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Data and Decentralization to Realize Flexibility in Energy Systems

通过数据和非集中化以实现能源系统的灵活性

Prof Tim Green
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Imperial College London

2019 World Industrial and Energy Internet Expo
Changzhou, Jiangsu Province, China.

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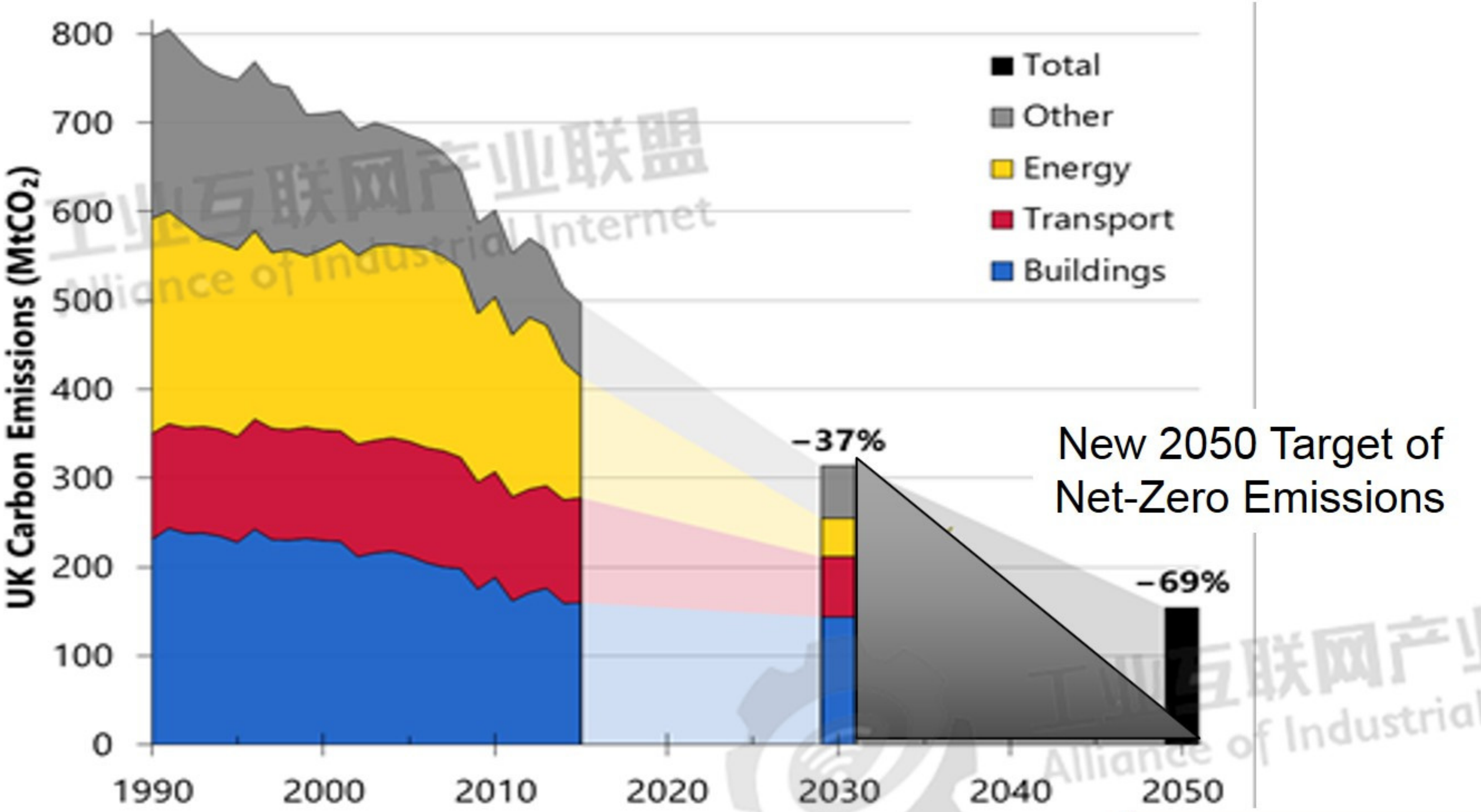
UK CO_2 Emissions Plans

Report by Committee on Climate Change

气候变化委员会报告：英国二氧化碳排放规划



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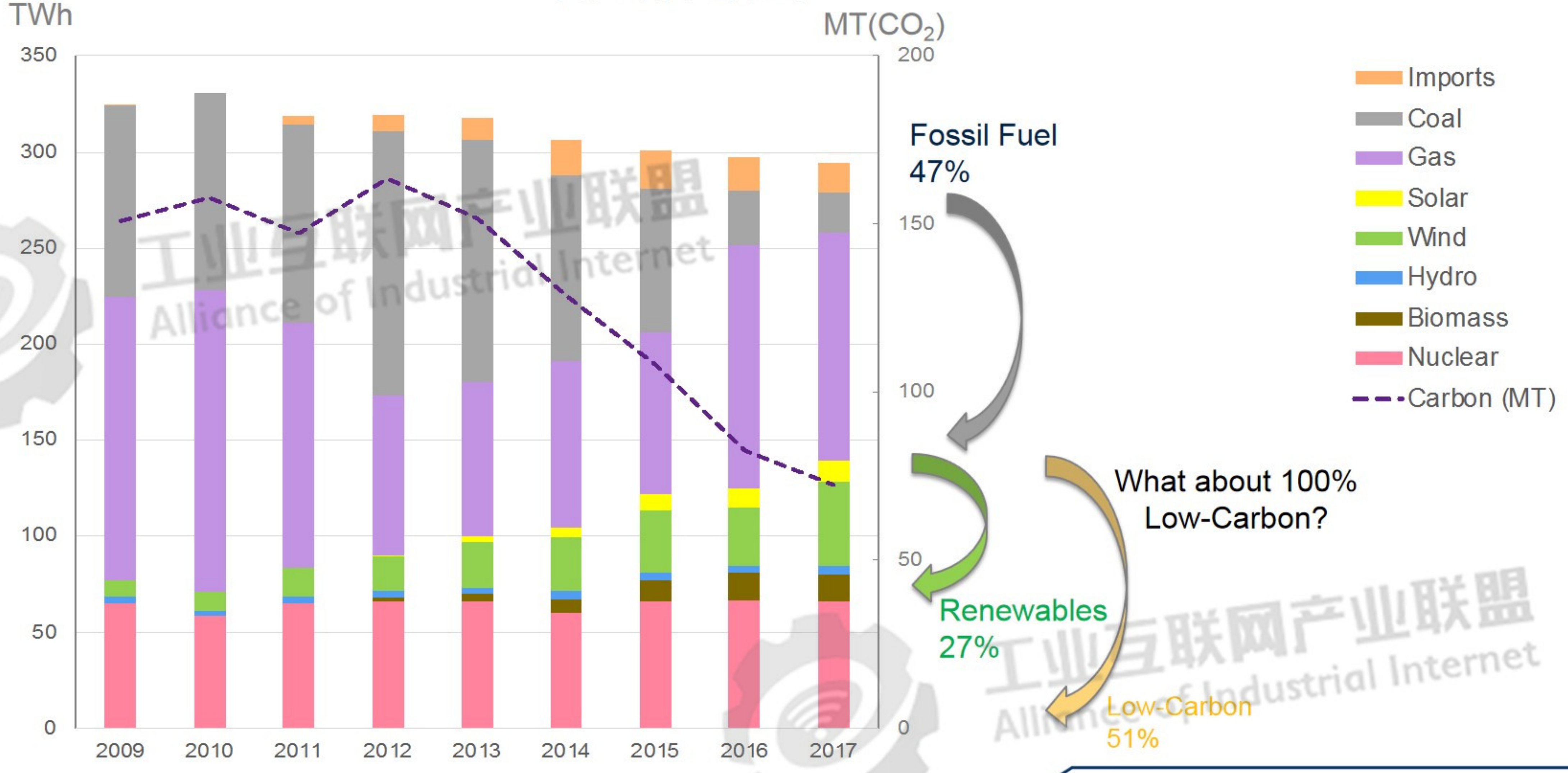
UK Annual Electricity Production

英国年度电力生产



Data from elecricinsights.co.uk

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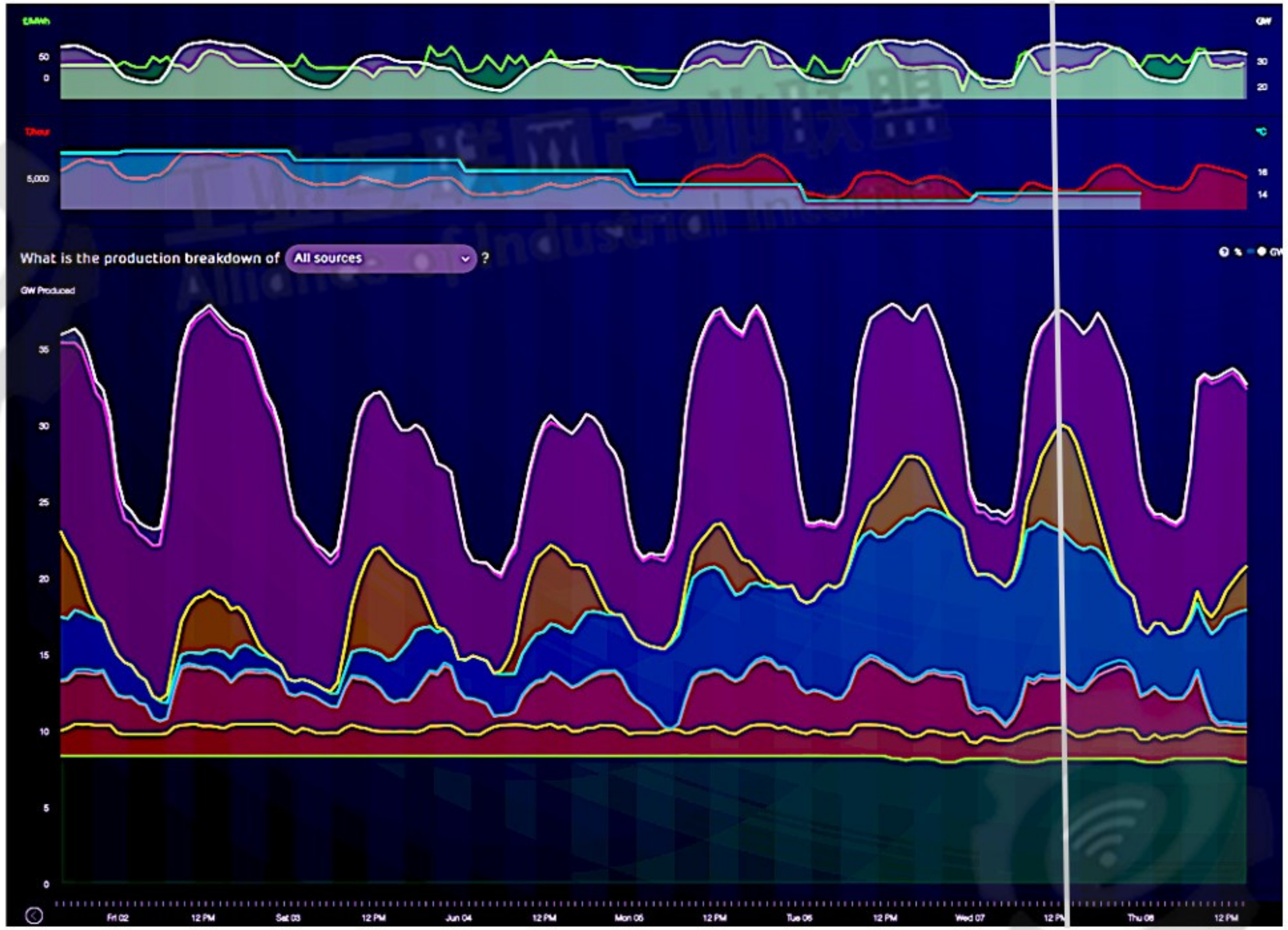
Electricity in Great Britain – 8th June 2017
50% Renewables, No Coal and 20% Gas

2017年6月8日英国电力使用情况：50%可再生能源+ 零煤炭 + 20% 天然气



Emissions 93g/kWh

Demand 36.8 GW

Coal 0.0 GW (0%)

Gas 7.5 GW (20%)

Solar 7.0 GW (19%)

Wind 9.4 GW (25%)

Hydro 0.2 GW (0.4%)

Imports 3.3 GW (9%)

Biomass 2.0 GW (5%)

Nuclear 8.2 GW (22%)

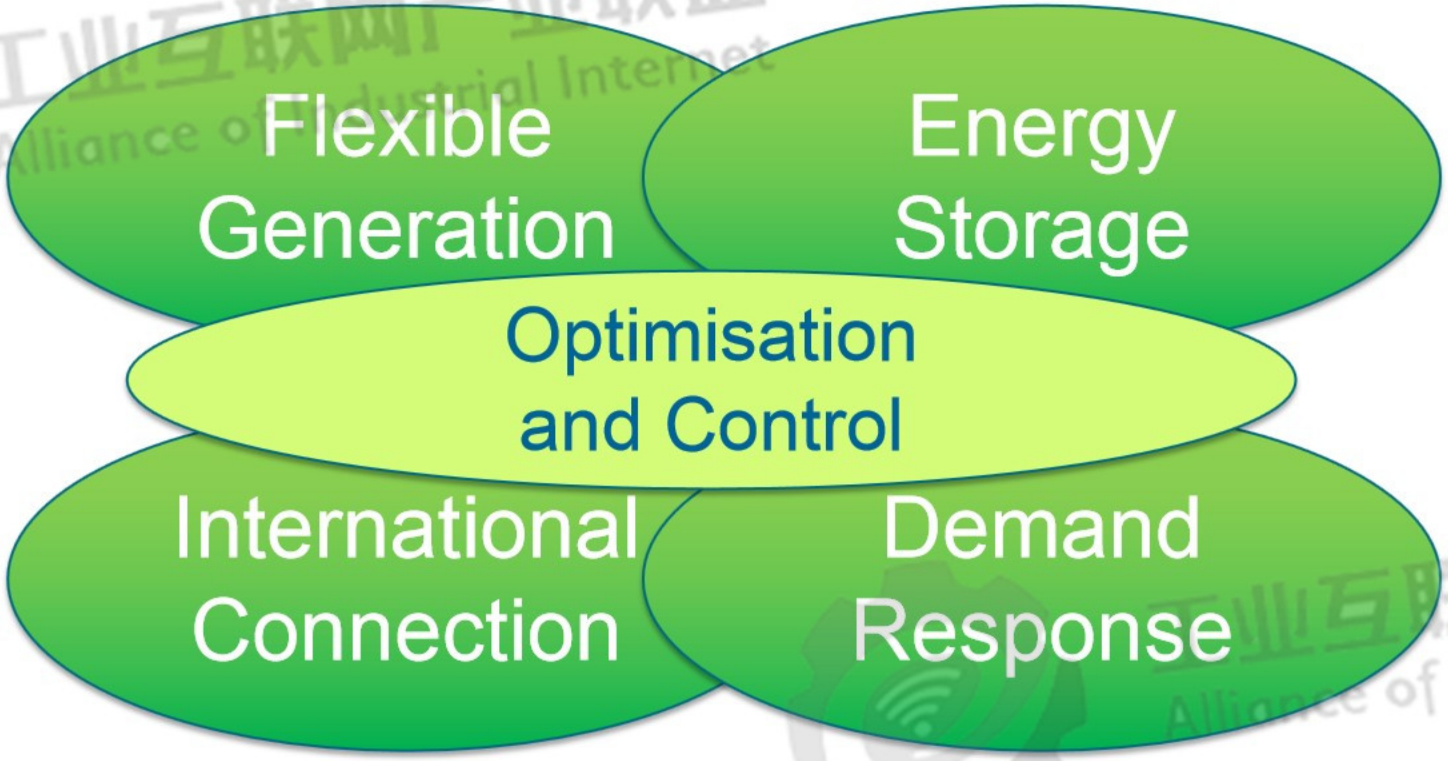
Challenges for 100% Renewables

100%可再生能源供给的挑战

- We need to reduce the cost of energy from renewable sources and *reduce the cost of integrating those sources*
- We need to grow the supply to meet rising demand in newly electrified sectors of transport and building heating/cooling
- *We need to maintain long-term security of supply and short-term stability despite variability of wind and solar energy*
- *We need to find new sources of control functions previously supplied by fast-acting fossil-fueled generation*

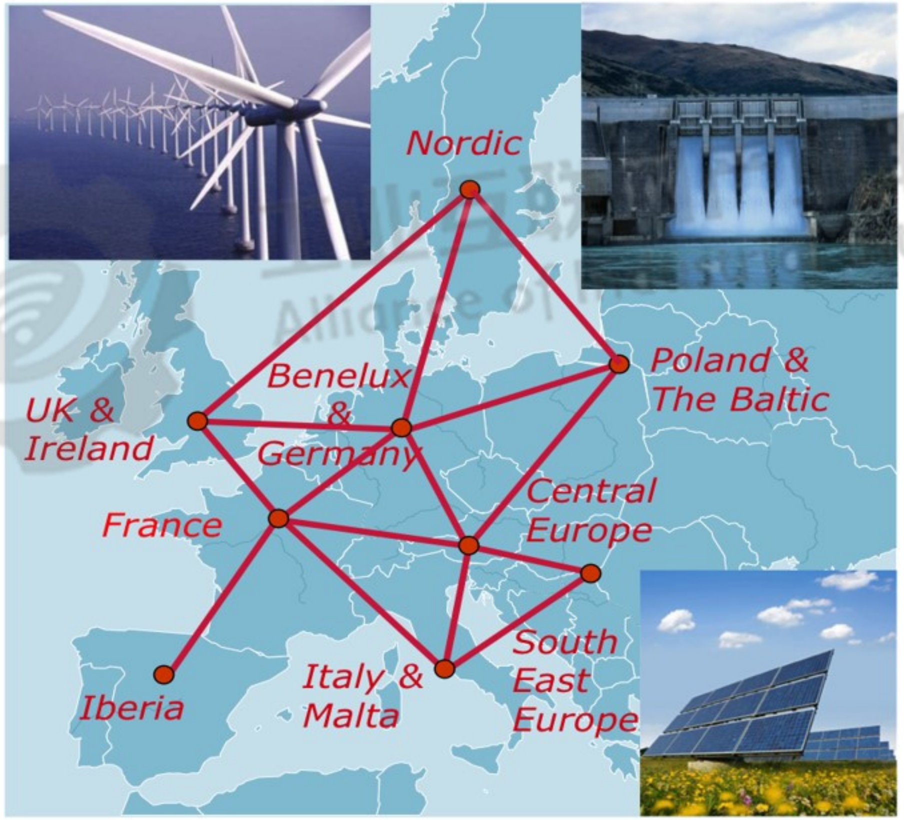
Solutions for 100% Renewables
100%可再生能源供给的解决方案

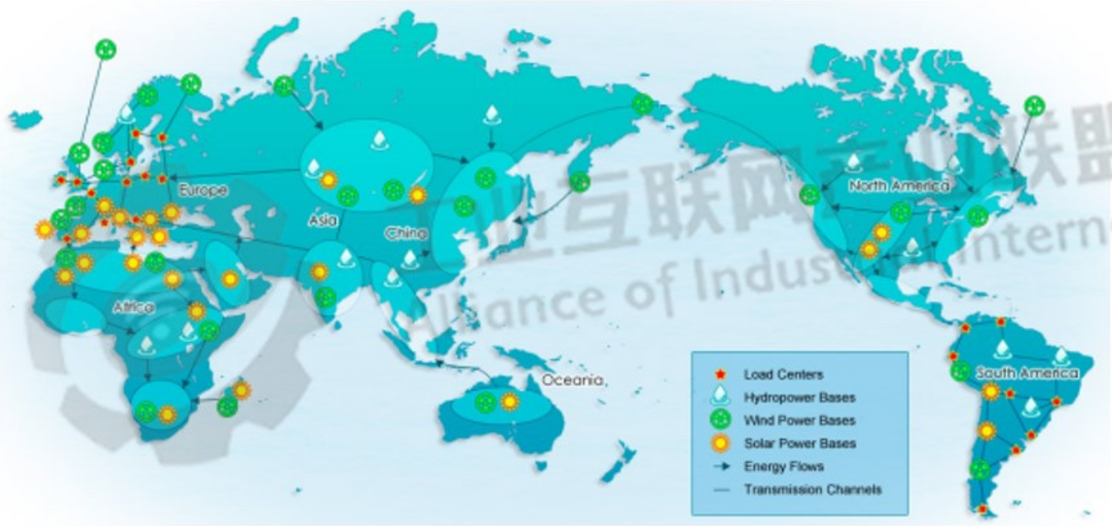
The key is "flexibility": being able to adjust energy consumption and/or production to respond quickly to changes elsewhere



Interconnections for International Diversification of Energy

国际能源多样化的互联互通





Global Energy Interconnection
Development and Cooperation Organization
全球能源互联网发展合作组织

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Challenges in Controlling Energy Systems

能源系统控制方面的挑战

- Harnessing demand-side control actions requires a much more fine-grained and nuanced understanding of human behaviour and the link between consumption of services and energy
- Energy systems are becoming more inter-dependent and complex, and therefore more challenging to optimise and control
- Expectations continue to rise on the control people have over their working and home environments in terms of comfort, responsiveness and dependability

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Data-Driven Energy Systems for Exploiting Flexibility

利用灵活性的数据驱动能源系统

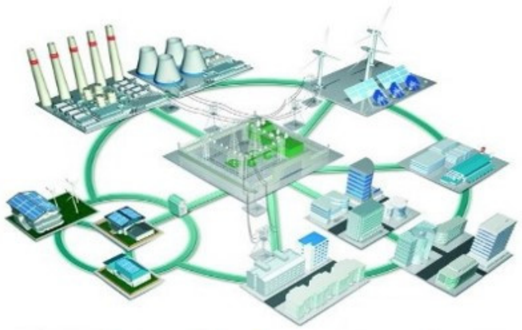
Whole-System Planning (years)

- Multi-Space-Time Modelling
- Scenario Reduction

Energy Market (hours/minutes)

- Consumer Characterization
- Pricing & Bidding Policy

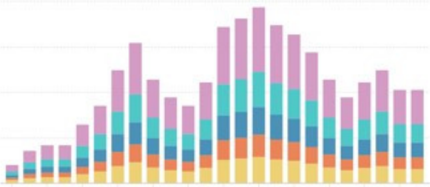
Real-Time Operation (seconds)



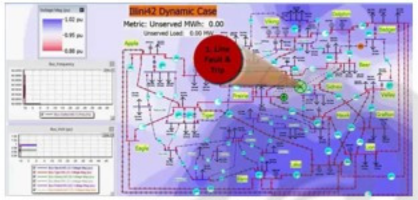
- Security Assessment
- Decentralized Control

Data-Driven Analysis and Optimization

Smart Meter Data



Historical Data



Digital Simulation

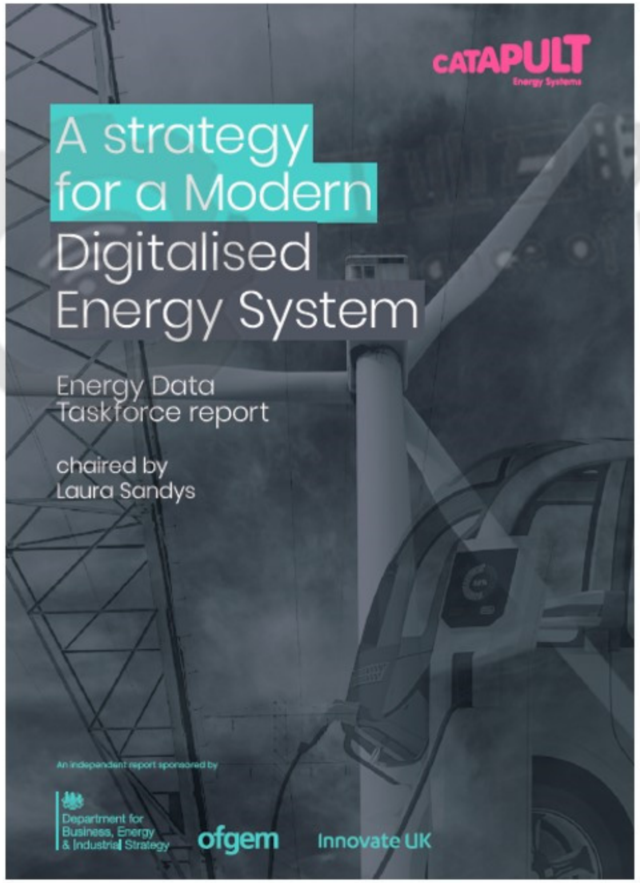
- Reinforcement Learning: Policy Iteration, Q Learning
- Unsupervised Learning: Auto Encoder, C-Vine Clustering
- Decentralized Control: Multi-Agent System, Block Chain

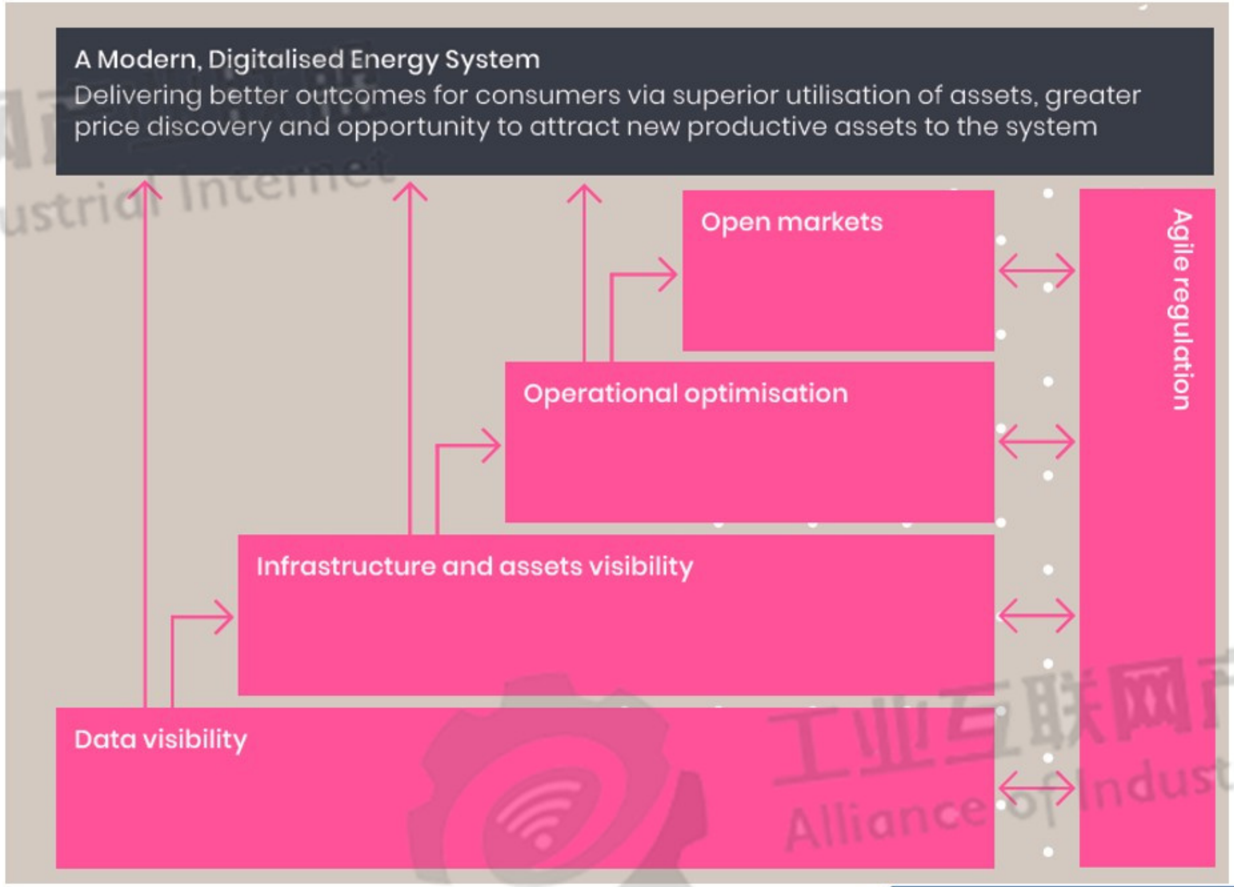
A Strategy for a Modern Digitalised Energy System

现代数字化能源系统的策略

Report of the UK's Energy Data Task Force

英国能源数据工作组报告





Five Areas of Data Exploitation

五个数据挖掘领域

- **Agile Regulation**（敏捷监管）: Enabling regulators to adopt a much more agile and risk reflective approach to regulation of the sector, by giving them access to more and better data.
- **Open Markets**: Achieving much better price discovery, through unlocking new markets, informed by time, location and service value data.
- **Data Visibility**: Understanding the data that exists, the data that is missing, which datasets are important, and making it easier to access and understand data.
- **Operational Optimisation**: Enabling operational data to be layered across the assets to support system optimisation and facilitating multiple actors to participate at all levels across the system.
- **Infrastructure and Asset Visibility**: Revealing system assets and infrastructure, where they are located and their capabilities, to inform system planning and management.

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ABB's View of Digitalisation of Energy

Slide from Ian Funnel, CEO ABB UK

ABB的能源数字化愿景，摘自：英国ABB CEO Ian Funnel

Mapping digitalisation to grid operations

ABB

Necessary architecture and key applications to harvest the benefits of digitalisation in the energy sector

Value adding solutions

Planning and design
- Technical and economic analysis for grid planning
- Use of operational data for design
- Solutions to support the definition of new grid connection codes

Operations
- Data driven predictive operations
- Autopilot functionalities
- Operate closer and beyond the current limits
- New operating principles
- Weather related contingencies

Maintenance
- Predictive outage management
- Diagnostics based predictive maintenance
- Digitally connected workforce
- Optimal crew and assets dispatching

Yield
- Business KPIs reporting
- Business expansion planning
- Business strategy support

Interfaces
- Market interfaces
- Services interfaces
- Asset interfaces (DERMS)
- Market place

Analytics
- Grid analytics solutions to support migration to data driven operations
- Asset digital twins (health, stress and lifetime monitoring)

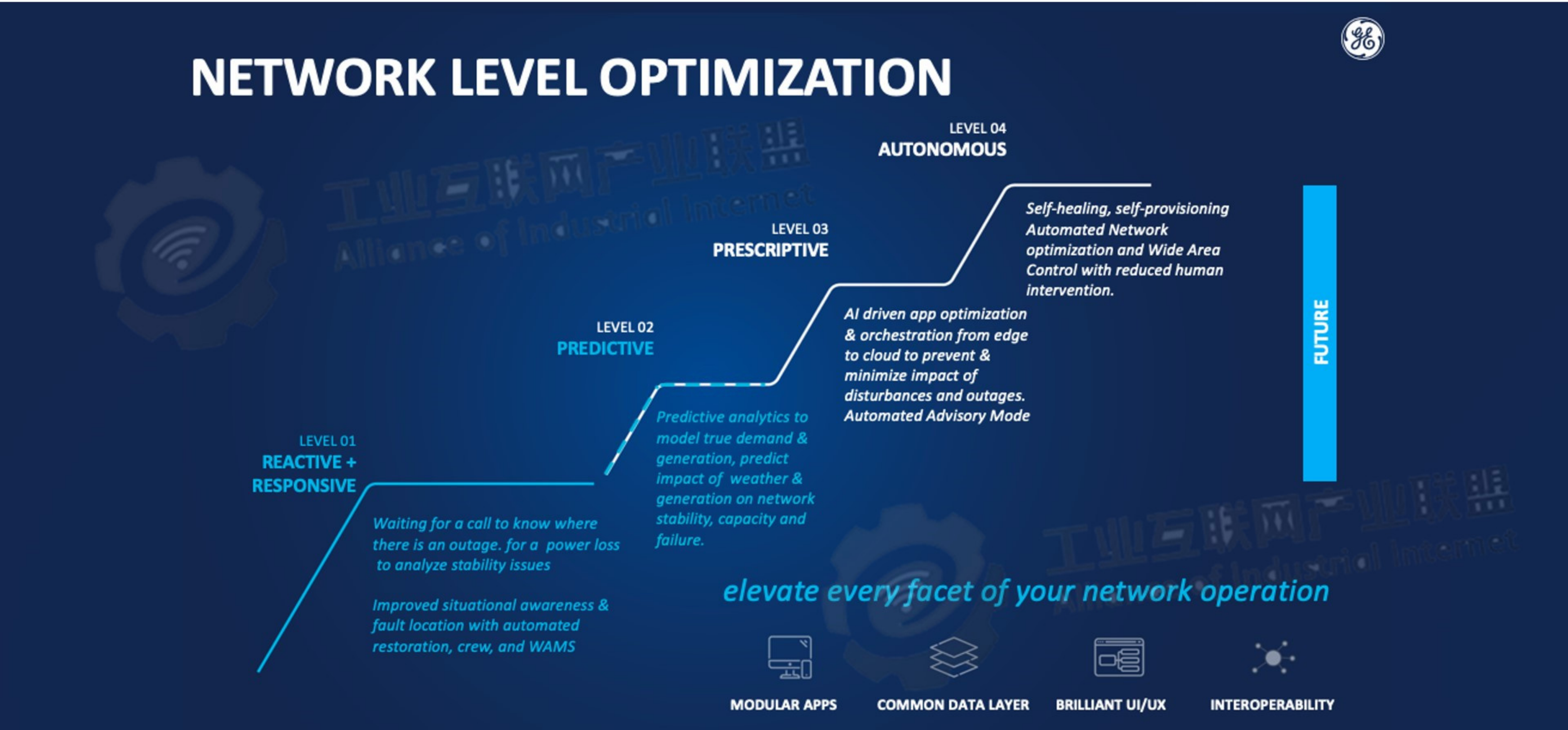
Digitised sectors

Digital generation | Digital transmission | Digital distribution | Digital grid edge

GE's View of the Transformation to Autonomous Control

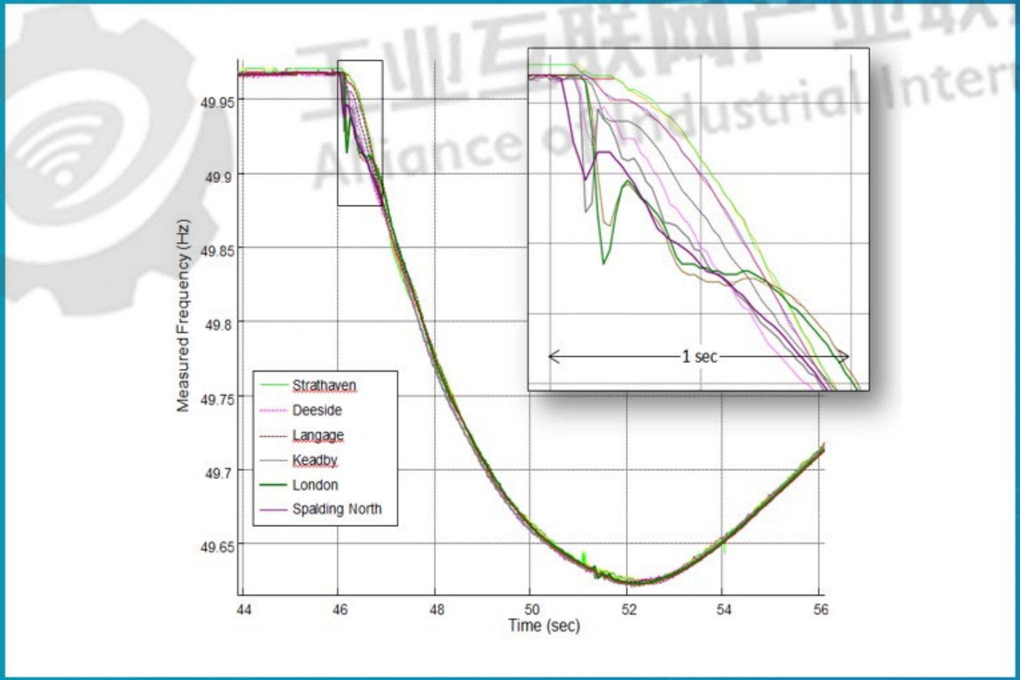
Slide from Vera Silva, CTO GE Grid Solutions

GE的自主控制转变愿景，摘自：GE电网解决方案CTO Vera Silva

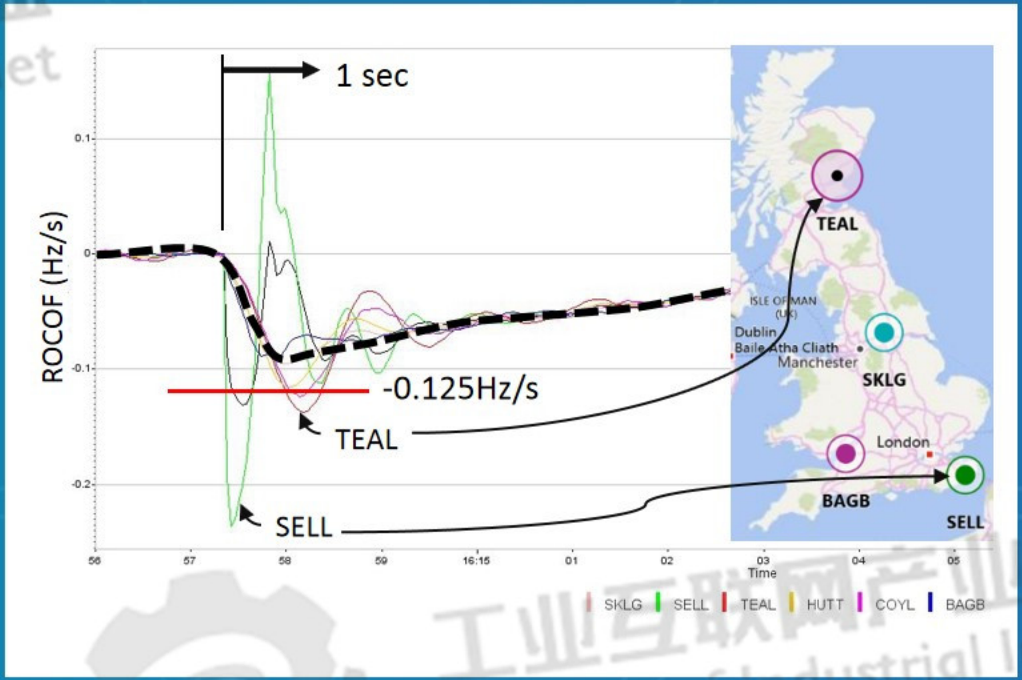


THE INERTIA CHALLENGE - EFFECT OF SPARSE CENTRES OF INERTIA 惯性挑战：惯性稀疏中心的影响

Frequency change takes time to propagate
→ Angles diverge → Stability risk



ROCOF hits loss-of-mains limits in north & south



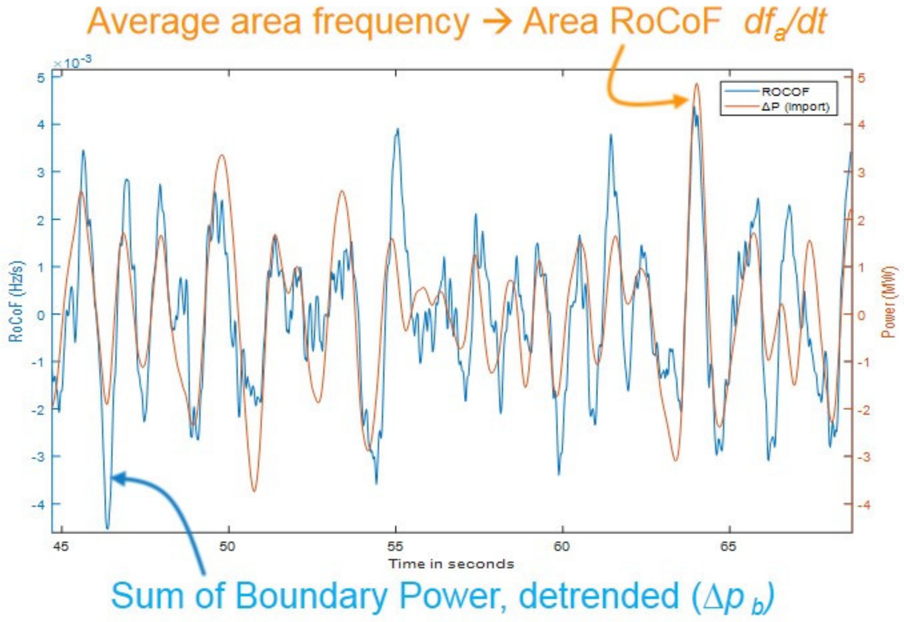
Average system RoCoF within GB 0.125Hz/s limit, but threshold exceeded in both the north & south GB (not Midlands). Risk of regional DER tripping, or in extreme case, loss of angle stability in network.

MEASURING THE EFFECTIVE AREA INERTIA WITH PMUs 通过PMU方法量测惯性有效区域

Example shows section of Scotland data

- **Area RoCoF** for Scotland COI
- **Net Boundary Power** across the Scotland boundary

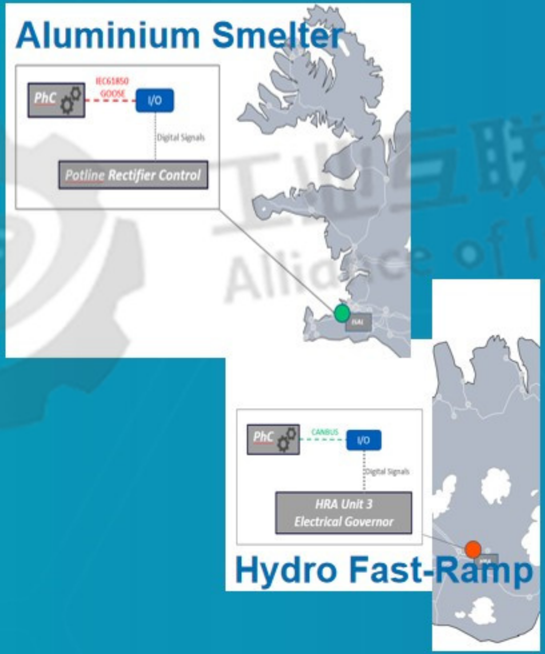
These signals are used to compute effective inertia using correlated changes.

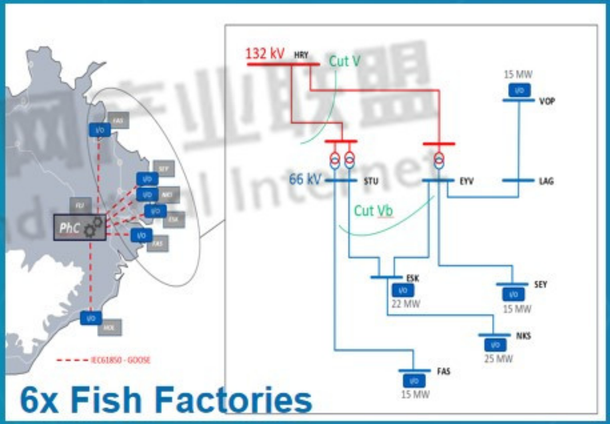


Effective Area Inertia estimation for
(e.g. 30-min windows, steps 1 min)

$$H_{EA} = \frac{\Delta p_b(t)}{2\frac{df_a(t)}{dt}}$$

IMPLEMENTATION OF FAST FREQUENCY RESPONSE RESOURCES 快速频率响应资源的应用





PhasorController

Lessons learned

Wide area control is working well

- Fast acting (<0.5s) & reliable with fault-tolerant distributed control.
- Handles complex multi-event sequences.
- Frequency containment improved.
- Reduced islanding probability & impact with sparse inertia
- More connection capacity: 107MW load able to connect with WAC scheme
- Landsnet plans to extend to more sites & new use cases

Enables flexible fast frequency services

- Diverse loads & generators can contribute. New service capability easily added.
- Cost effective – no new capital equipment or dedicated batteries

MIGRATE

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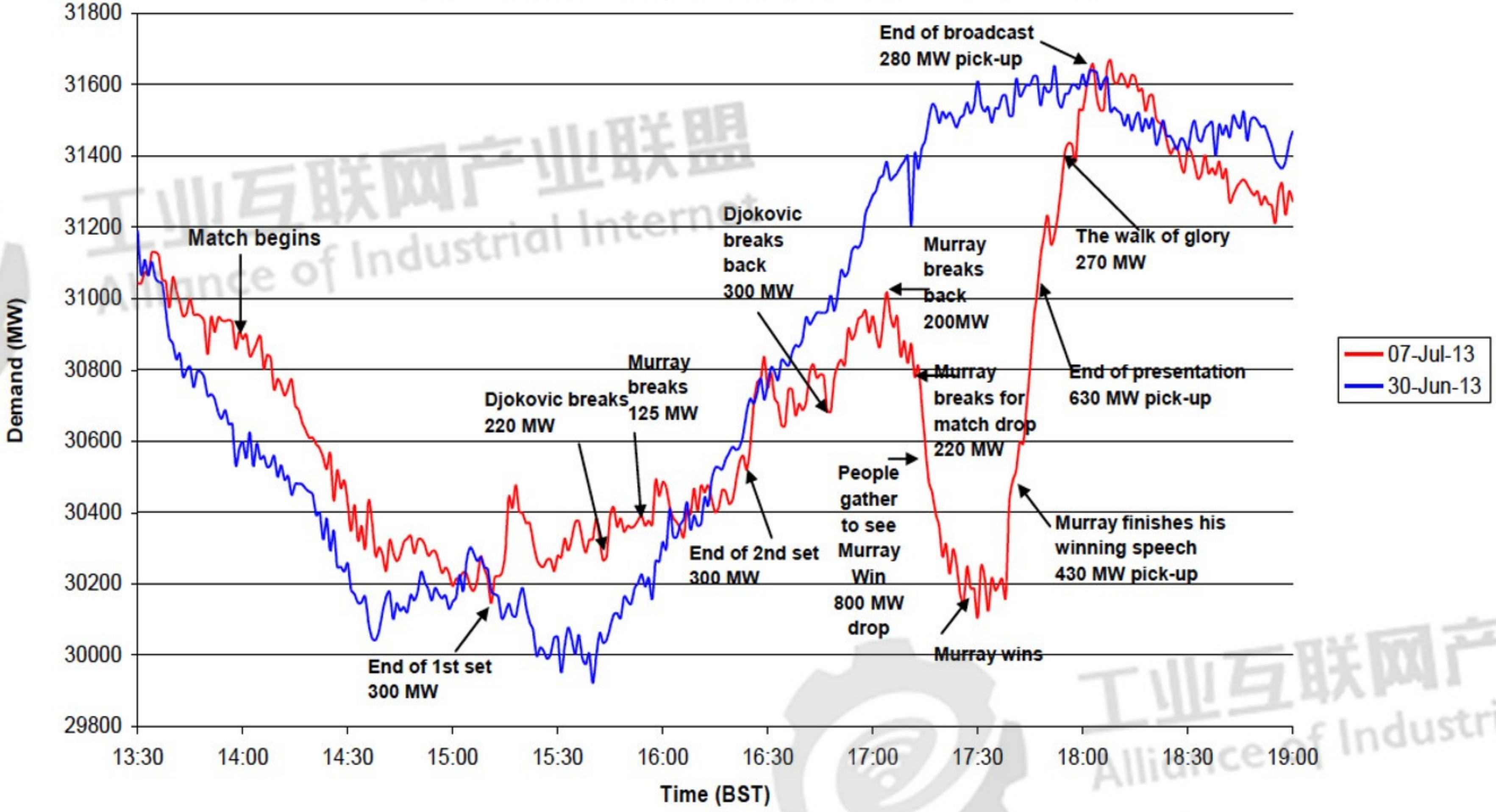
Demand Prediction: good at national level, until something unusual happens

需求预测：擅长国家层面处理异常事件



UK demand during Murray versus Djokovic Wimbledon Final
Source: National Grid Summer Outlook 2015

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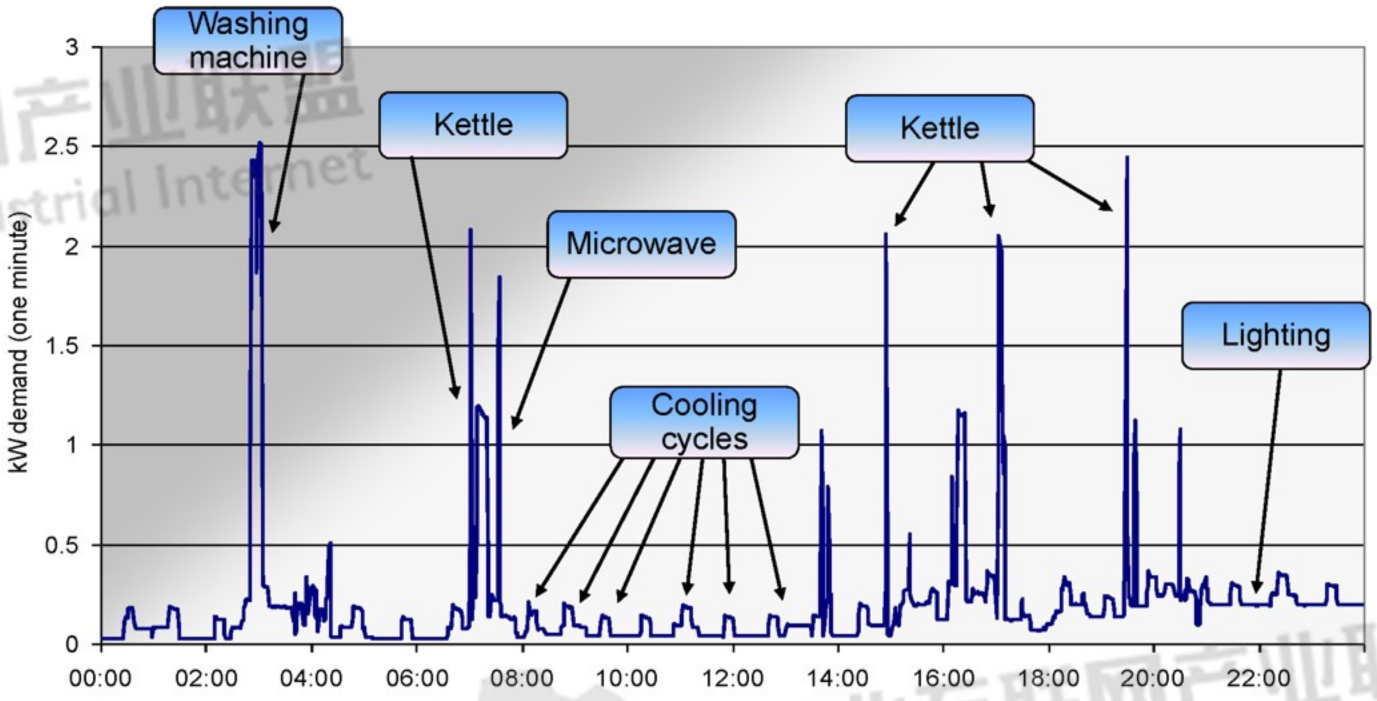
Demand at Household Level is Even More Difficult to Predict

居民家庭层面的需求难以预测

- We need to predict at local level for solving constraint problems in urban networks
- For this we also need to predict how readily demand might be delayed or displaced



(Data source: CREST and E.ON UK)

Perhaps deep-learning method applied to smart-meter data will provide the answers

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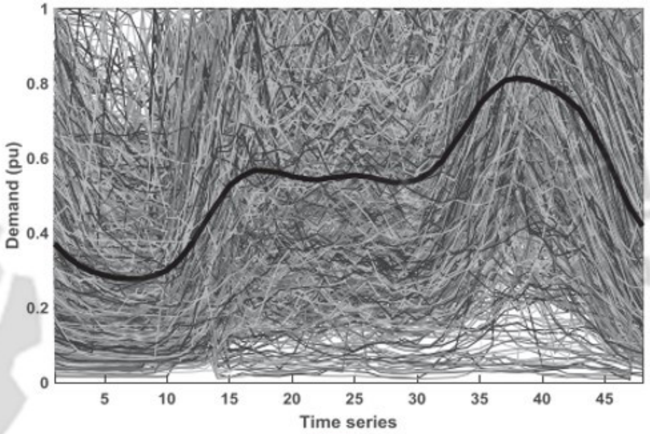
Consumer Characterization

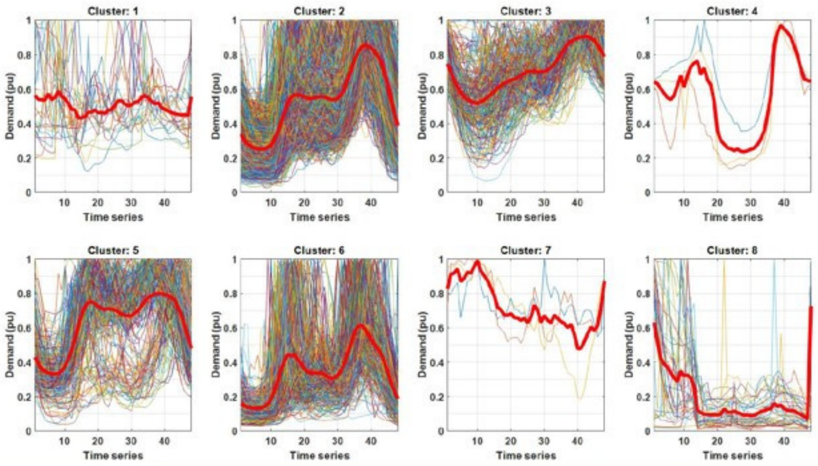
Example of finding base-line for demand response verification

消费者特征 发现需求响应验证基线的示例

Consumer Clustering

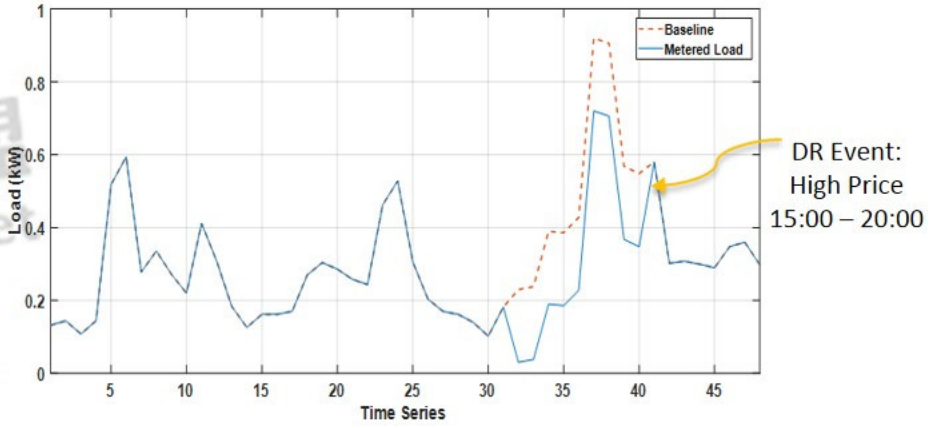


C-Vine Copula Mixture Model

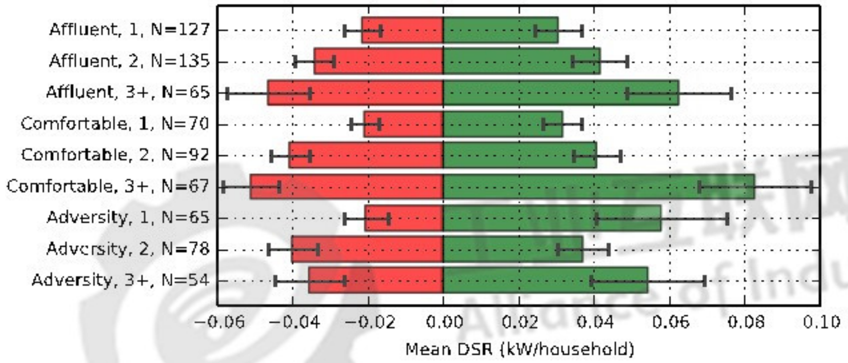


Similarity

Baseline Estimation: Demand Respond Pricing



Socio-Demographic Analysis



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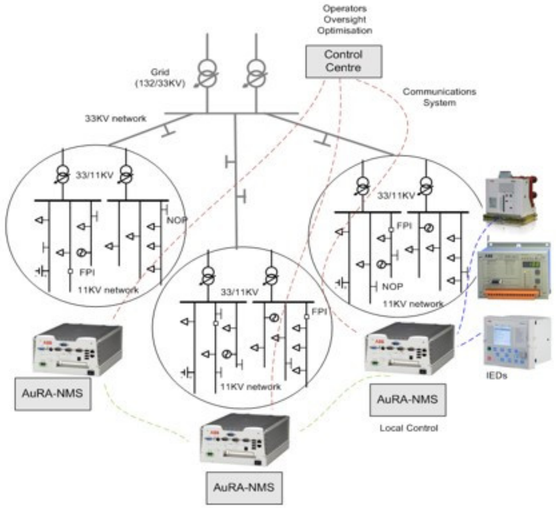
Demand Prediction Using Machine Learning
利用机器学习进行能量需求预测

- A good application is the assessment of how flexible different groups of customers will be under different incentive schemes
- Difficulties are:
  - Size and configuration of trials with customer to generate enough meaningful data
  - Identifying the contextual data for demand such as size of household; work-patterns; household income; caring responsibilities;
  - Respect for privacy

Centralised Versus Decentralised Control
集中与分散控制



- With growing number of control points (distributed generators, batteries and demand side actions); central control faces:
  - High data communication volume
  - High computational burden
  - High-impact failure modes
- The response could be:
  - Partition control tasks
  - Use more local controllers with autonomy
  - Multi-agent control

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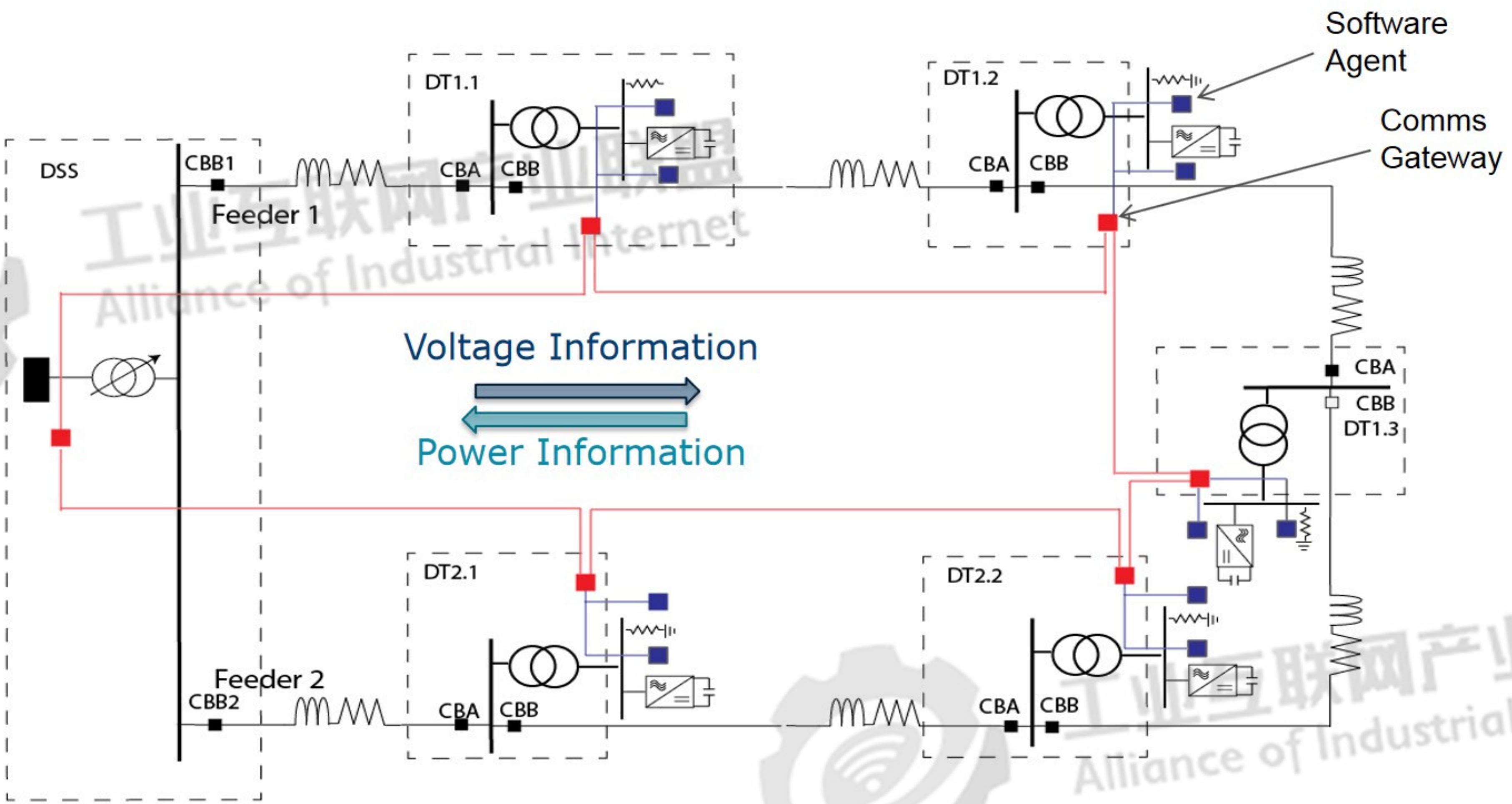
Decentralised Network Control Using Multi-Agent Systems

使用多智能系统的分散式网络控制



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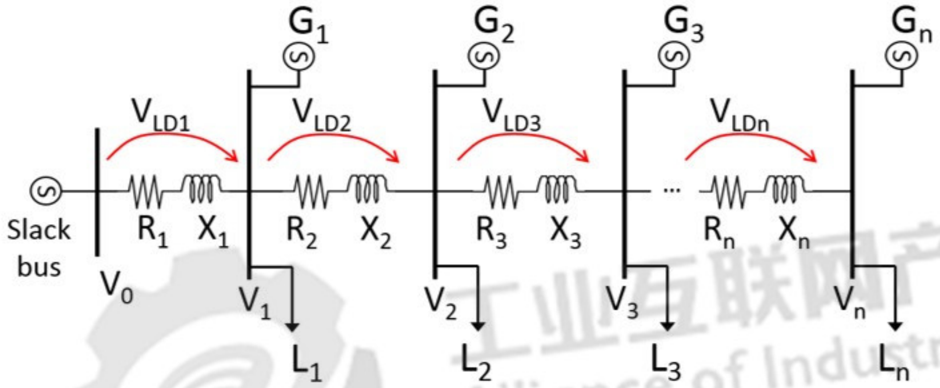
Decentralised Control of Voltage using Estimation of Sensitivity

基于灵敏度估计的电压分散控制



1. Voltage drops between neighbouring nodes nodes depends on power flow

$$V_{LDi} = \frac{R_iP_i + X_iQ_i}{V_i} + j\frac{X_iP_i + R_iQ_i}{V_i}$$

$$\frac{\partial V_i}{\partial P_i} \cong -\frac{1}{2}\sum_{k=1}^{i-1}\left(\frac{R_k}{|V_k|}\right) + \frac{1}{2}\frac{\left(|V_i| + \frac{R_iP_i + X_iQ_i}{|V_i|}\right)\left[\sum_{k=1}^{i-1}\left(\frac{R_k}{|V_k|}\right)\right] - 2R_i}{\sqrt{\left(|V_i| + \frac{R_iP_i + X_iQ_i}{|V_i|}\right)^2 - 4(R_iP_i + X_iQ_i)}}$$

2. Sensitivity of nodal voltage can be estimated from a sum of such voltage drops.

$$Voltage\ sensitivity_P^{Original} \Rightarrow Voltage\ sensitivity_P^{Modified}$$

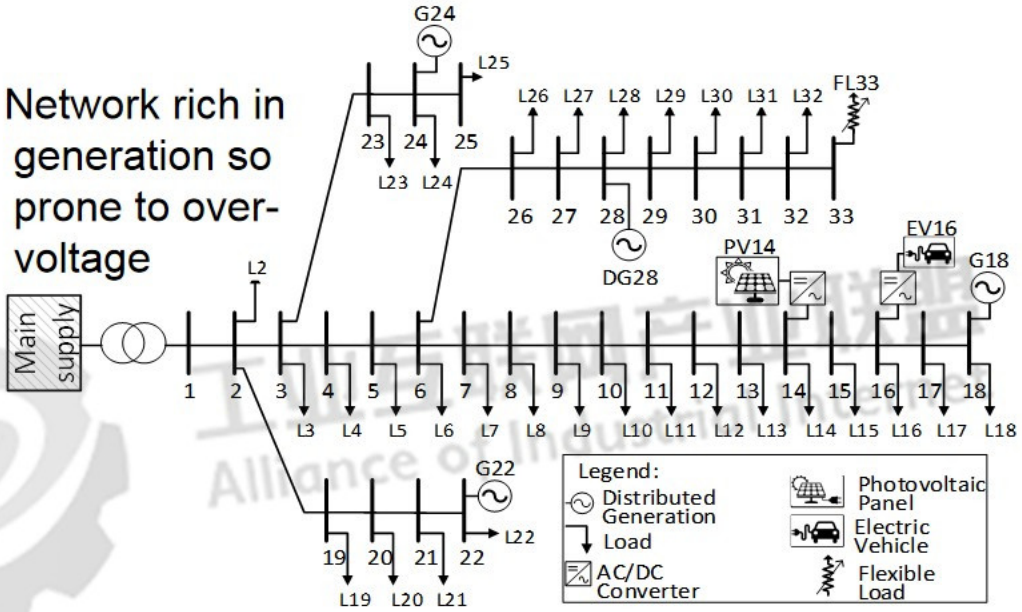
$$\begin{bmatrix}
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_2} & \frac{\partial V_1}{\partial P_3} & \frac{\partial V_1}{\partial P_4} & \frac{\partial V_1}{\partial P_5} & \frac{\partial V_1}{\partial P_6} \\
\frac{\partial V_2}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_3} & \frac{\partial V_2}{\partial P_4} & \frac{\partial V_2}{\partial P_5} & \frac{\partial V_2}{\partial P_6} \\
\frac{\partial V_3}{\partial P_1} & \frac{\partial V_3}{\partial P_2} & \frac{\partial V_3}{\partial P_3} & \frac{\partial V_3}{\partial P_4} & \frac{\partial V_3}{\partial P_5} & \frac{\partial V_3}{\partial P_6} \\
\frac{\partial V_4}{\partial P_1} & \frac{\partial V_4}{\partial P_2} & \frac{\partial V_4}{\partial P_3} & \frac{\partial V_4}{\partial P_4} & \frac{\partial V_4}{\partial P_5} & \frac{\partial V_4}{\partial P_6} \\
\frac{\partial V_5}{\partial P_1} & \frac{\partial V_5}{\partial P_2} & \frac{\partial V_5}{\partial P_3} & \frac{\partial V_5}{\partial P_4} & \frac{\partial V_5}{\partial P_5} & \frac{\partial V_5}{\partial P_6} \\
\frac{\partial V_6}{\partial P_1} & \frac{\partial V_6}{\partial P_2} & \frac{\partial V_6}{\partial P_3} & \frac{\partial V_6}{\partial P_4} & \frac{\partial V_6}{\partial P_5} & \frac{\partial V_6}{\partial P_6}
\end{bmatrix}
\quad
\begin{bmatrix}
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_1} \\
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} \\
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_3}{\partial P_3} & \frac{\partial V_3}{\partial P_3} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} \\
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_3}{\partial P_3} & \frac{\partial V_4}{\partial P_4} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} \\
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_5}{\partial P_5} & \frac{\partial V_5}{\partial P_5} \\
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_2}{\partial P_2} & \frac{\partial V_5}{\partial P_5} & \frac{\partial V_6}{\partial P_6}
\end{bmatrix}$$

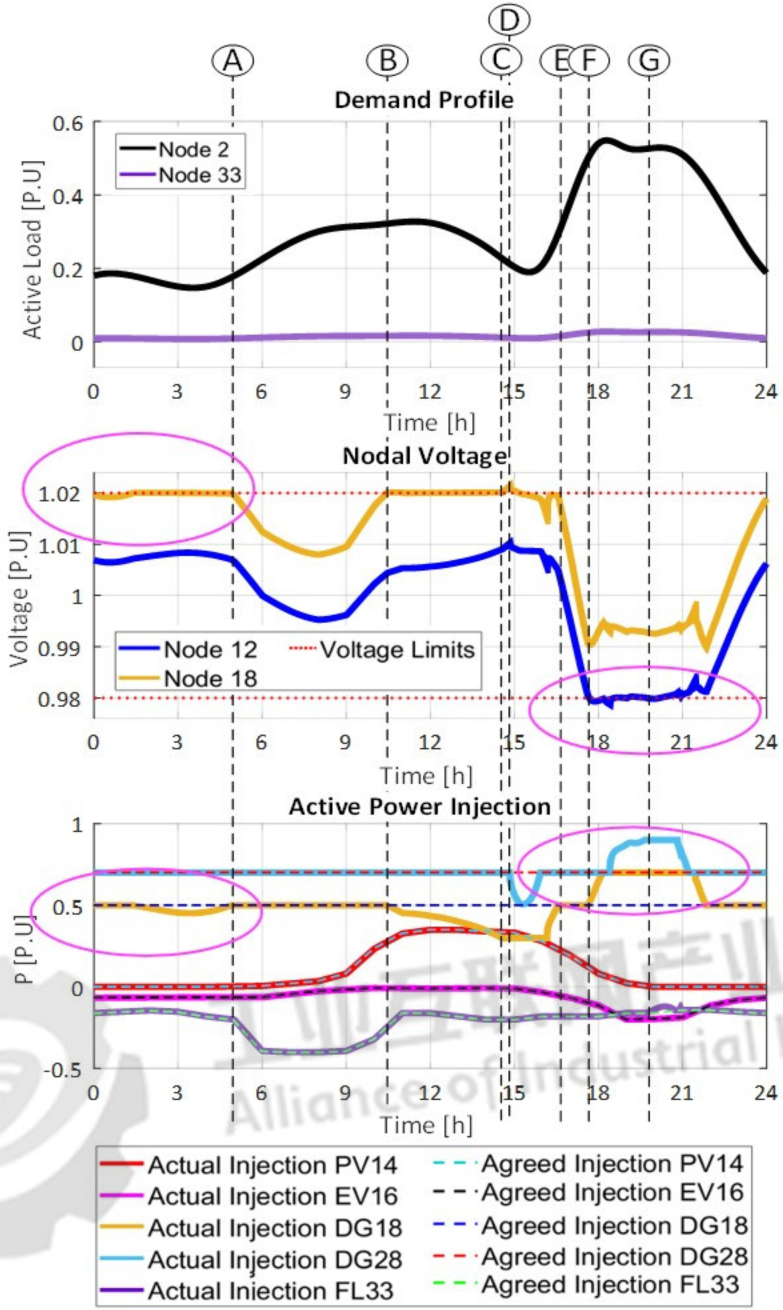
3. Estimates of voltage at one node to power injection at another node can be formed.
4. A local controller can estimate the impacts of remote actions on its local voltage.

Testing on 33-Bus Network

33-Bus网络测试

Network rich in generation so prone to over-voltage



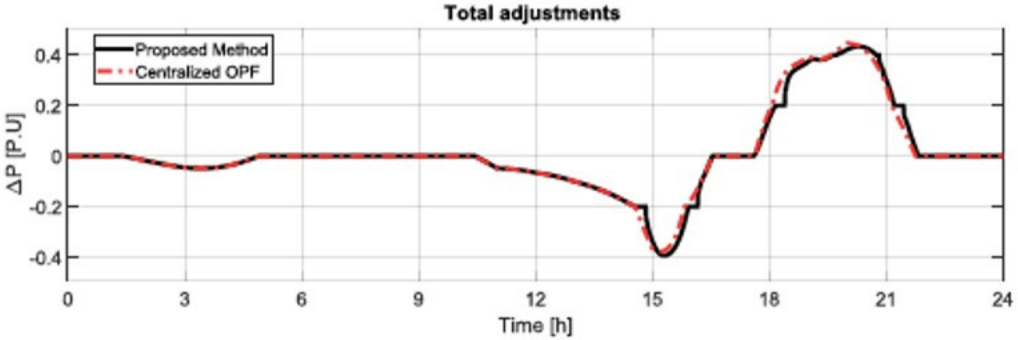


1. Local controller placed at each node.
2. Controllers pass messages about availability and price)of power injections (in addition to existing power flows from energy trading)
3. Each controller estimates impacts of local and remote actions
4. Controller that finds it is the best placed to correct a voltage or flow constraint takes action

Assessment of Accuracy of Local Control Based on Voltage Sensitivity

基于电压灵敏度的局部控制精度评估

1. Changes to power injections used by set of local controllers were compared to injections made by a centralised "optimal power flow".
2. Decentralised control takes almost exactly the same actions.



3. Comparison of local control and OPF was repeated for 500 different combinations of load and generation one four different networks
4. Mean error is very low
5. Processing time is quick (using many simple contollers)

Network	$\sigma_{mismatch}$ [p.u]	Mean [p.u]	Violation Cases [%]	Average Time [s] (proposed)	(OPF)
Simple 10 bus system	0.0394	0.0027	51	0.0012	0.0471
IEEE 15 bus system	0.0118	0.0035	58.2	0.0012	0.0436
IEEE 33 bus system	0.0313	0.0094	64	0.0015	0.0638
UKGDS 76 bus system	0.0223	0.0053	64	0.0014	0.0883

Data-Driven Decentralised Control
数据驱动的分散控制

1. An alternative to estimating voltage-sensitivity is to create control functions based on learning relationships between desired actions and key network measurements.
2. Very many combinations of demand and generation are created and an off-line Optimal Power Flow is used to find the best set of control actions.
3. Regression models are formed of these actions as a function of locally measured voltages and currents.

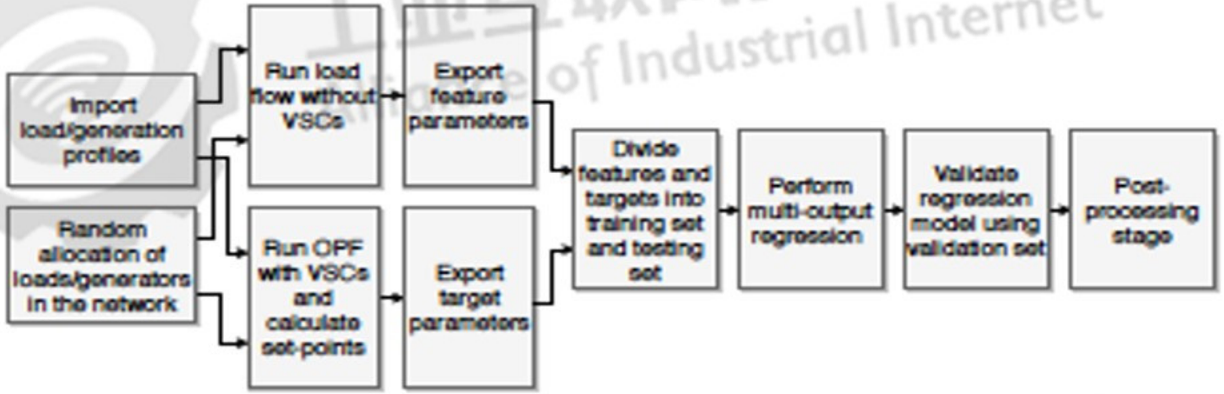


TABLE I
TRAINING AND VALIDATION RESULTS FOR 4 REGRESSION METHODS.

Model	R^2 train	MSE train	R^2 val	MSE val
Linear	0.908	0.169	0.673	1.04×10^{-4}
MLP	0.935	0.137	0.757	1.04×10^{-4}
RF	0.929	4.46×10^{-5}	0.218	1.63×10^{-4}
GBT	0.916	5.39×10^{-5}	0.259	1.78×10^{-4}

4. Candidates are: linear regression; multi-layer perceptron; random forests and gradient boosted trees.
5. MLP was found to give the best trade-off between accuracy and generalisation

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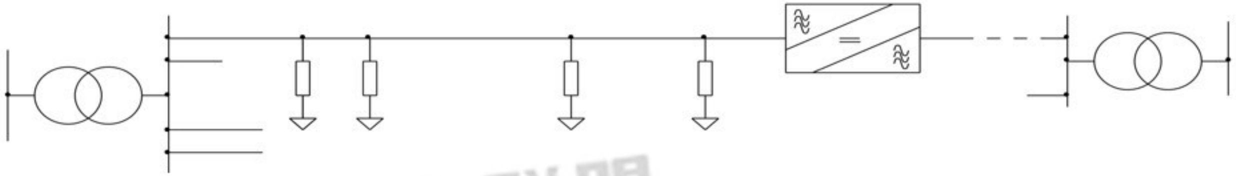
Application of Data-Driven Control to Soft-Open Points

数据驱动控制在软开放点中的应用



A Soft-Open point is a pair of power converters forming a AC-DC-AC bridge across a connection in a network that is normally left open. These have been used in field trials in London and Brighton

UK Power Networks

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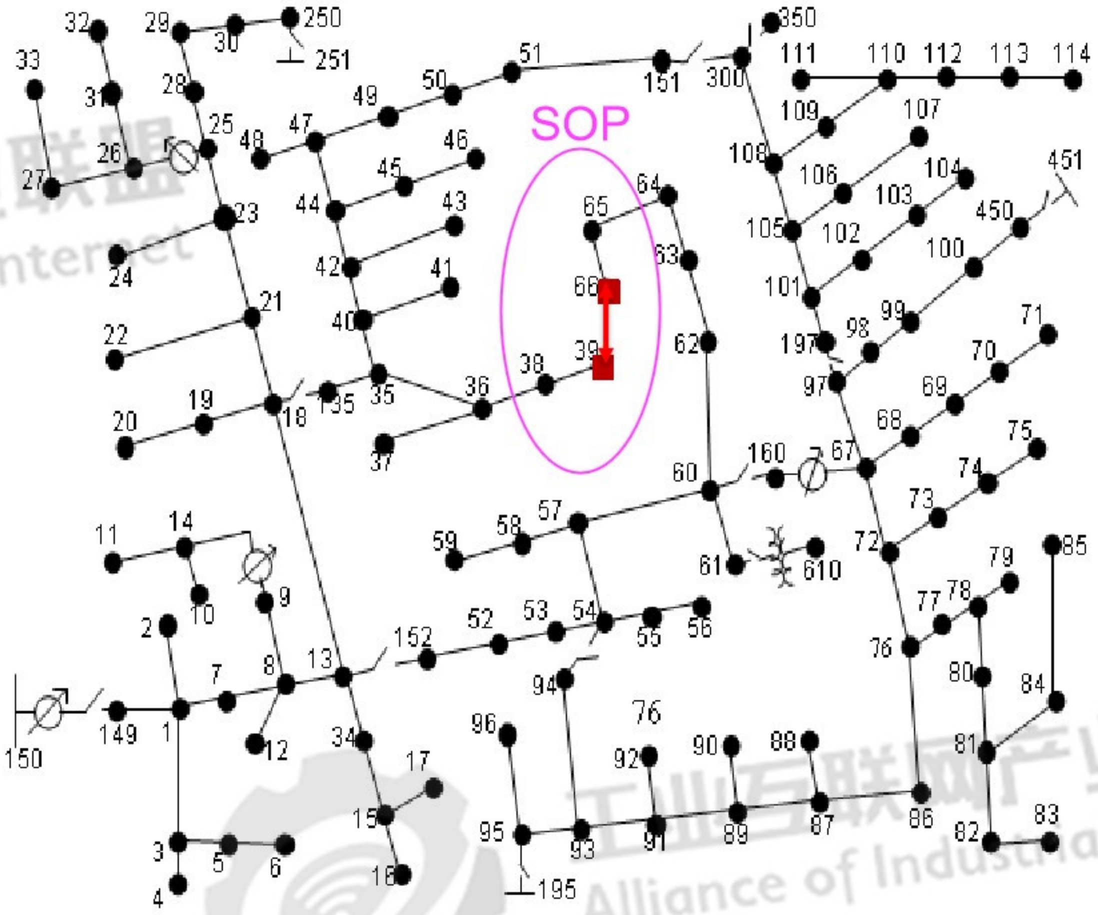
Assessment of Data-Driven Decentralised Control
数据驱动的分散控制评估

Controllers were trained on a 115-bus network.

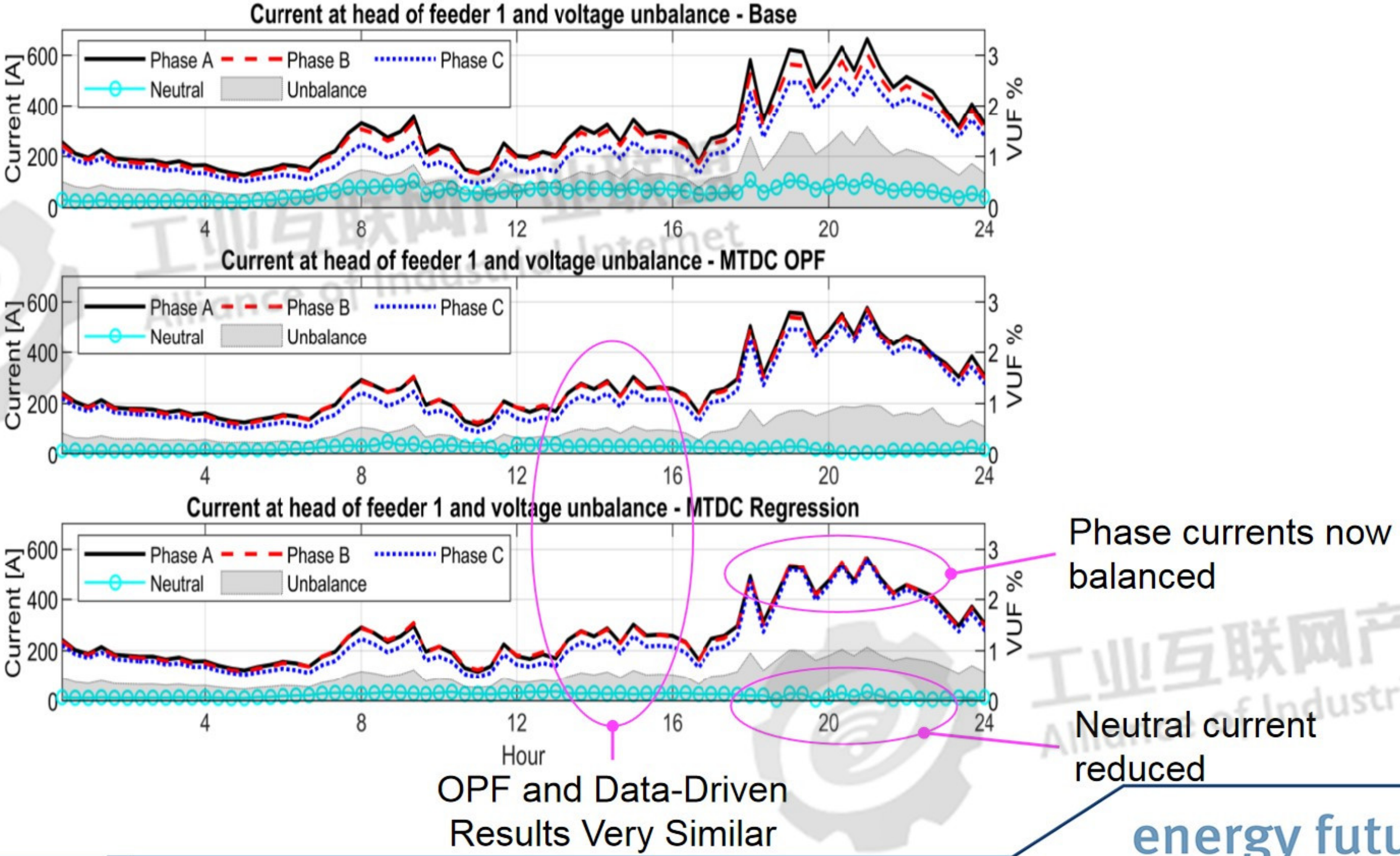
Objective was to reduce unbalance between phases and hence reduce power losses.



Imperial College London

Comparison of Base-Case, OPF and Data-Driven Control

基本案例、OPF 和数据驱动的比较



Conclusions
结论

- Each nation will face different challenges in reaching 100% renewable energy,
- But the challenges of integration have many common features globally.
- Harnessing large numbers of small local actions will be crucial but posses new challenges in analysis and control.
- Data science has potential to solve problems on many timescales: planning (years), markets (hours) and operations (seconds).
- Huge challenges exist in the scale and complexity of control; fresh ideas for decentralised, autonomous control are needed from computer and data sciences.
- Influencing consumer behaviour to aid supply-demand balancing is a big potential application of machine learning but will need expertise in psychology and human decision making also.
- Better understanding of asset aging through data analysis is crucial to providing secure supplies.