Data-Driven Assessment of Power System Stability

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OUTLINE

1 **Background:** what is the current status?

2 **Motivation:** why we need this research?

3 **Problem Description:** what are key research problems?

4 **Methodology**

- Feature selection
- Statistic error analysis
- Credibility evaluation
- Randomized learning
- Online assessment
- Real-time assessment
- Missing data
- Transfer learning
- Model updating

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Power System Stability

Definition

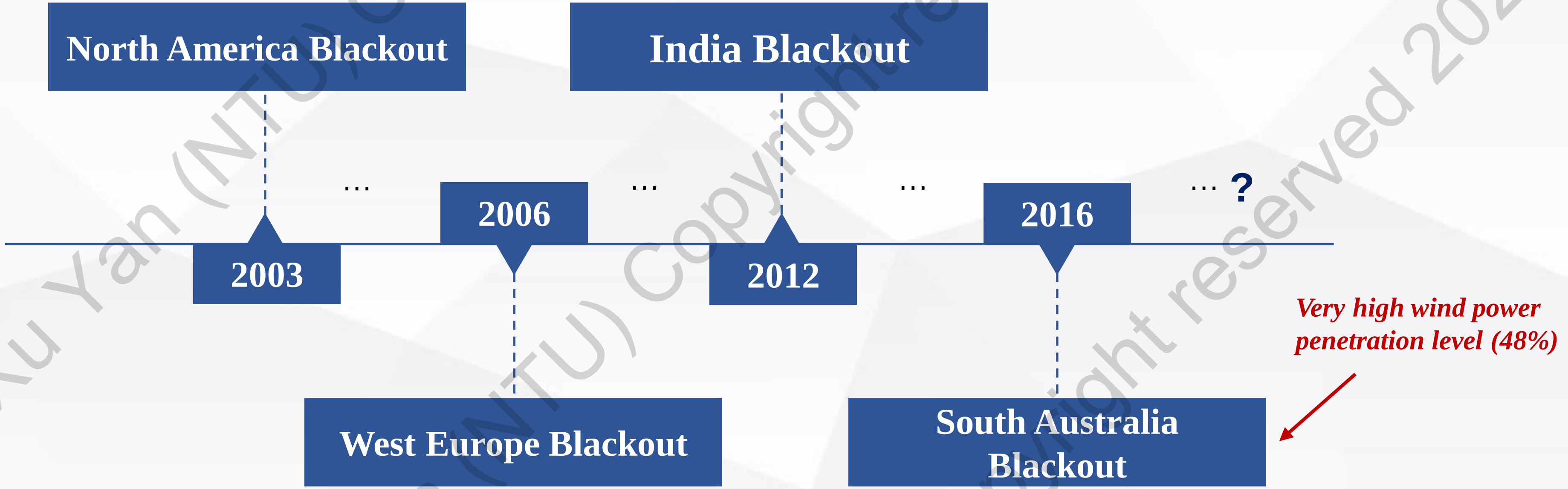
"The ability of an electric power system to regain a state of operating equilibrium after being subjected to a disturbance."

Conventional power grid → "Smart Grid"

- **Generation side**: high-level intermittent renewable energy integration
- **Demand side:** demand response, electric vehicle, distributed energy storage, etc.
- **Device-grid interface:** power-electronics converters

Higher operating uncertainties + Complicated system dynamics

Recent major blackout events



Classification for Power System Stability

- Rotor Angle Stability (large-disturbance and small-disturbance)
- Voltage Stability (short-term or long-term)
- Frequency Stability (short-term and long-term)

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{y}, \mathbf{p}, \boldsymbol{\lambda}) \qquad 0 = \mathbf{g}(\mathbf{x}, \mathbf{y}, \mathbf{p}, \boldsymbol{\lambda})$$

Classification for Stability Assessment and Control

On-line Stability Assessment → Preventive Control | Real-time Stability Assessment → Emergency Control

time

Steady State (pre-fault)

Contingency

Dynamic State (post-fault)

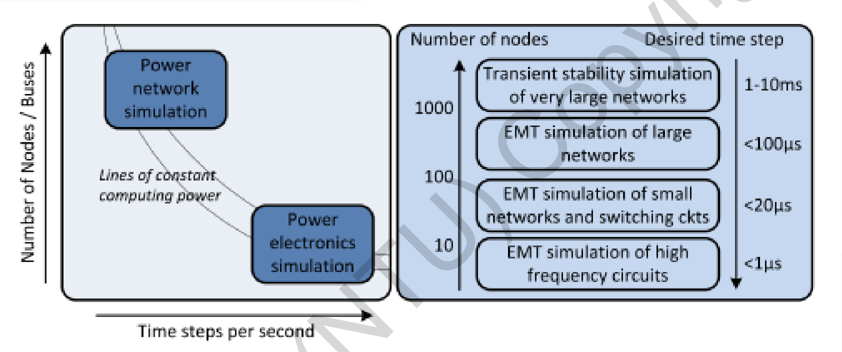
Steady State (pre-fault) ↓ **Accuracy, Speed, Knowledge** ↓ **the faster, the more faults can be assessed**

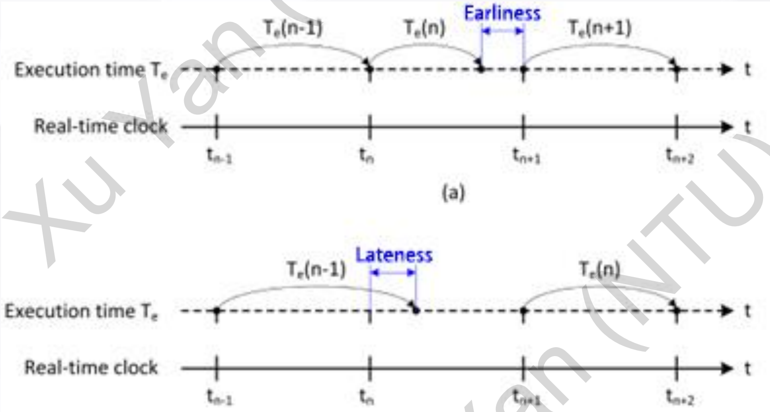
Dynamic State (post-fault) ↓ **Accuracy, Earliness, Robustness** ↓ **the earlier, the more time is left for control**

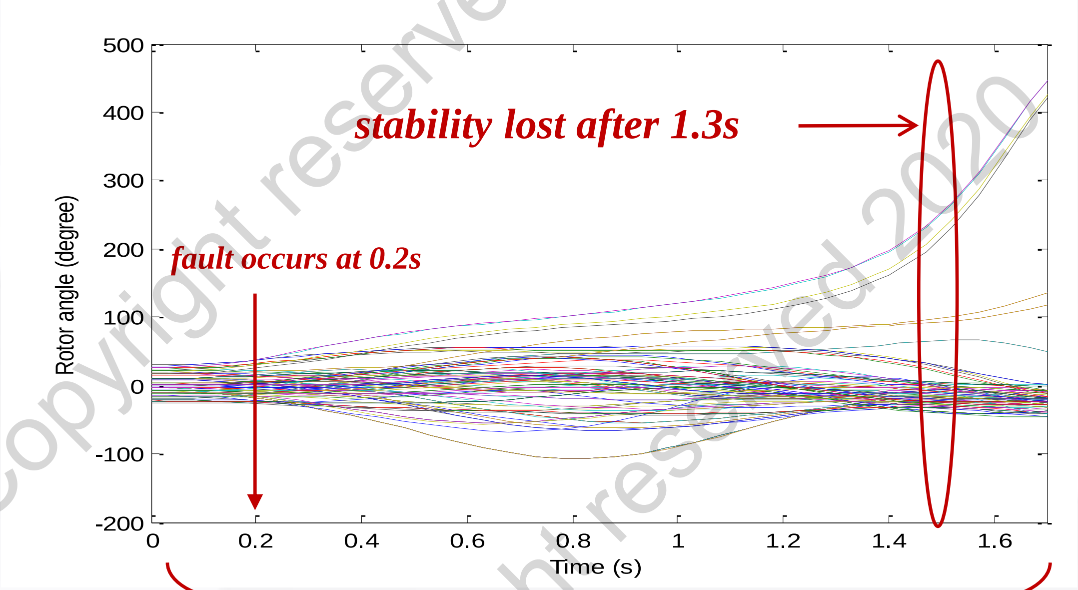
Conventional Methods (Model-based)

- **Time-domain Simulation:** to solve a large-scale differential-algebraic equation (DAE) set
- **Data requirement**: system model (static and dynamic), network topology, state-estimation, fault, etc.
- **Outputs**: system's time-varying trajectories
- **Event-based control:** lookup decision table, contingency indexing

"for a 14,000-bus system, one disturbance analysis could involve a set of 15,000 differential equations and 40,000 nonlinear algebraic equations for an simulation time duration of 10-20s; besides, the number of disturbances to be considered is also enormous, e.g., for the 14,000-bus system, the typical number of postulated disturbances is between 2000 and 3000."

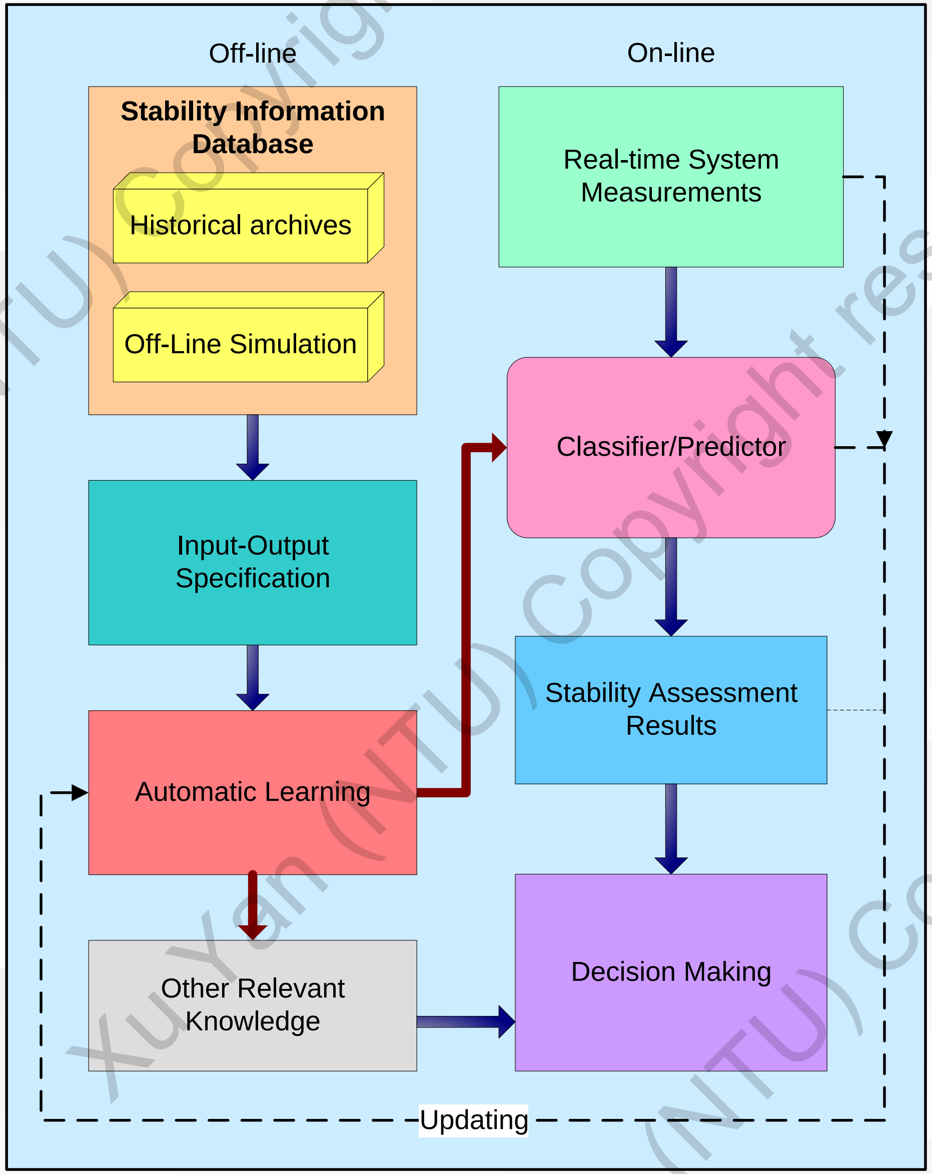


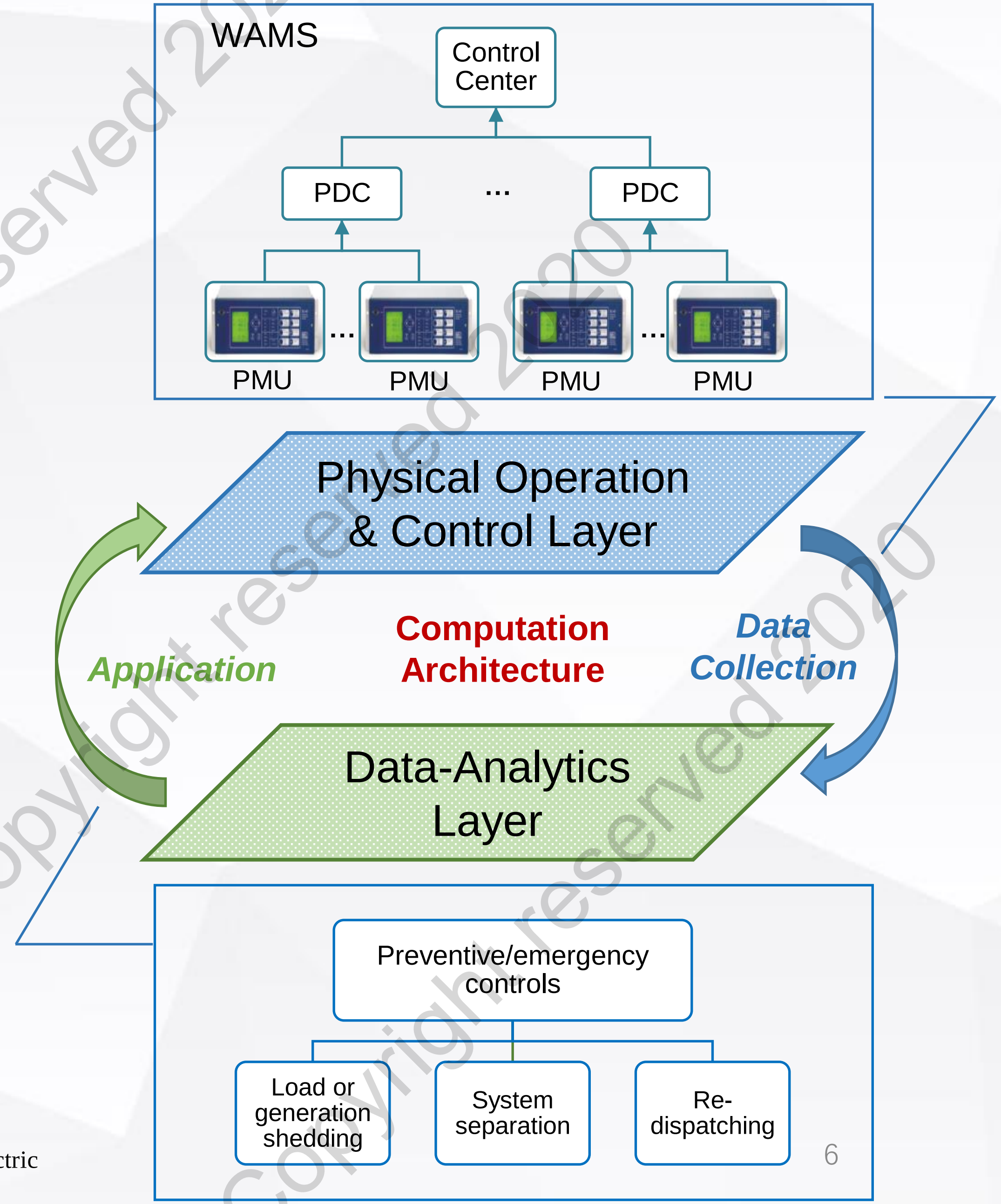




PSS/E simulation costs 2.2s CPU time

Data-Driven Method

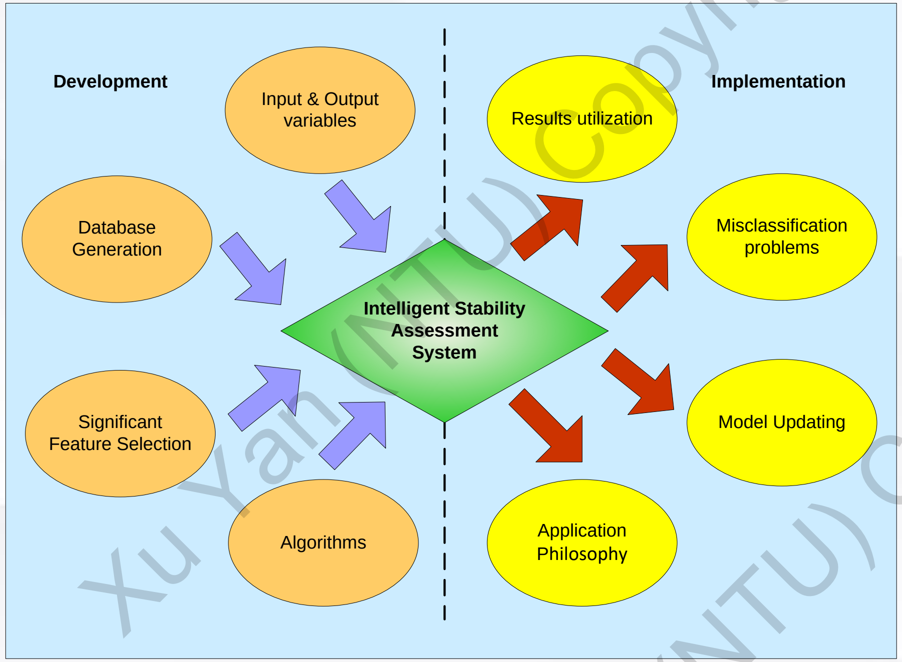




Z.Y. Dong, **Y. Xu**, P. Zhang, and K.P. Wong "Using intelligent system to assess an electric power system's real-time stability," ***IEEE Intelligent Systems Magazine***, 2013.

Key Research Problems (how to?)

- Generate a comprehensive stability **database**
- Improve the **accuracy, speed, and reliability**
- Extract **interpretable knowledge** to support stability control
- Mitigate abnormal situations, such as **missing data, communication delay**
- Adapt the trained model to unforeseen scenarios, e.g., **unexpected fault, topology, etc**.
- Select/extract **significant features**
- Develop effective data-analytics **algorithms**
- **Update** the model timely and efficiently



	Working institutes	Key Funders
2008-2011	South China University of Technology	NSFC
2009-2011	The Hong Kong Polytechnic University 香港理工大學	EPRI Electric Power Research Institute
2011-2016	The University of Newcastle Australia; The University of Sydney	Australian Government Australian Research Council; Ausgrid
2016-now	Nanyang Technological University Singapore	Ministry of Education Singapore; Rolls-Royce; National Research Foundation Prime Minister's Office Singapore

Z.Y. Dong, **Y. Xu**, P. Zhang, and K.P. Wong "Using intelligent system to assess an electric power system's real-time stability," ***IEEE Intelligent Systems Magazine***, 2013.

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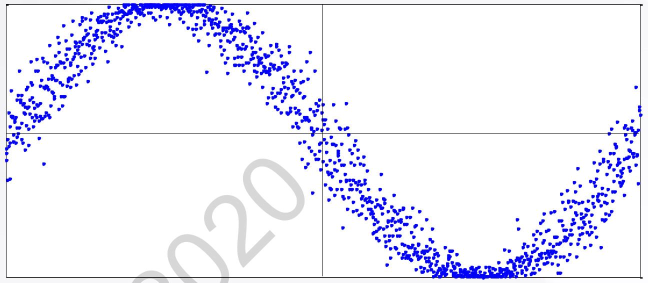
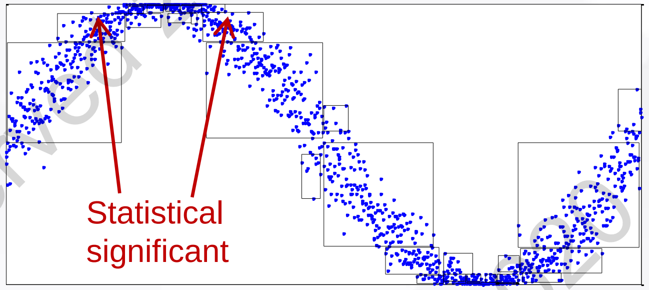
Distance-based Feature Evaluation and Residual Analysis

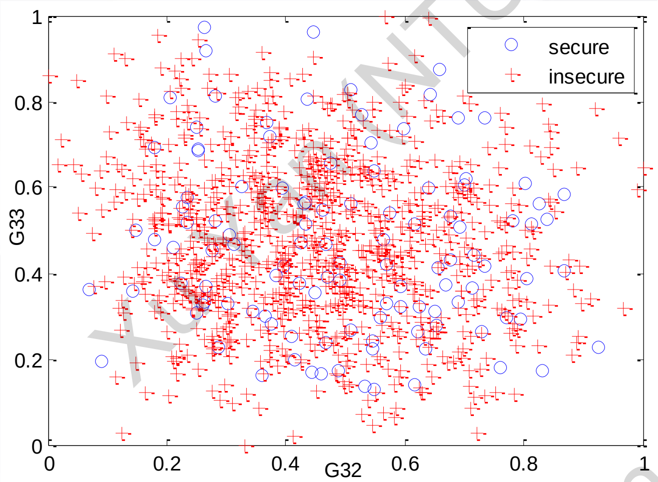
- Evaluate the quality of features according to **how well their values distinguish among instances near each other**; Consider both the difference in features' values and classes, as well as the distance between the instances; Good features can cluster similar instances and separate dissimilar ones in the distance space.

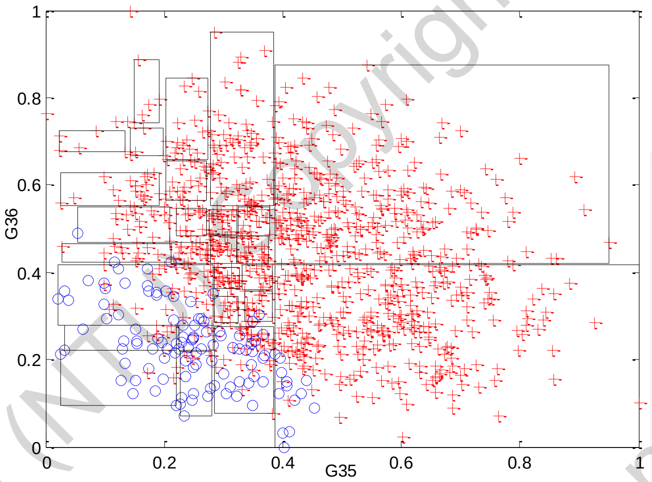
$$
\begin{cases}
diff(X,R,R') = \dfrac{|value(X,R) - value(X,R')|}{\max(X) - \min(X)} \\
W[X]^{i+1} = W[X]^{i} - \sum_{j=1}^{k} diff(X,R_i,H_j)/(m\cdot k) + \\
\sum_{C\neq class(R_i)}^{k} [\dfrac{P(C)}{1-P(class(R_i))} \cdot \sum_{j=1}^{k} diff(X,R_i,M_j(C))]/(m\cdot k)
\end{cases}
$$

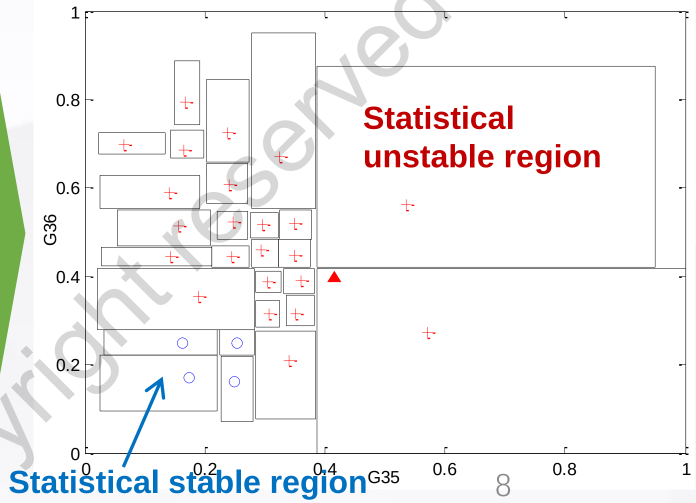




- **Residual:** the difference between an event's observed (actual) occurrence probability and expected occurrence probability.







Y. Xu, et al, "Preventive dynamic security control of power systems based on pattern discovery technique," ***IEEE Trans. Power Systems***, 2012.

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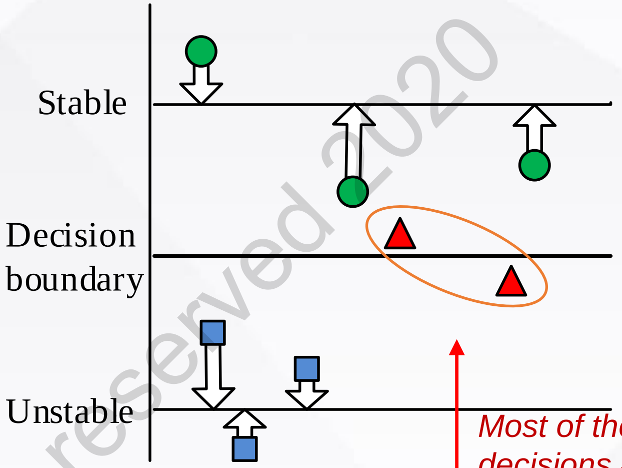
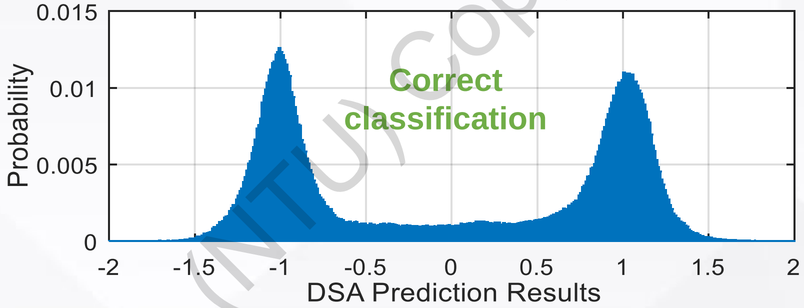
Statistical Error Analysis

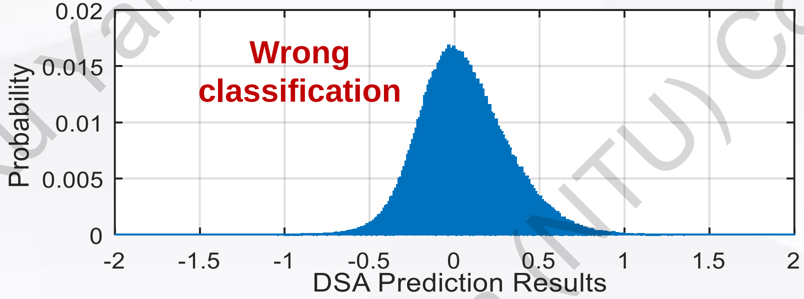
- The essence of **statistical learning** is to fit the historical distribution of a database, and assumes that the future unknown data follows this distribution.
- Error may stem from **1) imperfect fitting** and **2) variation of data distribution**
- How to convert a **numeric** value to a **class** label?

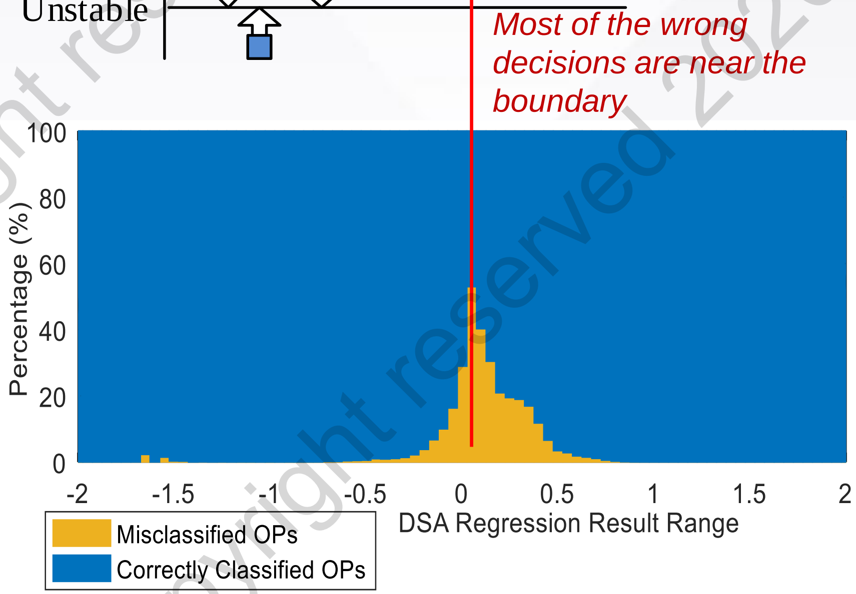
$$\text{If} \begin{cases} y > 0 \;\rightarrow\; y = 1 \text{ (stable)} \\ y \leq 0 \;\rightarrow\; y = -1 \text{ (unstable)} \end{cases}$$





(a)





Y. Zhang, **Y. Xu***, et al, "Intelligent early-warning of power system dynamic insecurity risk towards optimal accuracy-efficiency tradeoff," ***IEEE Trans. Industrial Informatics***, 2017.

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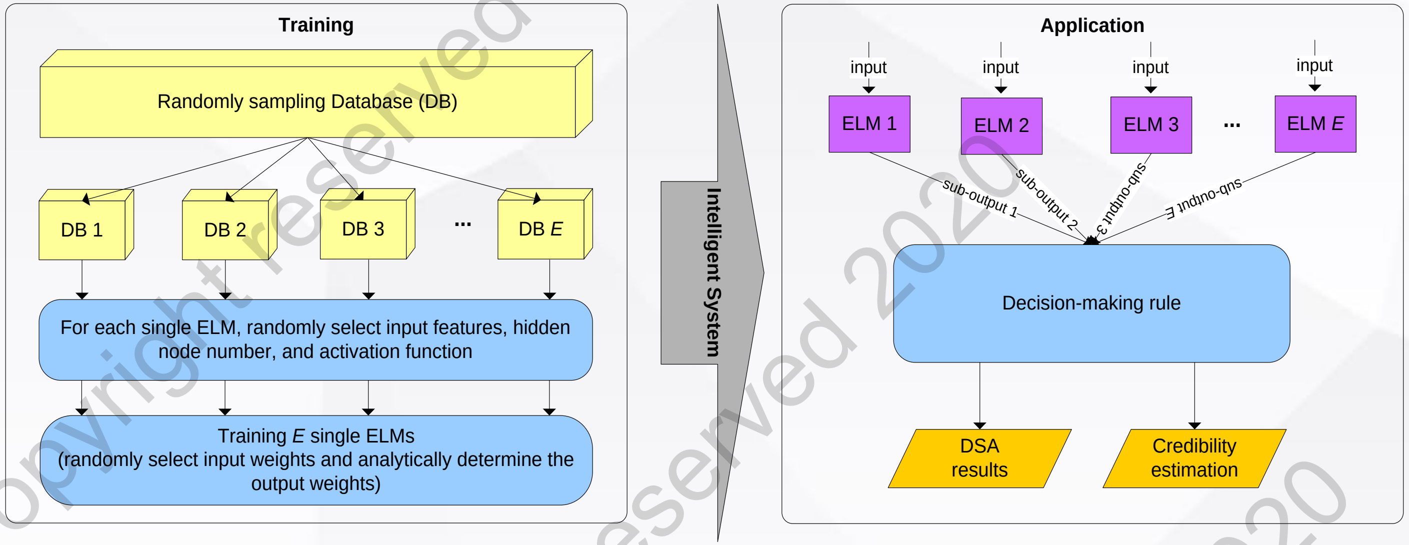
Credibility-Oriented Stability Assessment

If we are unable to avoid errors, can we identify them?

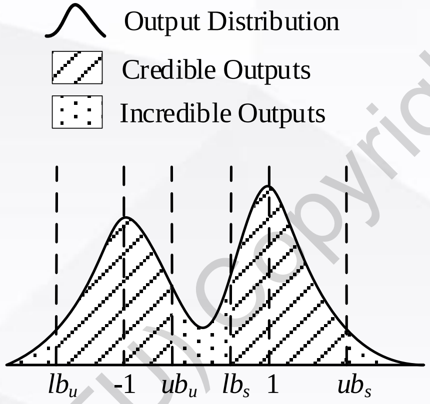
Ensemble Learning

- Combine a set of individual learners to make a **plurality decision**
- Single learners can compensate for each others, and the whole model can **reduce aggregated variance**



Credible Evaluation

- Evaluate an individual decision's "**credibility**" based on the difference between the observed value and the expect value
- Evaluate the whole decision's "credibility" based on the **consistence** of the individual members
- **Only** implement "credible" stability results in practice



$$\frac{\text{[dotted] area}}{\text{[hatched] area} + \text{[dotted] area}} < r \Rightarrow Y \text{ is credible}$$

otherwise, Y is incredible

If $\begin{cases} y \in [lb_s, ub_s] \Rightarrow y = 1 \text{ (stable)} \\ y \in [lb_u, ub_u] \Rightarrow y = -1 \text{ (unstable)} \\ y \in (ub_u, lb_s) \text{or} (-\infty, lb_u) \text{or} (ub_s, +\infty) \Rightarrow y = 0 \\ \qquad \text{(incredible output)} \end{cases}$

For E single learning units, suppose m of them generating incredible outputs, s of them generating stable outputs, and u of them generating unstable outputs:

If $m/E \geq r \Rightarrow Y = 0$ (incredible ensemble result)

Else If $\begin{cases} s > u \Rightarrow Y = 1 \text{ (secure instance)} \\ s \leq u \Rightarrow Y = -1 \text{ (risky instance)} \end{cases}$

Y. Xu, et al, "A reliable intelligent system for real-time dynamic security assessment of power systems," ***IEEE Trans. Power Systems***, 2012.

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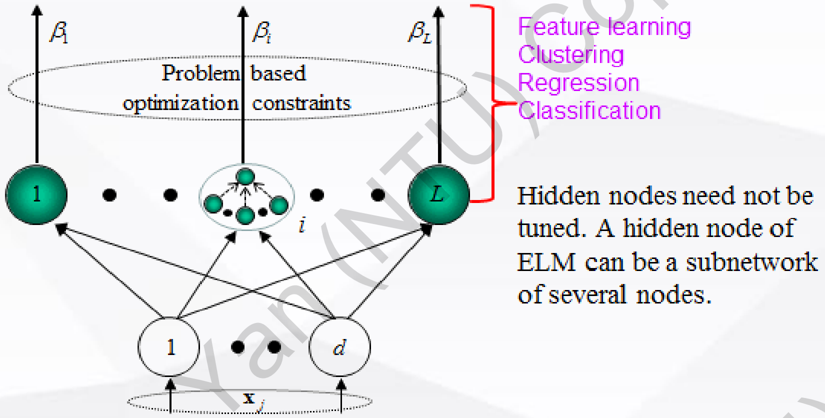
Randomized Algorithms for Ensemble Learning

Keys to Ensemble Learning

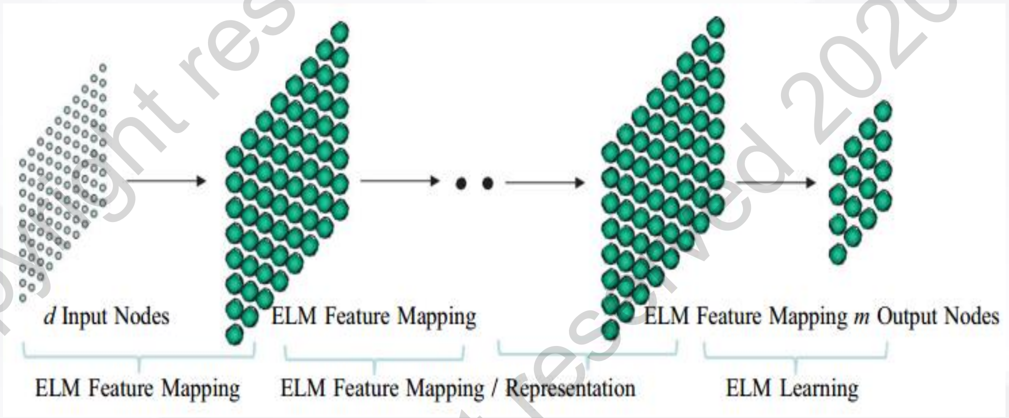
- **Diversity** (data, model structure and parameter)
- Learning and tuning **speed**



Extreme Learning Machine (ELM)

$$f_{\tilde{N}}(\mathbf{x}_j)=\sum_{i=1}^{\tilde{N}}\beta_i\cdot\vartheta(\mathbf{w}_i\cdot\mathbf{x}_j+b_i)=t_j,\quad j=1,2,\ldots,N$$

- **Randomly** selecting the input weights and biases for input weights and bias, **w** and b, and
- **Analytically** determining the output weights β



Other randomized learning techniques:

random vector functional link (RVFL)

Stochastic Configured Network (SCN)

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Pre-fault Online Stability Assessment/Contingency Filtering

IEEE 145-bus System Test Results
(Transient Stability Assessment)

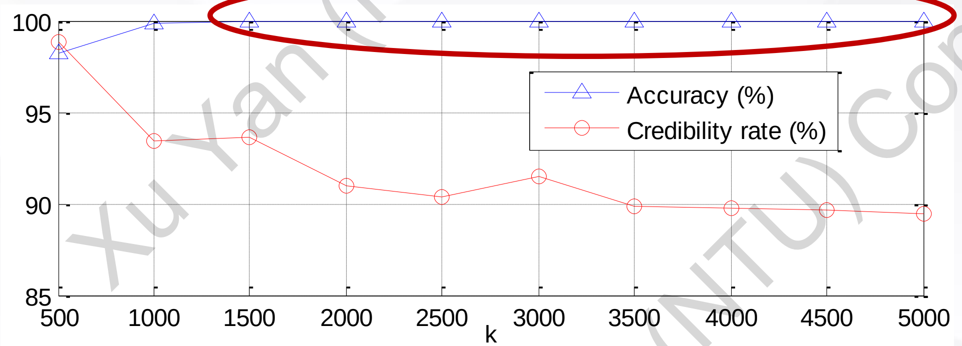
Contingency	Credibility	Accuracy
Fault at bus #1, tripping line 1-6	89.25%	100%
Fault at bus #2, tripping line 2-6	91.54%	100%
Fault at bus #6, tripping line 6-10	94.64%	100%
Fault at bus #89, tripping line 89-76	94.48%	100%
Average	92.48%	100%

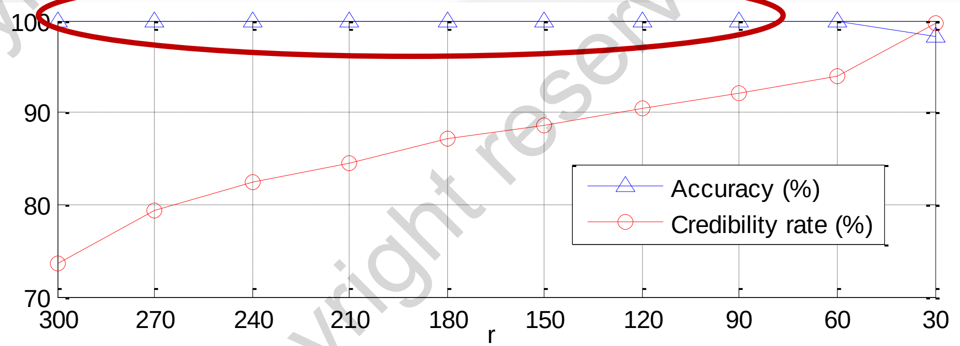
China Southern Power Grid Equivalent System
(CCT Estimation)

Contingency	Credibility	MAE
Fault at a 500kV corridor bus	96.82%	0.0115s

The "credible" decisions are highly (100%) accurate

High accuracy can be obtained on the cost of credibility rate.
If combined with T-D simulation: with 100% accuracy, 16 times faster than pure T-D simulation





Y. Xu, et al, "A reliable intelligent system for real-time dynamic security assessment of power systems," ***IEEE Trans. Power Systems***, 2012.

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Optimal Accuracy-Efficiency Trade-off

Multi-objective Optimization

- The parameters involved in the credible decision-making rule are user-defined. They can be further optimized.
- Optimally balance the tradeoff between **stability assessment accuracy** (A) and **efficiency** (C).

Objectives: $\min_{\mathbf{x}} \mathbf{q}(\mathbf{x}) = -\mathbf{p}(\mathbf{x})$

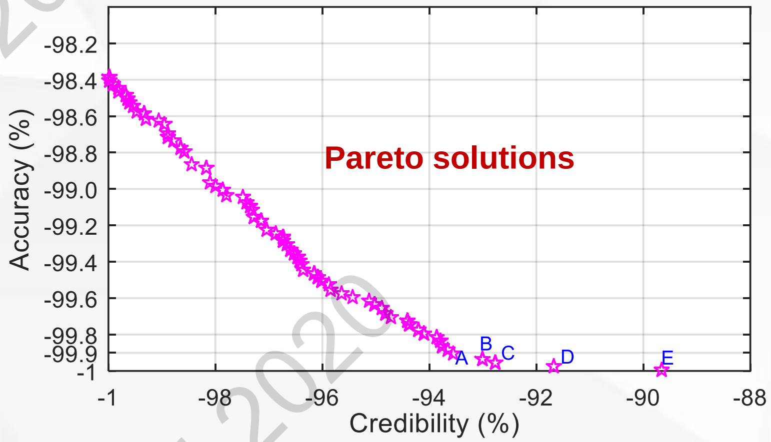
where, $\mathbf{x} = [lb_U, ub_U, lb_S, ub_S, r]$; $\mathbf{p}(\mathbf{x}) = [C, A] = [p_1(\mathbf{x}), p_2(\mathbf{x})]$

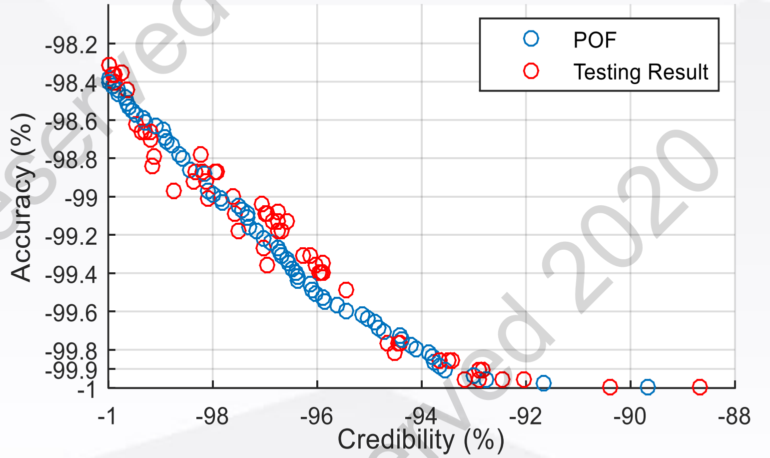
$$\text{Effciency} \propto C = \frac{\text{no. of credible results}}{\text{no. of testing instances}} \times 100\%$$

$$A = \frac{\text{no. of correctly classified instances}}{\text{no. of credible results}} \times 100\%$$

subject to: $lb_U < U;\ U < ub_U < \frac{U+S}{2}$

$$\frac{U+S}{2} < lb_S < S;\ ub_S > S;\ 0 < r < 1$$





Pareto Points	Testing Performance		Average Computation Time		
	Credibility	Accuracy	ELM Ensemble	T-D Simulation	Overall
A	92.82%	99.9%	5.12 s	11.7 min	11.8 min
B	92.47%	99.95%		13.3 min	13.4 min
C	92.02%	99.95%		15 min	15.1 min
D	90.39%	100%		18.3 min	18.4 min
E	88.66%	100%		21.1 min	21.2 min

15 times faster than pure T-D simulation

Y. Zhang, **Y. Xu***, et al, "Intelligent early-warning of power system dynamic insecurity risk towards optimal accuracy-efficiency tradeoff," ***IEEE Trans. Industrial Informatics***, 2017.

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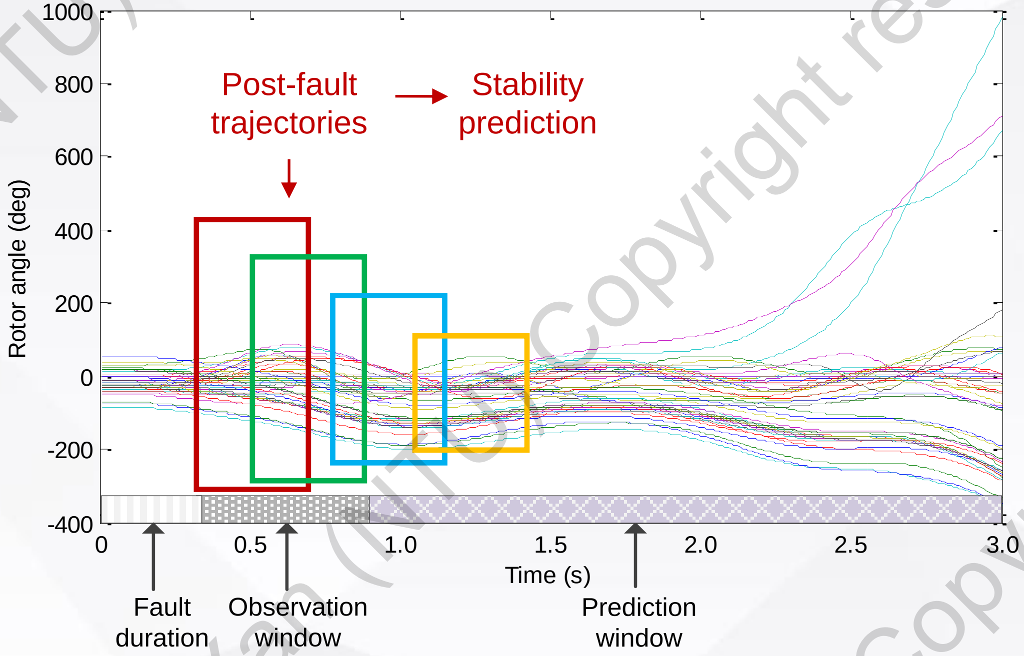
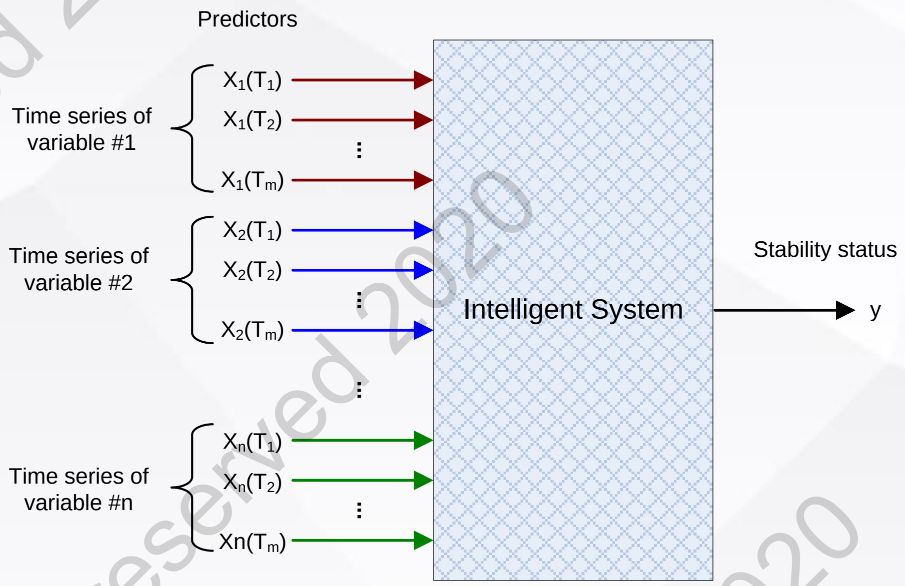
Post-Fault Real-Time Stability Assessment

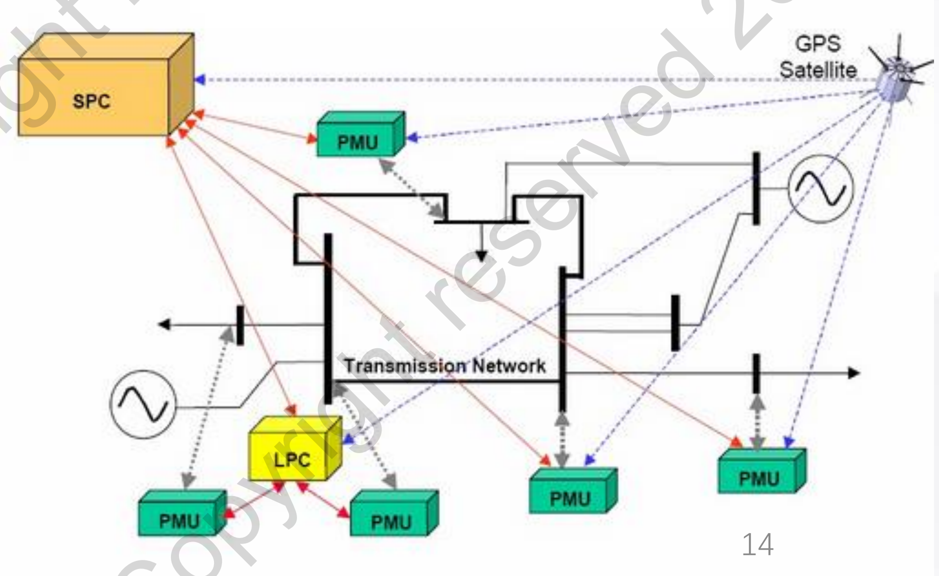
Response-based stability assessment and control

- More **robust, accurate, and generalized**
- **Decision speed**: the time-window length



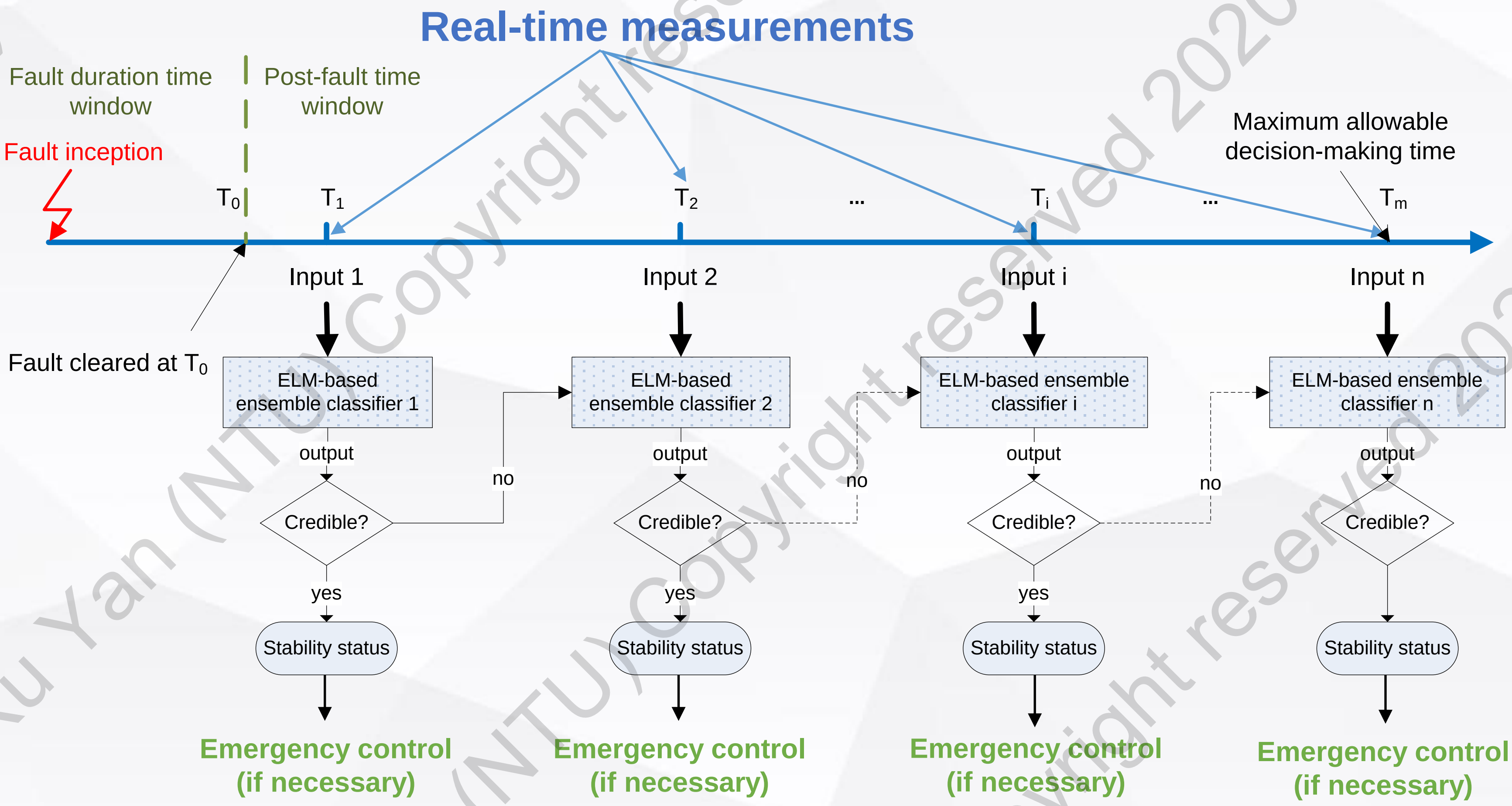


- **slower** decision speed → **more** dynamic information → tends to be **more accurate** → **less** time for control
- **faster** decision speed → **less** dynamic information → tends to be **less accurate** → **more** time for control



Time-Adaptive Method for Generalized Time-Series Decision-Making Problems

- **Adaptively** (in time domain) make decisions based on the output credibility
- Provide an accurate decision at an **appropriate earlier** time
- **Balance** the assessment accuracy and the decision speed



R. Zhang, **Y. Xu**, et al "Post-disturbance transient stability assessment of power systems by a self-adaptive intelligent system," ***IET Gen. Trans. & Dist.***, 2015.

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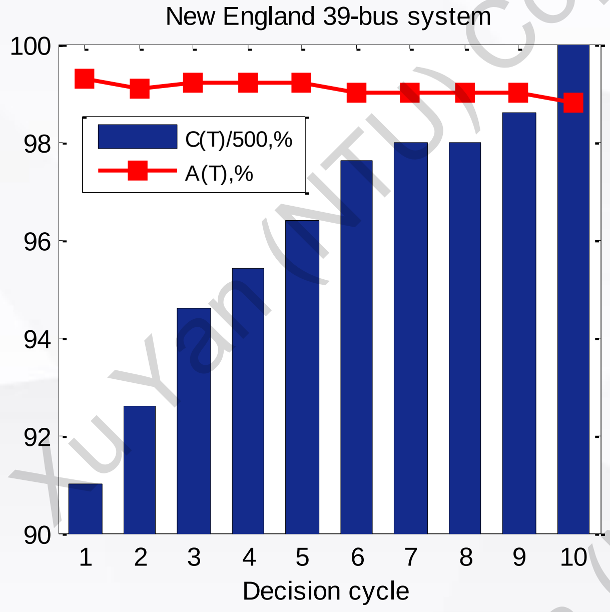
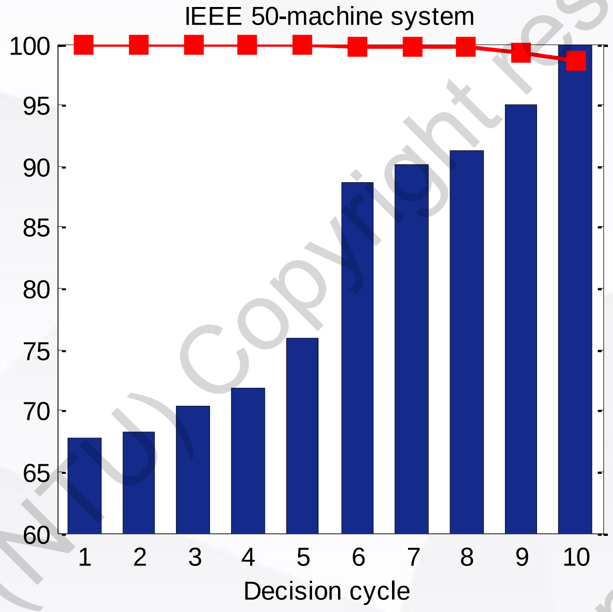
Test Results

Literature	Response time	Accuracy (%)
I. Kamwa, et al [10]	2 to 3s	96%~99.9%
I. Kamwa, et al [11]	1 or 2s	
I. Kamwa, et al [12]	150 and 300ms	
S. Rovnyak, et al [9]	8 cycles	
N. Amjady, et al [13]	6 cycles	
N. Amjady, et al [14]	5 cycles	
U.Annakkage, et al [16]	4 cycles	

Existing methods:
Fixed response time: 4 cycles-3s
Accuracy: 96%-99.9%





Our method:
Adaptive response time:
average 1.9 cycles;
average accuracy: 99.7%

R. Zhang, **Y. Xu**, et al "Post-disturbance transient stability assessment of power systems by a self-adaptive intelligent system," ***IET Gen. Trans. & Dist.***, 2015.

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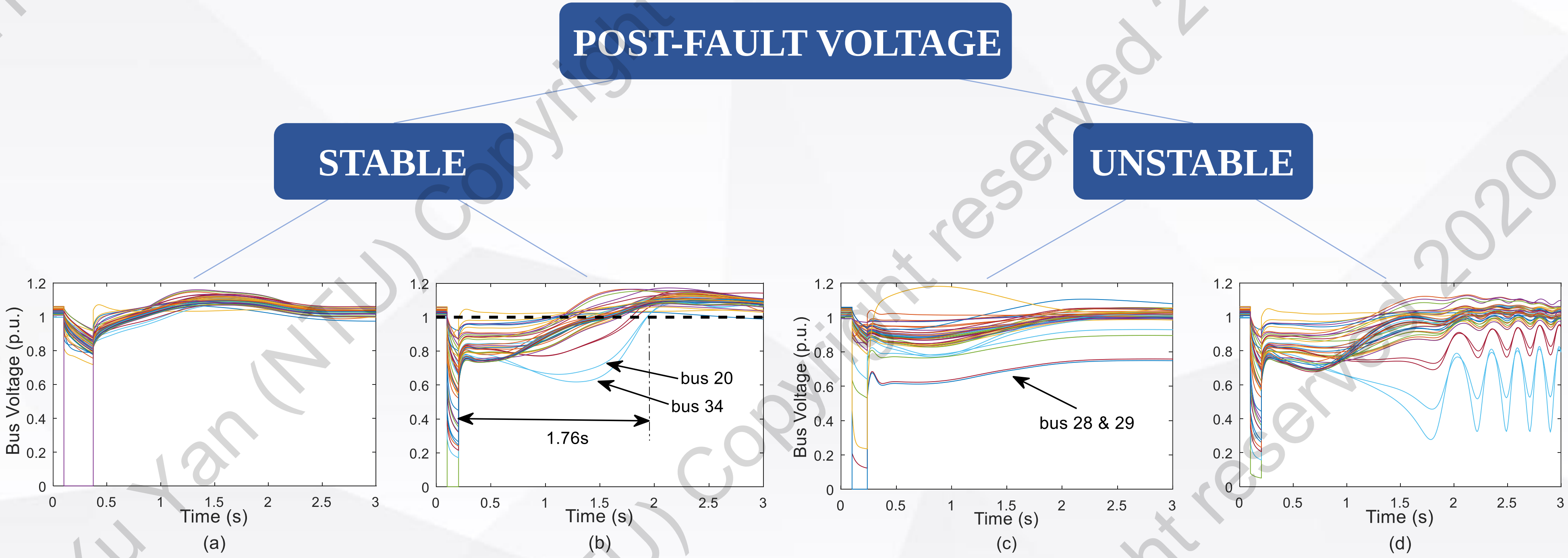
The Short-Term Voltage Stability (STVS) Problem

The STVS problem is concerned on:

- Fault-induced delayed voltage recovery (FIDVR) – pose risk for wind turbine to ride through
- Sustained low voltage without recovery – may lead to voltage collapse in the long-term
- Fast voltage collapse – usually associated with rotor-angle instability



Fast Recovery (satisfactory) | FIDVR (unacceptable) | Sustained Low Voltage (unacceptable) | Fast Collapse (unacceptable)

Y. Zhang, **Y. Xu**, et al "A hierarchical self-adaptive data-analytics method for real-time power system short-term voltage stability assessment," ***IEEE Trans. Ind. Infor.***, 2018.

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Short-Term Voltage Stability Indices

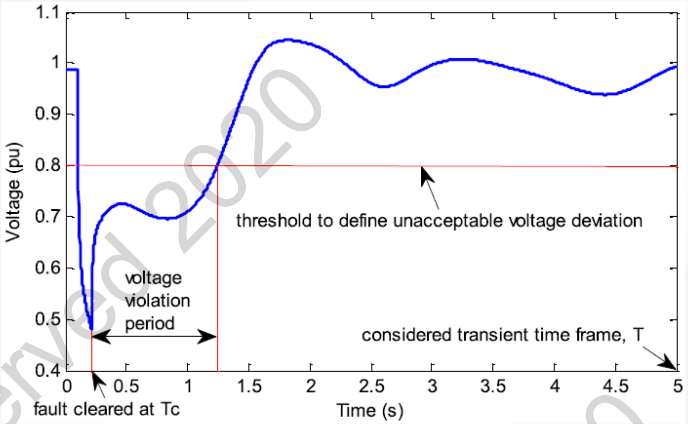
Index to evaluate voltage collapse :

- Transient Voltage Collapse Index (TVCI) – a binary index to decide whether or not the voltages are recovered

Indices to evaluate FIDVR severity :

1) Transient Voltage Severity Index (TVSI) [a]

- a continuous index
- an averaged index over all buses
- FIDVR severity is reflected by the magnitude and the duration time of voltage deviation

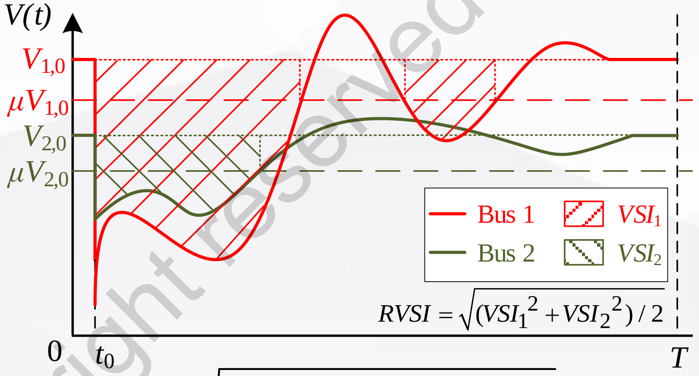


[a] **Y. Xu**, Z.Y. Dong, K. Meng, W.F. Yao, et al, "Multi-objective dynamic VAR planning against short-term voltage instability using a decomposition-based evolutionary algorithm," *IEEE Trans. Power Systems*, 2014.

$$\mathrm{TVSI} = \frac{\sum_{i=1}^{N}\sum_{t=T_c}^{T} \mathrm{TVDI}_{i,t}}{N \times (T - T_c)}$$

2) Root-mean-squared Voltage Severity Index (RVSI) [b]

- a continuous index
- adopt root-mean squared average instead of arithmetic mean
- ability to emphasize the buses with more severe voltage deviation
- FIDVR severity is reflected by the area covered by voltage deviation

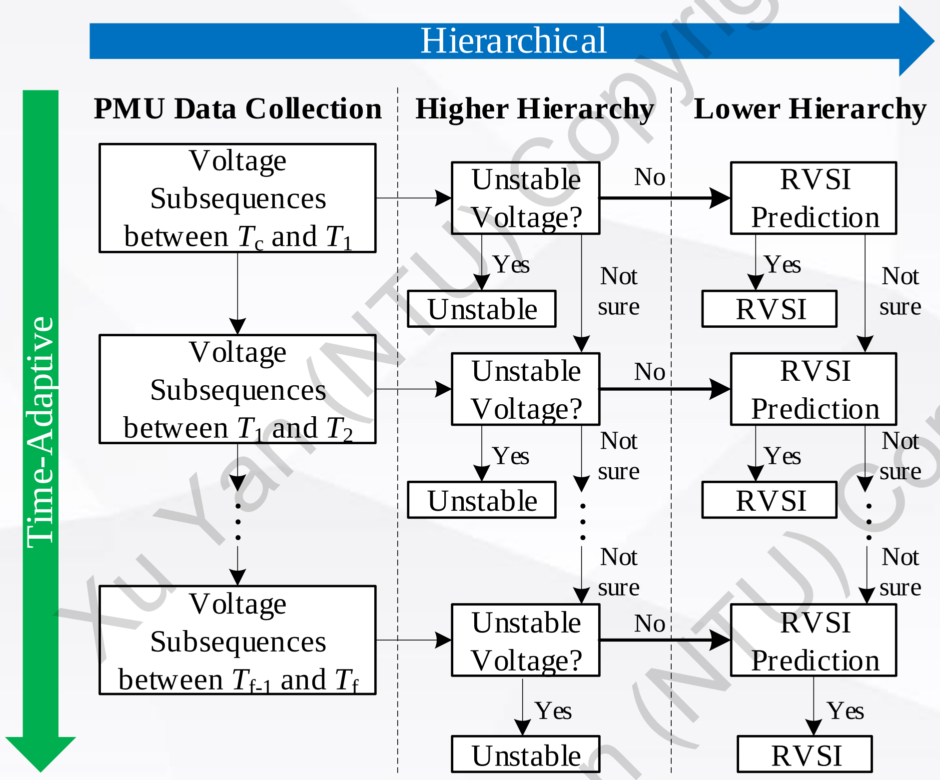


[b] Y. Zhang, **Y. Xu**, et al "A hierarchical self-adaptive data-analytics method for real-time power system short-term voltage stability assessment," ***IEEE Trans. Ind. Infor.***, 2018.

$$\mathrm{RVSI} = \sqrt{\frac{\sum_{i=1}^{N}\left(\int_{T_c}^{T} \mathrm{TVDI}_{i,t}\, dt\right)^2}{N}}$$

Hierarchical Time-Adaptive Method for Real-time STVS Assessment

- **Hierarchical**
  - voltage instability detection (higher hierarchy) & FIDVR severity prediction (lower hierarchy)
  - improve comprehensiveness of STVS assessment
- **Time-Adaptive**
  - adaptively deliver assessment results based on progressively collected data
  - provide an accurate result at the earliest opportunity
  - optimally balance the assessment accuracy and speed



T_i	Higher Hierarchy			Lower Hierarchy		
	Voltage Instability Detection			FIDVR Severity Prediction		
	$R_c(T_i)$	$S_c(T_i)$	$A_c(T_i)$	$R_r(T_i)$	$S_r(T_i)$	$E_r(T_i)$
1	1987	761	100%	276	0	N/A
2	1226	348	99.82%	524	0	N/A
3	878	204	99.85%	637	0	N/A
4	674	125	99.86%	660	0	N/A
5	549	199	99.70%	715	22	2.2%
6	350	49	99.70%	729	185	2.1%
7	301	24	99.71%	565	138	2.0%
8	277	9	99.71%	436	288	2.0%
9	268	11	99.71%	156	74	2.1%
10	257	19	99.71%	97	25	2.0%
…	…	…	…	…	…	…
20	66	66	99.09%	71	71	2.4%

R_c, R_r	The number of available samples.
S_c, S_r	The number of successfully assessed samples.
A_c	The accumulated accuracy.
E_r	The accumulated MAPE.

Y. Zhang, **Y. Xu**, et al "A hierarchical self-adaptive data-analytics method for real-time power system short-term voltage stability assessment," ***IEEE Trans. Ind. Infor.***, 2018.

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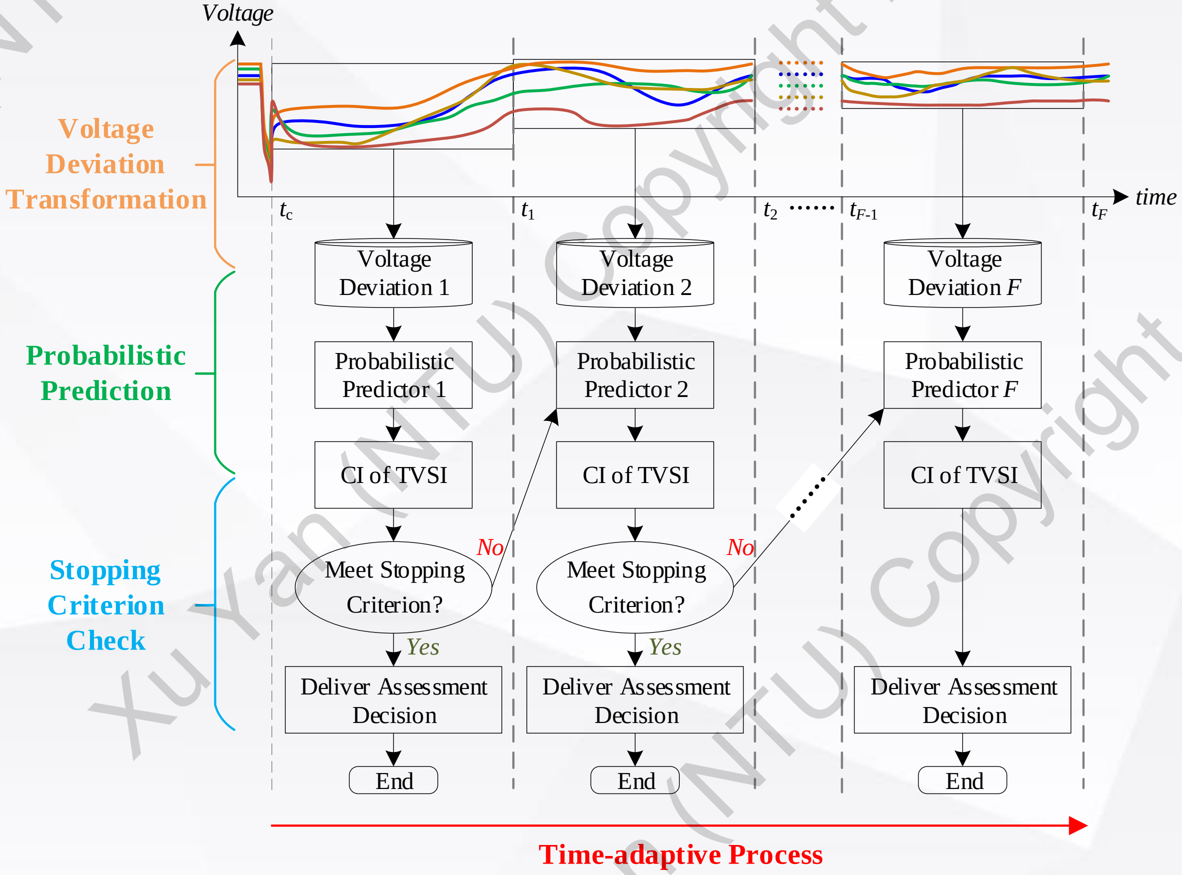
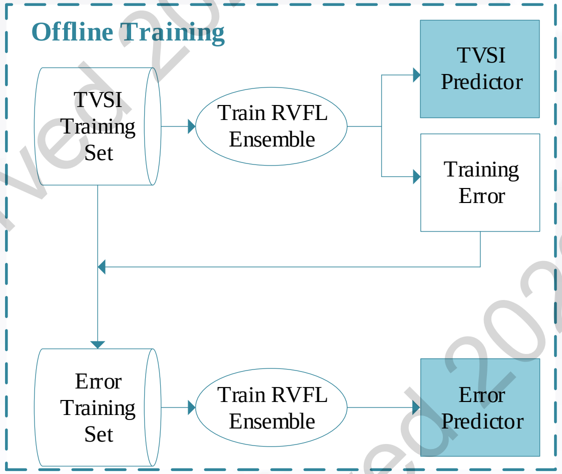
Probabilistic Time-Adaptive Method for Real-time FIDVR Assessment

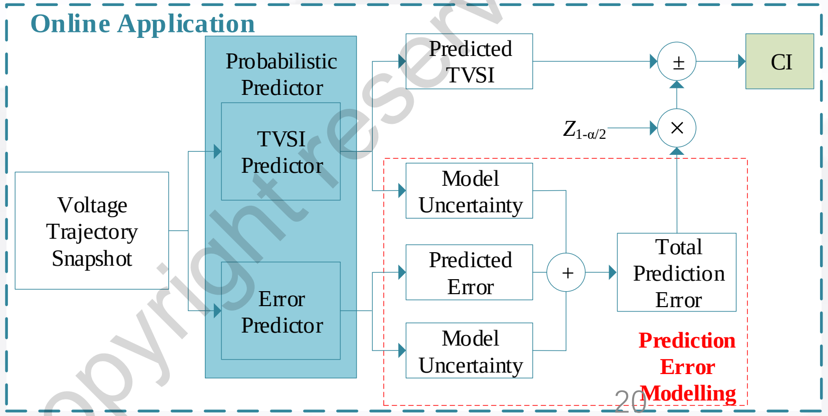
- **Credibility-Oriented Time-Adaptive Method**
  - credibility is evaluated according to the consistence among individual learners.
  - a large number of user-defined parameters to be tuned

improve

- **Probabilistic Time-Adaptive Method**
  - predict FIDVR severity on a probabilistic basis with a certain confidence level
  - non-parametric in nature
  - more robust in practice







Y. Zhang, **Y. Xu**, et al "Real-time assessment of fault-induced delayed voltage recovery: a probabilistic self-adaptive data-driven method," ***IEEE Trans. Smart Grid***, 2018.

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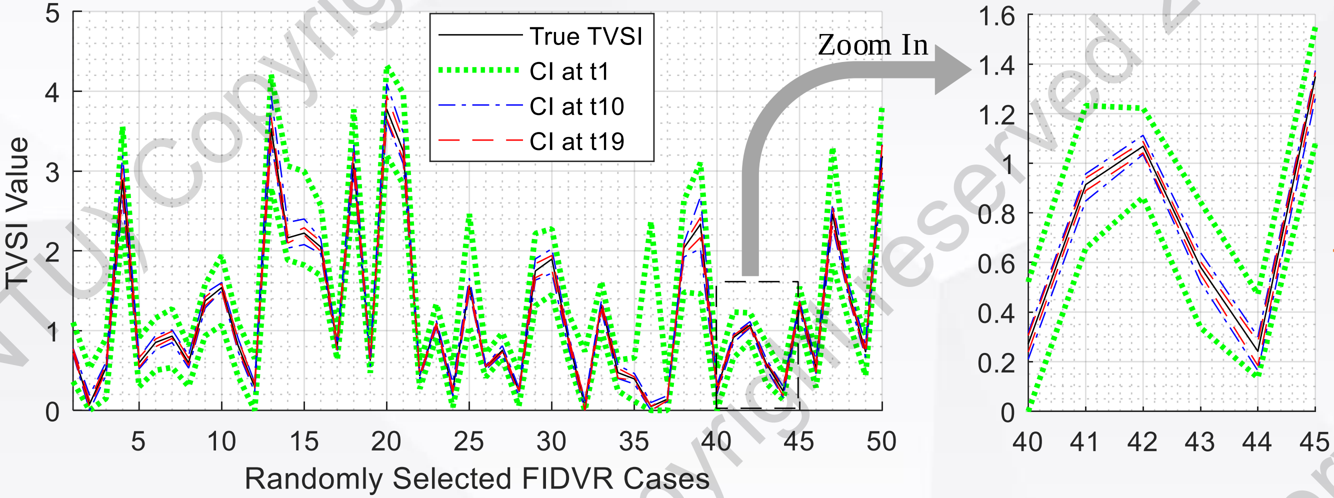
Test Results

Confidence Intervals (CI)



The composed CI shrinks over time, indicating the reduction of prediction error at a later decision cycle

FIDVR Assessment Accuracy and Speed

Time Points	No. of Assessed Cases	Assessment Accuracy	Time Points	No. of Assessed Cases	Assessment Accuracy
1	793	100%	11	13	100%
2	88	100%	12	5	100%
3	59	100%	13	8	100%
4	39	100%	14	6	100%
5	33	100%	15	3	100%
6	19	100%	16	2	100%
7	26	100%	17	1	100%
8	11	100%	18	2	100%
9	9	100%	19	0	N/A
10	14	100%	20	31	87.10%
Overall Accuracy		**99.66%**	Average Decision Time		**0.14 s**

Comparative Study Results

Methods	Method Type	Assessment Accuracy	Required Assessment Time
Our Method	self-adaptive	**99.66%**	**0.14 s**
DT	fixed-time	99.05%	0.75 s
SVM	fixed-time	99.66%	0.80 s
BLR	self-adaptive	98.37%	0.33 s

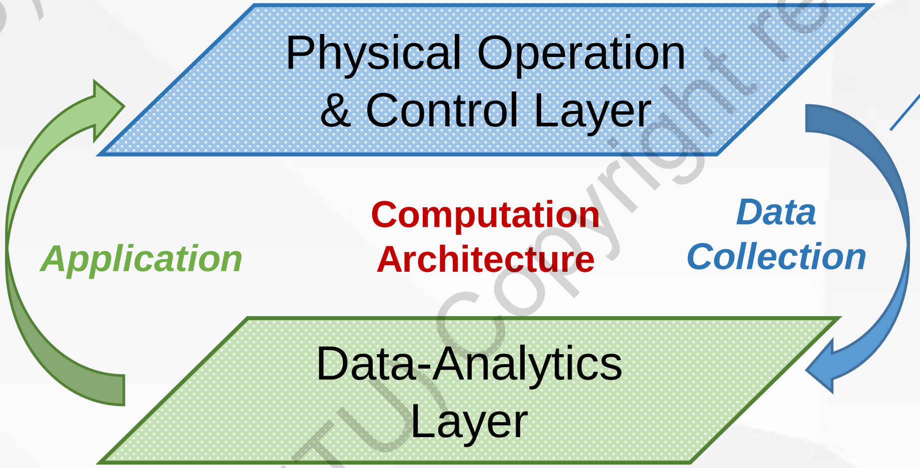
All 100% accuracy for early assessment, indicating the improved reliability in time-adaptive method.

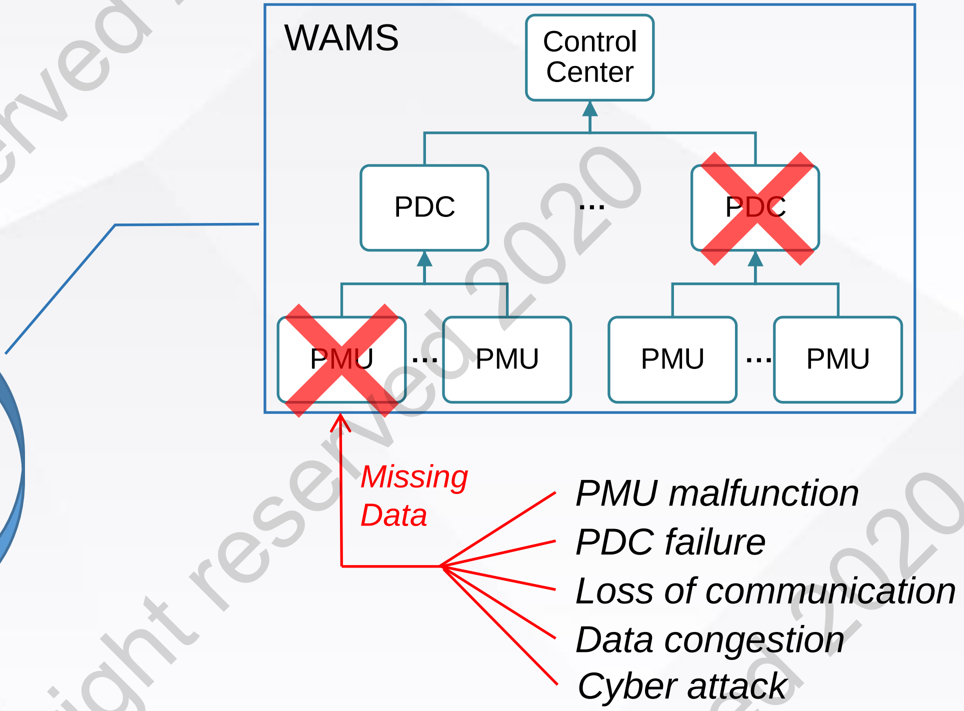
Y. Zhang, **Y. Xu**, et al "Real-time assessment of fault-induced delayed voltage recovery: a probabilistic self-adaptive data-driven method," ***IEEE Trans. Smart Grid***, 2018.

Data-Driven Method with Missing Data

The impacts of missing data:

- Incomplete input
- Fail to work
- Deterioration of assessment accuracy





Existing methods:

- Surrogate split for decision tree: T. Y. Guo, and J. V. Milanovic, "The effect of quality and availability of measurement signals on accuracy of on-line prediction of transient stability using decision tree method," *IEEE/PES ISGT Europe*, 2013.
- Random subspace-based decision tree ensemble: M. He, V. Vittal, "Online dynamic security assessment with missing PMU measurements: A data mining approach," *IEEE Trans. Power Syst.*, 2013.

Still suffer from low accuracy if the amount of missing data increases!

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Observability-Oriented PMU Clustering

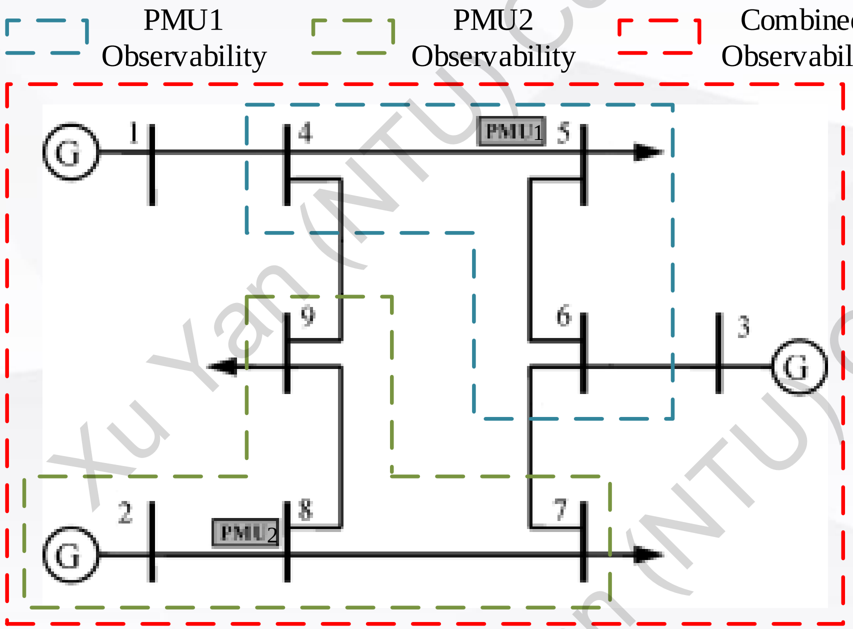
Observability: The grid region where the power system operating data can be measured.

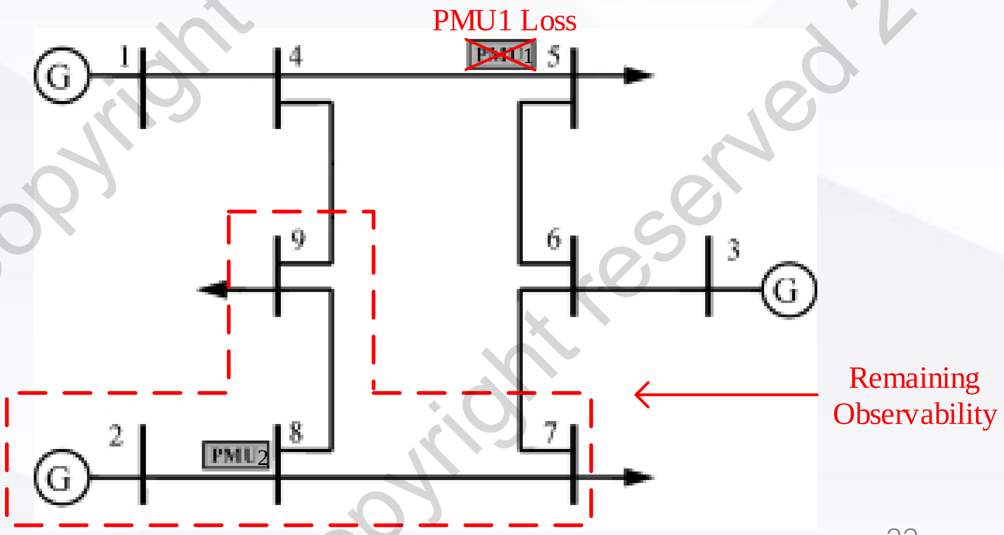
Complete observability: The condition where the observability covers the whole power grid.

Incomplete observability: The condition where some of the operating data cannot be measured.

Under missing data events, the observability will become incomplete, but the change in observability can be complicated:

- The combined observability of multiple PMUs can be larger than just simply adding up their own observability.
- Loss of one PMU can impair the observability in an larger region than its own observability.





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Analytical PMU clustering

- An **iterative** searching process over all the electric components.
- Search all the **non-redundant** PMU combinations that can observe each electric component.
- **Maximize** the grid observability under any PMU loss scenario – **rigorously proved**
- **Minimize** the number of PMU clusters – **rigorously proved**

F1.	*The union of the observability of each complete cluster in* ***P*** *equals to the remaining observability of the grid.*
F2.	*Upon F1 is satisfied, the number of clusters is minimized.*

F1 proof: F1 is equivalent to: $\mathbf{E}_1 = \mathbf{E}_2, \forall \mathbf{d} \in \mathbf{C}$ (1)

where $\mathbf{E}_1 = \mathrm{O}(\mathbf{d}), \mathbf{E}_2 = \bigcup_{\mathbf{m}_k \in \mathbf{P}} \mathrm{O}(\mathrm{V}(\mathbf{m}_k \mid \mathbf{d}))$ (2)

where $\mathrm{V}(\mathbf{m}_k \mid \mathbf{d}) = \begin{cases} \mathbf{m}_k \text{ if } \mathbf{m}_k \subseteq \mathbf{d} \\ \phi \text{ otherwise} \end{cases}$ (3)

In (1) - (3), $\mathrm{O}(\cdot)$ is the function to map a set of PMUs to their observability; $\mathbf{d}$ is the set of available PMUs; $\mathbf{C}$ includes all PMU combinations; $\mathbf{m}_k$ is a PMU cluster in $\mathbf{P}$ and the condition $\mathbf{m}_k \subseteq \mathbf{d}$ means $\mathbf{m}_k$ remains complete with only $\mathbf{d}$ in the system.

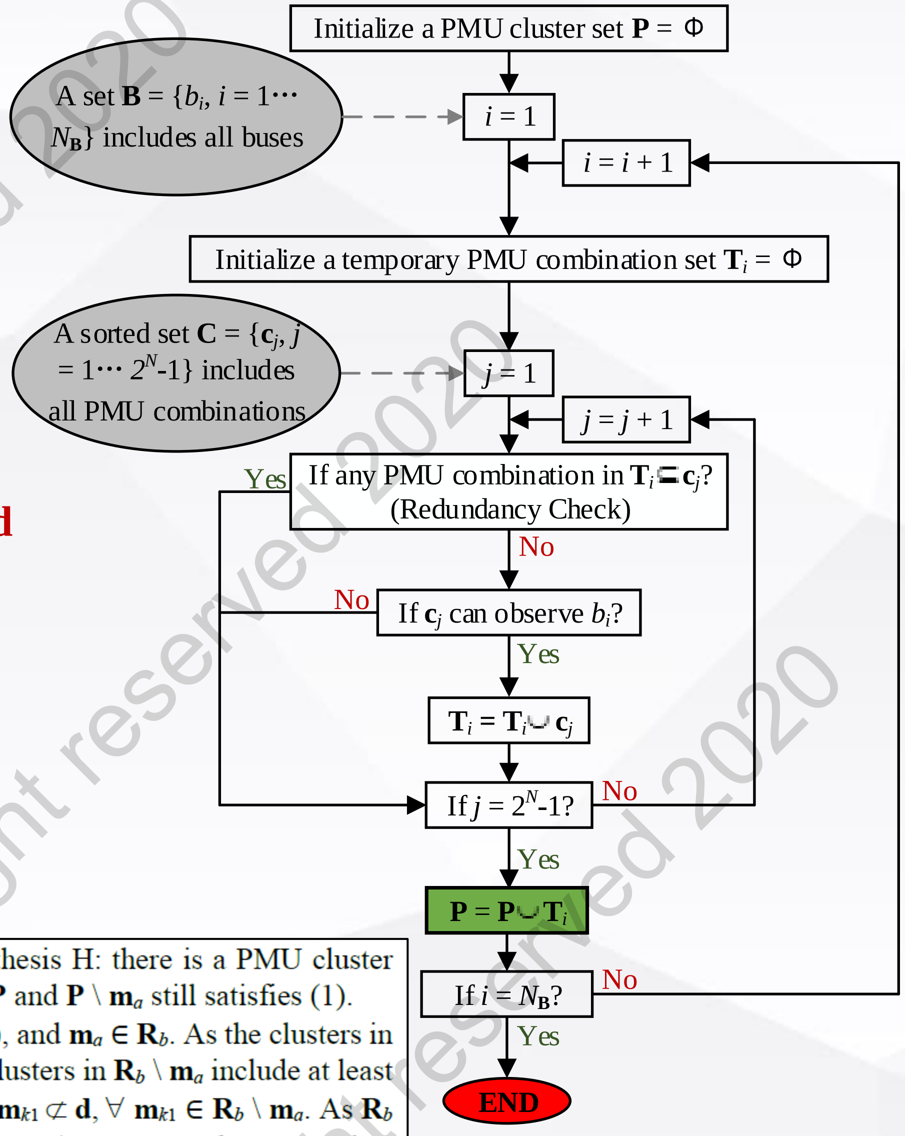
$\forall e_i \in \mathbf{E}_1 = \mathrm{O}(\mathbf{d})$, at least one non-redundant subset $\mathbf{d}_s \subseteq \mathbf{d}$ satisfies $e_i \in \mathrm{O}(\mathrm{V}(\mathbf{d}_s \mid \mathbf{d}))$. Since $\mathbf{R}_i$ includes all non-redundant PMU clusters for e_i, $\mathbf{d}_s \in \mathbf{R}_i \subseteq \mathbf{P}$, thus $e_i \in \mathbf{E}_2 \Rightarrow \mathbf{E}_1 \subseteq \mathbf{E}_2$. $\forall e_i \in \mathbf{E}_2$, at least a $\mathbf{m}_s \in \mathbf{P}$ satisfies $e_i \in \mathrm{O}(\mathbf{m}_s)$ and $\mathbf{m}_s \subseteq \mathbf{d}$, so $e_i \in \mathrm{O}(\mathbf{d}) = \mathbf{E}_1 \Rightarrow \mathbf{E}_2 \subseteq \mathbf{E}_1$. As $\mathbf{E}_1 \subseteq \mathbf{E}_2$ and $\mathbf{E}_2 \subseteq \mathbf{E}_1$, $\mathbf{E}_1 = \mathbf{E}_2 \Rightarrow$ F1.

F2 proof: we make a hypothesis H: there is a PMU cluster $\mathbf{m}_a$ that can be removed from $\mathbf{P}$ and $\mathbf{P} \setminus \mathbf{m}_a$ still satisfies (1).

Let $\mathbf{d} = \mathbf{m}_a$, $e_b \in \mathbf{E}_1 = \mathrm{O}(\mathbf{m}_a)$, and $\mathbf{m}_a \in \mathbf{R}_b$. As the clusters in $\mathbf{R}_b$ are non-redundant, all the clusters in $\mathbf{R}_b \setminus \mathbf{m}_a$ include at least one PMU that is not in $\mathbf{m}_a$, so $\mathbf{m}_{k1} \not\subset \mathbf{d}, \forall \mathbf{m}_{k1} \in \mathbf{R}_b \setminus \mathbf{m}_a$. As $\mathbf{R}_b$ includes all clusters observing e_b, $\mathbf{P} \setminus \mathbf{R}_b$ cannot observe e_b, thus

$$\begin{cases} \mathrm{O}(\mathrm{V}(\mathbf{m}_{k1} \mid \mathbf{m}_a)) = \phi, \ \forall \mathbf{m}_{k1} \in \mathbf{R}_b \setminus \mathbf{m}_a \\ e_b \notin \mathrm{O}(\mathrm{V}(\mathbf{m}_{k2} \mid \mathbf{m}_a)), \forall \mathbf{m}_{k2} \in \mathbf{P} \setminus \mathbf{R}_b \end{cases} \Rightarrow e_b \notin \mathrm{O}(\mathrm{V}(\mathbf{m}_k \mid \mathbf{m}_a)),$$

$\forall \mathbf{m}_k \in \mathbf{P} \setminus \mathbf{m}_a \Rightarrow e_b \notin \mathbf{E}_2 \Rightarrow \mathbf{E}_1 \neq \mathbf{E}_2$. Thus, H fails $\Rightarrow$ F2.



Y. Zhang, **Y. Xu**, et al "Robust ensemble data-analytics for incomplete PMU measurement-based power system stability assessment," ***IEEE Trans. Power Syst.***, 2017.

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Robust Data-Driven Method against Missing Data

At Offline Stage:

- Use the observability of each PMU cluster to train each single learning unit.
- Aggregate the single learning units in an ensemble learning model.

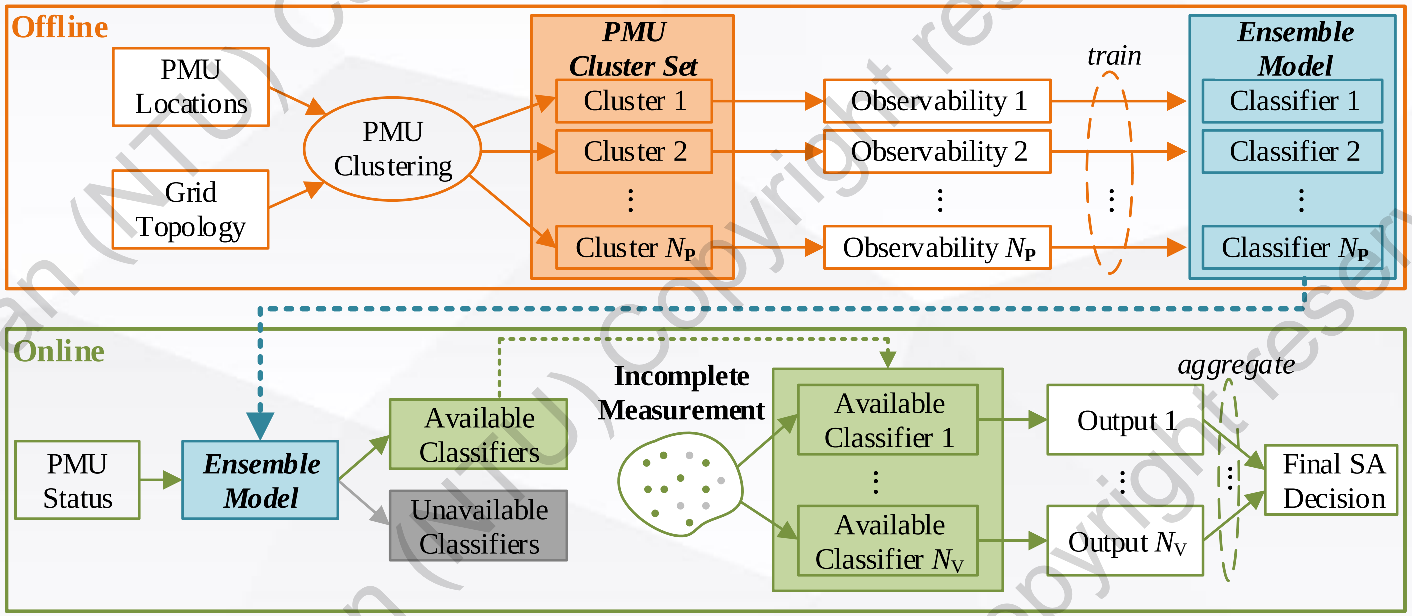
At Online Stage:

- Only the available single learning units (i.e. complete input data) generate DSA decisions.

Advantages:

- The remaining observability is fully captured by the ensemble learning model.
- Sustain DSA accuracy under missing data conditions.
- Minimum number of single learning models to achieve the robustness (i.e. minimum offline training and online computation burden).

Analytical PMU clustering + Ensemble Learning → Robustness against missing data



Y. Zhang, **Y. Xu**, et al "Robust ensemble data-analytics for incomplete PMU measurement-based power system stability assessment," ***IEEE Trans. Power Syst.***, 2017.

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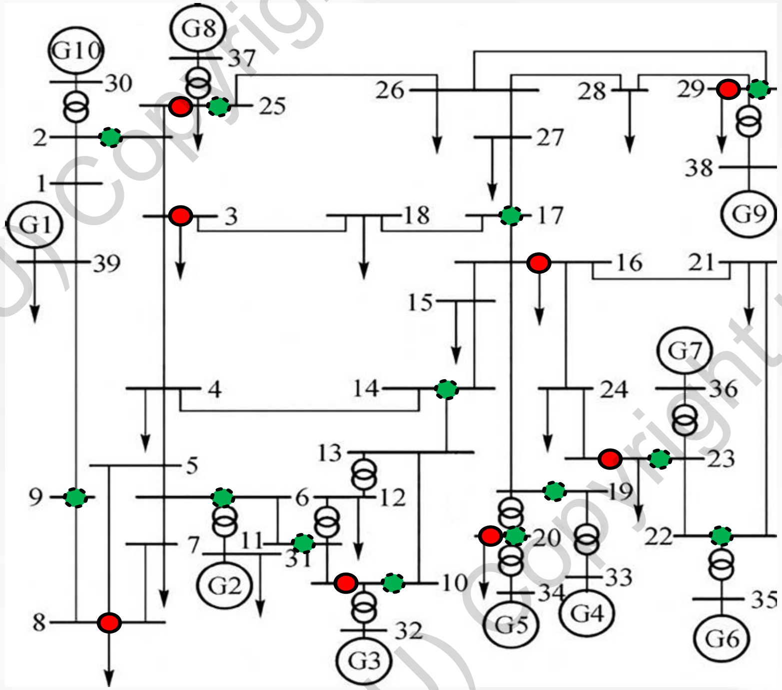
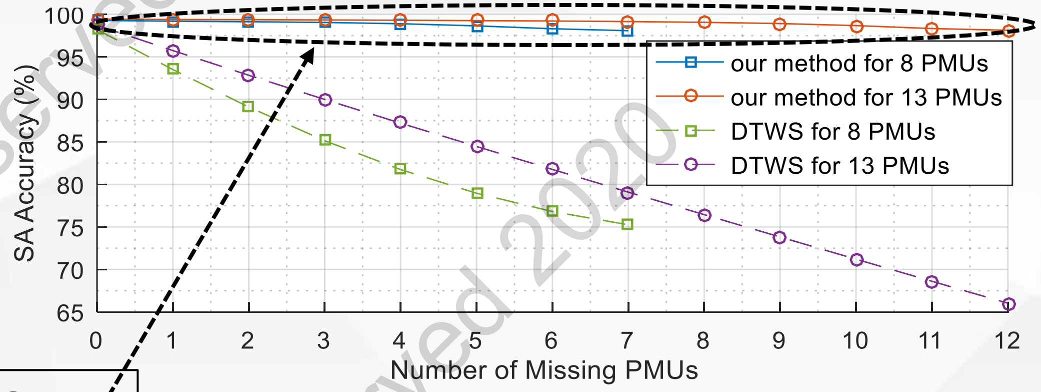


● **PMU Placement 1:**
8 PMUs with ZIB effect resulting in 19 PMU clusters: {3},{8},{10},{16},{20},{23},{25},{29},{3,8},{3,16},{8,25},{16,20},{16,23},{3,8,10},{3,8,25},{3,10,16},{3,16,25},{3,16,29},{3,16,25,29}

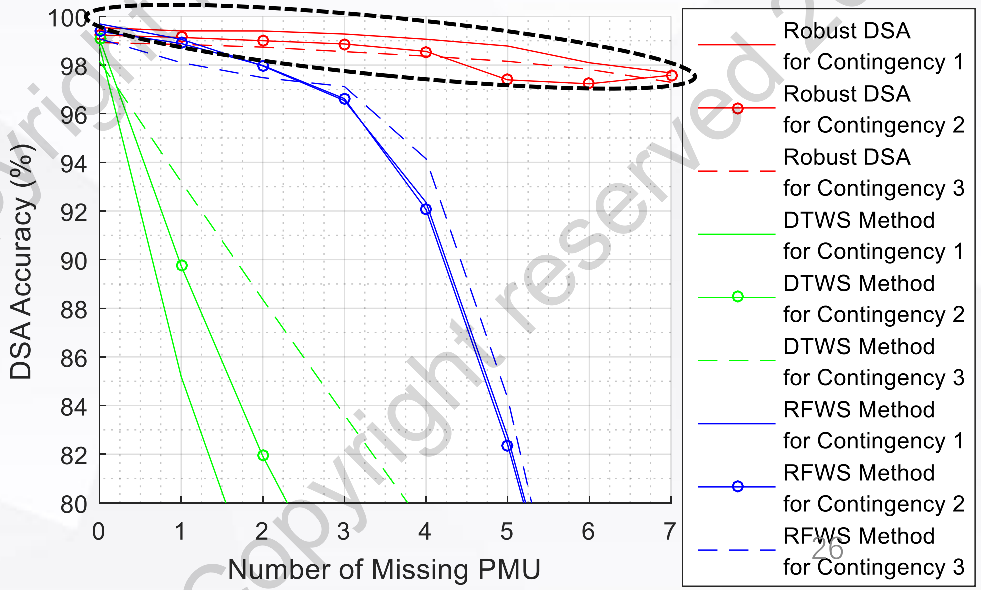
● **PMU Placement 2:**
13 PMUs without ZIB effect resulting in 36 PMU clusters: {2},{6},{9},{10},{11},{14},{17},{19},{20},{22},{23},{25},{29},{2,9},{2,14},{2,17},{2,29},{6,9},{6,14},{10,11},{11,14},{14,17},{14,19},{17,20},{17,22},{17,23},{17,25},{17,29},{19,22},{19,23},{2,6,14},{2,14,17},{2,17,29},{17,25,29},{14,17.19.22.23},{14.17.20.22.23}

ELM as the learning algorithm
DTWS – decision tree with surrogate split



Our method

Decision Tree as the learning algorithm
DTWS – decision tree with surrogate split
RFSS – random forest with surrogate split



Y. Zhang, **Y. Xu**, et al "Robust ensemble data-analytics for incomplete PMU measurement-based power system stability assessment," ***IEEE Trans. Power Syst.***, 2017.

Y. Zhang, **Y. Xu**, et al "Robust classification model for PMU-based on-line power system dynamic security assessment with missing data," ***IET Gen. Trans. & Dist.***, 2017.

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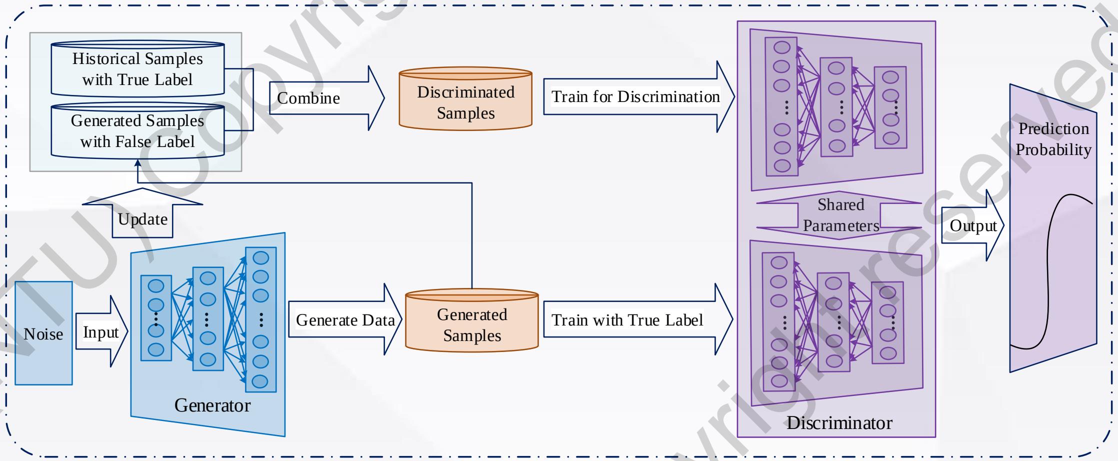
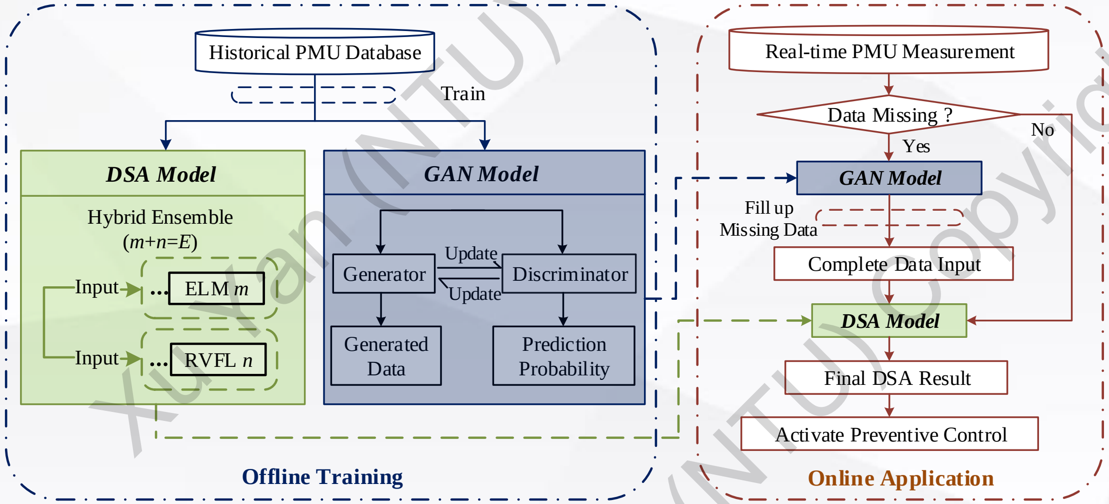
Generative Adversarial Network (GAN)-based method



Advantages:

- GAN is implemented with two deep neural networks without the need to fit an existing explicit model, called generator and discriminator, which contest with each other in a zero-sum game framework.
- Generate the missing data without depending on PMU observability and network topologies.

Generative Adversarial Network + Hybrid Ensemble Learning → GAN against missing data



At Offline Stage:

- DSA model is the classifier based on hybrid ensemble learning model of ELM and RVFL.
- GAN model can collectively provide an accurate complete data set against missing data.

At Online Stage:

- Fill up the missing data by GAN model, the complete input data can generate DSA decisions by DSA model.

C. Ren, **Y. Xu** "A Fully Data-Driven Method based on Generative Adversarial Networks for Power System Dynamic Security Assessment with Missing Data," ***IEEE Trans. Power Syst.***, 2019.

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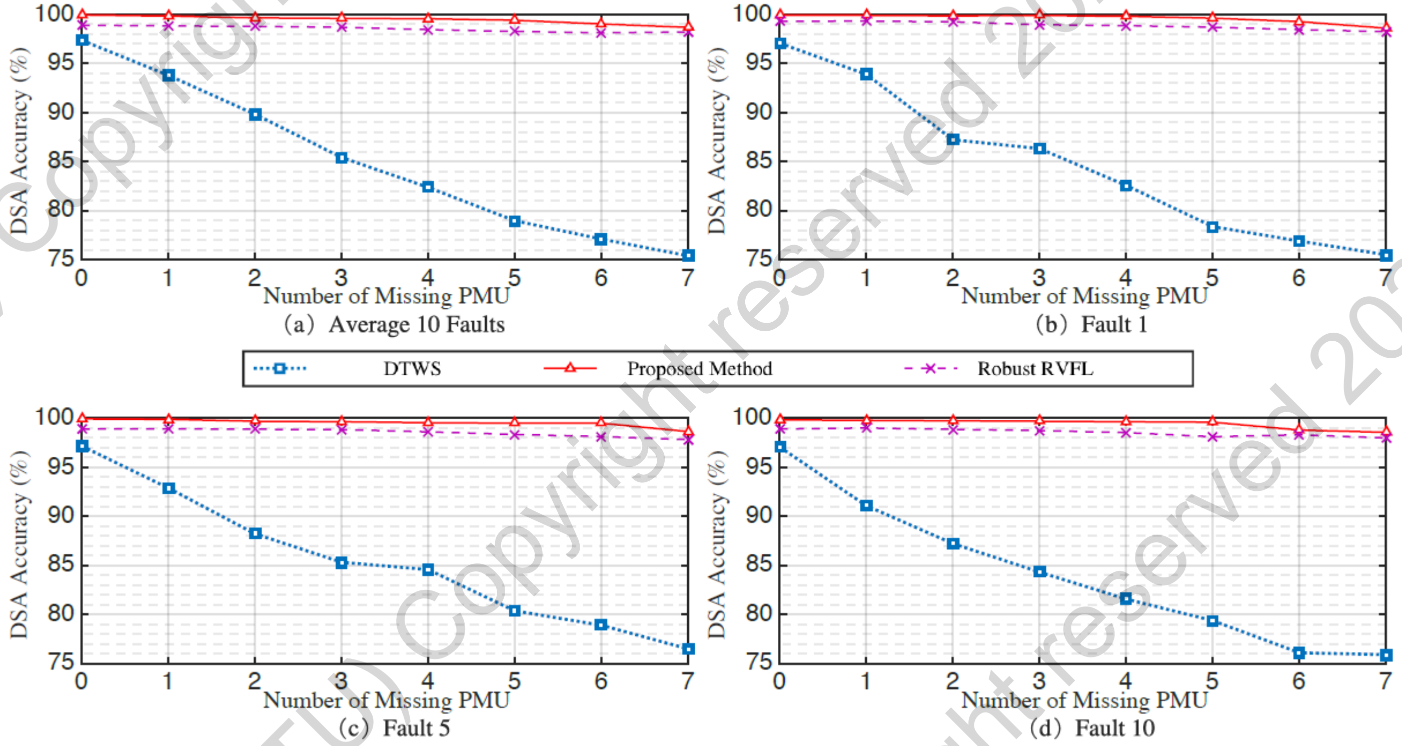

Fig. 6. DSA testing results of proposed method, robust RVFL ensemble and DTWS under the PMU placement option I. (a) average 10 faults, (b) fault 1, (c) fault 5, (d) fault 10

ADAI RESULTS AND COMPUTATIONAL EFFICIENCY OF DIFFERENT METHODS

Method	Computational Efficiency (No. of Classifiers)		ADAI	
	PMU Option I	PMU Option II	PMU Option I	PMU Option II
Proposed Method	1	1	99.40%	99.04%
Robust Ensemble Learning [6]	19	36	98.48%	97.96%
DTWS Method [4]	1	1	83.28%	80.81%
Feature Estimation [7]	255	8191	96.99%	96.12%

Our method: Higher accuracy and lower computational complexity

C. Ren, **Y. Xu** "A Fully Data-Driven Method based on Generative Adversarial Networks for Power System Dynamic Security Assessment with Missing Data," ***IEEE Trans. Power Syst.***, 2019.

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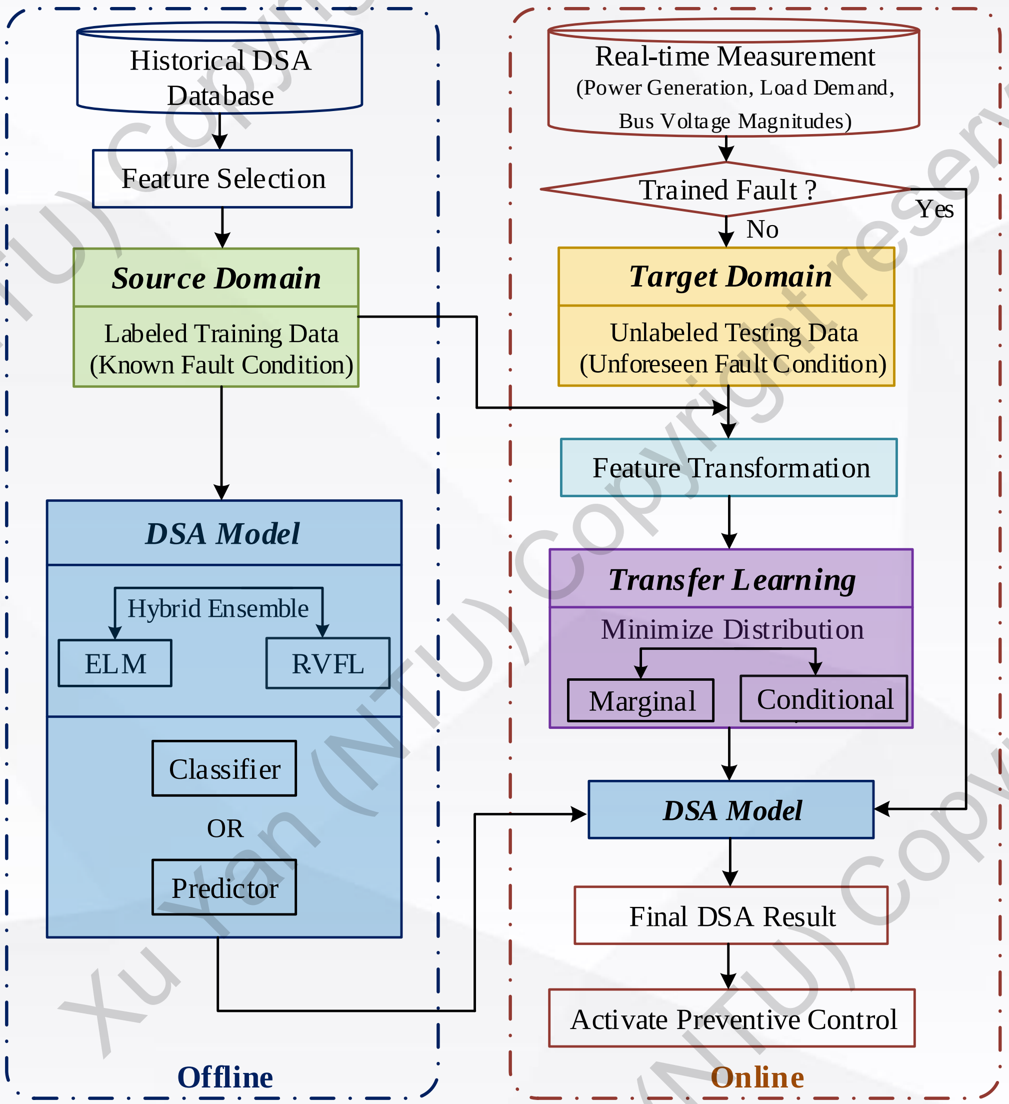
Transfer Learning: Using One Model to Assess Many Unlearned Faults



Problems:

- For pre-fault DSA, one model is trained for one fault
- Only a limited number of faults are considered.
- For online application, untrained faults may happen.
- How to use one model to assess many unlearned faults?

Maximum Mean Discrepancy (MMD):

- Measure the difference between different data distributions.

Feature transformation:

- Minimize the difference of the marginal distribution and conditional distribution between the target domain and source domain.

Byproduct:

- The correlation between different faults can be revealed, different faults can be aggregated as one.

C. Ren, **Y. Xu** "Transfer Learning-Based Power System Online Dynamic Security Assessment: Using One Model to Assess Many Unlearned Faults," ***IEEE Trans. Power Syst.***, 2019.

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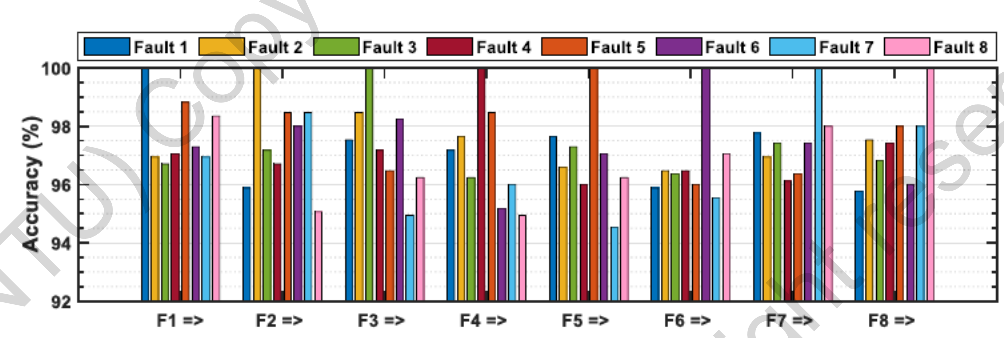
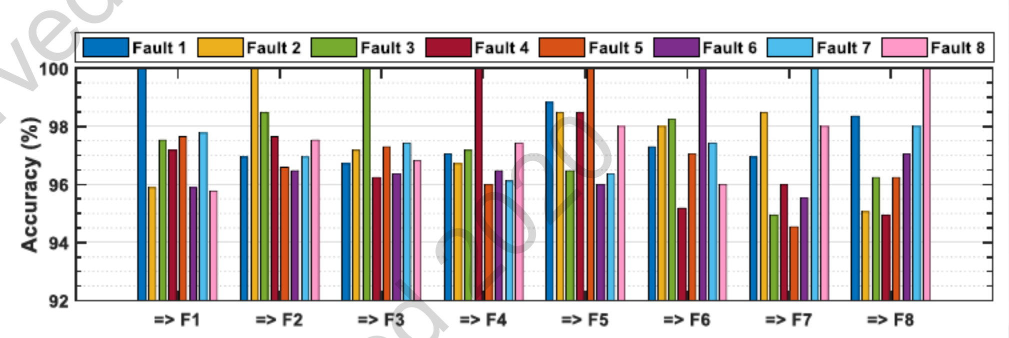
Transfer Learning: Using One Model to Assess Many Unlearned Faults

Testing Results



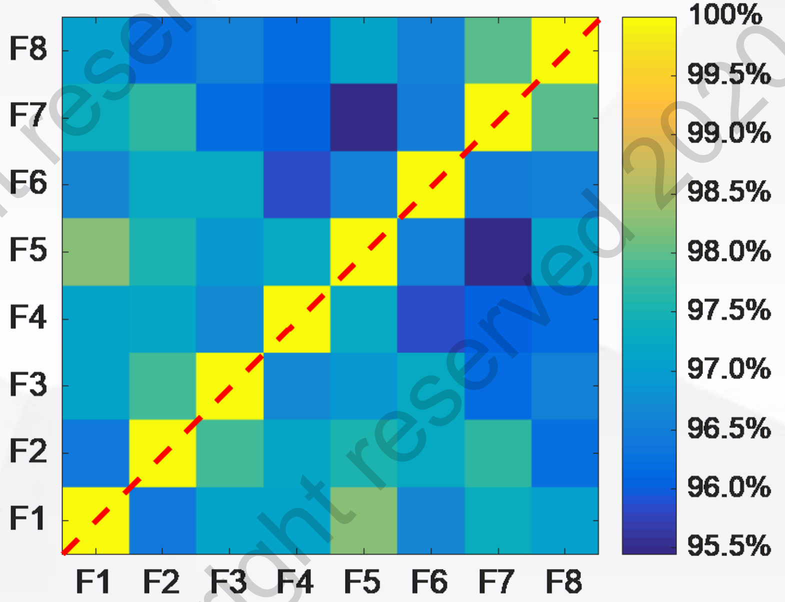
(a) each of fault is transferred to the remaining 7 faults



(b) each of 7 faults is transferred to the remaining 1 fault

AVERAGE ACCURACY OF DIFFERENT METHODS

Method	Average Accuracy
Original DSA Model without Transfer Learning	82.25%
Proposed method	97.27%



Mutual Transfer Accuracy Matrix

C. Ren, **Y. Xu** "Transfer Learning-Based Power System Online Dynamic Security Assessment: Using One Model to Assess Many Unlearned Faults," ***IEEE Trans. Power Syst.***, 2019.

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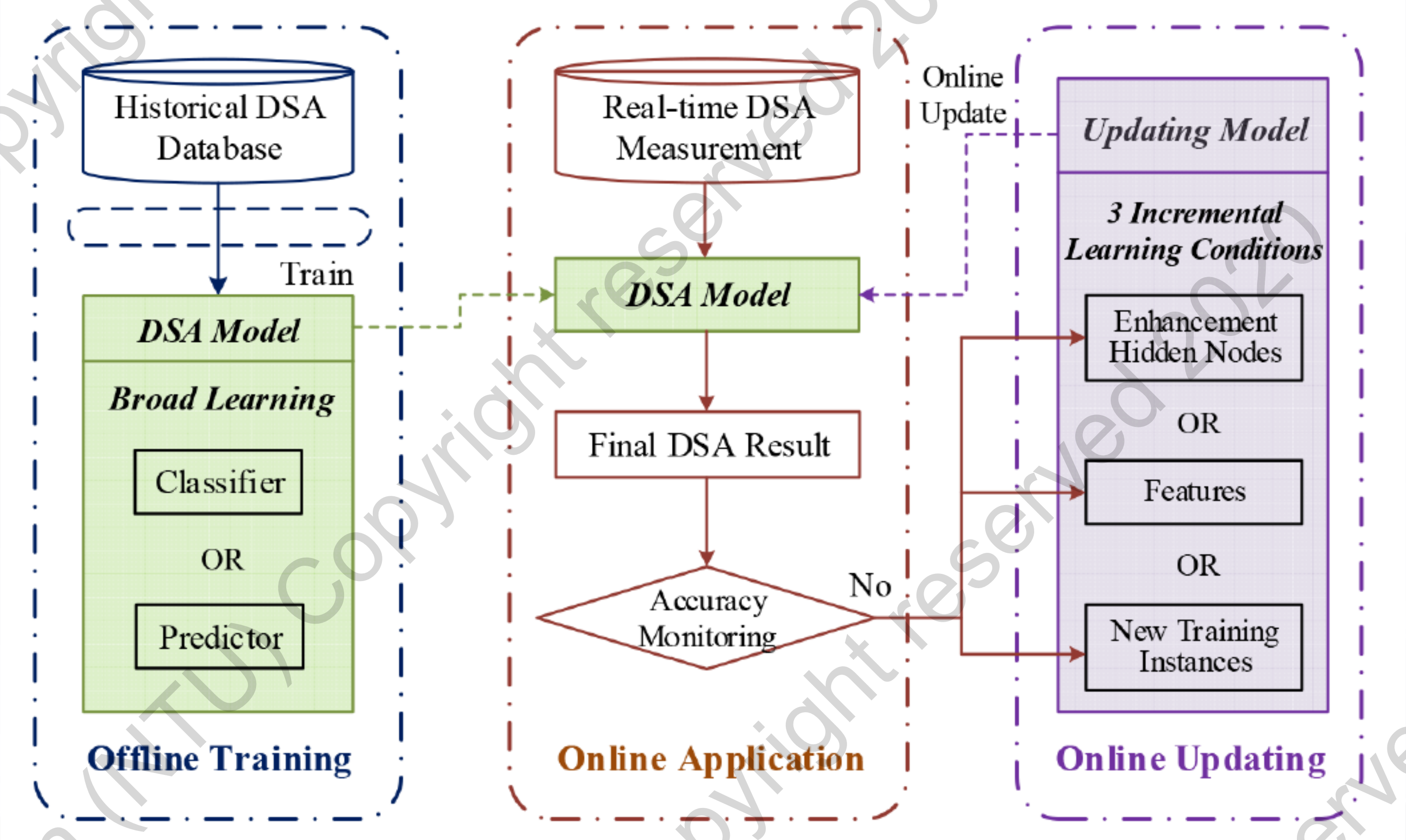
Incremental Learning: To Update the Model in Real-time



- For practical application, the stability assessment model's accuracy can not always be guaranteed
- Model updating is always needed to maintain and/or enhance the accuracy
- Traditional model updating is achieved by re-training, which is however, time-consuming.
- This work proposes an incremental broad learning method which can achieve real-time updating.

C. Ren and Y. Xu*, "Incremental Broad Learning for Real-Time Updating of Data-Driven Power System Dynamic Security Assessment Models," ***IET Gen. Trans. & Dist.***, 2020.

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Incremental Learning: To Update the Model in Real-time

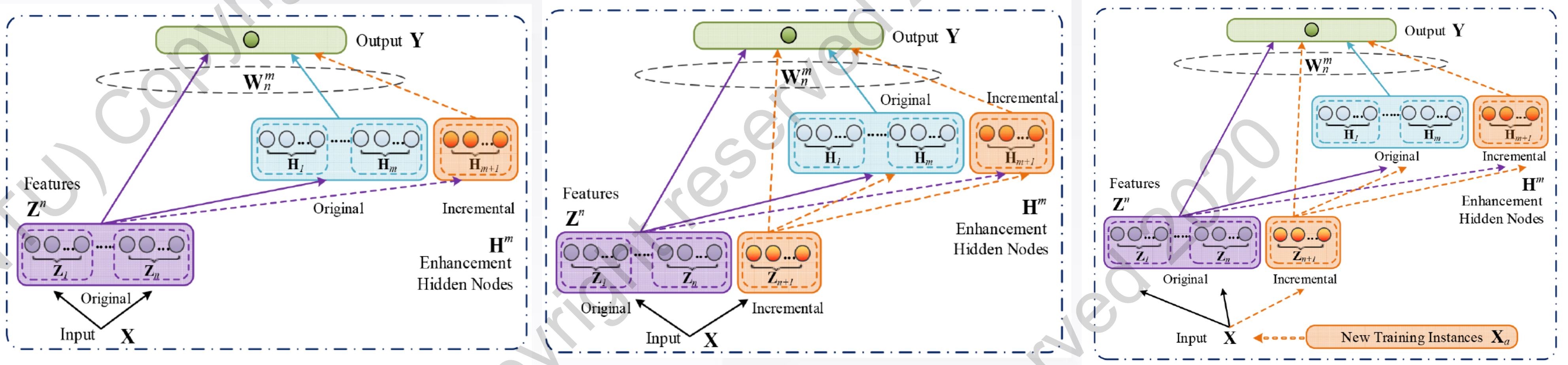

Fig. 1 *Different structure of the incremental broad learning for*
(a) Increment of enhancement hidden nodes, *(b)* Increment of features, *(c)* Increment of enhancement hidden nodes, features, and new training instances

Method	Number of training instances	Number of features	Number of enhancement nodes	Testing accuracy, %	Accumulative training times, s	Accumulative testing times, s
basic case	8000	240	400	**98.15**	**0.3212**	0.0474
increment of enhancement nodes (Algorithm 1 (Fig. 2))	8000	240	$200 \xrightarrow[50\times 4]{} 400$	**98.50**	**0.5806**	0.0817
increment of features (Algorithm 2 (Fig. 3))	8000	$80 \xrightarrow[40\times 4]{} 240$	$200 \xrightarrow[(20+30)\times 4]{} 400$	**98.55**	**0.7587**	0.0836
increment of input instances & feature nodes & enhancement nodes (Algorithm 3 (Fig. 4))	$2000 \xrightarrow[1500\times 4]{} 8000$	$80 \xrightarrow[40\times 4]{} 240$	$200 \xrightarrow[(20+30)\times 4]{} 400$	**98.60**	**0.4035**	0.0673

C. Ren and Y. Xu*, "Incremental Broad Learning for Real-Time Updating of Data-Driven Power System Dynamic Security Assessment Models," *IET Gen. Trans. & Dist.*, 2020.

Our representative publications

1. Y. Xu, Z.Y. Dong, K. Meng, R. Zhang and K.P. Wong, “Real-time transient stability assessment model using extreme learning machine,” *IET Gen. Trans. & Dist*., vol. 5, no.3, pp. 314-322, Mar. 2011.
2. Y. Xu, Z.Y. Dong, J.H. Zhao, P. Zhang, and K.P. Wong, “A reliable intelligent system for real-time dynamic security assessment of power systems,” *IEEE Trans. Power Systems*, vol. 27, no. 3, pp. 1253-1263, Aug. 2012.
3. Y. Xu, Z.Y. Dong, Z. Xu, K. Meng, and K.P. Wong, “An intelligent dynamic security assessment framework for power systems with wind power,” *IEEE Trans. Industrial Informatics*, vol. 8, no. 4, pp. 995-1003, Nov. 2012.
4. R. Zhang, Y. Xu*, Z.Y. Dong, and K.P. Wong, “Post-disturbance transient stability assessment of power systems by a self-adaptive intelligent system,” *IET Gen. Trans. & Dist*., vol.9, no.3, pp. 296-305, Feb. 2015.
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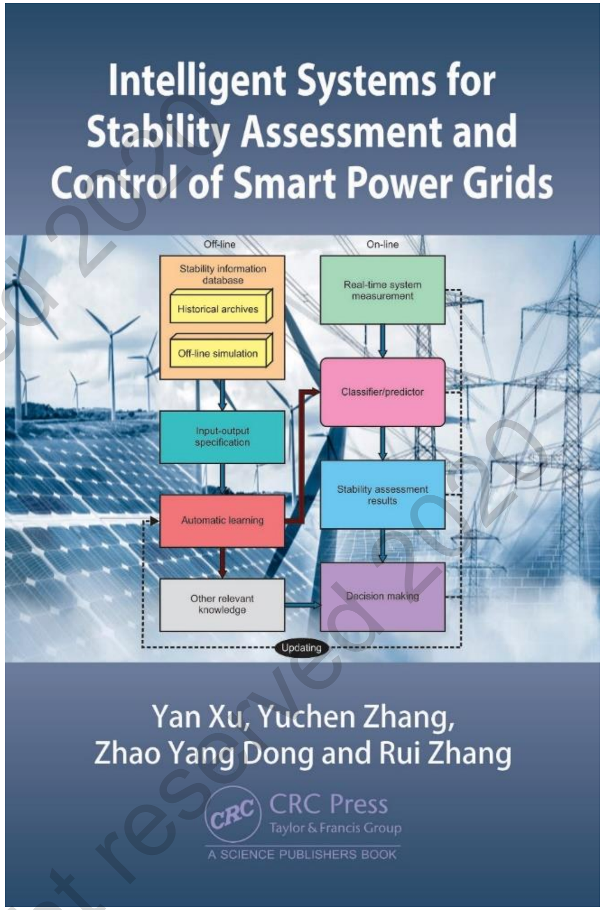

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THANKS

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