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Addressing the Complexity and Uncertainty in Future Power System Dynamic Behaviour

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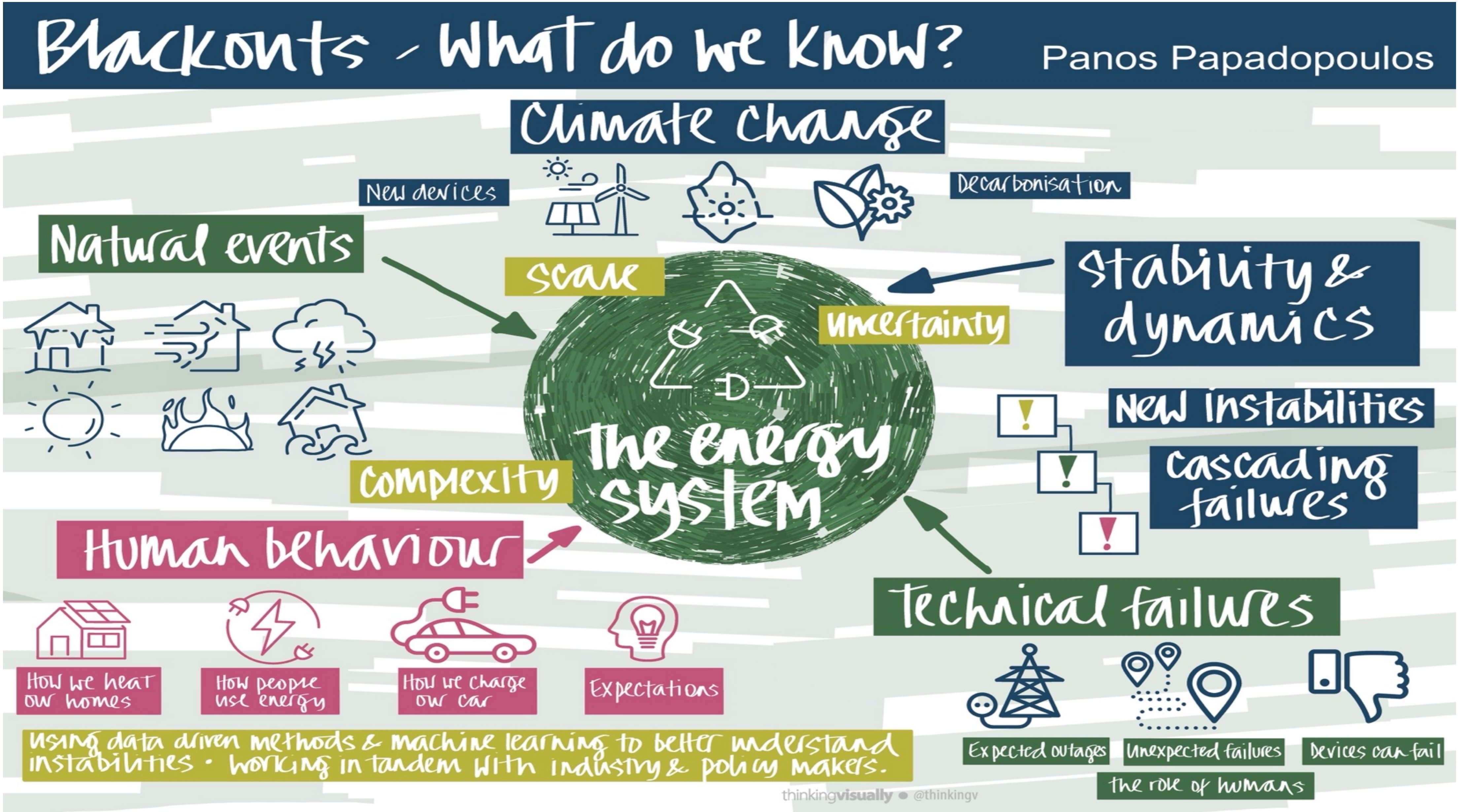
CIGRE UK C4 Technical Liaison Meeting: Developments and Challenges in Grid Integration and Power Systems Stability, SPHQ, 21/01/2025


Blackouts - What do we know?
Panos Papadopoulos
Climate change
New devices
Decarbonisation
Natural events
Scale
Uncertainty
Stability & dynamics
New instabilities
Cascading failures
The energy system
Complexity
Human behaviour
How we heat our homes
How people use energy
How we charge our car
Expectations
Technical failures
Expected outages
Unexpected failures
Devices can fail
The role of humans
Using data driven methods & machine learning to better understand instabilities • working in tandem with industry & policy makers.
thinkingvisually • @thinkingv

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Power system security under increasing complexity and uncertainty

Power system dynamic studies

- Power systems are dynamic nonlinear systems
  - Arguably one of most complex man-made systems
  - Up to hundreds of differential equations
- Numerical integration methods – simulations
  - Timescales from <ms up to tens of seconds
  - Computationally intensive

Dynamics increasingly important

- Machine learning and data-driven methods
  - increased visibility, enhanced control, decision support, automation
- Security, reliability and resilience improvement
  - Understanding and mitigating widespread events
- Maximise integration of low/zero carbon technologies
  - Cost efficient manner (“dynamics- aware” optimisation)

Increasing Complexity

- Very different dynamic behaviour of new technologies and high number – need for detailed models
  - Power electronic interfaced (wind, solar, batteries, HVDC links, electric vehicles, electrolysers)
  - Smaller timescales – faster dynamic phenomena
  - Governed by control
  - Strong nonlinearities – limiters, discrete control

Increasing Uncertainty

- Millions of devices (solar PV, wind farms, batteries, EVs)
- “Exploding” search-space of possible operating conditions
  - Intermittent energy sources and social behaviour
  - Billions of cases if we want to do exhaustive search
  - Affecting operational and planning timescales

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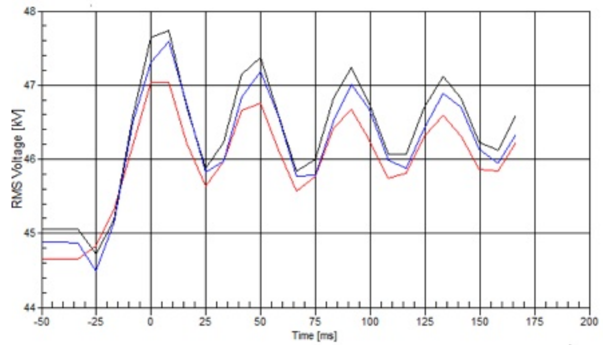
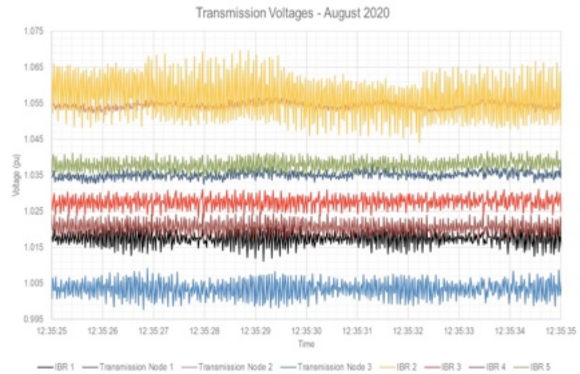
Power System dynamics under increasing complexity and uncertainty

- Modelling and representation of dynamics
  - Characterise systematically mechanisms of instability
  - Importance of investigating multiple operating conditions and understand sensitivities - data-driven and probabilistic approaches
  - Appropriate modelling frameworks (EMT, EMT-RMS, dynamic phasors, hybrid modelling)
- New types of dynamic phenomena and oscillatory interactions
  - Control governing dynamic behaviour and challenges with black-box vendor models (grid forming converters)
  - Fundamental understanding: what mechanisms, under what conditions, in which locations, what devices – this includes non-linear/hybrid dynamics
  - How to mitigate? – damping control, discrete control modes (e.g. for weak grid), sync. comp., operational constraints – services
- Impact on system stability (transient, voltage and frequency)
  - Complex impact with respect to location, control parameters, etc.
  - Not straightforward to understand critical operating conditions and faults – nonlinear dynamics
  - Low inertia and locational aspects more pronounced

Canada, Hydro One
(20 Hz, PVs, current control) [2]



Australia, AEMO
(19 Hz, PVs, PLL-shunts) [2]

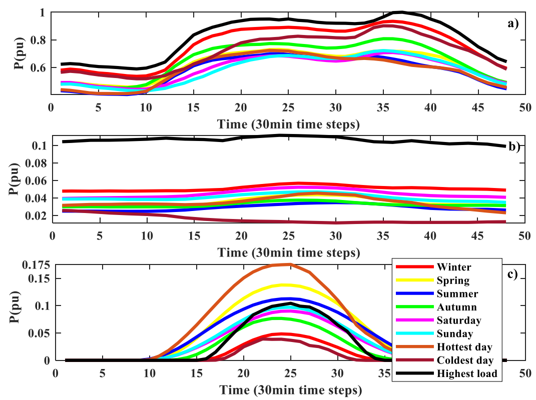


[1] U. Markovic, O. Stanojev, P. Aristidou, E. Vrettos, D. Callaway and G. Hug, "Understanding Small-Signal Stability of Low-Inertia Systems," IEEE Trans. Power Syst., vol. 36, no. 5, pp. 3997-4017, Sept. 2021.
[2] L. Fan *et al*., "Real-World 20-Hz IBR Subsynchronous Oscillations: Signatures and Mechanism Analysis," *IEEE Trans. Energy Conversion*, 2022, doi: 10.1109/TEC.2022.3206795.
[3] Luke Benedetti, Alexandros Paspatis, Panagiotis N. Papadopoulos, Agustí Egea-Àlvarez, Nikos Hatziargyriou, "Investigation of grid-forming and grid-following converter multi-machine interactions under different control architectures," Electric Power Systems Research, Volume 234, 2024, 110813, https://doi.org/10.1016/j.epsr.2024.110813.

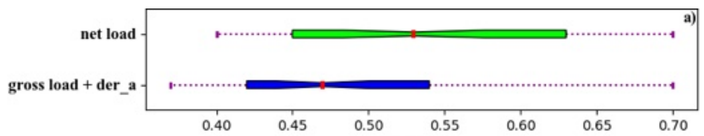
Dynamics and modelling needs for Active Distribution Networks

- Active Distribution Networks
  - Lack of situational awareness and equivalent model parameter sensitivity
  - Data-driven methods for extraction of representative parameters
  - Electric Vehicles (and Heating) changing the mix and dynamics of load (uncertainty due to social behaviour)
- Renewable generation and Electric Vehicles
  - Typical dynamic load model structures might not be adequate
- Interaction and services at the interface with transmission
  - How can we confidently procure services from distributed resources (generation, EVs, flexible demand) without activating constraints
  - Providing aggregation information to the ESO for dynamic studies

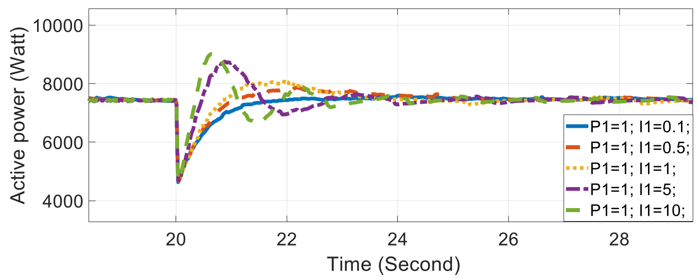
Typical profiles for a) load, b) wind, c) PVs



CCT for a typical day, modelled with and without accounting for ADN



EV responses for different control parameters



[1] I. S. Lamprianidou, D. Tzelepis, P. N. Papadopoulos, A. Oulis Rousis, "Impact of Active Distribution Networks on Transient Stability", ISGT Europe 2022, Novi Sad, Serbia, October 2022.
[2] Hengqing Tian, Eleftherios O. Kontis, Georgios A. Barzegkar-Ntovom, Theofilos A. Papadopoulos, Panagiotis N. Papadopoulos, "Dynamic modeling of distribution networks hosting electric vehicles interconnected via fast and slow chargers, International Journal of Electrical Power & Energy Systems, Volume 157, 2024, 109811, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2024.109811.

Power system transformation on the way to achieving net zero

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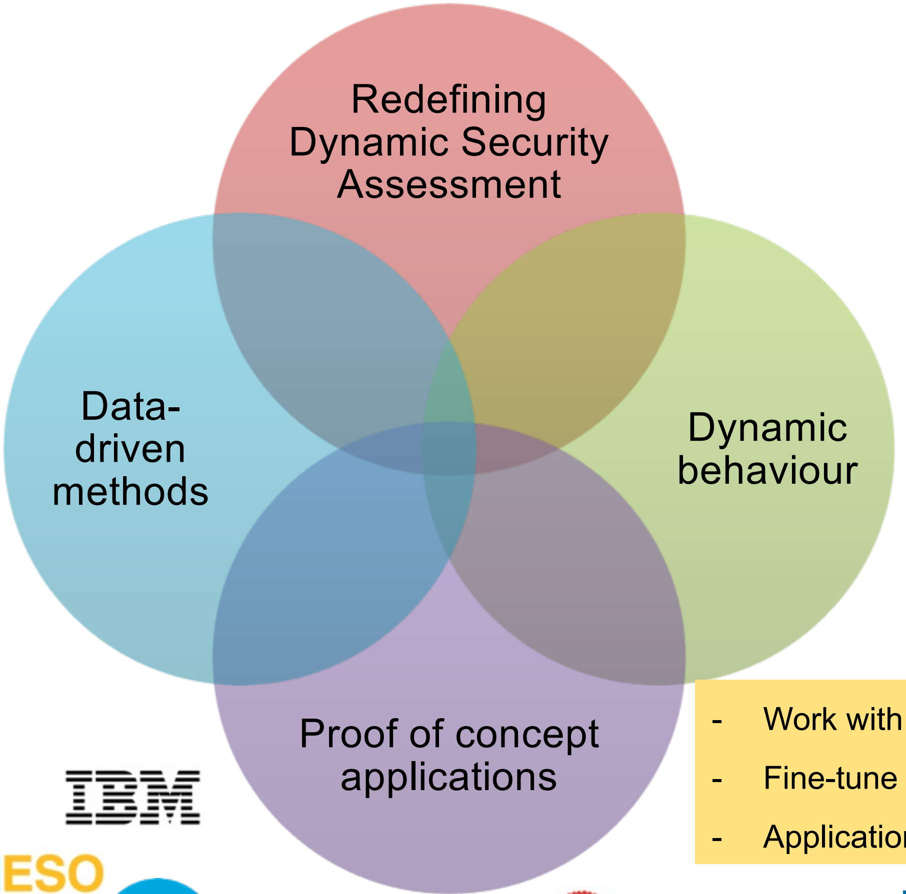
- Key driver for net zero
- System needs and services for secure and economic operation
- Enhanced monitoring, situational awareness and control
- Detailed dynamics
- Deal with complexity and uncertainty



- Measurements and machine learning
- As detailed as possible, real-time representation of power system dynamics
- Explainability/interpretability - Confidence and trust but also understanding
- Enable fast control and dynamics-aware optimisation
- Augment state of the art tools – what is the limit?

- Appropriate models and simulation frameworks to represent increasingly complex dynamic behaviour
- Investigate new dynamic phenomena, instabilities and new control approaches (black box vendor models)
- Dynamics of active distribution networks
- Resilience – cascading events

- Work with industrial partners and ML experts
- Fine-tune and test methods and tools
- Applications in control room

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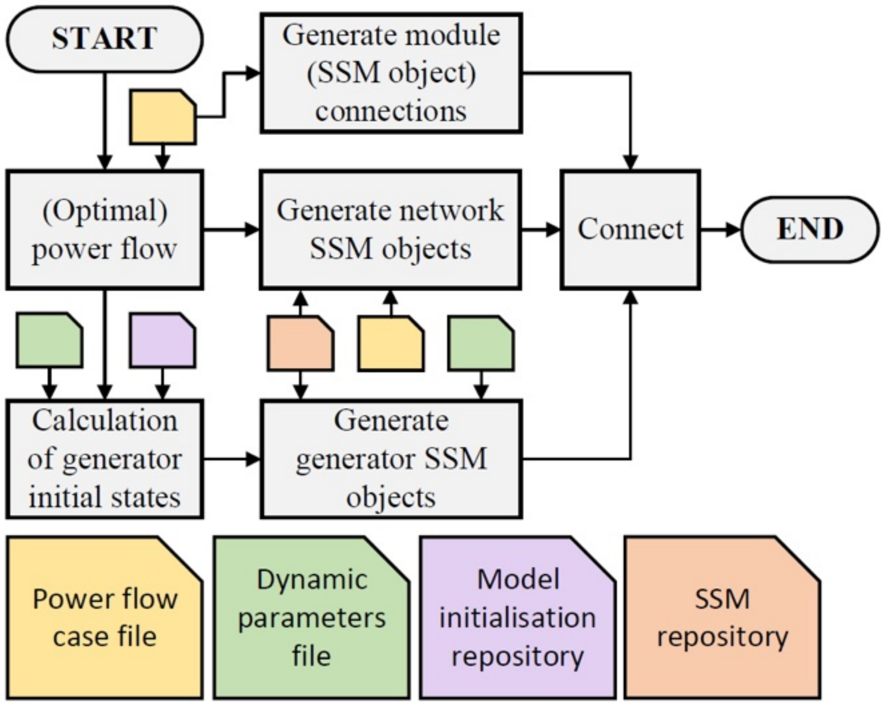
POWER SYSTEM SMALL-SIGNAL MODELLING TOOL

Power system small-signal modelling: A MATLAB-based tool

- Linearised models, analysis in small region around an operating point.
  - identify instabilities and/or problematic oscillations,
  - characterise oscillations/interactions/instability based on participation factors,
  - tune and/or design control systems (e.g. through parametric sweeps or more complex optimisation algorithms),
- EMT-level detail in dq0 (balanced)
- Inputs required: MATPOWER case file and Dynamic parameters file.
- Automatic (initialisation and library):
  - Can quickly initialise and generate small-signal models
  - A repository/library of components is provided (and users can add and/or edit as desired), including detailed grid-following and grid-forming controllers.
- Modular:
  - Easy to add or remove components to a system model.



Small-signal model creation flowchart.
SSM = small-signal model

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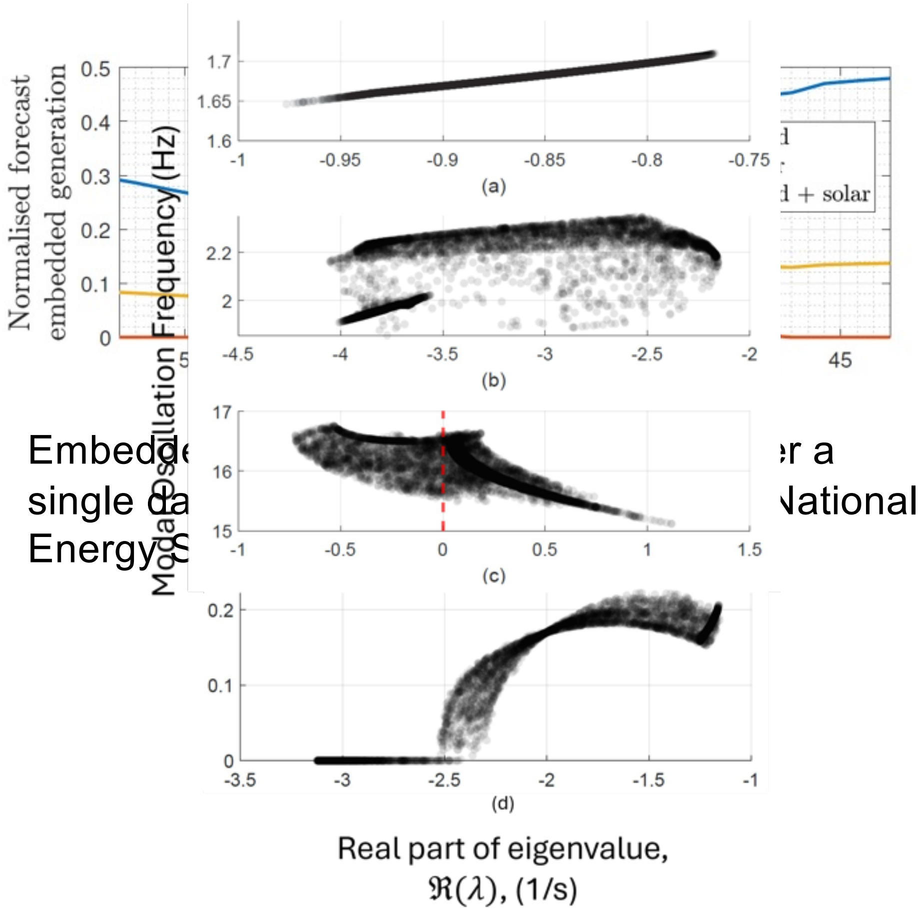
CHARACTERISING NEW TYPES OF DYNAMIC PHENOMENA

Probabilistic small signal stability assessment

L. Benedetti, A. Egea-Àlvarez, R. Preece and P. N. Papadopoulos, “Enabling Characterisation of Dynamic Interactions with Probabilistic Small-Signal Analysis in Converter-Integrated Power Systems," submitted to *IEEE Transactions on Power Systems*, under review.

Why do we need probabilistic small-signal analysis?

- Increase of variable renewable energy-sourced generation
- Increasing range, and uncertainty, of operating point
- How do new types of oscillations (e.g. SSOs) behave or change?
- Deterministic linear analysis around a single operating point is insufficient
  - E.g., eigenvalues can vary significantly, and in complex patterns
  - Can miss instability, mischaracterise novel interactions, and misinform design choices



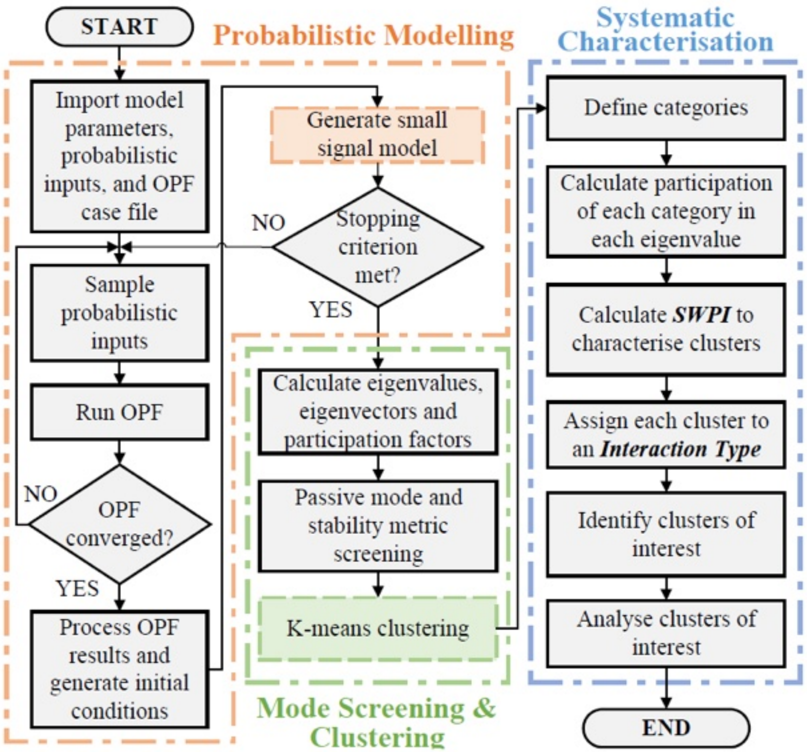
Eigenvalues varying with the operating point.

[1] National Energy System Operator, NESO Data Portal, https://data.nationalgrideso.com/, accessed Jul. 17, 2024.

Probabilistic small-signal interaction analysis framework

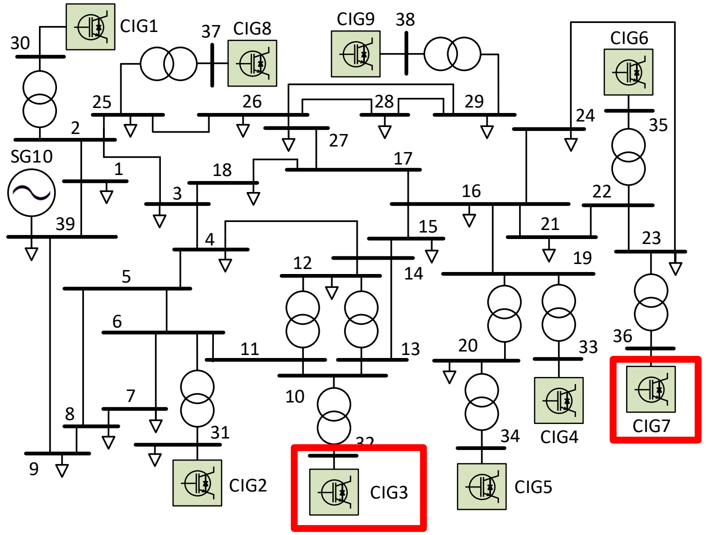
- Monte-Carlo analysis
- Large, complex systems
- Huge amounts of data
  - E.g., eigenvalues, eigenvectors & participation factors

- We propose a framework to condense the data into the ***key distinct dynamic phenomena*** (interactions) present on the system, across the full operating range.
  - Clustering based on participation factors.
- Furthermore, it enables ***characterisation and probabilistic analysis*** of the identified distinct dynamics.
  - Stability-weighted participation index (SWPI)

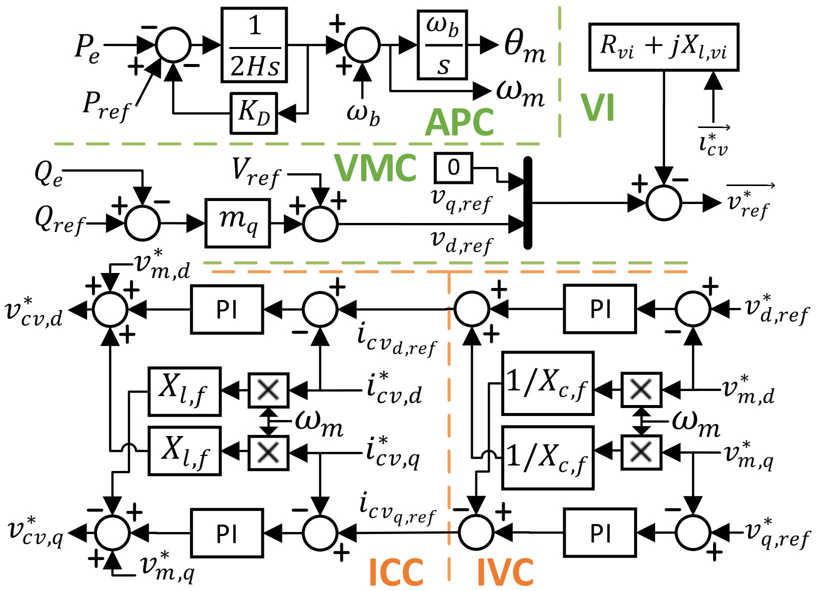


Application of proposed framework

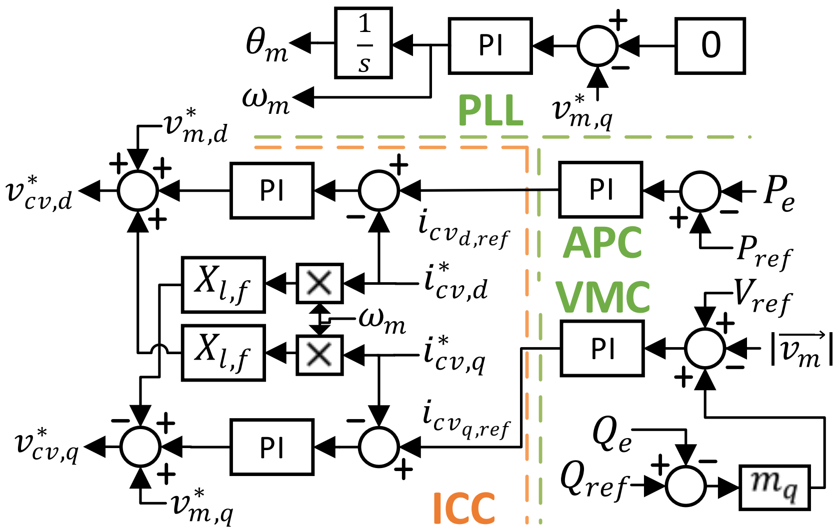
Modified IEEE 39-bus.
2 GFMs, 7 GFLs, 1 SG



Grid-forming (GFM) control

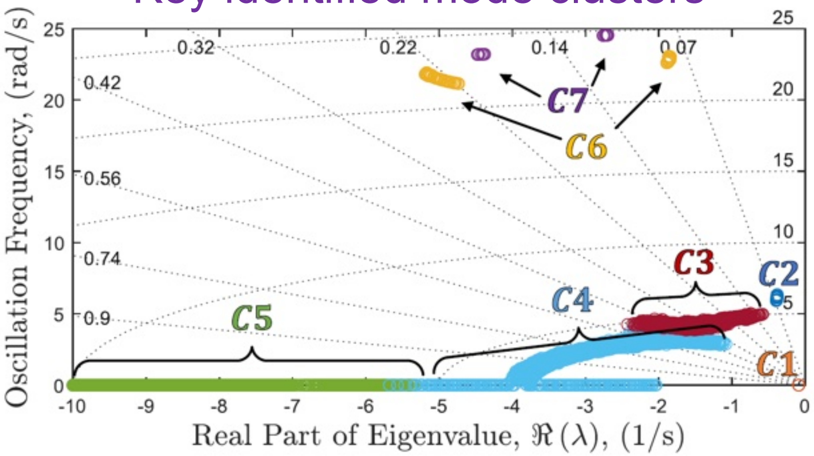


Grid-following (GFL) control



Application of the proposed framework

Key identified mode clusters



Modes grouped based on similar participation factor characteristics,

using K-means clustering

Characterisation of mode clusters

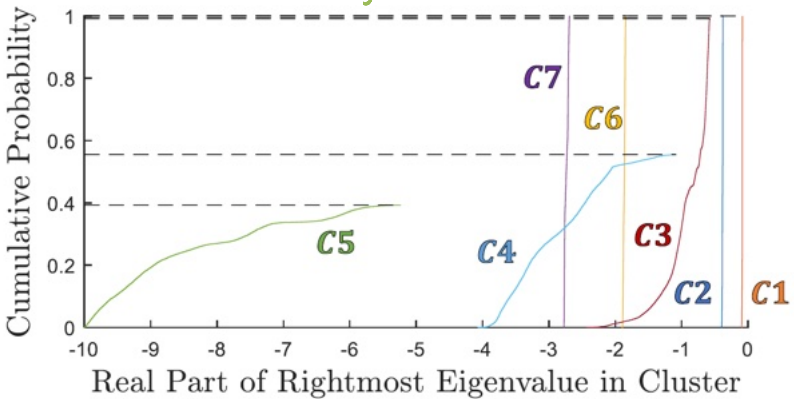
	C1	C2	C3	C4	C5	C6	C7
GFL1	0.7522	1.579e-05	0.003302	0.01481	0.009972	0.0005114	3.303e-05
GFL2	0.01146	0.0007601	0.01797	0.06919	0.09328	0.002349	0.001032
GFM3	0.001521	0.6166	0.278	0.07127	0.05086	0.3101	0.6829
GFL4	0.01018	0.0002126	0.03572	0.1459	0.2198	0.003597	3.375e-06
GFL5	2.907e-05	0.0001439	0.01991	0.1019	0.1187	0.001511	1.387e-06
GFL6	0.007004	0.001113	0.02982	0.1034	0.09972	0.00524	0.0003117
GFM7	0.0009061	0.3789	0.4762	0.1134	0.08147	0.6701	0.3152
GFL8	0.1202	4.045e-05	0.01538	0.07443	0.0831	0.00179	9.289e-05
GFL9	0.02208	4.757e-05	0.03236	0.1664	0.2007	0.003212	7.971e-05
SG10	0.07448	0.002212	0.09134	0.1393	0.04238	0.001587	0.0003577

	C1	C2	C3	C4	C5	C6	C7
P-F	0.1009	0.9645	0.9591	0.9012	0.8937	0.0289	0.02174
Q-V	0.8989	0.0001242	0.01101	0.06008	0.02901	0.000538	0.0002329
IVCr	7.851e-05	0.01708	0.01657	0.02557	0.0498	0.4772	0.4768
ICCr	6.069e-07	0.01671	0.005308	0.001818	0.007437	0.4789	0.4801
MF&Dr	3.291e-09	4.483e-06	2.683e-05	3.903e-05	0.0001423	0.0006528	0.0006985
Network	0.0001174	0.001578	0.00801	0.01127	0.01993	0.01377	0.02042

Stability-weighted participation index (SWPI) enables participation factor-like analysis of mode clusters.

What interactions do the clusters represent?

Probabilistic analysis of mode clusters



Can observe likelihood of a mode cluster to:

- Be unstable
- Be below a stability margin threshold
- Exist for any given operating point

DEFINING SYSTEM STRENGTH WHILE CONSIDERING DYNAMICS

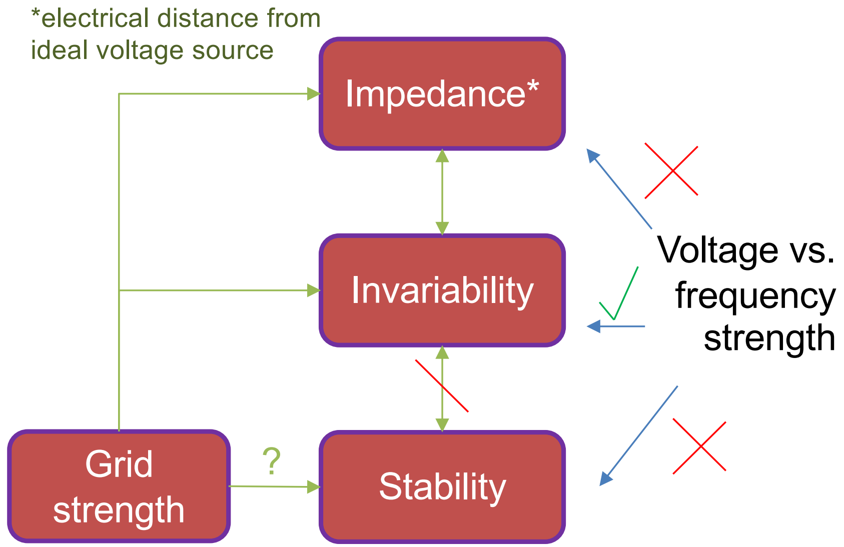
Small signal variability as a measure of system strength

L. Benedetti, P. N. Papadopoulos and A. Egea-Àlvarez, "A Modal Contribution Metric for Quantifying Small-Signal Variability in Power Systems With Converter-Interfaced Generation," in *IEEE Transactions on Power Systems (Early Access)*, 2024. doi: 10.1109/TPWRS.2024.3500786.

Small-signal *variability* and system "strength"

- A lot of commonly used system strength metrics are static in nature and neglect dynamics
- Recent approaches do consider dynamics (impedance-based approaches), mostly linking strength with stability margins
- Focus on how much a system variable (e.g. voltage or frequency) changes?
  - For a given disturbance in one location, how does voltage/frequency change throughout the network?
  - Similar to traditional metrics but considering dynamics
    - Not necessarily directly linked to stability but to how much output variables change/deviate
  - Decouples strength with respect to voltage and frequency
  - Uses modal responses to output variables and calculates maximum deviation
  - Captures how new types of interactions influence variability

Different perspectives of grid "strength"



Dataset available:
https://figshare.com/articles/dataset/Results_Data_A_Modal_Contribution_Metric_for_Quantifying_Small-Signal_Variability_in_Power_Systems_with_Converter-Interfaced_Generation/26412331

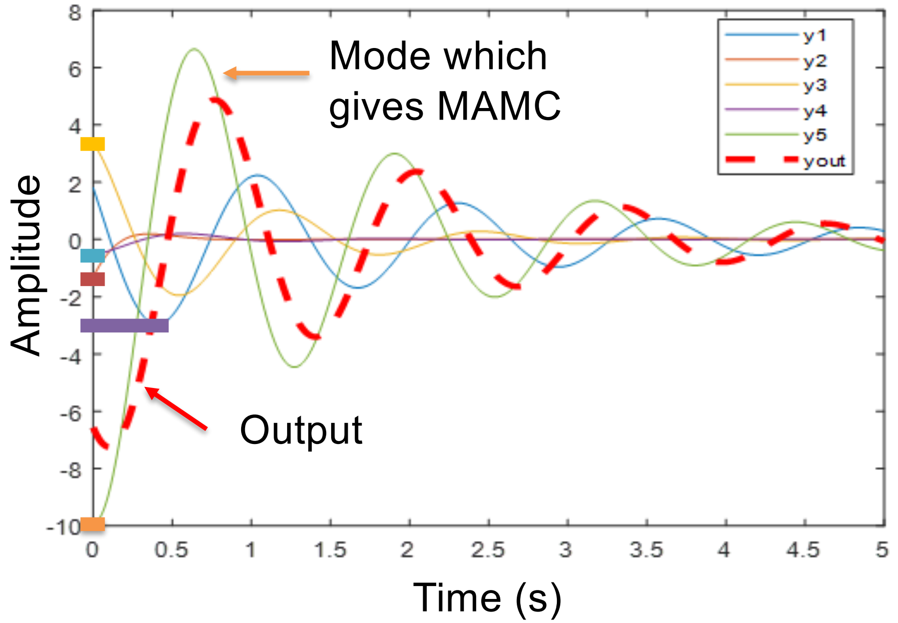
L. Benedetti, P. N. Papadopoulos, A. Egea, "A Modal Contribution Metric for Quantifying Small-Signal Variability in Power Systems with Converter-Interfaced Generation," available online, IEEE Transactions on Power Systems, https://pure.manchester.ac.uk/ws/portalfiles/portal/349631696/AModalContributionMetricforQuantifyingSmallSignalVariability.pdf .

Proposed methodology and quantification metric

Links specific modes/interactions to the variability of the output

- Modal contribution:
  - Maximum (absolute) deviation of the *decoupled modal response:* related to eigenvalues and eigenvectors
- Metric for small-signal variability of output: ***Maximum Absolute Modal Contribution (MAMC)***

Time-domain response of a linear system can be separated into a series of decoupled modal responses



$$\chi(t) = Ae^{\sigma t}cos(\omega t + \theta)$$

$$A = 2|\Phi_{j,n}c_n|$$

$$\theta = \angle\Phi_{j,n}c_n$$

$$\lambda_n = \sigma \pm j\omega$$

$$t_{max} = \frac{n\pi - \left(\theta + jlog\left(\pm\frac{\sqrt{-\sigma^2-\omega^2}}{\sigma+j\omega}\right)\right)}{\omega}$$ or 0 s

$$\Delta y_{j,n}^{max} = 2\left|\Phi_{i,n}c_n\right| e^{\sigma t_{max}} cos\left(\omega t_{max} + \angle\Phi_{i,n}c_n\right)$$

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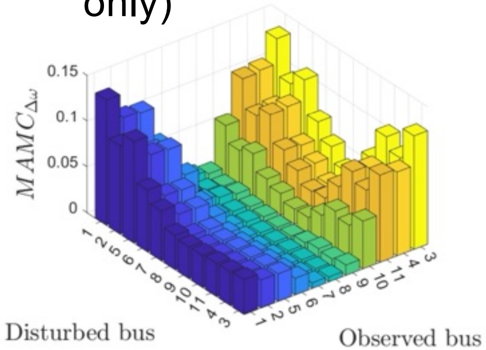
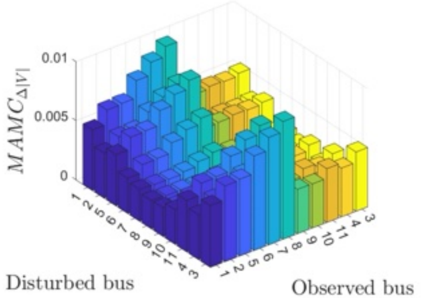
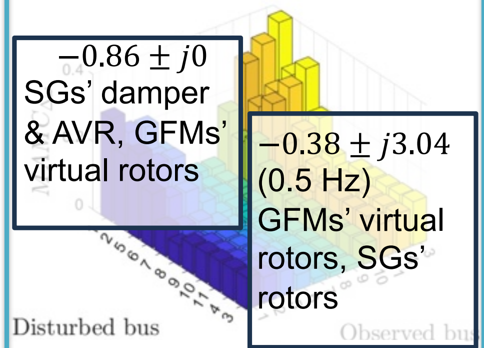
Application of the proposed methodology

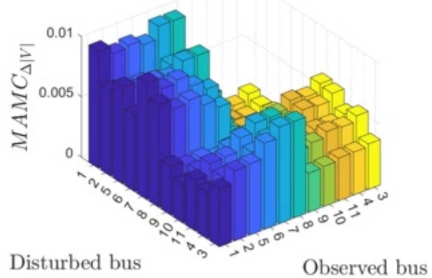
Base case (SGs only)



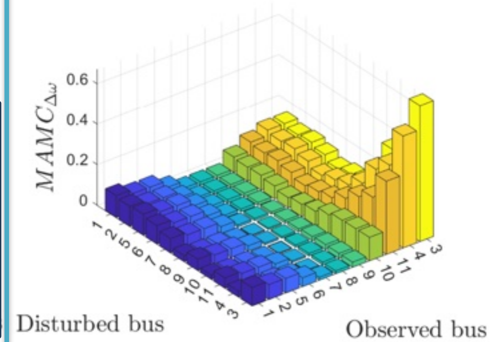


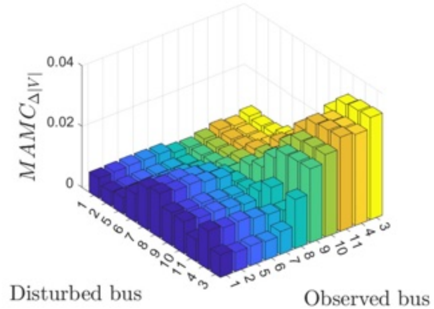
GFMs for G3 & G4

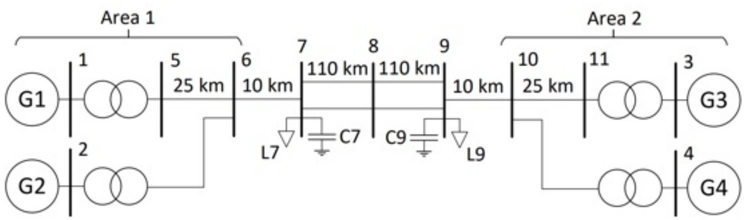




GFLs for G3 & G4







Kundur's 2-area, 4-generator system

Key takeaways

Voltage and frequency trends are independent

When generators in area 2 are GFMs:
- Variability is excited most by disturbances in area 1 (SGs area)
- Variability is observed in both area 1 and area 2

When generators in area 2 are GFLs:
- Variability is excited and observed most in area 2

Different modes can contribute most to variability for different

MACHINE LEARNING AND POWER SYSTEM DYNAMICS

Gaining trust, insights and improving situational awareness through explainability, physics-informed and graph-based approaches

Can machine learning help keep the system secure?

- Existing physics-based approaches
  - Based on first principles
  - Power Flow, Optimal Power Flow
  - Time domain simulations (RMS, EMT), eigen-analysis
- Increasing complexity and uncertainty
  - Renewables, Electric Vehicles, converter-interfaced – very different dynamic behaviour
  - New dynamic phenomena, not well understood, requiring a lot of modelling detail
  - A lot more scenarios to investigate – better understanding of risks and/or more cost-efficient operation
- What can Machine Learning do?
  - Speed up security/stability assessment – up to 100s of times (with the downside of getting it wrong sometimes)
  - Help in getting insights into complex underlying behaviours

We can consider stability/dynamics when computational effort does not currently allow us

[1] P. N. Papadopoulos, S. Chatzivasileiadis, A. Marot, "Can Machine Learning Help Keep the System Secure?," accepted on IEEE Power and Energy Magazine.

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How can machine learning help security assessment?

- Key advantage is speed and fast screening (100s of times faster)
  - Planning stage – too many scenarios (not enough time)
  - Operational time (closer to real time) – not enough time (a lot of scenarios to run on given time)
  - Need to balance hidden risks or over-securing (which comes at a cost)
- Situational awareness
  - Fast calculation of stability status/metrics
- Decision support
  - Offer options/insights
  - Optimisation (while considering detailed dynamics)
- Control (in cases where we can't do much with current tools)
  - Millions of devices
  - Fast corrective actions

P. N. Papadopoulos, S. Chatzivasileiadis, and A. Marot, "Can machine learning help keep the system secure? ," submitted to IEEE Power and Energy Magazine.

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Machine learning can help, but what do we need to get there?

- Trust to enable adoption – security of critical infrastructure and policy/regulatory advances (EU AI Act, UK govt)
  - POSTnote on AI and Energy Security https://post.parliament.uk/research-briefings/post-pn-0735/
  - DESNZ funded ADViCE Expert Working Group (AI for decarbonisation https://www.turing.ac.uk/research/research-projects/advice and relevant white paper.
  - DESNZ/OFGEM consultations

ADViCE | AI for Decarbonisation's Virtual Centre of Excellence

ADViCE Expert Working Group Whitepaper

AI for Decarbonisation: Policy and Regulation Alignment

Group Chair: Lucy Yu, *CEO, Centre for Net Zero (Octopus)*
Theme Lead: Pippa Robertson, *Deputy Director of Artificial Intelligence Policy (Ofgem)*

The **ADViCE project's mission** is dedicated to advancing innovation in AI to address decarbonisation challenges across four pivotal sectors: Energy, Built Environment, Manufacturing and Agriculture. ADViCE is a £500k project in the DESNZ Net Zero Innovation Portfolio, part of Stream 1 of the Artificial Intelligence for Decarbonisation Innovation Programme.

As part of these efforts, an Expert Working Group (EWG) has been established to contextualise the current opportunities and hurdles in adopting AI solutions for decarbonisation. The EWG engages a diverse array of experts, including sector representatives, startups, regulators, and academics. This white paper series, a main output of the EWG, compiles key observations and recommendations gathered during the sessions built around three themes:

- AI for Decarbonisation Policy and Regulation Alignment
- Unlocking and Enabling Investment and Innovation
- Data Accessibility and Capability

The EWG and the white paper series aim to inform policy and shape the design of future interventions in AI for decarbonisation for DESNZ.

The white paper series synthesises perspectives and themes identified during the EWG meetings, as well as findings from additional research across the project's activities, including the webinar series, the reports, and the programme partners' own expertise.

UK Parliament
POST

POSTnote 735

By Daniel Lewis, Josh Oxby
10 December 2024

Energy security and AI

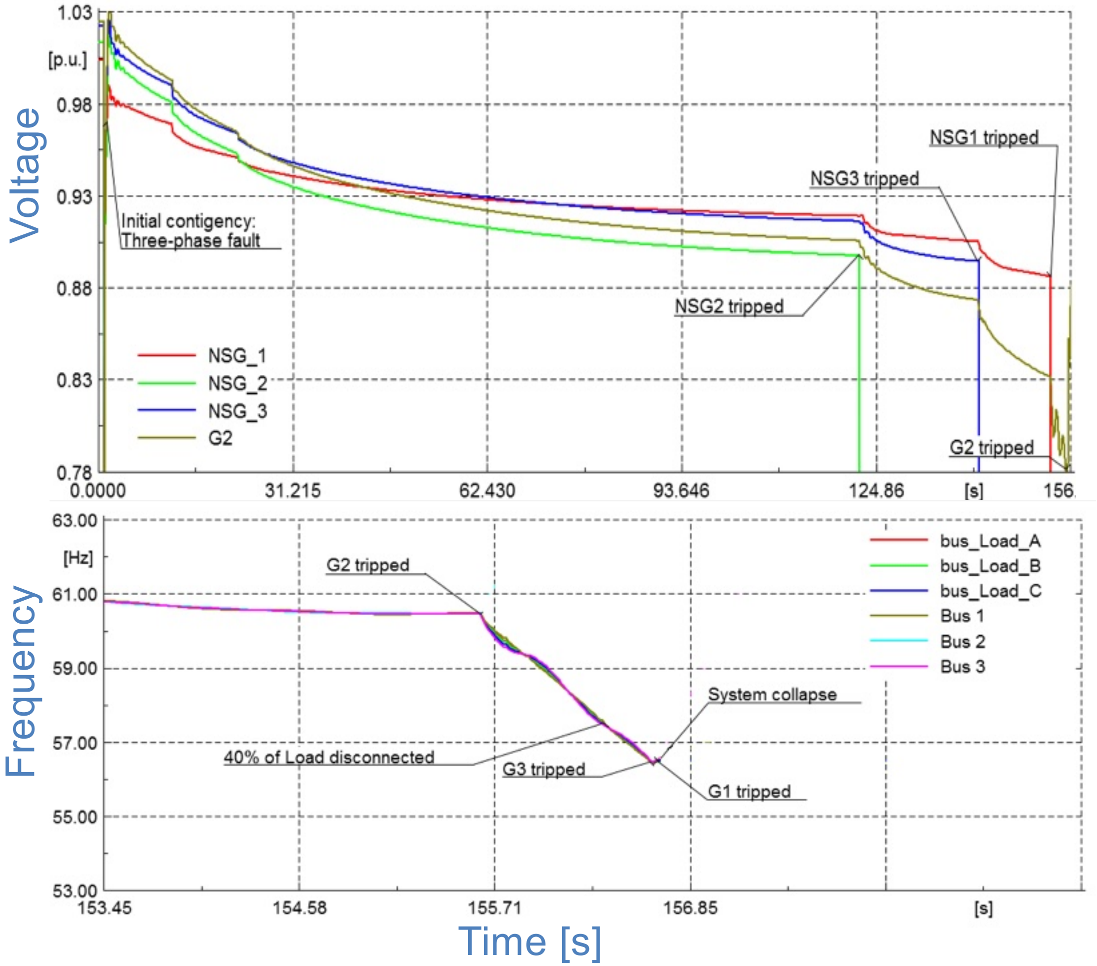
Overview

- Artificial intelligence (AI) and machine learning have a range of current and emerging applications within the energy sector, with the potential to optimise and accelerate energy planning, generation, and use.
- AI could use data from devices such as smart meters and substation monitoring to help address current regional renewable connection delays and excessive network congestion. It could also speed-up decarbonisation of the energy system as the UK strives to meet 2030 grid decarbonisation, 2050 Net Zero targets and reduce costs for consumers.
- There are technical and infrastructural barriers to wider adoption of AI in the energy system, including data access, regulation, skills gaps, and availability and reliability of the physical infrastructure that supports AI.
- Stakeholders have raised concerns around privacy, cyber security, energy use, fairness, ethical use, and operational challenges.
- Stakeholders suggest that more support is needed to develop AI in the sector, and that regulation needs to change to ensure optimal benefits can be gained from wider integration of AI in the energy system, while avoiding potential risks.

Machine learning can help, but what do we need to get there?

- Trust to enable adoption – technical advances
  - Explainability/interpretability – how machine learning models work and reach decisions
  - Physics-informed and graph-based methods – we know and can embed physics to some extent
  - Verification – performance guarantees
  - "failing without warning" – follow a complementary approach to existing methods
- Scalability - proof of concept applications
  - Is it possible to train and use models efficiently for very large realistic or real networks?
  - Open competitions useful in showcasing the potential and identifying gaps/shortcomings (what could go wrong?)
- Topology changes
  - Combinatorial problem, can we train for all possible topologies? – graph-based methods can help
- Data quality and access/availability
- Closer interactions with academia, industry and research organisations – real world cases

Time domain simulations for dynamics and stability



- Evolution of system states/variables in time
  - Computationally intensive, more detailed models (complexity), more scenarios (uncertainty)
  - Black box models
- Outcome classification
  - Stable/unstable, or more details through multiclass
- Stability metrics/indices
  - E.g. Voltage Stability Margin, critical clearing time, boundary transfer limits, etc.

Stability/security assessment using machine learning – going beyond the notion that ML models are just powerful black-boxes

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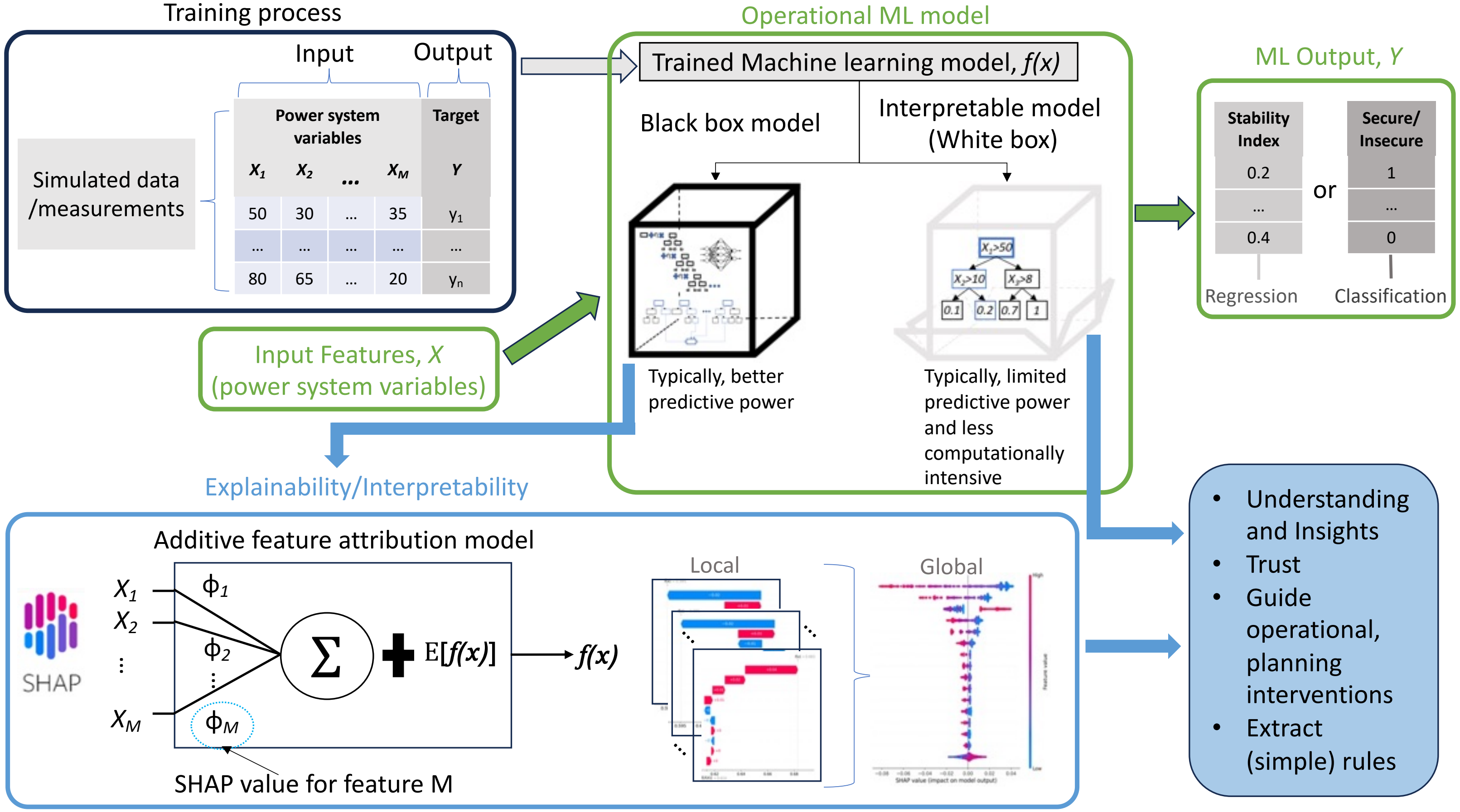
- Methods that take steady-state "snapshot" as input (SCADA/EMS)
  - Binary (safe/unsafe) or multiclass classification
  - Regression – calculation of a stability metric (e.g. critical clearing time or locational/regional RoCoF and nadir)
- Going beyond the notion that ML models are just powerful black box predictors

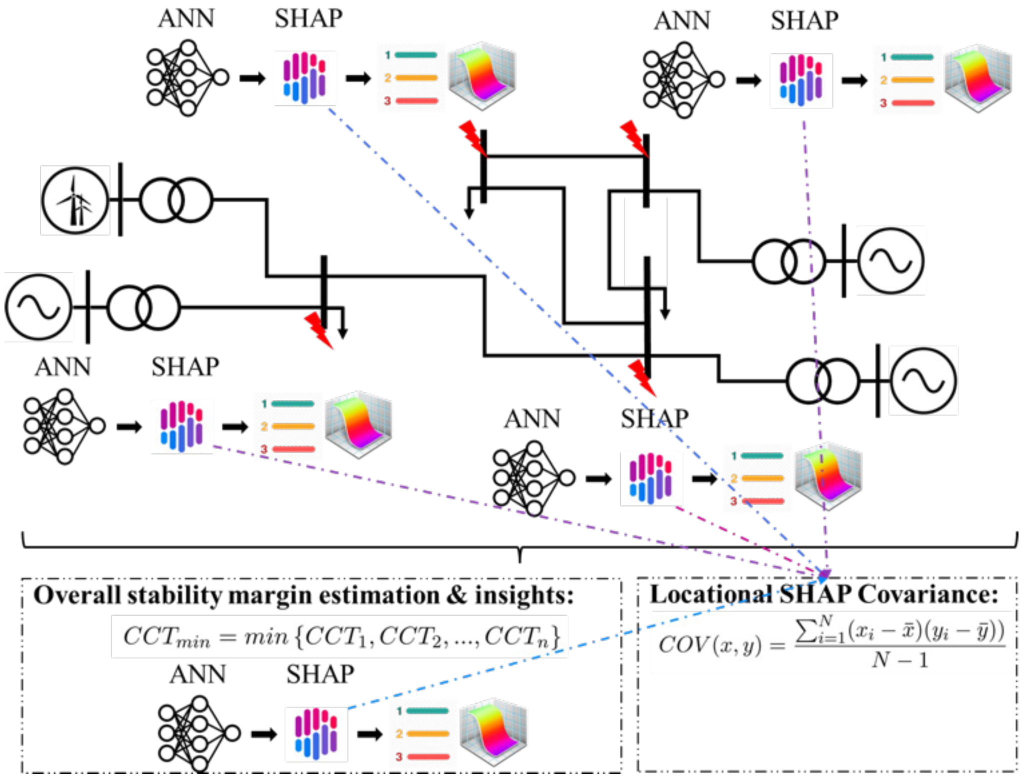


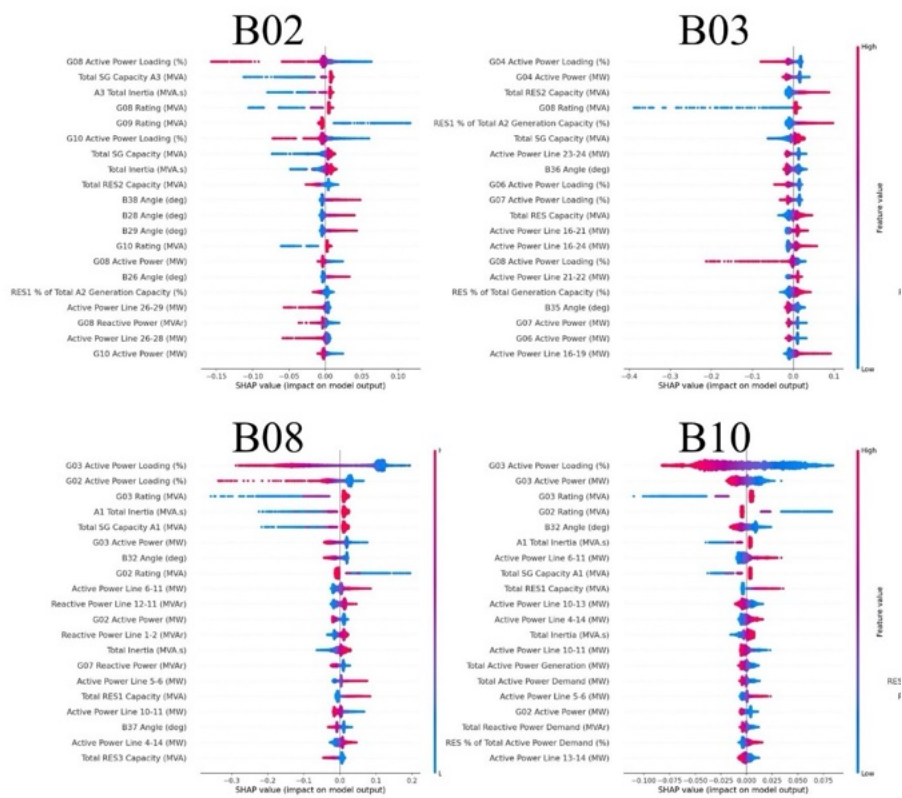
P. N. Papadopoulos, S. Chatzivasileiadis, and A. Marot, "Can machine learning help keep the system secure? ," accepted in IEEE Power and Energy Magazine.

R. I. Hamilton and P. N. Papadopoulos, "Using SHAP Values and Machine Learning to Understand Trends in the Transient Stability Limit," in *IEEE Transactions on Power Systems* ,doi: 10.1109/TPWRS.2023.3248941.

R. I. Hamilton, P. N. Papadopoulos, W. Bukhsh and K. Bell, "Identification of Important Locational, Physical and Economic Dimensions in Power System Transient Stability Margin Estimation," in *IEEE Transactions on Sustainable Energy*, vol. 13, no. 2, pp. 1135-1146, April 2022, doi: 10.1109/TSTE.2022.3153843.

Improving situational awareness





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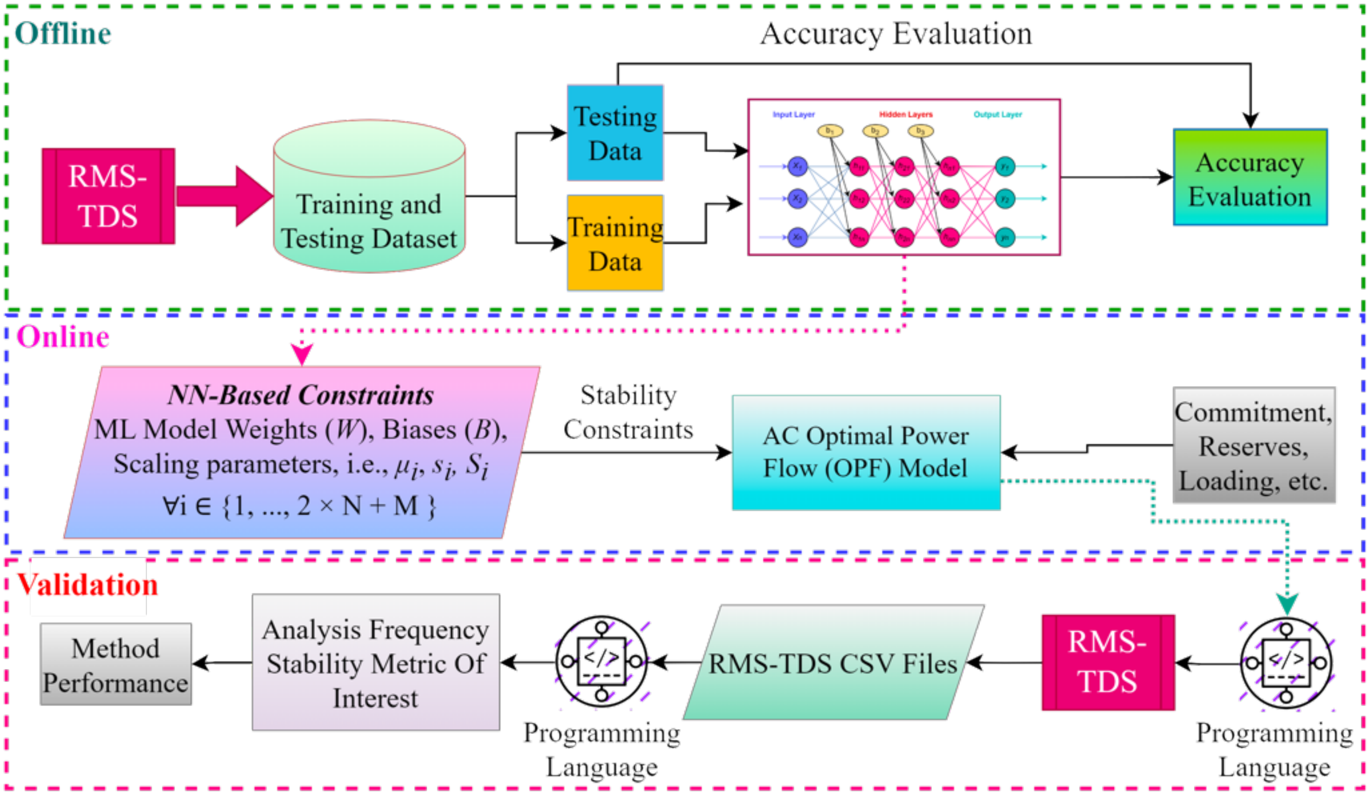
Introducing detailed constraints from dynamics into optimisation – decision support

- Train a Neural Network to capture detailed dynamics
  - Using time domain simulations so capturing detail
  - Application to regional frequency stability as example
- Linearise the trained neural network and formulate constraints to implement in optimization
- Maintain detail and avoid over-securing
  - Aid decision support
  - Preventive securing



[1] A. Kilembe, P. N.. Papadopoulos, W. Bukhsh "Neural Network-Constrained Optimal Power Flow for Locational Frequency Stability ," under 2nd round of reviews

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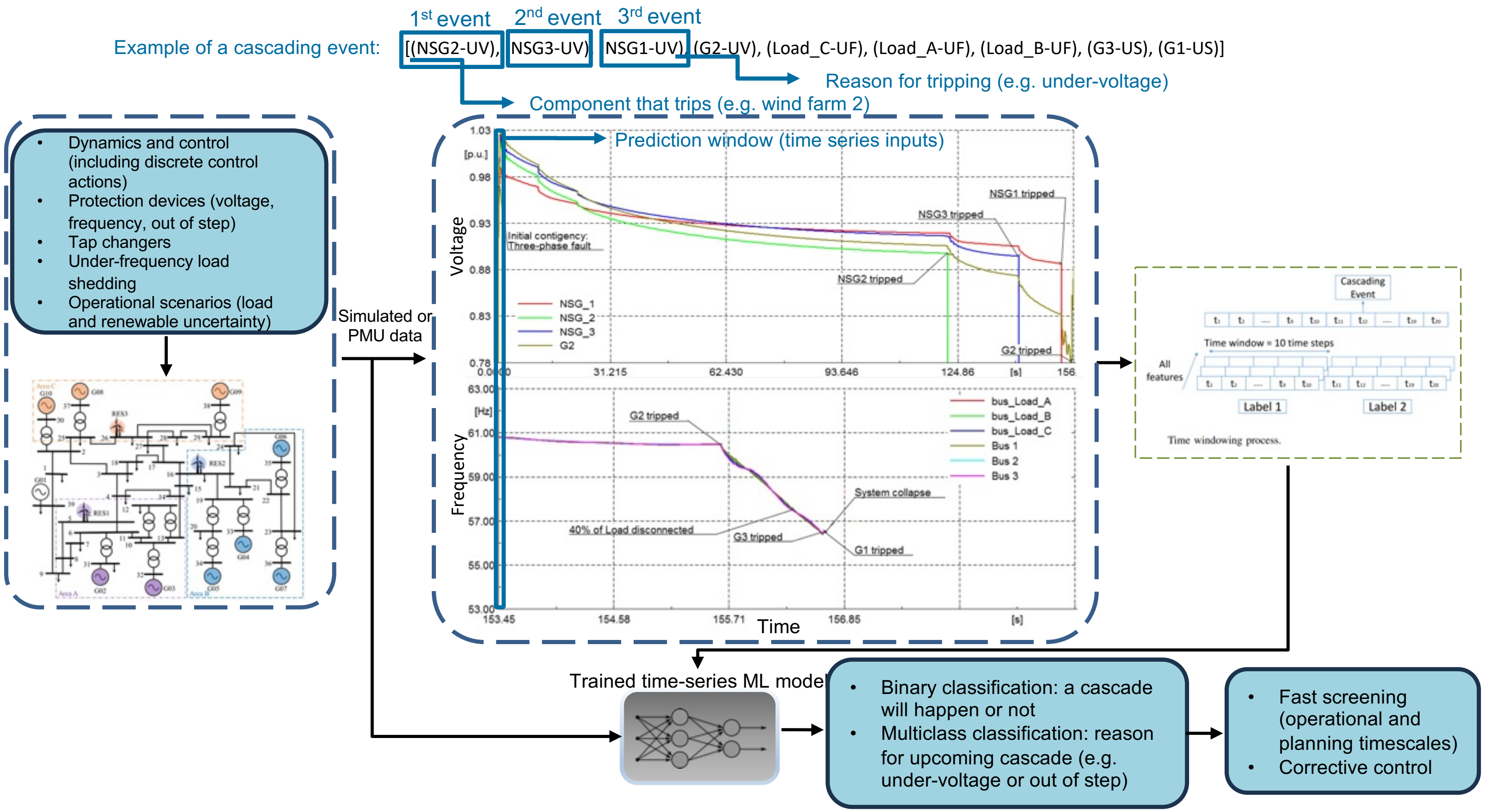
Stability/security assessment using machine learning in real time

- Methods that take a time window as input (WAMS/PMUs)
  - Binary/multiclass classification
  - Corrective control
  - Special protection schemes
- Control for situations we currently can't act on (e.g. through Reinforcement Learning)
  - Millions of devices
  - Emergency control (fast timescales)
- Performing simulations faster
  - Physics-Informed approaches



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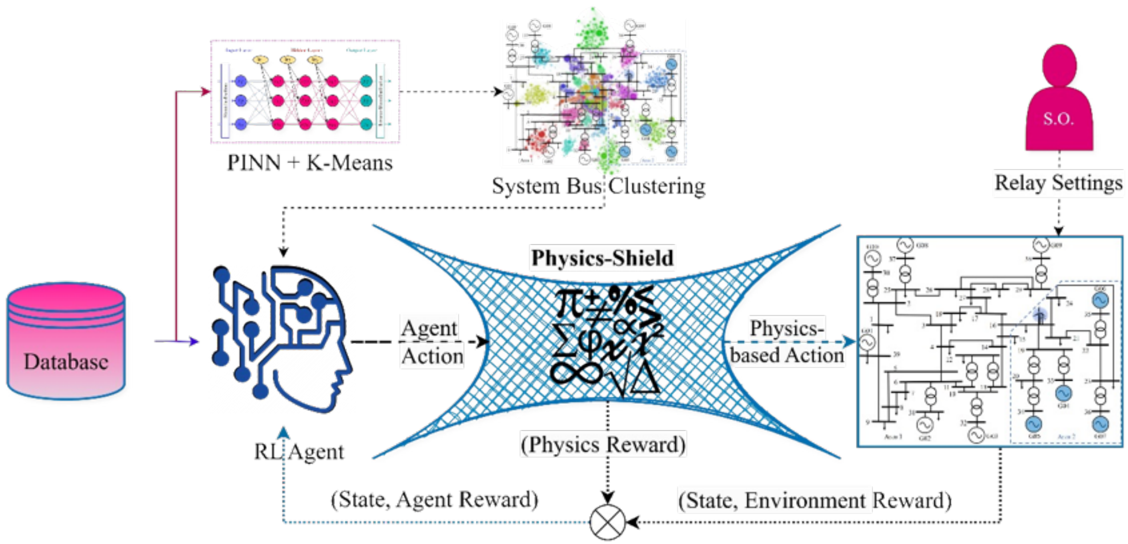
Adaptive Load Shedding through Physics-Informed Deep Reinforcement Learning

- Moving further from preventive securing of the system to real time emergency control
- Instead of pre-defined under-frequency load shedding settings, decide when, where and how much load to shed adaptively.
  - Utilising information from current operating condition through PMUs
  - Taking into consideration locational/regional frequency dynamics
- Physics Informed Reinforcement Learning (RL) **to address scalability (up to 2000 buses)**
  - Physics-Shield (swing equation based) and Physics Informed Neural Networks for coherent areas detection
  - Improves training and performance
- **Complementary** to Under-Frequency-Load-Shedding
  - UFLS can still be in operation as last resort



A. Kilembe, P. N. Papadopoulos, " *Adaptive Load Shedding using Physics-Informed Deep Reinforcement Learning,*" submitted.

Other use cases for ML in power systems (non-exhaustive) – CIGRE C2.42 Working Group

- Dynamic Security Assessment
  - Safe/unsafe classification, stability index and time series calculations, etc.
- Congestion management
  - Decision support on remedial actions
  - Huge optimisation problem to be solved close to real time (N-k security considerations)
- Forecasting
  - Load and renewables (wind and solar)
  - Minutes, hours, days, months
- Alarm management and reporting
  - Alarms can be overwhelming in control rooms
  - Grouping, contextualising alarms
- Visual Inspection
  - Equipment (transformers, power lines) and substations
- Predictive maintenance
  - Predict failures, remaining lifetime of assets, asset health monitoring, etc.
- Control
  - Millions of devices

CIGRE C2.42 WG TB "The impact of the growing use of machine learning/artificial intelligence in the operation and control of power networks from an operational perspective".

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Conclusions

- Increasing complexity and uncertainty in power system dynamics
  - New (or careful choice of existing) models, modelling tools, modelling frameworks
  - Fundamental understanding of (new) phenomena across range of operating conditions
  - “System strength”
- Measurement based/data-driven and machine learning methods
  - Fast assessment (100s times speed up)
  - Capture complex dynamics and provide unique insights
  - Important to build trust – no longer just a black box
- A three-step approach to implementation
  - Improved situational awareness and fast screening
  - Decision support
  - Automation
- Industry/academia/research organization collaboration for proof-of-concept applications

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