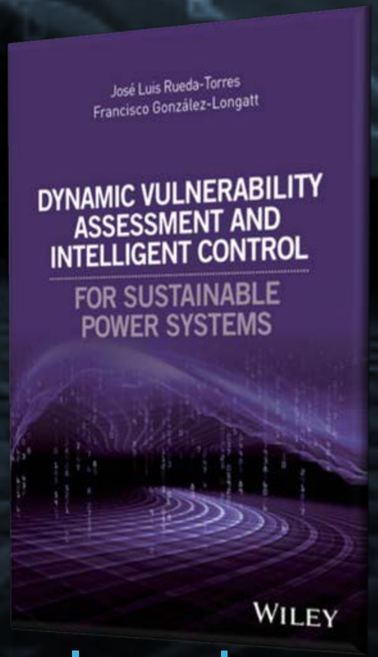
DYNAMIC VULNERABILITY ASSESSMENT AND INTELLIGENT CONTROL: For Sustainable Power Systems



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Friday, 20th April 2018
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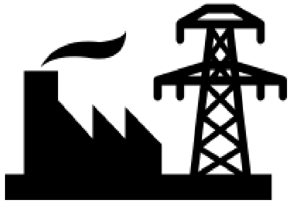
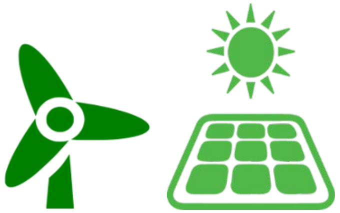
AGENDA

- Motivation
- What the book offers
- Key features
- Book statistics
- Book' Chapters
- About dynamic vulnerability assessment

Motivation





	AC	AC/DC
STABILITY	✓	⚡
CONTROL	✓	⚡
CLEAN	⚡	✓

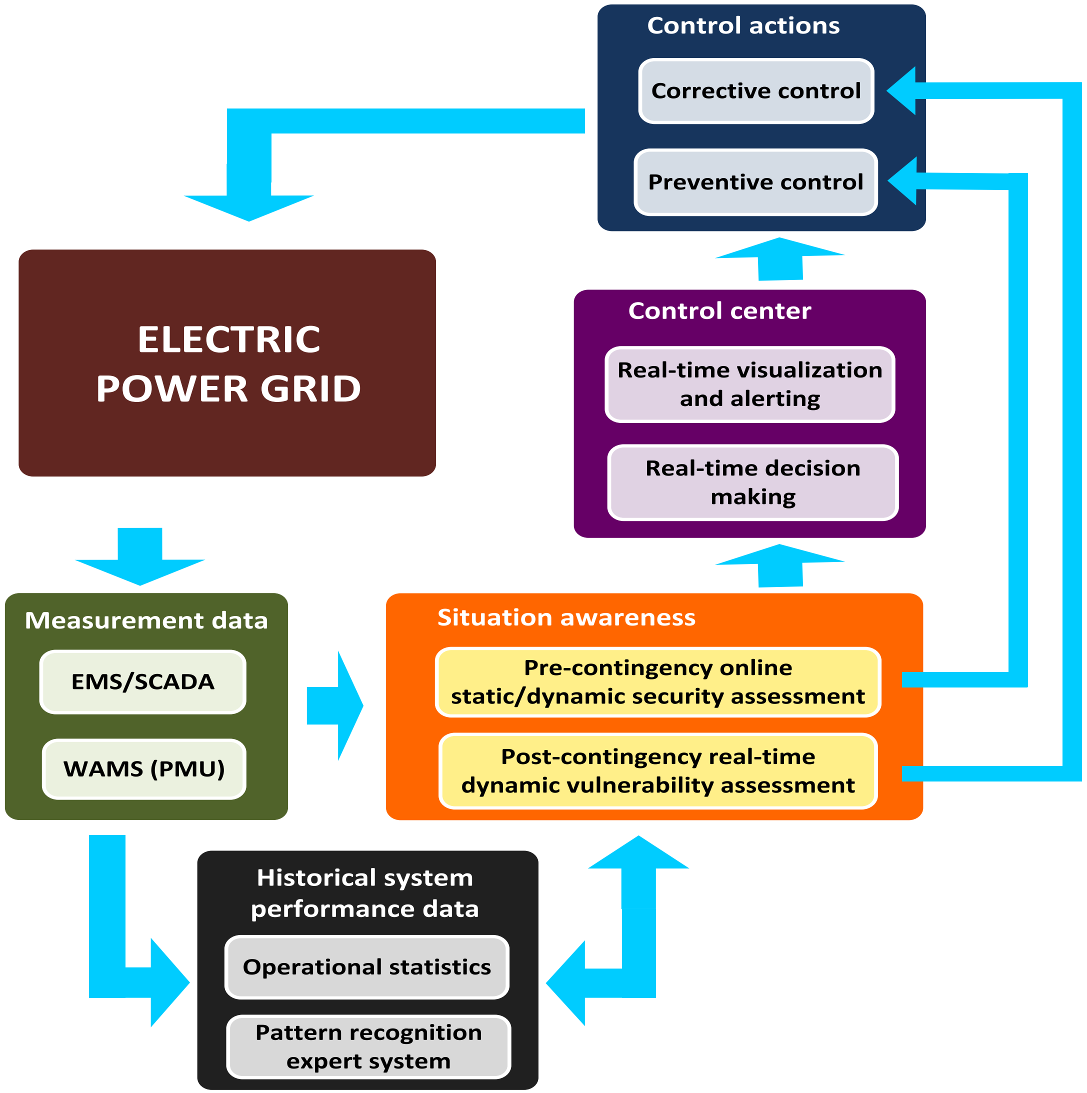
- **New methods to mitigate variability introduced by RES and ensure high level of system security**

What the book offers

- Fundamentals and application of recently developed methodologies for **assessment and enhancement of power system security** in **short-term operational planning** (e.g. *intra-day*, *day-ahead*, *a week ahead*, *and monthly time horizons*) and **real-time operation**.

- The methodologies involve:
    - ➢Data mining
    - ➢Probabilistic theory
    - ➢Computational intelligence

Key Features

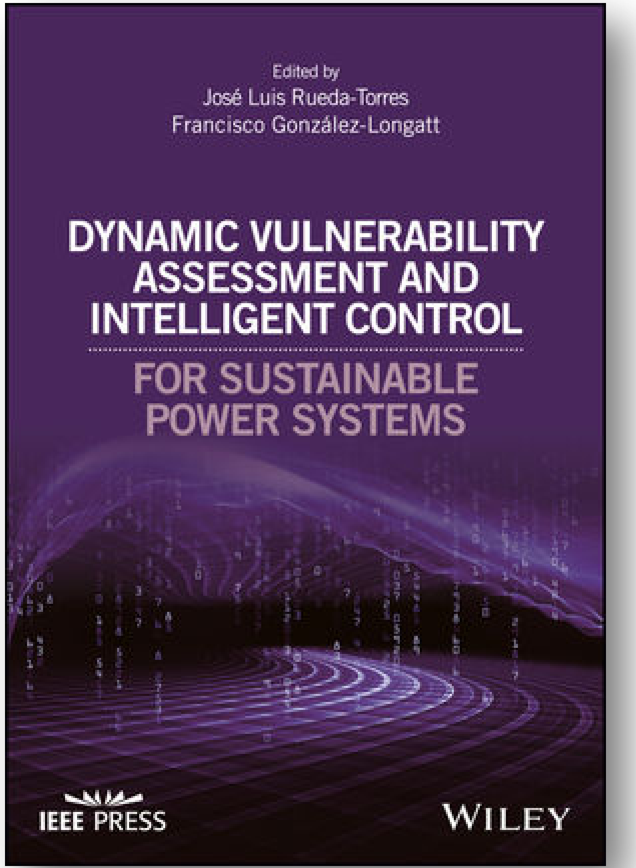


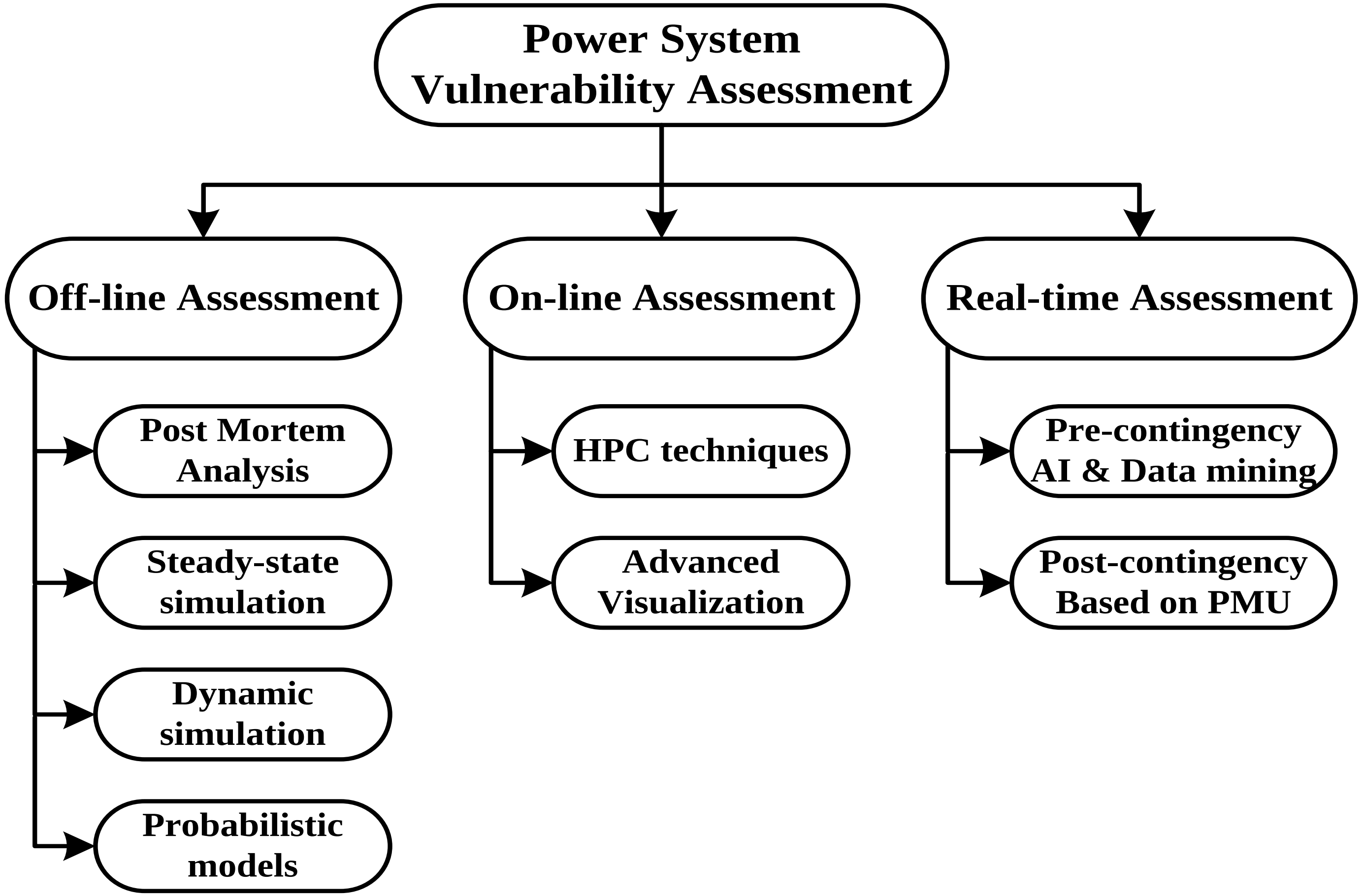
- Data mining based **behavioural recognition**
- Security constrained optimal power flow
- **Risk-based reliability** and **security** assessment
- **Dynamic vulnerability**
- **Data mining based intelligent** protection and controlled islanding
- Model predictive control
- Multi-agent and distributed control systems
- Real-world implementation of **self-healing applications** in **WAMPAC** (Wide Area Monitoring Protection and Control).

Book Structure

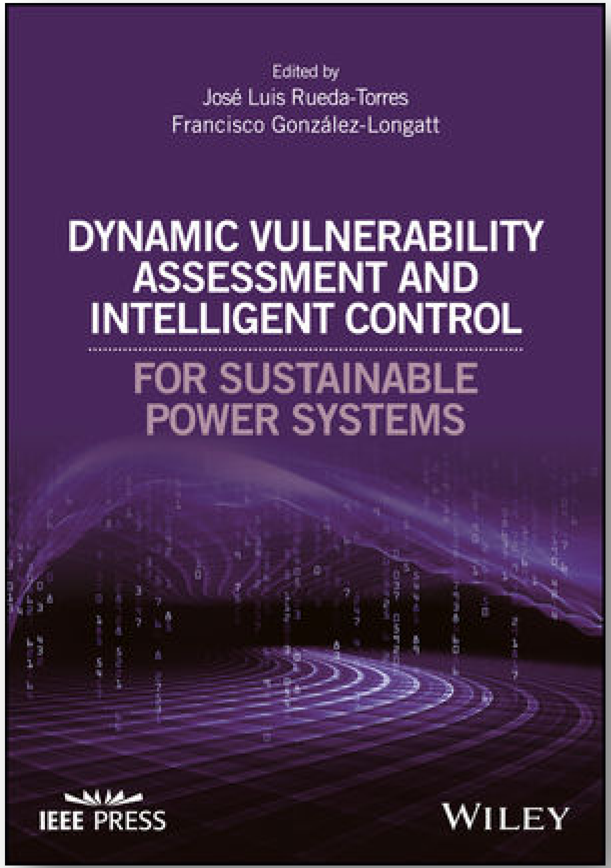
19 Chapters

PART I: Dynamic Vulnerability Assessment
PART II: Intelligent Control





Book Statistics



Dynamic Vulnerability Assessment and Intelligent Control: For Sustainable Power Systems

José Luis Rueda-Torres (Editor), Francisco González-Longatt (Editor)

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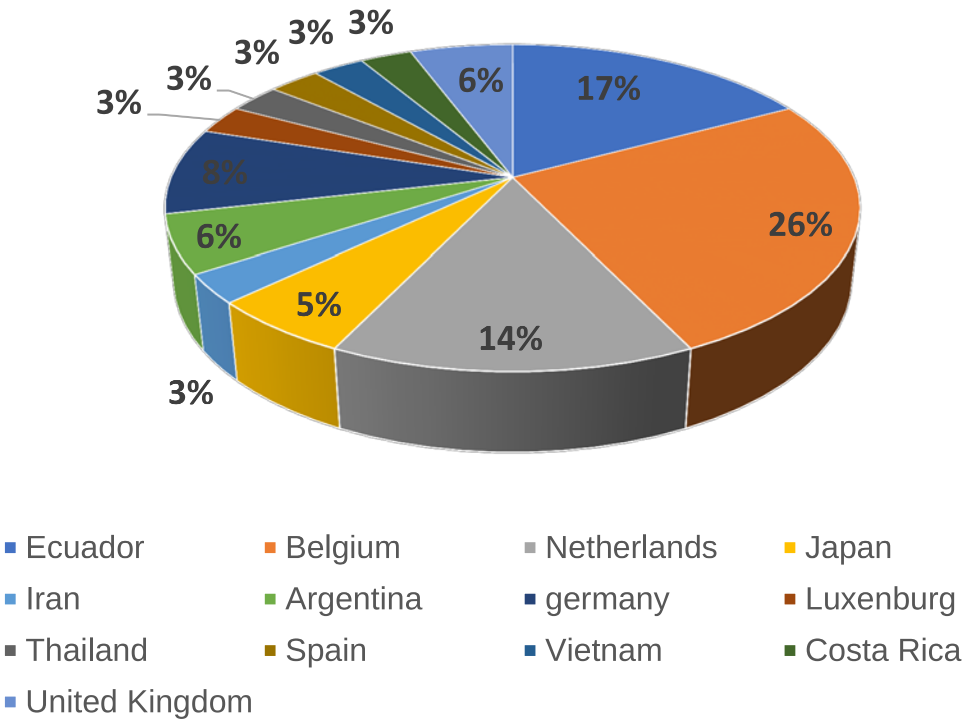
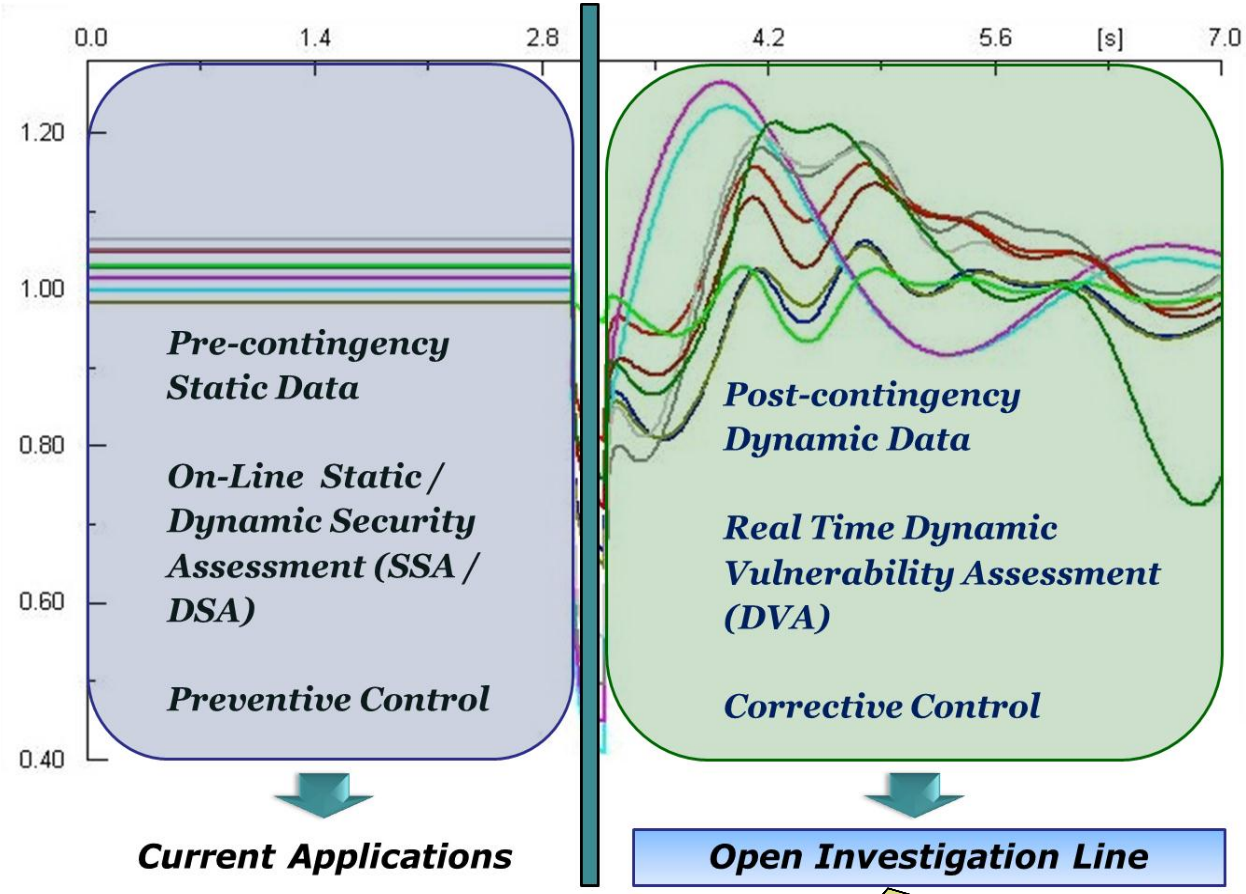
448 pages



35 Contributors

A brief view of Dynamic Vulnerability Assessment

Dynamic Vulnerability Assessment (DVA)



How to use post-contingency data from PMUs to ascertain the actual security status with respect to vulnerability boundaries?

Dynamic Vulnerability Assessment (DVA)

Actions and operations within the power system

Action or operation	***Time-frame***	
Electromagnetic transients	μs – ms	
Switching overvoltage	μs	
Fault protection	100 ms	
Electromagnetic effects in machine windings	ms – s	
Electromechanical transients – stability	ms – s	***DVA time-frame***
Electromechanical oscillations	ms – min	
Frequency control	1 s – 10 s	
Overloads	5 s – h	
Economic load dispatch	10 s – 1 h	
Thermodynamic effects	s – h	
Energy Management System applications	Steady state; ongoing	

Dynamic Vulnerability Assessment (DVA)

Grid blackouts registered around the world

Place	*Date*	*Cascade duration*	*Disconnected customers*	*Disconnected power*
Northwestern America	10/08/1996	6 min	7.5 millions	30 GW
Northeastern America	14/08/2003	1 h	50 millions	62 GW
Southern Sweden and Eastern Denmark	23/09/2003	5 min	4 millions	6.6 GW
Italia	28/09/2003	24 min	56 millions	24 GW
Ecuador	01/03/2003	20 s	3 millions	1.2 GW

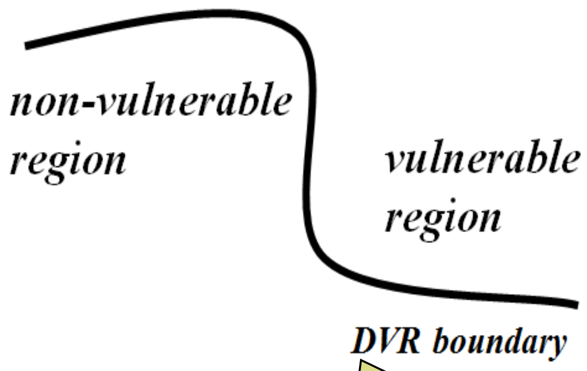
Dynamic Vulnerability Assessment (DVA)

Time delay of a WAMPAC scheme per process

Process	*Time delay in 60-Hz cycles*	*Time delay (ms)*
PMU measurement	3	50
Fiber-optic communications	2	33
PDC throughput	2	33
Transfer trip	1	17
Circuit breaker	2 – 5	33 – 83
Total WAMPAC time delay	10 – 15	167 – 217

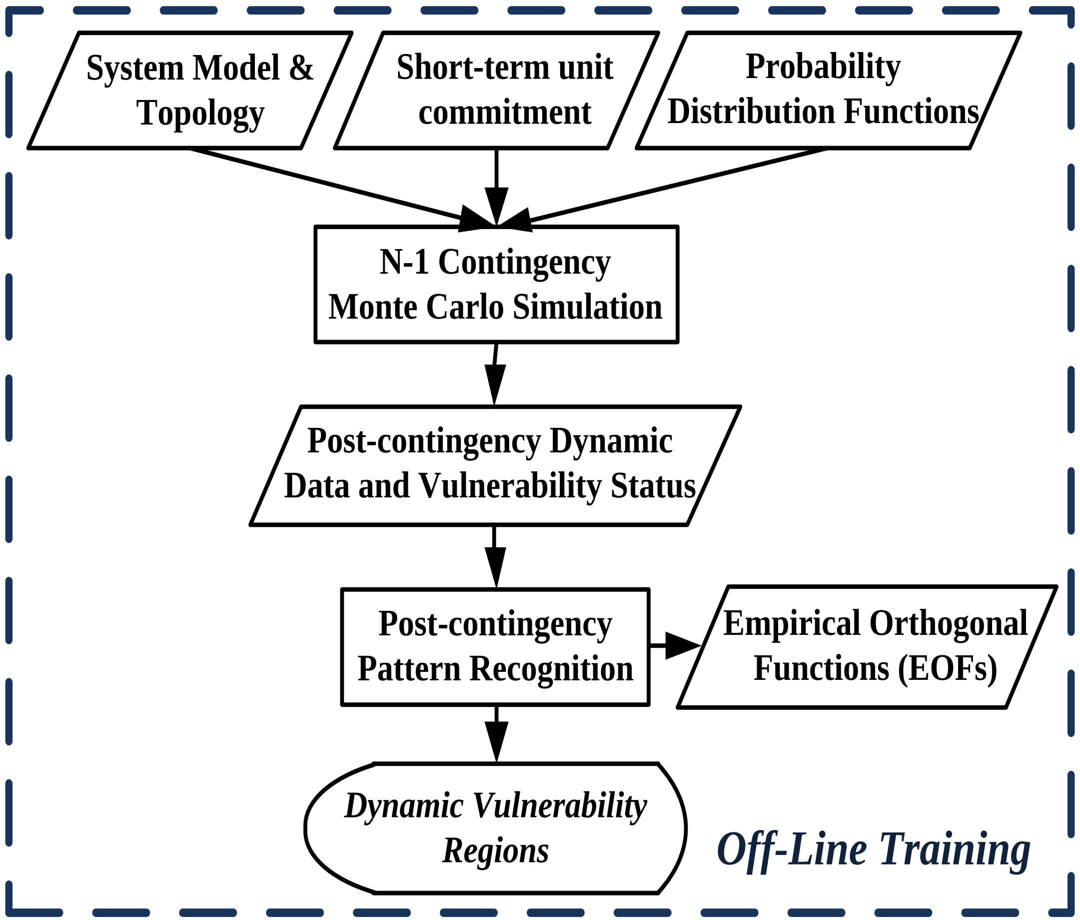
Dynamic vulnerability regions (DVRs)

DVR concept

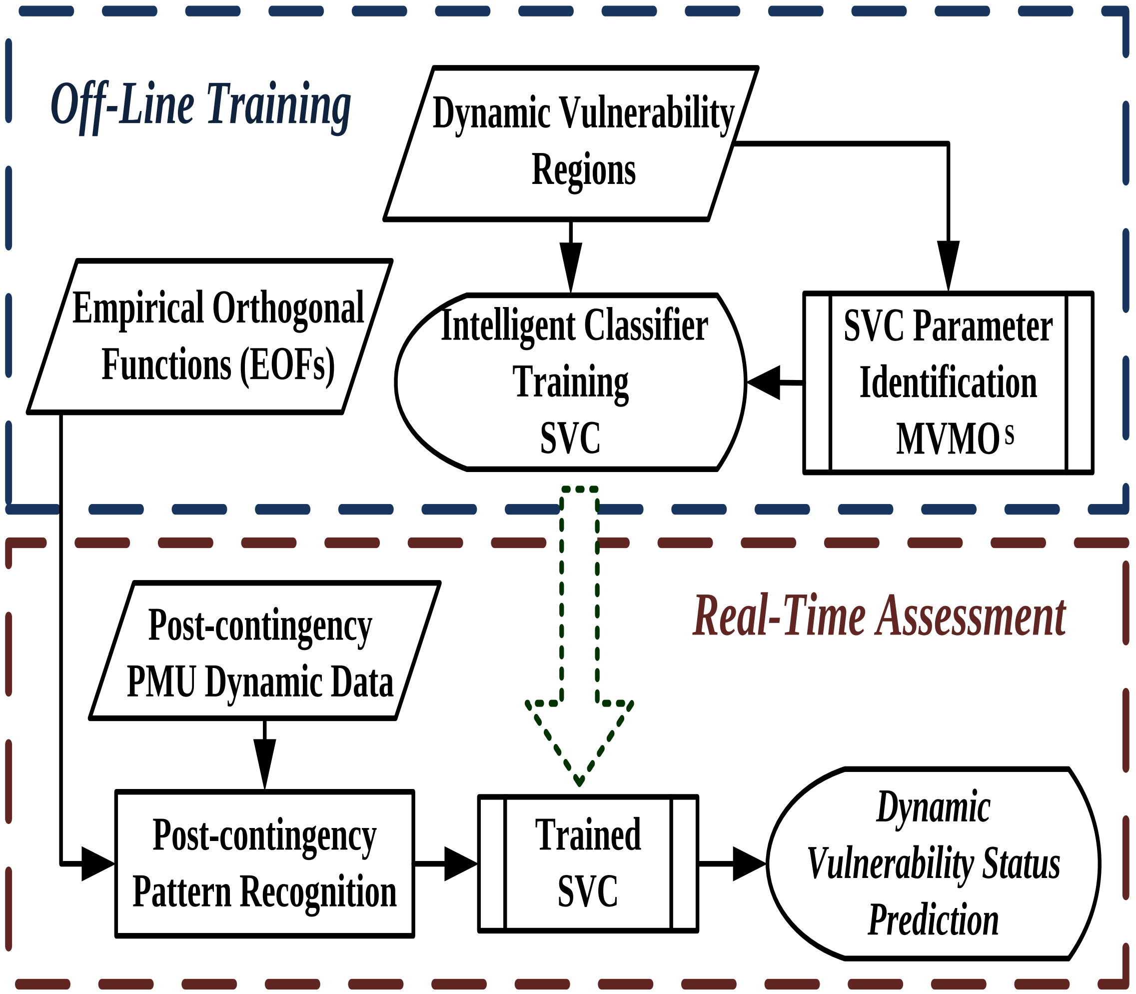


Hyper-plane boundaries
(Approximated numerically by mining post-contingency data from PMUs)

Recognition of DVRs



Post-contingency vulnerability status prediction



SVC: support vector classifier

Three short-term stability phenomena (transient stability, voltage stability and frequency stability -TVFS-)

Post-contingency vulnerability status prediction

To adequately capture the system response for TVFS stability phenomena, several time windows (TW) have to be defined:

$\Rightarrow$ The TWs are established according to the statistics of the triggering times of the relays, influenced by the WAMPAC communication time delay (t_{delay})

$$t_{\min} = \min_{i=1\ldots n}\left\{t_{OSR_i}, t_{VR_i}, t_{FR_i}\right\} - t_{delay}$$

n: Number of Monte Carlo simulations

t_{OSRi}: Tripping time of out-of-step relay

t_{VRi} : Tripping time of frequency relay

t_{FRi} : Tripping time of frequency relay

Post-contingency vulnerability status prediction

To adequately capture the system response for TVFS stability phenomena, several time windows (TW) have to be defined:

$\Rightarrow$ Since the post-contingency data comprise the samples taken immediately after the fault is cleared, the first time window (TW_1) is defined by the difference between t_{min} and the clearing time (t_{cl}).

$$TW_1 \leq t_{\min} - t_{cl}$$

Post-contingency vulnerability status prediction

To adequately capture the system response for TVFS stability phenomena, several time windows (TW) have to be defined:

$\Rightarrow$ The rest of the time windows are defined based on the statistical concept of confidence interval related to Chebyshev's inequality:

$$TW_k \approx 3 \cdot std\left\{t_{OSR/VR/FR}\right\} + TW_{k-1}$$

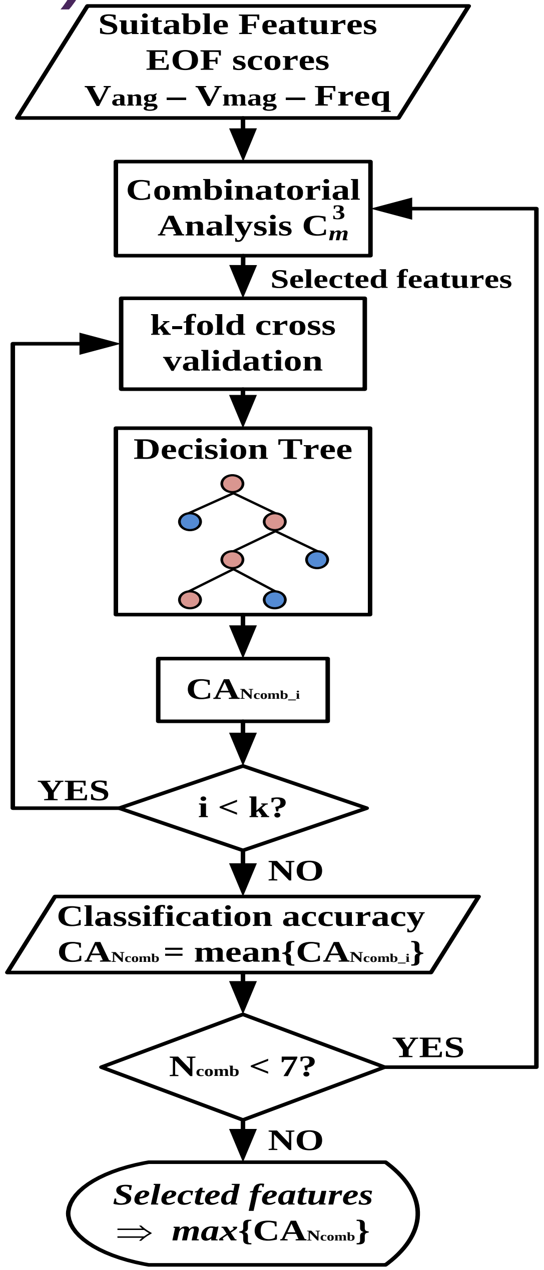
std{·} : standard deviation of the relay tripping time that most intersects the corresponding time window TW_k.

Support vector classifier (SVC)

Essential aspects for training the SVC:

- Choice of appropriate pattern vectors showing the evolution of specific phenomena (TVFS).

⇒ Feature selection procedure that maximizes the classification accuracy (CA) by using decision trees (DT)



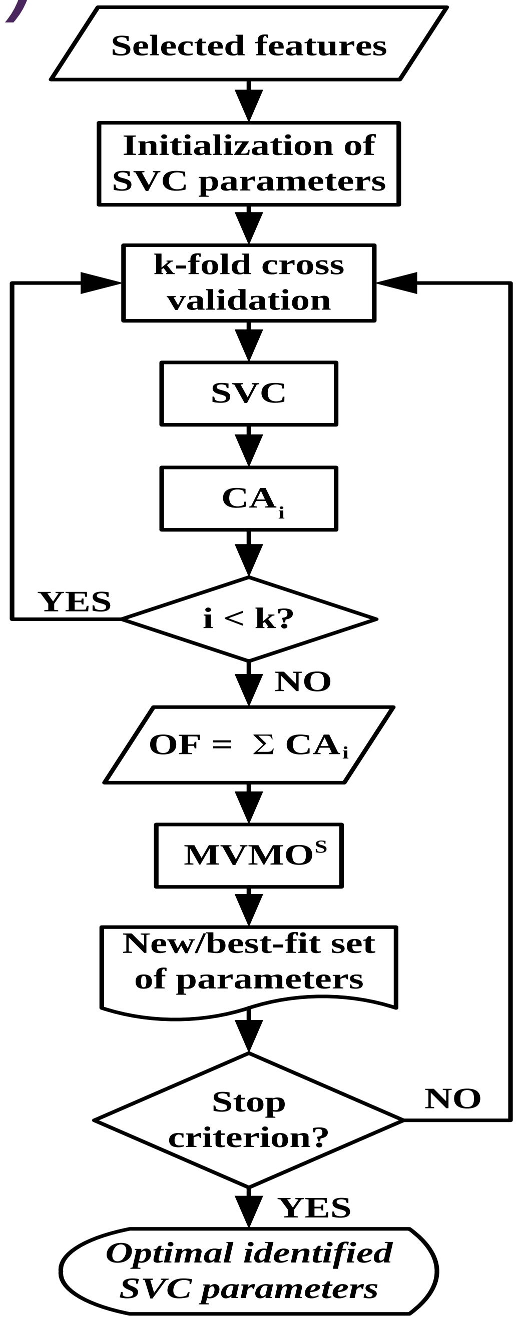
EOF: Empirical orthogonal function

Support vector classifier (SVC)

Essential aspects for training the SVC:

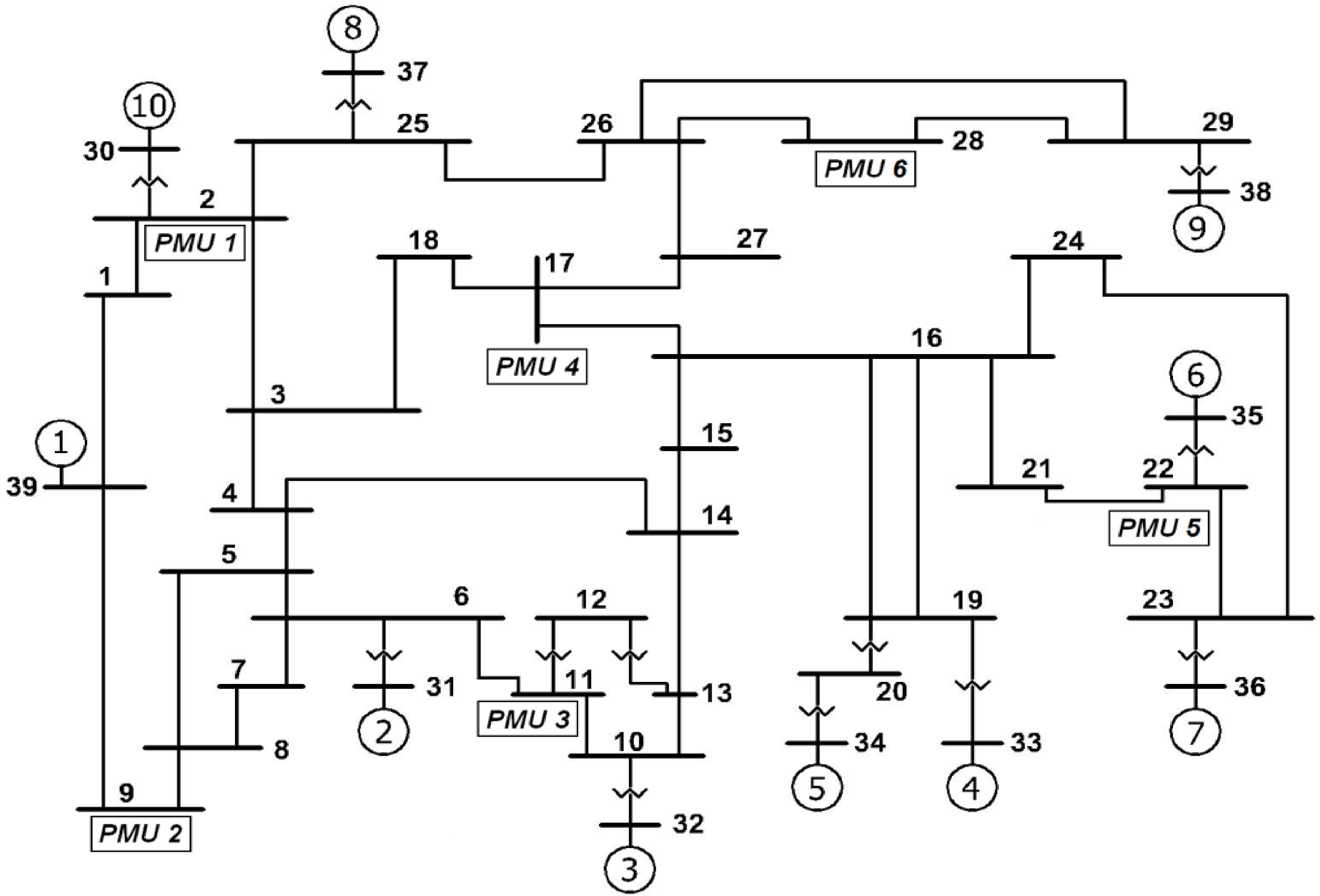
- Identification of the best parameters of SVC.

⇒ Parameter identification problem solved by using MVMO algorithm.



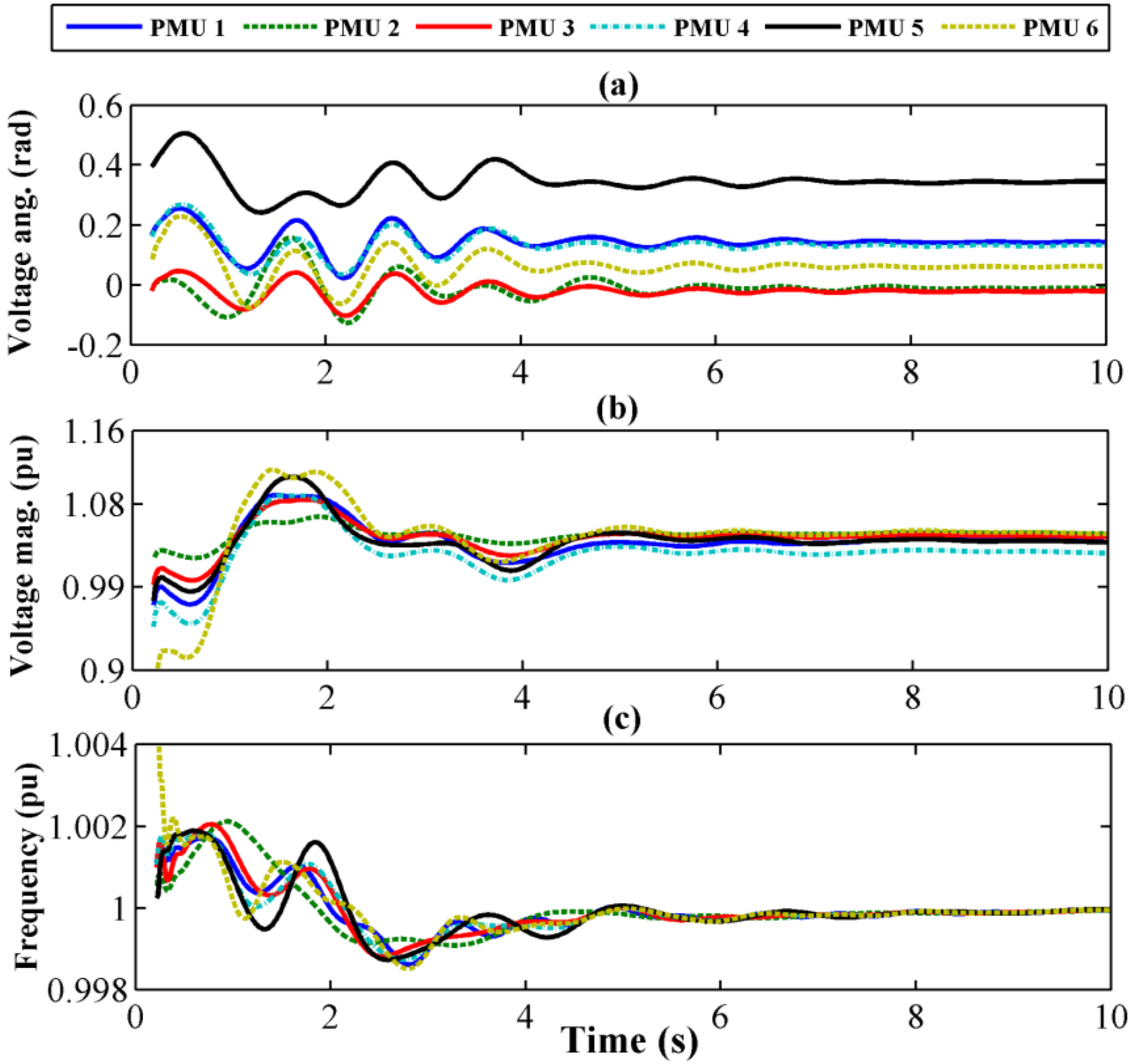
DVRs – Simulation results

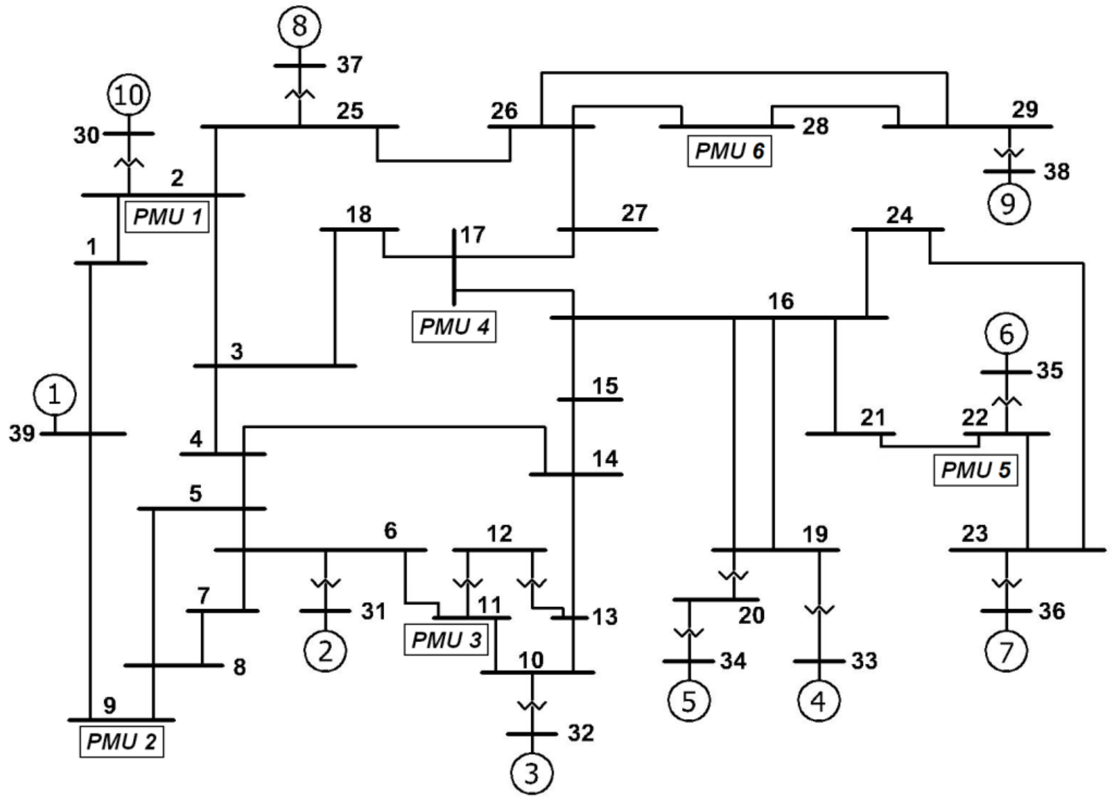
New England test system: Selected PMU locations



DVRs – Simulation results

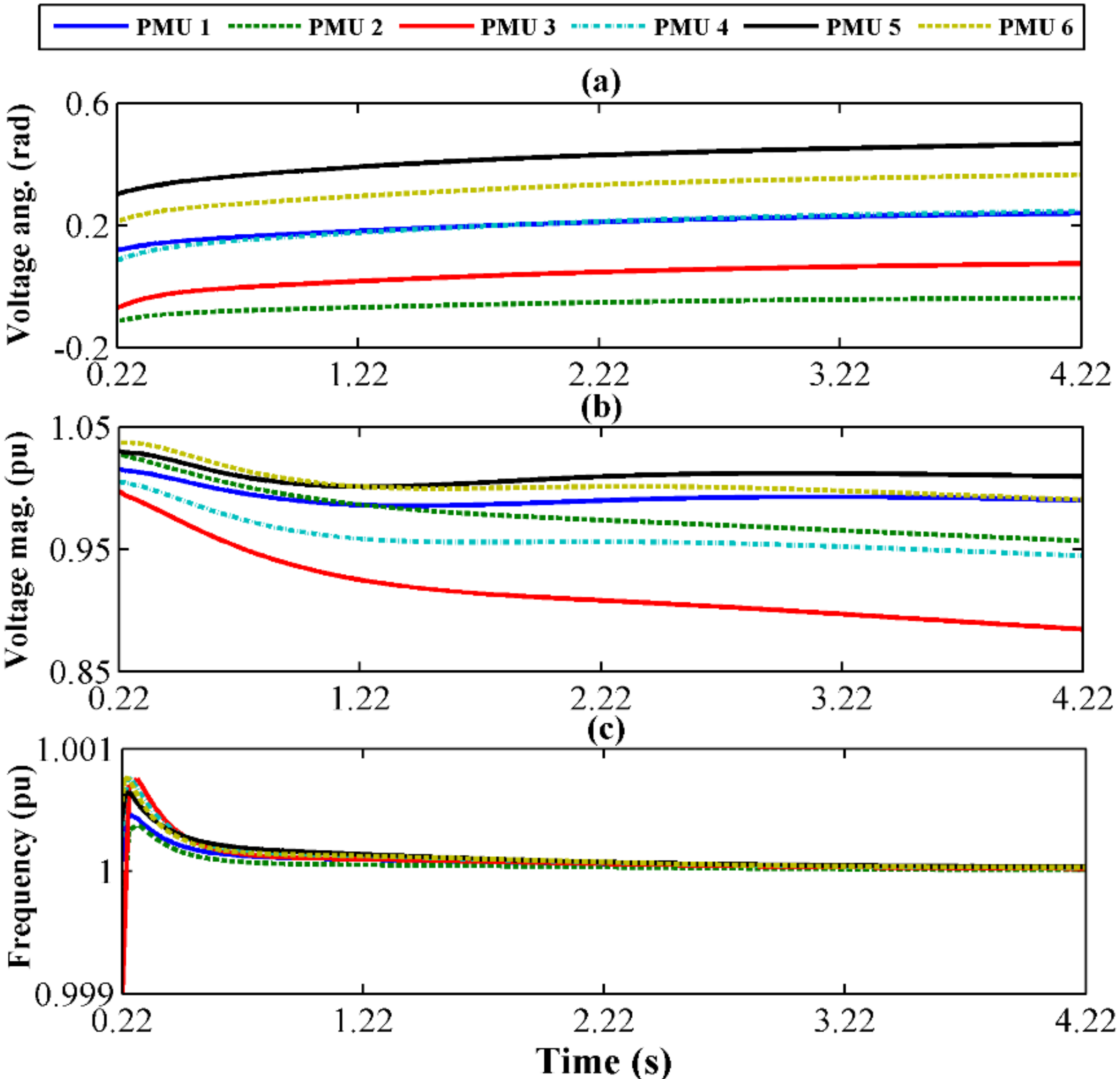
Example of non-vulnerable (stable) case

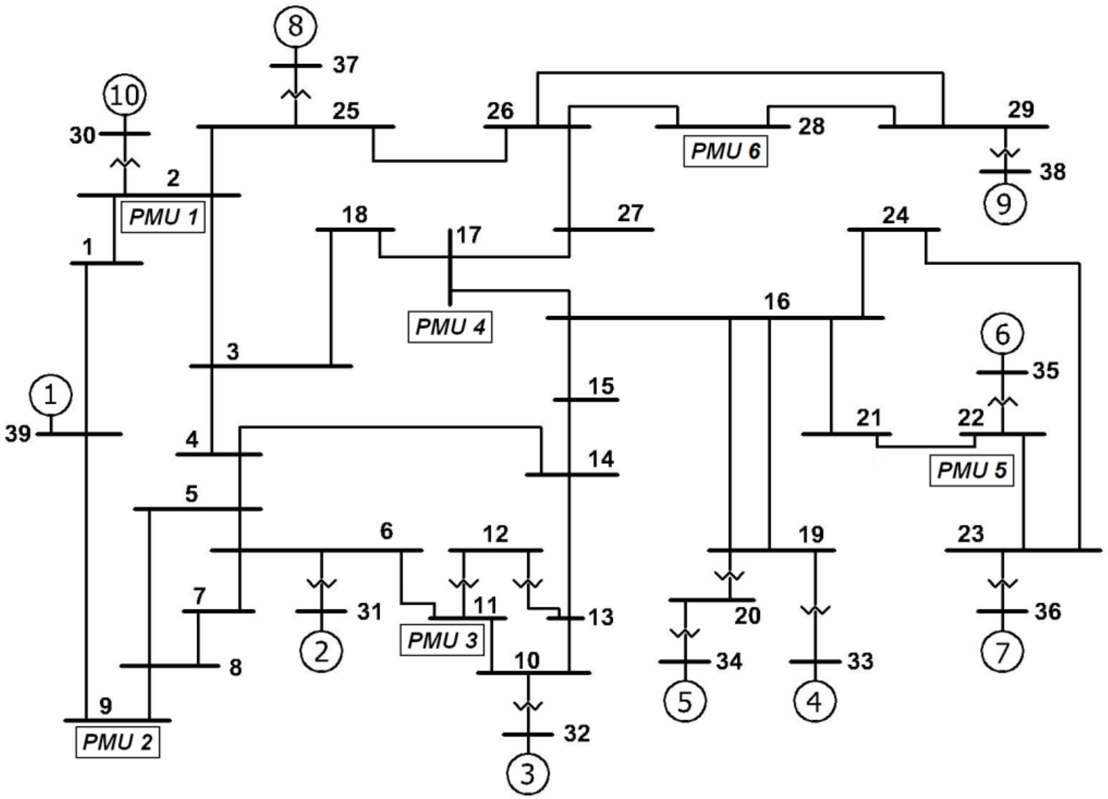




DVRs – Simulation results

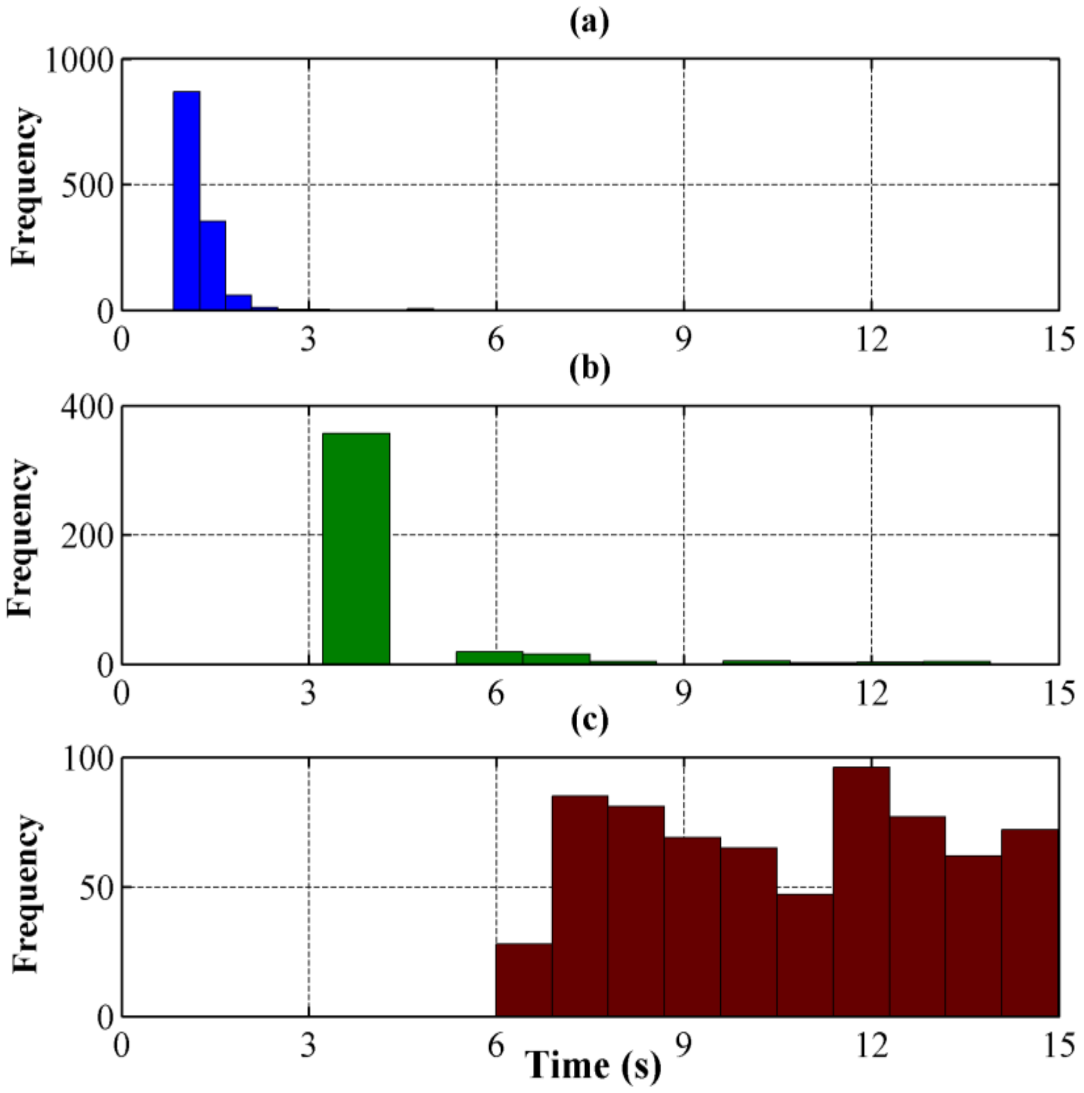
Example of vulnerable (unstable) case





DVRs – Simulation results

Relay tripping time histograms



a) Out-of-step protection

b) Under-voltage protection

c) Under-frequency protection

DVRs – Simulation results

Time window definition

Time Window	$std\{t_{OSR/VR/FR}\}$ (s)	$3 \times std\{t_{OSR/VR/FR}\} + TW_{k-1}$ (s)	*TW* (s)
TW_1	-	-	0.30
TW_2	0.3746	1.4238	1.50
TW_3	0.3746	2.6238	2.70
TW_4	0.3746	3.8238	3.90
TW_5	1.6872	8.9616	9.00

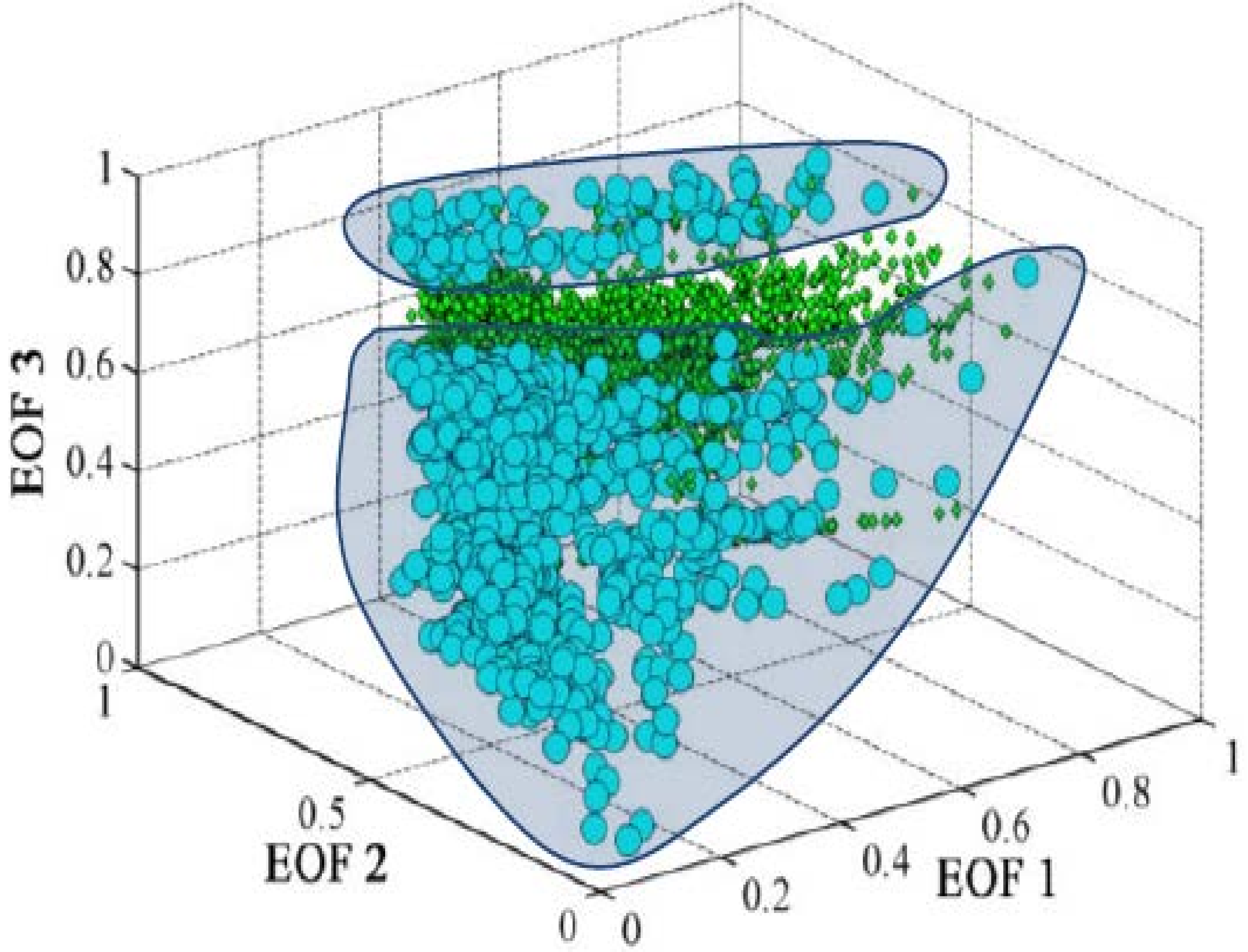
DVRs – Simulation results

Feature selection summary

Time Window	*Option*	*Feature*	*CA (%)*
TW_1	1	$[V_{ang}]$	97.477
	2	$[V_{mag}]$	96.779
	3	[Freq]	89.894
	4	$[V_{ang}, V_{mag}]$	98.030
	5	$[V_{ang}, Freq]$	98.103
	6	$[V_{mag}, Freq]$	97.773
	7	$[V_{ang}, V_{mag}, Freq]$	98.140
TW_2	1	$[V_{ang}]$	99.927
	2	$[V_{mag}]$	99.885
	3	[Freq]	99.832
	4	$[V_{ang}, V_{mag}]$	99.911
	5	$[V_{ang}, Freq]$	99.917
	6	$[V_{mag}, Freq]$	99.885
	7	$[V_{ang}, V_{mag}, Freq]$	99.906

DVRs – Simulation results

TW1: DVRs based on voltage angle recorded data



DVRs – Simulation results

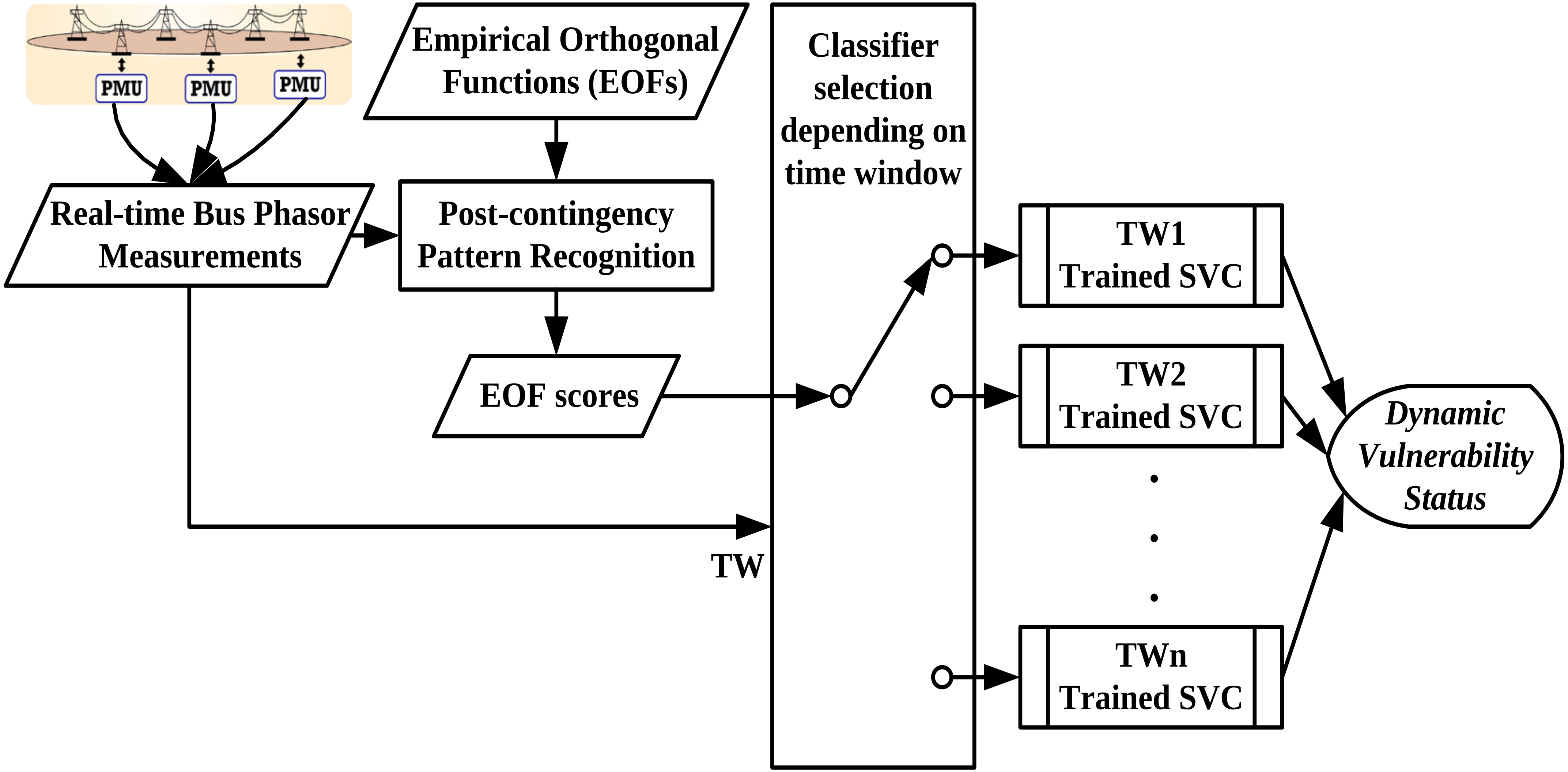
Classification performance

Classifier	mean{CA_i} for Time Window (%)				
	TW_1	TW_2	TW_3	TW_4	TW_5
DA	97.440	99.966	99.494	98.034	97.178
DTC	98.200	99.931	99.736	99.436	99.291
PRN	98.760	99.897	99.770	99.029	98.993
PNN	98.930	99.977	99.770	99.137	99.055
SVC	99.290	100.00	99.885	99.880	99.727

SVC outperforms all other classifiers in terms of classification accuracy

SVC: Support vector classifier
DA: Discriminant analysis
DTC: Decision tree classifier
PRN: feed-forward neural network
PNN: radial basis neural network

SVC real-time implementation in a control center



Thanks for your attention!

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