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Support Vector Machine (SVM) 기반 전압안정성 분류 알고리즘

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Support Vector Machine (SVM) based Voltage Stability Classifier

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Abstract - This paper proposes a support vector machine (SVM) based power system voltage stability classifier using local measurement data. The excellent performance of the SVM in the classification related to time-series prediction matches the real-time data of PMU for monitoring power system dynamics. The methodology for fast monitoring of the system is initiated locally which aims to leave sufficient time to perform immediate corrective actions to stop system degradation by the effect of major disturbances. This paper briefly describes the mathematical background of SVM, and explains the procedure for fast classification of voltage stability using the SVM algorithm. To illustrate the effectiveness of the classifier, this paper includes numerical examples with a 11-bus test system.

1. Introduction

With the advent of deregulated energy markets and the growing desire to fully utilize existing transmission and infrastructure, power system stability is becoming complex and critical. This economical pressure on electrical market forces the operation of power systems and equipments to the limits of system capacity and equipment performance. For these reasons, system conditions are more exposed to instability due to greater uncertainty in day to day system operations and increase in the number of potential components for system disturbances possibly resulting in voltage instability. Thus the evolution of electric power operation towards deregulation on electric markets introduces a necessity for dynamic security assessment.

The integrated SCADA/EMS system is crucial for current power system operation and its capability has greatly improved during recent years. Obviously, however, the SCADA/EMS system has a difficulty to capture dynamic responses after severe disturbances occur. To compensate this difficulty, phasor measurement units (PMU) was devised and proposed [1] in the power engineering field, which fulfill the requirement of fast monitoring for the view of dynamic responses. Time series data from PMUs can effectively give the outsight of system dynamics to system operators. Potentially, in addition, they can provide system stability identification through adequate data manipulation.

This paper focuses on local measurement based voltage stability identification with PMU data. Ref. [2] and [3] used Thevenin equivalent of the networks at a local bus for determination of how close the system is to voltage instability. The idea of them is based on comparison of the estimated Thevenin impedance and load impedance at a specific bus. This paper proposes a new methodology for identification of local voltage stability using a linear support vector machine (SVM) algorithm [4], which is one of machine learning techniques, assuming that PMUs are equipped at a specified location to capture the trajectory of system responses. The approach would use moving window to take snapshots of the continuous graph of the system responses during a period of time, and employ the learning algorithm to classify the time series of system state condition as stable or unstable. Using the support vector representing the SVM classification as the output of the classifier, test time-series data can be characterized into stable or unstable cases. In case study, numerical examples with a 11-bus test system are included, and Powertech TSAT program [5] is applied to make learning samples and test data.

2. Support Vector Machine

In this section, we consider the support vector machine (SVM) for binary classification [4]. The linear support vector machine is basically based on the hyperplane classifier, or the linear separability. The optimum separating hyperplane is a linear classifier with the maximum margin for a given finite set of learning patterns.

2.1 Linear separable case

Suppose we have N training data points $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_N, y_N)\}$ where $\mathbf{x}_i \in \mathbf{R}^d$ and $y_i \in \{\pm 1\}$.

$$f(\mathbf{x}) = \mathrm{sgn}\ (\mathbf{w}\cdot\mathbf{x} - \mathbf{b}) \quad (1)$$

The hyperplane which have a maximum separating ma rgin with respect to two classes is given by

$$\mathbf{H} : y = \mathbf{w}\cdot\mathbf{x} - \mathbf{b} = 0 \quad (2)$$

and the two hyperplanes parallel to it and with equal dis tances are:

$\mathrm{H}_1 : y = \mathbf{w}\cdot\mathbf{x} - \mathbf{b} = +1$ for class (+1) (2a)

$\mathrm{H}_2 : y = \mathbf{w}\cdot\mathbf{x} - \mathbf{b} = -1$ for class (-1) (2b)

with the condition that there are no data points between $\mathbf{H}_1$ and $\mathbf{H}_2$ and the distance is maximized. These positive data examples along $\mathbf{H}_1$ and negative data examples along $\mathbf{H}_2$ are called support vectors. Support vectors participate in the definition of the separating hyperplane. Other example data can be removed and/or moved around as long as they do not cross the planes $\mathbf{H}_1$ and $\mathbf{H}_2$.

The problem formulation is as follows:

$$\min\ \frac{1}{2}w^T w \qquad s.t.\ y_i\,(w\cdot x_i - b) \geqq 1 \quad (3)$$

Introducing Lagrange multipliers $\alpha_1, \alpha_2, \cdots, \alpha_N \geq 0$, we hav e the resulting Lagrangian function:

$$L(w,b,\alpha) \equiv \frac{1}{2}w^T w - \sum_{i=1}^{N}\alpha_i y_i\,(w\cdot x_i - b) + \sum_{i=1}^{N}\alpha_i \quad (4)$$

Given a constrained optimization problem with a convex cost function and linear constraints, a dual problem with the Lagrange multipliers which provides the solution can be formulated using Duality Theorem. That is by maximizing the $L(\cdot)$ with respect to α, subject to the constraints that the gradient of $L(\cdot)$ with respect to the primal variables $\mathbf{w}$ and $\mathbf{b}$ vanish:

$$\partial L/\partial w = 0 \text{ and } \partial L/\partial b = 0$$

and that $\alpha_i \geq 0$. From these two conditions, we obtain:

$$w = \sum_{i=1}^{N} \alpha_i y_i x_i \quad (5) \quad \text{and} \quad \sum_{i=1}^{N} \alpha_i y_i = 0 \quad (6)$$

Substituting these into L(·) yields:

$$L_D \equiv \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \quad (7)$$

in which the primal variables are eliminated.

Computing α_i, **w** and the threshold **b**, the classification of new object **x** can be determine by the following equation:

$$\begin{aligned} f(x) &= sgn(w \cdot x - b) \\ &= sng\left((\sum_{i=1}^{N} \alpha_i y_i x_i \cdot x - b \right) \end{aligned} \quad (8)$$

Note that the objective function and the solution, the training vectors $\mathbf{x}_i$ occurs only in the form of dot product.

2.1 Linear non-separable case

Extending SVM applications for allowing noise, or imperfect separable case which is commonly occurs in real applications. The main purpose is to definitely penalize the data points that cross the boundaries between the hyper-planes $\mathbf{H}_1$ and $\mathbf{H}_2$. Introducing a non-negative slack variables $\xi_i \geq 0$, so that

$$\mathbf{w} \cdot \mathbf{x} - \mathbf{b} \geq +1 - \xi_i \quad \text{for } yi = +1 \quad (9a)$$

$$\mathbf{w} \cdot \mathbf{x} - \mathbf{b} \leq -1 + \xi_i \quad \text{for } yi = -1 \quad (9b)$$

and adding a penalty term to the objective function yeilds:

$$\begin{aligned} &\min \ \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \\ &s.t. \ y_i (w \cdot x_i - b) + \xi_i - 1 \geqq 0 \\ &\xi_i \geqq 0 \end{aligned} \quad (9)$$

Lagrange function of (9) by introducing Lagrange multiplier α and β is as follows:

$$\begin{aligned} L \equiv &\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i - \\ &\sum_{i=1}^{N} (\alpha_i y_i (w \cdot x_i - b) + \xi_i - 1) + \sum_{i=1}^{N} \beta_i \xi_i \end{aligned} \quad (10)$$

The duality problem can be formulated as follows:

$$\begin{aligned} &\max \ L_D = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \\ &s.t. \ \sum_{i=1}^{N} \alpha_i y_i = 0, \ 0 \leqq \alpha \leqq C \end{aligned} \quad (11)$$

The only difference from the linear separable and linear non-separable case is that, α is now bounded above by C instead of ∞. The solution is the same for both cases to find the solution (8).

3. SVM based Voltage Stability Classifier

The proposed algorithm used in this paper uses phasor measurement units located locally to allow real-time observations of dynamic responses and developing disturbances of the system. In this way, the difficulties of SCADA/EMS to analyze system dynamics can be handled. A series of sets of data are contained in a moving window containing previous and real-time data thereby, tracking the system dynamics while storing its previous state conditions. The ability to perform in an event of infrastructure hardware failure or the lack of communication links due to high investment cost which gives burden for a wide area monitoring system are not critical factors.

3.1 Choice of input data

In this study, bus voltage and load active power were chosen as monitoring parameters in the determination of power system stability. Bus voltage at the high voltage side of the substation transformer is ideal to give insights of the transmission and generation networks condition since this value is not altered by tap-changing transformer response. The minimum time required for tap changer transformer (LTC) to complete one tap movement is usually close to 5 seconds. Although LTC are slow acting device, one way to ensure that the proposed approach is not affected by LTC load restoration is to choose data sampling time shorter.

Another input parameter used is the load active power which indicates load behavior either increasing or decreasing at specific time. The total load seen by bulk power delivery transformer is a composition of large number of individual loads consisting of components without restoration dynamics as well as of components with load restorations. Statistically, these aggregate loads tend to be quite consistent, but these loads behave differently at different time scales.

One advantage of using these parameters is that, absolute value of bus voltage and load active power can be easily obtain using substation monitoring instruments and/or using real-time monitoring equipment like PMU.

3.2 Input data pre-conditioning

Assume that from PMUs we can obtain time series data of all the required parameters that are needed here with a certain sampling frequency. The input data sets are classified into class (+1) for stable cases and class (-1) for unstable cases. In this paper, TSAT is primarily used to get the sampling data for emulation of real-time measurement. That is, these data were input in the SVM algorithm as to have almost as ideal with the actual PMU measurements.

The input data are pre-conditioned using the formula, $(X_o - X_n)/X_n$ in order to normalize input data, where X can be the parameters that are necessary in this approach, and the subscripts o and n denote the initial and n-th value of a parameter, respectively. Normalized value insures a generalized input data whenever this study is conducted in any bus of the power system. Every input data is a combination of normalized values of V (bus voltage) and P (load active power). We also assume that data combinations are taken every 0.5 second, but this sampling time can be modified.

3.3 Moving window in featured space

The moving window captures the behavior of the data combinations. A certain number of successive data combinations are contained in a window where used to test the proposed algorithm which comprises one training data. The next input data is taken from the next window containing the previous data points that include another new data point but exclude the first data point. The idea of this approach is to let every input data contain enough details of the system condition before and the last data point as basis for the detection of system instability and trajectory to system collapse. The process of obtaining series input data are done in this manner as shown in Fig. 1, thereby tracing the graph representing the combination P and V for every 0.5 second. Transforming every moving window data into input file data for training and classification can be made base on the required input data format of **SVM light**, which is the learning algorithm used here in this paper.

3.4 Machine learning with SVM light

With a chosen reference to voltage instability scenarios, assume that we have time trajectories both for stable and unstable cases. Even for unstable cases, the time trajectories can be divided into many window frames depending on the sampling frequency and the number of data in a window, and these data can be characterized into stable or unstable cases. In this paper, if the portion of the trajectories in the a window is on the upper PV curve, the window frame is considered stable; otherwise, it is considered unstable.

Then, in this paper, **SVM light**, which is an implementation of Vapnik's Support Vector Machine [6], is utilized for machine learning of voltage stability identification. In SVM light, data taken from a moving window are featured into a higher space dimension for linear classification, and it has scalable memory requirements and can handle problems with thousands of support vectors efficiently. From this learning, we can obtain the support vectors which can be used later to classify another set of input data whose voltage stability is not known yet.

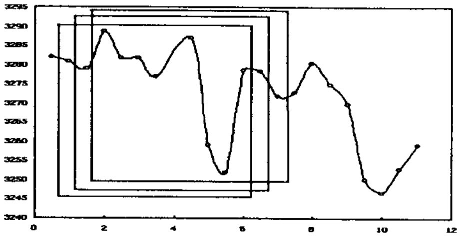


Fig. 1. Concept of moving windowing

4. Numerical Example

This section explains examples applying the SVM based voltage stability classifier into a 11-bus test system shown in Fig. 2.

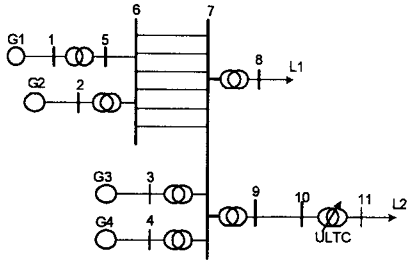


Fig. 2. 11-bus test system

4.1 Learning with SVM light

Using 35 input data for class (+1) and 35 input data for class (-1) as training data, the classification using SVM light program was performed. Verifying the trained SVM light to classify test data containing 5 class (+1) and 5 class (-1) data, the learning machine could now distinguish or classify test data to its respective classes. Further running this machine for classification of different test data, where some of the test data are taken from the nose of PV curve, some errors of classification occurs. Data which are taken from the nose of the PV curve are the most critical to classify. Increasing the training data from 105 to 600 input data both for class (+1) and (-1) makes the learning machine reliable in classification of data even in a critical case. The simulation result in the classifying is more accurate and test data which are taken even from the nose of PV curve are well classified.

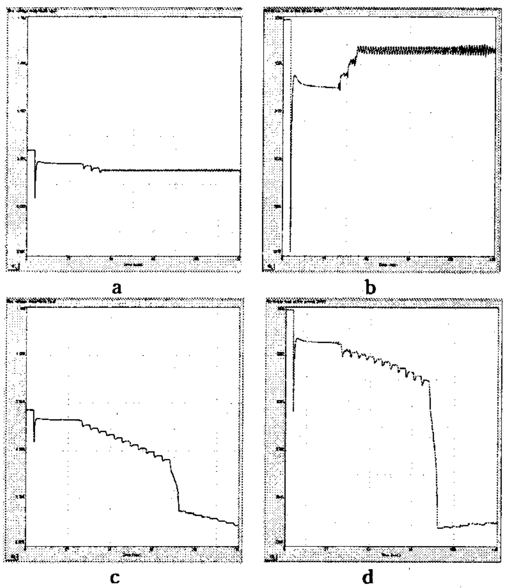
Related studies conducted in this research can be summarized as follows:

1. Increasing power system case scenario, thereby increasing training data for SVM light to learn and test the learning machine to classify accurately more test data.
   Cases of test data to classify after SVM light had been well trained
   a.) test data which are located in critical points (mostly on the nose of PV curves of various cases scenarios).
   b.) test data which are continuous points from the same case scenario to track the point of collapse of the system. (e.g. SVM might track the behavior of power system stability which is stable at first few windows and become unstable on the remaining windows).
2. Update training data by including well classified data taken in the critical points mostly on the nose of PV curves). This would update training data to insure SVM light is trained well for further data types.
3. Study the output of SVM light, which might be an index to indicate direction of power system stability trajectory and margin to system collapse.
4. Verify other SVM features like regression, kernel type and others for the benefits of power system stability study.

4.2 Results of simulations

Based on the result of this study, as the window data contains more data points the more the SVM couldclassify system stability as well as tracing the direction of trajectory. These have been verified using 4 data, 10 data and 20 data point window. Preprocessing of input data for stable and unstable case is observed so that accurate class classification of training data is obtained.

The algorithm is further simulated using the 11-bus test system considering different scenarios, like ramping of load at bus 11 and an outage inone of the line connecting bus 6 and 7. The graph of voltage at bus 10 and load active power at bus 11 areshown in Fig. 3.a, 3.b for stable cases and 3.c, 3.d for unstable cases.



a b c d

Fig. 3: Graph of (a) bus voltage (V), (b) load active power (P) for stable and (c) bus voltage (V), (d) load active power (P) for unstable case used for test data

Test data containing 35 data points both for stable and unstable case obtained from this graphs were tested for classification using trained SVM. The output of SVM is now plotted with respect to time for stable and unstable conditions. Considering system fast dynamics, in stable case, the time where the system is unstable for a short time and recovers and becoming stable again can be track using the magnitude of SVM. This can be demonstrated by Fig. 4.a and 4.b, showing the trajectory of SVM magnitude for stable and unstable respectively. The classification result of SVM test is 95.714%. 3 out of 70 test data were misclassified. The misclassifications happens on unstable test data on the first 3 points as seen in Fig. 4.b. This misclassified data for unstable case might be actually belongs to the stable case and the unstable case begins after the SVM output have crosses the reference axis exactly at third point. The turning point of the SVM output from positive to negative values can represent the point of system voltage collapse. In an event of misclassification, misclassified data are then added as a new training data. This will make SVM learned well and will helps in future classifications of SVM of critical data near the point of voltage collapse. Here, we have shown that the magnitude of SVM outputs plotted with respective to time is capable of tracking the direction of power system voltage stability and margin to collapse.

During the occurrence of system contingency, system begin to response and the graph of SVM outputwith respect to time is noticeably going down. Both for stable and unstable conditions have the same characteristics only for stable case, it begin to stabilize after reaching a specified magnitude. For unstable case, it keeps to go down. Within this system condition transition, it is evident here that in some cases the effect of system load restoration can be observed.

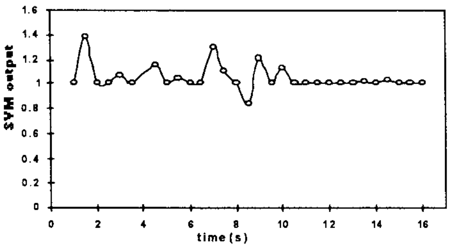


Fig. 4.a Plot of SVM output with respect to time for stable case

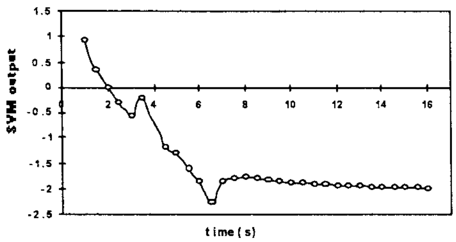


Fig. 4.b Plot of SVM output with respect to time for unstable case

Another test is performed on the 11-bus system without line outages. The load at bus 11 is gradually increased to obtain the PV curve of the system at base case. The network PV curve is shown in the Fig. 5. By examining Fig. 5, PV curve reveals that the point of voltage to collapse for this case occurs at the nose of the curve. The upper portion of the curve relates stable system condition and the lower portion for unstable condition.

TSAT has a feature "ramping of load"ideal for this purpose, thus providing our proposed algorithm a continuous data for the complete scenario. The complete continuous data points of this scenario are tested in the proposed algorithm. The output of SVM is plotted with respect to time of the occurrence of data which is shown in Fig. 6.

The positive values of the output in the early stage indicate the time when the system is stable. As the load in bus 11 is increased, it reflects a corresponding decrease of SVM output. The point where the magnitude of SVM output crosses the reference axis indicates almost exactly the point of voltage collapse of the system. This has been further verified by investigatingthe input data of the base scenario. After crossing the reference axis, the values of SVM outputs are negative indicating that the system is unstable. This is due to the fact that the load is still increasing even after reaching the point of voltage collapse. By using the characteristics of this graph, we can track the direction of system stability trajectory both for stable and unstable case.The severity of voltage instability or stability is related to the magnitude of SVM output.

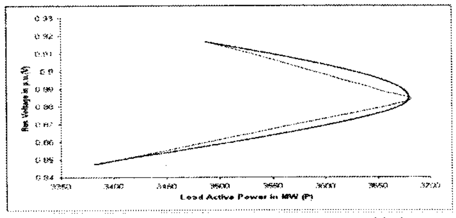


Fig. 5. The network base case PV curve of 11-bus system

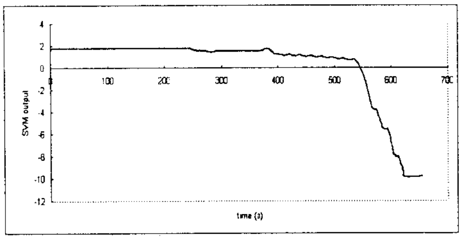


Fig. 6. SVM output of the base case scenario

5. Conclusions

In this paper, we introduced a new concept of power system stability classification using local measurements on dynamic trajectories. The support vector machine (SVM) based classifier with PMU data can offer an excellent performance in classification of handling the information related to long-term dynamics. The results with the classifier on the test system shows a promising application of the proposed SVM-based voltage stability classifier in the field of local monitoring and control of power system.

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