Transmission Expansion Planning – A Multiyear PSO Based Approach Considering Load Uncertainties

Manuel Costeira da Rocha
Dept. Eng. Eletrotécnica e Computadores, DEEC,
Faculdade de Engenharia da Univ. do Porto, FEUP, Portugal
manuel.rocha@fe.up.pt

João Tomé Saraiva
INESC/TEC, Dept. Eng. Eletrotécnica e Computadores, DEEC
Faculdade de Engenharia da Univ. do Porto, FEUP, Portugal
jsaraiva@fe.up.pt

***Abstract*—This paper describes a multiyear dynamic Transmission Expansion Planning, TEP, model to select and schedule along the planning horizon transmission expansion projects taken from a list supplied by the planner. The selection of the most adequate set of projects from this list is driven by the minimization of the investment plus operation costs while enforcing a number of constraints related with technical, financial and reliability issues. The developed approach also admits that nodal loads are modeled by triangular fuzzy numbers as a way to ensure obtaining more robust plans that is plans not only adequate for a deterministic set of future loads but plans that can accommodate load uncertainty. Finally, given the discrete nature of the problem, it was adopted a discrete version of the Evolutionary Particle Swarm Optimization algorithm, DEPSO, that proved very effective and shows good performance on several tests ran with the IEEE RTS system.**

***Index Terms*—Transmission Expansion Planning, multiyear problem, load uncertainties, fuzzy sets, Particle Swarm Optimization, Discrete Evolutionary PSO, DEPSO.**

I. INTRODUCTION

Before the restructuring of power systems, transmission expansion planning was typically addressed in the scope of vertically integrated companies together with generation expansion planning. More recently, the unbundling of the industry lead to the identification of several activities, namely generation, transmission, distribution and retailing, as well as coordination activities at the operational, market and regulatory levels. These four activities are usually developed by different agents and network transmission and distribution activities are typically provided under a regulated framework.

This unbundled model brought new challenges to long term expansion planning activities both for generation and transmission. Regarding generation, there are now several competing agents and each generation company should develop its own plan taking into account the possible reaction of the competitors, the available financial resources and technologies, the possible evolution of the demand and the increased presence of generation connected to distribution networks leading to the reduction of the demand seen by traditional large power stations. Regarding transmission, the expansion plans must now be developed so that the network can accommodate connection requests from generation, distribution and consumer agents, while coping with load uncertainty and possible changes of generation plans due, for instance, to changes in operation costs of traditional technologies or to the reduction of the liquid demand seen by transmission networks as the capacity directly connected to distribution grids increases. The increased complexity of transmission expansion planning can be observed considering for instance that the European Parliament and the European Council Directive 2009/72/EC, establishing common rules for the internal electricity market [1] states that transmission operators should ensure the long-term ability of the system to meet reasonable demands for the use of the networks. This ultimately means that they should adequately develop the networks so that reasonable new generation and demand requirements can be accommodated.

The publications on TEP models are numerous [2,3] and can be classified according to some general aspects as follows:

- some publications address generation and transmission expansion in an integrated way either because they are prior to the unbundling of the industry, or because in some geographical areas power systems are still organized in a vertically integrated way [4-6];
- some models have a static nature [7,8] while some others address the problem in a multiperiod way [9,10]. In the first case, each period in the planning horizon is addressed in a separate and sequential way so that the projects selected for the initial period are then considered as already available when solving the problem for subsequent periods. Static approaches have a major drawback given that they do not capture the holistic view over the entire planning horizon. In some cases, some projects may not be selected in the scope of a static problem, but may well be chosen in dynamic multiperiod approaches because, together with other projects, they lead to the most adequate plan to address bottlenecks in different periods. Given the complexity of multiperiod problems, several authors proposed simplifications based for instance in series of static sub problems leading to formulations often termed as pseudo-dynamic procedures, [4,11];

- finally, most of the approaches assume that the demand in future periods is known. This means that the selected plan is adequate for this future demand level but it can be risky if the demand does not behave exactly as that. It is then clear that modeling demand uncertainties is a crucial issue to better characterize the goodness of expansion plans and to identify robust ones that is plans regarding which the planner does not feel any regret if some change on the future demand occurs. Uncertainties in TEP are addressed in [12-14] using probabilistic and fuzzy set models.

Regarding the solution techniques, TEP models use a wide range of approaches namely classical optimization methods, dynamic, quadratic and mix-integer programming, decomposition techniques and metaheuristics. Regarding metaheuristics, [7,9] use Genetic and Evolutionary algorithms, Simulated Annealing is used in [10,15], Tabu Search is adopted in [7,16], Expert Systems are used in [8,17] and [11] details the use of Greedy Randomized Search.

This paper describes a multiyear TEP model to select a number of investment projects (transmission lines and transformers) from a list to be specified by the planner. The selection of the most adequate set of projects from this list should be done in a coordinated way to preserve the holistic view over the entire horizon, so that the final solution minimizes investment plus operation costs while enforcing technical operation, financial and reliability constraints. In order to deal with the risk of having to supply in the future loads different from the ones used in the planning process, the demand is modeled by triangular fuzzy numbers. Finally, this is a discrete optimization problem given the list of possible projects provided by the planner. This discrete nature was addressed using an adaptation of the Evolutionary Particle Swarm Optimization Algorithm. PSO was originally proposed in [18] and [19,20] describe a number of adaptations to give it an evolutionary flavour, EPSO, namely in terms of the evolution of the weights used in the PSO recombination rule. In this paper, we are using a set of enhancements to address discrete problems leading to the Discrete EPSO, DEPSO, that was originally applied in [21] admitting deterministic future load scenarios. The results reported in [21] were very promising and we are now describing the enhancements to consider loads defined by triangular fuzzy numbers.

Having these ideas in mind, Section II details the Discrete EPSO approach, and Section III provides the mathematical formulation of the TEP problem and the developed solution algorithm. Section IV addresses the integration of triangular fuzzy loads and Section V illustrates the application of this approach to a case study based on the IEEE 24 bus system. Finally, Section VI draws the most relevant conclusions.

II. Discrete Evolutionary PSO, DEPSO, Approach

Particle Swarm Optimization, PSO, is a population based approach in which the population is composed of a number of particles or agents forming a swarm. These particles evolve from one iteration to the next one according to a movement rule [18] stating that the position of particle p in iteration i+1 is determined by the addition of three terms. The first one is the inertia reflecting the position in iteration i. The second one is the memory term and it is related with the best particle identified along the iterative process in this position of the swarm that is by the best of the ancestors of particle p. The third is the cooperation term and it uses information about the best of all particles so far identified in the entire swarm.

This scheme proved to be able to make the swarm evolve to regions around the optimum but then it had increasing difficulty in fine-tuning towards the optimum. In 2002, [19,20] introduced an evolutionary flavour in PSO, leading to the EPSO algorithm. The position of particle p in iteration i+1 is given by (1) and it is the result of the addition of the particle in iteration i plus the velocity vector given by (2). This vector also integrates three terms, but each of them is multiplied by a weight that undergoes mutation along the iterative process, for instance using (3). In these expressions Cf is a communication factor allowing some dimensions of the best ever found particle to be communicated to particle p, σ is a learning parameter set externally, b_p is the best of the ancestors of particle p and b_G is the best ever found particle. Particle b_G also undergoes mutation using (3) leading to b_G^*. This evolutionary scheme is illustrated in Fig. 1.

$$X_p^{i+1} = X_p^i + V_p^{i+1} \tag{1}$$

$$V_p^{i+1} = W_{p1}^*.V_p^i + W_{p2}^*.\left(b_p - X_p^i\right) + W_{p3}^*.\left(b_G^* - X_p^i\right).Cf \tag{2}$$

$$W_p^* = W_p + \sigma.N(0,1) \tag{3}$$

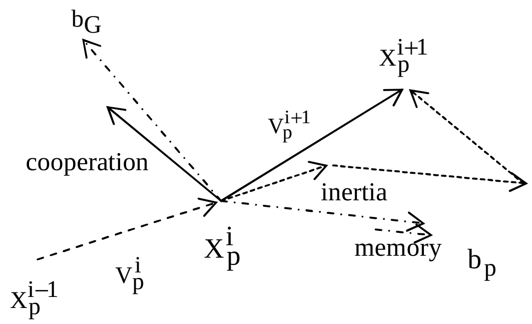

Figure 1. Illustration of the EPSO movement rule.

This scheme was adapted to address discrete problems thus leading to DEPSO. In DEPSO, all the dimensions of particle p are integers and so the velocity vector is rounded to the nearest integer before computing the particle p in iteration i+1. Several researchers as in [22,23] showed the advantages of using chaotic sequences to determine the weights in (2) for instance provided by sigmoid functions as a way to improve the convergence characteristics of the algorithm. As a result, in the DEPSO we adopted (4) to determine the values of the mutated weights to be multiplied by the inertia, the memory and the cooperation terms as well as to be used to mutate the best global particle. As a result, the recombination rule of the DEPSO algorithm uses the velocity vector computed by (2) in which the mutated weights are now given by (4).

$$w_p^{i+1*} = \left(0.5 + \mathrm{rand}() - \frac{1}{1 + \exp\left(-w_p^{i*}\right)}\right) \tag{4}$$

Finally, when dealing with discrete problems it is frequent that the rounded velocity vector yields zero values, meaning that the particle would remain unchanged from iteration i to i+1. If that occurs, we incorporate a Lamarkian evolution step as it was originally suggested in [24]. This Lamarkian step promotes a change of some dimensions of the particle acting at the fenotype or macroscopic level, rather than at the components used to obtain the velocity vector that is instead of changing the particle at the genotype level. This ultimately means that one is promoting a local search around a particle that eventually already displays promising characteristics.

III. General TEP Model for Deterministic Loads

A. *Statement of the Problem*

As defined above, the TEP problem aims at identifying a set of expansion projects taken from a list provided by the planner and to place them along the planning horizon so that the investment plus operation costs are minimized and a set of technical, financial and reliability constraints are enforced.

Let us assume that the list of investment projects has npj possible new lines or transformers that can be built, that the planning horizon has npd periods and that the population is formed by np particles. A population is coded by a matrix having np lines and npj columns. Each line in this matrix is denoted by X_p^i and it corresponds to a particle that has npj positions, each of them related with a particular project. For each of these projects, the corresponding position in this line is filled with an integer going from 0 to npd+1, indicating that the project was not adopted in this particle (value 0 or npd+1) or that it will be commissioned to start operation in period 1 to npd. This design of a particle with integers from 0 to npd+1, and in particular with one state below 1 and another above npd, is important because it makes it possible to evolve with the same difficulty from any state to 0, non selecting the project, or to npd+1, postponing the project. If the 0 and npd+1 states were not allowed, the roundings would be limited to 1, in the lower level, and to npd at the higher level and so the 1 and the npd states would be favored.

B. *TEP Formulation*

The TEP problem can be formulated by (5-8). According to this formulation, we aim at minimizing the investment and operation costs incurred along the planning horizon, while enforcing physical, financial and reliability constraints.

$$\min \ \mathrm{Cost}X_p^i = \sum_{pd=1}^{npd}\left[\sum_{pj=1}^{npj} IC_{pj}.K_{p,pj}^{pd} + OC_{p,pd}\right]/(1+dr)^{pd} \tag{5}$$

Subjected to:

Physical constraints; (6)

Financial constraints; (7)

Reliability constraints; (8)

p = 1, 2, ..., np; i = 1, 2, …, imax

Assuming a multiyear horizon, the objective function measures the goodness of each solution X_p^i and it includes operation and investment costs along the horizon referred to the initial year using a discount rate dr. In each period, the investment costs, IC_{pj}, are related with the projects that will be commissioned in that period. The total investment cost of solution X_p^i results from the addition of the investment costs per period using the rate dr mentioned above. In (5) $K_{p,pj}^{pd}$ represents a binary variable that in case of being 1 indicates that project pj in the project list is included in particle p and scheduled to start operation in period pd.

The operating costs in period pd for particle p, $OC_{p,pd}$ can include a variety of aspects as generation and maintenance costs, losses, and costs associated with ancillary services. In order to speed up the solution algorithm, the generation costs are estimated using a DC OPF model as (9 – 13). This is a typical formulation adequate for expansion planning studies that, in any case, was enhanced to include an estimate of transmission losses. In this formulation c_k, Pg_k and Pl_k are the variable generation cost, the generation and the load at node k, G is a penalty assigned to Power Not Supplied, PNS, a_{bk} is the sensitivity coefficient of the active flow in branch b regarding the injected power in node k, Pg_k^{min} and Pg_k^{max} are the minimum and maximum outputs of the generator connected to node k, and finally P_b^{min} and P_b^{max} represent the minimum and maximum active power flows in branch b.

$$\min f = \sum c_k.Pg_k + G.\sum PNS_k \tag{9}$$

Subject to:

$$\sum Pg_k + \sum PNS_k = \sum Pl_k \tag{10}$$

$$Pg_k^{min} \le Pg_k \le Pg_k^{max} \tag{11}$$

$$PNS_k \le Pl_k \tag{12}$$

$$P_b^{min} \le \sum a_{bk}.(Pg_k + PNS_k - Pl_k) \le P_b^{max} \tag{13}$$

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 (9). This means that using this strategy one inherently penalizes particles that are not adequate in terms of being unable to adequately connect generation and demand. On the other hand, this formulation assumes that the network is lossless. In order to increase the realism of the model, this DC-OPF can be enhanced to include an estimate of transmission losses according to the iterative procedure detailed below and already used in [10].

Procedure DC-OPF with Losses

i) Run an initial dispatch using (9-13);

ii) Compute voltage phases using the DC model;

iii) Estimate active losses in branch m-n using (14). In this expression, g_{mn} is the conductance of branch m-n and θ_{mn} is the phase difference across this branch;

$$Loss_{mn} \approx 2.g_{mn}.(1-\cos\theta_{mn}) \tag{14}$$

iv) Add half of the losses in branch m-n to the original loads in nodes m and n. Run a new dispatch using (9-13) and update 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 yielding the generation profile, the losses and eventually a non zero value of PNS for the entire system, PNS(N). If the level of losses exceeds a reference value, then this particle is penalized with a term α_1 in the fitness function and if the PNS(N) is not zero, then the penalty term α_2 is also introduced in the fitness function.

Regarding the financial constraints, the developed TEP model considers two types of limitations. The first one corresponds to the maximum number of projects that can be implemented per period. This limit can arise due to financial or operational reasons and if it is violated it is included a penalty term α_3 in the fitness function. The second one corresponds to the maximum investment value over the entire horizon and it models a global financial constraint. If it is violated, a penalty term α_4 is included in the fitness function.

Regarding reliability aspects, the developed approach 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 following the indications in the Grid Codes of several countries. This evaluation can be modified, extending the number of configurations to analyze or, in the limit, to run a Monte Carlo simulation for every particle, obviously leading to a large increase of the computation time. The penalty associated to PNS (N-1) is made using the term α_5.

Given this information, each solution is characterized by a fitness value given by (15), that results from (5) plus additive penalty terms in case of violating the maximum admitted level of losses, of displaying non zero values for PNS both for the entire system and for N-1 contingencies, of exceeding the maximum number of projects for each period and finally in case of exceeding the maximum investment value.

$$\min \mathrm{Cost}X_p^i = \sum_{pd=1}^{npd}\left[\sum_{pj=1}^{npj} IC_{pj}.K_{p,pj}^{pd} + OC_{p,pd}\right]/(1+dr)^{pd} + \sum_{t=1}^{5} pen_t \qquad (15)$$

C. TEP Solution Algorithm for Deterministic Loads

Let us consider the TEP problem assuming that loads are modeled by deterministic values. In this case, the TEP solution algorithm evolves as follows:

i. <u>Initialization</u> - the DEPSO is initialized by randomly sampling an initial population that is by sampling integers from 0 to npd+1 for each position of the matrix mentioned in Section III.A;

ii. <u>Replication</u> - the current population obtained at the end of each iteration is cloned twice, so that the algorithm is actually working with two populations;

iii. <u>Mutation of weights</u> - the Inertia, the Memory and the Cooperation weights mentioned in Section II are mutated using (4);

iv. <u>Mutation of the best global</u> - the best global particle is a vector with as many positions as the elements of the project list. Its npj positions also undergo mutation as a way to introduce changes in the current best global particle to make a local search around it. To do this, the corresponding weight is mutated using (4) and then each position j undergoes mutation using (16);

$$b_{Gj}^{*} = b_{Gj} + \mathrm{round}\left(2.W_{bGj}^{i+1*} - 1\right) \qquad (16)$$

v. <u>Recombination</u> - having mutated the Inertia, the Memory and the Cooperation weights and some positions of the best global so far identified particle, we use the same recombination rule of the EPSO (1, 2) to compute the movement from iteration i to i+1;

vi. <u>Lamarkian evolution step</u> – if a zero velocity vector is obtained indicating that particle p wouldn't move when going from iteration i to iteration i+1, we introduce a Lamarkian step to induce some extra diversity. If that is the case, 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 (16);

vii. <u>Evaluation of the particles</u> – once all particles are mutated, it is computed the value of the evaluation function (15) for each of them. This means considering the projects in this particle in the corresponding year of the planning horizon, running the DC-OPF model (9 – 13) for each year and checking the physical, financial and reliability constraints specified for the problem;

viii. <u>Selection</u> – in this step, we go along the two populations, we take particle p from population 1 and particle p from population 2 and it survives the one having better fitness that is the one having the lowest value for (15). 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;

ix. <u>Convergence checking</u> – in this step we check if the maximum number of iterations, imax, was completed or if a convergence criterium is valid. In the first case, the algorithm stops without converging suggesting that a larger number of iterations should be done. 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. If the algorithm did not stop yet, then it returns to step ii.

IV. HANDLING FUZZY TRIANGULAR LOADS

Uncertainties can be addressed by probabilistic models if the events have a random nature and can be repeated under the same conditions. In some cases uncertainty reflects incomplete data or is implicit in expressions as "larger than" or "approximately" that are common in human language. In these cases, fuzzy sets are adequate to model propositions as "the demand is around 100 MW". This knowledge can be represented by a triangular fuzzy number as the one in Fig. 2.

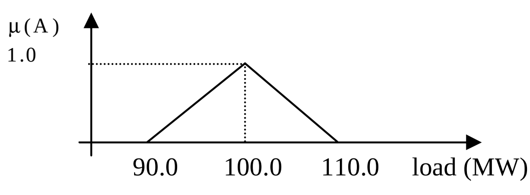

Figure 2. Illustration of a triangular fuzzy number.

The value 100 MW is the most credible one, thus having a 1.0 membership degree, but the planner doesn't want to completely discard values from 90 to 100 MW and from 100 to 110 MW. Given the particular shape of these numbers, the number in Fig. 2 is denoted by (90.0; 100.0; 110.0) MW.

Triangular fuzzy loads can be considered in the TEP algorithm detailed in Section III.C by introducing an enhancement in the Evaluation Step. In the previous algorithm the loads were assumed as deterministic that is each of them was represented by a real non negative number. When looking at a triangular fuzzy number as the one in Fig. 2, we can see that the deterministic analysis corresponds to a particular case of the fuzzy load situation. In fact, the combination of load values each of them associated with the membership degree of 1.0 corresponds to a deterministic situation. Regarding the number in Fig. 2, this would mean using the value of 100.0 MW for this load. Then, the algorithm in Section III.C evolves evaluating each particle in the population just using this deterministic load combination.

If now we are using triangular fuzzy loads, we can start discretizing each triangular fuzzy number in a number of α-cuts that is intervals of load values with membership degree not inferior than α. In the developed solution algorithm we adopted the 0.0 and 0.5 cuts. For the number in Fig. 2, these cuts correspond to $[90.0;100.0]$ and $[95.0;105.0]$. Then, for each particle in the population, the DC OPF model (9-13) is run considering the load combinations formed by the extreme values of each of these cuts to check if the associated plan can still accommodate these load combinations with zero PNS values. If non zero values for PNS are obtained for any of these combinations, then a new positive penalty term in introduced in (15) meaning that this particle is associated with an expansion plan that is exposed to load uncertainties, namely if load combination different from the deterministic case are considered. This new penalty term changes the value of the evaluation function thus affecting the selection step of the algorithm in Section III.C.

V. RESULTS

The approach described in Sections III and IV was tested using several networks, namely networks that are commonly used as reference ones in TEP studies. In the first place, it was tested using the 6 bus Garver network, originally described in [25]. For this network we conducted single period and multiperiod analysis and the results are reported in [21]. Just for illustration of the quality of the results that were obtained for the Garver network, the graphs in Fig. 3 characterize the convergence of the DEPSO algorithm. The algorithm was run 100 times for populations having 10, 20, 30, 50 and 80 particles and each curve indicates the percentage of runs that lead to the optimal final configuration as the number of iterations increases. As an example, for a 10 particle population the convergence was more difficult, 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 close. For populations with 30 particles the optimum plan was obtained in 95% of the runs after 42 iterations, while with 80 particles we get similar results in just 20 iterations.

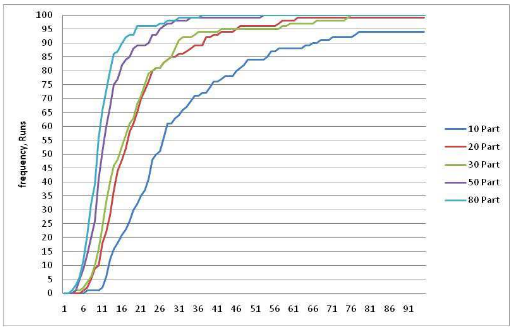

Figure 3 – Results for a multiperiod analysis for the Garver network.

Then, the DEPSO algorithm was tested using the IEEE 24 bus RTS system [26]. Regarding this system, the demand was set at 8,550 MW and the installed generation capacity is 10,215 MW, 3 times more than the original values in [26]. This increase is in line with the values used by many researchers and is explained given that the original values lead to a very lightly loaded system. The list of possible expansion projects is partially displayed in Table I including for each branch the extremes nodes, the resistance, reactance, transmission capacity and investment cost. In this case we admitted that already existing corridors were used. The resistance and reactance of the new branches correspond to the ones of the already existing branches in the same corridor.

TABLE I – PARTIAL LIST OF POSSIBLE NEW BRANCHES.

Br no	From bus	To bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10^6\$)
1	3	24	0,0000	0,4195	400	500
2	9	11	0,0000	0,4195	400	500
3	10	11	0,0000	0,4195	400	500
4	10	12	0,0000	0,4195	400	500
…	…	…	…	…	…	…
24	20	23	0,0140	0,1080	500	300
25	11	13	0,0305	0,2380	500	660
26	12	13	0,0305	0,2380	500	660
27	11	14	0,0305	0,2380	500	580
28	14	16	0,0250	0,1945	500	540

The planning exercise was done considering a 4 year horizon and a 5% yearly load increase. The DEPSO was run considering deterministic loads in the first place and populations of 30, 100 and 150 particles. The best plans identified in these three runs are as follows:

- 30 particles – period 1 - line 10-12, line 1-5, line 6-10, line 7-8, line 11-13; period 2 - line 2-6, line 7-8; period 3 - line 11-13; investment cost 2599.16 M$;
- 100 particles - period 1 - line 10-12, line 1-5, line 6-10, line 7-8, line 11-13; period 2 - line 7-8; period 3 - line 11-13; period 4 - line 2-6; investment cost 2527.44 M$;
- 150 particles - period 1 - line 10-12, line 1-5, line 6-10, line 7-8, line 11-13; period 2 - line 7-8; period 4 - line 3-14, line 16-17; investment cost 2427.72 M$;

Apart from the 5% yearly demand rate, the DEPSO algorithm was then run considering uncertainties. To do this, the crisp previous loads were assigned the 1.0 membership level and the extreme values of the 0.0 cut of each triangular number were set at 0.95 and 1.05 of the crisp value. The main conclusions that were obtained in this analysis are as follows:

- running the DEPSO for a 100 particle population, the particles in the final population proved to be very robust in accommodating the demand uncertainties;
- this means that among the 100 final particles, only 19% of them displayed non zero PNS and the corresponding evaluation function was therefore penalized;
- among these ones, it was concluded that solutions that did not include neither a new line 1-5 nor a new line 11-23 in the expansion plan were very prone to the demand uncertainties and were in general less robust;
- using a 100 particle population, the best expansion plan coincides with the one identified in the deterministic demand analysis indicated above. This ultimately means that for the specified level of uncertainty of $\pm 5\%$, the best expansion plan identified in the deterministic exercise is still very robust when admitting demand uncertainties;
- as a final test, the best plan was subjected to larger demand uncertainties of $\pm 10\%$. As a result, non zero PNS values occurred, indicating a degradation of the robustness of the plan. If the planner wanted to accommodate $\pm 10\%$ demand uncertainties, then a plan having larger investment cost would have to be adopted as a way to regain robustness.

VI. CONCLUSIONS

This paper details a multiyear mixed integer optimization problem for TEP that is solved using a discrete version of the Evolutionary PSO algorithm. The tests that were conducted showed that it is important to model this problem in a multiperiod way in order to maintain an holistic view on the entire planning horizon. On the other hand, uncertainties should be addressed in this type of problems to get more insight on the merits of each candidate plan thus allowing the decision maker to take more robust and less risky decisions. As a whole, the developed approach can contribute to give more insight on the merits of possible expansion plans thus allowing taking more sounded investment decisions.

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