Abstract – This paper presents a discrete approach, based on an improved integer version of the evolutionary particle swarm optimization (EPSO) algorithm, to solve the dynamic transmission expansion planning (TEP) problem. TEP corresponds to a mixed integer optimization problem that typically aims at identifying a schedule for transmission additions along an extended planning horizon considering operation and investment costs as well as a reliability index to measure the ability the system has to convey electricity from generation to consumers. After detailing the mathematical formulation of the TEP problem, this paper describes the enhanced EPSO algorithm and details its application to the TEP problem. The paper also includes a Case Study based on the IEEE 24 bus / 38 branch system to illustrate the application of the developed procedure.

Keywords: dynamic transmission expansion planning, heuristic techniques, population-based methods, discrete evolutionary particle swarm optimization.

1 INTRODUCTION

In the last 20 years, power systems went through a process of liberalization and restructuring that determined changes at different levels. Apart from peculiarities that characterized this process in different countries, there are some relevant common aspects. These include the segmentation of the traditional vertically integrated utilities namely in generation, transmission, distribution and retailing, the advent of independent regulation, the increase of the number of agents namely in the generation and retailing activities now provided under competitive schemes and the decoupling between market functions, assigned to Market Operators, and technical operation and monitoring functions assigned to System Operators. On the other hand, the nature of electricity and of the required investments, typically lead to regulated monopolies to provide transmission and distribution services.

This modification of traditional utilities also had important consequences in terms of tariffs and regarding operation and planning activities. Regarding tariffs, till the advent of liberalization and restructuring there were no clear cost allocation procedures to each activity so that cross subsidies were common and final end user tariffs were typically determined using average approaches. The segmentation of the industry imposed the clarification of this process, the clear identification of costs and their assignment to the agents or activities responsible for them and the construction of additive tariff systems based on elementary tariffs per activity, namely including tariffs for the use of transmission and distribution networks to pay operation, management and investment costs. On the other hand, operation planning is now done in day ahead markets or via bilateral contracts and these economic schedules have to be submitted to System Operators for technical checking and for contracting ancillary services. Finally, in the past expansion planning was typically done in an integrated way in the sense that long-term studies regarding new capacity typically included the planning of the required transmission expansion and reinforcement. This integrated view no longer exists since now generation companies prepare their own expansion plans based on expectations on future profits and taking into account uncertainties affecting, for instance, the demand, the electricity price and the operation and investment costs.

In view of this more decentralized and uncertain environment, transmission providers face a more challenging task in preparing their expansion plans. On the legal and regulatory side, the European Parliament and the European Council approved the Directive 2003/54/CE, aiming at establishing common rules for the European internal market of electricity. TEP is clearly identified as a major responsibility of Transmission System Operators (TSO), as these operators are responsible for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity. More recently, the Commission Regulation (EU) No 838/2010 of 23 September 2010, on laying down guidelines relating to the inter-transmission system operator compensation mechanism states that “(…) the union-wide assessment of electricity transmission infrastructure associated with facilitating cross-border flows of electricity should be carried out by the Agency for the Cooperation of Energy Regulators as the body responsible for coordinating the activities of regulatory authorities who must carry out a similar function at a national level.”

At a national level, the Portuguese electricity code determines that the TSO prepares 6-year expansion plans every two years to be submitted to the Regulatory Agency for approval. This means that building new lines and substations has to be justified namely because their costs, once approved, will then be reflected in the tariffs paid by consumers for the use of transmission networks.

This new environment, the increased complexity of the TEP problem and its impact on society given the level of investments is the motivation for this research. In this paper we present a multiyear dynamic model for the TEP problem considering investment and operation costs together with a reliability index to evaluate the adequacy of each solution. The mix integer nature of this problem sug-
gested the use of an enhanced version of the Evolutionary Particle Swarm Optimization (EPSO) specifically designed to address discrete problems (DEPSO).

Having in mind these aspects, this paper is structured as follows. After this Introduction, Section 2 reviews several approaches to the TEP published in the literature and Section 3 describes the enhanced Evolutionary Particle Swarm Optimization algorithm. Section 4 details the mathematical formulation of the TEP and describes the application of the DEPSO to this problem. Finally, Section 5 includes two Case Studies based on the Garver system and on the IEEE 24 bus / 38 branch test system and Section 6 presents the most relevant conclusions.

2 THE TEP PROBLEM IN THE LITERATURE

A dynamic, or multiyear, TEP model aims at determining the timing, the type and the location of the new transmission facilities to add to an existing network along a planning horizon in order to ensure an adequate transmission capacity taking into account future generation options and load requirements, in a long-term horizon. This definition means there is a long-term horizon typically organized on a yearly basis and all these sub periods are considered in the planning exercise at the same time. This means that there are couplings between sub periods and that building a line required at a given sub period can eventually be anticipated if it can contribute to solve other transmission bottlenecks in previous years. In a different and simplified way, several approaches address this problem on a yearly and sequential basis, in the sense that the output obtained for a sub period is then considered as input for the study to run for the next one. Solving TEP in this static way means that the holistic and multiyear view is lost and so the addition of partial yearly plans will be not better than the result of the integrated dynamic multiyear study. Apart from this differentiation between several approaches to the TEP problem, some other issues can also be considered as the integration of uncertainties, the consideration of several criteria and the adoption of different optimization techniques. Given the large number of publications on this issue, references [1, 2] enumerate and classify publications addressing the TEP problem.

Regarding static formulations, references [3, 4] describe approaches in which the multiyear horizon is decoupled in several isolated periods that are treated separately and in sequence. The models described in references [5, 6] consider the multiyear nature of the TEP problem. For instance, reference [6] describes a multiyear approach considering four criteria – the investment cost, the operation cost, a reliability index and an exposure index – and load requirements, in a long-term horizon. This definition means there is a long-term horizon typically organized in the following steps: initialize a random population \( P \) of \( \mu \) elements; repeat reproduction (by recombination and/or mutation), evaluation, selection and test, until test (for termination criteria is valid, based on fitness, on number of generations or other criteria) is positive.

Evolutionary computation offers several advantages [16]: conceptual simplicity, broad applicability, outperform classic methods on real problems, potential to use knowledge and hybridize with other methods, parallelism, robust to dynamic changes and capability for self-optimization.

3 DISCRETE EVOLUTIONARY PARTICLE SWARM OPTIMIZATION

3.1 Heuristic methods

Heuristic methods go step-by-step generating, evaluating, and selecting solutions, with or without interacting with the planner [1]. Taking advantage of the planners experience, the computational performance of heuristic methods is usually better than that of mathematical methods. In some cases, local searches are performed following rules defined by the planner. The solutions are classified according to these rules and consider information like technical, financial and service data. The process is stopped when no further improvement is possible on the best-found solution. Heuristic Tools include evolutionary algorithms and particle swarm optimization. Evolutionary algorithms are usually organized in the following steps: initialize a random population \( P \) of \( \mu \) elements; repeat reproduction (by recombination and/or mutation), evaluation, selection and test, until test (for termination criteria is valid, based on fitness, on number of generations or other criteria) is positive.

Evolutionary computation offers several advantages [16]: conceptual simplicity, broad applicability, outperform classic methods on real problems, potential to use knowledge and hybridize with other methods, parallelism, robust to dynamic changes and capability for self-optimization.

3.2 Particle Swarm Optimization

The classical particle swarm optimization (PSO) was proposed by Kennedy in 1995, based on the parallel exploration of the search space by a swarm, a set of “particles”, the solutions or alternatives, which are transformed along the process [17]. PSO concept is very simple. The swarm is a set of particles, and each particle is a possible solution. These particles proceed through the search space, that is, the space where feasible solutions can be found. Each
particle coordinates are associated with two vectors, its position $X_i$ and its velocity $V_i$, where $i$ is the particle position in the swarm. When exploring the search space, the particles movement is influenced by three elements: its own position, the position of the best particle ever found on its position and the best particle ever found on the swarm. PSO has many key advantages over other optimization techniques like: it is a derivative-free algorithm unlike many conventional techniques; it is flexible to form hybrid tools together with other optimization techniques; it is less sensitive to the nature of the objective function, e.g., convexity or continuity; it has less parameters to adjust unlike other evolutionary techniques; it has the ability to escape from local minima; it is easy to implement and program; it can handle objective functions with stochastic nature; it does not require a good initial solution to start the iterative process. More detailed information about PSO applications in power systems can be found in [18] and [19].

### 3.3 Discrete Particle Swarm Optimization

The original PSO model was developed to tackle problems in continuous search spaces. However, many real problems have discrete nature and recently different discrete PSO models were proposed. The first discrete PSO approach was proposed by Kennedy and Eberhart for binary-valued solution elements. In this case, the position of each particle is a vector in the d-dimensional binary solution space, $x_i \in \{0,1\}^d$ and the velocity is a vector in the d-dimensional continuous space. Al-kazemi and Mohan [20] introduced another PSO method, whose particles are influenced alternatively by their own best position and by the best position among their neighbours. Other researchers proposed different approaches that proved adequate for some particular problems, but the implementation complexity turned difficult their dissemination to other applications. In [21] it is proposed a different approach that abandons the concept of velocity given that the search space is non continuous and the movement is discrete. For this reason, the weights in (2) are interpreted as probabilities, which make each particle to behave randomly or to be guided by the effect of the attractors. In such discrete search space, the moves are jumps from one solution to another and so this approach is termed Jumping Particle Swarm Optimization (JPSO).

### 3.4 Evolutionary Particle Swarm Optimization

In 2002 Miranda and Fonseca [22] introduced the Evolutionary Particle Swarm Optimization (EPSO), joining the best features of both particle swarm methods and evolutionary algorithms. EPSO focuses in regions of the search space where one can find better contributions for the solution, instead of conducting a blind sampling of the space. In [22] it was adopted the general scheme of the movement rule of PSO and concluded that the new particles are a combination of four particles: its direct ancestor, the ancestor of its ancestor, a distant past best ancestor and the current global best of the swarm. This recombination rule pushes the population towards the optimum. The evolutionary flavor is given by the self-adaptive mechanism to determine the best values to the weight terms. As in PSO, vectors represent possible solutions in EPSO. The generic EPSO algorithm is presented below.

<table>
<thead>
<tr>
<th>Procedure EPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initialize a random population $P$ of $\mu$ elements</td>
</tr>
<tr>
<td>Repeat</td>
</tr>
<tr>
<td><strong>Replication</strong></td>
</tr>
<tr>
<td><strong>Mutation</strong></td>
</tr>
<tr>
<td><strong>Recombination</strong></td>
</tr>
<tr>
<td><strong>Selection</strong></td>
</tr>
<tr>
<td><strong>Test</strong></td>
</tr>
<tr>
<td>Until test is positive</td>
</tr>
<tr>
<td>End EPSO</td>
</tr>
</tbody>
</table>

The off-springs are generated by recombination of the particles, following the recombination rules (1) and (2).

$$X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1}$$

In this formulation:

- $X_{i}^{k}$ location of the particle $i$ in generations $k$ and $k+1$;
- $b_1$ best solution found by particle $i$ in its past life up to the current generation;
- $G$ best overall solution found by the swarm in its past life up to the current generation;
- $V_{i}^{k} = X_{i}^{k} - X_{i}^{k-1}$ velocity of particle $i$ at generation $k$;
- $W_{i}^{*}$ weight conditioning the inertia term;
- $W_{i}^{*}$ weight conditioning the memory term;
- $W_{i}^{*}$ weight conditioning the cooperation term;
- $P$ communication factor.

The communication factor $P$ is a diagonal matrix affecting all dimensions of a particle, containing binary variables of value 1 with probability $p$ and value 0 with probability $(1-p)$. The $p$ value controls the flow of information within the swarm and is 1 in classical formulations. The symbol * indicates that the parameter will undergo mutation. Mutation is a relevant operation because it can provide extra chances for the swarm to escape local minima and also the necessary focus and zoom in the optimum, when the inertia and memory weights are reduced and the cooperation weight is larger.

### 3.5 Discrete Evolutionary Particle Swarm Optimization

The discrete EPSO used in this paper is a new approach of the EPSO model able to tackle problems with non-continuous and integer search spaces. Its main characteristics will now be detailed.

#### a) Characterization of the population

The population is characterized by the number of particles ($n_{part}$, population size, 1st dimension, $i$), the number of positions of a particle ($n_{pos}$), particle size, 2nd dimension, $j$) and the number of possible states in each particle position ($n_{per}$, 3rd dimension). Each particle is a possible solution to the problem and the main difference between this approach and classical EPSO is that the elements in this particle are integers, and not real.
b) Algorithm main blocks

We follow the same structure of classic EPSO, and the algorithm is organized as follows:

- **Replication**: in each iteration the population is cloned twice;
- **Mutation of weights**: as in the classical EPSO approach, there are three weights that are subjected to mutation: inertia, memory and cooperation. The mutation is performed as indicated in (3);
  \[
  W_{ij}^* = \left(0.5 + \text{rand}() - \frac{1}{1 + \exp(-W_{ij})}\right)
  \]
  (3)
- **Mutation of best global**: the global best particle is a vector, whose positions are mutated only when randomly generated numbers \( N \in [0.1] \) take values less than \( k_c < 0.1 \). The weights are updated by (3) and the mutation of particle bg is obtained by (4);
  \[
  b_{ij} = b_{ij} + \text{round}[2W_{ij}^* - 1]
  \]
  (4)
- **Recombination**: we adopted the same expressions of the classic EPSO, which we round up to integers. Accordingly, we shall not consider a continuous velocity spectrum, but jumps from one admissible position to another admissible position in the search space. When the particles exceed the search space boundaries, they are returned to the search space, either being placed on the edge or in a contiguous position, according to a random generation (5 and 6);
  \[
  X_{ij} = 0 + \text{round}(\text{rand}())
  \]
  (5)
  \[
  X_{ij} = \text{nper} - \text{round}(\text{rand}())
  \]
  (6)
- **Recombination by Lamarckian evolution**: when the velocity of a particle is zero, meaning that it will not move, it is promoted a Lamarckian evolution of that particle using (7). In this particular evolution the particle only sees some of his positions mutated, those when randomly generated numbers \( N \in [0.1] \) take values less than \( k_b \); \( k_a \) is set to nper.
  \[
  V_{a_j} = \text{round} \left[ 2ka \times \frac{0.5 + \text{rand}() - \frac{1}{1 + \exp(-\text{rand}())}}{1 + \exp(-\text{rand}())} - k_{a} \right]
  \]
  (7)
- **Selection**: at each position of the population survives the clone whose fitness is better than the best particle of the same position. The best global will be updated if some of the best particles has best fitness.

c) Local search and search spreading technique

This model is boosted by local search nearby the best solutions ever founded. When a particle has a good fitness, it is assumed that other particles in their vicinity may be of interest. Thus we create a new population on which we run an additional search. This population will result from the evolution of clones of the best global or a randomly selected particle among the best population. The Lamarckian evolution is also promoted using (7).

d) Advantages of this approach

We conducted numerous tests to compare the performance of this approach with conventional EPSO approaches. The results were very promising given that the new approach was able to escape from local minima in more than 95% of the analyzed cases and also because it was possible to identify good quality solutions with less iterations and smaller populations than previously.

4 TEP MODELING USING DISCRETE EPSO

4.1 Project list, solution and search space

We modelled TEP by defining an investment plan project list, based on \( Pr \) projects, and a time frame, based on \( P_e \) periods, typically associated to yearly stages. Each new project, either a new line or a new transformer, is defined by the following information: origin bus, destination bus, technical data and investment. A solution \( X_t \) of the TEP problem corresponds to a plan that includes a number of projects selected among this list as well as their location in the time frame. The search space under analysis is discrete and integer. It typically includes a large number of possible alternative plans, given by \( Pr^P_e \).

4.2 General TEP modelling

The general formulation of the TEP is given by (8-11).

\[
\text{Min Cost} (X_t) = \text{Investment} (X_t) + \text{Oper. cost} (X_t) + n_i
\]
(8)

Subject to:

- Physical constraints (generation; power flow limitations); (9)
- Financial constraints (global and period constraints); (10)
- Quality of service constraints (reliability) (11)

The list of possible projects mentioned in 4.1 may include not only new lines to establish in new corridors, but also lines to install in existing corridors or projects associated with the upgrade of the capacity of existing lines, for example increasing the voltage level. Each of these projects is characterized by its investment cost. Then if a particular project is selected for a particular period, its investment cost is referred to the period 0, using an interest rate appropriate to the risk of this type of investment. Operation Costs in (8) are evaluated solving a linearized DC.OPF problem as (12-16) for each period. In each period the network integrates the installations commissioned previously and the forecasted demand.

\[
\text{min } f = \sum_{k} P_{g_k} + G \times \sum \text{PNS}_k
\]
(12)

\[
\text{subj } \sum P_{g_k} + \Sigma \text{PNS}_k = \sum P_{l_k}
\]
(13)

\[
P_{g_k}^{\text{min}} \leq P_{g_k} \leq P_{g_k}^{\text{max}}
\]
(14)

\[
\text{PNS}_k \leq P_{l_k}
\]
(15)

\[
P_{b_k}^{\text{min}} \leq \Sigma \text{a}_{b_k} (P_{g_k} + \text{PNS}_k - P_{l_k}) \leq P_{b_k}^{\text{max}}
\]
(16)

In this formulation:

- \( c_k \), \( P_{g_k} \) and \( P_{l_k} \) - variable generation cost, generation and load connected to node \( k \);
- \( G \) - penalty assigned to Power Not Supplied, PNS;
- \( a_{b_k} \) - sensitivity coefficient of the active flow in branch \( b \) regarding the injected power in node \( k \);
- \( P_{g_k}^{\text{min}} \), \( P_{g_k}^{\text{max}} \) - minimum and maximum output of the generator connected to node \( k \);
- \( P_{b_k}^{\text{min}} \), \( P_{b_k}^{\text{max}} \) - minimum and maximum active
power flow in branch b.

This DC-OPF was enhanced to include an estimate of transmission losses according to the following scheme.

**Algorithm**

i) Run an initial dispatch using (12) to (16);

ii) Compute voltage phases using the DC model;

iii) Estimate active losses in branch m-n using (17). In this expression, $g_{mn}$ is the conductance of branch m-n and $\theta_{mn}$ is the phase difference across this branch;

\[ \text{Loss}_{mn} = 2g_{mn}(1 - \cos \theta_{mn}) \]  (17)

iv) Add half of the losses in branch m-n to the original loads in nodes m and n. Run a new dispatch using (12) to (16) and compute voltage phases;

v) End if the difference of voltage phases in all nodes is smaller than a specified threshold. If not, return to iii).

The convergence of this iterative process is usually reached in less than 5 iterations and at the end we get the generation cost, the level of losses and the eventual non-zero value of Power Not Supplied. These terms are computed for every period of the horizon, are then referred to period 0 and correspond to the Operation Cost.

4.3 Constraints

The formulation (8-11) includes a number of constraints as follows: physical limits of the network, physical limits of the generators, financial limitations of the transmission provider, number of projects that can be developed simultaneously, value of a reliability index to ensure the quality of the expansion plan. Several of these constraints are inherently considered in the DC-OPF formulation (12-16). This includes the limits of the branches and of the generators. On the other hand, if a particular plan displays in a particular year of the horizon a non-zero value of PNS then this is penalized in (8) and so the global cost of this particle also becomes penalized.

To turn the problem more realistic we also admitted that the planner can specify limits associated with the financial resources or with the number of projects that can be implemented simultaneously. Regarding the financial limitations we can specify a maximum value for the yearly investment cost and if this value is exceeded for a particular plan then the corresponding cost is penalized.

Regarding the reliability evaluation, the developed approach penalizes plans in which the PNS is non-zero for configurations of the network associated to N-1 contingencies and for a selected number of N-2 contingencies. This follows the indications in the Grid Codes of several countries that explicitly indicate that the system should be able to supply the demand for all N-1 contingencies and for a number of N-2 contingencies selected according specific criteria. This evaluation can be modified, extending the number of configurations to analyse or, in the limit, to run a Monte Carlo simulation for every particle. This strategy would obviously lead to a dramatic increase of the computation time. The penalties over Power Not Supplied will be made by the term $\alpha_{t}$ present in the objective function (8), which will be assigned a very large value.

5 CASE STUDIES

The developed model was applied to the well-known Garver Network and to the IEEE 24 bus Reliability Test System. The algorithm was programmed in MATLAB, and with MATPOWER libraries. We used an HP Pavilion dv 6000 with 2CPU Core T5600 processor at 1.83 GHz, 2 GB RAM and 32-bit operating system. The particle used in the tests was a vector of integers, where the number of positions corresponds to the number of candidate projects and the number of possible states is the number of periods in the expansion plan. To make results easier to compare with literature, we chose a fitness function based only on the value of the investment, without considering losses. We have consider physical, PNS (n) and PNS (n-1) constraints.

5.1 Garver Network

In the first test we used the Garver network with the generation capacity and load published in [23]. The initial configuration of this network includes six buses and six lines. Table 1 indicates the list of projects based on several publications using this network. The size of the search space, in the case of a single period is $2^{17} = 131*10^{3}$ positions, and in the case of four periods is $5^{17} = 762*10^{9}$ positions. The network should be expanded from the original situation to the demand levels of 80 MW in node 1, 240 MW in node 2, 40 MW in node 3, 160 MW in node 4 and 240 MW in node 5. To evaluate PNS, we considered fictitious generators connected to each bus.

<table>
<thead>
<tr>
<th>Branch no</th>
<th>From bus</th>
<th>To bus</th>
<th>Resist. (pu)</th>
<th>React. (pu)</th>
<th>Cap. (MW)</th>
<th>Cost (10^5$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>6</td>
<td>0.0800</td>
<td>0.0300</td>
<td>100</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>6</td>
<td>0.0800</td>
<td>0.0300</td>
<td>100</td>
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<td>100</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>4</td>
<td>0.1000</td>
<td>0.4000</td>
<td>100</td>
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</tr>
<tr>
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<td>5</td>
<td>6</td>
<td>0.1476</td>
<td>0.6100</td>
<td>78</td>
<td>61</td>
</tr>
<tr>
<td>6</td>
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<td>0.2000</td>
<td>100</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>5</td>
<td>0.0500</td>
<td>0.2000</td>
<td>100</td>
<td>20</td>
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<tr>
<td>8</td>
<td>3</td>
<td>5</td>
<td>0.0500</td>
<td>0.2000</td>
<td>100</td>
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</tr>
<tr>
<td>9</td>
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<td>6</td>
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<td>6</td>
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<td>0.3000</td>
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<td>30</td>
</tr>
<tr>
<td>11</td>
<td>4</td>
<td>6</td>
<td>0.0800</td>
<td>0.3000</td>
<td>100</td>
<td>30</td>
</tr>
<tr>
<td>12</td>
<td>4</td>
<td>6</td>
<td>0.0800</td>
<td>0.3000</td>
<td>100</td>
<td>30</td>
</tr>
<tr>
<td>13</td>
<td>4</td>
<td>6</td>
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<td>0.3000</td>
<td>100</td>
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</tr>
<tr>
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</tr>
<tr>
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<td>0.2000</td>
<td>100</td>
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<tr>
<td>16</td>
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<td>2</td>
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<td>0.4000</td>
<td>100</td>
<td>40</td>
</tr>
<tr>
<td>17</td>
<td>2</td>
<td>3</td>
<td>0.0500</td>
<td>0.2000</td>
<td>100</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 1: Line data for the Garver network expansion problem.

The first test was performed for a single period. The solution obtained was the same as that found in the literature, although others have also been identified with the same investment value (which did not suffer any penalty for PNS): branch 3-5, 1 line; branch 4-6, 3 new lines. The algorithm was run 100 times with populations of 10, 20, 30 and 50 particles and Figure 1 details number of times in which it was possible to obtain the best solution out of the 100 runs, for each of these populations. The performance of new DEPSO was remarkable, given that convergence...
was obtained for a very small number of iterations, even for populations of 10 particles. For populations with at least 20 particles in 98% of cases the optimal solution was found in less than 10 iterations.

Figure 1. Convergence in Garver Network test, 1 period.

The four periods test was designed with the following assumptions: load increase of 5% per period; fixed investment costs (for the sake of simplicity, it was considered that the effect of technological and market competitiveness outweighed the effect of inflation and capital discount rates); lines available from the year of its entry into service (network configuration, and the corresponding power flow, for subsequent years depend on previous years configuration). Several solutions were identified with the same fitness value, which corresponds to an investment of 160 M$. In some cases the solution to four periods completes the one period solution with two more lines (Ex. Period 1: 2-6, (1 line); 3-5 (1); 4-6 (3), 1-5 (1)). Others solutions are different from what was obtained for the single period (Ex. Period 1: 2-6 (1); 3-5 (1); 4-6 (1); 1-5 (1); Period 3: 4-6 (1); Period 4: 3-5 (1)).

Figure 2. Convergence in Garver Network test, 4 periods.

As for the one period test mentioned before, the algorithm was run 100 times with populations of 10, 20, 30, 50 and 80 particles. The 10 particles population showed a higher convergence difficulty, but in 94% of cases reached the optimum in 100 iterations. The performances for 20 and 30 particles were very similar, and the performances for 50 and 80 particles were also relatively similar. Using populations of 30 particles one reaches the optimum in 95% of cases after 42 iterations, while with 80 particles we get similar results in 20 iterations.

5.2 IEEE RTS (24 nodes) Network

The IEEE RTS has 24 nodes, 35 lines and 32 generators. The demand is 8550 MW and the installed generation capacity is 10,215 MW [24]. To handle the load increased in multi-period analysis (5% per period), were added two generators: one in bus 4 (300 MW, similar to the generators in bus 7), and another in bus 19 (591 MW, similar to the generator in bus 13). The list of new projects is shown in Table 2. The dimension of the search space is $2^{28} = 268*10^6$ positions, for a single period, and $5^{28} = 37*10^{18}$ positions, for a four period analysis.

<table>
<thead>
<tr>
<th>Branch no</th>
<th>From bus</th>
<th>To bus</th>
<th>Resist. (pu)</th>
<th>React. (pu)</th>
<th>Cap. (MW)</th>
<th>Cost (10^6$)</th>
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</thead>
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<td>0.1945</td>
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<td>0.0032</td>
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<td>0.2389</td>
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</tbody>
</table>

Table 2. List of possible expansion projects.

We used a fitness function based on the value of the investment. The update for the period 0 was made at a 10% rate per period. The solutions which did not respect either the physical constraints, or PNS(n)=0, or PNS(n-1) > 5% of load, were penalized. The test for a single period, with a population of only 50 particles, converged to the solution in 11 iterations. This solution has a fitness value of 1381.8 M$ (investment), PNS(n)= 0, and PNS(n-1) = 360.8 MW, and includes a new transformer (10-12), and new lines (6-10, one line; 7-8, 2 lines; 16-17, one line). The four periods analysis converged in 53 iterations using a 50 particle population. This solution has a fitness value of 4.106 M$, PNS(n)= 0, and PNS(n-1) = 416 MW for the whole set of n-1 contingencies, and it includes the new branches indicated in Table 3. Solutions with more reduced on even zero PNS can be obtained enlarging the penalty term $\alpha_i$ in the objective function (8). In this test we confirmed that the dynamic approach, embodied by the anticipation of projects, had advantages because the problem was addressed in a more global and holistic way.
The anticipation of projects allows solving some bottlenecks in one period using branches that otherwise would only be required afterwards. This has a positive impact in reducing the global investment cost.

<table>
<thead>
<tr>
<th>Period</th>
<th>New Lines and Transformers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Transformers: 10/12; Lines: 6/10; 7/8; 11/13; 11/23;</td>
</tr>
<tr>
<td>2</td>
<td>Transformers: 3/24; Lines: 1/5;</td>
</tr>
<tr>
<td>3</td>
<td>Lines: 16/17, 7/8;</td>
</tr>
<tr>
<td>4</td>
<td>Transformers: 9/11; Lines: 15/21, 14/16.</td>
</tr>
</tbody>
</table>

Table 3. Four periods expansion solution of IEEE RTS network.

6 CONCLUSIONS

This paper proposes a discrete approach of the evolutionary particle swarm optimization (EPSO) algorithm, to solve a dynamic version of the Transmission Expansion Planning (TEP) problem. This topic is of high interest and worldwide the authorities are developing efforts to ensure the long-term ability of the networks to meet reasonable demands, to meet the requirements for electricity markets to work without physical constraints and to ensure the integration of larger amounts of RES. The results show that the convergence rate is very high and fewer particles are required than in classical particle swarm optimization (PSO) algorithms. The results also demonstrate that it is accurate, and allows the identification of good quality solutions. Future developments include the optimization of the code to reduce the computation time and to test this approach to real sized transmission systems.

7 REFERENCES


