Critical Contingencies Ranking for Dynamic Security Assessment Using Neural Networks

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Abstract - **An important number of contingencies simulated during dynamic security assessment do not result in unacceptable values of state variables, due to their small influence on system operation. Their exclusion from the set of contingencies to be simulated in the security assessment would achieve a significant reduction in computation time. This paper defines a critical contingencies selection method for on-line dynamic security assessment. The selection method results from an off-line dynamical analysis, which covers typical scenarios and also covers various related aspects like frequency, voltage, and angle analyses among others. Indexes measured over these typical scenarios are used to train neural networks, capable of performing on-line estimation of a critical contingencies list according to the system state.**

Index Terms - **Critical Contingencies, Dynamic Security Assesment, Neural Networks**

I. Introduction

Recently, as a consequence of the deregulation of power industry, modern power system has been shifting from a regulated and vertically integrated system to a competitive and uncertain market environment. The introduction of competitive supply and corresponding organizational separation of supply, transmission, and system operation has resulted in more highly stressed operating conditions, more vulnerable networks, and an increased need to assess the dynamic security level of such modern power system. The importance of the dynamic security assessment is due to that, if the system is operating in an insecure state, control actions must to be determined and applied, so to bring the system to a more secure operation state. Dynamic security assessment, for any given state, is generally performed by simulating contingencies like line outage and generator outage in the power system, estimating their consequences on the system such as line overloading, relays operation, angle stability loss or voltage drop, and comparing these results with their corresponding acceptable values. It is important to mention that it is unnecessary and impractical to study all credible contingencies in detail, due to the fact that most contingencies simulated during dynamic security assessment do not result in unacceptable values of state variables, mainly due to their small influence on system operation [1][2]. Their exclusion from the set of critical contingencies to be simulated would achieve a significant reduction in computation time, which is an important issue for an on-line implementation of the dynamic security assessment [3][4][5]. Finding these critical contingencies for each state under study, requires for each system component a detailed analysis of its characteristics, its response to possible perturbations and its interaction with other system components. From the set of possible failures a subset must be obtained containing those regarded as most significant (i.e. critical) according to system operation state. The conventional analytical techniques used in contingency selection and ranking are usually time consuming and therefore not always suitable for on-line applications. Moreover, many performance indexes based on analytical methods suffer from the problem of misclassification and false alarm. Misclassification arises when a critical contingency is classified as non-critical. A false alarm occurs when a non-critical contingency is classified as critical. Given that, in general, the problem of contingency selection and ranking can be characterized by lack of precise mathematical model, and large volume of information to be handled, it would be possible to fulfill the requirements of critical contingencies analysis when working on-line by employing artificial intelligence (AI) techniques [6][7]. In recent years, there has been a growing interest in using AI and specifically artificial neural network based methods to screen and rank contingencies. In relation with the analytical methods, artificial neural network based methods are faster, requiring a less computational burden and also they have a better accuracy for on-line contingency ranking [8]. Bibliography presents a variety of techniques that can be used to carry out critical contingency selection and ranking using AI, but only a little experience exists related to carrying out this not only important but also necessary task quickly and effectively as is required by an on-line implementation of dynamic security assessment. In [9] a contingency ranking method is presented. The contingencies are ranked according to a performance index (PI), which is a scalar that reflects the severity degree of a contingency. In [10] it is presented an approach based on radial basis function neural network (RBFN) to rank the contingencies expected to cause steady state bus voltage violations. In [11] a three-layer perceptron artificial neural network with back propagation learning technique is designed for line flow contingency ranking. In this paper two new indices are defined (a severity index and a margin index for line flow). In [12] it is proposed an AI (fuzzy set) based contingency ranking. The post contingency system variables

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are first expressed in fuzzy set notation, and then the heuristic rules employed by the system operators are used to code in the form of fuzzy reasoning rules. In [13] it is used a method based on a coupled scheme (artificial neural network and expert system) for power system security enhancement, combining artificial neural network based contingency screening with an expert system based preventive control. An extended Hopfield neural network is used for evaluating the change in the performance index to determine the ranking of a contingency. The change in the performance index is realized as the energy function of the extended Hop field network. The mayor disadvantage of the proposed approach [9]-[13] is that the only includes only one issue regarding to dynamic security assessment in the contingency ranking process (for example voltage stability, power flow limits, etc.); without analyzing others important transient effects, as is necessary in a complete dynamic security assessment. This paper proposes a novel critical contingencies selection method for on-line dynamic security assessment. The selection method results from an off-line dynamical analysis, which covers typical scenarios. Indexes measured over these scenarios are used to train neural networks, capable of performing on-line estimation of a critical contingencies list according to the system state.

II. Critical Contngencies Selection

Conformation of critical contingencies list is done by comparing the severity level in which each contingency affects the system. The greater consequences suffered by the system, the higher the severity level will be. Due to inherent power system dynamics it becomes necessary to analyze the phenomena involving a failure not only from a stationary viewpoint but also from a dynamic one. In addition, the need of establishing contingencies severity levels as a measure of all aspects (stationary and dynamic) when a failure in some system component appears. The severity level indicator approach presented in this paper attempts to include the following phenomena which may arise after a failure: a) Significant increases in transmission lines currents, b) Voltage deviations which impact power quality, c) Variations in frequency, maximum deviation, duration, d) Load disconnections that interrupt energy supply to users. A failure in some component causes a perturbation, influencing certain system variables (undesirable failure consequences). These influences must be analyzed to get the failure security level. The method employed to find the security level consists in taking the distance from the security state for the new operation state to the security margin function. Security state is determined from indexes which somehow summarize failure consequences, while the security margin function represents a hyper-surface over which the system is secure.

III. Contingency Selection Methodology

The process of computing severity level involves two steps, the first done in an **off-line** stage and other in an **on-line** stage.

A. Off-line Stage

The **off-line** stage (see Fig. 3) aims to train two groups of neural networks, one group for estimating post contingency security state indexes and the other group for determining the security margin function. Training information for neural network is taken from the typical system state (base case scenario) and several scenarios extracted from the base case changing the load and generation in small steps ①. Once the scenarios are defined a list with all the contingencies to be ranked is created ②. For each scenario a power flow calculation is done ③, all the nodal voltages, line currents and power flows results are used to calculate the pre-contingency indexes ⑥. These indexes represent: the system state before contingency happens, and the failure characteristics. More detail of these indexes is given in the next sections. Using the obtained scenarios and the failure list, a power flow calculation ⑤ and a dynamic simulation ④ is done for each contingency following the N-1 security criteria. Using the results of the dynamic simulations and the power flow calculations the post-contingency indexes are calculated ⑦. More detail of these indexes is given in the next sections. To estimate the severity level ⑧ an expert system operator must analyze the results (dynamic simulations, power flows calculations, pre and post contingencies indexes) for each contingency in each scenario. From this analysis and his/her experience in the system operation the operator has to choose the most appropriate value. This is an empiric evaluation and the severity level is an empiric positive value that must measure the operating point deviation from the secure zone. For this reason a severity level of 0 indicates a secure state and this value increases as the security decreases. With the pre-contingency indexes as inputs and the calculated post-contingencies indexes as output a neural network is trained for post-contingencies index estimation in the on-line stage ⑨. To train the Severity Level Neural Network ⑩, the pre and post contingency indexes are employed as inputs and the Expert Severity Level Estimation is used as the output (see Fig. 1 for training details). Once this neural network is trained, the Security Margin Function ($f(\mathbf{x})$) is extracted. This function defines a hyper-surface where the system is totally safe [6]. This function is used in the on-line stage to estimate the Security Margin. To determine whether neural networks have been correctly trained, a new test scenario is extracted from the base scenario. Over this tests scenario all failures are simulated, indexes are computed from simulations and compared to those obtained from neural networks.

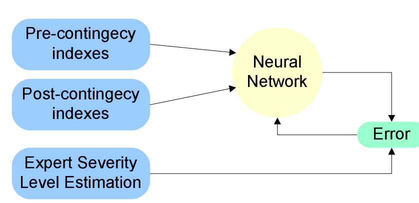

Fig. 1 Neural networks training to get the Security Margin Function.

B. On-line Stage

On the **on-line** stage the goal is to rank the contingencies for the current system state. This task is performed in several steps (see **Fig. 2**) but none of them is computationally intensive, some power flow calculations are done but no dynamic behavior is simulated. From the current load and generation scenario ① and the list with all the generators contingencies to be ranked ② power flow calculations are done for the current system state ③ and for each generator contingency ④. The power flow calculations are used to calculate the same pre-contingency indexes used in the off-line stage ⑤. The post-contingency indexes that were calculated in the off-line stage using dynamic simulations to train the post-contingency index estimation neural network are now estimated for each contingency in the list using the same trained neural network ⑥. These indexes define the estimated security state (**x**).To estimate the severity margin for each contingency, the distance between estimated security state and the surface given by security margin function is computed ⑦. Once each severity margin for each contingency is estimated, they are placed in decreasing order to get the contingency ranking ⑧.

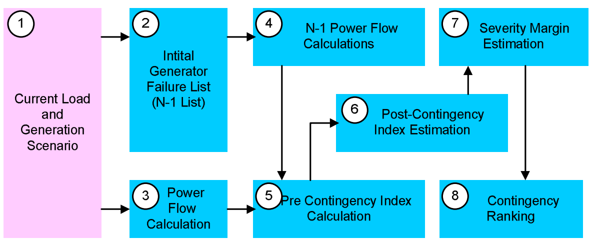

Fig. 2 On-line stage.

IV. Pre-contingency State Indicators

Pre-contingency state indicators are indexes expressing the system state before failure (1)(2) and also the magnitude of the failure (3)(4)(5). These indexes are used as input data in the on-line stage, so, they must be quickly computable to minimize estimation delay. The pre-contingency indexes are divided into three groups:

A. Power flow margin index MI, voltage margin index MTI

This group of indexes evaluates the system state before a contingency. The *MI* index gives a measurable value of the apparent power flow (current flow) capacity margin. *MTI* index measures the global voltage change margin.

$$MI = \sum_{1}^{NL} wl_i \left(\frac{I_i^{pre}}{I_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NL} wl_i \quad (1)$$

NL : Number of lines. I_i^{pre} : Current on line *i*. $I_i^{\lim}$: Limit current on line *i*. wl_i : Line weight factor, between 0 and 1.

$$MTI = \sum_{1}^{NN} wn_i \left(\frac{V_i^{pre} - V_i^{n}}{\Delta V_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NN} wn_i \quad (2)$$

NN : Number of nodes. V_i^{pre} : Voltage on node *i* before contingency. V_i^{n} : Nominal voltage on node *i*. $\Delta V_i^{\lim}$: Voltage deviation limit on node *i* (e.g.: 5% Vn). wn_i : Node weight factor, between 0 and 1

B. Quasi-stationary power flow index MQI and quasi-stationary voltage index MTQI

These indexes evaluate the system considering the component outage but calculating the system state using only stationary tools (AC power flow). They are defined as quasi-stationary indexes. *MQI* has the same meaning that the *MI* index but using the quasi-stationary power flow results. The same comparison applies to index *MTQI* with index *MTI*

$$MQI = \sum_{1}^{NL} wl_i \left(\frac{I_i^{quasi}}{I_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NL} wl_i \quad (3)$$

I_i^{quasi} : Current on line *i* after quasi-stationary failure.

$$MTQI = \sum_{1}^{NN} wn_i \left(\frac{V_i^{quasi} - V_i^{n}}{\Delta V_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NN} wn_i \quad (4)$$

V_i^{quasi} : Voltage on node *i* after quasi-stationary failure.

C. Disconnected generation index GI

This index evaluates the failure's magnitude comparing the disconnected generation produced by the failure with total system generation.

$$GI = \left(G_{out} / G_{total}\right) \cdot Fp \quad (5)$$

G_{out} : Power of failed generator. G_{total} : Total power system generation. Fp : Weight factor.

V. Post-contingency State Indicators

These indicators define the estimated security state during a contingency. These indicators are modeled by 4 groups of

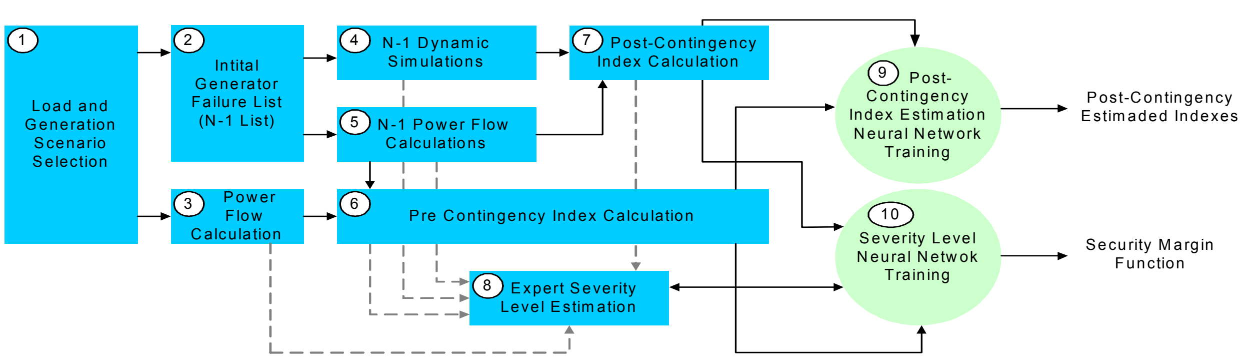

Fig. 3 Off-line stage

indexes:

A. Power flow index SI

The index is calculated by computing a weighted average of differences between current limit flow $I_i^{\lim}$ and the one after contingency I_i^{pos} [10] which is calculated as the final current value obtained after the system dynamic simulation. A weight is assigned to each transmission line in accordance with its importance in the power system; weight wl_i is the same value used in the pre-contingency (1) and in the quasi-stationary indexes (3). This weight is defined by the system operator. The equation used is:

$$SI = \sum_{1}^{NL} wl_i \left(\frac{I_i^{pos}}{I_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NL} wl_i \tag{6}$$

I_i^{pos} : Current on line *i* after failure.

B. Voltage index STI

Weighted average of differences between voltage deviation before and after failure and the acceptable voltage limit [4] are computed. The weight value corresponds to the importance assigned to each node by an expert operator as used in equation (2) and (4). The expression used is:

$$STI = \sum_{1}^{NN} wn_i \left(\frac{V_i^{pos} - V_i^{n}}{\Delta V_i^{\lim}}\right)^2 \Big/ \sum_{1}^{NN} wn_i \tag{7}$$

V_i^{pos} : Voltage on node *i* after failure.

C. Frequency deviation indexes FI and FT

Frequency deviation is a clear indicator of the system's dynamic evolution after a contingency. Two indexes are calculated: maximum frequency deviation index (8) and total frequency deviation index (9).

$$FI = \Delta F_{\max} \big/ \Delta F_{\max\, admissible} \tag{8}$$

$$FT = \int_0^{ts} \Delta F(t)dt \Big/ \Delta F_{admissible} \cdot ts \tag{9}$$

ΔF_{max} : Maximum frequency deviation. $\Delta F_{admissible}$: Maximum admissible frequency deviation.

D. Load shedding index PDI

This index indicates the amount of load disconnected after a failure. As the frequency deviation index this is an important indicator of the system state after a failure (10).

$$PDI = \Delta P_{disconnected} \big/ P_{total} \tag{10}$$

$\Delta P_{disconnected}$: Load disconnected through load shedding.

P_{total} : Total load before failure.

VI. Severity margin SM

In the off-line stage the pre and post contingency indexes are used to train the security margin neural network. Once this neural network is trained the security margin function is extracted. In the on-line stage the pre contingency indexes are calculated and the pos contingency indexes are estimated using the first group of neural network. The values of this indexes defines the operation security state of the system and are used to compute the severity margin by measuring the distance from this point to the security margin function. The security margin function is a multidimensional surface and the operational security point defines a point in this space. Fig. 4 shows an example of measuring the severity margin with only two indexes.

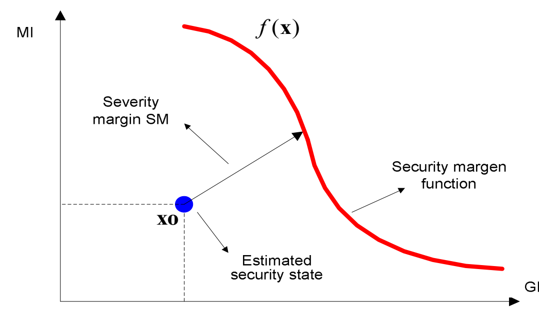

Fig. 4 Example of a Severity Margin calculated using only two indexes

The SM value is calculated by solving the following optimization problem:

$$\min|\mathbf{x} - \mathbf{xo}|\ ;\ \textbf{Subject To: } f(\mathbf{x}) = 0 \tag{11}$$

VII. Dynamic simulation

A. Power system components

The tool used for the dynamic simulations has an accurate representation for each power system component. The generation units, the grid and the load are mathematically modeled to reach simulation results similar to the reality. For the generation units three types of turbines are modeled: hydraulic, steam and gas. The electric generator is modeled as a synchronous machine. The speed and voltage regulators are also modeled. For the grid the lines and transformers are modeled as passive pi networks. Two types of loads are modeled: motor load and non motor load. The main characteristic of the motor load is that its active power consume make smaller when frequency drops. The non motor loads are modeled as a linear relation with the frequency and a non linear with the voltage. Automatic load disconnection is also modeled in two types, frequency relays and low voltage relays. Frequency relays disconnects load in steps, depending on the frequency value, or by gradient, measuring the rate of change of frequency. Low voltage relays disconnect load when the voltage violates the preset voltage limits.

B. Simulation time

The dynamics of interest in dynamic security assessment are, among others, the automatic load shedding, speed regulators, voltage regulators; all are mechanism that helps in the pos contingency state recovery. Starting from the system equilibrium point, the outage of a generation unit triggers a power unbalance. This unbalance is initially compensated by the rotating mass kinetic energy slowing down the system frequency. The frequency drop compensates in part the unbalance due to the frequency dependency of some loads. At some frequency deviation the generation units speed regulator start to act increasing the active power generated, in thermal units by increasing the steam output and in hydraulic units by increasing the water flow throw the turbine (primary regulation). This increment in power helps to take the system to a new equilibrium point. If this actions are not enough to reach the system equilibrium point, then the load disconnection is the last (and the worst) way to reach it. This mechanism helps to bring the system to a new stationary state. The new state of equilibrium is reached within approximately 20 seconds after the generator outage. This time period depends on the size of the system, the extent of the disturbance, the types of governors, the availability of spinning reserve, and the amount of load that can be disconnected. In order to include the dynamics of such mechanisms that help to recover the system operation, it is necessary to assess the performance of the system 20 seconds following the disturbance [12]. This is the time-frame considered in this work.

VIII. Application Example

The Argentinean 500 kV power system is taken as a test model system (see Fig. 5). The main characteristic of this system is its radial topology. Because of being a radial system it exhibits the disadvantage of having some unique paths for energy to go from generators to loads. This topology implies other problems such as the conformation of islands when important radial lines fail and the difficulty in replacing generation lost by the remaining generators when one generator fails. Due to these problems, Argentine power system is ill-conditioned, exposed to collapse after the occurrence of large failures. The initial failure list used in this example is composed by outages in main generators, and by outages of lines that join node GMZA500-RGRAN500 and YACIR500-RINCO500.

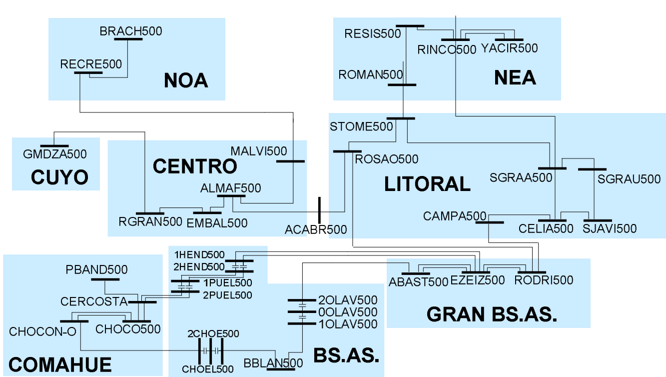

Fig. 5 500 kV Test System

A. *Off-line stage neural networks training*

Three load and generation scenarios are proposed, and failures for each single generator are simulated in the off-line stage. Proposed scenarios are: a) Scenario A = Base scenario. Generation: 5650 MW. Load: 5517 MW; b) Scenario B = A scenario + 500 MW load distributed among all load nodes; c) Scenario C = A scenario – 500 MW load distributed among all load nodes. TABLE I shows a critical contingencies list for each proposed scenario. Instead of using an expert operator to estimate the severity level of each contingency, the level was calculated adding each post-contingency index with a weighting factor. The severity level neural network was trained with these values, the Severity Margin Function was extracted and the SM values shown in TABLE I were calculated using this function. It can be seen that for scenarios A and C the list is similar up to the sixth contingency, this do not happen with scenario B where the similarity with the other two is up to the first contingency. This behavior is explained by analyzing security state indexes: for the RODRI500 generator contingency, the value of disconnected generation is similar in all of three scenarios 3.5 % 3.3 % and 3.9 % respectively, index flow values are also similar, but voltage index values are not similar, in scenario A is 0.0776, in scenario C is 0.139689 and in scenario B is 0.377309, higher than previous ones. Differences in contingencies list was to be expected since scenarios have different load levels.

TABLE I: CC For Scenarios A, B, C

Scenario A		Scenario B		Scenario C	
Outage	SM	Outage	SM	Outage	SM
YACIR500-RINCO500	43.662326	YACIR500-RINCO500	44.449091	YACIR500-RINCO500	45.996232
CHOCO500	3.58661	RODRI500	3.49964	CHOCO500	4.473781
EMBA500	2.670967	CHOCO500	3.207076	EMBA500	3.548333
CCOST500	1.764373	EMBA500	2.355602	CCOST500	2.256529
BBLA500	1.610828	CCOST500	1.58545	BBLA500	2.129098
GMZA500-RGRAN500	1.362748	ABAST500	1.496355	PILAR132	1.809512
RAMA220	1.348878	BBLA500	1.483668	RAMA220	1.749722
ABAST500	1.348025	GMZA500-RGRAN500	1.342004	OLAVA500	1.720783
ATUCH220	1.345319	ATUCH220	1.277675	SNICO132	1.690918
PILAR132	1.321216	RAMA220	1.261	ABAST500	1.674846
OLAVA500	1.299286	PILAR132	1.216443	ATUCH220	1.674553
SNICO132	1.276531	OLAVA500	1.212177	GMZA500-RGRAN500	1.635527
RODRI500	1.266391	SNICO132	1.199055	RODRI500	1.632284

B. *On-line stage test*

An intermediate scenario between the training ones was used as tests scenario. This tests scenario is described by: Scenario D = Base scenario + 250 MW load distributed among all load nodes. Results from this scenario are not used to train neural networks, they were employed only to obtain estimated indexes values and from them to get a severity level for each contingency. Once the indexes are estimated, the same failures are simulated and indexes and severity margin for each contingency are calculated. A comparison between contingencies lists obtained by estimation and by simulation is shown in TABLE II. It can be seen that the first four contingencies are the same, while the rest does not, the error in the contingencies list estimation is due to an existing error in security state indexes estimation.

TABLE II: Simulated and Estimated CC for Scenario D

Scenario D (Simulated)		Scenario D (Estimated)	
Outage	SM	Outage	SM
YACIR500-RINCO500	44.317445	**YACIR500-RINCO500**	44.480546
CHOCO500	3.356028	**CHOCO500**	3.708806
EMBA500	2.244625	**EMBA500**	2.282154
CCOST500	1.662381	**CCOST500**	2.013404
BBLA500	1.536574	RODRI500	1.932605
GMZA500-RGRAN500	1.351459	SNICO132	1.928779
ABAST500	1.300225	RAMA220	1.636928
ATUCH220	1.296962	BBLA500	1.583393
RAMA220	1.289881	OLAVA500	1.491689
PILAR132	1.258326	ATUCH220	1.470355
OLAVA500	1.246194	ABAST500	1.455058
SNICO132	1.226863	GMZA500-RGRAN500	1.427926
RODRI500	1.223033	PILAR132	1.340695

C. *Final test and On-line stage*

Given the not so much satisfactory results obtained when comparing contingencies lists in TABLE II the tests scenario is included as training data for neural networks, as an attempt to improve indexes estimation. To verify whether improvement exists when adding scenario D as training data, another tests scenario (Scenario E) was derived from the base scenario. This scenario consists in adding to the base scenario a 150 MW load uniformly distributed. The indexes and SM index were estimated for each failure in this scenario, and all failures were dynamically simulated and indexes are calculated for each contingency. TABLE III shows a comparison between contingencies lists obtained by estimation and by simulation.

TABLE III: SIMULATED AND ESTIMATED CC FOR SCENARIO E

Scenario E (Estimated)		Scenario E (Simulated)		Scenario E (Estimated)	
Outage	SM	Outage	SM	Outage	SM
YACIR500-RINCO500	44.359917	**YACIR500-RINCO500**	44.377559	**YACIR500-RINCO500**	44.400873
EMBA500	3.298236	**EMBA500**	3.222287	**EMBA500**	3.092986
CCOST500	2.962575	**CHOCO500**	2.863401	**CHOCO500**	2.946154
CHOCO500	2.319165	**CCOST500**	2.320389	**CCOST500**	2.279349
ABAST500	1.982618	**BBLA500**	2.034767	**BBLA500**	2.143031
RODRI500	1.923749	**RODRI500**	1.945171	**RODRI500**	1.908641
GMZA500-RGRAN500	1.821868	RAMA220	1.822203	ATUCH220	1.640684
ATUCH220	1.704511	ATUCH220	1.780764	ABAST500	1.616711
BBLA500	1.682856	ABAST500	1.692207	RAMA220	1.607112
RAMA220	1.424001	**GMZA500-RGRAN500**	1.484978	**GMZA500-RGRAN500**	1.539526
SNICO132	1.386794	**SNICO132**	1.405988	**SNICO132**	1.312402
OLAVA500	1.244918	**OLAVA500**	1.312675	**OLAVA500**	1.290389
PILAR132	1.206226	**PILAR132**	1.257427	**PILAR132**	1.276881

In the first column are the estimated indexes before adding D scenario as training data. In the second column are the simulated values of the severity indexes, this values are the reference, and the estimations must match them. The third column gives the estimated indexes after adding scenario D as training data. As can be seen, the third column list of contingencies is closer than the first column, due to the addition of scenario D as training data. Comparing this table the second and third columns of TABLE III with TABLE II, significant improvements are noticed in the contingency list estimation, however, errors prevail in some positions, mostly in those contingencies with similar severity level values (e.g. for nodes ATUCH220, ABAST500 and RAMAL220).

IX. CONCLUSIONS

The new competitive environment in that power systems operates, has created a need of an on-line dynamic security assessment, due to the necessity of predicting future operation conditions. In order to carry out a complete on-line assessment, it is necessary to evaluate the power system dynamic behavior when contingencies occur for a given operating state. This is a time-consuming task and most contingencies simulated do not result in unacceptable values of state variables, mainly due to their small influence on system operation. Therefore, previous selection of critical contingencies becomes necessary, specially to get an on-line dynamic security assessment implementation. This paper presents a new approach useful for selection and ranking of critical contingencies. The process of selection involves several steps, some of them done in an off-line stage and some in an on-line stage. Five pre-contingency state indicators and five pos-contingency state indicators are defined. It's true that proposed indexes not cover all the phenomena in the power system dynamics, buy they not pretend to be a security system measurement. However they are enough for contingencies selection because they provide information about the worst dynamic effects of systems failures. On the off-line stage the pre and pos-contingency indexes are calculated using dynamic simulations. A neural network is used for pos-contingency index estimation on the on-line stage. The method presented here for contingency ranking is an extension to similar methods used for contingency selection where no dynamic effects are considered. The extension proved to be effective in the example case based only in the proposed indexes.

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