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Improving Power System Static Security Margins By Means Of A Real Coded Genetic Algorithm

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***Abstract*—This paper introduces a new method of removing thermal overloads and voltage limits in an electric power system by means of the Evolution of Corrective and Preventive control Actions (ECPA). The goal is to find the minimun number of control actions that solve the identified limit violations at minimum cost. A recombination operator based on form theory allows the codification of control actions in a natural and simple way. ECPA has been tested on the IEEE 30-bus and the IEEE 118-bus systems. The limit violations are solved at minimum cost and with fewer control actions on average than alternative methods.**

***Index Terms*—Control actions, steady state security, evolutionary algorithms, optimization.**

I. Introduction

THE aim of an electric power system (EPS) is to provide electricity supply ensuring an appropriate level of security. In order to guarantee the security, it is essential that the EPS remains in its normal state of operation [1]. In the normal state, all the energy demand is provided at the adequate voltage and frequency levels, and all the elements of the EPS work within their thermal limits. Moreover, an EPS in its normal state of operation must fulfill these security requirements under contingency, which can be defined as a perturbation giving rise to the loss of one or more elements of the EPS.

If an EPS that is functioning in its normal state fails to comply with the security requirements under contingency, but keeps fulfilling the rest of conditions, it is said to be in its alert state [2], or, according to others authors, unsecure normal state [3]. The actions that must be taken to return the EPS to its normal state are named preventive control actions. When some elements of the EPS are working beyond its thermal limit, or the voltages are out of limits without the presence of contingencies, the EPS is said to be in the emergency state, and it is necessary to use the so called corrective control actions to return it to its normal state.

The following are some of the key control actions that can be used to recover the normal state of an EPS:

- Redispatching active power of generators. This action is used to change active power flows.
- Adjustments of controllable voltage magnitudes, which allow modifying bus voltages and reactive power flows.
- Adjustments of transformers tap-changer positions, giving rise to variations of both power flows and voltages.
- Reactive compensation, connecting or disconnecting voltage control elements (reactors and capacitors). In this case, voltages are changed by locally increasing or decreasing reactive power consumption.
- Switching maneuvers to change the EPS topology and modify power flows and voltages.
- Adjustment of phase-shifters angle, modifying power flows and removing or alleviating thermal overloads.
- Load curtailment to reduce power flows, only used when there are no other resources available.

The main objective of this work is to introduce a new algorithmic approach to design the control actions that allow an EPS to return to its normal state of operation from any other state and, by using a limited number of control actions, to provide solutions sufficiently adapted to practical needs.

A. Related work

The determination of corrective and preventive control actions in an EPS is addressed in the literature by means of different methodologies. When corrective control actions are the main concern, it is quite common to use optimal power flow algorithms (OPF). OPF algorithms take constraints into account and optimally determine all of the EPS control variables. Reference [4] introduces an OPF algorithm enhanced and optimized to handle discrete control variables. In [5], a new OPF is proposed to increase power system security margins by means of re-dispatching generator outputs. Reference [6] makes use of a method to remove overloads in the IEEE Reliability Test System (RTS). Constraints are taken into account in order to improve the stability of the EPS. Reference [7] focus on the calculation of generation redispatches by means of a minimum number of control actions to recover the normal state of the EPS. The performance of the proposed method is assessed in three different EPSs: Nordic 60-bus, standard IEEE 118-bus and a RTE 618-bus. Another OPF example is given in [8], applied to the removal of the overloads in a modified IEEE 30-bus test system.

The scope of SCOPF algorithms is broader than that of OPF algorithms because they allow to calculate both corrective and preventive control actions. These algorithms solve an optimal power flow in which security constraints are also taken into account in order to recover the EPS normal state, no matter what the previous state (alert or emergency) may be. Reference [9] provides a full review of the state of the art in the field. The main challenges identified by this work are the following: the need of a limited number of control actions, the need to reduce the problem size, the modeling of voltage and transient

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stability constraints, the handling of discrete control variables, and the increasing levels of uncertainty in the operation and planning of the EPS. For example, reference [10] solves an SCOPF taking uncertainty into account. In [11] a new iterative method is described and tested in three systems of 60, 118 and 1203 buses, respectively. The size of the problem is reduced by using a contingency filtering technique. In [12] an application of these algorithms to the calculation of control actions is introduced and applied to the IEEE 30-bus. A similar application is presented in [13], solving the OPF by means of the generalized Benders decomposition (GBD) and testing the model's performance on the IEEE 118-bus. In reference [14] an evolutionary algorithm is used to solve an SCOPF problem, and its performance is assessed on the IEEE 30-bus.

As demonstrated in [15] and [12], linear programming (LP) is a proper and computationally efficient technique whenever control actions are to be calculated. This efficiency allows to address realistic size problems and develop real time applications that yield results within a reasonable time. Graph theory and model predictive control (MPC) have also been applied to the computation of control actions. Reference [3] introduces an algorithm based on directed acyclic graphs (DAG) that computes preventive control actions (including generation redispatch, switching, reactive compensation and load curtailment), checking its performance on the IEEE 30-bus. Finally, in [16] an MPC model is used to determine the optimal sequence of control actions. The validity of this approach is tested on a custom 4-bus EPS.

Last but not least, evolutionary algorithms (EA) have been widely applied to the calculation of control actions. One of the main advantages of this kind of algorithms is that they provide a whole population of alternative solutions to the problem. A comprehensive review of EA applied to EPSs can be found in reference [17], making clear the increasing interest and usefulness of these techniques. In [18] an EA is proposed to calculate the switching maneuvers necessary to remove the overloads of a German 73-bus EPS. Microgenetic algorithms (μGA) are introduced as a feasible option to the calculation of redispatches, switching, reactive compensation and load curtailment. Their performance is checked on a Central African 58-bus EPS. Genetic algorithms are also efficient for the identification of EPS's critical contingencies and its posterior fixing by means of control actions [19]. In reference [20], the calculation of corrective control actions is accomplished by means of a multi objective genetic algorithm (MOGA), that behaves successfully in both IEEE 5-bus and 14-bus EPSs. Reference [21] proposes a hybrid computational strategy which combines an evolutionary algorithm and an interior-point method. This model is tested on the IEEE 14-bus and 118-bus test systems.

B. Justification

The complexity of the problem addressed by this paper is due mainly to the non-linear and multi-objective nature of the objective function together with the large number of constraints. These are the main reasons why this field of research is still open. The following are some of the drawbacks of the models proposed to date:

- Unique solutions: most algorithms, apart from EAs, return a unique optimal or suboptimal solution. For problems such as these, there exist many feasible solutions, and it is desirable that the algorithm offer a set of alternative solutions, leaving the final decision to be made by an expert.
- Modular approach: in general, out of limit voltages and overloads are addressed independently. Therefore, the control actions used to remove voltage violations may worsen the overload problem and viceversa.
- Unfeasibility: despite the mathematical correctness of the given solutions, the movement of a large number of controls is unrealistic when only a small number of limit violations are identified.

For these reasons, the authors consider justified the research on new algorithmic approaches that help alleviate some of these limitations.

A drawback of our approach is its computational burden. It is true that evolutionary algorithms are very flexible and capable of incorporating multiple objectives in a graceful way. Alternative approaches such as linear programming or Benders decomposition are faster in general. However, the combination of a power flow algorithm together with the evolutionary pressure alleviates the problem and, in fact, ECPA can be applied to real size networks with of a modest increase in the number of evaluated power flows.

The rest of the paper is organized as follows. The problem is formulated in Section II as an optimization problem with multiple constraints. Section III provides a description of the proposed algorithm, including each of the operators. The results of the tests are discussed in Section IV. Finally, in Section V the conclusions and future research path are presented.

II. Problem Formulation

Our approach is the following: given an EPS for which a security analysis has identified voltage violations or overloads, the goal is to find a set of control actions that eliminate or at least alleviate those violations in order to restore the normal state of operation.

Let us consider an EPS with N buses, R branches and G generators. From an static point of view, the EPS is in its normal state if, with or without the presence of contingencies, the flows (F) through the branches remain within the thermal limits ($-F^{max}, F^{max}$):

$$-F_i^{max} < F_i < F_i^{max},\ i = 1, ..., R \tag{1}$$

and the voltage (V) in all of the buses is above a minimum value (V^{min}) and below a maximum value (V^{max}):

$$V_j^{min} < V_j < V_j^{max},\ j = 1, ..., N. \tag{2}$$

From the list of available control actions introduced in section I, only the following will be taken into account: modifications of active power in the generators, controllable voltage magnitudes and transformer tap ratios. The active power values (P) of the generators must lie between their operating limits (P^{min} and P^{max}):

$$P_l^{min} \leq P_l \leq P_l^{max},\ l = 1, ..., G. \quad (3)$$

Also, the reactive power values (Q) of the generators must lie between their operating limits (Q^{min} and Q^{max}):

$$Q_l^{min} \leq Q_l \leq Q_l^{max},\ l = 1, ..., G. \quad (4)$$

Finally, the transformer tap ratios (T) must lie between their operating limits (T^{min} and T^{max}):

$$T_k^{min} \leq T_k \leq T_k^{max},\ k = 1, ..., TR. \quad (5)$$

where TR is the total number of transformers in the EPS.

A solution ($\mathbf{S}$) to the problem may be coded in the following way:

$$\mathbf{S} = (\Delta P_1, ..., \Delta P_{N_g}; \Delta V_1, ..., \Delta V_{N_v}; \Delta T_1, ..., \Delta T_{N_t}) \quad (6)$$

where:

- N_g is the maximun number of active power changes.
- N_v is the maximun number of controllable voltage magnitude changes.
- N_t is the maximun number of modifications of transformer tap ratios.

As an example, a solution with $N_g = 3$, $N_v = 2$ and $N_t = 2$ is shown in Table I.

TABLE I
EXAMPLE OF SOLUTION WITH $N_g = 3$, $N_v = 2$ AND $N_t = 2$

ΔP_1	ΔP_2	ΔP_3	ΔV_1	ΔV_2	ΔT_1	ΔT_2
-45	-20	0	0.010	-0.001	0.003	-0.250

As the example of Table I makes clear, some of the active power changes may be null, i.e., it is not necessary to modify all of the generators involved in the solution. For instance, the active power of generator 3 is not changed. Thus, the maximum number of generators N_g, controllable voltage magnitude changes N_v and modifications of transformer tap ratios N_t, are upper limits which may not be necessarily reached. This simple but flexible codification allows to generate more realistic solutions than other conventional approaches. Finally, the economic cost incurred by each solution is taken into account. The total cost $C(\mathbf{S})$ of a given solution is defined as the sum of the costs $C(S_i)$ of each specific modification:

$$C(\mathbf{S}) = \sum_{i=1}^{N_g+N_v+N_t} C(S_i). \quad (7)$$

As expected, among all of the solutions to a given problem fulfilling (1), (2), (3), (4) and (5), the preferred ones are those minimizing (7). The upper limits on the number of control actions together with the minimization of the cost (7) will encourage the evolution of as simple solutions as possible, i.e., solutions with as few control actions as the process can reach.

III. Evolutionary Approach

This paper introduces a new genetic algorithm [22] with a set of improvements designed to better calculate the set of control actions in a more realistic way than other approaches. Genetic algorithms are optimization algorithms that work with a population of individuals, where each individual is a coded solution to the optimization problem. The initial population is generated randomly while taking the operative limits (3), (4) and (5) into account. They simulate the evolutionary processes of selection, recombination and mutation, and let the candidate solutions in the population compete for room in future generations.

A fitness function is needed to determine the relative merit of each individual. The probability of selection of an individual is proportional to its fitness value. This guarantees that the better the fitness of an individual the higher its probability of becoming parent of future offspring. Recombination is the process of generating new offspring from previously selected parents. The codes of the parents are combined to yield new codes, i.e., new individuals. Mutation alters one or more characteristics of one individual giving rise to a new one which can differ in fitness value. Appendix A contains the pseudocode of ECPA. Next, a detailed description of each of its components is given.

A. Fitness function

The objective function to maximize is the following:

$$F(\mathbf{S}) = \sum_{i=1}^{N_f} \varphi_i(\mathbf{S}) \quad (8)$$

where

- $\mathbf{S}$ is a solution (6).
- N_f is the total number of factors to consider, 9 in this work.
- $\varphi_1(\mathbf{S})$ is the normalized overload improvement, calculated as follows:

$$\varphi_1(\mathbf{S}) = \frac{OL(\mathbf{S_0}) - OL(\mathbf{S})}{OL(\mathbf{S_0})} \quad (9)$$

  where
  - $OL(\mathbf{S_0})$ and $OL(\mathbf{S})$ are the sum of the square of the overloads present in the EPS before taking any control actions ($\mathbf{S_0}$) and after taking the control actions ($\mathbf{S}$), respectively:

$$OL(\mathbf{S}) = \sum_{i=1}^{N_{OL}} (F_i - F_i^{max})^2 \quad (10)$$

    where
    * N_{OL} is the total number of overloads in $\mathbf{S}$.
    * F_i and F_i^{max} are the flow and the thermal limit of branch i, respectively.
- $\varphi_2(\mathbf{S})$ is the normalized overvoltage improvement, calculated as follows:

$$\varphi_2(\mathbf{S}) = \frac{OV(\mathbf{S_0}) - OV(\mathbf{S})}{OV(\mathbf{S_0})} \quad (11)$$

where

- $OV(\mathbf{S_0})$ and $OV(\mathbf{S})$ are the sum of the square of the overvoltages present in the EPS before and after taking the control actions, respectively:

$$OV(\mathbf{S}) = \sum_{i=1}^{N_{OV}} (V_i - V_i^{max})^2 \tag{12}$$

  where

  - N_{OV} is the total number of overvoltages in $\mathbf{S}$.
  - V_i and V_i^{max} are the voltage and the maximum voltage of bus i, respectively.

- $\varphi_3(\mathbf{S})$ is the normalized undervoltage improvement, calculated as follows:

$$\varphi_3(\mathbf{S}) = \frac{UV(\mathbf{S_0}) - UV(\mathbf{S})}{UV(\mathbf{S_0})} \tag{13}$$

where

- $UV(\mathbf{S})$ and $UV(\mathbf{S_0})$ are the sum of the square of the undervoltages present in the EPS before and after taking the control actions respectevily:

$$UV(\mathbf{S}) = \sum_{i=1}^{N_{UV}} (V_i^{min} - V_i)^2 \tag{14}$$

  where

  - N_{UV} is the total number of undervoltages in $\mathbf{S}$.
  - V_i and V_i^{min} are the voltage and the minimum voltage of bus i, respectively.

- $\varphi_4(\mathbf{S})$ represents the improvement in the violations of reactive limits in generators, calculated as follows:

$$\varphi_4(\mathbf{S}) = \frac{QL(\mathbf{S_0}) - QL(\mathbf{S})}{QL(\mathbf{S_0})} \tag{15}$$

where

- $QL(\mathbf{S_0})$ and $QL(\mathbf{S})$ are the sum of the square of the reactive limit violations in the generators present in the EPS before and after conducting the control actions, respectively:

$$QL(\mathbf{S}) = \sum_{i=1}^{N_{RL}} (QV_i)^2 \tag{16}$$

  where

  - N_{RL} is the total number of reactive limit violations in $\mathbf{S}$.
  - QV_i is the magnitude of the reactive limit violation of generator i, calculated as follows:

$$QV_i = \begin{cases} Q_i - Q_i^{max} & \text{if } Q_i > Q_i^{max}, \\ Q_i^{min} - Q_i & \text{if } Q_i < Q_i^{min}. \end{cases} \tag{17}$$

    where

    - Q_i is the reactive power at generator i.
    - Q_i^{max} and Q_i^{min} are the reactive limits of generator i.

- The flows and voltages of the EPS (F_i, V_i and Q_i) are calculated in this work by means of a commercial power flow algorithm [23].
- Factors $\varphi_5(\mathbf{S})$, $\varphi_6(\mathbf{S})$, $\varphi_7(\mathbf{S})$ and $\varphi_8(\mathbf{S})$ are equivalent to $\varphi_1(\mathbf{S})$, $\varphi_2(\mathbf{S})$, $\varphi_3(\mathbf{S})$ and $\varphi_4(\mathbf{S})$, respectively, but for preventive instead of corrective control actions.
- Finally, factor $\varphi_9(\mathbf{S})$ is the normalized total cost of the control actions associated to solution $\mathbf{S}$:

$$\varphi_9(\mathbf{S}) = \begin{cases} \dfrac{C_{max} - C(\mathbf{S})}{C_{max}} & \text{if } C(\mathbf{S}) \leq C_{max}, \\ 0 & \text{if } C(\mathbf{S}) > C_{max}. \end{cases} \tag{18}$$

where:

- $C(\mathbf{S})$ is the total cost (7) of the applied control actions specified by solution $\mathbf{S}$.
- C_{max} is the maximum cost above which the contribution of factor $\varphi_9(\mathbf{S})$ to the fitness function is null.

B. Selection

The selection operator identifies good solutions based on their fitness value for later recombination. More specifically, tournament selection is used in this paper because of its simplicity and efficiency [24]. In order to generate two parents, a couple of individuals is randomly chosen from the population. This couple takes part in a tournament, i.e., the individual with higher fitness becomes one of the parents. This process is repeated one more time to generate the other parent.

In order not to lose the best individual in the population, elitism is applied [25]. The best individual is always allowed to pass from the current generation to the next.

C. Recombination

The recombination operator of the algorithm acts on two individuals to generate one offspring. The individuals are modeled as sets because the order of the power variations is totally irrelevant. This allows to use the random equivalence recombination operator (RER), based in form theory [26]. The goal in the design of the RER operator is to select a random child from the set of all candidate solutions which, for each basic equivalence relation, are equivalent to some parents. Recombination is applied with probability p_r. The algorithm pseudocode is included in appendix B.

D. Mutation

Four mutation operators are applied with probabilities p_{m1}, p_{m2}, p_{m3} and p_{m4}, respectively. The first one starts by randomly selecting two generators G_i and G_j. First, a Gaussian $N(0, \sigma_{ij})$ perturbation is applied to the active power of the first generator G_i. Then, the second generator G_j is subject to a modification with the same absolute value of the Gaussian perturbation but opposite sign. In this way, the power balance of the solution is maintained.

The deviation σ_{ij} is calculated taking into account the generation limits of the mutated generators (P_i^{max}, P_j^{max},

P_i^{min} and P_j^{min}), and a parameter d which adjusts the range of the perturbation as follows:

$$\sigma_{ij} = \frac{min(R_i^U, R_j^U, R_i^D, R_j^D)}{d} \tag{19}$$

where

$$R_i^U = P_i^{max} - P_i \tag{20}$$

$$R_j^U = P_j^{max} - P_j \tag{21}$$

are the upward power reserves of generators i and j, and

$$R_i^D = P_i - P_i^{min} \tag{22}$$

$$R_j^D = P_j - P_j^{min} \tag{23}$$

are the downward power reserves of generators i and j, where P_i is the active power output of generator i, and P_j is the active power output of generator j. The operative limits of the generators (3) are guaranteed by applying equations (19)-(23) inside of the mutation operator. The second mutation operator acts on a different level. Instead of mutating the active power of a couple of generators, this operator replaces one of the generators in the individual with another from the EPS. Two conditions have to be met:

- In order to maintain the power balance of the individual, the active power output of the new generator must be equal to the value of the replaced one. The operative limits (3) of the new generator are checked.
- The new generator and the replaced one must belong to the same geographical area, so to encourage local changes.

The third and fourth mutation operators work in the same way as the first mutation operator, modifying controlled voltage magnitudes and transformer taps ratios, respectively. Operative limits (4) and (5) are taken into account as in the first mutation operator.

IV. Numerical results

A. Test systems

The algorithm has been tested with the IEEE 30-bus (Fig. 1) and with the IEEE 118-bus test systems. The generation, transmission and load data of the IEEE 30-bus system have been taken from [12]. The IEEE 118-bus test system's data have been obtained from references [21] and [27]. A summary of the features of the systems is provided in Table II.

TABLE II
MAIN CHARACTERISTICS OF THE POWER SYSTEMS

System	Buses	Generators	Lines	Transformers	Loads
30-bus	30	6	35	7	21
118-bus	118	54	177	9	99

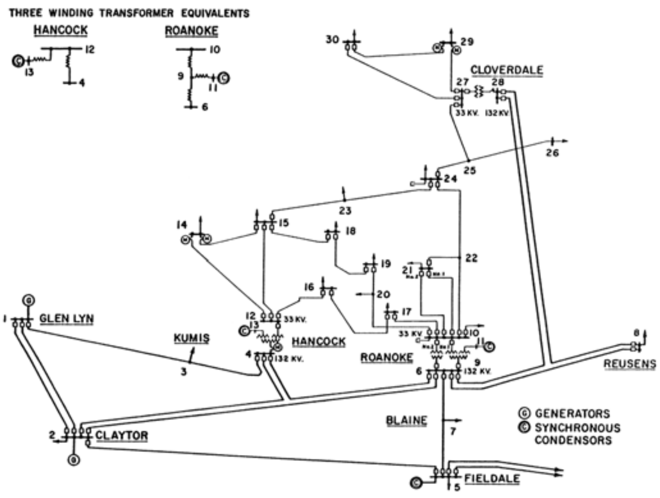

Fig. 1. IEEE 30 bus-system.

B. Experimental setup

The performance of ECPA in the design of corrective and preventive control actions has been measured in terms of the following indicators:

- Initial and final status of the controls.
- Values of limits violations before and after applying the control actions.
- Generation costs.

More specifically, the generation cost ($C(S_i)$) of each generator in solution S_i is calculated as follows:

$$C(S_i) = a_i + b_i P_i + c_i P_i^2 \tag{24}$$

where P_i is the active power generation of generator number i, and the cost coefficients a_i, b_i and c_i are defined in [12] for the IEEE 30-bus test system, and in reference [27] for the IEEE 118-bus test system.

Three different scenarios have been considered in the simulations:

- Corrective control actions (subsection IV-D). The results obtained with ECPA are compared with those from references [12], [14] and [28] for the IEEE 30-bus test system. A sensitivity analysis is performed with the IEEE 118-bus test system to assess the impact of ECPA's upper limits (maximum number of active power changes and controllable voltages) on the final solution of corrective control actions.
- Preventive control actions (subsection IV-E). The ECPA's results for the IEEE 30-bus test system are compared with the results from references [12], [14] and [28]. Additionally, the results of ECPA for the IEEE 118-bus test system are compared with those from reference [21].
- Computational requirements and scalability (subsection IV-F). The ECPA's computational burden for the IEEE 30-bus system is compared with that from references [14] and [28]. The computational burden for the IEEE 118-bus is also analyzed. More specifically, the convergence of the fitness function is compared with that of references [14] and [21].

C. Initial parameter setting

Table III depicts the parameters of the evolutionary algorithm, including a short description in the first column, the symbol in the second column and, finally, the type of data in the third column.

TABLE III
PARAMETERS OF THE EVOLUTIONARY ALGORITHM

Parameter	Symbol	Type
Population size	Ps	Integer
Max. number of generators	N_g	Integer
Max. number of controlled volt. bus	N_v	Integer
Max. number of transformer taps	N_{tap}	Integer
Probabilty of recombination	p_r	Real
Probability of mutation 1	p_{m1}	Real
Probability of mutation 2	p_{m2}	Real
Probability of mutation 3	p_{m3}	Real
Probability of mutation 4	p_{m4}	Real
Mutation 1 deviation coef.	d	Real

In order to find the optimal values of the parameters, a multivariate gradient descent algorithm (see appendix C for details) has been applied to the IEEE 30-bus test system. The initial values of the parameters were taken from [14]. Tables IV and V show the results of this calculation for corrective control actions (N), and preventive control actions (N-x).

TABLE IV
OPTIMAL VALUES OF THE PARAMETERS (INTEGERS)

	Ps	N_g	N_v	N_{tap}
N,OPF	140	5	5	4
N-x,SCOPF	112	5	5	4

TABLE V
OPTIMAL VALUES OF THE PARAMETERS (REALS)

	p_r	p_{m1}	p_{m2}	p_{m3}	p_{m4}	d
N,OPF	0.610	0.157	0.069	0.118	0.089	1.33
N-x,SCOPF	0.652	0.237	0.109	0.093	0.003	2.55

D. Results of corrective control actions

This section focuses on the results obtained from corrective control actions. Table VI displays the initial and final values of the control variables for the IEEE 30-bus test system according to references [12], [14], [28] and ECPA. The first column of Table VI is the name of the control variable. The second column is the initial value of the control variable, which is the same in all cases. The following four columns are the final values of the control variables in the three references used for comparison and ECPA, respectively.

It is important to notice that in the method proposed in [14], no transformer tap adjustments are used, and therefore all the values of these control variables remain constant. In ECPA, one power generator, three controllable bus voltages and one transformer tap ratio are kept constant in the solution, which is an advantage over the other methods.

TABLE VI
INITIAL AND FINAL STATUS OF CONTROLS FOR CORRECTIVE ACTIONS (IEEE 30-BUS)

Variable	Ini. Val.	[12]	[14]	[28]	ECPA
P [MW]					
P_2	80.00	48.84	50.20	48.03	49.30
P_5	50.00	21.51	21.80	21.65	21.90
P_8	20.00	22.15	23.80	22.38	Const.
P_{11}	20.00	12.14	10.80	12.03	12.60
P_{13}	20.00	12.00	12.30	12.00	12.00
V [pu]					
V_1	1.0500	Const.	0.9660	Const.	Const.
V_2	1.0450	1.0382	0.9987	1.0366	1.0356
V_5	1.0100	1.0114	0.9590	1.0105	Const.
V_8	1.0100	1.0194	0.9688	1.0198	1.1000
V_{11}	1.0500	1.0912	1.0266	1.0789	Const.
V_{13}	1.0500	1.0913	0.9500	1.0839	1.0875
Tap [pu]					
T_{6-9}	0.9780	1.0027	Const.	0.9920	Const.
T_{6-10}	0.9690	0.9600	Const.	0.9608	0.9182
T_{4-12}	0.9320	1.0047	Const.	0.9951	0.9925
T_{27-28}	0.9680	0.9410	Const.	0.9417	0.9397

There are no limit violations in the test system neither before nor after the application of the corrective control actions. There are no available data regarding generators reactive limit violations in [14].

Finally, Table VII includes the initial and final value of the generation cost.

TABLE VII
FINAL GENERATION COST AFTER APPLYING CORRECTIVE ACTIONS (IEEE 30-BUS)

	Ini. Val.	[12]	[14]	[28]	ECPA
Gen. cost [$\pounds/h$]	900.76	802.40	802.32	802.40	802.22

On the basis of these results, it can be concluded that the proposed method produces the minimum generation cost. The authors want to emphasize that ECPA, due to its evolutionary nature, yields a whole set of alternative solutions. A human operator can benefit from this set of solutions before taking a final decision.

In order to assess the impact on final solution of the upper limits on the number of corrective control actions, 10 simulations for the IEEE 118-bus test system have been conducted. The simulations have been defined by combining the values of the maximum number of active power changes (N_g) and the maximum number of controlled bus voltages (N_v), as shown in Table VIII. All of the system's data and generation cost coefficients in this test case have been obtained from references [21] and [27].

The first column of Table VIII is the simulation's number. The second and third columns are the maximum number of active power changes (N_g) and the maximum number of controllable voltage buses (N_v) respectively. The fourth

TABLE VIII
INFLUENCE OF UPPER LIMITS ON BEST INDIVIDUALS OF FINAL SOLUTIONS (IEEE 118-BUS)

N	N_g	N_v	$\hat{N}_g$	$\hat{N}_v$	$Cost$
1	14	6	7	4	128560.1
2	10	6	8	5	128555.9
3	6	6	6	5	128628.1
4	2	6	2	5	129329.0
5	2	5	2	5	129323.1
6	2	4	2	4	129312.3
7	2	3	2	2	129396.3
8	2	2	2	2	129330.6
9	2	1	2	1	129396.6
10	2	0	2	0	129438.6

column is the actual number of active power changes in the best individual ($\hat{N}_g$) of the simulation. The fifth column is the actual number of controllable voltage bus changes ($\hat{N}_v$) in the best individual. The sixth column depicts the total generation cost in $\$/h$ for the best individual of the simulation.

The best individuals of all of the simulations are free from limit violations. Furthermore, in all of the simulations, ECPA yields lower generation costs than the one published in [21], which is 130191.3 $\$/h$ for the OPF case. The minimum generation cost is reached in simulation number 2. This comes as no surprise since it is the solution with the highest number of actual controls in the simulation. From the third simulation onwards, as limits are reduced, simpler solutions are obtained but at a higher generation cost. Despite the higher generation cost, the simplicity of the solution can become very attractive for the system's operator.

Table IX shows the best solution obtained from simulation number 2. Active power changes with respect to base case values are given in [MW], and changes in controllable voltage buses are given in pu. Security limits and original values of control variables are available in references [21] and [27].

TABLE IX
BEST SOLUTION FOR THE IEEE 118-BUS TEST SYSTEM WITH $\hat{N}_g = 8$ AND $\hat{N}_v = 5$

ΔP_4	ΔP_{10}	ΔP_{15}	ΔP_{40}	ΔP_{42}	ΔP_{61}	ΔP_{89}
35.2	-133.8	34.8	56.1	50.1	-2.2	-104.8
ΔP_{104}	ΔV_{10}	ΔV_{55}	ΔV_{62}	ΔV_{66}	ΔV_{107}	
99.1	-0.0207	0.0370	0.0629	0.0116	0.0292	

E. Results of preventive control actions

33 contingencies are specified for this simulation, each one involving the outage of one of the branches in the IEEE 30-bus test system. The notation C_{x-y} in Tables XI and XII indicates the outage of the branch from bus x to bus y, I_{x-y} denotes an overload in the branch from bus x to bus y, V_x indicates a voltage violation (high or low) in bus x and Q_x represents a reactive limit violation of the generator in bus x. Table X displays the final status of the control variables that have been used in the three references and in ECPA. The first column of Table X is the name of the control variable. The following four columns are the final values of the control variables in the three references used for comparison and the proposed algorithm, respectively. The method proposed in [14] makes use of four thyristor controlled series capacitors (TCSC) as additional control variables. The location and the optimal values of the setting of the TCSC are fully described in [14].

TABLE X
FINAL STATUS OF CONTROLS FOR PREVENTIVE ACTIONS (IEEE 30-BUS)

Variable	**[12]**	**[14]**	**[28]**	**ECPA**
P [MW]				
P_2	57.56	43.00	57.36	56.90
P_5	24.56	23.88	24.46	24.40
P_8	35.00	25.03	34.86	34.90
P_{11}	17.93	11.27	18.03	17.30
P_{13}	16.91	19.22	17.28	17.10
V [pu]				
V_1	1.0500	Not avail.	1.0500	1.0500
V_2	1.0338	Not avail.	1.0350	1.0294
V_5	1.0058	Not avail.	1.0081	0.9923
V_8	1.0230	Not avail.	1.0236	1.1000
V_{11}	1.0913	Not avail.	1.0630	1.0457
V_{13}	1.0883	Not avail.	1.0765	1.0897
Tap [pu]				
T_{6-9}	1.0154	Const.	1.0281	0.9941
T_{6-10}	0.9628	Const.	0.9467	0.9000
T_{4-12}	1.0128	Const.	1.0109	1.0214
T_{27-28}	0.9580	Const.	0.9568	0.9587

As was the case in the previous section, no transformer tap adjustments are used in [14], and therefore this control variable remains constant.

Tables XI and XII show the limit violations under contingency, as a result of a security analysis performed before applying any preventive action.

TABLE XI
LIMITS VIOLATIONS BEFORE APPLYING PREVENTIVE ACTIONS 1/2 (IEEE 30-BUS)

Violations	**[12]**	**[14]**
Flow limits	C_{1-2}: I_{1-3},I_{3-4},I_{4-6} C_{1-3}: I_{1-2} C_{3-4}: I_{1-2} C_{2-5}: I_{2-6},I_{5-7}	C_{1-2}: I_{1-3},I_{3-4},I_{4-6} C_{1-3}: I_{1-2},I_{2-6} C_{3-4}: I_{1-2},I_{2-6} C_{2-5}: I_{2-6} C_{4-6}: I_{1-2},I_{2-6} C_{27-28}: I_{22-24},I_{24-25}
Voltage limits	C_{4-6}: V_{12} C_{24-25}: V_{27} C_{25-27}: V_{27}	Not avail.
Reactive limits	C_{1-3}: Q_1 C_{3-4}: Q_1 C_{4-6}: Q_1	Not avail.

After applying the preventive control actions that have been calculated with ECPA, there are no limit violations in the EPS. This is also the case in references [12], [14] and [28], and

TABLE XII
LIMITS VIOLATIONS BEFORE APPLYING PREVENTIVE ACTIONS 2/2 (IEEE 30-BUS)

Violations	[28]	ECPA
Flow limits	C_{1-2}: I_{1-3},I_{3-4},I_{4-6}	C_{1-3}: I_{1-2}
	C_{1-3}: I_{1-2}	C_{2-5}: I_{2-6},I_{5-7}
	C_{2-4}: I_{1-2}	C_{3-4}: I_{1-2}
	C_{2-5}: I_{2-6},I_{5-7}	
	C_{4-6}: I_{2-6}	
Voltage limits	C_{4-6}: V_{12}	C_{6-7}: V_{10},V_{12},V_{27}
		C_{10-17}: V_{10}
		C_{10-20}: V_{10}
		C_{25-26}: V_{27}
		C_{25-27}: V_{27}
Reactive limits	C_{1-3}: Q_1	C_{1-3}: Q_1
	C_{2-4}: Q_1	C_{3-4}: Q_1
	C_{4-6}: Q_1	

TABLE XIII
FINAL GENERATION COST AFTER APPLYING PREVENTIVE ACTIONS (IEEE 30-BUS)

	[12]	[14]	[28]	ECPA
Gen. cost [$\pounds/h$]	813.74	812.49	813.73	813.21

therefore no distinctions can be made with respect to this issue. Table XIII includes the final value of the generation cost. ECPA is only outperformed by the one proposed in [14], in which additional control variables have been used.

ECPA's performance for preventive control actions has also been evaluated for the IEEE 118-bus test system. For this purpose, a comparison between the results published in reference [21] and those for ECPA has been made. All of the system's data, generation cost coefficients and security limits have been taken from references [21] and [27]. The total generation cost in the base case is 130191.3 \$/h, and the status of control variables (active power changes) and the results from the initial N-1 security analysis for the base case are given in [21].

Table XIV compares the final active power values of the generators in reference [21] with those of ECPA. The first column is the name of the generator. The second and third columns are the final active power values of the generators in [21] and ECPA, respectively. The values in brackets correspond to those generators whose values have changed with respect to the original base case value. The fourth, fifth and sixth columns have the same information as the first, second and third columns, respectively.

It can be seen in Table XIV that 45 generators have been modified in the solution proposed in [21], while only 7 generators have been changed in ECPA's solution. The total generation cost of the solution proposed in [21] is 131026.6 \$/h, while the total cost of ECPA's solution is 130933.0 \$/h. In addition, the solution of [21] contains two unsolved contingencies (C_{8-5} and C_{30-17}) versus none in ECPA.

TABLE XIV
FINAL STATUS OF CONTROLS FOR PREVENTIVE ACTIONS (IEEE 118-BUS)

P [MW]	[21]	ECPA	P [MW]	[21]	ECPA
P_1	(49.1)	44.4	P_{65}	(323.6)	353.6
P_4	(8.2)	0.2	P_{66}	(365.9)	(357.0)
P_6	(30.1)	23.6	P_{69}	(273.5)	455.2
P_8	(2.1)	0.0	P_{70}	(6.0)	0.0
P_{10}	(262.9)	262.7	P_{72}	(7.4)	0.0
P_{12}	(88.6)	(129.4)	P_{73}	(12.1)	0.0
P_{15}	(42.6)	32.8	P_{74}	(30.4)	19.0
P_{18}	(32.9)	(35.1)	P_{76}	(44.3)	24.3
P_{19}	(31.3)	30.7	P_{77}	0.0	0.0
P_{24}	0.0	0.0	P_{80}	(450.4)	432.0
P_{25}	(192.9)	196.1	P_{85}	0.0	0.0
P_{26}	(258.7)	(269.1)	P_{87}	(3.8)	(1.6)
P_{27}	(25.0)	16.2	P_{89}	(481.8)	502.5
P_{31}	(7.4)	7.3	P_{90}	0.0	0.0
P_{32}	(30.3)	21.6	P_{91}	0.0	0.0
P_{34}	(22.5)	12.8	P_{92}	0.0	0.0
P_{36}	(8.3)	17.6	P_{99}	0.0	0.0
P_{40}	(67.8)	53.2	P_{100}	(238.2)	231.6
P_{42}	(41.2)	43.1	P_{103}	(39.1)	38.3
P_{46}	(19.8)	19.1	P_{104}	(7.7)	0.0
P_{49}	(201.2)	193.9	P_{105}	(16.8)	5.7
P_{54}	(51.1)	49.6	P_{107}	(35.1)	29.3
P_{55}	(60.3)	33.7	P_{110}	(24.5)	7.3
P_{56}	(29.0)	34.2	P_{111}	(35.6)	35.3
P_{59}	(155.9)	(175.1)	P_{112}	(19.1)	(56.4)
P_{61}	(155.2)	148.9	P_{113}	(12.0)	3.0
P_{62}	0.0	0.0	P_{116}	0.0	0.0

F. Computational requirements and scalability

In this section ECPA's computational burden for the IEEE 30-bus system is compared with that of two other evolutionary approaches. At the end of the section, ECPA's behavior on the IEEE 118-bus system is addressed.

In order to assess the computational burden of the new algorithm, a comparison between ECPA and the evolutionary methods published in [14] and [28] has been conducted. For this purpose, the number of power flow evaluations before reaching a solution in the IEEE 30-bus system has been considered. The system's data are obtained from reference [12] as was done in previous simulations. The results of this comparison are provided in Table XV. In the SCOPF case, N_c represents the number of evaluated contingencies. These figures prove that ECPA's performance is of the same order of magnitude as that of the other evaluated approaches.

TABLE XV
NUMBER OF POWER FLOW EVALUATIONS FOR THE IEEE 30-BUS SYSTEM

	[14]	[28]	ECPA
OPF	1800	1000	1760
SCOPF	$1800N_c$	$1000N_c$	$1800N_c$

ECPA has also been applied to the IEEE 118-bus test system, whose data are obtained from references [21] and [27].

The purpose of this experiment is to test the performance of the new algorithm in a larger scale system.

A set of 10 OPF and 5 SCOPF cases have been solved. 186 contingencies have been considered in the SCOPF case. Table XVI shows the average number of power flow evaluations required to achieve a solution. N_c represents the number of contingencies in the SCOPF case.

TABLE XVI
AVERAGE NUMBER OR POWER FLOW EVALUATIONS FOR THE IEEE 118-BUS TEST SYSTEM

	OPF	**SCOPF**
IEEE 118	2067	$2100N_c$

The data from Tables XV and XVI show that ECPA solves OPF and SCOPF problems in the IEEE 118-bus system with a modest increase in the number of power flows.

Fig. 2 shows the evolution of the fitness value during a typical ECPA-SCOPF run for the IEEE 118-bus system. The convergence rate is very fast and a reasonable solution is obtained after only 20 generations. This convergence behavior is similar to the one published in [21] for the IEEE 118-bus system, and outperforms the results published in [14].

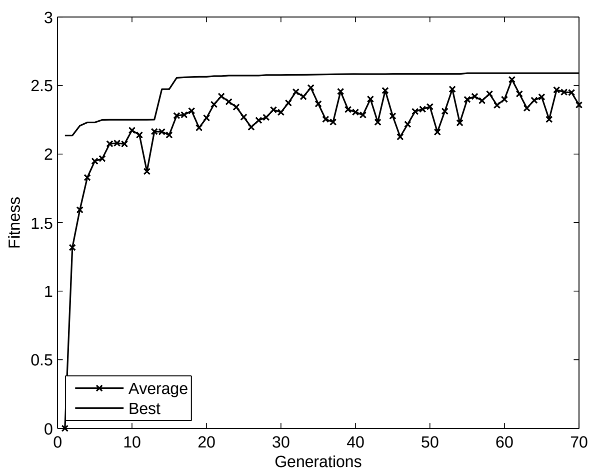

Fig. 2. Fitness function convergence of a typical execution of ECPA (IEEE 118-bus system).

V. CONCLUSIONS

This paper introduces a new method of removing thermal overloads and voltage limits in an electric power system by means of the Evolution of Corrective and Preventive control Actions (ECPA). The upper limits on the number of control actions together with the minimization of the cost function makes this algorithm find solutions with fewer control actions than other approaches. Besides, the numerical results confirm the effectiveness of ECPA. For example, in the corrective case and for the IEEE 30-bus system, the cost incurred by the best solution is below the best results that have been obtained in the literature, and fewer control actions are needed. In the preventive case, the proposed method is only surpassed by one work in which additional control variables have been used. Since ECPA is a genetic algorithm, the final solution is a whole population of individuals, which allows users to choose among alternative options. ECPA's computational burden for the IEEE 30-bus system is similar to that of other evolutionary alternatives. The method has also been applied to the IEEE 118-bus system. In this larger-scale network, the number of evaluated power flows is only slightly increased. Our future work will focus on the extension of the algorithm to a multi objective version.

APPENDIX A
PSEUDOCODE OF A GENETIC ALGORITHM

The following algorithm adapts a population $P(t)$ (t is the iteration number) of n individuals or solutions $\mathbf{x}_i^t$ ($i = 1, \ldots, n$):

$$P(t) = \{\mathbf{x}_1^t, \mathbf{x}_2^t, \ldots, \mathbf{x}_n^t\} \tag{25}$$

Procedure Genetic Algorithm
Start
$t \leftarrow 0$
Create $P(t)$
Evaluate $P(t)$
while Stop Condition = False **do**
    $t \leftarrow t + 1$
    Select $P(t)$ from $P(t-1)$
    Modify $P(t)$
    Evaluate $P(t)$
end while

The algorithm iterates until a stopping condition is reached, the simplest of which may well be "a fixed number of iterations is achieved". The function named Evaluate calculates the fitness of each individual in the population, which has to be maximized. Function Select makes use of these fitness values in order to create a pool of individuals that will be later used by function Modify in order to create the next population of individuals.

APPENDIX B
RER OPERATOR

The random equivalence recombination operator allows to generate a new individual $\mathbf{x}^t$ with size K from two parents $\mathbf{x}_1^{t-1}$ and $\mathbf{x}_2^{t-1}$ of the previous population, in the following way:

Procedure Random Equivalence Recombination
$\mathbf{x}^t = \emptyset$
$U = \mathbf{x}_1^{t-1} \cup \mathbf{x}_2^{t-1}$
while $|\mathbf{x}^t| < K$ **do**
    Randomly Select an item (s) from U
    Remove the selected item (s) from U
    $\mathbf{x}^t = \mathbf{x}^t \cup \{s\}$
end while

APPENDIX C
GRADIENT DESCENT ALGORITHM

The following code corresponds to the algorithm used in Section IV-C in order to set the values of the parameters:

1: Procedure Parameter Setting (N_s, N_{max})
2: Start
3: $\mathbf{p}^0 \leftarrow (p_1^0, p_2^0, p_3^0, ..., p_7^0)$
4: $f^0 \leftarrow f(\mathbf{p}^0)$
5: $\hat{f} \leftarrow f^0$
6: $\hat{\mathbf{p}} \leftarrow \mathbf{p}^0$
7: $i \leftarrow 1$
8: **while** $i \leq N_{max}$ **do**
9: $\quad \mu_j^i \leftarrow \hat{p}_j^{i-1} \qquad \forall j = 1, \ldots, 7$
10: $\quad \sigma_j^i \leftarrow \frac{\hat{p}_j^{max} - \hat{p}_j^{min}}{3} \qquad \forall j = 1, \ldots, 7$
11: $\quad p_j^i \leftarrow N(\mu_j^i, \sigma_j^i) \qquad \forall j = 1, \ldots, 7$
12: $\quad \mathbf{p}^i = (p_1^i, p_2^i, p_3^i, ..., p_7^i)$
13: $\quad f^i \leftarrow f(\mathbf{p}^i)$
14: $\quad$ **if** $f^i > \hat{f}$ **then**
15: $\qquad \hat{\mathbf{p}} \leftarrow \mathbf{p}^i$
16: $\qquad \hat{f} \leftarrow f^i$
17: $\quad$ **end if**
18: $\quad i \leftarrow i + 1$
19: **end while**

Notice that in order to calculate f in point number 13 above, ECPA is run N_s times because f is the mean best fitness value (MBF). N_{max} is the maximum number of iterations used. It has been set to 30 for corrective actions and 20 for corrective and preventive actions.

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