A hierarchical data-driven method for online event-based load shedding against FIDVR in power systems

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OUTLINE

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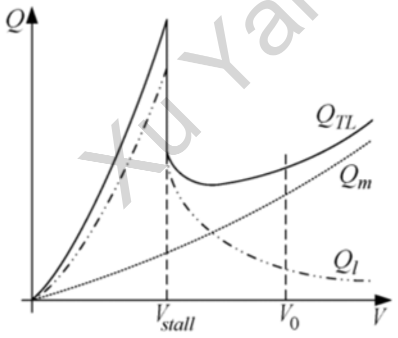
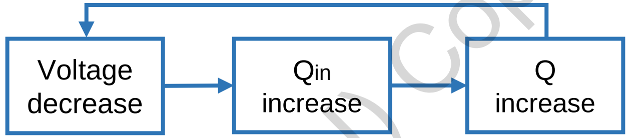
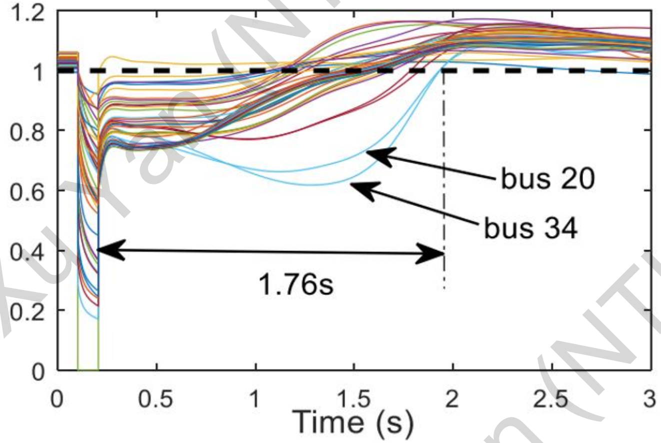
A hierarchical data-driven method for online event-based load shedding against FIDVR in power systems

1 Introduction: Fault-induced delayed voltage recovery (FIDVR)

Fault-induced delayed voltage recovery (FIDVR) *is the phenomenon that power system experiences a significant long-time delayed voltage recovery following a severe fault*





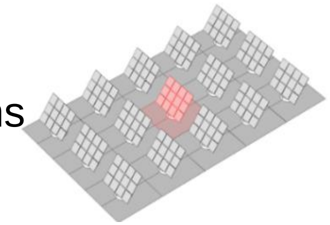


Fault ride-through
Cascaded failure
Wide-spread blackout

Conventional Power Grid → Smart Grid

- Large-scale integration of renewables
- More participation from the demand side
- Wide-spread deployment of ICTs

- More complicated system dynamics
- Faster changes in steady-state power flow magnitude and directions.
- Highly uncertain operating conditions



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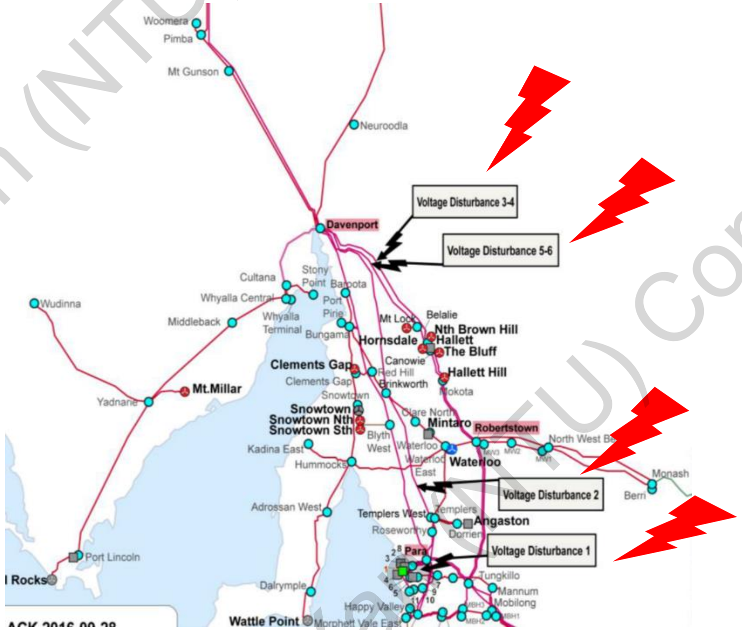
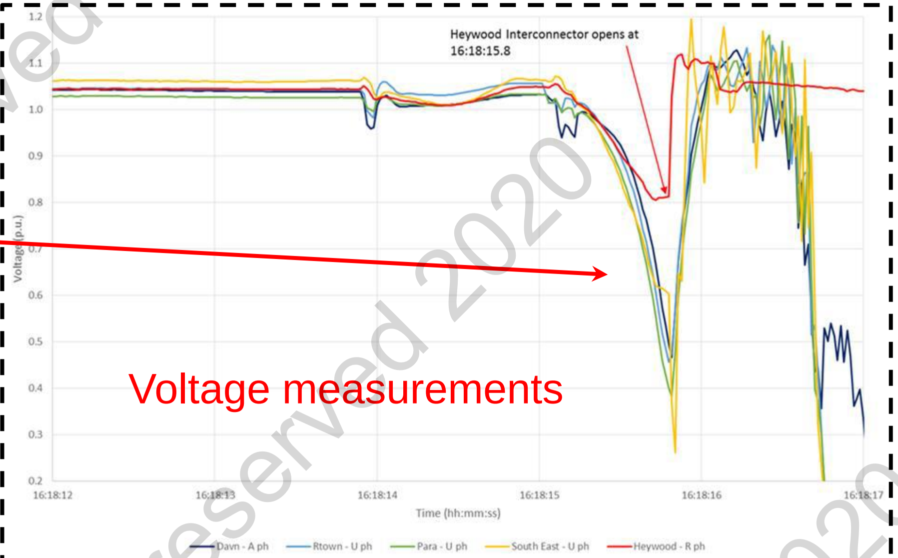
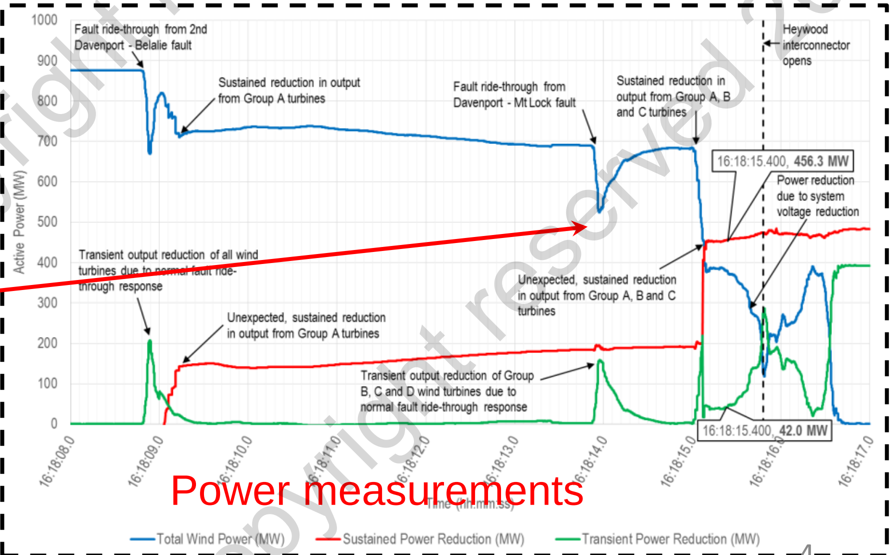
1 Introduction: 2016 South Australia blackout

- 6 successive voltage disturbances caused by storm





- Wind farms tripped due to voltage disturbances
- Eventually led to a state-wide blackout
- Affected over 850k customers



AEMO, "2016 South Australia separation event - Final report," Australian Energy Market Operator Limited, Brisbane, Australia, 2016.

1 Introduction: Remedial Countermeasures

Remedial Countermeasures

Demand side

Load shedding

- Activated after the fault
- Cost-effective

Supply side

Dynamic VAR comprehension (STATCOM, SVC) [1]-[6]

- Devices are expensive
- Limited to installation place

Cost

Load Shedding Strategies

Event-based load shedding (ELS)

- The ELS is determined preventively and initiated immediately after a contingency is detected.
- Faster and more cost-efficient

Undervoltage load shedding (UVLS)

- UVLS is response-based, which is triggered when the voltage decreases below pre-defined threshold after certain time delays.
- More precise and robust

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1 Introduction: Conventional event-based load shedding (ELS)

ELS Decision Table

Contingency & Operating Condition → (Matching) → ELS Location and Amount

Dynamic optimization model

Contingency information; Pre-fault operating features →

$$\min_{l_i} f(l_i) = \sum_{i=1}^{m} l_i$$

Subject to constraints.

TDS need to be conducted iteratively to solve DAEs.

→ Optimal ELS solutions

Offline Simulation — Fast but it may have mismatching problem

Online Pre-decision — More adaptive but need computation capability

Online Decision — Require both fast and adaptive decision tools

Data-driven methods

- ✓ Make decision immediately
- ✓ Accommodate unseen scenarios

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1 Introduction: Literature review for data-driven ELS

Rule-based control method [a], [b]

Learn DSA model → Learn security rules → Predict security

Learn security rules → Formulate security rules as MILP constraints → Navigate operation /control

Short-term operating and control

- Limited to the tree structure;
- Poor generalization ability to high-dimensional feature space;

Direct learning method [c]- [f]

$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x})$ Direct learn from offline optimized cases;

$\boldsymbol{x}$: system operating conditions

$\boldsymbol{y}$: system security status ➡ **control variables**

Data-driven Control

1. Reinforcement learning (RL) [c]
2. Artificial neural network (ANN) [d]
3. Extreme learning machine (ELM) [e]
4. Graph convolutional network (GNN) [f]

- Not accurate in solving control problem with hybrid decision variables;
- Impact by imbalanced data distribution;

[a] I. Genc, R. Diao, V. Vittal, S. Kolluri, and S. Mandal, “Decision trees-based preventive and corrective control applications for dynamic security enhancement in power systems,” IEEE Transactions on Power Systems, vol. 25, no. 3, pp. 1611–1619, Aug. 2010
[b] J. L. Cremer, I. Konstantelos, S. H. Tindemans and G. Strbac, "Data-Driven Power System Operation: Exploring the Balance Between Cost and Risk," IEEE Transactions on Power Systems, vol. 34, no. 1, pp. 791-801, Jan. 2019.

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1 Introduction: Literature review for data-driven ELS

- Existing data-driven approaches are still insufficient:

Ref.[c] develops a DRL-based controller that can conduct UVLS in discrete action place.

Ref.[d] utilize ANN to predict the optimal coordinated control actions for long term voltage stability .

Ref.[e] proposed a GNN-embedded LS scheme, where an optimal LS ratio is predicted to eliminate over-load lines.

Ref. [f] proposed an ELM-based method that predicts the LS amount of each load bus, to counteract frequency instability.

Not cost-efficient for control strategy design:

- A fully discrete control without specific control amount (e.g. [c] and [d]),
- A fully continuous control without identifying best control location (e.g. [e] and [f]).

◆ Key Reference:

[c] Q. Huang, R. Huang, W. Hao, J. Tan, R. Fan and Z. Huang, "Adaptive Power System Emergency Control Using Deep Reinforcement Learning," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1171-1182, March 2020.

[d] H. Cai, H. Ma and D. Hill, "A Data-Based Learning and Control Method for Long-term Voltage Stability," *IEEE Transactions on Power Systems*, pp.1-10, Early access.2020.

[e] K. Kim, P. Balaprakash, and M. Anitescu. “Graph Convolutional Neural Networks for Optimal Load Shedding under Line Contingency,” *Proc. 2019 IEEE PES General Meeting*, Atlanta, USA, 2019.

[f] Y. Dai, Y. Xu, Z. Y. Dong, K. P. Wong and L. Zhuang, “Real-time prediction of event-driven load shedding for frequency stability enhancement of power systems,” *IET Generation, Transmission & Distribution*, vol. 6, no. 9, pp. 914-921, September 2012.

2 Proposed ELS model

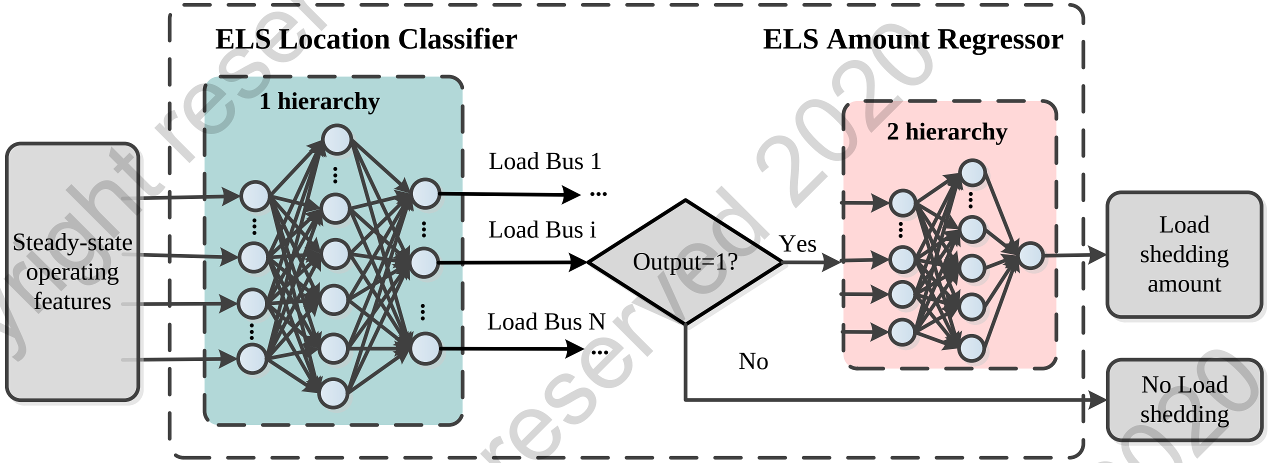
Motivation

- The optimal ELS location vary with different system conditions;
- Uncritical buses may be shed without distinguishing critical buses under different conditions.

Hierachical structure

A hierarchical model is developed, which consists:

- A classification sub-model to identify the best shedding location;
- A regression sub-model to predict the minimum shedding amount;



Advantage

- ✓ Critical bus selection
- ✓ Sparsity elimination
- ✓ Prediction accuracy enhancement

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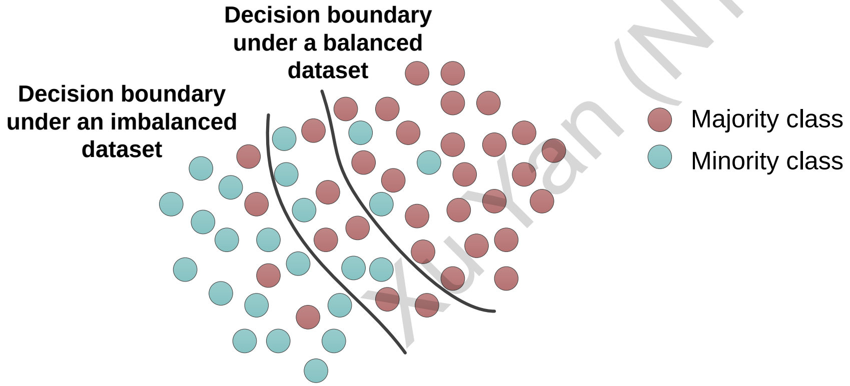
2 Proposed ELS model

Motivation

The previous research works haven't consider the imbalanced data distribution:

- Severe post-fault conditions usually happen less frequently in a realistic power system;
- A sparse and imbalanced database will train a biased model.
- The minority yet more critical cases will be overlooked.



Weighted learning scheme

Conventional

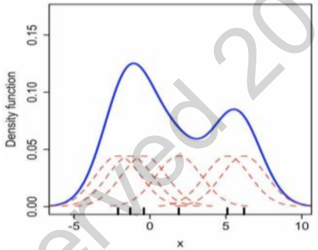
$$\min \ \boldsymbol{Loss} = \frac{1}{2}\sum_{i=1}^{N}\|\xi_i\|^2$$

$$\text{s.t.} \ \ \xi_i^T = \mathbf{t}_i^T - \mathbf{y}_i^T, \ i=1,..,N$$

A biased predictive model

$$\min \ \ L_{\mathbf{ELM}} = \frac{1}{2}\|\beta\|^2 + C\mathbf{W}\frac{1}{2}\sum_{i=1}^{N}\|\xi_i\|^2$$

$$\text{s.t.} \ \ \mathbf{h}(\mathbf{x}_i)\beta = \mathbf{t}_i^T - \xi_i^T, \ i=1,..,N$$



Classification

$$\mathrm{w}_{ii} = \frac{1}{c(t_{ki})}$$

Regression

$$\mathrm{w}_{ii} = \frac{1}{\hat{f}(t_i)}$$

$$\hat{f}(t) = \frac{1}{Nh}\sum_{j=1}^{N} K\left(\frac{t-t_j}{h}\right)$$

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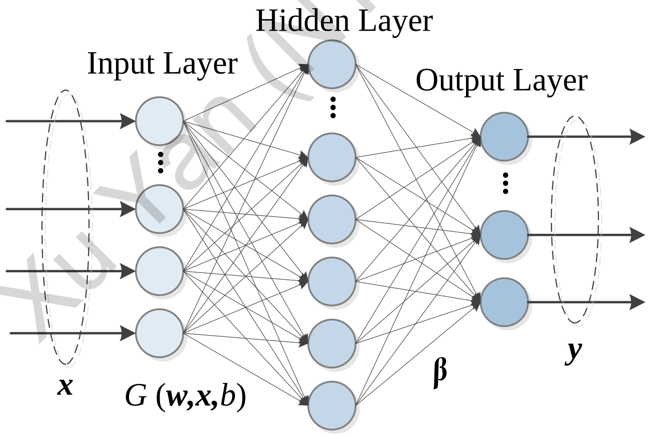
2 Proposed ELS model: WKELM algorithm

Single layer neural network



$$\mathbf{H}\,\boldsymbol{\beta} = \mathbf{Y}$$

$\boldsymbol{\beta}$ is the output weight matrix. $\mathbf{Y}$ is the target matrix. $\mathbf{H}$ is the hidden layer output matrix.

$$\mathbf{H} = [\mathbf{h}(\mathbf{x}_1), \ldots, \mathbf{h}(\mathbf{x}_N)]^T$$

Extreme learning machine (ELM)

$$\min\ L_{\mathbf{ELM}} = \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\frac{1}{2}\sum_{i=1}^{N}\|\xi_i\|^2 \quad \text{s.t. } \mathbf{h}(\mathbf{x}_i)\boldsymbol{\beta} = \mathbf{t}_i^T - \xi_i^T,\ i=1,\ldots,N$$

H of original ELM is determined by **randomly assigned input weights**

Kernel extreme learning machine (KELM)

$$\Omega_{\mathrm{ELM}\ i,j} = \mathbf{h}(\mathbf{x}_i)\mathbf{h}(\mathbf{x}_j) = K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/\sigma)$$

$$\mathbf{f}(\mathbf{x}) = \mathbf{h}(\mathbf{x})\boldsymbol{\beta} = [K(\mathbf{x},\mathbf{x}_1), \ldots, K(\mathbf{x},\mathbf{x}_N)]\left(\frac{\mathbf{I}}{C} + \boldsymbol{\Omega}_{\mathrm{ELM}}\right)^{-1}\mathbf{Y}$$

Weighted Kernel extreme learning machine (WKELM)

$$\min\ L_{\mathbf{ELM}} = \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\mathbf{W}\frac{1}{2}\sum_{i=1}^{N}\|\xi_i\|^2 \quad \text{s.t. } \mathbf{h}(\mathbf{x}_i)\boldsymbol{\beta} = \mathbf{t}_i^T - \xi_i^T,\ i=1,\ldots,N$$

$$\mathbf{f}(\mathbf{x}) = \mathbf{h}(\mathbf{x})\boldsymbol{\beta} = [K(\mathbf{x},\mathbf{x}_1), \ldots, K(\mathbf{x},\mathbf{x}_N)]\left(\frac{\mathbf{I}}{C} + \mathbf{W}\boldsymbol{\Omega}_{\mathrm{ELM}}\right)^{-1}\mathbf{W}\mathbf{Y}$$

W. Zong, G. Huang, Y. Chen. "Weighted extreme learning machine for imbalance learning,". Neuro computing, vol. 101, pp. 229-242, 2013

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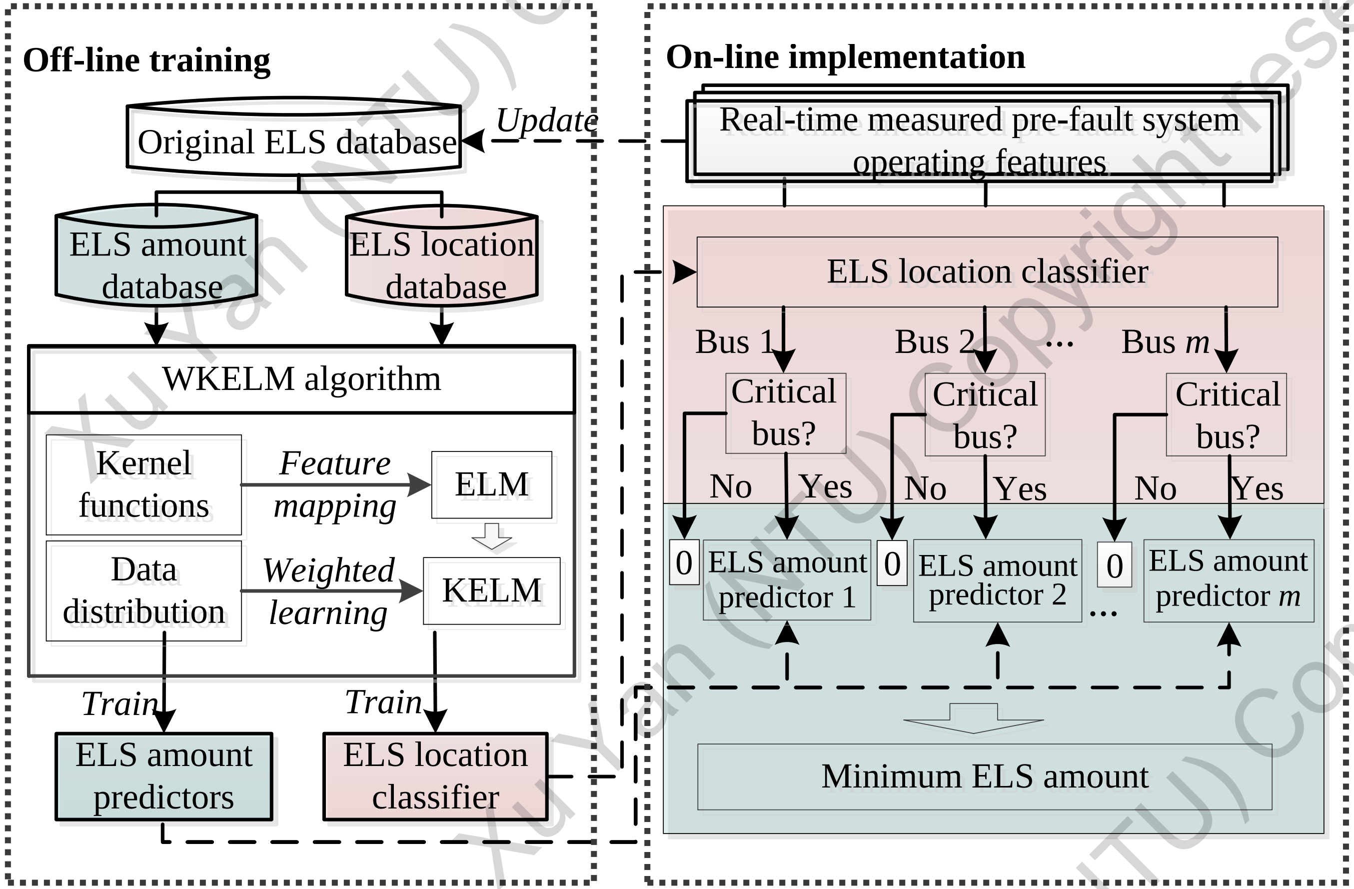
2 Proposed ELS model: The framework



Framework of proposed data-driven ELS model

- **At Offline stage**
  - Generate ELS database with optimized control cases;
  - Pre-process the original database;
  - Train ELM location classifier and amount predictors by WKELM algorithm.
- **At online stage**
  - Once a fault is detected, the pre-fault system measurements are first provided to the classifier;
  - **If a bus is identified critical, the inputs are provided to the predictor to estimate the minimum load to shed.**
  - Otherwise, the bus is considered to be uncritical, and ELS will not be executed.

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⌗ 3 Database generalization: transient voltage severity index (TVSI) [g]

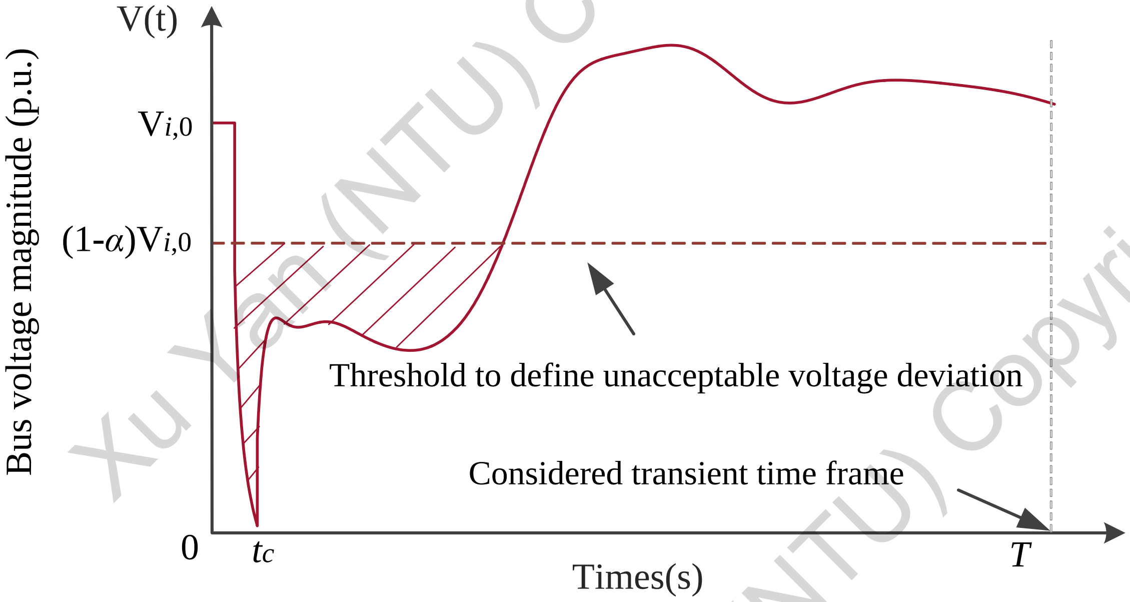

Illustration of the concept of TVSI

$$TVSI = \frac{\sum_{i=1}^{m}\sum_{t=t_c}^{T} TVDI_{i,t}}{N_b \times (T - t_c)}$$

$$TVDI_{i,t} = \begin{cases} \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}}, if \ \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}} \geq \alpha \\ 0, otherwise \end{cases} \quad \forall t \in [t_c, T]$$

Conventional criteria :NERC criteria.

- It only define the unacceptable voltage-dip magnitude and duration time;
- It only provide a binary answer to the stability status;

Quantitative criteria : TVSI index.

- It is based on the average accumulated relative voltage deviation of all buses;
- It quantitatively evaluates the FIDVR performance;

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

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3 Database generalization: dynamic security constrained-optimization

Mathematical model

$$\min_{\Delta P_i} L = \sum_{i=1}^{m} \Delta P_i$$

$$s.t. \begin{cases} (\Delta\eta + \eta_0) \le \eta_e \\ \Delta\eta = \varphi(\Delta P_i) \\ 0 \le \Delta P_i \le P_i \end{cases}$$

FIDVR constraint

LS limit of the load bus

LP model of short-term voltage stability constraints

$$\min_{\Delta P_i} \Delta\eta = \sum_{i=1}^{m} \Phi_i(\eta, P_i)\Delta P_i$$

$$s.t. \begin{cases} \sum_{i=1}^{m} \Delta P_i = \varepsilon \\ 0 \le \Delta P_i \le P_i \end{cases}$$

Pre-defined total LS amount (step size) at the current stage

LS limit of the current stage

◆**Trajectory sensitivity**

Taylor series expansions

$$\phi(x_0, t, \lambda + \Delta\lambda) = \phi(x_0, t, \lambda) + \frac{\partial\phi(x_0, t, \lambda)}{\partial\lambda}\Delta\lambda + \varepsilon^{\phi}$$

Omission of higher order

$$\Delta x(t) = \phi(x_0, t, \lambda + \Delta\lambda) - \phi(x_0, t, \lambda) \approx \frac{\partial\phi(x_0, t, \lambda)}{\partial\lambda}\Delta\lambda \equiv \Phi(x_0, t, \lambda)\Delta\lambda$$

Trajectory sensitivity

$$\Phi(x_0, t, \lambda) = \frac{\phi(x_0, t, \lambda+\Delta\lambda) - \phi(x_0, t, \lambda)}{\Delta\lambda}$$

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3 Database generalization

Initialization

- A new operating point

Initial data input

- The inputs are the OPF results and credible contingencies.

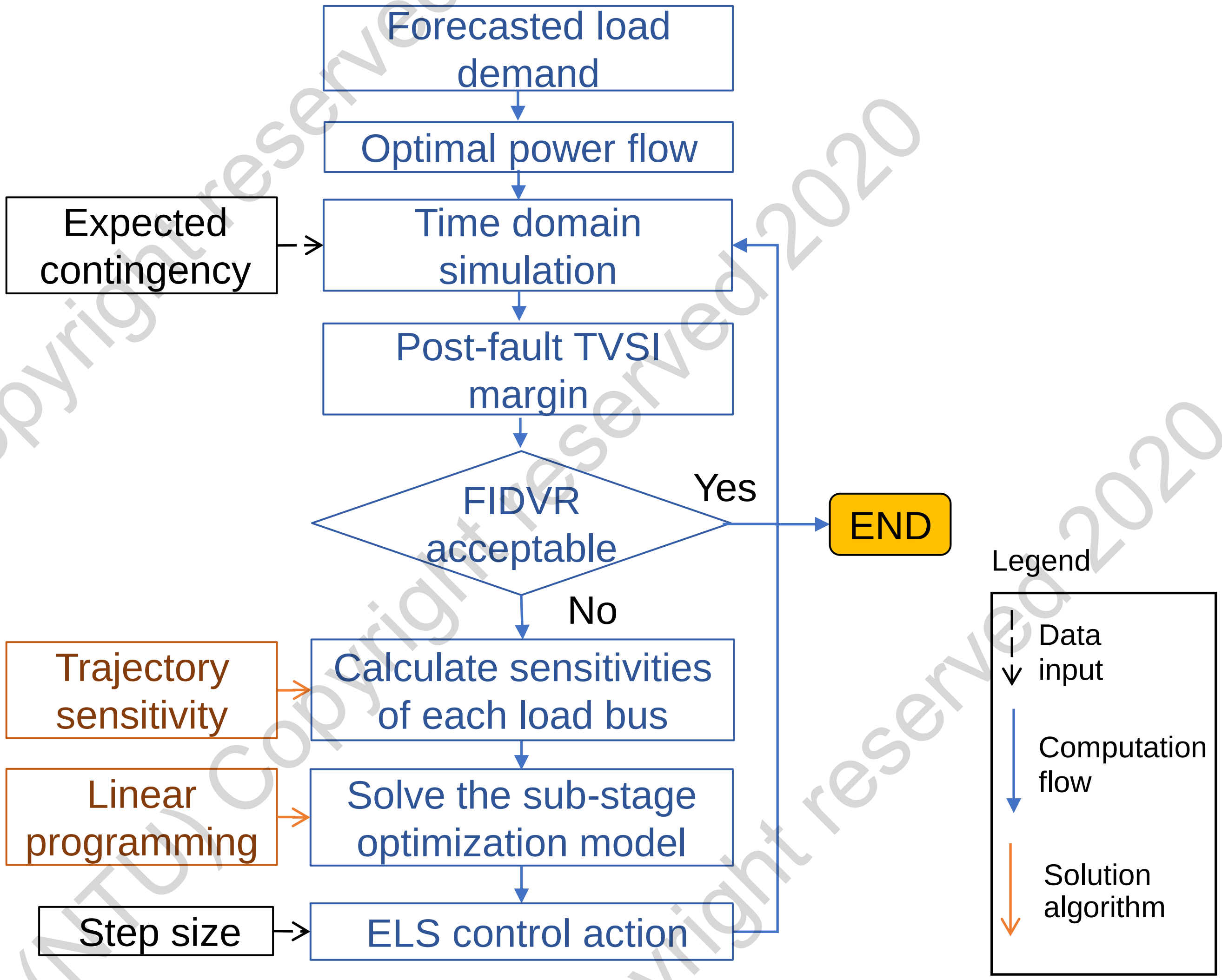
Solution algorithm

- Trajectory sensitivity is applied for searching the optimal load shedding solution.

Output

- The outputs are the optimized ELS actions.

- Iterative process
- Linear programming



Flowchart of the database generation

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4 Case Study

- The proposed method is verified on the New England 10-machine 39-bus system
- Two database regarding two contingencies are tested

Contingency Set

Contingency ID	Fault bus	Fault clearance	Tripped line
Fault #1	Bus 17	0.15s	Line 17-27
Fault #2	Bus 21	0.15s	Line 21-22

Data description

Input: 1) generator P, Q generation, voltage magnitude and angle 2) load bus P, Q load, voltage magnitude and angle 3) power flow on the branches;

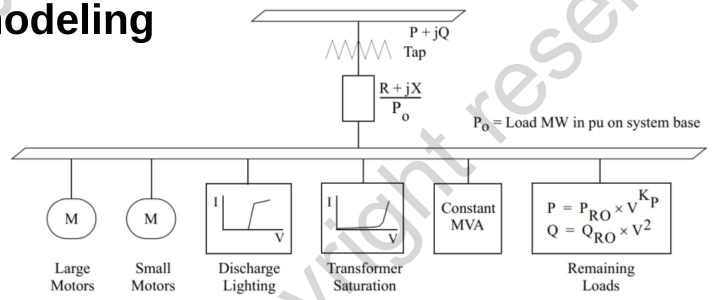
Output: ELS location and amount on load bus ;

Simulation parameter configuration

Parameter setting

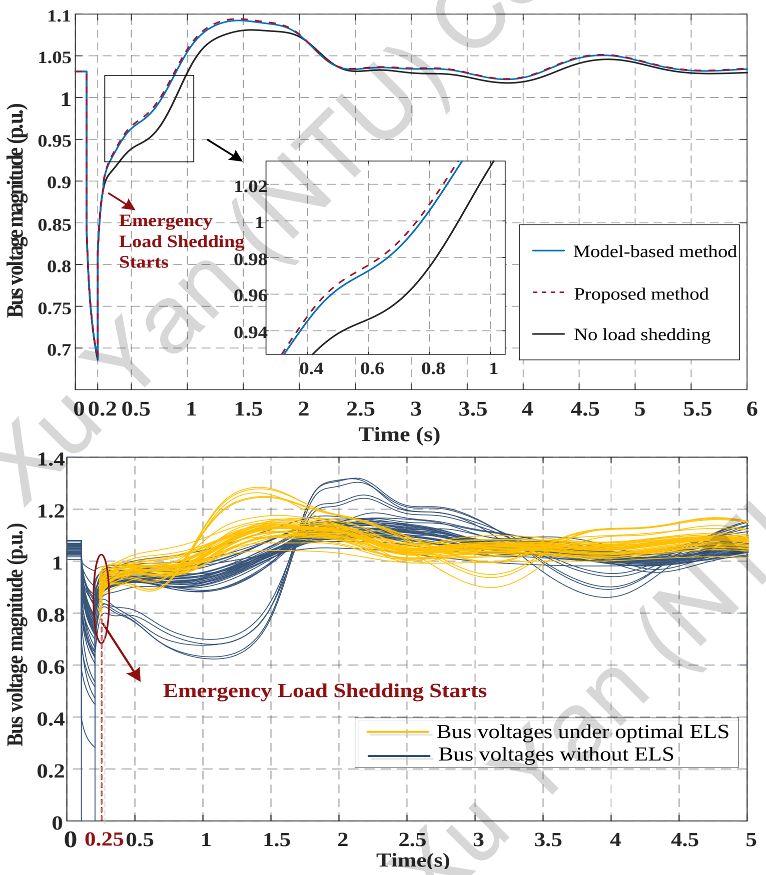
LM	20%	Simulation step	0.01s
SM	30%	Simulation time	5s
Discharge lighting	5%	Threshold of voltage deviation magnitude	20%
Transformer exciting current	5%	Unacceptable FIDVR threshold	1.2
Constant power load	20%	Load demand variation	0.8-1.2
Remaining load	20%	Load bus number	19

Load modeling



The industry-standard composite load model CLOD

4 Case Study: Comparison with the model-based method



The average bus voltage curve (a) and all the 39 bus voltage curves (b) of a new operating point after fault#1

Numerical values

Summary of Computation Time

Prediction time	Proposed method	Model-based method
t	0.137 ms	28.47 min

Control Performance of the Proposed method

	Fault #1			Fault #2		
	Bus8	Bus9	Bus27	Bus9	Bus24	Bus25
Accuracy	99.18%	99.79%	98.15%	97.71%	99.69%	97.52%
MAPE	2.26%	2.61%	0.68%	3.42%	1.67%	3.58%
MAD	1.37	2.39	0.39	3.51	2.18	4.78
MOSA	1.08	2.33	0.30	3.48	2.10	4.82
ER		99.60%			98.51%	

MOSA : mean over-shedding amount

MAD : mean absolute deviation

MAPE : mean average percentage error

ER : effectiveness rate

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4 Case Study: Comparison with the nonhierarchical method

Numerical comparisons

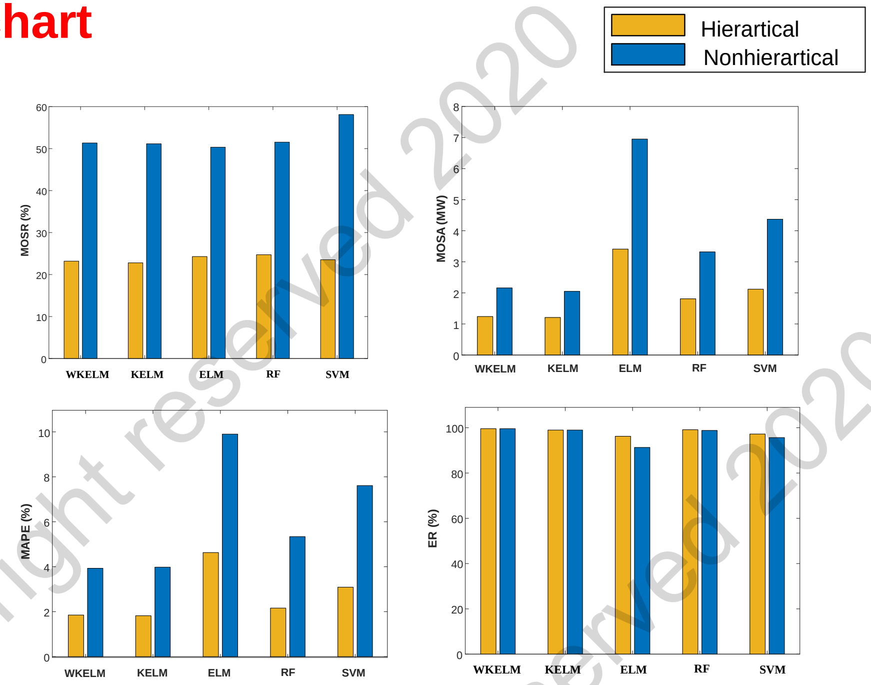
Performance Comparison of Hierarchical and Nonhierarchical Methods Under Fault #1

Model		Fault #1 MOSR	MOSA	MAPE / MAD	ER
WK-ELM	**Hierartical**	**23.20%**	**1.24**	**1.85% / 1.38**	**99.60%**
	Nonhierartical	51.34%	2.16	3.93% / 2.46	99.60%
K-ELM	Hierartical	22.79%	1.21	1.82% / 1.43	98.99%
	Nonhierartical	51.15%	2.05	3.98% / 2.37	98.99%
ELM	Hierartical	24.29%	3.41	4.63% / 3.62	96.24%
	Nonhierartical	50.34%	6.95	9.90% / 9.69	91.30%
RF	Hierartical	24.73%	1.81	2.16% / 1.74	99.14%
	Nonhierartical	51.54%	3.32	5.34% / 3.51	98.81%
SVM	Hierartical	23.53%	2.12	3.09% / 2.29	97.23%
	Nonhierartical	58.12%	4.37	7.61% / 5.15	95.65%

MAD : mean absolute deviation
MOSR : mean over-shedding rate
MOSA : mean over-shedding amount
MAPE : mean average percentage error

ER : effectiveness rate
RF: random forest
SVM: support vector machine

Bar chart



Effects:

- Eliminate almost half of the over-predicted cases
- The hierarchical method achieves almost half of the regression error and over-shedding amount of direct regression
- The effectiveness rate is significantly improved due to the reduction in prediction error for ELM and SVM

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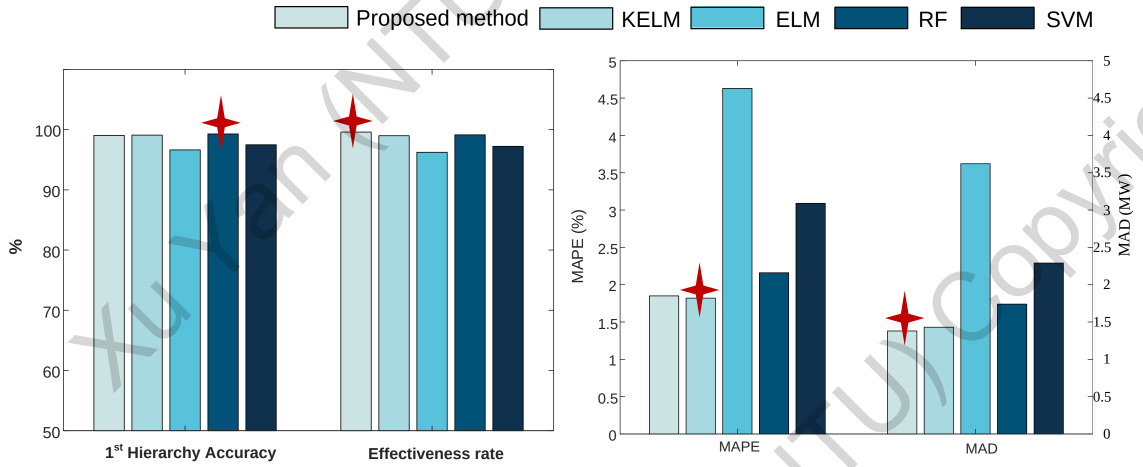
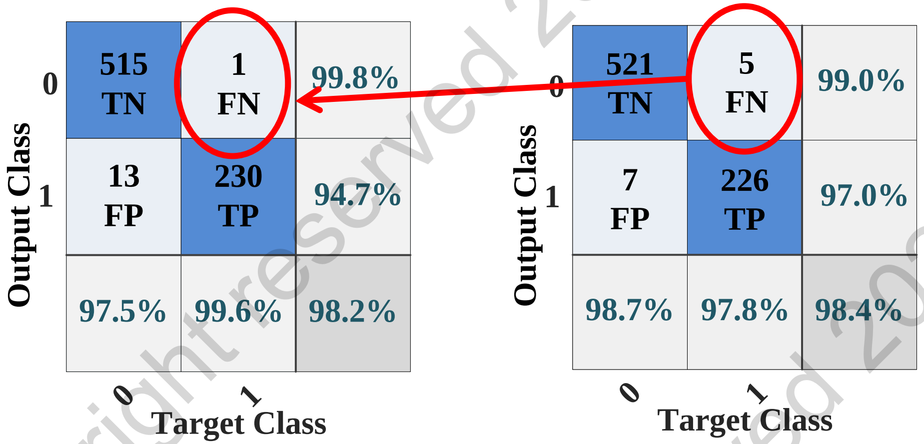
4 Case Study: Comparison with the other learning algorithms

- **Summary of Performance with Other State-Of-The-Art Algorithms**



Model	Fault #1		
	1st Hierarchy Average classification accuracy	2nd Hierarchy Average prediction MAPE / MAE	ER
Proposed method	**99.04%**	**1.85% / 1.38**	**99.60%**
KELM	99.09%	1.82% / 1.43	98.99%
ELM	96.64%	4.63% / 3.62	96.24%
RF	99.29%	2.16% / 1.74	99.14%
SVM	97.49%	3.09% / 2.29	97.23%

- **Comparison of weighted and unweighted algorithms**



(a) Confusion Matrix of WKELM. (b) Confusion Matrix of KELM

TP: true positive	1 → 1		
FP: false positive	0 → 1	Over-shedding	
TN: true negative	0 → 0		
FN: false negative	1 → 0	Insufficient control	

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5 Conclusion and future work

◆ **To provide more accurate, efficient and effective online event-based load shedding control:**

(1) A hierarchical data-driven control structure is proposed;

(2) A data distribution-based weighted learning scheme is established to provide additional emphasis on the rare yet critical cases and balance the ELS database.

◆ **Future work:**

- More efficient and more reliable real-time under-voltage load shedding method;
- Coordinated control against FIDVR and transient instability.

◆ **Full paper:** Q. Li, Y. Xu*, and C. Ren, "A Hierarchical Data-Driven Method for Event-based Load Shedding Against Fault-Induced Delayed Voltage Recovery in Power Systems," *IEEE Trans. Industrial Informatics*, vol. 17, no. 1, pp. 699-709, Jan. 2021.

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6 Relevant works: data-driven stability assessment

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3. 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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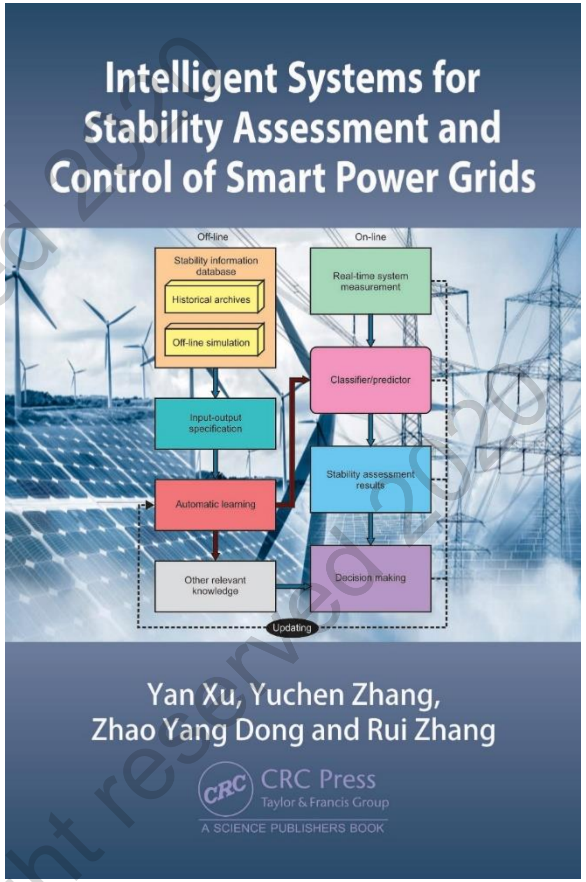

Our latest book for the completed research works

6 Relevant works: dynamic VAR planning for voltage stability enhancement

1. 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 algorithm," *IEEE Trans. Power Systems*, vol. 29, no.6, pp. 2813-2822, Nov. 2014.
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3. Y. Chi and Y. Xu*, "New Zoning-based Candidate Bus Selection for Dynamic VAR Planning in Power System towards Voltage Resilience," *IET Gen. Trans. & Dist*., vol. 14, no. 6, pp. 1012-1020, Mar. 2020.
4. Y. Chi and Y. Xu*, "Multi-stage Coordinated Dynamic VAR Source Placement for Voltage Stability Enhancement of Wind-Energy Power System," *IET Gen. Trans. & Dist*., vol.14, no. 6, pp. 1104-1113, Mar. 2020.
5. Y. Chi, Y. Xu*, and R. Zhang, "Many-objective Robust Optimization for Dynamic VAR Planning to Enhance Voltage Stability of a Wind-Energy Power System," *IEEE Trans. Power Delivery*, accepted in Mar. 2020.
6. Y. Chi and Y. Xu*, "Candidate Bus Selection for Dynamic VAR Planning towards Voltage Stability Enhancement Considering Copula-based Correlation of Wind and Load Uncertainties," *IET Gen. Trans. & Dist*., accepted in Oct. 2020.
7. Y. Chi, Y. Xu*, and T. Ding, "Coordinated VAR Planning for Voltage Stability Enhancement of a Wind-Energy Power System considering Multiple Resilience Indices," *IEEE Trans. Sustainable Energy*, vol. 11, no. 4, pp. 2367-2379, Oct. 2020.

Specific technical contributions in above works include:

- Novel voltage stability and voltage resilience indices
- Candidate bus selection methods
- Multiple & many-objective planning methods
- Multi-stage coordinated planning models
- Robustness index to address planning uncertainties

Thank You!