Data-Driven Analytics for Power System Stability

Dr Yan Xu
Nanyang Assistant Professor
School of Electrical & Electronic Engineering
Nanyang Technological University
Singapore
Email: xuyan@ntu.edu.sg

Xu Yan (NTU) Copyright reserved
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
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 \(\rightarrow\) “Smart Grid” \(\rightarrow\) “Energy Internet (?)”
- **Generation side**: high-level intermittent renewable energy integration
- **Demand side**: demand response, electric vehicle, distributed energy storage, etc.
- **Device-grid interface**: power-electronics converters

Recent major blackout events

**North America Blackout**
- 2003

**West Europe Blackout**
- 2006

**South Australia Blackout**
- 2012

**India Blackout**
- 2016

Very high wind power penetration level (48%)

Higher operating uncertainties + Complicated system dynamics

Motivation

Problem description

Methodology
### 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)

\[
\dot{x} = f(x, y, p, \lambda), \quad 0 = g(x, y, p, \lambda)
\]

### Classification for Stability Assessment and Control

- **On-line Stability Assessment**
  - 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

- **Preventive Control**

- **Real-time Stability Assessment**

- **Emergency 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

![Diagram showing the integration of various data-driven methods in a power system stability assessment framework.]


- **On-line**: Real-time System Measurements, Classifier/Predictor, Stability Assessment Results, Decision Making.

- **Application Architecture**: Physical Operation & Control Layer, Computation Architecture, Data Collection, Preventive/emergency controls, Load or generation shedding, System separation, Re-dispatching.

- **WAMS**: Control Center, PDC, PMU.

---

**Background**

**Motivation**

**Problem Description**

**Methodology**

---

**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**
- Extend to other applications, e.g., **equipment fault diagnosis and health management**

---

**Development**
- Database Generation
- Significant Feature Selection
- Algorithms

**Implementation**
- Results utilization
- Misclassification problems
- Model Updating

---

**Database Generation**

**Input & Output variables**

**Significant Feature Selection**

**Algorithms**

**Intelligent Stability Assessment System**

**Results utilization**

**Misclassification problems**

**Model Updating**

**Application Philosophy**

---

**Background**

**Motivation**

**Problem description**

**Methodology**

---

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.

\[
\text{diff}(X, R, R') = \frac{\text{value}(X, R) - \text{value}(X, R')}{\max(X) - \min(X)}
\]

\[
W[X]^{+1} = W[X] - \sum_{j=1}^{k} \text{diff}(X, R_i, H_j) / (m \cdot k) + \sum_{C=\text{class}(R)} \frac{P(C)}{1 - P(\text{class}(R))} \sum_{j=1}^{k} \text{diff}(X, R_i, M(C)) / (m \cdot k)
\]

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

Statistical Error Analysis

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

\[
\begin{align*}
    y > 0 & \rightarrow y = 1 \text{ (stable)} \\
    y \leq 0 & \rightarrow y = -1 \text{ (unstable)}
\end{align*}
\]

Most of the wrong decisions are near the boundary.
Credibility-Oriented Stability Assessment

**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 observable 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

---

Randomized Algorithms for Ensemble Learning

Keys to Ensemble Learning

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

Extreme Learning Machine (ELM)

\[
f_N(x_j) = \sum_{i=1}^{N} \beta_i \cdot g(w_i \cdot x_j + b_i) = t_j, \quad j = 1, 2, ..., N
\]

- Randomly selecting the input weights and biases for hidden nodes \( w \) and \( b \), and
- Analytically determining the output weights \( \beta \)
Pre-fault Online Stability Assessment/Contingency Filtering

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

<table>
<thead>
<tr>
<th>Contingency</th>
<th>Credibility</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault at bus #1, tripping line 1-6</td>
<td>89.25%</td>
<td>100%</td>
</tr>
<tr>
<td>Fault at bus #2, tripping line 2-6</td>
<td>91.54%</td>
<td>100%</td>
</tr>
<tr>
<td>Fault at bus #6, tripping line 6-10</td>
<td>94.64%</td>
<td>100%</td>
</tr>
<tr>
<td>Fault at bus #89, tripping line 89-76</td>
<td>94.48%</td>
<td>100%</td>
</tr>
<tr>
<td>Average</td>
<td>92.48%</td>
<td>100%</td>
</tr>
</tbody>
</table>

China Southern Power Grid Equivalent System
(CCT Estimation)

<table>
<thead>
<tr>
<th>Contingency</th>
<th>Credibility</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault at a 500kV corridor bus</td>
<td>96.82%</td>
<td>0.0115s</td>
</tr>
</tbody>
</table>

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.

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: $\min q(x) = -p(x)$
where, $x = [lb_U, ub_U, lb_S, ub_S, r]$; $p(x) = [C, A] = [p_1(x), p_2(x)]$

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

subject to: $lb_U < U < ub_U < U/2$,
$U + S/2 < lb_S < S; \quad ub_S > S; \quad 0 < r < 1$

<table>
<thead>
<tr>
<th>Pareto Points</th>
<th>Testing Performance</th>
<th>Average Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Credibility</td>
<td>Accuracy</td>
</tr>
<tr>
<td>A</td>
<td>92.82%</td>
<td>99.9%</td>
</tr>
<tr>
<td>B</td>
<td>92.47%</td>
<td>99.95%</td>
</tr>
<tr>
<td>C</td>
<td>92.02%</td>
<td>99.95%</td>
</tr>
<tr>
<td>D</td>
<td>90.39%</td>
<td>100%</td>
</tr>
<tr>
<td>E</td>
<td>88.66%</td>
<td>100%</td>
</tr>
</tbody>
</table>

15 times faster than pure T-D simulation
Post-fault (Short-term Voltage) Online Stability Assessment

Background
Motivation
Problem description
Methodology
- Feature selection
- Statistic error analysis
- Credibility evaluation
- Randomized learning
- Online assessment
- Real-time assessment
- Missing data
- Transfer learning

- The hybrid randomized ensemble model consists of multiple randomized learning algorithms to improve the learning diversity.
- Optimally balance the tradeoff between stability assessment accuracy ($A$) and speed ($S$).
- Given such faster assessment speed, the proposed method can activate the emergency control actions at an earlier stage, which improves the control effectiveness and reduce the load shedding amount.

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

- **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

---


### Test Results

#### [1] Large power system stability assessment

<table>
<thead>
<tr>
<th>Literature</th>
<th>Response time</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Kamwa, et al [10]</td>
<td>2 to 3s</td>
<td>96%~99.9%</td>
</tr>
<tr>
<td>I. Kamwa, et al [11]</td>
<td>1 or 2s</td>
<td></td>
</tr>
<tr>
<td>I. Kamwa, et al [12]</td>
<td>150 and 300ms</td>
<td></td>
</tr>
<tr>
<td>U. Annakkage, et al [16]</td>
<td>4 cycles</td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Literature</th>
<th>Speed</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[18]</td>
<td>5 cycle</td>
<td>90.0</td>
</tr>
<tr>
<td>[19], [20]</td>
<td>0.125s</td>
<td>94.45</td>
</tr>
<tr>
<td>[21]</td>
<td>23.9ms</td>
<td>98</td>
</tr>
<tr>
<td>[10]</td>
<td>150ms</td>
<td>95.6</td>
</tr>
<tr>
<td>[22], [23]</td>
<td>0.23s</td>
<td>100</td>
</tr>
</tbody>
</table>

Our method: average decision speed: 1.1 cycle; average accuracy 99.3%

---


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

Background
Motivation
Problem description
Methodology
Feature selection
Statistic error analysis
Credibility evaluation
Randomized learning
Online assessment
Real-time assessment
Missing data
Transfer learning

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:
- Transient Voltage Severity Index (TVSI)
  - a continuous index
  - an averaged index over all buses
  - the FIDVR severity is reflected by the magnitude and the duration time of voltage deviation

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

\[
TVSI = \sum_{i=1}^{N} \sum_{t=T_c}^{T} \frac{TVDI_{i,t}}{N \times (T - T_c)}
\]

\[
RGSI = \sqrt{\sum_{i=1}^{N} \left( \frac{j_{T_c}^{T_c} TVDI_{i,t} \, dt}{N} \right)^2}
\]

---

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

### Table

<table>
<thead>
<tr>
<th>T_i</th>
<th>Voltage Instability Detection</th>
<th>FIDVR Severity Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R_c(T_i)</td>
<td>S_c(T_i)</td>
</tr>
<tr>
<td>1</td>
<td>1987</td>
<td>761</td>
</tr>
<tr>
<td>2</td>
<td>1226</td>
<td>348</td>
</tr>
<tr>
<td>3</td>
<td>878</td>
<td>204</td>
</tr>
<tr>
<td>4</td>
<td>674</td>
<td>199</td>
</tr>
<tr>
<td>5</td>
<td>549</td>
<td>199</td>
</tr>
<tr>
<td>6</td>
<td>350</td>
<td>49</td>
</tr>
<tr>
<td>7</td>
<td>304</td>
<td>24</td>
</tr>
<tr>
<td>8</td>
<td>277</td>
<td>9</td>
</tr>
<tr>
<td>9</td>
<td>268</td>
<td>11</td>
</tr>
<tr>
<td>10</td>
<td>257</td>
<td>19</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>20</td>
<td>66</td>
<td>66</td>
</tr>
</tbody>
</table>

- **Legend**
  - R_c: The number of available samples.
  - S_c: The number of successfully assessed samples.
  - A_c: The accumulated accuracy.
  - E_r: The accumulated MAPE.
Probabilistic Time-Adaptive Method for Real-time FIDVR Assessment

- **Credibility-Oriented Time-Adaptive Method**
  - credibility is evaluated under a rule-of-thumb scheme (lack mathematical rigorosity)
  - a large number of user-defined parameters to be tuned
  - heavily impact robustness

- **Probabilistic Time-Adaptive Method**
  - predict FIDVR severity on a probabilistic basis with a certain confidence level
  - make confident/reliable assessment decision at the earliest opportunity
  - non-parametric in nature
  - more robust in practice

---


**Background**

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

**Motivation**

**Problem description**

**Methodology**

- Confidence Intervals (CI)
- Test Results
- FIDVR Assessment Accuracy and Speed

<table>
<thead>
<tr>
<th>Time Points</th>
<th>No. of Assessed Cases</th>
<th>Assessment Accuracy</th>
<th>Time Points</th>
<th>No. of Assessed Cases</th>
<th>Assessment Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>793</td>
<td>100%</td>
<td>10</td>
<td>13</td>
<td>100%</td>
</tr>
<tr>
<td>2</td>
<td>88</td>
<td>100%</td>
<td>11</td>
<td>5</td>
<td>100%</td>
</tr>
<tr>
<td>3</td>
<td>59</td>
<td>100%</td>
<td>12</td>
<td>8</td>
<td>100%</td>
</tr>
<tr>
<td>4</td>
<td>39</td>
<td>100%</td>
<td>13</td>
<td>6</td>
<td>100%</td>
</tr>
<tr>
<td>5</td>
<td>33</td>
<td>100%</td>
<td>14</td>
<td>3</td>
<td>100%</td>
</tr>
<tr>
<td>6</td>
<td>19</td>
<td>100%</td>
<td>15</td>
<td>2</td>
<td>100%</td>
</tr>
<tr>
<td>7</td>
<td>26</td>
<td>100%</td>
<td>16</td>
<td>1</td>
<td>100%</td>
</tr>
<tr>
<td>8</td>
<td>11</td>
<td>100%</td>
<td>17</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>9</td>
<td>9</td>
<td>100%</td>
<td>18</td>
<td>2</td>
<td>100%</td>
</tr>
<tr>
<td>10</td>
<td>14</td>
<td>100%</td>
<td>19</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>99.66%</td>
<td>Overall Accuracy</td>
<td>87.10%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Comparative Study Results**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Method Type</th>
<th>Assessment Accuracy</th>
<th>Required Assessment Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Method</td>
<td>self-adaptive</td>
<td>99.66%</td>
<td>0.14 s</td>
</tr>
<tr>
<td>DT</td>
<td>fixed-time</td>
<td>99.05%</td>
<td>0.75 s</td>
</tr>
<tr>
<td>SVM</td>
<td>fixed-time</td>
<td>99.66%</td>
<td>0.80 s</td>
</tr>
<tr>
<td>BLR</td>
<td>self-adaptive</td>
<td>98.37%</td>
<td>0.33 s</td>
</tr>
</tbody>
</table>

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

All 100% accuracy for early assessment, indicating the improved reliability in time-adaptive method.
Data-Driven Method with Missing Data

The impacts of missing data:
- Incomplete input
- Fail to work
- Deterioration of assessment accuracy

Existing methods:

Still suffer from low accuracy if the amount of missing data increases!
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 a larger region than its own observability.
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

\begin{align*}
F1. & \quad \text{The union of the observability of each complete cluster in } P \text{ equals to the remaining observability of the grid.} \\
F2. & \quad \text{Upon } F1 \text{ is satisfied, the number of clusters is minimized.}
\end{align*}

**F1 proof:** F1 is equivalent to: \( E_1 = E_2, \forall d \in C \)
where \( E_1 = O(d), E_2 = \bigcup_{m \in P} O(V(m_{d} \backslash d)) \) (2)
where \( V(m_{d} \backslash d) = \begin{cases} m_i, & \text{if } m_i \leq d \\ \phi, & \text{otherwise} \end{cases} \) (3)

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

\( \forall e_i \in E_1 = O(d), \) at least one non-redundant subset \( d_i \subseteq d \) satisfies \( e_i \in O(V(m_{d} \backslash d_i)) \). Since \( R \) includes all non-redundant PMU clusters for \( e, d_i \in R, \) \( e_i \in d \subseteq E_i \subseteq E_1 \), \( \forall e_i \in E_1 = O(d) \), at least a \( m \) in \( P \) satisfies \( e_i \in O(m) \) and \( m \subseteq d \), so \( e_i \in O(d) = E_1 = E_i = E_2 = E_1 \).

\begin{align*}
F2 proof: & \quad \text{we make a hypothesis } F2 \text{ there is a PMU cluster } m \text{ that can be removed from } P \text{ and } P \backslash m \text{ still satisfies (1).} \\
& \text{Let } d = m, e_j \in E_1 = O(m) \text{ and } e_j \in R_0. \text{ As the clusters in } R_0 \text{ are non-redundant, all the clusters in } R_0 \backslash m \text{ include at least one PMU that is not in } m, \text{ so } m \subset d, \forall m \in R_0 \backslash m. \text{ As } R_0 \text{ includes all clusters observing } e_j, P \cup R_0 \text{ cannot observe } e_j, \text{ thus } O(V(m_{d} \backslash m)) = \phi, \forall m_{d} \backslash m \in R_0 \backslash m \Rightarrow e_j \notin O(V(m_{d} \backslash m)), e_j \notin O(V(m_{d} \backslash m)), m_{d} \backslash m \in P \cup R_0 \Rightarrow m_{d} \backslash m \in P \cup R_0, \forall m_{d} \in P \cup R_0, e_j \notin E_i = E_i = E_1 \text{. Thus, } \text{H fails } \Rightarrow F2.
\end{align*}

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

Generative Adversarial Network (GAN)-based method

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.

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

Test Results

PMU Placement 1:
8 PMUs with ZIB effect
resulting in 19 PMU clusters:

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}, {2, 6, 14}, {2, 14, 17}, {2, 17, 29}, {17, 25, 29}, {14, 17, 19, 22, 23}, {14, 17, 20, 22, 23}


**Test Results**

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

**DTWS**
- decision tree with surrogate split

**RFSS**
- random forest with surrogate split

**Methodology**

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

---


Transfer Learning - Using One Model to Assess Many Unlearned Faults

At Offline Stage:
- DSA model is the classifier based on hybrid ensemble learning model.
- The RELIEF-F algorithm is used to select the critical features.

At Online Stage:
- Feature transformation and transfer learning via minimizing marginal distributions and conditional distribution differences between the unknown features and the known features.

Advantages:
- Using One Model to Assess Many Unlearned Fault.
  - The correlation between different faults can be revealed, thus different faults can be aggregated as one.

Selected Publications in data-driven stability assessment and control

Selected Publications in data-driven stability assessment and control

