ISSN 2229-5518

Power System Real-time Transient Instability Preventive Control by Using Catastrophe Theory and SVRM

M. M. ElAdany, A. A. ElDesouky, A. A. Sallam
mai_eladany@eng.psu.eg, aza.ahmed@eng.psu.edu.eg, aasallam@eng.psu.edu.eg
Electrical Power Department, Port Said University, Egypt.

ABSTRACT- Real-time transient instability preventive control in power systems is applied to enable the system to withstand future uncertain events in a secure way and keeping its stability. Therefore, transient stability must be assessed as fast as possible in real-time to adequately be improved. At that moment, it necessitates to select the strategy being applied to decide the desired enhancement. Requiring accurate and fast evaluation, catastrophe theory (CT) is applied for assessing the transient stability directly without any assumptions and provide online visualized monitoring for the operating points. This paper focuses on generation rescheduling as a preventive control technique in order to maintain system's stability. A proposed technique is based on contingency scanning and recording in a lookup table as a database for all possible stresses and congestions in the system under study. Stresses are represented by a three-phase fault, as the most severe fault, located frequently in each line of the power system, whereas congestions are considered as sudden increase of loads. In order to determine which generators being at each fault rescheduled location, assification and regression treecl (CART) technique is used. Then, the required generated power for rescheduled units could be predicted online at any operating condition by using support vector regression machine (SVRM). For doing that, SVRM is trained offline with pre-optimized values that obtained by particle swarm optimization (PSO) technique to guarantee system's stability. Simulation of New England 39-bus test system verifies the performance and effectiveness of the proposed strategy. The results confirm its feasibility and are validated in comparison with those obtained through time domain simulation (TDS).

Index Terms—Catastrophe Theory, Critical clearing time, Preventive Control, Real-time Transient Instability, Support vector regression machine.

1.Introduction

Transient stability problem is one of the most important issues that affect the performance of power systems as it evaluates the ability of power system generators to retain their synchronism with the rest of the grid, after a given disturbance [1]. So, to avoid disastrous outages, power utilities should arrange for a proper control action. Real-time preventive control is considered one of this necessary arrangement. In order to be able to carry out a proper real-time transient instability preventive control, a fast and accurate real-time transient stability assessment is required. The problem of online transient stability assessment has been discussed in literature along the last few decays with different techniques aiming at improving the real-time system transient stability. One of these techniques is the TDS which gives accurate and precise results of stability assessment by using numerical methods for solving the power system differential equations but its major drawback is consuming long computation time. A hybrid of TDS and extended equal area criterion is presented in [2] to reduce the computation time. Authors of Ref. [3], also, make a real-time simulation of large-scale power systems feasible by speeding up computation efficiency of power system simulation with the help of EnFuzion-based distributed computing method.

Another method for online stability assessment is the direct method which is based on the transient energy function concept such as the Lyapunov theory, which is applied in many papers as one of the direct methods. Its major weakness is the deficiency of precise modeling [4]. Catastrophe theory (CT) also can be considered as a direct online transient stability assessment method, which is characterized to be a qualitative mathematical theory for studying the transient and steady-state stability of power systems. CT with its precise indication of the bounds of stability is a strong candidate for such online indicator [5]. So, for online transient stability assessment computational burden can be alleviated by using CT [6]. The region of transient stability in terms of the control variables in the catastrophe bifurcation set is determined by specifying one of the seven catastrophe manifolds which are defined as an equilibrium surface of critical points and calculating the control variables as functions of the operating conditions of the system generators. Thus, stability is easily and precisely determined without the need to solve the swing equations making it suitable for online transient stability assessment.

CT is studied in [7] to provide the convenient swallowtail manifold by which the multi-machine power system online transient stability can be assessed. With the swallowtail catastrophe, values of three control variables are computed in terms of system parameters at different operating conditions. These values define a corresponding operating point in the control space and its location with respect to the stability boundaries. In addition, CT has been applied to transient stability assessment of multi-machine power system by defining the stability region in a cusp bifurcation surface in terms of its control variable [8].

Artificial intelligence (AI) learning such as machine learning, pattern recognition, neural network, and statistical methods nowadays are also considered for online transient stability assessment because of the advances of computer technologies that enable creating a massive database to be used to train and test agents [9], [10], [11]. A. M. Haidar et al [12] present a transient stability index to be evaluated by generalized regression neural network to assess transient stability. TDS is used to learn the generalized regression neural network, which predicts the stability of the applied test system with high accuracy. Transient stability classification of the large power system is introduced in [13] ,[14]. Transient stability classification for different three-phase fault locations in applied test system is done by using probabilistic neural network. The training data is achieved by TDS. The performance of probabilistic neural network is tested once with reduced features by principal component analysis (PCA), and another without PCA where the results are compared.

Real-time transient stability assessment process should be followed by rapid control action to avoid loss of synchronism when a disturbance occurs. The disturbance could be a sudden change of load or a three-phase short circuit, which is considered as the most severe disturbance. Preventive Control includes many methods of control actions comprising generation rescheduling, load curtailment, and reactive compensation. Generation rescheduled is used in several research works as an effective action for transient instability prevention [15]. The kinetic energy change at the fault clearing time is computed in case of severe contingencies in [16]. An assumed linear relationship between the critical clearing time and the generator output is used in order to obtain the ratio of the generation rescheduling.

A proposed generation rescheduling is done based on the coherency between the generators by bringing the generators' rotor speeds identical after considering a three-phase fault [17]. A scaling factor is allocated to scale the speed trajectory of the contingency for each critical contingency. Overall transient stability of power systems can also be improved by using the risk-based technique for generation rescheduling and load shedding [18]. Generation rescheduling against transient instabilities is used for improving dynamic security using the security regions calculated by decision trees [19], which are approximated by using data mining [20]. Then, the optimal preventive control strategies are calculated by chaotic particle swarm optimization in combination with the two-stage SVM. Power generations for eradicating possible transient stability threat is optimally reallocated by using the augmented Lagrangian method iteratively [21]. Here, sensitivity-based transient stability constraints of the rescheduling are developed by the idea of angle norm model to evaluate the sensitivity factor of the angle norm at maximum swing angle to the power input of the generators. Critical clearing time (CCT) as indices for transient stability is considered in [22]. Generator output rescheduling and generator terminal voltage control are used as a strategy for transient stability preventive control to attain a more stable power system operating point. The proposed strategy is done by finding a linear correlation between CCTs and both of generator rotor angles and active powers of transmission lines. Generation rescheduled is also considered as an effective method in congestion management. Generation rescheduling and load shedding with the realistic voltage-dependent load modeling are utilized as congestion management approach in [23]. Objectives of generation and load shedding cost minimization, load shedding minimization, and load served error minimization are optimized by using multi-objective strength Pareto evolutionary algorithm.

In this paper, a new strategy for real-time transient instability prevention is proposed. Before the application of online assessment and restoration, an offline preprocessing stage is done. In this stage, CART is used in order to decide which generators should be rescheduled at each fault location according to stability state represented by the operating point location (that is defined by the control variables) in the stability region and the values of CCT. PSO is also applied at this stage to optimize the values of the generation, which are used in SVRM training. Training and testing of SVRM are done in this stage at different loading condition for each fault location. In the online stage, SVRM is then used to predict the rescheduled generated active power rapidly to retain power system's stability. The transient stability is reassessed next by CT.

The forthcoming sections are organized as: Section II presents a brief description of the tools used in the proposed strategy. Section III provides an explanation of the proposed real-time transient instability prevention strategy. Test System and Results are presented and validated in Section IV. Section V summarizes the finding of this work and draws conclusions. Section VI contains the references. Finally, an Appendix to illustrate some details toward CT.

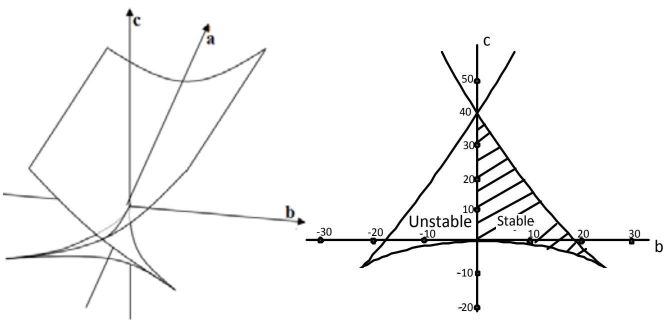
2.Tools of the proposed real-time preventive control strategy

To maintain real-time stability on required levels it is crucial to distinguish the system condition at any instant to be able to respond fast in case of any contingency or system congestion. To ensure fast assessment of transient stability assessment, CT is used, whereas CART is used in order to select the best transient stability preventive control action and rescheduled generators, which highly impact the value of CCT. SVRM is then used in order to predict the new values of a rescheduled generation. Time-consuming computational procedures such as training both CART and SVRM are done as preprocessing offline stage. Training of SVRM is obtained by a pre-optimized values of rescheduled generation that are calculated by an AI optimization technique such as PSO method. The proposed strategy exploits different tools; each has its own intimate role as described below.

i) CT: It has been applied to power system transient stability assessment by deriving a swallowtail catastrophe function expressed as [7]:

$$y^4 + ay^2 + by + c = o \quad (1)$$

where y is a state variable calculated in terms of the critical clearing angle, *a*, *b* and *c* are the control variables expressed in terms of system parameters. It is to be noted that a = - 12 in this application, and so, the swallowtail bifurcation set is only dependent on *b* and *c*. The derivation is given in Appendix A and the graph of both swallowtail catastrophe bifurcations in three- and two-dimension space is shown in Fig. 1.



(a) (b)

Fig. 1. Schematic outline of swallowtail bifurcation set. (a) in three-dimension space, (b) in two-dimension space (the shaded area represents the stable region)

ii) CART technique belongs to AI methods and becomes highly popular in the age of modern computers [24]. It bases on a sequence of questions that can be answered with yes or no. Each question asks whether a predictor satisfies a given condition, whereby the predictors can be both continuous and discrete. Depending on the answer to each question, one can either proceed to another question or arrive at a response value, splitting rule of CART is shown in Fig.2. As CART is an acronym of classification and regression tree, so when it is used to predict a response or a class then it is called a classification tree and when it is used to generate a real number and not a class, it is called regression tree [25].

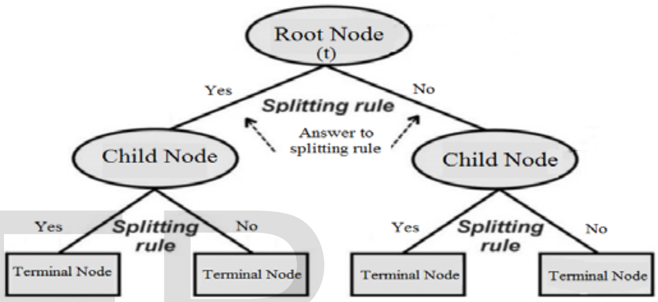


Fig. 2. Splitting algorithm of CART

CART also is used to determinate bands with highly discriminatory influence between classes. This process is also identified as feature selection, which is considered in this study. The main role of CART here is to determine the most effective generators being rescheduling regarding the CCT with the goal of transient instability prevention. The training of CART is done at each fault location by feeding 4000 cases into the root node of CART and checked to get which input attributes are selected to split the tree. Input operating points are generated in the vicinity of the given initial operating point by randomly changing +5% to -5% of each generated active power, P, +5% to -5% of each load bus's active power demand, P_D, and reactive power demand, Q_D, and +30% to-30% of the line reactance, X .The output matrix is the corresponding minimum critical clearing time at each input operating points.

iii) SVRM is created to solve the problem of regression where the solution generated is a real number. The regression valuation problem is observed as finding the mapping between an input vector $x \in R^d$ and an output $y \in R$ from a given set of independent and identical distributed samples, $\{(x_i, y_i)\}_{i=0}^{n}$. The standard support vector machine explains this problem by finding the regressor of support vector w and b that minimizes [26]

$$\frac{\|w\|^2}{2} + c\sum_{-1}^{n} l_v(y_i - (\varphi^{\tau}(x_i)w + b))$$
(2)

where $\varphi(.)$ is a nonlinear transformation to higher dimensional space. This transformation can be represented by kernel function given by

$$k(x_i, x_j) = \varphi^{\tau}(x_i)\varphi(x_j)$$
(3)

Different types of kernel function are available. The kernel function used in the proposed generated power predictive model is Gaussian kernel function which is given by

$$K(x_i, x_j) = e^{\left(-\|x_i.x_j\|^2/\sigma^2\right)}$$
(4)

σ is known as the Gaussian parameter. $L_v(.)$ is Known as the Vapnik ε- insensitive loss-function, which is equal to 0 for $|y_i - (\varphi^T(x_i)w + b)| < \varepsilon$ and equal to $|y_i - (\varphi^T(x_i)w + b - \varepsilon$ for $yi-(\varphi Txiw+b)\geq\varepsilon$.

Eqn. 2 is solved by finding w and b such that the absolute error equal or greater than ε [27]. The model is created in MATLAB with eighty-three input features and one output, which is the rescheduled generation as shown in Fig.3. The input parameters used are the sampled values of the predictor variables, which are: pre-fault real and reactive power outputs of all generators (P_g, Q_g), total real and reactive demand of the system (P_D, Q_D), internal voltage angle of generators (δ_g), voltage behind quadrature reactance of each generator (E_d), and kinetic energy (K.E) of all generators calculated by catastrophe theory. To generate the training and testing data for SVRM, operating points are generated by the same way for training CART as mentioned before.

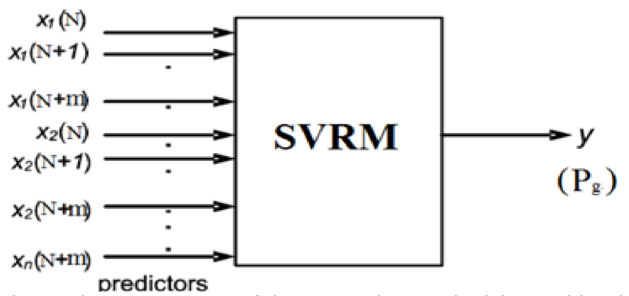


Fig. 3. The arrangement of the generation reschedules and level of compensation prediction scheme.

iv) PSO technique is one of the most effective metaheuristics algorithms with many successful real-world applications [28]. The role of PSO in this study is to optimize the values of the rescheduled generation, which maximize the CCT being used next in the training of SVRM. Based on CT, it represents the value of CCT as derived in Appendix A and given by (A.37). Thus, the objective function can be formulated as [7]

Maximize $$F=\sqrt{\frac{2M(\delta_c-\delta_0)}{(P_{in}-P_e(t_{0+}))}}$$

(5)

Subjected to

Equality constraints:

δ_c = the smallest positive real root of (1).

Inequality constraints:

In order to satisfy the system stability, the coordinates of the operating point (b,c) in (1) should not violate the boundary of stability region. Hence,

$$0 < b < b_{max}$$
(6)

$$c_{min} < c < c_{max}$$
(7)

$$-10\%P_{gi,rate} < P_{gi} < +10\%P_{gi,rate}$$
(8)

where,

$\delta_c \triangleq$ critical clearing angle.

$\delta_o \triangleq$ minimum angle of oscillation.

$P_{in} \triangleq$ input mechanical power.

$P_e(t_{o+}) \triangleq$ electrical power at the instant of fault.

M ≜ machine inertia constant.

b and c ≜ the control parameters, which are the coordinates of generator operating point in the bifurcation set [7]. They are a function of the power delivered by the generator during and after the fault as derived in Appendix A and can be calculated by (A.32) and (A.33).

(b_{max}, c_{max}), (0, c_{min}) ≜ coordinates of the points located on the boundary of the stable region.

$i \triangleq$ number of generators.

$P_{gi} \triangleq$ rescheduled generated active power of each generator.

$P_{gi,rate} \triangleq$ rated generated active power of each generator.

3.Description of the Proposed Real-time Transient Instability Prevention Strategy

In the proposed algorithm there are two main stages; offline (pre-processing) and online (processing) stage. First, in the offline stage training of the learning-based tools, which are CART and SVRM is done. Next, in the online stage, accurate real-time transient stability assessment by using CT is required. The state of system's stability is monitored by visualizing the location of operating points in the CT's stability region. Therefore, the preventive control is summoned up in case of critical stability state of the system. The suggested preventive control strategy is based mainly on generation rescheduling with aim of increasing CCT, which in turn increases system's security and overall stability. As CART plays a significant role to find out important features that have a major effect on CCT, the most effective generators to be scheduled at each three-phase fault is determined. A lookup table is constructed containing each fault and its

ISSN 2229-5518

corresponding generators being rescheduled. Last, in order to predict the value of new generation after rescheduling at any real-time operating condition, SVRM is used and transient stability is re-evaluated by CT to confirm that the preventive control is achieved. Fig. 4 depicts the proposed strategy, the yellow blocks represent the offline process and blue blocks represent real-time actions.

Table 1. Generation to be rescheduled at each faulted line

Fault-Line, L #	Fault-line (From-To)	Generators to be rescheduled						Fault-Line, L #	Fault-line (From-To)	Generators to be rescheduled					
1	2-1	P_1	P_9	P_8	P_3	P_7	P_5	**24**	26-25	P_1	P_9	P_6	P_4	P_7	P3
2	5-8	P_1	P_9	P_6	P_4	P_7	P_5	**25**	27-26	P_1	P_9	P_6	P_4	P_7	P_5
3	6-7	P_1	P_9	P_4	P_6	P_3	P_7	**26**	28-26	P_1	P_9	P_6	P_4	P_7	P_3
4	11-6	P_1	P_9	P_6	P_4	P_7	P_8	**27**	29-26	P_1	P_3	P_4	P_6	P_7	P_5
5	7-8	P_1	P_9	P_5	P_6	P_7	P_4	**28**	29-28	P_1	P_9	P_3	P_4	P_7	P_5
6	8-9	P_1	P_9	P_6	P_4	P_8	P_5	**29**	2-25	P_1	P_9	P_6	P_4	P_8	P_5
7	39-9	P_1	P_9	P_6	P_4	P_3	P_5	**30**	3-4	P_1	P_3	P_6	P_4	P_7	P_5
8	10-11	P_1	P_9	P_6	P_4	P_7	P_3	**31**	18-3	P_1	P_9	P_6	P_4	P_7	P_8
9	10-13	P_1	P_9	P_6	P_3	P_8	P_7	**32**	4-5	P_1	P_9	P_6	P_4	P_7	P_5
10	13-14	P_1	P_9	P_6	P_4	P_7	P_3	**33**	14-4	P_1	P_3	P_6	P_4	P_7	P_5
11	15-14	P_1	P_3	P_9	P_4	P_6	P_8	**34**	6-5	P_1	P_9	P_6	P_4	P_7	P_8
12	1-39	P_5	P_6	P_4	P_9	P_7	P_1	**35**	13-12	P_1	P_9	P_3	P_4	P_7	P_5
13	15-16	P_1	P_9	P_3	P_4	P_6	P_8	**36**	2-30	P_1	P_9	P_6	P_4	P_8	P_5
14	16-17	P_1	P_9	P_6	P_8	P_7	P_5	**37**	6-31	P_1	P_9	P_6	P_4	P_3	P_8
15	16-19	P_1	P_9	P_6	P_4	P_3	P_5	**38**	19-20	P_1	P_9	P_6	P_3	P_7	P_5
16	21-16	P_1	P_3	P_5	P	P_7	P_5	**39**	10-32	P_1	P_9	P_8	P_4	P_3	P_5
17	24-16	P_1	P_3	P_5	P_9	P_7		**40**	20-34	P_1	P_9	P_3	P_4	P_7	P_5
18	17-18	P_5	P_9	P_6	P_4	P_1	P_7	**41**	23-36	P_1	P_9	P_6	P_4	P_7	P_8
19	17-27	P_5	P_6	P_7	P_9	P_4	P_1	**42**	22-35	P_1	P_3	P_6	P_4	P_7	P_5
20	22-21	P_1	P_9	P_6	P_4	P_7	P_5	**43**	19-33	P_1	P_9	P_6	P_4	P_8	P_5
21	23-22	P_5	P_9	P_4	P_1	P_6	P_7	**44**	11-12	P_1	P_8	P_6	P_4	P_7	P_5
22	24-23	P_1	P_9	P_6	P_4	P_7	P_5	**45**	29-38	P_1	P_9	P_6	P_4	P_7	P_3
23	2-3	P_1	P_9	P_6	P_4	P_7	P_3	**46**	25-37	P_1	P_9	P_6	P_4	P_8	P_5

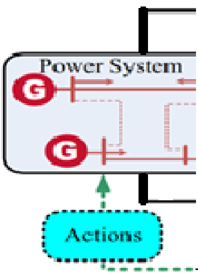


Fig. 4. The architecture of the proposed preventive control strategy

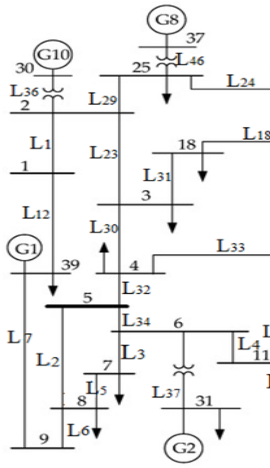


Fig. 5. 39-bus ten machines New England test system with line numbers

4.Test System and Results

The proposed algorithm is applied to 39-bus, ten machines, New England test system as shown in Fig. 5. System data can be found in [29]. To evaluate its performance, simulations have been done using MATLAB programming codes. Tracing the proposed strategy sequence, results of the offline stage will be discussed first, then the real-time stage will come next. According to the strategy of offline stage, training of CART and SVRM is done. For each fault location, most effective generation powers, which should be rescheduled are achieved by CART and results are recorded as a database

in the utility, Table 1 shows the generators being rescheduled for each faulted line.

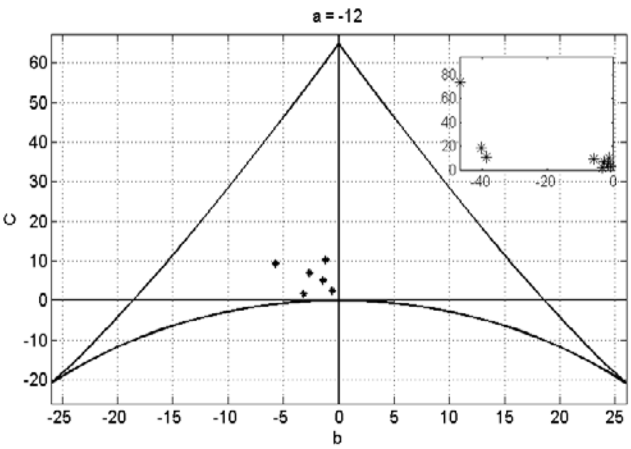
A three-phase fault, which is considered as the most severe fault, occurred at line 17 (24- 16) near bus 24 in addition to 40% increase in the largest load are considered in order to show a numerical example, the

Table (2) SVRM results for generation rescheduled at the faulted line (L#17)

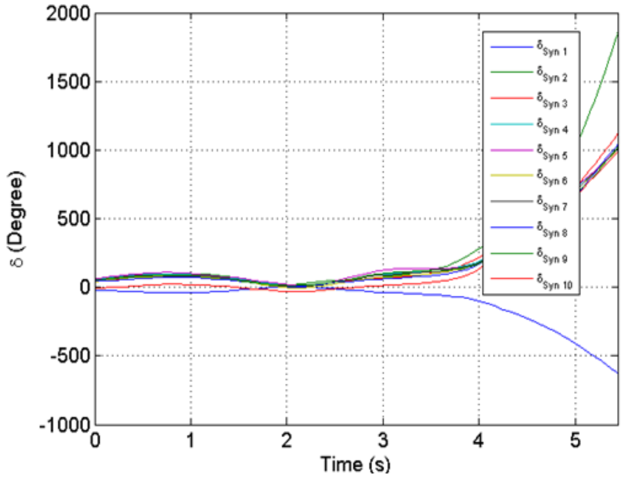
Faulted line	From	To	Rescheduled generators				
17	24	16	P_1	P_3	P_5	P_9	P_7
			Before rescheduling				
			10	6.5	5.08	8.3	6.32
			After rescheduling				
			11	7.15	5.588	9.13	7.16

fault is cleared after 0.1 sec by tripping the faulted line. The system is unstable as the location of operating points is out of stability region of the swallowtail bifurcation as shown in Fig. 6a, in order to compare the result with TDS, Fig. 6b shows the delta versus time curve at the same fault location and fault clearing time. It confirms the instability state of the system.

According to the proposed algorithm, SVRM is summoned up to predicted values for the generation rescheduled for this fault location. Table 2 gives SVRM results for generation rescheduled at the faulted line (L#17). Then, the stability is checked again by CT to indicate that the system is stable, Fig. 7. The proposed strategy for online transient stability is implemented by using MATLAB R2015b. Although the offline stage consumes a relatively large computation time in the optimization and training/testing the SVRM at each fault location, the assessment and enhancement of transient stability by using CT and SVRM, respectively are done fast



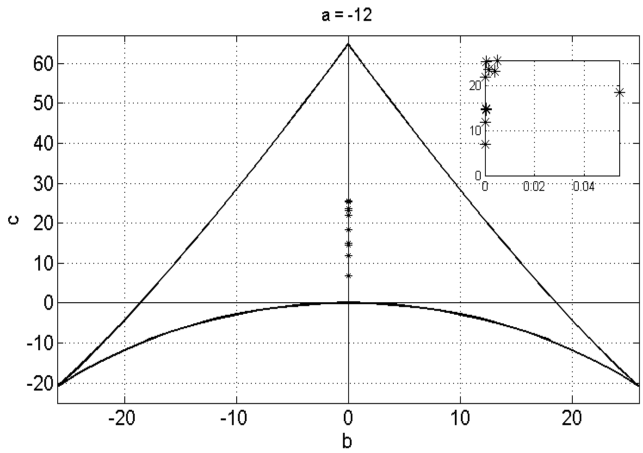
(a)



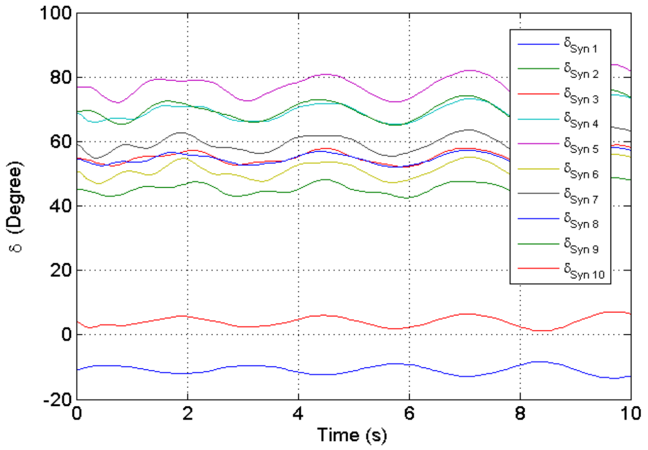
(b)

Fig. 6. State of the system before generation rescheduled for a transient contingency. (a) Location of operating points in bifurcation set and (b) power angle δ° versus time in s.

The computation time of calculating the CT control parameters and locate it in the stability region of bifurcation set is accomplished in 0.058 s and the prediction of the control values by SVRM is done in 0.01 s with a mean square error of 0.0074 by Inter® Core™ i7-4720HQ CPU. The proposed strategy is valid for any operating point and any loading condition as the swallowtail bifurcation set is valid for the power system encountering any type of stresses and congestion. SVRM is trained by optimized inputs using PSO at different loading condition for each fault location in the offline stage.



(a)



(b)

Fig. 7. State of the system after generation rescheduled for a transient contingency. (a) Location of operating points in bifurcation set (b) Power angle δo versus time in s

. 5. Conclusion

This paper has presented a new strategy for real-time transient instability preventive control using generation rescheduling by SVRM combined with the CART, and CT. Transient stability is assessed by CT in addition to providing the operator with visualized monitoring of the state of the power system. CART is used here as a feature extractor in order to figure out the generators to be rescheduled.The training inputs of the SVRM are optimized first by PSO to obtain the optimal values of control variables at different operating points and different loading condition. The proposed strategy is characterized by its speed, accuracy and ability of visualizing monitoring

The effectiveness of the proposed strategy has been demonstrated by computational studies on 39-bus ten-machine New England power system. Comparing results from the proposed algorithm with TDS provides the proposed algorithm an extra dimension for confirmation and validation.

6. References

[1] Prabha Kundur, John Paserba, Venkat Ajjarapu, Göran Andersson, Anjan Bose, Claudio Canizares, Nikos Hatziargyriou, David Hill, Alex Stankovic, Carson Taylor, Thierry Van Cutsem, and Vijay Vittal, "Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions," *IEEE Transactions on Power Systems*, vol. 19, no. 2, MAY 2004, doi: 10.1109/TPWRS.2004 .825981

[2] K. W. Chan, Q. Zhou, T. S. Chung , "Transient stability margin assessment for large power system using time domain simulation based hybrid extended equal area criterion method," *Advances in Power System Control, Operation and Management*, 2000. APSCOM-00. 2000 International Conference on 30 Oct.-1 Nov. 2000, doi: 10.1049/cp:20000432.

[3] K. Meng, Z. Y. Dong, K. P. Wong, Y. Xu, and F. J. Luo, "Speed-up the computing efficiency of power system simulator for engineering-based power system transient stability simulations," *IET Generation, Transmission & Distribution*, April 2009, doi: 10.1049/iet-gtd.2009.0701.

[4] Mania Pavella "Power system transient stability assessment - traditional vs modern methods," *Control Engineering Practice*, vol. 6, no. 10, pp. 1233-1246, October 1998, doi.org/10.1016/S0967-0661(98)00073-2.

[5] A. A. Sallam, J. L. Dineley, "Catastrophe theory as a tool for determining synchronous power system dynamic stability," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-102, no. 3, pp. 622–630, March 1983, doi: 10.1109/TPAS.1983.317983.

[6] A. A. Sallam, J. L. Dineley, "catastrophe theory applied to power system steady state stability – a comparison with the energy- balanced approach," *Proceedings of the Eighth Power Systems Computation Conference*, Helsinki, pp. 19-24, August 1984.

[7] A. A. Sallam, "Power systems transient stability assessment using catastrophe theory," *IEE Proceedings C - Generation, Transmission and Distribution*, vol. 136, no. 2, March 1989, doi: 10.1049/ip-c.1989.0016.

[8] A. M. Mihirig, M. D. Wvong, "Transient stability analysis of multimachine power system by catastrophe theory," *IEE Proceedings C - Generation, Transmission and Distribution*, vol. 136, no. 4, Jouly 1989, doi: 10.1049/ip-c.1989.0033.

[9] J. D. E. Echeverría, C. J. C. Cepeda, and D. G. Colomé," Real-time transient stability assessment of electric power systems using predictive-SIME based on machine learning," *Innovative Smart Grid Technologies Conference* - Latin America (ISGT Latin America), IEEE PES, 2017, doi: 10.1109/ISGT-LA.2017.8126760.

[10] R. Zhang, Yan Xu, Zhao Yang Dong, and Kit Po Wong," Post-disturbance transient stability assessment of power systems by a self-adaptive intelligent system," *IET Generation, Transmission & Distribution*, vol. 9, no. 3, pp. 296 – 305, 2015, doi: 10.1049/iet-gtd.2014.0264.

[11] Yang Li and Xueping Gu, " Power system transient stability assessment based on online sequential extreme learning machine." *Power and Energy Engineering Conference (APPEEC)*, 2013 IEEE PES Asia-Pacific, December 2013, doi: 10.1109/APPEEC.2013.68 37163.

[12] Ahmed M. A. Haidar, M. W. Mustafa, Faisal A. F. Ibrahim, Ibrahim A. Ahmed, "Transient stability evaluation of electrical power system using generalized regression neural networks," *Applied Soft*

Computing, vol. 1, no. 4, pp. 3558-3570, June 2011, doi.org/10.1016/j.asoc.2011.01.028.

[13] Noor Izzri, Abdul Wahab, Azah Mohamed, "Transient Stability Assessment of Power Systems using Probabilistic Neural Network with Enhanced Feature Selection and Extraction," *International Journal on Electrical Engineering and Informatics*, pp. 103-114, vol. 1, no. 2, 2009.

[14] Noor Izzri, Abdul Wahab, Azah Mohamed, "Transient Stability Assessment of a Large Actual Power System using Probabilistic Neural Network with Enhanced Feature Selection and Extraction," *International Conference on Electrical Engineering and Informatics,* Selangor, Malaysia, August 2009, doi: 10.1109/ICEEI.2009.5254758.

[15] Kusum Verma, K.R. Niazi, "A coherency based generator rescheduling for preventive control of transient stability in power systems," *International Journal of Electrical Power & Energy Systems*, February 2013, doi.org/10.1016/j.ijepes.2012.08.072.

[16] Y. Katoh, H. Takada, and S. Iwamoto," Transient stability preventive control using kinetic energy and critical clearing time," *Proceedings on Power System Technology,* Perth, Australia, December 2000, doi: 10.1109/ICPST.2000.900047.

[17] Mohammed Mahdi and V. M. Istemihan Genc," A coherency based generation rescheduling against multiple contingencies," *Smart Grid Congress and Fair (ICSG)*, Istanbul, Turkey, April 2016, doi: 10.1109/SGCF.2016.7492424.

[18] Zhen Wang, Xiaozhe Song, Huanhai Xin, Deqiang Gan, and Kit Po Wong," Risk-Based Coordination of Generation Rescheduling and Load Shedding for Transient Stability Enhancement," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4674 – 4682, November 2013, doi: 10.1109/TPWRS.2013.2262719.

[19] Istemihan Genc, Ruisheng Diao, Vijay Vittal, Sharma Kolluri, and Sujit Mandal, "Decision Tree-Based Preventive and Corrective Control Applications for Dynamic Security Enhancement in Power Systems," *IEEE Transactions on Power Systems*, vol. 25, no. 3, pp. 1611 – 1619, August 2010, doi: 10.1109/TPWRS.2009.2037006.

[20] Yanzhen Zhoua, Junyong Wua, Luyu Jia, Zhihong Yub, Kaijun Lina, and Liangliang Haoa," Transient stability preventive control of power systems using chaotic particle swarm optimization combined with two-stage support vector machine," *Electric Power Systems Research,* pp. 111–120, 2018, doi.org/10.1016/j.epsr.2017.10.007.

[21] D. Z. Fang, W. Sun, and Z. Y. Xue, "Optimal generation rescheduling with sensitivity-based transient stability constraints," *IET Generation, Transmission & Distribution,* vol. 4, no. 9, pp.1044 – 10511, September 2010, doi: 10.1049/iet-gtd.2009.0711.

[22] T. W. Wang, L. Guan, and Y. Zhang, "A modified pattern recognition algorithm and its application in power system transient stability assessment, " *IEEE Power and Energy Society General*, 2008, doi: 10.1109/PES.2008.4596483.

[23] S. Surender Reddy, "Multi-Objective Based Congestion Management Using Generation Rescheduling and Load Shedding," *IEEE Transactions on Power Systems*, vol. 32, pp. 852 - 863, March 2017, doi: 10.1109/TPWRS.2016.2569603.

[24] Lingshuang Du and Haifeng Hu, "Modified classification and regression tree for facial expression recognition with using difference expression images," *Electronics Letters,* vol. 53, no. 9, pp. 590 – 592, 2017, doi: 10.1109/ISGT-LA.2017.8126760.

[25] Tong Wang, Zengping Wang, Jizhen Liu, James S. Thorp, and Yuan Yang, "Classification and regression tree-based adaptive damping control of inter-area oscillations using wide-area signals," *IET Generation, Transmission & Distribution*, vol. 8, no. 9, pp. 1516 – 1527, Sept. 2014, doi: 10.1049/iet-gtd.2013.0601.

[26] Ruby Nageema and Jayabarathi R, "Predicting the Power Output of a Grid-Connected Solar Panel Using Multi-Input Support Vector Regression," *Procedia Computer Science*, pp. 723–730, 2017, doi.org/10.1016/j.procs.2017.09.143.

[27] M. Sanchez-Fernandez, M. de-Prado-Cumplido, J. Arenas-Garcia, F. Perez-Cruz, "SVM multiregression for nonlinear channel estimation in multiple-input multiple-output systems," *IEEE Transactions on Signal Processing*, vol. 52, no. 8, pp. 2298 – 2307, August 2004, doi: 10.1109/TSP.2004.831028.

[28] P. YengYin, "*Modeling, Analysis, and Applications in Metaheuristic Computing: Advancements and Trends*," in, USA., 2012, 1St ed., pp. 109-130.

[29] K. R. Padiyar, " *Power System Dynamics: Stability and Control*," Hyderabad, BS Pub, 2nd ed., 2006.

Appendix

As reported in [7], a generator connected to an integrated power system can generally configure as shown in Fig. A1. The electrical output power P_{ei} of generator G_i is

$P_{ei}=Re[I_iE_i^*]$

(A.1)

$I_i=(E_q-E_i)/jX_q$

(A.2)

$E_i=(-1/Y_{ii})\sum_{J=1, \neq i}^{N} Y_{ij}E_j$

(A.3)

where,

I_i=generator current following into terminal bus bar

E_i=terminal bus bar voltage

N=number of the network bus bars plus the internal machine bus bars.

Y_{ij}=off-diagonal element of the admittance matrix.

E_q=machine internal voltage source behind quadrature-reactance.

therefore,

$$E_i = \frac{1}{\left(\frac{1}{jX_n}\right)+\sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{1}{jX_{ij}}\right)}\sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{E_j}{jX_{ij}}\right)$$
(A.4)

Assuming e and f, are the real and imaginary components of the voltage E, respectively. Substituting (A.4) into (A.1), we get:

$$\text{Pei=Re}\left[\frac{e_q+jf_q}{jX_q}\left(\frac{1}{\frac{1}{jX_n}+\sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{1}{jX_{ij}}\right)}\sum_{\substack{j=1\\ \neq 1}}^{N}\frac{e_j+jf_j}{jX_{ij}}\right)-\frac{1}{jX_q}\left(e_i^2+f_i^2\right)\right] \quad (A.5)$$

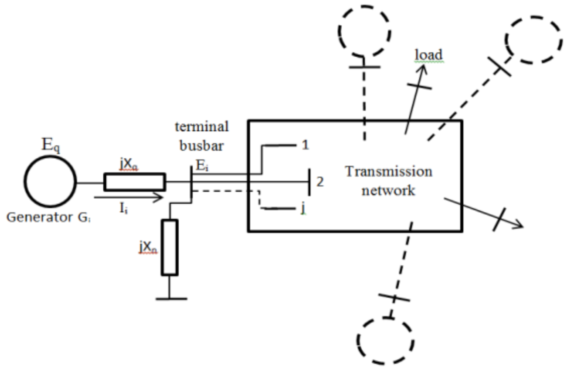


Fig. A1. Representation of generator G_i connected to an integrated power system.

i.e.,

$$\text{Pe}=\frac{\frac{1}{X_q}}{\frac{1}{X_n}+\sum_{\substack{j=1\\ \neq i}}^{N}\frac{1}{X_{ij}}}\left[f_{qi}\sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{e_j}{X_{ij}}\right)-e_{qi}\sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{f_j}{X_{ij}}\right)\right]$$
(A.6)

Let

$$\psi = \left(\frac{1}{X_q}\right)/\left(\frac{1}{X_n}+\sum_{\substack{j=1\\ \neq i}}^{N}\frac{1}{X_{ij}}\right)$$
(A.7)

$$\sigma_1 = \sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{e_j}{X_{ij}}\right)$$
(A.8)

$$\sigma_2 = \sum_{\substack{j=1\\ \neq i}}^{N}\left(\frac{f_j}{X_{ij}}\right)$$
(A.9)

$$A_1 = \psi E_q \sigma_1$$
(A.10)

$$A_2 = \psi E_q \sigma_2$$
(A.11)

Then, (A.6) becomes

P_{ei}=$A_1 \sin \delta_i$-$A_2 \cos \delta_i$ (A.12)

where

$\delta_i = tan^{-1}\left(\frac{f_q}{e_q}\right)$= machine power angle referred to the common reference axes of the system.

The equation of motion of generator G_i with respect to the common reference axes of the network is

$$M_I \ddot{\delta_i} = P_{in} - P_{ei}$$
(A.13)

where,

M_i= inertia constant of machine i.

P_{in}= input mechanical power.

Multiplying (A.13) by $d\delta/_{dt}$ and integrating, we obtain

$$\left(d\delta/_{dt}\right)^2 = \int_{\delta_0}^{\delta_m}(P_{in}-P_{ei})d\delta$$
(A.14)

Where, δ_0, δ_m are the minimum and maximum angles of oscillation, respectively. The machine will again retain synchronism after a disturbance when dδ/dt = 0, i.e., the RHS of (A.14) must equal zero. In other words, the machine is stable if the kinetic energy generated during the fault is less than, or equal (totally converted) to, the potential energy during the post fault period. The equality of both energies takes place in the critical clearing case,

i.e.,

$F=F_{ke}+F_{pe}=0$

(A.15)

By catastrophe theory, the equilibrium surface U of a smooth function F is given by

U= $\nabla F_c(x)$ =F=$F_{ke}+F_{pe}$=0

(A.16)

and the singularity set S which is defined as the set of steady-state stability limits is obtained by

$\nabla^2 F_c(x)$ =0

(A.17)

The transient kinetic energy can be evaluated by the amount of output power reduction during the fault. Therefore, it is expressed by

F_{ke}= $\int_{\delta_0}^{\delta_c}(P_{in}-P_{ei})\ d\delta$

(A.18)

The potential energy after the fault is

F_{pe}=$\int_{\delta_c}^{\delta_m}(P_{in}-P_{ei})\ d\delta$

(A.19)

From (A.16), (A.18), and (A.19), the following relation is obtained:

$(A_{1D}+A_{1A})\cos\delta_c+(A_{2A}-A_{2D})\sin\delta_c+K=0$

(A.20)

where,

A_{iD} = the coefficient A_i, (i = 1,2) during the fault

A_{iA} = the coefficient A_i, (i =1,2) after fault

δc = critical clearing angle

K= constant = K_2 - K_1

K_1=$A_{1D}\cos\delta_0$-$A_{2D}\sin\delta_0$-$P_{in}\delta_0$

(A.21)

K_2=-($A_{1A}\cos\delta_m$+$A_{2A}\sin\delta_m$+$P_{in}\delta_m$)

(A.22)

Replacing sin and cos by their expansion, and assuming = x, (A.20) can be rewritten as:

$(A_{1D}+A_{1A})\left(1-\frac{x^2}{2!}+\frac{x^4}{4!}\right)+(A_{2A}-A_{2D})\left(x-\frac{x^3}{3!}+\frac{x^5}{5!}\right)+K=0$
(A.23)

If the series expansion in (A.23) is trunked up to fourth order terms, it gives

$B_4x^4+B_3x^3+B_2x^2+B_1x+B_0=0$
(A.24)

$B_0=A_{1D}+A_{1A}+K$
(A.25)

$B_1=A_{2A}-A_{2D}$
(A.26)

$B_2=-(A_{1A}+A_{1D})/2$
(A.27)

$B_3=(A_{2D}-A_{2A})/6$
(A.28)

$B_4=(A_{1D}+A_{1A})/24$
(A.29)Equation (A.24) is four-determinate and closely equivalent to (A.20). The cubic term can be eliminated by taking x = y-α and α = $B_3/4B_4$ to get the form

$y^4+ay^2+by+c=0$
(A.30)

where,

$a=(6B_4\alpha^2-3B_3\alpha+B_2)/B_4$
(A.31)

$b=(3B_3\alpha^2-2B_2\alpha+B_1)/B_4-4\alpha^3$
(A.32)

$c=\alpha^4+(B_0-B_1\alpha+B_2\alpha^2-B_3\alpha^3)$
(A.33)

The smallest positive real root of the swallowtail equation, y, satisfying the relation $\delta o< y-\alpha<\delta m$ gives the critical clearing angle δ_c for the stable machines in the system. They can be represented by operating points which lie inside the bifurcation set B. CCT can be calculated by using Taylor approximations for δ_c and its derivative $\delta^{\cdot}{}_c$, which gives a good result for the first swing analysis, as follows:

$\delta_c = w_c = \gamma t_c$
(A.34)

where,

$\gamma \triangleq$ machine acceleration at the istant of fault occurance
$= \left({}^1\!/_M\right)[P_{in}-P_e(t_{o+})]$
(A.35)

and

$\delta_c = \delta_0 + \frac{1}{2}\gamma t_c^2$
(A.36)

then,

$$\mathrm{CCT} = \sqrt{\frac{2}{\gamma}(\delta_c-\delta_0)}$$
$$= \sqrt{\frac{2M(\delta_c-\delta_0)}{(P_{in}-P_e(t_{o+}))}}$$
(A.37)