Advanced Prediction Techniques Applied to Smart Grids

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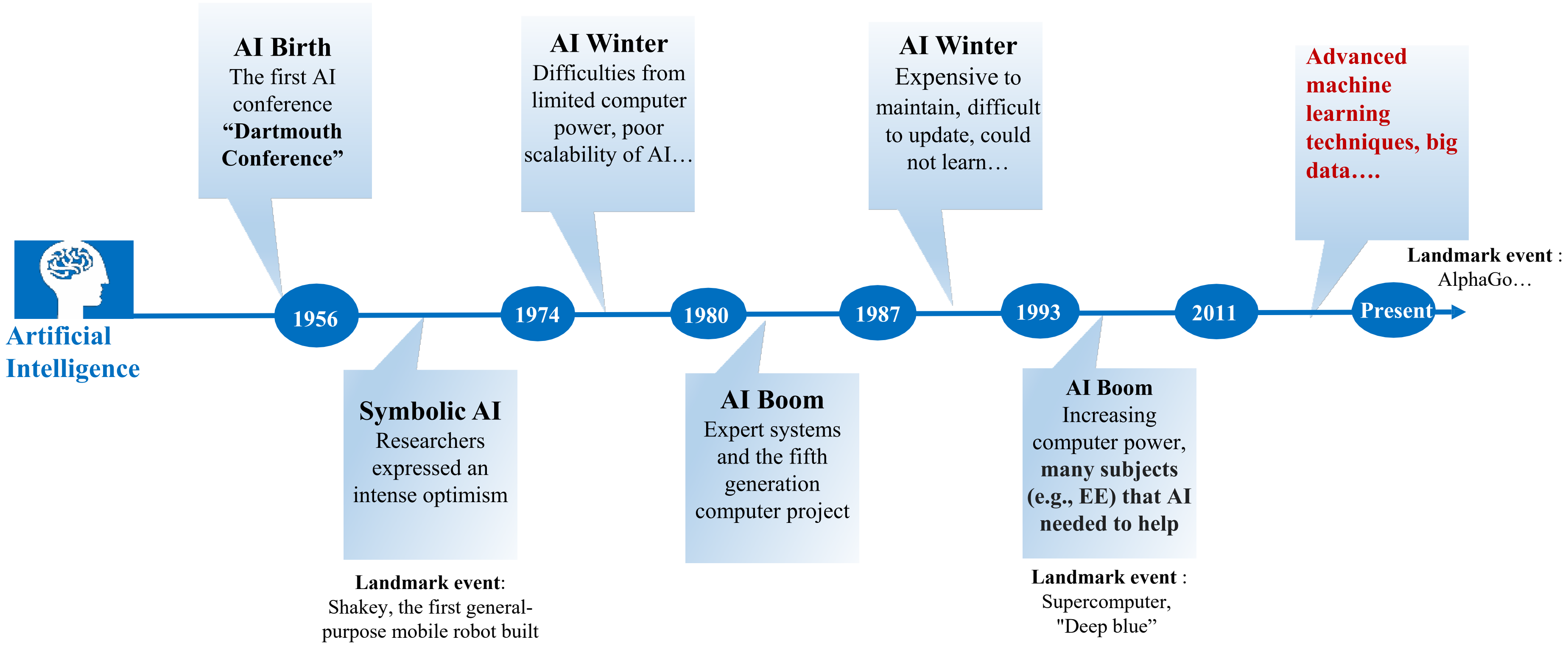
Outline

- Introduction to Advanced Prediction Techniques
- Their Applications in Smart Grids
- Conclusions

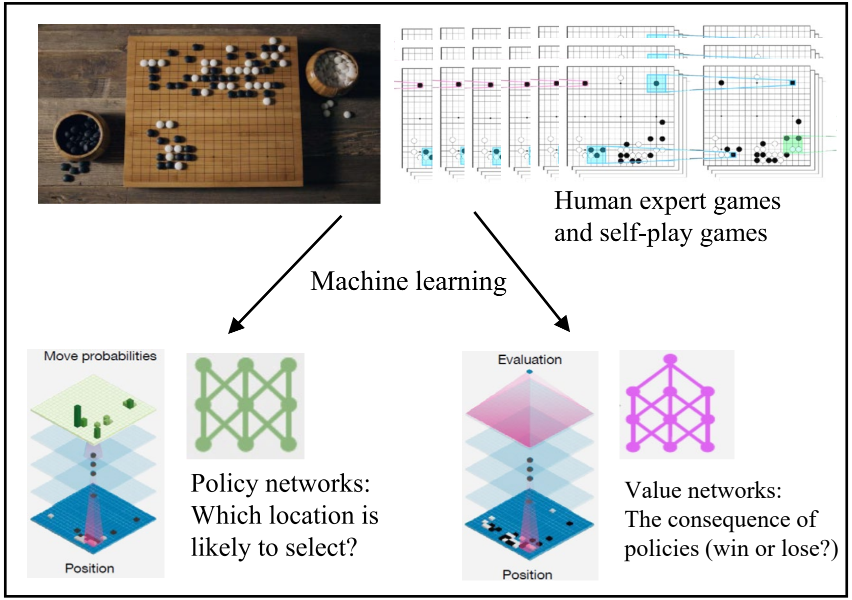
Introduction to Advanced Prediction Techniques

Fast Development of Artificial Intelligence

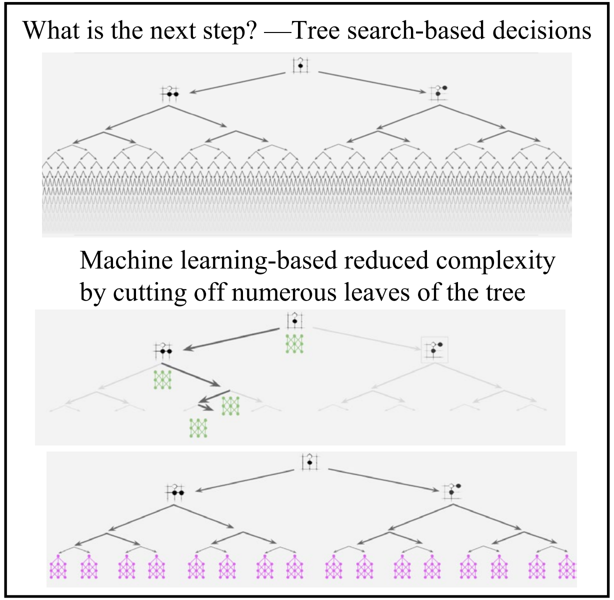


Fantastic Application: AlphaGo

- Advanced **machine learning techniques** (e.g. convolutional neural networks, supervised learning, reinforcement learning) are combined with **tree search techniques**.
- Human players (e.g. Lee Sedol (9p), Fan Hui(2p)) were beaten.



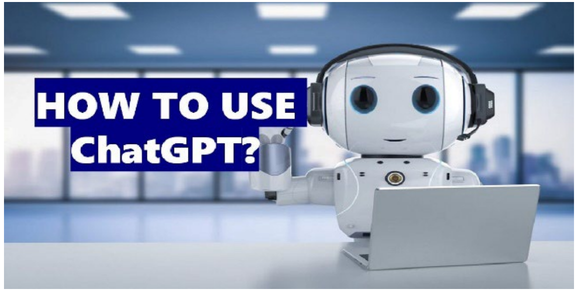
Aid decision-making for the current situation

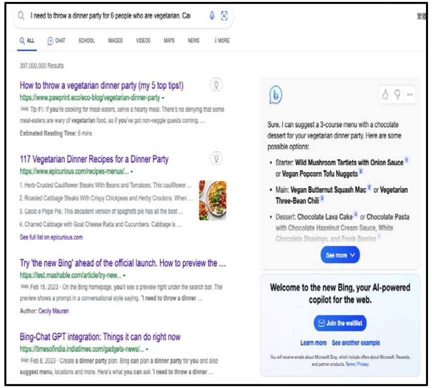


Source: https://www.davidsilver.uk/wp-content/uploads/2020/03/AlphaGo-tutorial-slides_compressed.pdf

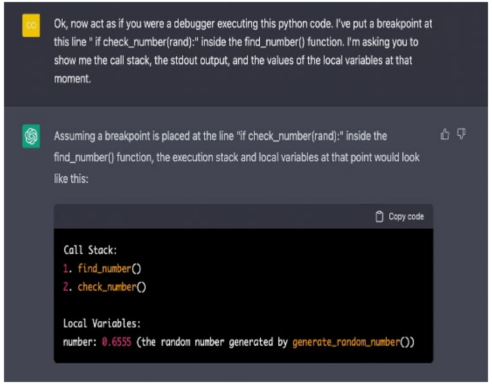
Fantastic ChatGPT

- **A language model** released by OpenAI in 2022, capable of **interacting** with users on various topics
  - Answer questions (e.g., factual question)
  - Write and debug computer programs
  - Generate texts (e.g., student essays)
  - Emulate systems (e.g., a Linux system….)
  - ……

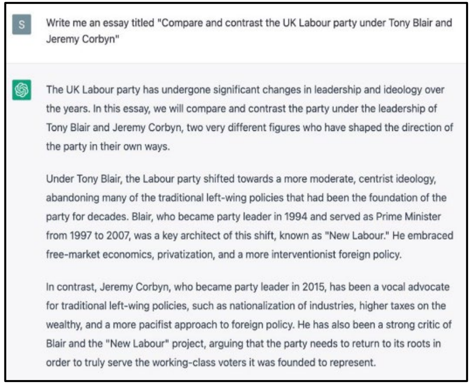




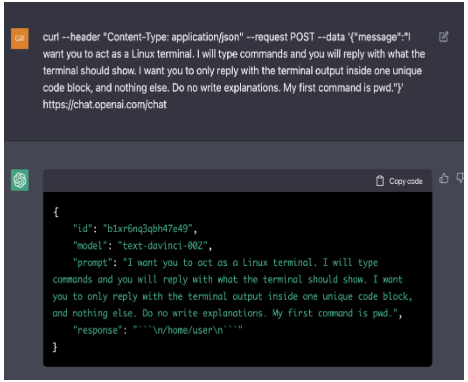
Answer to a question in Microsoft Bing



A paragraph of codes



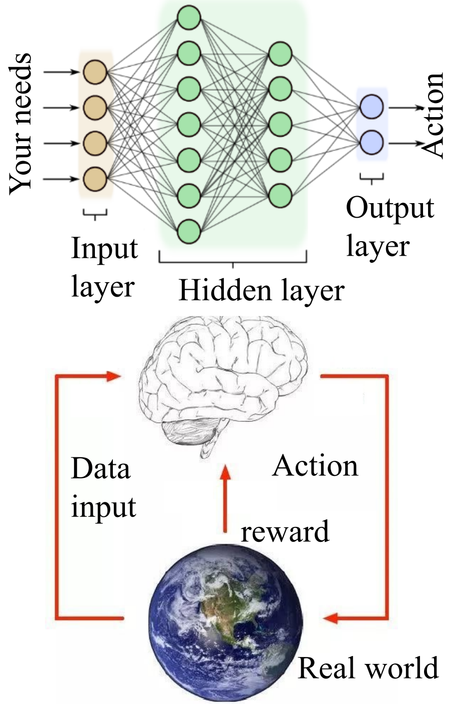
An essay



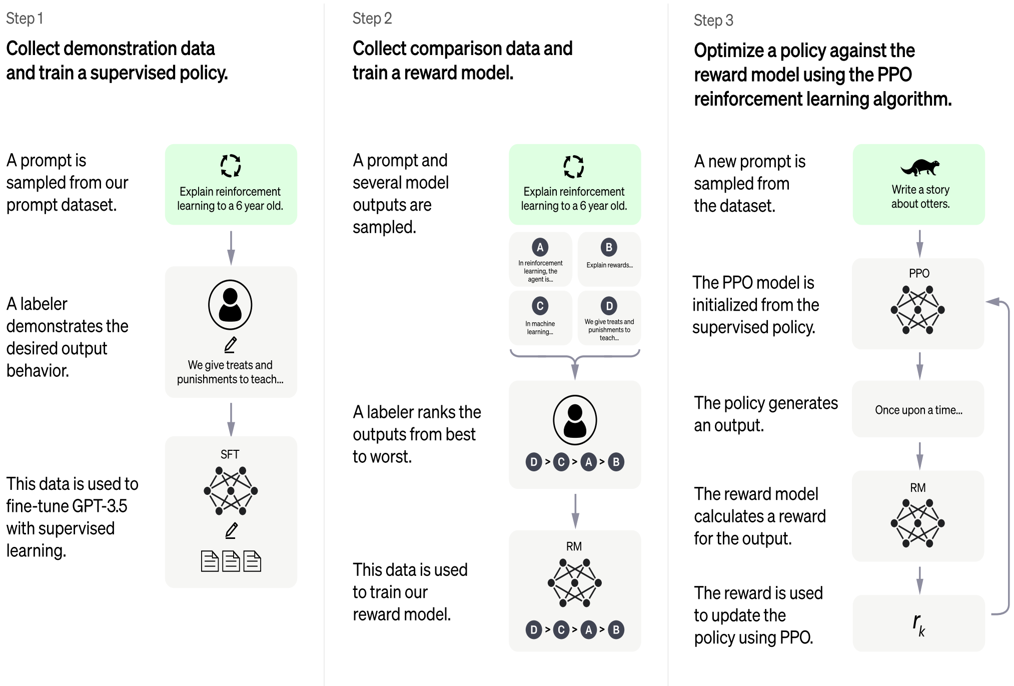
An emulation of Linux

AI Techniques Behind ChatGPT

- The success of ChatGPT comes from AI techniques (e.g., deep neural networks and reinforce learning)



AI techniques



Three training steps

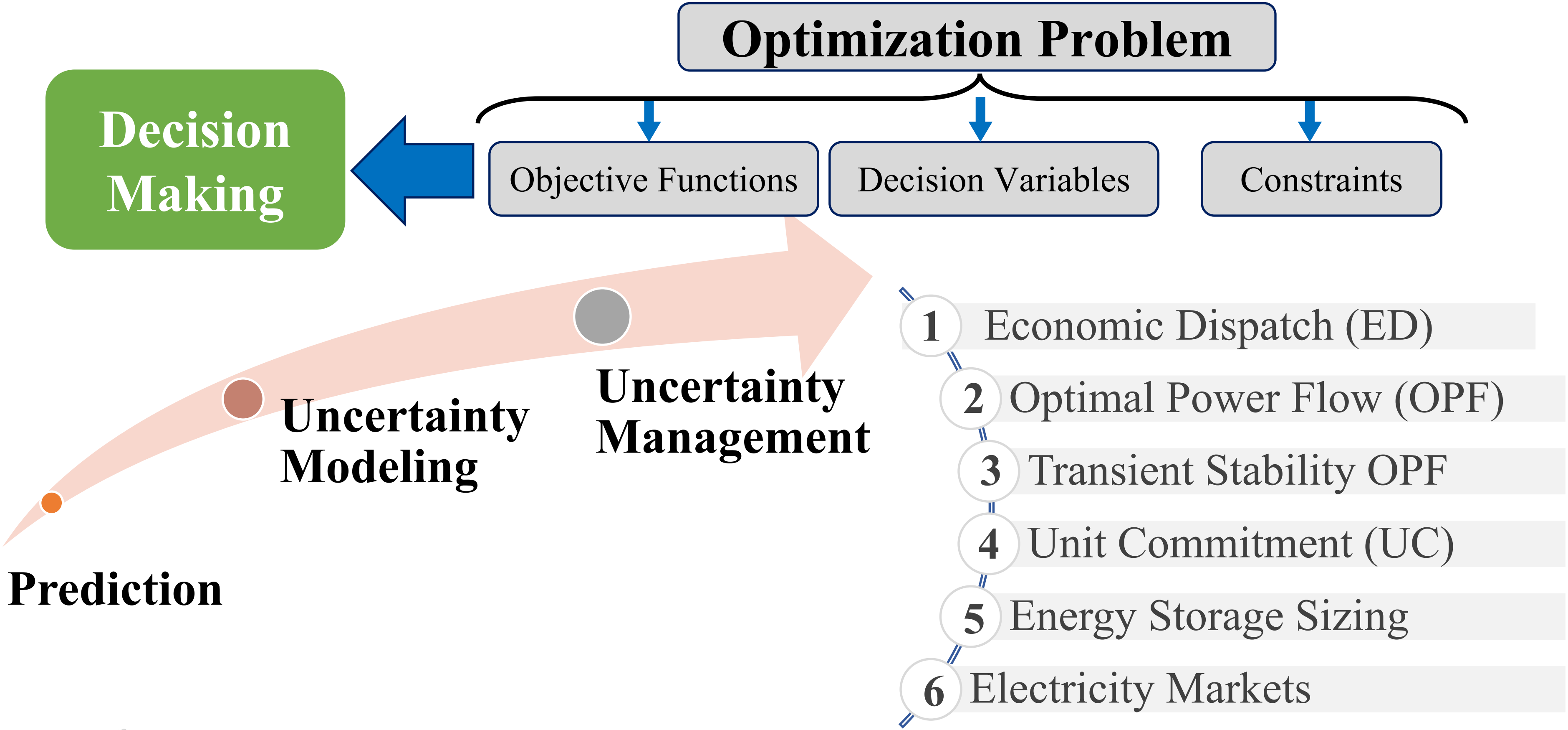
Many uses

Microsoft Bing

……

Source: https://openai.com/blog/chatgpt

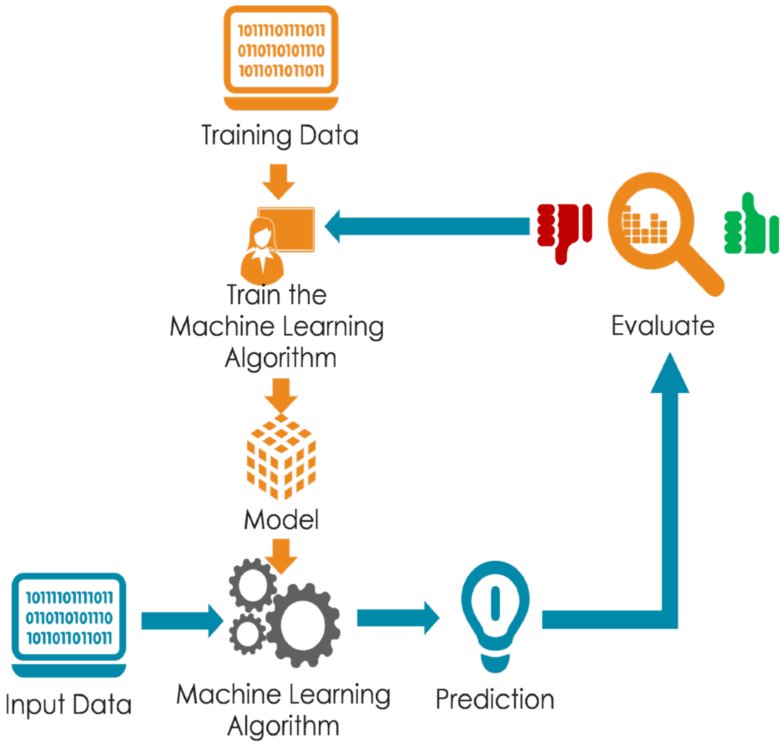
Decision Making in Power System Planning and Operation



Prediction Techniques

Statistical	**Aims at inferring relationship between variables**
Machine Learning-based	**Focus on training the prediction models and make predictions as accurate as possible.**
Hybrid	**Both statistical and Machine learning-based techniques are employed in an integrated framework to improve accuracy.** For example, statistical techniques can be employed for data processing, feature extraction/selection, or dimension reduction, and then having the Machine learning-based techniques as the prediction engine.

Framework of Machine Learning-based Prediction Techniques



https://www.7wdata.be/

Data Collection
- Historical Input Data
- Historical Output Data

Data Preprocessing
- Data Refining
- Feature Extraction/Selection

Model Training
- Model Selection
- Parameter Selection

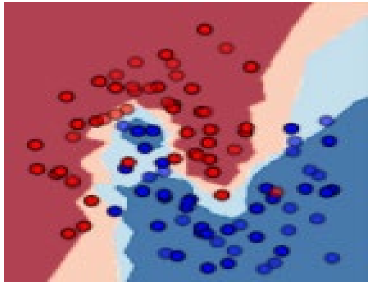
Model Testing
- Testing Data
- Performance Indicators

- **Find correlated factors**
- **Improve data quality**
- **Develop prediction model**
- **Evaluate performance**

Conventional Machine Learning Techniques

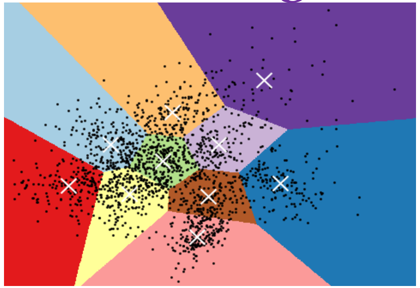
Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT), Ensemble Learning, Etc.

Classification



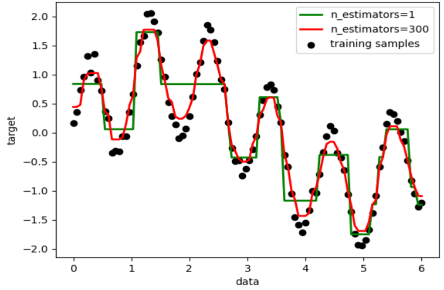
Predict the instance class from pre-labeled (classified) instances.

Clustering



Find grouping of instances given un-labeled data

Regression



Predict a continuous attribute

Applications in power system area:
Classification: Power system status prediction, e.g., stability prediction;
Clustering: clustering of consumers' electricity usage pattern;
Regression: wind power forecasting, etc.

High-dimensional Big Data of Power Systems

- The data from power systems are collected at large scale and at high rate. For example:

Multi-channel PMUs providing voltage and current phasors at a sampling rate of up to 60 samples per second

Smart meters providing electricity consumption data every 1 to 15 minutes interval

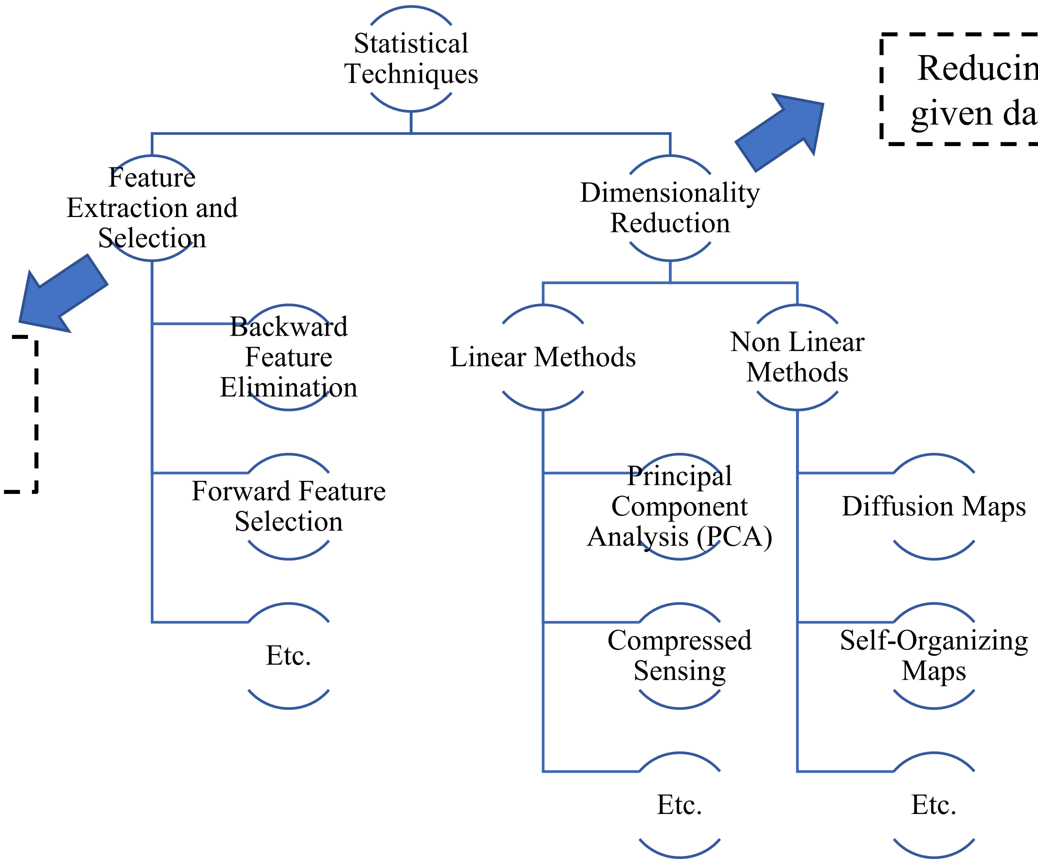
Big Data
4V's:
Volume (High)
Velocity (High)
Variety (High)
Veracity (High)

- The high-dimensional big data of power systems introduces several challenges :

- High mathematical complexity
- High computational burden
- Large data storage requirements
- Low algorithmic efficiency

Curse of dimensionality

Advanced Statistical Modeling for High Dimensional Cases



Reducing the dimensions of the given data by transforming them

Extracting and selecting suitable dimensions without modifying them

Deep Learning Technique

Machine Learning-based prediction Methods

For Big Data Applications

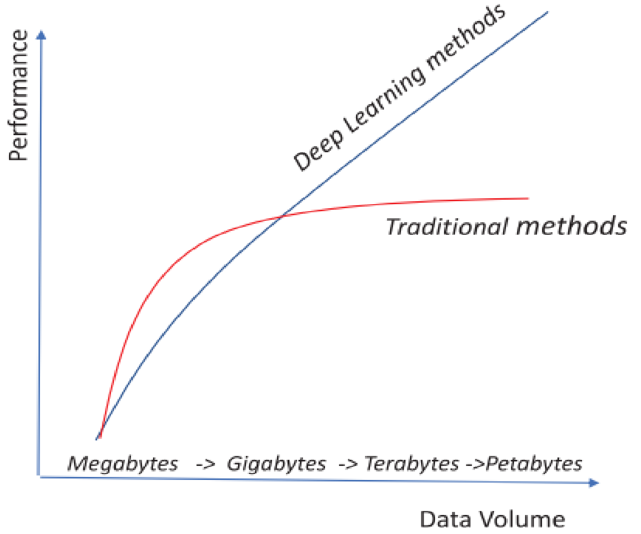
Deep Learning

Popular Network Architectures in Deep Learning:

- Recurrent Neural Network; Long/Short Term Memory (LSTM),
- Convolutional Neural Networks,
- Boltzmann Machine,
- Deep Belief Networks,
- Stacked Auto-encoders,
- Etc.

- Handling big data problems;
- Great performance in high-dimensional search spaces;
- Capturing long-term dependencies amongst data.

Performance comparison of traditional methods versus deep-learning methods



Uncertainties in Power Systems and Modeling Approaches

Uncertainties in Power Systems

- Renewable energy sources
- Load demand
- Dynamic line rating
- Line/Generator outage
- Fuel/Energy price
- Market regulations, etc.

Uncertainty Modeling Approaches

- Probabilistic models
- Possibilistic models
- Probabilistic/Possibilistic models
- Robust optimization
- Information gap decision theory
- Interval analysis

Applications of Advanced Prediction Techniques in Smart Grids

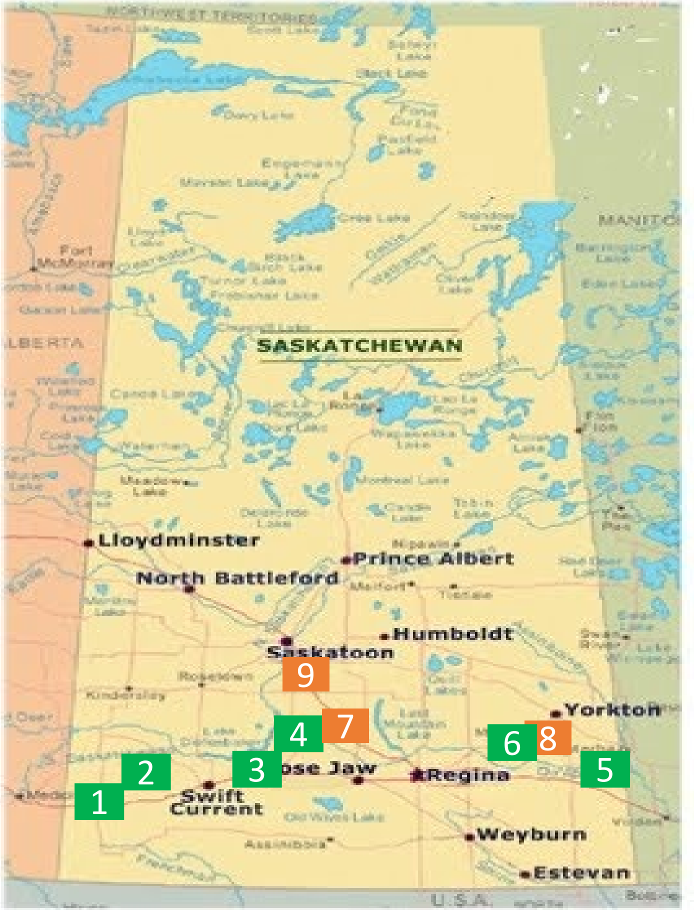
Example I: Wind Power Prediction

Wind Power Facilities in Saskatchewan

1	Cypress Wind Power Facility	10.6 MW
2	SunBridge Wind Power Facility	11.2 MW
3	Centennial Wind Power Facility	149.4 MW
4	Morse Creek Wind Power Facility	23 MW
5	Red Lilly Wind Power Facility	26.4 MW
6	Summerberry Wind Power Facility	20 MW
7	Chaplin Wind Power Facility	177.1 MW
8	Western Lily Wind Power Facility	20 MW
9	Riverhurst Wind Power Facility	10 MW

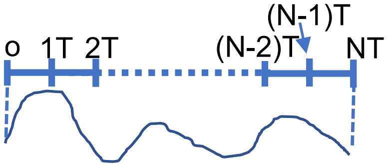
⋮

Increasing wind power penetration to 30% (= 2100 MW) by 2030



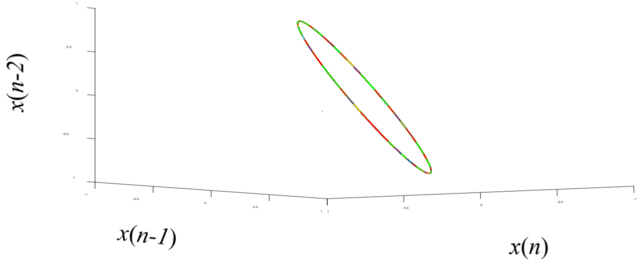
Wind Power Time Series Plots

Time Series $\{P(t)\}_{1T}^{NT}$

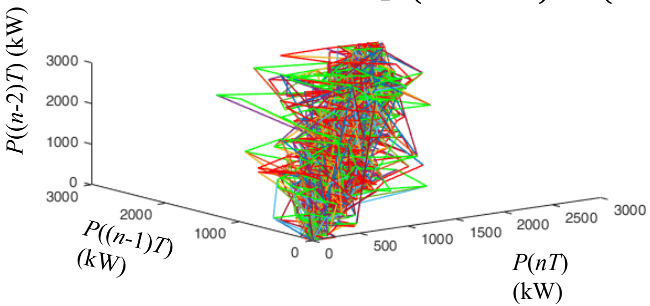


Hankel Matrix

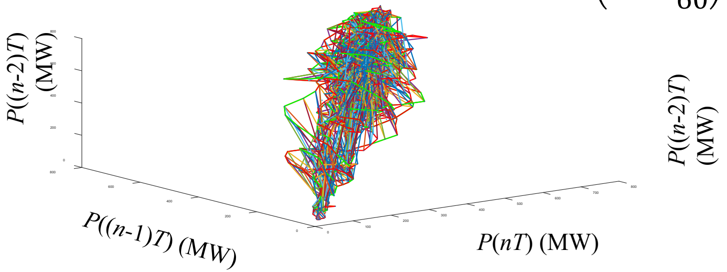
$$\begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_{N-2} \end{bmatrix} = \begin{bmatrix} P(1T) & P(2T) & P(3T) \\ P(2T) & P(3T) & P(4T) \\ \vdots & \vdots & \vdots \\ P\big((N-2)T\big) & P\big((N-1)T\big) & P(NT) \end{bmatrix}$$



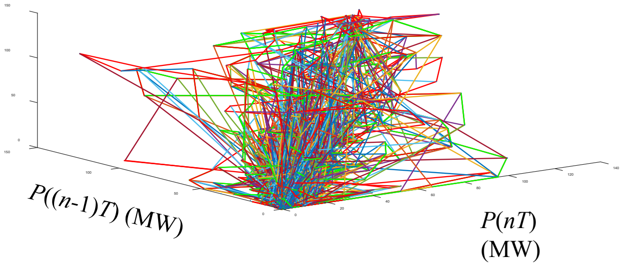
Perfect Periodic Time Series ($x(n) = \sin\left(2\pi \times \frac{n}{60}\right)$ **)**



Sotavento Wind Farm, Spain



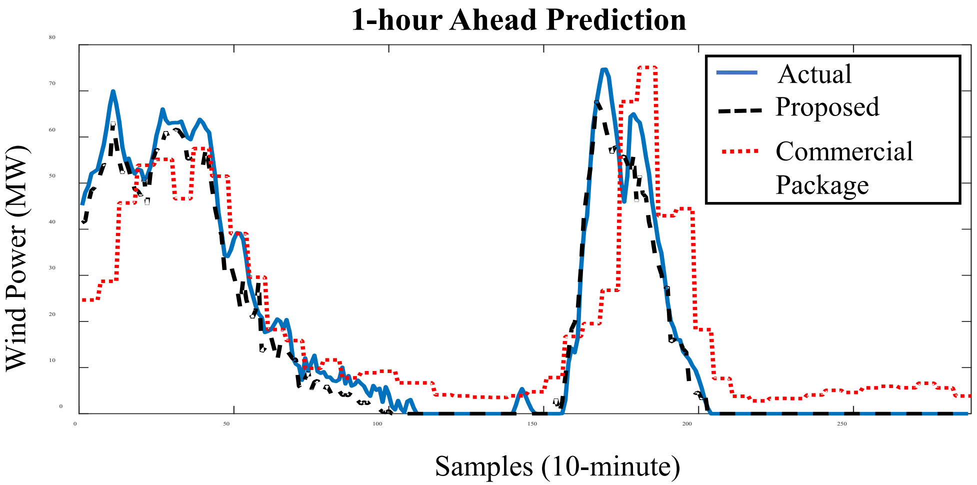
Alberta Electric System Operator (AESO)'s Wind Power Generation, AB, Canada



Centennial Wind Farm, SK, Canada

Novel Short-Term Wind Power Prediction Method

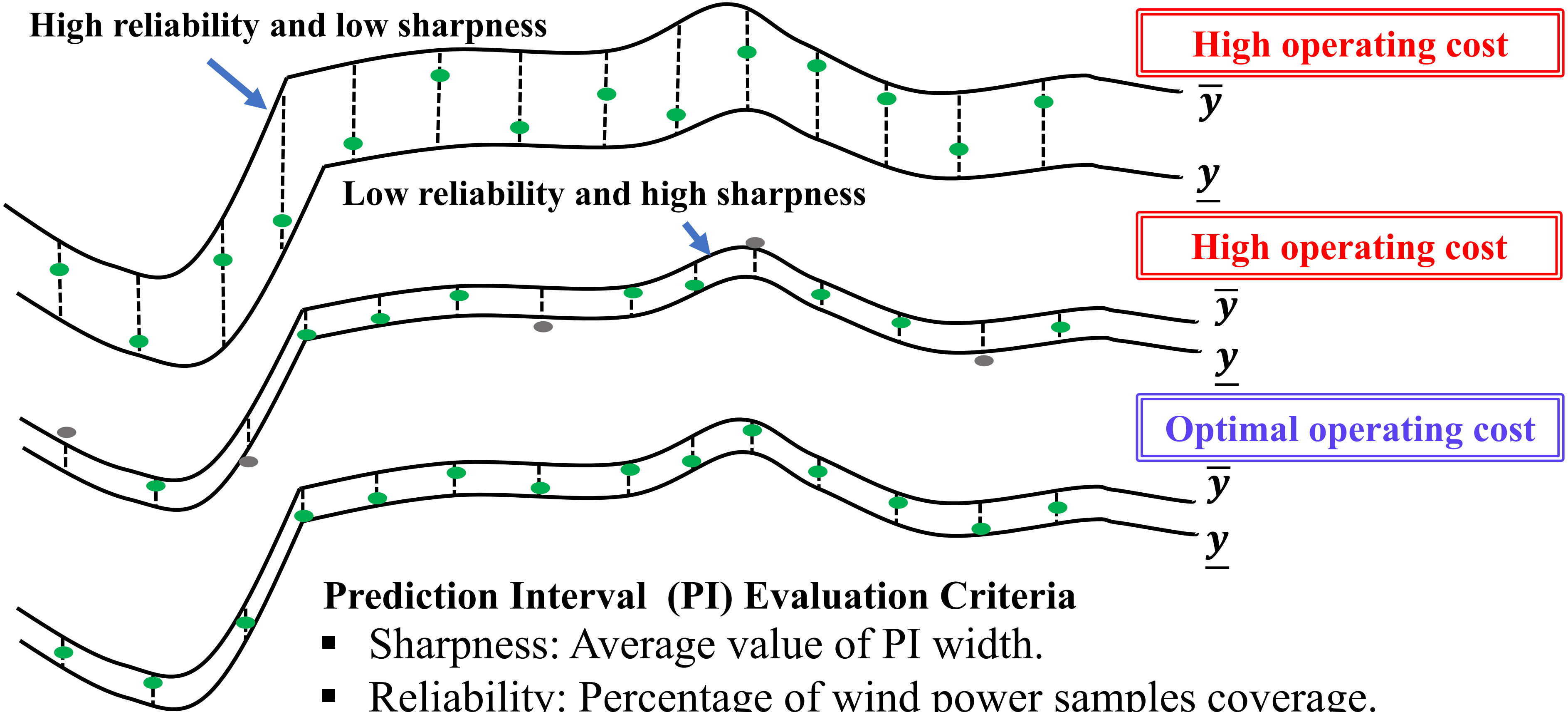
- **Chaos** is a property of certain non-linear systems with highly wild, random-looking and non-periodic behavior.
- Existing wind power prediction methods cannot handle the chaosity of wind power time series.



- A novel multi-step short-term wind power prediction method [2] is proposed:
  - Ensemble Empirical Mode Decomposition (EEMD) to separate wind power time series into several components with different time-frequency characteristics (scales).
  - Chaotic Time Series Analysis to determine chaotic components.
  - Multi-Scale Singular Spectrum Analysis (MSSSA) to smoothen the chaotic components by eliminating extremely rapid changes with low amplitude (Maintain the general trend!).

[2] N. Safari, C. Y. Chung, and G. C. D. Price, “A novel multi-step short-term wind power prediction framework based on chaotic time series analysis and singular spectrum analysis”, *IEEE Transactions on Power Systems.*

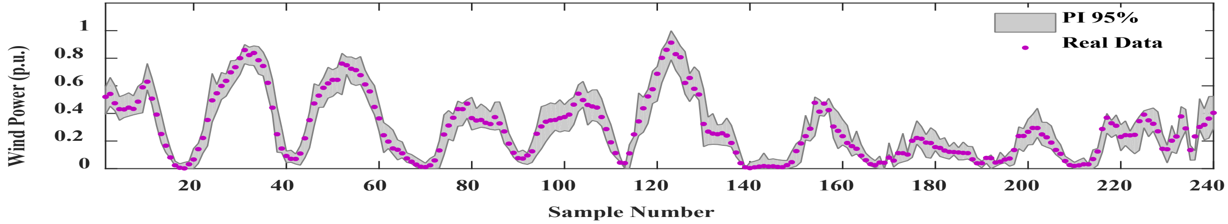
Prediction Interval (PI) Construction for Modelling Wind Power Uncertainty



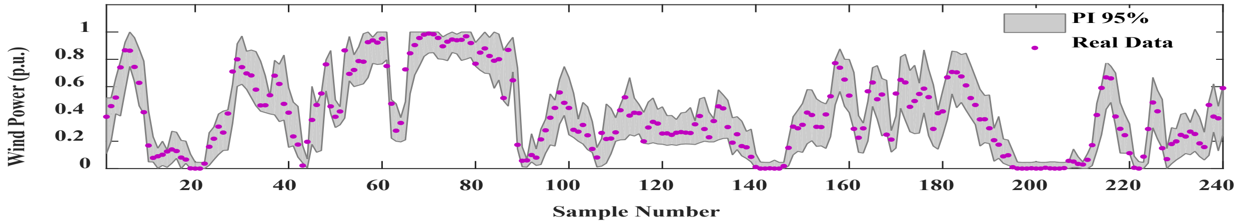
Prediction Interval (PI) Evaluation Criteria

- Sharpness: Average value of PI width.
- Reliability: Percentage of wind power samples coverage.

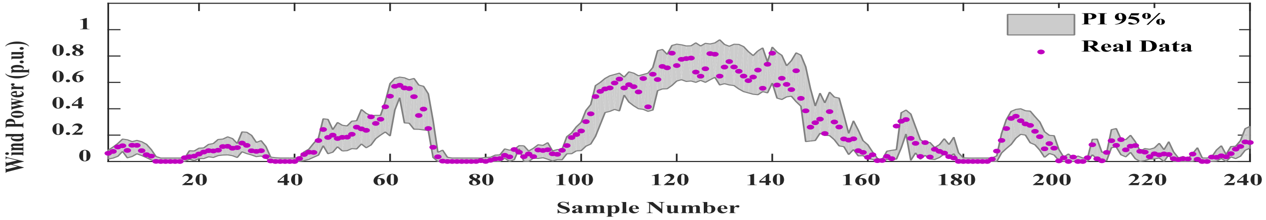
Performance of the Proposed PI Construction



The constructed PI for 1-hour prediction horizon for **AESO dataset**.



The constructed PI for 1-hour prediction horizon for **Centennial dataset**.



The constructed PI for 1-hour prediction horizon for **Sotavento dataset**.

- PI Construction Framework [3] developed by improving diffusion-based kernel density estimators.
- Highly reliable and sharp PIs obtained.

[3] B. Khorramdel, C.Y. Chung, and N. Safari, G.C.D. Price, "A Fuzzy Adaptive Probabilistic Wind Power Prediction Framework Using Diffusion Kernel Density Estimators," *IEEE Trans. on Power Systems*.

Example II: Real-time Thermal Rating (Overhead Lines)

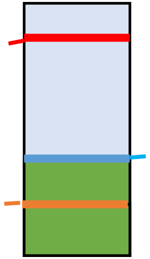
Real-time Thermal Rating (RTTR) vs. Static Thermal Rating (STR)

Measuring RTTR

- Relieve congestion
- Avoid/defer new investment
- Lower risk (avoid blackouts)

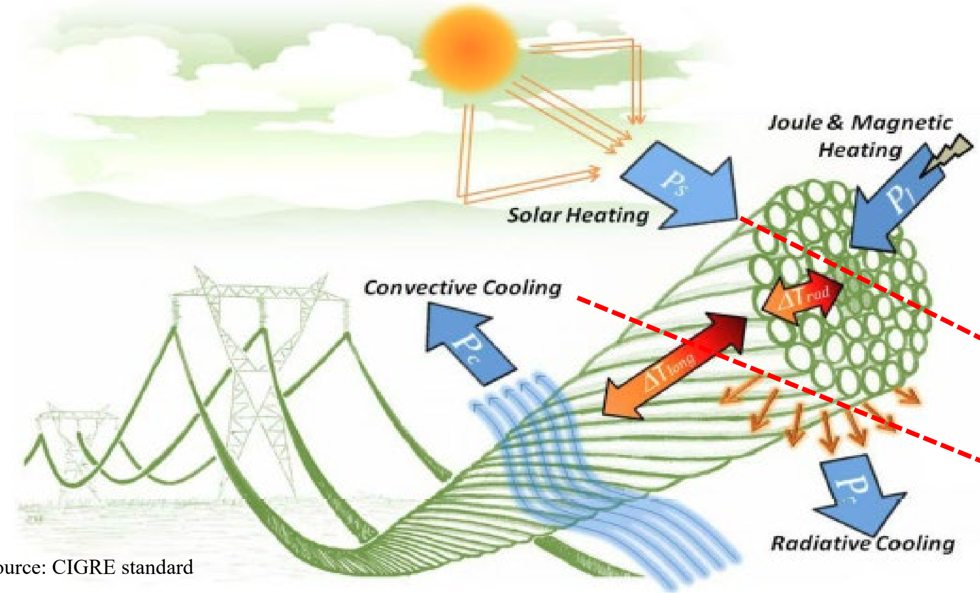
Usually

Sometimes



Static Thermal Rating (STR)

- *Inaccurate*
- *Conservative*



Source: CIGRE standard

- Heat balance equation
  - Joule & Magnetic Heating (P_J) , Solar Heating (P_S)
  - Convective Cooling (P_c), Radiative cooling (P_r)
  - CIGRE, IEEE

$$P_J + P_S = P_c + P_r$$

- Affecting factors
  - Solar radiation
  - Wind speed
  - Wind direction
  - Ambient temperature

Five Types of RTTR Monitoring Systems

Traditional propeller-type & ultrasonic anemometers

Power donut

Sagometer

Tension Monitoring Systems-Loadcell Monitors

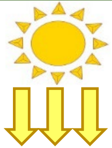
- Weather
- Conductor temperature
- Sag
- Tension
- Clearance

Hand-held SONAR

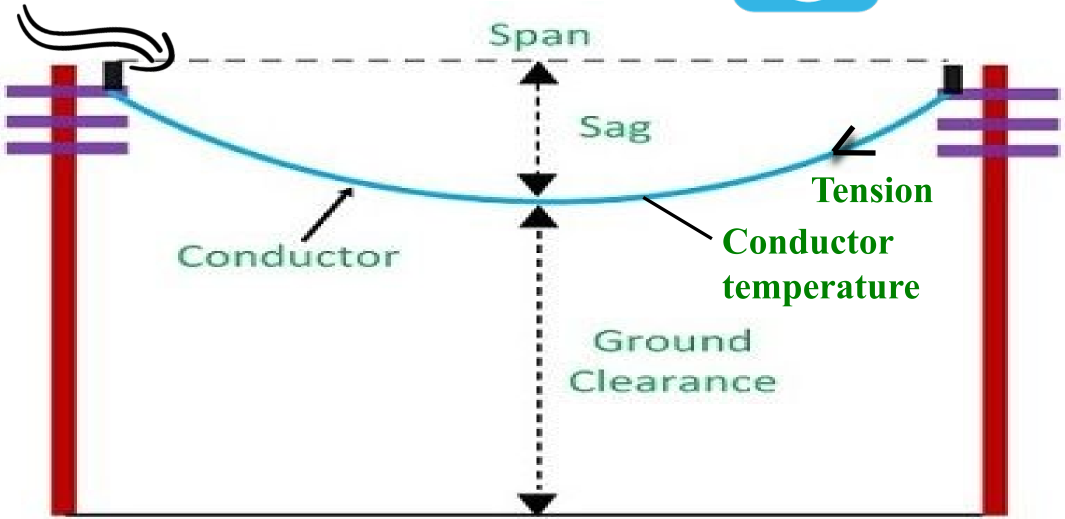
Conductor model directional anemometer

Wind speed & direction

Solar radiation



Ambient temperature



Heat Balance Equation is required in each monitoring system to calculate the RTTR.

RTTR Prediction for Operation

Measurement
- *Suitable locations and spans*

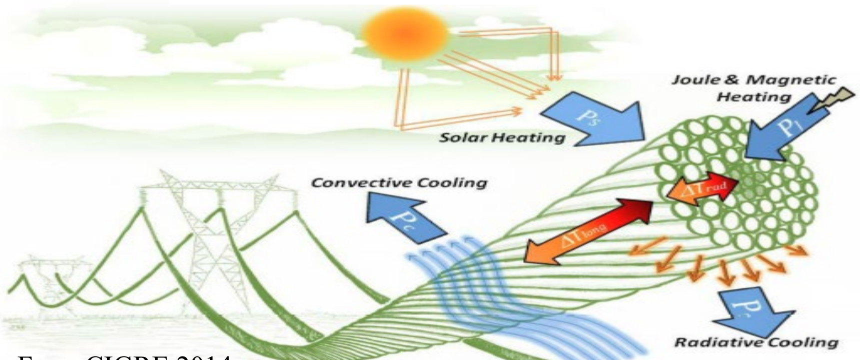
Four Weather Factors

Wind speed	Wind direction
Ambient temperature	Solar radiation

Prediction
- *Method:* Statistical and machine-learning based
- *Output: Predicted values for each factor*

Heat Balance Model
- *CIGRE, IEEE, IEC standards*
- *Consider four weather factors*

$$P_J + P_S = P_c + P_r$$

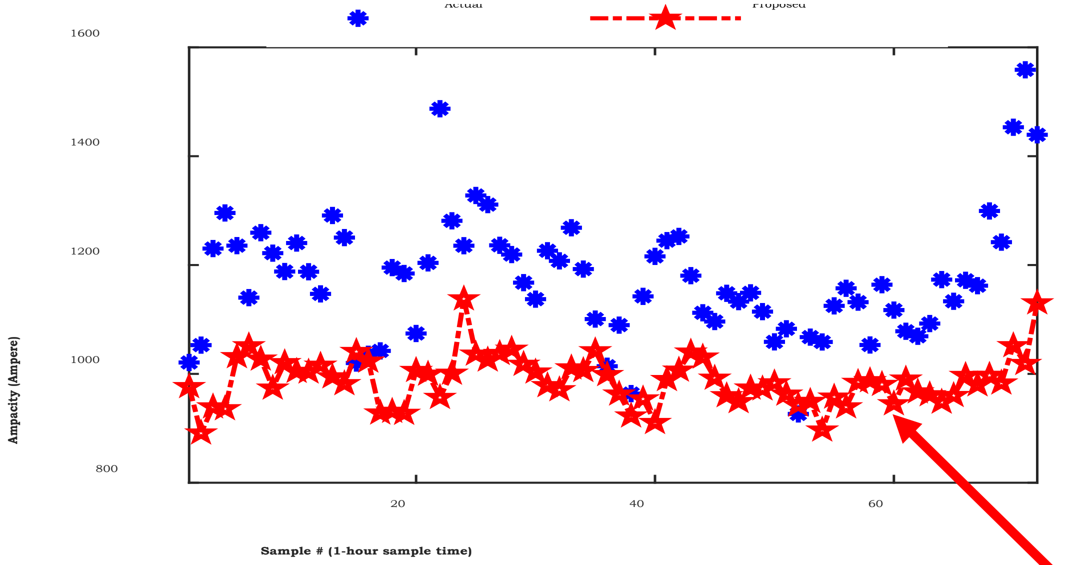


From CIGRE 2014

Predicted RTTR

Probabilistic RTTR Prediction for Operation

Static Thermal Line Rating = 685A



- Any overestimation of RTTR can lead to lifetime degradation and failure of OHL, safety hazards, etc.
- A secure yet sharp probabilistic prediction model [4] for an hour ahead forecasting of RTTR is proposed.

$CL^{*} = 95\%$

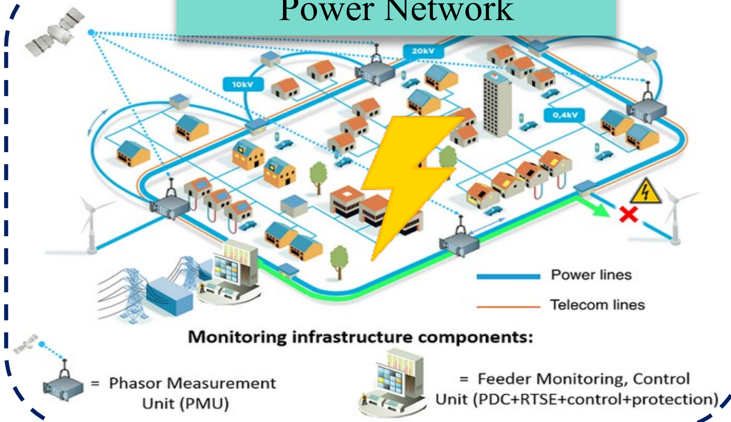
CL*: specified confidence level

[4] N. Safari, M. Mazhari, C. Y. Chung, et.al., "A Secure Deep Probabilistic Dynamic Thermal Line Rating Prediction" Journal of Modern Power Systems and Clean Energy (MPCE).

Example III: Transient Stability Prediction of Power Systems With High Wind Power Penetration

Transient Stability Prediction

Power Network

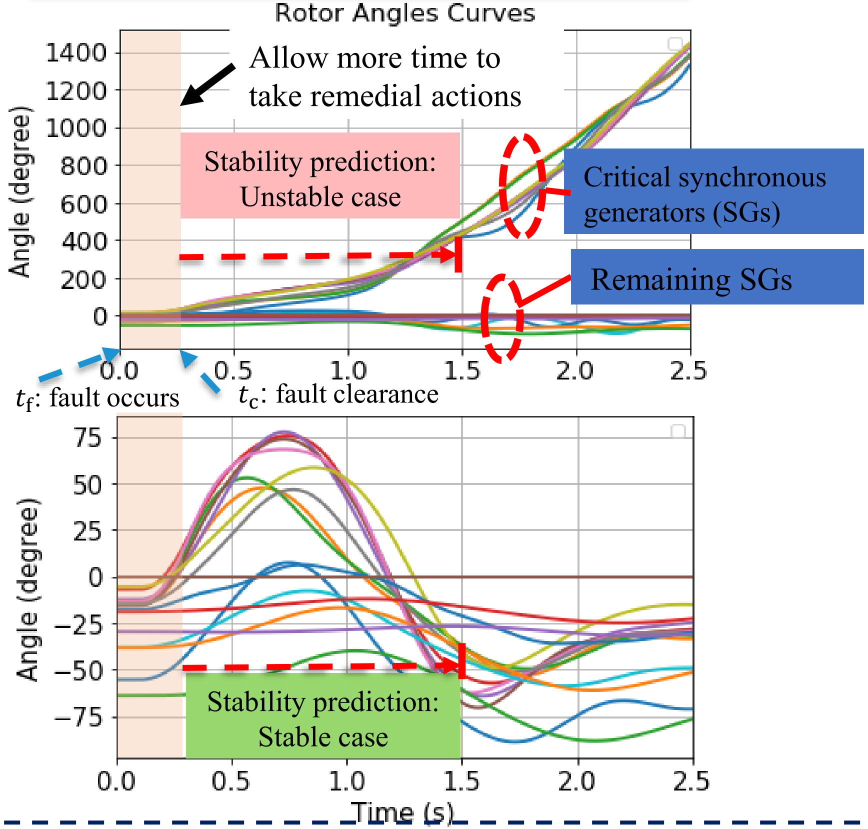


Real-Time Phasor Measurement Units (PMU) Data

Data Process

Prediction & Decision

Fast Prediction For a Post-Fault System

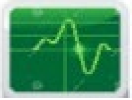


Real-Time Transient Stability Prediction Using Machine Learning and PMUs

REAL-TIME DATA

INSTANTANEOUS PREDICTION

PMUs



Use the data (voltage, rotor speed, etc.) for before-, during-, and post-fault as **features** for stability prediction

Machine Learning

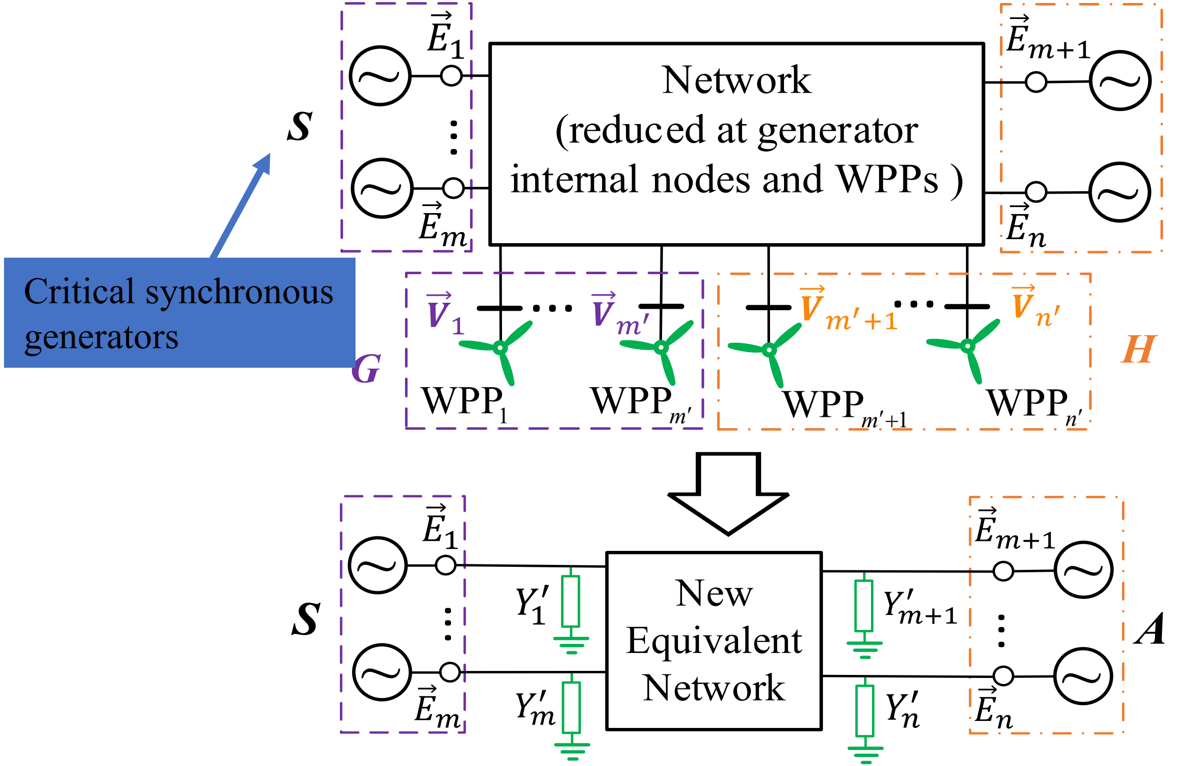
These features may no longer be so useful:

Integration of wind power plants:

- Can impose **multisource uncertainties** to power systems and **exponentially increase** the possible system operating conditions;
- Can frequently change the generation schedule and **system inertia.**

The amount of required training data exploded

Equivalent the Wind Power Plant as Dynamic Admittances [5]



Equivalent Circuit of WPPs

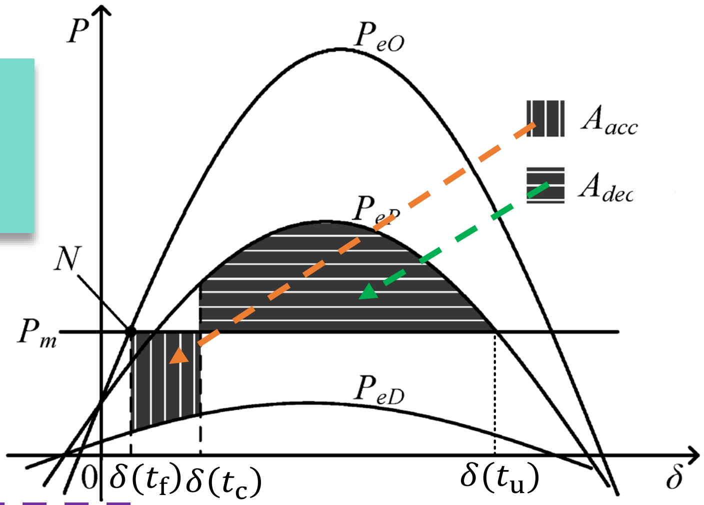
$$Y_i' = \sum_{g\in G}\left[\left(1-\frac{\vec{V}_g}{\vec{E}_i}\right)Y_{ig}\right] + \sum_{h\in H}\left[\left(1-\frac{\vec{V}_h}{\vec{E}_i}\right)Y_{ih}\right]$$

[5] Y. Chen, M. Mazhari, C.Y. Chung, and B. Pal, "Rotor Angle Stability Prediction of Power Systems with High Wind Power Penetration Using a Stability Index Vector," *IEEE Trans. on Power Systems.*

Estimated Stability Index (SI) Column Vector for Stability Prediction

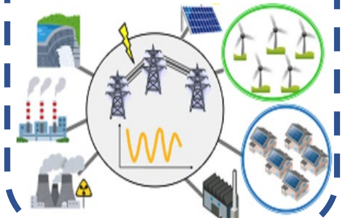
Calculate the stability index (*SI*) utilizing Extended Equal Area Criterion (EEAC) considering the dynamic admittances

$$SI = \frac{A_{dec} - A_{acc}}{A_{acc}}$$



t_f: fault time;
t_c: fault clearance time;
t_u: time instant when the system reaches the unstable equilibrium point

Real-Time Data



Extend *SI* to an *SI* column vector

All Possible Instability Modes (IMs)

$IM_1 \rightarrow SI_1$

$IM_2 \rightarrow SI_2$

$\vdots$

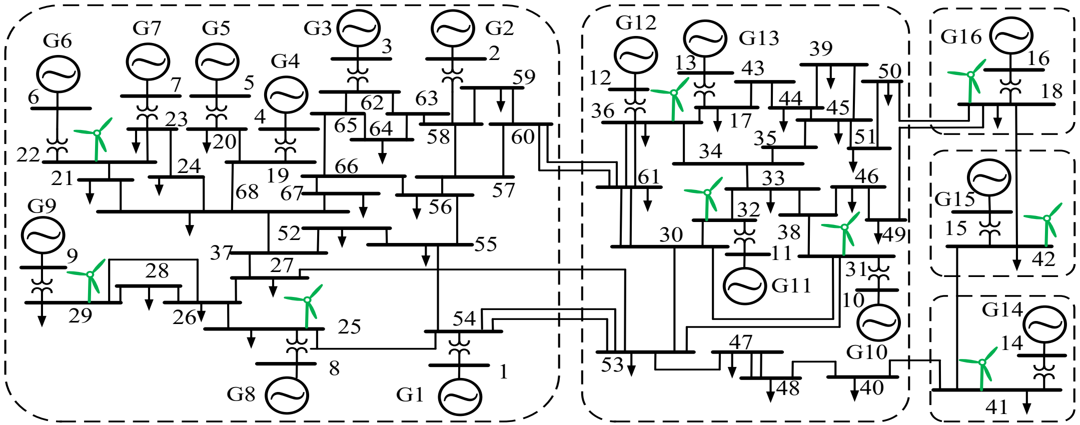
$IM_n \rightarrow SI_n$

SI vector

$$\begin{bmatrix} SI_1 \\ SI_2 \\ \vdots \\ SI_n \end{bmatrix}$$

Decision Made by Machine Learning

Case Studies



The modified 16-machine network with 9 wind power plants (WPPs)

Details of Simulation Analyses

- Fault is applied on each line randomly
- Fault duration is select between 6-15 cycles randomly
- Load level and WPP generation is sampled from historical data for each simulation
- All WPPs use DFIG wind turbines
- All the dataset are trained and tested by **ensemble decision tree**
- **7000 cases** are simulated for each penetration

Comparison of the accuracy of different features

	Features			
WIC*	Rotor angles (δ)	Rotor speeds (ω)	Terminal voltages (V_G)	**Proposed (*SI* vector)**
10%	93.61%	97.05%	96.88%	**98.98%**
20%	92.59%	95.38%	95.79%	**98.59%**
30%	92.18%	94.82%	94.42%	**98.46%**
40%	91.14%	92.06%	92.29%	**98.17%**
50%	89.56%	91.24%	91.35%	**97.96%**

*WIC: Wind power Installed Capacity ratio

Example IV: Load Forecasting in Distribution Systems

Unlock the Value of Smart Meter Data

- The remarkable evolution of smart meters has provided better network visibility of the distribution networks through advanced metering infrastructure.

Interval consumption, demand and voltage data

Aggregation

Virtual meter data of transformer, feeder and substation from GIS

Integration

SCADA

Simple applications

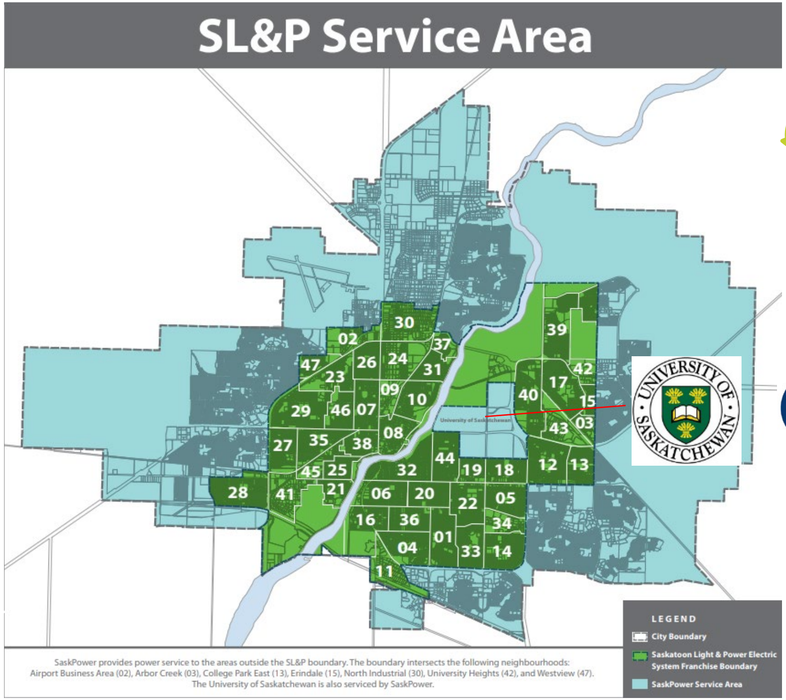
- Billing/Prepayment
- Customer relationship management (CRM)
- Load monitoring

Advanced applications

- Field operation & planning
- Asset management
- Outage management

Rely on accurate load forecasts

Smart Meters Analysis in City of Saskatoon



Data source: https://www.saskatoon.ca/

Saskatoon Light and Power (SL&P) have installed smart meters in **all** of the communities within its service area (Over 99% of more than **65,000** customers)

Total capital costs: CAD 24 M
System operation costs: CAD 22 M
Total **projected savings**: CAD 76 M
Payback period: ~ 11 years

Our **research** focuses on using SL&P smart meters data for customers segmentation and load forecasting.

Aims

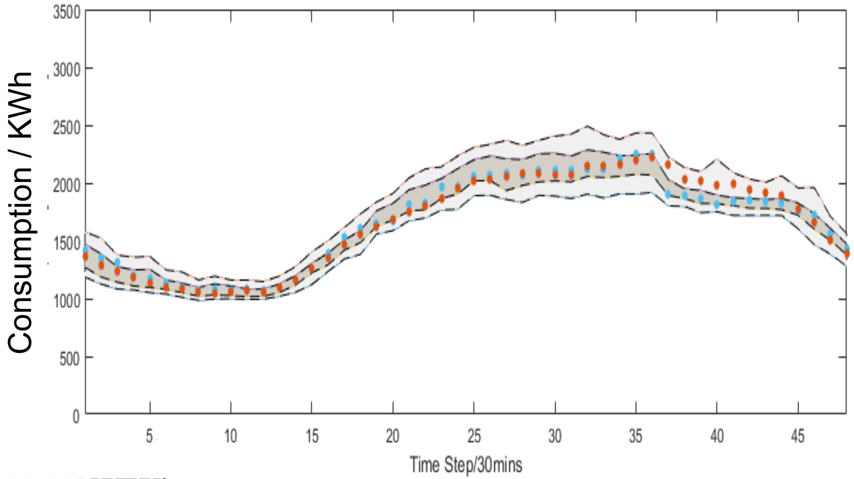
- ✓ Facilitate system operation & planning
- ✓ Optimize asset management
- ✓ Implement demand response
- ✓ Encourage energy efficiency

Customer Segmentation and Load Forecasting

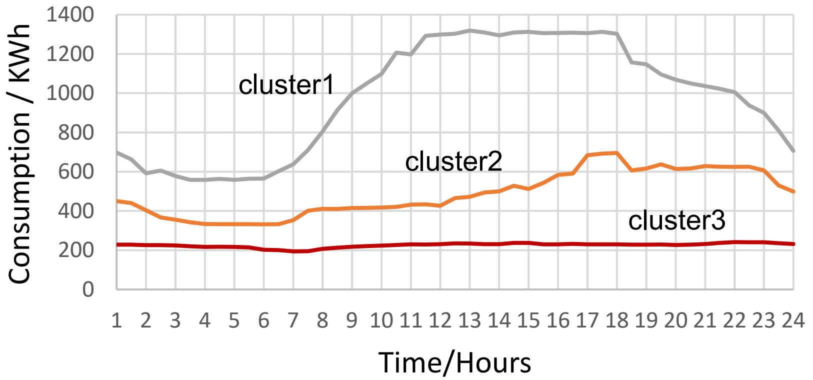
Total: 3500 customers

Cluster	No. of Customers
1	1641
2	1352
3	360
Outliers	147

Outliers are defined as those whose average consumption is lower than 0.1 KWh per 30 mins (unoccupied).



Typical daily profile in summer season



Forecast Evaluated by MAPE

Method	MAPE
Proposed	**2.98%**
Proposed without segmentation	5.79%

MAPE: The *Mean Absolute Percentage Error*

90% prediction intervals

50% prediction intervals

real consumption value

forecasted consumption value

Conclusions

Conclusions

- Power systems are facing a revolutionary transformation to incorporate various smart grids components.
- Such components tightly integrated with ICT and IoT and consequently generated a vast amount of data suitable to support different applications in a smart grid.
- Four different examples were discussed to showcase the applications of advanced prediction methods to resolve current barriers in power systems.
- Power industries are facing many new technical problems => Huge research opportunities.

A Candidate for PES President-Elect: CY Chung

My goals for PES: fostering global collaboration, innovation, and inclusion.
(Target a sustainable, reliable, and equitable energy future with special attention to boosting the role of Women in Engineering and underprivileged regions.)

My vision leverages PES's strengths to lead the global transition towards decarbonization, digitalization, and decentralization of power and energy systems.

Propose a five-step plan:

(i) establishing stronger local partnerships,
(ii) internationalizing PES through diverse connections,
(iii) developing targeted marketing and outreach,
(iv) boosting region- and minority-tailored membership development,
(v) enhancing member support.

Ensuring PES remains a vital resource worldwide.

Thanks!