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A New Methodology For The Optimal Transmission Planning

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Abstract: - The paper describes a new procedure for solving a long-term transmission expansion planning problem in a market environment. The main feature analyzed is the evaluation of transmission system flexibility indexes, that define the attitude to use branches residual power capability when new power injections, in a defined nodes set, occur. The procedure, based on the use of Genetic Algorithms (GA), has been tested on some simple networks; in the paper some preliminary test results are presented.

Key-Words: - Transmission Planning, Flexibility, Optimization Problems, and Genetic Algorithms

1 Introduction

In a market environment the transmission planning problem is affected by a significant degree of uncertainty. The liberalization of electric energy markets brought along significant changes of bulk electric power systems, in particular the unbundling of the vertically integrated utilities into new independent generation and transmission network companies. As a consequence the electrical transmission planners experience a much larger degree of uncertainty about siting, sizing and commissioning of new power plants. Given the uncertainties about generation expansion and operation, it becomes necessary to identify new parameters for the optimal solutions characterization with reference to structural (branches admittances, distribution factors, etc.) and operational issues (total transfer capability, power flows, residual power capability, etc.) [1-8]. In this framework many authors have taken as suggestion the "system flexibility" defined as the attitude to adapt the transmission system development, quickly and with limited costs, to every change, from the initial planning conditions.

In this context, with a particular regard to changes in generation, an heuristic Uncertainty Scenario Flexibility Index (USFI), taken into account both structural and operational parameters, has been defined by the authors [9]; in particular the distribution factors and the residual transmission power capability on the different network branches, defined as "power margin", have been chosen. Its validation has been made with application to simple test networks and to an actual network [10]. The encouraging results involved in the formulation of a new methodology for transmission system flexibility computation, through the definition of indexes and criteria that include both technical and economical information [11]. These indexes, called Technical USFI (T-USFI) and Technical Economical USFI (TE-USFI), are calculated for the whole system (system indexes) and for some network areas (area indexes). The procedure for their calculation includes two optimization problems solved with GA, implemented in MatLab 7 workspace [12].

In fact, in general, the introduction of new parameters for a more careful evaluation of alternative transmission expansion plans involves the need for methods that are able to synthesise optimal transmission expansion plans: as in a vertically integrated scenario the transmission planning problem is based on optimization problems that can be solved by the use of traditional methods, in a competitive environment the transmission planning problem is an hard, large-scale combinatorial problem and the number of options to be analysed increases exponentially with network size. The practice has shown that conventional optimization procedures became unable to produce optimal solutions for larger networks. As an alternative to conventional optimization methods, different heuristic search algorithms, rooted in natural and physical processes, have been investigated: for example, simulated annealing (SA), genetic algorithms (GA) and evolutionary programming (EP) [13-21]. It is generally recognized that GA approach is an efficient tool to solve transmission planning optimization problems [22-25]. It is based on the natural selection principles: the optimization procedure follows an evolutionary strategy to find the best solution of a search problem. Thus, starting from an initial population of individuals, each one representing a possible solution, the evolution takes place and changes the population in order to form the next generation until a convergence criterion is fulfilled. So the solution is given by the best individual. GA generates a sequence of populations (generations) by using three basic mechanisms: selection, crossover and mutation. The three operators are applied to the current population to determine the next generation, which has a high probability to be made of better individuals.

Besides, for algorithm success, it is necessary to choice:
(i) the control parameters values;
(ii) the exact roles of crossover and mutation;
(iii) the search landscapes amenable to optimization;
(iv) convergence properties.
In the paper all these issues are fully addressed: some small example systems, for which optimal are known, have been used to tune the main parameters of the genetic algorithm.
Obviously the ability to solve large-scale practical problems has to be verified: GA method has to be applied to a larger example system for which no optimal solutions are known. This work is in progress.
So in the paper section 2 reports the mathematical model of the optimization problems for the flexibility indexes calculation, section 3 describes the formulation proposed for the genetic algorithm, and in section 4 a test case is shown.

2 Optimization Problem: Mathematical Model

2.1 List of Symbols

In the paper the following symbols with the specified meanings are used:

- NGnew, NGold: number of the nodes which are possible sites of new plants, and with already active sites,
- NG= NGnew+ NGold: number of the nodes with generation,
- NL: number of branches,
- P_c: system load,
- P_k : injection at node k,
- ΔP_k : additional injection at node k,
- P_{ij} : power flow on the ij branch,
- M_{ij} : power margin of the ij branch capability,
- I_{ij}: current on the ij branch,
- R_{ij}: resistance of the ij branch,
- $CINF_{ij}{}^{k}$: distribution factors of the node k with respect to the ij branch,
- P_{ij}^{losses} : power loss on the ij branch,
- $CINF_{kk}{}^{k}$: distribution factors of the node k with respect to a nodes subset,
- ΔP_k^{MIN}, ΔP_k^{MAX}: minimal and maximum additional injection at node k in NGnew set,
- P_k^{MIN}, P_k^{MAX}: minimal and maximum injection at node k in NGold set,
- $P^{max}{}_{ij}$: limit carrying capability of the ij branch,
- $C_k(P_k)$: generation cost at node k in NGold set.

2.2 Technical and Technical Economical Uncertainty Scenario Flexibility Indexes

In order to characterize the network scenarios, system indexes (T,TE-USFI$_S$) and area indexes (T,TE-USFI$_A$) have been chosen. The network scenarios are referred to a predefined temporal horizon, for which the load is already known.
The system flexibility indexes are defined as:

$$\text{T,TE-USFI}_S = \Sigma_{NGnew}\, \Delta P_k^{T,TE} \qquad (1)$$

As a consequence of the already mentioned importance of both operational and structural parameters, two different area flexibility indexes, with reference to the single node, have been computed: the one as function of operational parameters (power margins on branches) and the other as function of structural parameters (distribution factors of the branch with respect to nodes). In particular they are expressed as:

$$\text{T,TE-USFI}_A{}^{I}(k)=\alpha_k\cdot\Delta P_k^{T,TE} \qquad (2)$$

$$\text{T,TE–USFI}_A{}^{II}(k) = \Delta P_k^{T,TE} - \Delta P_k^{T,TE\,*} \qquad (3)$$

with:

$$\alpha_k = f_{\alpha k}(CINF_{kk}{}^{k}, \Sigma_{NLk} M_{ij}{}^{T,TE}) \qquad (4)$$

$$\Delta P_k{}^{T,TE\,*} = f_{\Delta Pk}(CINF_{ij}{}^{k}) \qquad (5)$$

In particular α_k is a node coefficient related to $CINF_{kk}{}^{k}$, distribution factors of the node k with respect to the nodes subset for which power injections involve an unloading of the network, and to $\Sigma_{NLk}M_{ij}{}^{T,TE}$, total variation of the power margins on branches flowing into the k node that decrease due to injections ΔP_k; $\Delta P_k{}^{T,TE\,*}$is a reduction factor related to $CINF_{ij}{}^{k}$ that are distribution factors of the node k with respect to all the branches directly flowing into the node k.
For the calculation of USFI it is necessary to evaluate ΔP_k^{T}, ΔP_k^{TE} which are the results of two minimization programs, whose input are suitable data computed by a previous Montecarlo simulation.

2.3 T-USFI Calculation: Minimization Algorithm

The problem involves in transmission system nodes injections computing, only minimizing the power margins on the transmission system, disregarding any consideration of generation cost.
The control variables of the problem are the injections at generation nodes (ΔP_k^{T}), both the already active sites and the possible sites of new plants built in connection with the deregulated electrical market, that are separated in two different clusters.
The constraints involve plants generation limits and therefore their corresponding injections at the generation nodes, limits of flowing power on the branches, local and total power balance between the overall generation and the constant loads, bulk system equations.
The minimization problem can be written as:

$$f_{obj} = \Sigma_{NL}\, M_{ij}{}^{T} = \Sigma_{NL}\, (\, P^{max}{}_{ij} - |\, P_{ij}{}^{T}\, |\,) \qquad (6)$$

where:

$$[P_{ij}^T] = [CINF_{ij}^{\ k}]*[P_k^T] \quad (7)$$

$$P_k^T = P_k + \Delta P_k^T \quad (8)$$

So the f_{obj} becomes:

$$f_{obj} = \Sigma_{ij}^{NL} \left(P^{max}_{ij} - \left| \Sigma_k^{NN} CINF_{ij}^{\ k} * P_k \right| \right) = \\ = \Sigma_{ij}^{NL} \left(P^{max}_{ij} - \left| \Sigma_k^{NN} CINF_{ij}^{\ k} * (P_k + \Delta P_k^T) \right| \right) \quad (9)$$

About constraints:

- $0 \le \Delta P_k^{MIN} \le \Delta P_k \le \Delta P_k^{MAX}$, k=1 NGnew (10)
- $\Delta P_k \le 0$ and $P_k^{MIN} < P_k < P_k^{MAX}$, k=1, NGold (11)
- $|P_{ij}| < P^{max}_{ij}$, ij=1,NL (12)
- $\Sigma_k \Delta P_k = 0$, k =1, NG (13)

The superscripts T are used for the results of the GA, because they are employed for the T-USFI calculation; their absence refers to initial values.

2.4 TE-USFI Calculation: Minimization Algorithm

The problem involves in transmission system nodes injections computing, minimizing the power margins on the transmission system, the additional generation cost per unit and the additional losses cost per unit.

The control variables of the problem are the new injections constrained by costs at the nodes (ΔP_k^{TE}), both the already active sites and the possible sites of new plants built in connection with the deregulated electrical market, that are separated in two different clusters.

The constraints involve plants generation limits and therefore their corresponding injections at the generation nodes, limits of flowing power on the branches, local and total power balance between the overall generation and the constant loads, bulk system equations.

The minimization problem can be written as:

$$f_{obj1} = \Sigma_{NL} M_{ij}^T = \Sigma_{NL} \left(P^{max}_{ij} - \left| P_{ij}^T \right| \right) \quad (14)$$

$$f_{obj2} = \Delta C'_{GEN} = \Sigma_{NGold} C_k'(P_k)^{TE} - \Sigma_{NGold} C_k'(P_k) \quad (15)$$

$$f_{obj3} = \Delta C'_{LOSSES} = \\ = \Sigma_{NL}[\Sigma_{NGold} C_k'(P_k)][(P_{ij}^{lossesTE} - P_{ij}^{losses})/P_{ij}^{losses}] \quad (16)$$

where:

$$[P_{ij}^{TE}] = [CINF_{ij}^{\ k}]*[P_k^{TE}] \quad (17)$$

$$P_k^{TE} = P_k + \Delta P_k^{TE} \quad (18)$$

$$C_k'(P_k) = C_k(P_k) / P_c \quad (19)$$

$$P_{ij}^{\ losses} = R_{ij} I_{ij}^2 \quad (20)$$

About constraints:

- $0 \le \Delta P_k^{MIN} \le \Delta P_k \le \Delta P_k^{MAX}$, k=1 NGnew, (21)
- $\Delta P_k \le 0$ and $P_k^{MIN} < P_k < P_k^{MAX}$, k=1, NGold (22)
- $|P_{ij}| < P^{max}_{ij}$, ij=1,NL (23)
- $\Sigma_k \Delta P_k = 0$ k=1, NG (24)

The superscripts TE are used for the results of GA, because they are employed for the TE-USFI calculation; their absence refers to initial values.

3 Optimization Problem: Model for GA

3.1 Coding

The GA objective is to quantify the additional power injections set that minimizes the total margin, with and without cost constraints, for an assigned nodes set where the additional injections could be located. For this reason the chosen coding is real vector. Each individual is represented by a vector of real numbers (double precision) whose length is equal to the number of control variables, that is the number of (present and future) generation nodes.

3.2 Fitness Function: Objective and Penalty Functions

3.2.1 T-USFI Calculation: Fitness Function

The fitness function for the minimization problem contains: a term (total network power margin) which is the objective function (f_{obj}^T) with the control variables (ΔP_k^T); six penalty functions pf_i which subtract value to fitness penalizing the solutions that don't respect the constraints.

In particular the fitness is a linear combination of f_{obj} and pf_i with coefficient that are opportunely chosen through heuristic tests:

$$fitness^T = [f_{obj}^T(\Delta P_k^T)] + \Sigma_{i=1,6}\, \alpha_i \cdot pf_i \quad (25)$$

where pf_1 is related to limits of flowing power on the branches, pf_2 and pf_3 to generation limits for nodes located in already active sites and in new sites, pf_4 to total power balance between the overall generation and constant loads, pf_5 and pf_6 to the difference in sign of injections between present and future plants.

3.2.2 TE-USFI Calculation: Fitness Function

The fitness function for the minimization problem contains: a term (total network power margin) which is the first objective function (f_{obj1}^{TE}) with the control variables (ΔP_k^{TE}); a term (additional generation cost per unit) which is the second objective function (f_{obj2}^{TE}) with the control variables (ΔP_k^{TE}); a term (additional losses cost per unit) which is the third objective function (f_{obj3}^{TE}) with the control variables (ΔP_k^{TE}); six penalty functions pf_i which subtract value to fitness penalizing the solutions that don't respect the constraints equal to pf_i used in the first minimization problem. In particular the fitness is a linear combination of f_{obji} and pf_i with coefficient that are opportunely chosen through heuristic tests:

$$fitness^{TE} = [\gamma_1 f_{obj1}^{TE}(\Delta P_k^{TE}) + \gamma_2 (\Delta C'_{GEN}) f_{obj2}^{TE}(\Delta P_k^{TE}) + \\ + \gamma_3 (\Delta C'_{LOSSES}) f_{obj3}^{TE}(\Delta P_k^{TE})] + \Sigma_{i=1,6}\, \alpha_i \cdot pf_i \quad (26)$$

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It is worth pointing out that the coefficients γ_2 and γ_3 are respectively variable as function of $\Delta C'_{GEN}$ and $\Delta C'_{LOSSES}$, because the objective functions f_{obj2} and f_{obj3} have to weight differently according to values of additional generation and losses cost (per unit).
Through this formulation the GA find an initial solution of the minimization problem that in the space of the solutions constitutes an alternative of good quality that, thanks to the values given to the weights γ_1, γ_2 and γ_3, satisfies the objective of the minimization of the power margins on the transmission system (as a master function), but it may not be able to satisfy the needs on the other two objective functions that can be considered as slave functions.

3.2.3 Explaining about Fitness

In GA approach, the fitness (f) represents the quality of a configuration (the value associated to an individual of a population). Higher-quality configurations have better chances to generate offsprings. Conventional GA are formulated as maximization problems. So in a minimisation problem, the fitness function cannot coincide with the objective function itself but the problem must be transformed into equivalent maximization problem. The transformation here implemented and tested is the following:

$$\min f = \max (f_0 - f) \tag{27}$$

where f_0 is the value of fitness for the initial configuration, that is without ΔP_k.
It is well known that during the initial stages allowing the violation of some constraints, that means allowing the survival of some configurations with pf_i different to 0, is very important because it makes easier for the GA to move through the search space. On the contrary towards the end of the optimization process, the value of pf_i should be high enough to discourage any type of solution out of constraints. For this reason the *fitness scaling technique* has been adopted, which also allows a better control of the convergence characteristics. The scaling function converts raw fitness scores returned by the fitness function to values in a range that is suitable for the selection function. In particular the *Scaling function technique* chosen is the *fitness ranking* that scales the raw scores based on the rank of each individual, rather than its score. The rank of an individual is its position in the sorted scores. *Rank fitness scaling* removes the effect of the spread of the raw scores.

3.3 GA setting

The genetic operators used are selection, crossover, mutation and elitism.
The selection function chooses parents for the next generation based on their scaled values from the fitness scaling function. As *selection function* has been adopted the *stochastic uniform* that lays out a line in which each parent corresponds to a section of the line of length proportional to its expectation. The algorithm moves along the line in steps of equal size, one step for each parent. At each step, the algorithm allocates a parent from the section it lands on. The first step is a uniform random number less than the step size.
Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. The *crossover function* selected is *scattered type*. It creates a random binary vector and then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.
Mutation functions make small random changes in the individuals in the population, which provide genetic diversity and allows the GA search capability to be increased. The *mutation function* selected is *Gaussian type*: it adds a random number to each vector entry of an individual. This random number is taken from a Gaussian distribution centred on zero. The variance of this distribution can be controlled with two parameters: the scale and the shrink parameter.
The elitism keeps the best individual of the previous generation in the next one, in order not to loose the best information contained in the previous population. The number of individuals that are guaranteed to survive to the next generation has to be set.
The control parameters are: the Population Size that specifies how many individuals there are in each generation; the Elite Count that specifies the number of individuals that are guaranteed to survive to the next generation; the Crossover Fraction that specifies the fraction of the next generation, other than elite individuals, that are produced by crossover; the Mutation Factors that are the *scale parameter* for the variance at the first generation and the *shrink parameter* for the control how variance shrinks as generations go by; the Elite Count that specifies the number of individuals that are guaranteed to survive to the next generation Typical values for these control parameters are reported in the literature, but there is no agreement on the optimal way of tuning such parameters, and a particular choice of parameter values is highly dependent on the application. Moreover, these parameters are closely related and the value chosen for one of them may affect the optimal values of the others. In this research, parameter values have been determined in a number of tests with smaller networks, and this information will be used for extrapolating parameters values for larger networks. The values set is the following: population size equal to 40; for the mutation the scale parameter equal to 1,

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the shrink parameter equal to 1; crossover rate equal to 0.8; elite count equal to 2.

Finally a controlled random generation for the initial population has been chosen; in particular a random initial population with a uniform distribution has been created.

About stopping criteria, that determine what causes the algorithm to terminate, many possible convergence criteria have been tested on both algorithms. In particular the process can stop when:

1. the genetic algorithm performs a maximum number of iterations equal to 600 (Generation limit);
2. the maximum time for which the genetic algorithm runs arrives to 6000 seconds (Time limit);
3. the best fitness value is less than or equal to 100 (Fitness limit);
4. there is no improvement in the best fitness value for the 100 generations (Stall generations limit);
5. there is no improvement in the best fitness value for an time interval of 600 seconds (Stall time limit).

It has been verified that the first convergence criterion stops the search. Really by the analysis of fitness trend it can be noted that in many cases the convergence is obtained at 300-th iteration.

4 Test and Results

4.1 Test Network Description

In order to tune the main parameters of the genetic algorithm (control parameters values, roles of crossover and mutation, and convergence properties) firstly some smaller example systems, for which optimal are known have been used [9-11]. As example the results obtained for a small test network, shown in figure 1, are reported.

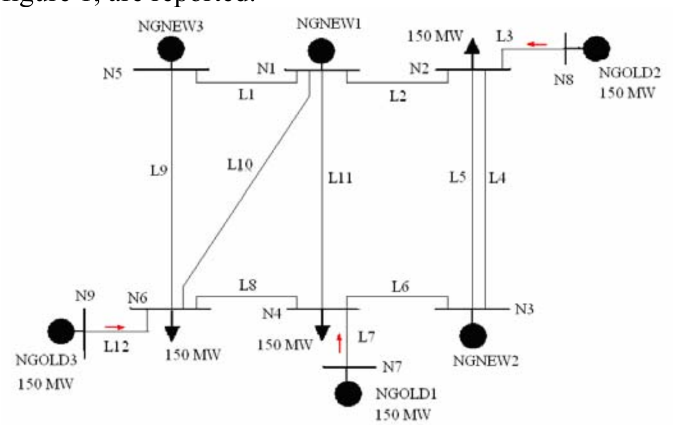

Fig.1 - Test Network

The network has three possible future power plants in three generation nodes (N1, N3, N5), three present power plants in other three generation nodes (N7, N8, N9) and three load nodes (N2, N4, N6). The branches number is even 12. For sake of simplicity, loads have been considered spatially uniform and even 150 MW for node.

In order to implement and to test the GA procedure, the deterministic input used is referred to the result of a LFCC for peak load simulation. The initial power set is reported in figure 1. Obviously, since the three present power plants are directly connected with the loads, in the initial conditions only these connection branches are loaded.

4.2 Results

Two GA gives in output the injections set that allows of minimum total power margins with and without cost constraints, respectively used for T,TE-USFI computation.

The obtained results are shown in figure 2.

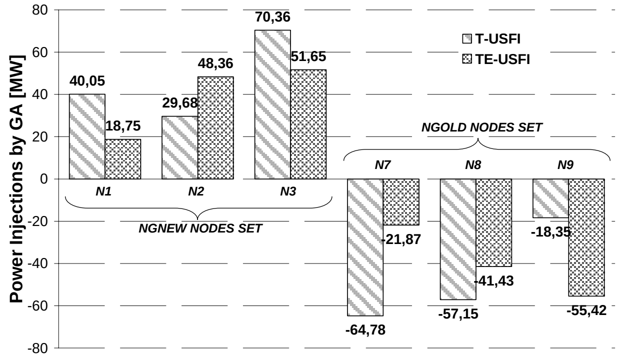

Fig. 2 - GA Output: Injections Set for T,TE-USFI Calculation

For these injections set, T-USFI$_S$ is equal to 140 MW, TE-USFI$_S$ is equal to 119 MW.

It is worth to point out that the two injections sets are very different, so for the single nodes T-USFI$_A$ and TE-USFI$_A$ are different. Their difference can be used as a suggestion about the weight that additional generation and losses cost have on local flexibility.

The programs gives also the total power margins and all the pf$_i$ trends. As example figure 3 reports total power margin trend in output for two GA:

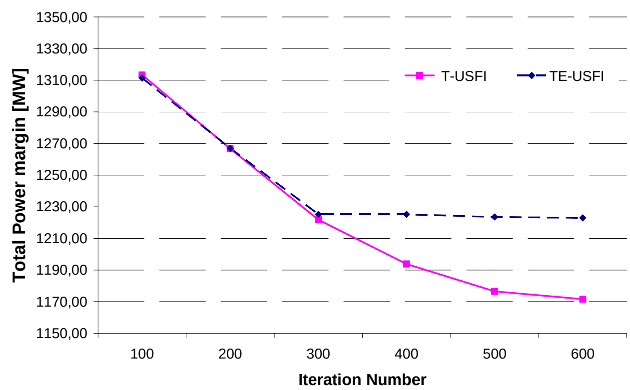

Fig. 3 - Total Power Margin Trend

It is worth to notify that the GA for TE-USFI gives a smaller reduction of total power margin because of the presence of costs constraints.

5 Conclusion

The paper describes a new procedure, based on Genetic Algorithms (GA), for the resolution of a long-term transmission expansion planning problem in a market environment, and in particular for the evaluation of the system and network areas flexibility.
Its application on some simple test networks allows of tuning the main parameters of the GA. The results analysis shows a good accuracy of the procedure.
Work is in progress about its application to real network and about the GA formulation for the technical-economical indexes evaluation, in order to make automatic the setting of the weights and to obtain the absolute optimum in the space of the solutions.

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