Modelling and analysis of future data rich and uncertain power systems

Prof Jovica V. Milanović

Dipl.Ing., MSc, PhD, DSc, CEng, FIET, FIEEE, Foreign member of SAES

Deputy Head of School & Head of Electrical Energy and Power Systems Group

School of Electrical & Electronic Engineering

Manchester, M13 9PL, United Kingdom

18st December 2015, Sveučilište Josipa Jurja Strossmayera, Osijek, & Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia

Overview of the presentation

- Structure, operation and key attributes of Future netwroks
- Modelling and control challenges
- Examples of current thinking and potential solutions
- Summary

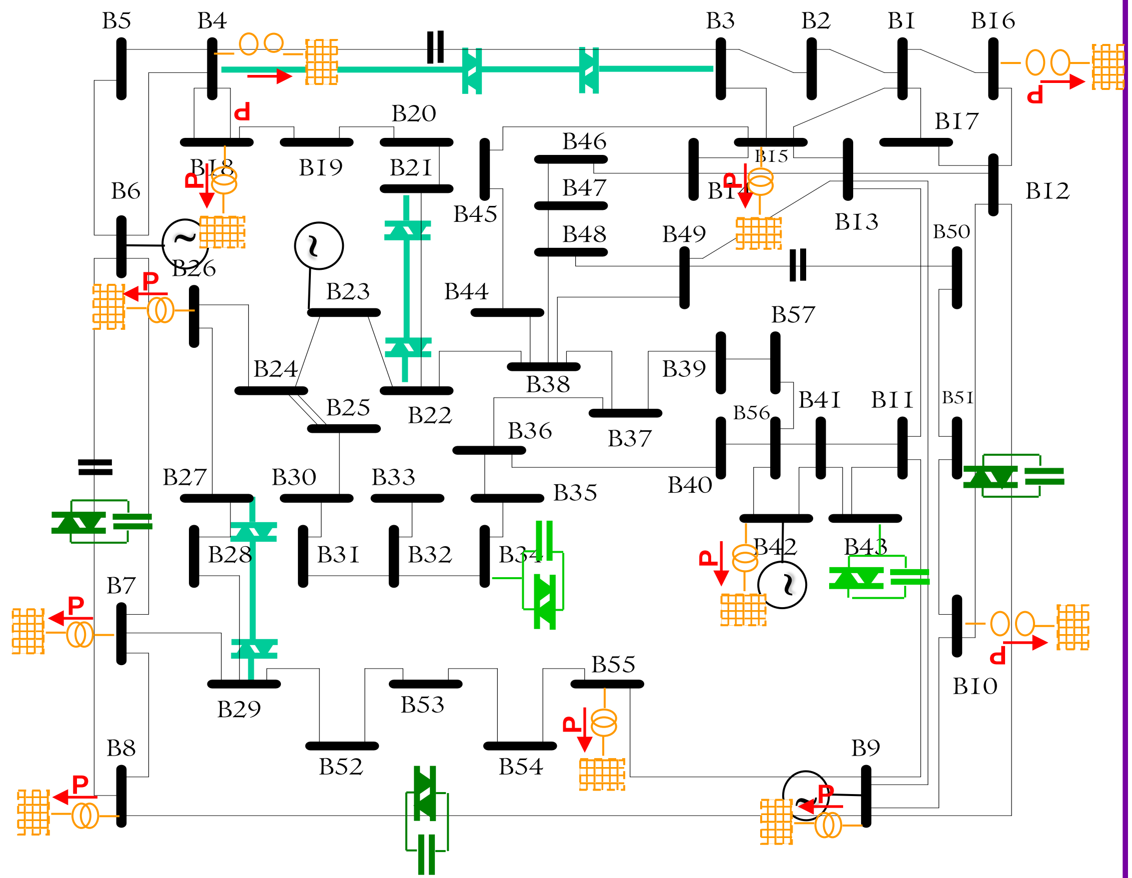
Structure, operation and key attributes of Future networks

Evolving Power Network - Future

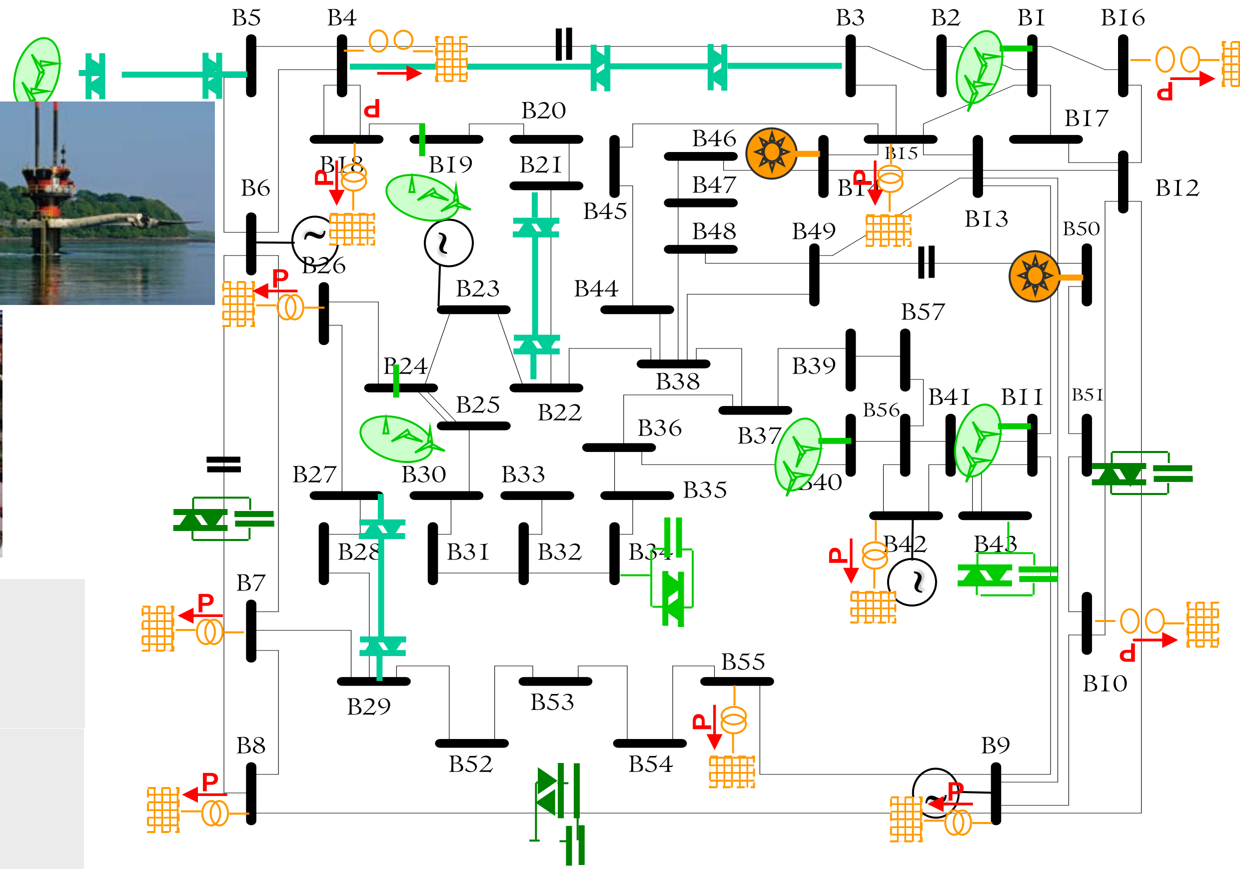
- Liberalised market
- Increased cross-boarder bulk power transfers to facilitate effectiveness of market mechanisms

- Increased use of HVDC lines of both, LCC and predominantly VSC MMC technology (in meshed networks and as a super grid)

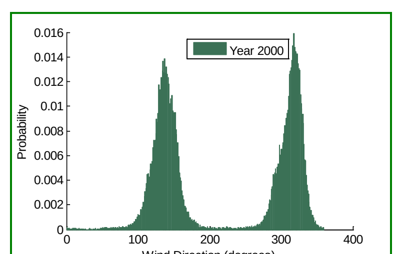
- Increased presence of static and active shunt and series compensation
- Increased deployment of FACTS devices in general

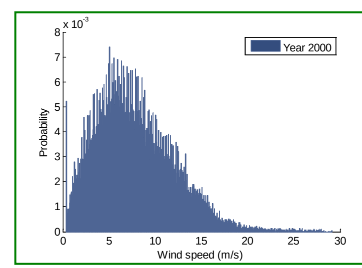


Evolving Power Network - Future

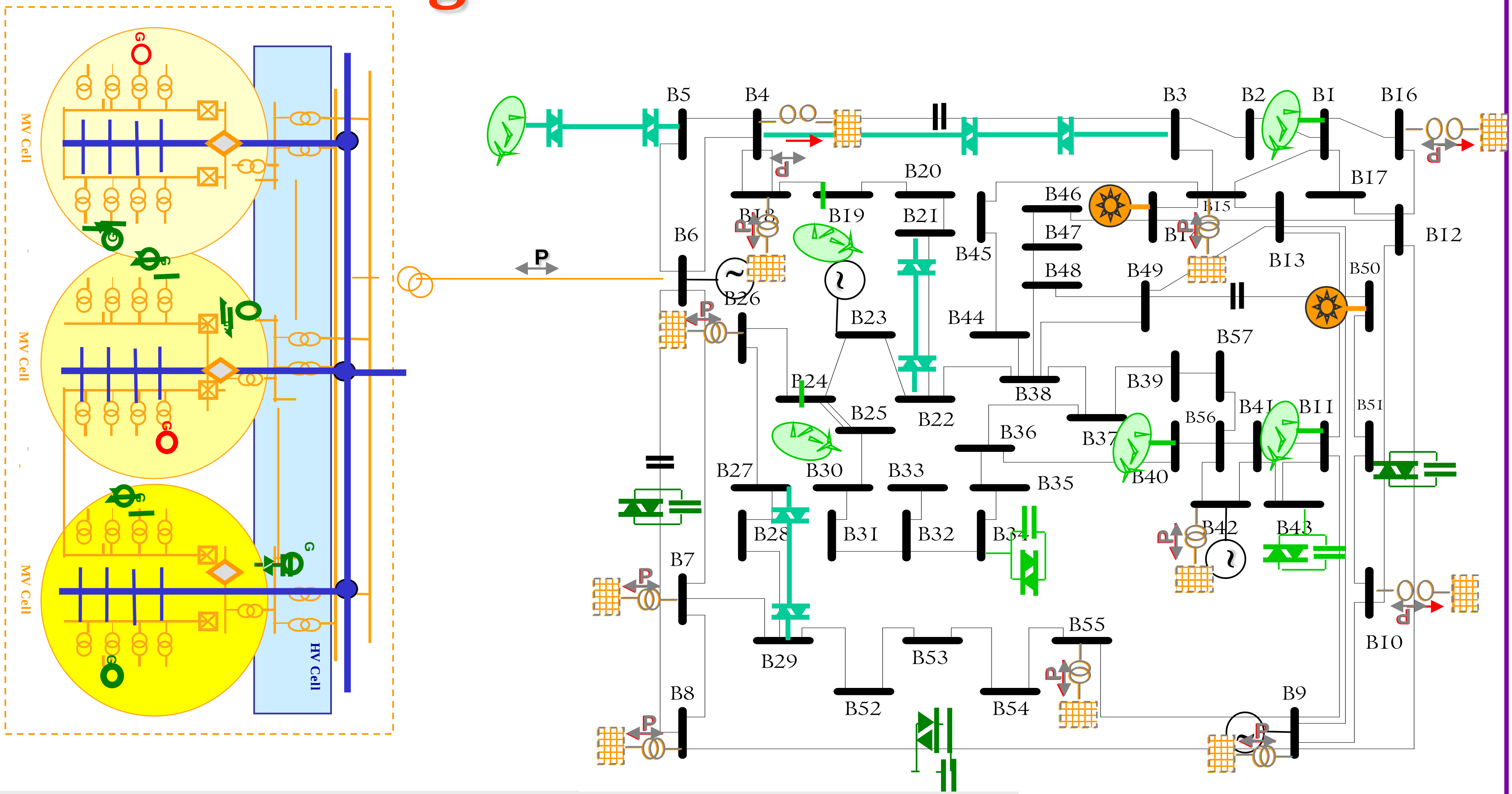


- Large on-shore and off-shore wind farms
- Proliferation of non-conventional renewable generation – largely stochastic and intermittent (wind, PV, marine) at all levels and of various sizes





Evolving Power Network - Future

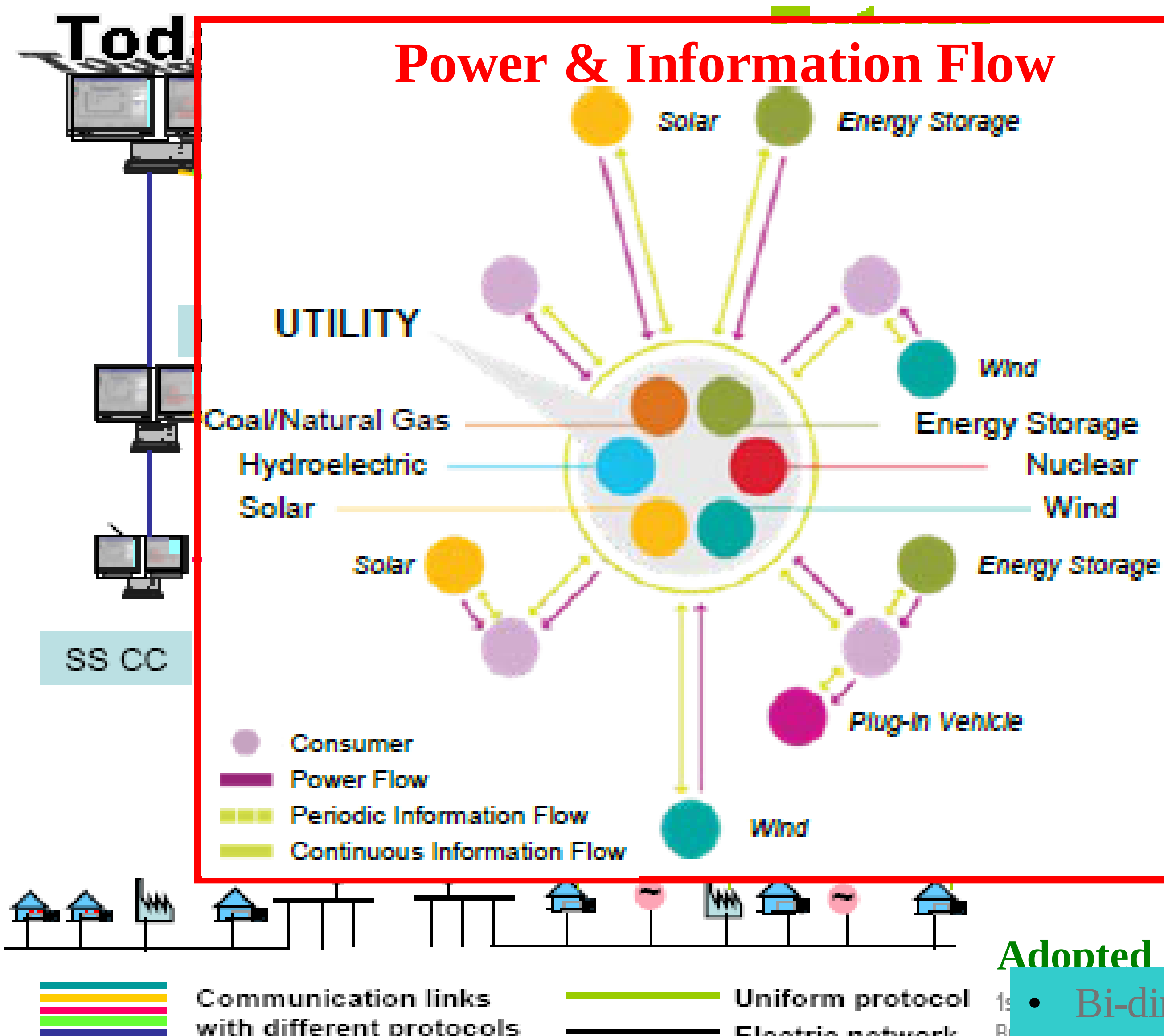


- Small scale (widely dispersed) technologies in DN
- Active distribution networks
- New types of loads within customer premises (PE, LED)

- Electric vehicles (spatial and temporal uncertainty)
- Integrated "intelligent" PE devices
- Integrated ICT & storage

- Bi-directional energy flow
- Different energy carriers

Communications in power systems



Control Centre
ubstation
Virtual Power Plant
Regional

Adopted from presentations at

- Bi-directional info flow

Uncertainties

- There are generally two forms of uncertainty
  - Aleatory uncertainty (*irreducable uncertainty and variability*) represents the inherent random behaviour of a system
    - ➢ Commonly modelled by probabilistic distribution functions and propagated by probability based approaches (sampling, analytical methods, probabilistic chaos expansion)
  - Epistemic uncertainty (*reducible uncertainty and state of knowledge uncertainty*) models the uncertainty in parameter estimation due to data shortages or model simplification
    - ➢ To avoid the subjective assignment of uncertainty due to data deficiency different representation and quantification methods can be used, e.g., Fuzzy sets, Possibility theory, Evidence theory, etc.
    - ➢ Representation depends on amount and accuracy of available data. With sufficient data it can be modelled by specific probability density functions, otherwise uniform or normal distribution is used within specific range

Sources of uncertainties

- Network
  - topology, parameters & settings (e.g., tap settings, temperature dependent line ratings)
  - observability & controlability
- Generation
  - pattern (size, output of generators, types and location of generators, i.e., conventional, renewable, storage)
  - parameters (conventional and renewable generation and storage)
- Load (time and spatial variation in load, load composition (mix), models and parameters)
- Controls
  - parameters of generator controllers (AVRs, Governors, PSSs, PE interface), network controllers (secondary voltage controller), FACTS devices and HVDC line controllers
- Contractual power flow (consequence of different market mechanisms and price)
- Faults (type, location, duration, frequency, distribution, impedance)
- ICT related uncertainties (noise, measurement errors, time delays, loss of signals, bandwidth)
- Weather/climate related uncertainties (wind speed, wind direction, temperature, solar irradiation, tidal/wave conditions)

Too many uncertainties to justify conventional deterministic modelling

Sources of "Big Data" in Power System

- SCADA *(Supervisory Control And Data Acquisition)* systems (1-5min updates)
- WAMS *(Wide Area Monitoring Systems)* (50-60 updates per second) (by the end of 2013 China State Grid Corporation installed 2027 PMUs at V>110kV)
- Advanced metering devices, IEDs ("Intelligent/Smart" meters with some degree of monitoring capabilities - even in low cost smart meters for hundreds of thousands household customers)
- Bi-directional communication enabled mobile (e.g. EVs) and stationary devices (e.g. domestic appliances)
- Conventional PQ monitoring and energy/power metering at load and generation (including RES) buses (3-5sec updates)
- Historical monitoring and incident/control reporting data
- Customer surveys
- Internet resources (related to network and generation performance, customer behaviour and preferences, user and generation groups /associations)

Integrated monitoring system reporting to some other hierarchical systems such as distribution or transmission management system

Data Analytics

Depending on the application the data may have different characteristics:

- Multidimensional
- Multiscale
- Spatially distributed
- Time series
- Event triggered
- Faulty (sensing and/or communication problems)
- Incomplete

- *Analytics* - discovery and communication of meaningful patterns in *data*.
  - Analysing
    - ➢ structured information
    - ➢ unstructured big data (e.g.,, video, images and content from sensors, social and mobile devices)
  - to support continuous data load, run multiple concurrent queries,
  - deliver analytics in real-time supported by massive I/O bandwidth.

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Data...Questions that need to be asked?

- What do we want to learn from collected data and why (for what purpose)?
  - How will this facilitate "better" network control and operation?
- Do we know what data we already have and what to do with them?
- Do we already have all the data that we need?
- What "additional data" do we need?
  - Where and how should we collect the data? Do we have a choice? Can we collect (privacy issues) all the data that we need?
  - What should be the "sampling" rate and the "quality " of additional data?
- Do we know what techniques to use to efficiently and effectively process new (and old) data?

Have we answered any of these questions yet, or at least have we asked them?

If not, isn't it the time to start doing so?

So, Future Power Network will be

- Monitoring (WAMS, SCADA, IED)
- Management of uncertainties
- Multi energy carriers
- Multivariable optimisation/control
- Mixed generation
- Market enabling

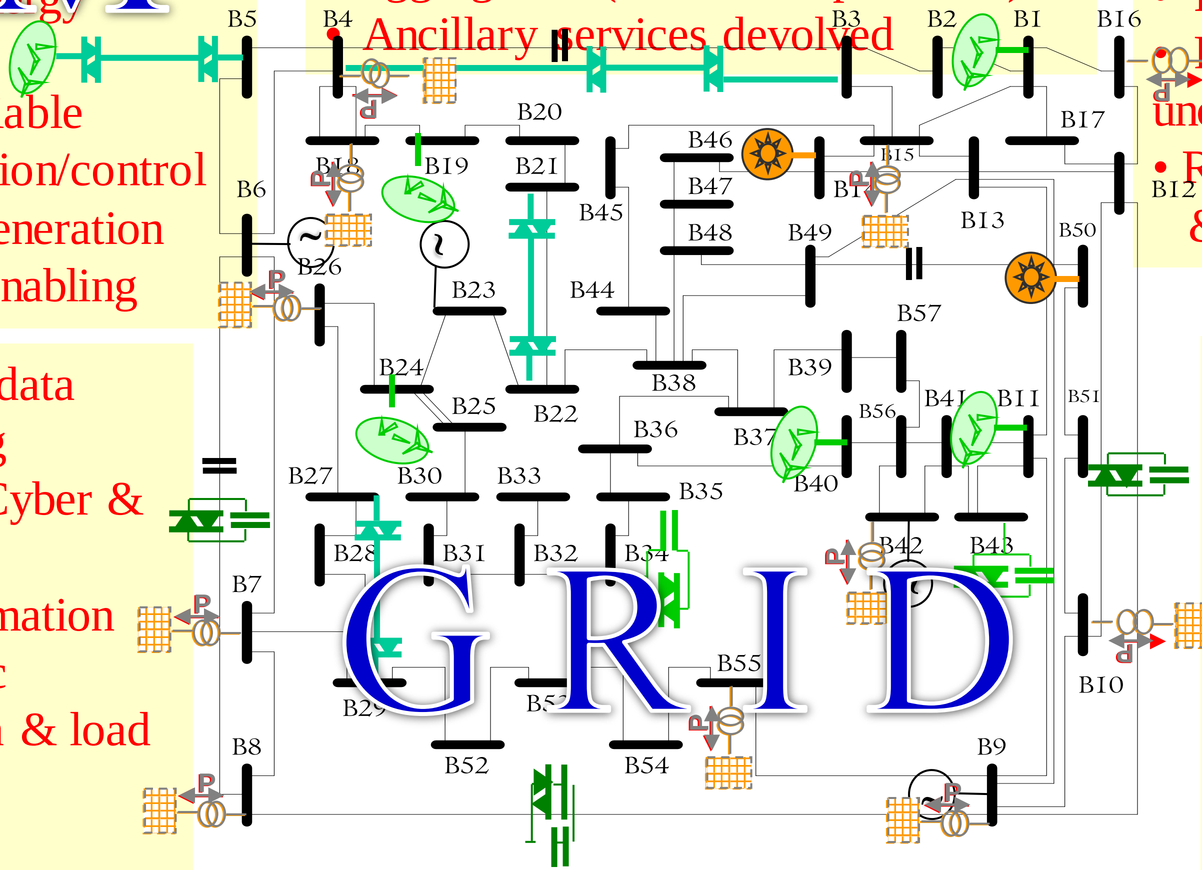
- Adaptive, hierarchical, distributed control
- Augmented power transfers (FACTS/HVDC)
- Affordable solutions
- Aggregators (for service provision)
- Ancillary services devolved

- Robust
- Responsive & Involved demand
- Reliable
- RES friendly
- Real time control
- Reduced uncertainty
- Risk based designed & managed

- Signal & data processing
- Secure (Cyber & energy)
- State estimation
- Stochastic generation & load
- Self*

- Trans national/ continental
- Tailored for individuals
- Tolerant to behavioural patterns
- Trade-off analysis

S M A R T(er) GRID



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The question therefore is

Considering evolving power system with increased uncertainties and abundance of measurement data, are the tools currently in use for system modelling and analysis adequate, and if not, how should we modify them, or what other tools should we be using?

What
Modelling and Control Challenges
this new "environment" will result in?

Challenges - 1

- Efficient use and reliance on existing and new global monitoring data (WAMS) for state estimation, static and dynamic equivalents and control (including real time control)
  - Efficient data management (signal processing, aggregation, transmission) and ICT network reliability are essential for both static and dynamic observability
  - Optimal placement of monitoring devices (PMU) may not be an issue due to perceived high deployment of those

- Modelling requirements for steady state & dynamic studies
  - Large interconnected networks with mixed generation, FACTS and short/long distance bulk power transfers using HVDC lines
  - Clusters of RES (generation and storage) of the same or different type
  - LV and MV distribution network cell (DNC) with thousands of RES
  - Demand, including new types of energy efficient and PE controlled loads, customer participation and behavioural patterns, EV, etc.

Data Analitics

Probabilistic modelling

Challenges - 2

- Design of supplementary controllers based on WAMS to control and stabilise large system (including real-time) or parts of it (which may vary) with uncertain power transfers and load models and stochastically varying and intermittent PE connected generation, demand and storage – *stochastic/probabilistic control of systems with reduced inertia*

- Design of new control systems/structure *(distributed or hierarchical, adaptive, close to real time)* for power networks with fully integrated sensing, ICT technologies and protection systems – *risk limiting control*

- Modelling/analysis of efficient and effective integration of different energy carriers into self sufficient energy module/cell

Real time risk limiting control

Risk is an uncertain event or condition that, if it occurs, has an effect on at least one objective, it is the probability of something happening multiplied by the resulting cost or benefit if it does.

Examples of current thinking and potential solutions

6 Examples

1. Dynamic equivalent models of Wind farm using probabilistic clustering
2. Data mining for on-line transient stability assessment (TSA)
3. Modal estimation with Probabilistic Collocation Method (PCM)
4. Reduction of number of uncertain parameters
5. Probabilistic demand response and composition forecasting
6. Probabilistic estimation of PQ performance of active distribution network

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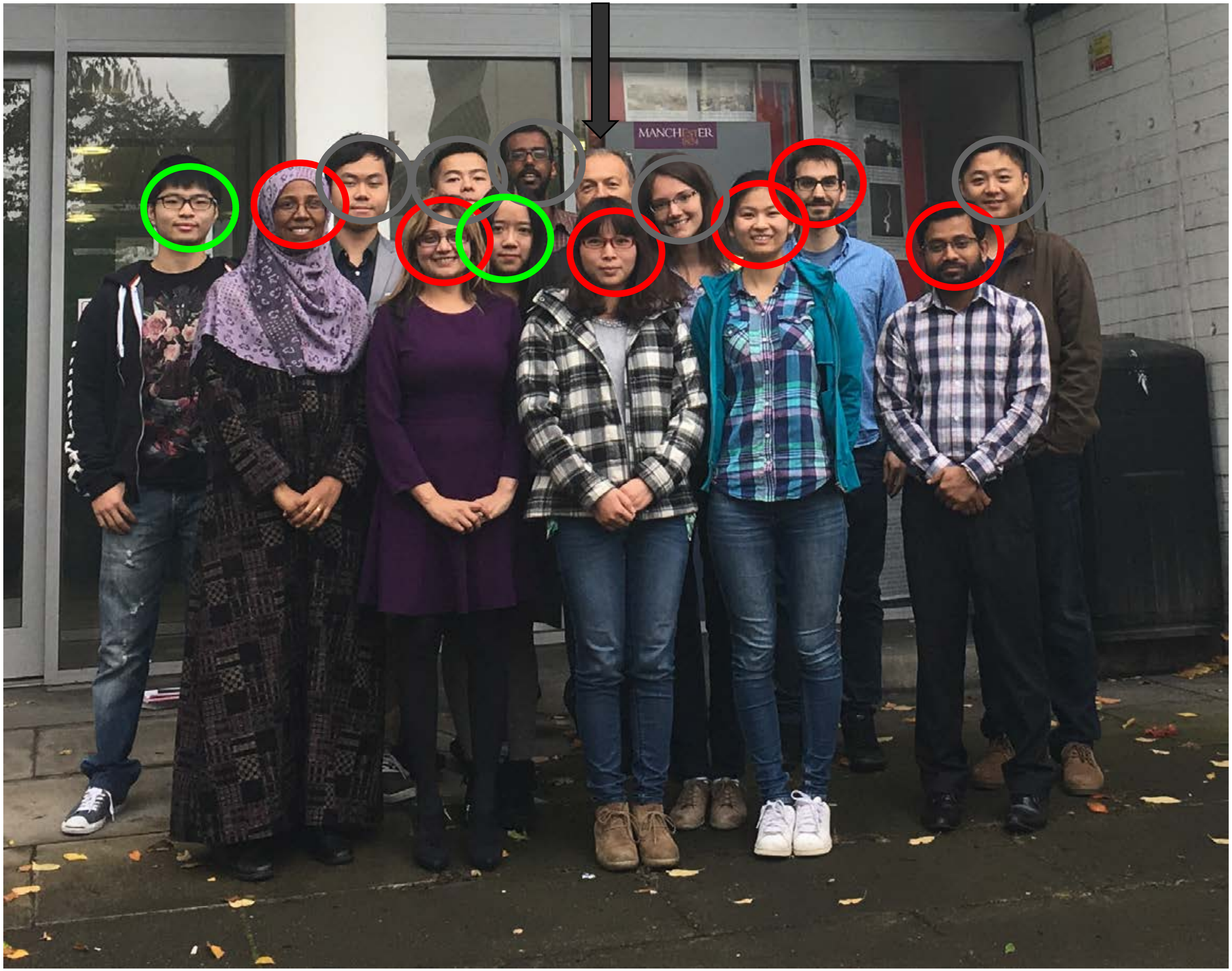
- 6 Postdoctoral Research Associates *(Dr H. Liao, Dr P. Papadopoulos, Dr A. Adrees, Dr K. Hasan, Dr X. Tang, Dr T. Guo)*
- 5 PhD students *(Mr S. Abdelrahman, Miss J.Ponocko , Mr Y.Zhou, Mr W. Zhou, Mr B. Qi))*
- 2 Advanced MSc students
- 5 Final year project students

Some of them and many (100+) other researchers who worked with me in the past contributed to different extent and at different stages of research to the results presented on the following slides

Current Research Team



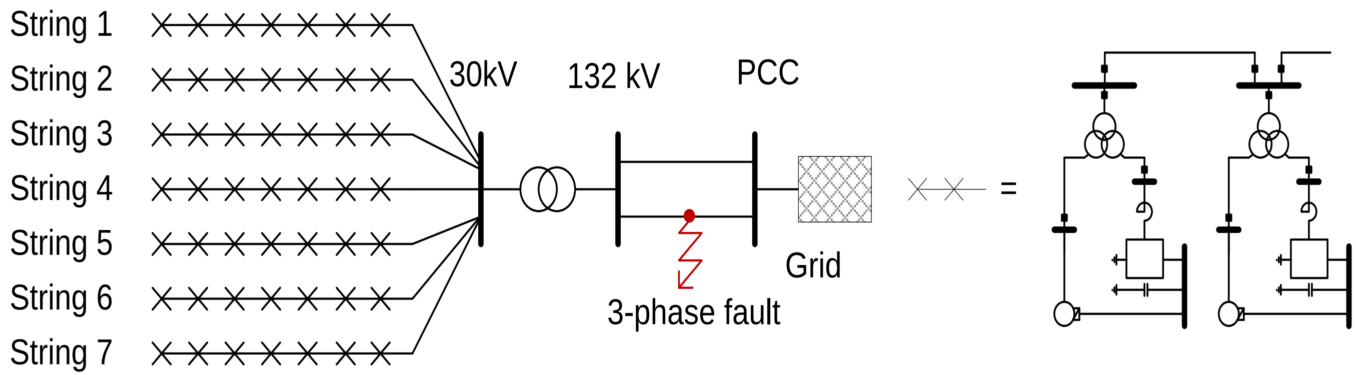
7 PDRA

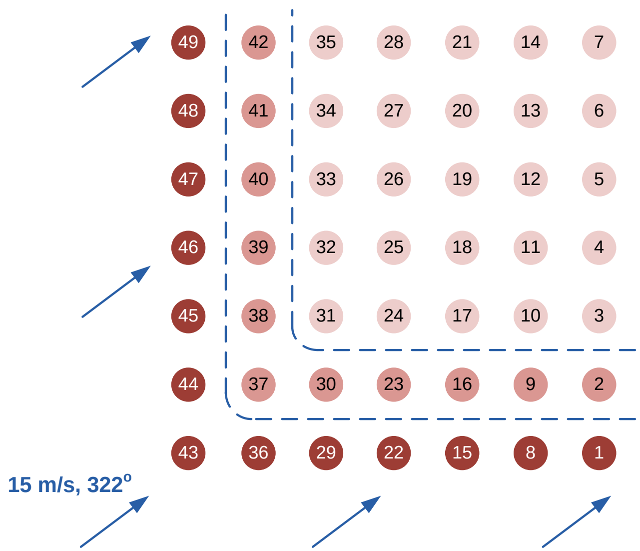
5 PhD

2 AMSc

Dynamic equivalent models of Wind farm using probabilistic clustering

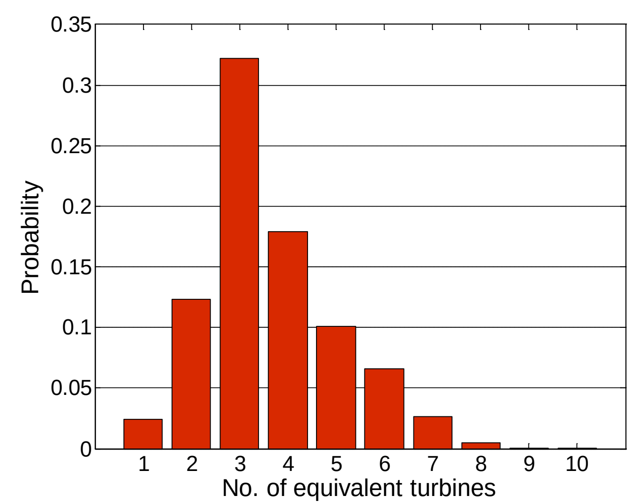
E1





Wind speed variation inside a wind farm at 15 m/s, 322°

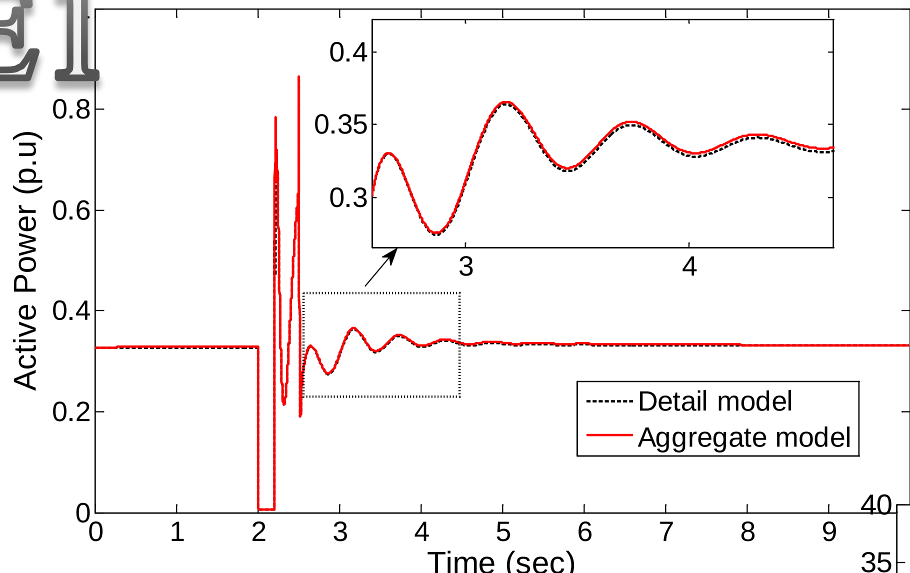
Support Vector Machine based clustering



Probability of equivalent turbines

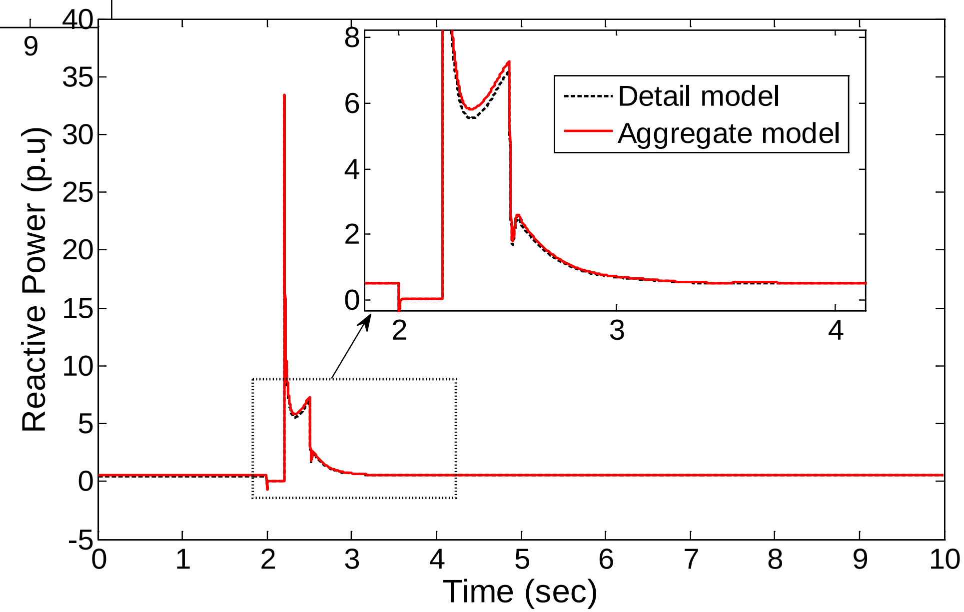
Dynamic equivalent models of Wind farm using probabilistic clustering

E1



P and Q response for Detailed and Probabilistic model at wind speed = 10 m/s, wind direction = 100°

In the case studied, simulation time was reduced by up to 96%.

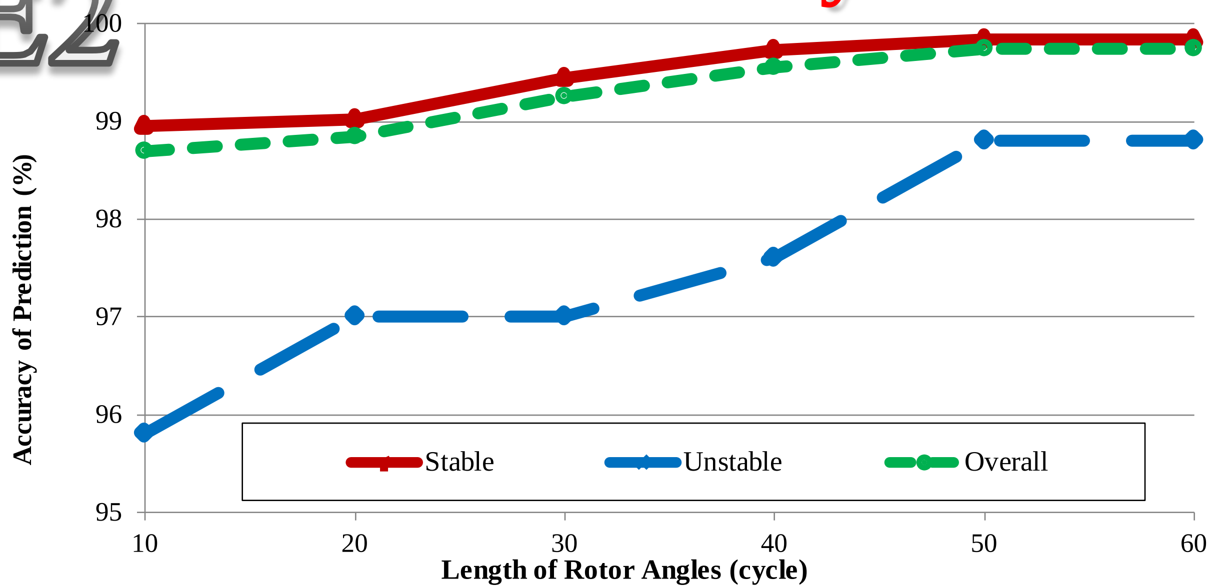


Dynamic equivalent models of Wind farm using probabilistic clustering

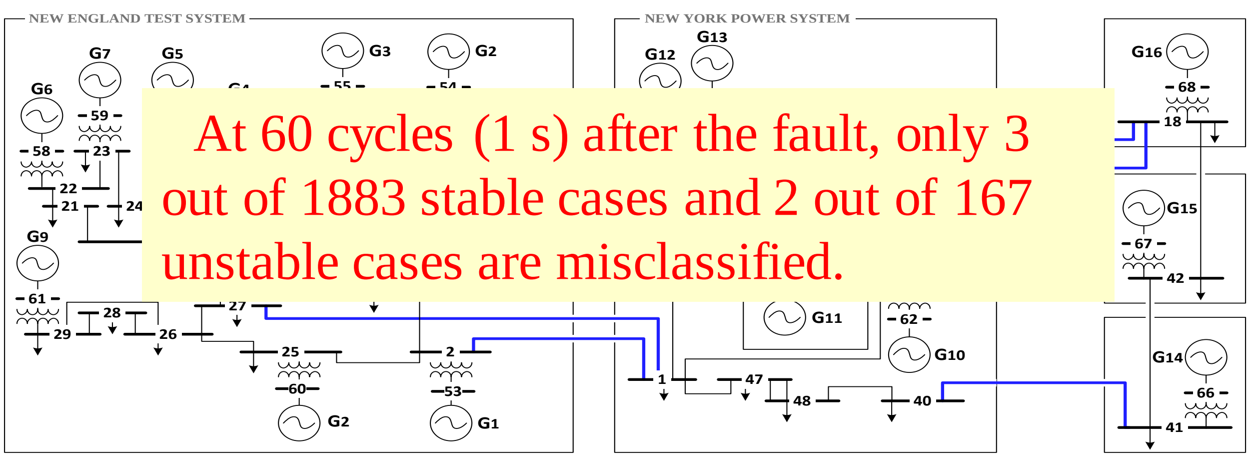
M.Ali, Irinel-Sorrin Ilie, J.V.Milanović and Gianfranco Chicco,“Wind farm model aggregation using probabilistic clustering”, *IEEE Transactions on Power Systems*, Vol. 28, No 1, 2013, pp. 309-316

E2

Data mining for on-line transient stability assessment (TSA)



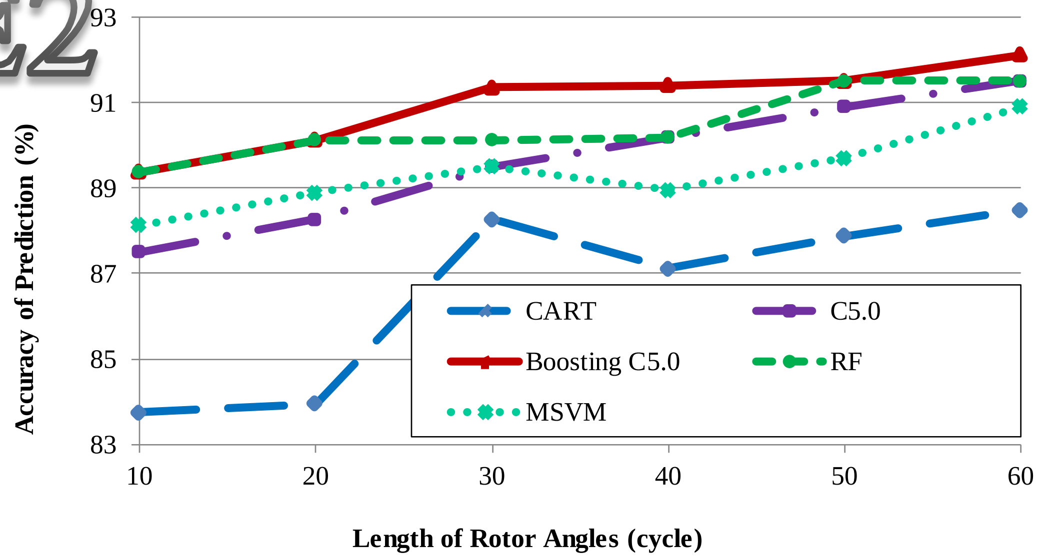
For any type and duration of fault at any possible location and any system load level, the Decision Tree predicts the system stability status correctly using 12 input signals from PMUs (rotor angles and speeds) with over 98.5% accuracy within 10 cycles (0.2 s) after the clearance of the fault, and it is close to 100% accurate after about 1 s.



At 60 cycles (1 s) after the fault, only 3 out of 1883 stable cases and 2 out of 167 unstable cases are misclassified.

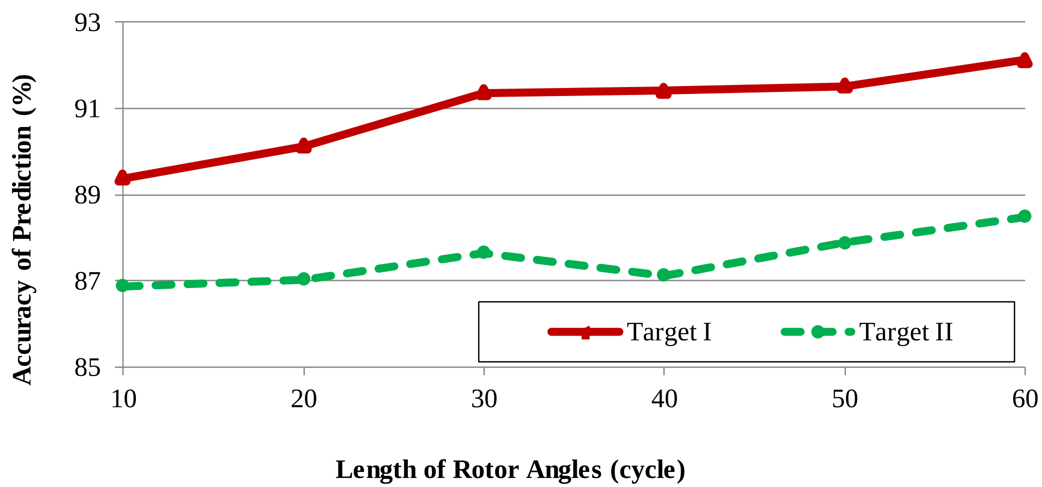
Data mining for on line TSA – Hierarchical Clustering & Multiclass Classification

E2



Accuracy of prediction of generator grouping in case of unstable dynamic behavior.

The aim is identify characteristic patterns of unstable dynamic behavior of a power system (and generators that lose synchronism) when the number of groups ***is not specified in advance***



Accuracy of prediction of both generator grouping and unsynchronized groups

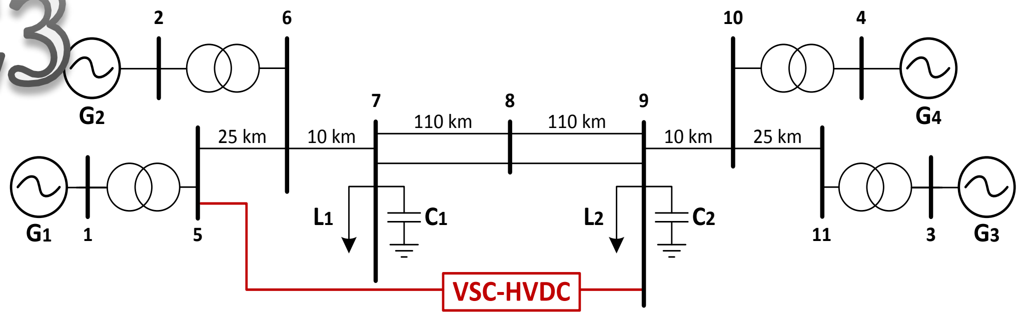
Data mining for on line TSA – Hierarchical Clustering & Multiclass Classification

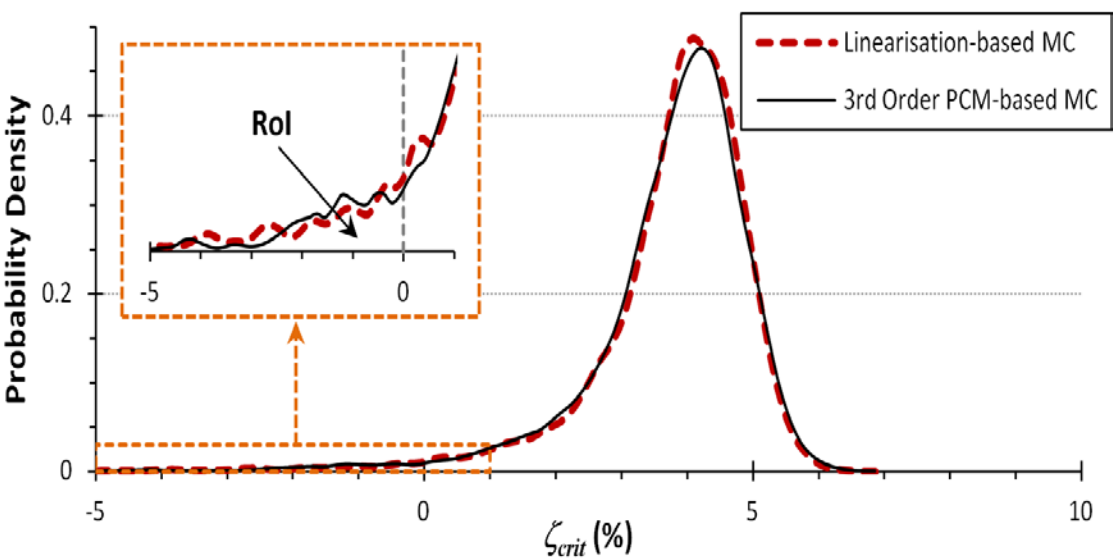
Tingyan Guo and J.V.Milanović, “Probabilistic framework for assessing the accuracy of data mining tool for on-line prediction of transient stability”, *IEEE Transactions on Power Systems*, Vol. 29, No 1, 2014, pp. 377 – 385

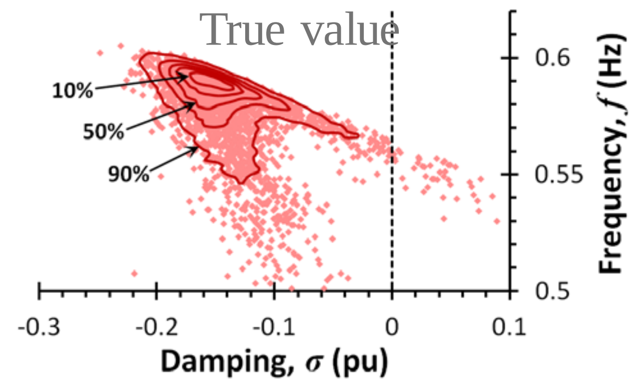
Tingyan Guo and J.V.Milanović, “On-line identification of power system dynamic signature using PMU measurements and data mining”, *accepted for publication in the IEEE Transactions on Power Systems*, TPWRS-00940-2014 (2/06/15)

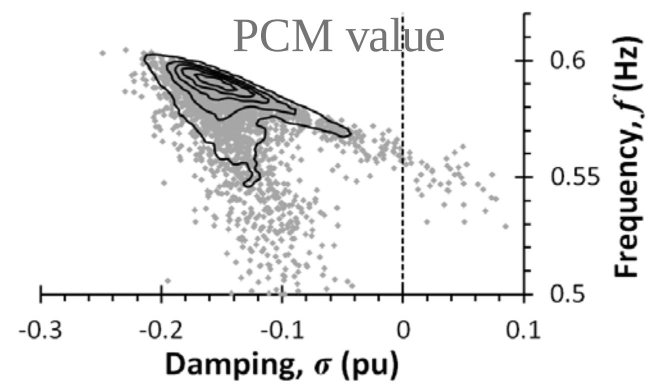
Modal estimation with Probabilistic Collocation Method (PCM)

E3









PCM can be used to quickly assess the **Risk of Instability** (RoI).
True value = 1.91%; PCM-based value = 1.89%.

Modal estimation with Probabilistic Collocation Method (PCM)

R.Preece, J.V.Milanović A.M.Almutairi and O.Marjanovic, "Probabilistic evaluation of damping controller in networks with multiple VSC-HVDC lines", *IEEE Transactions on Power Systems*, Vol. 28, No 1, 2013, pp. 367-376

R.Preece, N.C.Woolley and J.V.Milanović, "The probabilistic collocation method for power system damping and voltage collapse studies in the presence of uncertainties", *IEEE Transactions on Power Systems*, Vol. 28, No 3, 2013, pp. 2253-2262

R.Preece and J.V.Milanović, "Tuning of a damping controller for multi-terminal VSC-HVDC grids using the probabilistic collocation method", *Special Issue of IEEE Transactions on Power Delivery: HVDC Systems and Technologies*, Vol. 29, No 1, 2014, pp. 318-326

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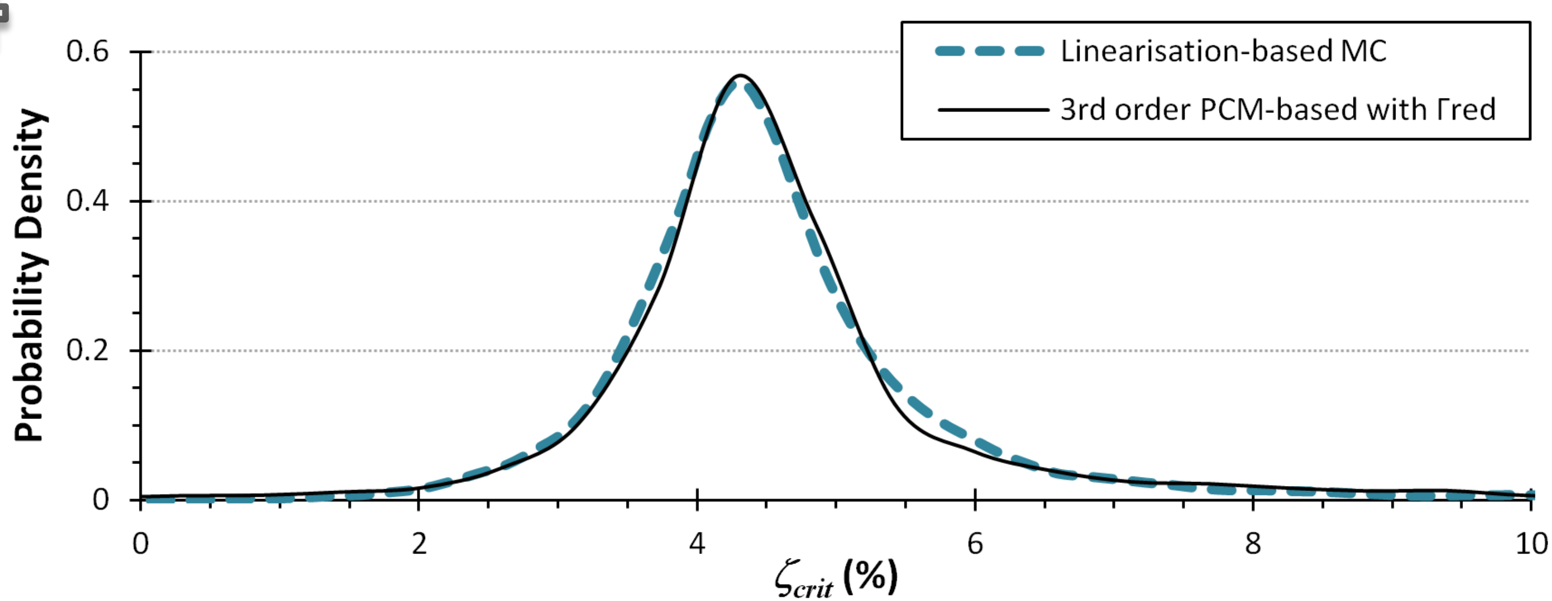
Modal estimation with PCM and reduction of uncertain parameters – large network

E4



- Large Test System with 2 VSC HVDC lines
- **Fifty-one** uncertain parameters reduced to **eight** using ranking Method based on eigenvalue sensitivites
- Completed in just 2.44% of the time required for standard (full-simulation) technique – **over forty times faster**.

Modal estimation with PCM and reduction of uncertain parameters – large network

R.Preece, Kaijia Huang and J.V.Milanović, "Probabilistic small-disturbance stability assessment of uncertain power systems using efficient estimation methods", *IEEE Transactions on Power Systems*, Vol. 29, No 5, 2014, pp. 2509 - 2517

R.Preece and J.V.Milanović, “Risk-based small-disturbance security assessment of power systems", *IEEE Transactions on Power Delivery,* Vol. 30, No 2, 2015, pp. 590 – 598

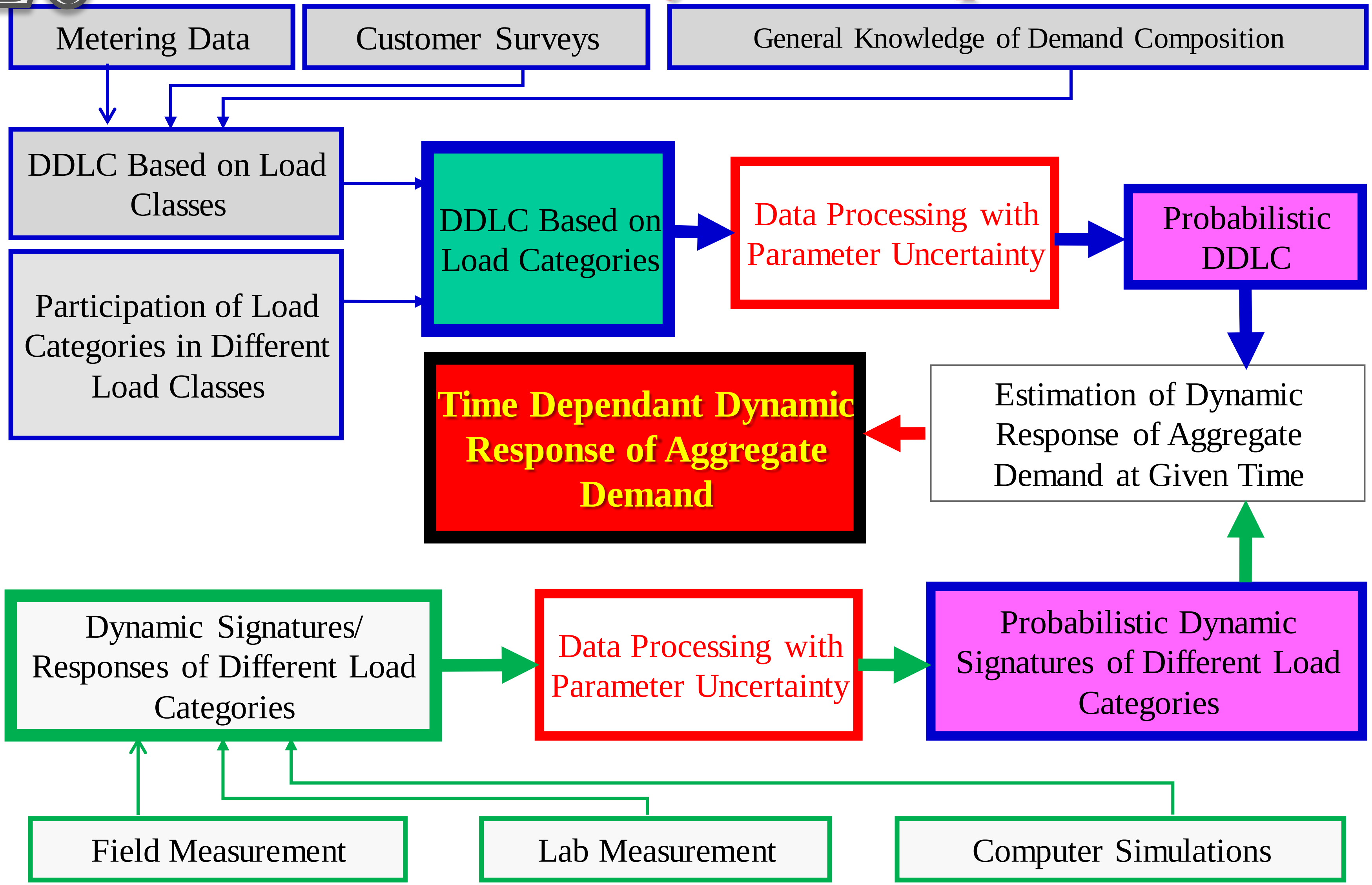
R.Preece and J.V.Milanović, "Probabilistic risk assessment of rotor angle instability using fuzzy inference systems", *accepted for publication in the IEEE Transactions on Power Systems*, TPWRS-01355-2013 (14/8/14)

R.Preece and J.V.Milanović, "Efficient estimation of the probability of small-disturbance instability of large uncertain power systems", *accepted for publication in the IEEE Transactions on Power Systems*, TPWRS-00963-2014 (23/3/15)

R.Preece and J.V.Milanović, "Assessing the applicability of uncertainty importance measures for power system studies", *accepted for publication in the IEEE Transactions on Power Systems*, TPWRS-01564-2014 (22/06/15)

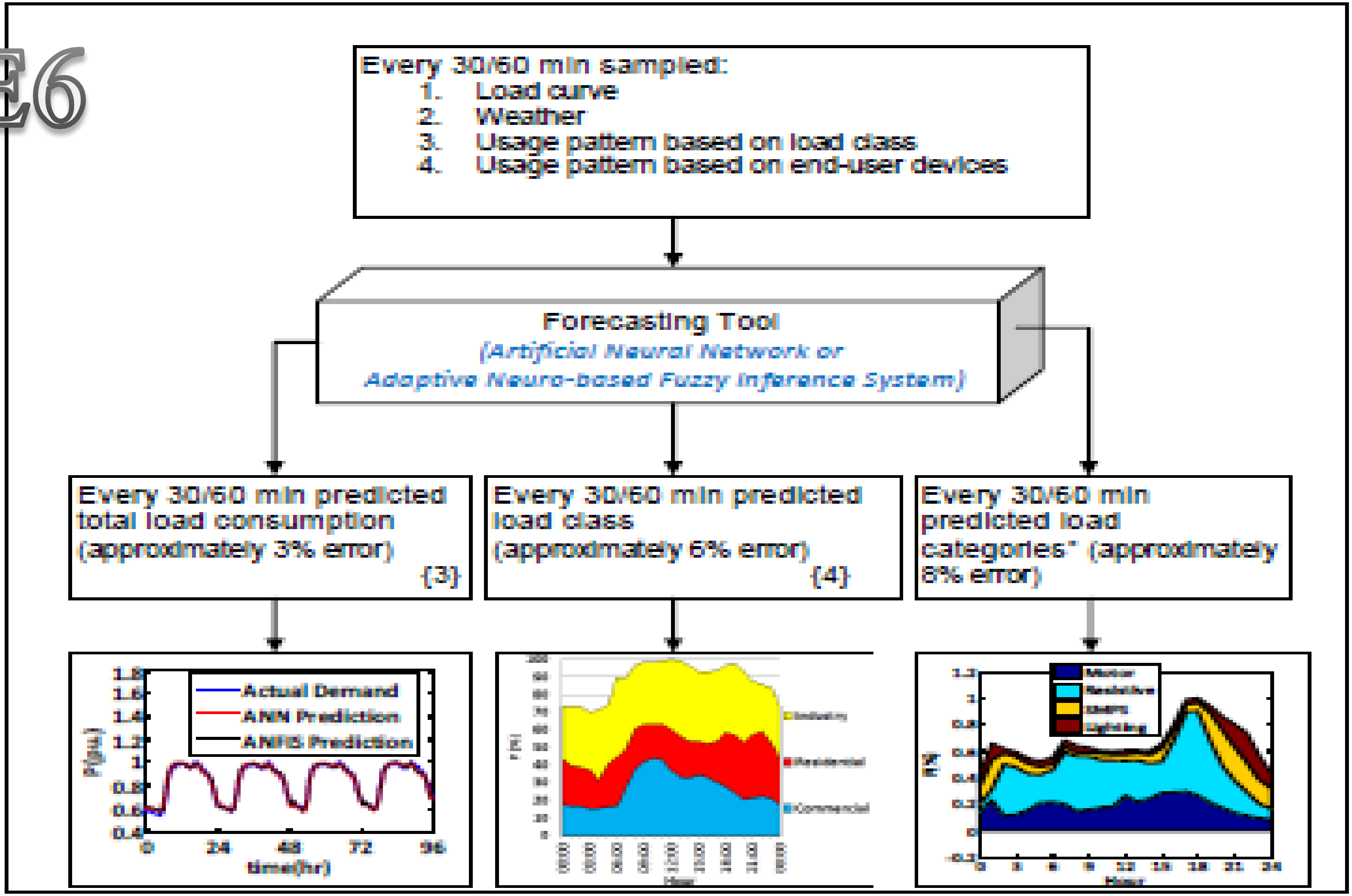
E6

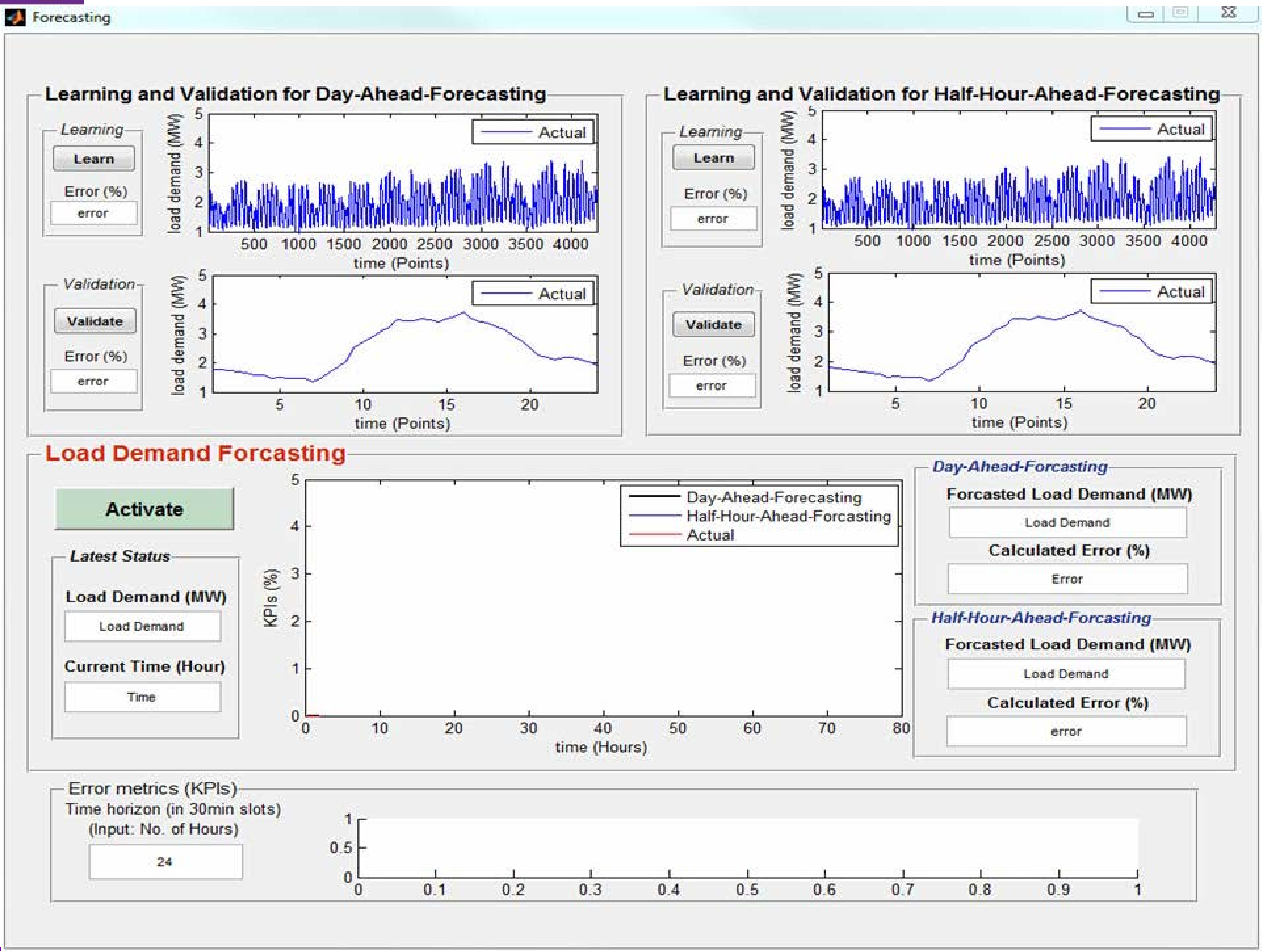
Probabilistic forecasting of demand controllability and response



Demand composition forecasting

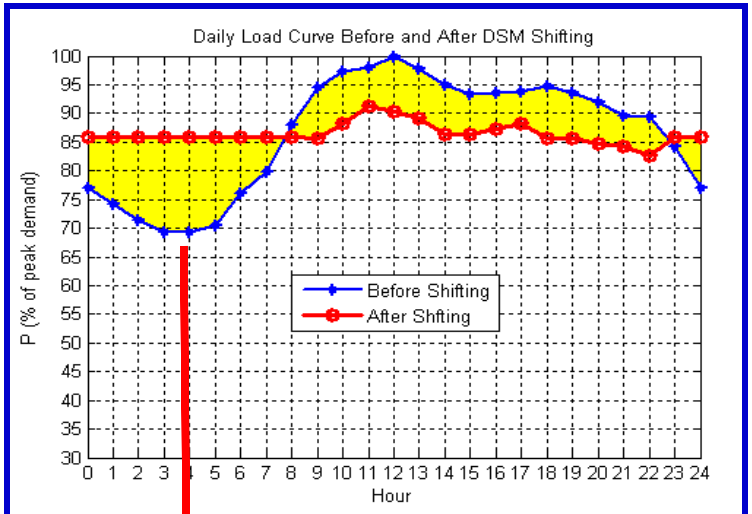
E6

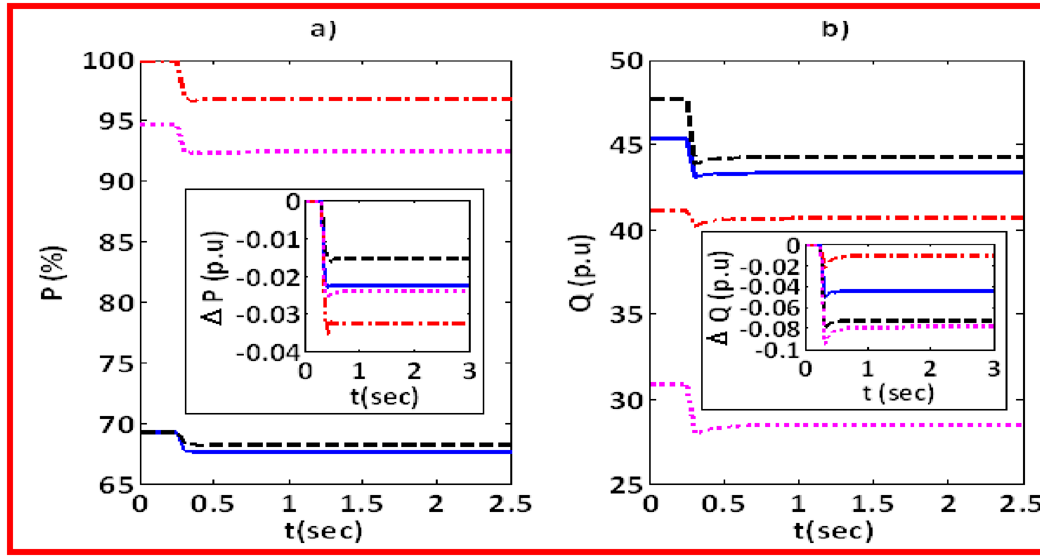


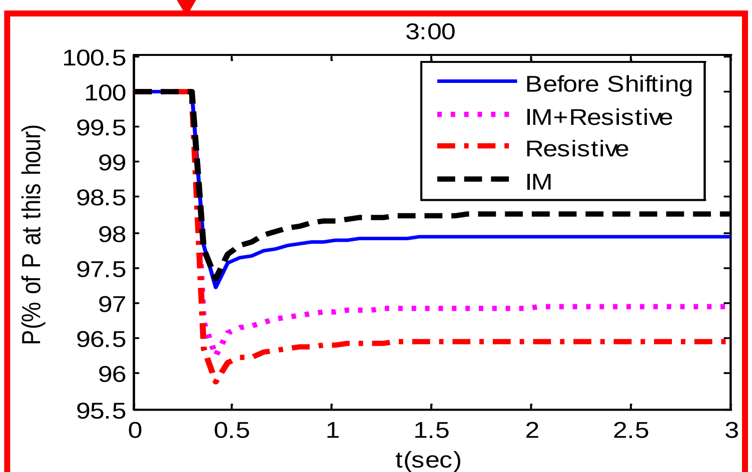

Forecasting
Learning and Validation for Day-Ahead-Forecasting
Learning
Learn
Error (%)
error
Validation
Validate
Error (%)
error
Actual
load demand (MW)
time (Points)
Learning and Validation for Half-Hour-Ahead-Forecasting
Learning
Learn
Error (%)
error
Validation
Validate
Error (%)
error
Actual
load demand (MW)
time (Points)
Load Demand Forcasting
Activate
Latest Status
Load Demand (MW)
Load Demand
Current Time (Hour)
Time
Day-Ahead-Forecasting
Half-Hour-Ahead-Forcasting
Actual
KPIs (%)
time (Hours)
Day-Ahead-Forcasting
Forcasted Load Demand (MW)
Load Demand
Calculated Error (%)
Error
Half-Hour-Ahead-Forcasting
Forcasted Load Demand (MW)
Load Demand
Calculated Error (%)
error
Error metrics (KPIs)
Time horizon (in 30min slots)
(Input: No. of Hours)
24

Forecasted demand response

E6







Comparison of different a) P and b) Q responses at different times of day (solid line: 03:00; dashed line: 04:00; dash-dot line: 12:00; dotted line: 18:00)

Forecasted demand response

E6

Yizheng Xu and J.V. Milanović, “Artificial intelligence based methodology for load disaggregation at bulk supply point”, *IEEE Transactions on Power Systems*, Vol. 30, No 2, 2015, pp. 795 – 803

J.V. Milanović and Yizheng Xu, “Methodology for estimation of dynamic response of demand using limited data”, *IEEE Transactions on Power Systems*, Vol. 30, No 3, 2015, pp. 1288 – 1297

Yizheng Xu and J.V. Milanović, “Day-ahead Prediction and Shaping of Dynamic Response of Demand at Bulk Supply Points ”, *accepted for publication in the IEEE Transactions on Power Systems*, TPWRS-00371-2015, (5/9/15)

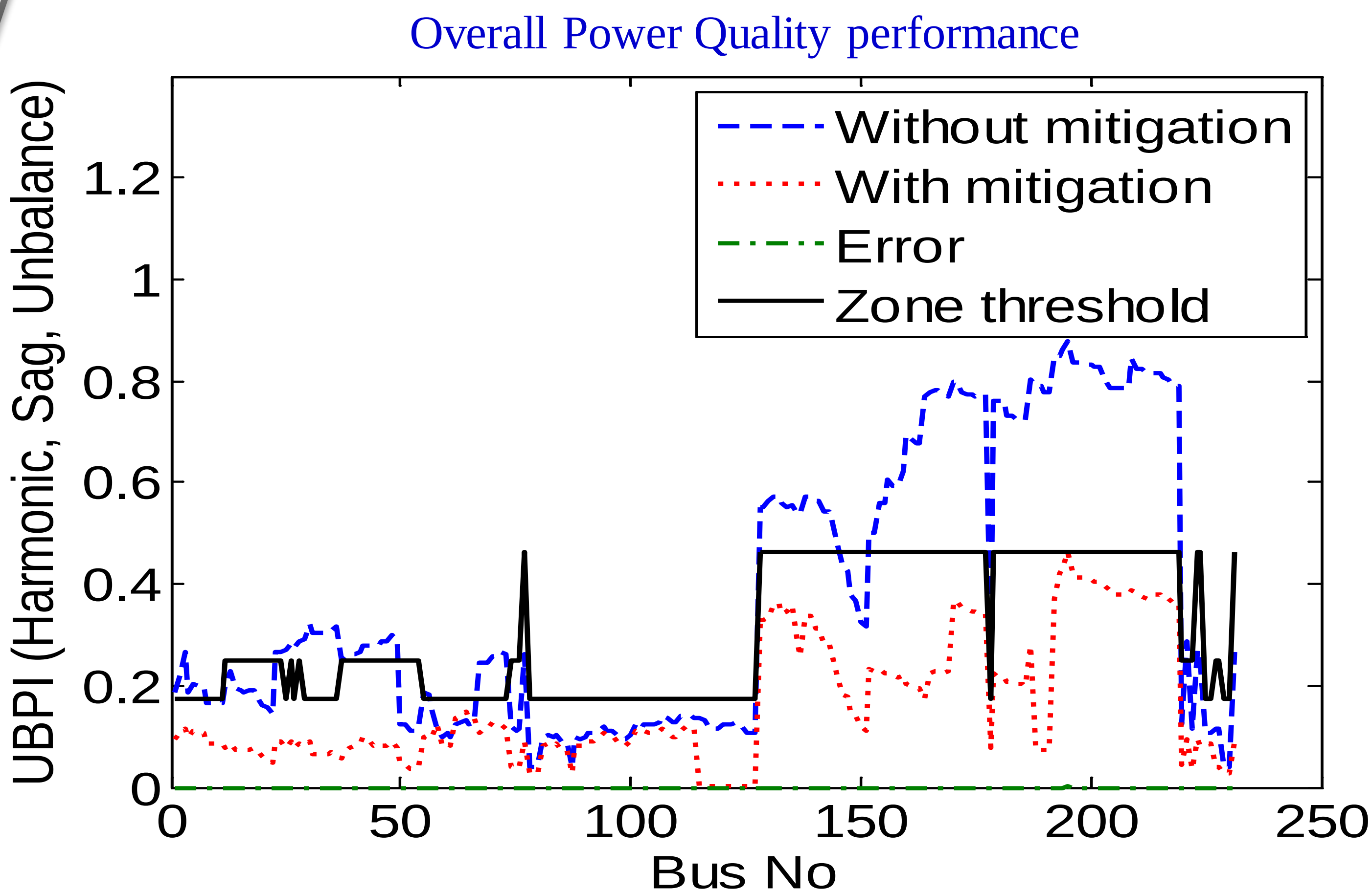
Probabilistic estimation of PQ performance of active distribution network

E7

- Load profiles (industrial, commercial and domestic loads):
  - Load profiles taken from a day in August 2012 in UK.
  - Different load types/classes follow different loading curves.
- Variation of DG outputs:
  - *Wind turbines*: based on practical outputs of wind turbines in UK.
  - *Photovoltaic:* based on true data available in the network.
  - *Fuel cell:* assumed variable daily output
- Power quality phenomena:
  - Unbalance: 9 fixed unbalance loads whose power factors follow pre-set normal distribution; twenty-one single phase connected DGs.
  - Harmonic current injection: 10 fixed non-linear loads; 20 randomly selected non-linear loads; wind turbines; photovoltaic; fuel cell – as above. The ratio of magnitude of the injected harmonic current to that of the fundamental component follow pre-set normal distributions.
  - Voltage Sag:s based on statistic fault rates of components in the network.

Probabilistic estimation of PQ performance of active distribution network

E7



Provision of "contracted PQ" for individual zones using FACTS & PHF only

Probabilistic estimation of PQ performance of active distribution network

Huilian Liao, Sami Abdelrahman, Yue Guo and J.V. Milanović, "Identification of weak areas of network based on exposure to voltage sags—Part I: Development of sag severity index for single-event characterization", *accepted for publication in the IEEE Transactions on Power Delivery,* TPWRD-01430-2013 (5/10/14)

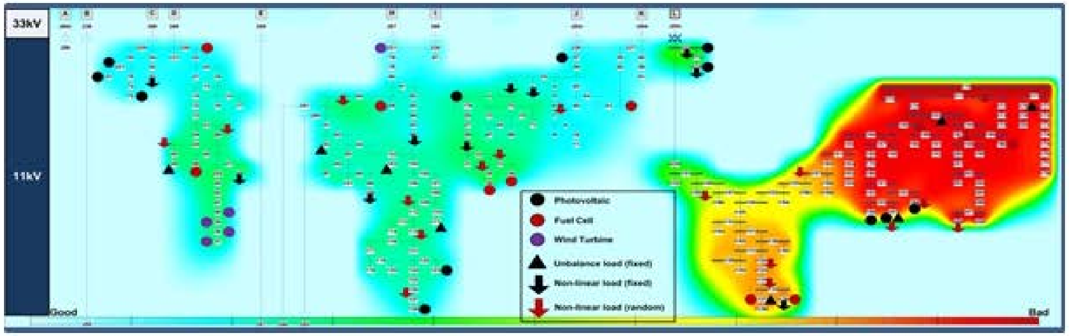
Huilian Liao, Sami Abdelrahman, Yue Guo and J.V. Milanović, "Identification of weak areas of network based on exposure to voltage sags — Part II: Assessment of network performance using sag severity index", *accepted for publication in the IEEE Transactions on Power Delivery,* TPWRD-01434-2013 (5/10/14)

Huilian Liao, Zhixuan Liu, J. V. Milanović, and Nick C. Woolley, "Optimisation Framework for Development of Cost-effective Monitoring in Distribution Networks", *accepted for publication in the IET Generation, Transmission and Distribution, GTD-2015-0757,* (16/09/15)

Probabilistic annual estimation and optimisation of PQ performance of distribution network

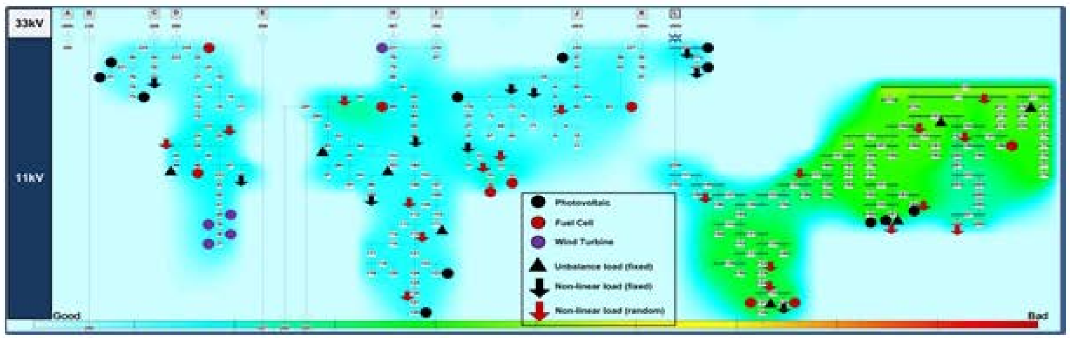
E7

Operating Point 1



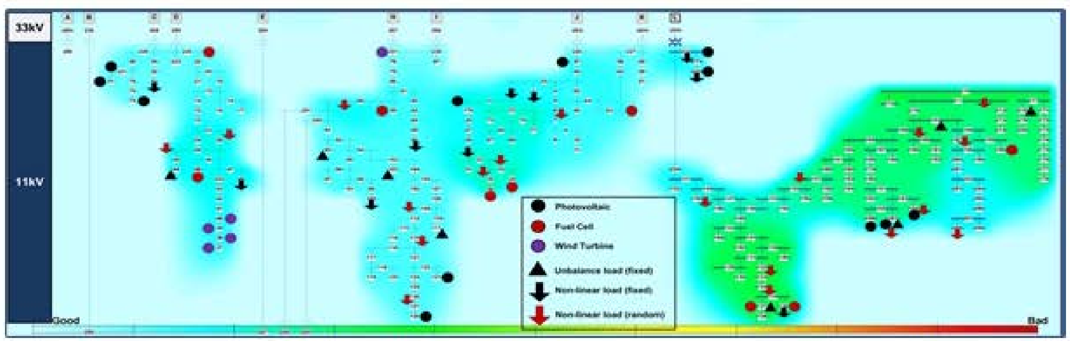
Heatmap of UBPIs indicating PQ performance with DGs based on without mitigation

Annual performance



Heatmap of UBPIs with mitigation (using FACTS devices and network based techniques)

Optimised annual technical performance



Heatmap of UBPIs with mitigation (based on economic assessment)

Optimised annual techno – economic performance

Summary

Summary

Future power networks need to be (will likely be) modelled and operated by exploiting possibilities offered by state-of-the-art WAMS, integrated ICT systems and "intelligent" PE devices and using

- Non-deterministic & close to real time approaches for (energy) system control and operation
- Stochastic, probabilistic and computer intelligence based models, data handling and methodologies to
  - **minimise** the effect of uncertainties and
  - **maximise** the use of information contained in available data

MANCHESTER 1824

The University of Manchester

Key areas to watch

Data Analitics

Probabilistic modelling

Real time risk limiting control