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A multiyear dynamic transmission expansion planning model using a discrete based EPSO approach

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ABSTRACT

This paper presents a multiyear dynamic transmission expansion planning, TEP, model aiming at minimizing operation and investment costs along the entire planning horizon while ensuring an adequate quality of service and enforcing constraints modeling the operation of the network along the planning horizon. The developed model profits from the experience of planners when preparing a list of possible branch (lines and transformers) additions each of them associated to the corresponding investment cost. The objective of solving a TEP problem is to select a number of elements of this list and provide its scheduling along the planning horizon such that one is facing a mixed integer optimization problem. In this case, this problem was solved using a discrete evolutionary particle swarm optimization algorithm, DEPSO, based on already reported EPSO approaches but particularly suited to treat discrete problems. Apart from detailing the developed DEPSO, this paper describes the mathematical formulation of the TEP problem and the adopted solution algorithm. It also includes results of the application of the DEPSO to the TEP problem using two test networks widely used by other researchers on this area.

1. Introduction

In the last two decades power systems went through a restructuring process aiming at introducing market mechanisms to link the generation and the demand and liberalizing progressively the access to the networks. As this process developed, new challenges were introduced namely in terms of decoupling distribution network activities from retailing. As a result, most countries that went through restructuring typically implemented competitive mechanisms in the extreme activities of the value chain, generation and retailing, while keeping network activities as regulated monopolies. In the first years after this move, a larger accent was put on short term activities, for instance illustrated by the implementation of day-ahead markets. As time passed, long term expansion planning activities regained interest and continue to be a major concern of generation and transmission companies. Regarding transmission, expansion plans must now be prepared in a decoupled way from generation and from distribution. Transmission networks will now have to follow and in most cases to anticipate the requests both from new generation and new demand introducing a new level of uncertainty regarding the location of connection points. The increasing number of wind parks together with their increasing installed capacity leads to power surplus in some distribution networks that now start to inject in transmission. As the installed capacity of wind parks increase, connection points are also moving from distribution to transmission creating new challenges to transmission planners. Furthermore, in Europe long term plans are under development in order to build a super transmission grid enabling moving large amounts of energy at longer distances, for instance using hydro resources in Scandinavia and solar and wind resources in southern countries, as Spain and Portugal. Considering all these aspects, transmission expansion planning problems are even more complex than in the past due to a number of aspects:

- they have a multiperiod dynamic nature and it should be maintained an holistic view over the entire horizon, eventually discretized in a number of annual periods. This holistic view means that running an expansion exercise over *np* periods is not the same as running *np* independent exercises in a sequential way. Treating the whole horizon in the same problem means that when commissioning a project for a period we are taking not only into account the requirements of that period but also its impact in the future;
- they exhibit a geographic coupling in the sense that new installations will not be selected as answers to local problems. In meshed networks as transmission ones, solving a problem can

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also address and have positive impacts on bottlenecks in other locations, so that there is a global view that should be maintained;
- they are discrete problems due to the nature of investment alternatives;
- they are affected by load uncertainty over the horizon. A plan should be adequate not only for a given load evolution but the decision maker should not feel any relevant regret whatever the future. This immediately leads to risk analysis under which flexible solutions are most welcome.

So according with these indications, the TEP problem can be defined as a complex optimization problem involving a large number of variables and constraints that aims at scheduling a number of investments on transmission assets along an extended horizon. This problem has a mixed integer non linear programming nature, which, in fact, corresponds to a combinatorial problem and it can be formulated considering several objectives, that are usually contradictory.

The literature on this topic includes a large number of publications that can be gathered in two large groups. On one side, there are applications designed to analyze pre-prepared expansion plans. Most of these formulations correspond to software packages developed by utilities or by research centers that were related with them. Packages as TRELSS and CREAM developed by EPRI and several others implemented by CEPEL in Brazil, ENEL in Italy and EDF in France are examples of these approaches. On the other hand, there are optimization models designed to build expansion plans according to some criteria. The number of publications on this topic is very large [1] and there is not a common and general transmission expansion formulation adopted by all researchers. Traditionally, the expansion formulations included continuous variables to represent the capacity of new branches thus requiring approximations to obtain a final technically feasible solution. For instance, Refs. [2,3] describe linear and non-linear approaches to the TEP problem. Some other papers as [4–7] describe mixed integer formulations and adopt, for instance, Branch & Bound and Benders Decomposition based methods in a way to preserve the discrete nature of investments. Some others select investments according to a Merit Index or to a trade-off relation between the investment cost and the resulting benefit [8–11].

More recently several emergent techniques as Simulated Annealing, Genetic Algorithms, Tabu Search and Game Theory started to be applied to this problem. Refs. [12,13] describe the application of Genetic Algorithms to the transmission expansion problem [14], details the use of Tabu Search [15], adopts Simulated Annealing and [16] uses Grasp. Finally, ref. [17] describes a multi agent implementation based on cooperative games. These authors mention the advantages of these approaches to address this complex combinatorial problem in terms of identifying a feasible solution in a manageable computation time.

In view of the characteristics of the TEP problem, this paper describes a multiyear dynamic approach that aims at minimizing the investment and operation costs along the planning horizon while enforcing limits for reliability indices, namely considering $N-1$ contingencies, and for the maximum investment cost and for the number of on-going projects in each period of the horizon. Given the mixed integer nature of the resulting problem, we adopted a discrete evolutionary particle swarm optimization (DEPSO) approach to solve this problem that corresponds to an enhancement of original PSO algorithms both in terms of introducing an evolutionary flavor to the rule of generation of new particles and treating discrete variables in a more adequate way. Accordingly, the proposed dynamic TEP model based on DEPSO is the main contribution of this paper and allows foreseeing the application of DEPSO to other complex combinatorial problems.

As a result of these ideas, this paper is structured as follows. After this Section 1, Section 2 details the discrete evolutionary particle swarm optimization, DEPSO, and Section 3 details the TEP mathematical formulation and the application of the implemented DEPSO to this problem. Section 4 presents results for two Case Studies, namely providing comparisons with results reported in the literature by other researchers and finally Section 5 draws the most relevant conclusions of this research.

2. Discrete evolutionary particle swarm optimization

2.1. Heuristic tools

Heuristic methods go step-by-step generating, evaluating, and selecting solutions, with or without interacting with the planner. Taking advantage from planers experience inputs, the computational performance of heuristic methods is usually better than that of classical mathematical methods. In some cases local searches are also performed. The solutions are evaluated and classified according to the fitness function that considers technical, financial and service criteria and data. Heuristic Tools include, among others, evolutionary algorithms and particle swarm optimization. In particular, evolutionary algorithms are usually organized in the following steps:

initialize a random population P of *npt* elements;
repeat – reproduction (by recombination and/or mutation), evaluation, selection and test;
until test is positive (for termination criteria based on fitness, on number of generations or other criteria).

Evolutionary computation offers several advantages when facing difficult optimization problems [18]: as its conceptual simplicity and broad applicability, it outperforms classic methods on real problems and it has a large potential to use knowledge and hybridize with other methods. The classical particle swarm optimization, PSO, was proposed by Kennedy in 1995, based on the parallel exploration of the search space by a set of “particles” or alternatives that are successively transformed along the process [19]. The basic PSO model is defined according to (1) and (2). Under this scheme, the movement rule of a particle *pt* is given by (2) and it is used to change the position of the particle X_{pt}^{i} obtained for iteration *i* to its new position X_{pt}^{i+1} in the following iteration $i+1$.

$$X_{pt}^{i+1} = X_{pt}^{i} + V_{pt}^{i+1} \tag{1}$$

$$\begin{aligned} V_{pt}^{i+1} = {} & V_{pt}^{i} + Rnd_{mem,pt}^{i+1} \cdot W_{mem} \cdot (b_{pt} - X_{pt}^{i}) \\ & + Rnd_{coop,pt}^{i+1} \cdot W_{coop} \cdot (b_G - X_{pt}^{i}) \end{aligned} \tag{2}$$

This movement rule includes three terms as follows:

- the Inertia Term given by V_{pt}^{i}. This term indicates that the movement of the particle *pt* is influenced by the movement it had in the previous iteration;
- the Memory Term indicating that the movement of the particle is attracted by the best of its ancestors, b_{pt}, or, in other words, by the best particle that was obtained in previous iterations in this position of the population. This term is determined by the memory weight W_{mem} set in the beginning of the process and by a random number $Rnd_{mem,pt}^{i+1}$ sampled in each iteration from an uniform distribution in [0.0; 1.0];
- similarly, the Cooperation Term includes information about the best global particle so far identified in the entire population in all previous iterations, b_G. This term is also determined by the cooperation weight W_{coop} typically set in the beginning of the process and by a random number $Rnd_{coop,pt}^{i+1}$ sampled from an uniform distribution in [0.0; 1.0] in each iteration.

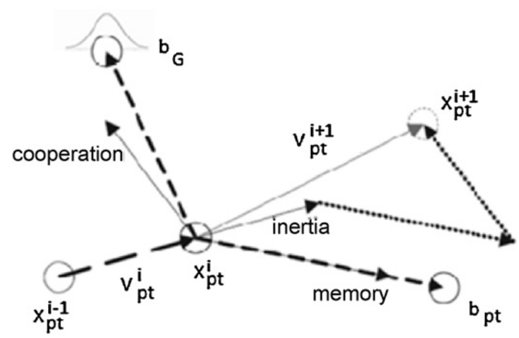

Fig. 1. Movement rule in the EPSO algorithm.

Some refinements were introduced in this scheme namely because several tests indicated that this movement rule was adequate to make the swarm converge to the zone where the optimum was but failed to fine tune the convergence to the accurate optimum position.

2.2. Discrete evolutionary PSO, EPSO

In 2002 Miranda and Fonseca [20] introduced the evolutionary particle swarm optimization (EPSO) that joints the most interesting features of particle swarm methodologies and evolutionary algorithms. The structure of the EPSO algorithm is summarized below [21].

Initialize a random population P of *npt* particles
Repeat
Replication, mutation, reproduction, selection, test
Until test is positive

EPSO focuses in regions of the search space where better contributions for the solution can be found, instead of conducting a blind sampling of the space. In this case, the movement rule of particle *pt* also includes the Inertia, the Memory and the Cooperation Terms mentioned above and the velocity V_{pt}^{i+1} determining the new position of this particle, X_{pt}^{i+1}, is now given by (3) and this scheme is illustrated in Fig. 1.

$$V_{pt}^{i+1} = W_{ine,pt}^{i+1*} \cdot V_{pt}^{i} + W_{mem,pt}^{i+1*} \cdot (b_{pt} - X_{pt}^{i}) + W_{coop,pt}^{i+1*} \cdot (b_G^* - X_{pt}^{i}) \cdot P \tag{3}$$

In expression (3) $W_{ine,pt}^{i+1*}$, $W_{mem,pt}^{i+1*}$ and $W_{coop,pt}^{i+1*}$ represent the Inertia, the Memory and the Cooperation weights. In the first place, the algorithm samples the weights $W_{ine,pt}^{i+1}$, $W_{mem,pt}^{i+1}$ and $W_{coop,pt}^{i+1}$ that are then mutated in $W_{ine,pt}^{i+1*}$, $W_{mem,pt}^{i+1*}$ and $W_{coop,pt}^{i+1*}$ using (4) in which τ represents a learning parameter fixed externally. In these expressions the sign * denotes mutated values. The best global particle, b_G, also undergoes mutation according to (5) so that a local search around the current best global particle is performed.

$$W_{pt}^{i+1*} = W_{pt}^{i+1} \cdot [\log N(0, 1)]^{\tau} \tag{4}$$

$$b_G^* = b_G + W_{bG}^{i+1*} \cdot N(0, 1) \tag{5}$$

Finally, the Cooperation Term is also influenced by a communication factor *P*. When the particles have several dimensions and are represented by a vector, the communication factor *P* is modeled by a diagonal matrix having 0 and 1 values on the diagonal. The 1 values are used to communicate the information in some dimensions of b_G^* to the new particle. The 1 values in this matrix have probability *p* and the 0 values have probability $1 - p$. Several reported tests showed that *p* values set at 0.2 or 0.3 lead to better results when compared with more classical and more deterministic schemes where $p = 1$.

The approach introduced in this paper is based on a discrete modeling of EPSO, DEPSO. Possible solutions are represented by vectors of integers in the sense that both the velocity vector V and the particles X are forced to be integers, using a rounding process of the output of (3). This model is boosted by local search nearby the best global solutions ever founded. These features enhance the successful progression of DEPSO toward the most promising solutions. Further details regarding the application of the DEPSO to the TEP problem are provided in Section 3.3.

3. Transmission expansion planning model

3.1. General modeling issues

As indicated in Section 1, the TEP problem exhibits a number of features that contribute to turn it into a complex problem namely in terms of the holistic view that should be maintained along the entire horizon and regarding the discrete nature of expansion projects. As a result of these concerns, in the developed formulation we explicitly consider a planning horizon structured in *np* periods that will be represented at a time in the mathematical problem and we also consider a project list based on *nproj* projects including new lines and transformers that are technically implementable. Each of these projects is characterized by the pair of nodes between which it can be built, by the technical data of the line or the transformer and by the investment cost. The objective of the TEP problem is therefore to identify the best possible solution that integrates a number of elements of this project list, adequately scheduled along the years of the planning horizon, so that we minimize a criterium to be specified and a number of constraints are enforced.

The search space that will be analyzed in the TEP problem is discrete and it typically includes a large number of possible alternative plans given by np^{nproj}, where *np* is the number of periods in the planning horizon and *nproj* is the number of investment projects in the project list defined by the planner. A solution X_{pt} corresponds to an expansion plan and it includes a number of projects selected among this list. The first population *X* of the DEPSO including *npt* particles is randomly generated and it corresponds to a matrix of $npt \times nproj$. Each line of this matrix corresponds to a particle in the population, that is, to a possible solution to the TEP problem. Each element of this line is associated with each project in the project list and it contains information about:

- the year in which it will be commissioned, that is an integer between 1 and *np*;
- or 0 if this particular project was not selected to this particular particle;
- or $np + 1$ meaning it was postponed.

This design of a particle with integers from 0 to $np + 1$, and in particular with a possible states below 1 and above *np*, is relevant when using DEPSO because it should be possible to evolve with the same difficulty from any state to 0, non selecting the project, or to $np + 1$, postponing the project beyond the possible defined states. If the 0 and $np + 1$ states where not allowed, the roundings with be limited to 1, in the lower level, and to *np* at the higher level and so the 1 and the *np* states would be artificially favored eventually leading to inadequate plans.

3.2. Mathematical formulation

The formulation of the TEP model is given by (6)–(9). For a particular particle *pt* in iteration *i*, the objective function is given by (6) and it corresponds to the addition of the investment and the operation costs in each period adequately transferred to the initial period using an interest rate rr. In this formulation, pt is the index of a particle in the population, i is the iteration counter, p and j are integers representing a period in the planning horizon and a project in the project list. On the other hand, $OC^{i}_{pt,p}$ represents the operation cost of this particle in period p, IC_j is the investment cost of project j, $K^{i}_{pt,p,j}$ is a binary variable indicating that project j is scheduled to start operation at period p in the expansion plan associated to particle pt.

$$\min \quad Cost^{i}_{pt} = \sum_{p=1}^{np} \left(\frac{(OC^{i}_{pt,p} + \sum_{j=1}^{nproj} IC_j \cdot K^{i}_{pt,p,j})}{(1+rr)^p} \right) \tag{6}$$

Subjected to:

$$\text{Power flow and generator limits for each period} \tag{7}$$

$$\text{Financial constraints, global or for each period} \tag{8}$$

$$\text{Reliability constraints} \tag{9}$$

The operation cost associated with each particle pt in iteration i is estimated solving a DC OPF algorithm for each period p in the planning horizon according to (10)–(14). In this formulation c_k is the operating cost of the generator connected to bus k, in \$/MWh, Pg_k is the output of the generator connected to bus k, PNS_k models a ficticious generator to represent the Power Not Supplied in bus k, having a large penalization cost given by G, Pd_k represents the load in bus k, $Pg^{\min}_k$ and $Pg^{\max}_k$ are the minimum and the maximum generations in bus k, $P^{\max}_b$ is the maximum flow in branch b of the transmission network and a_{bk} is the DC sensitivity coefficient relating the injected power in bus k with the active power flow in branch b. For each branch b with extreme nodes m and n, these coefficients are derived dividing the difference of the phases between nodes m and n by the branch reactance. Then, the phase in node m and the phase in node n are sustituted by expressions established using the elements in lines m and n of the inverse the admittance matrix of the DC model multiplied by the injected power in each node k of the system. Making this substitution, finally yelds for branch b an expression written in function of the injected powers in each node k. The coefficients of this expression are the so-called sensitivity coefficients of the flow in branch b regarding the injected powers in the system nodes, that is the coefficients a_{bk}. In this case, given that we are considering fictitious generators to represent Power Not Supplied, the injected power in node k is given by the addition of the generation Pg_k with PNS_k and subtracted from the demand, Pd_k. The flow in branch b is finally constrained by a minimum and a maximum value that are usually symmetrical of each other, that is, $P^{\min}_b = -P^{\max}_b$, indicating that the flow can range from $-P^{\max}_b$ to $P^{\max}_b$, thus leading to constraints (14). For each particle in the population, this problem is solved for every period $p = 1, \ldots, np$ considering the equipments (lines and transformers) that are included in that particle to start operation in period p.

$$\min OC = \sum c_k \cdot Pg_k + G \sum PNS_k \tag{10}$$

Subject to:

$$\sum Pg_k + \sum PNS_k = \sum Pd_k \tag{11}$$

$$Pg^{\min}_k \le Pg_g \le Pg^{\max}_k \tag{12}$$

$$PNS_k \le Pd_k \tag{13}$$

$$-P^{\max}_b \le \sum a_{bk} \cdot (Pg_k + PNS_k - Pd_k) \le P^{\max}_b \tag{14}$$

The objective function of this problem minimizes the generation cost, subjected to a global balance Eq. (11), to the generation limits (12), to nodal limits on the Power Not Supplied in each bus (13) and to the branch flow limits (14). Non zero values of Power Not Supplied are undisirable and so the variables associated with these ficticious generators have a large penalization given by G in (10). On the other hand, it is clear that if the generation plus transmission system is unable to supply the demand, non zero values of Power Not Supplied will be obtained in some nodes. In any case, given that Power Not Supplied models a demand reduction, it becomes clear that PNS in node k cannot exceed the demand initially specified for that node, thus justifying the integration of constraints (13). Regarding this model, the DC-OPF is solved using a simplex code programmed in Matlab, and included in the Matpower library.

While solving this problem, network and generator limit constraints are enforced but if transmission capacity is unsufficient then PNS will be non zero thus increasing the value of the objective function (10). This formulation assumes that the network is lossless. In order to increase the realism of the model, this DC-OPF can be modified to include an estimate of transmission losses according to the following scheme that typically converges in less than 5 iterations. The use of the optimization problem (10)–(14) with the estimate of the transmission losses is illustrated in [22] considering the Portuguese transmission system. It provided accurate results in 4–5 iterations, namely considering that in well-developed transmission systems the level of transmission losses is typically reduced and it varies in the range from 1 to 1.5% of the load.

Algorithm to include an estimate of branch active losses

(i) run an initial DC-OPF using (10)–(14) and compute voltage phases using the DC model;
(ii) estimate active losses in branch m-n using (15). In this expression, g_{mn} is the conductance of branch m-n and θ_{mn} is the phase difference across this branch;

$$Loss_{mn} \approx 2 \cdot g_{mn} \cdot (1 - \cos\theta_{mn}) \tag{15}$$

(iii) add half of the losses in branch m-n to the original loads in nodes m and n. Run a new dispatch using (10)–(14) and update voltage phases;
(iv) end if the difference of voltage phases in all nodes is smaller than a specified threshold. If not, return to (ii).

In order to characterize each particle in the population, we use a fitness function based on (6) plus a number of penalty terms as follows. These penalty terms are set at predefined large positive numbers, which are added to the fitness function when any threshold is violated. If for a given particle, any threshold is violated, the corresponding fitnesse function assumes a large positive value and so it gets penalized, given that we are addressing a minimizing problem when solving the TEP problem.

In the first place, after solving the previous DC dispatch problem, we get the generation cost, the level of losses and the eventual non zero value of PNS for the entire system, $PNS(N)$. If the level of losses exceeds a maximum percentage regarding the total generation in the system, then this particle is penalized with a term α_1 in the fitness function and if $PNS(N)$ is not zero, then the penalty term α_2 is also introduced in the fitness function. On the other hand, each of the projects is characterized by its investment. When a project is selected for a particular period, its investment is referred to the initial period, using the interest rate rr already used in (6) and in line with the level of risk of this type of investment. Regarding these costs, we can establish two kinds of constraints. The first one corresponds to the maximum number of projects that can be implemented per period or the maximum investment cost per period. This limitation arises due to financial or operational reasons and if it is violated we consider a penalty term α_3 in the fitness function. The second one corresponds to the maximum number of projects or the maximum investment over the entire horizon and it models a global financial constraint. If it is violated, then a penalty term α_4 is included in the fitness function. Finally, regarding reliability aspects, the fitness function also penalizes plans in which the *PNS* is non-zero for network configurations associated to $N-1$ contingencies. It is also possible to include penalties for a selected number of $N-2$ contingencies given that the Grid Codes of several countries typically detail a list of contingencies, namely $N-2$, regarding which the system is supposed to survive. The penalty over *PNS* $(N-1)$ and eventually regarding other higher order contingencies is made using the penalty term α_5.

As a result of all these considerations, the fitness function, $F_{function,pt}$, characterizing the quality of each particle *pt* in the population in a particular iteration of the algorithm is given by (16) that corresponds to (6) plus these five penalty terms.

$$F_{function,pt} = \sum_{p=1}^{np} \left(\frac{(OC_{pt,p}^{i} + \sum_{j=1}^{nproj} IC_j \cdot K_{pt,p,j}^{i})}{(1+rr)^p} \right) + \sum_{y=1}^{5} \alpha_y \tag{16}$$

Using this expression, we evaluate each particle in the population so that we can apply the movement rules of the DEPSO algorithm that will be detailed in the next section. At this point it is important to mention that when calculating the value of the fitness function for a particle pt with expression (16), the *OC* values in each period are not recalculated. In fact, for each period and for each particle we already have information about the projects to be implemented. These new projects together with the initial transmission network define the network to analyze in that period. Using this information, the DC-OPF detailed above was run to estimate the operation costs for every period. These costs are then used in (16) to obtain the fitness function of the particle under analysis..

3.3. Solution algorithm

The discrete nature of the TEP problem inspired the adoption of a set of changes in the EPSO algorithm. As mentioned above, a population is a matrix with $npt \times nproj$ positions that has an integer from 0 to $np+1$ in each position. To introduce more diversity on the search, the DEPSO works with two populations that correspond to clones of the best population, obtained at the end of a particular iteration. Similarly to the EPSO, the DEPSO is initialized by randomly sampling an initial population, that is, by sampling integers from 0 to $np+1$ for each position of the matrix mentioned before. After this initialization procedure, the DEPSO evolves as follows:

- *Replication* – the best population obtained at the end of the previous iteration is cloned twice, so that in each iteration the algorithm is actually working with two populations;
- *Mutation of weights* – the Inertia, the Memory and the Cooperation weights mentioned in Section 2.2 are mutated using (17). This expression uses the weight from the previous iteration and it includes the logistic function to induce a chaotic search pattern. Due to the non-repetition characteristic of chaotic functions, their adoption allows higher speeds on overall searches than stochastic ergodic searches that depend on probabilities [23]. It should be noticed that these weights are computed for every position of every particle;

$$W_{pt,j}^{i+1*} = \left(0.5 + \frac{1}{1+\exp^{-w_{pt,j}^{i*}}}\right) \tag{17}$$

- *Mutation of the best global* – the best global particle is a vector with as many positions as the elements of the project list. Its *nproj* positions are also mutated in case randomly generated numbers $N(0, 1)$ take values less than a parameter $k_{bg} \in [0,\ 1]$. This allows introducing changes in the current best global particle, so that we make a local search around the current best global. To do this, the corresponding weight is mutated in the first place using (17) and then each position *j* of the best global undergoes mutation using (18);

$$b_{Gj}^{*} = b_{Gj} + round(2 \cdot W_{bGj}^{i+1*} - 1) \tag{18}$$

- *Recombination* – after having mutated the Inertia, the Memory and the Cooperation weights and having mutated some positions of the best global so far identified particle, we use the same recombination rule of the EPSO (3) to compute the movement from iteration *i* to $i+1$. In each iteration of the DEPSO we are concerned in obtaining technically feasible solutions, so that at each step we round the value obtained from (3) to the nearest integer. The new particle *pt* is then the result of the addition of the particle *pt* in the previous iteration with the computed velocity vector. It is also important to notice that as a result of this movement rule, each position of each particle is filled with an integer that can eventually exceed the search space, namely $np+1$. If that is the case, the particle lies outside the search space and it is then returned back to the search space by placing it either on the edge of that space, that is integers larger than $np+1$, are replaced by $np+1$;
- *Recombination by Lamarkian evolution* – when applying the movement and the recombination rules (3), it is possible to obtain a zero velocity vector. If that is the case, that particle would not move when going from iteration *i* to iteration $i+1$. In these cases, to induce some extra diversity, we also used the ideas of Jean Baptiste Lamarke, a biologist that lived in the XVIII/XIX centuries. Lamarke developed what can be called a proto evolution theory that privileged changes at the macroscopic or fenotype level according to which living beings would be transmutated along time in order to generate more complex entities. Using this macroscopic idea, if a particle has a zero velocity, then some of its positions are mutated, namely the ones regarding which randomly generated numbers $N(0, 1)$ take values less than a parameter $k_{Lam} \in [0, 1]$. The mutated element in position *j* of such a particle is computed using an expression similar to (18) also including the logistic function in order to introduce a chaotic search pattern;
- *Selection* – at this point, all particles in the two populations were mutated and so we can evaluate them computing the fitness function given by (16). Then, we go along the two populations, we take the particle *pt* from population 1 and the particle *pt* from population 2 and it survives the one having better fitness, a more reduced value for (16) in this case. This tournament scheme yields the new population, which corresponds to the output of iteration $i+1$. At the end of this step, the best particle in the new population is compared with the current best global particle to update the best global so far identified;
- *Termination step* – finally, it is checked whether this iterative scheme ends. This corresponds to check if the maximum number of iterations was already completed or if a convergence criterium is valid. In the first case, the algorithm stops without having converged eventually suggesting that a larger number of iterations should be completed. In the second case, the algorithm converges if, for instance, the best global particle was not updated for a pre-specified number of iterations or if the value of the fitness function of the best global particle did not change more than a threshold for a pre-specified number of iterations.

The output of the algorithm is a population of solutions, among which is the best particle. The planner can then simply choose the best global solution or conduct a final decision step taking into account a trade-off analysis.

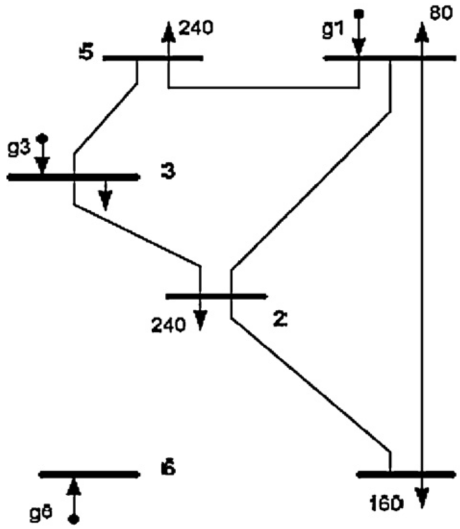

Fig. 2. Single line diagram of the 6 bus Garver network.

4. Case Studies

4.1. Garver network

4.1.1. Data

The Garver network was detailed in the seminal paper [24] and since then it has been used by several other researchers namely to compare different TEP approaches. This network is presented in Fig. 2 and it includes 6 buses and 6 lines. In the initial configutaion, bus 6 is not connected to the rest of the system and the existing demand in buses 1–5 is 760 MW while the installed generation capacity in these interconnected nodes is just 510 MW. As a result, the expansion planning exercise will obviously have to promote the interconnection of bus 6 to the rest of the system in order to prevent Power Not Supplied. Table 1 details the bus data, namely the installed generation capacity and the active power demand. Regarding the generator operating costs used in the objective function (10) of the DC-OPF model described in Section 3.2 we used 25 $/MWh for the generators connected to bus 1 and 40 $/MWh for the generators connected to buses 4–6. On the other hand, the coefficient G that penalizes non zero PNS values was set at 10,000 $/MWh. The penalty coefficients used in (16) in case some established threshold is violated were set at 100,000 so that any violation strongly penalizes the associated particle. Table 2 indicates the branch data and finally Table 3 details the project list that includes 17 possible addtions.

4.1.2. Single period analysis

Using the data above we solved a single period TEP exercise. The DEPSO algorithm was run in several tests namely to evaluate several design options as the size of the populations, the introduction of the Lamarkian operator in case a null velocity vector is obtained and the mutation of the best global ever found particle as a way to induce some local search. In this paper and due to space limitations we will summarize some of the results that were obtained along this research. In this scope, Fig. 3 illustrates the influence of several choices of the parameter k_{bG} associated with the mutation of the best global particle and Fig. 4 presents the influence of the parameter k_{Lam} determining the use of the Lamarkian evolution when the velocity of a particle is zero.

Finally, regarding this single period analysis, it is important to stress that the optimal identified solution is the same as the solution mentioned in the literature although the final populations may include other solutions having the same total investment cost and having zero Power Not Supplied. This solution includes one new branch between nodes 3 and 5 and 3 new branches between nodes 4 and 6. This final solution was obtained in the scope of a number of tests in which the DEPSO ran 100 times for 10, 20, 30 and 50 particles in each population and Fig. 5 illustrates the convergence characteristcs of the algorithm. The performance of the DEPSO is very good because it provided very large rates of identification of the optimal solution in a reduced number of iterations even for small populations of 10 particles. For example, for a population with 20 particles after 10 iterations the best solution was identified in 100% of the runs, that is in all the 100 TEP exercices.

Table 1
Bus data – installed generation capacity (MW) and active power demand (MW).

Bus number	Installed capacity (MW)	Active power demand (MW)
1	150	80
2	0	240
3	360	40
4	0	160
5	0	240
6	600	0

Table 2
Branch data, resistance (pu), reactance (pu) and capacity (MW).

From bus	To bus	Resistance (pu)	Reactance (pu)	Capacity (MW)
1	2	0.10	0.40	100
1	4	0.15	0.60	80
1	5	0.05	0.20	100
2	3	0.05	0.20	100
2	4	0.10	0.40	100
3	5	0.05	0.20	100

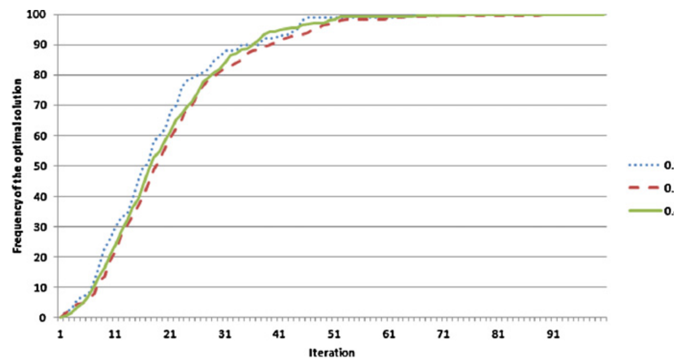

Fig. 3. Influence of several choices of the parameter k_{bG} associated with the mutation of the best global particle on the frequency of the identification of the optimal solution.

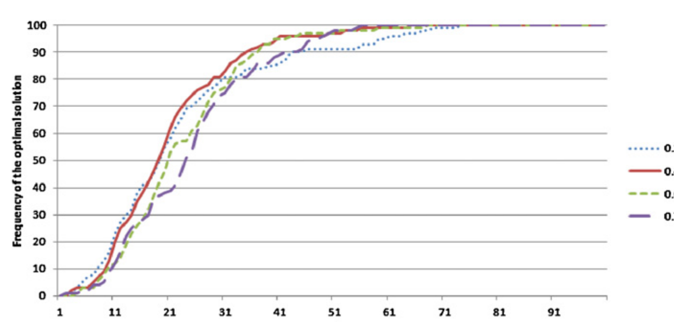

Fig. 4. Influence of the parameter k_{Lam} determining the use of the Lamarkian evolution when the velocity of a particle is zero on the frequency of the identification of the optimal solution.

Table 3
Project list including extreme nodes of possible new branches and investment cost.

Branch number	From bus	To bus	Resistance (pu)	Reactance (pu)	Capacity (MW)	Inv. cost (10^6 $)
1	2	6	0.08	0.03	100	30
2	2	6	0.08	0.03	100	30
3	2	6	0.08	0.03	100	30
4	2	4	0.10	0.40	100	40
5	5	6	0.1476	0.61	78	61
6	3	5	0.05	0.20	100	20
7	3	5	0.05	0.20	100	20
8	3	5	0.05	0.20	100	20
9	4	6	0.08	0.30	100	30
10	4	6	0.08	0.30	100	30
11	4	6	0.08	0.30	100	30
12	4	6	0.08	0.30	100	30
13	4	6	0.08	0.30	100	30
14	1	4	0.15	0.60	80	60
15	1	5	0.05	0.20	100	20
16	1	2	0.10	0.40	100	40
17	2	3	0.05	0.20	100	20

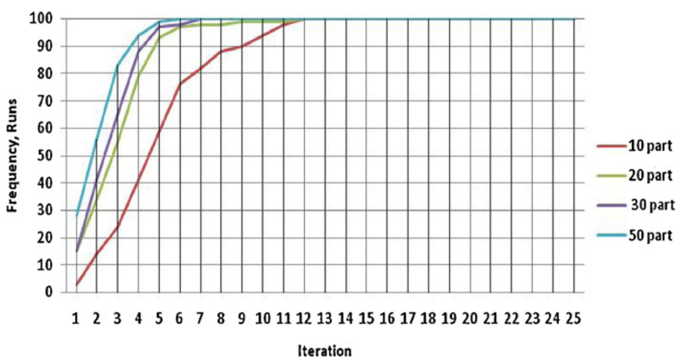

Fig. 5. Performance of the DEPSO algorithm for 10, 20, 30 and 50 particles in terms of the frequency of the identification of the best solution.

4.1.3. Multiperiod analysis

In a second step, we used again the Garver network presented in Fig. 2 to run a four period test. In this case, the project list still contains the 17 projects in Table 3 but the search space is much larger than in the single period test and it includes 6^{17} possible combinations. Recall that each position j of each particle can be filled with an integer from 0 to $np + 1$, that is, from 0 to 5 in this case. Regarding the results, the best solution includes the construction of 6 lines spread by the 4 periods as follows:

- in period 1 – 1 line 1–5, 1 line 2–6, 1 line 3–5 and 1 line 4–6;
- in period 2 there is no new addition;
- in period 3 – 1 line 4–6;
- in period 4 – 1 line 3–5.

This solution has an investment cost of 150 M$. It was obtained not considering the penalty term in (16) over the losses and it was admitted that the demand increased at a rate of 5% per period. The evolution of the network since the initial configuration in Fig. 2 to period 1, and finally to period 4 is displayed in Fig. 6.

The performance of the DEPSO was evaluated running the TEP exercise 100 times for populations with 10, 20, 30, 50 and 80 particles. Fig. 7 illustrates the results in terms of the frequency of the identification of the best solution. These graphs show that populations with 30 particles yield very good results since the best solution is identified in 95% of the cases after 40 iterations. If the number of particles is larger, 80 in this case, a similar percentage is obtained after 20 iterations.

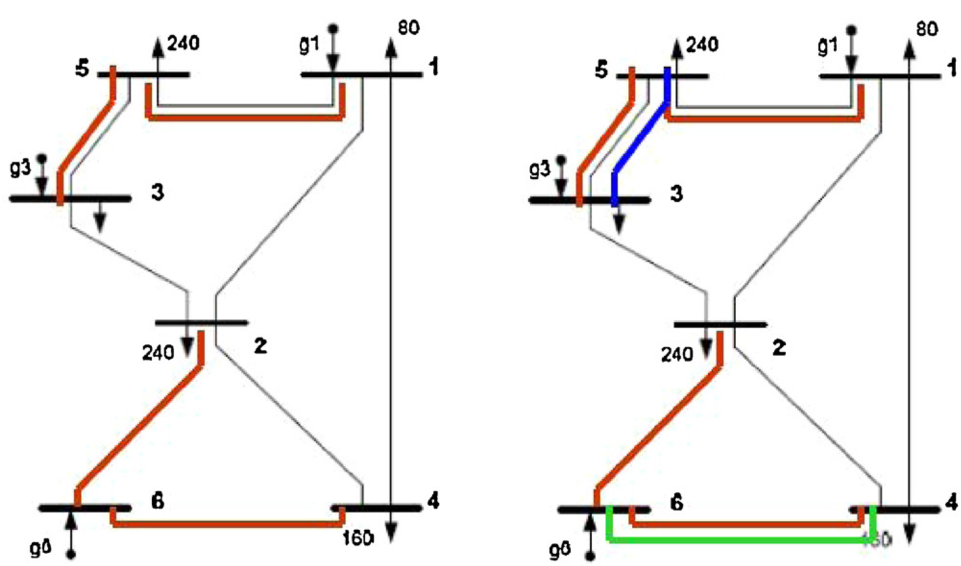

Fig. 6. Evolution of the network from periods 1 to 4 – period 1 on the left side and period 4 on the right.

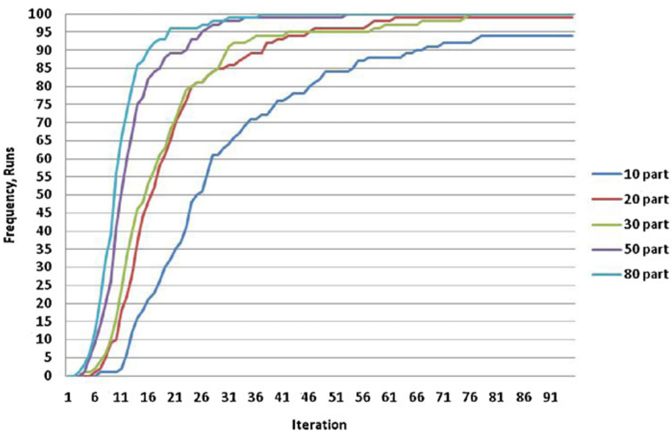

Fig. 7. Frequency of identification of the best solution for 10, 20, 30, 50 and 80 particles.

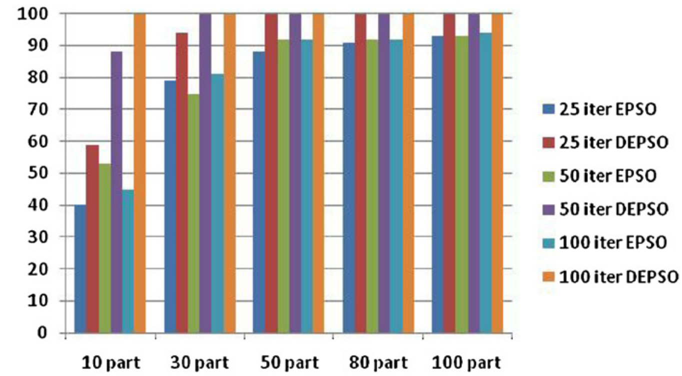

Fig. 8. Comparison between the EPSO and the DEPSO for different population sizes and iterations.

Finally, the performance of the DEPSO was compared with the one of the EPSO as reported in [21]. Fig. 8 shows the rate of convergence of the EPSO and of the DEPSO algorithms for populations with 10, 30, 50, 80 and 100 particles considering that in each case the algorithm was run 100 times. As shown in this Figure, the DEPSO performs better than the EPSO for the same number of particles and iterations. This indicates that the DEPSO was able to identify the best solution more times than the EPSO under the same conditions, in terms of the number of particles and iterations. On the other hand, for populations with 50 particles or more the DEPSO identified the best solution in all the 100 runs of the algorithm.

4.2. IEEE reliability test system

4.2.1. Data

The IEEE Reliability Test System, RTS, was originally described in [25]. Since 1979 it has been used by several researchers for different purposes and it was subjected to a number of adaptations in order to turn it more suitable to test particular applications. The original system includes 24 nodes and 38 branches (lines and transformers) at the voltage levels of 138 and 230 kV. The original total demand is 2850 MW and the installed generation capacity is 3405 MW. Several tests conducted in the scope of reliability calculations showed that the transmission system of the RTS network was lighly loaded and so in this paper we increased the demand and the installed generation capacity to the triple of their original values, that is, to 8550 MW and to 10,215 MW while maintaining the charateristics of the transmission system, namely in terms of the branch capacities reported in [25]. This reference also contains the complete data for this system namely the branch resistance and reactance values and the generator operating cost values.

On the other hand, when doing the multiperiod analysis we used a 10% value for the *rr* rate and we admited that the demand increased in all buses by 5% per period. Given this demand increase, we admitted that the transmission system also had to accommodate the connection of two new generators as follows: one connected to bus 4 with a capacity of 300 MW and another one to bus 19 with a capacity of 591 MW. Finally, apart from the operation and the investment costs, the fitness function also included

Table 4
Project list including extreme nodes of possible new branches, type and investment cost.

Branch number	From bus	To bus	Type	Resistance (pu)	Reactance (pu)	Capacity (MW)	Inv. cost (10^6 $)
1	3	24	Transf.	0.0	0.4195	400	500
2	9	11	Transf.	0.0	0.4195	400	500
3	10	11	Transf.	0.0	0.4195	400	500
4	10	12	Transf.	0.0	0.4195	400	500
5	1	5	Line	0.1090	0.4225	175	220
6	1	5	Line	0.1090	0.4225	175	220
7	2	4	Line	0.1640	0.6335	175	330
8	2	4	Line	0.1640	0.6335	175	330
9	2	6	Line	0.2485	0.9600	175	500
10	2	6	Line	0.2485	0.9600	175	500
11	6	10	Line	0.0695	0.3025	175	160
12	7	8	Line	0.0795	0.0032	175	160
13	7	8	Line	0.0795	0.0032	175	160
14	8	10	Line	0.2135	0.8255	175	430
15	11	13	Line	0.0305	0.2389	500	660
16	12	13	Line	0.0305	0.2380	500	660
17	14	16	Line	0.0250	0.1945	500	540
18	15	21	Line	0.0315	0.2450	500	680
19	15	24	Line	0.0335	0.2595	500	720
20	16	17	Line	0.0165	0.1295	500	360
21	16	17	Line	0.0165	0.1295	500	360
22	16	19	Line	0.0150	0.1150	500	320
23	17	18	Line	0.0090	0.0720	500	200
24	20	23	Line	0.0140	0.1080	500	300
25	11	13	Line	0.0305	0.2389	500	660
26	12	13	Line	0.0305	0.2380	500	660
27	11	14	Line	0.0305	0.2380	500	580
28	14	16	Line	0.0250	0.1945	500	540

Table 5
Best identified expansion plans obtained in several runs.

Test	*npt*	Inv. cost (M$)	Expansion projects included in the best identified plans										
			3–24	10–12	1–5	1–5	2–6	6–10	7–8	7–8	11–13	11–13	16–17
4 periods	30	2599.16	–	1	1	–	2	1	1	2	1	3	–
4 periods	100	2527.44	–	1	1	–	4	1	1	2	1	3	–
4 periods	150	2427.72	4	1	1	–	–	1	1	2	1	–	4
1 period	100	1280.00	–	–	1	1	–	1	1	1	–	–	1

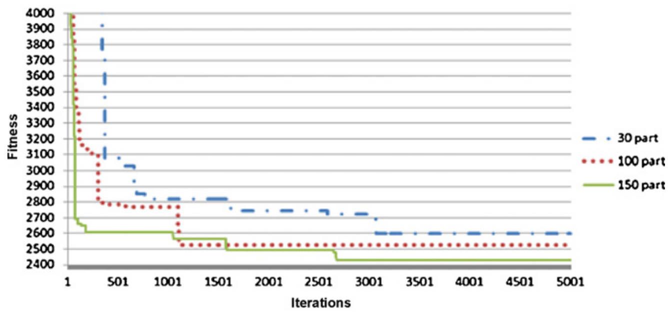

Fig. 9. Evolution of the fitness function for 30, 100 and 150 particles for the four period test.

penalty terms if the number of projects per period exceeded 6 and if *PNS* was not zero for the *N* system and for $N-1$ contingencies. In this case, we used the same values for the penalty terms that were mentioned in Section 4.1.1 for the Garver network.

Regarding the stopping criteria of the DEPSO algorithm, we conducted numerous runs considering a maximum of 5000 iterations. The algorithm would also stop if 1000 iterations were completed without improving the current best global solution. In order to conduct these tests, we admitted that the planner specified a list of possible investment projects containing 28 new branches, lines and transformers. The main characteristics of these projects are detailed in Table 4.

4.2.2. Single period analysis

In this case, the DEPSO algorithm was tested with populations including 10, 30 and 100 particles and it was possible to conclude that 10 particles was too short to ensure an adequate frequency of identification of the best solution, even after running 1000 iterations. On the other hand, for a population of 30 particles a 95% frequency of the best solution was achieved after 900 iterations while for a population of 100 particles a 100% frequency was obtained after 590 iterations. The best solution that was identified has an investment cost of 1280 M$ and it includes building the following 6 branches: two new branches connecting nodes 1 and 5, one new branch connecting nodes 6 and 10, two new branches connecting nodes 7 and 8 and one new branch connecting nodes 16 and 17. For a population of 30 particles, the algorithm analyzed (30 particles $\times$ 2 populations $\times$ 900 iterations) = 54×10^3 possible investment plans while the total number of particles in the search space was $3^{28} \approx 22.9 \times 10^{12}$.

4.2.3. Multiperiod period analysis

Finally, the developed DEPSO was also tested considering a four period horizon. In this case, we used the same project list with 28 new possible equipments, meaning that the search space now includes $6^{28} \approx 6.1 \times 10^{21}$ potential solutions. In this case, we conducted several tests namely using populations with 30, 100 and 150 particles and Fig. 9 displays 3 examples of the fitness evolution. Table 5 characterizes the solutions that were obtained in these three runs together with the solution from the single period study. For each run, this table indicates the period in which each equipment should start operation. The projects not listed are not considered in any of these solutions. These results deserve some comments:

- there are significant differences among the single period and the multiperiod solutions. For instance, building a branch connecting nodes 16 and 17 is included in the single period solution while it is only included in period 4 of the multiperiod solution obtained with a population of 150 particles;
- on the other hand, one of the projects 7–8 is delayed from period 1 to period 2 when going to the multiperiod analysis;
- several projects not elected in the single period solution are included in the multiperiod solutions that were obtained. These include installing the transformers 3–24 and 10–12 and the lines 2–6 and 11–13;
- finally, these results and the differences between the solution obtained for the single period analysis and for the multiperiod tests confirm that a multiperiod study is not necessarily a combination of static schedules obtained in sequence for each planning period. In fact, the set of projects elected for the single period solution is not equal to the projects included in the first period of any of the three reported multiperiod solutions. This means that explicitly modeling in the problem all the periods along the planning horizon imposes a new dynamic to the solution identification that is not adequately captured by solving independently a sequence of yearly planning exercises.

5. Conclusions

This paper describes a discrete approach of the evolutionary particle swarm optimization, DEPSO, that was used to solve a multiyear transmission expansion planning problem. This problem is very complex due to its mathematical characteristics and its typically large combinatorial nature. This means it is important to develop models that adequately address this problem, namely in view of the involved invesment costs that are ultimately reflected in the tariffs paid by newtork users. The results that were obtained and that are partially reported in this paper demonstrate that the developed DEPSO approach is accurate and that it allows the identification of good quality solutions with less particles and less iterations when compared with classical particle swarm optimization algorithms. On the other hand, the results that were obtained namely for the IEEE RTS system also compare in a favorable way to other results reported by other research teams.

Finally, this research line will be followed in future publications namely to enhance the TEP model so that it addresses uncertainties that are typically present in this type of exercices. These uncertainties can affect the evolution of the demand along the planning horizon and will lead to the inclusion of risk concepts in this approach. Another point of possible development consists of enhancing the developed model so that it can accommodate DC transmission systems given the growing interest on them. Regarding this issue, it is important to notice that the general formulation of the TEP problem is still valid in case DC transmission systems are considered. The incorporation of these systems would require extending the list of candidate projects to be supplied by the user and to modify the operation problem of the transmission network detailed in Section 3.2 to allow considering DC systems. These two topics correspond to new research areas justifying a renewed interest on the TEP problem.

References

[1] G. Latorre, R.D. Cruz, J.M. Areiza, A. Villegas, Classification of publications and models on transmission expansion planning, IEEE Transactions on Power Systems 18 (2003) 938–946.
[2] R. Villasana, L.L. Garver, S.J. Salon, Transmission network planning using linear programming, IEEE Transactions on Power Apparatus and Systems PAS-104 (1985) 349–356.
[3] H. Youssef, R. Hackam, New transmission planning model, IEEE Transactions on Power Systems 4 (1989) 9–18.
[4] N. Alguacil, A. Motto, A.J. Conejo, Transmission expansion planning: a mixed-integer LP approach, IEEE Transactions on Power Systems 3 (2003) 1070–1077.
[5] A.P. Meliopoulos, R.P. Webb, R. Bennon, J. Juves, Optimal long range transmission planning with AC load flow, IEEE Transactions on Power Apparatus and Systems PAS-101 (1982) 4156–4163.
[6] T.L. Stephen, L.H. Kenneth, H. Esteban, Transmission expansion by branch-and-bound integer programming with optimal cost–capacity curves, IEEE Transactions on Power Apparatus and Systems PAS-93 (1974) 1390–1400.
[7] A. Seifu, S. Salon, G. List, Optimization of transmission line planning including security constraints, IEEE Transactions on Power Systems 4 (1989) 1507–1513.
[8] A. Monticelli, M. Pereira, S. Cunha, B. Parker, J. Praça, Interactive transmission network planning using a least-effort criterion, IEEE Transactions on Power Apparatus and Systems PAS-101 (1982) 3919–3925.
[9] M. Morozowski, A. Melo, M. Pereira, L. Pinto, Priority evaluation and ranking of transmission system projects – computer models and results, IEEE Transactions on Power Systems 5 (1990) 1017–1023.
[10] J.R. Barros, A.C.G. Melo, A.L. Silva, Optimization of transmission expansion planning and impact in the reliability tariff – methodology and case study, in: Proceedings of the VIII SEPOPE, Symposium of Specialists in Electric Operational and Expansion Planning, Brasília, Brazil, 2002.
[11] R. Romero, C. Rocha, J. Mantovani, I. Sanches, Constructive heuristic algorithm for the DC model in network transmission expansion planning, IEE Proceedings – Generation Transmission and Distribution 152 (2005) 277–282.
[12] H. Rudnick, R. Palma, E. Cura, C. Silva, Economically adapted transmission systems in open access schemes – application of genetic algorithms, IEEE Transactions on Power Systems 11 (1996) 1427–1440.
[13] E.L. Silva, H.A. Gil, J.M. Areiza, Transmission network expansion planning under an improved genetic algorithm, IEEE Transactions on Power Systems 15 (2000) 1168–1175.
[14] A.L. Silva, L.A. Manso, L. Resende, L. Rezende, Tabu Search applied to transmission planning considering losses and interruption costs, in: Proceedings of the 10th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2008, Puerto Rico, 2008.
[15] A. Braga, J.T. Saraiva, A multiyear dynamic approach for transmission expansion planning and long term marginal cost computation, IEEE Transactions on Power Systems 20 (2005) 1631–1639.
[16] S. Binato, G.C. Oliveira, J.L. Araújo, A greedy randomized adaptive search procedure for transmission expansion planning, IEEE Transactions on Power Systems 16 (2001) 247–253.
[17] J. Contreras, F.F. Wu, A kernel-oriented algorithm for transmission expansion planning, IEEE Transactions on Power Systems 15 (2000) 1434–1440.
[18] D. Fogel, Introduction to evolutionary computation, in: K. Lee, M. El-Sharkawi (Eds.), Modern Heuristic Optimization Techniques: Theory and Applications to Power Systems, John Wiley & Sons, New Jersey, 2008, pp. 3–20.
[19] J. Kennedy, R.C. Eberhart, Particle swarm optimization, in: Proceedings of the IEEE International Conference on Neural Networks 1995, vol. 4, Perth, Australia, 1995, pp. 1942–1948.
[20] V. Miranda, N. Fonseca, EPSO – evolutionary particle swarm optimization, a new algorithm with applications in power systems, in: Proceedings of the IEEE Transmission and Distribution Asia-Pacific Conference 2002, vol. 2, Yokohama, Japan, 2002, pp. 745–750.
[21] R. Pringles, V. Miranda, F. Garces, Optimal expansion of transmission systems using EPSO (in Spanish), in: Proceedings of the VII Latin American Congress on Electricity, Generation and Transmission, Valparaiso, Chile, 2007 (Paper C074).
[22] J.T. Saraiva, Evolution of the congestion rent of the Portuguese national transmission company – evolution from 1998 to 2008, in: Proceedings of the 9th International Conference on the European Electricity Market, Florence, Italy, 2012.
[23] L. Coelho, V. Mariani, A novel chaotic particle swarm optimization approach using Henon map and implicit filtering local search for economic load dispatch, Chaos, Solutions and Fractals 30 (2009) 510–518.
[24] L.L. Garver, Transmission network estimation using linear programming, IEEE Transactions on Power Apparatus and Systems PAS-89 (1970) 1688–1697.
[25] Reliability Test System Task Force, IEEE reliability test system, IEEE Transactions on Power Apparatus and Systems PAS-98 (1979) 2047–2054.

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