

# Hybrid Discrete Evolutionary PSO for AC Dynamic Transmission Expansion Planning

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**Abstract** — Multiyear Transmission Expansion Planning (TEP) aims to determine how and when a transmission network capacity should be expanded taking into account an extended horizon. This is an optimization problem very difficult to solve and that has unique characteristics that increase its complexity such as its non-convex search space and its integer and nonlinear nature. This paper describes a hybrid tool to solve the TEP problem, including a first phase to select a list of equipment candidates conducted by a Constructive Heuristic Algorithm (CHA), and a second phase that uses Discrete Evolutionary Particle Swarm Optimization (DEPSO) for the final planning. Both phases use the AC power flow model as a way to improve the realism of the developed tool. The paper includes a case study based on the IEEE 24-Bus Reliability Test System and the results show that tools based on swarm intelligence applied to reduced search spaces are able to find good quality solutions with low computational effort.

**Index Terms** — Multiyear Transmission Expansion Planning, DEPSO, Search Space Reduction, AC Optimal Power Flow.

## I. INTRODUCTION

The increasing demand for electricity and the changes in its consumption profile, with the introduction of distributed generation and micro grids for example, require a thorough analysis of how the system should evolve along an extended period of time. In this scope and using pre-defined list of candidate equipment (transmission lines, cables, transformers, etc) to be inserted on the grid, Transmission Expansion Planning (TEP) has the purpose of identifying the ones to be built and their commissioning date to minimize the operation and investment costs while supplying the forecasted demand. Furthermore, the transmission planning analysis must also take into account issues as security and reliability, which makes it a very complex problem.

TEP models and approaches can be classified as static or dynamic (multi-year). Regarding static approached, each period is considered at a time and equipment selected in a given period is considered as available on the next one. Dynamic approaches take the horizon in a holistic way and the problem is solved at a single run because we aim at

identifying the equipment to be built as well as locating them along sub periods. It is noteworthy that when the TEP is done dynamically the holistic planning view is preserved and this is essential for long-term actions.

Regarding the optimization model that is incorporated in TEP models, we can choose among 3 alternatives:

- **Deterministic Model:** it includes a set of predicted values for specific variables and these are considered immutable, as generation, demand, market behavior, etc. This model provides an unique expansion planning solution [1].
- **Probabilistic Model:** The forecasts admit probabilistic randomness and allow working with different scenarios. Obviously, this approach is closer to reality and its solutions are interpreted as estimates of the true system characteristics [2].
- **Uncertainty Model:** This type of models admit that some uncertain data are affected by lack of complete knowledge and this incomplete information is usually modeled with fuzzy numbers [3].

Generally, the TEP problem considers the expansion cost as its objective function to be minimized. However, it can also be formulated using other objectives as alleviating transmission congestion, minimizing the risk associated to the investments, increasing the reliability of the network, increasing the flexibility of system operation while reducing the network charges, minimizing the environmental impacts or providing a better voltage profile.

Besides, TEP has some peculiarities that increase its difficulty in terms of developing new tools such as:

- Non-convex search space, so that solution algorithms may converge to local optima;
- Integer nature leading to the phenomenon of combinatorial explosion of investment alternative plans which in turn requires a high computational effort to identify good quality plans;

- In some cases there are isolated smaller systems, which can lead to convergence problems.

Given the difficulties mentioned above, several tools have been proposed in the literature for its solution. Usually these tools are organized into three large groups: Classical Optimization [4], Constructive Heuristic Algorithms (CHA), [5] and Metaheuristics [6]. The first one is able to find optimal and sub-optimal solutions for small systems, but requires a high computational effort that usually turns its application prohibitive in realistic problems. Constructive Heuristics are able to find acceptable solutions through a low computational effort, and Metaheuristic algorithms are usually based on nature patterns, corresponding to powerful tools that are able to find optimal solutions and sub-optimal through a typically large computational effort.

Metaheuristics based on swarm intelligence are reported to show good behavior to solve the TEP problem. This kind of technique has even better results when the particles are initialized in a good position in the search space and if the number of expansion alternatives are drastically reduced [1]. On the other hand, the integer behavior of the problem requires a more accurate modeling of the swarm. This justifies the use of Discrete Evolutionary Particle Swarm Optimization (DEPSO) described in [6] given the good performance in solving problems with non-continuous and integer search spaces.

The hybrid DEPSO will be introduced in this paper to the multiyear and deterministic TEP problem. Therefore, TEP was addressed in a hybrid way, considering in two phases as follows: The first one uses a CHA to select a reduced number of candidate equipment from an initial larger list and the second phase uses the DEPSO to build and refine the final solution. This approach was developed using the AC power flow (AC-OPF) operation model, bearing in mind the gap between the AC and DC models [7].

Regarding the structure of the paper, following this Introduction, Section II presents the AC model used in the scope of the TEP problem and Section III provides a brief description of the Constructive Heuristic Algorithm, CHA, that was adopted in the developed methodology. Section IV details the Discrete Evolutionary Particle Swarm Optimization, DEPSO, and Section V presents the results obtained in the simulations. Finally Section VI includes some comments and provides the conclusions about this work

## II. TEP MATHEMATICAL FORMULATION

The optimization techniques used to solve the AC model must be extremely efficient to deal with the required computational effort. On the other hand, the AC model takes into account the reactive power, the losses and the voltage limits on the bars, which makes this model more adequate and realist to reflect the operation conditions of the network and therefore to estimate the operational cost of a power system.

The AC-OPF used in this paper is formulated by (1) to (9).

$$\text{Min } C_{OP} = \sum \alpha_{i1} \cdot P_i^2 + \alpha_{i2} \cdot P_i + \alpha_{i3} \quad (1)$$

$$\text{subject to } P(V, \theta, n) - P_G + P_D = 0 \quad (2)$$

$$Q(V, \theta, n) - Q_G + Q_D = 0 \quad (3)$$

$$P_{G \min} \leq P_G \leq P_{G \max} \quad (4)$$

$$Q_{G \min} \leq Q_G \leq Q_{G \max} \quad (5)$$

$$V_{\min} \leq V \leq V_{\max} \quad (6)$$

$$(N + \overset{\circ}{N})S^{from} \leq (N + \overset{\circ}{N})S_{\max} \quad (7)$$

$$(N + \overset{\circ}{N})S^{to} \leq (N + \overset{\circ}{N})S_{\max} \quad (8)$$

$$0 \leq n \leq n_{\max} \quad (9)$$

In this formulation  $P(V, \theta, n)$  and  $Q(V, \theta, n)$  are calculated by (10) and (11), and the bus conductance  $G$  and susceptance  $B$  are given by (12) and (13).

$$V_i \sum V_j [G_{ij}(n) \cdot \cos \theta_{ij} + B_{ij}(n) \cdot \sin \theta_{ij}] \quad (10)$$

$$V_i \sum V_j [G_{ij}(n) \cdot \sin \theta_{ij} - B_{ij}(n) \cdot \cos \theta_{ij}] \quad (11)$$

$$G = \begin{cases} G_{ij}(n) = -(n_{ij} \cdot g_{ij} + \overset{\circ}{n}_{ij} \cdot \overset{\circ}{g}_{ij}) \\ G_{ii}(n) = \sum_{j \in \Omega_i} (n_{ij} \cdot g_{ij} + \overset{\circ}{n}_{ij} \cdot \overset{\circ}{g}_{ij}) \end{cases} \quad (12)$$

$$B = \begin{cases} B_{ij}(n) = -(n_{ij} \cdot b_{ij} + \overset{\circ}{n}_{ij} \cdot \overset{\circ}{b}_{ij}) \\ B_{ii}(n) = b_{ij}^{sh} + \sum_{j \in \Omega_i} [n_{ij} (b_{ij} + b_{ij}^{sh}) + \overset{\circ}{n}_{ij} (\overset{\circ}{b}_{ij} + \overset{\circ}{b}_{ij}^{sh})] \end{cases} \quad (13)$$

The apparent flows  $S^{from}$  and  $S^{to}$  are calculated by (14) and (15) where  $P_{ij}^{from}$ ,  $Q_{ij}^{from}$ ,  $P_{ij}^{to}$  and  $Q_{ij}^{to}$  are given by (16) to (19).

$$S_{ij}^{from} = \sqrt{(P_{ij}^{from})^2 + (Q_{ij}^{from})^2} \quad (14)$$

$$S_{ij}^{to} = \sqrt{(P_{ij}^{to})^2 + (Q_{ij}^{to})^2} \quad (15)$$

$$P_{ij}^{from} = V_i^2 \cdot g_{ij} - V_i \cdot V_j (g_{ij} \cdot \cos \theta_{ij} + b_{ij} \cdot \sin \theta_{ij}) \quad (16)$$

$$Q_{ij}^{from} = -V_i^2 \cdot (b_{ij}^{sh} + b_{ij}) - V_i \cdot V_j (g_{ij} \cdot \sin \theta_{ij} - b_{ij} \cdot \cos \theta_{ij}) \quad (17)$$

$$P_{ij}^{to} = V_j^2 \cdot g_{ij} - V_i \cdot V_j (g_{ij} \cdot \cos \theta_{ij} - b_{ij} \cdot \sin \theta_{ij}) \quad (18)$$

$$Q_{ij}^{to} = -V_j^2 \cdot (b_{ij}^{sh} + b_{ij}) + V_i \cdot V_j (g_{ij} \cdot \sin \theta_{ij} + b_{ij} \cdot \cos \theta_{ij}) \quad (19)$$

In the objective function (1)  $\alpha_{i1}$ ,  $\alpha_{i2}$  and  $\alpha_{i3}$  are coefficients of the quadratic generator cost function.  $P_G$  is the real power generation,  $Q_G$  is the reactive power generation,  $P_D$  is the real power demand,  $Q_D$  is the reactive power demand,  $V$  is the voltage magnitude,  $S^{from}$  and  $S^{to}$  are the branch apparent flows in both terminals,  $g_{ij}$  and  $b_{ij}$  are the conductance and the susceptance of branch  $i$ - $j$ ,  $\mathbf{N}_o$  and  $\mathbf{N}$  are diagonal matrices containing the equipment in the base topology and the added equipment respectively

## III. MULTI-YEAR APPROACH

TEP Multi-year has the objective of minimizing the total system costs, that is, the sum of operating and investment costs, brought to the present as shown in (20).

$$fitness = \sum_{p=1}^{np} \frac{(C_{INV,p} + C_{OP,p})}{(1+r)^p} + \beta.PNS \quad (20)$$

In this equation,  $np$  is the number of considered periods,  $C_{INV,p}$  is the investment cost in period  $p$  given by (21),  $r$  is the return rate, and  $\beta_1$  is the penalty factor for Power Not Supplied (PNS). In (21)  $c_{ij}$  is the cost of installing a network equipment in path  $i$ - $j$  and  $\eta_{ij}$  is the number of equipment of that type to install in parallel in that path.

$$C_{INV} = \sum c_{ij} \cdot \eta_{ij} \quad (21)$$

The dynamic multi-year approach for the TEP problem involves solving a problem of greater complexity due to the combinatorial explosion much larger than in the static or single period problems. In single period approaches the goal is to minimize the operation and investment costs for the specific year under analysis while in multi-year approaches it becomes the minimization of the sum of all costs along the extended planning horizon. This holistic view allows the problem to eventually select an investment alternative that is more expensive in a particular period, but that has advantages and becomes cheaper when the whole set of periods in the horizon are considered.

#### IV. CONSTRUCTIVE HEURISTIC ALGORITHM

The Constructive Heuristic Algorithms (CHA) are tools that use a function as a sensitivity criterion to assess the system performance and iteratively build solutions, in the sense that at each iteration new additions are included as a way to obtain the final solution. These characteristics typically enable CHAs to have low computational effort and reasonable efficiency. The CHAs have been proposed to solve the TEP problem since the 70's by several authors [8], [9]. However it continues to be used mainly incorporated in hybrid tools in which the mentioned characteristics are used in a profitable way to reduce the search space of the TEP problem [1], [10].

At each iteration, the CHA uses a sensitivity criterion having local nature to assess the most adequate equipment to allow a power system to operate properly, that is, without PNS. The search space reduction is obtained via the list of candidate equipment that forms its final output. The equipment in this list is then taken as input to a second phase of the TEP algorithm to build the final expansion plan.

In this paper it was used the Least Effort CHA proposed by [11] to select a list of equipment to be candidates to be built and included in the transmission system. This list is a subset of a wider set of possible equipment and so the CHA promotes a reduction of the search space of the TEP problem. In this CHA the sensitivity function used evaluate the interest in having a specific equipment in this subset is the power flow in the equipment, that is, at each iteration the most congested equipment is included in the subset until the PNS is canceled. Fig. 1 displays the main steps of the iterative process of the Least Effort CHA.

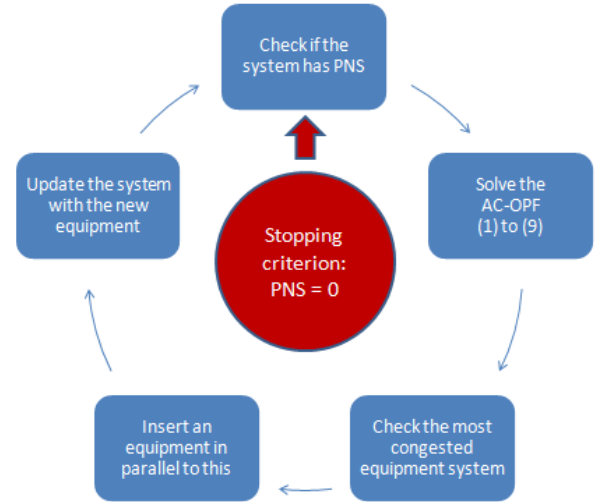


Figure 1: Least Effort CHA – Iterative process.

When this iterative process ends, the CHA provides a list of equipment that will be considered as the input to the DEPSO algorithm, that is, as the list of equipment candidates from which a final combination will be extracted and organized as the solution to the TEP problem.

#### V. DISCRETE EVOLUTIONARY PARTICLE SWARM OPTIMIZATION

The DEPSO was developed by Rocha and Saraiva [12] in 2011 and its main objective was to adapt the EPSO to solve problems with non-continuous and integer search spaces as the TEP problem. Basically, this tool combines some concepts of evolutionary computation and multi agent population, using the standards blocks that are typical in Genetic Algorithm and Particle Swarm Optimization.

In this tool the population is formed by a set of particles that carry information about the projects for the system expansion. Each particle is encoded using integer numbers which represent the period in which a particular equipment will be inserted into the network. If the position of a particular equipment in a particle has the number 0 then this equipment is not used in the expansion planning. Therefore, considering the dynamic TEP problem discretized in  $np$  periods, there are  $np + 1$  integer numbers (from 0 to  $np$ ) that can be associated to each equipment. Fig. 2 shows a coding example regarding a list of 5 candidate equipment. In this case, this particle includes information about the time allocation of equipment 1, 2, 3, and 5 to each of the 3 periods while equipment 4 is not included in the plan associated to this particle.

Period	List of Candidates Equipment
2	Equipment 1
1	Equipment 2
3	Equipment 3
0	Equipment 4
1	Equipment 5

Figure 2: Illustration of the particle codification.

In this example, equipment 2 and 5 will be inserted in the first period, equipment 1 will be built in the second period and equipment 3 in the last period. Equipment 4 was not included in this plan.

According to this coding strategy, each particle is represented by a vector with  $N_{proj}$  positions – amount of equipment in the list of candidates. Since each position is filled with an integer from 0 to np, then the size of the search space (SSS) is defined by (22).

$$SSS = (np + 1)^{n_{proj}} \quad (22)$$

The main DEPSO blocks are presented below:

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**Procedure DEPSO**

Set the list of candidate equipment having  $N_{proj}$  elements

Initialize a random population with ps particles

Repeat

Replication

Mutation

Recombination

Evaluation

Selection

Stop Test

Until test is positive

End DEPSO

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In the Replication block the population is cloned r times. Then according the ideas proposed in [12], in the Mutation block the weights and the best particle until now (that will be used in Recombination Block) are mutated using equations (23) and (24) in which the symbol \* represents the mutation and rand() is a random number between 0 and 1.

$$w_{ij}^{*it+1} = 0,5 + rand() - \frac{1}{1 + \exp(-w_{ij}^{*it})} \quad (23)$$

$$gbest^* = gbest + round(2 \cdot w_{i4}^{*it+1} - 1) \quad (24)$$

In (23) j=1 to 4 so that this expression is used to mutate the four weights used in the algorithm and i is the index associated to a particle. Accordingly, for j=1,  $w_{i1}^{*it+1}$  is the weight conditioning the inertia term, for j=2  $w_{i2}^{*it+1}$  is the weight conditioning the memory of each particle (reflecting its history and individual knowledge), for j=3  $w_{i3}^{*it+1}$  is the weight conditioning the cooperation inside the swarm (associated to the collective knowledge of the swarm) and finally for j=4  $w_{i4}^{*it+1}$  is the term that is used to mutate the gbest particle, that is, the best particle founded until the current iteration.

In the Recombination block new offsprings are created for each particle of cloned population using the EPSO movement

rule for each particle i and rounding up the value obtained for each position in the vector to integers, as described by (25) and (26) and illustrated in Fig. 3.

$$V_i^{it+1} = w_{i1}^{*it+1} \cdot V_i^{it} + w_{i2}^{*it+1} \cdot (pbest_i - X_i^{it}) + w_{i3}^{*it+1} \cdot (gbest - X_i^{it}) \cdot P \quad (25)$$

$$X_i^{it+1} = X_i^{it} + V_i^{it+1} \quad (26)$$

The first term in (25) represents the inertia of the particle, that is, its trend to follow its previous movement, the second term represents its individual knowledge, that is, it induces a movement towards the best position that was found so far for this particle and, finally, the last term represents the collective knowledge of the swarm in the sense that it is introduced a component to move the particle towards the best particle so far identified in the entire swarm. P is the communication factor described in [13]. It typically takes values 0 or 1 so that if 0 is used for a position of the particle vector then the collective knowledge is not passed to this particle in the next iteration.

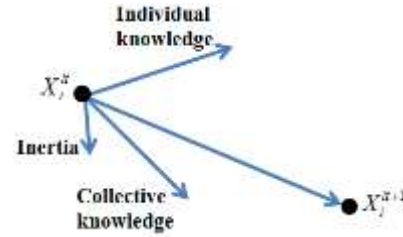


Figure 3: Particle movement in typical PSO algorithms.

If the velocity of some particle is zero this would mean that particle would not move from one iteration to another. However, to introduce more diversity and following again the approach described in [3, 12], a Lamarckian evolution with symmetric probability is applied according with (26). This means that the particle would not move because microscopic or genotype changes given by (25) were insufficient but a change at the macroscopic or phenotype level was introduced in order to reach more perfect and adapted solutions. This borrows the ideas of the French biologist Baptiste Lamarke that is often considered as a proto evolutionist.

$$V_i^{it+1} = round(np \cdot (0,5 + rand() - 1)) \quad (26)$$

When the new position of a particle is out of the search space, that is in some of its positions the values are larger or smaller than the maximum or minimum values, then the particle is returned back to the search space by setting at 0 the values smaller than 0 and by sampling a value smaller or equal to np if the original value was larger than np (27).

$$X_i^{it+1} = np - round(rand()) \quad (27)$$

After the Recombination step, the offsprings are evaluated using (20). Finally, the selection is made through an elitist process. In this step recall that we have r clones each of them having ps particles. The selection procedure takes the first particle of each r clone and it survives the one that has the best fitness function. This procedure is repeated for all ps particles so that at the end a new population is created having the same size of the initial one and the values of gbest and pbest are

updated. The process ends when gbest does not change after running a pre specified number of iterations.

## VI. TESTS AND RESULTS

The system used to test the developed TEP approach is the modified IEEE 24 BUS RTS system. This system has some differences regarding the original one proposed in [14] as described below:

- Maximum allowed flow in emergency condition for all branch;
- The loads are modeled as negative real power injections with associated negative costs as described in [15]. This modeling is performed using a negative output generator, ranging from a minimum injection equal to the negative total load to a maximum injection of zero. This means the AC OPF problem has enough flexibility to reduce the demand if that is required to maintain feasibility. Additionally, if a particular nodal real load is not entirely supplied then the reactive demand is also reduced in the same proportion as a way to keep the power factor of the original load unchanged.
- Reactive power sources are located in particular buses, as suggested in [16] and according to Table I;
- The values of all loads and of the installed capacity of all generators were tripled (real and reactive) in order to turn the network more stressed and the maximum voltage variation was set at 10%.

TABLE I. VOLTAGE CORRECTION DEVICES

VOLTAGE CORRECTION DEVICES			
DEVICE	BUS	MVAR	CAPABILITY
SYNCH. CONDENSER	3	350	CAPACITIVE
SYNCH. CONDENSER	9	510	CAPACITIVE

The tests were performed considering the multiyear TEP model with 3 periods and using a load increase of 5% per period. The Least Effort CHA was applied to select a list of candidate equipment considering a static TEP problem for each period. After solving 23 AC-OPFs, using the MATPOWER tool described in [15], running in MATLAB with an Intel i7, 3.4GHz, 8 GB RAM, the output of the CHA is given in Table II.

It is important to note that the majority of papers existing in TEP literature consider that the branches of the departing topology are also candidates with a maximum number of additions usually set at 3. The excessive number of elements in the candidate list may cause the computational effort to be so large that it prevents or turns it very difficult to solve the problem. Using the CHA proposed in this paper, to build a subset of candidate equipment taken from the large initial list promotes the reduction of the search space by 99.99% from  $(3+1)^{38} \approx 10^{23}$  to  $(3+1)^{19} \approx 10^{11}$ .

After this initial step, DEPSO was run using 100 particles in the swarm, PNS penalty factor used in (20)  $\beta = 10^{12}$ , 50

iterations with the same gbest as stopping criterion and P communication factor equal to one as in classical formulations. DEPSO solved 68724 AC-OPFs in about 3.4 hours achieving the best solution after running 57 iterations. This solution is displayed in Table III and Figure 4 displays the evolution of the fitness function (20) of the best particle.

TABLE II. OUTPUT LIST OF EQUIPMENTS OF THE CHA ALGORITHM

no.	Equipment
1	138 kV line connecting bus 1 to 5
2	138 kV line connecting bus 1 to 5
3	Transformer between bus 3 and 24
4	Transformer between bus 3 and 24
5	138 kV cable connecting bus 6 to 10
6	138 kV cable connecting bus 6 to 10
7	138 kV line connecting bus 7 to 8
8	138 kV line connecting bus 7 to 8
9	138 kV line connecting bus 7 to 8
10	230 kV line connecting bus 14 to 16
11	230 kV line connecting bus 14 to 16
12	230 kV line connecting bus 14 to 16
13	230 kV line connecting bus 15 to 24
14	230 kV line connecting bus 15 to 24
15	230 kV line connecting bus 16 to 17
16	230 kV line connecting bus 16 to 17
17	230 kV line connecting bus 17 to 18
18	230 kV line connecting bus 17 to 18
19	230 kV line connecting bus 20 to 23

TABLE III. BEST SOLUTION IDENTIFIED BY THE DEPSO

Period	New Equipment (no.)	Investment Cost (€)	Operational Cost (€/h)	PNS
1	5, 7, 10	86000000	1549986	0
2	---	0	1745338	0
3	5, 15, 17	72000000	1733134	0

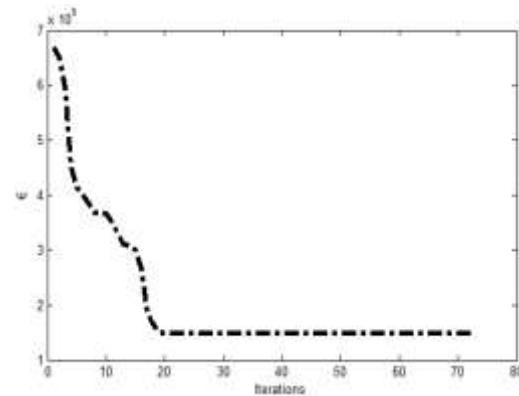


Figure 4: Evolution of the fitness function of the *gbest* particle.

According to this solution, investing in Period 1 in equipment no. 5, 7 and 10 allows the system to gain



flexibility enough to accommodate the demand increase in Period 2 so that no new equipment are required in Period 2. New equipment is therefore postponed for Period 3, which decreases the present value of the investment. This solution is the best one that was identified in all simulations.

In order to evaluate the performance of the reducing search space technique in terms of not eliminating equipment that afterwards should be used to build the best solution, DEPSO was also simulated without using the CHA technique described in Section IV. In this simulation the original complete list of 38 equipments was used and the DEPSO parameters were the same as the ones used in the simulation including the CHA (namely the number of particles and the convergence rule). Not using CHA, the best solution also includes 6 equipments. However the total present investment cost is 95% higher than the value of the solution that was obtained using the CHA technique. These equipments are distributed by the three periods as follows – 3 in period 1, 0 in period 2 and 3 in period 3. Comparing this solution with the one obtained using the CHA technique it happens that in periods 1 and 2 the two solutions are similar but in period 3 the solution not using the CHA includes equipments that increase the cost. As a comment to these results, it is clear that the DEPSO by itself was not able to identify the best solution to the problem at least with the parameters that were used. However, when the CHA technique is used prior to the DEPSO, the search space gets reduced, the combinatorial nature of the problem is also reduced and DEPSO is now able to build a higher quality solution. Therefore, using the described CHA shows two advantages. In the first place, it reduces the computational effort to solve the problem given the reduction of the search space. If a solution of comparable quality was to be obtained, then the DEPSO not running the CHA in the first place would certainly require more iterations and thus an increased computation time. Secondly, it does not compromise the quality of the final solution. In fact, DEPSO is now able to build a much better solution given that the combinatorial nature of the problem is reduced.

## VII. CONCLUSIONS

This paper presents a hybrid methodology to solve the Dynamic Transmission Expansion Planning Problem. The developed methodology was applied to a modified version of the IEEE 24-Bus Reliability Test System that includes two voltage control devices and the network operating conditions were stressed tripling the generation capacities and the loads.

The developed approach is organized in two stages. In the first one it is used the Least Effort Constructive Heuristic Algorithm to build a reduced list of candidate equipment. This CHA is used for each of the periods in the horizon considering that the demand increases 5% per period. In the second stage the Discrete Evolutionary Particle Swarm Optimization, DEPSO, was applied using the reduced list of candidate equipment as input to build the final expansion plan. In each period the operation of the system was analyzed using an AC-OPF model that was preferred regarding DC based versions in view of the gap between solutions obtained using these two models in the solution of the TEP problem.

This paper is an evolution of the approach described in [1], since a dynamic model is now used and DEPSO replaces the traditional PSO metaheuristic. The major contribution in this paper is twofold – the use of the CHA to reduce the search space as well as the computational effort and the use of both DEPSO and the AC OPF models thus increasing the realism of the solution of the multiyear TEP problem.

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