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VOLTAGE STABILITY ANALYSIS OF ELECTRIC POWER SYSTEMS USING A FUZZY ARTMAP NEURAL NETWORK

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Abstract— This work presents a new methodology for evaluating electrical power systems static voltage stability. This methodology is referred to a neural inference system based on a fuzzy ARTMAP neural architecture whose training is realized from a data base generated by simulation using a computational program: load flow, security margin and data base construction (constituting the input/output of the neural network). This system presents precise results with faster answers, allowing the users to work with flexibility where structural modifications are required (real situations in system operation), when compared to other neural networks. To illustrate the proposed neural structure, results are presented considering a power system composed of 45 buses, 73 transmission lines and 10 synchronous machines.

Keywords— Artificial Neural Network, Adaptive Resonance Theory, Electrical Power Systems, Static Voltage Stability.

Resumo— Este artigo apresenta uma nova metodologia para estimar a estabilidade de tensão de sistemas elétricos, a qual é referida como um sistema de inferência neural baseado em uma arquitetura ARTMAP fuzzy cujo treinamento é realizado com uma base de dados gerado por simulação de um programa computacional: fluxo de carga, margem de segurança, e construção de uma base de dados que se constitui na entrada/saída da rede neural. Este sistema apresenta resultados precisos com uma rápida resposta permitindo aos usuários trabalhar com flexibilidade em situações de modificações estruturais (situações reais), comparando com outras redes neurais. Para ilustrar a metodologia proposta, apresentam-se resultados para um sistema de potência real composto por 45 barras, 73 linhas de transmissão e 10 máquinas síncronas

Palavras-chave— Redes Neurais, Teoria da Ressonância Adaptativa, Sistemas Elétricos de Potência, Estabilidade de Tensão.

1 Introduction

Angle and voltage stability are a very important investigation procedure in electric power systems [Wehenkel, 1997]. This procedure analyses and executes strategies to guarantee the energy supplying with quality and avoids or at least minimizes interruptions of electric energy supplying. Stability associated to angles corresponds to transient stability, evaluating effects from perturbations that cause great and undesirable oscillations on the synchronous machines angles Voltage stability investigates the behavior of the voltage profile, specially observing and identifying voltage problems from an increasing of the power consumption.

Voltage stability can be approached in two forms: static and dynamic. The dynamic behavior is modeled by a set of non-linear ordinary differential equations [Vu, et al. 1995]. It is a complex analysis specially when dealing with large systems. A simpler form of voltage stability is referred to observe nodal voltage behavior considering the gradual increase of the system loading profile, *i. e.* the qualitative analysis of the operation point. In this case, the analysis can be treated as a linear problem. The inferences on the system are based on analyzing the behavior of the balance point, mainly from analyzing the Jacobian ($\boldsymbol{J^o}$) matrix of the nodal power equations which is a power flow problem formulated by Newton Raphson method [Arya, et al. 2008; Jia and Jevasurya, 2000; Nan, et al. 2000; Sinha and Hazarika, 2000; Tiranuchit and Thomas, 1988].

Thus, from the analysis of the Jacobian J^o matrix, it is possible to determine the stability of the system. This analysis can be effectuated, for example using eigenvalue/eigenvector decomposition of the Jacobian matrix, tangent vectors, among other techniques. The behavior of the system for small perturbations can be analysed by the eigenvalues of the Jacobian $\boldsymbol{J^o}$ matrix. If all eigenvalues are real and positive, the system is stable for small perturbations. However, if there is one eigenvalue with real part negative, it is unstable. The problem occurs when the Jacobian matrix $\boldsymbol{J^o}$ becomes singular (there is at least one eigenvalue equal to zero). Therefore, the Jacobian J^o matrix determinant is also zero. This is the form that is frequently approached on the appropriated bibliographic references.

This paper proposes to develop a neural system to execute the voltage stability diagnosis (static) of electrical power systems. Neural networks are structures implemented in hardware and/or software, based on the human brain mechanisms and therefore able to learn with experience [Haykin, 1994]. To obtain the desired results, *i.e.* the network presents conditions to effectuate complex diagnosis, such networks must be formed by several neural unities (or processing elements), disposed in layers composing a complex interconnected arrangement [Widrow and Lehr, 1990]. These interconnections are composed by weights which must be adjusted. The neural network processing is composed of two fundamental steps: training and analysis. The training phase requires much processing time while the analysis phase is processed almost without computational effort. Therefore, this is the principal justification to use neural networks to solve complex problems that needs fast solutions, as the applications in real time. The training phase is mainly executed with backpropagation procedure [Widrow and Lehr, 1990], which is not so fast and sometimes without convergence specially when working with huge data bank. New neural structures have been approached to solve the problem of excessive processing time for training. Thus, the neural networks of ART (Adaptive Resonance Theory) family [Carpenter, et al. 1992], that present the characteristics of stability (capacity to learn by adjusting the weights) and plasticity (capacity to continue learning including new patterns without loosing the memory related to the previous patterns) are emphasized.

This paper presents a neural system to execute the voltage static stability diagnosis. The neural network used is an ART-descendent architecture, *i.e.* a fuzzy ARTMAP including improvements to become more precise when compared to the original formulation [Carpenter, et al. 1992]. Some proposals for voltage stability analysis with neural networks are found on the literature: [Pandit, et al. 2007; Wan and Ekwue, 2000], among others. But, most of them are based on backpropagation training, or similar techniques, whose associated problems were previously described.

The training criterion of this neural network is a security margin index (already developed) based on the sensitivity analysis of the determinant function of $\boldsymbol{J}^{\mathbf{o}}$ matrix, which is calculated using the Kronecker [Geromel, 1987] algebra concepts. This procedure is used in this paper to validate the proposed methodology (fuzzy ARTMAP neural network). Nevertheless, this conception can be modified to realize other security index that can produce less conservative results, e.g., based on the continuation methods (according to Arya et al., 2008). The security index is generated forming a data base to the execution of the training phase using the computational program named *Simul* [Ferreira, et al. 2006]. To obtain such indexes some modifications were included in the *Simul* program to generate random or pseudo random combinations of generation/load profiles simulating a major quantity of operational situations [Ferreira, et al. 2006] and, consequently obtaining the corresponding security indexes. This procedure of obtaining random generation/load profiles is used as a more real processing analysis, instead of those commonly used on the literature using the proportionality criterion of the referred profiles.

Therefore, this paper presents a formulation of a new neural methodology to voltage stability analysis of electrical power systems. Considering the performance characteristics of this methodology (faster training, precision of the results, and flexibility to adapting to the topological diversities of the electrical network), it is possible to use in analysis of real electrical power systems.

2 Proposed Methodology

The proposed schema (neural system) to execute the voltage stability analysis for electrical power systems is presented as follows. Neural network processing is basically divided in two principal phases: (1) training or learning; (2) tests and diagnosis. The neural network used is a fuzzy ARTMAP architecture [Carpenter, et al. 1992]. The training phase is executed using a teacher represented by a simulator (computational program) [Ferreira, et al. 2006] that effectuates electrical network calculus: network matrices, load flow and transient stability analysis. This program was also adapted to execute the calculus associated to the static voltage stability according to the criterion presented on Section 3, and the data base constituted of input/output patterns of the neural network training.

The input data when available for executing the voltage stability analysis being a ($\boldsymbol{P}$, $\boldsymbol{Q}$, $\boldsymbol{Z}$) vector is used associated to the ($\mathcal{M}$) output to be inserted on the data base adapting the weights. The vector $\boldsymbol{Z}$ contains the binary information, which codifies the electrical network topology, the contingency data, etc.

3 Static Voltage Stability Analysis Criterion

The static stability analysis of electrical power systems consists of behavioral investigation of a model corresponding to the linearized solution of power system equations [Tiranuchit and Thomas, 1988], except the reference bus:

$$\begin{bmatrix} \Delta \boldsymbol{P} \\ \Delta \boldsymbol{Q} \end{bmatrix} = \begin{bmatrix} \boldsymbol{J}^{\mathrm{O}} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{\theta} \\ \Delta \boldsymbol{V} \end{bmatrix} \tag{1}$$

where:

$\Delta \boldsymbol{P}$ = vector of active power of busses PV and QP;

$\Delta \boldsymbol{Q}$ = vector of reactive power of busses PQ;

$\Delta \boldsymbol{\theta}$ = vector of angles on busses PV and PQ;

$\Delta \boldsymbol{V}$ = vector of nodal voltages of busses PQ;

$\boldsymbol{J}^{\mathbf{o}}$ $\underline{\Delta}$ Jacobian matrix

$= \begin{bmatrix} \boldsymbol{H} & \boldsymbol{N} \\ \boldsymbol{M} & \boldsymbol{L} \end{bmatrix}$

The matrices $\boldsymbol{H}$, $\boldsymbol{N}$, $\boldsymbol{M}$ and $\boldsymbol{L}$ are the sub matrices of $\boldsymbol{J}^{\mathbf{o}}$ corresponding to $\partial \boldsymbol{P}/\partial \boldsymbol{\theta}$, $\partial \boldsymbol{P}/\partial \boldsymbol{V}$, $\partial \boldsymbol{Q}/\partial \boldsymbol{\theta}$ and $\partial \boldsymbol{Q}/\partial \boldsymbol{V}$, respectively.

This paper investigates the static voltage stability using the security margin obtained by estimating the critical eigenvalue [Isoda, et al. 2008]. The critical eigenvalue $\lambda_{\min}(\boldsymbol{J}^{\mathbf{o}})$, which is defined as the least positive eigenvalue of the Jacobian matrix $\boldsymbol{J}^{\mathbf{o}}$, corresponds to the eigenvalue used for the voltage stability analysis, considering that it is the nearest one of the voltage collapse and therefore, presents the most possibility to become zero as the electrical demand increases. Monitoring $\lambda_{\min}(\boldsymbol{J}^{\mathbf{o}})$ is an important instrument of analyzing voltage stability of electrical power systems, according to the literature [Arya, et al. 2008; Jia and Jevasurya, 2000; Nan, et al. 2000; Sinha and Hazarika, 2000; Tiranuchit and Thomas, 1988]. Such security margin is estimated based on the sensitivity analysis of the determinant function of the $\boldsymbol{J}^{\mathrm{o}}$ matrix, calculated from the Kronecker algebra concept [Isoda, et al. 2008] as follows:

$$\lambda_{\min}\left(\boldsymbol{J}^{\mathrm{o}}\right) \geq \sqrt{\frac{1}{<\boldsymbol{\alpha},\boldsymbol{\alpha}>}}$$

where:

$\boldsymbol{\alpha} = [C_{11} \ \ldots \ C_{p1} \ \ldots \ C_{1p} \ \ldots \ C_{pp}]^{\mathrm{T}}$ and

$$[(\boldsymbol{J}^{\mathbf{o}})^{-1}]^{\mathrm{T}} = \begin{bmatrix} C_{11} & \cdots & C_{1p} \\ \vdots & \vdots & \vdots \\ C_{p1} & \cdots & C_{pp} \end{bmatrix}.$$

Therefore, the index

$$\mathcal{M} = \sqrt{\frac{1}{<\boldsymbol{\alpha},\, \boldsymbol{\alpha}>}} \geq 0$$

is the security margin and represents the pessimist estimation (favorable to the system security) of the $\lambda_{\min}(\boldsymbol{J}^{\mathbf{o}})$ parameter and is used as the electric power systems voltage stability inference criterion by neural networks.

4 Fuzzy ARTMAP Neural Network

The fuzzy ARTMAP neural network [Carpenter, et al. 1992] is composed of two fuzzy ART modules interconnected by a mechanism called inter ART as described below. Firstly the Fuzzy ART module is described. Lines represent the vectors instead by columns as usual adopted on the literature for the ART descendent neural networks.

The input data are denoted by vector $\boldsymbol{a} = [a_1 \cdots a_M]$ M-dimensional, and it is normalized to avoid proliferation of categories. Thus:

$$\bar{\boldsymbol{a}} = \frac{\boldsymbol{a}}{|\boldsymbol{a}|}$$

where:

$\bar{\boldsymbol{a}}$ = normalized input vector;

$|\boldsymbol{a}|$ = $\sum_i a_i$.

The input vector is a $2M$-dimensional one denoted by:

$$\boldsymbol{I} = [\ \bar{\boldsymbol{a}}\ \bar{\boldsymbol{a}}^{\,c}\ ] \equiv [\bar{a}_1 \ldots \bar{a}_M\ \bar{a}^{\,c}_1 \ldots \bar{a}^{\,c}_M]$$

where:

$\bar{\boldsymbol{a}}^{\,c}$ = $\bar{a}^{\,c}_i = 1 - \bar{a}_i$.

The activity vector of F_2 is represented by $y = [y_1, y_2, \ldots, y_N]$ where N is the quantity of categories created in F_2. This way:

$y = 1$, if node J of F_2 is active

$y = 0$, on the contrary.

The parameters used on the fuzzy ART network processing are: choice parameter ($\alpha > 0$), training rate ($\beta \in [0,1]$) and the vigilance parameter ($\rho \in [0,1]$). Firstly, all the weights are equal to 1, indicating that there is no active category. The algorithm that shows all procedures used on the ARTMAP neural network is found on reference Lopes, et al. (2005).

ARTMAP neural network [Carpenter, et al. 1992] is a supervised neural network, *i.e.* based on input-output stimulus. It is composed of two fuzzy ART modules: ART_a and ART_b interconnected by associative memory inter ART module F^{ab}, that has a mechanism named match tracking that maximizes the generalization and minimizes the error of the network.

The input vector of ART_a network is represented by $\boldsymbol{a} = [a_1 \ldots a_{M_a}]$, M_a-dimensional, and the input vector of ART_b (that corresponds to the desired output referred to the input pattern of ART_a network) is represented by $\boldsymbol{b} = [b_1 \ldots b_{M_b}]$ M_b-dimensional [Carpenter, et al. 1992].

The parameters used on fuzzy ARTMAP network are the same used on fuzzy ART network. The difference on fuzzy ART neural network is the vigilance parameter of inter-ART module ρ_{ab} ($\rho_{ab} \in [0,1]$).

ARTMAP neural network processes the two ART networks (ART_a and ART_b), and afterwards the resonance is confirmed in each network, as follows:

- J = active category for ART_a network;
- K = active category for ART_b network.

The match tracking process verifies if the active category on ART_a corresponds to the desired output vector presented on ART_b . The vigilance criterion is given by [Carpenter, et al. 1992]:

$$\frac{\left| y^b \wedge w^{ab}_{Jk} \right|}{\left| y^b \right|} \geq \rho_{ab} \tag{2}$$

where:

y^b = output vector of ART_b (activity pattern of $F^{\,b}_2$).

If (2) is not satisfied, the vigilance parameter of ART_a, is incremented minimally such as to exclude the current category and select another category to become active and entering again on the process until (2) is satisfied. With resonance confirmed the weights of modules ART_a and ART_b are updated using the same criterion of fuzzy ART neural network. The adaptation of fuzzy ART is effectuated as follows:

$w^{ab}_{JK} = 1$ for $k = K$

$w^{ab}_{JK} = 0$ for $k \neq K$.

4.1 Input Stimulus of the Fuzzy ARTMAP Neural Network

The proposed neural structure aims to analyze the transient stability of electric energy systems, which corresponds to determine the security margin considering three phase short circuits with transmission line outages. The input pattern vectors of the neural network are defined as:

$$\boldsymbol{X} = [\boldsymbol{P}\ \ \boldsymbol{Q}\ \ \boldsymbol{Z}]$$

where:

- $\boldsymbol{X}$ = neural network input pattern vector;
- $\boldsymbol{P}$ = $[P_1\ \ P_2\ \ldots P_n]$;
- $\boldsymbol{Q}$ = $[Q_1\ \ Q_2\ \ldots Q_n]$;
- $\boldsymbol{Z}$ = vector containing the information in binary code;
- P_i = active power of the i^{th} bus of the system;
- Q_i = reactive power of the i^{th} bus of the system;
- n = number of busses of the system.

The training execution – extract the knowledge based on input/output stimulus – is proceed presenting a set of data, $\boldsymbol{X} = [\boldsymbol{P}\ \boldsymbol{Q}\ \mathbf{Z}]$ (input) and $\boldsymbol{Y}$ (output), constituting a set of training pair. It is the formation of vectors $\boldsymbol{P}$ and $\boldsymbol{Q}$, for generation and load by a proceeding of random generation distribution (random dispatch to attend the demand) and also random load distribution (random demand) as shown below [Ferreira, et al. 2006]. The vector $\boldsymbol{Z}$ formed by information (binary code) representing the topology of the electrical network, the contingency data, etc.

Consider a system with a determined topology containing *NB* busses, where *NG* is the generation busses and the others are load busses ($NL = NB - NG$). Yet consider, that is desired to effectuate the generation dispatch to attend a variable demand taking as reference the base case: $\boldsymbol{PG}^o$, $\boldsymbol{QG}^o$, $\boldsymbol{PL}^o$ and $\boldsymbol{QL}^o$,

where:

- $\boldsymbol{PG}^o$ = active power vector of the generators for the base case;
- $\boldsymbol{QG}^o$ = reactive power vector of the generators for the base case;
- $\boldsymbol{PL}^o$ = active power vector of the loads for the base case;
- $\boldsymbol{QL}^o$ = reactive power vector of the loads for the base case.

To generate a large variation of the demand, the criterion used is referred to a random distribution of the demand and consequently of the generation to attend the demand. Therefore, the generation is varied in percents toward the base case (considering the generation/load profile of 100%). For example, with a 10% variation, several generation/load profiles can be realized, proceeding generation dispatches and defining the load of the system, with a random distribution of the generation and the load on the busses of the system according to the percent arbitrated

The active power of the generation busses is defined as [Ferreira, et al. 2006]:

$$PG_i = PG_i^o + \Delta PG_i$$

where:

- PG_i = active power on the i[th] generator fixed randomly (or pseudo-randomly);
- ΔPG_i = PG^o_{total} x Per x AG_i / KG
- $PG^o_{\text{total}} = \sum_{i\,\in\,\Omega(G)} PG^o_i$
- $\Omega(G)$ = set of generation busses;
- Per = percent of the demand variation (positive and negative values: for example, $Per = \pm 10\%$ corresponds to 90% and 110% of the base case, respectively;
- AG_i = random number of a sequence of *NG* numbers generated from a given seed. Varying the seed a different sequence of values is obtained and this variation is within 0 and 1: $AG_i \in [0,1]$;
- KG = $100\ AG_{total}$
- $AG_{total} = \sum_{i\,\in\,\Omega(G)} AG_i$.

The reactive power of the synchronous machines is determined on the routine referred to the power flow (PV busses).

In relation to the active loads, the variation profiles (variable demand curve) can be obtained by [Ferreira, et al. 2006]:

$$PL_i = PL_i^0 + \Delta PL_i$$

where:

- PL_i = active power on the i[th] load fixed randomly;
- ΔPL_i = PL^o_{total} x Per x AL_i / KL
- $PL^o_{\text{total}} = \sum_{i\,\in\,\Omega(L)} PL_i^o$
- AL_i = random number from sequence of *NL* number generated from a given seed, $AL_i \in [0,1]$.
- KL = $100\ AL_{\text{total}}$
- $AL_{\text{total}} = \sum_{i\,\in\,\Omega(L)} AL_i$.
- $\Omega(L)$ = set of load busses.

The reactive loads are fixed considering a distribution that preserves the power factor referred to the base case. This procedure tries to set a distribution with a inter relation level with the most plausible active power when compared to [Ferreira, et al.

2006]. However, it is also possible to search for other distribution forms of the active loads that will be investigated in another work.

4.2 Output Stimulus of the Fuzzy ARTMAP Neural Network

The output stimulus is the security margin ($\mathcal{M}$). The training patterns correspond to the parameters:

$\boldsymbol{X}_j = [\, \boldsymbol{P}_j \;\; \boldsymbol{Q}_j \;\; \boldsymbol{Z}_j]$ (inputs)

$\boldsymbol{Y}_j = [\, \underline{\mathcal{M}}_j]$ (outputs)

$j = 1, 2, \ldots, np$.

where:

$\underline{\mathcal{M}}_j$ = j^{th} security margin represented by severity classes;

np = number of pattern pairs for the training phase.

The output, M_i, is codified by classes (in binary code), where each class expresses the severity grade of the contingencies.

5 Applications

Results are presented considering a power system composed of 45 busses, 73 transmission lines and 10 synchronous machines [Ferreira, et al. 2006]. The system diagram and the data of the synchronous machines and the transmission system are related on reference [Ferreira, et al. 2006]. The neural network training is executed considering a set of 700 generation/load profiles and respective security margins $\mathcal{M}$. Each profile corresponds to a generation redispatch in relation to the base case, effectuated in a random way to attend the demand also fixed in a random way in each bus. The variation interval is within 65 and 135%, in relation to the total load of the system. Therefore, each profile is generated considering a percent toward the nominal state (base case) and a determined seed for the process of random sequence generation. Thus, for a same percent, different seeds can generate different generation dispatches for different load profiles. Afterwards the network training the tests (voltage stability analysis) are effectuated whose results are shown at Table 1. The results are presented in classes from 1 to 15. These classes are adopted to constitute the outputs in binary code, which is more adequate to use in neural networks of the ART family. Thus, the following definition is adopted for classes 1, 2, ... ,15 (representation with 4 bits) corresponding to $0 \le \mathcal{M} \le 0.1$, $0.1 \le \mathcal{M} \le 0.2$, ..., $1.4 \le \mathcal{M} \le 1.5$, respectively. Therefore, the distances, which each generation/load profile is in relation to the voltage stability limit, can be inferred. Such intervals associated to the classes can be defined increasing or decreasing according to the user interests. In this case, the number of bits must be adjusted in function of the major or minor size of the interval used. It is emphasized that the correct results of the neural network are greater than 85% considering the 700 simulations effectuated. This result is superior to 95%, when there is relaxing on a neighbor class since it corresponds to the most critical class, i.e. favorable to the system security. This percent certainly is going to increase while new patterns will be incorporated to the data base by the continuous training process.

Table 1. Comparison of Fuzzy ARTMAP and *Simul* Methods.

%	Seed	$\mathcal{M}$ by Simul	$\underline{\mathcal{M}}$ Simul	$\underline{\mathcal{M}}$ Fuzzy ARTMAP
67.5	123	.5994	6	6
72.5	51	.7413	8	8
77.5	614	.7096	8	8
87.5	31	.6551	7	8
92,5	123	.7003	8	7
97.5	7116	.7134	8	8
102.5	102	.6897	7	7
112.5	74	.6694	7	7
112.5	31	.7048	8	7
117.5	123	.6722	7	7
117.5	6691	.6183	7	7
122.5	145	.6055	7	6
122.5	221	.6528	7	7
122.5	377	.5662	6	6
127.5	7116	.4389	5	4
127.5	8555	.5840	6	6
132.5	123	.5873	6	6
132.5	421	.5054	6	5

6 Conclusions

A new methodology for multimodal electric power system stability analysis is presented. It is a methodology using a fuzzy ARTMAP network whose training is effectuated by a data base generate with simulations (using the computational program *Simul*); load flow calculus as well as other parameters that were implemented to attend the needs of the proposed study. Considering the strategy of obtaining this data base (defining the generation/load profile randomly) a large variation of operational states is provided allowing simulating real operational states. The fuzzy ARTMAP architecture as well as other ART family architectures presents the characteristics of plasticity that is an advantage in relation to other neural networks commonly used on the literature.

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