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Advanced Data-Analytics for Smart Grid

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1 Overview
- "Smart grid"
- Data resources in the smart grid
- Our research framework

2 Data-analytics for power grid
- Stability assessment & Control
- Frequency control
- Optimal power flow

3 Data-analytics for customers
- Non-intrusive load monitoring
- Home energy management

4 Data-analytics for power assets
- Power converter fault diagnosis
- Li-ion battery health monitoring

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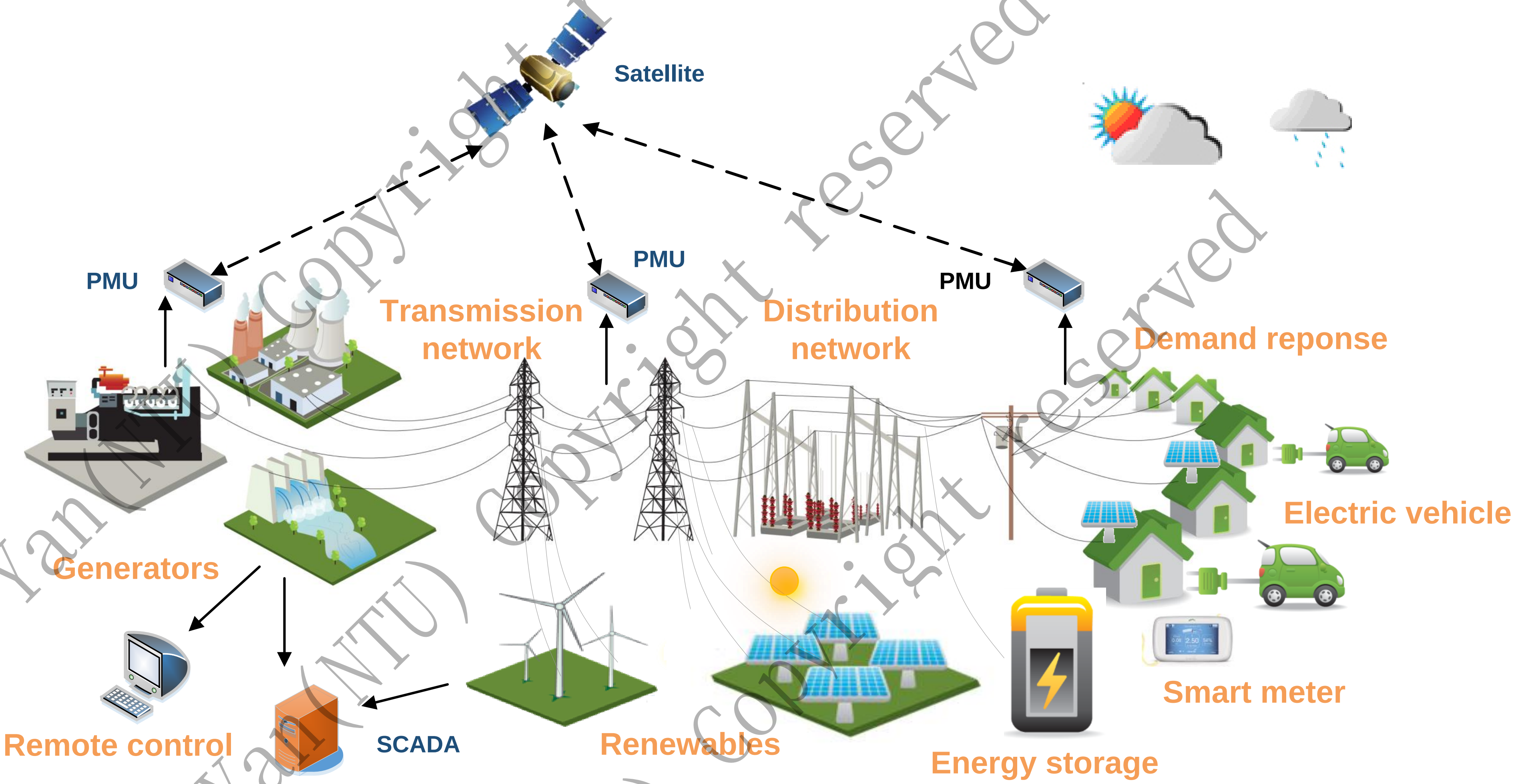
What is a “Smart Grid”?



A modernized power grid with high-level renewable energy sources (RES), more distributed energy resources (DERs), and wide-spread deployment of advanced ICT infrastructure

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Data Recourses in the Smart Grid

Wide-spread deployments of advanced ICT can provide more data and information about the power system at different levels.

Grid Monitoring System
(Phasor measurement unit (PMU), SCADA, etc.)

Customer Meters
(Residential smart meter, Industrial metersetc.)

Asset Sensors
(PQ sensor, battery management system, PD sensors, etc.)

Source of figures: website (searched in Google)

Illustration of Grid Data

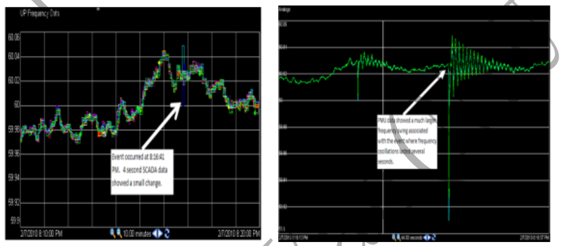


Illustration of Customer Data

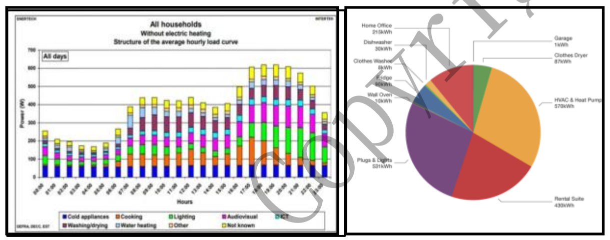
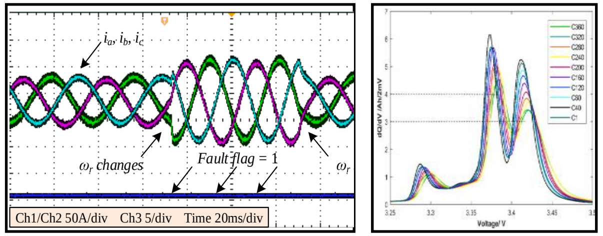


Illustration of Asset Data



How to make use of these data to support power system's monitoring, operation & control ?

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Our Research Framework

Advanced data-analytics for smart grid

Feature selection & extraction | Supervised learning | Unsupervised learning | Reinforcement learning

Research Problems

Grid Level
- Data-driven power system stability analysis → Assessment; Control
- Data-driven power system control & operation → LFC; OPF

Customer Level
- Smart meter-based non-instructive load monitoring (NILM)
- Data-driven home energy management (HEM)

Asset Level
- Power converter system fault diagnosis
- Li-ion battery health monitoring

Funding sources

National Research Foundation, Prime Minister's Office, Singapore — Research . Innovation . Enterprise
Ministry of Education Singapore
Singtel
LITEON
jtc — Breaking New Ground
Rolls Royce
Infineon

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Data-driven Power System Stability Analysis: Background

Conventional power grid → "Smart grid"

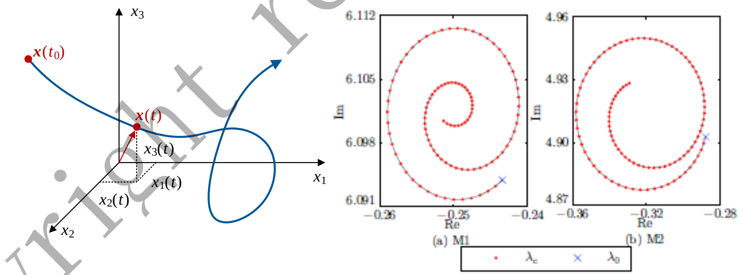
Generation side:
Higher-level intermittent renewable energies.

Demand side:
Demand response, distributed energy storage units, etc.

Device-grid interface:
Power-electronic converters.

Higher operating uncertainties

Complicated system dynamics



- The lose of stability may result in catastrophic consequences, such as **cascading failure** and even **wide-spread blackout.**
- Conventional methods, e.g., time-domain simulation (TDS), is time-consuming for **online and real-time applications.**

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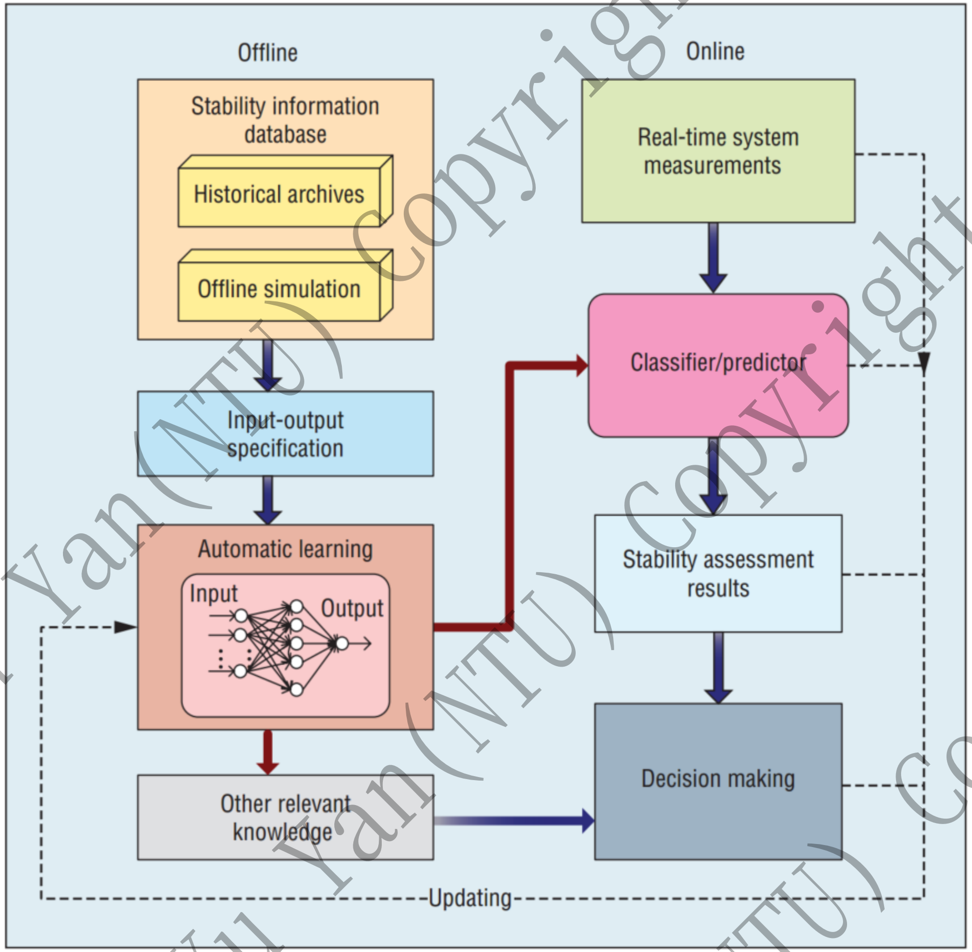
Data-driven Power System Stability Analysis: Principle and Framework

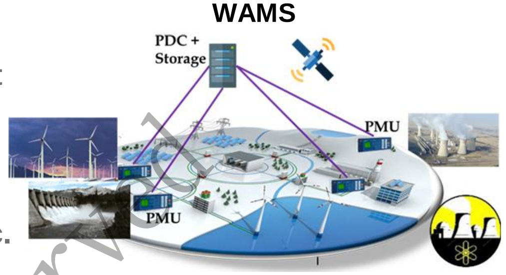
Typical process of data-driven power system stability analysis [1]

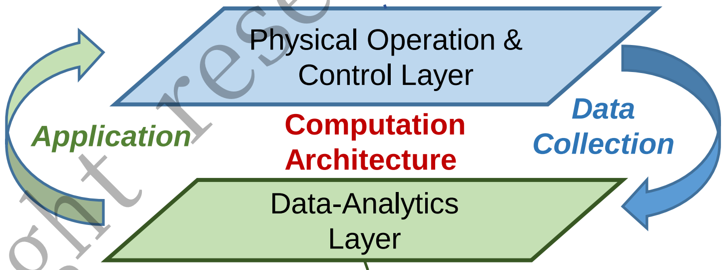


◆ Key research problems

Physical Layer

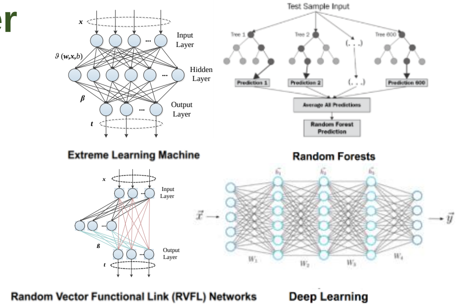
- Data measurement
- Feature selection
- Against bad data and time-delay, etc.





Data-Analytic Layer

- Accuracy
- Speed
- Reliability
- Robustness



[1] 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.**
[2] Y. Xu, Y. Zhang, Z.Y. Dong, and R. Zhang, "***Intelligent Systems for Stability Assessment and Control of Smart Power Grids***," CRC Book Press, 2020.

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Credibility-Oriented Stability Assessment : Our Originally Proposed Methodology

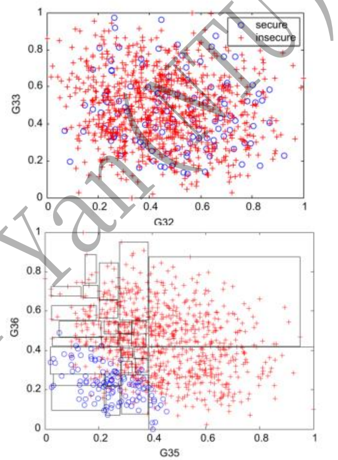
On-line Stability Assessment → Preventive control | Real-time Stability Assessment → Emergency Control

Steady State (Pre-fault)

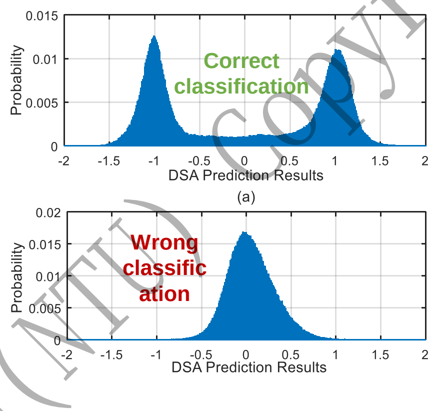
Contingency

Dynamic State (Post-fault)

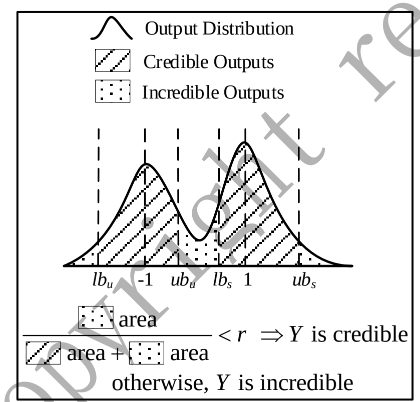
Feature selection [1]



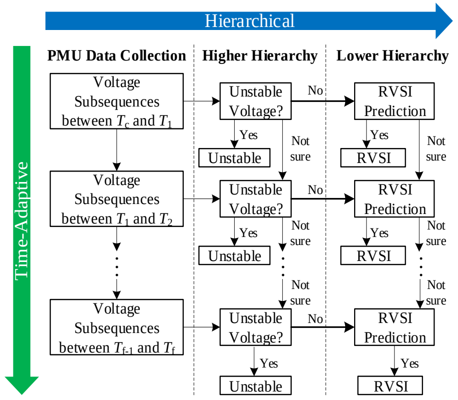
Statistic error analysis [2,3]



Credibility evaluation [4]



Time-adaptive decision-making [5,6]



[1] Y. Xu, Z.Y. Dong, et al. "Preventive dynamic security control of power systems based on pattern discovery technique." **IEEE Trans. Power Systems , 2012**.
[2] Y. Xu, Z.Y. Dong, et al, "Real-time transient stability assessment model using extreme learning machine," **IET Gen. Trans. & Dist., 2011.**
[3] Y. Zhang, Y. Xu, et.al," Intelligent early warning of power system dynamic insecurity risk: Toward optimal accuracy-earliness tradeoff," **IEEE Trans. Industrial Informatics,2017**
[4] Y. Xu, Z.Y. Dong, et al. "A reliable intelligent system for real-time dynamic security assessment of power systems." **IEEE Trans. Power Systems, 2012**
[5] 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.**
[6] 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.**

A more detailed PPT about our research works on data-driven power stability analysis can be found at:
https://eexuyan.github.io/soda/resource/Data-driven%20analytics%20for%20power%20system%20stability-1911.pdf

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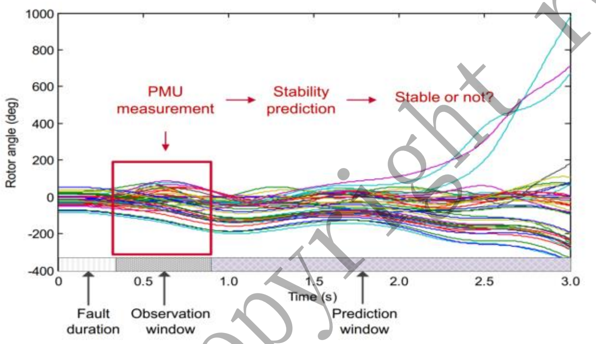
Credibility-Oriented Stability Assessment : Simulation Results



For pre-fault application: speedup time-domain simulation for online use

+

For post-fault application: trigger response-based protection & control

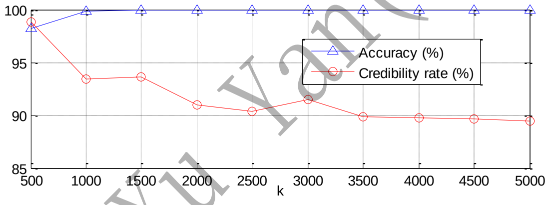
Pre-fault stability assessment

IEEE 145-bus System Test Results [1]

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	Time
Fault at a 500kV corridor bus	96.82%	0.0115s

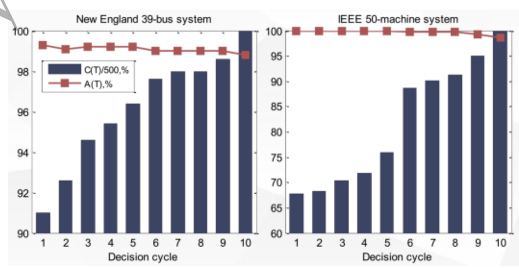


High accuracy (100%) can be obtained on the cost of a slightly low credibility rate.

Post-fault stability assessment

Comparison results [2]

Literature	Response time	Accuracy (%)
I. Kamwa, et al 2001	2 to 3s	96%~99.9%
I. Kamwa, et al 2009	1 or 2s	
I. Kamwa, et al 2010	150 and 300ms	
S. Rovnyak, et al 1994	8 cycles	
N. Amjady, et al 2007	6 cycles	
N. Amjady, et al 2010	5 cycles	
U.Annakkage, et al 2010	4 cycles	



Our method:
Average decision speed: 1.9 cycle;
Average accuracy: 99.7%

[1] Y. Xu, Z.Y. Dong, et al. "Preventive dynamic security control of power systems based on pattern discovery technique." **IEEE Trans. Power Systems, 2012.**
[2] 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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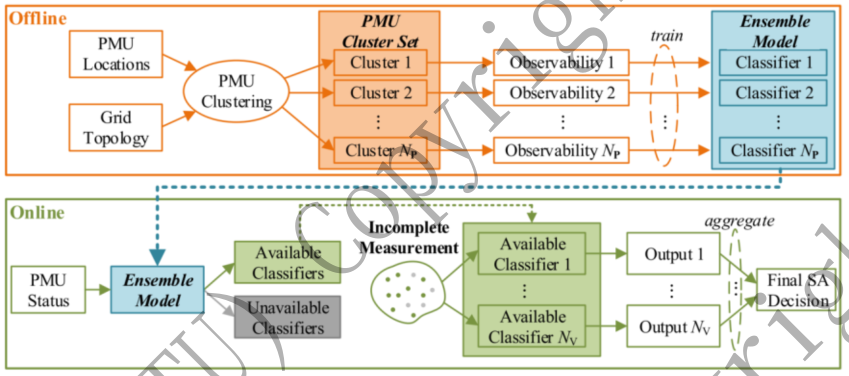
Data-driven Stability Assessment with Missing Data

1) Observability-Oriented PMU Clustering Method [1]

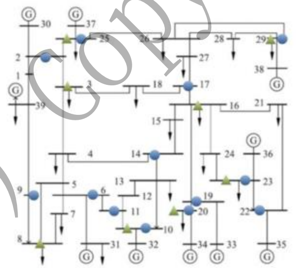
Analytical PMU clustering + Ensemble Learning → Robustness against missing data

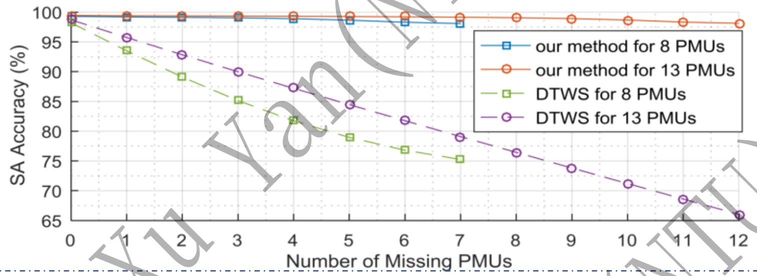


◆ Simulation study

PMU PLACEMENT LOCATION

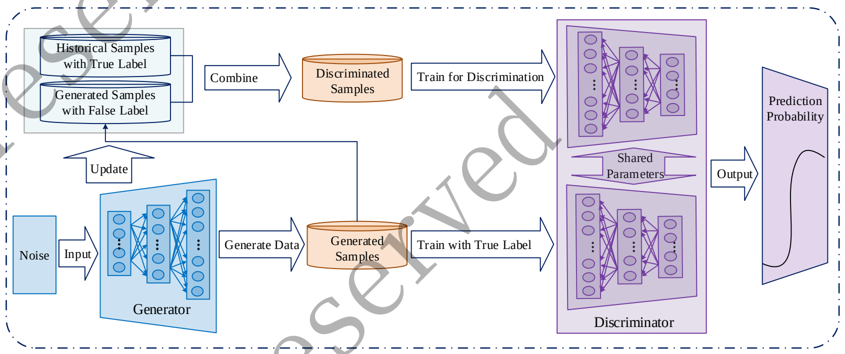
PMU Placement Options	PMU Installation Buses	No. of PMUs
▲ I	3, 8, 10, 16, 20, 23, 25, 29	8
● II	2, 6 ,9, 10, 11, 14, 17, 19, 20, 22, 23, 25, 29	13



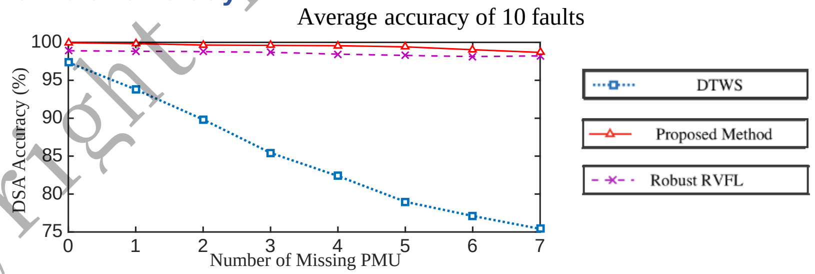


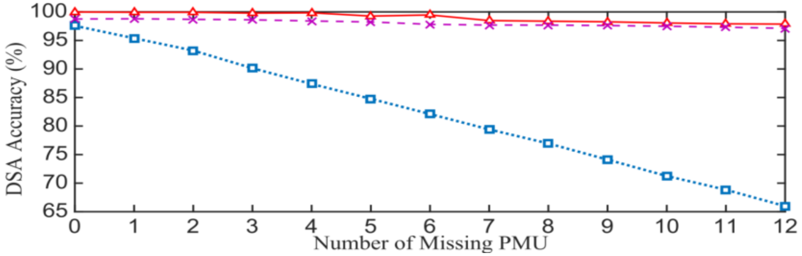
2) Generative Adversarial Network (GAN) based method [2]

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



◆ Simulation study





[1] Y. Zhang, Y. Xu, et al "Robust ensemble data-analytics for incomplete PMU measurement-based power system stability assessment," **IEEE Trans. Power Syst., 2017.**
[2] 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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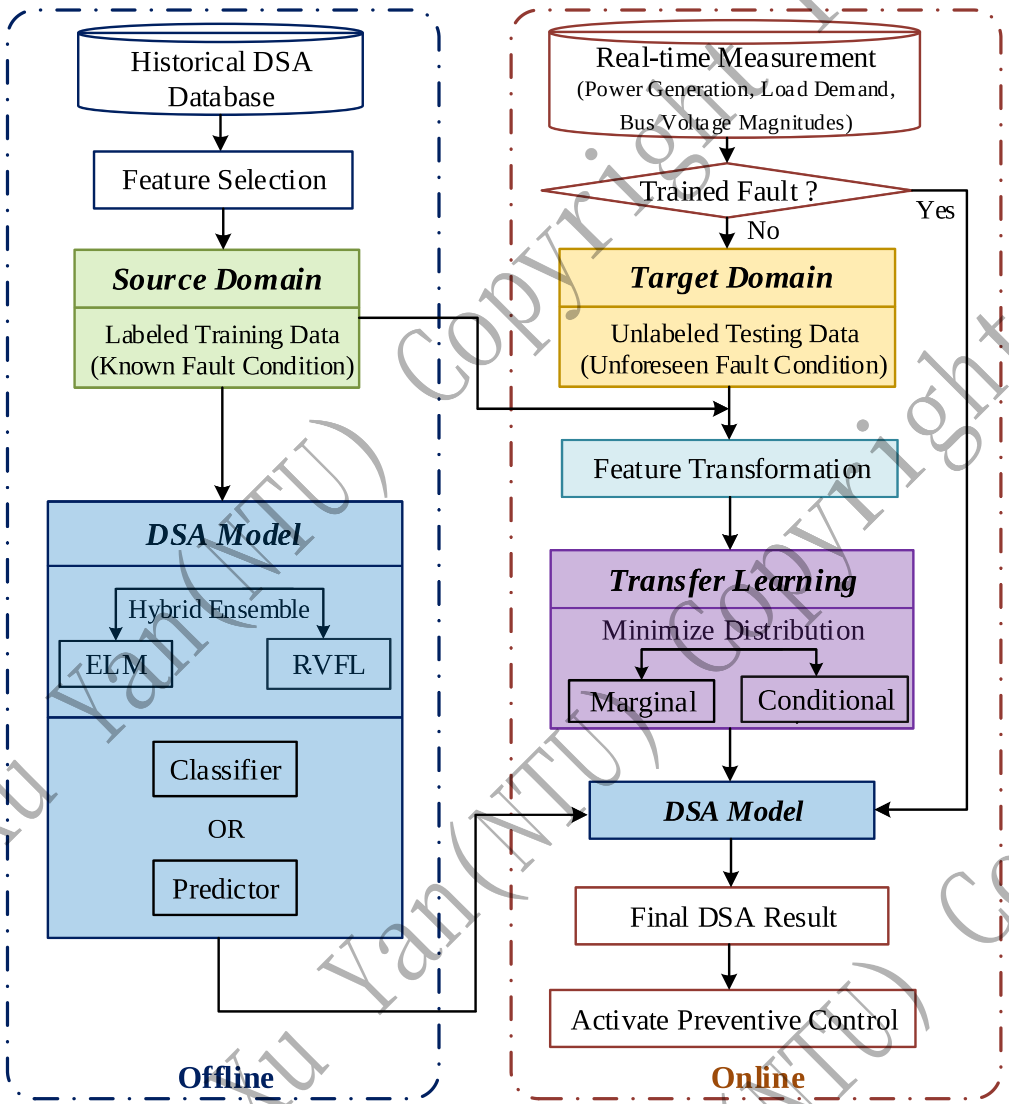
Using One Model to Assess Many Unlearned Faults: Transfer Learning



Problem descriptions:

- For pre-fault stability assessment, 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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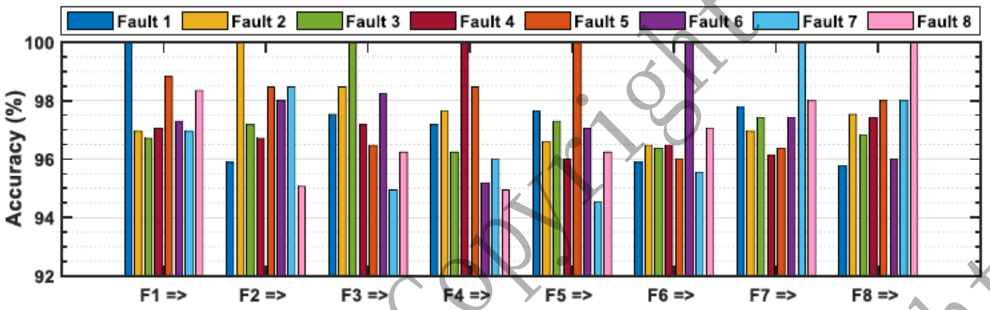
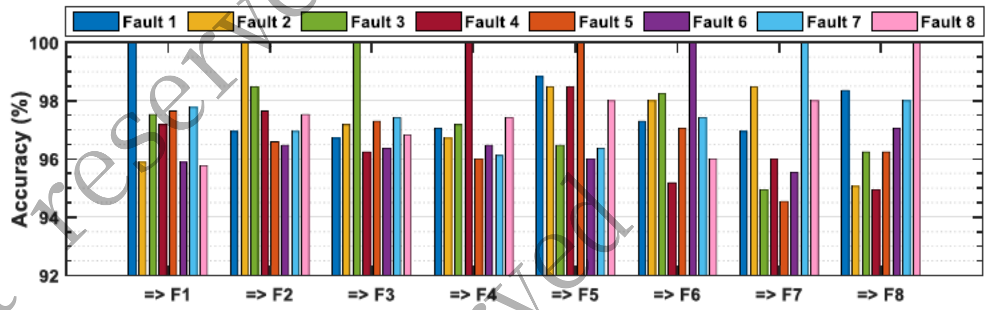
Using One Model to Assess Many Unlearned Faults: Transfer Learning

Testing Results



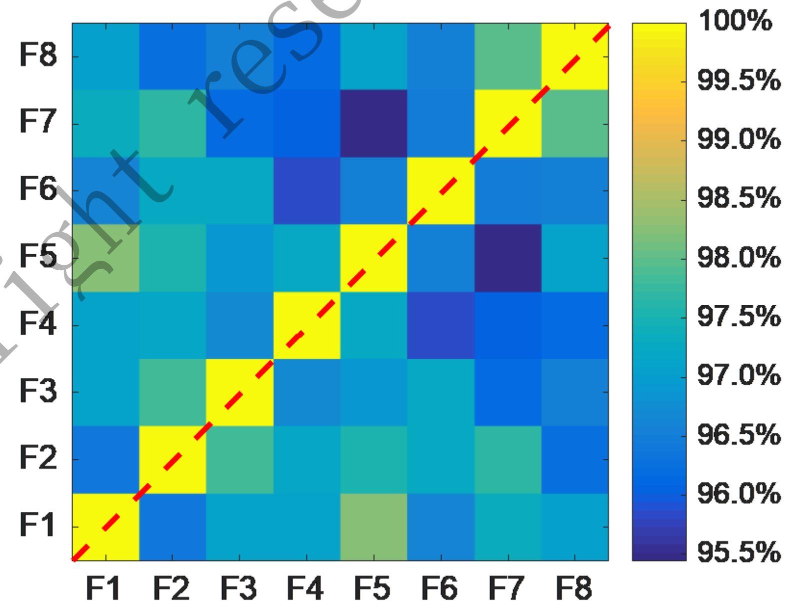
(a) each of fault is transferred to the remaining 7 faults



(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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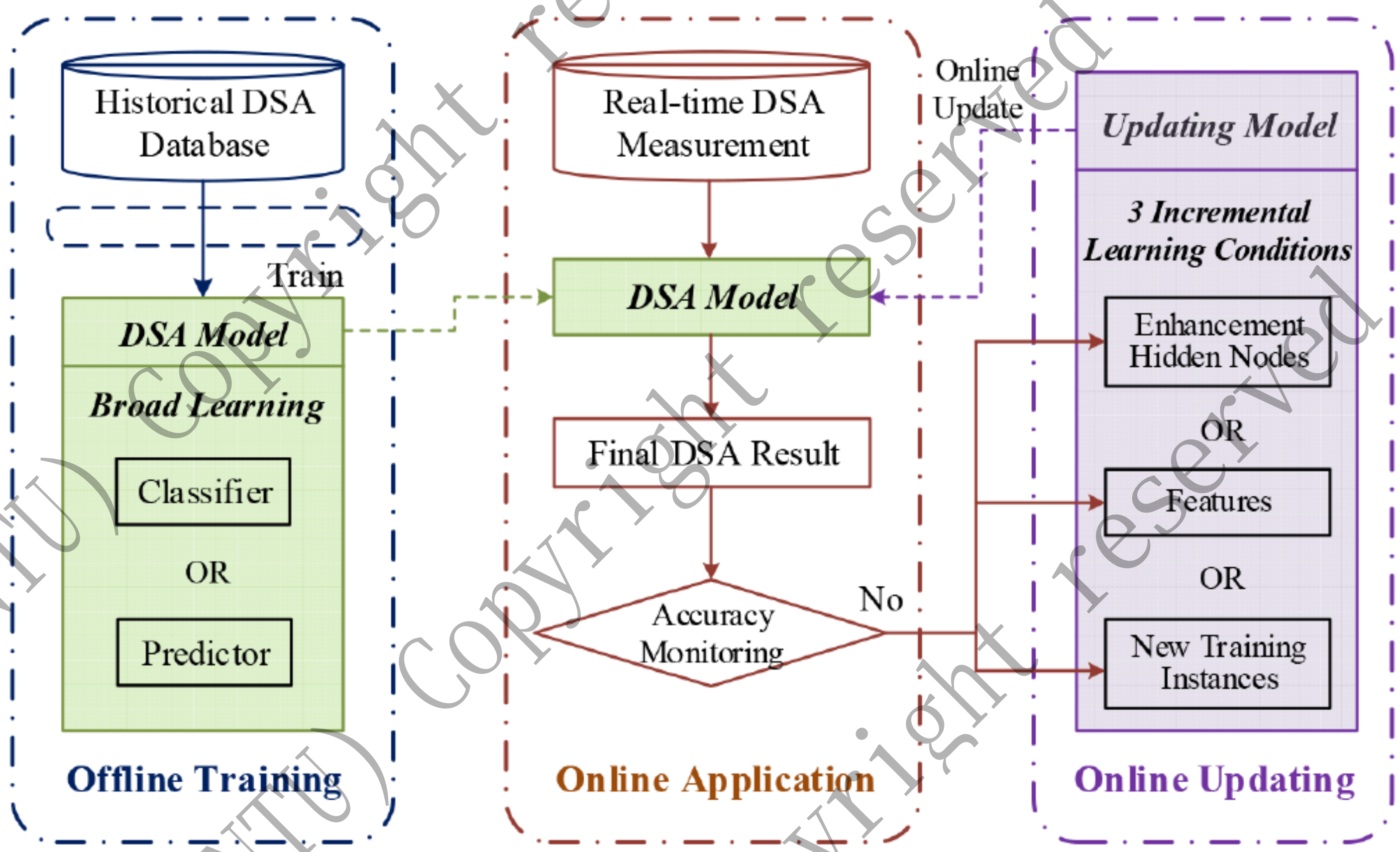
Updating the Model in Real-time: Incremental Learning



Problem descriptions:

- 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.

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Updating the Model in Real-time: Incremental Learning

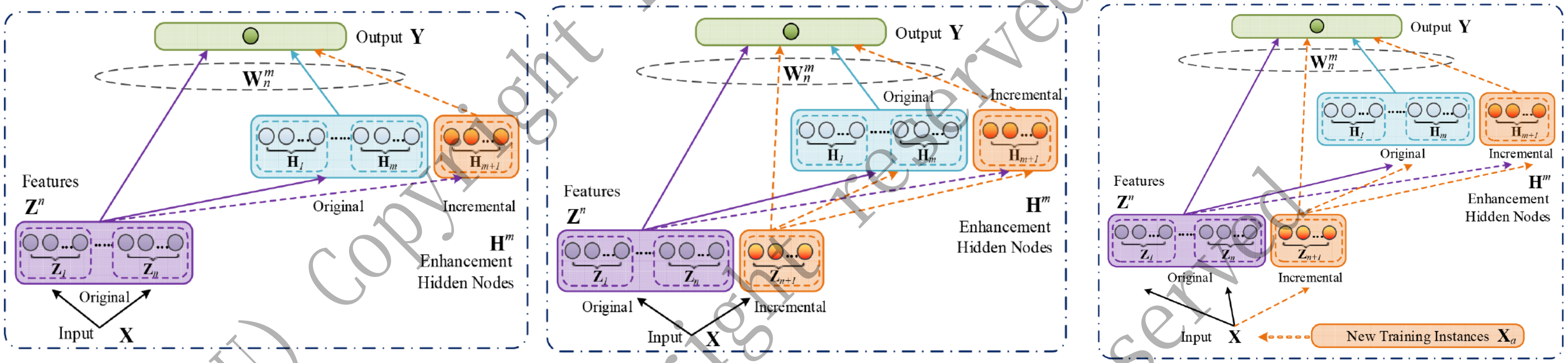

Fig. 1 *Different structure of the incremental broad learning for*
(a) Increment of enhancement hidden nodes, *(b)* Increment of features, *(c)* Increment of enhancement hidden nodes, features, and new training instances

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.**

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Data-driven Stability Control : Preventive Generation Rescheduling

- 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.

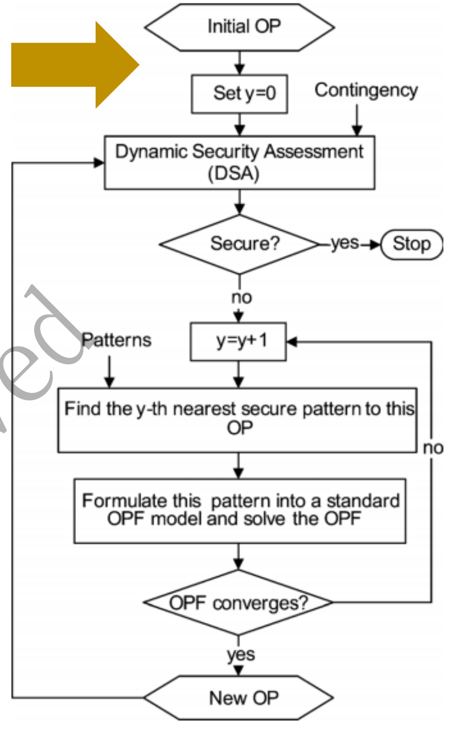
$$diff(X,R,R') = \frac{|value(X,R) - value(X,R')|}{\max(X) - \min(X)}$$

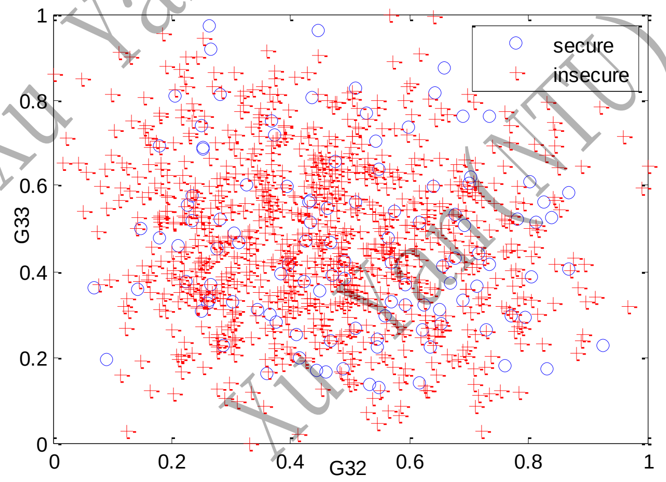
$$W[X]^{i+1} = W[X]^{i} - \sum_{j=1}^{k} diff(X,R_i,H_j)/(m \cdot k) +$$

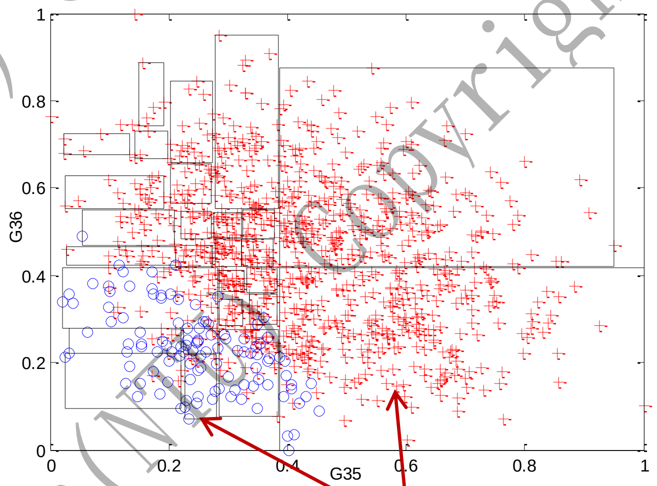
$$\sum_{C \neq class(R_i)}^{k} [\frac{P(C)}{1-P(class(R_i))} \cdot \sum_{j=1}^{k} diff(X,R_i,M_j(C))]/(m \cdot k)$$

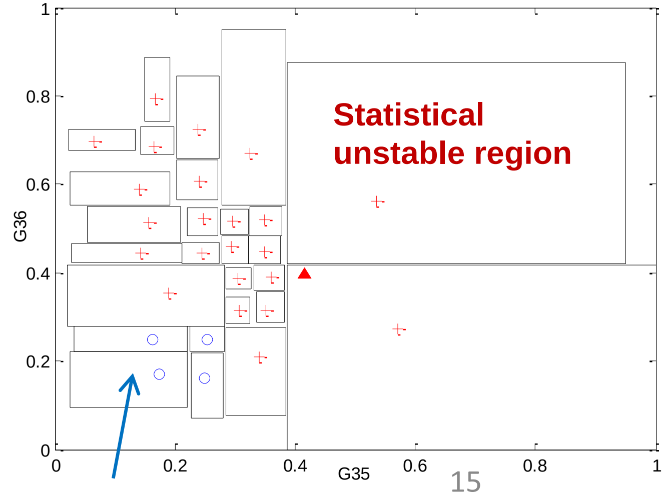
- **Residual analysis:** the difference between an event's observed (actual) occurrence probability and expected occurrence probability.

Substitute the region boundaries into the Optimal Power Flow (OPF) model as linear constraints, resulting to stabilized operating state.









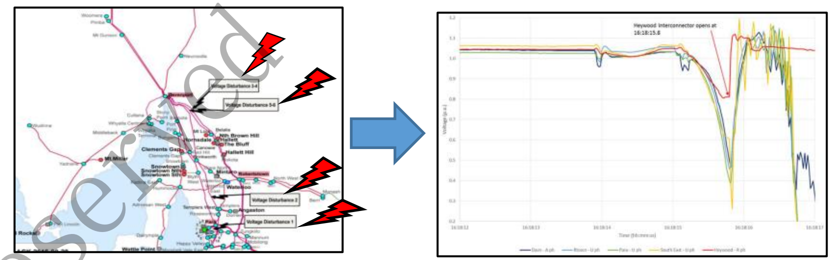
Y. Xu, Z.Y. Dong, L. Guan, et al. "Preventive dynamic security control of power systems based on pattern discovery technique." **IEEE Trans. Power Systems , 2012.**

Statistically significant

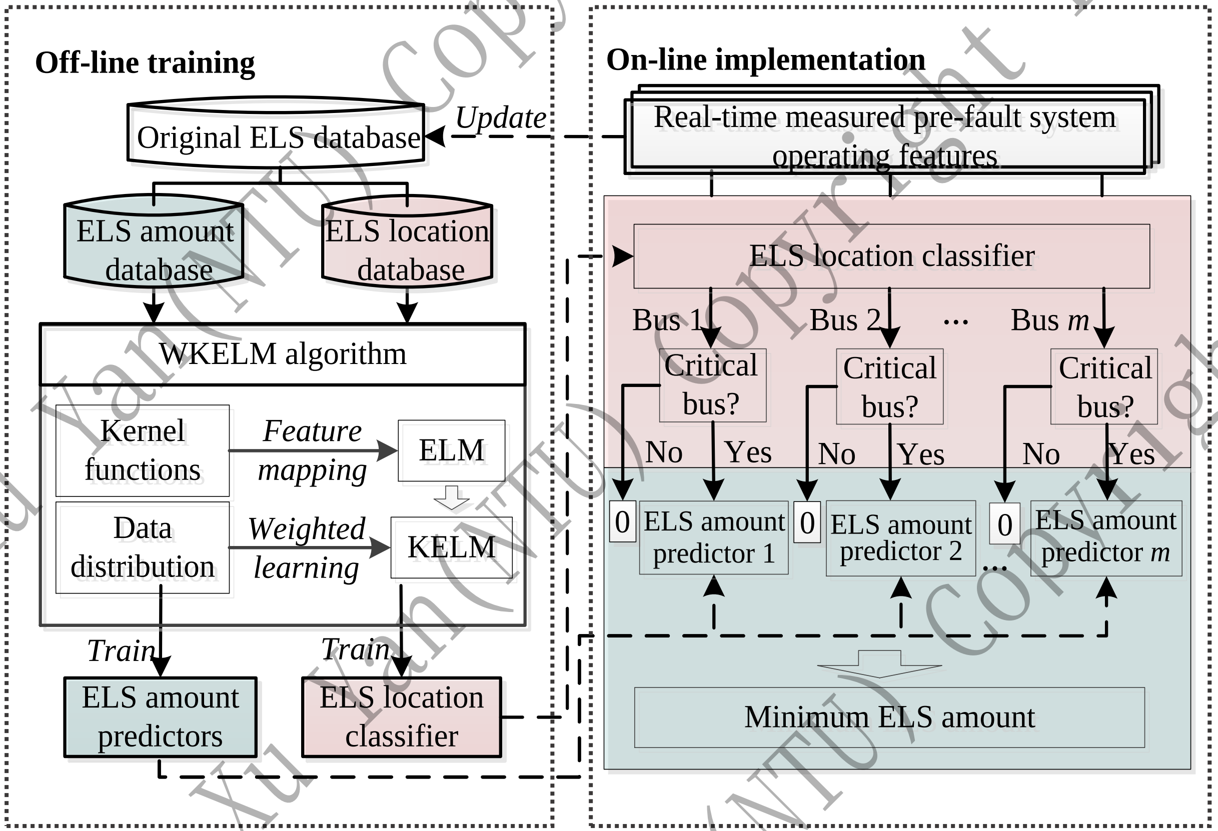
Statistical stable region

Data-driven Stability Control : Emergency Load Shedding

- **Problem descriptions:** Conventionally, the emergency load shedding (ELS) location and amount are decided by a pre-defined decision table, which may suffer from serious mismatching problem in an ever-changing power system operating scenario.



- **Framework of proposed data-driven ELS model**

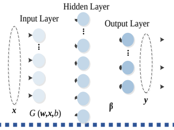


- **Learning algorithm**

Weighted learning scheme

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

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



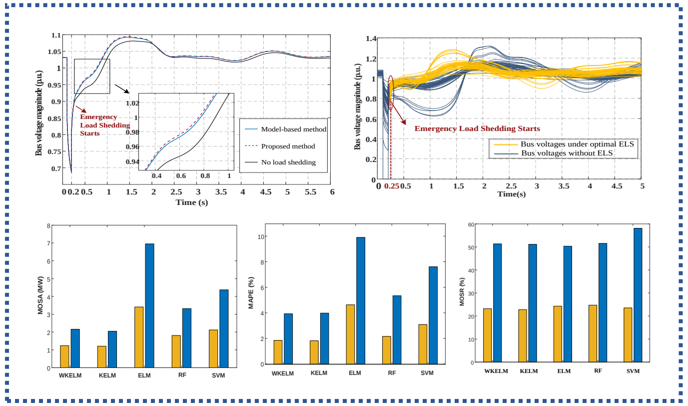
Classification

$$w_{ii}=\frac{1}{c(t_{ki})}$$

Regression

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

- **Simulation results**



Q. Li, Y. Xu, C. Ren, "A Hierarchical Data-Driven Method for Event-based Load Shedding Against Fault-Induced Delayed Voltage Recovery in Power Systems," **IEEE Transactions on Industrial informatics, 2020.**

For more detailed information, please visit https://eexuyan.github.io/soda/resource/Data-driven%20event-based%20load%20shedding-Nov11-2020.pdf

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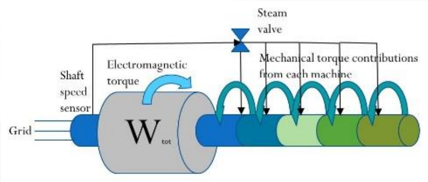
Power System Load frequency control (LFC)

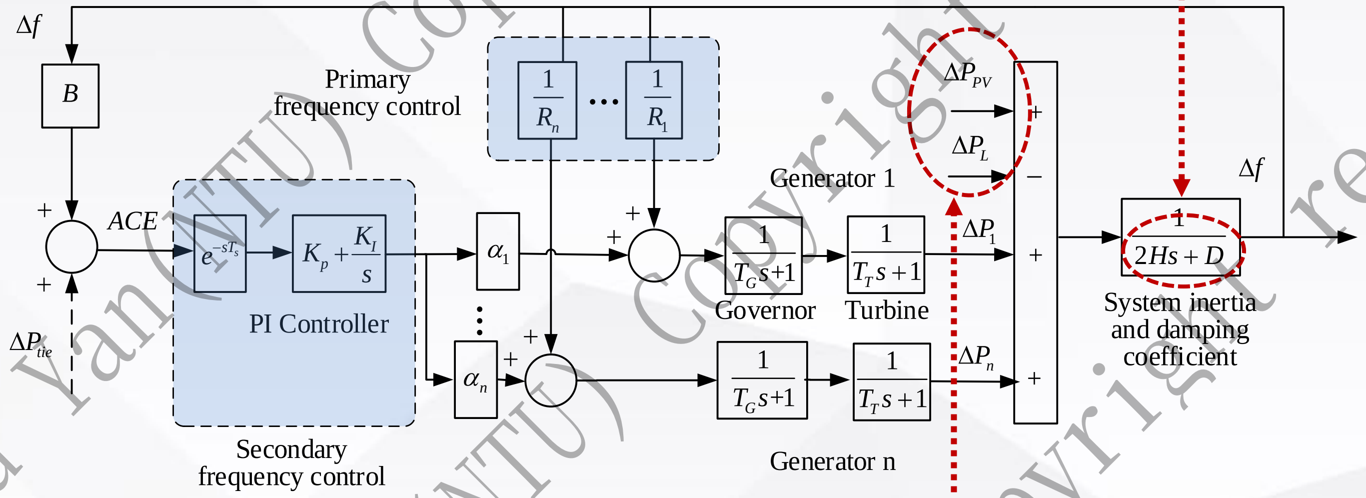
➢ Lower inertia and load damping:



Generation side: power-converter interfaced generators (wind, solar).

Transmission side: asynchronous interconnection through HVDC links.

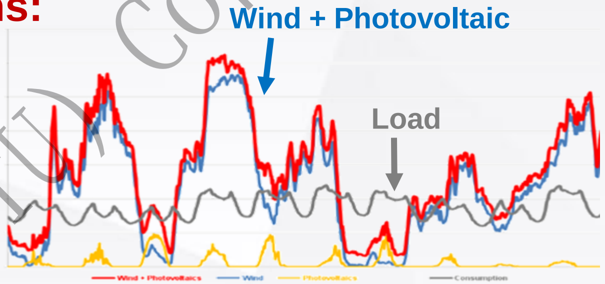
Load side: inverter-based loads.



➢ Larger and faster power fluctuations:

Generation side: intermittent renewable power generation

Load side: demand response program, EV charging load, etc.

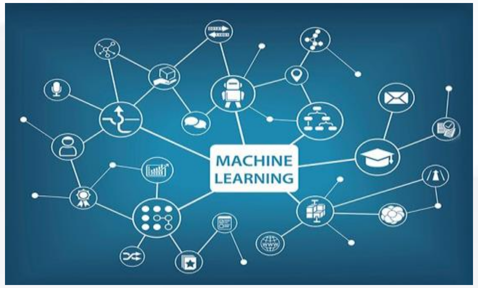


Conventional methods

Model-based:

1. Robust control
Parametric uncertainties.
2. Fuzzy control
Adaptive for unknown system.
3. Variable structure control
Robustness and response speed.
4. Disturbance rejection control
Augmented model to reject effects.
5. Model-predictive control
Predict system's behavior and control.
6. etc.

Data-driven methods



- Stronger modelling capability
- Better control performance
- Higher flexibility and scalability
- etc.

For more information, please visit https://eexuyan.github.io/soda/resource/Data-driven%20power%20system%20frequency%20control-Nov11-2020.pdf

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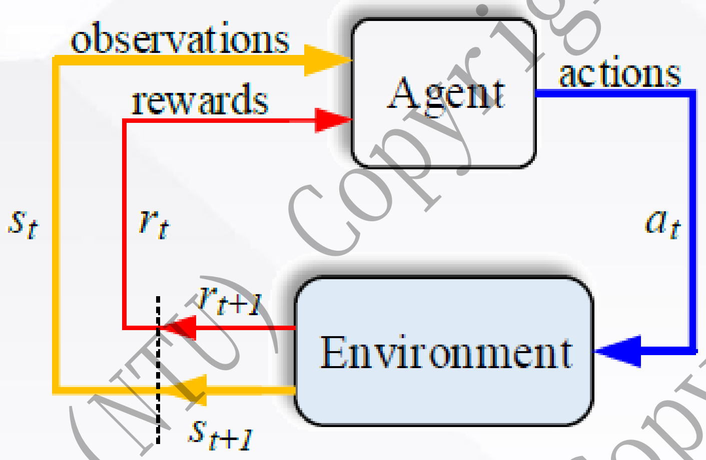
Reinforcement Learning (RL)

Principle & Framework

- **Principle**: training an **agent** via iterative interactions with the **environment**.



- **Agent**: decision-maker → frequency controller
- **Environment**: physical world → power system
- **State (s)**: current situation of the agent → f, ACE, P
- **Action (a)**: agent's decision → generation control signal
- **Reward (r)**: feedback from the environment → power system's frequency performance (at time t)
- **Action value (Q-value)**: total expected reward over T

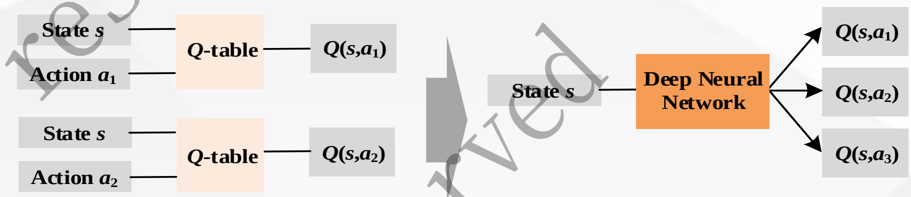
➢ How to **model** the frequency control problem into a RL process?
➢ How to **solve** the RL training process considering power system's own characteristics/model?

RL methods

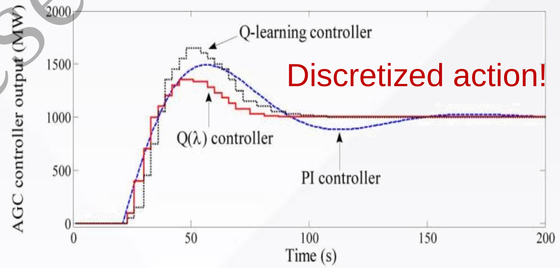
1. Value-based methods – train a Q-value predictor (Q-table)

Given an action, it evaluates the how good the action is.

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha(R_{t+1} + \gamma \max_{a} Q(s_{t+1},a_t) - Q(s_t,a_t))$$



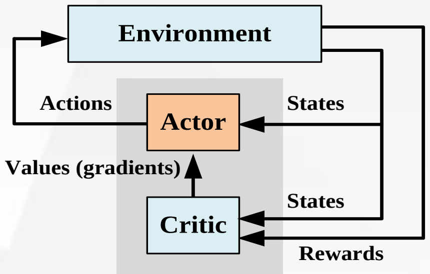
Disadvantages:
- Discretized action.
- Non-satisfactory performance due to discretized action space.



2. Policy-based methods – train an action predictor (actor)

Explicitly learn a mapping policy $\pi: s \rightarrow a$

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s,a)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s=s_i}$$



Advantages:
- Continuous action space.
- Better performance in convergence and stability.

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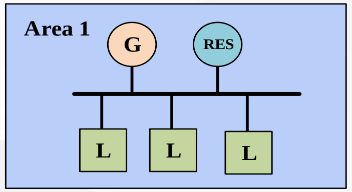
Data-Driven LFC: Our Research Works

Single-area controller [1]

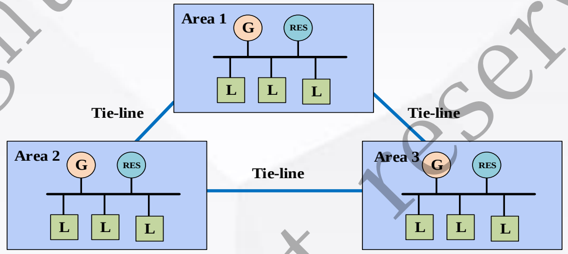


G: generation; L: load;
RES: renewable energy resources;
BESS: battery energy storage system

- Developed a policy-based DRL model for single-area power system frequency control
- Minimize expected frequency deviations
- Model-assisted gradients derivation
- Stacked denoising auto-encoder (SDAE) for feature learning

[1] Z. Yan, Y. Xu, "Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Reinforcement Learning Method With Continuous Action Search," **IEEE Trans. Power Systems, 2019.**

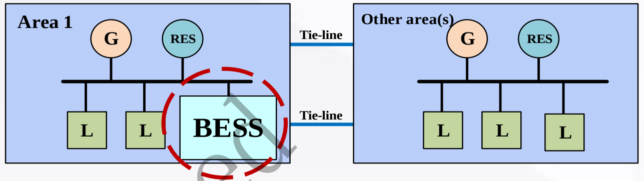
Multi-area controllers [2]



- Developed a set of cooperative DRL models for multi-area power system
- Centralized learning, decentralized implementation
- Optimize global action-value function
- Constraints-aware gradients derivation
- Network initialization to quick start

[2] Z. Yan, Y. Xu, "A Multi-Agent Deep Reinforcement Learning Method for Cooperative Load Frequency Control of Multi-Area Power Systems," **IEEE Trans. Power Systems, 2020.**

BESS controller for frequency support [3]

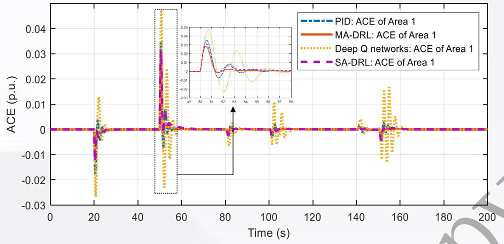


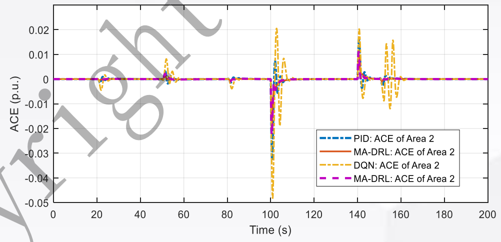
- Optimal control of BESS for f support
- Minimize expected total control cost considering the degradation of battery
- Modelling of BESS lifetime degradation
- Actor-critic framework
- Cost approximation with critic

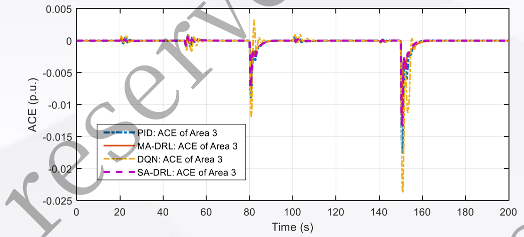
[3] Z. Yan, Y. Xu, et al, "Data-driven Economic Control of Battery Energy Storage System Considering Battery Degradation," **IET Generation. Transmission & Distribution, 2020.**

Testing Results: LFC model

- Linearized LFC model (no physical limits):

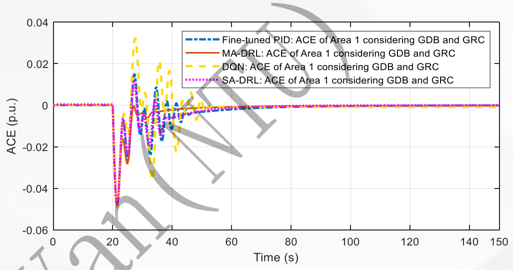


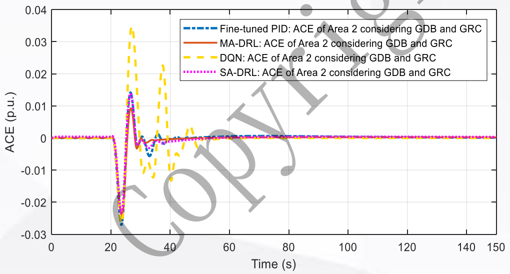


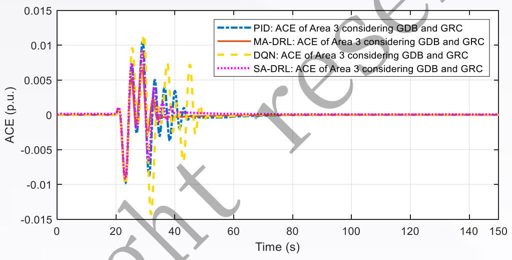


- Less expected frequency deviations: 87.7% better than DQN, 57.5% better than PID.
- Smaller frequency nadir: 39.6% better than DQN, 17.1% better than PID.

- Nonlinearity (GRC&GDB):

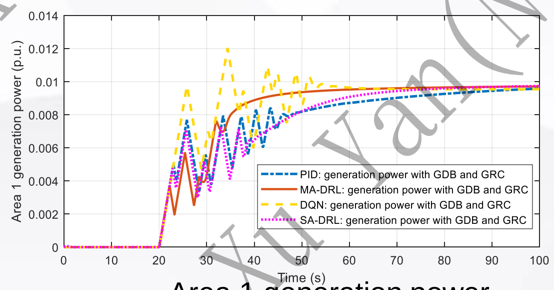




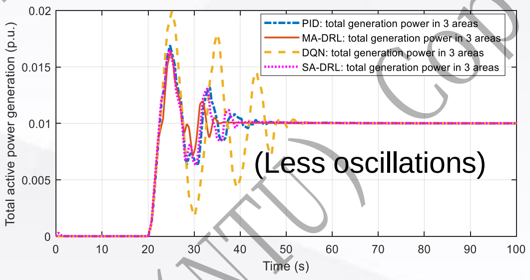


- Less deviations: 62.5% better than DQN, 22.2% better than PID.
- Improves the LFC performance by better coordination among all the areas

- Generation power under GRC&GDB:



Area 1 generation power



Total generation in 3 areas

Method	Q	Mean |ACE| %	Max |ACE| [p.u.]
Fine-tuned PID	-0.0247	0.037	0.035
(Deep) Q-learning	-0.0851	0.093	0.048
Proposed method	-0.0105	0.023	0.029
Fine-tuned PID (GRC and GDB)	-1.8e-3	0.042	0.049
(Deep) Q-learning (GRC and GDB)	-3.2e-3	0.061	0.049
Proposed method (GRC and GDB)	-1.2e-3	0.029	0.048

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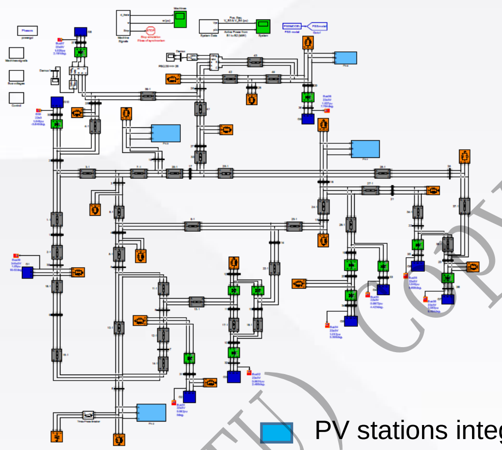
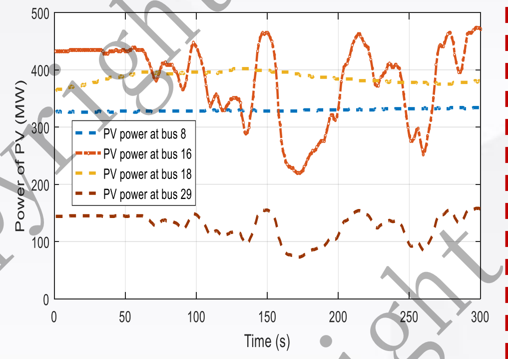
Testing Results: Time-Domain Model

- NE 39-bus system with full dynamic model:





PV stations integrated at load bus 8, 16, 18, 29.

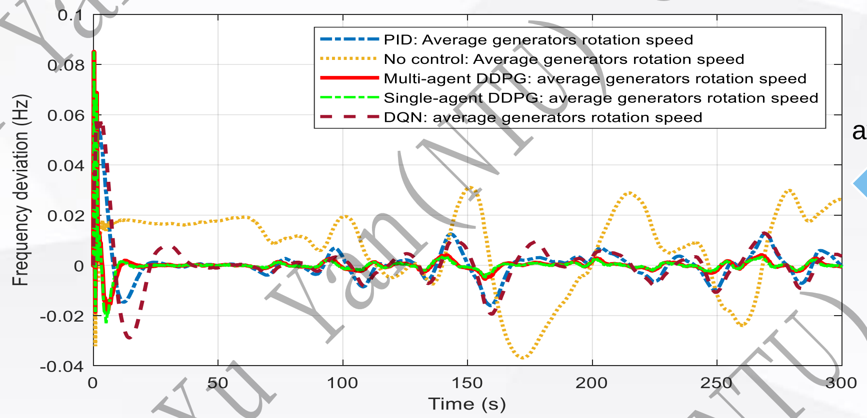
- Numeric comparison

Method	Q	Mean |ACE| %	Max |ACE| [p.u.]
Fine-tuned PID	-7.0e-05	0.0095	0.002
(Deep) Q-learning	-1.35e-4	0.0119	0.002
Single-agent DDPG	-3.4e-05	0.0044	0.002
Proposed MA-DRL	**-3.2e-05**	**0.0047**	0.002
No control	-0.013	0.21	0.002

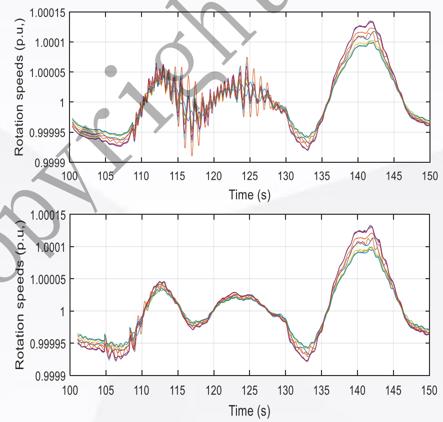
Objective function: less frequency deviations in data-driven methods

More related with system's inertia

- System frequency for different methods



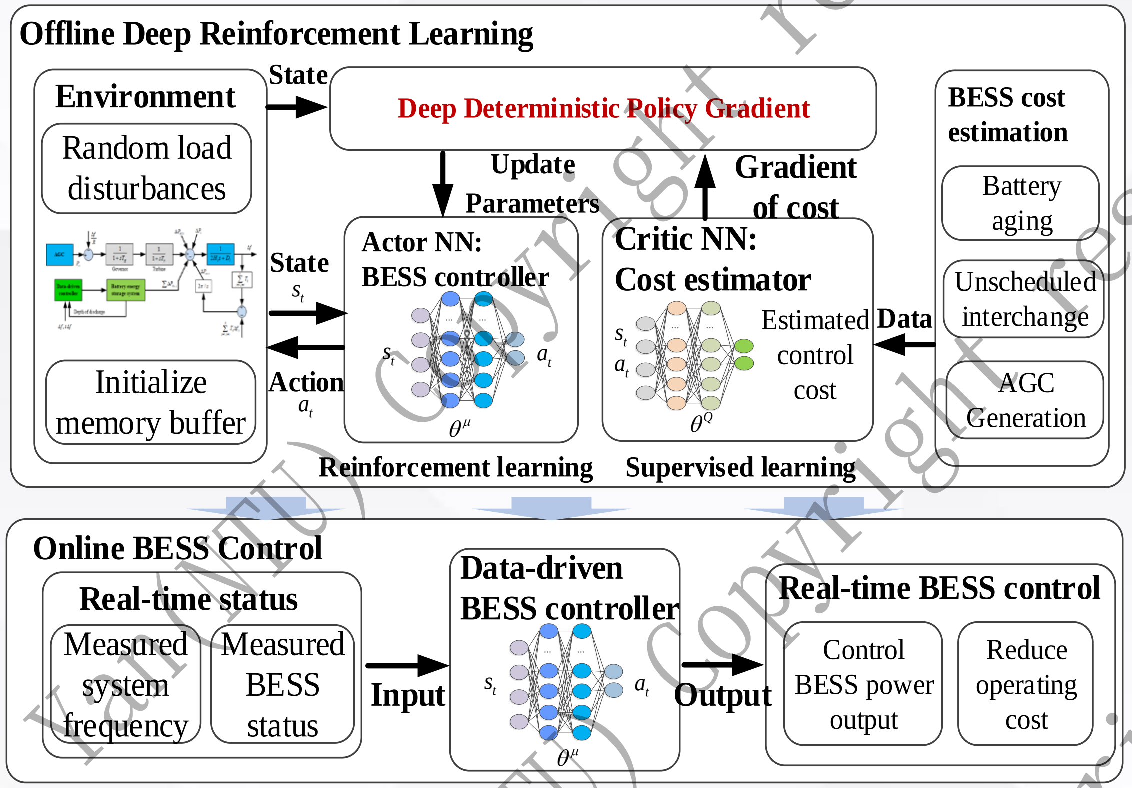
average



Rotation speed of 9 different generators

- **Less frequency deviations**: 76.3% better than DQN, 54.3% better than PID.
- Better **coordination** among all the agents

Battery Energy Storage System (BESS) control for frequency support



Agent-Environment Interaction

- Expected action-values:

$$\underset{\theta^\mu}{\text{Maximize}}\, E_D[\,Q^\mu(s_t, a_t)]$$

- Cost: battery marginal aging, unscheduled interchange, AGC generation
- Cost approximation with critic:

$$Q^\mu(s_t, a_t) = -\sum_T [c_b(t) + c_u(t) + c_g(t)]\Delta t$$

$$\min_{\theta^Q} ||Q_R - h_{\theta Q}^{(n)}[\dots h_{\theta Q}^{(1)}(\boldsymbol{s}, a))]\ ||^2$$

- Training process

$$\theta^{\mu\prime} = \theta^\mu + \eta \cdot \nabla_{\theta^u} J$$

$$\nabla_{\theta^u} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)\ \nabla_{\theta^\mu}\mu(s|\theta^\mu)$$

Critic-based gradients

Gradient of objective to BESS action

$$Q_R \approx h_{\theta Q}^{(n)}[\dots h_{\theta Q}^{(1)}(\boldsymbol{s}, a))$$

$$\nabla_a Q(s, a) \approx \nabla_a h_{\theta Q}^{(n)}[\dots h_{\theta Q}^{(1)}(\boldsymbol{s}, a))$$

DNN Updating rule

Gradient of action to agent' parameters

$$\nabla_{\theta^\mu}\mu(s|\theta^\mu) = \nabla_{\theta^\mu}(f_\theta^{(n)}[\dots f_\theta^{(1)}(X))])$$

- Offline Deep Reinforcement learning

The critic NN approximates total control cost and actor gradients. The actor NN (BESS control agent) is optimized with actor gradients.

- Online BESS control

The real-time control action by the optimized DRL agent already considers the control cost.

[3] Z. Yan, Y. Xu, et al, "Data-driven Economic Control of Battery Energy Storage System Considering Battery Degradation," **IET Generation. Transmission & Distribution, 2020.**

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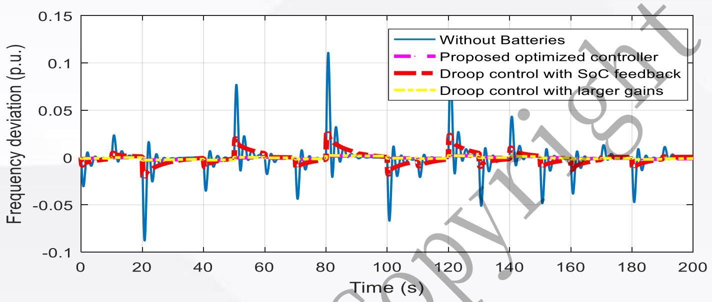
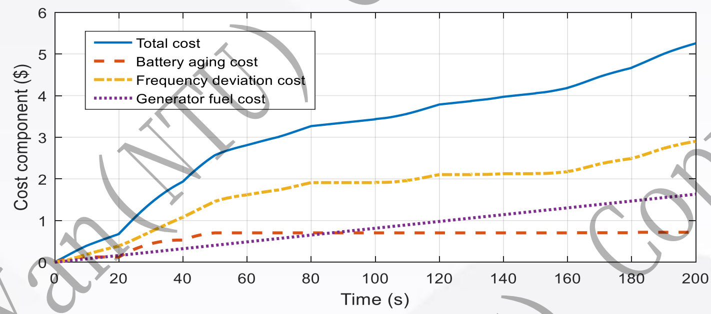
BESS Control for Frequency Support: Simulation Results

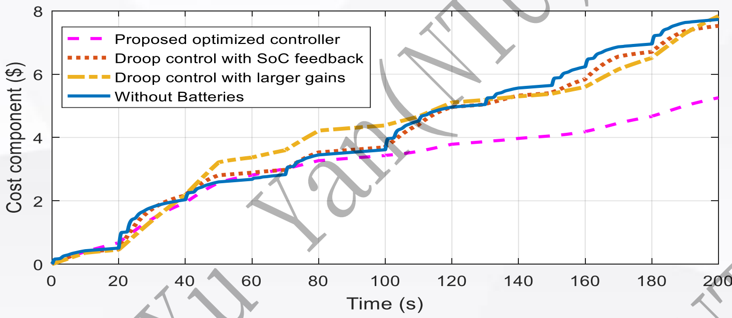
- System frequency in 3 areas



- Accumulative cost (each component)



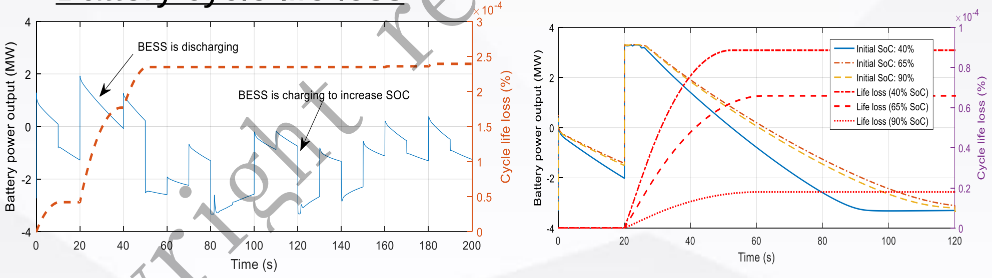
- Accumulative cost (total)



- Numerical results (random load changes)

Method	C ($)	C_b ($)	C_u($)	C_g ($)	Saving (%)
No Batteries	7.73	0.00	6.10	1.63	0.0
Proposed	5.25	0.72	2.90	1.63	32.1
Droop with SoC	7.53	1.43	4.47	1.62	2.6
Droop with larger gains	7.83	4.92	1.29	1.62	-1.3

- Battery cycle life loss



- **Reduced 32.1%** total control cost.
- The BESS control is improved by **avoiding discharging when depth-of-discharge is relatively high**

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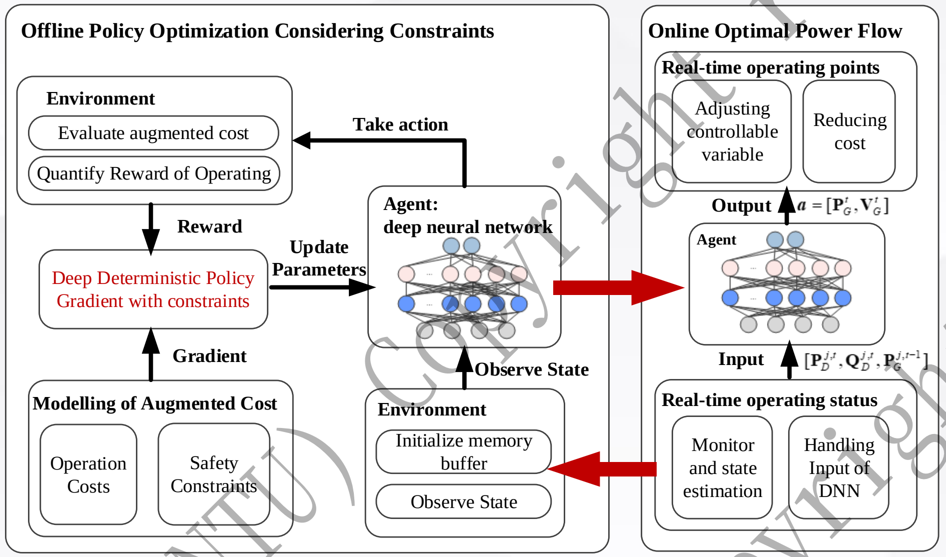
Real-Time Computation of Optimal Power Flow (RT-OPF)



Train the DRL agent by optimizing augmented action-value function to consider constraints

$$\min_{\theta} \sum_{i}^{N} L_i(a_i, \theta, \lambda, \mu)$$

$$\boldsymbol{L}(\boldsymbol{a}_t, \theta, \lambda, \mu) = \sum_{\boldsymbol{i}=1}^{N_G} \boldsymbol{C}_{Gi}(\boldsymbol{a}_t) + \sum_{\boldsymbol{j}=1}^{N_\lambda} \lambda_j \boldsymbol{g}_j(\boldsymbol{a}_t) + \sum_{\boldsymbol{k}=1}^{N_\lambda} \mu_k \boldsymbol{h}_k(\boldsymbol{a}_t)$$

***Lagrangian* function**
(primal-dual reinforcement learning)

Method	Average generation cost (USD\$)	Average absolute errors of P_G (MW)	Inequality Constraints	Average time saving
IP method OPF (benchmark)	1.3018×10^5	0.00	All satisfied	0.0%
DC OPF	1.3076×10^5	0.610	Branch flow and nodal voltage not satisfied	90.1%
Supervised learning using a DNN	1.2997×10^5	5.018	Branch flow and generator ramping not satisfied	99.8%
Proposed method	1.3018×10^5	0.186	All satisfied	99.8%

Model-assisted gradient derivation

Expand with mini-batch gradient descent:

$$\nabla_\theta L = \nabla_{\boldsymbol{a}} L \cdot \nabla_\theta \boldsymbol{a}$$

$$\nabla_{\boldsymbol{a}} L = \nabla_{\boldsymbol{a}}(C'_{P_G}(\boldsymbol{a})) + \nabla_{\boldsymbol{a}}(\sum_{k=1}^{N_\lambda} \mu_k h_k(\boldsymbol{a}))$$

$$\nabla_\theta \boldsymbol{a} = \nabla_\theta(f_\theta^{(n)}[\ldots f_\theta^{(1)}([\mathbf{P}_D^{j,t}, \mathbf{Q}_D^{j,t}, \mathbf{P}_G^{j,t-1}]^T))])$$

$$\begin{bmatrix} \nabla_{\boldsymbol{a}} L \\ \Delta\lambda \end{bmatrix} \approx \begin{bmatrix} W & G^T \\ G & 0 \end{bmatrix}^{-1} \left[\begin{matrix} -\nabla C(\boldsymbol{a}) - H^T \mu \\ -g(\boldsymbol{a}) \end{matrix} - \begin{pmatrix} H^T \\ 0 \end{pmatrix} \Delta\mu \right]$$

where, $G = \partial g(\boldsymbol{a}) / \partial \boldsymbol{a}$, W is the Hessian matrix of Lagrangian, $H = \partial h(\boldsymbol{a}) / \partial \boldsymbol{a}$.

Z. Yan and Y. Xu, "Real-Time Optimal Power Flow: A Lagrangian based Deep Reinforcement Learning Approach," **IEEE Trans. Power Systems, 2020.**

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Data-analytics for customers

Big Question:

How to **leverage data for customer analysis and management**, i.e., to improve their energy efficiency, reduce their energy cost.

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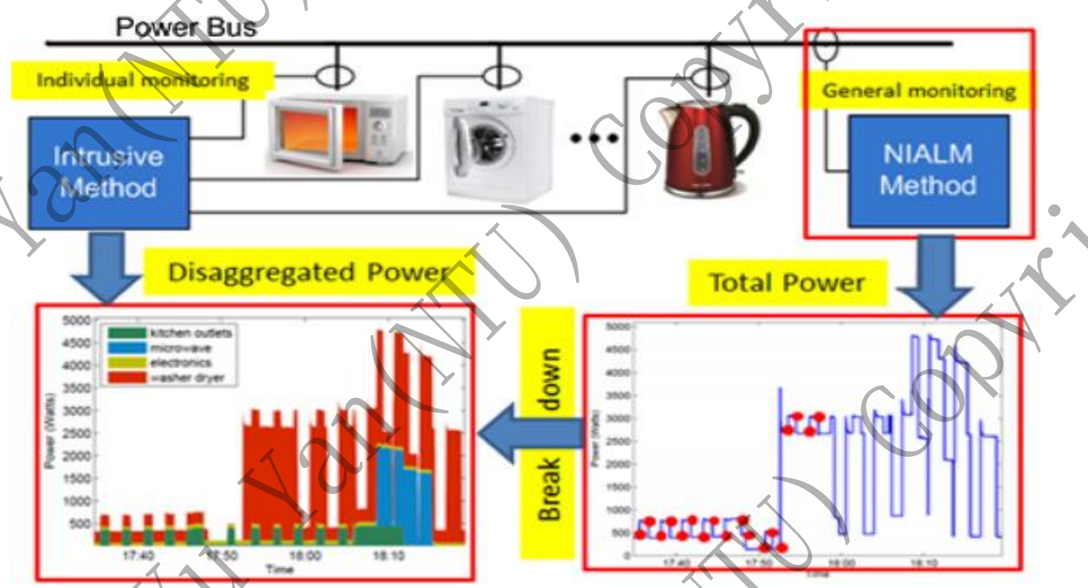
Non-Intrusive Load Monitoring (NILM): Introduction

Non-Intrusive Load Monitoring (NILM)

- Using a single aggregated power meter measurement to disaggregate the different components non-intrusively
- Optimization-based method [1]
- Machine learning-based method (this project)
- Concept is applied to Industrial Building Cooling Systems

A Typical NILM Residential Network Application



Application Benefits

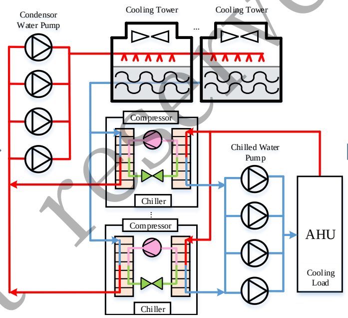
- Improves system visibility with only 1 aggregated meter. Do not need full sub-metering. Significant saving of infrastructure investment.
- Increases the monitoring system reliability without having to be fully dependent on single point of failure
- Allows for operation analytics to identify upgrades for energy savings
- Itemized energy use for dynamic demand response assessment
- Develop energy usage pattern for Load Management Schemes and Electricity Retail Schemes Recommendation

[1] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo and Y. Xu, "Improving Nonintrusive Load Monitoring Efficiency via a Hybrid Programing Method," **IEEE Transactions on Industrial Informatics, 2016.**

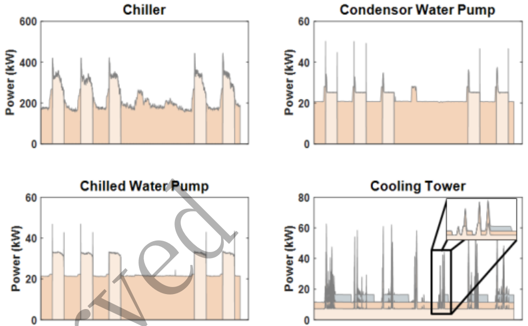
Non-Intrusive Load Monitoring (NILM): A Case Study for Chiller Plant Data

Nanyang Technological University's Clean Tech One Building

Chiller Plant System



System Diagram



Cooling Sub-System Exploratory Data Analysis

Conventional System Monitoring Approach

- Rely on accurate physical model of building systems
- Difficulty in model parameters estimation due to lack of detailed building system operating information
- Requires multiple domain expert to build up accurate physical building system model

Data-Driven NILM Approach

- A end-to-end machine learning black box approach
- Rely on data processing, features engineering and extraction, machine model design and output post processing to build a accurate machine model of the system
- Requires minimal domain knowledge to build up machine model.

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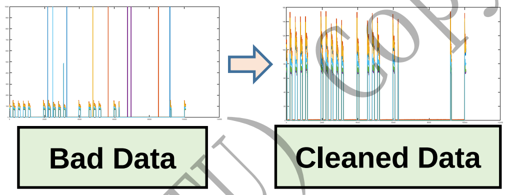
Non-Intrusive Load Monitoring (NILM): Deep Learning Methodology

Data Preprocessing

- Data Time Stamp Synchronization
- Bad Data Identification
- Empty Data Filling



Exploratory Data Analysis

- Identify Input-Output Data Relations such as correlation analysis and
- Identify System Operation such as Sequential or Stacked Mode of Operation
- Identify Load Percentage Composition

Features Extraction

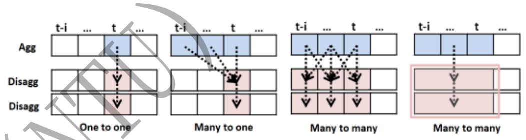
- Minimal Power Domain Knowledge; i.e. Complex Power (S), Power Factor (PF)

$$S = \sqrt{P^2 + Q^2}, \quad PF = \frac{P}{S}$$

- Minimal Cooling System Domain Knowledge; i.e. Cooling Tower Operation is correlated with outdoor wet bulb temperature.

Features Engineering

- Sub-System operates over a period of time; i.e. Data Modelling



Machine Model Design

- Input-Output Model Design; i.e. Multi-Input-Single-Output, etc.
- Base Neural Network Architecture Selection; i.e. RNN, CNN, Attention, etc.
- Parameter Tuning
- Weighted Loss Design

$$Loss = \sqrt{\frac{\sum_{i,j=\{1,1\}}^{i,j=\{T,N\}} w_{i,j}\left(P_{i,j} - y_{i,j}\right)^2}{T * N}}$$

Output Post Processing

- Output Aggregation for Multi-Output Machine Model Prediction
- Minimal Sub-System Operation Time, Power and Time of Use

B. S. H. Chew, Y. Xu, et al "An Ensemble Modal Approach for Load Monitoring / Profiling of Low Correlated Equipment for a Chiller Plant System", **copyrighted software**, TD/2019-303, Oct. 2019. – transferred to Singtel.

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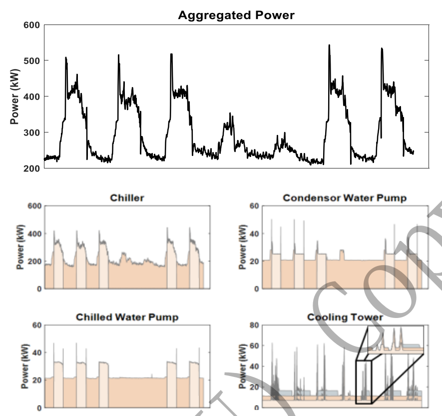
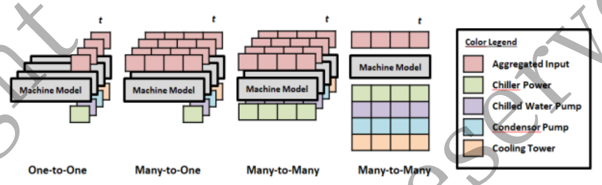
Non-Intrusive Load Monitoring (NILM): Simulation Results

Training Period: 22/10 to 31/10



Low Correlation

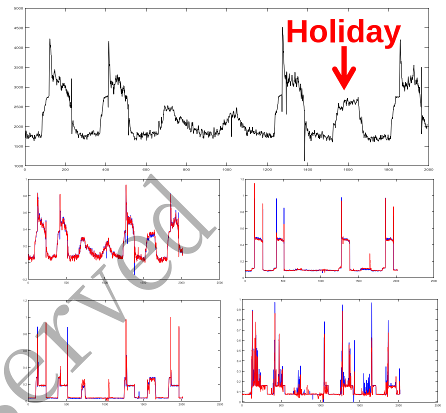
Model Design Iteration



Input Output Correlation Analysis

	CH	CDWP	CHWP	CT	Total (A)
CH	1.000	0.774	0.896	0.493	0.995
CDWP	0.774	1.000	0.740	0.466	0.799
CHWP	0.896	0.740	1.000	0.468	0.909
CT	0.493	0.466	0.468	1.000	0.571
Total (A)	0.995	0.799	0.909	0.571	1.000
Total (R)	0.926	0.979	0.752	0.533	0.939
ODWBT	0.621	0.432	0.449	0.110	0.586

Testing Period: 01/11 to 07/11



Blue: True Value
Red: Estimated Value

Simulation (Mean Absolute Percentage Error)

Case	Chiller MAPE (%)	CHWP MAPE (%)	CDWP MAPE (%)	CT MAPE (%)
1	2.026	1.297	2.538	15.246
2	1.886	1.084	1.542	10.856
3	**1.899**	**0.916**	**1.157**	**9.718**

Case 1: Base Case (LSTM and 1 Layer of Neurons)
Case 2: Case 1 with Multi-Input-Multi-Output Data Modeling
Case 3: Case 2 with Dynamic Weights based on the ratio between of predicted and true values

Simulation Discussion

- Design of Features Engineering and Data Modelling is effective to account for minimal domain expert knowledge
- Deep Network may not be effective when you have low amount and unequal classes of training data.
- Weighted Loss Function is effective when the weights are based on a function between the true and predicted value
- Machine learning is applied due to non-visible event-based features signature in the load profile

B. S. H. Chew, Y. Xu, et al "An Ensemble Modal Approach for Load Monitoring / Profiling of Low Correlated Equipment for a Chiller Plant System", **copyrighted software**, TD/2019-303, Oct. 2019. – transferred to Singtel.

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Data-driven Home Energy Management (HEM): Background

Importance of HEM

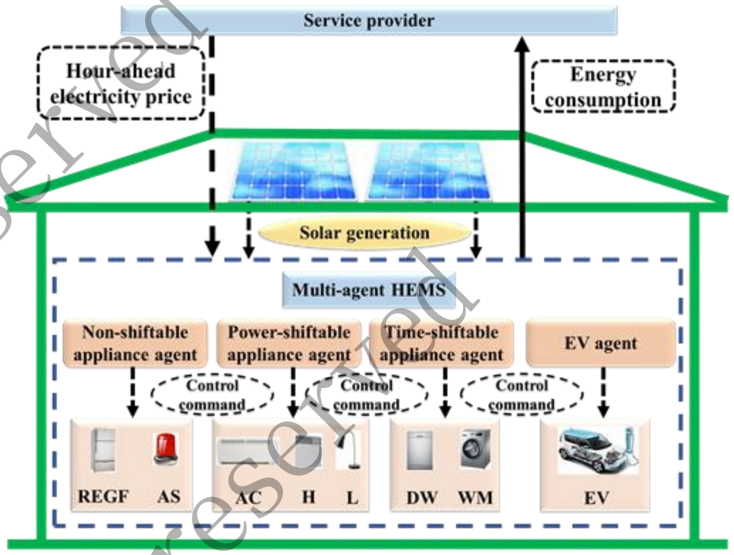
- Power Grid: local renewable energy consumption
- Consumers: Reduction of electricity bills (demand response)

Different load types

- Non-shiftable loads, e.g. refrigerator and alarm system
- Power-shiftable loads, e.g. air conditioner, heating and light
- Time-shiftable loads, e.g. wash machine and dishwasher

limits of classic optimization methods

- Low computation efficiency
- Non-optimal results for nonlinear and nonconvex models

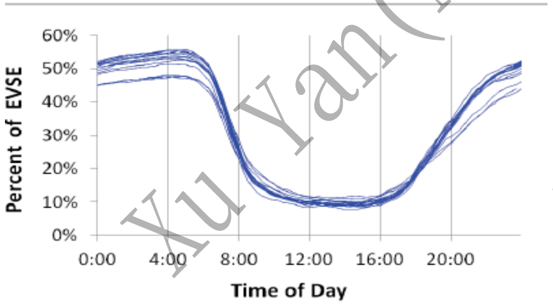


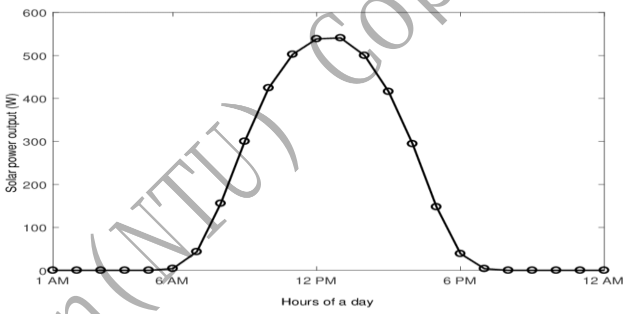
Data-driven based HEM

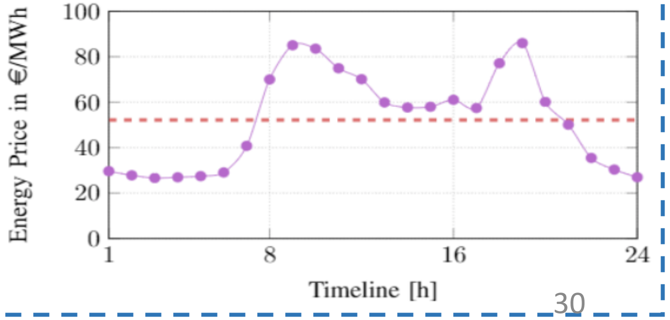
- Uncertainty prediction
- On-line optimal energy scheduling

Uncertainties

- Electric vehicle (EV) loads
- Rooftop photovoltaic (PV) generation
- Electricity prices







0. Outline
1. Overview
2. Power Grid
2.1 Stability analysis
2.2 Frequency control
2.3 Optimal power flow
3. Customer
3.1 Load monitoring
3.2 Home energy management
4. Power Assets
4.1 Power converter
4.2 Battery energy storage

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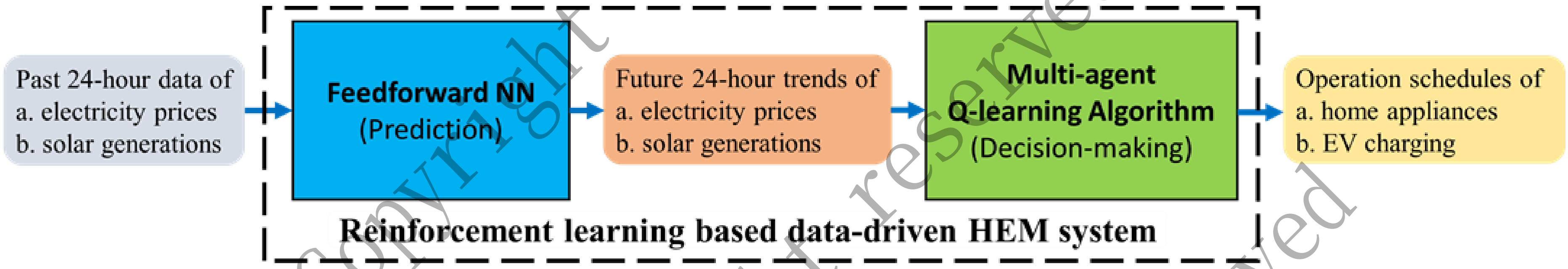
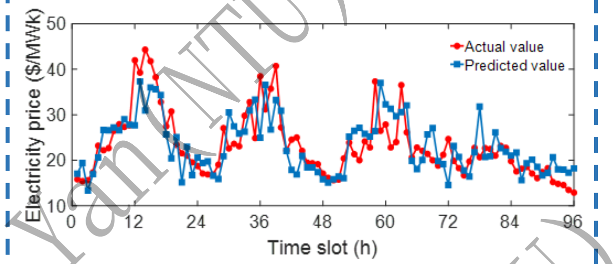
Data-driven Home Energy Management (HEM): Methodology

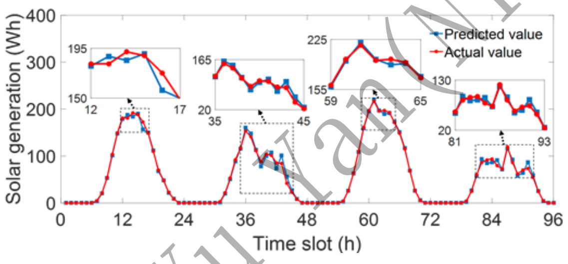
Schematic of the reinforcement learning based data-driven HEM system



Neural Network (NN) based Uncertainty Prediction

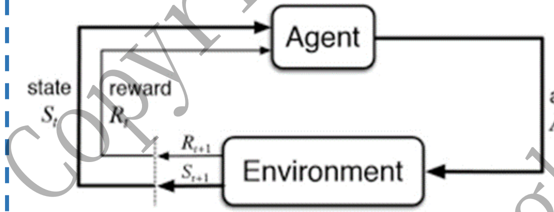


Electricity prices



PV generation

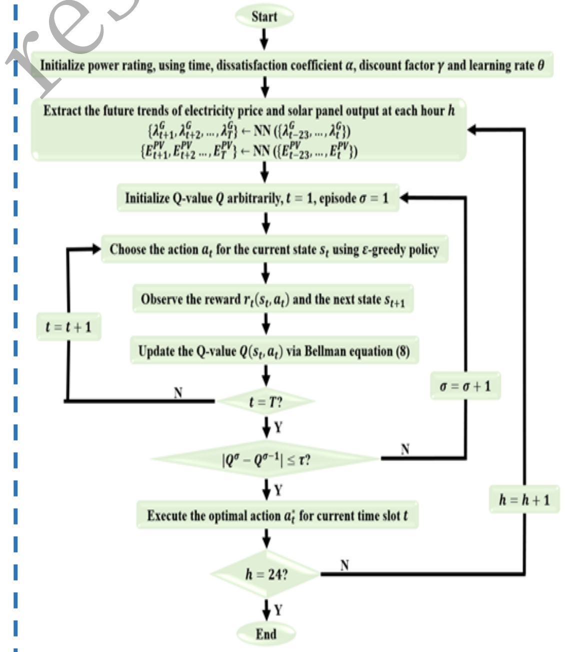
Markov Decision Process (MDP)



- Agent: house owner
- State: predicted information
- Action: energy scheduling
- Reward: (-) utility cost

$$R = -\sum_{t\in T}\left\{ \lambda_t^G \left(\begin{array}{l} [P_{it}^{d,NS} - E_{it}^{PVs}]^+ - [P_{jt}^{d,PS} - E_{jt}^{PVs}]^+ \\ -[u_{mt}P_{mt}^{d,TS} - E_{mt}^{PVs}]^+ - P_{nt}^{d,EV} \end{array} \right) - \left(\begin{array}{l} \alpha_j^{PS}(P_{j,\max}^{d,PS} - P_{jt}^{d,PS})^2 - \alpha_m^{TS}(t_m^s - t_m^{ini})^2 \\ -\alpha_n^{EV}(P_{n,\max}^{d,EV} - P_{nt}^{d,EV})^2 \end{array} \right) \right\}$$

Q-learning Algorithm



X. Xu, Y. Jia, Y. Xu, Z. Xu, et al, "A Multi-agent Reinforcement Learning based Data-driven Method for Home Energy Management," **IEEE Trans. Smart Grid, 2020.**

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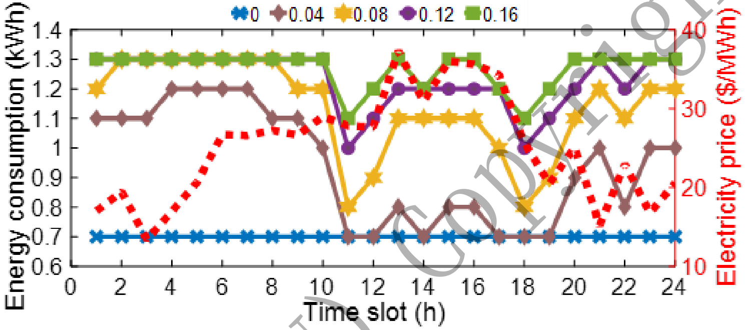
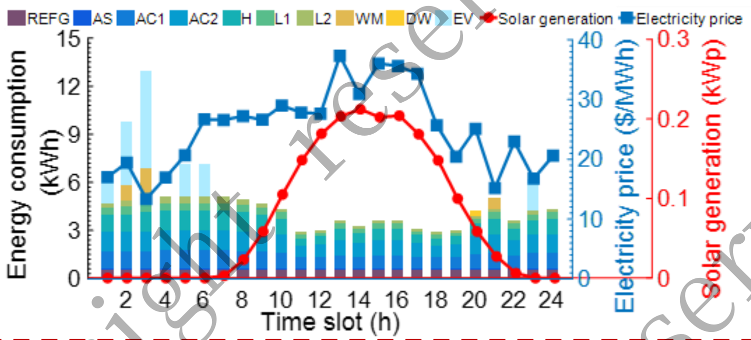
Data-driven Home Energy Management (HEM): Results

Performance of proposed data-driven model

- Reduce electricity costs (via demand response)

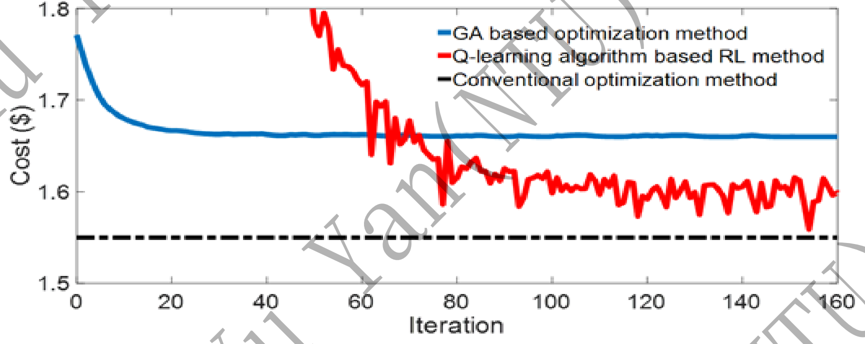


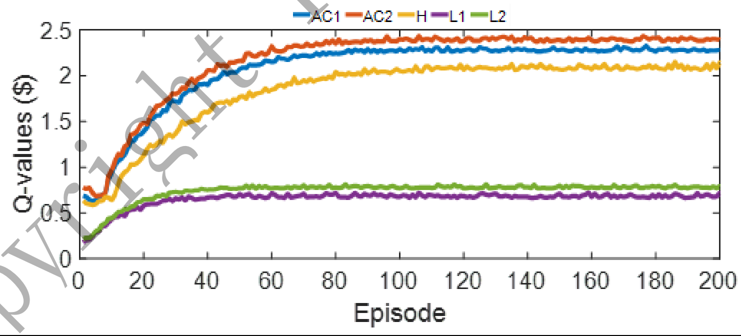


Item ID	Electricity cost ($)	
	With DR	Without DR
REFG	0.492	0.492
AS	0.098	0.098
AC1	0.836	1.378
AC2	0.942	1.378
H	0.731	1.476
L1	0.301	0.591
L2	0.223	0.591
WM	0.023	0.051
DW	0.012	0.012
EV	0.399	1.262
Total	4.057	7.329

Comparison with genetic algorithm

- Higher computation efficiency
- Near-optimal results





	Average computation time of running 1000 times
GA based optimization method	46.296 s
Q-learning algorithm based RL method	1.107 s

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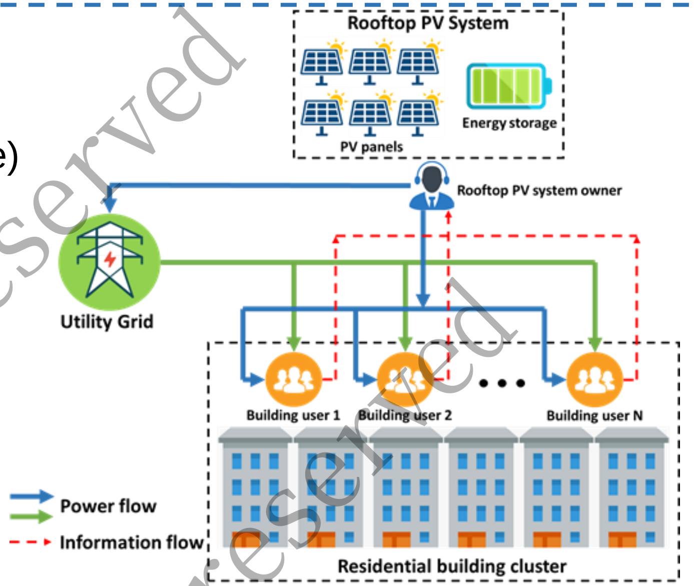
Data-driven Energy Sharing among Buildings: Background

Importance of energy sharing among builidngs
- Power Grid: local renewable energy consumption
- Consumers: reduction of electricity bills (demand response)
- PV system owner: profits

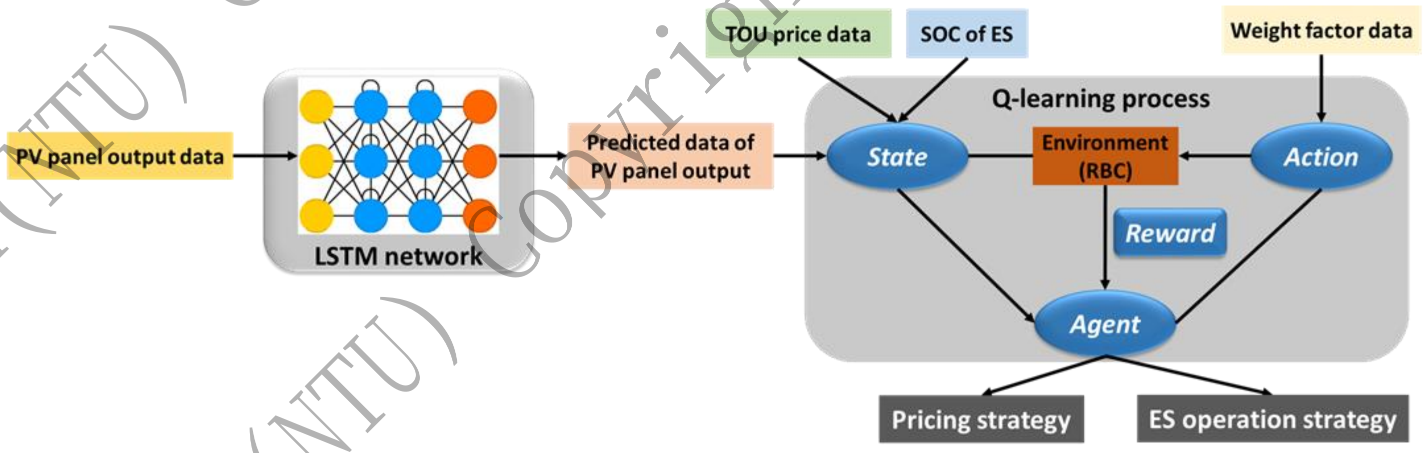
Several deficiencies
- Uncertain renewable generation
- Multiple electricity consumers
- Conflicts of interest

Limits of iterative optimization methods
- Certain assumptions and simplifications for convergence
- Impractical to be used



Data-driven Game-based Energy Sharing

Advantages
- Off-line training and on-line implementation
- Uncertainty consideration
- Near-optimal results



X. Xu, Y. Xu, M. Wang, Z. Xu, J. Li, and S. Chai, "Data-driven Game-based Pricing for Sharing Rooftop Photovoltaic Generation and Energy Storage in the Residential Building Cluster under Uncertainties," **IEEE Trans. Industrial Informatics, 2020.**

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Data-driven Energy Sharing among Buildings: Framework

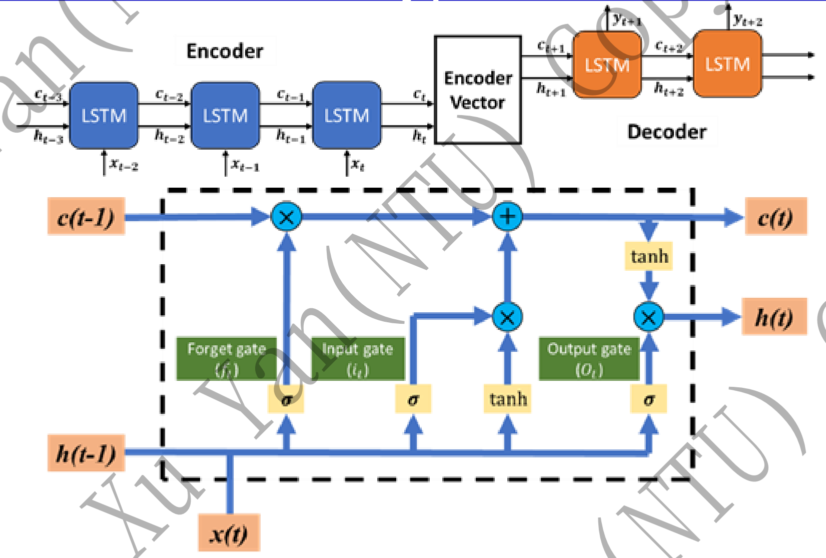
Schematic of the data-driven game-based energy sharing

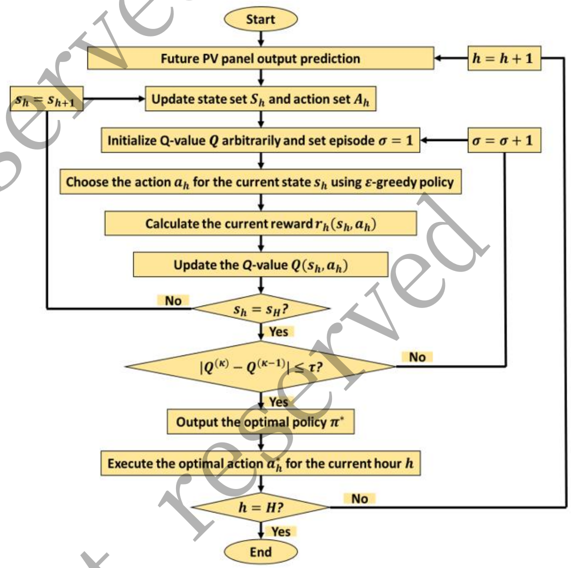
Stackelberg game-based energy sharing

- Leader: Rooftop PV system owner
- Followers: consumers

$$G=\begin{Bmatrix} (Owner \cup Building\ Users) \\ \{\lambda_h^U\},\{P_h^{ES_{in}}\},\{P_h^{ES_{grid}}\} \\ \{P_{ih}^{PV_{user}}\},\{P_h^{ES_{user}}\},\{P_{ih}^G\} \\ \{Rev_h^O\},\{U_{ih}^C\} \end{Bmatrix}$$

Long short-term memory (LSTM) based uncertainty prediction





Markov Decision Process (MDP)

- Agent: Rooftop PV system owner
- State: all system information
- Action: pricing strategies
- Reward: revenue

$$Rev^O=\sum_{h\in H}\begin{Bmatrix} \sum_{i\in N^C}\lambda_h^U(P_{ih}^{PV_{user}}+P_{ih}^{ES_{user}}) \\ +\lambda^{FiT}(P_h^{PV_{grid}}+P_h^{ES_{grid}}) \\ -\lambda_h^{TOU}[\sum_i(P_{ih}^{PV_{user}}+P_{ih}^{ES_{user}})-\bar{P}_h^{PV}]^+ \end{Bmatrix}$$

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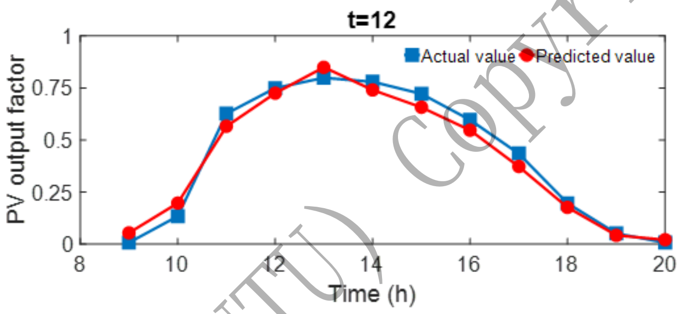
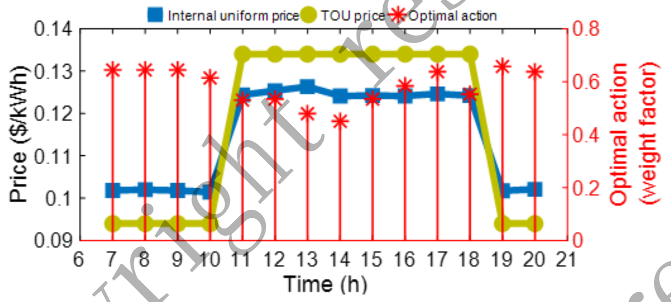
Data-driven Energy Sharing among Buildings: Results

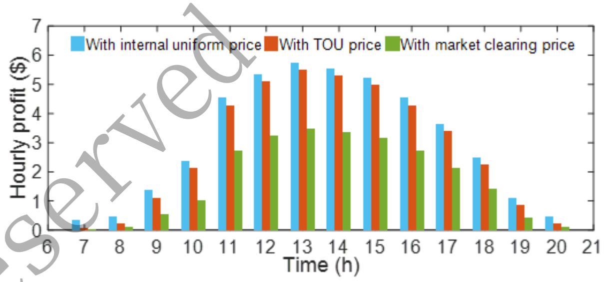
Performance of proposed method

- Accurate PV prediction
- High daily profit
- Well utilization of PV energy

Pricing strategy	Daily profit ($)
Strategy 1: Internal uniform price	41.99
Strategy 2: TOU price	39.71
Strategy 3: Market clearing price	24.47

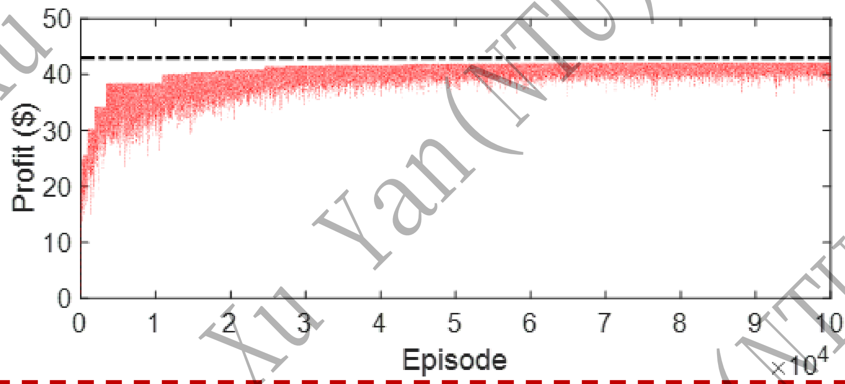


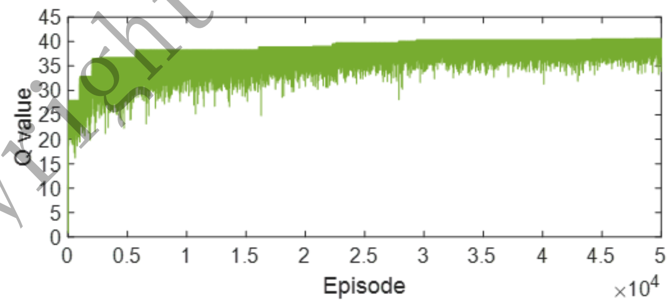




Comparison with optimization solvers

- High computation efficiency
- Near-optimal results





Solution method	Profit ($)	Computation time (s)
Conventional optimization method	43.075	3400.42
Q-learning algorithm	41.994	15.339

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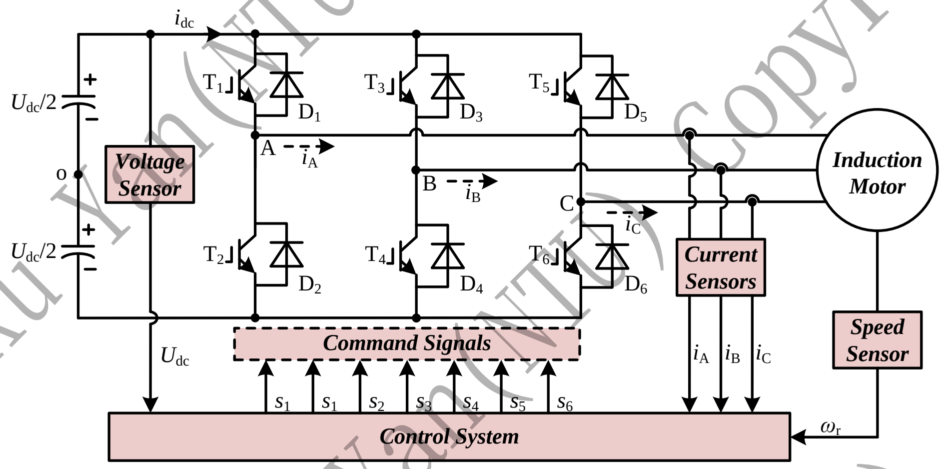
Data-driven Fault Diagnosis of Power Converter Systems: Background

Industrial Application
- High-speed electric train
- HVDC power grid
- Microgrid
- …



Three-Phase Inverter fed induction motor drive system

Two types of fault:

I. Power switch (IGBT) fault

a) Short-circuit fault – can be detected and cleared by the protection system

b) open circuit fault
- **Single IGBT** open-circuit fault
- **Double IGBTs** open-circuit fault

II. Sensor fault
- **Current** sensor
- **Voltage** sensor
- **Speed** sensor

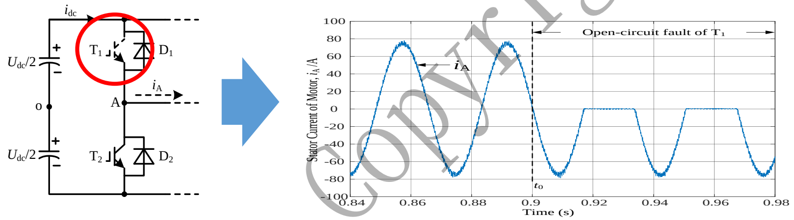
Our research focus

Data-driven Fault Diagnosis of Power Converter Systems: Problem Modeling

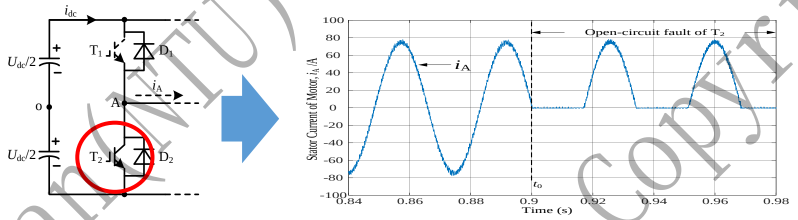
1. Power switch IGBT open-circuit fault

- System keeps up as an abnormal state for sustained period
- Degrade the working performance

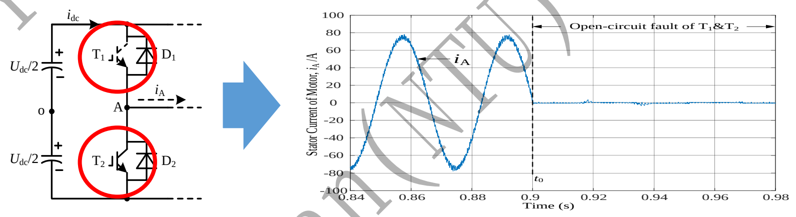
1) The **upper** switch is under open-circuit



2) The **lower** switch is under open-circuit



3) **Both switches** are under open-circuit

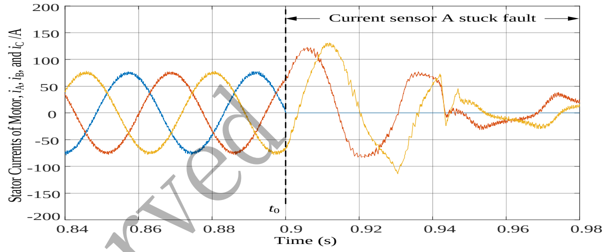


2. Sensor fault

- Equipment aging, environment interference…
- Stuck fault, offset fault, noise fault

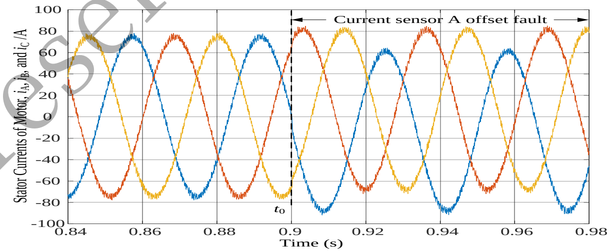
1) **Stuck** fault

$$y = \begin{cases} y_n, & 0 \le t < t_0 \\ C_1, & t \ge t_0 \end{cases}$$



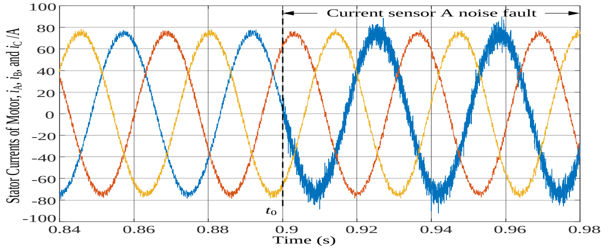
1) **Offset** fault

$$y = \begin{cases} y_n, & 0 \le t < t_0 \\ y_n + N_o, & t \ge t_0 \end{cases}$$



1) **Noise** fault

$$y = \begin{cases} y_n, & 0 \le t < t_0 \\ y_n + C_2, & t \ge t_0 \end{cases}$$



[1] B. Gou, Y. Xu, Y. Xia, et al, "An online data-driven method for simultaneous diagnosis of IGBT and current sensor fault of 3-Phase PWM inverter in induction motor drives," **IEEE Trans. Power Electron., 2020.**
[2] Y. Xia, B. Gou, and Y. Xu, "Current Sensor Fault Diagnosis and Fault-Tolerant Control for Single-Phase PWM Rectifier based on a Hybrid Model-Based and Data-Driven Method," **IET Power Electronics, 2020.**
[3] Y. Xia, Y. Xu and B. Gou, "A data-driven method for IGBT open-circuit fault diagnosis based on hybrid ensemble learning and sliding-window classification," **IEEE Trans. Ind. Inform., 2020**.
[4] B. Gou, Y. Xu, Y. Xia, et al, "An intelligent time-adaptive data-driven method for sensor fault diagnosis in induction motor drive system," **IEEE Trans. Ind. Electron., 2019.**

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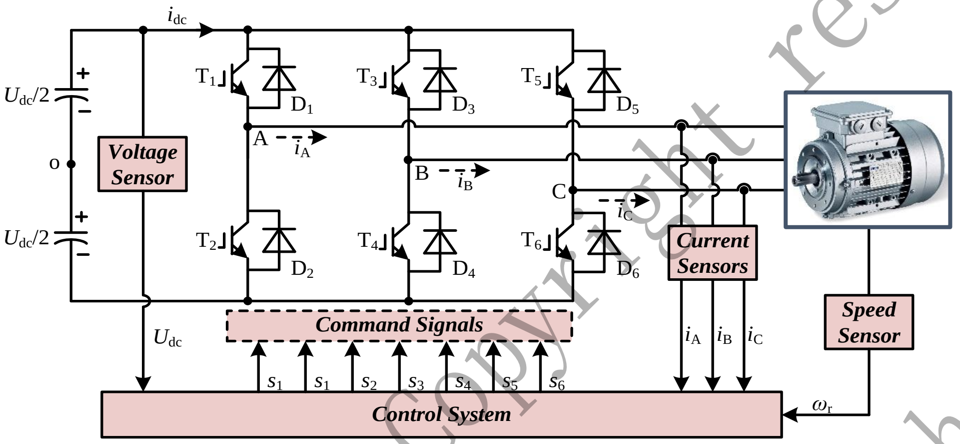
Data-driven Fault Diagnosis of Power Converter Systems: Problem Modeling



Conventional fault diagnosis

1) Model-based methods
- Difficulty to **build an accurate model** of a practical system
- Affected by **model uncertainty** and measurement **noise**

2) Signal-based methods
- **Time-consuming** in signal processing
- Easily affected by **load variation**

Data-driven methods (Multi-Classification)

- Principle: knowledge extraction from a **fault database**
- Advantages: model-free, well generalization ability, robust
- Drawbacks: long decision time, excessive training process

Fault Labelling:

1. IGBT open-circuit fault labelling

- **Single IGBT** open-circuit fault
- **Double IGBTs** open-circuit fault

Fault Type	Label	Fault Type	Label
The Normal State	1	T_1&T_6 Open-circuit	12
T_1 Open-circuit	2	T_2&T_3 Open-circuit	13
T_2 Open-circuit	3	T_2&T_4 Open-circuit	14
T_3 Open-circuit	4	T_2&T_5 Open-circuit	15
T_4 Open-circuit	5	T_2&T_6 Open-circuit	16
T_5 Open-circuit	6	T_3&T_4 Open-circuit	17
T_6 Open-circuit	7	T_3&T_5 Open-circuit	18
T_1&T_2 Open-circuit	8	T_3&T_6 Open-circuit	19
T_1&T_3 Open-circuit	9	T_4&T_5 Open-circuit	20
T_1&T_4 Open-circuit	10	T_4&T_6 Open-circuit	21
T_1&T_5 Open-circuit	11	T_5&T_6 Open-circuit	22

2. Sensor fault labelling

- Current sensor
- Voltage sensor
- Speed sensor

- Stuck fault
- Offset fault
- Noise fault

Fault Type	Label	Fault Type	Label
No Fault	1	DC-link Voltage Sensor Offset Fault	6
Current Sensor of Phase A Stuck Fault	2	DC-link Voltage Sensor Noise Fault	7
Current Sensor of Phase A Offset Fault	3	Speed Sensor Stuck Fault	8
Current Sensor of Phase A Noise Fault	4	Speed Sensor Offset Fault	9
DC-link Voltage Sensor Stuck Fault	5	Speed Sensor Noise Fault	10

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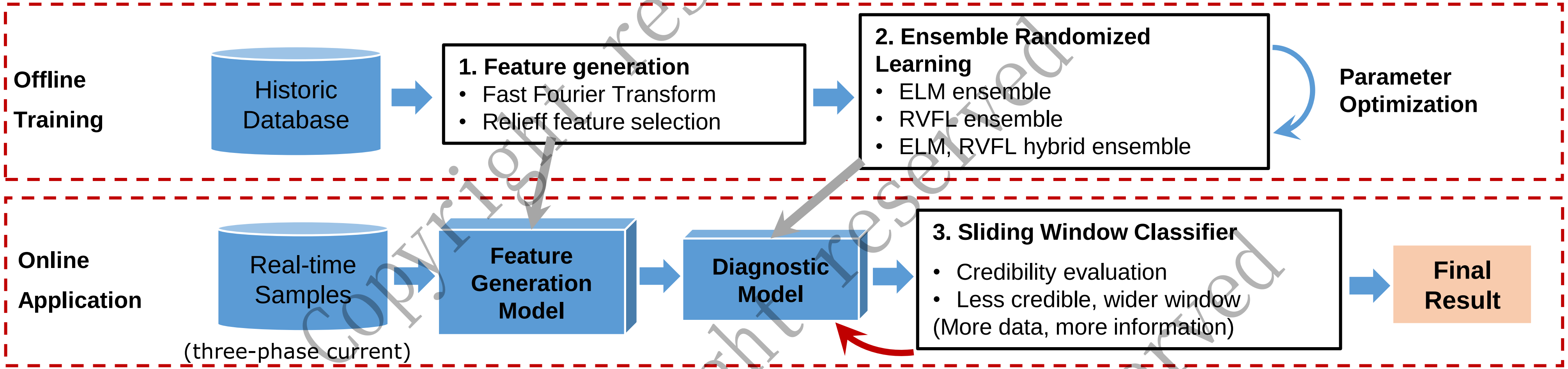
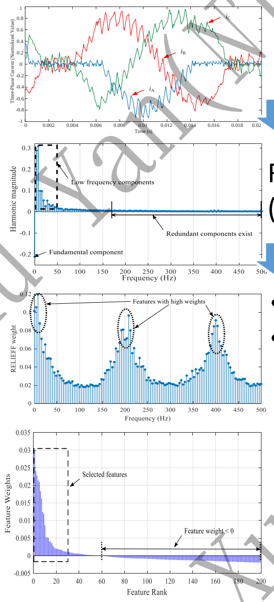
Data-driven Fault Diagnosis of Power Converter Systems: Proposed Methodology



1. Feature generation



Original data
- High dimensionality
- Irrelevant/redundant data

Fast Fourier Transform (FFT)

Frequency-domain components (still high dimensionality)

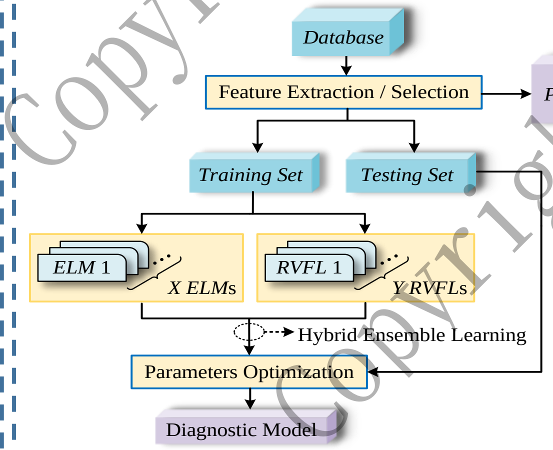
Relieff feature selection

- Calculate feature score
- Rank and select **top** scoring features

$$W[F_i] = W[F_i] - \text{diff}(F_i, \mathbf{x}_k, \mathbf{x}_H)/m + \text{diff}(F_i, \mathbf{x}_k, \mathbf{x}_M)/m$$

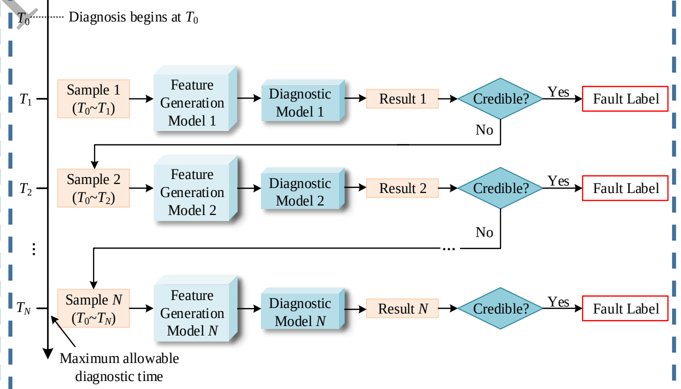
$$\text{diff}(F_i, \mathbf{x}_{k1}, \mathbf{x}_{k2}) = \frac{|\text{value}(F_i, \mathbf{x}_{k1}) - \text{value}(F_i, \mathbf{x}_{k2})|}{\max(F_i) - \min(F_i)}$$

2. Ensemble Randomized Learning



Hybrid Ensemble Learning
- Extreme Learning Machine **(ELM)** + Random Vector Functional Link **(RVFL)**
- **Improve the overall performance**

3. Sliding Window Classifier



- Aim: **Fast decision time with high accuracy**
- Credibility evaluation

Grubbs' outlier test:

$$G = \frac{|\max(o_j) - \mu|}{\sigma} \quad (j = 1, 2, \dots m) \qquad \sigma = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m} |o_j - \mu|^2}$$

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Data-driven Fault Diagnosis of Power Converter Systems: Offline Tests

IGBT Open-circuit Fault Diagnosis

kth classifier	C_k	A_k	M_k	$A_{overall}$	R_k
0	-	-	-	-	1100
1	1048	98.95%	11	98.95%	52
2	45	100%	0	98.99%	7
3	7	100%	0	99.00%	0

C_k: the number of instances which deliver a credible result in the kth classifier

A_k: the accuracy of the kth classifier

M_k: the number of misdiagnosis

$A_{overall}$: **the diagnostic accuracy of all instances**

R_k: the instance number remaining for next classifiers.

Comparison with other algorithms

Diagnosis method	Diagnostic accuracy	Offline test time
FFT+PCA+BN	81.75 %	1.2340 s
PCA+RVM	94.59 %	7.3723 s
Time-domain feature + SVM	87.47 %	3.3140 s
Ensemble ELM	93.03 %	1.4170 s
Ensemble RVFL	91.67 %	1.4231 s
The proposed method	96.70 %	1.3799 s

Sensor Fault Diagnosis

W_i	$U(W_i)$	$C(W_i)$	$C(W)$	$M(W_i)$	$M(W)$	$A(W_i)$	$A(W)$
0	660	-	-	-	-	-	-
1	60	600	600	6	6	99.0%	99.0%
2	38	22	622	1	7	95.5%	98.9%
3	26	12	634	0	7	100%	98.9%
4	21	5	639	0	7	100%	98.9%
5	1	20	659	6	13	70.0%	98.0%

W_i: the ith time-window

$U(W_i)$, $C(W_i)$: the number of unclassified and classified instances during the current time- window

$C(W)$: the total number of accumulative classified instances

$M(W_i)$, $M(W)$: the current and accumulative number of misclassified instances

$A(W_i)$, $A(W)$: the current and accumulative accuracy of the time-window

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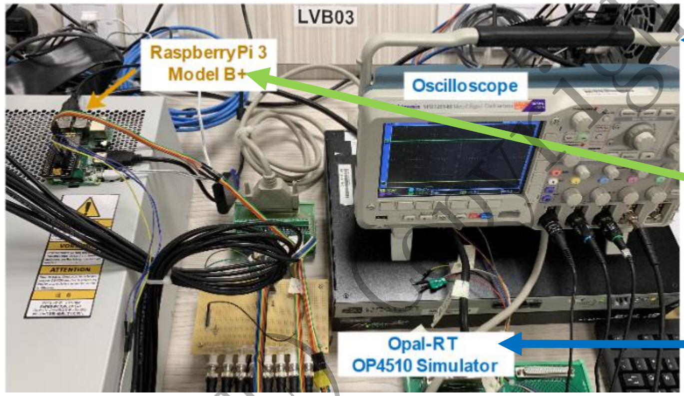
Data-driven Fault Diagnosis of Power Converter Systems: Hardware-in-the-loop Real-Time Tests

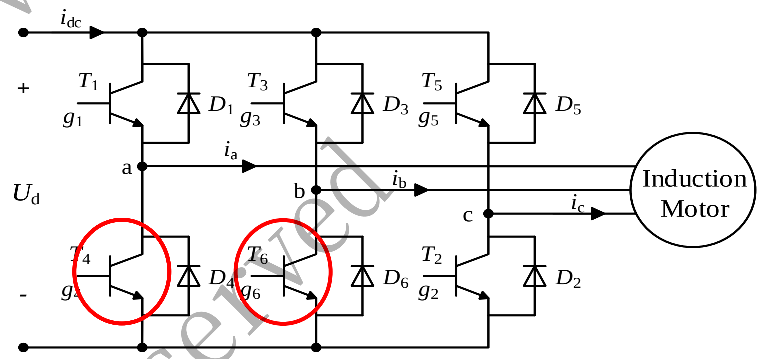
Experimental Platform



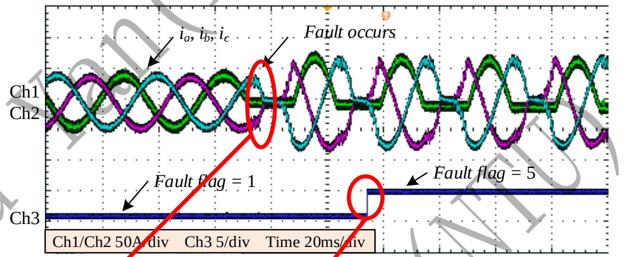
Computer: Real-time control interface

RaspberryPi3 microcontroller: The proposed data-driven fault diagnosis

Opal-RT OP4510 simulator: Hardware circuits of the load and converter topology

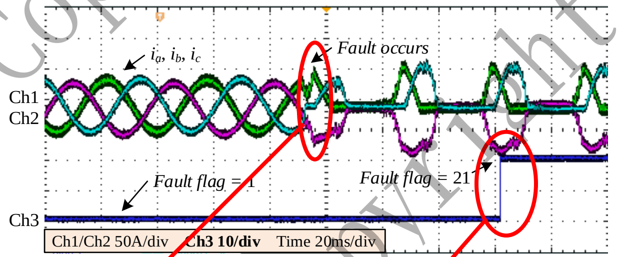


IGBT open-circuit fault diagnosis



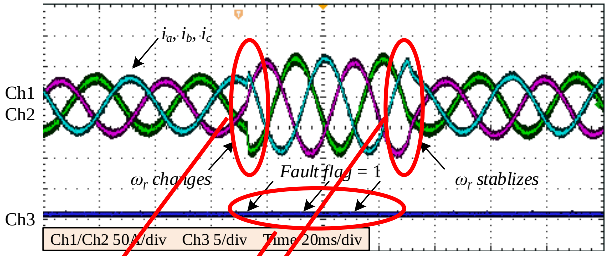
T_4 open-circuit fault occurs

Diagnostic result (**Fault flag 5**) is obtained within one cycle sampling time



T_4, T_6 double open-circuit fault occurs

Diagnostic result (**Fault flag 21**) is obtained with **two-cycle** sampling data



Load variation (speed changes)

No fault detected as this is just a load change (**Fault flag 1**)

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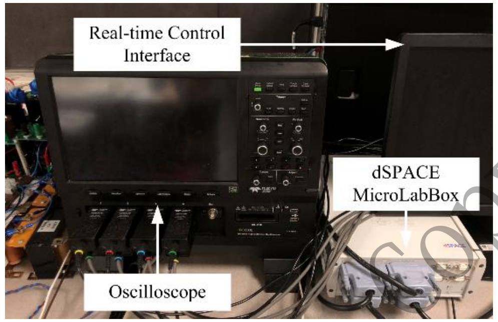
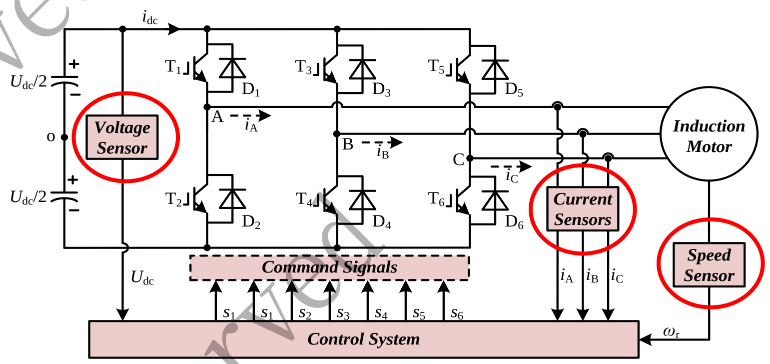
Data-driven Fault Diagnosis of Power Converter Systems: Hardware-in-the-loop Real-Time Tests

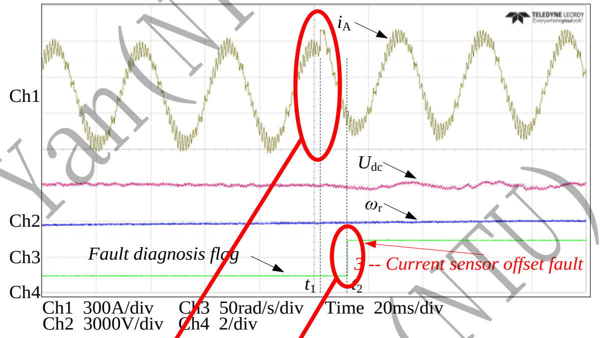
Experimental Platform

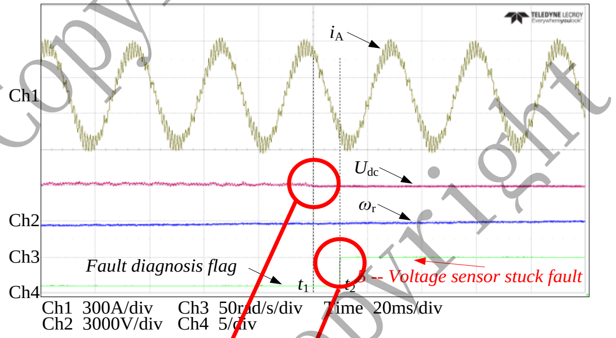


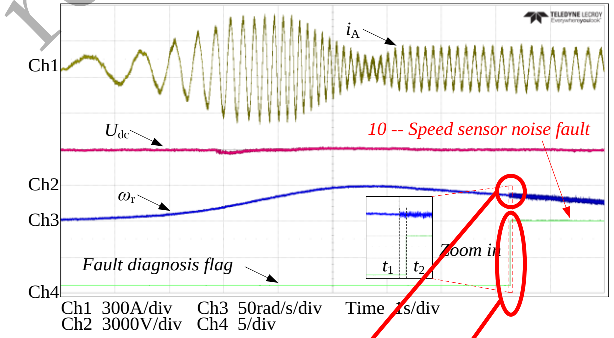
- **A controller**: generate command signals of IGBTs
- **A dSPACE MicroLabBox simulator**: hardware circuits and sensors
- **A computer**: a real-time control interface



Sensor fault diagnosis







Current Sensor of Phase A **Offset** Fault

Diagnostic result (**Fault flag 3**) is obtained within 10ms

Voltage Sensor Stuck Fault

Diagnostic result (**Fault flag 5**) is obtained within 10ms

Speed Sensor Noise Fault

Diagnostic result (**Fault flag 10**) is obtained within 10ms

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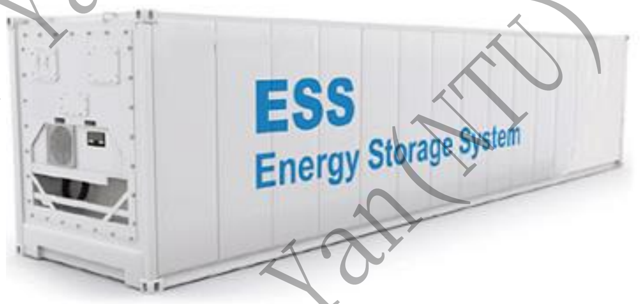
Battery State-of-Health (SOH) Monitoring : Background

Wide application of Li-ion batteries:

- Electric vehicles (EVs)
- Energy storage systems (UPS, power grid support)
- Consumer electronics (smart phones, laptops, cameras)
- …

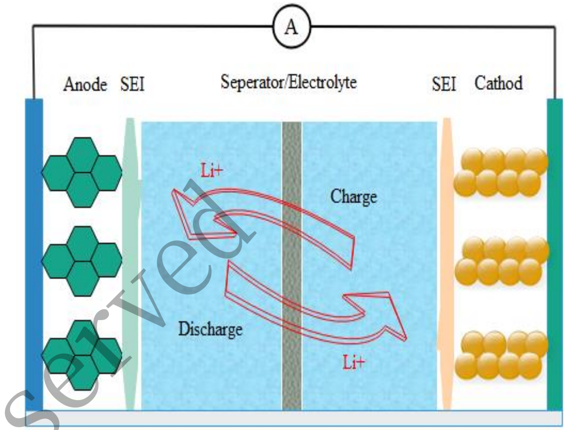
EV

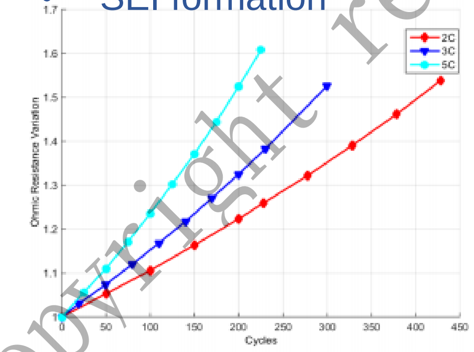


Energy storage systems

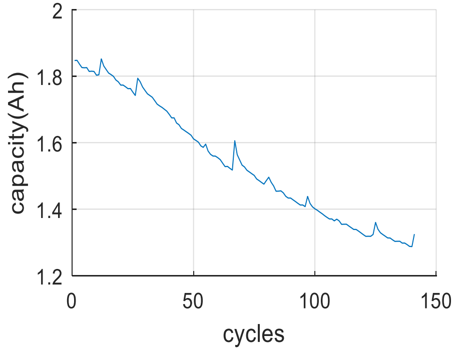
Health degradation of Li-ion batteries:

- Lithium consumption
- Lithium plating
- Electrolyte decomposition
- Electrode expansion
- Gas evolution
- Insoluble products
- SEI formation





Internal resistance ↑



Remaining capacity ↓

Monitoring the battery state of health (SOH) and predicting the remaining useful life (RUL) are necessary in a Battery Management System (BMS).

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SOH estimation: Conventional Methods

1) Direct measurement method

A. Internal resistance measurement via pulse current injection

$$R = \frac{\Delta U}{\Delta I}$$

$$\mathrm{SOH} = \frac{R_{EOL} - R_{current}}{R_{EOL} - R_{initial}} \times 100\%$$

- Can only be conducted offline
- Special testing equipment required
- Complex process

B. Capacity measurement via full charging & discharging (Column counting)

$$Cap_{current} = \int_{t1}^{t2} I(t)dt$$

$$\mathrm{SOH} = \frac{Cap_{current}}{Cap_{nominal}} \times 100\%$$

- Time-consuming
- Difficult to implement in practice

2) Model-based method

A. Electrochemical model

$$J_{FD,i} = J_{0,i}\left[\exp\left(\frac{\alpha F}{RT}\eta_i\right) - \exp\left(-\frac{(1-\alpha)F}{RT}\eta_i\right)\right]$$

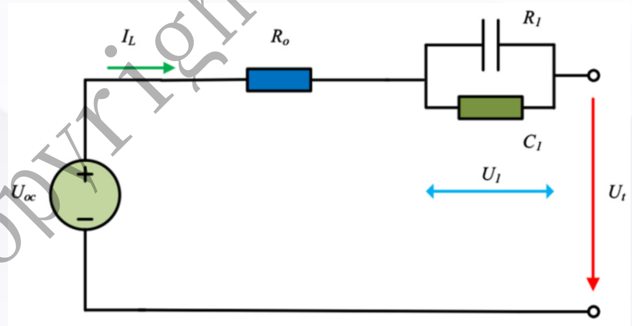
Butler–Volmer equation

$$\frac{\partial C_{1,i}}{\partial t} = \frac{D_{1,i}}{r_i^2}\frac{\partial}{\partial r_i}\left(r_i^2 \frac{\partial C_{1,i}}{\partial r_i}\right)$$

Fick's second law

- Describes the dynamics of electro-chemical reactions of the charging/discharging process
- Accurate but too complex

B. Equivalent circuit model



Thevenin model

- Neglects the internal aging mechanism
- Difficult for parameter estimation

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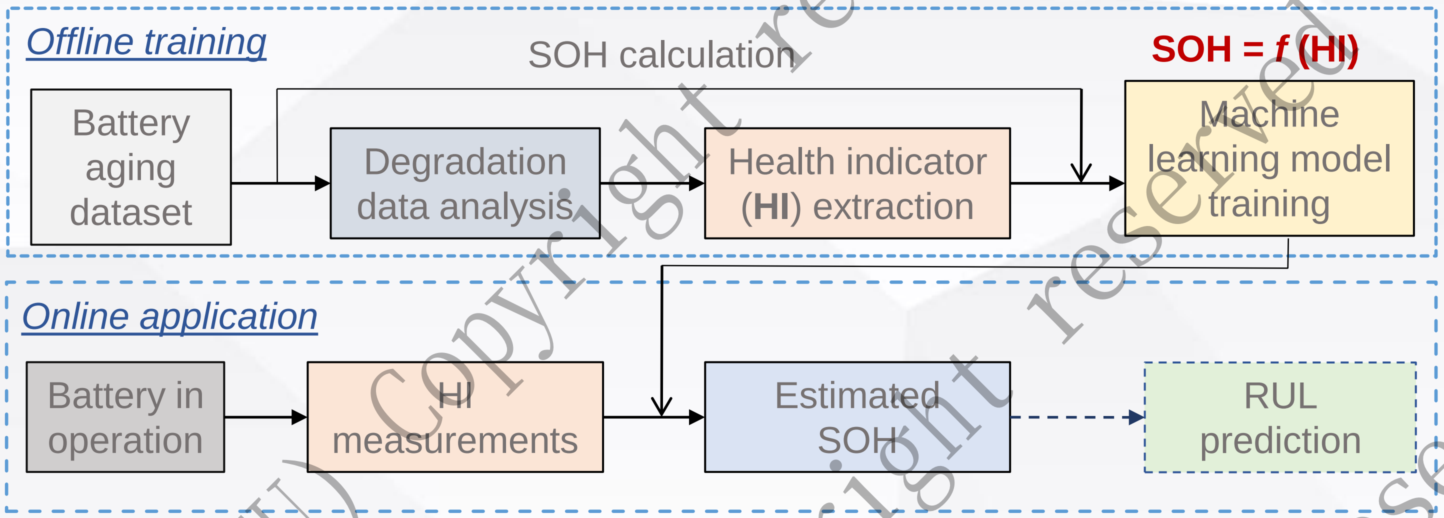
SOH estimation and RUL prediction: Data-driven methods



Principle of data-driven SOH estimation & RUL prediction

Advantages:

- No need for the aging mechanism modeling or equivalent circuit models
- Flexible and easy to apply
- Online/real-time computation

Limitations of existing data-driven methods:

- *Conventional health indicators*
  - Extracted from constant current charging/discharging process
  - A wide range of voltage curve required
  - Operating conditions of the training and testing batteries are the same
- *Conventional machine learning algorithms*
  - Artificial neural network, Regression tree, etc.

Our research efforts:

- *Extract novel health indicators*
  - Adaptable to different working conditions
  - Easy to obtain
  - Highly correlated with SOH
- *Develop advanced learning models*
  - Strong approximation ability
  - Low computational cost
  - High reliability
  - Transferrable

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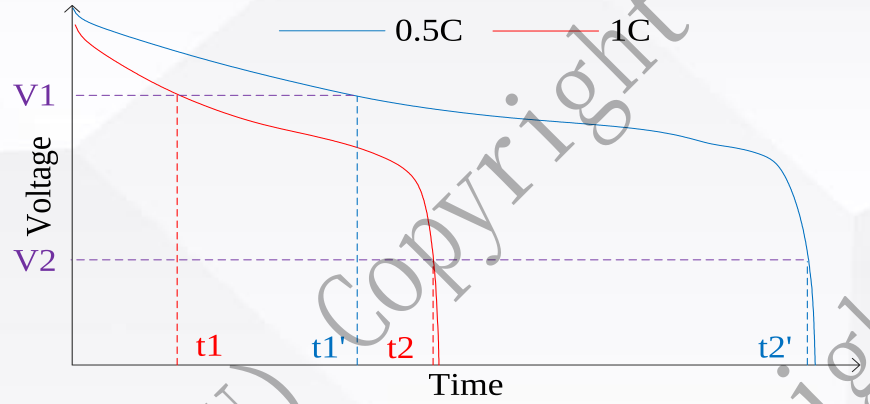
Health Indicators (HIs): Our Method

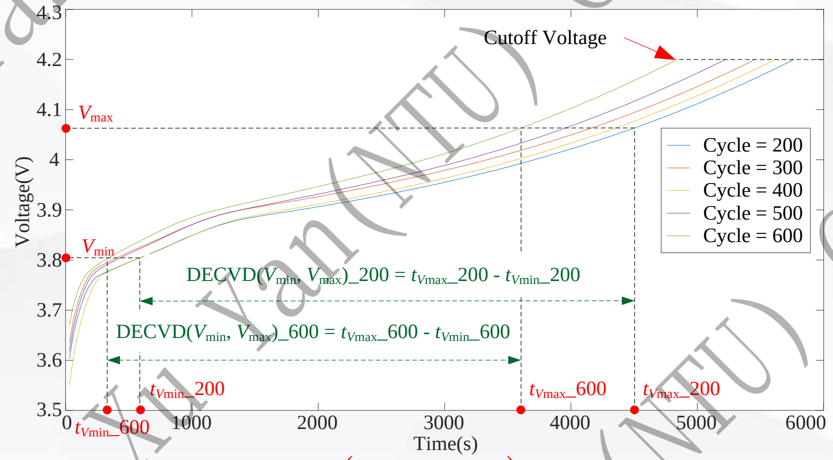
HI #1: Energy of an equal discharging voltage difference (**EEDVD**) – for discharging mode



$$EEDVD = \int_{t1}^{t2} v(t) \cdot I dt$$

- The EEDVD is extracted from the discharging process.
- The discharging current is constant.
- A wide range of voltage segment is needed for HI extraction.
- The discharging currents of the training and testing batteries can be different.

HI #2: Duration of equal charging voltage difference (**DECVD**) – for charging mode



$$DECVD\left(V_{\min}, V_{\max}\right) = t_{V_{\max}} - t_{V_{\min}}$$

- The DECVD is extracted from the charging process, which is more controllable in some applications (i.e., EVs, cell phones).
- A wide range of voltage segment is needed for HI extraction.
- The charging current is constant.
- The charging currents of the training and testing batteries are identical.

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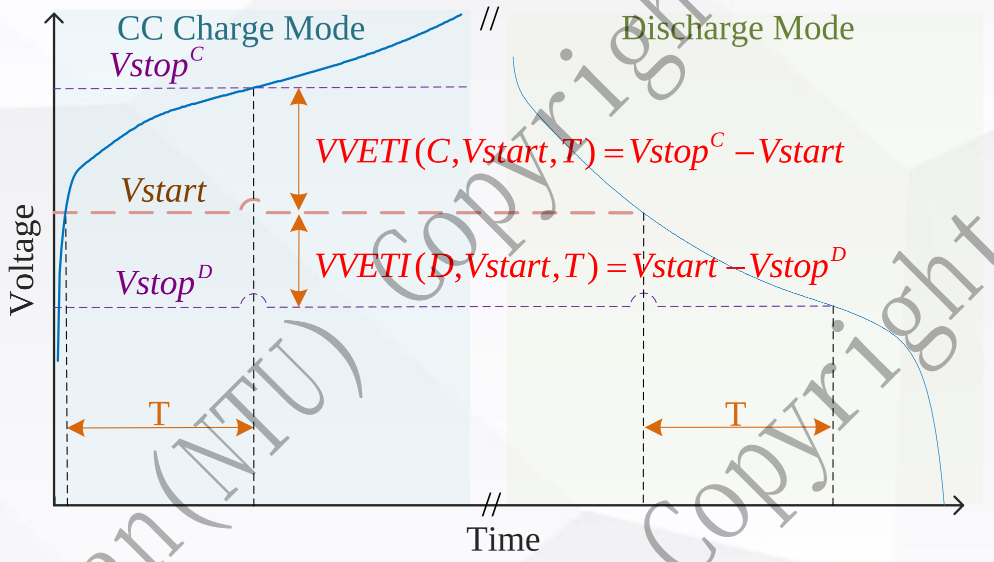
Health Indicators (HIs): Our Method

HI #3: Voltage variance of an equal time interval (**VVETI**) – for both charging and discharging mode



1) Determine the starting point of voltage $Vstart$ and record the corresponding time point $t1$.
2) Decide time interval *T*.
3) Read the voltage $Vstop$ at $t2 = t1 + T$.
4) VVETI is computed as

$$VVETI(M, Vstart, T) = |Vstop - Vstart|$$

where M is either C or D, referring to charging and discharging modes, respectively.

- The VVETI can be extracted from both the charging and discharging processes.
- A very small range of voltage segment is needed for the HI extraction.
- The voltage range for HI extraction is flexible.
- The charging/discharging current is constant.
- The charging currents of the training and testing batteries are identical.

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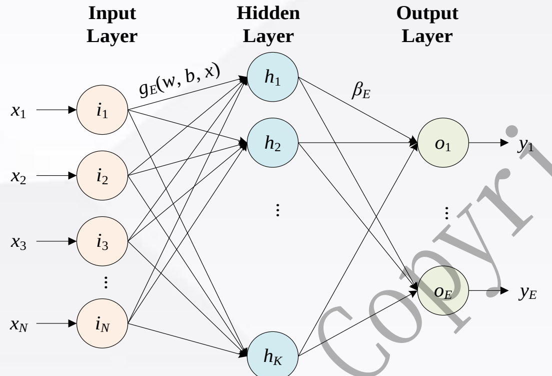
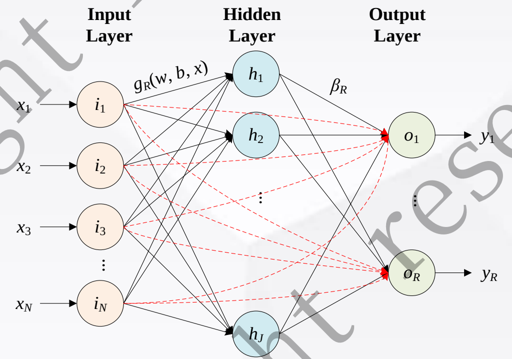
Machine Learning: Our Method

0. Randomized learning algorithms



Extreme learning machine (ELM)
- Proposed by Prof. G.B. Huang (NTU)

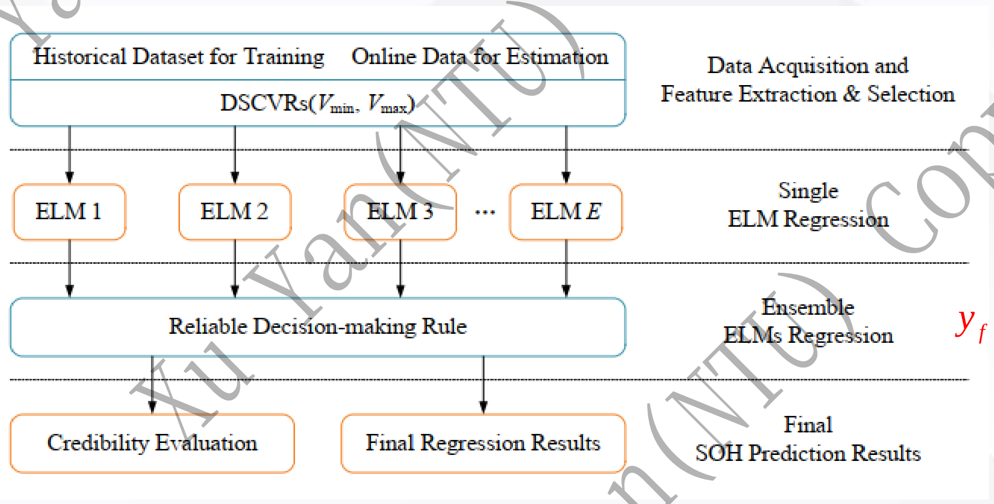
$$Y = g(W \cdot X^T + b)^T \cdot \beta$$



Randomized vector functional link (RVFL)
- Proposed by Prof. P. N. Suganthan (NTU)

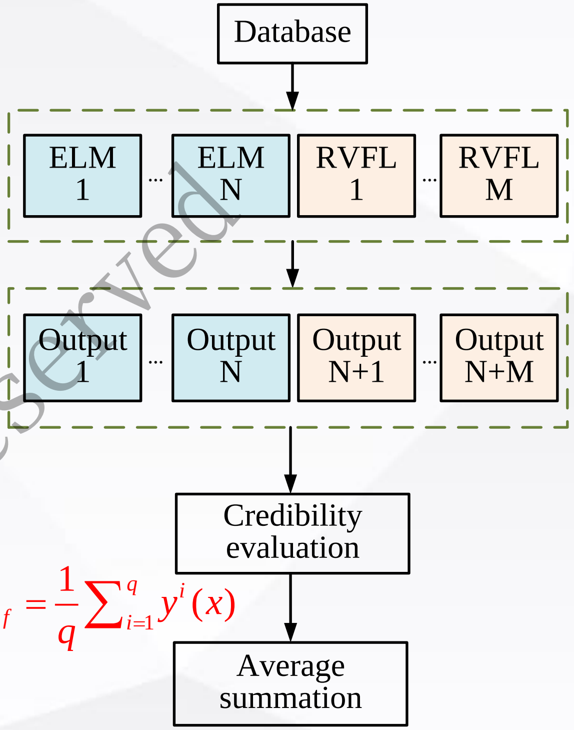
$$Y = [X, g(W \cdot X^T + b)^T] \cdot \beta$$

1. Ensemble of ELM model



$$y_f = \frac{1}{q}\sum_{i=1}^{q} y^i(x)$$

2. Hybrid ensemble of ELM & RVFL



$$y_f = \frac{1}{q}\sum_{i=1}^{q} y^i(x)$$

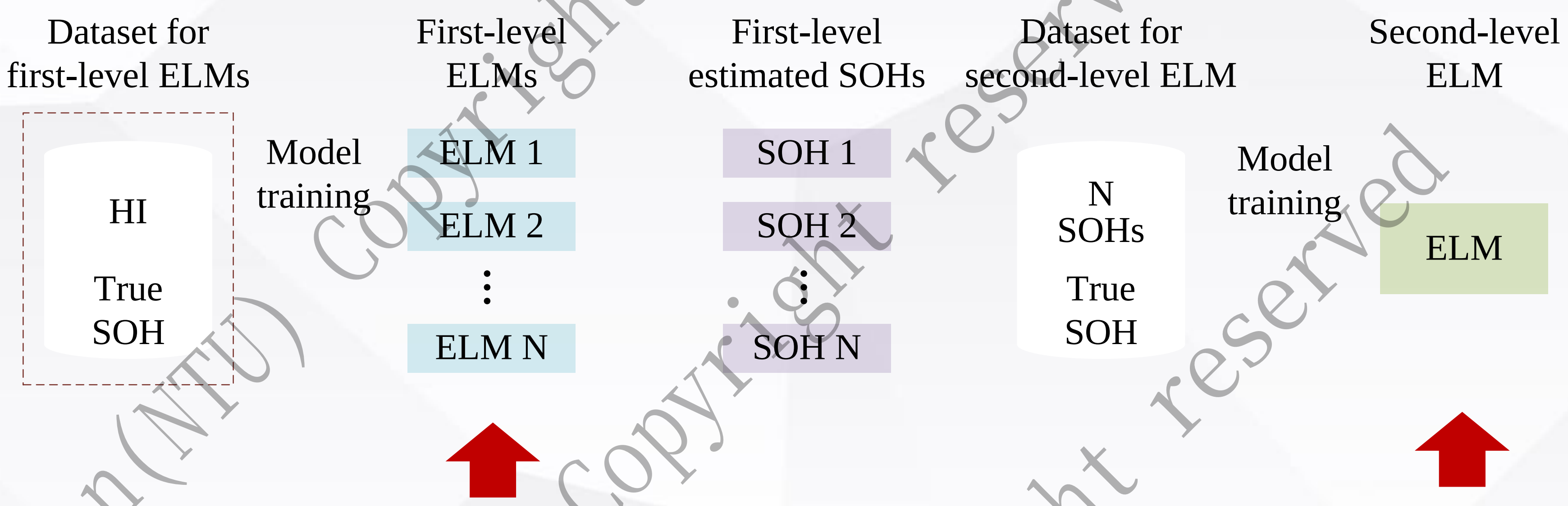
Credibility evaluation of outputs

$$\begin{cases} \left|y^i - \bar{y}^i\right| \le \alpha \times \bar{y} \rightarrow \text{credible} \rightarrow \text{keep} \\ \left|y^i - \bar{y}^i\right| > \alpha \times \bar{y} \rightarrow \text{incredible} \rightarrow \text{discard} \end{cases}$$

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

Machine Learning: Our Method

3. Hierarchical ensemble ELM model



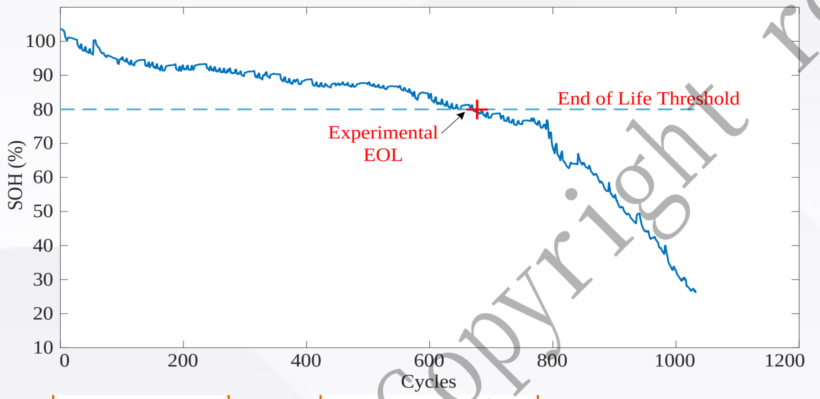
First-level: N extreme learning machines (ELM) are separately trained.

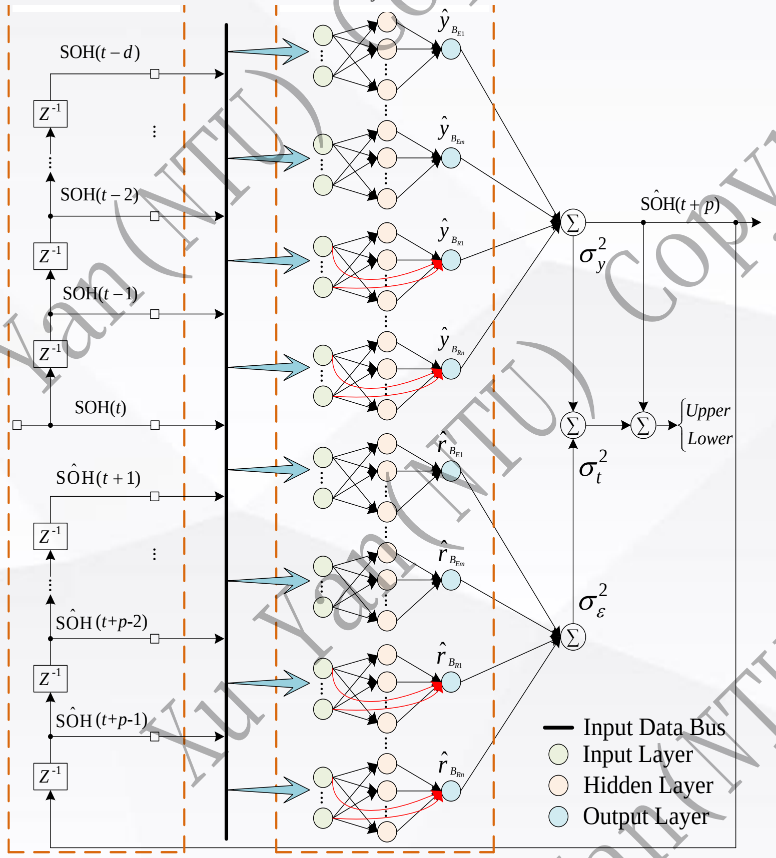
$$y^i = g(W_1^i \cdot x^T + b_1^i)^T \cdot \beta_1^i$$

Second-level: another ELM is trained to aggregate the ensemble outputs from the first-level ELMs

$$y_f = g(W_2 \cdot [y^1, y^2, \dots y^N]^T + b_2)^T \cdot \beta_2$$

Non-linear autoregressive exogenous (NARX) model for RUL prediction





RUL = Cycle no. (at 80% capacity) – Current cycle no.

So, we need to predict the SOH degradation trend

- The battery health conditions are time-varying and dynamic.
- In a conventional static structure, there is no exogenous input. The network can be represented by

$$\hat{y}(\mathbf{x}_i) = F(\mathbf{x}_i; \hat{\mathbf{w}}, \hat{b}, \hat{\beta})$$

- Having feedback connections, NARX contains the present and past information and can build autoregressive models.

$$\hat{y}(t) = F(\mathbf{x}(t), \mathbf{x}(t-1), \dots, \mathbf{x}(t-d_1), \hat{y}(t-1), \hat{y}(t-2), \dots, \hat{y}(t-d_2); \hat{\mathbf{w}}, \hat{b}, \hat{\beta})$$

- By incorporating the past and present information, NARX can improve the RUL prediction accuracy.

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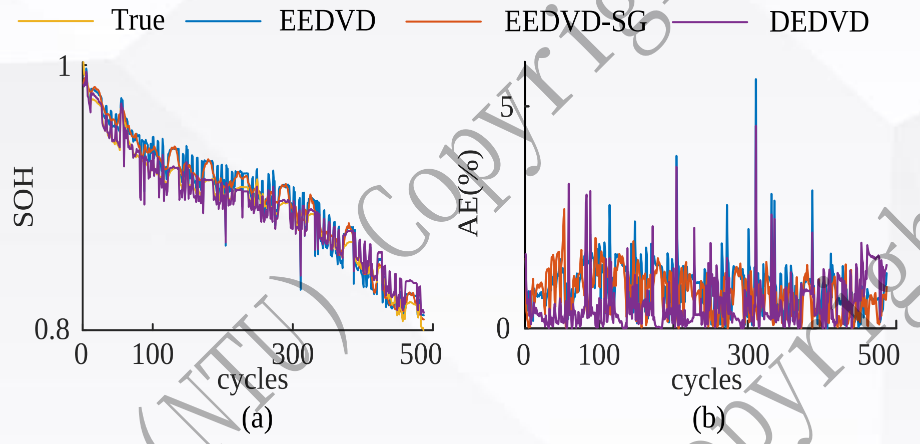
SOH estimation for discharging mode

Identical discharging rate

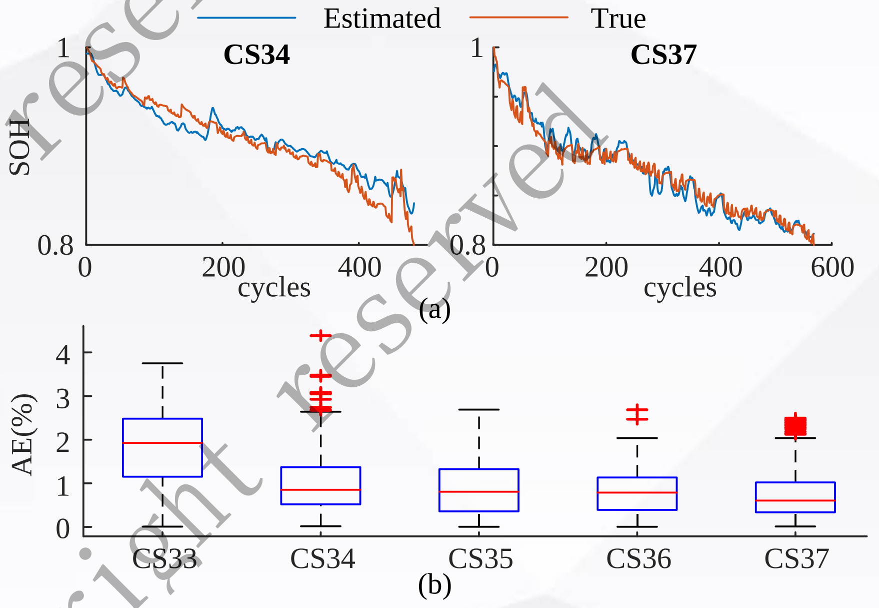


Estimation results at identical discharge rate. (a) estimated and true SOH. (b) absolute errors.

ERRORS IN RMSE (%) USING DIFFERENT HIs

HI	CS35	CS36	CS37	Mean
TIEDVD	0.92	0.80	0.92	0.88
EEDVD	0.94	0.81	0.93	0.89
EEDVD +filter	0.74	0.73	0.71	0.73

Different discharging rates



Estimation results at different discharging rates. (a) estimated and true SOH; (b) absolute errors.

Mean RMSE:
Identical discharging rate: 0.73%
Different discharging rates: 1.23%

W. Liu and Y. Xu, "Data-Driven Online Health Estimation of Li-Ion Batteries Using A Novel Energy-Based Health Indicator," **IEEE Trans. Energy Conversion, 2020.**

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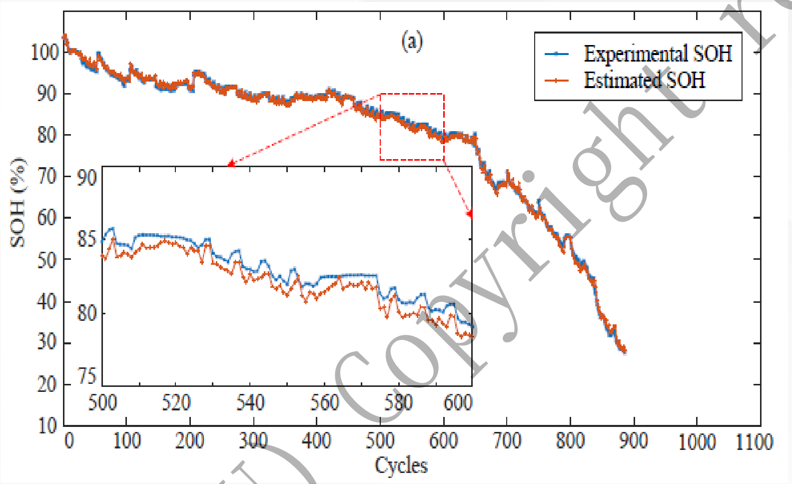
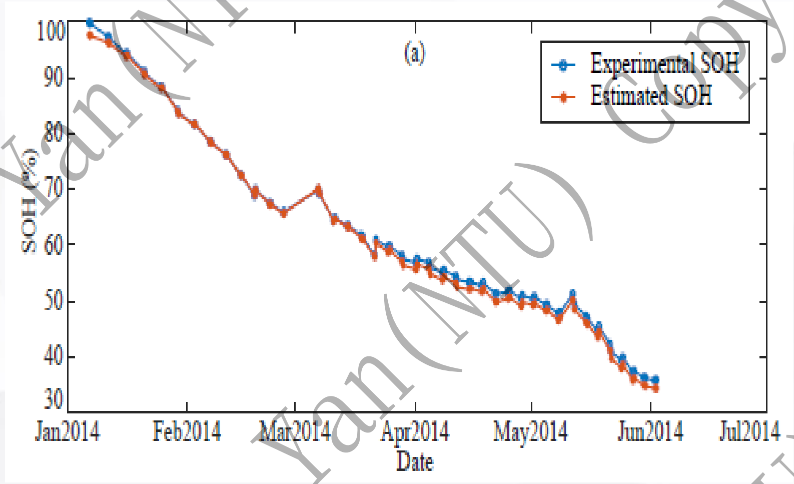
SOH estimation for charging mode



SOH estimation results (CS35)



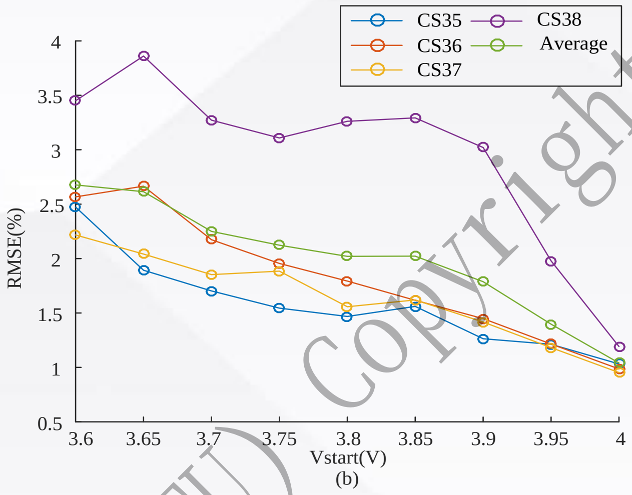
SOH estimation results (RW09)

RMSEs OF ESTIMATION RESULTS FOR DIFFERENT ALGORITHMS (%)

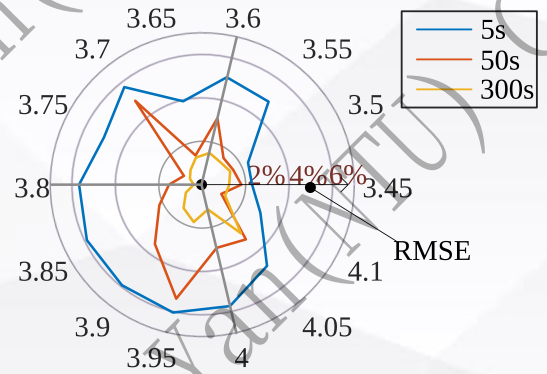
Methods	CS35	CS36	CS37	CS38	Average
Proposed method	0.69	0.86	0.69	0.86	0.78
Single ELM	0.77	0.87	0.74	0.87	0.81
SVM	0.78	1.03	0.76	0.88	0.86
DT	0.93	1.08	0.83	0.97	0.95
kNN	1.16	1.17	0.83	1.03	1.05
RF	0.81	0.90	0.71	0.79	0.80
RNN	0.78	1.07	0.81	0.79	0.86
LR	1.18	1.38	1.23	1.17	1.24

B. Gou, Y. Xu, et al, "An Ensemble Learning-based Data-Driven Method for Online State-of-Health Estimation of Lithium-ion Batteries," **IEEE Trans. Transportation Electrification, 2020.**

SOH estimation for both charging and discharging modes



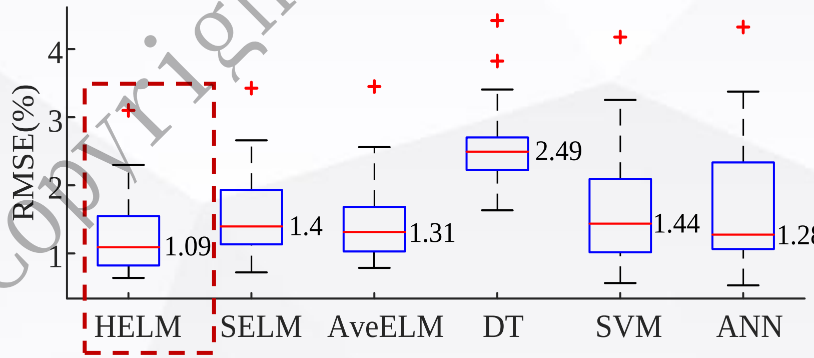
Estimation results (CALCE) based on the discharging process (300s)



RMSE for different starting voltages and time intervals (Oxford, discharging)

RMSE (%) of Oxford Dataset Based on the Charging process (300s)

Vstart (V)	Cell5	Cell6	Cell7	Cell8	Ave
2.8	0.80	0.54	1.92	1.12	1.09
2.9	0.76	0.49	1.78	1.06	1.02
3	0.75	0.51	1.57	0.98	0.95
3.1	0.62	0.43	1.27	0.91	0.81
3.2	0.48	0.47	1.17	0.93	0.76
3.3	0.43	0.45	0.59	1.04	0.63
3.4	0.40	0.56	0.59	0.86	0.60
3.5	0.38	0.47	0.55	0.91	0.58
3.6	1.44	0.80	1.74	1.80	1.45
3.7	0.91	1.55	2.13	1.25	1.46
3.8	0.35	0.44	0.69	0.35	0.46



Comparison of different methods (NASA, discharging 300s)

W. Liu, Y. Xu et al, "A Hierarchical and Flexible Data-Driven Method for Online State-Of-Health Estimation of Li-ion Battery", **IEEE Transactions on Vehicular Technology, 2020.**

0. Outline

1. Overview

2. Power Grid

2.1 Stability analysis

2.2 Frequency control

2.3 Optimal power flow

3. Customer

3.1 Load monitoring

3.2 Home energy management

4. Power Assets

4.1 Power converter

4.2 Battery energy storage

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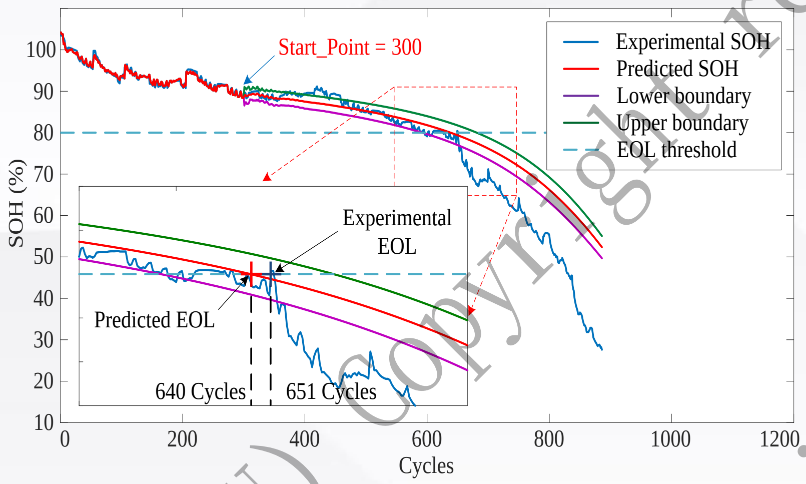
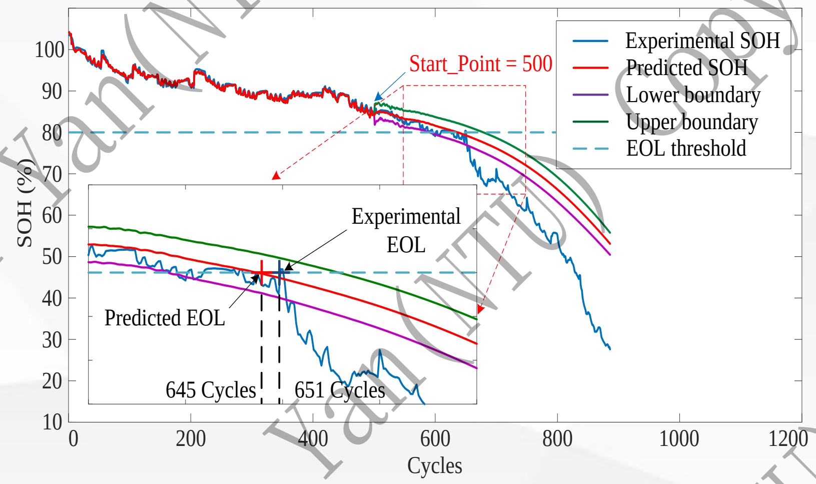
SOH estimation and RUL prediction for charging mode



RUL prediction (CS35) starting from 300th cycle



RUL prediction (CS35) starting from 500th cycle

RUL Prediction Results when Start Point is 500th Cycle

Cells	Actual RUL	Predicted RUL	AE	99% Confidence Interval	RE (%)
CS35	151	145	6	[592, 679]	3.97
CS36	55	57	2	[531, 601]	3.64
CS37	130	132	2	[591, 676]	1.54
CS38	177	176	1	[632, 715]	0.56

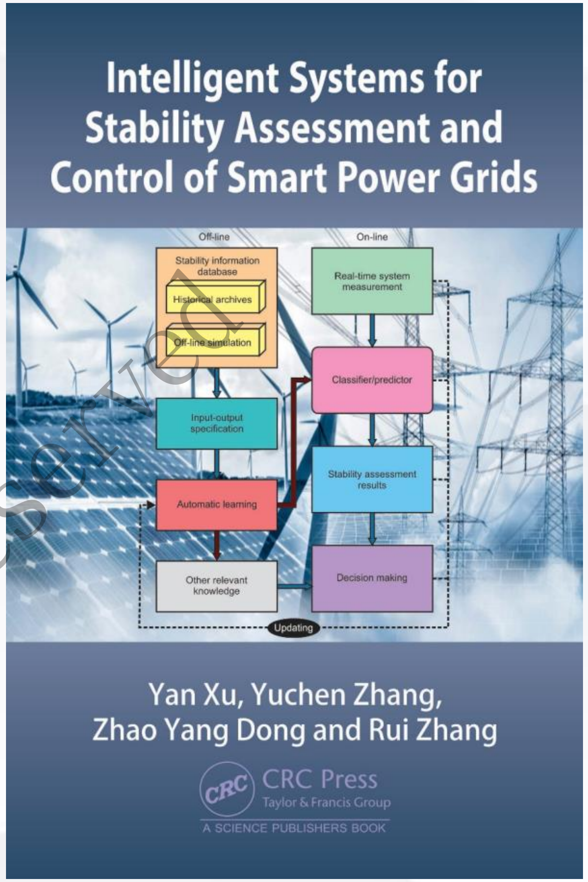
RUL Prediction Performance of Different Learning Algorithms

Algorithm	Training time/s	Training error RMSE/%	Testing time/s	Testing error RMSE/%	RUL AE (cycle)
Proposed method	69.76	0.54	318.83	1.57	6
ELM	0.45	0.59	5.39	2.35	27
RVFL	0.62	0.88	5.48	2.23	18
SVM	1.58	0.91	5.83	3.57	16
ESN	4.70	1.02	1.52	3.13	33
RF	50.52	0.61	220.02	1.95	13
SDA	2164.83	1.31	10.59	3.96	25

B. Gou, Y. Xu, et al, "State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-ion Battery Using A Hybrid Data-driven Method," **IEEE Trans. Vehicular Technology, 2020.**

Most Representative Publications in Data-Analytics Area

1. 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, 2012.**
2. Y. Xu, Z.Y. Dong, et al. "Preventive dynamic security control of power systems based on pattern discovery technique." **IEEE Trans. Power Systems , 2012.**
3. Y. Zhang, Y. Xu, Z.Y. Dong, “Robust ensemble data-analytics for incomplete PMU measurement-based power system stability assessment,” **IEEE Trans. Power Systems, 2017.**
4. Y. Zhang, Y. Xu, Z.Y. Dong, “Real-Time Assessment of Fault-Induced Delayed Voltage Recovery: A Probabilistic Self-Adaptive Data-driven Method,” **IEEE Trans. Smart Grid, 2018.**
5. 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 Systems, 2019.**
6. C. Ren, Y. Xu “Transfer Learning-Based Power System Online Dynamic Security Assessment: Using One Model to Assess Many Unlearned Faults,” **IEEE Trans. Power Systems, 2019.**
7. Z. Yan, Y. Xu, "Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Reinforcement Learning Method With Continuous Action Search," **IEEE Trans. Power Systems, 2019.**
8. Z. Yan, Y. Xu, "A Multi-Agent Deep Reinforcement Learning Method for Cooperative Load Frequency Control of Multi-Area Power Systems," **IEEE Trans. Power Systems, 2020.**
9. Z. Yan, Y. Xu, “Real-Time Optimal Power Flow: A Lagrangian based Deep Reinforcement Learning Approach,” **IEEE Trans. Power Systems, 2020.**
10. Q. Li, Y. Xu, C. Ren. "A Hierarchical Data-Driven Method for Event-based Load Shedding Against Fault-Induced Delayed Voltage Recovery in Power Systems,” **IEEE Trans. Indu. informatics, 2020.**
11. X. Xu, Y. Jia, Y. Xu, Z. Xu, et al, “A Multi-agent Reinforcement Learning based Data-driven Method for Home Energy Management,” **IEEE Trans. Smart Grid, 2020.**
12. B. Gou, Y. Xu, Y. Xia, "An online data-driven method for simultaneous diagnosis of IGBT and current sensor fault of 3-Phase PWM inverter in induction motor drives," **IEEE Trans. Power Electronics, 2020.**
13. B. Gou, Y. Xu, Y. Xia, "An intelligent time-adaptive data-driven method for sensor fault diagnosis in induction motor drive system," **IEEE Trans. Industrial Electronics, 2019.**
14. B. Gou, Y. Xu, et al, “State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-ion Battery Using A Hybrid Data-driven Method,” **IEEE Trans. Vehicular Technology, 2020.**
15. W. Liu, Y. Xu et al, “A Hierarchical and Flexible Data-Driven Method for Online State-Of-Health Estimation of Li-ion Battery”, **IEEE Trans. Vehicular Technology, 2020.**
16. W. Liu, Y. Xu, “Data-Driven Online Health Estimation of Li-Ion Batteries Using A Novel Energy-Based Health Indicator,” **IEEE Trans. Energy Conversion, 2020.**
17. C. Ren, X. Du, Y. Xu, Q. Song, Y. Liu and R. Tan, "Vulnerability Analysis, Robustness Verification and Mitigation Strategy of Machine Learning-based Power Systems Stability Assessment Models under Adversarial Examples," **IEEE Transactions on Smart Grid, 2021.**



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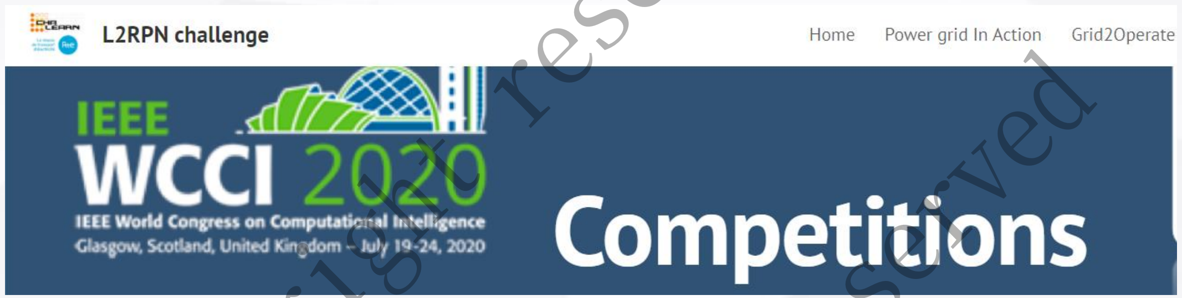
Academic Awards in Data-Analytics Area



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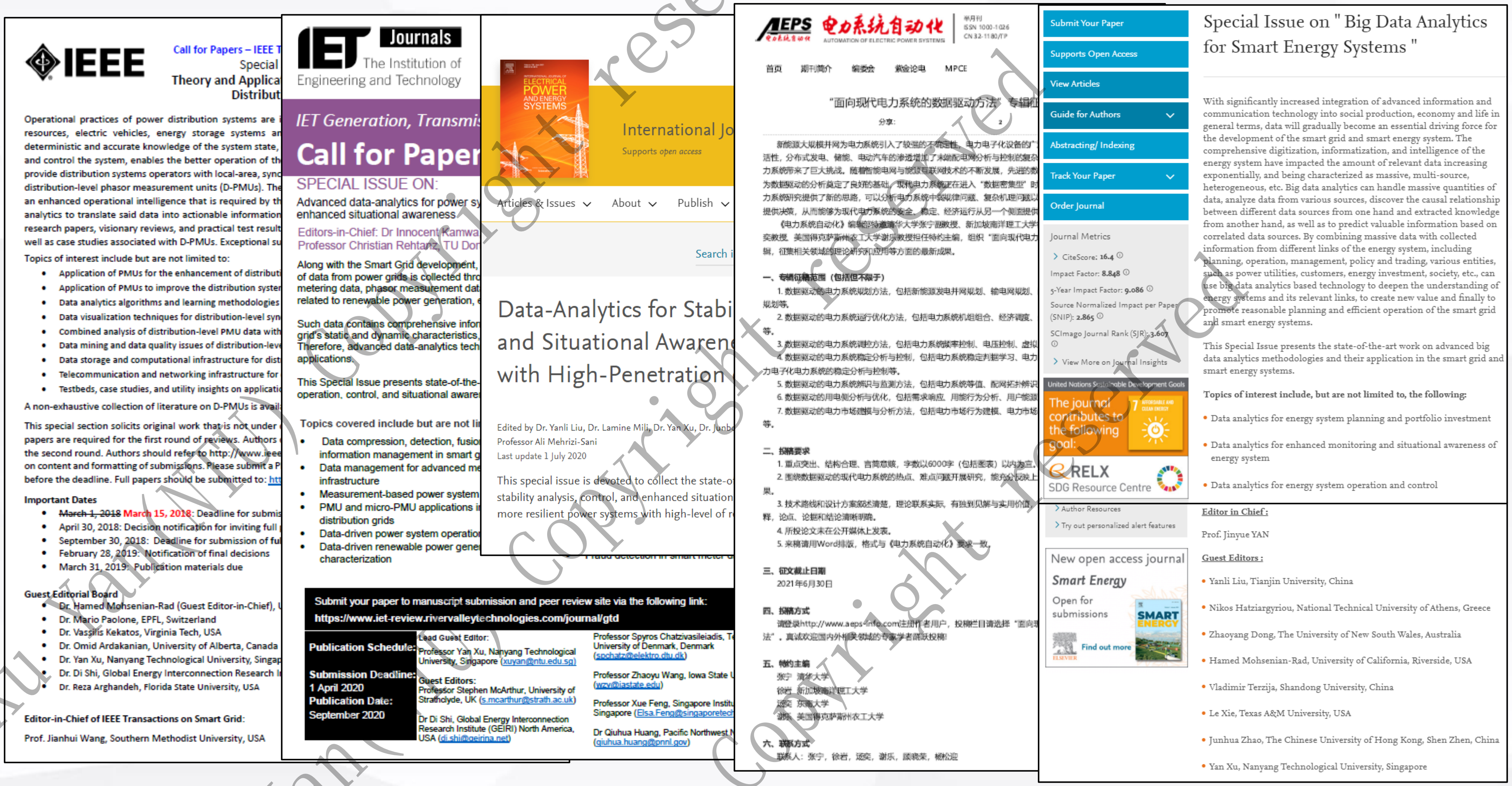
Edited Special Issues on Data-Analytics Topics



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Thank You!