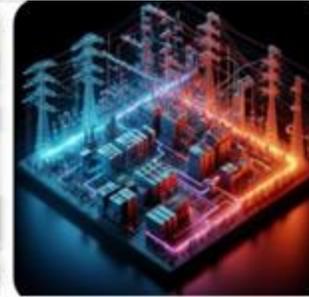


AI-Day for grid operations

18th November 2024
RTE – La Défense



Morning

9-10h Welcome Café

10-12h / AI for simulation

- **ML for Physical Simulation Challenge: the power grid use case**
sponsored by IRT SystemX, RTE, NVIDIA, Exion, INRIA
 - o IRT SystemX introduction (Milad Leyli-abadi, IRT SystemX)
 - o Competition design
 - o Winners presentations
- **Panel & Round Table –**
 - o **Medha Subramanian - Moderator**
 - o **Speakers:**
 - **Panagiotis Papadopoulos** – Dynamic Simulation (Univ Manchester)
 - **Antonello Monti** – TwinEU project (RWTH)
 - **Hendrik Hamann** – Foundational Models (IBM)

12-13h15 Lunch Buffet

Event Page at www.tinyurl.com/aiday4powergrid

Afternoon

13h15-16h **CIGRE C2.42 Tutorial "The impact of AI/ML for grid operations"**

- **Introduction** ~ 15min
- **Part 1** ~ 1h **Break** 15 min **Part 2** ~ 45 min
- **Q&A and Mirror brazilian group** ~ 30 min

16-16h45 **Spotlights** 7-8min presentations

- **Other Community Organizations**
 - o RDIC W5 (Digital Twin & AI) - ENTSOE
 - o Linux Foundation for Energy - LFE
- **European Horizon R&D Projects**
 - o AI4REALNET – INESC TEC
 - o AI-EFFECT - EPRI Europe
- **TSO Projects:**
 - o AssistFlux - RTE
 - o Granular Load Forecasting - HydroQuebec

17-19h **Cocktail & Demo Sessions**

- **Smart Alarm Management** - Elia & Hitachi
- **GridOptions Tool** - TenneT & Artelys
- **Decision Support for Voltage Control** - N-side & Elia

Words of Introduction

Konstantin Papailiou
President of CIGRE

Jean Nakache
President of CIGRE French National Committee



C2.42 WG Tutorial

The impact of the growing use of AI-ML in the operation and control of power networks from an operational perspective

18 November 2024



cigre

For power system expertise

Working Group Activity Overview

C2.42 WG overview

- Started on **March 2022** within Study Committee C2 (Power System operations)
- Members**
 - Antoine Marot @RTE (Convenor) – Ricardo Bessa @INESC TEC (Secretary)
 - 27 experts: 14 R&D / Academia, 9 System Operators, 3 industry, 1 regulators / policymakers
 - 18 different countries worldwide



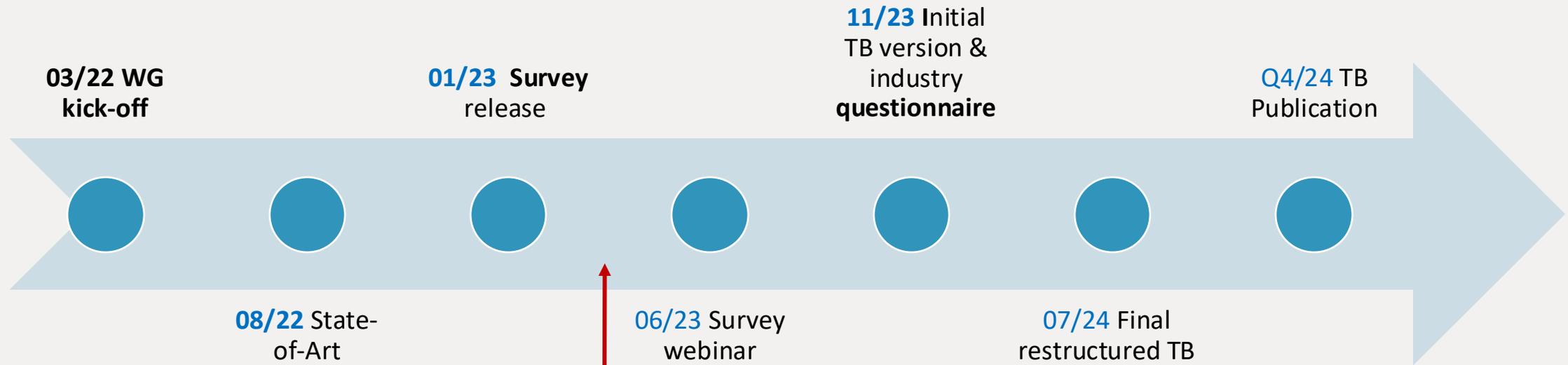
Members

Antoine Marot, Convenor	FR
Adrian Kelly	IE
Panagiotis Papadopoulos	UK
Fabian Heymann	CH
Medha Subramanian	IE
Sjoerd Kop	NL
Amarsagar Reddy Ramapuram Matavalam	US
Karin Rodrigues	AU
Rohit Anand	IN
Victor Meza	CO
Jingyu Wang	CN
Rohit Trivedi	IE
Miktor Eriksson Möllerstedt	SE
Mouadh Yagoubi	FR

Ricardo Bessa, Secretary	PT
Milos Subasic	DE
Alberto Kopiler	BR
Jochen Cremer	NL
Samuel Young	UK
Marija Ilic	US
Ming Dong	CA
Guangchao Geng	CN
Teerasak Arunthanakij	TH
Wolf Berwouts	BE
Koen Vandermot	BE
Spyros Chatzivasileiadis	DK
Arnaud Zinflou	CA

WG activity timeline

Release a TB in less than 3-year timeframe to keep up with the pace of developments in AI



Which new AI breakthrough happened there ?

New AI breakthrough in 2023 ?

Deep Learning

Apple Intelligence

Generative AI

Artificial General Intelligence

New AI breakthrough in 2023 ?

Deep Learning

Apple Intelligence

Generative AI

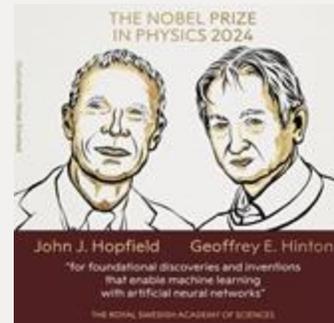
Artificial General Intelligence

AI maturity – A timely WG

Relentless innovation for the past 10 years:

- Ability to speak and write in natural language, generate images and videos
- Advances in consumer products and in industries with autonomous vehicles (Waymo), biology and medicine (protein folding), science (particle physics, astronomy, maths)
- Billions of investments, Tech Giants trying to stay ahead with AI

Recognition of impact



Strong Regulations are coming



WG Scope

- Can the power system community benefit from AI innovations, for system operations in particular ? What are the needs ? How to prioritize use cases ?
- What are current early real-world examples of using AI in system operations ? What are the lessons learned ?
- Are people eager to use AI? How can they remain in control (trust) ?
- How ready is our IT team to integrate more advanced AI? What are the new requirements? How do you adopt a data-driven mindset ?
- What are the risks and challenges to cope with ?
- How can the AI community inspire us to develop and implement AI at scale ? How can our community make shared efforts to make stronger advances ?

Technical Brochure overview



- Balance interest for target audience (control room manager + innovation Lead + IT digitalization lead)
- 100 pages at its core (streamlined 5 core chapters) + large appendix

[TB available online on e-cigre](#)



1. Introduction
2. Fundamentals of AI and Machine Learning
3. Applications and Use Cases
4. AI Role in Flexible Operation
5. Challenges, Risk Assessment and Mitigation
6. Implementing AI in System Operation Organizations
7. Conclusions



Home | Publications | The impact of the growing use of machine learning/artificial intelligence in the operation and control of power networks from an operational perspective



TECHNICAL BROCHURES

The impact of the growing use of machine learning/artificial intelligence in the operation and control of power networks from an operational perspective

Ref 946 • 2024

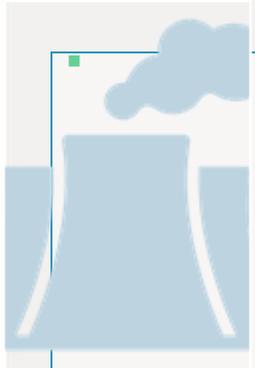
New

- This publication is free only for CIGRE members
- Price for non member: 300 €

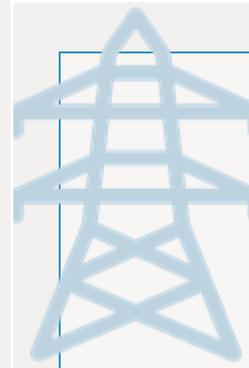
[Download \(PDF • 7 MB\)](#)

CHAPTER 1: Introduction

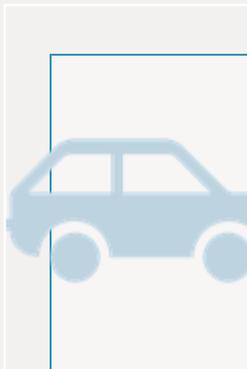
Challenges to Power System Operation



Large electro-mechanical resources are being replaced by smaller electronically-controlled, inverter-based resources



Large transmission assets and infrastructure are being augmented (but not replaced) by inverter interfaced, electronic grid enhancing technologies; such as special protection schemes, dynamic line rating, FACTS, HVDC

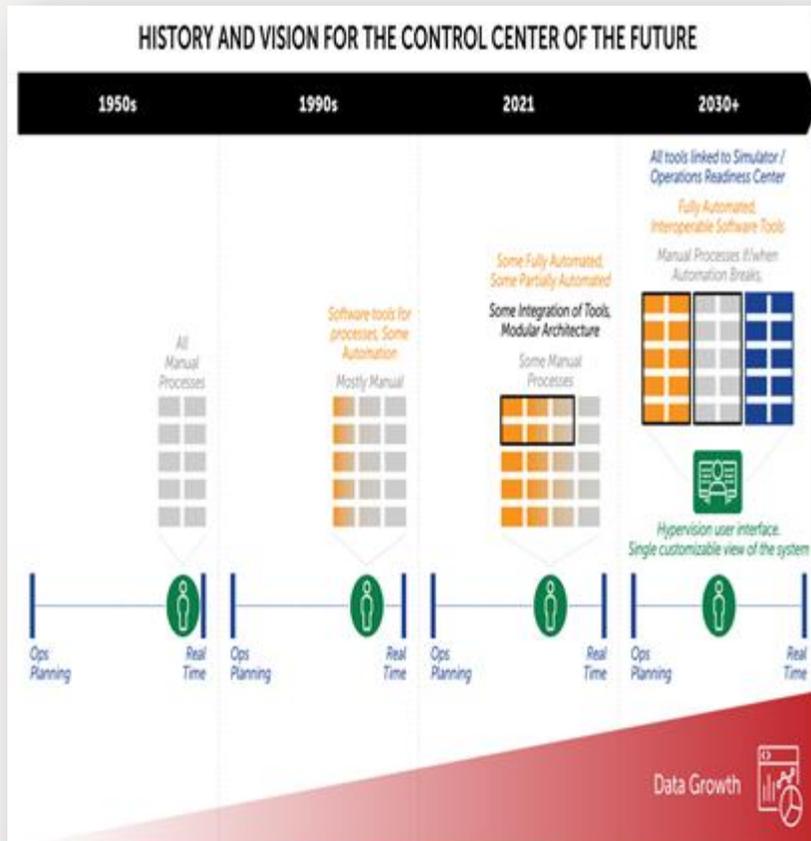


Electro-mechanical motor-based demand has been replaced by inverter-interfaced demand, through electrification, smart devices with smart meters tracking energy usage in minute detail

Towards Future Operations in Future Control Rooms

Evolution of the Control Center Manual Reactive to Automated and Proactive

Need for automation of manual processes, with operator oversight.
Use AI as a Tool to Augment, Sense Making, Decision Making and Actions



Operators anticipate events, try to decipher alarms, oscillations, trends, weather, prices in real time

Operators, simulate, troubleshoot, optioneer, risk assess, evaluate, decide on an action

Operators create switching plans, execute actions, report, dispatch.



Leveraging AI to Help Network Operators

The Cognitive Modes for Operators are Under Threat

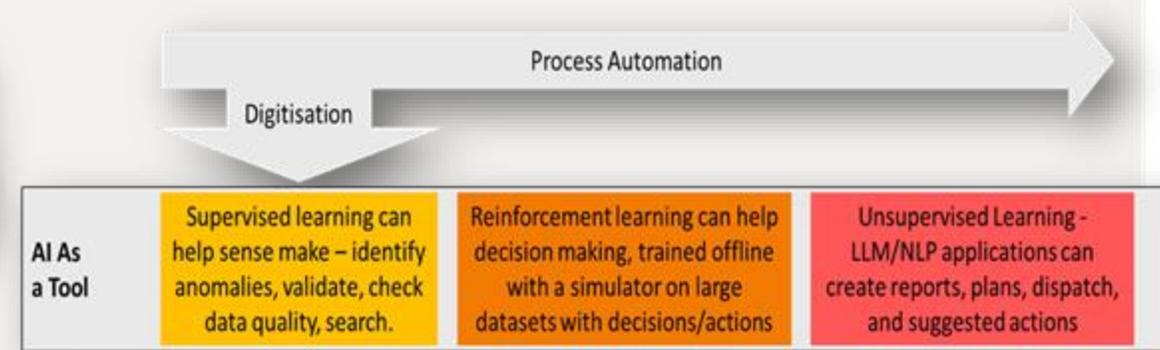
Too much data,
too many systems
fragmentation of
networks, digitisation of
assets, new sensors, new
models
new markets
new market participants
weather, Climate

Multi-factor decision
making
Interconnected network
entities
New challenges, less
experience
Need to "look ahead"

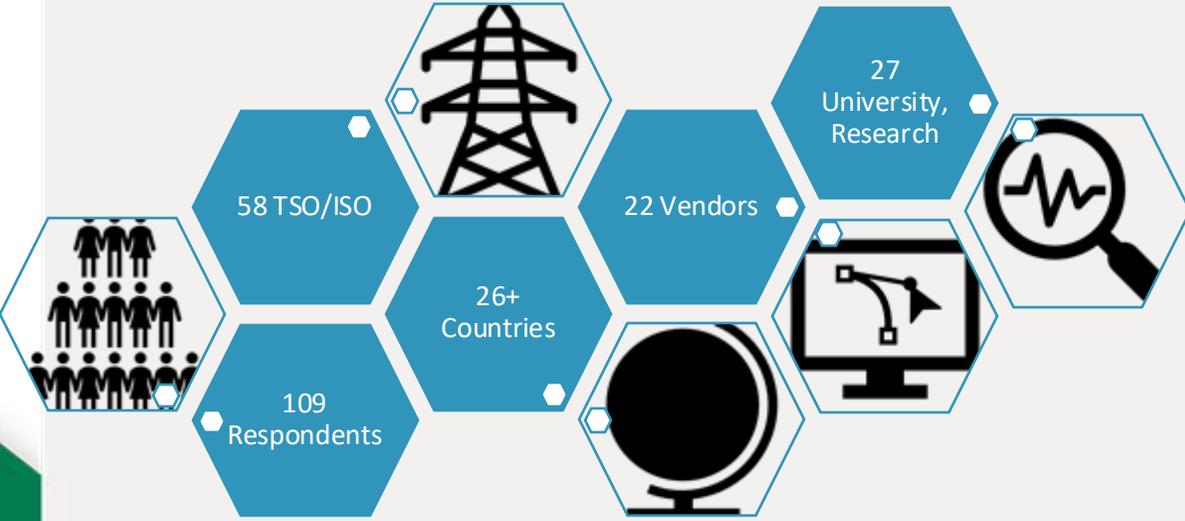
More reporting,
administration,
automation,
interventions
More assets, resources
to be controlled
Network complexity
Safety procedures



AI Can be Used as a Tool for Process automation through Digitisation



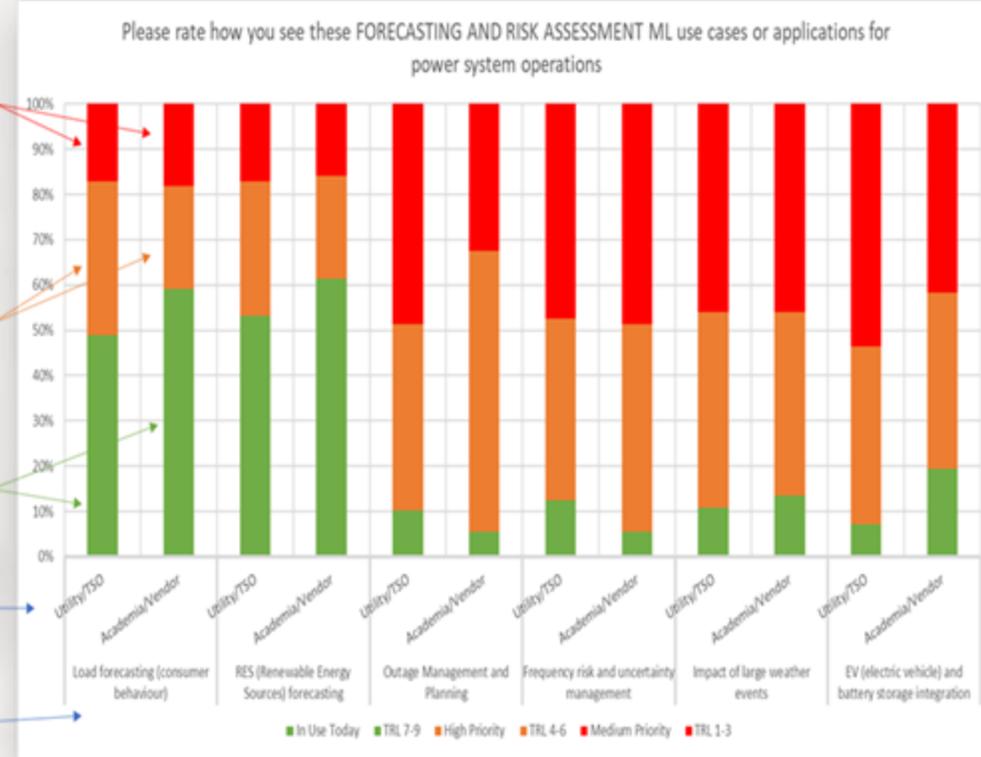
2022-3 Survey of System Operators and Industry



Red=Medium Priority for Utilities, Research TRL for Academia/Vendors

Orange=High Priority for Utilities, Development TRL for Academia/Vendors

Green=In Production, Deployment TRL



System Operators / Utilities	Industry and Academia
In production	In production
A high priority but not in production	High Technology Readiness Level (TRL) (7-9)
A medium priority	Medium Technology Readiness Level (TRL) (4-6)
A low priority not in production	Low Technology Readiness Level (TRL) (1-3)
Not relevant or not applicable	Not relevant or not applicable

Key Points and Highlights of Survey

A lot of interest and good commentary in the survey. Good split between utilities/TSO and vendor, academia

Forecasting applications are the most prominent use cases in use today by utilities.

Beyond these there are a low percentage of applications implemented

Congestion management, economic dispatch, dynamic security, weather/large event analysis are seen as the highest priority use cases by utilities

Outage management, seen as a high priority for industry but less so for utilities

Baseline of 56% for how seriously utilities are valuing ML applications. Will test again.

Quality and efficacy of data referenced a lot in terms of the journey and for use case development.

Most important driver is to enhance decision making in operations. Also to utilize datasets and software available

Open source tools and on-prem tool sets are commonly deployed across all sectors. On demand cloud is less utilized in utilities.

Development of an AI/ML team leader, team and strategy are seen as the key non-technical enablers.

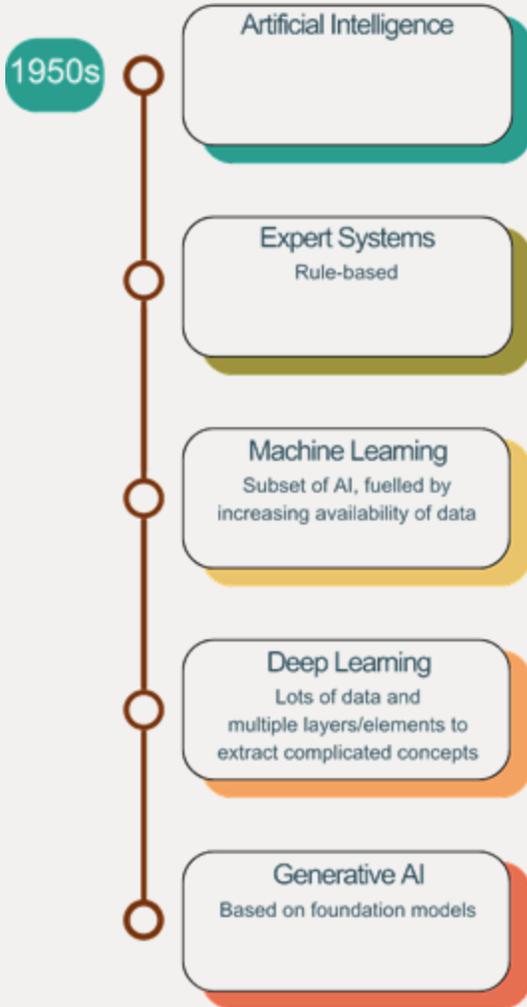
Acceptance and explainability seen as the key challenges for development, especially utilities.

Governance, regulation or legal constraints are not seen as major barriers to development. Key barrier is the risk to high reliability systems.

➤ Survey insights fed into TB Chapter Content

CHAPTER 2: Fundamentals of AI and machine learning

What is Artificial Intelligence?



OECD definition

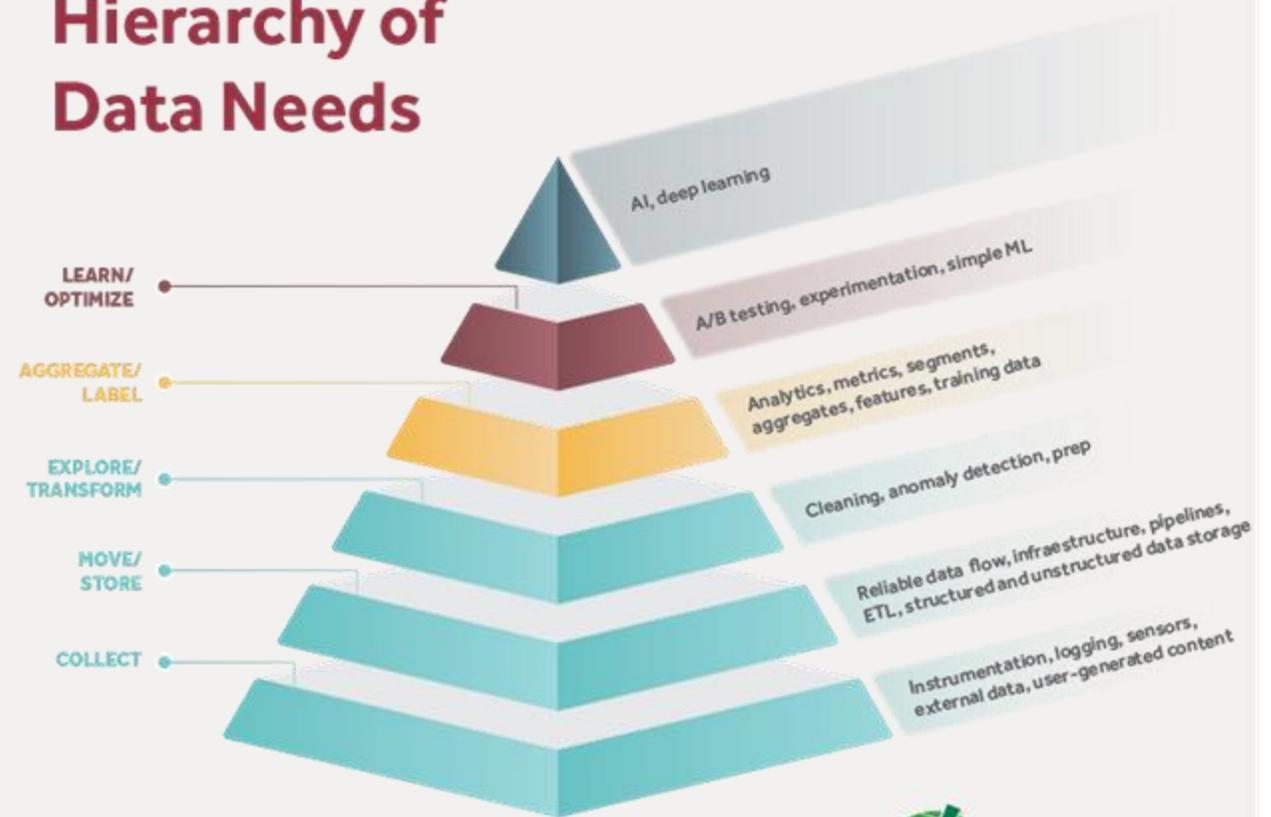
An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment

A data-driven paradigm

Shift from physics-based to data-driven approaches

- Power flows and time domain simulations
- With AI/ML parameters and rules are learned through training
 - ✓ Requires measurement data (e.g. WAMS) or simulations
 - ✓ Useful when rules not explicitly known or are complex
 - ✓ Speed-up a key advantage
- AI/ML enables augmenting existing physics-based approaches or addressing challenges that are otherwise hard to solve
- One of key factors for success of AI in the last years is the free availability of datasets and benchmarks

Hierarchy of Data Needs



A general overview of ML methods

Overview Schematic for AI Power System Taxonomy

AI/ML methods

Expert systems
Intelligent agents

Machine Learning
Supervised/Unsupervised
/Reinforcement

Tree-based methods,
Support Vector Machines
ANNs, RNNs, CNNs
Physics-Informed
Graph based methods
Transfer learning
Generative AI
Graph based methods,
Clustering

Cross-cutting aspects

Explainability/Interpretability
Feature Importance
Dataset collection/preparation
(Based on measurements,
existing data, simulations)
Trustworthiness/verification

Task and output

Classification
Regression
Time-series/sequence prediction

Power System Applications

Forecasting, state estimation, dynamic
Security/stability assessment,
operation and planning optimization,
emergency and extreme events,
asset management

Functionality

Situational awareness/Decision
support/Control

Or alternatively:

Perception/Decision/Action point

Also linked to:

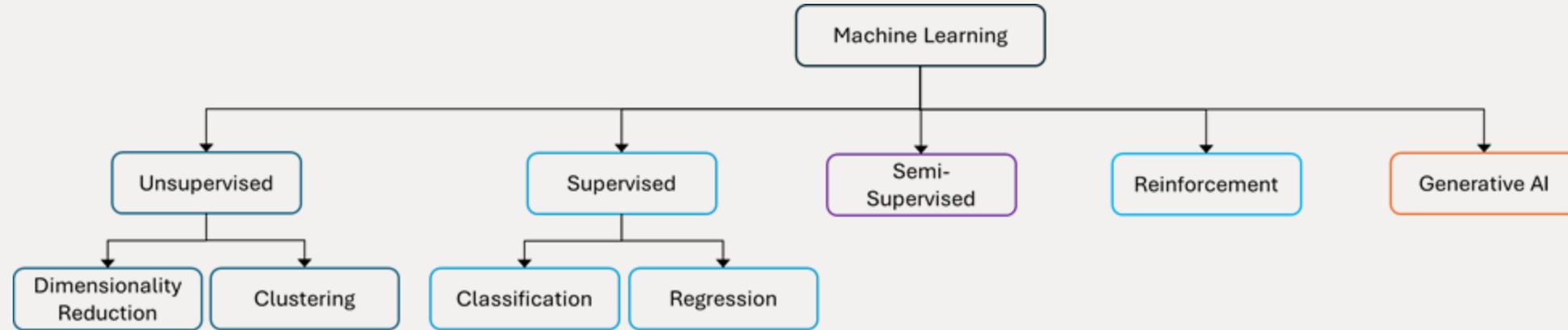
Descriptive/predictive/prescriptive

Implementation aspects and risk

Process/Function/Role/Responsibility
and accountability
Error metrics
Trust

ML methods categories

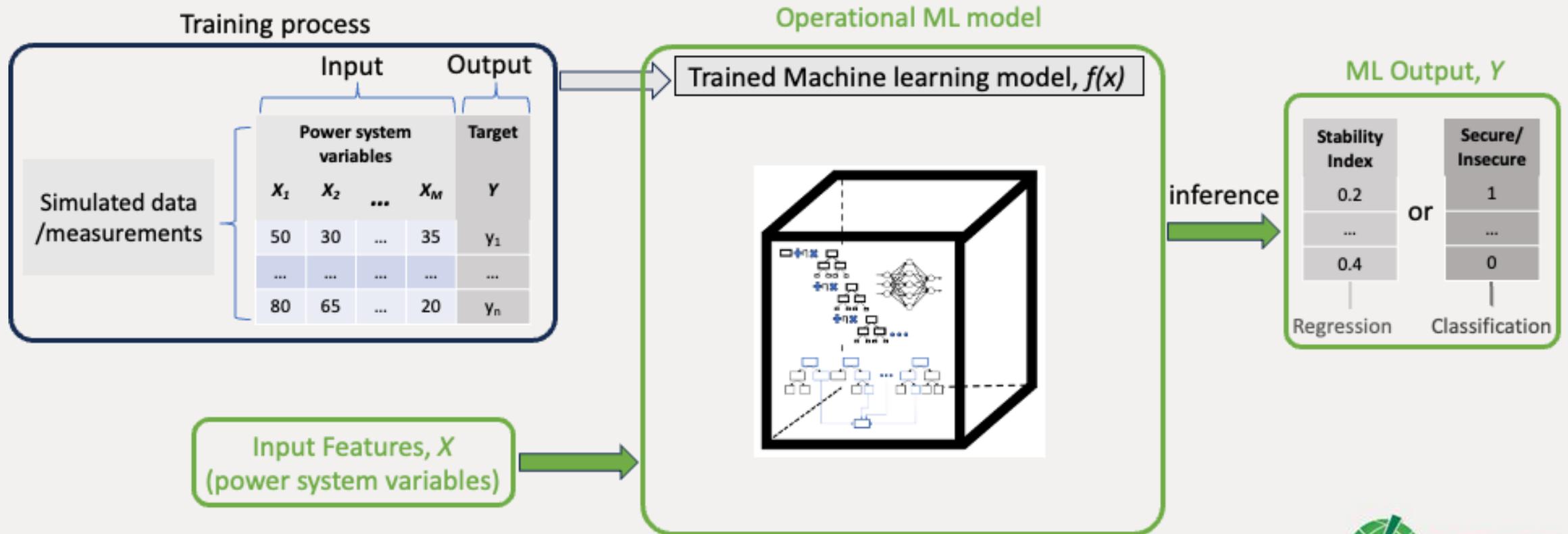
Considerations when choosing ML methods and models for use cases



- Main types of ML
 - ✓ Supervised, unsupervised, semi-supervised, reinforcement learning, foundation models (generative AI)
 - ✓ Smaller specialized models to solve specific tasks or large foundation models for multi-purpose tasks
- Output task and type
 - ✓ Classification, regression, clustering
- Several ML models exist
 - ✓ Simpler (linear regression, decision trees, etc.) and more complex (neural networks, transformers, etc.)
- Examples: CNNs for solar power, GenAI for alarm management, RL for congestion management

How do ML methods work?

An example of supervised learning (e.g. for dynamic security assessment use case)



AI/ML methods and related aspects

Additional considerations related to ML and specific use cases

- Data collection, preparation and quality
 - ✓ Relevant to several power system use cases (e.g. forecasting, grid monitoring, etc.)
- Physics aware ML
 - ✓ Particularly useful for simulation-based power system use cases
- Graph-based methods
 - ✓ Useful in dealing with topology changes in power systems
- Trustworthiness/verification
 - ✓ Important for critical infrastructure applications
- Interpretability/Explainability
 - ✓ Breaking the notion that ML are just black box predictors
 - ✓ Useful for gaining insights into complex behaviours (e.g. for Dynamic Security Assessment use case)

Summary and conclusions

- Introduction to AI/ML and relevance to power system applications
- Conceptual AI taxonomy for power systems
- What types of power system challenges can AI/ML be useful for?
 - ✓ **ML models, methods, and general considerations**
- Foundation for concrete use cases presented in use cases of Chapter 3 and throughout the TB

CHAPTER 3: Applications and use cases

Outline

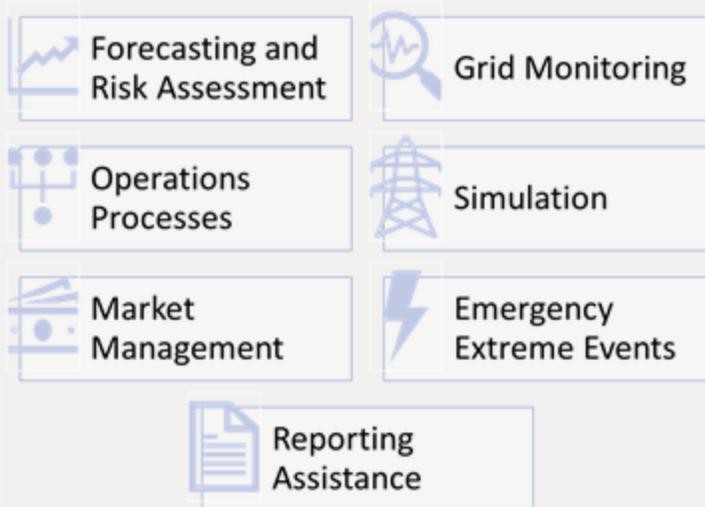
- **Overview of the current system operator solutions**
 - ❑ **CIGRE survey analysis**
 - ❑ **Follow-up questionnaire: current tools in control rooms**
- **Selected AI use cases**
 - ❑ **Renewable energy forecasting**
 - ❑ **Dynamic security assessment**
 - ❑ **Alarm management and reporting assistant**
 - ❑ **Visual inspection**
 - ❑ **Congestion management**
- **Conclusions and AI role in flexible operation**



CIGRE survey analysis

Ratings of low/high priority use cases for AI/ML in the survey responses

36 potential use cases for ML/AI applications



Use Case	Not relevant/low priority [%]	Medium/high priority [%]	Already in use [%]
Forecasting Load and DER	4	48	48
Risk assessment	26	65	9
Grid monitoring	27	65	8
Operations processes	34	60	6
Simulation	36	57	7
Market management	36	57	7
Unplanned, extreme emergency	35	60	5
Reporting assistance	45	49	6

CIGRE survey analysis

Additional key findings from the survey

- Use cases related to **EVs and storage** are more advanced within the research community compared to the Utility/SO sector
- **Asset monitoring** applications have a higher potential for the utility/SO
- **Alarm management** applications have very low in-operation applications but have high or medium-priority
- **More mature applications of ML for WAMS** in research/vendor compared to production-level systems in utility/SO
- **Congestion management** has very few AI/ML applications, and research/vendors rate higher the maturity level

Follow-up questionnaire: current tools in control rooms

Baseline for AI innovation

Answered by **5 TSOs** (RTE, TenneT, Svenska kraftnät, EirGrid, EGAT) and **1 vendor** (N-SIDE)

- **Higher maturity**
 - ✓ **RES and load forecasting**
 - ✓ Pilot projects with satellites, sky cameras, and better weather predictions
- **Limited use of AI**
 - ✓ **Steady-state security analysis**. AI could **reduce computational times**
 - ✓ **Visual inspections** and **condition monitoring** have significant **manual intervention**
 - ✓ The impact of AI in state estimation is **not expected to be high in transmission grids**

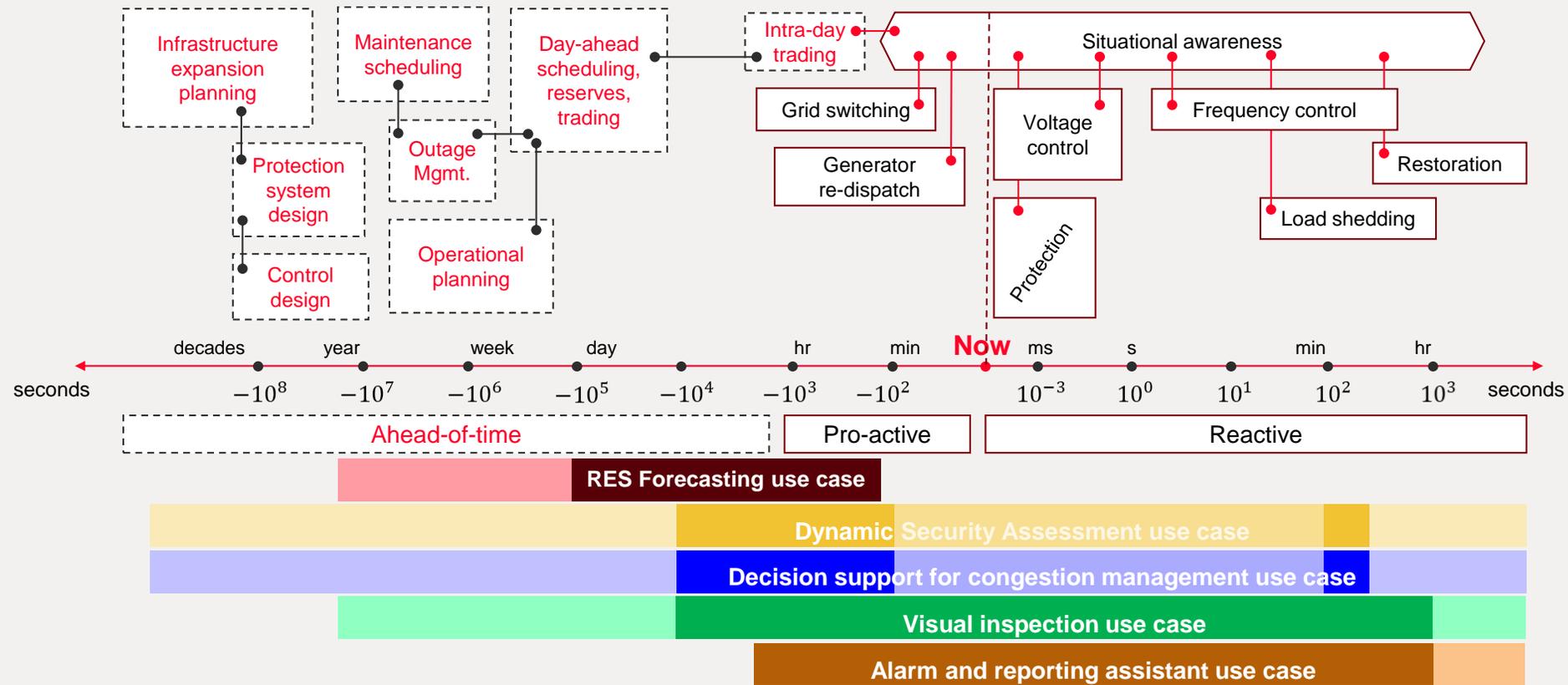
Pros and cons of the current solutions at TSO control rooms

Pros
Good convergence of numerical results
Reliable N-1 contingency analysis
Human supervision and control
Parallel computation of results
Model-based, leveraging decades of knowledge

Cons
Slow computation (e.g., limit real-time application)
Require inputs such as complete nodal injection and topology
Needs of manual intervention; difficulty to integrate human feedback/preferences
No probabilistic risk assessment
Current application ecosystem fragmented

Grid habitat and selected AI/ML use cases

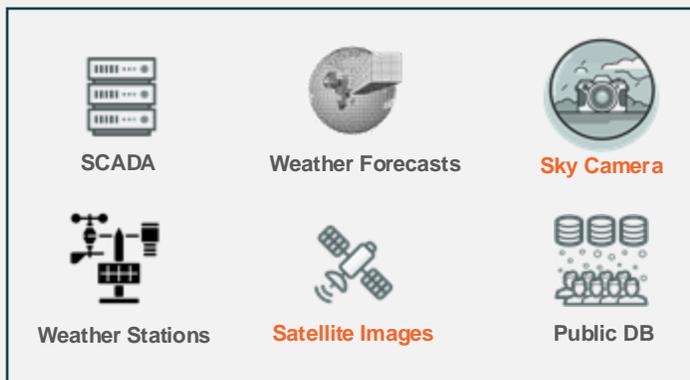
Most important operational processes & the 5 use cases



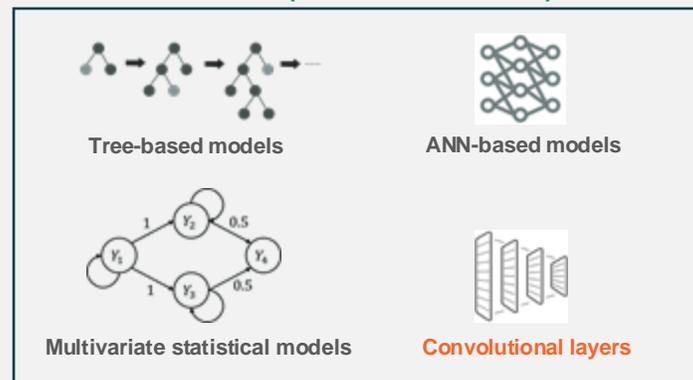
Renewable energy forecasting

Use case

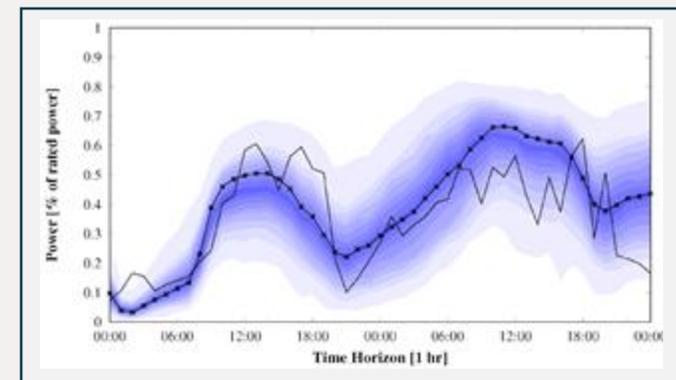
INPUT



AI/ML MODEL TYPE (NON-EXHAUSTIVE)



OUTPUT



Maturity level: already available in the market “as-a-service” or in-house product

Key benefits of AI/ML

- Improve RES predictability, e.g., fusion of heterogenous information sources
- Capacity to generate uncertainty forecasts for risk management
- AI-powered weather forecasts were shown to accelerate 4-5 orders of magnitude physically-based models

Renewable energy forecasting

Challenges/risks and lessons learned

Challenges and risks

- Lack of access to real-time data from individual RES systems
- Getting engagement with control room users to determine future features or changes
- Communication of forecast uncertainty
- Evaluation procedure for forecast value is necessary

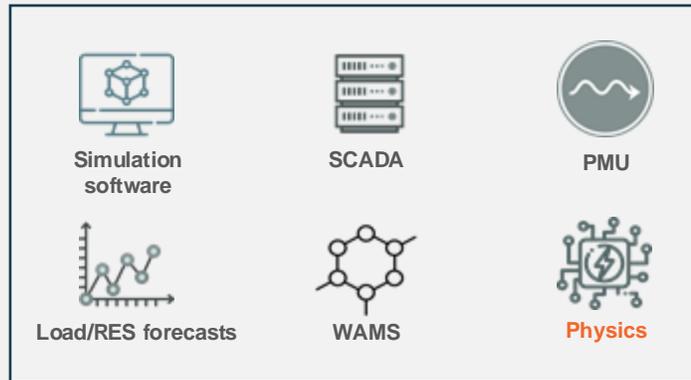
Lessons learned

- Never underestimate the importance of data cleaning & checking
- Using microservices to “start simple and iterate” accelerates development
- Engaging specialist UX/UI skills for uncertainty forecast communication
- Building internal hardware infrastructure for the forecasting service may pose challenges for a small team
- Large ML models (e.g., deep learning) are harder to productionize

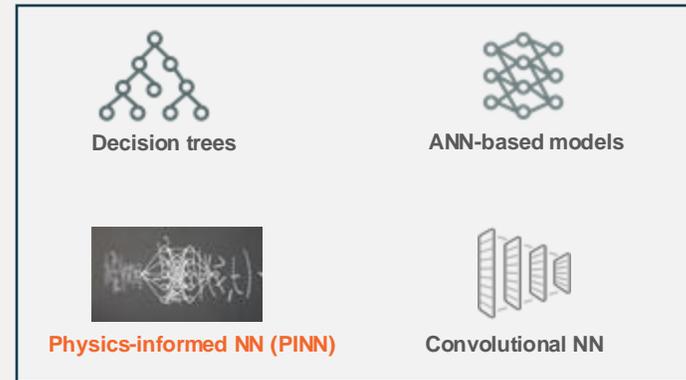
Dynamic Security Assessment

USE CASE: Analysis performed to ensure a power system meets specified reliability and security criteria in both transient ('ms') and steady-state ('min') time frames for a list of credible contingencies

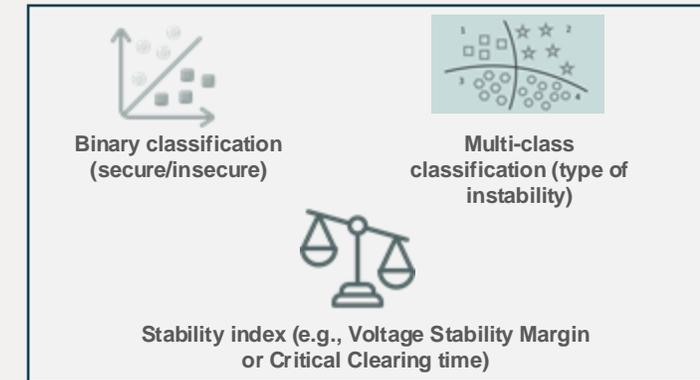
INPUT



AI/ML MODEL TYPE (NON-EXHAUSTIVE)



OUTPUT



Maturity level: tested in simulation environments. Yet, operational decision trees in Hydro-Québec

Key benefits of AI/ML

- Improve the computational efficiency of DSA and speed up simulation/assessment time
- Consideration of complex dynamic behavior in routines where, traditionally, the computational complexity does not allow (e.g., for large-scale optimization)
- Support preventive corrective control measures

Dynamic Security Assessment

Challenges/risks and lessons learned

Challenges and risks

- Trust and performance guarantees that enable adoption
- Understand how ML models work → development of formal verification methods for ANN
- Large number of time domain simulations might be needed for appropriate training
- Scalability in real-world systems
- Lack of in-house expertise and relevant skills concerning AI/ML

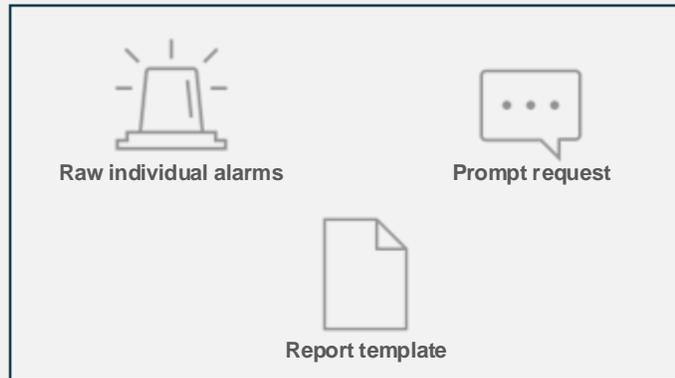
Lessons learned

- Training ANN on GPUs (and UNIX) instead of CPUs is a game changer (about 100x acceleration)
- No need to train the PINN to learn the dynamics of a component for long time horizons. PINNs learn the model itself
- There is no formal way to assess the accuracy/quality of a reduced-order model (or PINN) except by inspection
- Explainability/interpretability methods can aid understanding of complex dynamic phenomena affecting the stability boundary

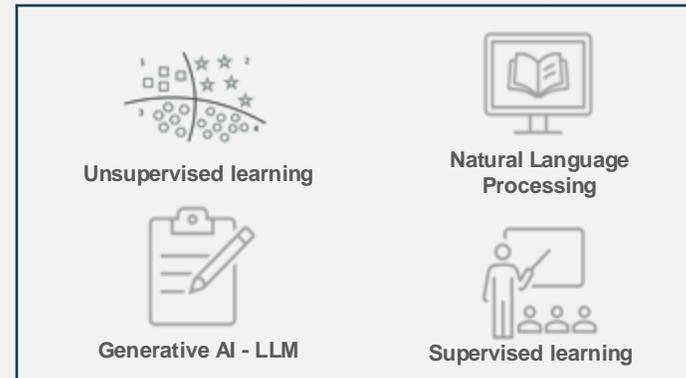
Alarm management and reporting assistant

Dealing with increased information complexity in the digitising control room

INPUT



AI/ML MODEL TYPE (NON-EXHAUSTIVE)



OUTPUT



Maturity level: advanced promising experiments on real grids

Key benefits of AI/ML

- More situational awareness while reducing cognitive effort
- Better decision making and managing risks
- Improved knowledge sharing on past events

Alarm management and reporting assistant

Challenges/risks and lessons learned

Challenges and risks

- Incorrect grouping, filtering, and logging – human feedback and editing needed
- Scalability for supervised learning
- Training data
- Cloud & confidentiality
- Difficulty to automatically evaluate/benchmark

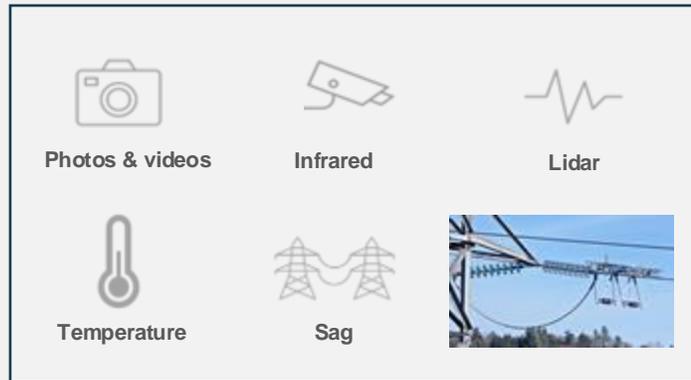
Lessons learned

- TSO/DSO operators need smart alarm management and reporting assistant
- Adapted deployment needed in tight interaction with operators for capitalization of human interactions, choices or corrections for continuous improvements
- Aim at information hygiene
- Leave some control to the operator to configure, edit, reprioritize and look for more information
- Manual inspection and human judgment most likely needed

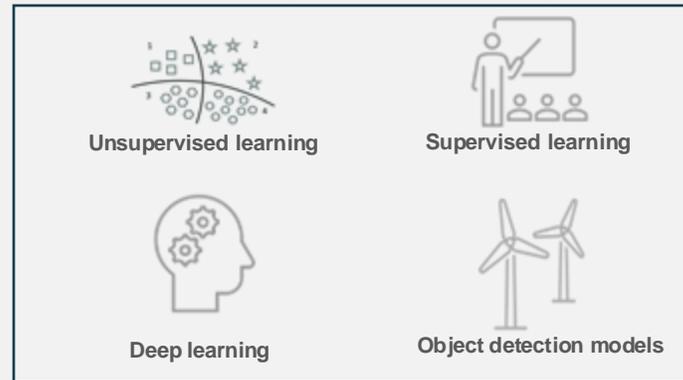
Visual inspection

Digital and visual measurements for inspection of assets, health monitoring, vegetation management and for robots to undertake tasks that are dangerous for engineers.

INPUT



AI/ML MODEL TYPE (NON-EXHAUSTIVE)



OUTPUT



Maturity level: operational deep learning models at Hydro-Québec

Key benefits of AI/ML

- Safety
- Labour and cost efficiency
- Predictive maintenance
- Inspection quality

Visual inspection

Challenges/risks and lessons learned

Challenges and risks

- Data privacy and security
- Integration with existing systems
- Skills and training
- Lack of labeled training data

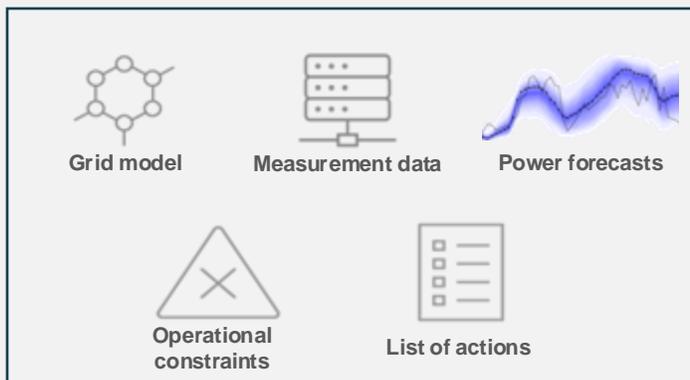
Lessons learned

- Necessity to establish a comprehensive global dataset
- Human expertise remains crucial for final decisions

Congestion management

Decision support to optimize remedial actions

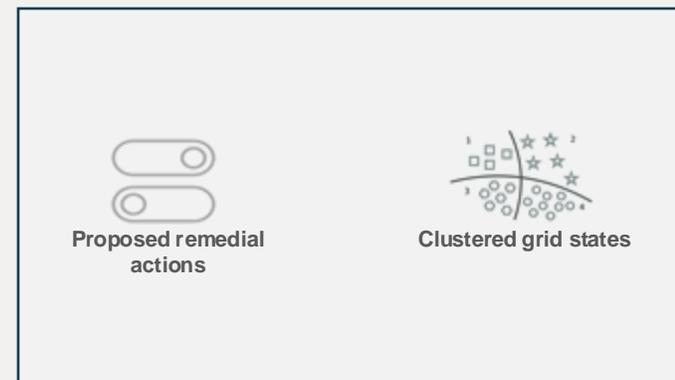
INPUT



AI/ML MODEL TYPE (NON-EXHAUSTIVE)



OUTPUT



Maturity level: promising demonstrations with RL on real world data

Key benefits of AI/ML

- Manage congestion in an optimised way, lowering costs
- Able to deal with the huge solution space
- Security of supply
- Operator effort, complexity and response time

Congestion management

Challenges/risks and lessons learned

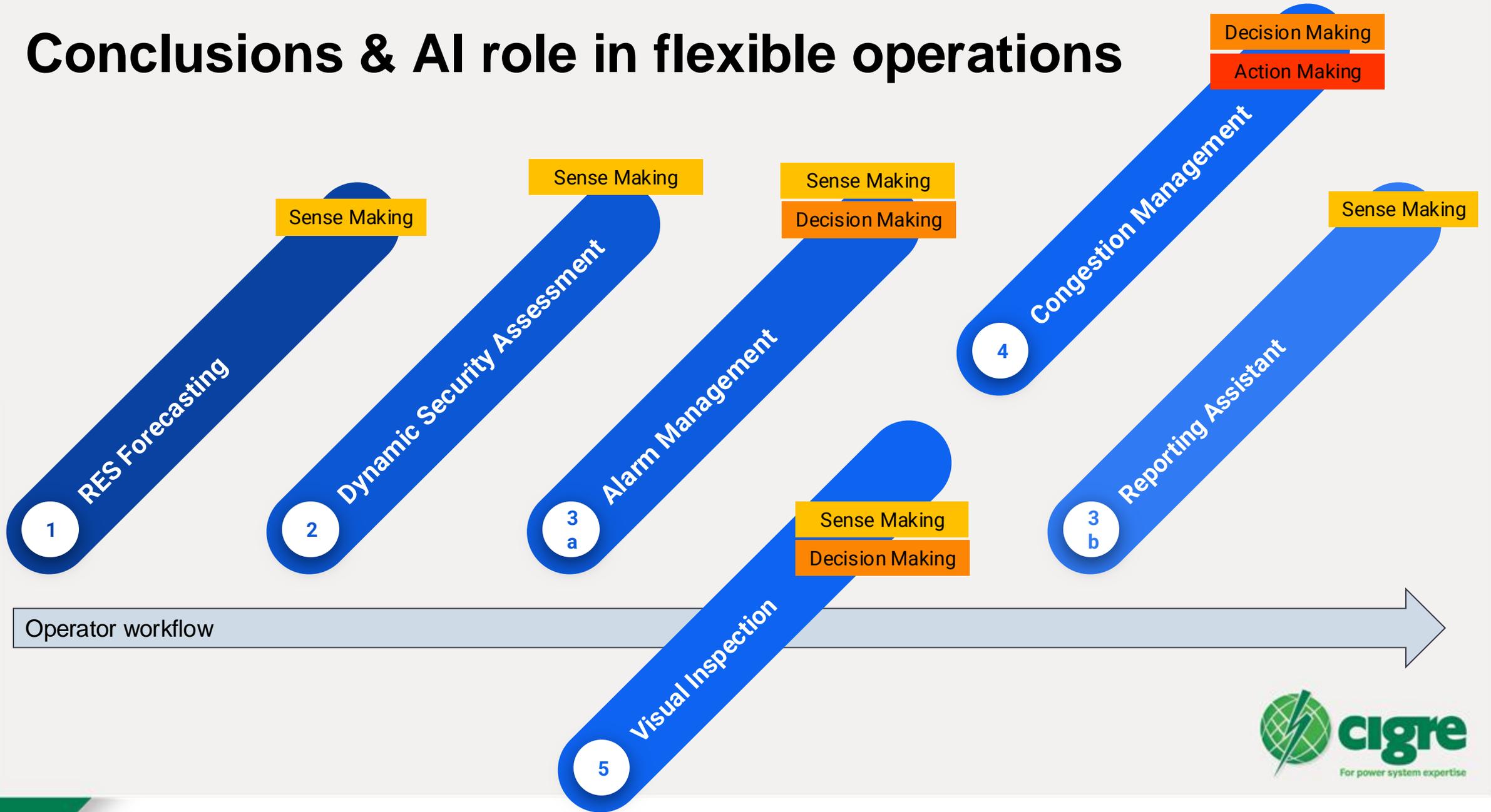
Challenges and risks

- Practically infinite solution space
- Multi-objective problem
- Model must perform well in a changing grid
- Risk of deskilling the operator
- Adoption

Lessons learned

- Involve users from the start
- Start small and incrementally add functionality
- Build up historical data as soon as possible

Conclusions & AI role in flexible operations



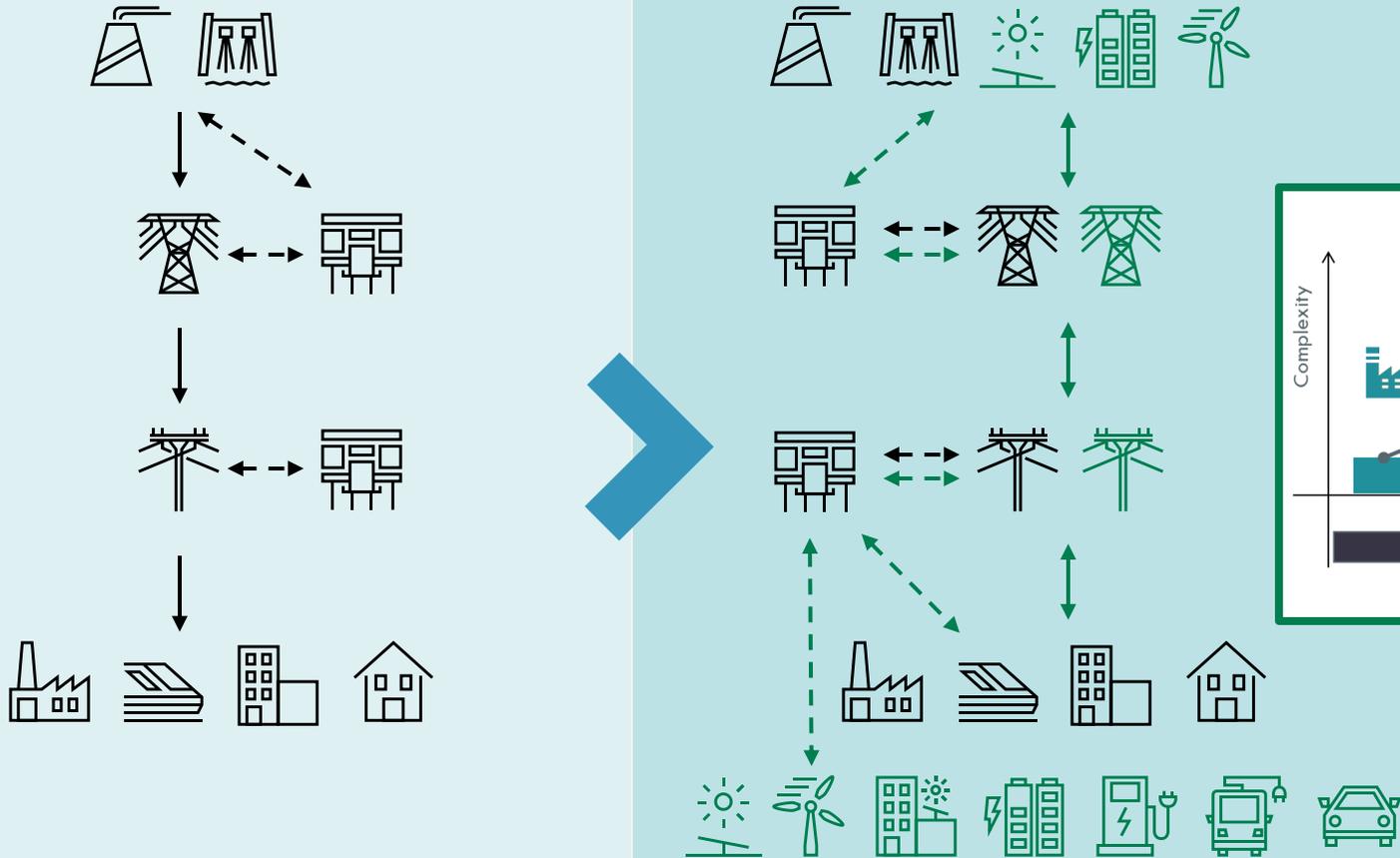
CHAPTER 4: AI role in flexible operation

Outline

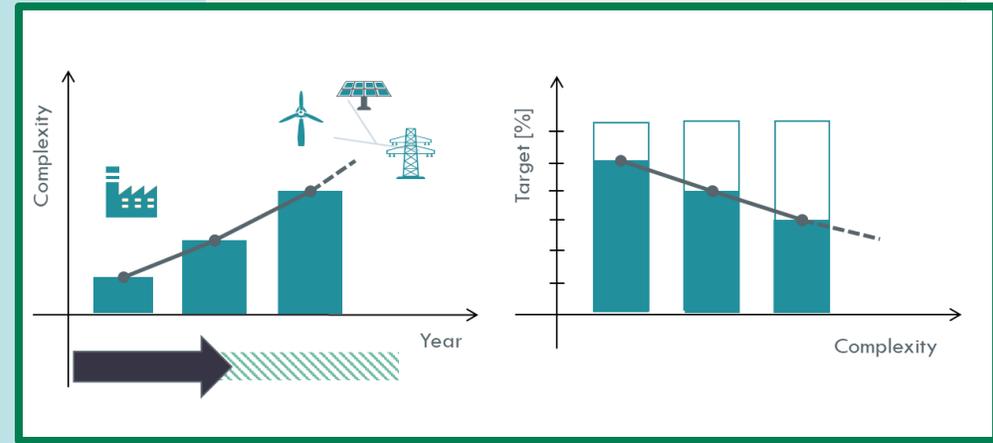
- **Introduction**
- **Intelligent System**
- **Flexible Operator**
- **Unlocking the Flexible Operator**
- **Conclusions**



Evolution of the Power System



↔ data ↔ electricity



Intelligent System

Classic automation control room

Deterministic System



Computation



Human Role



Handling of **deterministic** tasks

Computation taken over by automated systems

Human role: understand, analyze and act

Control room supported by increased intelligence

Nondeterministic System



Computation Learning

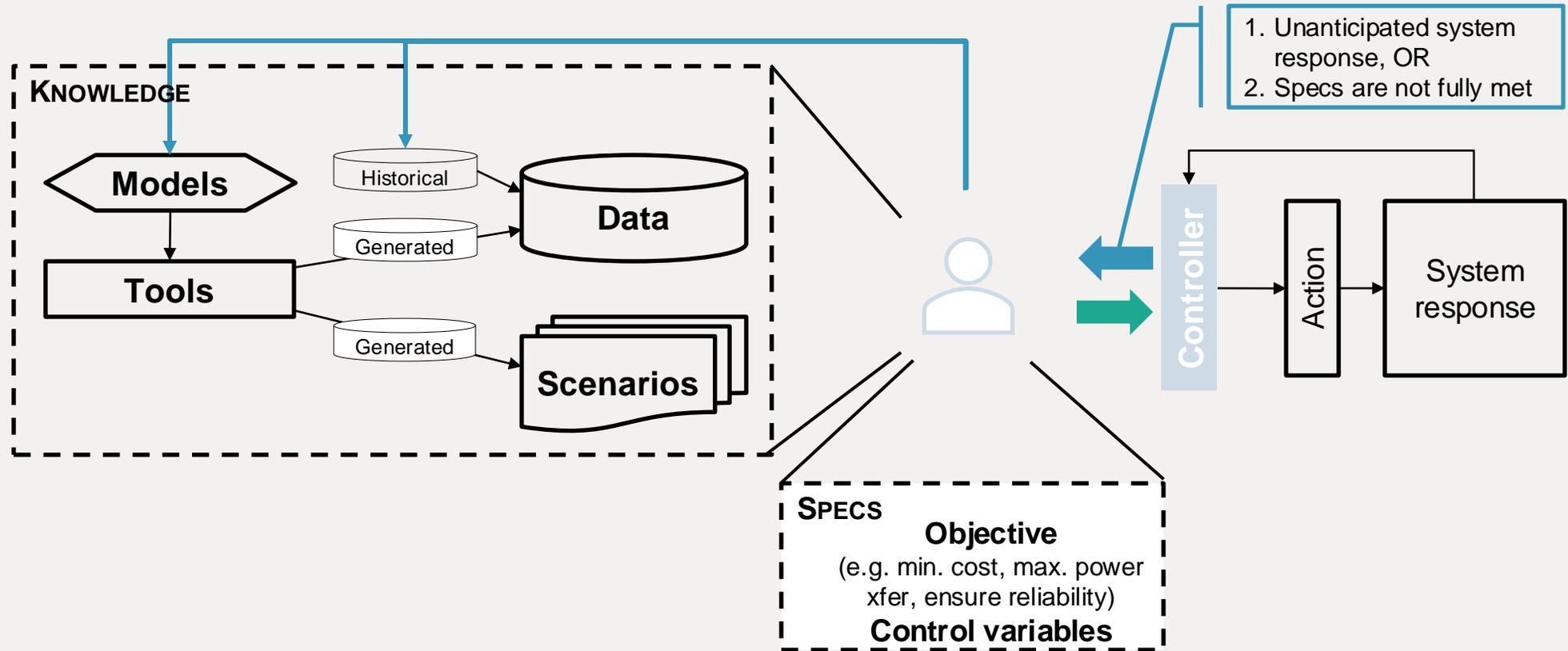


Human Role



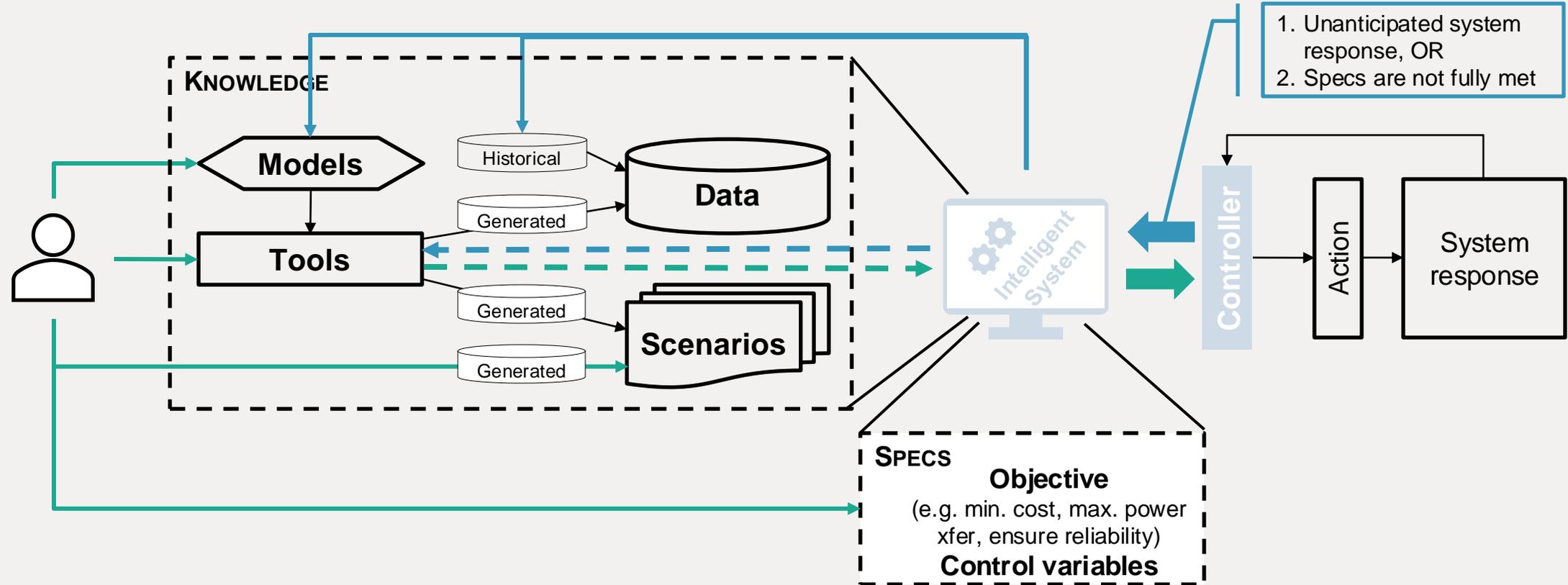
- Handling of **nondeterministic** tasks
- **Computation** and **learning** taken over by the autonomous systems. Autonomous system learns from available sources
- **Human role evolves:** Intelligent automation is likely to take on tasks traditionally performed by people.

State-of-the-art Power System Control



Intelligence Enhanced Power System Control

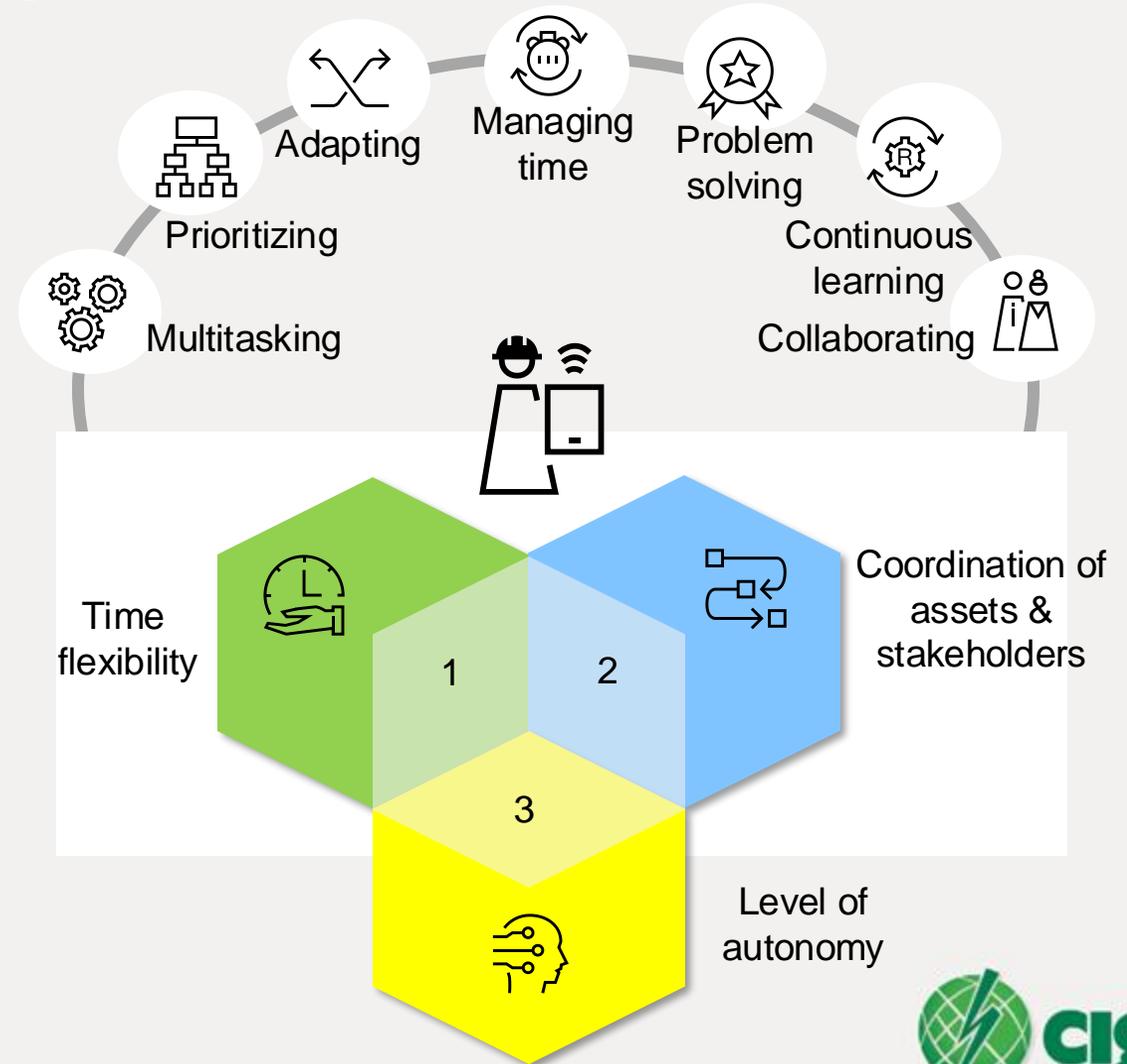
Human in-the-loop



Definition of the Flexible Operator

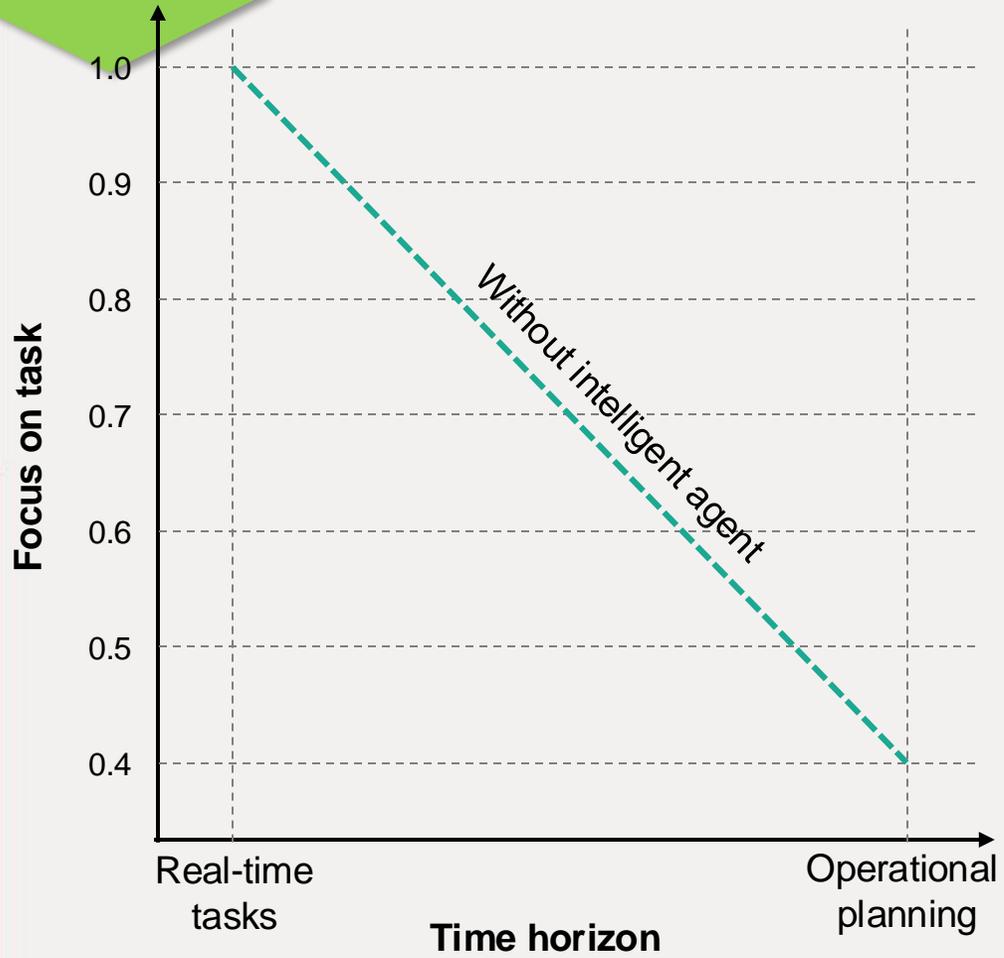
Flexible Operator

A flexible operator is skilled at multitasking, prioritizing tasks, adapting to changing system dynamics, managing time effectively, problem-solving, continuous learning, and collaborating with others. He/she possess the ability to handle a diverse set of tasks within the power system control center, ensuring efficient and reliable operations



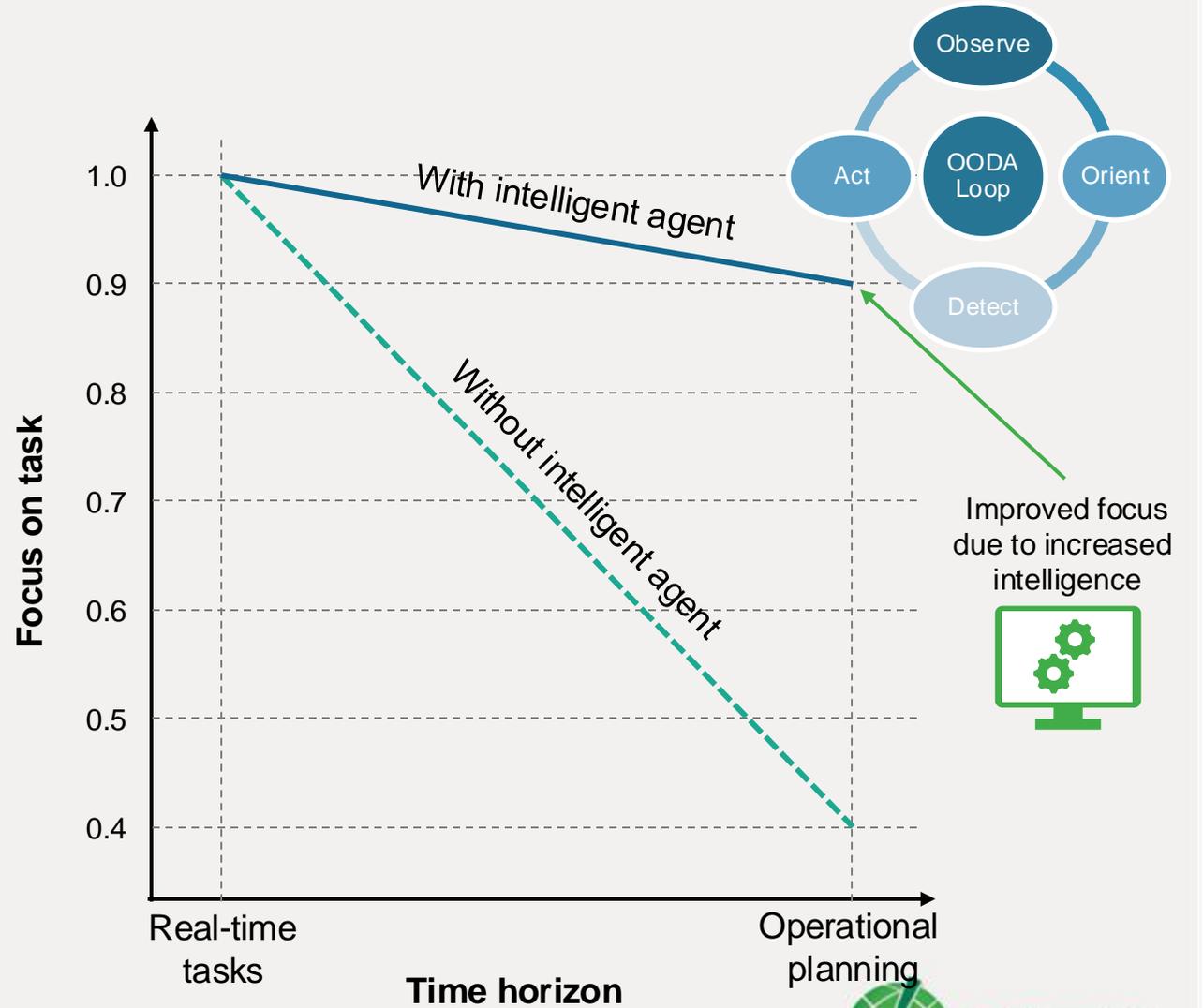
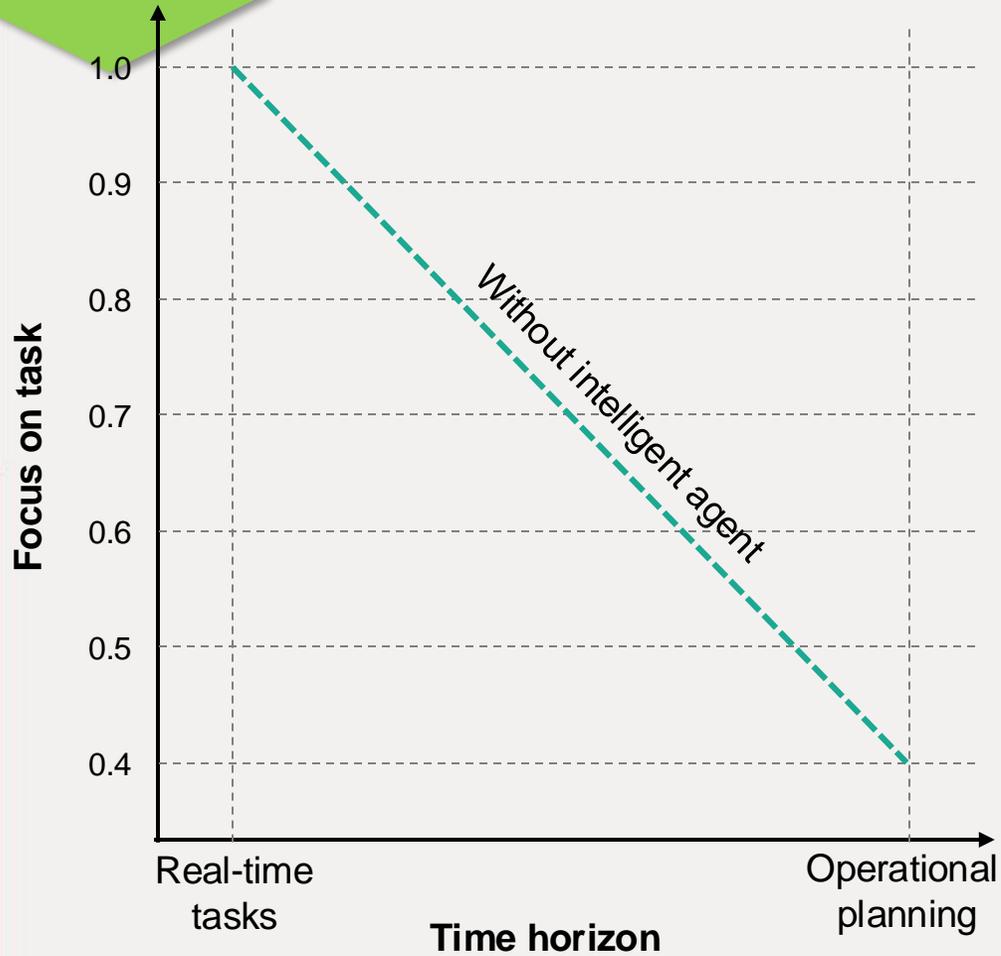


Time Flexibility

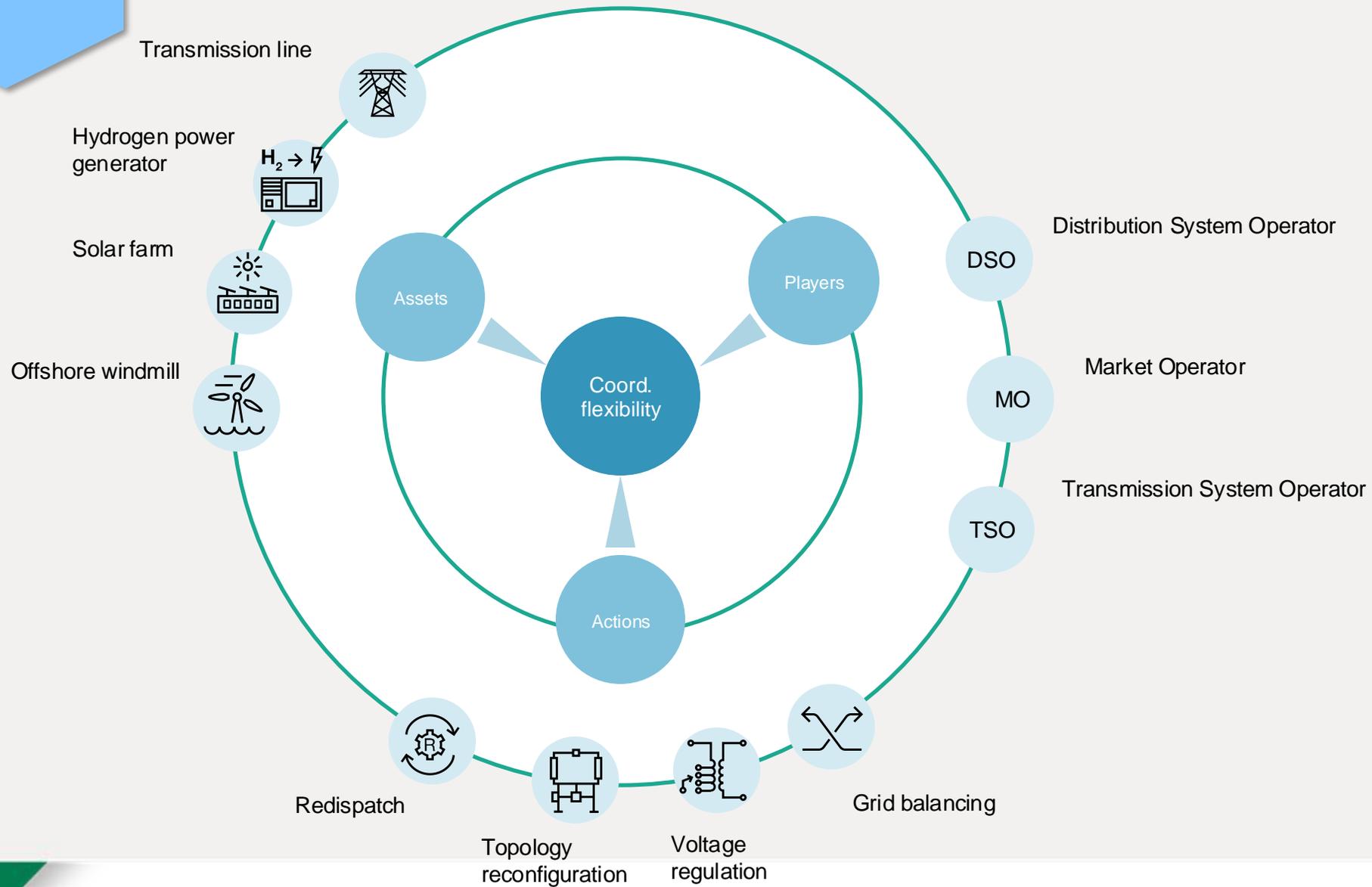




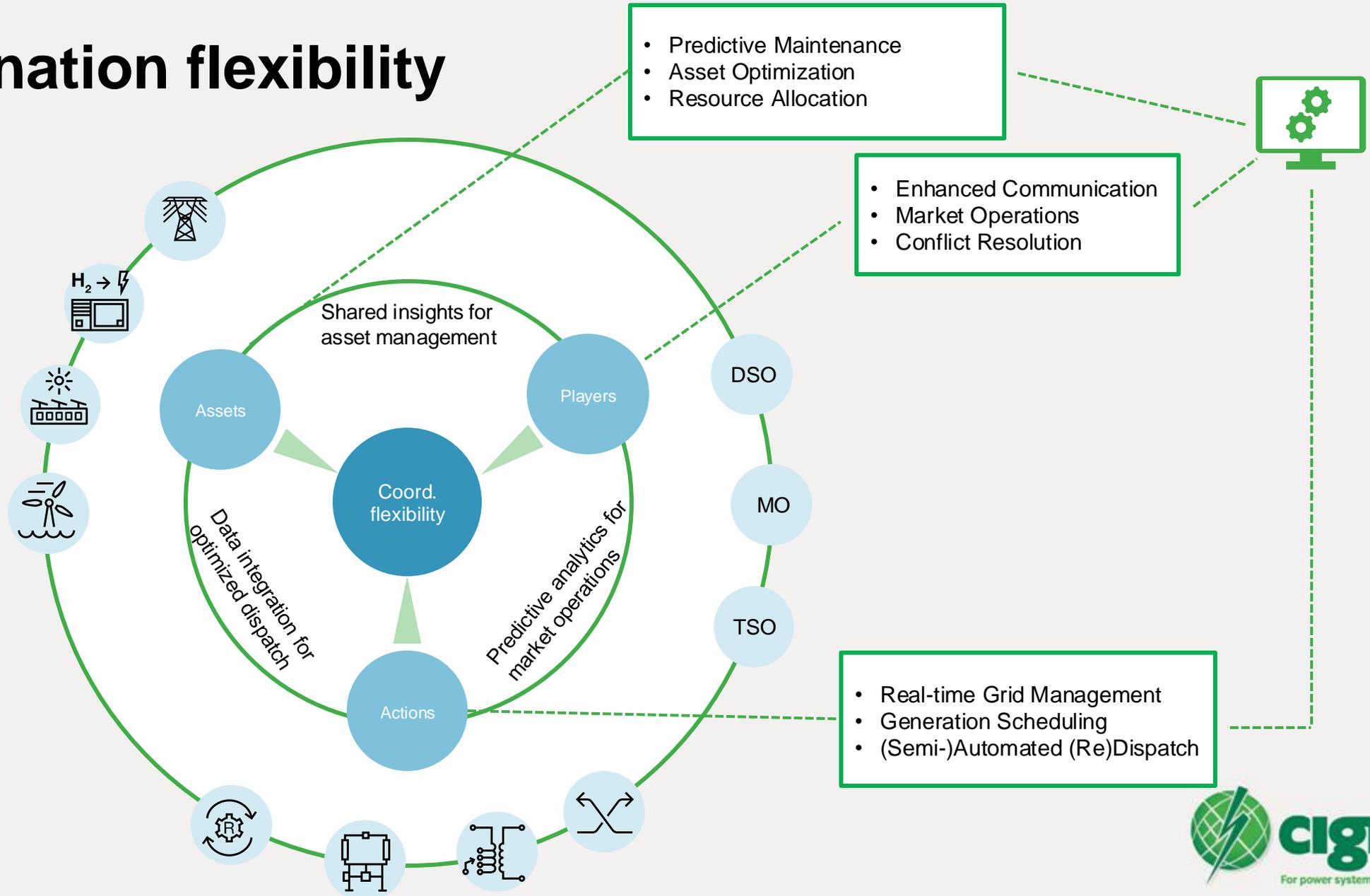
Time Flexibility



Coordination flexibility



Coordination flexibility



Level of Autonomy Flexibility

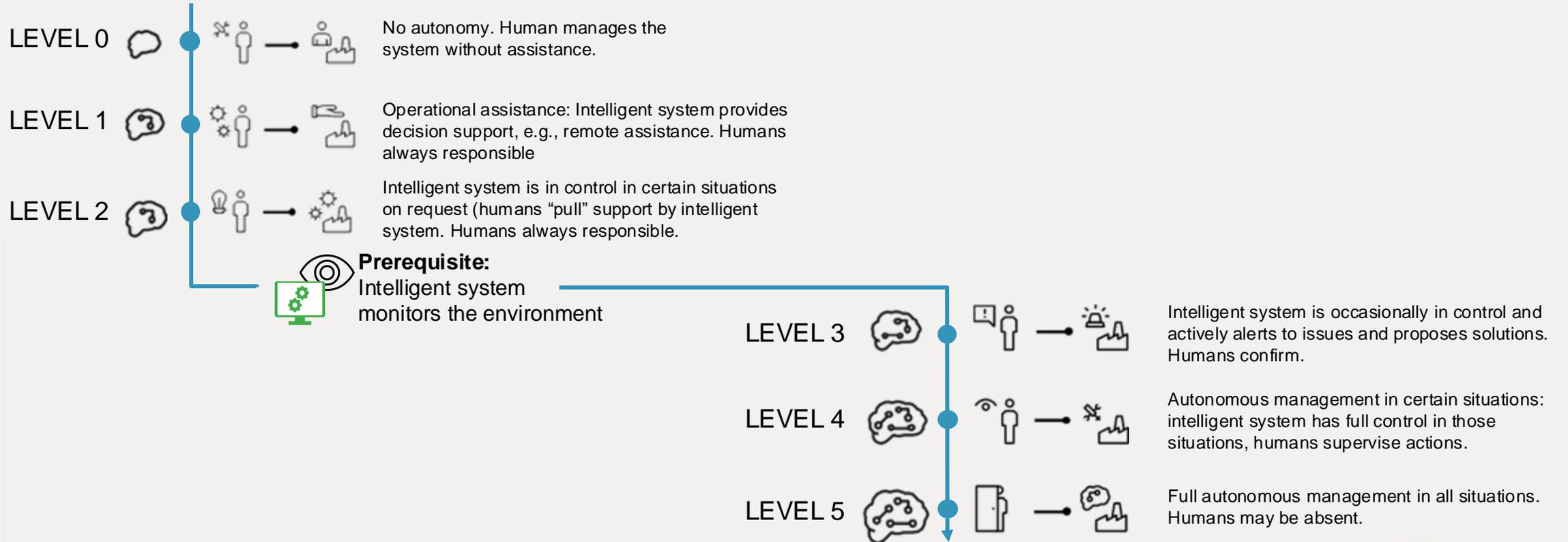


- LEVEL 0**   →  No autonomy. Human manages the system without assistance.
- LEVEL 1**   →  Operational assistance: Intelligent system provides decision support, e.g., remote assistance. Humans always responsible
- LEVEL 2**   →  Intelligent system is in control in certain situations on request (humans “pull” support by intelligent system. Humans always responsible.



Prerequisite:
Intelligent system monitors the environment

Level of Autonomy Flexibility



Level of Autonomy Flexibility



Prerequisite:
Intelligent system
monitors the environment



What's in for the operator:

- Streamlined routine tasks
- Execution of the advance sequence of actions
- Deployment of the automation on different spatial levels closer to the assets (edge, fog computing) and control release to the autonomous agent
- Take-over of the actions between the agent and the operator

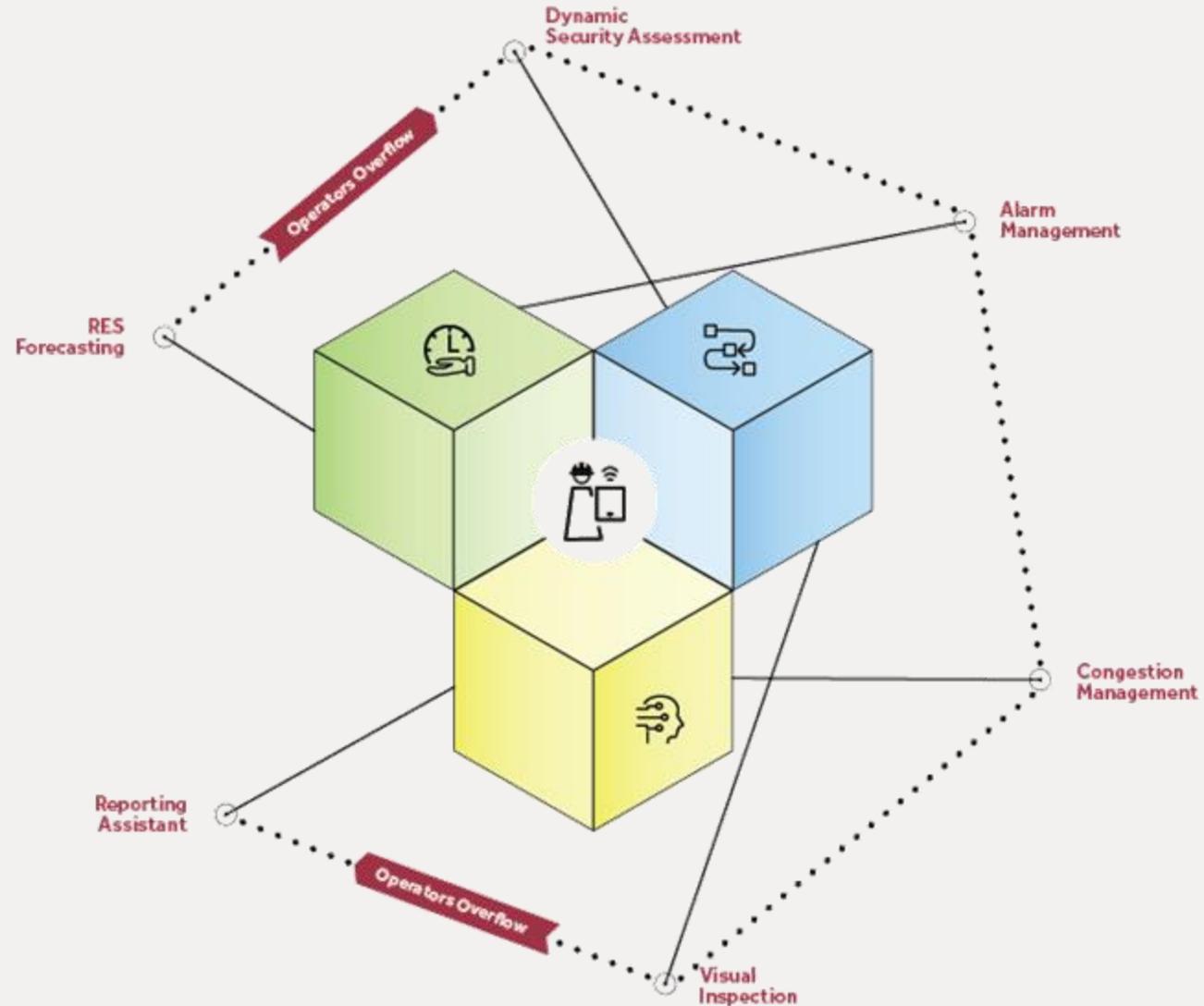


Building blocks:

- Advanced algorithms
- AI/ML
- Expert systems
- Real-time monitoring and control systems



... through selected use cases



... and reimagined HMI with AI/ML interaction

Alerts

Overload on line
Sec.
55_57_148
Attention, line 55_57_148 is loaded to 117.45%

N-1 security risk
Sec.
62_58_180
Impacted line 60_61_159 loaded to max 184.8%

N-1 security risk
Sec.
62_63_160
Impacted line 60_61_159 loaded to max 184.8%

Line 48_50_136
Sec.
disconnected
Line 48_50_136 is disconnected

Timeline

Overload on line 55_57_148

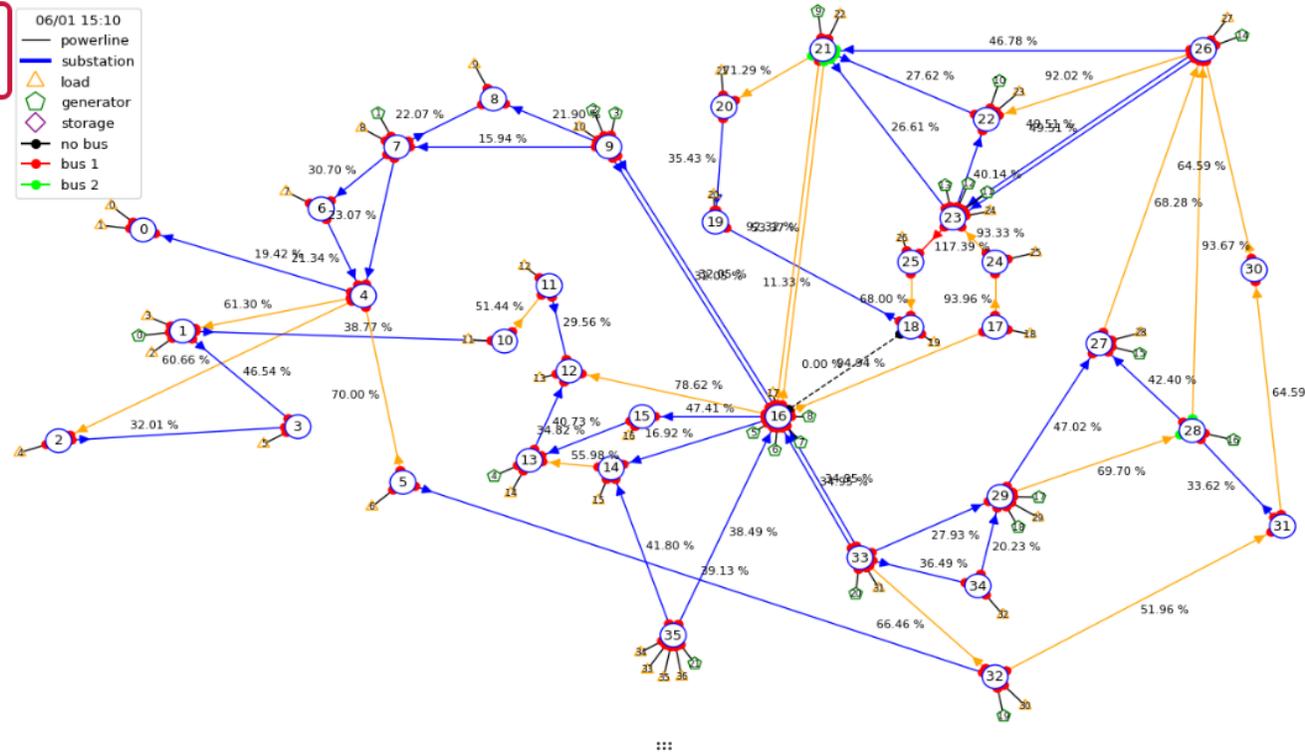
N-1 security risk on line 62_58_180

Context



06/01 15:10

- powerline
- substation
- load
- generator
- storage
- no bus
- bus 1
- bus 2



Recommendations

Cost | LTTD > 2h

Topology switch: switch at the position 23

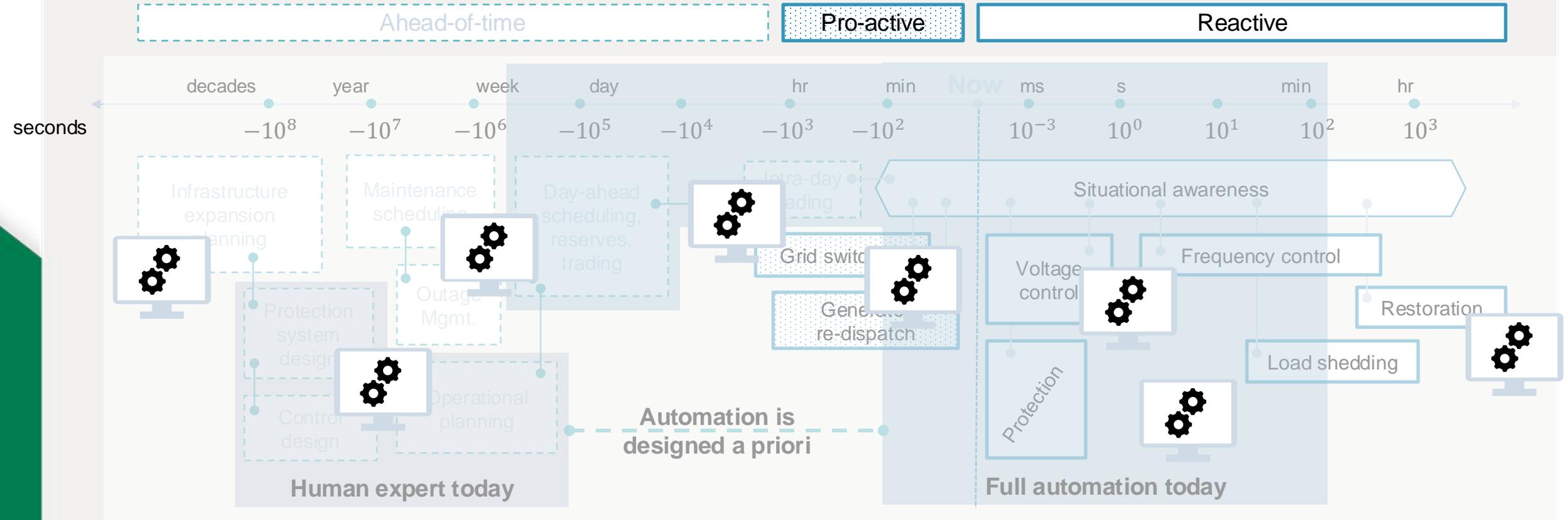
Topology switch: switch at the position 19

Topology switch: switch at the position 16

Default topology

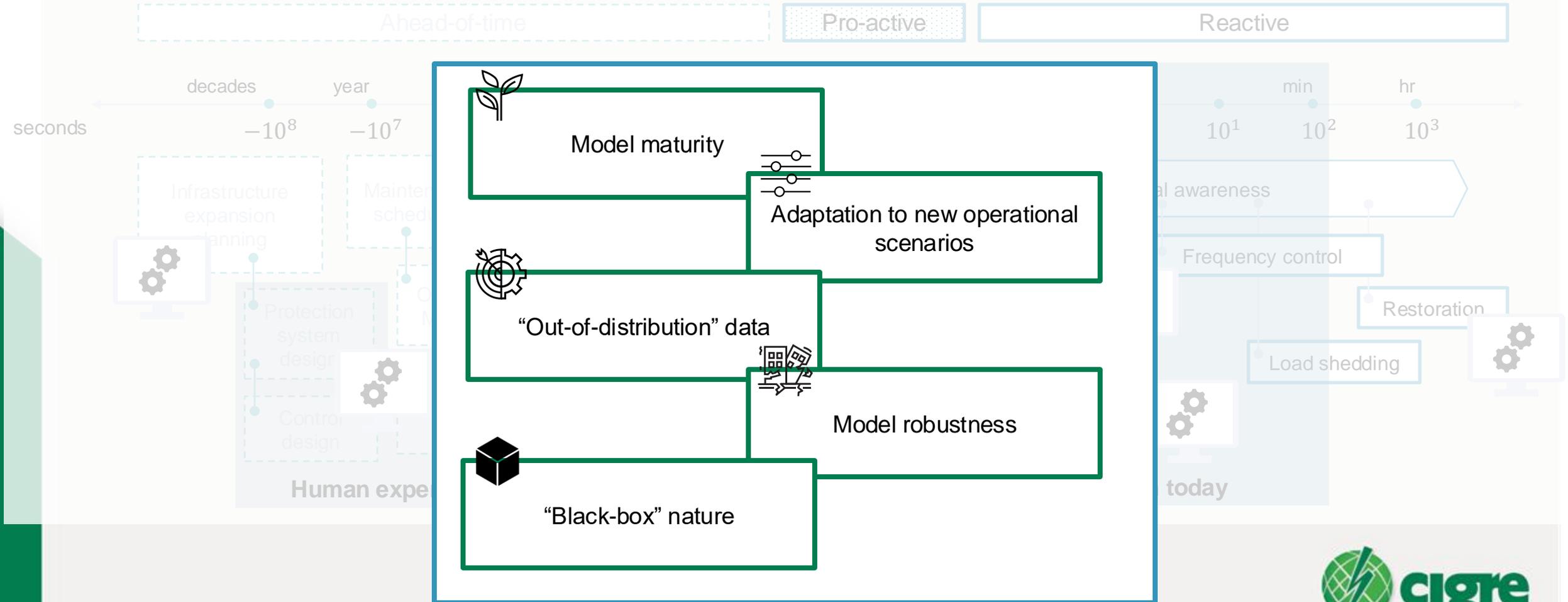


Conclusions and limitations



Intelligent system

Conclusions and limitations



CHAPTER 5: Challenges, risk assessment, mitigation and regulation

Outline

- **Challenges and Risks**
- **Accountability of AI/ML**
- **Risk mitigation actions of AI/ML**
- **Overview of some global regulatory initiatives**
- **Evaluation risks of AI/ML**
- **Summary**



How are the risks and challenges organized?

Societal

- AI and ethics
- Trustworthiness
- Workforce displacement
- Human-centric considerations

Technological

- AI cyber security
- Data and technology

Organisational

- Lack of (or slow) regulatory framework
- Slow evolution of the market framework
- Lack of acceptance by the industry

Use Cases	RES Forecasting	DSA	Decision Support for Congestion Management	Visual Inspection	Alarm and Reporting Assistant
Risks and Challenges					
Data Quality and Security Risks					
Cyber Security Threats					
Algorithm Bias and Fairness					
Over Reliance on AI					
Regulatory and Compliance Risks					
Ethical Concerns					
Maintenance and Technical Challenges					
Scalability Issues					
Dependency on External AI Services					
Operational Risks					

Risk

No risk

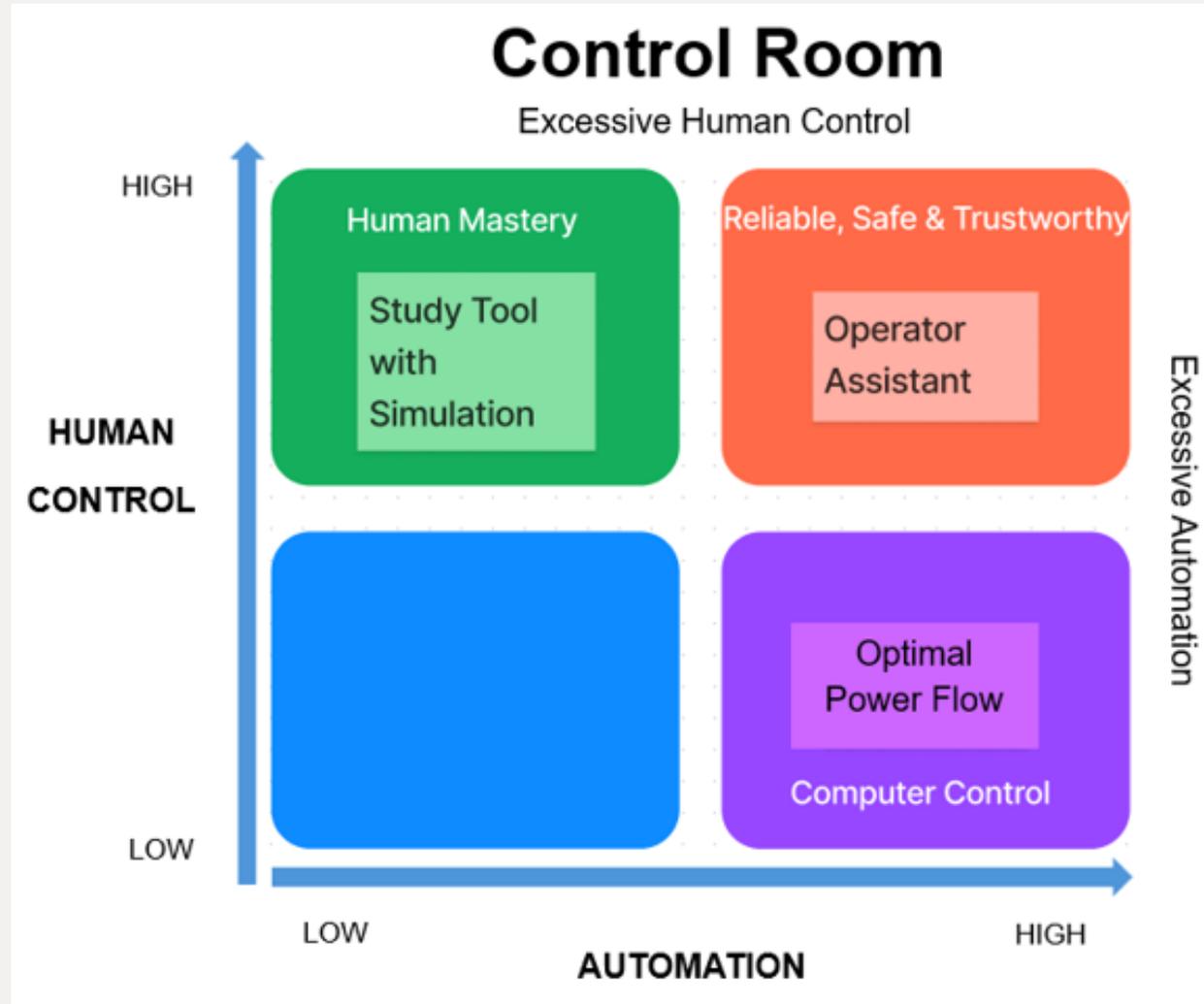
Societal

Technological

Organisational

Risk and Challenges x Use Cases

Further considerations on Human-centred AI



Who is responsible for the AI decisions?

Stakeholders



Control Room Operators



AI System Developers



Utility or Grid Operator

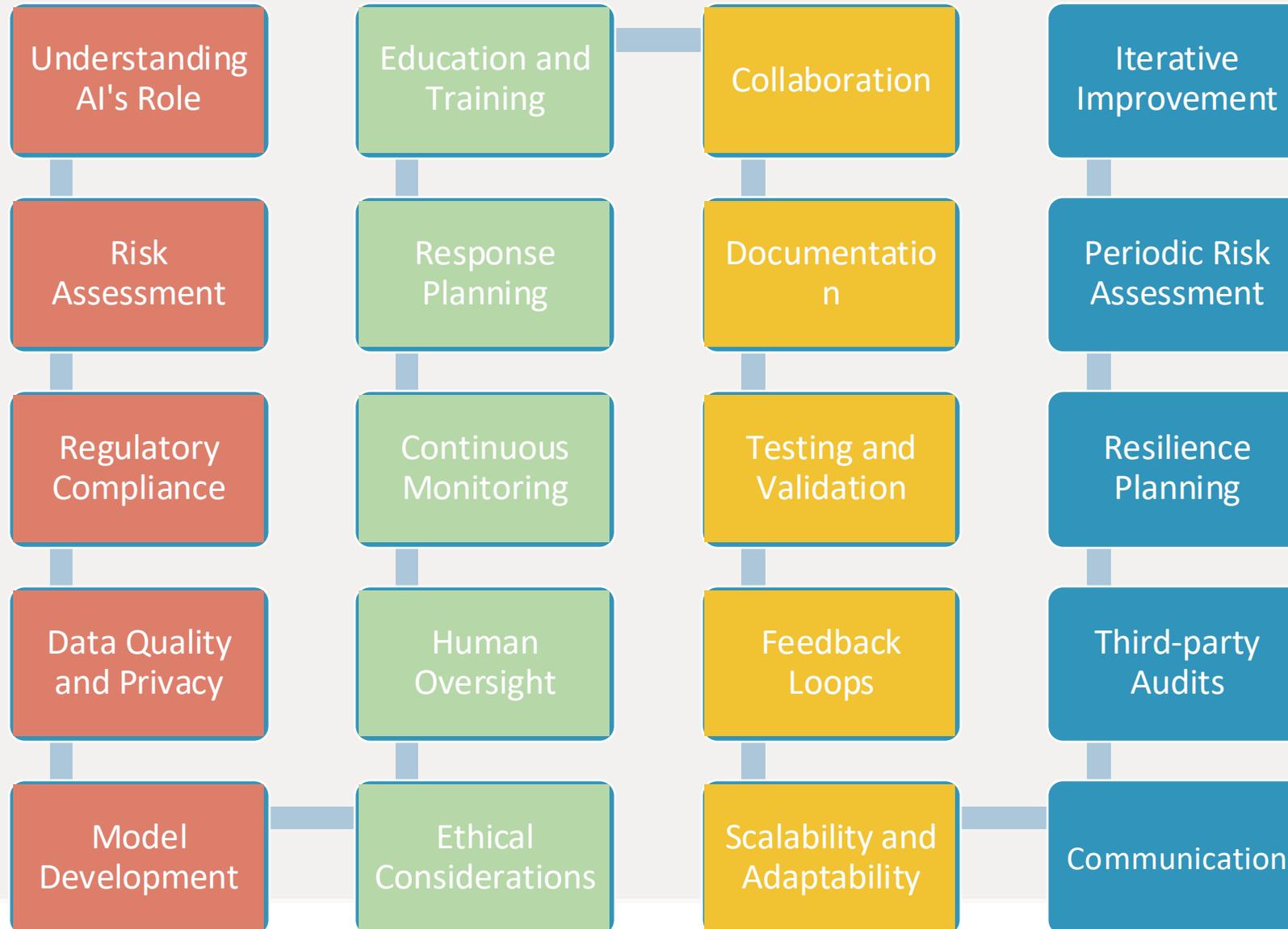


Regulatory Bodies



Legal Framework

Aspects to be considered to mitigate risk deployment in AI/ML



Regulatory frameworks for AI/ML use are rapidly evolving: case studies across 4 regions

European Union



01	Focus areas	Horizontal
02	Approach to Risk	Binding
03	Regulatory requirements	Human supervision, documentation, post-market monitoring
04	Monitoring and enforcement	Obligatory; enforcement bodies in-charge

Sources: Roberts et al., (2023): A Comparative Framework for AI Regulatory Policy; Heymann et al. (2023): Regulating Artificial Intelligence in the EU, United States and China-Implications for energy systems.

Regulatory frameworks for AI/ML use are rapidly evolving: case studies across 4 regions

United States of America



01	Focus areas	Vertical
02	Approach to Risk	Not-binding
03	Regulatory requirements	Relies on existing regulations
04	Monitoring and enforcement	De-centralised + Self-monitoring

Sources: Roberts et al., (2023): A Comparative Framework for AI Regulatory Policy; Heymann et al. (2023): Regulating Artificial Intelligence in the EU, United States and China-Implications for energy systems.

Regulatory frameworks for AI/ML use are rapidly evolving: case studies across 4 regions

India



01	Focus areas	Horizontal
02	Approach to Risk	Binding (dependent on user-harm)
03	Regulatory requirements	Early-stage; regulatory bodies in place
04	Monitoring and enforcement	Obligatory; enforcement bodies in the works

Sources: Roberts et al., (2023): A Comparative Framework for AI Regulatory Policy; Heymann et al. (2023): Regulating Artificial Intelligence in the EU, United States and China-Implications for energy systems.

Regulatory frameworks for AI/ML use are rapidly evolving: case studies across 4 regions

China

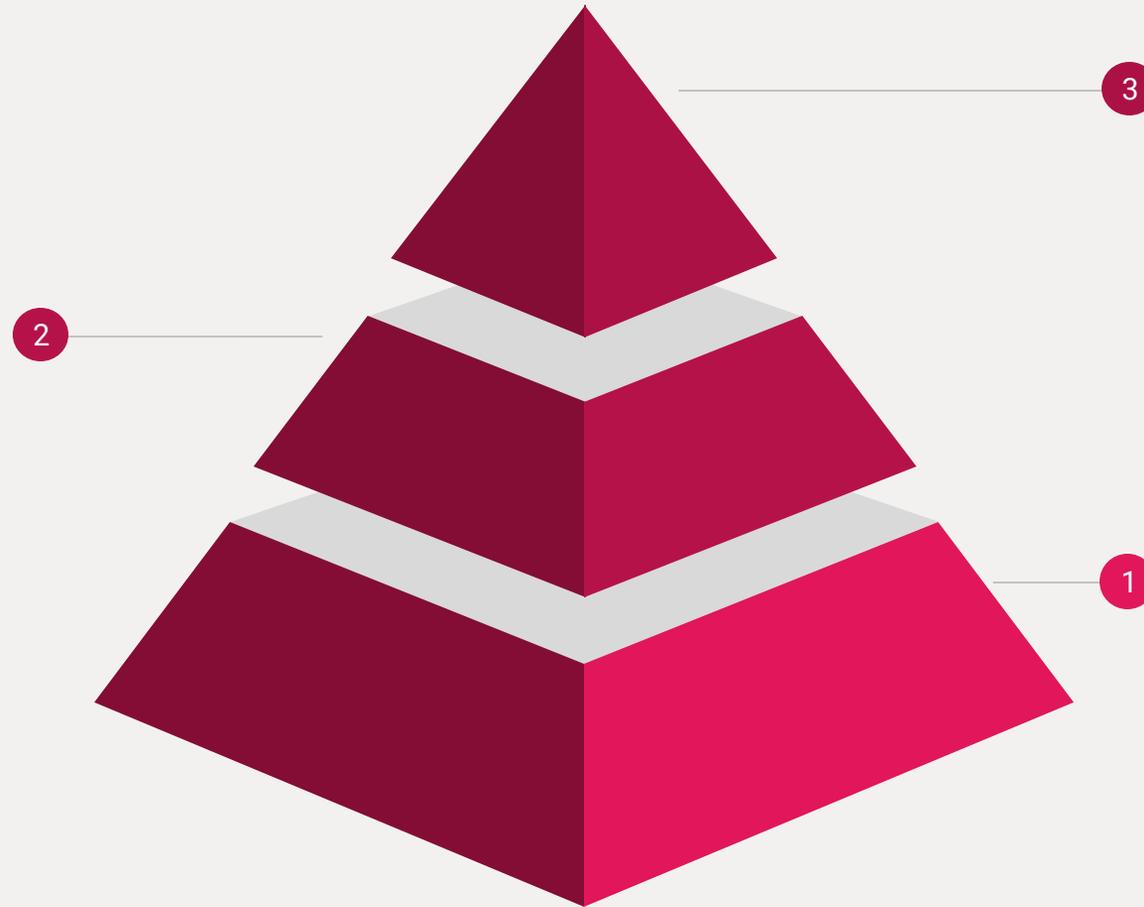


01	Focus areas	Hybrid
02	Approach to Risk	Mixed (binding and non-binding depending on level of risk)
03	Regulatory requirements	Regular examination of AI algorithms (Separate rules for specific AI tech)
04	Monitoring and enforcement	Through existing government enforcement bodies

Sources: Roberts et al., (2023): A Comparative Framework for AI Regulatory Policy; Heymann et al. (2023): Regulating Artificial Intelligence in the EU, United States and China-Implications for energy systems.

Current frameworks vs future frameworks

three-dimensional framework considering a detailed taxonomy of AI algorithms, criticality of tasks and model capabilities (human senses)



3 Focus on specific risk domains (like Data, Model, Task, Environment) and assess each domain with specific criteria

1 Assessment of AI across various criteria: (user competency, impact on job quality, degree of employment)

Sources: Heymann et. al (2024): Risk evaluation of AI systems in the energy sector-three case studies from TSO business

Proposed framework x Use Cases

Risk Domain	Criteria
Data	Human sensed
	Real-time/ streamed
	Privacy sensitive
Models	Blackbox
	Dynamic updates
	Automation
Task	Individual harm / local damage
	Regional damage
	Societal harm/ system-wide damage
Environment	Critical infrastructure

Proposed framework x Use Cases

Risk Domain	Criteria	RES/Load Forecasting	DSA	Congestion Management
Data	Human sensed			Critical
	Real-time/ streamed		Critical	Critical
	Privacy sensitive			
Models	Blackbox		Critical	Critical
	Dynamic updates		Critical	Critical
	Automation	Critical	Critical	Critical
Task	Individual harm / local damage	Critical	Critical	Critical
	Regional damage	Critical	Critical	Critical
	Societal harm/ system-wide damage	Critical	Critical	Critical
Environment	Critical infrastructure	Critical	Critical	Critical

Critical
Not Critical

Chapter summary

Regulation is essential

- 1 When developing and deploying AI/ML systems there are opportunities and benefits on one hand, but there also challenges and risks to be addressed.
- 2 Among the benefits there are increased efficiency and improved decision-making, but risk assessment should be taken into consideration.
- 3 Important to have a human-centred view of AI/ML systems, as they should be trusted by the operator, or else they will not succeed.
- 4 All stakeholders must balance risks and benefits, and mitigate risks. Regulation is a key point to achieve this goal.



How can human-centred AI/ML be deployed in practice?

CHAPTER 6: Implementing AI in system operator organisations

Outline

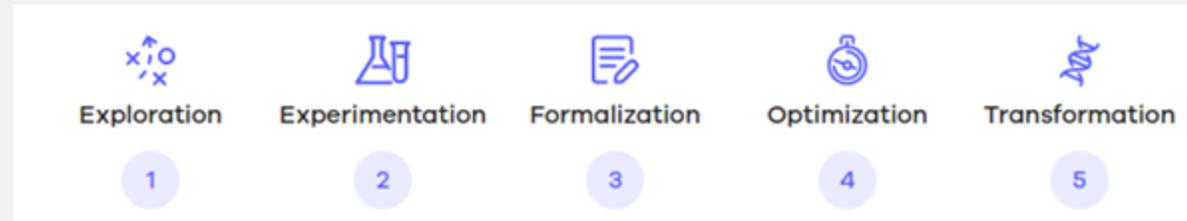
- **AI journey & AI project**
- **Practical considerations for technical requirements**
- **Developing your organisation and prioritisation of projects**
- **Chapter conclusion**



A start: Assessing AI maturity levels of your organisation

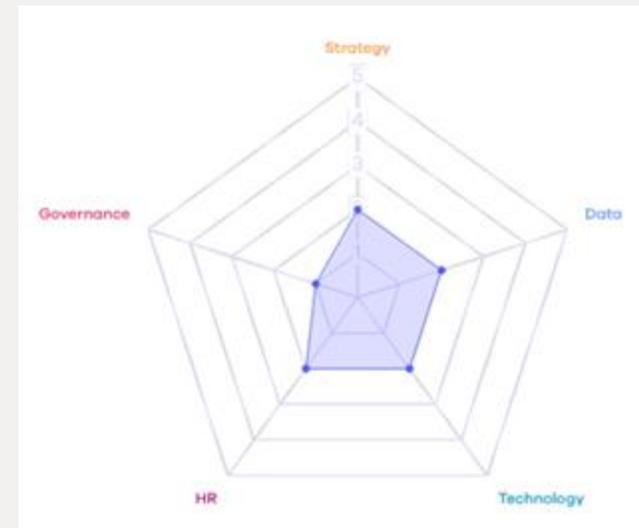
What is the maturity of AI developments in your organization?

- 5 steps to assess maturity



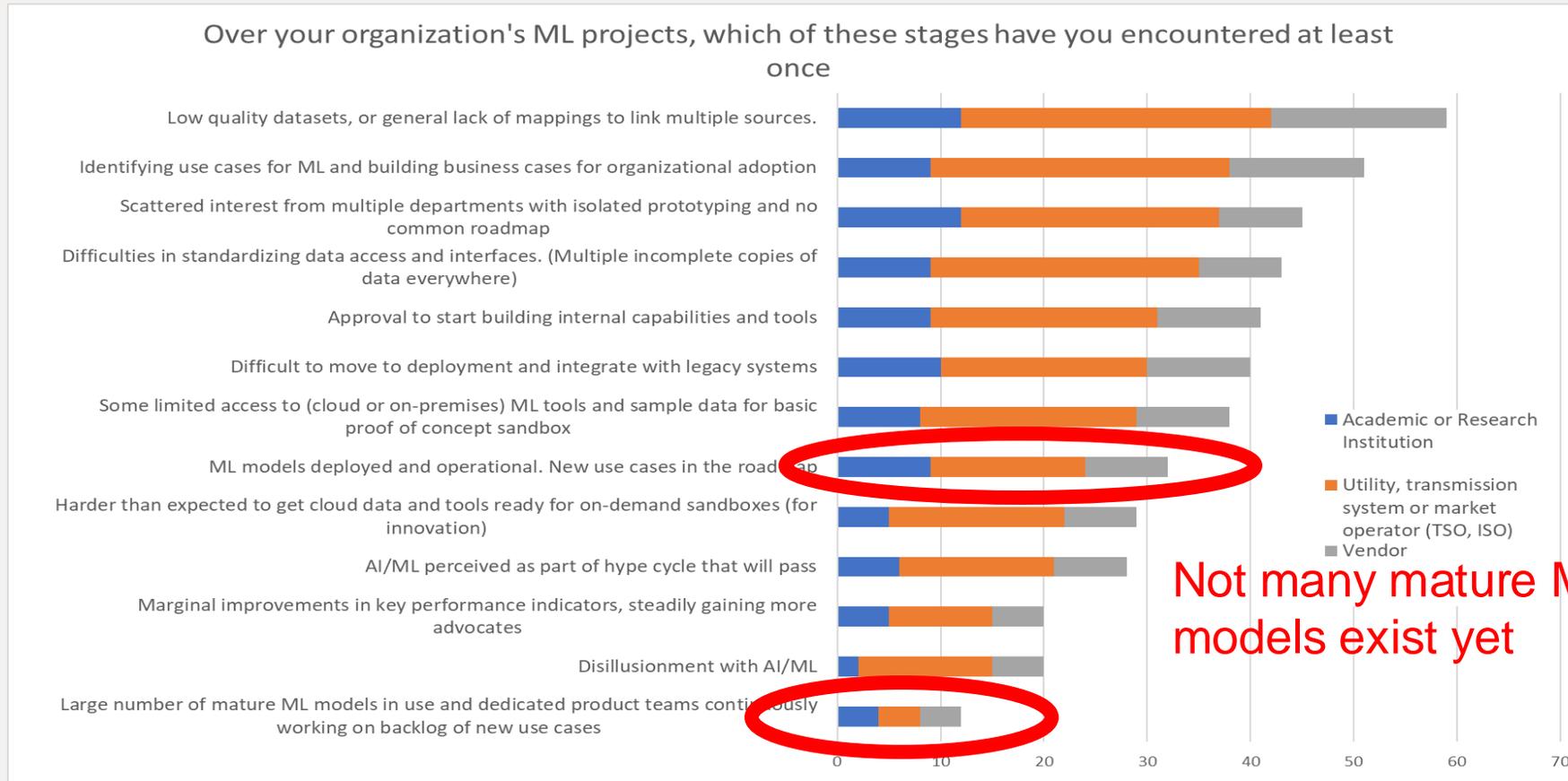
- Questionnaire to assess maturity: <https://vitrine.ia.quebec/en/maturity/form>

- Output of assessment is pentagon



Assessing starting point of developing with AI

Over your organisation's ML projects, which of these stages have you encountered at least once?



Not many mature ML models exist yet

Differences between a standard and AI application project

AI vs. Traditional Software Development in ML Lifecycle

AI Project Stages



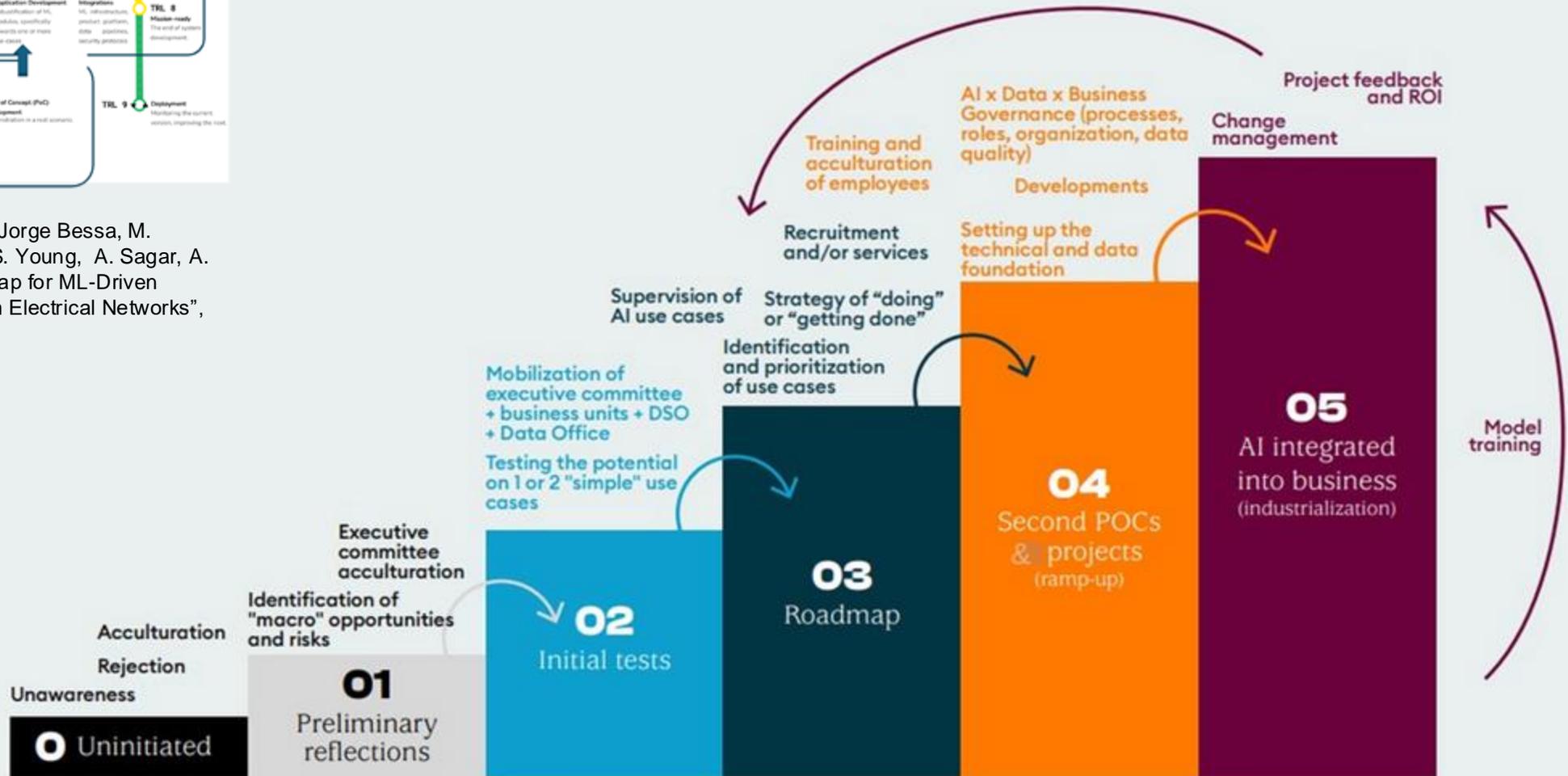
- **Problem Definition:** Traditional applications have clear requirements from the start, whereas AI development often involves evolving goals.
- **Data Needs:** AI requires diverse, often unstructured, data with extensive preprocessing; traditional applications use standardized data formats.
- **Model Design:** AI relies on algorithm training and optimization; traditional development follows pre-set rules.
- **Testing and Debugging:** AI tests emphasize model generalization and data-driven adjustments, while traditional tests are often deterministic.
- **Deployment & Updates:** AI models can continuously adapt and update based on new data, unlike periodic updates in traditional software.

Understanding the AI journey from concept to deployment

AI journey from test & learn phase up to scaling up

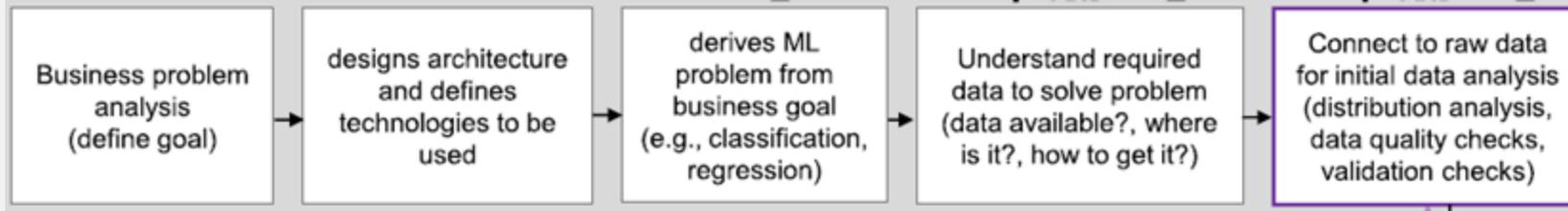


[1] J. L. Cremer, A. Kelly, R. Jorge Bessa, M. Subasic, P. Papadopoulos, S. Young, A. Sagar, A. Marot, "A Pioneering Roadmap for ML-Driven Algorithmic Advancements in Electrical Networks", IEEE ISGT Europe 2024



How to start your first project?

Experimentation & Validation



Experimentation Phase

- Assemble Team: Include a data scientist, developer, data engineer, and business expert
- Set Up Environment: Use version control and organize code and data pipelines; start with Jupyter notebooks.
- Data Collection and Prep: Gather historical data, clean, label, and analyze for usability
- Define Evaluation Metrics: Set KPIs, baselines, and test scenarios
- Model Training: Begin with standard algorithms and track experiments using tools like Weights & Biases

Validation Phase

- Analyze Results: Report on models vs. KPIs and baseline performance
- Assess with Experts: Review cases to ensure robustness
- Visualize Results: Use tools like Streamlit for interactive views
- Iterate as Needed: Refine based on feedback, avoiding over-investment
- Set Performance Targets: Define "good enough" benchmarks for integration readiness

Business canvas



Step-by-Step AI Project Evolution

Example in Congestion Management

1. Start with Simulation-Based (Safety-by-Anticipation):

- Easiest to implement with existing components
- Builds a performance baseline using expert rules and simulations

2. Hybrid SCOPF Approach:

- Combines traditional security-constrained optimization with some ML support
- Reduces online computation costs, requires high-performance computing resources

3. Fully ML-Driven (Reinforcement Learning):

- Offers multiple scenario-based recommendations and is highly adaptive
- Involves extensive offline computation, ideal when human supervision in decision-making is still desired

Practical & technical enablers

What are the technical enablers for your organization to use ML for power system operations?



Data management & cleaning is the strongest enabler of utilities

Enablers from AI community:

- plethora of curated datasets and benchmarks,
- increase of GPU compute and model size,
- open-science and open-source

Important practical considerations (data, enables & blockers)

1. Data Collection at Scale

- Large labeled datasets (~100k+ examples) needed; ~10% high-quality data.
- Use data augmentation to enhance datasets.
- Prioritize quality management: avoid "garbage in, garbage out."
- Enable data fusion by breaking silos for context-rich access.

2. Coding Tools & Infrastructure

- Python with PyTorch/TensorFlow dominates for ML flexibility.
- Low-code tools (Google, AWS) use foundational models to minimize data needs.
- Scalable pipelines and cloud tools ensure efficient, reproducible workflows.

3. ML Engineering Cycle

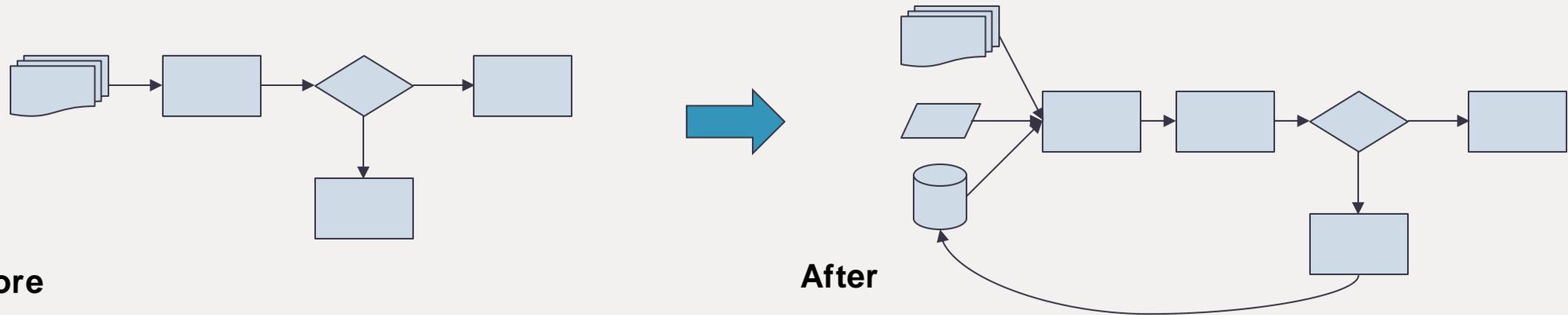
- Iterative "V-cycle" approach: problem specification to deployment.
- Trustworthiness: prioritize security, robustness, and explainability.

4. Insights & Best Practices

- Blockers: Data history, pipeline gaps, labeling, MLOps platform lack.
- Enablers: Pre-trained models, open source, sandbox testing, end-user engagement.
- Use tools like Git, Jupyter, and Weights & Biases for streamlined experimentation and tracking.

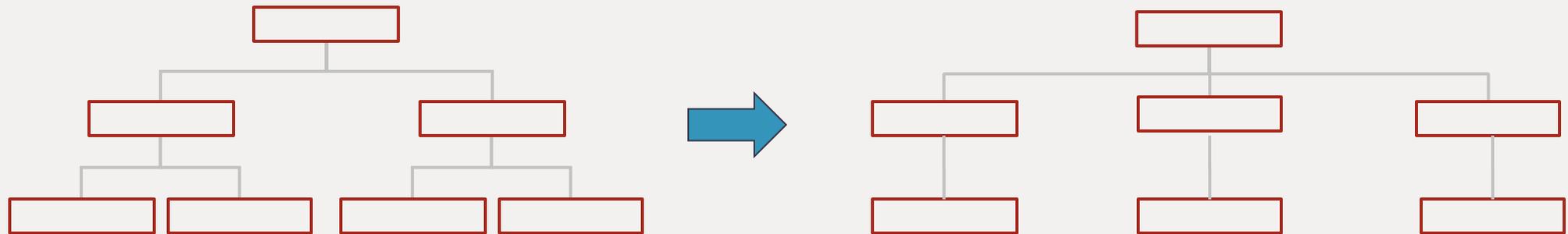
Getting your organisation up to speed

Transformative AI will require changes to your organisation



Before

After

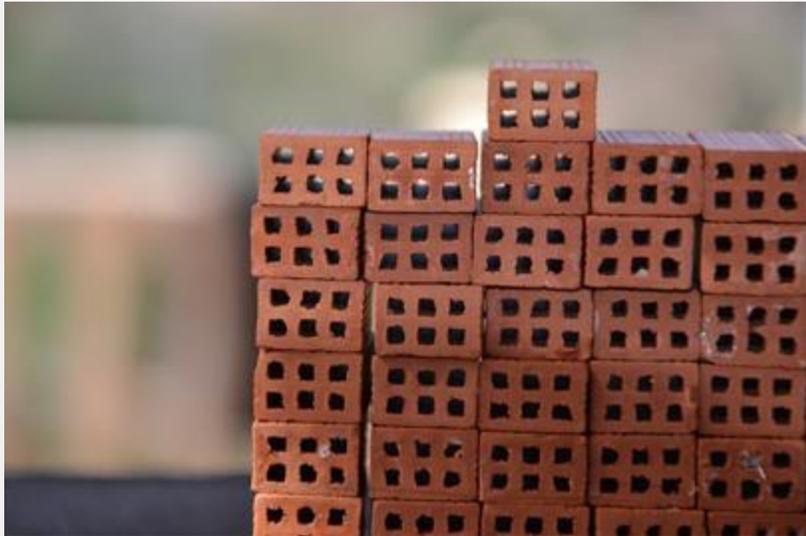


Recommendations

1. Be intentional about adopting an organisational change approach
2. Include thinking about organisational change in AI roadmapping

Getting your organisation up to speed

Choose a build vs buy strategy



Build



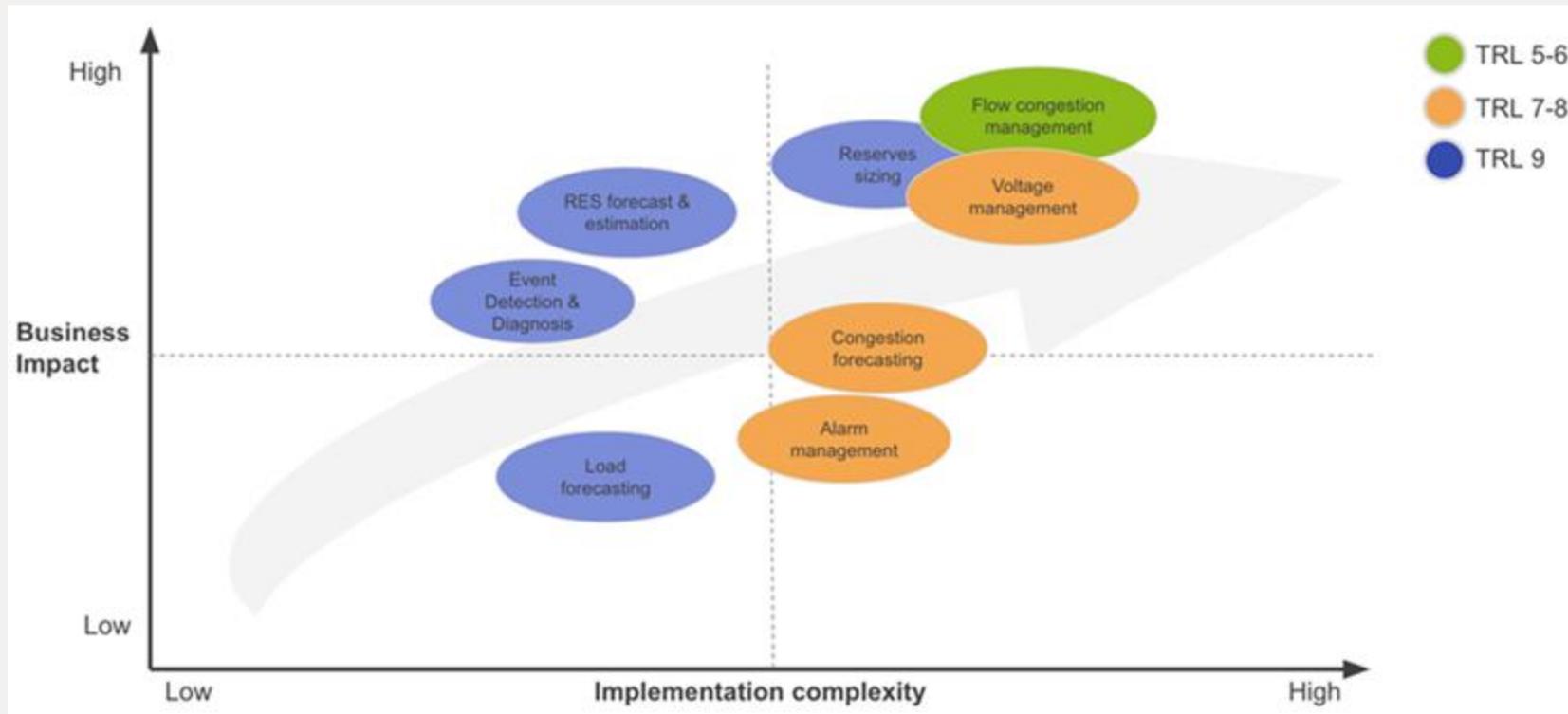
Buy

Recommendations

1. If “buying”, think carefully about delivering culture and process change, not just new tools
2. If “building”, adopt a broad strategy for attracting talent, including research partnerships, innovation challenges, and engaging with open-source communities

Prioritising use cases

Weigh up business impact and implementation complexity



Note: use case scoring in the above is illustrative - it will vary by organisation

Recommendations

1. Ensure there is a big enough early success to build sustained support
2. A large “lighthouse” project can be effective in building momentum

Prioritising use cases

Integrate use cases into a roadmap that builds organisational capability



Speed up

Projects driven primarily by capability building

Renewable forecasting -> Congestion management



Team up

Projects driven primarily by strong existing support from an area

Visual inspection -> Alarm management and reporting assistant



Human-centred

Projects driven primarily by need to build buy-in with end users

Alarm management and reporting assistant -> Renewable forecasting



Ramp up

Projects driven by medium-term goal of achieving a specific advanced use case

Static security assessment -> Dynamic security assessment

Chapter summary

A strategic roadmap is essential

- 1 Delivering AI effectively in an organisation requires a coordinated, strategic approach that lays both technical and organisational foundations
- 2 The optimal approach will depend on existing foundations and the level of buy in from different stakeholders
- 3 Try to ensure early use cases build capability for future use cases rather than standing alone
- 4 Ensure you are always delivering clear business impact at every step of the roadmap
- 5 Remember that organisational change can often be harder than technology change

CHAPTER 7: Conclusions

Conclusion

AI can unlock flexible operations

- Recent advances in artificial intelligence and machine learning capabilities offer significant opportunities for system operators.
- This tutorial has explored some of these opportunities in detail, and how they could be combined to enable a paradigm shift in system operations.
- The key use cases of AI for system operators include:
 - ✓ **Renewable energy forecasting**
 - ✓ **Dynamic security assessment**
 - ✓ **Alarm management and reporting assistant**
 - ✓ **Congestion management**
 - ✓ **Visual inspection.**

Conclusion

Successful application of AI requires several key foundations

To successfully integrate AI/ML into the power industry, the following considerations are essential

- **Data quality and quantity**
- **Human-in-the-loop and interdisciplinary cooperation**
- **Incorporation of prior knowledge in the design of AI solutions and Interpretability**
- **Rigorous evaluation methodology**
- **Organisational awareness and training**
- **Understanding limitations**

Open-source software, publicly available datasets and benchmarks, and shared development platforms can accelerate AI adoption and democratize access to advanced AI technologies

Conclusion

AI adoption is not just about technology; it's about people, processes and culture

Successful AI adoption in power systems operation involves a holistic approach:

- **Robust data practices,**
- **Appropriate models,**
- **Transparency,**
- **Interdisciplinary collaboration,**
- **Embracing change..**

The best place to start is to develop small, foundational use cases that enable learnings and form the basis for future decisions and investment

Q&A Session

**Thank you for your attention
Time for questions and discussion !**

The impact of the growing use of machine learning/artificial intelligence in the operation and control of power networks



Comitê Nacional de Produção e Transmissão de Energia Elétrica

Technical Brochure n° 35
Cigre-Brasil - GT C2.42

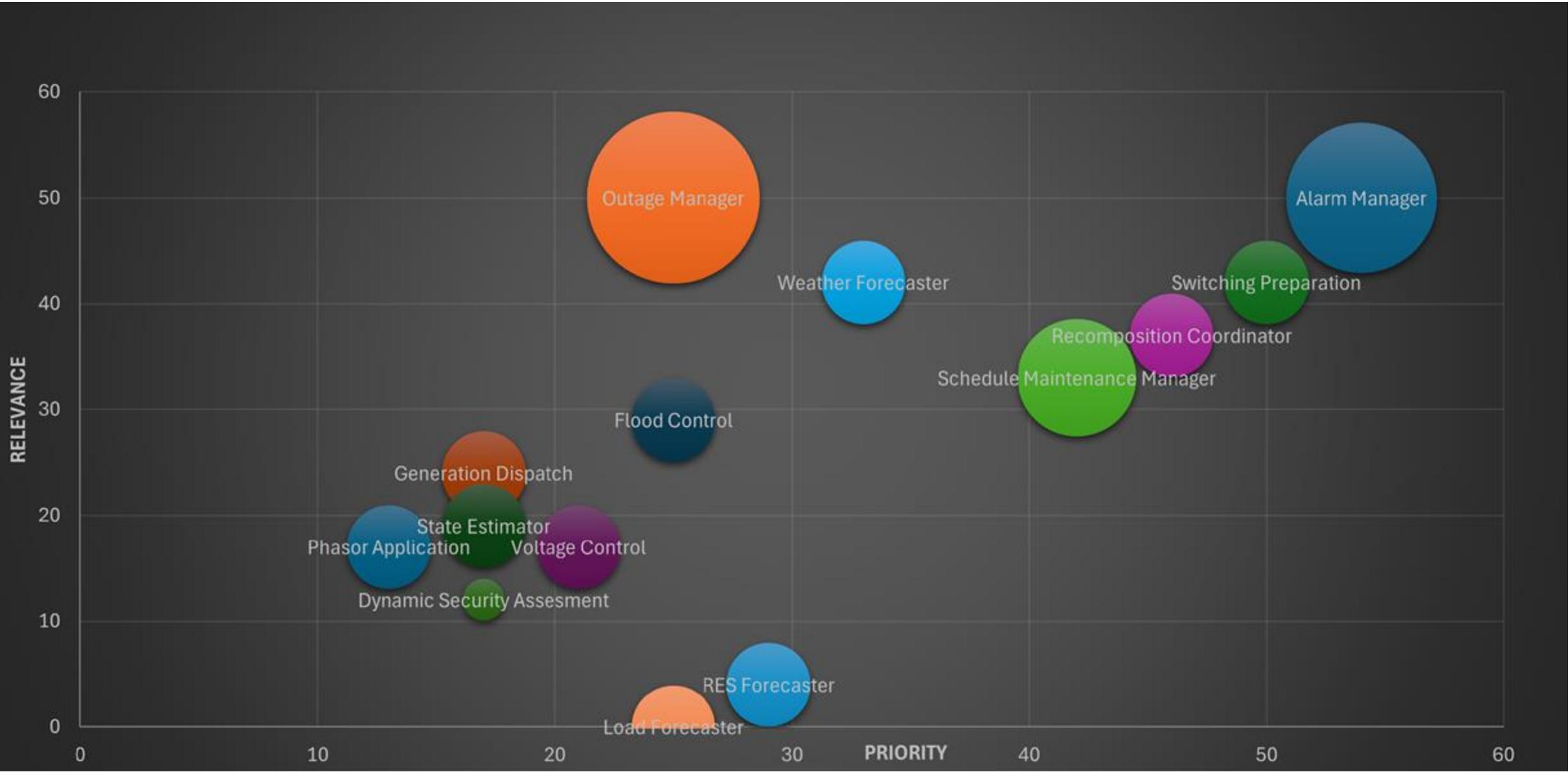
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Comitê de Estudos C2.42

O Impacto do Uso Crescente da IA na Operação e Controle de Sistemas de Potência





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