DYNAMIC PROGRAMMING – EFFICIENT TOOL FOR POWER SYSTEM EXPANSION PLANNING

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Abstract - The paper is focusing on dynamic programming use for power system expansion planning (EP) – transmission network (TNEP) and distribution network (DNEP). The EP problem has been approached from the retrospective and prospective point of view. To achieve this goal, the authors are developing two software-tools in Matlab environment. Two techniques have been tackled: particle swarm optimization (PSO) and genetic algorithms (GA). The case study refers to Test 25 buses test power system developed within the Power Systems Department.

Keywords: dynamic programming, artificial intelligence; dynamic expansion planning; optimization; transmission network; software-tool.

1. INTRODUCTION

The network expansion planning is discussed within this paper. This problem is discussed based on two approaches: static and dynamic manner. In the 1st case the problem is tackled in a retrospective manner. In case of the dynamic problem, both retrospective and prospective manners have been tackled. A set of network expansion candidates is proposed for both approaches. The power flow is performed using conventional methods. The optimal power flow (OPF) is computed for the maximum expansion solution (including all the expansion scenarios) using particle swarm optimization (PSO) and genetic algorithms (GA). Having the optimal maximum expansion solution, the optimal expansion solution is computed also using PSO and GA. For all these purposes own software-tools have been developed in Matlab environment. They are able to be linked with other well-known computer aided power system analysis software, importing the power system database. Two types of GAs are used within this paper. Binary coded GA for the expansion planning stage and real coded GA for the OPF computing.

The network expansion planning problem is able to be discussed for both distribution and transmission networks.

A very simple dynamic programming based method in presented in [1]. Solutions are analysed only checking the network elements' loading level. Developed method allows the users to established quasi-optimal solutions, based on project experience. Stochastic dynamic programming is recommended in [2], allowing flexible use of time moments when decisions are going to be take. Also, authors are proposing to combine the dynamic programming with a heuristic and Bender technique.

A hybrid method is proposed in [3], including an evolutive meta-heuristic algorithm, a meta-heuristic searching method and discrete dynamic programming with finite horizon. The case study refers to a small scale test power system.

It is highlighted that, within the literature, there is a reduced number of papers dealing with dynamic network expansion planning. The case studies are focusing on small scale test power systems.

The use of a heuristic algorithm is proposed in [4] to solve the distribution network expansion planning. A nonlinear optimization problem is solved having as a goal to compute a sensitivity index. The nonlinear programing is obtained "relaxing" the binary integer variables – they are replaced with real variables within the [0, 1] range. The objective function includes the network expansion costs and also the ones corresponding to its operation (real power losses' costs).

An evolutionary algorithm is proposed in [5] for medium voltage, urban, distribution network expansion. A real distribution network is used as cases study. The reconfiguration problem is also tackled from the real power losses minimization point of view. The constraint relations are referring to voltage level and network element loading level. The objective function refers to real power losses minimization and new network elements' costs. The authors are providing details regarding the settings for the proposed evolutionary algorithm: initial population, mutation, crossover and selection operators, objective function.

An improved genetic algorithm is proposed in [6] to establish the electrical substations' optimal placement and distribution network expansion and reconfiguration.

A differential evolutionary algorithm is presented in [7] for optimal distributed network expansion planning. In this case the global optimum is obtained applying a "fitness sharing" technique. The algorithm proves to be accurate, fast and robust.

The use of linear programming technique has been proposed by Garver in [8] for transmission network expansion planning (TNEP) solving. The initial data being represented by: power system configuration, consumed power forecast and real power sources' evolution plan. The optimization problem is solved using linear programming techniques. Such an approach has the following drawbacks: a linear mathematical model is used for power flow computing, reactive power flow is not tackled, real power losses are neglected, objective function (OBF) refers to the power system branch overloading cost minimization, etc. [9].

In [10] it is stipulated that the TNEP is a mixed nonlinear optimization problem, with real and integer variables. In [11] the real power losses are approximately considered.

Also, the OBF is extended referring to the total cost minimization formed by investment cost and generating units' operation cost. These type of problems are solved in [12] applying a meta-heuristic technique for exploring the solution space. In [13] an additional term is added to the OBF expression, taking into consideration aspects related to the power system safety operation. It is computed based on several *N-1* criterion operating conditions.

In [17] the TNEP is solved based on a dynamic discrete PSO problem. The PSO algorithm specific parameter numerical values are discussed for an optimal method tuning (population size, maximum admissible velocity, convergence). The TNEP issue is defined in [12] as a mixed nonlinear optimization problem, implemented within a discrete PSO algorithm. The power flow is solved in d.c., small scale test power systems have been used. In [15] an adaptive PSO algorithm is considered for TNEP solving. It has been applied on IEEE 24 test power system. A discrete PSO evolutionary algorithm is discussed in [20].

Following the introduction already presented, the 2nd section refers to the programming. theoretical background. The mathematical model and software-tool are briefly described within the 3rd section. The 4th section refers to the case study and the results' discussion. Finally, the conclusions are synthesized.

2. DYNAMIC PROGRAMMING. THEORETICAL BACKGROUND

Dynamic programming represents an optimal solution selection methodology considering specific constraints, following a step-by-step decision process [18]-[21]. It has been developed by Bellman as a decision process optimization method. The word "programming" refers to "planning" not programming from the computer science point of view. The word "dynamic" refers to the intermediary solutions results tables corresponding to different stages from the decision process.

Discrete dynamic programming with finite horizon is discussed within the current paper. In this case, decisions are taken at specific "time moments", following a finite number of computing steps. As an example, we are talking about the transmission network expansion for 20 years' time horizon, considering 5 years step. Year 0 represents the initial situation, then expansion solutions are searched for year 5, year 10, year 15 and year 20 – corresponding to the final state of the transmission network configuration.

Let us consider a system having Y_0 initial state characterized by $y_{1,0}, y_{2,0}, ..., y_{m,0}$ values for the m state variables $y_1, y_2, ..., y_m$. D_1 decision is taken at t_1 "time moment", corresponding the $x_{1,1}, x_{2,1}, ..., x_{p,1}$ values for the p decision variables. The new state y_1 of the system described using values $y_{1,1}, y_{2,1}, ..., y_{m,1}$ of the state variables depends on the initial state and approved decision.

$$Y_1 = Y_1(y_0, D_1) \tag{1}$$

Going further, at t_j time moment D_j decision is taken corresponding $x_{1,j}, x_{2,j}, ..., x_{p,j}$ values of the decision variables. As a consequence the system is passing from the Y_{j-1} state (characterized by $y_{1,j-1}, y_{2,j-1}, ..., y_{m,j-1}$ values of the state variables) into Y_j state (characterized by $y_{1,j}, y_{2,j}, ..., y_{m,j}$ values of the state variables).

Y_j state depends on the previous state Y_{j-1} and D_j decision:

$$Y_j = Y_j(Y_{j-1}, D_j) \tag{2}$$

Finally, at n computing step, t_n time moment, the system is going to be in y_n state once the D_n decision is taken:

$$Y_n = Y_n(Y_{n-1}, D_n) \tag{3}$$

Based on relations (2) and (3) it yields that the final state of the system depends on the initial state and approved decisions:

$$Y_n = Y_n(Y_0, D_1, D_2, ..., D_n) \tag{4}$$

The taken decisions' set $D_1, D_2, ..., D_n$ represents the decision policy or strategy.

Decisions have to fulfil specific constraints at every moment:

$$D_j \in \Delta_j, \quad j = 1, 2, ..., n \tag{5}$$

where Δ_j represents the possible decisions' set at t_j time moment.

Also, the state variables are subjected to different constraints:

$$Y_j \in \varepsilon_j, \quad j = 1, 2, ..., n \tag{6}$$

where ε_j represents the possible decisions' set at t_j time moment.

For the previously discussed model the system states are conducted in forward manner (from initial state, to the final one). This represents the *prospective analysis*. But, it could be also discussed the backward approach for the system state (from the last one, to the initial one). In this case we are talking about *retrospective analysis*.

A partial objective function (OBF) φ_j is considered for each computing step j, $j = 1, 2, ..., n$. Its value depends on the D_j decision and y_j system state (once the decision is taken):

$$\varphi_j = \varphi_j(D_j, Y_j) \tag{7}$$

φ_j function value characterizes from the OBF point of view, the D_j decisions and obtained y_j system state. A global OBF corresponds to the entire strategy (including all the partial φ_j functions):

$$OBF = \varphi_1(D_1, Y_1) + \varphi_2(D_2, Y_2) + ... + \varphi_n(D_n, Y_n) \tag{8}$$

The strategy that maximizes or minimizes – depending on the desired objective – the OBF in relations (8) is searched. The minimization is the objective for the current paper. The strategy that leads to the OBF extreme value represents the optimal strategy $D_1^*, D_2^*, ..., D_n^*$.

The dynamic optimization problem may be discussed as follows: starting from an initial Y_0 state the optimal strategy $D_1^*, D_2^*, ..., D_n^*$ is requested to be established, leading the system to final state Y_n, having as a goal to minimize the OBF:

$$OBF = F(Y_0, D_1^*, D_2^*, ..., D_n^*) = \underset{D_j}{Min}\left[\sum_{j=1}^{n} \varphi_j(D_j, Y_j)\right] \tag{9}$$

satisfying all the constraints.

Solving the optimization problem through exhaustive solution domain searching is very difficult and time consuming. High computing amount is obtained. The only feasible solution refers to the use of dynamic programming. It is based on R. Bellman's optimal principle: an optimal strategy is based on the fact that whatever the initial state of the system and previously adopted decisions would be, the remaining decisions have to be taken in such a way to compose an optimal strategy regarding the current state.

Thus, the following recursive relation is obtained for the use of dynamic programming method:

$$F_j = \underset{D_j}{Min}\left[F_{j-1} + \varphi_j(D_j, Y_j)\right], \in \quad j = 1, 2, ..., n \quad (10)$$

The partial objective function φ_j includes the cost of passing from the Y_{j-1} state to the Y_j state and also, the system operation in Y_j state.

The use of relation (10) drastically reduces the number of analysed solutions for optimal value searching, comparing with any other exhaustive or (quasi)heuristic searching method.

3. DYNAMIC EXPANSION PLANNING MATHEMATICAL MODEL

3.1. Problem statement

The dynamic TNEP is discussed for the following time steps: 2014 year – initial stage, 2019, 2024, 2029 years – intermediary stages and 2034 year – final stage. It is approached as:

- prospective search (forward direction);
- retrospective search (backward direction).

Two issues have to be solved:

- consumed power forecast correlating the power generation capacity;
- admissible solution domain definition – it contains the network elements' list that are allowed to be part of the optimal solution corresponding to the final stage (2034 year).

According to the prospective analysis, the starting point refers to the 2014 year. In the following, the expansion solutions are computed step-by-step for the successive years: 2019, 2024, 2029 and 2034. The provided results for 2034 year represent the final solution for the entire 20 years analysed period.

The admissible solutions' domain has been considered to be the maximum expansion one extracting the network elements already introduced for each expansion stage.

A static expansion planning solving is applied for each intermediary stage. The nonlinear optimization problem is solved using evolutionary techniques: PSO and GA.

According to the retrospective analysis, the starting point is represented by the maximum expansion solution, year 2034. In the following, the expansion solutions are computed step-by-step for the successive years: 2034, 2029, 2024 and 2019. The results obtained for 2019 year represents the final solution.

The comments provided at the prospective analysis for the admissible solution domain definition and static expansion solving at each intermediary stage are suitable for this case too.

The use of both approaches (prospective and retrospective) offers the advantage of comparing the intermediary solutions (2019, 2024, 2029 years) and, especially, the final one (2034 year).

Mathematical model for transmission network expansion planning is presented. Two solving techniques from the artificial intelligence field have been tackled: particle swarm optimization (PSO) and genetic algorithms (GA).

The optimization problem is a multi-criterial one. The following components are included within the objective function [21]:

- investment equivalent yearly cost related to new power transmission capacities (overhead lines, autotransformers);
- power system operating costs (OPF OBF value);
- safety operation, quantified based on risk factor computing:
- total available transmission capacity.

The mathematical model for the dynamic optimal expansion planning is developed based on GA and PSO methodologies.

3.2. PSO based approach

The swarm $\boldsymbol{S} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_{np}\}$ contains a set of feasible solutions, formed by n_p particles. Each particle represents a possible solution for the network expansion problem. It is formed by *d* components corresponding to the candidate network elements status. These components are rounded real values ranging between [0, 1] (0 – disconnected, not included within the solution, 1 – connected, included within the solution).

Particles' evaluation is performed based on OBF value. A valid solution is obtained once the OBF value is not able to be improved.

The PSO based TNEP algorithm steps are described in detail in [22], [23]:

a) particles are randomly;
b) initial population is evaluated based on OBF value. The *gbest* position is established in case of each particle;
c) for a particular *t* computing step $t = 0, 1, 2, \ldots$, the particle velocities are computed;
d) for the same *t* computing step, the velocities are adjusted according to the velocity limiting concepts and adaptive velocity;
e) for the same *t* computing step, the new particle positions are computed;
f) optimal operating condition is determined for each particle configuration, based on the PSO algorithm;
g) for the same *t* computing step, the current population is evaluated based on OBF value. The *pbest* and *gbest* positions for each particle are determined;
h) for the same *t* computing step, the stopping criterion is checked: the OBF value $OBF(\boldsymbol{gbest})$ is not improving. Once this condition is satisfied the computing process is ending. The solution defined by the last *gbest* represents the optimal solution. Contrary, the algorithm continues with point *b*).

In case of complex power systems (hundreds, thousands of buses) point *f*) of the algorithm leads to an increased computing time. Thus, the authors have developed and tested a simplified version of the algorithm. Its characteristics being the following ones:

- point *f*): OPF is replaced using power flow computing;
- OPF is computed only for the *gbest* solution;
- new population is generated as follows: 1st particle is considered to be *gbest* and the following ones are randomly obtained;
- this process is repeated until the *gbest* value is not improved;
- new population is generated within the final step, having smaller n_p dimensions: *gbest* is considered to be the 1st particle. The following ones are obtained by controlled updates related to *gbest*;
- the process finishes once *gbest* is not improving.

PSO based TNEP algorithm (modified as previously discussed) has been tested on small scale test power systems and even on complex ones. The optimal solutions have been obtained, but within considerable smaller computing time effort.

3.3. GA based approach

The $\boldsymbol{P} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_{nc}\}$ population represents a set of possible solutions. Each chromosome forming the population contains binary digits (0 and 1), representing the state for the network expansion candidates. Thus, for this stage we are dealing with binary coded genetic algorithms.

Each chromosome is evaluated based on the objective function. The computing process finishes, if the solution is not able to be improved for a specific number of computing steps.

The algorithm stages are described in detail in [22], [23]:

a) chromosomes forming the population are randomly initialized with 0 and 1 values;
b) GA based OPF is computed for the configuration coded by each of the chromosomes;
c) initial population is evaluated based on OBF value;
d) for a specific *t* computing step (t = 0, 1, 2, ...) the chromosomes forming the population subjected to recombination are selected;
e) chromosomes that are subjected to crossover are formed;
f) offspring are formed;
g) number of chromosome genes subjected to mutation is computed;
h) 1st chromosome belonging to the population obtained at previous step is replaced with the best of the old population;
i) optimal power flow is computed for the configurations coded by each chromosome. Current population is evaluated based on OBF value;
j) if the OBF value is not able to be improved, the computing process finishes. Contrary, computing step is increased with 1 and the algorithm is repeated starting with point *c*).

3.4. Software-tool

Two software-tools have been developed in Matlab environment based on PSO and GA approaches: *PowerOpt PowerplanPSO* and *PowerOptPowerplanGA*. Each one has two modules linked through a graphical user interface [23], [24]:

- 1st module – used for power system optimization. Also, it is able to be used as a stand-alone module;
- 2nd module – used for dynamic transmission network expansion planning.

PowerOptPowerplanPSO's main window for the OPF module is presented in Fig. 1. Once the power system database has been loaded, the user is able to select the optimization type he desires by selecting the control variables. 7 optimization types are available: *V* – generating groups terminal voltage, *P* – real generated power, *k* – transformer ratio. The lower part of the main window (Fig. 1) allows the user to set the PSO parameters: maximum computing steps, capping iterations, error, swarm dimension.

The main window for the software-tool 2nd module (expansion planning module) is presented in Fig. 2.

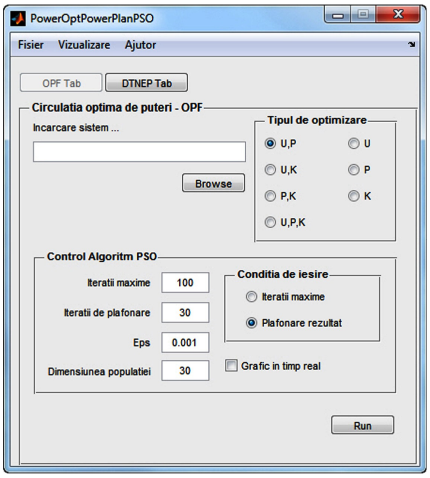

Fig. 1. PowerOptPowerplanPSO. OPF module main window

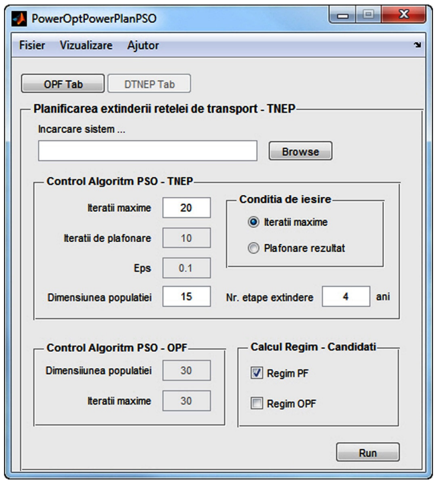

Fig. 2. PowerOptPowerplanPSO – dynamic network expansion window

The 2nd developed software-tool based on GA is named *PowerOptPowerplanGA*. The provided comments and characteristics for the PSO approach are suitable for this case too. Also, screen captures and behaviour are very similar, with few differences specific to the GA mechanism (for details see [23], [24]).

4. RESULTS AND DISCUSSIONS

The case study refers to Test 25 buses test power system developed within the Power Systems Department. It has a number of 25 buses (6 PV buses, 19 PQ buses) and 29 network elements (18 overhead lines – OHLs – 110 kV, 220 kV, 400 kV, 11 autotransformers) (Fig. 3) [25].

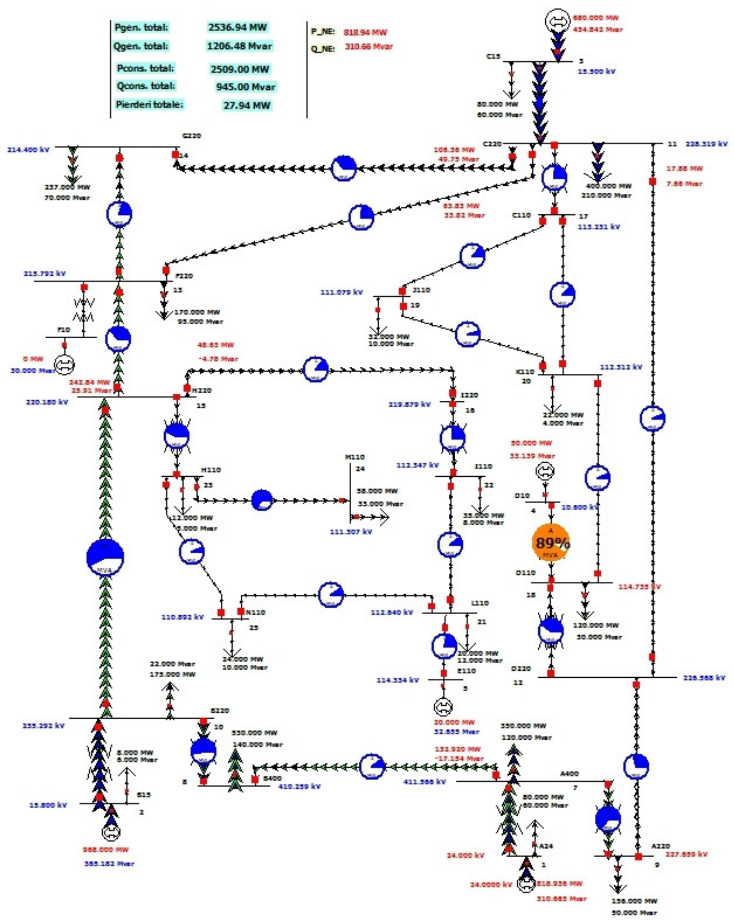

Fig. 3. Test 25 buses test power system – one line diagram

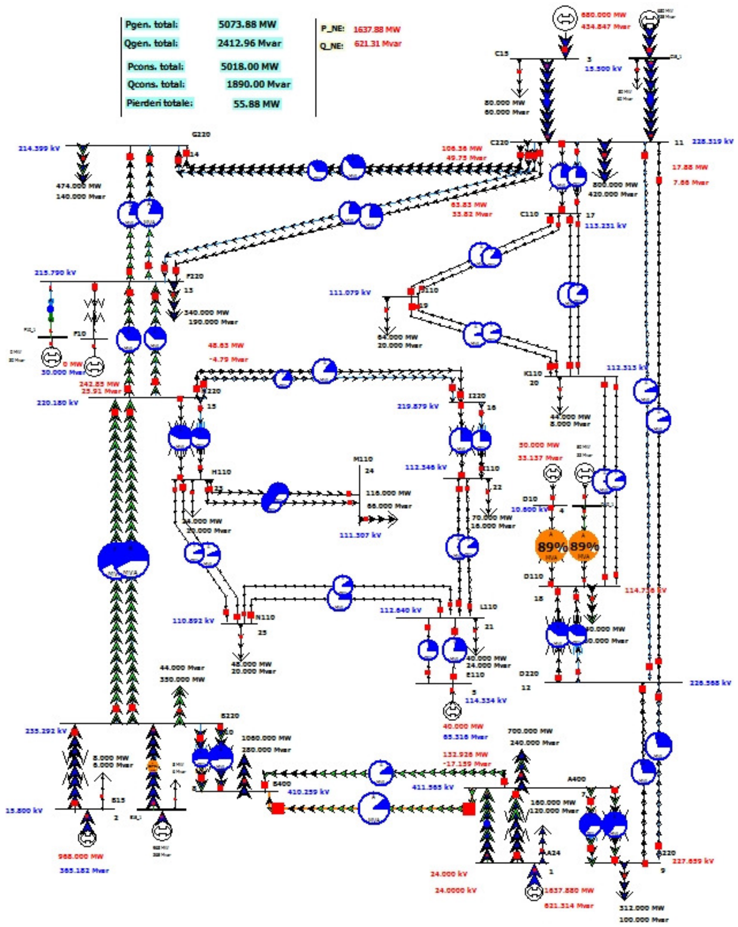

Fig. 4. Maximum expansion solution one-line diagram

The dynamic transmission network expansion planning is performed (retrospective and prospective approach). This process is step-by-step discussed within the following subsections.

4.1. Base case – year 2014

Base case has been computed using conventional methods. Bus voltages are ranging between 0.95 and 1.10 p.u. (meaning 104.5-121 kV, respectively 209-242 kV). PV buses terminal voltage limits are set between 0.95 and 1.15 p.u.

The total consumed power is Pc = 2509.0 MW, the real generated power Pg = 2536.9 MW and real power losses ΔP = 27.9 MW.

4.2. Maximum expansion solution – year 2034

The transmission network expansion planning is discussed for a 20 years, based on the last year consumed power forecast. For this case the total consumed power is Pc = 5018.0 MW. The generation capacity has been extended. New generating units have been considered for the following buses: 26, 27, 28 and 29.

The one-line diagram of the power system corresponding to the maximum expansion solution is presented in Fig. 4. It has 29 buses (10 PV buses, 19 PQ buses) and 58 network elements (36 overhead lines – 110 kV and 20 kV voltage levels, 22 (auto)transformers).

29 new transmission network elements (18 OHLs – existing circuit has been doubled, 10 autotransformers and 1 transformer) have been introduced (considered as candidates within the expansion list). Thus, the expansion scenario is the following one:

- 2nd circuit for 110 kV OHL 5-21, 17-19, 17-20, 18-20, 19-20, 21-22, 21-25, 23-24, 23-25;
- 2nd circuit for 220 kV OHL 9-12, 10-15, 11-12, 11-13, 11-14, 13-14, 13-15, 15-16;
- 2nd circuit for 400 kV OHL 7-8;
- 2nd 220 / 110 kV autotransformer 11-17, 12-18, 15-23, 16-22;
- 2nd 400 / 220 kV autotransformer 7-9, 8-10;
- 2nd 400 / 24 kV transformer 1-7.

Using the software-tool *PowerOptPlanPSO* the OPF has been computed for the maximum expansion solution. Real power losses are equal to ΔP = 40.38 MW, compared to 55.89 MW for the maximum expansion solution base case. Thus, 26 % decreasing has been recorded.

The PSO algorithm evolution for OPF is given in Fig. 5.

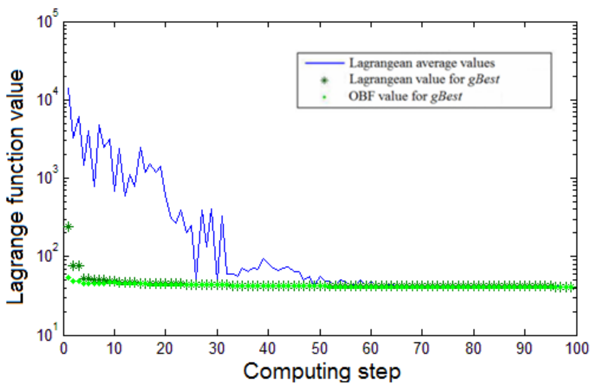

Fig. 5. PSO algorithm evolution for OPF computing

The average OBF values for the entire swarm are represented using blue color. The notched shape of the graph highlights diversity within the population. The solution space is efficiently explored for the initial population generation. The algorithm convergence is highlighted by the graphical plot flattening, for the last computing steps.

gBest OBF values are represented using light green color, representing the OPF solution. An accentuated decrease is recorded, during the first ten computing steps. *gBest* Lagrangean function values are represented using dark green color.

The equivalent OBF and Lagrangean values highlight the absence of constraint relations' violations.

4.3. Optimal expansion solution

◊ Retrospective approach

Before the dynamic transmission network expansion planning the load forecast for 20 years period (2014-2034) has been performed. The results are presented in Table 1.

Table 1. Consumed Power Forecasting

	$P_{c\ total}$ [MW]	$Q_{c\ total}$ [Mvar]
2014	2509.0	945.0
2019	2983.7	1123.8
2024	3548.3	1336.4
2029	4219.6	1589.3
2034	5018.0	1890.0

The starting point is represented by the maximum expansion solution, year 2034 and the expansion solutions for all the stages: 2034, 2029, 2024 and 2019. The result for 2034 year represents the final solution of the problem (for the entire 20 years planning horizon).

The solution admissible domain for each expansion stage has been defined based on the previous results.

The following elements have been resulted within the optimal expansion solution:

- 2nd circuit for 110 kV OHL 5-21, 17-20, 21-22, 23-24;
- 2nd circuit for 220 kV OHL 10-15, 11-14;
- 2nd 220 / 110 kV autotransformer 11-17, 12-18, 15-23, 16-22;
- 2nd 400 / 220 kV autotransformer 7-9, 8-10;
- 2nd 400 / 24 kV transformer 1-7.

The optimal expansion solution (Fig. 6) is characterized by 29 buses (10 PV buses, 19 PQ buses) and 42 network elements (24 overhead lines, 18 (auto)transformers).

The relative OBF value (Fig. 7) has been computed being the ration between the expansion solution OBF and the one corresponding to the maximum expansion solution. It is highlighted that, practically, the solution is found at the 2nd computing step. It is explained due to the power system reduced scale and number of transmission network expansion candidates.

The dynamic retrospective TNEP results are synthesized in Table 2.

Final solution for 2034 year has been obtained based on the several quasi-optimal solutions (with close OBF values).

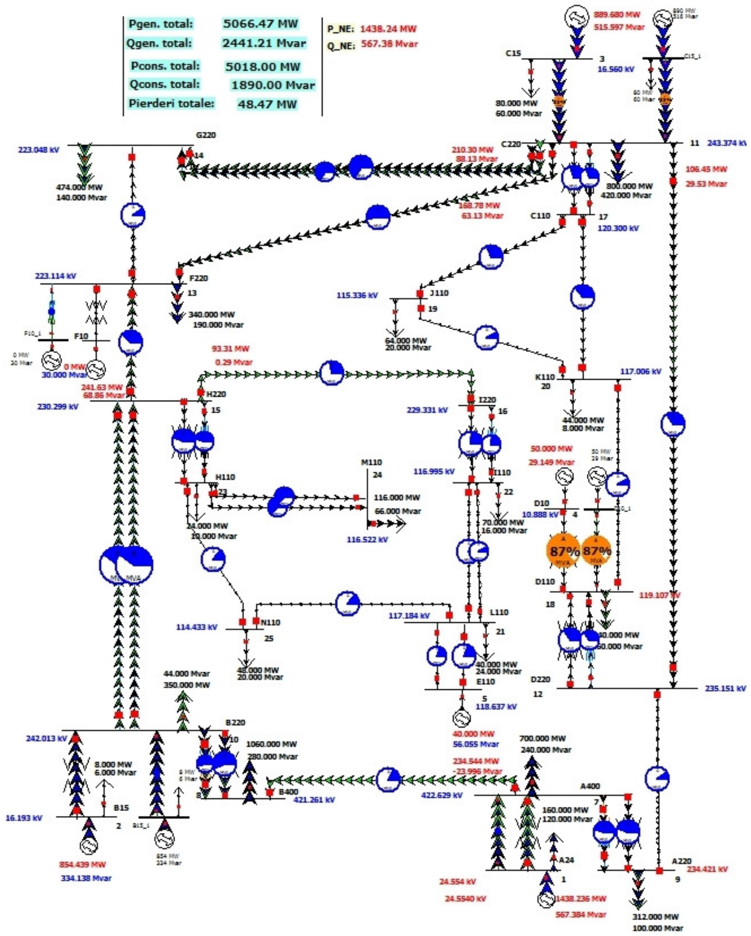

Fig. 6. Optimal expansion solution one-line diagram

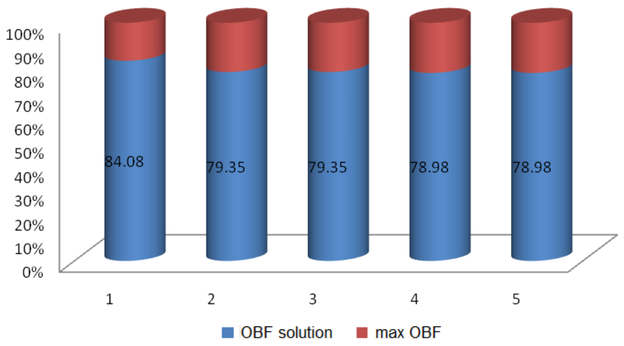

Fig. 7. OBF evolution

Table 2. Retrospective Analysis Results

	2019	2024	2029	2034
	3 from 26	6 from 26	9 from 26	14 from 26
OHL and ATR	–	–	110 kV 5-21	110 kV 5-21
	–	–	–	110 kV 17-20
	–	–	–	110 kV 21-22
	kV 23-24	110 kV 23-24	110 kV 23-24	110 kV 23-24
	220 kV 10-15	220 kV 10-15	220 kV 10-15	220 kV 10-15
	–	–	220 kV 11-14	220 kV 11-14
	–	–	220 kV 11-14	ATR 220/110 kV 11-17
	–	ATR 220/110 kV 12-18	ATR 220/110 kV 12-18	ATR 220/110 kV 12-18
	–	ATR 220/110 kV 15-23	ATR 220/110 kV 15-23	ATR 220/110 kV 15-23
	–	–	–	ATR 220/110 kV 16-22
	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9
	ATR 400/220 kV 8-10	ATR 400/220 kV 8-10	ATR 400/220 kV 8-10	ATR 400/220 kV 8-10
	–	TR 24/400 kV 1-7	TR 24/400 kV 1-7	TR 24/400 kV 1-7

◊ Prospective approach

The starting point is represented by the initial situation corresponding to the 2014 year. Expansion solutions for each future stage are computed step-by-step (2019, 2024, 2029, 2034 years). Results for 2034 year are representing the final solutions for the 20 years' analysed period.

The admissible solutions' domain has been considered to be the one defined by the maximum expansion solution, excluding the network elements already introduced at each stage of the prospective dynamic expansion.

The dynamic prospective TNEP results are synthesized in Table 3.

Table 3. Prospective Analysis Results

	2019	2024	2029	2034
	3 from 26	6 from 26	9 from 26	14 from 26
OHL and TR	–	–	110 kV 5-21	110 kV 5-21
	–	–	–	110 kV 21-22
	110 kV 23-24	110 kV 23-24	110 kV 23-24	110 kV 23-24
	220 kV 10-15	220 kV 10-15	220 kV 10-15	220 kV 10-15
	–	–	–	220 kV 11-12
	–	–	220 kV 11-14	220 kV 11-14
	–	–	220 kV 11-14	ATR 220/110 kV 11-17
	–	ATR 220/110 kV 12-18	ATR 220/110 kV 12-18	ATR 220/110 kV 12-18
	–	ATR 220/110 kV 15-23	ATR 220/110 kV 15-23	ATR 220/110 kV 15-23
	–	–	–	ATR 220/110 kV 16-22
	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9	ATR 400/220 kV 7-9
	–	ATR 400/220 kV 8-10	ATR 400/220 kV 8-10	ATR 400/220 kV 8-10
	–	TR 24/400 kV 1-7	TR 24/400 kV 1-7	TR 24/400 kV 1-7

4.4. Discussions

Comparing the results gathered from both approaches the following conclusions are highlighted:

- very similar solutions have been provided based on the two dynamic programming approaches. One single difference is highlighted: 2nd circuit for 110 kV OHL 17-20 (retrospective approach) is replaced with the 2nd 110 kV OHL circuit 11-12;
- solutions provided for 2024 and 2029 years are identical;
- 2019 year solution is different – 400 / 200 kV ATR 8-10 is missing within the prospective approach. It appears only in 2014 year.

5. CONCLUSION

The developed software-tools are able to be used in case of large scale, complex transmission networks. They behave as hybrid software-tool, the PSO and GA techniques being used for the OPF and network expansion stages.

For both prospective and retrospective approaches the software-tools are able to provide quasi-optimal solutions.

Slight differences are able to appear between the results provided by prospective and retrospective analyses. They may occur once the 1st computing step (or the last one) is finished or even at intermediary results (stages).

The initial solution (one the 1st) for the prospective approach may be more or less different to the one provided by the retrospective approach.

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