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Data-mining model based adaptive protection scheme to enhance distance relay performance during power swing

Rahul Dubey [a,*], Subhransu Ranjan Samantaray [b], Bijay Ketan Panigrahi [a], Vijendran G. Venkoparao [c]

[a] *Department of Electrical Engineering, Indian Institute of Technology, Delhi, India*
[b] *School of Electrical Sciences, Indian Institute of Technology, Bhubaneswar, India*
[c] *Robert Bosch Engineering and Business Solutions Ltd, Bengaluru, India*

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ABSTRACT

The paper presents a data-mining model based adaptive protection scheme enhancing distance relay performance during power swing for both compensated and uncompensated power transmission networks. In the power transmission network, the distance relays are sensitive to certain system event such as power swings, which drive the apparent impedance trajectories into the protection zones of the distance relay (zone-3) causing mal-operation of the distance relay, leading to subsequent blackouts. Further, three-phase balanced symmetrical fault detection during power swing is one of the serious concerns for the distance relay operation. This paper proposed a new adaptive protection scheme method based on data-mining models such as DT (decision tree) and RF (random forests) for providing supervisory control to the operation of the conventional distance relays. The proposed scheme is able to distinguish power swings and faults during power swing including fault zone identification for series compensated power transmission network during stress condition like power swing. The proposed scheme has been validated on a 39-bus New England system which is developed on Dig-Silent power factory commercial software (PF4C) platform and the performance indicate that the proposed scheme can reliably enhance the distance relay operation during power swing.

Introduction

Power swing is a phenomena occurs in an interconnected electric power transmission system due to sudden removal of faults, loss of synchronism or changes in direction of power flow as a result of switching and creates oscillations in power flow [1]. In a stable power swing, these fluctuations die down whereas unstable swings result in progressive separation of angle between the two areas causing large oscillations of power flows, large fluctuations of voltages (V) and currents (I) and eventually loss of synchronism between such areas [1–3]. A CIGRE study found that major portion of bulk power system disturbances resulted from false trips of the protection system. This is mainly due to the fact that conventional local protection devices are not able to consider a system view and therefore, are not able to take optimized and coordinated actions. Recent blackouts offer testimonies of the crucial role played by protection relays in a reliable power system [4–6]. The most recent blackout in India in July 2012 was initiated by the tripping of zone-3 relay of the 400 kV Bina-Gwalior line due to load encroachment [7,8]. Further, lack of real-time data and lack of coordinated controls are also some of the major causes of blackouts [9].

There are numerous schemes available for fault detection and power-swing blocking (PSB) with distance relays to identify the power swing [10–22]. Concentric characteristic and blinder methods are based on the rate of change in apparent impedances [10–13]. These methods require wide range offline stability study to obtain the settings [11]. Again, these methods do not respond to faults during a blocking period and fail to distinguish a fast swing condition from the faults. Since resistance seen by the relay changing during power swing and remains constant during the fault period, the rate of change of resistance is a good indicator of a fault [13]. However, the response time becomes a concern since the rate of change in resistance becomes significantly slower in the transient period. To detect the power swing by combining concentric characteristic and continuous monitoring of apparent impedance, a method is proposed in [14]. A power swing detection scheme based on swing centre voltage (SCV), is available in [15]. This technique takes more than two cycles to detect a fault during the power swing.

In [16] an adaptive distance protection scheme resistant to the power swing is presented. In [17,18], a supervised learning

* Corresponding author. Tel.: +91 8527457072.
E-mail address: rahul.dubey2011@gmail.com (R. Dubey).

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methods, such as support vector machine (SVM) and adaptive neuro-fuzzy inference system (ANFIS), are applied to develop the PSB function for distance relay utilizing several input signals. These methods require many simulations to train for wide ranges of faults and power-swing conditions, and suffers due to high computational time of SVM. A wavelet transform coefficients of the voltage and current signals are used to distinguish the power swing from the fault proposed in [19]. In [20], a fault detector using superimposed components of the current is proposed. In [21], a cross-blocking method based on the derivative of the three-phase active and reactive power is used to detect symmetrical faults during the power swing. In [22], a symmetrical fault detector based on the relative presence of decaying dc in the current waveforms during the power swing is proposed. However, the challenges are compounded when the transmission network is embedded with Flexible AC Transmission Systems (FACTS) devices.

FACTs devices are increasingly for improving steady-state and transient stability improvement. Among those Thyristor Controlled Series Capacitor (TCSC) is used for enhancing power transfer capability by variation of series compensation. However, variation in series compensation introduces number of protection challenges for the distance relay operation. Voltage inversion, current inversion, reach measurement and relay coordination are some of the major concerns in series compensated lines [23,24]. Overreaching of distance elements is the most critical problem with series compensated lines. Also the distance function may fail to pick up for low-current faults [25]. The evaluation and performance assessment of different power swing detectors for a series-compensated line has been discussed in [26–28].

Looking at the aforementioned protection issues, there is a strong motivation in building an intelligent protection relay that can provide a comprehensive adaptive protection to prevent the maloperation of distance relay during power swing for the both compensated and uncompensated power transmission system. The proposed scheme helps in minimizing the likelihood of manifestation of hidden failures and potential cascading events by adjusting the security/dependability balance of protective relays to suit prevailing system conditions. The main contribution of this proposed research work is to demonstrate the effectiveness of the data-mining model [29–35,17,36–38] approaches for symmetrical fault detection and out-of-step detection during power swing. Data-mining is a non-parametric statistical analysis which is best suited for power systems with complex nonlinear behaviours involved.

In the present study, the New England 39 bus system is considered (Fig. 1(a)) where a modification has been incorporated by providing 70% compensation at the beginning of line 16–17 (Fig. 1(b)) for evaluating the performance of the proposed technique. In Section "Protection challenges with series compensated line and power swing", the protection challenges with SC-line during power swing is defined. The proposed scheme for an adaptive and intelligent security/dependability protection scheme is presented in Section "Proposed scheme". Simulation results and different case studies are presented in Section "Results and analysis". Performance assessments and discussion presented in Section "Performance assessments and discussions". Conclusions followed by references are presented in section "Conclusion".

Protection challenges with series compensated line and power swing

Series compensation in power transmission network increases power transfer capability and improves power system stability. Series compensation imposes various protection problems as discussed in literature [23–28]. The fault detection during the power swing in a metal oxide varistors (MOV) protected series-compensated transmission network is very challenging. The variation of the fault current during such a period relies on the operation of the MOV. To study the variation in the current signal patterns for faults during the power swing, a symmetrical fault is created at 1.9 s for two different locations of fault (20% and 75%) from the relay end in T-16 following the removal of T29–T26. The corresponding current signal are shown in Fig. 2(a) and (b), respectively. It is clearly observed from Fig. 2(a) that in the case of the a–b–c fault at the far end. The level of fault current is smaller

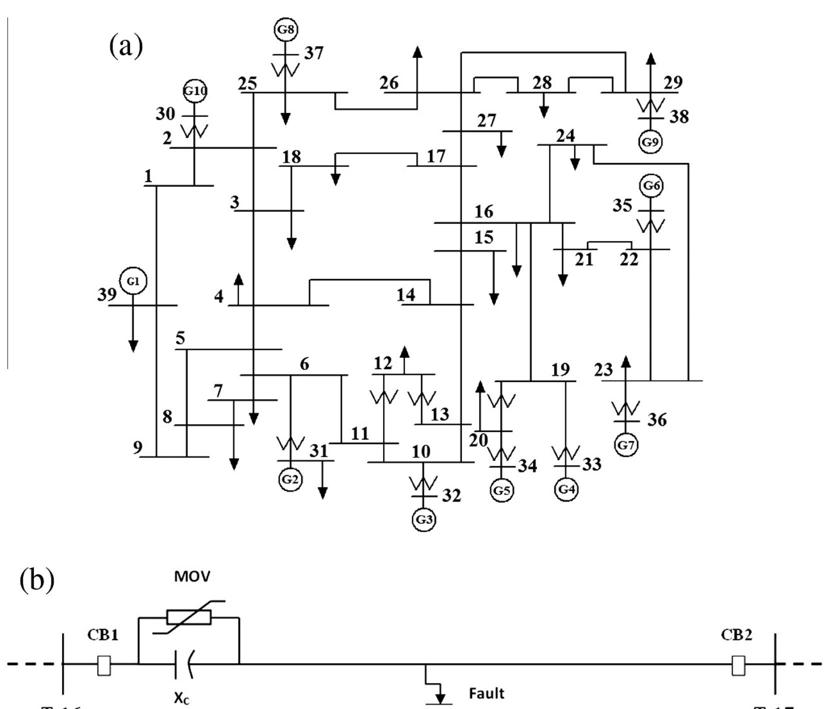

Fig. 1. (a) IEEE 39-bus New England system, and (b) series compensated line.

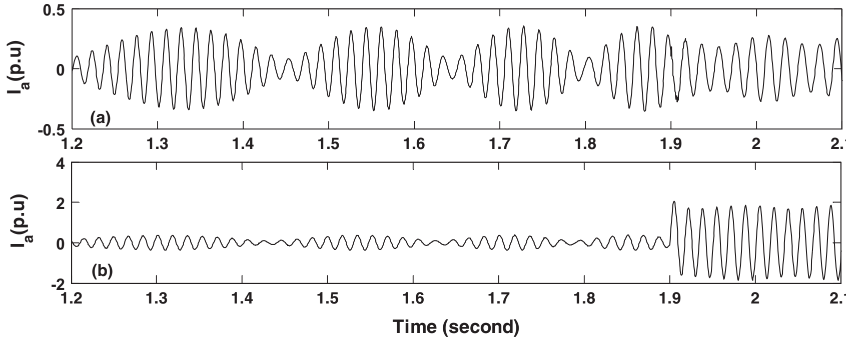

Fig. 2. Phase-a current at the relay bus for a three-phase fault during the power swing at 1.9 s at locations of (a) 20% and (b) 75%.

than the power swing current which does not enable MOV conduction and results in sub-synchronous. However, in case of an a–b–c fault at the near end (Fig. 2(b)), the current level as seen from the graph is larger than the swing current which causes the MOV to operate. As a result, in most portions of the fault, the series capacitor is bypassed and no oscillation is observed in the fault current.

Further, the impedance trajectory during power swing enters zone-1 of the relay, as shown in Fig. 3 which corresponds to an unstable power swing. In case of stable power swing the impedance trajectory enters to the zone-3. However, for stable or unstable power swings, relays should not operate and the operation must be blocked. This research work develops a data mining model based fault/power swing detector to issue the trip/block command accordingly for secured operation of the power system.

Proposed scheme

System studied

The New England 39 bus system shown in Fig. 1(a) has 10 synchronous generators, 39 buses and 45 AC transmission lines with constant active and reactive power loads distributed throughout the network is considered for the study where a modification has been incorporated by providing 70% compensation at the beginning of line 16–17 as the test system for evaluating the performance of the proposed technique. The studied power network is developed using Dig-Silent power factory commercial software package. A three-phase-to-ground fault with fault resistance of 1 Ω occurs on line T26–T29 at $t = 0.5$ s and cleared at $t = 0.75$ s by disconnecting the line. This creates the power swing in interconnected transmission line. Fig. 4 shows the schematic diagram of the proposed data-mining model based intelligent differential protection scheme to prevent the maloperation of distance relay during power swing for series compensated line. The inputs used for building the intelligent relay are as follows:

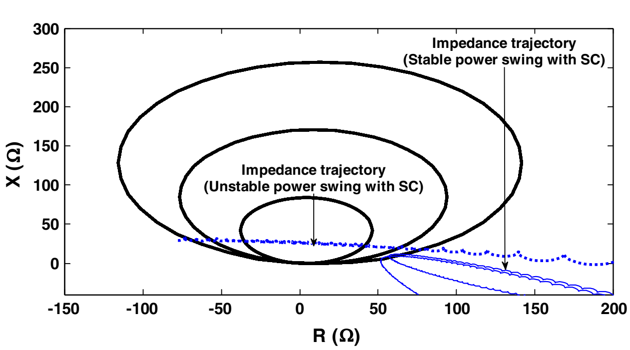

Fig. 3. Impedance locus during power swing.

- $X_1 = d(P_{sa} - P_{ra})/dt$: (Rate of change of active power phase-A difference).
- $X_2 = d(P_{sb} - P_{rb})/dt$: (Rate of change of active power phase-B difference).
- $X_3 = d(P_{sc} - P_{rc})/dt$: (Rate of change of active power phase-C difference).
- $X_4 = d(Q_{sa} - Q_{ra})/dt$: (Rate of change of reactive power phase-A difference).
- $X_5 = d(Q_{sb} - Q_{rb})/dt$: (Rate of change of reactive power phase-B difference).
- $X_6 = d(Q_{sc} - Q_{rc})/dt$: (Rate of change of reactive power phase-C difference).
- $X_7 = d(I_{2s} - I_{2r})/dt$: (Rate of change of negative sequence current difference).
- $X_8 = d(V_{2s} - V_{2r})/dt$: (Rate of change of negative sequence voltage difference).
- $X_9 = d(I_{1s} - I_{1r})/dt$: (Rate of change of positive sequence current difference).
- $X_{10} = d(V_{1s} - V_{1r})/dt$: (Rate of change of positive sequence voltage difference).
- $X_{11} = d(I_{0s} - I_{0r})/dt$: (Rate of change of zero sequence current difference).
- $X_{12} = d(V_{0s} - V_{0r})/dt$: (Rate of change of zero sequence voltage difference).
- $X_{13} = d(I_{sa} - I_{ra})/dt$: (Rate of change of current I_A difference).
- $X_{14} = d(I_{sb} - I_{rb})/dt$: (Rate of change of current I_B difference).
- $X_{15} = d(I_{sc} - I_{rc})/dt$: (Rate of change of current I_C difference).
- $X_{16} = d(V_{sa} - V_{ra})/dt$: (Rate of change of voltage V_A difference).
- $X_{17} = d(V_{sb} - V_{rb})/dt$: (Rate of change of voltage V_B difference).
- $X_{18} = d(V_{sc} - V_{rc})/dt$: (Rate of change of voltage V_C difference).
- $X_{19} = d(phi_s - phi_r)/dt$: (Rate of change of phase angle difference).
- $X_{20} = d(delta_s - delta_r)/dt$: (Rate of change of Load angle delta).

Differential feature selection

Conventionally, the phasor is defined for steady state sinusoidal signals with constant amplitude and angle. In the dynamic condition, the amplitude and phase (angle) varies with time, which introduces the concept of dynamic phasor [39]. Due to lack of recommended specific algorithm to estimate phasor in IEEE Std. C37.118, phasor estimation has attracted a lot of attention [40]. Different algorithms are proposed to estimate the dynamic phasors [41–46]. The performance of all these techniques depends on the accuracy of phasor estimation. Because of substantial error in phasor estimation during power swing, the negative sequence component becomes significant even for non-fault situation, which may lead to incorrect protection decision. Higher threshold value could be set for sequence components to address such inaccuracies, which may result in unreliable fault detection. In this paper, the

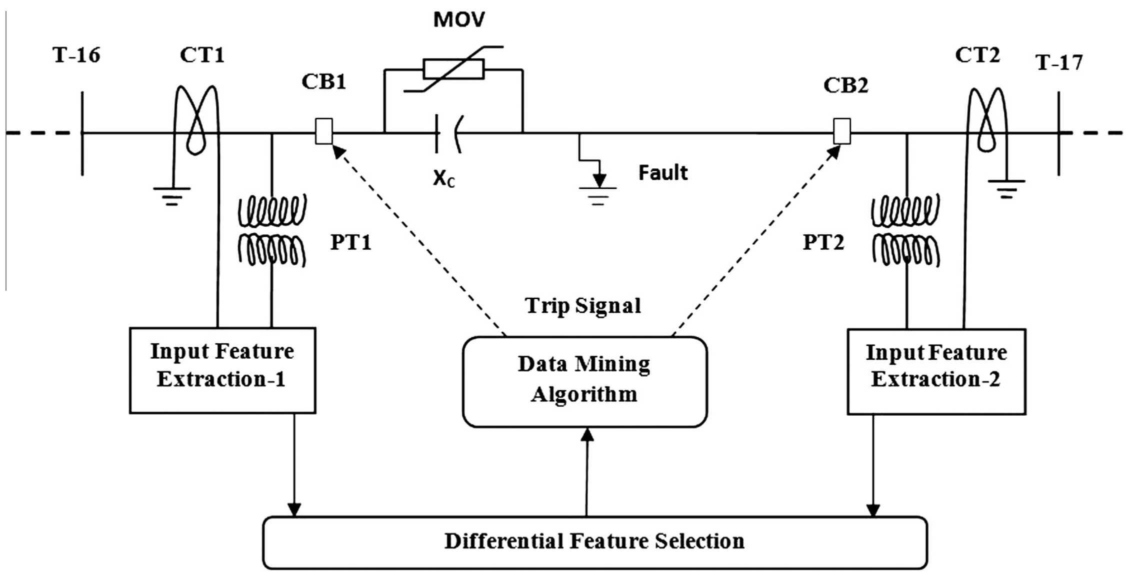

Fig. 4. Data-mining model based proposed intelligent differential protection scheme for symmetrical fault detection and out-of-step blocking.

amplitude and phase of the power system variables are considered as time dependent and the proposed study uses least squares (LS) technique based PMUs [47,48] for phasor estimation and corresponding feature extraction.

In the proposed study, 20 differential features are derived, which could be mostly affected during the fault condition and are measured locally as follows $f_i = f_{i,16} - f_{i,17}$, where f_i is the differential feature, $i = 1, 2, 3, \ldots, 21$ and (No. of features), $f_{i,16}$ is the ith feature estimated at bus-16, and $f_{i,17}$ is the ith feature estimated at bus-17. 16 and 17 are the buses at both ends of the target feeder, on which the fault occurs.

Data sets generated for data mining model

The proposed study considers wide variation in operating conditions during power swing as follows. (a) Variations in fault resistance from 0 to 300 Ω; (b) variations in source impedance by 40% from normal value; (c) variations in fault location: 20–95% of the line; (d) variations in fault inception angle (FIA): 0–90°; (e) all 10-types of fault during power swing like ground fault (i.e. a–g, b–g, c–g, a–b–g, b–c–g, a–c–g) and unground fault (i.e. a–b, b–c, a–c, a–b–c) (f) three-phase fault in harmonic condition during power swing; (g) three-phase fault in noisy condition during power swing; (h) load increasing up to 50% during power swing; (i) variations in compensation level: 50–70%.

Total simulations carried for fault during power swing are $5R_F$ (fault resistance) × $2Z_S$ (source impedance) × 5(fault location) × 5 (FIA) × 11 (types of fault) × 2 (compensation level) + 50 (three-phase fault in harmonic condition) + 45 (load increasing) = 5595. The complete data set generated considering above variations are used to train and test the data-mining model.

Proposed DT based scheme distinguishing faults and power swing

The classification approach using DTs to prevent distance relay maloperation under power swing is shown in Fig. 6. Post fault differential features (both end of compensated i.e. T-16 and T-17) are used as inputs to the decision trees (i.e. DTs) against target outputs “1” for faults and “0” for power swing. The DT is trained to build a data-mining model with an extensive data sets derived from a series of fault simulations. The proposed technique is tested on wide variations in operating parameters in the power system network, including a noisy environment and, was found to be accurate and robust for fault/power swing identification in series compensated transmission lines.

The proposed scheme is divided into three stages (i.e. Fig. 5). In the first stage based on input feature selection DTs-1 identify fault (1)/power swing (0) and send accordingly tripping/blocking command. In the second stage DT-2 classify type of swing for unstable power swing (Out-of-step) where the target output is ‘1’ and for stable power swing with target output as ‘0’. Similarly, in the third stage DT-3 classify type of fault during power swing for grounded fault as target output ‘1’ and for ungrounded fault target output is ‘0’. The differential input features considered in the proposed study are discussed in the earlier section. The hierarchical structure of classification scheme using data-mining models to prevent distance relay maloperation under power swing is shown in Fig. 6 and the trained DT for the proposed scheme is shown in Fig. 7.

Results and analysis

The data-mining models are developed using the features extracted from the least squares (LS) based PMU for deriving final decision. Thorough comparisons are made between different data-mining models such as DT, RF and SVM ranging from transparent

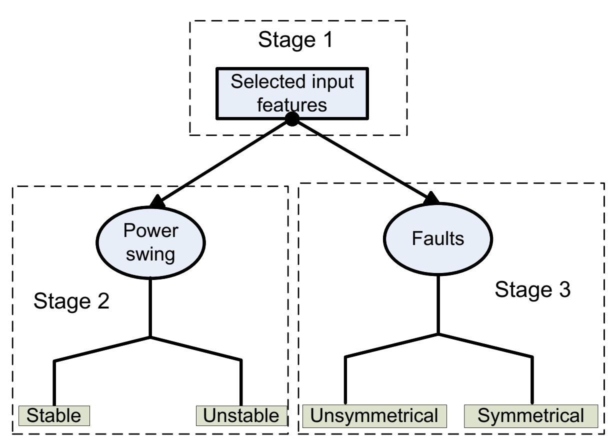

Fig. 5. Three stage classification approach.

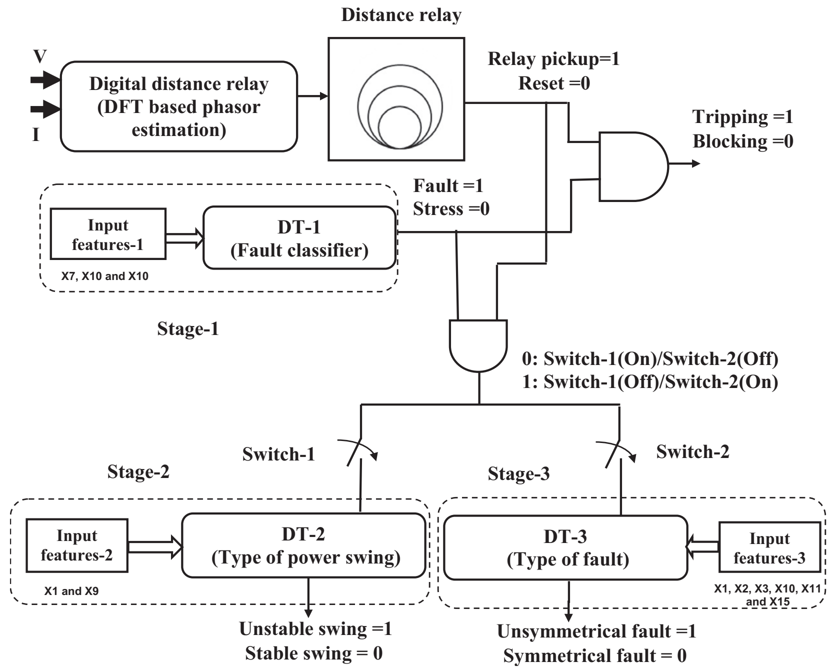

Fig. 6. Classification scheme using decision tree to prevent distance relay maloperation during power swing.

to black-box solutions, respectively. It is observed that there is a trade-off between transparency and accuracy while looking at the performance of the data mining models. The data-mining models developed in this study use open-source software R [38], which includes the implementation of conventional DT, RF and SVM.

Classifier-1:- fault versus power swing

In the proposed study, an extensive data set is generated to train and test the data-mining model (DTs, RFs and SVM) for developing an accurate and robust classifier to prevent distance relay maloperation under power swing. The data-mining model is trained and tested for different combination of data sets, such as (80–20), (70–30), (30–70), and (20–80) for training and testing purpose, respectively. For example in combination of (70–30) data set, 70% of data are considered for training purpose and 30% of data for testing purpose. The confusion matrix generated for the above system is depicted in Table 1, provides the comparison results between the actual and predicted faults during testing for the given data set. Data-mining model provides confusion matrix only on testing data set. For example, (80–20%) data set mean, the confusion matrix provides classification results on 20% of total data set. Table 1 also shows the effect of increase in training data set on the yield of Data-mining model and it is observed that either for [70–30%] or [80–20%] combination of data set, the Data-mining model provides three nine i.e. 99.9% accuracy in case of ensemble decision tree (random forest) and 99.6%, 99.4% for DT and SVM case respectively. Thus, further results assessment has been carried out considering 80–20% training–testing data sets.

It is observed from Fig. 7 that the actual or optimal number of features taking part in DT construction, for classification of fault versus power swing, are X_7, X_{10}, X_{11}, even though 20 features are initially fed to the Data-mining model as inputs. This clearly shows the optimal feature selection capability of DT for decision making. The accuracy of the classification is strongly dependent on the quality of the attributes or inputs. This complementary behaviour is highlighted by the importance analysis results from the random forest learning as shown in Fig. 8 for fault versus power swing (X_{10}, X_{11} and X_{17} in Mean Decrease Gini). Out-of-bag accuracy-based ranking results in approximately the same top three, although X_7 is substituted to the highly correlated X_{17}. However, the difference in accuracy loss between these three variables is so tenuous that they are all equally important for achieving a predictor with good generalization capabilities.

Classifier-2:- stable versus unstable power swing

If there is no fault exists during power swing then distance relay output is ‘1’ and classifier-1 output is ‘0’ and thus, both output pass through the AND logic gate which gives ‘0’ output for digital relay. Its means that the relay block during power swing and power system is in safe state during stress condition. Again, data-mining model based classifier-2 used for classifying stable power swings from unstable ones. The accuracy of different data-mining technique for 80–20% are depicted in Table 2, which gives the comparison result between the DT, RF and SVM during testing period for a given data set.

Classifier-3:- symmetrical versus unsymmetrical fault during power swing

If the fault exists during power swing, then distance relay output is ‘1’ and classifier-1 output is also ‘1’ and thus, both output pass through the AND logic gate which gives ‘1’ output for digital relay. Its means that the relay issues the tripping signal during power swing. Again, data-mining model based classifier-3 used for classification of symmetrical versus unsymmetrical fault during power swing. The accuracy of different data-mining techniques (80–20%) for this situation is depicted in Table 3, which provides the comparison result between the DT, RF and SVM during testing period for a given data set.

Fault zone identification during power swing

In the proposed study, an extensive data set is generated to train and test the data-mining model for developing also an

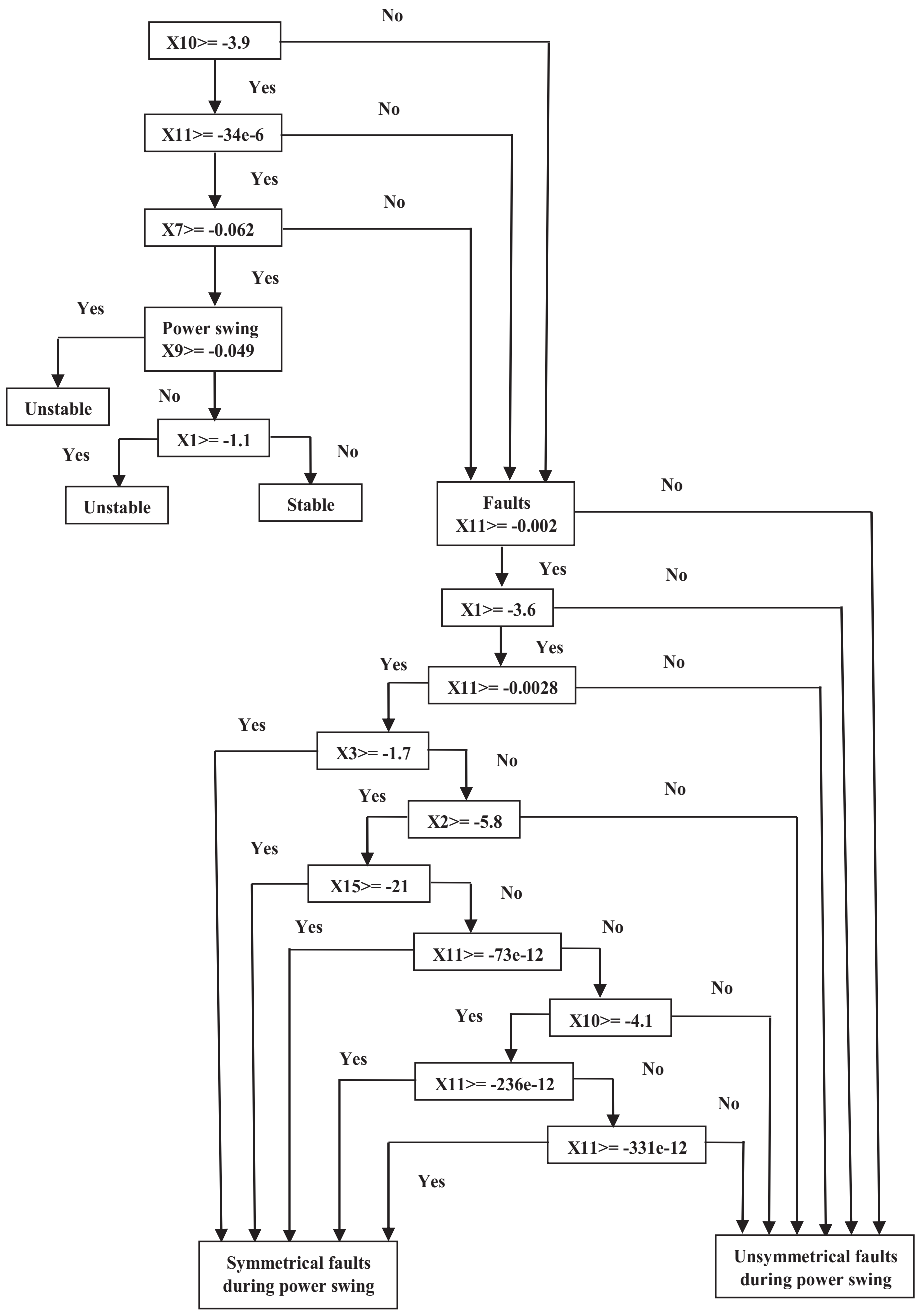

Fig. 7. Cascaded DT generated structure.

accurate and robust classifier for fault-zone identification in series compensated transmission line during power swing. The total data sets generated for series compensated lines is 800. It is observed from Fig. 9 that the actual or optimal number of features taking part in DT construction for fault-zone identification in series compensated transmission are X_1, X_2, X_8, X_9, X_{11}, X_{16} and X_{20}, even though 20 features are initially fed to the Data-mining model as input. This clearly shows the optimal feature selection capability of DT for decision making. The overall performance assessment for the above combination is depicted in Table 4, which provides the comparison result between the DT, RF and SVM during testing period for a given data set. For fault-zone identification three data mining algorithms are used, however there exists a trade-off in accuracy and transparency between them. RF provides performance accuracy close to DT, however, DT is transparent and finds easy implementation on real time compared to other two black box solutions (SVM and RF).

Fault classification during power swing

In the proposed study, an extensive data set is generated to train and test the data-mining model for developing an accurate and robust classifier for single fault identification in series compensated transmission line during power swing. The total data sets generated for series compensated lines is 800. The overall accuracy for the above combination is depicted in Table 5, which provides the comparison result between the DT, RF and SVM during testing period for a given data set.

Real time testing and validation

To test the robustness of the proposed adaptive protection scheme, the validation is also carried out on field-programmable gate array (FPGA) board. Performance testing on FPGA platform

Table 1
Confusion matrix for fault versus power swing.

Performance indices	DT Actual		RF Actual		SVM Actual	
Predicted	0	1	0	1	0	1
Test 1	80% Training and 20% Testing					
0	107	3	107	3	104	6
1	2	1007	0	1009	0	1009
Accuracy (%)	99.55		99.73		99.46	
Misclassification	5		3		6	
Test 2	70% Training and 30% Testing					
0	155	3	157	1	149	9
1	3	1518	0	1521	0	1521
Accuracy (%)	99.64		99.94		99.46	
Misclassification	6		1		9	
Test 3	30% Training and 70% Testing					
0	344	6	345	5	327	23
1	5	3562	0	3567	0	3567
Accuracy (%)	99.71		99.87		99.41	
Misclassification	11		5		23	
Test 4	20% Training and 80% Testing					
0	397	6	397	6	374	29
1	5	4068	0	4073	0	4073
Accuracy (%)	99.75		99.844		99.353	
Misclassification	11		6		29	

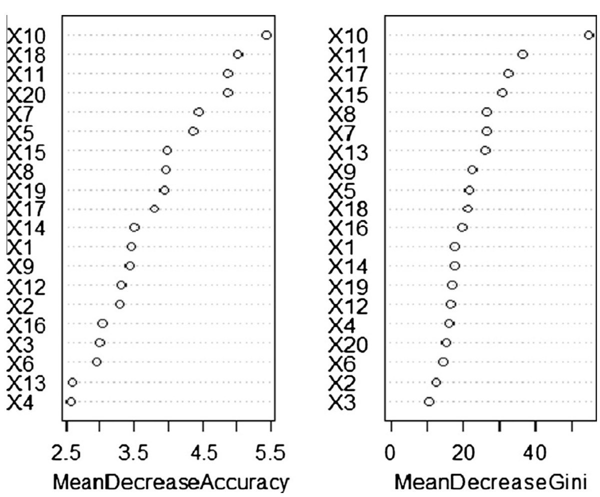

Fig. 8. Top-down importance of the variables according to the accuracy loss or misclassification rate reduction (gini) for fault vs. power swing.

Table 2
Stable versus unstable power swing results.

Method	Accuracy (%)
DT	99.12
RF	100
SVM	100

Table 3
Symmetrical versus unsymmetrical fault during power swing results.

Method	Accuracy (%)
DT	99.68
RF	99.11
SVM	89.21

indicates the ability of the developed data-mining model based intelligent relays to perform on real-time application. The proposed decision tree classifier (DTC) architecture (Figs. 7 and 9) was implemented on a Xilinx ML310 board which is a Virtex-II Pro-based embedded development platform. It includes a Xilinx XC2VP30 FPGA with two embedded PowerPC processors, 256 MB DDR DIMM, 512 MB compact flash card, PCI slots, Ethernet and standard I/O on an ATX board. The XC2VP30 FPGA contains 13696 slices and 136 Block RAM modules. We used Xilinx XPS 8.1i and ISE 8.1i software's to implement our architecture on the board. The results of FPGA testing (for proposed DT with 30% testing dataset-1678 cases) are presented in Table 6. It is observed that the dependability stays at >99% while the security stays at >97%.

Further, the response time of the proposed scheme is compared with that of other differential existing schemes [49–52] along with their dependability for 167 cases of crucial different fault situations during power swing. The comparative assessments based on response time and dependability (in FPGA board) are presented in Figs. 10 and 11 respectively. It is concluded that the proposed scheme is most dependable among all the existing relaying schemes with a faster response time. The response time of the proposed relay is 1.75-cycles from the fault inception, which includes 30 ms (1.5 cycles) for LS-PMU for accurate phasor estimation during power swing [48] and differential feature computation, and 5 ms for DT processing. It is observed that the dependability stays at 99% against 85% and 80% for the remote end faults at 95% of the uncompensated and compensated line, respectively as depicted in Table 7.

Performance assessments and discussions

The previous section deals with building data-mining model for (i) fault versus power swing classification, (ii) stable versus unstable power swing classification, (iii) symmetrical versus unsymmetrical fault during power swing classification, (iv) fault-zone identification during power swing for series compensation at middle of the line T16–T17, (v) fault classification during power swing and, (vi) real time testing and validation. Post fault differential features from both the ends of compensated line to be protected are used to build the classification data-mining model for disturbance classification. To assess the performance of the proposed intelligent relay, three statistical metrics are defined as follows:- (1) Dependability: Total number of fault cases predicted correctly during power swing/Total number of actual fault cases during power swing. (2) Security: Total number of no-fault cases predicted correctly during power swing/Total number of actual no-fault cases during power swing. (3) Accuracy: Total number of correctly predicted (fault + no fault) cases during power swing/Total numbers of actual (fault + no fault) cases during power swing.

The performance comparison between DT, RF and SVM is depicted in Table 6. Although RF, SVM provides similar performance compared with DT, the model complexity makes the implementation difficult on the digital signal processor/field-programmable gate array board in case of RF and SVM. At the same time, DT, being the transparent tool, can be implemented based on the set thresholds of the decision variables and thus attracts widespread attention as one of the emerging data-mining tools for engineering applications and their commercial implementations. The scheme proposed in this article main aims to reduce the likelihood of hidden failures and potential cascading events due to stress condition like power swing by adjusting the security/dependability balance of protection systems. Aided with wide-area measurements based on PMU data, the methodology tailors the security/dependability balance to suit prevailing system conditions. When the power system is in a “safe” state (i.e. no power swing

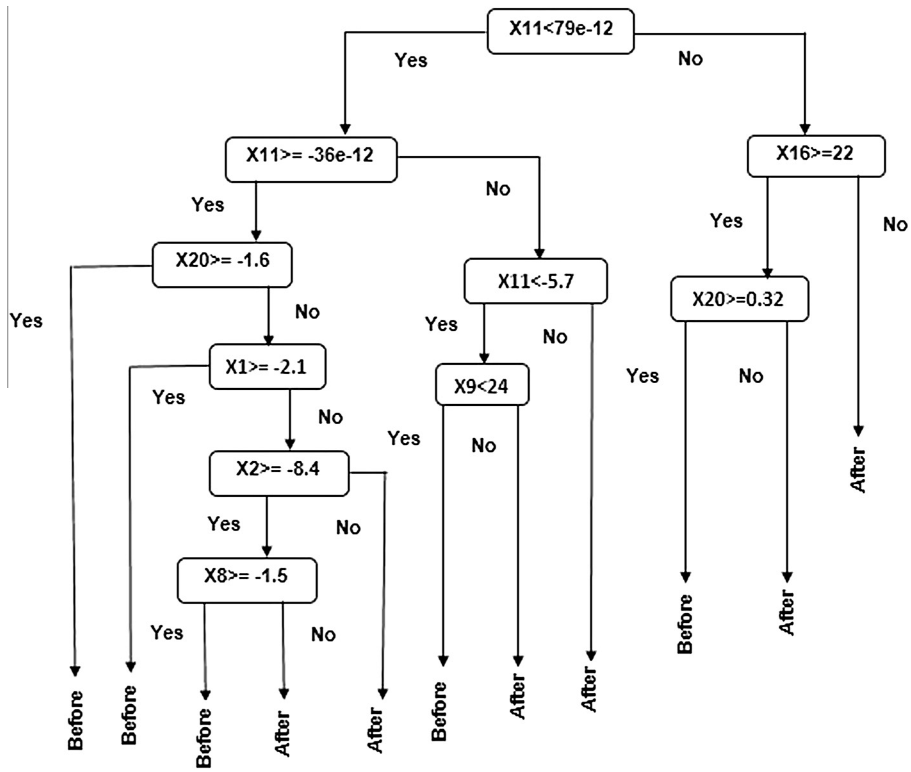

Fig. 9. DT generated structure for fault zone identification.

Table 4
Fault zone identification results during power swing.

Method	Accuracy (%)
DT	95.52
RF	95.62
SVM	81.87

Table 5
Single fault classification during power swing.

Fault cases	Accuracy (%) (testing 20% and training 80%)		
	DT	RF	SVM
1(a–g)	99.31	100	100
2(b–g)	99.38	100	100
3(c–g)	99.04	100	100
4(a–b)	99.05	100	100
5(b–c)	99.7	100	100
6(c–a)	99.67	100	100
7(a–b–c)	99.67	100	100
8(a–b–g)	99.35	100	100
9(b–c–g)	99.7	100	100
10(c–a–g)	99.1	100	100
11(a–b–c–g)	99.67	100	100

Table 6
Performance assessments.

Sl. no.	Relay performance	DT (%)	RF (%)	SVM (%)
1	Dependability	99.80	100	100
2	Security	97.27	97.27	94.55
3	Accuracy	99.55	99.73	99.46

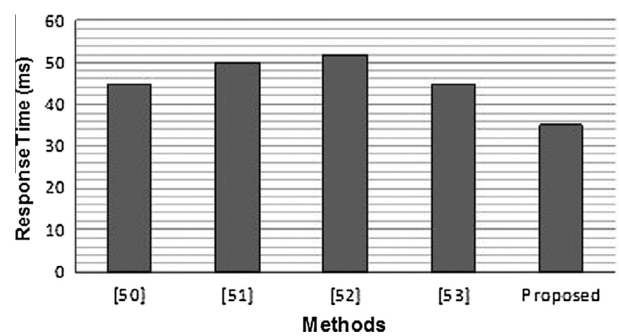

Fig. 10. Comparative assessments based on response time.

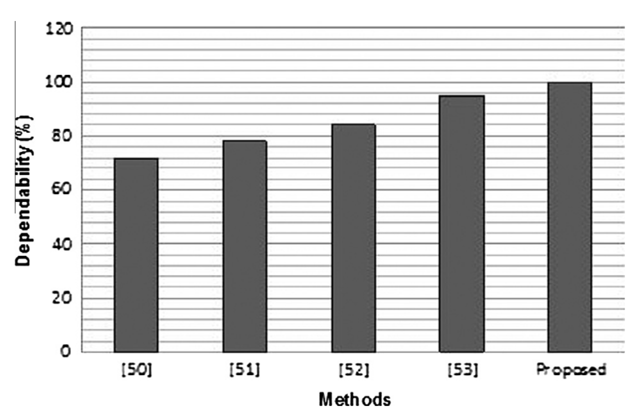

Fig. 11. Comparative assessments based on dependability.

condition), a bias toward dependability is desired. Under such conditions, not clearing a fault with primary protection has a greater impact on the system than a relay misoperation due to lack of security. However, when the power system is in a "stressed" state (i.e. power swing condition), unnecessary line trips can greatly exacerbate the severity of the outage, contribute to the geograph-

Table 7
Dependability comparison with respect to one both end features.

Conditions	Proposed method (features)	Dependability (fault at 30% of line) (%)	Dependability (fault at 95% of line) (%)
Uncompensated power network	One end	99	85
	Both end	**99**	**99**
Compensated power network	One end	99	80
	Both end	**99**	**99**

Bold stands for "results of proposed scheme".

ical propagation of the disturbance, and may even lead to cascading events and subsequent blackouts. Under such states, it is desirable to alter the reliability balance in favour of security. The proposed scheme alters the functionality of a group of relays without directly modifying relay settings.

Conclusion

This paper presents a data-mining based intelligent differential relaying scheme for series compensated transmission network. The process starts at pre-processing the voltage and current signals using least square (LS)-based PMU and the derived differential features are used to generate the optimal data-mining models for distinguishing faults and power swing. The proposed scheme is extensively tested for New England 39 bus test system which is developed on Dig-Silent power factory commercial software (PF4C) platform for evaluating the performance of proposed technique. The results obtained on security/dependability indicate the effectiveness of the proposed relaying scheme in distinguishing stressed conditions such as power swing from faults with a response time 1.75-cycles from the fault inception. Furthermore, testing on FPGA platform ensures the reliability of the proposed relaying scheme.

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References

[1] Horowitz SH, Phadke AG. Power system relaying. 2nd ed. New York: Wiley; 1995.
[2] Phadke AG, Thorp JS. Computer relaying for power systems. 2nd ed. Hoboken (NJ): Wiley; 2009.
[3] Novosel D, Bartok G, Henneberg G, Mysore P, Tziouvaras D, Ward S. IEEE PSRC report on performance of relaying during wide area stressed conditions. IEEE Trans Power Del 2010;25(1):3–16.
[4] NYISO. Blackout August 14, 2003 final rep; 2005.
[5] UCTE. Final report of the Investigation Committee on the 28 September 2003 blackout in Italy; 2004.
[6] UCTE. Final report: system disturbance on 4 November 2006; 2006.
[7] Report of the enquiry committee on grid disturbance in Northern region on 30th July 2012 and in Northern, Eastern and North-Eastern region on 31st July 2012. Tech rep. Power-grid, New Delhi, India; August 2012. <http://www.powermin.nic.in>.
[8] Horowitz SH, Phadke AG. Third zone revisited. IEEE Trans Power Del 2006;21(1):23–9.
[9] Pourbeik Pouyan, Kundur Prabha S, Taylor Carson W. The anatomy of a power grid blackout. IEEE Power Energy Mag 2006;4(5):22–9.
[10] Tziouvaras D, Hou D. Out-of-step protection fundamentals and advancements; 2003. <http://www.selinc.com>.
[11] IEEE Power System Relaying Committee of the IEEE Power Engineering Society. Power swing and out-of-step considerations on transmission line. Rep PSRCWG D6; July 2005. <http://www.pes-psrc.org>.
[12] Mooney JPE, Fischer N. Application guidelines for power swing detection on transmission systems. In: Proc power syst conf; 2006. p. 159–68.
[13] Khoradshadi-Zadeh H. Evaluation and performance comparison of power swing detection algorithms. In: Proc IEEE power eng soc gen meeting, vol. 2; June 2005. p. 1842–8.
[14] Martuscello L, Krizauskas E, Holbach J, Lu Y. Tests of distance relay performance on stable and unstable power swings reported using simulated data of the August 14th 2003 system disturbance. In: Proc IEEE 62nd annu conf protect relay eng; May 2009. p. 236–55.
[15] Benmouyal G, Hou D, Tziouvaras D. Zero-setting power swing blocking protection; 2004. <http://www2.selinc.com/techpprs/6172_ZeroSetting_20050302.pdf>.
[16] Lin X, Li Z, Ke S, Gao Y. Theoretical fundamentals and implementation of novel self-adaptive distance protection resistant to power swings. IEEE Trans Power Del 2010;25(3):1372–83.
[17] Seethalekshmi K, Singh SN, Srivastava SC. A classification approach using support vector machines to prevent distance relay maloperation under power swing and voltage instability. IEEE Trans Power Del 2012;27(3):1124–33.
[18] Zadeh HK, Li Z. A novel power swing blocking scheme using adaptive neuro-fuzzy inference system. Electr Power Syst Res 2008;78:1138–46.
[19] Brahma SM. Distance relay with out-of-step blocking function using wavelet transform. IEEE Trans Power Del 2007;22(3):1360–6.
[20] Apostolov AP, Tholomier D, Richards SH. Superimposed components based sub-cycle protection of transmission lines. In: Proc IEEE power eng soc power syst conf expo, vol. 1; October 2004. p. 592–7.
[21] Lin X, Gao Y, Liu P. A novel scheme to identify symmetrical faults occurring during power swings. IEEE Trans Power Del 2008;23(1):73–8.
[22] Lotfifard S, Faiz J, Kezunovic M. Detection of symmetrical faults by distance relays during power swings. IEEE Trans Power Del 2010;25(1):81–7.
[23] Novosel Damir, et al. Problems and solutions for microprocessor protection of series compensated lines; 1997. p. 18–23.
[24] Altuve HJ, Mooney JB, Alexander GE. Advances in series compensated line protection. In: Proceedings of the 35th annual western protective relay conference, Spokane, WA; October 2008.
[25] Kasztenny Bogdan. Distance protection of series compensated lines-problems and solutions. In: Proceedings of the 27th annual western protective relay conference; 2001. p. 22–5.
[26] Esmaeilian, Ghaderi A, Tasdighi M, Rouhani A. Evaluation and performance comparison of power swing detection algorithms in presence of series compensation on transmission lines. In: Proc 10th int conf environment electr eng; May 8–11, 2011. p. 1842–8.
[27] Rao JG, Pradhan AK. Differential power based symmetrical fault detection during power swing. IEEE Trans Power Del 2012;27(3):1557–64.
[28] Nayak PK, Pradhan AK, Bajpai P. Detecting fault during power swing for a series compensated line. Presented at the int conf energy, autom, signal, bhubaneswar, Odisha, India; December 28–30, 2011.
[29] Kamwa I, Samantary SR, Joos G. Catastrophe predictors from ensemble decision-tree learning of wide-area severity indices. IEEE Trans Smart Grid 2010;1(2):144–57.
[30] Kamwa I, Samantaray SR, Joos G. Development of rule-based classifiers for rapid stability assessment of wide-area post-disturbance records. IEEE Trans Power Syst 2009;24(1):258–70.
[31] Kamwa I, Grondin R, Loud L. Time-varying contingency screening for dynamic security assessment using intelligent-systems. IEEE Trans Power Syst 2001;16(3):526–36.
[32] Kamwa I, Samantaray SR, Joos G. On the accuracy versus transparency trade-off of data-mining models for fast-response PMU-based catastrophe predictors. IEEE Trans Smart Grid 2012;3(1):152–61.
[33] Abonyi J, Feil B. Cluster analysis for data mining and system identification. Basel-London-Berlin: Birkhauser; 2007. p. 319.
[34] Breiman L. Random forests. Mach Learn 2001;45:5–32. <http://www.stat.berkeley.edu/users/breiman/RF>.
[35] Liaw A, Wiener M. Classification and regression by random forest in R. R News 2002;2(3):18–22. <http://www.r-project.org>.
[36] Dash PK, Samantaray SR, Panda G. Fault classification and section identification of an advanced series-compensated transmission line using support vector machine. IEEE Trans Power Del 2007;22(1):67–73.
[37] Parikh UB, Das B, Maheshwari RP. Combined wavelet-SVM technique for fault zone detection in a series compensated transmission line. IEEE Trans Power Del 2008;23(4):1789–94.
[38] Rattle (the R Analytical Tool to Learn Easily), by D. Williams, ver. 2.6; December 2010. <http://rattle.togaware.com/>.
[39] de la o serna JA. Dynamic phasor estimates for power system oscillations. IEEE Trans Instrum Meas 2007;56(5):1648–57.
[40] IEEE Standard for Synchrophasors for power system. IEEE std C37. 118–2005, sponsored by the power system relaying committee.
[41] Platas M, Serna J. Dynamic phasor and frequency estimates through maximally flat differentiators. IEEE Trans. Instrum. Meas. 2010;59(7):1803–11.
[42] Mai R, He Z, Fu L, Kirby B, Bo Z. A dynamic synchrophasor estimation algorithm for online application. IEEE Trans Power Del 2010;25(2):570–8.
[43] Serna J. Phasor estimation from phasorlets. IEEE Trans Instrum Meas 2005;54(1):134–43.
[44] serna J, Rodriguez-Maldonado J. Instantaneous oscillating phasor estimates with Taylor–Kalman filters. IEEE Trans Power Syst 2011;26(4):2336–44.
[45] serna J, Rodriguez-Maldonado J. Taylor–Kalman–Fourier filters for instantaneous oscillating phasor and harmonic estimates. IEEE Trans Instrum Meas 2012;61(4):941–51.

[46] Munoz A, Serna J. Shank method for dynamic phasor estimation. IEEE Trans Instrum Meas 2008;57(4):813–9.
[47] Khodaparast J, Khederzadeh M. Three-phase fault detection during power swing by transient monitor. IEEE Trans Power Syst 2015;30(5):2558–65.
[48] Rao JG, Pradhan AK. Accurate phasor estimation during power swing. IEEE Trans Power Del 2015. http://dx.doi.org/10.1109/TPWRD.2015.2441132. early access.
[49] Jamehbozorg A, Shahrtash SM. A decision-tree-based method for fault classification in single-circuit transmission lines. IEEE Trans Power Del 2010;25(4):2190–6.
[50] Dambhare S, Soman SA, Chandorkar MC. Adaptive current differential protection schemes for transmission-line protection. IEEE Trans Power Del 2009;24(4):1832–41.
[51] Taalab A-MI, Darwish HA, Ahmed ES. Performance of power differential relay with adaptive setting for line protection. IEEE Trans Power Del 2007;22(1):50–8.
[52] Jena MK, Samantaray SR. Data-mining-based intelligent differential relaying for transmission lines including UPFC and wind farms. IEEE Trans Neural Network Learn Syst 2015. http://dx.doi.org/10.1109/TNNLS.2015.2404775. early access.