2007년도 대한전기학회 하계학술대회 논문집 2007. 7. 18 - 20

SVM 기반 전압안정도 분류 알고리즘

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A Support Vector Machine Based Voltage Stability Classifier

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Abstract - This paper proposes a new concept of support vector machine (SVM) based voltage stability classifier using time-series phasor data. The classifier, based on a linear SVM, can provide very effective signals for identification of long-term voltage stability. In addition, the SVM output is applicable as an voltage stability indicator when an amount of corrective controls are performed just to make the system reach around at the maximum deliverable point.

1. Introduction

Voltage instability is a dynamic phenomenon in power systems. For the last two decades, several voltage stability indices were proposed as the indicators of the given system condition. The algorithms based on the estimation of Thevenin impedance [1] use Z indicator as the voltage stability index, which was originally proposed in [8]. Even though they utilize time-series input from local measurement, the time-series input is just for the estimation of Thevenin impedance. That is, they do not directly deal with the information of time-series data.

This paper is to propose an algorithm for local voltage stability identification in terms of long-term dynamics, as one of applications with the real-time phasor data. The method is based on the assumption that several sets of time-series phasors with a specific sampling frequency can be obtained at a local bus, and that voltage stability for each set of phasors can be identified in advance using one of pattern recognition technologies.

2. Support Vector Machines (SVM)

2.1 SVM Fundamental

For the purpose of local voltage stability classification, we mainly use the linear non-separable SVM, which is to find an adequate hyperplane classifying the learning samples in the feature space. For non-separable cases, the optimization formulation of SVM [2], to find out the hyperplane separating the two classes, can be described as follows:

$$\begin{aligned} \min \quad & \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \\ s.t. \quad & y_i (w \cdot x_i + b) + \xi_i \ge 1, \quad 1 \le i \le N \\ & \xi_i \ge 0, \quad 1 \le i \le N \end{aligned} \tag{1}$$

2.2 Solution technique

For implementation of SVM in this paper, a nonlinear interior point method (NIPM) is applied as the solution technique. For the dual problem of (1), after introducing slack variables Sl and Su for converting the inequality constraints into equality ones and applying log barrier penalty functions for them, Lagrangian function can be obtained as follows:

$$\begin{aligned} L = & f(\alpha) - z^T(\alpha - s_L) - w^T(\alpha + s_U - C) - \lambda\, y^T \alpha \\ & - \mu \sum_{i=1}^{N} (\ln s_{Li} + \ln s_{Ui}) \end{aligned} \tag{2}$$

$$f(\alpha) = -\sum_{i=1}^{N} \alpha_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \tag{3}$$

where z and w are Lagrangian multipliers for the converted lower and upper inequality constraints; λ is a scalar Lagrangian multiplier for the equality constraint; denotes barrier parameter.

The KKT first-order necessary optimality condition of the Lagrangian function can be derived as follows:

$$\begin{aligned} & L_\alpha \equiv \nabla f(\alpha) - z - w - \lambda y = 0 \\ & L_\lambda \equiv y^T \alpha = 0 \\ & L_z \equiv \alpha - s_L = 0 \\ & L_w \equiv (\alpha + s_U - C) \\ & L_{s_L} \equiv Ze - \mu S_L^{-1} e = 0 \qquad \underline{L}_{s_L} \equiv S_L Ze - \mu e = 0 \\ & L_{s_U} \equiv We + \mu S_U^{-1} e = 0 \qquad \underline{L}_{s_U} \equiv S_U We + \mu e = 0 \end{aligned} \tag{4}$$

where S_L and S_U are diagonal matrices whose diagonal elements are the elements of s_L and s_U, respectively; Z and W are diagonal matrices whose diagonal elements are the elements of z and w, respectively; e is the vector whose all elements are 1. For easy manipulation of the KKT first-order condition, the last two equations in (4) are changed. From a given initial guess for the variables in (3), Newton method is applied to find a solution satisfying (4). For this purpose, this paper uses the reduced correction equations as describe in [3].

2.1 Application of SVM based voltage stability classifier

In this paper, bus voltage (V) and active load demand (P) at a substation are chosen as the monitoring parameters for identification of local voltage stability. Bus voltage at the high-voltage side of the substation transformer is appropriate to give insights of the networks condition in terms of voltage stability, and active load demand can indicates the load restoration behavior when the systems are in voltage unstable cases. In addition, the two parameters are usually used for the conventional voltage stability analysis [4-5].

Here, two typical scenarios are briefly illustrated for long-term voltage stable and unstable cases. For the stable case, with Fig. 1a assume that the system is operation at point a. After a contingency is applied, the system's short-term dynamics could reach point b, if the system is transiently stable. Then, load restoration dynamics force the system states along the P-V curve of the contingency. If the long-term load characteristic is constant power, as shown in Fig. 1a, the equilibrium point of the total system dynamics will reach point c and settle down.

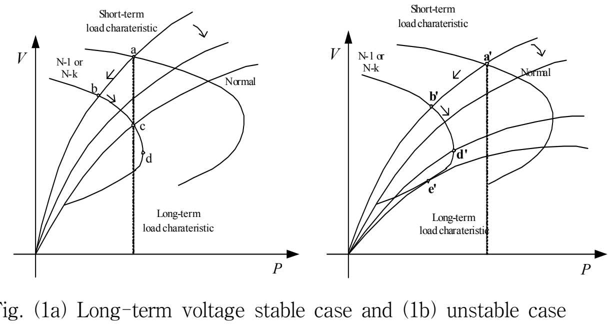

Fig. (1a) Long-term voltage stable case and (1b) unstable case

For the unstable case with Fig. 1b, the initial system load cannot be fully restored after the contingency, and the system states pass the maximum deliverable point, d′, and come close to point e′, where there is only one intersection of the contingent network P-V curve and short-term load curve. If the system load is slightly more restored from point e′, the system may collapse.

With a chosen reference to voltage instability such as the maximum power deliverable point, it is rather easy to decide the system condition (stable or unstable) as well as its trajectory towards instability using the information in every window frame. The nose point (d or d′ in Fig. 1a and 1b) can be selected as the reference. If data in a window are below the chosen reference, the system is unstable; otherwise, stable. The direction of the data towards/away the chosen reference indicates the direction of trajectory of system state condition.

4. Numerical Examples

This section depicts illustrative examples applying the proposed approach with 11-bus test system, which is shown in Fig. 2. In this paper, we extend the previous works related to SVM voltage stability identification presented in [5]. Due to some suggestions and comments on previous work, further studies were conducted on the SVM based vs classifier which include comparisons with other machine learning tools, and increasing number of data points. Simulation results show the advantages of SVM than other machine learning tools for this algorithm applications and faster learning and better accuracy can be achieved by using larger data points.

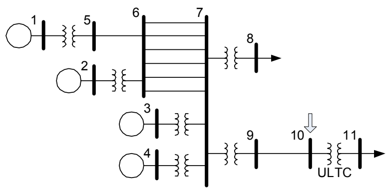

Fig. 2 11-bus test system [7]

4.1 Summary of results of previous works

We assume that bus 10 is the target bus for identification of local voltage stability, and that local measurement devices are equipped to obtain P and V at the bus. Findings on previous work includes the following; i) the magnitude of SVM outputs when plotted with respect to time is capable of tracking the direction of power system voltage stability, ii) the zero-crossing point of SVM output of the optimal hyperplane depends on the optimal hyperplane determined by the SVM classifier and the learning examples for the classifier and iii) in addition, the severity of the disturbance on local voltage stability can be viewed from the SVM output (e.g. the more severe the disturbance is, the more the SVM output approach the reference axis).

4.2 Power system stability determination consistency

Addition of load shedding to maintain power system margin was conducted to test the SVM vs classifier accuracy. The 11-bus test system was simulated to have an outage of one of line connecting bus 6 and 7 after 5 sec and 2 seconds later a ramping of load at bus 11 follows. The scenario will degrade the power system condition more while still on the process of load restoration and driving the system to collapse. After 63 sec load shedding is perform at bus 11 to maintain power margin and to keep the system back to stable condition. The graphs of the voltage and real power obtained from this scenario are shown in Fig. 13.a and 13.b, show the disturbances in the system for the whole scenario.

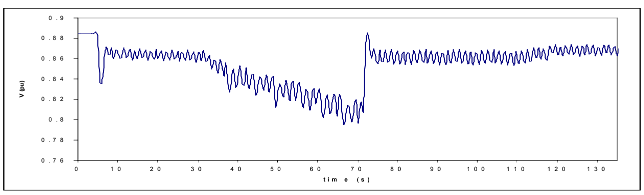

Fig. 3.a t-V curve for testing

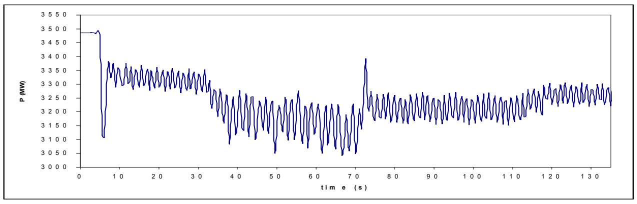

Fig. 3.b t-P curve for testing

Again, power system stability is verified using the SVM vs classifier for the whole scenario and the output of SVM is shown in Fig. 14. The effect of the outage of line 6-7 can be seen as well as the load restoration in the beginning of the graph for a short period before load increase occurs can be noticed. The effect of ramping of load which causes the system stability to degrade (as what the SVM vs classifier output decrease implies) is well-illustrated by the graph. And also, the effect of load shedding on a stressed power system which brought back the system to stable condition.

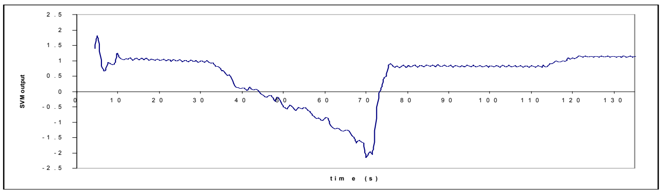

Fig. 4 SVM output when applying the load increase and load shedding scenario

The results provided by the algorithm when it comes to voltage stability identification can be verified using the graph of Fig. 14. The magnitude of the SVM during the normal operating condition at stable case is different from that of the system recovering from N-1 contingency (higher compare to the later condition). This simply shows that the system has a different network PV curve due to the outage of one of its transmission line (as what have discussed using Fig. 1a and 2a). The information obtain shows the consistency and robustness to provide proximity of system stability and trajectory to voltage collapse as well as outsight of current system condition.

5. Conclusion

This paper introduces a new concept of a local voltage stability classifier using a support vector machine (SVM) with a nonlinear interior point method. As inputs to this classifier, local phasor measurement data for active power load and voltage magnitude need to be provided for application of the proposed approach. The test results for feasibility study shows that the classifier can offer an excellent performance in classification with time-series measurements in terms of long-term voltage stability.

6. References

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