pay to avoid curtailment factor for all transactions.

The table 5 present the curtailment weights for multilateral contract load at each bus and table 6 shows the voltage limits. The bus 1 is the slack bus and the base is 100 MVA.

Table I
System Data

Line	From bus	To bus	R	X	MW Limit
1	1	2	0.03	0.1	100
2	1	4	0.025	0.06	120
3	2	3	0.025	0.08	140
4	2	5	0.02	0.05	130
5	3	5	0.02	0.1	100
6	3	6	0.02	0.1	100
7	4	5	0.02	0.08	100
8	5	6	0.01	0.05	100

Table II
Pool Data

Bus	Type	Min	Max	A	b	Preferred	W
1	G	0.0	200.0	0.06	6.00		
2	G	0.0	200.0	0.03	3.00		
3	D	0.0	100.0	0.00	9.00	100.0	20.0
5	D	0.0	80.0	0.00	10.00	80.0	20.0

Table III
Bilateral Contract Data

Bus	Type	Min	Max	Preferred	W
1	G	0.0	100.0	100.0	
3	D	0.0	100.0	100.0	15.0

Table IV
Multilateral Contract Data

Bus	Type	Min	Max	Preferred	W
1	G	0.0	100.0	100.0	
2	G	0.0	100.0	100.0	
3	D	0.0	50.0	50.0	15.0
4	D	0.0	100.0	100.0	15.0
6	D	0.0	50.0	50.0	20.0

Table V
Multilateral Curtailment Weight

Bus	Type	Transaction	Weight
3	D	Multilateral	0.25
4	D	Multilateral	0.50
6	D	Multilateral	0.25

Table VI
Bus Voltages Magnitudes

Bus	Vmin	Vmax
1	1.02	1.02
2	1.04	1.04
3	0.95	1.05
4	0.95	1.05
5	0.95	1.05
6	0.95	1.05

If initial schedules submitted by the three types of transactions are honored by the ISO, they would cause congestion in lines 2, 3 and 4, as shown in table 7.

Table VII
Line Flows of Initial Schedules

Line	From bus	To bus	Pij	Pji	MW Limit
2	1	4	***158.91***	***-152.84***	120
3	2	3	***177.77***	***-170.27***	140
4	2	5	***164.08***	***-158.86***	130

Based on the optimization the proposed DE framework for this optimization problem the congestion could be solved. The results of the case are shown in tables 8 and 9. Those results are compared with the results obtained by [11].

Table VIII
Optimization Results: Generation Values

Bus	Type	Transaction	Pref	MO Final Value	DE Final Value
1	G	Pool	100.0	33.59	37.20
2	G	Pool	80.0	129.50	125.57
1	G	Bilateral	100.0	77.50	78.06
1	G	Multilateral	100.0	50.06	50.17
2	G	Multilateral	100.0	100.00	99.90

Table IX
Optimization Results: Load Values

Bus	Type	Transaction	Pref	MO Final Value	DE Final Value
3	D	Pool	100.0	80.58	83.51

5	D	Pool	80.0	66.70	65.81
3	D	Bilateral	100.0	77.55	78.06
3	D	Multilateral	50.0	37.51	37.52
4	D	Multilateral	100.0	75.03	75.03

Table X
Optimization Results: Objective Function

MO Final Value	DE Final Value
$55,215.81	$43,509.13

As shown, Differential Evolution improves the solution obtained with a traditional optimization technique.

2. Modified IEEE 14-bus system test case

The proposed framework is also applied to the modified IEEE 14–bus test system shown in Figure 2. In this system we consider only bilateral and multilateral transaction, because those are the common transaction in deregulated environments. Tables A.1 – A.3 of the appendix provide the system data used for this case.

Two multilateral groups sell and buy energy in this market. The group 1 makes transfer from generators at buses 2 and 6 to loads at buses 4, 9, 11, 12 y 14 and the group 2 makes transfers from generator at bus 1 to loads at buses 5, 10 and 13.

For simplicity we assume that the generator at bus 3 was designated by the ISO for loss compensation, so that bus was selected as slack bus and the generator at bus 8 work as synchronous capacitor.

If initial schedules submitted by the both groups are honored by the ISO, they would cause congestion in lines 2, 4, 5 and 11, as shown in Table XI.

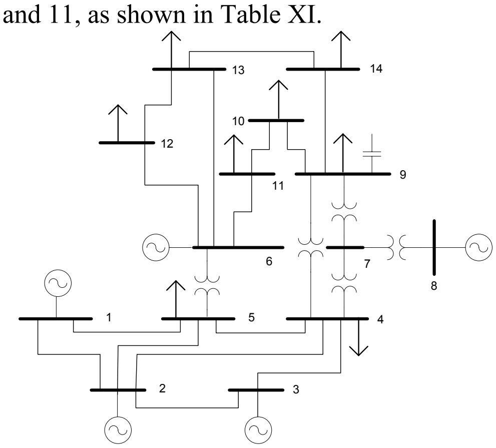

Figure 2: Modified IEEE 14-Bus Test System

Table XI
Line Flows of Initial Schedules

Branch	From Bus	To Bus	Sij	Sji	MVA Limit
2	1	5	114.28	104.92	110
4	2	4	113.72	104.13	110
5	2	5	112.52	103.20	110
11	6	11	62.21	57.99	55

Some curtailment strategies were considered:

a) The group curtailment strategy (11) is employed by both groups and the group curtailment relationship takes the simple linear form stated in (12). The willingness to pay to avoid curtailment for both groups is $5\,\$/MW^2$.

b) The willingness to pay to avoid curtailment of group 2 is increased to $15\,\$/MW^2$, but the other information remains as in the case a).

c) Group 1 selects the separate curtailment strategy (13). The willingness to pay to avoid curtailment for generator at bus 2 is set at $15\,\$/MW^2$ while value at bus 6 remains at $5\,\$/MW^2$.

d) Group 2 abandon the group curtailment strategy (11) and adopt the point – to – point curtailment strategy (10) for the three individual contracts (1 – 5, 1 – 10 and 1 – 13). The willingness to pay to avoid curtailment of each individual contract is $5\,\$/MW^2$ and the group 1 maintains the group curtailment strategy as case a).

e) The willingness to pay to avoid curtailment for the individual contract 1 – 10 is increased to $15\,\$/MW^2$ while willingness to pay to avoid curtailment of the contracts 1 – 5 and 1 – 13 remain at $5\,\$/MW^2$. The other information is the same as in the case d).

The results of the optimization process for all cases treated are shown in Table XII. In this case, the optimal dispatch procedure results in uncongested system solutions for all cases.

Table XII
Original and Curtailed Generation and Load Data for the Modified IEEE 14 – Bus Test System

Bus	Type	Desired MW	Curtailed Data				
			Case A	Case B	Case C	Case D	Case E
Loss Compensation							
3	G	35.05	28.03	27.77	27.87	27.82	27.77
Group 1							
2	G	157.7	157.7	150.13	153.16	155.65	155.14
6	G	98	78.08	81.71	80.26	80.75	78.79
4	D	102.9	94.88	93.3	93.93	95.14	94.14
9	D	57.8	53.3	52.41	52.76	53.44	52.88
11	D	53.5	49.33	48.51	48.84	49.46	48.95
12	D	16.1	14.85	14.6	14.7	14.89	14.73
14	D	25.4	23.42	23.03	23.19	23.48	23.24
Group 2							
1	G	214.1	202.45	206.7	205	203.39	203.68
5	D	167.8	158.67	162	160.67	164.11	163.19
10	D	19	17.97	18.34	18.19	15.43	17.51
13	D	27.3	25.82	26.36	26.14	23.85	22.99

In Case 2.A (the base case), when both groups have the same curtailment strategy and the same willingness to pay to avoid curtailment factor, the generation and load of group 1 was curtailed most severely than the generation and load of group 2. This is because of the congested lines 4 and 5 serve the heaviest loads of this group, while for the group 2 the main restriction is on line 2 that serve the load at bus 5.

The Case 2.B shows a very modest increase in generation and demand of group 2, when the willingness to pay to avoid curtailment for the group was increased to $15\,\$/MW^2$.

In Case 2.C when group 1 becomes more selective, the results show a lightly increment in generation of the generator 2, compared with the Case B. Those cases shown the complex character of the economic risk that markets participants assume in a competitive environment.

In Case 2.D, when the group 2 shift to a point to point curtailment strategy, the load at bus 10 is reduced in comparison with the base case, while the load at buses 5 and 13 increases. The load is partially restored in case 2.E, when the willingness to pay to avoid curtailment for this contract is increased to $15\,\$/MW^2$.

5. Conclusion

In deregulated power systems, with open transmission access, congestion management is one of the most challenging operational problems. With the trend of an increasing number of bilateral and multilateral contracts submitted for electricity market trades, the possibility of insufficient resources in the transmission system may be unavoidable.

In this statement, the role for the transmission system operator is to create a set of rules that ensure sufficient control over producers and consumers to maintain an acceptable level of power system security and reliability in the short term and long term operation. An optimal power flow, with two simultaneous objectives: cost minimization and minimization of transaction deviations, can be developed to solve the congestion problem.

Differential Evolution (DE) is an optimization algorithm that solves real-valued problems based on the principles of natural evolution. As a robust optimization routine, it can be used for the solution of various optimization problems in power systems, including OPF formulations.

The results obtained showed that the willingness to pay and the curtailment strategy selected by market participants are two factors that will significantly affect the constrained dispatch. Obviously, while higher the willingness to pay, less the curtailment of the transaction requested, but as it was suggested by Fang and David in [6], the complex interactions among market participants highlight the need for careful design of the dispatch strategies.

6. References

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7. Appendix

Table A.1
Transformer Data

Transformer	From	To	R	X	Transformer Tap Ratio	MVA Limits
1	4	7	0.0000	0.2091	0.978	70
2	4	9	0.0000	0.5562	0.969	40
3	5	6	0.0000	0.2520	0.932	70
4	7	8	0.0000	0.1762	1.000	55
5	7	9	0.0000	0.1100	1.000	70

Table A.2
Line Data

Line	From	To	R	X	1/2 B	MVA Limits
1	1	2	0.0194	0.0592	0.0264	220
2	1	5	0.0540	0.2230	0.0246	110
3	2	3	0.0470	0.1980	0.0219	110
4	2	4	0.0581	0.1763	0.0187	110
5	2	5	0.0570	0.1739	0.0170	110
6	3	4	0.0670	0.1710	0.0173	110
7	4	5	0.0134	0.0421	0.0064	110
8	6	11	0.0950	0.1989	0.0000	55
9	6	12	0.1229	0.2558	0.0000	55

10	6	13	0.0662	0.1303	0.0000	55
11	9	10	0.0318	0.0845	0.0000	55
12	9	14	0.1271	0.2704	0.0000	55
13	10	11	0.0821	0.1921	0.0000	55
14	12	13	0.2209	0.1999	0.0000	55
15	13	14	0.1709	0.3480	0.0000	55

Table A.3
Bus Voltage Magnitudes and Reactive Power Demanded by Loads

Bus No.	V (pu)	Qd (MVAR)	Qc (MVAR)
1	1.08		
2	1.08		
3	1.08		
4	0.97-1.10	54.9	
5	0.97-1.10	31.6	
6	1.08		
7	0.97-1.10	0.0	
8	1.09		
9	0.97-1.10	16.8	19.0
10	0.97-1.10	5.8	
11	0.97-1.10	7.8	
12	0.97-1.10	6.6	
13	0.97-1.10	5.8	
14	0.97-1.10	10.0	