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VULNERABILITY EVALUATION IN ELECTRICAL POWER SYSTEMS

EVALUACION DE VULNERABILIDAD EN SISTEMAS ELECTRICOS DE POTENCIA

PhD. Fredy A. Sanz CINVESTAV-GDL, Department of Electrical Engineering, Bosque Av. 1145, Zapopan, Jalisco, Mexico, <u>fsanz@gdl.cinvestay.mx</u> PhD. Juan M. Ramirez CINVESTAV-GDL, Department of Electrical Engineering, Bosque Av. 1145, Zapopan, Jalisco, Mexico, jramirez@gdl.cinvestay.mx PhD. Rosa E. Correa Universidad Nacional de Colombia, Facultad de Minas, Carrera 80 No. 65-223. Medellín, Colombia, rcorrea@unal.edu.co

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Resumen: en la actualidad los sistemas de potencia operan cada vez más cerca de su capacidad, por lo cual es de gran importancia poder monitorear las variables eléctricas en tiempo real, para así poder inferir sobre la salud de la red frente a cada condición de contingencia o carga que se presente en la red eléctrica. Adicionalmente, el concepto de *Smart-grid* ha planteado diferentes retos, entre los cuales se destaca la evaluación de la seguridad en la red, para poder tomar decisiones anticipadas que eviten que el sistema pueda entrar en situaciones que pongan en riesgo la continuidad del suministro de energía. Considerando que, en la mayoría de los casos, los problemas de seguridad se traducen en una inestabilidad de voltaje, se plantea una estrategia a través de la cual pueda obtenerse una estimación de la cercanía al colapso de tensión, que se ha denominado vulnerabilidad, con la premisa de que no se requeriré el cálculo de flujos de potencia, necesitando saber Únicamente los voltajes en los buses del sistema.

Palabras clave: vulnerabilidad, estimación estadística, voltaje colapse, VCPI, modelos estadísticos

Abstract: nowadays power systems increasingly operate near to their capacity, therefore it is very important the electrical variables real time monitoring, in order to infer on the power grid health for each load condition or contingency. Additionally, the smart grid concept has posed different challenges, among which stands out the online assessment of network security to make early decisions avoiding some situations that put at risk the power supply continuity. Whereas in most cases security problems result in voltage instabilities, is proposed a strategy that permit a voltage collapse proximity estimation, which has been called vulnerability, the premise is that power flow calculation is not required, requiring only to know the bus voltages.

Keywords: vulnerability, statistical estimation, voltage collapse, VCPI, statistical models.

1. INTRODUCTION

A power system may become vulnerable for everal reasons: natural calamities, component failures, protection and control failures, information and communication failures, instability due to disturbances, human errors, inadequate security assessment procedures, sabotage, and missing or uncertain information in decision making [1]. Causes of instability that are internal to the civil infrastructure may be reduced by decreasing the probability and severity of occurrences through the improved engineering of related systems. On the other hand, causes of instability that are external to the infrastructure (e.g., different contingencies) may be reduced by decreasing the severity of occurrences by constructing defender restoration systems [2].

The vulnerable system concept means that systems operate with a reduced level of security that renders it vulnerable to small changes in electrical variables (charge, generation, or moderate disturbances). In this definition, it is noted that it is weird that a major system failure is the result of one catastrophic disturbance [1,3]. Power system stability implicates the system evolution when a disturbance evolves into a change in the operating point. Although small changes in electrical variables do cause alterations in system performance and can be studied as small signal security, system security is generally concerned with large changes, which are known as contingencies [4].

In the context of Security Analysis (SA), the study of system behavior is subject to a set of contingencies, to identify whether the system has the necessary security conditions to survive after an event or contingency. The power system's behavior and its restrictions depend on its nature and configuration. Therefore, risks derived from contingencies could be affected in different ways, within which may be mentioned: tripping lines, transformers, and generators, or a combinations of the above, etc. [5, 6].

2. VOLTAGE COLLAPSE

The conventional quasi-steady state power system model for voltage stability analysis is generally expressed by differential and algebraic equations as follows [7, 8]:

$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{y}, \lambda) \tag{1}$$
$$0 = g(\mathbf{x}, \mathbf{y}, \lambda)$$

Where x is the vector of state variables; y is the algebraic variables vector, and A is a parameter that slowly changes, so that the power system moves from an equilibrium point to another until reaching the point of collapse according to,

$$P_{D,i} = P_{D,i}(1 + k_{P,i}\lambda)$$

$$Q_{D,i} = Q_{D0,i}(1 + k_{Q,i}\lambda) = P_{D0,i} \tan(\phi_i)(1 + k_{Q,i}\lambda)$$
(2)

Where P_{DI} and Q_{DI} represent the active and reactive power demand at *i-th* bus, respectively; P_{DOI} and Q_{DOI} are the initial active and reactive power demand before the load changes, respectively; k_P and are constants representing changes (either increments or decrements) in active and reactive power demand at *i-th* bus, respectively; *co*, is the power factor at bus i. The active power output of the *i-th* generator should be modified to accommodate the changed power demand according to [7, 9]:

$$P_{G,i} = P_{G0,i}(1 + k_{G,i}\lambda)$$
(3)

Where P_{GOI} is the *i*-th initial active power generation; K_{GI} is the constant specifying the rate of change in generation when λ is varied.

2.1. Steady-state stability

Ordinarily, four analysis approaches may be used for the steady-state stability assessment: (*i*) direct method; (*ii*) modal analysis; (*iii*) continuation method; and (*iv*) optimization method [8]. In this paper, the continuation method is used.

Continuation power flow method (CPF): In this approach, the voltage profiles depicted in the PV and QV curves have a practical use to determine the collapse proximity, so that operators can take proper preventive control actions to safeguard the system. To achieve the complete voltage profile, successive power flow solutions or the continuation method can be used. The latter overcomes certain difficulties of the successive power flow method, because the complete voltage profile is generated by automatic changes of the loading parameter A, and overcomes the singularity problem of the system equations in the voltage stability limit neighborhood [7, 9]. In the continuation method the system is initially at the equilibrium state (z., k.). Using a known equilibrium point the vector direction Az, is computed, and a change AX, in the so called predictor step, which thereby generates an initial guess $(z, +Az_{1}, X + AX_{2})$ detecting if this point may be not an equilibrium state. Consequently, the corrector step is applied to compute a new equilibrium point $_{(Z2, X2)}$.

The predictor step with the initial guess is $(z, +Az, \Lambda + A\Lambda)$, the actual point (z_2, Λ_2) on the system profile must be computed by solving the following equations for z and Λ

$$F(\mathbf{z}, \lambda) = 0$$

$$\rho(\mathbf{z}, \lambda) = 0$$
(4)

The first equation corresponds to the system-state (in this case power flow) equations. The second one is a phase condition that ensures non-singularity of the system Jacobian matrix at the bifurcation point. Two phase conditions have been successfully used in the corrector strategies [7].

2.2. Voltage stability indices

The Voltage Collapse Proximity Index (VCPI) investigates the stability of each bus in the grid [10, 11]. It is derived from the basic power flow equations. Its derivation begins from finding the complex power injected into bus k.

The calculation of this index requires the voltage phasor information of buses as well as the bus admittance matrix. The VCPI for the k-th bus is defined as,

$$VCPI_{k} = \left| 1 - \frac{\sum_{m=1,m \neq k}^{N} V_{m}'}{V_{k}} \right|$$
(5)

$$V_m' = \frac{Y_{km}}{\sum_{j=1, j \neq k}^{N} V_m}$$
(6)

where, V, is the voltage phasor at bus k, V. is the voltage phasor at bus m, K. is the admittance between bus k and bus m, 3^7 , is the admittance between bus k and bus j, k is any monitoring bus, m is other bus connected to bus k. The VCPI value ranges in the interval [0, 1]. If the index is zero, the voltage at bus k is assumed quite stable and if the index is 1, a voltage collapse is expected. For the operating condition, the *Global VCPI* is defined as the maximun VCPI found among in all buses at any given time.

Different studies have been carried out to evaluate the predictive ability of VCPI index. Comparison of stability index based on powers and voltages is presented in [11]. Researches have shown that VCPI is a reliable vulnerability indicator, due to it captures the accurate proximity to voltage collapse.

3. VULNERABILITY EVALUATION

In order to quantify the system's vulnerability modification under load increments on each bus, in this paper the VCPI behavior is analyzed. Loads are increased until the voltage collapse point, which has been verified by the CPF method. The CPF is not used due to its two main drawbacks, namely: (*i*) the high computational burden, and (*ii*) the information on the load increment directions. The first issue is due to multiple power flow calculations are required during the continuation process. Secondly, the direction of load and generation increments are not readily available on real-time basis [9, 12, 13]. The 14-bus IEEE test system is used to illustrate the proposition.

In the process of seeking alternatives to find a method that provides a system vulnerability measure under real-time context, it is possible to be aware that much of the sciences progress comes from performing experiments. The study of variation, including the construction of experimental designs and the development of models which describe variation, characterizes research activities in the field of statistics [14].

The paper approach is based on statistical methods. Thus, the use of data is necessary. The data used in this research comes from simulations using power flows under different loading conditions and different line contingencies. From a pragmatical standpoint, historical data should be used, which may include: contingencies, load changes and other associated phenomena. The main steps for building the model are described in the sequel.

Thus, the proposed evaluation technique is applied to the IEEE 14-bus test system, resulting in a model to voltage collapse proximity estimation for any voltage profile. The used database is obtained by simulation through gradual load increments and through the N-1 contingency method. The proposed



Fig. 1 Variable selection

technique demonstrates the model prediction ability for the conditions taken into account. The modeling process is explained in the following.

3.1. Scoping and statement of voltage collapse problem.

Due to the problem is based on the voltage collapse proximity estimation on real-time, it is necessary to define the decision variables that meet the real-time concept. Variables' selection depends on technical and analytical aspects: In this case, the technical aspects are limited by existing equipment, currently PMU's and SCADA.

The designed experiment has the main aim to become a reliable method leading to a voltage collapse proximity estimation model. In this application, the database is obtained by simulation, *considering load variations in all buses and singleline contingencies.* Therefore, it is expected that the resulting model is robust under such events.

3.2. Variable selection

In this paper, the system vulnerability is based on voltage stability and is quantified through the VCPI. Explicitly, the independent variables are the bus voltages. In order to reduce the number of independent variables in the model, a regression procedure is suggested [15].

Thus, the bus voltages are the independent variables X_1 , while the global VCPI is the dependent variable. In order to reduce the required independent variables, a stepwise regression is executed. The Root Mean Square Error (RMSE) is defined by,

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^{2}}$$
(7)

Where y are the VCPI predicted values and y are the computed values obtained from pwer flows, for *n* predictions. The RMSE is calculated and evaluated in order to take (or not) variable X, into account as a relevant variable. Thus, the adopted process by stepwise regression is shown in Fig. 1, where the upper plot shows the variable dependence.

The lengths of the horizontal bars indicate the 95% confidence interval. A p-value greater than 0.05 is not acceptable since it indicates the level of the expected error. Notice that variables X₁, X₂, X₃, X₆, X₇, X, (bus voltages) are excluded from the model due to the observed errors and the p-value are close to 1. The lower plot shows the RMSE for each bus voltage included in the model. Thus, for the test system under

Study, voltages at buses 1, 2, 3, 6, 7, and 8 are not transcendental from voltage collapse viewpoint. Each power system will require a similar analysis to verify those buses which are transcendental. Thus, for the IEEE 14-buses test system bus voltages v_4 , v_5 , v_9 , v_{10} , v_{11} , v_{12} , v_{13} , and v_{14} are selected as independent variables.

3.3. Model selection

Some specific models are selected in order to evaluate their predictability [17]: linear model, interactions model (variables' interaction by pair is included), full quadratic model (linear, interaction, and quadratic parameters are included), and pure quadratic (linear and quadratic parameters are included), Fig. 2. Residual plots behavior are helpful to determine whether one model is to be preferred to another using some specific criteria, such as error terms evaluation. Then, using the appropriate metric, each model is examined. Plots are presented in Fig. 3, where a non-normality behavior is noticed in all plots. The RMSE is a good indicator about model reliability when non-normality is observed. In this case, results become: RMSElinear = 0.0748; RMSEpure quadratic 0.0658; RMSE interaction = 0.0555; RMSE full quadratic = 0.0536

Thus, the average residues for the linear model are not quite different each other. Additionally, the required parameters for the linear model are significantly lower than those required for the other models. For these reasons, the linear model may be appropriate for this test system, and it is selected. Therefore, the linear model is evaluated to verify that the estimations are consistent respect to expectations. Its equation is written as,

$$VCPI = b_0 + b_1 V_{bus4i} + b_2 V_{bus5i} + b_3 V_{bus9i} + b_4 V_{bus10i} + b_5 V_{bus11i} + b_6 V_{bus12i} + b_7 V_{bus13i} + b_7 V_{bus13i} + (8)$$

Where coefficients 13, are derived based on the regression procedure, and V, $_{m}$, represents the *i*-th sample of voltage magnitude at bus m.

3.4. Model validation

Usually, model validation involves checking a candidate model respect to independent data, different from that used in the regression procedure (*step 4*). Three ways of validating a regression model are: (*i*) new data collection to check the model and its predictive ability; (*ii*) compare results with theoretical expectation, earlier empirical results, and simulation results; (*iii*) use of a holdout sample to check the model and its predictive ability.



Fig. 2 Different type of models



Fig. 3. Residual plots for different models: (a) linear model; (b) pure quadratic model; (c) interaction model; (d) full quadratic model

A mean of measuring the actual predictive capability of the selected regression model is using this model to predict each case in the new data set and then to calculate the Mean Squared Prediction Errors (MSPR), defined as [18]:

$$MSPR = \frac{\sum_{i=1}^{n^{*}} (vy - \hat{i})^{2}}{n^{*}}$$
(9)

where y, is the variable response value for the *i-th* validation case, ^iyis the predicted value for the *i-th* validation case based on the model-building data set, n^* is the number of cases in the validation data set.

Thus, the MSPR and the Means Square Error (MSE) are compared to infer about model validity,

Where the MSE is defined by,

$$MSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}$$
(10)

Where *n* is the number of observations. In the analyzed case n=985 and n*=197. In this case, $MSPR_{Linearmodel} = 0.0068$ and $MSE_{Linearmodel} = 0.0055$, so that $MSPR_{linearmodel} > MSE_{Linearmodel}$ this implies that a reliable model's prediction is attained [17].

4. CONCLUSIONS

Power systems voltage collapse estimation is addressed from the viewpoint of analysis and design of experiments. The proposed robust predictor uses a 95% confidence boundary, estimating the voltage collapse proximity when bus voltages vary.

The VCPI index is a collapse proximity measure. In this case, the VCPI dependence was assessed in relation to different bus voltages, load changes, and line contingencies. Thus, the test system is subjected to statistical tests, where data are obtained by simulation, although historical data may be used as well. Results indicate that a statistical model is able to infer about voltage collapse proximity.

The vulnerability evaluation technique is able to predict the system voltage collapse proximity using the bus voltages as predictor variables. At each step, theoretical tools are defined to be used according to the nature of data. The proposed method is applied to the IEEE 14-bus test system, obtaining a reliable model under simulated conditions using checking data. Results indicate that the proposal gives a right picture of what could be expected, since they may be corroborated respect to the widely used continuation power flow method (CPF). The method is quite promising for on-line application.

5. REFERENCES

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