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Market-based transmission expansion planning by improved differential evolution

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ABSTRACT

The restructuring and deregulation has exposed the transmission planner to new objectives and uncertainties. As a result, new criteria and approaches are needed for transmission expansion planning (TEP) in deregulated electricity markets. This paper proposes a new market-based approach for TEP. An improved differential evolution (IDE) model is proposed for the solution of this new market-based TEP problem. The modifications of IDE in comparison to the simple differential evolution method are: (1) the scaling factor F is varied randomly within some range, (2) an auxiliary set is employed to enhance the diversity of the population, (3) the newly generated trial vector is compared with the nearest parent, and (4) the simple feasibility rule is used to treat the constraints. Results from the application of the proposed method on the IEEE 30-bus test system demonstrate the feasibility and practicality of the proposed IDE for the solution of TEP problem.

1. Introduction

In regulated electricity markets, the transmission expansion planning (TEP) problem consists of minimizing the investment costs in new transmission lines, subject to operational constraints, to meet the power system requirements for a future demand and a future generation configuration. The TEP problem in regulated electricity markets has been addressed by mathematical optimization as well as by heuristic models [1,2]. Mathematical optimization models for TEP problem include linear programming [3], dynamic programming [4], non-linear programming [5], mixed integer programming [6], Bender's decomposition [7], and hierarchical decomposition [8]. Heuristic models for the solution of TEP problem include sensitivity analysis [9], simulated annealing [10], expert systems [11], and genetic algorithms [12].

There are two main differences between planning in regulated and deregulated electricity markets form the point of view of the transmission planner: (1) the objectives of TEP in deregulated power systems differ from those of the regulated ones, and (2) the uncertainties in deregulated power systems are much more than in regulated ones.

The main objective of TEP in deregulated power systems is to provide a nondiscriminatory and competitive environment for all stakeholders, while maintaining power system reliability. TEP affects the interests of market participants unequally and this should be considered in transmission planning. The TEP problem in deregulated electricity markets has been addressed by probabilistic and stochastic methods [13]. Probabilistic methods for the solution of TEP problem include probabilistic reliability criteria method [14], market simulation [15], and risk assessment [13,16]. Stochastic methods for the solution of TEP problem include game theory [17] and fuzzy set theory [18].

Nowadays, the TEP problem has become even more challenging because the integration of wind power into power systems often requires new transmission lines to be built [19].

This paper proposes a general formulation of the transmission expansion problem in deregulated market environment. The main purpose of this formulation is to support decisions regarding regulation, investments and pricing [20–22], so the main users of this model are regulatory authorities. This formulation is based on the concept of a reference network [20]. The determination of such a reference network requires the solution of a type of security-constrained optimal power flow (OPF) problem [22]. A market-based TEP problem that optimizes the line capacities of an existing network has been formulated in [21,22]. This paper extends the work presented in [21,22] by formulating a more complex market-based TEP problem that optimizes the topology and the line capacities of a transmission network. Moreover, this paper proposes a differential evolution model for the solution of the market-based TEP problem.

Differential evolution (DE) is a relatively new evolutionary optimization algorithm [23,24], which has been used for the solution of power system problems [25–27]. Many studies demonstrated that DE converges fast and is robust, simple in implementation and use, and requires only a few control parameters. In spite of the prominent merits, sometimes DE shows the premature convergence and slowing down of convergence as the region of global optimum is approached. In this paper, to remedy these defects, some modifications are made to the simple DE. An auxiliary set is employed to

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increase the diversity of population and prevent the premature convergence. In the simple DE, the trial vector, or offspring, is compared with the target vector with the same running index, whereas in this paper, the trial vector is compared with the nearest parent in the sense of Euclidean distance. Moreover, the comparison scheme is changed according to the convergence characteristics. The scaling factor F that is constant in the original DE is varied randomly within some specified range. The above modifications form an improved differential evolution (IDE) algorithm that is applied for the solution of TEP problem. The proposed IDE algorithm is extensively tested on the IEEE 30-bus system and the results of the proposed IDE are compared with the results of the simple DE as well as with the results obtained by the genetic algorithm method.

The paper is organized as follows. Section 2 formulates the market-based TEP problem. Section 3 describes the solution of the reference network subproblem using an iterative algorithm based on security-constrained direct current (dc) power flow. The simple differential evolution is described in Section 4 and the improved differential evolution is presented in Section 5. Section 6 presents an overview of the proposed IDE solution to the TEP problem. Section 7 contains results from the application of the proposed method to the IEEE 30-bus test system. Conclusions are presented in Section 8.

2. Problem formulation

2.1. Definition

The objective of the market-based TEP problem is to optimize the transmission network topology by selecting the transmission lines that should be added to an existing transmission network so as to minimize the overall generation and transmission cost, subject to generating unit and transmission network constraints. The market-based transmission expansion problem is composed of two interrelated problems: (1) the optimum network problem, and (2) the reference network subproblem that is part of the optimum network problem.

2.2. Reference network subproblem

The formulation of the market-based TEP problem is based on the concept of a reference network [20]. A reference network is topologically identical to an existing (or expanding) transmission network, and generators and loads are unchanged. On the other hand, each transmission line has an optimal capacity. The reference network subproblem determines the optimal capacities of transmission lines by minimizing the sum of the annual generation cost and the annuitized cost of transmission, Eq. (1), subject to constraints defined by Eqs. (2)–(9). Alternatively, a different objective could be also considered such as maximizing the social welfare [28–30]. By comparing the capacities of individual lines in the optimum reference network and the initial network (i.e., the network before expansion), the needs for new investment in transmission lines can be identified.

The objective function of the reference network subproblem is expressed as follows [22]:

$$\min_{P_{pg},T_b}\left[\sum_{p=1}^{np}\tau_p\cdot\sum_{g=1}^{ng}C_g\cdot P_{pg}+\sum_{b=1}^{nl}k_b\cdot l_b\cdot T_b\right] \tag{1}$$

where P_{pg} (MW) is the output of generator g during demand period p, T_b (MW) is the capacity of transmission line b, np is the number of demand periods, τ_p is the duration of demand period p, ng is the number of generators, C_g is the operating cost of generator g, nl is the number of transmission lines, k_b is the annuitized investment cost for transmission line b in \$/(MW·km·year), and l_b is the length of transmission line b in km.

This optimization is constrained by Kirchhoff's current law, which requires that the total power flowing into a node must be equal to the total power flowing out of the node:

$$A^0\cdot F_p^0-P_p+D_p=0\quad\forall p=1,\ \dots,\ np \tag{2}$$

where A^0 is the node–branch incidence matrix for the intact system (initial network), F_p^0 is the vector of transmission line flows for the intact system during demand period p, P_p is the vector of nodal generations for demand period p, and D_p is the nodal demand vector for period p.

The Kirchhoff's voltage law implies the constraint (3) that relates flows and injections:

$$F_p^0=H^0\cdot(P_p-D_p)\quad\forall p=1,\ \dots,\ np \tag{3}$$

where, H^0 is the sensitivity matrix for the intact system.

The thermal constraints on the transmission line flows have also to be satisfied:

$$-T\leqslant F_p^0\leqslant T\quad\forall p=1,\ \dots,\ np \tag{4}$$

where, T is the vector of transmission line capacities, and p corresponds to each one of the np periods in the load duration curve.

It should be noted that the constraints (2)–(4) have been derived using a dc power flow formulation neglecting losses.

The constraints (2)–(4) must also be satisfied for contingencies, i.e., for credible outages of transmission and generation facilities. As a result, the constraints (5)–(7) have also to be satisfied:

$$A^c\cdot F_p^c-P_p+D_p=0\quad\forall p=1,\ \dots,\ np;\quad c=1,\ \dots,\ nc \tag{5}$$

$$F_p^c=H^c\cdot(P_p-D_p)\quad\forall p=1,\ \dots,\ np;\quad c=1,\ \dots,\ nc \tag{6}$$

$$-T\leqslant F_p^c\leqslant T\quad\forall p=1,\ \dots,\ np;\quad c=1,\ \dots,\ nc \tag{7}$$

where, A^c is the node–branch incidence matrix for contingency c, F_p^c is the vector of transmission line flows for contingency c during demand period p, H^c is the sensitivity matrix for contingency c, and nc is the number of contingencies.

The optimization must respect the limits on the output of the generators:

$$P^{\min}\leqslant P_p\leqslant P^{\max}\quad\forall p=1,\ \dots,\ np \tag{8}$$

where, $P^{\min}$ is the vector of minimum nodal generations and $P^{\max}$ is the vector of maximum nodal generations.

Since the objective of the optimization is to find the optimal thermal capacity of the lines, this variable can take any positive value:

$$T\geqslant 0 \tag{9}$$

2.3. Optimum network problem

The optimum network problem is in fact the same with the overall market-based transmission expansion problem. The objective of the optimum network problem is to select the new transmission lines that should be added to an existing transmission network so as to minimize the overall generation and transmission cost.

The solution of the optimum network problem can be found by considering an exhaustive list of candidate new transmission lines, and determining which transmission lines, belonging in the exhaustive list of candidate new transmission lines, should be added to an existing transmission network so as to minimize the overall generation and transmission cost. In the process of finding the solution to the optimum network problem, the reference network subproblem should be solved for every examined combination of new transmission lines. The above presentation shows that the market-based transmission expansion problem (optimum network problem) is a complex mixed integer non-linear programming problem.

3. Solution of the reference network subproblem

3.1. Data

The data of the reference network subproblem are the following:

1. Network topology.
2. Number of demand periods.
3. Duration (h) of each demand period.
4. Load (MW) at each bus during each period.
5. Minimum generation (MW) at each bus.
6. Maximum generation (MW) at each bus.
7. Operating cost of each generator. The production (operating) cost for each unit is considered a quadratic function of the unit output.
8. Marginal annuitized investment cost ($/(MW·km·year)) of each transmission line.
9. Length (km) of each transmission line.
10. Number of contingencies (outages).
11. Outages of transmission and generation facilities.

3.2. Design variables

The values of the design variables determine the optimal solution of the reference network subproblem. These design variables are the following:

1. The vector of generation dispatch in each demand period.
2. The vector of line power flows in each demand period.
3. The vector of the optimal transmission line capacities valid in all demand periods.

3.3. Solution algorithm

The reference network subproblem is solved using the following iterative algorithm [22]:

1. Solve the optimal power flow for each demand period.
2. Study all system conditions using a dc power flow.
3. Identify the overloaded transmission lines for each system and each demand level.
4. If all transmission line flows are within limits then go to step 6, else go to step 5.
5. Add a constraint to the optimal power flow for each overloaded transmission line and then go to step 1.
6. The optimal capacities of the transmission lines are found and the algorithm terminates.

4. Simple differential evolution

The procedure of DE is almost the same as that of the genetic algorithm (GA) whose main process has mutation, crossover, and selection. The main difference between DE and GA lies in the mutation process. In GA, mutation is caused by the small changes of the genes, whereas in DE, the arithmetic combinations of the selected individuals carry out mutation. DE maintains a population of constant size that consists of PN real-valued vectors $\mathbf{x}_i^G$, $i = 1, 2, \ldots, PN$, where i indicates the index of the individual and G is the generation. The evolution process of the DE algorithm is as follows.

4.1. Initialization

To construct a starting point for the optimization process, the population with PN individuals should be initialized. Usually, the population is initialized by randomly generated individuals within the boundary constraints:

$$x_{j,i}^0 = \text{rand}_{j,i}[0, 1] \cdot (x_j^{(U)} - x_j^{(L)}) + x_j^{(L)} \tag{10}$$

where, $i = 1, 2, \ldots, PN$, $j = 1, 2, \ldots, VD$, VD is the variable dimension, $x_j^{(L)}$ and $x_j^{(U)}$ are the lower and upper boundary of the j component, respectively, and $rand_{j,i}[0, 1]$ denotes a uniformly distributed random value in the range [0, 1].

4.2. Mutation

For each target vector, or parent vector $\mathbf{x}_i^G$, a mutant vector is generated according to:

$$\mathbf{v}_i^{G+1} = \mathbf{x}_{n1}^G + F \cdot (\mathbf{x}_{n2}^G - \mathbf{x}_{n3}^G) \tag{11}$$

where, random indexes $n1$, $n2$, and $n3$ are integers, mutually different, and also chosen to be different from the running index i. In the initial DE scheme [23], the parameter F is a real and constant factor during the entire optimization process, and the variable range is $F \in [0, 2]$.

4.3. Crossover

The trial vector $\mathbf{u}_i^{G+1}$ is generated using the parent and mutated vectors as follows:

$$\mathbf{u}_{j,i}^{G+1} = \begin{cases} \mathbf{v}_{j,i}^{G+1}, & \text{if rand}_{j,i}[0, 1) \leqslant CR \text{ or } j = k \\ \mathbf{x}_{j,i}^G, & \text{otherwise} \end{cases} \tag{12}$$

where $k \in \{1, 2, \ldots, VD\}$ is the randomly selected index chosen once for each i, and CR is the parameter that is a real-valued crossover factor in the range [0, 1] and controls the probability that a trial vector component comes from the randomly chosen, mutated vector $\mathbf{v}_{j,i}^{G+1}$, instead of the current vector $\mathbf{x}_{j,i}^G$. If CR is 1, then the trial vector $\mathbf{u}_i^{G+1}$ is the replica of the mutated vector $\mathbf{v}_i^{G+1}$.

4.4. Selection

To decide the population for the next generation, the trial vector $\mathbf{u}_i^{G+1}$ and the target vector $\mathbf{x}_i^G$ are compared, and the individual of the next generation $\mathbf{x}_i^{G+1}$ is decided according to the following rule for minimization problems:

$$\mathbf{x}_i^{G+1} = \begin{cases} \mathbf{u}_i^{G+1}, & \text{if } f(\mathbf{u}_i^{G+1}) \leqslant f(\mathbf{x}_i^G) \\ \mathbf{x}_i^G, & \text{otherwise} \end{cases} \tag{13}$$

The feature of DE selection scheme is that a trial vector is compared with only one individual, not all the individuals in the current population. Due to the greedy selection scheme, all the individuals of the next generation are as good as or better than their counterparts in the current generation.

5. Improved differential evolution

This section presents the modifications to the simple DE method that lead to an improved differential evolution (IDE) algorithm. The modification proposed is justified by the fact that the IDE provides better solution to the TEP problem in comparison to simple DE, as is shown in Section 7.

5.1. Scaling factor F

In the initial DE, the scaling factor F in Eq. (11) is constant during the optimization process and F takes values in the range [0, 2]. However, no optimal choice of F has been proposed in the bibliography of DE. All the studies used an empirically derived value, and in most cases F varies from 0.4 to 1. This means F is strongly problem-dependent and the user should choose F carefully after some trial and error tests. In this paper, F is varied randomly within some specified range, as follows:

$$F = a + b \cdot \mathrm{rand}_i[0, 1] \quad (14)$$

where a and b are positive and real-valued constant, and the sum of a and b is less than 1.

Consequently, F is different for each generation, and the computation of F by Eq. (14) is effective when the optimal value of F is difficult to be determined for complicated problems like TEP.

5.2. Selection scheme

In the original DE, the trial vector or offspring $\mathbf{u}_i^{G+1}$ is compared with the target vector $\mathbf{x}_i^G$ whose index is the same as running index i using Eq. (13). In the modified DE, the trial vector is compared with the nearest target vector in the sense of Euclidean distance. This comparison scheme is employed in the crowding DE algorithm for multimodal function optimization [31]. By this scheme, as the optimization proceeds, the individuals are scattered and gathered around the local optimal points. However, in this paper, only global optimization is considered, and if there is no improvement of the optimal value during a predefined number of generations, then the comparison scheme is changed to that of the original DE. Therefore, in the initial period of optimization, the DE algorithm explores to find not only global but also local optima, and in the later stage, it searches only for the global optima with greedy selection scheme.

5.3. Auxiliary set

In selection of the next generation individual, if the trial vector is worse than the target vector, then the trial vector is discarded. To enhance the explorative search and the diversity of the population, an auxiliary set is employed. The auxiliary set P_a has the same number of population PN, and the initialization process is the same as that of the main set using Eq. (10). At each generation, if the trial vector $\mathbf{u}_i^{G+1}$ when compared with the corresponding target vector in the main set is found to be worse than its target vector, then the rejected trial vector is compared with the point $\mathbf{w}_i^G$ with the same running index i in the auxiliary set P_a. If $f(\mathbf{u}_i^{G+1}) < f(\mathbf{w}_i^G)$, then $\mathbf{u}_i^{G+1}$ replaces $\mathbf{w}_i^G$.

To use the solutions in P_a, after a predefined number of generations, several of the worst solutions in the main set are periodically replaced with the best ones in the auxiliary set by comparing the objective function value.

5.4. Treatment of constraints

Most optimization problems in the real world have constraints to be satisfied. One common approach to deal with constraints is to penalize constraint violations using an appropriate penalty function [32]. In this approach, considerable effort is required to tune the penalty coefficients. In this paper, three selection criteria are used to handle the constraints of the TEP problem:

1. If two solutions are in the feasible region, then the one with the better fitness value is selected.
2. If one solution is feasible and the other is infeasible, then the feasible one is selected.
3. If both solutions are infeasible, then the one with the lower amount of constraint violation is selected.

5.5. Handling of integer variables

DE in its initial form is a continuous variables optimization algorithm, and was extended to mixed variables problem [33]. During the evolution process, the integer variable is treated as a real variable, and in evaluating the objective function, the real value is transformed to the nearest integer value as follows:

$$f = f(Y): \quad Y = y_i \quad (15)$$

where,

$$y_j = \begin{cases} x_j, & \text{if } x_j \text{ is integer} \\ \mathrm{INT}(x_j), & \text{if } x_j \text{ is continuous} \end{cases} \quad (16)$$

where $\mathrm{INT}(x_j)$ function gives the nearest integer to x_j, and the solution vector is $\mathbf{x} = [x_1, x_2, \ldots, x_{VD}]$.

6. Overview of the proposed differential evolution solution to the transmission expansion problem

The proposed differential evolution solution for the market-based transmission expansion problem (optimum network problem) is composed of the following steps:

1. Given the initial transmission network topology and the planned new generators, create an exhaustive list of candidate new transmission lines.
2. Create an initial population of candidate solutions. The initial population is randomly created from the exhaustive list of candidate new transmission lines using Eq. (10).
3. While the termination criterion is not met, the differential evolution algorithm iterates over the following three phases:
   a. Evaluation of the candidate solutions using the security-constrained optimal power flow algorithm.
   b. Crossover and mutation (with randomly varied scaling factor F).
   c. Selection with the use of the auxiliary set concept.
4. As soon as the termination criterion is met (maximum number of generations), the solution proposed by the improved differential evolution is the one with the minimum operating and investment cost, which simultaneously satisfies all the constraints.

7. Results and discussion

The proposed IDE algorithm has been extensively tested on the initial transmission network of Fig. 1 that is based on the IEEE 30-bus system [34] and the results of the proposed IDE have been compared with the results of the simple DE as well as with the results obtained by the genetic algorithm method. Actual cost data of the Hellenic transmission system have been used in the computations. As can be seen from Fig. 1, the initial transmission network is composed of 32 transmission lines and 28 buses. Bus 11 is a new power plant to be connected to the network, so initially there is no existing transmission line between bus 11 and any bus in the initial network. Bus 13 also corresponds to a new power plant. Table 1 presents the transmission line codes of the 32 transmission lines of the initial network of Fig. 1 together with the exhaustive

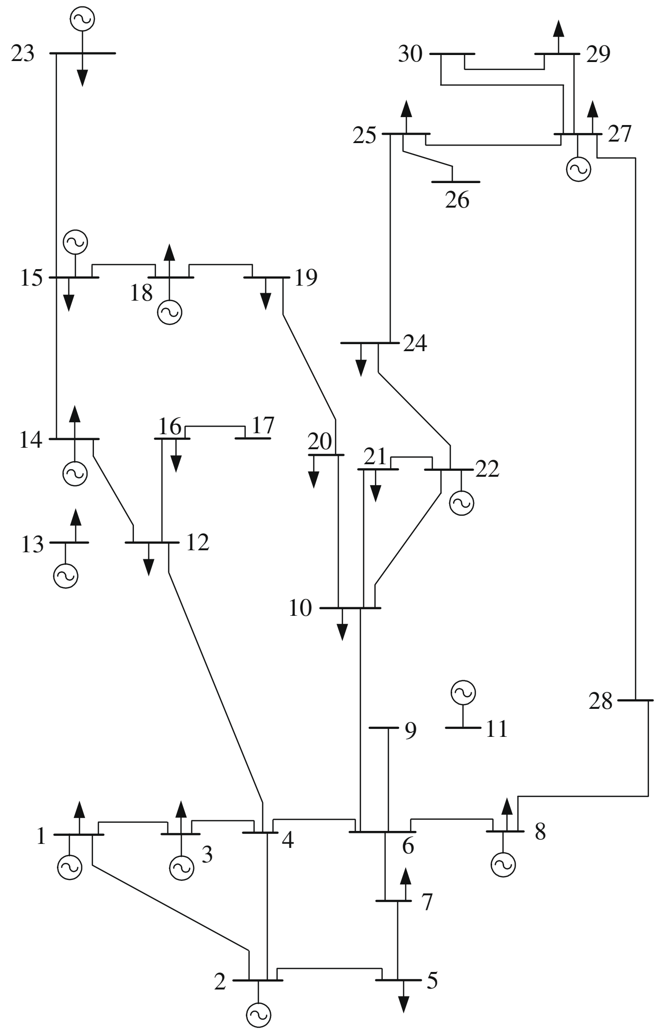

Fig. 1. Single line diagram of the initial transmission network for the IEEE 30-bus system.

Table 1
Transmission lines of the initial network of Fig. 1 (type = I) together with the exhaustive list of candidate new transmission lines (type = C).

Code	Line	Type	Code	Line	Type
1	1–2	I	29	25–27	I
2	1–3	I	30	27–28	I
3	2–4	I	31	27–29	I
4	2–5	I	32	27–30	I
5	3–4	I	33	2–6	C
6	4–6	I	34	6–28	C
7	4–12	I	35	9–10	C
8	5–7	I	36	9–11	C
9	6–7	I	37	10–17	C
10	6–8	I	38	12–13	C
11	6–9	I	39	12–15	C
12	6–10	I	40	23–24	C
13	8–28	I	41	5–6	C
14	10–20	I	42	6–11	C
15	10–21	I	43	10–11	C
16	10–22	I	44	10–12	C
17	12–14	I	45	10–16	C
18	12–16	I	46	10–28	C
19	14–15	I	47	11–28	C
20	15–18	I	48	12–18	C
21	15–23	I	49	13–14	C
22	16–17	I	50	13–16	C
23	18–19	I	51	15–16	C
24	19–20	I	52	16–18	C
25	21–22	I	53	17–20	C
26	22–24	I	54	19–24	C
27	24–25	I	55	20–24	C
28	25–26	I	56	23–25	C

Table 2
Comparison of optimization results for the solution of TEP problem.

	Method		
Parameter	GA	DE	IDE
Annual generation and transmission cost (M$)	7129	7104	7043
Annual generation and transmission cost (% of GA)	100.0	99.6	98.8
CPU time (min)	6.3	5.3	5.4
CPU time (% of GA)	100.0	84.1	85.7

Table 3
The list of candidate transmission lines of Table 1 that have been selected by GA, DE, and IDE.

Transmission line		Method		
Code	Line	GA	DE	IDE
33	2–6	√	√	√
34	6–28	√	√	√
35	9–10	√	√	√
36	9–11	√	√	√
37	10–17	√	√	√
38	12–13	√	√	√
39	12–15	√	√	√
40	23–24	√		
56	23–25		√	

list of 24 candidate new transmission lines that have been considered for the solution of the transmission expansion problem for the power system of Fig. 1.

Table 2 presents the comparison of the results obtained from the proposed IDE, the simple DE, and the genetic algorithm. It can be seen from Table 2 that only the IDE manages to find the global optimal solution that corresponds to annual generation and transmission investment cost (AGTIC) that is 1.2% lower than the AGTIC obtained by the GA. The application of IDE leads to significant AGTIC savings of 86 million $ in comparison with GA and 61 million $ savings in comparison with simple DE. Moreover, both DE methods, the simple DE and the IDE, are faster than the GA method, as Table 2 shows. Consequently, the proposed IDE is very suitable for the solution of the TEP problem.

The proposed IDE has the following four modifications in comparison to the simple DE: (i) the scaling factor F is varied randomly within some range, (ii) an auxiliary set is employed to enhance the diversity of the population, (iii) the newly generated trial vector is compared with the nearest parent, and (iv) the simple feasibility rule is used to treat the constraints. The above four modifications are the possible reasons why IDE outperforms simple DE. Because of its advanced features, IDE also outperforms simple GA.

By applying the proposed IDE method, it has been found that the optimum expanded transmission network has selected the 7 out of the 24 candidate new transmission lines of Table 1. These 7 transmission lines are shown in Table 3. Moreover, Table 3 shows the transmission lines that have been selected by GA and DE. Fig. 2 presents the optimum expanded transmission network for the IEEE 30-bus system. As can be seen from Fig. 2, the optimum expanded transmission network is composed of 39 transmission lines and 30 buses.

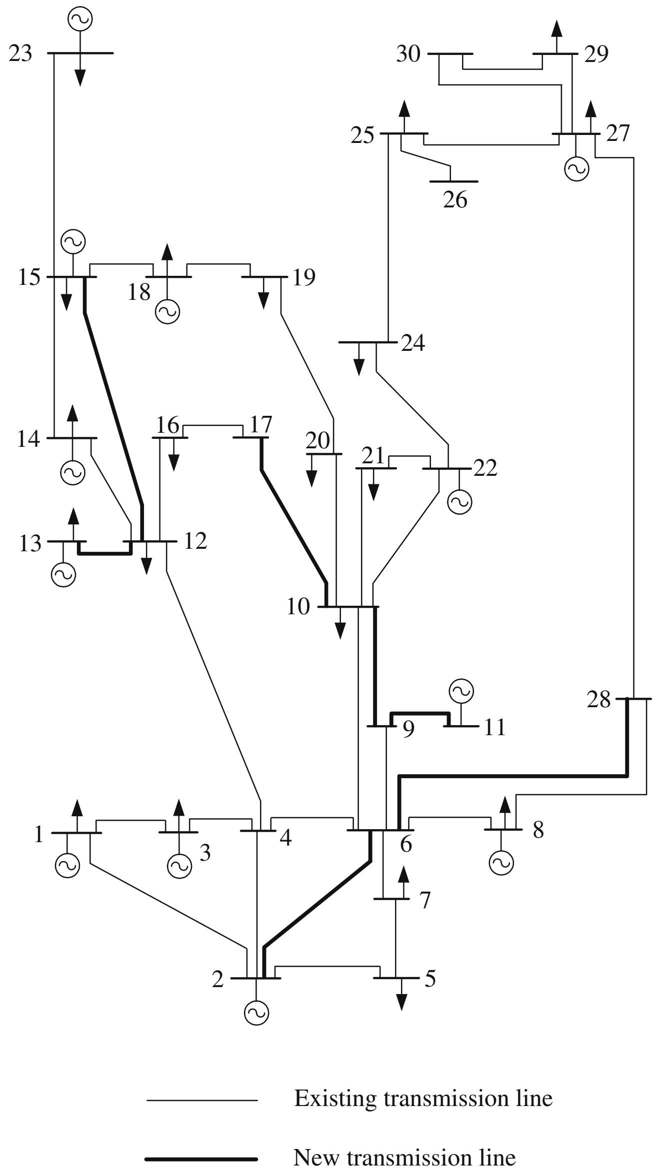

Fig. 2. Single line diagram of the optimum expanded transmission network for the IEEE 30-bus system.

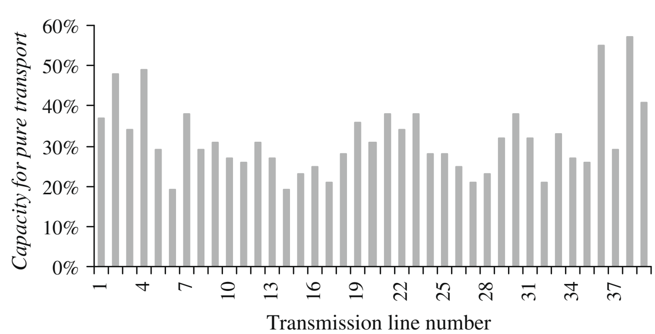

Fig. 3. Capacity for pure transport in each one of the 39 transmission lines of the optimum expanded transmission network (Fig. 2) as a percentage of the optimal capacity of the respective transmission line.

Fig. 3 presents the capacity for pure transport in each one of the 39 transmission lines of the optimum expanded transmission network (Fig. 2) as a percentage of the optimal capacity of the respective transmission line, where the optimal capacity is the sum of two components: (1) the capacity for pure transport, and (2) the capacity for security. For example, Fig. 3 shows that the transmission line with code 7, i.e., the transmission line between the buses 4 and 12 (Table 1), has 38% capacity for pure transport, while the rest 62% is its capacity for security. It can be concluded from Fig. 3 that, except for a small number of transmission lines, capacities for pure transport are well below 50% of the optimal capacities even during the period of maximum demand. This observation confirms the importance of taking security into consideration when solving the transmission expansion problem.

8. Conclusions

A general formulation of the transmission expansion problem in deregulated market environment is proposed in this paper. The main purpose of this formulation is to support decisions regarding regulation, investments and pricing. The market-based transmission expansion problem is composed of two interrelated problems: (1) the optimum network problem, and (2) the reference network subproblem that is part of the optimum network problem. The market-based TEP problem is a complex mixed integer non-linear programming problem. This paper proposes an improved differential evolution model for the solution of the market-based TEP problem. The proposed method is applied on the IEEE 30-bus test system and the results show that only the proposed IDE is able to find the global optimum solution to the TEP problem, while the simple DE and the GA converge to suboptimal solutions. The IDE results show that, except for a small number of transmission lines, capacities for pure transport are well below 50% of the optimal capacities and this observation confirms the importance of taking security into consideration when solving the transmission expansion problem.

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