Advancing Power Grid Decision-Making: Enabling Collaborative Intelligence for Congestion Management Across Operational Timeframes

Graduation project

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ACKNOWLEDGEMENTS

It feels strange to have reached the end now. This project has been a journey and a half. I am glad it is over, yet part of me feels reluctant to let it go. Over the past months, I have learned an incredible amount. Not only about the topic itself but also about what design means to me, I've learned more about about my interests, limits, and capabilities.

I began this project as a challenge: to step outside my comfort zone and put my developing design skills to the test after transitioning from mechanical engineering. I wanted to prove to myself that I could navigate an unfamiliar domain and still deliver meaningful work. It demanded depth and persistence, but looking back, I am proud of how far I have come.

I could not have done it by myself; My sincere thanks go to my supervisor, Evangelos Niforatos, for his trust, patience, and steady encouragement throughout this process. I also want to thank Ujwal Gadiraju for his guidance during the early stages of the project.

I am grateful to TenneT for welcoming me into the PROD team and sharing their expertise. Although my time there was limited, I've felt welcome from day one. Thanks to Sjoerd and Johanna, for showing me around at the start of the project and thanks to Mario and Anne as well as Twan and the rest of the control room operators for their insights, feedback and their time. A special thanks is due for Jan Viebahn, who gave me the chance undertake this journey in the first place, even though I had no prior experience in the field. Throughout the entire proces Jan was there to push me to do better and saw to It that i had everything that I needed to take my work to a higher level. This effort made my experience on this project and with TenneT both challenging and deeply rewarding.

Finally, I thank my friends and family for their love and encouragement, and Sophie, for her understanding and support while my mind was often elsewhere during the duration of this project. Your presence kept me grounded.

ABSTRACT

The integration of renewable energy sources has fundamentally altered the operating environment of transmission system operators (TSOs). While essential for achieving a sustainable and low-carbon energy system, their volatility introduces significant uncertainty and volatility into the power grid. For operators in control rooms, this has led to more frequent congestion events, narrower safety margins, and rising information demands across multiple fragmented systems. In this context, timely and effective decision-making becomes increasingly challenging.

The first AI-based decision support tools (DSTs) have been deployed in TSO control rooms, for example, the GridOptions tool at TenneT TSO. These DSTs remain in the assistance mode of decision support by providing context and recommendations to the human operator in a one-directional fashion. However, timely and effective decision-making under uncertainty requires bi-directional human-AI communication, feedback, and co-learning. Consequently, this study investigates how AI-based DSTs can move from an assistance mode to joint AI-human decision making.

By employing novel concepts like the Supportive AI Framework and the Joint Control Framework, this study examines how human-AI teaming can evolve across different decision-making contexts and how interfaces can dynamically adapt to situational demands in both time-critical and less urgent scenarios. In particular, human cognitive needs figure prominently in how adaptable AI-powered interfaces can support operators in maintaining grid stability under uncertainty.

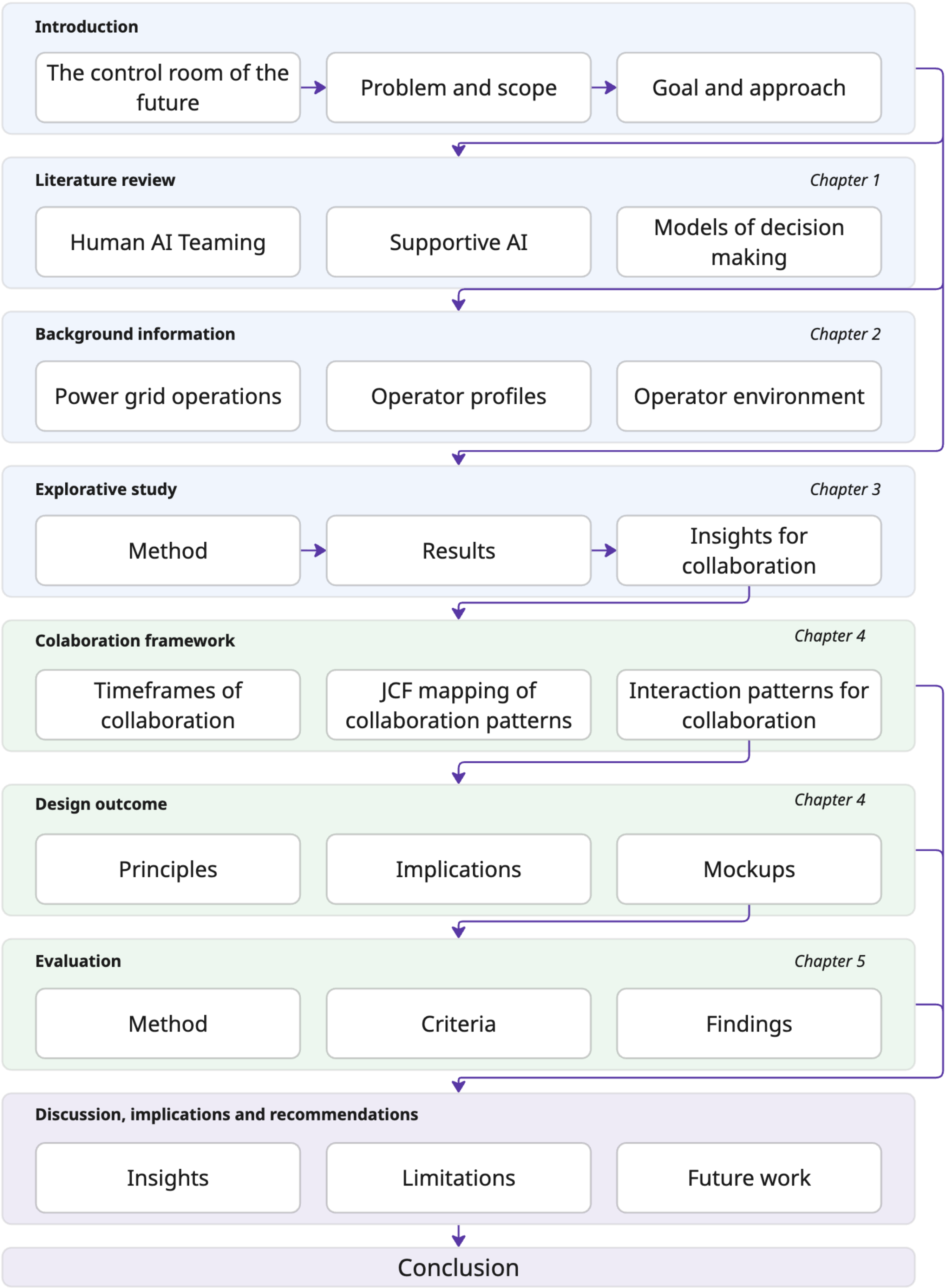
Drawing from observation, collaborative interaction patterns were developed to describe how human-AI teamwork can evolve across congestion operation timeframes. These patterns reveal opportunities and challenges in dynamically allocating initiative between humans and AI, maintaining situational awareness, and safeguarding human agency in safety-critical contexts.

Ultimately, this research seeks to contribute to the design of adaptive and supportive DSTs that unify data, reduce cognitive load, and facilitate reflection and learning. By addressing the dual challenge of information overload and uncertainty, the work aims to enhance the resilience of grid control strategies, stimulating effective human-AI collaboration, and enable the continued integration of renewable energy sources into the power system.

GLOSSARY

Term	Definition
TenneT	Dutch Transmission System Operator responsible for maintaining grid stability and reliability.
TSO (Transmission System Operator)	Operator of high-voltage transmission networks.
DSO (Distribution System Operator)	Operator of regional and local distribution grids.
AI4REALNET	European research collaboration developing AI applications for real-world network operations.
Control Room of the Future (CRoF)	TenneT programme exploring AI integration and new collaboration models in control rooms.
GridOptions	AI-based decision support tool used at TenneT for analysing and recommending congestion mitigation strategies.
Hypervision	Conceptual vision for an AI-enhanced control environment enabling shared situational awareness and collaborative decision-making.
Congestion	Condition where transmission capacity is insufficient to transport available power.
Congestion Management	Process of identifying and mitigating overloads in the transmission network.
Congestion Remediation	Operational actions taken to resolve or prevent congestion events.
Curtailment	Reduction of power generation to relieve network overloads.
Redispatch	Adjustment of generation or load to redistribute power flows and avoid violations.
Topological Remediation	Mitigation of congestion through reconfiguration of grid connections.
Topology Optimisation	Planning or automated selection of grid configurations to improve efficiency and reduce congestion.
Substation Configuration	Arrangement of switching elements and lines defining how power flows through a substation.
Realtime	Immediate operational timeframe where actions address live system conditions.
Intraday	Short-term planning horizon within the same operational day, adjusting to updated forecasts.
Day-Ahead	Planning horizon for scheduling grid operations one day in advance based on forecasts.
Strategy	Long-range course of action guiding system behaviour across timeframes.
Plan	Concrete sequence of actions addressing specific operational objectives.
Study	Calculation run to test specific grid configurations or operational scenarios to evaluate their effects on power flows and constraints.
JCF (Joint Control Framework)	Model describing shared human-AI control and decision-making across abstraction levels.
HMI (Human-Machine Interface)	Interface layer enabling operator interaction with control systems.
SA (Situational Awareness)	Operator's perception and projection of grid states.
HAT (Human-AI Teaming)	Collaboration approach combining human judgement with AI analytical capacity.
RES (Renewable Energy Sources)	Variable generation sources such as wind and solar.

STRUCTURE AND PROCESS



Inspiration of style and format from Lu, (2025)

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INTRODUCTION

The Control Room of the Future (CRoF) project explores how the increasing capabilities of artificial intelligence can be leveraged to assist operators of safety-critical systems. The ambition is not to replace human expertise or deskill operators, but to design tools that enhance their capabilities over time. This requires new forms of co-adaptive interaction, where the system learns from the operator as the operator learns from the system. To be effective, such systems must fit seamlessly into real-world work practices, supporting situational awareness, decision-making, and communication under both normal and crisis conditions.
This work does not stand in isolation. Across Europe, multiple transmission system operators and research institutions are investigating similar challenges through collaborations such as the AI4REALNET project. While the present thesis is rooted in the Dutch context, it draws inspiration from this broader network of research, which underlines that the questions addressed here are part of a larger endeavour in rethinking the role of AI in control rooms.

Hypervision

Hypervision is in many ways the starting point of this project. It encapsulates the overarching vision around which the Control Room of the Future is formed. While the term may initially evoke the image of a futuristic, augmented cockpit, its meaning is more fundamental. Hypervision represents a decision support system that unifies fragmented tools and interfaces into a coherent operator environment. Its role is not limited to presenting data, but extends to synthesising, contextualising, and recommending courses of action.

In short, Hypervision aims to:

- Unify data, tools, and interfaces into a coherent operator environment.
- Collecting and synthesizing data, functioning as the bridge between data layers and the operator
- Support the operator in both proactive and reactive decision-making.
- Enable bi-directional, collaborative communication between operator and machine.

Thus the Hypervision concept can be seen as a AI enabled interface that is the critical bridge between the operator and the vast amounts of data. It is envisioned as the central, and potentially sole, interface through which operators engage with the power system as well as the tools and algorithms that assist the operators in power grid operation processes like congestion management and monitoring.

Hypervision directly addresses two of the operator's most pressing challenges: fragmentation of systems and cognitive overload. By unifying the existing landscape of tools into a single interface, it reduces the need for constant cross-checking and manual correlation across different systems. At the same time, Hypervision seeks to reduce cognitive load by applying AI to synthesise information and surface what matters most. Its guiding principle is to provide "the right information to the right person at the right time" (RTE, 2025; Leyli-abadi et al., 2025), ensuring that operators can focus attention on critical decisions while still retaining access to underlying details when necessary.

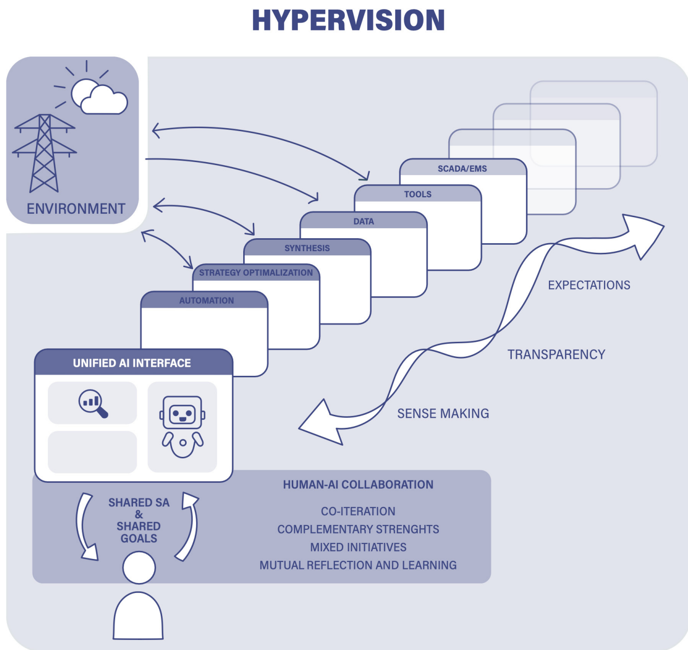


Figure 1: Hypervision as the central point in of the operator's decision support system, inspired by Marot (2022)

Importantly, Hypervision as a concept defines what it should be and do, but it does not yet define how the interaction between operator and AI should take shape. This gap the need to explore what collaboration actually looks like in practice is the central focus of this thesis.

From Vision to Practice

While Hypervision presents a forward-looking vision of a unified, AI-enabled control room, its ambitions extend far beyond what is currently feasible in daily operations. It imagines a future where automation and intelligent assistance are deeply embedded in every aspect of grid management. However, this vision is not yet grounded in existing work practices or tools.
This thesis therefore takes Hypervision as its conceptual starting point, using it as a theoretical lens to explore what human–AI collaboration could and should become. At the same time, it adopts a tangible, design-oriented approach focused on enhancing collaboration within current operational systems. In doing so, it aims to bridge the gap between long-term vision and present-day realities, making the path toward Hypervision more concrete, grounded, and actionable.

Problem Statement

As concerns about climate change continue to rise, there is an increasing demand for energy sources that are not dependent on limited resources and contribute to zero carbon emissions. Renewable energy sources (RES) such as solar, and wind play a crucial role in this transition. However, their inherent variability, caused by dependence on weather conditions, introduces significant uncertainty on the power grid. At the same time, the energy transition challenges the overall capacity as well.

For Transmission System Operators (TSOs) such as TenneT, who are responsible for maintaining a stable and reliable electricity supply in the Netherlands, this shift represents a fundamental change in how they operate. Today, power grid operations are becoming increasingly complex, and dealing with real-time congestion is more persistent than ever before. As a result, operators must work within tighter safety margins and intervene more frequently to maintain a secure grid state. These interventions take the form of topological remediations, as well as alternative and often less optimal measures such as redispatch or curtailment.

Grid operations are a constant balancing act. Operators must maintain redundancy and operational safety while making trade-offs to find the most optimal solution. They balance cost and risk while working under constraints such as limited time and available resources. Increasingly, finding the most optimal outcome has become difficult in the face of growing complexity and uncertainty. As reactive remediation becomes more frequent, operators face greater constraints and have less time to optimise their decisions, forcing them to accept less favourable outcomes.

At the same time, in an effort to assist the operator in making these decisions, control rooms have become increasingly information-dense environments with the introduction of new tools and functions. Operators now rely on many systems and interfaces that provide both raw data and synthesised, high-level information. While these systems provide valuable support to operators, the scattered nature of tools and the sheer volume of data remain challenging. At the same time, misalignment between forecasts and real-time conditions forces operators to reactively navigate large amounts of information across fragmented sources to identify suitable remediations. As a result, the frequency of unexpected congestion events and narrower operating margins leave operators under growing pressure, higher cognitive loads and more frequent unsafe grid states.

To address these challenges, there is a clear need for advanced support systems that can unify information streams, provide more accurate forecasts, and assist operators in identifying and evaluating response strategies. TenneT is taking a multi-pronged approach to addressing these challenges. While the physical capacity of the network is being upgraded, significant effort is directed toward shaping the Control Room of the Future. On one side, this involves developing forecasting and strategy optimisation tools that enable operators to take a more proactive stance on congestion management through prevention. On the other, the broader initiative under the umbrella of Hypervision aims to create a unified, AI-enabled platform that redefines the interaction between human and machine.

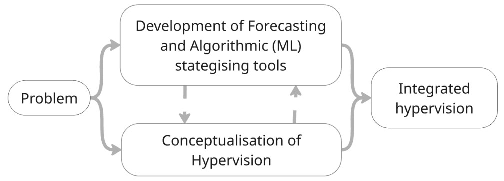


Figure 2. Simplified development paths within the scope of the project

Artificial intelligence is increasingly seen as a key enabler in this transition. In collaboration with other TSOs, TenneT has begun conceptualising how AI can be integrated into the control room within the Hypervision framework. However, it remains unclear how these systems should interact with human operators across different decision-making contexts.

Motivation

The integration of artificial intelligence into power grid control rooms offers the potential to unify fragmented systems, improve forecasting, provide actionable recommendations, and enable humans and AI to work together toward better operational outcomes.

However, significant challenges remain in how such systems can be effectively adopted. Key issues include the move toward more collaborative decision-making between humans and AI, the human motivation to engage with these systems, the design of interactions that support meaningful collaboration, and how these interactions can adapt across different decision-making timeframes within operational workflows.

In addition, different modes of Human–AI teaming must be better understood, particularly how interface design can support the dynamic environment of grid operations while ensuring operators remain in control of safety-critical decisions.

The motivation for this research lies in the need to better understand the opportunities and limitations of Human-AI teaming in grid operations. The aim is to explore how different teaming roles and styles evolve across decision-making contexts and what implications these have for interface design.

Scope

The scope of this thesis is grounded in the present operational reality of power grid management at TenneT. It focuses on how AI-driven interfaces can enhance collaboration between operator and system within existing control-room environments. The goal is to design for current systems, recognising that these will form the foundation of future developments such as Hypervision.

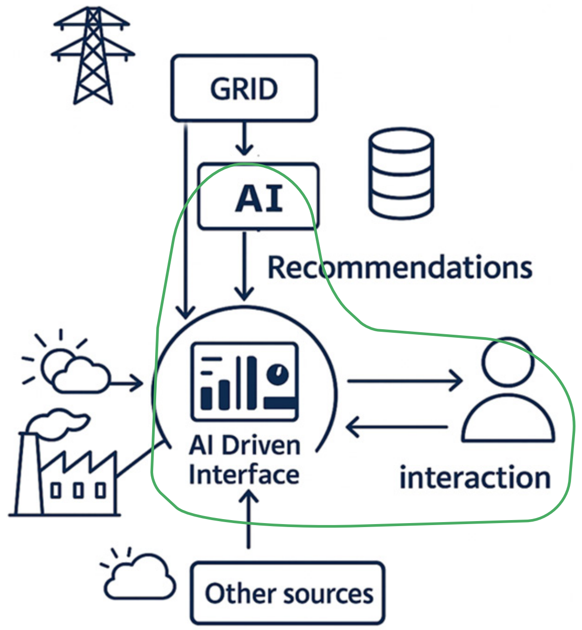


Figure 3 : Scope of the project

As illustrated in Figure 3, the research concentrates on the interaction zone between the operator and the AI-driven interface, where information is exchanged, interpreted, and acted upon. This includes studying how AI-generated recommendations are understood, used, and validated by operators in real decision-making contexts. GridOptions, the AI powered strategy optimisation tool serves as the representative system within this scope, providing a grounded congestion-management toolkit that allows development towards hypervision and shows AI-based recommendations through which human–AI collaboration can be explored.

The focus is on interaction and collaboration design, not on developing underlying AI algorithms or automation logic. The thesis examines the human–AI interface as the critical layer connecting data-driven intelligence with operational expertise. Within this trajectory, Hypervision represents an overarching vision for the future control room rather than a fixed stage in the path toward potential automation.
Current machine-learning systems already provide forecasts and remedial-action proposals, but these remain isolated modules with very limited capabilities that add to system fragmentation. This thesis therefore focuses on identifying how human–AI decision-making can be supported through interface design, clarifying where collaboration adds value and how it might evolve within the Hypervision vision, as outlined by Leyli-abadi et al. (2025).

Goal

The goal of this thesis is to visualise and conceptualise what collaboration could look like within the envisioned framework of Hypervision, using the emerging tools and context of the Control Room of the Future.

This work seeks to make the transition toward Hypervision more tangible and to understand it through its core principles, such as collaboration and bi-directional communication between human and AI. While Hypervision provides an overarching vision, the underlying principles and theories that support it are still evolving. By drawing from these emerging foundations, this research aims to gain a clearer understanding of what meaningful human–AI collaboration entails and how it could take form in practice.

The following research questions guide this exploration:

Main Research Question

How can interface design support the evolution of collaborative congestion management in power-grid control operations?

Sub-questions

1. What principles can be drawn from existing research, and how do they contribute to the development of the Hypervision concept for human-AI collaboration in power-grid operations?
2. How do existing decision-making processes and human-machine interactions shape current power-grid control-room operations?
3. How can the understanding of current decision-making and interaction patterns be translated into concrete design implications for future collaborative human-AI operations?

Approach

This thesis follows a design-research approach that integrates conceptual framing with empirical grounding. The research combines theory-driven exploration that seeks to define Hypervision within the scope of this project and to examine complementary theories that align with its principles.

Conceptually, the work draws from theories of human–AI teaming, cognitive control, and human psychological needs in decision-making contexts to understand how collaboration could function in safety-critical environments. Rather than viewing AI as a static decision-support tool, the focus lies on mixed-initiative interaction, where initiative and control shift dynamically between operator and

system depending on the situation. The foundation of this approach is co-iterative and collaborative, emphasising a continuous exchange of insights and adaptation between human and system. This framing guides the interpretation of collaboration patterns and supports the formulation of design implications for the envisioned Hypervision environment.

Empirically, the research is grounded in observations of control-room practice at TenneT, as well as in collaboration with domain experts, researchers, and supporting resources within the organisation. These observations document how operators navigate uncertainty, varying timeframes, and fragmented tool landscapes, providing insight into how decision-making unfolds in real operations. To complement these insights, scenario-based explorations using the GridOptions tool simulate realistic congestion-management cases. These scenarios explore how operators could interact with AI-generated recommendations in a more collaborative manner, informed by theoretical insights and Hypervision principles.

The conceptual and empirical strands inform one another iteratively. Observations ensure that theoretical insights remain connected to operator practice, while conceptual models help interpret observed behaviour and identify design opportunities. Together, this integrated approach enables the development of design principles for Hypervision as a collaborative interface that enhances situational awareness, fosters co-iteration between human and AI, and supports accountable decision-making in complex grid operations.

CHAPTER 1
LITERATURE REVIEW

Literature review

To position this project within the broader academic and industrial landscape, this chapter reviews existing research and design practices related to AI-based decision support in safety-critical infrastructures as well as bringing in the human cognitive aspect. As outlined in the introduction, integrating AI into control-room operations introduces challenges. Operators must rely on systems that process vast data streams while still supporting human judgment under uncertainty. Understanding how AI can function as a collaborative partner rather than a purely assistive tool is central to addressing these challenges

This chapter addresses Research Question 1:

> What principles can be drawn from existing research, and how do they contribute to the development of the *Hypervision* concept for human-AI collaboration in power-grid operations?

It establishes the theoretical foundation for understanding collaborative human-AI operations and situates the project within the broader context of ongoing developments in intelligent control-room systems.

1.1 DECISION MAKING MODELS

Decision-making has been studied across disciplines such as psychology, human factors, and engineering, producing a range of models that explain how humans detect, interpret, and act on information. Some of these models have become especially influential in complex and safety-critical environments such as control rooms. Here, monitoring and decision-making form the operator's core tasks, as they must constantly observe the system, interpret developments, and determine appropriate courses of action under time pressure.

One such framework is Rasmussen's Decision Ladder (Rasmussen, 1986), which depicts decision-making as a sequence of steps from problem detection to action implementation. While the model presents this process in a structured order, in practice experienced operators may skip steps or take shortcuts based on their knowledge of the system and the urgency of the situation. The model also highlights how observations are progressively abstracted: raw data and signals are first detected, then interpreted in terms of system states, and eventually translated into goals and possible actions. This illustrates the sensemaking process, where operators move from concrete observations to higher-level understanding that underpins decision-making. The ladder is particularly useful for describing how decision strategies vary with expertise and has been recognised as a relevant lens for analysing operator behaviour in power system control contexts (Marot et al., 2022)

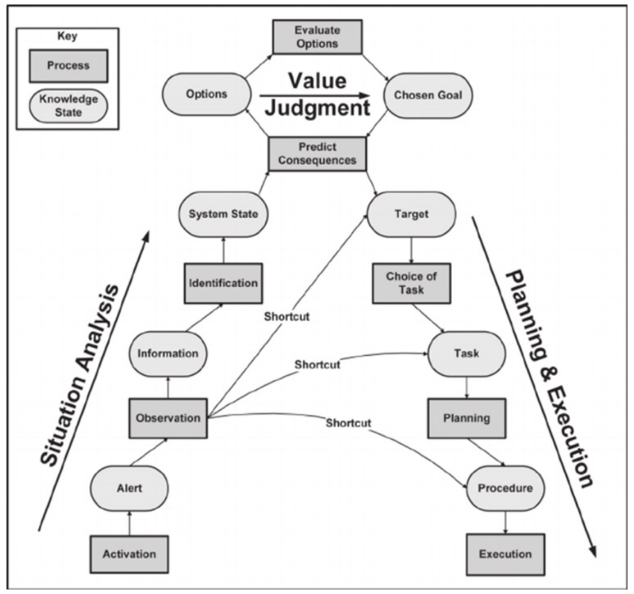


Figure 1.1: Ramussen's decision ladder depicts decision-making as a series of stages from problem detection to action, illustrating how information is progressively abstracted into higher-level understanding. Although sequential in structure, experienced operators may shortcut across steps depending on expertise and context (Marot et al., 2022)

Another well-known framework is Endsley's model of Situational Awareness (SA) (Endsley, 1995). This model similarly distinguishes between perception, comprehension and projection. It explains how humans maintain an understanding of their environment and anticipate future states. It highlights how operators must continuously monitor the environment and make sense of it in order to reach confident and comprehensive decisions. Knowing what is going on at all times is essential for making more effective decisions when time is limited.

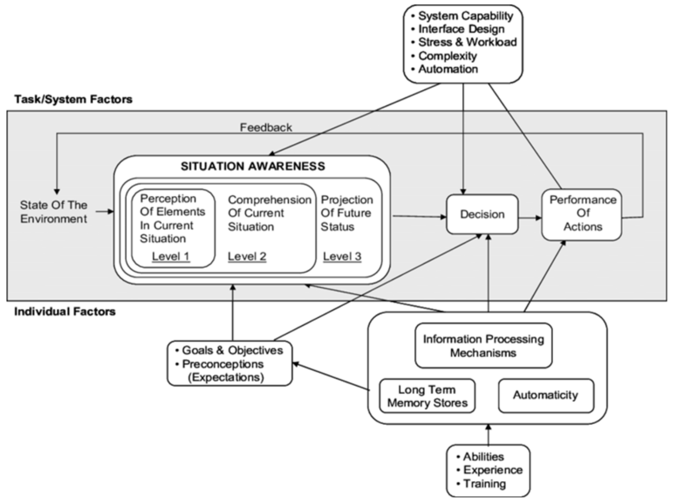


Figure 1.2: Endsley's model of situational awareness is described in three levels: perception of system elements, comprehension of their meaning, and projection of their future state. The model highlights that maintaining awareness across these levels is essential for effective decisions under time pressure (Endsley, 1995).

For operators, decision-making is not a one-off sequence but a continuous process of sensemaking. They are constantly updating their understanding of the system, interpreting new developments, and projecting potential consequences. A system like Hypervision should be designed to aid this ongoing cycle. It can reduce fragmentation at the perception stage by unifying information, support comprehension through synthesis and contextualisation, and strengthen projection with predictive insights. By aligning with these cognitive processes, Hypervision has the potential to reinforce operators' ability to sustain situational awareness and make effective decisions under pressure.

1.2 COLLECTIVE LEARNING

While decision-making models describe the cognitive processes of operators, it is equally important to consider how humans and AI systems can learn together over time. The introduction of AI into complex environments is not a static intervention but a dynamic relationship that evolves as both humans and systems adapt.

Recent work on Reflective Hybrid Intelligence (RHI) stresses that hybrid systems require continuous monitoring and improvement to remain effective. The conditions of hybrid human-AI systems imply that alignment cannot be taken for granted. To remain effective, they require continuous monitoring and mechanisms for improvement, a process captured by the notion of Reflective Hybrid Intelligence (RHI) (Krafft et al., 2023). This perspective highlights that collaboration is not achieved once and for all, but must be actively sustained through feedback loops that allow both the AI and the human to recalibrate their roles.

Empirical studies further suggest that humans and AI contribute complementary strengths. AI excels at large-scale data processing, pattern recognition, and rapid response, while humans bring contextual awareness, value judgements, and the ability to adapt strategies in uncertain situations (Brynjolfsson, Li, & Raymond, 2022). Over time, hybrid teams can improve performance by learning from each other: humans refine their mental models through exposure to AI recommendations, and AI systems improve through human feedback and corrections.

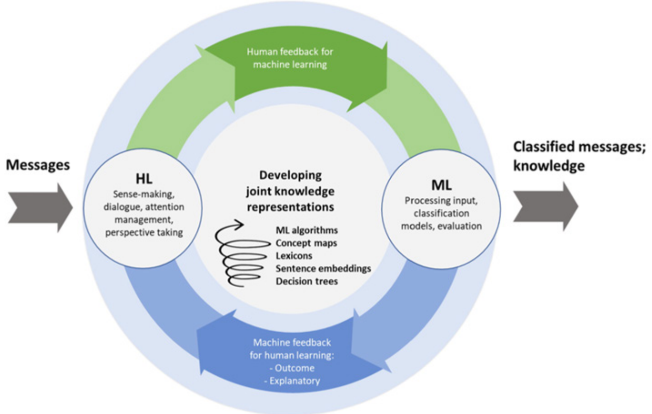


Figure 1.3: The model illustrates how humans and AI systems co-evolve through feedback loops. Calibration ensures that system outputs remain reliable, while reflection and adaptation on both sides foster continuous improvement. Together these mechanisms create sustained alignment, allowing human and AI agents to remain effective partners over time. (Te'eni et al., 2023)

For Hypervision, this implies that the interface should not only provide outputs but also foster an environment of co-learning. Operators must be able to understand, challenge, and adjust AI outputs, while the system should capture this interaction to improve its recommendations. Such an approach ensures that human-AI collaboration strengthens rather than erodes expertise, and that decision support evolves alongside operator practice.

The conditions of hybrid human-AI systems imply that alignment cannot be taken for granted. To remain effective, they require continuous monitoring and mechanisms for improvement, a process captured by the notion of Reflective Hybrid Intelligence (RHI) (Jonker et al., 2023).

1.3 LEVELS OF AUTOMATION

Although the Hypervision concept is future focussed, its real-world implementation will need to be gradual and realistic. A fully autonomous AI taking over sections of the operator's workload is a envisioned, but not the starting point. According to guidance from EASA, AI integration must follow a stepwise path, progressing through defined levels of automation: from basic support and recommendation (Level 1) to collaborative decision-making (Level 2), and eventually toward advanced automation (Level 3) (EASA, 2024; EC, 2025). Skipping steps isn't feasible as each level demands increasing system maturity, explainability, and trust. Crucially, higher automation also requires extensive operational data and validated performance. In this stage of the development, the design focus should therefore be on collaborative AI, where the system shares the decision-making process with the human operator, not replaces them. This approach supports real-time transparency, preserves human oversight, and creates the data foundation needed for future evolution.

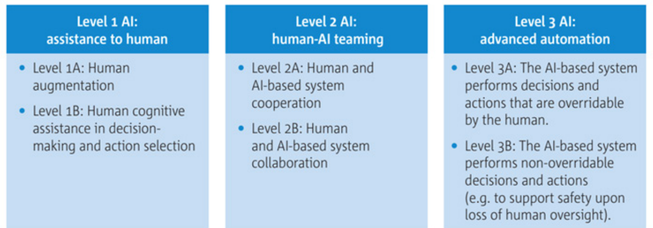


Figure 1.4. Levels of AI automation from EASA AI Roadmap 2.0 (European Union Aviation Safety Agency, 2023)

1.4 COLLABORATIVE AI

Within hypervision, the aspiration is to move beyond augmentation or even cooperation, towards collaboration. Collaboration implies that both the operator and the AI system engage in the same task and work towards shared goals, rather than performing parallel activities. This requires bi-directional communication and the establishment of a common ground in terms of situational awareness. The Framework and Key Technologies of Human-machine Hybrid-Augmented Intelligence study highlights that human-machine collaborative systems must integrate reasoning at the knowledge level, allowing both sides to share representations and engage in joint problem solving (Fan et al., 2024). This kind of knowledge-level interaction ensures that the operator does not merely receive output but is part of the reasoning process itself.

1.5 Complementary Strengths

Collaboration between humans and AI is powerful because it draws on complementary strengths. Human operators excel in contextual judgement, ethical reasoning, and flexible problem solving under uncertainty. AI systems contribute speed, precision, and the ability to process large datasets in real time. Combining these qualities creates synergies that neither side can achieve alone. Fan et al. (2024) describe this as the core of hybrid intelligence in power grid control: humans provide interpretive depth and remain strong in keeping situational awareness and nuance, while machines deliver computational efficiency and rapid information accessibility. Such integration supports three key objectives in operational settings:

1. Real-time decision making in complex environments.
2. Adaptive responses to evolving conditions.
3. Innovation through collaborative problem solving.

By capitalising on these complementary capabilities, collaborative AI can enhance resilience and improve the quality of decisions under pressure. These objective suggest complementary qualities in complex environments [1], the ability to dynamically allocate tasks and shift collaboration in different circumstances [2] and find new approaches or solution by combining skillsets over time [3].

An important dimension of collaboration is therefore how tasks are divided between human and AI teammates. The RL-HAT framework (Jafari Meimandi, Bolton, & Beling, 2023) proposes that tasks can be dynamically assigned based on three criteria: complexity, urgency, and the capability profiles of human and machine. These profiles can be quantitatively modelled, allowing the system to optimise allocation under performance constraints. This approach goes further than static delegation and creates a flexible teaming model where responsibilities can shift according to context. For example, routine or time-critical computations may be machine-led, while novel or ambiguous scenarios remain in human control. This dynamic allocation reflects a more equal distribution of agency and supports adaptive collaboration. One could even argue that it is one of the defining factors distinguishing cooperation from collaboration.

1.6 HUMAN NEEDS

Traditional explainable AI assumes that users want a justification for recommendations, but this paradigm risks either undermining or over-inflating trust. Miller (2023) critiques the "recommendation-driven" model, showing that users often disengage from explanations or place blind trust in them. Instead, he proposes Evaluative AI, which does not simply offer recommendations but supports the human's decision-making process by presenting evidence for and against possible options. In collaborative AI, this means the human maintains agency and can evaluate multiple hypotheses with system support, rather than being forced into accepting or rejecting machine outputs. Such a model better aligns with natural cognitive processes such as sensemaking and abductive reasoning, which are crucial for expert decision-making in dynamic domains like power grid operations.

While technical frameworks define how tasks and information are shared, collaboration ultimately depends on human needs. Greitzer and Podmore (2008) show that through naturalistic decision-making research that operators rely on experience-based cues, recognition, and mental simulations to guide critical decisions in the power grid. Collaborative AI should therefore not only provide computational support but also align with these cognitive processes to foster trust and motivation.

At the same time, systems should create opportunities for human learning and adaptation, ensuring that expertise is not eroded but augmented. A balance must be maintained: AI should move beyond serving recommendations, but without removing human agency. This perspective redefines AI not as a passive tool, but as an active teammate. Mussi et al. (2025) extend this position by stressing that human-AI collaboration must explicitly support broader human needs. Their Supportive AI Framework identifies four ways in which AI can scaffold human cognition: exploration, animation, mirroring, and transparency. Exploration enables humans to test ideas, simulate scenarios, and probe the AI itself to understand its limitations, which is essential for building trust. Animation draws attention to patterns or anomalies that might otherwise pass unnoticed, prompting reflection and surfacing tacit assumptions. Mirroring supports self-reflection by showing humans their own decision-making styles and behavioural patterns, making biases or tendencies visible. Finally, transparency ensures that AI systems remain comprehensible by revealing the rationale behind outcomes, not only to justify decisions but also to provide feedback for learning.

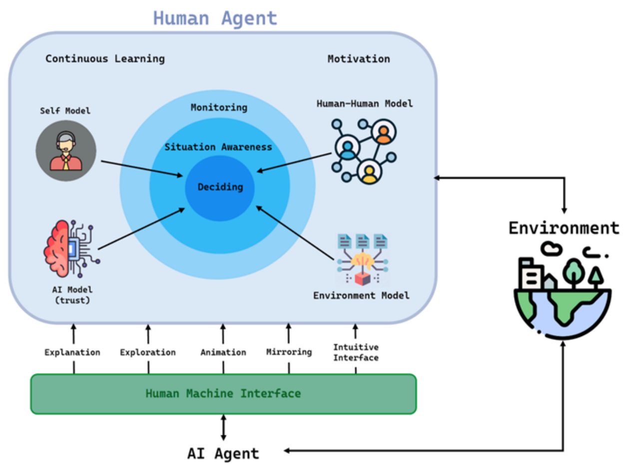


Figure 1.5. Model of human needs in human-AI collaborative decision-making (Mussi et al., 2025)

Together, these functions help frame AI as a partner in decision-making, continuous learning, trust calibration, and intrinsic motivation (Mussi et al., 2025). By stimulation of reflective processes, encouraging exploration, and explainable suggestions, supportive AI addresses the shortcomings of explainability alone. The AI within the HAT should cater to human cognitive needs by actively supporting the way people decide, learn, trust, and stay motivated.

1.7 TEAM SITUATION AWARENESS

One of the key pillars of teaming and thus Human-AI collaboration, is that it requires shared situational awareness (SA). The Agent Teaming Situation Awareness (ATSA) framework (Gao et. Al., 2023) extends Endsley's classic three-level SA model to Human-AI Teams by highlighting bidirectional and transactive awareness. Both human and AI agents must form, maintain, and share mental models of the situation. The framework highlights that effective collaboration is only possible when the machine is not just an information source but an active participant in constructing situational understanding. In this sense, SA becomes a team property rather than an individual one, supporting coordination, cooperation, and joint decision making. For Hypervision, this implies interfaces must facilitate communication throughout every aspect of the system. The human and machine both need to be able to keep eachoteher in the loop in order to maintain this shared mental model of the current grid state, evaluation of past events, but also what's to come.

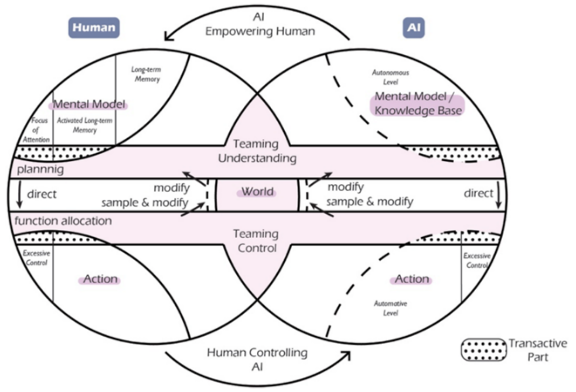


Figure 1.6: Situational Awareness Framework (Gao et. Al., 2023)

1.8 DESIGNING FOR COMPLEXITY

Along-standing principle in control room design has been the idea of providing "the right information, at the right time, to the right person, in the right format." While this sounds great in theory, this statement implicitly assumes that the system can always know what is "right." Such an assumption is problematic not simply because current machines lack intelligence, but because no system can ever anticipate all possible contexts and operator states. What counts as the "right" information or format is dependant oncircumstances, workload, and mindset, and most importantly, often only becomes clear in hindsight. As Hollnagel and Woods (2005) note, the "right-right-right" rule risks becoming a hindsight bias: it suggests that if only a certain piece of information had been presented in a specific way, a different outcome would have followed, ignoring the unpredictability and variability of real-world operations. Over time, it becomes clear that the operator must remain in command of what constitutes the right time and the right form. Automation may eventually learn to anticipate informational needs, but this is likely a matter of decades of accumulated interaction data rather than an immediate design feature. Instead, a balanced approach is needed where the system synthesises and prioritises information while keeping all underlying data transparently available. When the operator needs to dig, the machine should facilitate this. This of course goes hand in hand with the human needs of exploration and transparency as discussed by Mussi et. Al. This ensures that the machine supports the reduction of cognitive overload through data synthesis while the human maintains agency in exploration. More importantly, it also retains the feeling of control as the operator retains accessibility to the raw and untampered data.

Operators must therefore remain in a position to make their own deductions and cross-check them against the system's recommendations or conclusions. The results of this process can then serve as a basis for team reflection, both from a performance perspective and a psychological one. For example, why did the human need to intervene, whether the information was clear enough, and what elements may have been missing from the initial prompt by the agent.

From a Cognitive Systems Engineering perspective, this reflects the shift from designing for simplicity to designing for complexity (Hollnagel, 2005). Designing for simplicity attempts to reduce complexity by filtering and simplifying, yet risks creating complications when unanticipated scenarios are encountered. Designing for complexity, by contrast, accepts that operators must be able to cope with variability and uncertainty. The role of the interface is therefore not to prescribe a fixed "right" representation, but to facilitate feedback and feedforward control: operators should be able to drill into synthesised representations, trace them back to raw data, and project possible future states.

In this view, the Hypervision interface is not a gatekeeper that decides what the operator sees, but a gateway to layered data. It synthesises patterns and provides contextualised recommendations, yet simultaneously enables exploration across levels of abstraction. Transparency must remain intact: everything is available, but the flow of "the right information" emerges dynamically from human-machine interaction. This way, the system becomes a joint cognitive partner, amplifying the operator's ability to maintain control under varying circumstances while avoiding the pitfalls of over-simplification.

1.9 TRUST

Trust is not a static quality of an AI system but the outcome of continuous interaction between operator and interface Marot et al. (2022). For Hypervision to be successful, it

must foster calibrated trust. The operator should neither blindly follow nor systematically disregard machine recommendations. Instead, trust should rest on an informed understanding by the operator of how the AI works, where it is strong, and where its limitations lie.

Trust requires understanding, not blind acceptance. Marot's study on power network operation demonstrated that operators engage more effectively with AI when it provides comparisons of alternative strategies, rather than single "answers." This aligns directly with the principles of Evaluative AI (Miller, 2023), and was an early adoption into TenneT's view of hypervision as well. It supports judgment by surfacing evidence for and against possible actions. Within Hypervision, this means that recommendations should be presented with contextualised trade-offs, enabling operators to test their own reasoning against the system's output.

However, trust is fragile. Empirical studies show that mistakes or unpredictability by AI lead to significantly larger drops in trust than successes do in regaining it—that is, failures impact trust more deeply than successes can rebuild it (Yang, Schemanske, & Searle, 2021). This asymmetry underscores the fragility of trust and the importance of reliability from the outset. A systematic review by Hoff and Bashir (2015) models trust across three layers—dispositional, situational, and learned trust—highlighting how trust develops unevenly over time and across contexts. Trust also grows through interaction. As Marot et al. (2022) showed, operators gain confidence when they can question, test, and occasionally override the system. This resonates with Mussi et al.'s (2025) Supportive AI Framework, in which exploration and mirroring are crucial for learning. By making its reasoning transparent and allowing operators to probe it, Hypervision supports reflective practices that both strengthen expertise and build long-term trust.

Another factor is transparency in uncertainty. Operators need not only to know what the system recommends but also how confident it is and what limitations it faces. Mussi et al. (2025) highlight transparency and animation as key functions for surfacing uncertainties and drawing attention to anomalies that might otherwise pass unnoticed.

Trust is also shaped by time pressure. Under severe time constraints, operators often rely more heavily on AI suggestions, especially when their own observation time is limited (Cao, Gomez, & Huang, 2023). At the same time, when sufficient decision time is available, humans are more likely to critically weigh AI outputs against their own judgments, sometimes overriding the system. This dynamic shows the importance of adaptive trust support in Hypervision. In urgent contexts the system should deliver concise, high-confidence outputs, whereas in less pressured scenario's it should promote reflection and exploration.

Lastly, trust connects to broader human needs in collaboration. As noted earlier (Section 1.5), systems must also support human learning, maintain motivation, and safeguard agency (Greitzer & Podmore, 2008). Trust is nurtured when operators feel the system enhances their expertise rather than replacing it. Hypervision must therefore act as a partner, supporting cognitive processes such as sensemaking and reflection, and ensuring that the operator remains clearly in command of decisions. Both the HARTU project and the EASA AI Roadmap 2.0 stress that trustworthiness is central to Human-AI teaming. Operators must feel confident that AI-generated recommendations are transparent, robust, and accountable. Trust is not static: it must be continuously calibrated as the AI demonstrates reliability, handles edge cases, and provides meaningful explanations.

1.10 DEALING WITH UNCERTAINTY

Uncertainty has become an inherent feature of modern power grid operation. For operators, the challenge is not only technical but also cognitive: they must act under conditions where information is incomplete, ambiguous, or rapidly shifting. (Hu et al. 2024).

Effective communication of uncertainty is as critical as the forecasts themselves. Operators presented with only deterministic forecasts are often forced into binary judgments, while probabilistic forecasts that display a range of possible outcomes (through tools such as fan charts or confidence intervals) stimulate more resilient decision strategies. Communicating uncertainty transparently helps calibrate operator expectations, improves risk awareness, and reduces the likelihood of overconfidence in single-point predictions.

This communication imperative aligns with earlier insights on trust and human needs. As Mussi et al. (2025) argue, operators require systems that support reflection and exploration, not only filtered outputs. Uncertainty, if communicated properly, becomes a tool for reflection: it allows operators to compare their own expectations with system outputs, explore trade-offs, and maintain a sense of control. Similarly, Marot et al. (2022) demonstrate that uncertainty expressed as confidence levels can strengthen calibrated trust in AI support. A future decision support tool should therefore, by making both synthesized recommendations and underlying uncertainty available, by simultaneously responding to the human need for transparency and the cognitive need for confidence calibration.

Beyond decision quality, uncertainty also intersects with situational awareness. Endsley's model, extended into Human-AI teams (Gao et al., 2023), stresses that anticipation of future states is central to effective SA. Representing uncertainty in forecasts does not weaken situational awareness but strengthens it by encouraging operators to consider multiple plausible trajectories, thereby expanding the shared mental model of human-machine teams.

Two recent studies reinforce this perspective. Nadav-

Greenberg and Joslyn (2009) show that when uncertainty is explicitly communicated, even non-expert decision-makers make higher-quality judgments than when provided with deterministic forecasts. In power system contexts, Roald and Andersson (2016) argue that incorporating probabilistic uncertainty into operational optimisation enables operators to balance risk and reliability more effectively. Together, these findings suggest that uncertainty should not be an essential part of the design of a decision support system.

For Hypervision, this means reframing uncertainty from an unknown to a resource. Rather than striving for illusory precision, the interface should facilitate exploration of uncertainty ranges, support reflection on trade-offs, and give operators the ability to test responses across scenarios. In doing so, it aligns with the larger shift toward designing for complexity (Hollnagel, 2005). Here resilience is not achieved through simplification, but through transparency, adaptability, and shared reasoning under uncertainty.

1.11 HUMAN AI TEAMING

The increasing complexity of power grids has highlighted the limits of traditional automation. While automated tools can provide forecasts, diagnostics, or suggested actions, they are often confined to fixed functions and lack the adaptability required in dynamic and uncertain conditions. Especially decision making contexts. In contrast, the concept of teaming recognises that humans and artificial intelligence systems should function as partners in decision-making rather than as operators and tools. This framing shifts the discussion from automation, where machines replace specific human functions, to collaboration, where both agents actively contribute to shared goals.

Human-AI teaming (HAT) is therefore not simply about inserting AI into existing workflows, but about designing joint cognitive systems where humans and AI coordinate, cooperate, and collaborate.

Essential Elements of Teaming

Teaming implies that humans and AI act as teammates working toward shared goals, dynamically coordinating their roles and actions. A team, as defined by Salas et al. (2017), is "two or more individuals that adaptively and dynamically interact through specified roles as they work towards shared and valued goals." In the Human-AI teaming (HAT) context, both human operators and AI systems are considered agents capable of perception, reasoning, and action.

Three foundational elements of teaming are often referred to as the 3Cs (Salas et al.):

1. **Coordination** - the arrangement of tasks and resources across the team to ensure timing and dependencies are managed effectively.
2. **Cooperation** - negotiation and conflict resolution, ensuring agents can balance competing priorities.
3. **Collaboration** - joint decision-making and the of shared rules, norms, and strategies over time.

For Human-AI teaming to succeed, these elements must be underpinned by team cognition. This includes shared mental models, mutual prediction of behaviours, and dynamic adjustment of roles in response to evolving contexts.

Situation Awareness as a Core Mechanism

As established earlier, shared situation awareness (SA) is critical to all high-performing teams. The ATSA (Agent Teaming Situation Awareness) framework extends this principle to Human-AI teams, where both humans and AI must maintain their own perceptual cycles of perceiving, comprehending, and projecting events, while also exchanging information with teammates.

Key mechanisms for SA in teaming include:

- Teaming Understanding (TU) - the shared mental product that encompasses knowledge of team members, tasks, and communication protocols.
- Teaming Control (TC) - the behavioural aspect of team SA, where authority and tasks are dynamically allocated between human and AI agents.
- The World - the shared environment that constrains and informs both human and AI agents, closing the loop of perception, comprehension, and action.

Unlike traditional automation, AI is expected not only to act but also to explain its reasoning and adapt its internal models to human expectations (value alignment). This enables mutual predictability, which is vital for trust and effective teaming.

1.12 MIXED INITIATIVE

Mixed-initiative systems are increasingly recognised as a cornerstone of Human-AI teaming. Unlike fixed automation, where the division of tasks between human and machine is predefined, mixed-initiative interaction allows both agents to take the lead depending on context. This dynamic alternation creates a more flexible and adaptive relationship, ensuring that initiative is not monopolised by either the operator or the AI. In safety-critical domains, such as power grid operations, mixed-initiative design supports resilience by enabling the AI to act proactively when necessary while ensuring humans retain authority over critical decisions (Methnani et al., 2024; Kim et al., 2021).

The essence of mixed-initiative interaction is its contextual adaptability. AI systems can monitor task demands, operator workload, and environmental changes, prompting interventions or suggestions at the right time. At the same time, operators must be able to query, override, or redirect the AI, ensuring that the system remains a teammate rather than an uncontrollable autonomous agent. In this way, mixed-initiative interaction builds the foundation for trust calibration, efficient collaboration, and robust decision-making.

Initiative Across Teaming Modes

Teaming modes are not fixed but evolve across contexts. Hoc (2013) identifies several modes that Human-AI collaboration may shift between, including:

- Perception support - AI enhances the operator's sensing of the situation (e.g., anomaly detection).
- Mutual control - AI critiques human actions against standards.
- Shared control - both agents act simultaneously on the same variable.
- Delegation - AI takes over specific functions.
- Full automation - AI operates without human intervention, though oversight remains essential.

What makes these modes effective is the way initiative shifts within them. In perception support, the AI takes initiative by highlighting anomalies, while the operator chooses whether and how to act on this input. In mutual control, initiative flows in both directions: the human initiates an action and the AI responds by critiquing, or vice versa. In shared control, initiative is constantly negotiated moment by moment as both agents act simultaneously. Delegation and full automation push initiative further toward the AI, but even then, operators must retain the ability to reassert control when needed.

1.13 PITFALLS

While human-AI teaming offers clear opportunities, introducing systems like Hypervision also comes with well-documented risks. One of the most prominent is automation bias, the tendency of humans to over-rely on automated recommendations. This bias can manifest as acting on incorrect AI suggestions (errors of commission) or failing to act because the AI did not issue an alert (errors of omission). Over time, highly accurate systems can encourage uncritical trust, reducing operators' inclination to question or double-check outputs. In a safety-critical context like a control room, such misplaced confidence can have severe consequences if the AI fails or produces misleading recommendations (Romeo & Conti, 2025).

A related issue is deskilling, the gradual erosion of human expertise when automation takes over tasks that operators previously performed themselves. As AI tools become more capable, human operators risk shifting from active problem-solvers to passive supervisors. This "use it or lose it" effect can make it harder to retain or develop critical competencies, leaving teams vulnerable if automation fails. Deskilling can also inhibit the growth of new expertise, since junior operators may have fewer opportunities to practise complex decision-making when AI systems consistently provide ready-made answers (Agarwal et al., 2025).

Another pitfall is complacency and loss of situational awareness. When automation reliably handles routine tasks, operators may disengage, leading to the well-documented "out-of-the-loop" effect (Endsley & Kiris, 1995). Reduced vigilance means that when unexpected events occur, operators may be slower to detect problems or lack the recent practice to intervene effectively. This undermines the very oversight role that humans are expected to play in high-automation environments.

Finally, accountability gaps can emerge in human-AI teams. If AI systems take on more responsibility, it can become unclear who is ultimately accountable for decisions. This diffusion of responsibility risks placing humans in what has been called the "moral crumple zone," where they absorb blame for system failures without having had meaningful control over the outcome (Elish, 2019). For Hypervision, it is therefore essential to define roles clearly and ensure that responsibility remains anchored in human expertise, even as AI systems grow more capable.

Summary and relevance

The reviewed literature highlights a shift in operational and decision-support paradigms from automation-centred systems toward collaborative intelligence, where AI augments rather than replaces human reasoning. Frameworks such as Joint Cognitive Systems and Human–AI Teaming describe this evolution as a move from predefined assistance to shared, adaptive sensemaking across operational timescales. These perspectives emphasise that future power-grid operations will depend on collaborative processes, transparency, and explainable system behaviour to retain trust and accountability under uncertainty.

By synthesising these insights, this chapter addresses **Research Question 1** by identifying the principles that underpin the development of the Hypervision concept. The findings show that Hypervision can be positioned as a framework that embraces system complexity rather than reducing it, placing collaboration at the centre of human–AI interaction. The concept emphasises **co-iterative planning,** where **both** the operator and the system **contribute** to **developing** and **refining strategies**. Through this process, the **interface becomes the shared workspace** that **fosters mutual awareness**, allowing human and AI agents to remain **aligned** in their understanding of the situation. Within such a workspace, **transparency** must be maintained by synthesising information while keeping underlying data layers accessible to inform operator judgment.

Moreover, **mixed-initiative interaction** should be supported so that the AI can offer insights from large-scale data while the human can test hypotheses and challenge outcomes through exploration. The tools should **facilitate** this **collaborative iteration** and mixed initiative to satisfy human cognitive needs and strengthen joint decision-making. These principles form the conceptual basis for the next chapters, which examines how current decision-making processes and human–machine interactions reflect or diverge from these envisioned forms of collaboration.

CHAPTER 2
POWER GRID OPERATIONS

This chapter provides the background necessary to understand the context of AI integration in power-grid control rooms. It outlines key concepts, frameworks, and developments that shape ongoing transitions toward collaborative human-AI operations. While not directly addressing the research questions, it establishes the technical and conceptual foundation on which later chapters build.

2.1 CONGESTION MANAGEMENT

Among the many challenges faced in control rooms, congestion is the most prevalent and increasingly recurring issue. Congestion occurs when the power flows on transmission lines or transformers approach or exceed their operational limits, threatening stability and reliability. Unexpected contingencies, such as equipment trips or weather-related events can quickly escalate into congestion issues in power lines or nodes.
While congestion is the most visible and frequent problem operators manage on a daily basis, other operational issues include:

- Voltage stability problems, where local or system-wide deviations from nominal voltage threaten equipment and grid reliability
- Frequency stability, as imbalances between load and generation lead to deviations that can cascade if not quickly corrected
- Grounding or star point issues which ensure can occur from grid segmentation as a result of fixing congestion issues.

Operators continuously navigate these overlapping problems under conditions of uncertainty and time pressure. Congestions may occur concurrently, requiring prioritisation and coordination across regions, while at the same time predictive assessments must anticipate the effect of future outages or load changes.
In practice, every intervention, whether a topological change, redispatch, or voltage correction carries trade-offs between cost efficiency and grid security. The operators therefore treat congestion management not as a single-objective problem but as a multi-objective decision process, surfacing a range of strategies that balance resilience, operational complexity, and financial implications (Viebahn et al., 2024).

2.2 SOLUTION TOOLBOX

When confronted with grid issues such as congestion, frequency deviations, or voltage instability, operators have a solution toolbox of measures they can deploy. These measures are not simple on-off interventions, but carefully weighed actions that balance system stability, redundancy, and economic consequences.

1. Topological Measures (Re-routing Power Flows)

The most common approach to congestion management is to re-route power through alternative paths in the network. By changing the configuration of substations and lines, operators can relieve overloaded elements and redistribute flows. Although this is a binary switching action, it relies more relies on the physical principle that power flows according to impedance. By opening or closing busbar couplers, or shifting configurations, operators can steer flows away from congested lines. These changes must always respect N-1 redundancy, ensuring that if one element fails, the grid can still withstand the loss. Operators therefore not only assess the immediate effect, but also validate that the new topology remains secure under future scenarios and forecast conditions. This means there is a strong strategical element to this decision making.

2. Redispatch of Generation

When topological actions alone do not fully resolve congestion, operators turn to redispatch. In redispatch, generation is scaled down in certain locations to solve congestion. This can involve both fossil-based units and renewables, and while it is effective, it comes at a financial cost, since producers need compensated for reducing their output. Redispatch is therefore a secondary but essential measure, often used in combination with topological actions to secure grid stability while minimising overload risks. Note that the process of redispatch costs time, as there is lengthy communication required between TenneT and external parties.

3. Temporary Loss of Redundancy

In critical situations, operators may place the grid temporarily in a non-redundant state. This involves deliberately reducing backup capacity. For example, creating a local "pocket" to isolate congestion, at the expense of robustness. While this can resolve an overload in the short term, it reduces system security and increases vulnerability if a new contingency occurs. Operators must therefore weigh the risks carefully and under close monitoring.

4. Frequency and Voltage Control

Beyond congestion, operators must ensure frequency stability by maintaining a balance between load and generation, and voltage stability by managing reactive power and transformer tap changers. These actions often operate in tandem with congestion management. For example, a topology change that relieves an overload may also affect voltage in a region, requiring compensatory measures.

In practice, the operator toolbox is less about choosing a single solution and more about balancing trade-offs: preserving redundancy versus resolving congestion, minimising redispatch costs versus ensuring security of supply, and addressing immediate risks while safeguarding the system for future scenarios. It is these trade-offs that are getting harder to navigate due to the increasing volatility and complexity and where a hypervision system can aid the most.

Operators must constantly weigh trade-offs when resolving problems in the grid. Rarely is there a single optimal solution; instead, decisions involve balancing competing objectives, including:

- Time - the need to act quickly under pressure.
- Compute power - limits on the complexity and scope of computational processes
- Cost - financial impact of remedial actions and operational choices. This also affects number of switching actions as more switching requires more maintenance and induces more wear.
- Safety and redundancy - maintaining reliability and avoiding unacceptable risks.

2.3 CONTROL ROOM OPERATOR PROFILE

Grid operators form the front-line of transmission system operation, managing both routine activities and unexpected events. They are highly skilled professionals responsible for maintaining real-time stability and safety of the power grid. Their role requires a deep understanding of infrastructure and protocols, as well as the physics of high voltage power systems. Their professional background is typically rooted in field work, with many having hands-on experience at substations before transitioning into the control room. Educational levels vary: some operators hold HBO-level technical degrees, a smaller number come from university backgrounds, while many at the 110 kV system control room begin as field workers and transition into operational

Aspect	Regular Operator	Senior Operator
Scope	Manages a region of the grid	Oversees the entire grid
Experience	Usually less experienced	Very experienced
Tasks	Day-to-day monitoring- Switching operations- Routine maintenance coordination	Strategic planning- Congestion mitigation and management- Redispatch decisions
Congestion Role	Handles smaller, straightforward congestion issues (often under supervision)	Takes over complex or critical congestion problems. -Strategic congestion mitigation
Communication	Contacts colleagues and stakeholders for switching and maintenance	Coordinates across regions and external parties
Decision Context	Works within set procedures; escalates when needed	Makes system-wide decisions under uncertainty and time pressure

Table 2.1: Differences between regional and senior operators

controller once they have experience. Control room operators are trained internally, as there is no education that aligns with the required knowledge and skill set. This mix of practical and theoretical knowledge shapes culture in control rooms.

Regular and senior operators

The operation of the power grid is organised into distinct roles, with regular operators focusing on local, day-to-day execution and senior operators overseeing system-wide strategy and crisis management. While their tasks overlap in areas such as congestion handling, the level of responsibility, complexity, and scope differs significantly. The table below (2.2) summarises the key differences:

Task category	Core Functions
Monitoring & Interpretation (CORE)	Analyse real-time SCADA, EMS, and weather data- Anticipate instability or overload scenarios
Decision-Making (CORE)	Resolve grid conflicts under time pressure- Optimise for competing goals (e.g., reliability vs. efficiency)
Communication & Coordination	Interface with DSOs, suppliers, and consumers- Collaborate across internal operator teams
Incident Management	Respond rapidly to outages, alarms, and faults

Figure 2.2: Control room operator tasks

Tasks and responsibilities

The work of grid operators is structured around a continuous cycle of monitoring, assessing, planning, and executing actions, with responsibilities differing by context and operator role.
At the core of every shift lies monitoring: operators track real-time grid status, detect deviations, and identify emerging issues. From this baseline activity, their responsibilities branch into two directions:

- Routine operations, such as checking schedules, coordinating maintenance (VNB), and executing planned switching actions.

- Unexpected events (ONB), such as equipment failures, unforeseen weather impacts, or congestion problems, which require rapid assessment and intervention.

When a congestion or system issue arises, operators assess the situation, run studies, and draft plans. Depending on severity, either the regular operator carries out switching actions or the senior operator takes over for complex remedial measures or strategic planning. Sometimes, the congestion issue does not require switching, as market dynamics or weather change will solve the issue by itself. The decision process typically involves communication with colleagues, external parties, or market stakeholders before executing the chosen solution.

The flow of activities can vary widely. In simple congestion problems, the process may consist of detecting an overload, making a quick topological change, and returning to monitoring. In complex problems, however, operators may need to coordinate redispatch, wait for external parties, and implement long-term solutions alongside short-term mitigation that may put the system at risk temporarily.
A typical operator shift illustrates this balance. Throughout the day, operators juggle routine monitoring, frequent maintenance activities, and interventions. Planned maintenance often dominates daytime shifts, while nights are quieter operationally but different challenges. Major interventions, especially those requiring coordination with external parties, can span hours and disrupt the flow of routine tasks.

2.4 MAINTAINING THE GRID STABILITY

Congestion management in the transmission grid is inherently a multi-objective problem. Operators must weigh system security against operational complexity, stability, and cost, often under significant uncertainty. The GridOptions tool approaches this through multi-objective optimisation, generating strategies that balance several objectives such as (Viebahn et al., 2024).:

- Minimising N-0 and N-1 load flows (grid security and contingency resilience) (see next subchapter).
- Limiting the amount of switching timestamps and topological depth (operational simplicity).
- Minimising switching distance between topologies (reducing complexity)

Beyond these, operators must also consider frequency stability, star point (grounding) security, and maintaining target voltages across different areas of the grid. Dispatch actions are often on the table as well, where market dynamics play a central role solving congestion issues. This expands the decision space far beyond purely technical optimisation, reflecting the reality that there is rarely a single "right" answer.
With all these layers of uncertainty and competing objectives, operators are effectively navigating a Pareto frontier: multiple valid solutions exist, each reflecting a different trade-off. In practice, the balance is often framed between two ultimate goals: cost efficiency and system security.

2.5 REDUNDANCY IN THE POWER GRID

In grid operations, different reliability scenarios are used to assess system security, most commonly the N-0 (normal operation) and N-1 (single component failure) conditions. In this context, redundancy is built not only into the cabling system but also into key components such as transformers. Every connection is designed with parallel infrastructure to practically guarantee reliability, even if part of the system fails.

The N-0 scenario represents the current live state of the grid, where all components are functioning as intended. It reflects the full, available capacity including redundant systems. The N-1 scenario models the grid under the assumption that one critical component has failed, whether it's a transformer, cable, or another asset. This is used as a standard safety benchmark to ensure the grid remains operational even under stress. In this context, the system is considered «secure» only if it can handle full operational load even with one component out of service.
As a result, operational planning typically treats only half of the physical capacity as usable under N-1 conditions. This ensures that if any single component fails, the remaining infrastructure can handle the full load without causing outages. In practice, however, operators may temporarily allow the N-1 capacity to reach 100-120% utilisation, which corresponds to 50-60% of the actual physical capacity. This means they are knowingly accepting some risk: if the wrong component fails during this period, an overload could occur. There is also some flexibility depending on the thermal properties of the cables. Operators account for this when assessing how far they can push the limits. For example, underground cables have limited cooling and offer less tolerance, whereas air-suspended cables cool more effectively and allow slightly more leeway.

2.6 MARKET DYNAMICS

The electricity market plays a central role in affecting the behaviour of both producers and consumers through price signals. Expected electricity prices influence supply and demand: when prices are high, producers are incentivised to generate more, while consumers may shift or reduce their consumption (Clean Energy States Alliance, 2022).
The increasing penetration of renewable energy sources (RES) has amplified price fluctuations in wholesale markets. A recent study of six European markets shows that price volatility has significantly increased since 2021, largely due to the weather-dependent nature of wind and solar energy (Pavlík, 2025). This volatility underlines the importance of flexible balancing mechanisms and demand-side response to stabilise the system.

For grid operators, these market dynamics directly affect daily work. Changing electricity prices alter the behaviour of producers and consumers, creating fluctuations in supply and demand that operators must constantly monitor. In situations of congestion, operators may attempt to scale the market down by requesting producers to reduce output, often relying on mechanisms such as buy-outs. Market prognoses play a key role: if forecasts suggest that price signals will naturally curb demand or incentive producers to reduce generation, operators may decide to wait and let the market balance itself before intervening. Whether or not such forecasts prove accurate is secondary. What matters is that operators use them as a basis for their decisions.

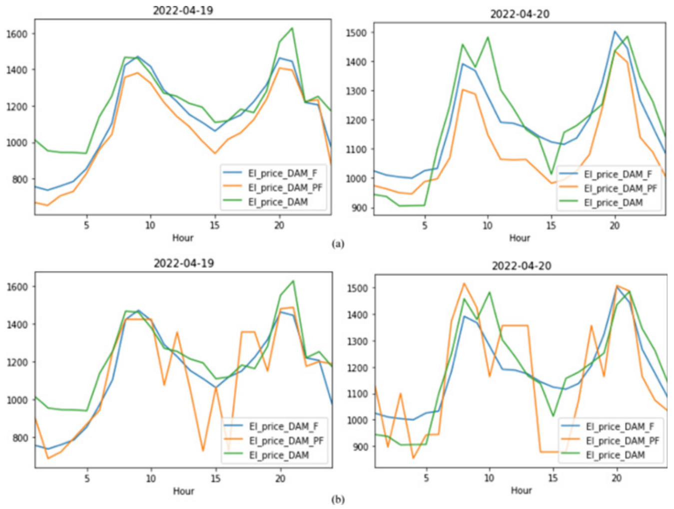


Figure 2.1. A series of energy price plots, highlighting the cyclic but voletile nature of the grid (Henriques & Colón-Ardila, 2023)

2.7 The Dutch National power grid

The Netherlands' transmission grid, operated by TenneT, is a multi-layered system structured by voltage levels and interconnected through substations and nodes. Understanding this topology is key to appreciating the operational complexity and the differentiated roles of grid operators.

Grid Topology and Voltage Levels

TenneT oversees the high-voltage system across multiple tiers:

- **150/110 kV (High Voltage)** : Serves as a regional network and interfaces directly with Distribution System Operators (DSOs) like Alliander. This level connects local consumption zones and serves as a buffer for voltage transformation.
- **220 kV and 380 kV (Extra High Voltage)**: These tiers form the transmission backbone that supports long-distance power flow, cross-border interconnectivity, and integration of large-scale generation, including offshore wind farms.

Nodes and substations are connection points between power lines and interfaces between TSOs and DSOs. Switching at this level is done tomanage voltage transformations and circuit switching. Substations also interface between different power grid voltage levels and connection to other countries' national power grids.

Each voltage level corresponds to a distinct operational domain:

- 110 kV control rooms focus on regional stability and coordination with DSOs. Operators here must manage local load patterns and resolve congestions in collaboration with parties like Alliander. This network lends itself well are the development ground for the control room of the future, as more topological optimisation are possible at this levels and redispatch possibilities are limited.
- 380 kV (and 220 kV) control rooms handle broader-scale operations, including international interchanges and supply security. These operators oversee cross-border flows and the balancing of large generation blocks, like HVDC subsea links and offshore wind integration.

Figure 2.2. An overview of different interface power grid, distinguished by the use of different colours (Palensky, 2024)

2.8 Interdependencies and Operational Impact

A change at one voltage level can cascade across the network. For instance, re-routing or switching at 150 kV may affect congestion in the 380 kV backbone, given the interconnectedness of substations. Operators must therefore not only manage their own domain but also monitor adjacent networks to anticipate potential impacts downstream or upstream.

In essence, while operators are focused on their assigned voltage level, they must maintain a holistic awareness across the grid. This layered control architecture enables resilience and agility in responding to dynamic grid conditions.

2.9 Control room scenarios

The operation of the power grid is structured around defined modes of operation, which place all operators in the same frame of reference. These modes reflect the state of the system and dictate both the focus of attention and the level of authority operators hold.

- **Normal**: Nothing unusual is happening. Operators monitor the system and ensure stability but do not need to enforce changes. If planned maintenance would risk creating unresolvable congestion, it is simply postponed.
- **Alert**: A threshold has been exceeded and potential congestion is developing. Operators begin to prepare solutions, such as requesting producers to scale down generation. If producers refuse, operators can initiate Buiten System Om (BSO) buy-outs to compensate those who need to reduce output.
- **Emergency**: A critical state has been reached where immediate action is necessary for safety. Operators have full authority to instruct producers directly, bypassing voluntary agreements. Plants must be informed of the instructions but no consent is required.
- **Blackout**: The most severe state, functionally similar to emergency conditions, where operators exercise full directive authority to restore or stabilise the grid.

Although grid operators make the final decisions and physically initiate switching actions, their authority is shaped by well-defined operational states and protocols. Even routine actions such as moving a switch or coupler require coordination with personnel on site to guarantee safety, as switching operations are loud and may endanger maintenance staff working nearby.

While operators are always the ones "pressing the button," their scope of authority is highly dependent on the operational state, with a shift from advisory roles in normal and alert modes to full directive authority in emergency and blackout situations.

CHAPTER 3

EXPLORATIVE STUDY IN THE CONTROL ROOM

3.1 INTRODUCTION (STUDY AIM)

The observation study aimed to gain a first-hand understanding of how control room operators manage the challenges of modern grid operation. It focused on how operators handle congestion, interact with current systems and tools, and deal with information flow challenges. The goal was not only to document decision-making in practice but also to understand the human perspective that must remain central in future control room design. Grounding the analysis in operators' daily realities provides insight into the situation that future decision-support concepts, such as Hypervision, must align with.

This study also serves a broader purpose within the thesis: identifying gaps and opportunities where design can provide value. Observing real practices links conceptual discussions of human-AI collaboration to operators' realities and highlights where current systems fall short. The study therefore forms the empirical foundation for subsequent design work.

Observations focused on key themes: communication between senior and regular operators, tool use and workarounds, forecasting practices and limitations, and how operators build and maintain situational awareness. Particular attention was given to how decision-making unfolds under varying workloads and how decisions are substantiated throughout the day.

Research Question

This chapter addresses the second research question, which examines how existing decision-making processes and human-machine interactions shape current power-grid control-room operations. The analysis presented here provides the empirical foundation for understanding the current limitations and opportunities for future human-AI integration.

How do existing decision-making processes and human-machine interactions shape current power-grid control-room operations?

3.2 METHOD

Participants

The participants were control room operators working at the 150/110 kV network within TenneT. This system works separately from the other power grids networks that are also operatated by TenneT. In total, eight operators were observed during the study period. Direct conversations were held with four of them. These included two senior operators, observed across two different shifts, and two regular operators. The senior operators primarily handled congestion events, while the regular operators were responsible for day-to-day tasks and communication with the senior operator about ongoing issues. thus, both offerened different w that are relevant in understanding the total context.

Setting

The study took place in TenneT's 150 kV control room (location classified for confidentiality). Observations were conducted across two half workdays, comprising the final four hours of one shift and the first four hours of the following shift, including the crew handover. During these sessions, several congestion events occurred, providing insight into how both routine work and high-pressure interventions are managed. Operations are conducted in the control room, which, as the name suggests is a single room where operations are concluded. Access to the room is restricted for most people as the operators have a critial job. It was therefore not possible to interview the operators directly and in a single session. A long-term obversation was therefore done that allowed observation during operation while comments and questioning about these operations in the moments between critical tasks were executed.

3.3 PROCEDURE

The researcher adopted a shadowing role, observing operator activities and using a "think-aloud" approach wherever possible. Reflective and explanitory questions were asked during periods of low cognitive load, such as in between decision-making episodes or after actions had been completed, to avoid disrupting operators during critical tasks. Data was captured through handwritten notes, sketches of system interfaces and processes (as photography was not permitted). Audio notes were recorded for personal use.
The observations were broad in scope, as no specific focus had been defined prior to the study. Attention was therefore given to a wide range of activities, including monitoring, communication, responding to congestion events, redispatch coordination, and routine decision-making processes.

3.4 DATA COLLECTED

The study produced field notes, timestamped descriptions of operator actions, sketches of systems and processes, descriptive accounts of decision flows and rough flowcharts to map system interactions.

3.5 SCOPE AND LIMITATIONS

The study was exploratory and qualitative in nature, intended to provide contextual understanding rather than systematically coded data. Although guiding questions were prepared in advance, they were used sparingly, as the focus was on naturalistic observation of real events. The study was limited by confidentiality constraints: recording devices and photography were not allowed, and the location cannot be disclosed. Furthermore, the data reflects a single workday (two half-shifts), although permission was granted to extend the study further.

3.6 RESULTS

The results are organised by theme. Each theme groups related findings from the study and highlights the key patterns that emerged. For every theme, a short set of take-aways is provided to summarise what matters for design and to make comparison across themes straightforward.

3.6.1. Technical restrictions and problems in forecasting

During the observations, prediction systems like forecast and strategy optimisations played a role in how operators anticipated and responded to congestion events. Operators were seen to frequently view forecasts to guide their situational awareness, yet in practice these tools often fell short of providing the support needed for reliable decision-making. What became apparent was a recurring struggle: while forecasts were available, they were not always aligned with real-time conditions, forcing operators to compensate through manual checks, additional analysis, and extensive backtracking.

These episodes also highlighted several technical shortcomings of the current systems. The accuracy and scope of forecasts are often insufficient, and the long update intervals reduce their usefulness for real-time operations. Operators stressed that both the amount and thus frequency and quality of available data must improve to make these systems more reliable and usable in practice. There is also clear potential for automation of specific routine tasks. For example, dispatch requests and operator-energy producer communications could be partially automated to reduce workload during high-pressure situations. Similarly, AI could play a role in continuously cross-checking forecast values against real-time measurements to detect deviations early.

One congestion event illustrated these issues vividly. A problem emerged that had not been forecast. The senior operator quickly implemented a “pocket” solution, isolating a section of the grid to reroute flows and relieve local overload. While this intervention was effective in the short term, it was described as a “quick and dirty” fix, putting the system temporarily at an increased risk. The operator then had to backtrack extensively across fragmented systems to find the root cause of the congestion. This involved comparing forecast data with real-time outputs and manually identifying discrepancies.

The episode showed that (take-aways):

1. Despite frequent forecasting, unexpected events still occur, especially due to weather or equipment failures. These cannot be entirely avoided but can sometimes be anticipated or mitigated.
2. Forecasts and real-time data can be poorly aligned, forcing operators to manually cross-check systems and forecasts with realtime.
3. Forecasts are often incomplete and run only every 1-3 hours, which means they are quickly outdated. Operators note that this limits their usefulness in real-time decision-making.
4. Forecasts lack explanations and fail to indicate why a problem occurs.
5. Systems are fragmented, requiring operators to dig through multiple layers of different tools to reconstruct the situation.
6. Operators themselves try to link congestion events to possible causes (weather patterns, scheduled maintenance, demand fluctuations) but the system provides no explanatory feedback and thus operators need to build this explanation themselves.
7. Operators rely on this cross-checking step to validate both the system’s output and their own choice before making a decision. There is a need for this verification as the operator bears responsibility.
8. Backtracking, cross-checking and verifying as a result of a misalignment between real-time and the forecast comes with a huge cognitive and time load.
9. The longer the final solution takes to be implemented, the longer the system is at risk.

3.6.2. Monitoring and operator activities

Observations showed that operators are continuously engaged in a cycle of monitoring, routine task execution, and decision-making. Their work can be described as a process of building and refining situational awareness by cross-checking data across different systems. Operators repeatedly move between tools to confirm or disprove emerging hypotheses about the state of the grid. For instance, a predicted load forecast might be checked against market forecasts to estimate whether a congestion issue will resolve itself without intervention. Such cross-checking does not occur continuously, but at specific moments when workload and situation allow. During monitoring, operators may proactively seek the causes of upcoming forecast events. This often involves checking market trends, weather forecasts, or maintenance schedules to anticipate whether a predicted congestion issue will materialise. These actions prepare them to intervene more effectively when the event arises.

3.6.3. Task Dynamics During Congestion

Task priorities shift dramatically when a congestion event occurs. At that moment, operators concentrate exclusively on resolving the immediate problem. In these high-pressure states, operators will occasionally only monitor the most indicative metric, which is thee loadflow capacity bar charts on the centre display in the control room. Additional information about strategic or long-term issues is counterproductive as attention is fully absorbed

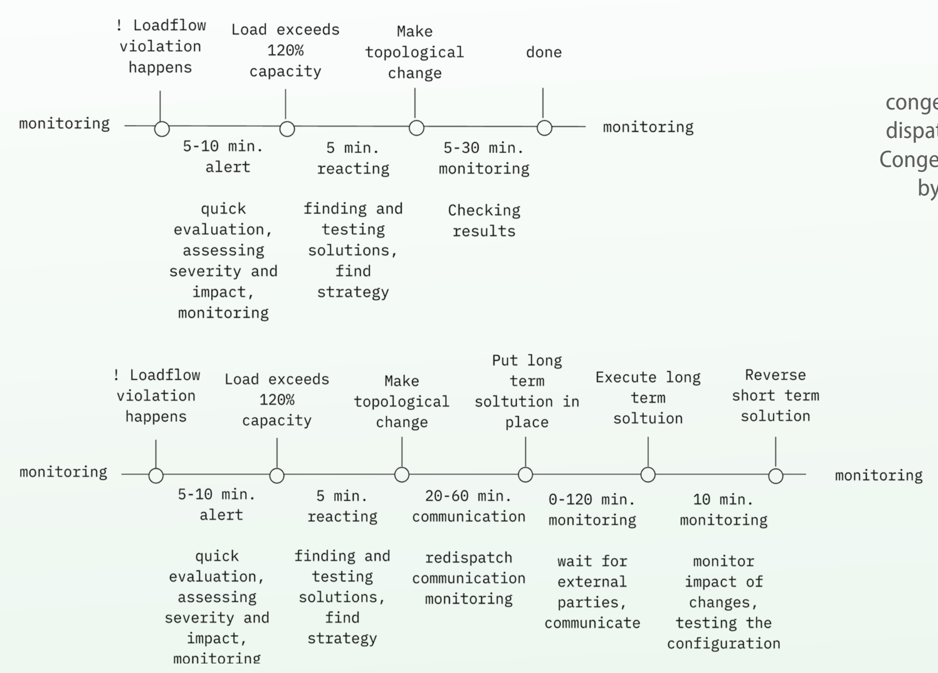


Figure 3.1 and 3.2: Top: congestion event that requires dispatch as a solution. Bottom: Congestion event that is solved by topological remediation

by the current task. During my observation for example, the solution was to scale back production of a power generation plant. Operators, following protocol must wait for responses of these companies before proceeding (Figure 3.1).Operators then return to monitoring activities, checking alarms and scanning the grid topology and running studies. These calmer moments create opportunities for additional information. At other times, congestion issues can be solved by making a quick change to the topology of the grid (Figure 3.2).

3.6.4. Routine and operator roles

The senior operator’s primary responsibility lies in congestion management and strategic planning. When not actively solving a congestion problem, seniors remain in a monitoring state, scanning for changes that could affect long-term planning or signal the onset of the next congestion event.

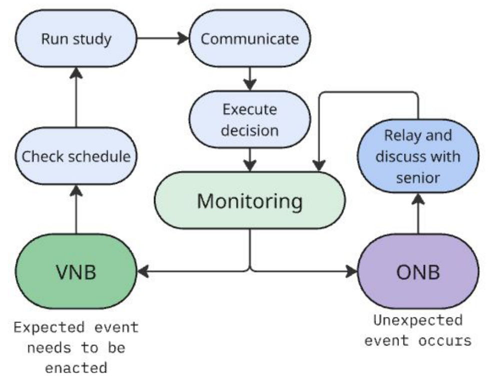


Figure 3.3: Senior operator task flowchart

By contrast, regular operators focus on planned maintenance coordination and communication. While they sometimes address simpler congestion issues, their routine work revolves around ensuring maintenance is communicated and executed safely and informing seniors and interfacing regional operators of local developments.

Both operator roles cycle between active intervention and monitoring phases, depending on system conditions.

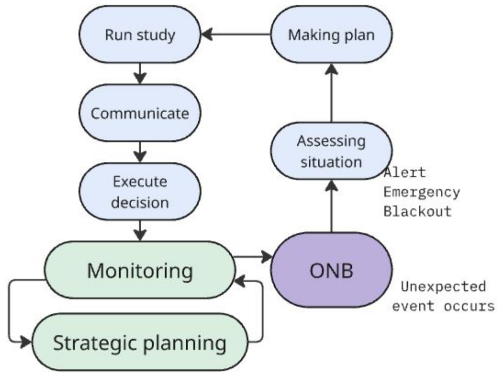


Figure 3.4: Regional/regular operator task flowchart

The diagrams from the observation illustrate this dynamic interplay: operators alternate between monitoring, running studies, communicating, and executing decisions. Unexpected events (ONB) and expected interventions (VNB) both act as triggers that move them out of monitoring mode into cycles of assessment, planning, communication, decision making and execution.

3.6.5. Simultaneous tasking

In figure 3.3 we find a typical, hypothetical activity timeline for a senior operator. It is inferred from the observations, but not directly observed. The timeline highlights nature of congestion management and maintenance tasks. The regional operator is handling maintenance task on a regular, planned and continuous basis. The senior operator, dealing with congestion management has a less regular set of activities. Congestion can happen at any time, in short succession of another and simultaneously with other congestion events. Some interventions are short in nature, while others take a longer time to implement. This is often when interfacing with other parties like production companies (energy suppliers) in the case of curtailment or redispatch. Note also how monitoring is a continuous process, always happening in the background. This is due to the sense-making nature in monitoring where any observation is evaluated for their meaning on the larger system.

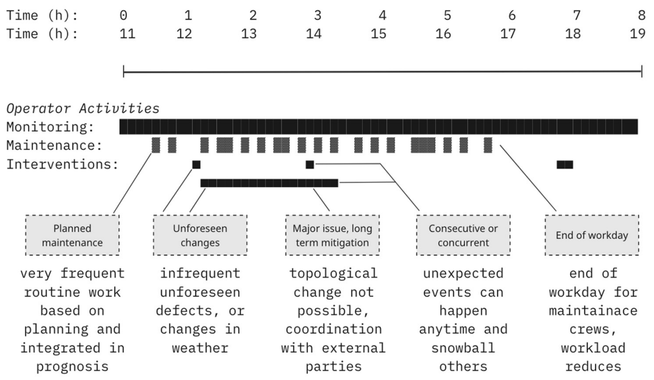


Figure 3.5: Typical control room activities and interventions plotted in time.

Take-aways:

1. Roles are clearly divided: seniors prioritise congestion management and strategy, while regular operators focus on planned maintenance and communication. Both roles depend on smooth coordination to avoid overlooking critical updates.
2. Monitoring is hypothesis-driven, not passive. Operators don't just watch data streams; they form working theories (and then seek confirmation or contradiction across systems. This means situational awareness is an active construction process, not a passive state.
3. Timing dictates whether exploration is possible. During high-pressure congestion events, operators narrow focus to the issue at hand. Only when having no higher priorities do they return to exploring other systems.
4. When operators are firefighting there is no time for exploration. This shows that information timing is as important as information quality.
5. Studies are an essential part of monitoring, serving as the operator's main tool to test and verify their own hypotheses about the grid's real-time state.
6. Monitoring spans not only technical data streams but also contextual and human factors, meaning operators must integrate heterogeneous sources to maintain situational awareness.

3.6.6. System overview

Monitoring spans multiple domains, combining technical system status with contextual factors. Operators track, among others:

- System status: load flow capacities, voltage, frequency, line status, alarms in SCADA/EMS
- Tools and models: PowerFactory simulations, GoPax, GridOptions strategy recommendations, FAB Dashboard
- External factors: real-time and forecast weather, fire/flood threat maps, market forecasts
- Planned interventions: switching plans, maintenance permits, active limitations.
- Ongoing anomalies: deviations from forecasts, unexpected alarms, unusual topology states.
- Human/team context: handover notes, informal reminders, confidence levels, and signs of cognitive strain.

While these are all sources of information, a key part of monitoring is running studies that test an operator's hypothesis on the real-time state of the grid. This happens in the real-time part of the system, called SCADA/EMS (Supervisory Control and Data Acquisition / Energy Management System).

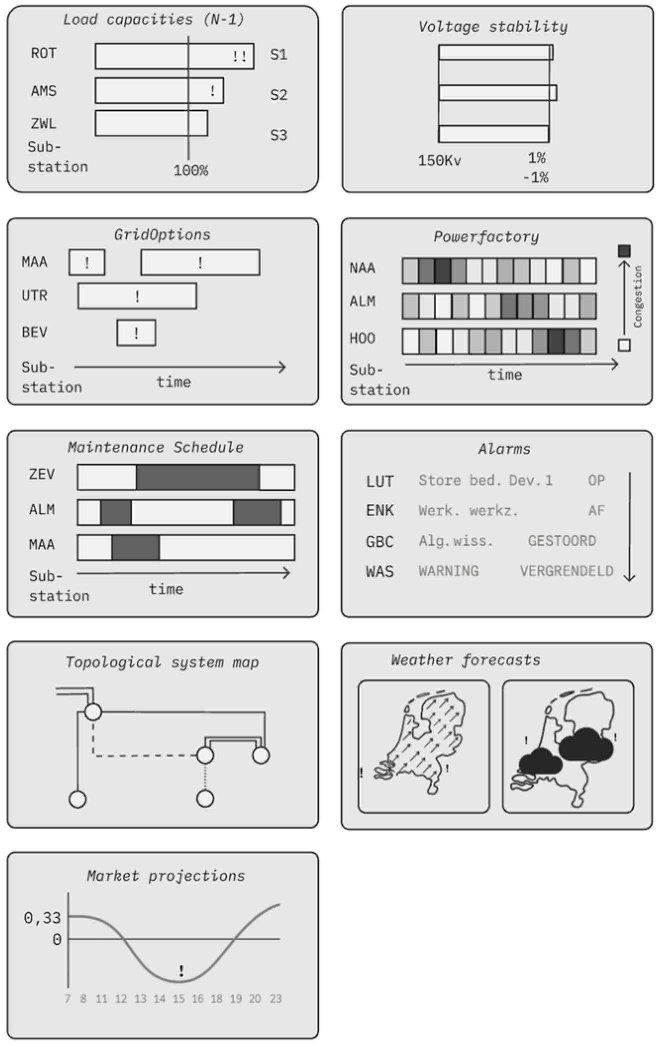


Figure 3.6: Examples of data types and visualisations that are used in the control room

The control room relies on a wide range of tools and interfaces, each providing a piece of the operational picture. Operators continuously shift between these systems, combining outputs to construct situational awareness and make decisions. While each tool has its own function, the value emerges only when operators cross-check and interpret the information across multiple systems.

3.6.7. Overview of Tools

- SCADA / EMS: Core monitoring systems that provide real-time grid status, alarms, and the topological map. Operators rely on these for immediate situational awareness and for validating whether interventions have the intended effect through studies.
- PowerFactory: Forecasting software used to get a sense of the forecasted load on every load on the intraday timespan.
- GridOptions: A decision-support tool that is powered by the data from Powerfactory. It proposes strategies to manage congestion. Operators consult it to compare system-recommended options against their own judgement. The program is in an early stage of development.
- GoPax: Provides an interface to communicate with interfacing companies and stakeholder, mainly about their prognosis of power consumption and production. Contains T-prognosis of production.
- Market Projections: Forecast graph showing the price of a kWh of electricity for the next 24hrs. Operators use these to judge whether congestion issues may resolve on their own. When it costs money to produce, companies will scale down as a result of the market.
- Maintenance Schedules: Displays planned interventions and active jobs for a long timespan.
- Alarms Dashboard: Flags anomalies or deviations requiring attention. This is one of the first triggers operators act upon.
- Weather Forecasts (e.g. Buienradar): Show real-time and projected weather conditions, used to anticipate congestion, validate forecast assumptions and help explain anomalies.
- Phone and Communication Tools: Used for direct coordination with producers, regional operators, and maintenance teams. These remain essential, especially when human confirmation is required.

Note that some examples can be found in figure 3.6. The exact interfaces cannot be shared inthis document for security reasons.

In figure 3.7 below some of the interfaces are layed out. It contains the operators' personal system layout (below) and the shared monitor wall that is present in the control room (above). For the latter - 1. Topological maps for each region showing the state of the grid, 2. Market forecast graph, 3 and

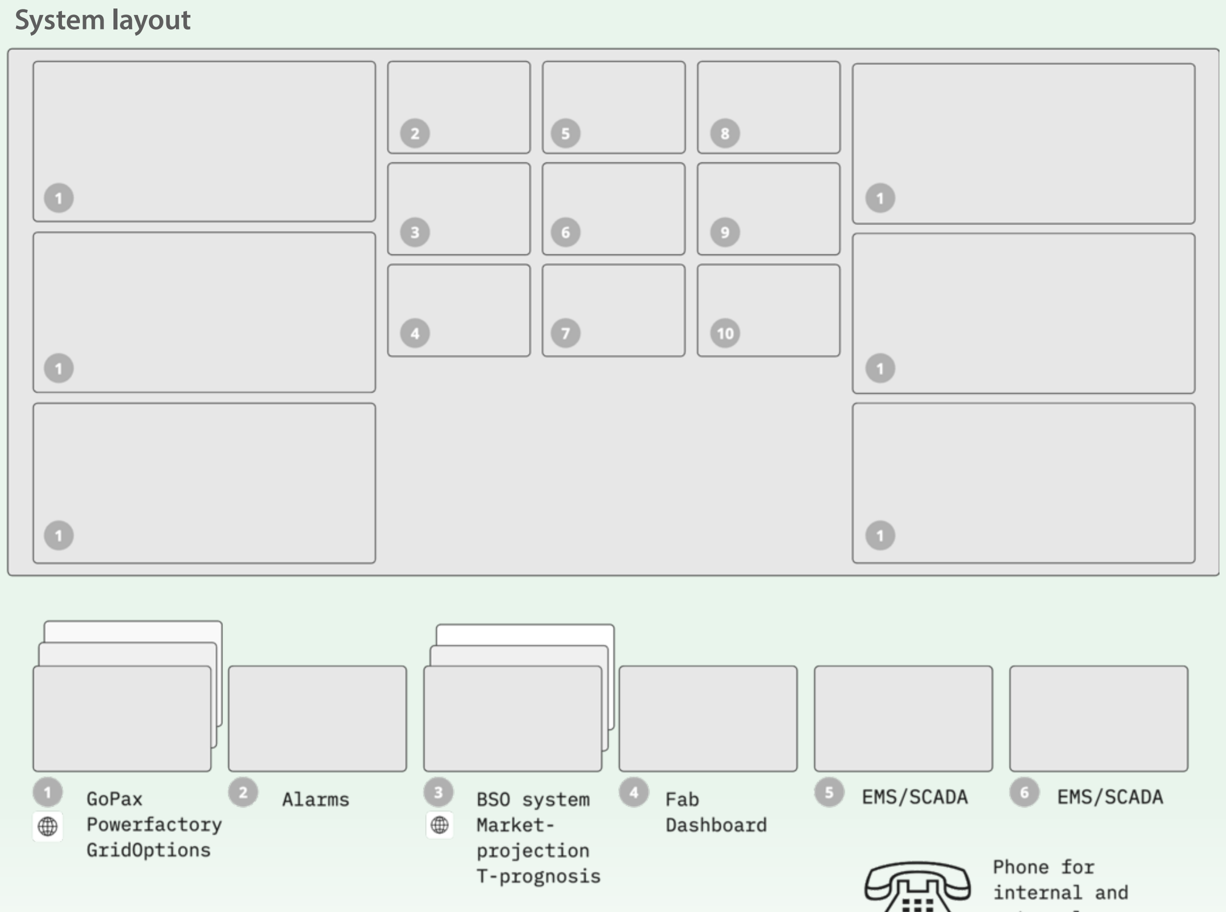


Figure 3.7: Above - Large control room display wall, Below - operator's personal workstation displays

4. Displays for renewable sources, 5. Buienradar, 6. Current Load flow status (N-1), 6. Current Load flow status N-0, 7. Incoming alarms, 8, 9 and 10 Graphs for supply/demand.

3.6.8. Synthesised vs. Raw Data

An important characteristic of the tool landscape is the balance between raw data and synthesised outputs. SCADA/EMS provides the rawest form of data — load flows, voltages, frequencies, and alarms. Tools like PowerFactory and GridOptions build on this, running simulations and producing recommendations that abstract away underlying complexity. This layered structure means that tools are interconnected: outputs from one feed into another, creating a chain of synthesis. While this can reduce complexity, it also introduces opacity.

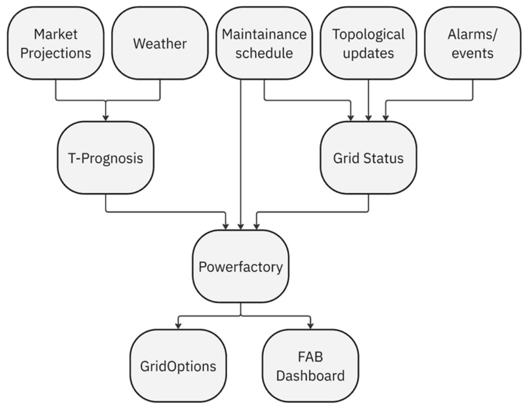


Figure 3.8: Data flow/data layering

3.6.9. The control room layout

The control room is laid out as follows: All desks are oriented towards a large screen (Figure 3.7, 1-10). Each desks houses a control room operator responsible for their own region. The senior operator sits in the middle. Besides the large screen that shows information for general use, each operator also has 6 individual displays at their desk.

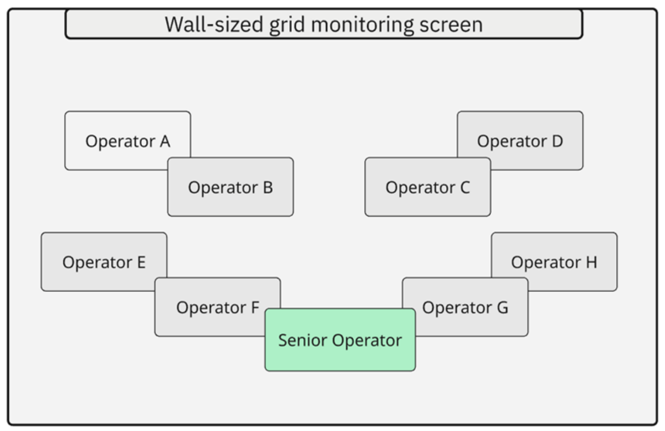


Figure 3.9: Floorplan of the 110Kv control room.

Take-aways

1. The control room layout reinforces hierarchy and collaboration. Senior operators are physically central, overseeing regional operators who each manage their own area. Shared displays provide a common reference, while personal screens allow focused regional monitoring. This physical setup mirrors the balance between individual responsibility and shared situational awareness.
2. Operators work with a fragmented but interconnected tool landscape. Each system provides only part of the picture, requiring operators to constantly switch between them. The value lies not in a single tool but in how their outputs are cross-referenced.
3. Data layering introduces both efficiency and opacity. Raw data from SCADA/EMS is transformed into increasingly abstract outputs in tools like PowerFactory and GridOptions. While this synthesis supports faster planning, it also distances operators from the underlying details they often need to validate.

3.6.10. Narrative building

During the observations it became clear that operators treat every emerging issue as an "open case" that needs to be followed until resolved. When an element goes offline or a congestion event occurs, the problem is mentally marked as active. Operators then track its development across time, updating their understanding as new information becomes available. Sometimes, notepads are used to keep track of open cases, but it needs to be noted that the operators are very good at keeping track of the ever-evolving situation, as if they are maintaining an internal list of open issues and associated to-dos.

What stood out was how operators related problems to the existing situation around these problems. Rather than seeing each alarm or overload in isolation, they wove events into the bigger picture: which substations were affected, which neighbouring nodes might be implicated, and how the situation connected to maintenance or regional patterns. This evolving image shapes the situational awareness.

The large topological map in the control room reinforced this process. Operators frequently glanced at the map, scanning it to anchor their mental storylines. While the map looked like a dense spaghetti to outsiders, operators read it with a quick glance, instantly recognising where problems were clustering and how flows were shifting. This ability to interpret the map highlighted the importance of pattern recognition, intuition and experience; skills that allowed them to project the situation forward and anticipate what might come next.

Story forming was not limited to reacting to alarms. Operators proactively correlated events with regional trends, market forecasts, or upcoming maintenance. In practice, this meant that situational awareness was always a mix of present monitoring and future planning.

3.6.11. Joint Control Framework analysis

During the observation study, a specific case presented itself that clearly illustrates how an operator interacts with the available systems when confronted with an unexpected event. This case involved a congestion incident that developed over time and required both immediate and longer-term interventions. Because it unfolded step by step, it provided a rich example for mapping the human-machine interaction using the Joint Control Framework.

The following description, structured into segments a-j, outlines how the operator perceived, decided, and acted in coordination with automation throughout the event.

To make the sequence accessible, the case is divided into segments labelled a-j, following the style of the Joint Control Framework examples. Each segment narrates the operator's reasoning and actions alongside the corresponding system responses. In the diagrams that follow, these steps are mapped as perception points (PP), decision points (DP), and action points (AP) on the operator's side, with presentation (P) and automation actions (A) on the system's side. This structure allows the reader to trace the interaction chronologically and to see at which abstraction levels the human and automation were operating. Note that the lines on the score sheet correspond to levels of abstraction. Where the bottom line represents Physical level, meaning sensors, buttons and datapoints that the operator or system may perceive or act with. Going up lines in the score sheet means going up in abstraction level. Starting at Physical, then Implication, Generic, Value, Effect and ending at Frame. Consult chapter 4 for in-depth explanation of how to interpret the framework.

Scenario narrative

a. Detection and initial monitoring

The operator notices a branch loading rise to 110%. While monitoring fluctuations, he decides not to intervene yet but to prepare a backup plan. He opens the topological map, scans the surrounding network, and identifies which nearby assets might provide relief if the situation worsens.

b. Cross-check with forecast

To understand the discrepancy, he opens the forecast system. The forecast shows no such congestion, leading him to perceive an inconsistency. He frames this as an unmodelled overload and begins hypothesising possible causes.

c. Escalation trigger

When the load climbs further to 120%, alarms confirm the severity. The operator recognises the threshold has been breached, decides immediate action is required, and initiates the procedure of exploring switching options.

d. Evaluating topological options

Using the topological map, he locates the problem area and forms two possible rerouting solutions. Each is tested by entering the configuration into SCADA contingency studies. The system executes the studies and presents results. The operator perceives the outcomes and judges that neither option adequately resolves the congestion.

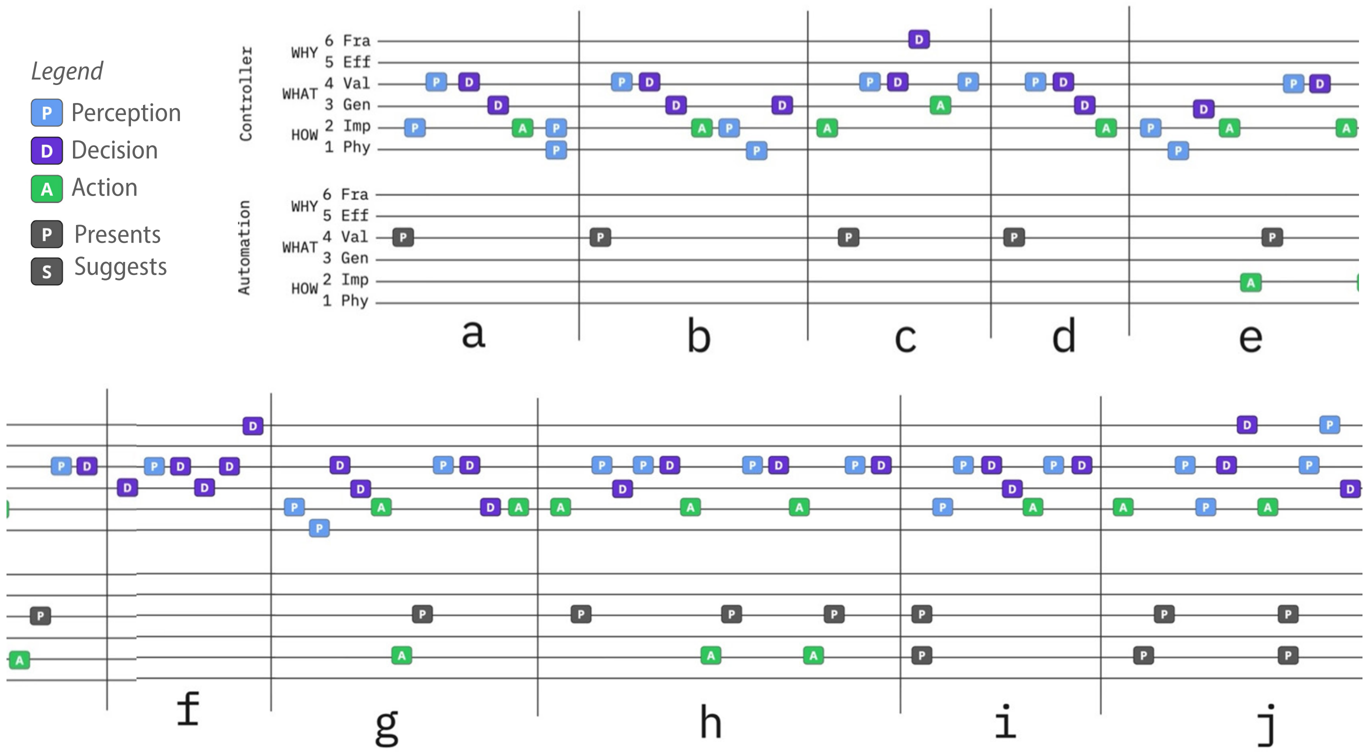


Figure 3.10: Joint Control Framework score sheet for the observed scenario in the control room.

e. Considering higher-level options

With switching insufficient, he turns to procedural alternatives. He recalls redispatch but recognises it is too slow for the current emergency. He then considers forced shutdown, but the risks remain high. Reframing the situation, he concludes that a short-term backup must be found outside the standard sequence.

f. Short-term backup through isolation

He returns to the topological map and identifies a possible isolation of a section. This would relieve the overload but reduce redundancy. He evaluates the trade-off, then follows procedure to test it in SCADA. The system runs the study and presents results confirming that congestion would be resolved at the cost of N-1 security. The operator accepts this compromise, specifies the switching sequence, and communicates it to the regional manager for execution.

g. Initiating redispatch

With the short-term fix active, he turns to GoPax for a long-term solution. The system presents the congestion surplus of 50 MW and the available producers. The operator interprets this, recalls the redispatch procedure, and selects a producer. He enters a redispatch ticket, the system processes it, and presents the expected relief. Seeing the reduction is insufficient, he submits a second ticket for another producer. The system confirms the combined relief meets the requirement, and the operator decides the long-term solution is in place.

h. Parallel monitoring

While waiting for redispatch to take effect, the operator continues to monitor the temporary isolation. Automation continuously presents the network state and overload values. The operator perceives the readings, judges the solution is holding, and maintains monitoring as a procedural routine, ready to react if conditions change.

I. root cause investigation

In parallel, he investigates the cause of the unexpected overload. He opens PowerFactory to check production forecasts against actuals. The system presents declared schedules (0 MW) and live measurements (70 MW). He perceives the mismatch, cross-checks with other systems, and reframes the situation: the surplus is due to a facility producing against its declaration.

J. closing the loop

Having stabilised the system through a temporary fix and long-term redispatch, and having identified the underlying cause, the operator now considers follow-up actions such as reporting the data discrepancy and ensuring forecasts are corrected.

Take-aways

What stands out in this case is the strong reliance on established procedures and recurring patterns of reasoning. Much of the operator's cognition follows a protocol-like flow: first monitoring values, then exploring switching options, and finally escalating to redispatch or shutdown when earlier measures prove insufficient. This highlights how procedural knowledge and structured routines shape decision making under pressure.

In contrast, the role of automation in the interaction is relatively limited. The systems are primarily used either to present values (such as flows, alarms, and forecasts) or to execute calculations (running contingency studies, processing redispatch tickets). They do not take on a more active or assistive role, such as suggesting alternative courses of action or highlighting inconsistencies across systems. The operator therefore remains the central agent in problem solving, with the machine functioning more as an information provider and calculator than as a collaborative partner.

Interactions with the system are very relatively limited. The systems are primarily used either to present values (such as flows, alarms, and forecasts) or to execute calculations (running contingency studies, processing redispatch tickets). They do not take on a more active or assistive role, such as suggesting alternative courses of action or highlighting inconsistencies across systems. The operator therefore remains the central agent in problem solving, with the machine functioning more as an information provider and calculator than as a collaborative partner.

3.7 Insights from the Observation Study

Firstly, the Joint Control Framework view highlights that in current control room operations, the machine has an assistive, automated role rather than a collaborative one. The system presents information and produces reports; operators have little ability to query, probe, or ask the system to try alternatives. Sense-making therefore depends on the operator digging into tools to correlate data manually. Strategy formation is likewise constrained because there is no practical way to try and test strategies against what is likely to come. This assistive role describes a one-way flow of information that does not pose any opportunities for interaction and iteration. Functions operate at relatively low abstraction Fragmentation compounds this: operators dig through multiple layers of different tools and information sources to reconstruct what is going on and often backtrack across systems. These findings indicate the forecasting tools are using as an information source rather than a teammate that helps frame develop proactive remediation strategies.

Secondly, power grid operations reflect a continuous cycle of sense-making/monitoring and decision-making. Operators build situational awareness, evaluate whether action is required, act when the moment arrives, then reassess. This effectively splits control-room work into two effective stages or modes: constructing and maintaining an evolving picture of the system, and deciding on actions based on that picture. In short we call these monitoring and congestion remediation. In practise monitoring forms an essential part of gaining situational awareness and that informs decision making. Most importantly, these processes are unstructured, dynamic and iterative processes. The root of which can be any trigger. The future system should allow for this initiative.

Thirdly, observations show a duality between uncertainty and the means to strategise that shift across timespans. Decisions in the moment are made in confidence because operators can see the immediate effects of their actions on realtime data. There is no need to speculate, because we know what the state of the grid in realtime is. However, the short windowed nature of reactive decision making leaves little time to optimise, and limits the available solutions due to procedural limitations. In intraday and day-ahead horizons, uncertainty is higher, which makes it difficult to comprehend what will happen and to stage strategies that prevent issues. Without a way to stage and evaluate options early, the work slides back into reactive responses that carry higher cognitive load and often lead to more expensive, sub-optimal outcomes. This highlights uncertainty shifting across timespans, along with goals and intentions, suggesting collaboration is not static.

Lastly, in terms of cognitive stimulation, the system underperforms as well. The tools does not stimulate exploration proactively. Operators mainly prepare to cope when events materialise, but they cannot readily explore or prevent because the tools do not allow them to test ideas, compare options, or iterate on prospective plans. While solving congestion brings pride and satisfaction, it also leaves a sense of limited agency over shaping the future state.

CHAPTER 4
DESIGNING FOR HUMAN AI COLLABORATION

4.1 DESIGN PRINCIPLES

Combining insights from the desk research in Chapter 2 and the observation study in Chapter 3, a clear pattern emerges in how operators interact with system tools and how these interactions could evolve toward future collaboration. The findings underline that while automation and optimisation tools already support grid operations, their role remains primarily assistive. To move towards a future state of hypervision, it becomes essential to understand how human-machine collaboration can better support operator cognition, decision-making, and adaptability in uncertain conditions. From these combined findings, the following summarisation can be drawn.

These insights highlight the need to translate the observed interaction patterns and operator practices into actionable design considerations. Doing so bridges the current assistive role of automation with the envisioned collaborative dynamics of future control-room operations.

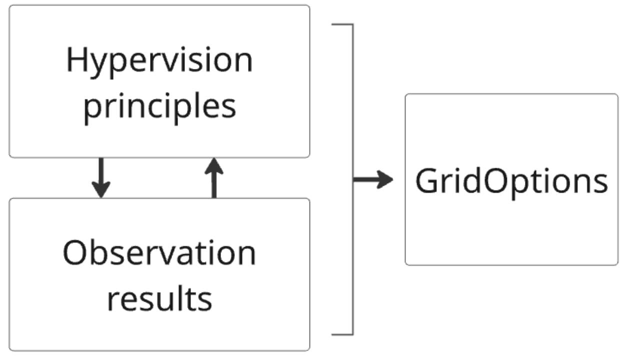


Figure 4.0. In this chapter we combine the theorhetical basis with results with the empical study in the control room and with power grid experts to inform the devlopment of GridOptions towards hypervision.

Research question 3
How can the understanding of current decision-making and interaction patterns be translated into concrete design implications for future collaborative human-AI operations?

Current human-machine interactions are assistive rather than collaborative. Operator processes of **sense-making are complex and dynamic**, and trying to fit a system that **simplifies power grid operations** is both **difficult and undesirable,** as it **inhibits human processes and cognitive needs**. The operator should be **cognitively motivated to develop hypotheses** and **stimulated to use system tools** to increase **situational awareness**, ultimately leading to better decisions.

There is a **significant opportunity to use forecasting and strategising tools to aid in the sense-making process**, but because current **functionalities are limited** and the interface **does not allow for human input,** much of this **potential remains untapped.** As we move towards **more proactive decision-making,** dealing with uncertainty will be key for effective congestion management. Current tools are **laying the groundwork for proactive, preventative strategisation and congestion remediation**, yet they **fall short** in their capabilities and UI functionalities.

From a hypervision point of view, the **system should play a central role in facilitating exploration** of operator ideas and hypotheses, while ensuring **transparency** in data layers and recommendations. Ultimately, this will leverage the **complementary strengths** in collaboration between human and AI.

Design considerations moving forward

Evolve from assistance to collaboration
Tools should support shared reasoning and co-creation, not just execute tasks.

Preserve cognitive depth
Avoid oversimplifying operations; design for human sense-making and hypothesis-driven exploration.

Empower proactive decision-making
Use forecasting and strategising tools to manage uncertainty and explore future scenarios

Ensure transparency and traceability
Make system logic, data layers, and recommendations visible and comprehensible to operators.

Leverage complementary strengths
Combine human intuition and contextual understanding with AI's analytical precision for genuine collaboration.

Reducing cognitive load
Overall, the system should aim to reduce cognitive load rather then add complexity and processes.

4.2 CHOOSING A DESIGN DIRECTION

Although a strong foundation for improvement exists within the current system, the scope for enhancement remains broad, and a clear focus is required. Collaboration is a broad and multifaceted concept that can be embedded at different stages of the congestion management process. From monitoring to decision-making and team reflection, there are numerous areas where collaborative practices could enhance both system performance and human engagement. The table below (4.1) highlights several key domains where collaboration offers potential for development.

Domain	Opportunities for Collaboration
Monitoring & Sense-Making	Exploration of emerging patterns
	Shared interpretation of system events
	Co-validation of forecasts and indicators
Congestion Remediation	Iteration on plans and strategies
	Joint evaluation of trade-offs and impacts
	Adaptive refinement of strategies during operation
Personal Improvement	Reflection on choices and behaviour
	Reflection on personal activities and performance
	Evaluation of decision-making strategies
Team Improvement	Reflection on team activities and performance
	Shared debriefing and post-event analysis
	Development of team strategies and norms
Cross-Shift Continuity	Shared situational handovers
	Collaborative event logging and annotations

Table 4.1. Opportunities for Collaboration across congestion management

Among the listed domains, **congestion remediation was selected as the primary focus area**. It represents one of the operator's main activities alongside monitoring and sense-making, making it central to the control process. Furthermore, the observation studies revealed a growing potential to shift from reactive towards proactive and preventative forms of congestion management. The forecasting and strategisation tools that enable this shift are still in early development and offer significant opportunities for refinement.

DESIGN GOAL

The previous paragraph establishes why collaboration is needed across the full congestion-management scope. Building on that foundation, this chapter sets out a concrete design target: to define and model co-iterative human-AI interaction scenarios (using the JCF) and, from these, derive the interface implications required to realise the intended interaction patterns in real life. Ultimately resulting in a mock-up interface that can then be tested and evaluated.

Goal

Define and mock-up a **collaborative congestion remediation platform** based on the **GridOptions** tool to help operators **understand, anticipate, and prevent** congestion across control-room scenarios

Output

1. **Collaborative interaction patterns** for three congestion remediation scenarios
2. **Design implications**, high-level elements/ functions that the interface must provide to enable scenarios the intended collaboration
3. **Interface design mockup,** based on the scenarios and design implications

4.3 DESIGN PROCESS

The design process was structured to bridge insights from research into an actionable framework for human-AI collaboration in power grid operations. Building on the outcomes of the observation studies and literature review, the process evolved through four key phases, each contributing to a progressively clearer understanding of how collaboration could be supported and made tangible through design.

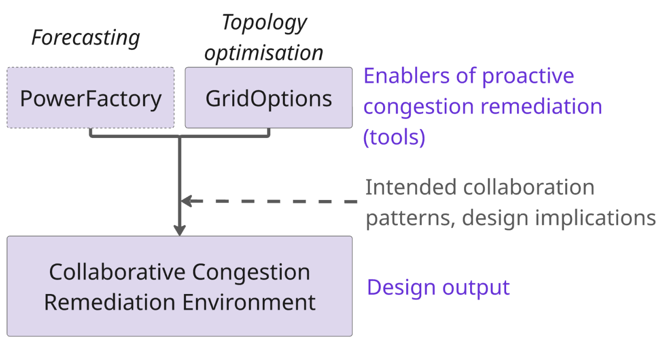


Figure 4.1. Showing existing tools as enablers for proactive congestion remediation, while using collaboration patterns and design implications to feed the design output.

a. Define Collaboration Timeframes

The first phase involved defining three control room collaboration timeframes—realtime, intraday, and day-ahead—to capture how uncertainty and time influence decision making. These timeframes provided a conceptual lens to understand how collaboration needs evolve as operational goals shift. By mapping these gradients of uncertainty, it became possible to study how roles, information needs, and initiative transition across contexts.

b. Map Collaboration Patterns Using the Joint Control Framework (JCF)

In the second phase, the Joint Control Framework was applied as a descriptive model to map intended human-system collaboration patterns across the three timeframes. Operator activities and system behaviours were analysed across levels of abstraction, revealing where initiative resides and how decisions emerge. This structured mapping exposed both strengths and limitations in the current system—showing, for instance, that the system predominantly acts as an executor rather than a collaborator. The resulting visualisation provided a grounded overview of existing workflows and the distribution of control.

c. Derive Needs and Design Implications through Scenario-Based Design

Building on the analytical and observational insights, the third phase used Scenario-Based Design to translate findings into actionable needs and design implications. This approach allowed the exploration of future interaction scenarios that reflected the desired human-AI collaboration patterns, identifying what capabilities, transparency, and feedback loops would be required to support them. These scenarios served as an intermediary step between analysis and design, ensuring that emerging concepts remained realistic and connected to operator practice.

d. Interface design

In the final phase, the design implications were synthesised into a mock-up interface demonstrating how collaborative interactions could unfold across timeframes. The prototype aimed to embody the intended collaboration patterns and design considerations identified earlier, showing how forecasting, strategisation, and plan iteration could become shared activities between human operators and AI systems. This outcome provided a concrete foundation for evaluating the proposed collaborative direction and guiding future development.

4.4 DESIGN OUTCOME:

Section A - Defining Collaboration Timeframes

This section building directly on insights from the observation study. The findings revealed that reactive decision making in the control room is guided by different goals and needs than proactive planning. This distinction suggested that collaboration itself evolves across time — as operational goals, uncertainties, and available resources shift between short-, medium-, and long-term contexts.

Using decision-making timeframes as a basis allows us to systematically describe how human-AI collaboration changes depending on temporal constraints and uncertainty levels. It captures the full spectrum of operational situations the tools must support, while reflecting the dynamic nature of operator needs.

Alligning with TenneT's operational structure, three timeframes were adopted: day-ahead, intraday, and real-time. Each represents a distinct mode of collaboration between operator and system. in figure 4.2 below, we find a visual representation of the changing decision making landscape across timescales.

- **Short-term (Real-time) - Reactive**
  At this stage, uncertainty is low but time is extremely limited. Operators must achieve a safe grid state as soon as possible.
- **Medium-term (Intraday) - Proactive Strategic**
  With moderate uncertainty and plenty of time, collaboration is about optimisation an iteration; making a robust plan. The human and the AI collaboratively work towards achieving that goal through iterations on strategies and staggering actions for robustness
- **Long-term (Day-ahead) - Proactive Explorative**
  Characterised by very high uncertainty but ample time, this phase supports joint exploration between human and AI. On this time-scale it is unfeasible to implement plans, as uncertainty will undoubtedly mean that forecast will change towards realtime. At this timescale we want to identity larger patterns and events that allow us to frame what is to come.

Together, these timeframes outline the key periods in which the Human-AI team operates. They are selected to show how collaboration evolves across operations, though their boundaries are not fixed. In practice, transitions are gradual as congestion events move closer to real time, shifting from uncertain to more predictable conditions.

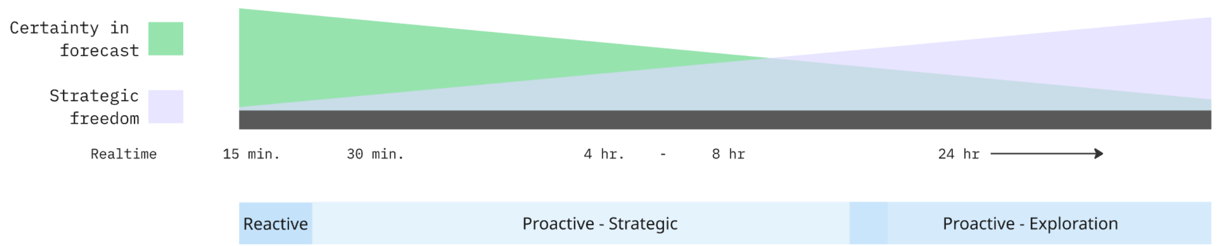


Figure 4.2: The inverse correlation between certainty in forecasting and the strategic freedom (time to make a decision and methods and tools that are available within that timeframe).

The Strategic Middle Ground

This diagram (figure 4.2) also shows the inherent effect that planning congestion does not happen in a single timeframe; A congestion forecast in the day-ahead stage gradually evolves into an intraday and eventually real-time issue as time progresses. As this happens, uncertainty decreases while time pressure increases. The theory underpinning this progression is that uncertainty inversely correlates with temporal proximity of the congestion events. As time extends away from real-time operations, uncertainty increases while time pressure decreases, giving operators more strategic freedom to explore, hypothesise, and shape long-term strategies together with the AI. In contrast, as events approach real time, uncertainty narrows, decisions become more constrained and time-critical, and collaboration shifts toward assisted execution and rapid validation.

Implementing strategies too far in advance is ineffective, as long-term forecasts inherently carry a high degree of uncertainty. Acting on them prematurely risks optimising for conditions that may never occur. This logic defines the strategic middle ground between day-ahead and real-time operations. The intraday timeframe offers a unique balance: it is early enough to allow for strategic freedom and meaningful intervention, yet close enough to real time for forecasts to hold sufficient accuracy. Within this window, collaboration between human and AI becomes most powerful as strategies can be adapted, evaluated, and implemented with confidence.

Early Identification as Leverage

Although it does not make sense to execute plans 24 hours in advance, it is crucial to identify critical patterns early. Detecting potential congestion early provides more than just foresight, it creates time as a resource. The earlier an issue is recognised, the longer operators and AI systems can track its evolution, test hypotheses, and refine their understanding of what is likely to occur. At this timeframe, there are also more remediation methods available then in the short term, like shifting maintenance.

This extended window enables iterative exploration rather than reactive problem-solving. Operators can continuously evaluate a broad range of remediation strategies, observing how each would influence the evolving system state. In practice, many of these strategies are first developed and refined during the middle of the intraday timeframe, when forecasts are sufficiently reliable to support meaningful planning.

However, even if a strategy is formed earlier, operators will often wait to act until conditions approach real time, when uncertainty has narrowed and confidence in outcomes is higher. This approach allows them to maintain flexibility for as long as possible while still benefiting from the deeper understanding gained through early identification and iteration.

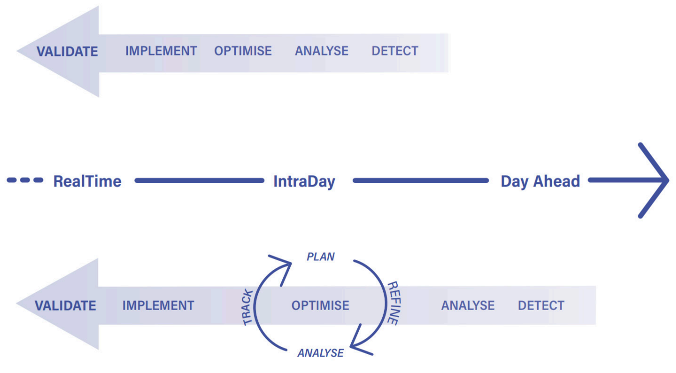


Figure 4.3: Opportunities in early adoption for congestion management

Section B - Mapping Collaboration Patterns Using the Joint Control Framework (JCF)

Understanding the Joint Control Framework

To analyse how human and system collaboration unfolds within different operational contexts, we used the Joint Control Framework (JCF) developed by Lundberg and Johansson (2021). The main reason this framework was used is to make the intended collaboration concrete and specific. The framework provides a way to describe how cognitive work, such as observing, deciding, and acting, is distributed between humans and automated systems over time. Rather than treating automation as a fixed "level", the JCF views collaboration as a joint control process in which initiative, responsibility, and information continuously shift between agents.

This approach is particularly relevant in power grid operations, where uncertainty, time pressure, and system complexity change dynamically. The JCF allows such interactions to be mapped and visualised, revealing how operators and AI share cognitive control across abstraction levels and timeframes. In essence, it translates complex collaborative behaviour into a structured, interpretable form that highlights both strengths and limitations in current workflows. However it can also be used to map intended workflow: collaboration.

Capturing Interaction Through Action, Decision, and Perception Points

At the core of the JCF is a temporal structure that traces how human-machine collaboration unfolds as a sequence of perception (P), decision (D), and action (A) points.

- **Perception points (P)** mark where information is received or interpreted, for example, when an operator identifies congestion in the system overview.
- **Decision points (D)** indicate moments where a choice is made based on that perception — such as selecting a line or time window for further investigation.
- **Action points (A)** represent the concrete steps taken to influence the process — for instance, activating a study or implementing a remedial plan.
- **Presentation points** are used to indicate that the system is prompting the operator with information
- **Suggestion points** are used when the system not only prompts the operator with information, but also proposes actions or strategies (recommendation)

By plotting these points across time, the JCF reveals the rhythm of collaboration: who perceives first, who decides, and who acts. This method also helps expose whether cognitive work is distributed appropriately — that is, whether the human remains meaningfully involved at higher cognitive levels while the system supports more routine or data-intensive tasks.

Cognitive Abstraction Levels in the Control Room

The JCF uses six levels of cognitive abstraction, each representing a different depth of reasoning and control. These levels describe what kind of cognitive work is taking place, ranging from direct interaction with equipment to abstract framing of operational situations. Together, they form the vertical axis of the framework, showing how collaboration shifts between physical actions and strategic reasoning.

Abstraction levels (Viebahn et. al., 2025)

- **Physical**. The location and status of the physical assets (e.g. lines, transformers, breakers) of the power grid. For the operator, observing the location and status of power grid elements, executing the giving of directions for a specific switching action via telephone.
- **Implementation**. A specific plan (i.e., sequence of actions), taking constraints into account (e.g., voltage or current limits when operating a specific breaker). For the operator, organizing the execution of a plan with the colleagues in the control room, in substations, or at other companies; limits on operator abilities to communicate with too many co-workers at the same time.
- **Generic**. A plan for substation reconfiguration, that can be potentially reused, that must be adjusted to the congestion situation, as well as to changing goals. Considering the operator, a procedure such as mitigating congestion in a certain region.
- **Values**. Performance indicators, such as the degree of safety and efficiency that is achieved, as well as trade-offs such as prioritizing safety over efficiency. Considering the operator, their workload can be described at this level.
- **Goals**. The goals that are generic to congestion management, such as safety goals and efficiency goals. The goals that the operators are currently concerned with in their work, such as having a backup plan for possible forthcoming issues in the grid, serving customers, and avoiding overloads by looking ahead.
- **Frames**. Power grid situations, such as congestion, voltage violation, maintenance execution - and the situations as observed by the operator.

Each level can involve both human and system contributions, and effective collaboration depends on maintaining coherence between them. For example, an AI tool might process data at the physical or implementation levels, while operators interpret and contextualise these insights at the values or framing levels. The JCF makes these transitions visible, helping to identify where collaboration aligns well and where gaps or redundancies exist.

JCF visualised

Figure 4.4 visualises the Joint Control Framework (JCF) abstraction hierarchy and control loops. It represents how human and system collaboration unfolds across levels of abstraction (from physical to frame) and levels of control (planning, acting, interpreting, and displaying). The circular part shows the decision making cycle as an interaction between human interpretation and system execution, while the timeline extension visualises how decisions, actions, and automation unfold over time. Note how interaction points are plotted as time progresses and how they occur at different levels of abstraction. The loop highlights the cyclic nature of the decision making process across abstraction levels. This is very much in line with our earlier assessment of Ramussen's Decision ladder.

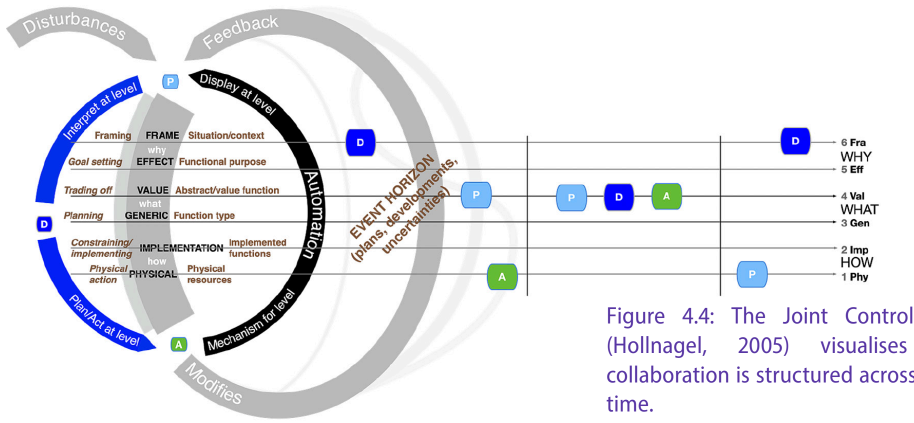


Figure 4.4: The Joint Control Framework (JCF) diagram (Hollnagel, 2005) visualises how human-automation collaboration is structured across abstraction levels and across time.

Defining collaborative interaction patterns

A series of three iteration patterns were developed to describe intended collaboration across congestion management timeframes using congestion management tools. Forecasting and strategising tools; PowerFactory and GridOptions play a central role in the narratives as they enablers of more proactive decision making.
The narratives were developed in collaboration with control room experts and evaluated with data scientists and lead engineers on the GridOptions project at Tennet to make sure it aligns with the intended direction and is achievable/realistic.

Legend
- P Perception
- D Decision
- A Action
- P Presents
- S Suggests

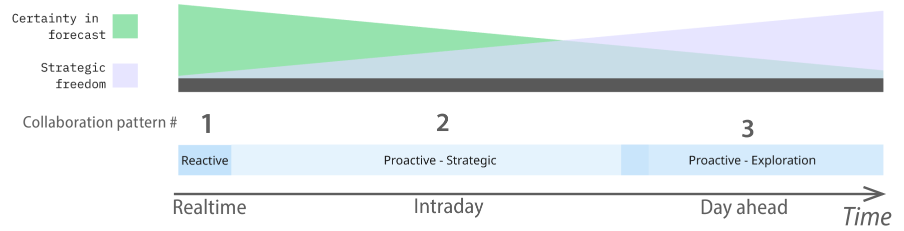


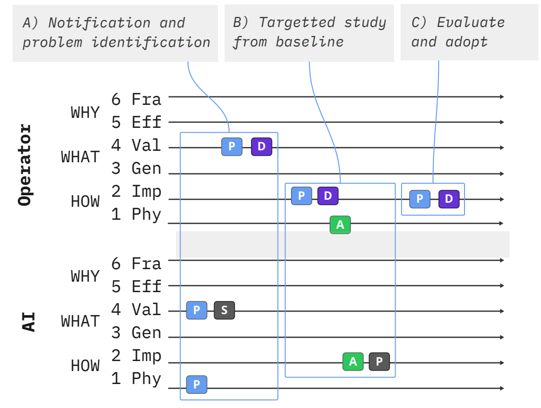
Figure 4.5: Mapped collaboration pattern timeframes

1. Realtime outage remediation

Section A - Identification
1. **AI[P][1-4]** Perceives outage of element and severe violation of security constraints
2. **AI[Suggests][4]** Conveys urgency to act based on violation
3. **Operator [P][4]** Perceives notification and identifies problem
4. **Operator[D][4]** Decides action is needed now

Section B - Congestion remedies optimisation
1. **Operator[P][2]** Looks at existing remediation plans based on N-1 calculation
2. **Operator[D][2]** Decides on quick N-2 validation with most recent data
3. **Operator[A][1]** Specifies constraints for optimisation (t<5 mins, focus on region X)
4. **AI[A][1]** Executes constrained N-2 optimisation
5. **AI[Present][1]**Shows results with trade-offs.

Section C - Evaluation
1. **Operator[P][4]** Evaluates results and effectiveness of options
2. **Operator[D][4]** Chooses plan than remediates congestion for N-2



2. Staggered Uncertainty Planning

Section A - Problem Identification
1. **AI[Presents][4]** Shows congestion is expected and remediation required
2. **Operator[P][4]** Comprehends the expected congestion
3. **Operator[D][5]** Decides to develop a staggered congestion remediation plan to cope with moderate uncertainty

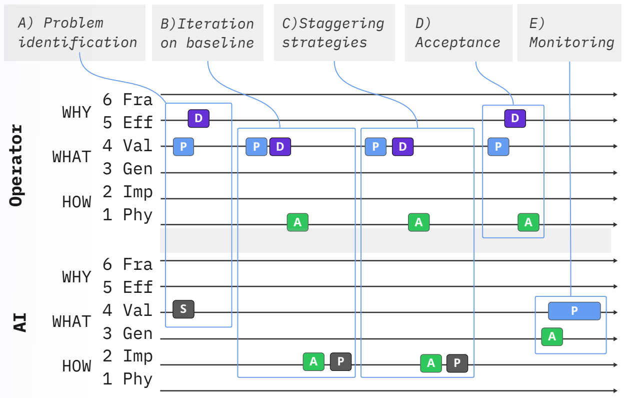
Section B - Iteration loop from effective baseline
1. **Operator [P][4]** reviews the N-1 strategy plans; one substation configuration dominates across effective strategies
2. **Operator [D][4]** judges strategy effective as starting point, but wants to balance reduction of congestion and the complexity of the plan
3. **Operator [A][1]** Set constraining substation configuration and request new N-1 optimisation for second substation configuration
4. **AI [A][2]** runs constrained N-1 Calculations
5. **AI [Suggests][4]** presents results and makes recommendation

Section C - Iteration loop for staggered strategies

6. **Operator[P][4]** Analyses results; highlighting persistent moderate congestion in 2 areas
7. **Operator[D][4]** Operator adopts most effective strategy; wants to target optimisation for residual congestion in region A and B
8. **Operator [A][1]** Set switch and staggered target regions, requesting new N-1 optimisation
9. **AI [A][2]** runs constrained N-1 Calculations
10. **AI [Presents][2]** presents constrained optimisation results for 2 scenarios

Section D - Acceptance and adoption
1. **Operator [P][4]** reviews results, uncertainty covered by staggered actions
2. **Operator [D][5]** judges remedial actions effective; adopts plan with staggered actions
3. **Operator [A][1]** Sets system to run subsequent optimisations on updated forecasts and to notify when congestion development increases to outside the capabilities of the plan

Section E - Monitoring
1. **AI [A][3]** System runs subsequent cyclic optimisations following the plan
2. **AI [A][4]** System monitors KPIs in order to notify operator when effectivity reduces



3. Scenario driven remediation exploration

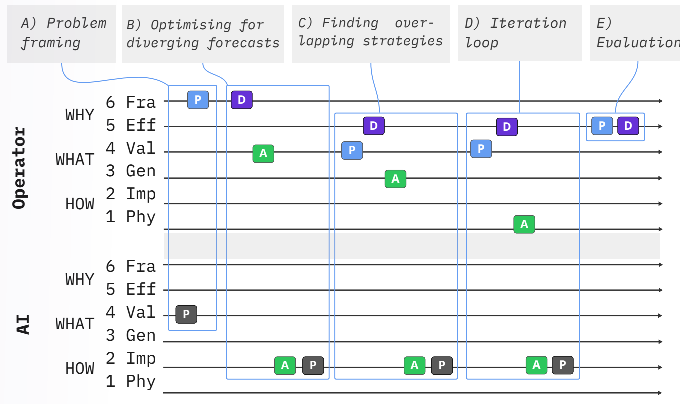
Section A - Problem framing
1. **AI[Presents][4]** Shows 4 different congestion forecasts; congestion is expected in all forecasts and remediation required
2. **Operator[P][6]** Notes congestion across forecasts differs in severity and location across grid and recognises a weather-driven uncertainty pattern: congestion is very likely to happen, but where and how much remains uncertain because it is significantly different between forecasts

Section B - Strategising diverging forecasts
1. **Operator[D][6]** Decides to develop a scenario-based remediation plans to account for (weather based) locational uncertainty
2. **Operator [A][4]** Requests a N-1 optimisation studies for 2 relevant diverging forecasts, possibly constrained
3. **AI [A][2]** Runs 2 new baseline forecasts (scenarios) N-1 optimisations
4. **AI [Presents][2]** presents constrained optimisation results for 2 scenarios/ forecasts

Section C - Finding overlapping strategies for single plan
1. **Operator[P][4]** Analyses results; different solutions have been found for each forecast
2. **Operator [D][5]** Operator wants to see if there is a strategy that works for both scenarios
3. **Operator[A][3]** Prompts the AI to runs studies, applying set of strategies from opposite scenarios
4. **AI [A][2]** Runs constrained set of strategies to find outcome
5. **AI [Presents][2]** Presents study results

Section D - Iteration loop for staggered strategies
1. **Operator[P][4]** Analyses results; strategies have an overlap
2. **Operator[D][5]** A robust plan that covers both scenarios can be adopted, but needs consecutive actions to be more effective. A staggered plan is required
3. **Operator [A][1]** Set constraining substation configuration and request new
4. N-1 optimisation
5. **AI [A][2]** Runs constrained N-1 Calculations
6. **AI [Presents][2]** Presents constrained optimisation results for 2 scenarios

Section E - Evaluation
1. **Operator[P][5]** Analyses results; staggered plan is robust effective
2. **Operator[D][5]** Operator decides to wait and monitor effectivity over time



Collaboration pattern	1	2	3
Description	**Realtime outage remediation**	**Staggered Uncertainty Planning**	**Scenario driven remediation exploration**
Uncertainty level	*Low*	*Medium*	*High*
Problem characteristics	*Reactive*	*Preventative*	*Explorative*
Tentative timeframe	*Realtime*	*Intraday*	*Day-ahead*
Abstraction level focus	*Implementation/plan*	*Value/trade-offs*	*Goal/ Frames*
Goal	*Specify single plan*	*Specify a set of staggered plans*	*Specify plan families for divergent scenarios*
Challenge	*High speed congestion remediation*	*Robust remediation under medium uncertainty*	*Probabilistic problem identification, explorative remediation*
Tasks — Operator	*Constrain and guide, implement*	*Prioritise, develop, plan, evaluate, implement*	*Identify congestion patterns and trends*
Tasks — AI	*Fast optimisation*	*Conditional optimisation*	*Probabilistic optimisation*

Table 4.2: Overview of the three interaction modes across time-scales, showing how uncertainty, abstraction level, and operator-system tasks evolve.

Insights from collaboration patterns

The table above (table 4.2) serves not as a result in itself, but as a way to distinguish how the three interaction modes differ in terms of uncertainty, abstraction, and reasoning. Across the three timeframe, the interaction patterns reveal how ambiguity, abstraction level, and operator reasoning evolve together. The differences can be understood through the lens of Rasmussen's Decision Ladder (Rasmussen, 1986), which describes how human decision-making progresses from observation and interpretation toward planning and action. When operators are experienced and the situation is familiar, they can take shortcuts, moving directly from perception to action without climbing the full ladder of evaluation and goal formation.

In the realtime remediation pattern, this shortcut behaviour is clearly visible. The problem is well defined, the goal is unambiguous, and time pressure is high. The operator identifies the congestion event and immediately applies a targeted optimisation to resolve it. There is no need for reinterpretation or broader goal analysis. The interaction therefore takes place at a low abstraction level, where perception and action are tightly coupled and decision time is minimised.

In the medium-term proactive optimisation, some ambiguity is introduced, yet the situation remains sufficiently structured for operators to rely on procedural shortcuts. The congestion problem is already understood, and the task involves selecting and refining among predefined strategies. Reasoning is evaluative rather than interpretive: the operator weighs alternatives and iteratively guides the system toward a balanced trade-off. While decision-making still occurs within a constrained problem frame, the activity shifts slightly upward in abstraction, involving value-level reasoning about competing goals.

In the long-term anticipatory framing, however, the operator can no longer rely on these shortcuts. Uncertainty is high, and both the nature and scope of the problem are fluid. Decision-making now involves moving through the full ladder (from observation and interpretation to goal formulation) before action can be planned. The operator compares diverging forecasts and frames the underlying uncertainties to define what constitutes a relevant or robust strategy. Collaboration at this level is exploratory.

Towards design

The key insight for design is that **decision-making in the control room is dynamic**, changing with time horizon and uncertainty. As ambiguity increases, operators reason at higher levels of abstraction—moving from procedural response to comparative assessment of strategies, and, at longer horizons, to interpretative sensemaking. An effective interface must therefore accommodate this evolving cognitive landscape rather than support a single, static mode of operation.

The current optimisation and forecasting tools are largely informational displays. They visualise the system state and potential outcomes but offer no means for operator input or interaction. As a result, they support observation and monitoring rather than active collaboration or reasoning. This limitation becomes particularly apparent when decisions move beyond routine procedures and require the exploration of ideas or testing of hypotheses. Operators are naturally motivated to understand why a situation occurs and to test what if scenarios, yet the current tools do not enable this kind of exploratory engagement.

Introducing collaboration into such tools means recognising that the nature of human-system interaction changes across decision-making timeframes:

- In **realtime remediation**, collaboration is about rapid convergence—the system assists the operator in targeting and executing quick, constrained actions.
- In **medium-term strategisation**, collaboration becomes iterative—the operator guides and adjusts system-generated strategies to balance multiple objectives.
- In **long-term exploration**, collaboration is sensemaking-oriented—the system aids in comparing forecasts, revealing patterns, and framing uncertainty.

Designing for collaboration therefore requires tools that can shift fluidly between these modes. Forecasting and optimisation should not only present data but also enable iteration, and exploration, to support both operational objectives and human motivation to explore, test, and understand.

Section C - Design implications

Following the scenario analysis, a need analysis was conducted to identify recurring needs and interaction patterns across the three collaboration patterns. After this, the needs were categorised using a thematic analysis. This process involved clustering observations and extracted needs into overarching themes that reflect how operators collaborate with AI tools in the different decision contexts. The themes provide a structured understanding of where collaboration challenges and opportunities arise.

In addition to the post-it analysis, the Claim Analysis technique from the Scenario-Based Design (SBD) method (Carroll & Rosson, 1992) was applied to analyse the narratives. A detailed outcome of this analysis is provided in Appendix X, while a simplified version using post-its was created to facilitate the thematic analysis process. Following the Claim method, each line of the narrative was examined to derive corresponding needs, decisions, or implications. An example of this process is illustrated in Figure 4.6.

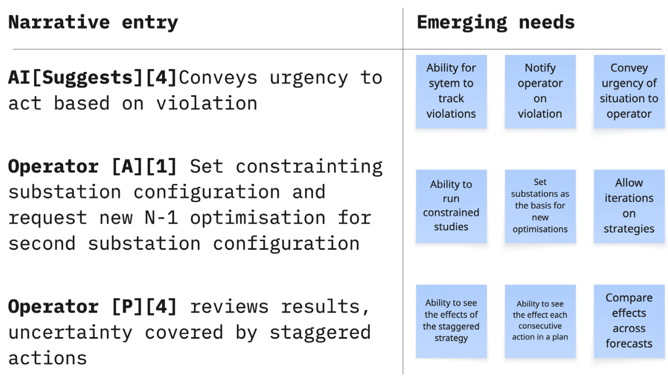


Figure 4.6: Example of using the claim method to derrive/ infer needs from scenario narratives

Thematic analysis

The thematic analysis of the interaction patterns resulted in six recurring themes that define how collaboration can be supported through interface design: Guidance & Control over Optimisation, Comparison & Sensemaking, Integration with Operational Systems, Notification & Communication of Change, Monitoring & Temporal Awareness, and Enabling Hypothesis Exploration. These themes represent complementary perspectives on human-system collaboration, each reflecting a distinct aspect of how operators engage with strategy optimisation, forecasting, and situational awareness in the control room context. Together, they provide a structured view of what effective collaboration requires from both the interface and the underlying system.

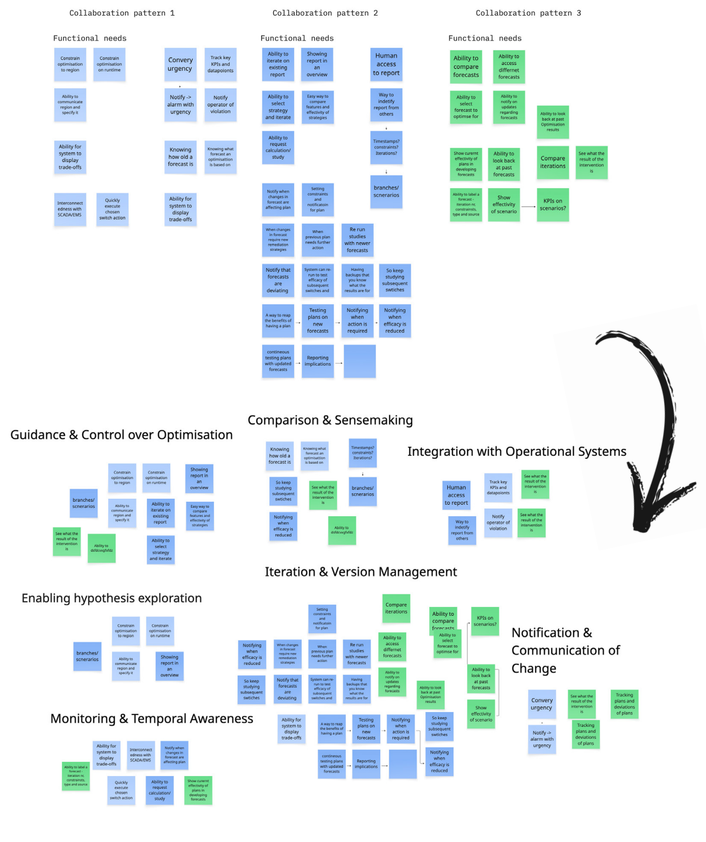


Figure 4.7: Top: Post-it notes with design with needs and implications for pattern 1-3. Bottom: Inferred themes

Structure of the Implications

Although all six themes contribute to shaping collaboration, their roles differ in scope and influence. The analysis showed that some themes directly enable collaborative decision-making, while others define the conditions or system attributes that make such collaboration sustainable. For this reason, the implications are organised into three categories:

- **Core Enablers** - These represent the primary mechanisms through which collaboration emerges. They concern how the operator interacts with and directs the optimisation process, and how hypotheses and ideas are explored through the interface.

Category	Theme	What it means	Why it matters for collaboration	What it implies for design
Core Enablers	**Guidance & Control over Optimisation**	Operators must be able to direct, constrain, and adjust optimisation processes, plans and studies	Ensures system output reflects human reasoning rather than replacing it.	Provide interactive control over existing studies and enable setting parameters for optimisation and constraining.
	Enabling Hypothesis Exploration	Operators need to explore ideas and test "what-if" scenarios.	Supports sensemaking and shared understanding under uncertainty. Reflects human needs	Allow user-initiated studies, comparisons, and visualisation of differences.
Inferred System Requirement	**Iteration Management**	Collaboration creates multiple versions and studies that need organisation, especially when identifying congestion day-ahead and iterating towards realtime.	Maintains continuity and traceability in exploration. Enables iteration from past versions and baselines. Enables human and AI to operate in the same environment, adding to SA. Enables comparison for collaborative analysis	Implement mechanisms to display, compare, and revisit iterations.
Supporting Attributes	**Integration with Operational Systems**	Forecasting tools must align or be compared with live operational data.	Keeps collaboration grounded in real-world conditions, shows deviations between hypothetical world and realtime.	Distinctions between realtime and hypothetical scenarios should be clear.
	Notification & Communication of Change	Operators need awareness of system and data changes.	Shows a critical element in shared understanding is monitoring change and the need for intervention, which is the trigger for collaborative interaction	Make updates visible, traceable, and communicable.
	Monitoring & Temporal Awareness	Operators must relate reasoning to unfolding timeframes.	Maintains situational grounding across time horizons. Enables collaborative sense making thorugh the use of the tools	Visualise temporal progression and system evolution.

Table 4.3. Example of using the claim method to derrive/ infer needs from scenario narratives

- **Inferred System Requirement** - While not directly identified as a theme, the need to manage multiple iterations and versions naturally follows from the iterative and exploratory character of collaboration.
- **Supporting Attributes** - These themes ensure that collaboration remains aligned with the operational context. They relate to how insights are integrated, communicated, and maintained within ongoing system operations.

This structure reflects the layered nature of collaboration: from enabling interaction and reasoning at the core, to supporting coherence and continuity within the wider control environment.

Design foundations

The thematic implications summarised in Table 4.3 reveal a layered understanding of what collaboration in congestion management demands from both human and system perspectives. While each theme highlights a distinct aspect of interaction, several broader findings stand out as central for guiding design.

1. **Collaboration requires interactive control and exploration** - At the core of collaboration are the abilities to guide system optimisation and explore hypotheses. These actions form the foundation for human-system co-creation, allowing operators not only to evaluate existing outcomes but also to shape and experiment with new ones. Collaboration emerges when the operator can meaningfully intervene, constrain, and test within the optimisation process. Thus transforming the tool from an informational display into a reasoning partner.
2. **Iteration management is essential to sustain collaboration** - The inferred requirement for Iteration Management underlines that collaboration is not a single act but a continuous, evolving process. Operators must be able to revisit, compare, and refine earlier studies. This demands a system architecture that records, relates, and visualises iterations to maintain continuity between short-term and long-term reasoning.

Collaboration depends on maintaining situational grip - The supporting attributes; Integration with Operational Systems, Notification & Communication of Change, and Monitoring & Temporal Awareness; emphasise that as collaboration becomes more exploratory, operators still need to maintain oversight. These elements help preserve a sense of what is happening, enabling operators to stay oriented, recognise changes, and connect ongoing activities across time. Maintaining this grip is what allows exploration and control to coexist.

Together, these findings indicate that designing for collaboration means **addressing both cognitive and systemic needs**: providing operators with **tools** for interaction, exploration, and continuity, while ensuring they retain **awareness and control** in a dynamic, uncertain environment. These insights form the conceptual basis for the following design phase, where they are translated into interface-level considerations and design principles.

Section D - Interface Design

Design principles

The following design principles translate the conceptual foundations of collaboration into practical guidance for the interface. They define how the system should behave to enable mutual awareness, human agency, interpretability, familiarity, and situational continuity. Each principle includes actionable directions that demonstrate how these ideas can be implemented through interaction design and information architecture.

Mutual Awareness

The interface acts as the shared cognitive workspace where collaboration occurs. It visualises both human and system activities, maintaining awareness of goals, actions, and changing system states.

Actionable design directions:

- Represent both human-initiated and system-initiated actions within a shared interface context.
- Display what the system is focusing on or processing (e.g., active forecasts, running optimisations).
- Provide visual continuity between operator actions, system responses, and outcomes.
- All actions utilise system functionalities and the system is used to store, present and monitor the results

Human Control & Exploration

The operator remains in charge of decision-making, able to guide and shape system actions. The tool enables exploration of curiosity, ideation, and testing of hypotheses to support sensemaking and creativity. Ultimately leading to human motivation.

Actionable design directions:

- Allow the operator to adjust optimisation parameters, set constraint for existing and baseliens strategies
- Allow the human to initiate new studies, optimisations, comparisons andother tool based forecasting or strategy related optimisations

Design for Complexity (Transparency & Data Availability)

The interface should reveal rather than conceal complexity. Operators must be able to access underlying data, understand how outcomes are generated, and navigate between layers of information without losing clarity.

Actionable design directions:

- Allow access to historical iterations, reports, and performance indicators.
- Display uncertainty explicitly where possible rather than oversimplifying outputs.
- Make uncertianty more tangible by tracking effect of strategies and configurations over time, implicitly offering transparency
- Use layered detail: overview first, deeper data access

Familiarity & Continuity

Collaboration should evolve naturally within the operator's established workflows. The interface should extend familiar tools, patterns, and layouts to reduce cognitive effort and ensure smooth integration.

Actionable design directions:

- Build on existing conventions (terminology, colour systems, data structures).
- Integrate seamlessly with current tools used for grid monitoring and planning.
- Introduce new functionalities through recognisable interaction patterns.
- Maintain consistent logic across modules to ensure intuitive navigation.

Maintaining Situational Grip

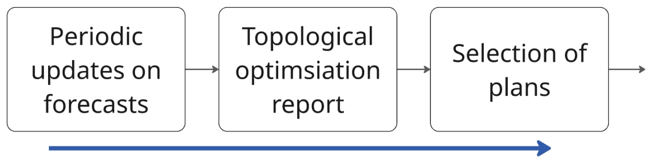
The interface must support ongoing awareness of live conditions while operators explore, plan, or iterate. Monitoring, tracking, and alarming functions ensure that exploration remains anchored in the operational situation.

Actionable design directions:

- Provide a continuous temporal overview (timeline or event layer).
- Integrate alerting mechanisms that flag deviations or emerging congestion.
- Visually link forecasts and current measurements to preserve context.
- Allow quick transitions between exploratory studies and live system views.

Building on these principles, the following design outcome demonstrates how collaboration between operator and system takes shape through the interface. The design translates the identified principles into concrete functionalities that align with the operator's workflow and cognitive needs.

The process of managing congestion is cyclical, characterised by continuous forecasting, optimisation, and planning. Each stage informs the next, and together they shape how operators monitor, explore, and respond to uncertainty in the grid.



The interface builds directly on this cycle. It connects forecast updates, optimisation reports, and the selection of plans into one continuous environment where operators can compare, refine, and evaluate their strategies.
What follows is a detailed explanation of how the interface enables this process by using time as a central element to understand uncertainty, evaluate strategies, and guide decision-making.

Congestion Remediation Dashboard

At its core, the interface is not only a tool for planning but also a tool for evaluation. Plans are continuously tracked across forecasts, allowing operators to observe how their interventions perform as congestion evolves. They can pin or select multiple plans and compare their effectiveness side by side, revealing which strategies remain stable and which begin to lose strength as conditions change.

This comparative view is central to the interface. It helps operators understand how interventions behave over time instead of seeing them as single, isolated actions. By observing plans across multiple forecasts, operators can recognise early when a strategy starts to drift from its intended outcome. The interface makes the interaction between intervention and system response visible, turning the abstract process of optimisation into something tangible and traceable.

Through this ability to evaluate and compare, the dashboard becomes both an operational and a learning environment. It provides feedback on decisions and builds intuition about which types of strategies remain robust under uncertainty.

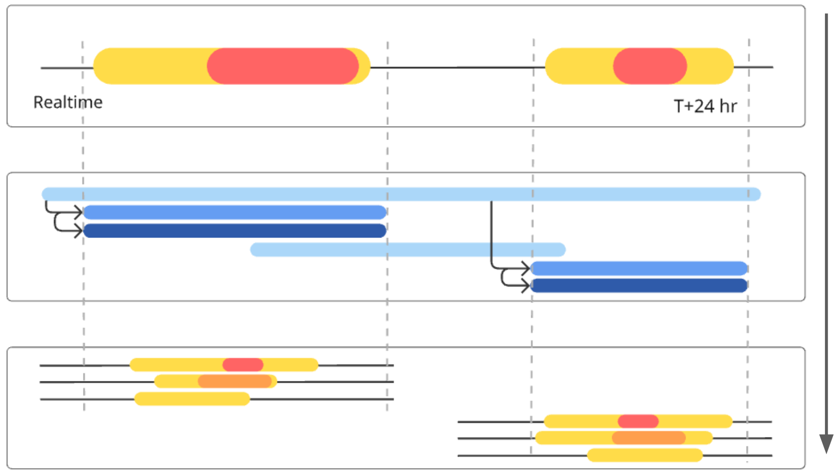


Figure 4.9. From identification to the adoption of plans, the interface vertically alligns forecasted congestion to related optimisastion reports, their iterations and their adopted plans. Simultaneously, it mirrors the natural proces of inferring optimsations from congestion and adopting plans from optimsations

1 Congestion Overview Panel

The Congestion Overview Panel forms the first layer of the dashboard and provides a real-time and forecast-based overview of congestion development. It allows operators to monitor incoming congestion based on the latest forecasts and to switch between previous versions through a dropdown menu.
By navigating between forecast versions, the operator can track how predicted congestion evolves over time and identify what has changed since earlier forecast, which is an essential aspect of maintaining situational grip.

A secondary dropdown enables the selection and comparison of forecast sources. Multiple sources can be unfolded simultaneously, revealing similarities and discrepancies between models. This function enhances transparency and supports a broader situational understanding by exposing the uncertainty inherent in forecasting.

(Design principles: Situational Grip, Design for Complexity, Mutual Awareness)

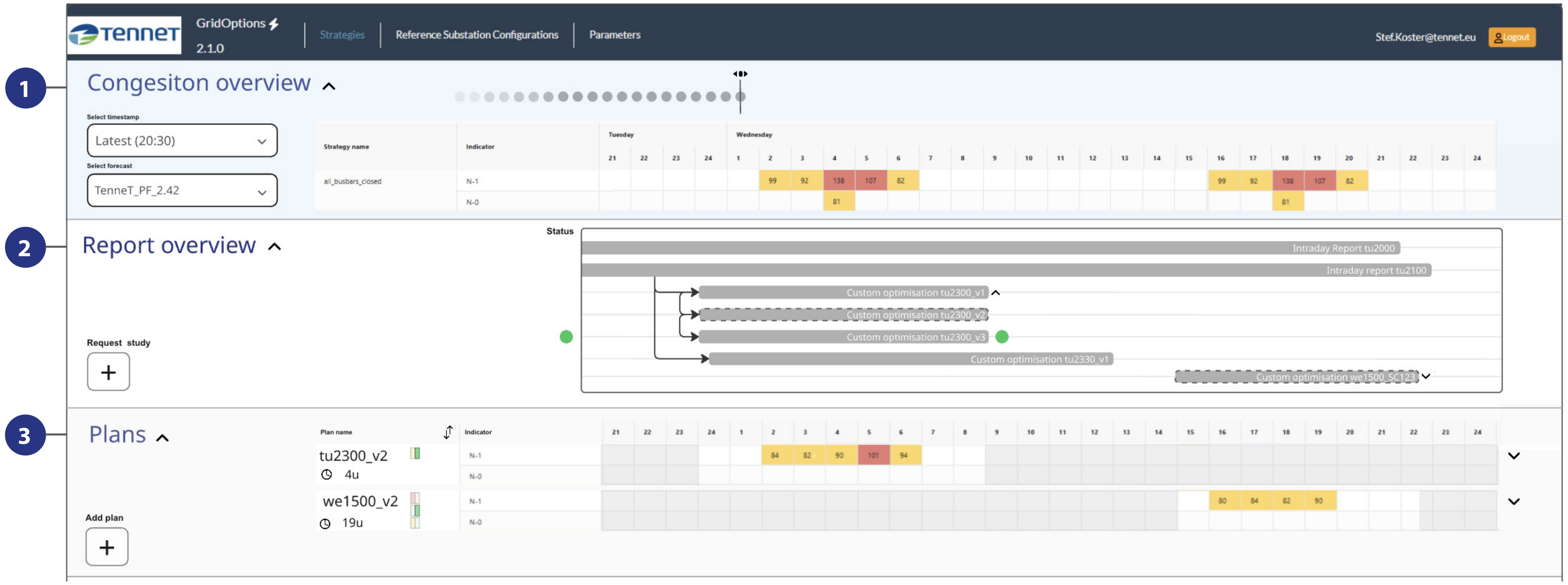


Figure 4.8. Mockup for the congestion remediation dashboard

2 Results overview panel

The Report Overview Panel acts as the version and data manager of the system. It forms the core workspace for organising and understanding optimisation studies. The starting point of these studies is the process of congestion remediation through topological optimisation, which is computationally intensive and often imperfect. These studies require a mix of algorithmic processing and human guidance to achieve meaningful results.

Operators can request new optimisation studies directly or view automatically triggered reports. The system periodically performs baseline optimisations whenever a new forecast is available. These provide a broad overview but are rarely the most effective. Operator-initiated studies, on the other hand, are more targeted and reflect the user's expertise and priorities.
The panel visualises these studies in a waterfall layout, showing relationships between reports, the strategies they contain, and their subsequent iterations. Connecting arrows link related studies, allowing operators to follow how optimisations evolve or branch out over time.

A key function of this panel is the ability to select and adopt strategies from reports and track their effect on the congestion forecasts. When a strategy is adopted, it becomes part of a Plan in the lower section of the dashboard. This connection between reports and plans allows users to follow how exploratory studies turn into actionable strategies, reinforcing the link between exploration and implementation.

(Linked principles: Human Control & Exploration, Design for Complexity, Mutual Awareness)

3 Plan Overview Panel

The Plans Panel contains all plans defined by the operator. A plan can range from a single switching action to a complex, staggered configuration strategy. It can also include multiple scenarios or subsets of strategies linked to diverging forecasts.

Plans can be proactive, developed ahead of time to prevent congestion, or reactive, used to monitor and adjust ongoing remediation. They can also serve as experimental concepts or hypotheses that the operator wants to observe over time as conditions change.

Any collection of strategies can be combined into a plan. Once defined, each plan can be tracked against evolving forecasts to evaluate its effectiveness. Having several plans active at once allows for comparison between approaches or between diverging forecasts.

The panel supports both detailed and compact views. In detailed mode, the operator can inspect each strategy, evaluate its performance, and explore refinements. The compact mode provides a minimal overview of essential indicators, ideal for background monitoring without distraction.

Plans can be added directly within this panel or created from strategies in the Report Overview. Because each plan can include multiple staggered strategies, small status indicators communicate how each iteration performs. These indicators make it easy to see when intervention or further refinement might be needed. This ability to track, compare, and adjust over time supports both situational awareness and collaborative iteration.

(Linked principles: Human Control & Explo-ration, Mutual Awareness, Situational Grip)

Visualising uncertainty over time

The essence of this intervention lies in using time as a tool to deal with uncertainty. By identifying congestion early and continuously monitoring how it develops, operators can track the effects of their interventions on the ever-evolving state of the grid.
The design introduces a way to see how actions play out across time, linking forecasts, plans, and live conditions into one continuous timeline.

Instead of reacting when congestion becomes critical, operators can now observe patterns, test strategies, and anticipate outcomes. Plans are no longer static responses; they become evolving hypotheses that can be followed, compared, and refined as new data arrives. This approach transforms uncertainty into something visible and traceable, which is an ongoing dialogue between prediction, intervention, and reality.

Through this temporal layer, the interface supports early identification, proactive planning, and continuous evaluation. It makes it possible to see not only where the grid stands today, but how it might behave tomorrow, and how well current strategies are holding up against change.

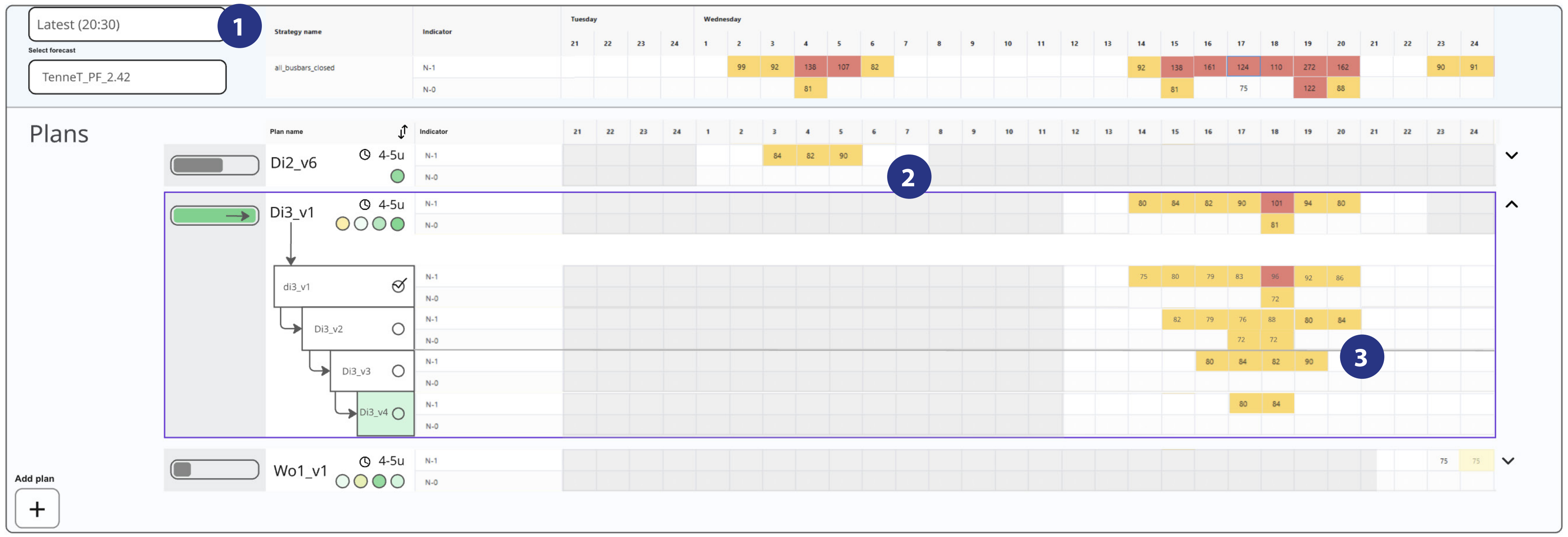


Figure 4.10. Mockup for plan interface

1 Timeline control

The first key functionality is the ability to scrub through time.
By moving along the timeline, the operator can review how congestion has developed across different forecasts. Older versions show what the predicted congestion looked like at that moment, and scrubbing back reveals how the forecast shifted with each update.

This same interaction also applies to solutions.
When scrubbing through time, we can see how the effectivity of a plan changes as the congestion evolves. It becomes immediately visible when a previously sufficient plan starts to lose effectiveness, or when a specific configuration begins to show strain.
This provides a clear sense of when to intervene and how our previous actions are holding up, helping the operator to plan and adjust with confidence.

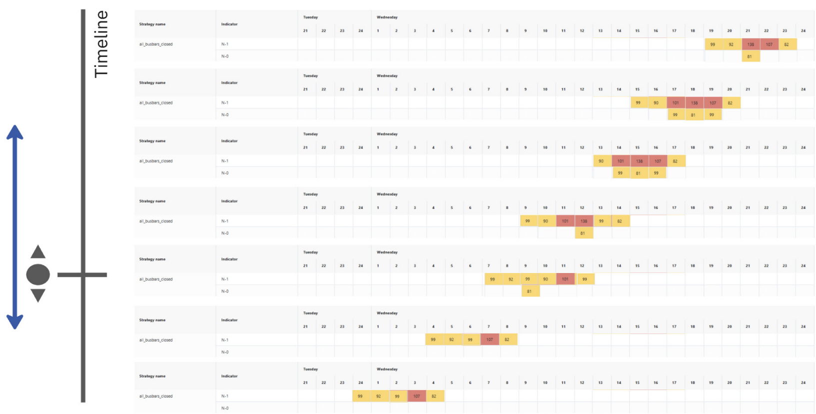


Figure 4.11. Scrubbing the timeline showing an stabalising forecast towards realtime

2 Tracking simple strategies

In one example scenario, a congestion event is addressed with two relatively simple plans. Initially, both are sufficient: the performance indicators show that either option would solve the problem.
However, as the event develops, the congestion changes character. The conditions shift, and the first plan quickly becomes ineffective. The second plan, on the other hand, continues to perform well.

This example highlights the importance of proactive planning and continuous tracking. By adopting and monitoring multiple plans early on, the operator can see which approach remains effective as new forecasts appear.
The interface doesn't just show whether congestion exists; it helps the operator understand how the system is responding to their interventions over time.

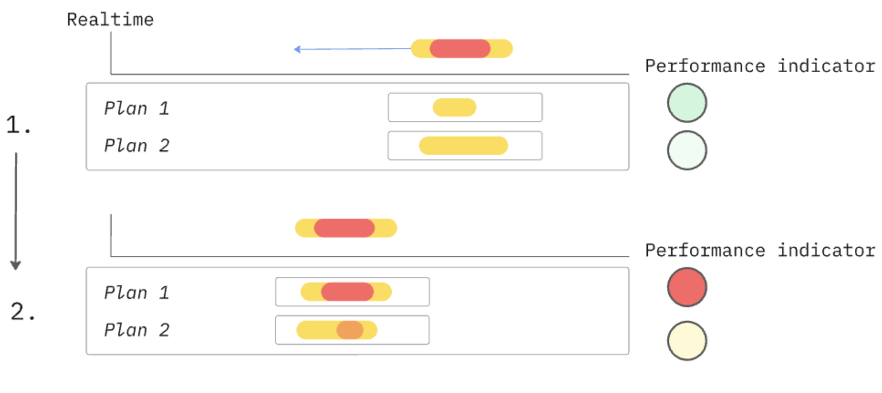


Figure 4.12. Impact of developing congestion on two remediation strategies on two, with performance indicators

3 Tracking staggered plans

The third example shows a more complex scenario: a congestion event managed through a staggered plan consisting of multiple iterations. Each iteration represents a different depth of intervention, from light adjustments to more invasive switching actions.

By tracking all these strategies within the staggered plan, the operator can see how deep the intervention needs to go to solve the congestion effectively.
This becomes especially valuable in the medium term, where actions can be applied consecutively as the situation progresses toward real time.

Having staggered actions available provides both flexibility and security—it ensures that backup strategies are always at hand, ready to be activated if the situation changes unexpectedly.
This layered approach to planning not only strengthens the operator's control but also transforms uncertainty into an organised framework for decision-making.

Figure 4.13 Impact of developing congestion on two strategies with staggered planning, with performance indicators

Constraining and guiding

A key aspect of the design is that it enables the operator to actively guide and constrain the optimisation process rather than simply viewing the outcomes. Every optimisation or forecasted configuration in the dashboard can be interacted with and used as a baseline, a starting point, or a reference for new studies (see Figures 4.15, 4.17).

Operators can click on any strategy, report, or plan and choose to set it as a baseline. Once selected, the system uses it as a point of comparison for new optimisations or as the foundation for follow-up studies. This allows operators to explore what changes matter and how far a new configuration deviates from a trusted setup (Figure 4.14).

Beyond selecting baselines, the interface also supports the creation of new optimisations directly from contextual menus (Figure 4.16). When initiating an optimisation, operators define constraints such as specific network regions, substations, or switching actions to include or exclude. These constraints allow expert judgement to steer the optimisation process, narrowing the search space and ensuring realistic and operationally sound outcomes.

The ability to both constrain and guide optimisations turns the system into a collaborative partner rather than an automated engine. It reflects a shift from passive assessment to interactive co-creation, where human intuition and machine computation complement one another. This strengthens human control, improves transparency in decision-making, and supports the iterative exploration of alternative grid strategies.

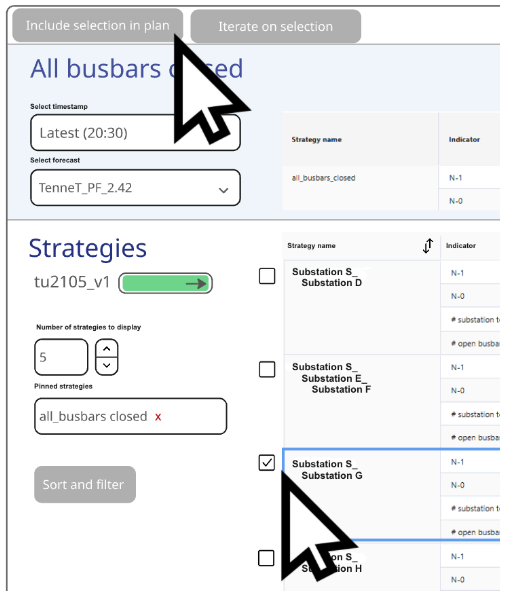


Figure 4.15. Interaction with congesiton remediation report, selecting a baseline

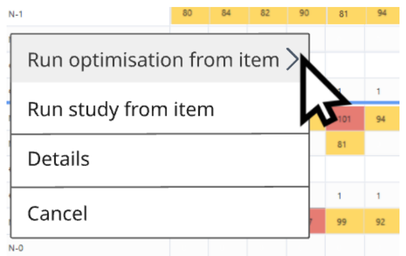


Figure 4.16. Interaction with interface to run a targetted study

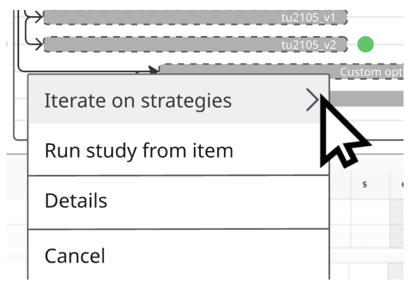


Figure 4.17. Interaction with interface elements to commence an iteration cycle.

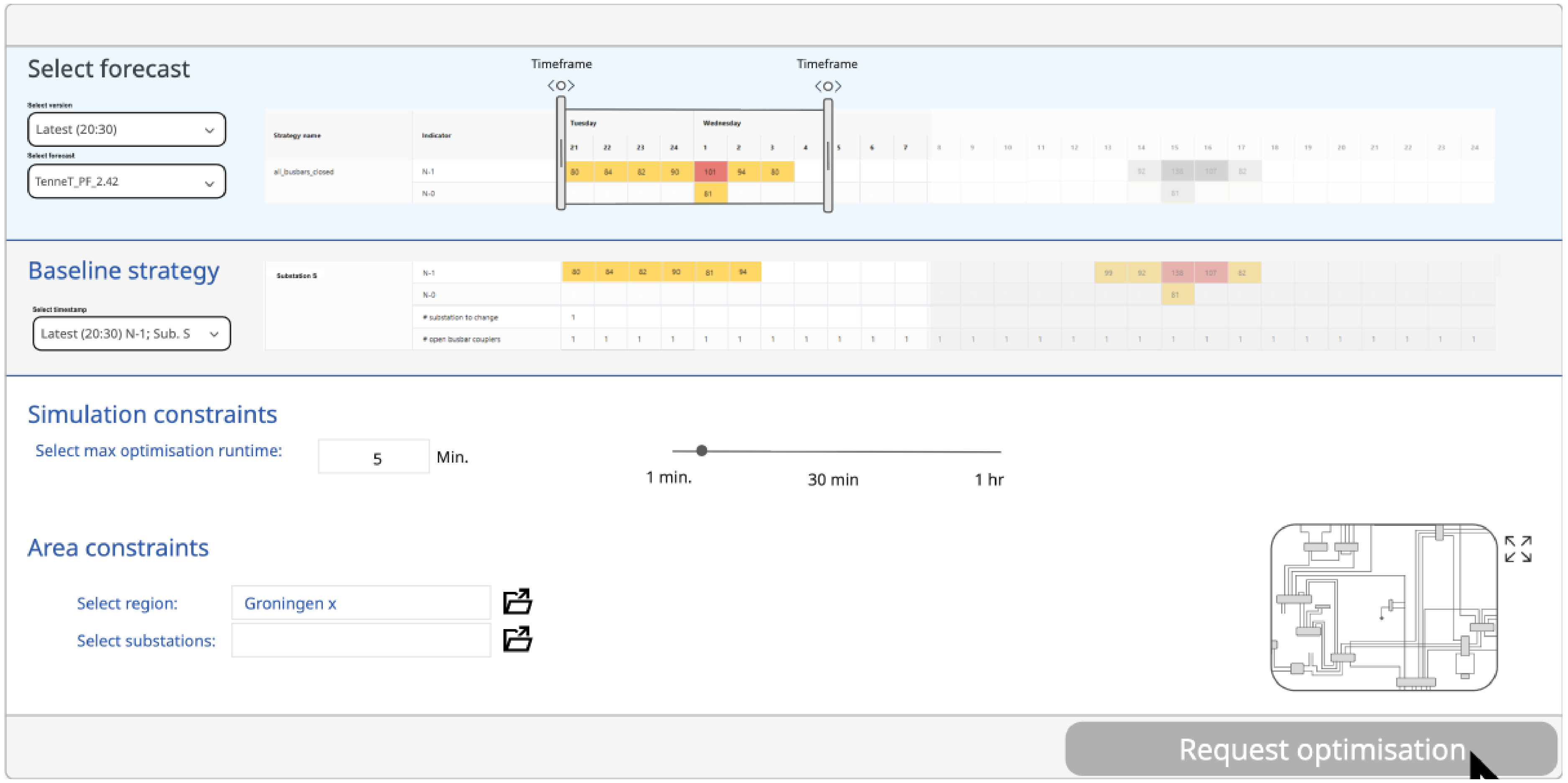


Figure 4.14. Custom study panel to request new optimsations with custom constraints or guides

Mixed initiation

The dashboard includes a dedicated pop-up panel that allows operators to request new optimisation studies based on their own insights or hypotheses. Rather than relying solely on automated forecasts or pre-generated studies, the operator can define the focus and parameters of an optimisation directly within the interface (see Figure 4.14).

Through this panel, the operator can select substations, branches, or specific configurations on a topological map and request an optimisation tailored to those elements. The interface prompts the user to define constraints and targets that help guide the optimisation process, ensuring that the study aligns with operational priorities and remains realistic in scope.

When requesting an optimisation, the operator can:

- Set a baseline from existing configurations or studies to define the reference state.
- Define a maximum runtime for the calculation, balancing accuracy and computational cost.
- Target specific substations, regions, or network areas where congestion is expected.

Select particular branches or assets that are currently overloaded.

- Specify a timeframe from day-ahead to real-time to align the study with operational planning.
- Preview the estimated optimisation duration and available compute resources before launching the study (new optional addition to improve awareness of computational load).

This functionality enables operators to run well-defined, custom studies that reflect their situational understanding and objectives. It strengthens the connection between human reasoning and system computation by making the optimisation process

interactive, traceable, and contextually guided.
Through this mechanism, the operator remains in control of both the problem definition and the boundaries within which the system explores solutions.
This mixed initiation approach where both automated and human-triggered optimisations coexist ensures that the system remains adaptive to changing forecasts while leaving room for operator-driven exploration and learning.within which the system explores solutions.

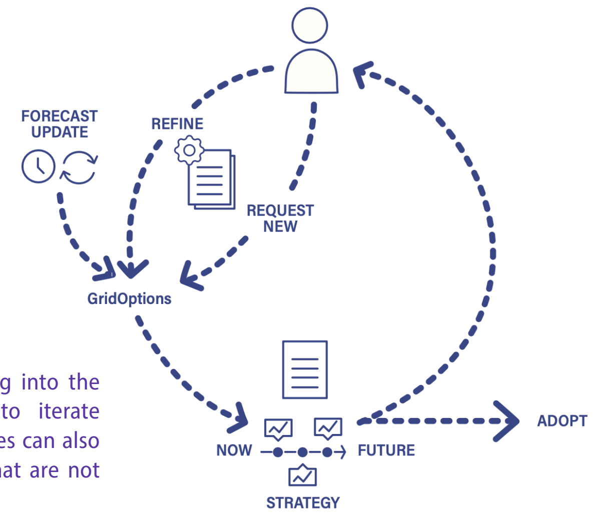


Figure 4.18. Forecasts coming into the system provide baselines to iterate from. The operator themselves can also request new optimsations that are not related to any baseline.

CHAPTER 5
EVALUATION

5.1 Empirical focus

The empirical strength of this project lies in the **continuous alignment with domain expertise** throughout all design phases. The work was developed in close collaboration with control-room experts and researchers from TenneT's *Control Room of the Future* initiative, as well as contributors from the broader *AI for RealNet* research group.
Rather than testing finished artefacts, the project focused on generating and verifying new collaboration models for future scenarios. This required continuous reflection on the **feasibility and relevance** of ideas within the operational and technical context of the power grid. Because grid operations are **highly complex** and interdependent, it is easy to overlook critical aspects or misinterpret system behaviour, making close **collaboration with experts essential to maintain accuracy and alignment throughout the process.**

The current system, tools, and capabilities are still far from the envisioned AI-assisted scenarios. In this environment, working directly with **domain experts and researchers** working at TenneT and interfacing companies, provided **a more meaningful basis for evaluation than limited user testing** (control room operators) could have offered. Through these collaborations, the project was able to extract and **align knowledge** from both **industry** and **academia**, ensuring that all design decisions were **grounded in current capabilities, ongoing developments, and realistic constraints.**

5.2 Method and process alignment

The evaluation took the form of **iterative feedback and verification** integrated across all stages of the design process.

- **Analysis of current interaction patterns** was reviewed with control-room experts to confirm accuracy and completeness.
- **New collaborative interaction patterns** were developed using the Joint Control Framework and iterated several times with expert feedback to ensure operational and technical plausibility.
- **Design implications** derived from these patterns were verified through discussions with TenneT researchers and developers, leading to the addition of one extra theme.
- **Interface functionalities** were discussed with tool developers to assess integration feasibility as well as the novelty and use of ideas.

This ongoing exchange made the generative work **empirically grounded in expert knowledge**. It created a design process that was not speculative but continuously informed by the people actively shaping future control-room capabilities.

5.3 Scope and limitations

While the involvement of active control-room operators would have added valuable perspectives, it was not feasible within the timeframe and operational realities of this project. Operator schedules are highly constrained due to staffing shortages and the critical nature of their work, making direct participation impractical. It proved difficult to plan and ultimately did not come into fruition.

At the same time, the project was positioned at an **early stage of development**, where many of the envisioned tools and capabilities were still being defined. In this context, conducting a mock-up study with operators would not have been as meaningful as later in the development proces, since the systems, workflows, and interfaces they would interact with do not yet exist in practice. Instead, the focus was placed on **co-developing the conceptual and collaborative foundations** of these systems together with stakeholders already shaping them.

The design process therefore relied on close collaboration **with front-end developers, power-system experts, and researchers within the Control Room of the Future** programme. These contributors represent the broader ecosystem responsible for building and maintaining control-room tools, and their input was essential for ensuring that the proposed concepts remained both technically and organisationally feasible.

5.4 Findings and reflections

The outcomes of this continuous alignment process are summarised in Table 5.1. Each phase of the project involved expert input to verify accuracy, relevance, and feasibility. This ensured that the evolving design remained grounded in operational knowledge and aligned with the technological direction of the Control Room of the Future programme.

Step	Evalution outcome
1. Current Interaction Analysis	Observation of existing workflows. Takeaways verified with TenneT experts to confirm behavioural observation and control room technicalities.
2. Temporal Framing	Identification of realtime, intraday, and day-ahead collaboration timescales. Experts confirmed relevance and novelty of idea.
3. New Collaboration Patterns	Developed and iterated 3–5 times with experts depending on interaction pattern. Framing of collaboration shifting across timeframes was confirmed by experts based on validated patterns. Client and control room expert agreed on adoption of timeframes as effective to portray collaboration across congestion remediation scenarios.
4. Design Implications	Thematic analysis reviewed with experts. Added one new theme through feedback, comfirmed others.

Table 5.1. Summary of evaluation outcomes across design stages showing how expert input was used to verify behavioural accuracy, feasibility, and relevance.

5. Final Design	Final interface developed independently, building on the validated collaboration framework. Expert feedback highlighted its clarity and relevance, and confirmed that the design direction is both feasible within current development trajectories and valuable for future evaluation with operators. Needs refinement and better allignment withdeeper system functionalities, but offers a good basis for further development of tool functionalities and interfaces.

Table 5.1. Summary of evaluation outcomes across design stages showing how expert input was used to verify behavioural accuracy, feasibility, and relevance.

Feedback from experts described the proposed concepts as **fresh, relevant, and grounded in real challenges**. The introduction of a temporal layer for comparing forecasts and tracking plan effectiveness was recognised as particularly promising for enhancing situational awareness. Some functions, such as operator-initiated optimisations, were discussed in relation to potential future automation, yet experts agreed that the principles of **transparency, comparability, and proactive evaluation** are essential for future systems.

Overall, the evaluation confirmed that the design successfully translates collaborative needs into feasible, forward-looking interface concepts. The process demonstrated that co-development with domain experts can produce designs that are both visionary and grounded in real operational knowledge.

5.5 Design Evaluation setup

The evaluation of the final interface concept was conducted through two online sessions using story-board style digital mockups. The goal was to explore how the proposed functionalities fit within real collaboration scenarios and to discuss their relevance and feasibility.

Each session began with a walkthrough of the interface, showing how different features support the previously defined collaboration patterns. During the walkthrough, the reasoning behind each design decision was explained, linking features to specific operational challenges and opportunities. This approach helped to spark discussion about the underlying process, the balance between automation and human control, and the potential role of temporality in supporting decision-making: the main deisgn suggestion.

In total, two 60-minute sessions were held: one with a researcher and control-room expert from TenneT, and one with the lead engineer responsible for the development of the optimisation tool that was used as the basis for the designs. These discussions provided both the operational and technical perspectives needed to assess the design's feasibility, conceptual alignment, and potential contribution to ongoing tool development.

5.6 Expert feedback on final design

The final interface concept was reviewed with two domain experts: the **lead engineer** responsible for tool development within the *Control Room of the Future* project, and a **researcher and control-room expert** from TenneT. Both sessions used digital interface mockups in online meetings to walk through collaboration scenarios and discuss how the proposed design fits the operational workflow and technological direction.

"A fresh and interesting take on an old problem."
The lead engineer described the design as a *fresh and relevant perspective* on congestion management, noting that it introduces *"a new way to visualise and manage congestion by pinning strategies and seeing their effects develop over time."*
The researcher echoed this, stating that the concept *"really lays the groundwork for the temporal aspect; adopting strategies and seeing how they unfold towards real time is a very relevant addition to the current tool, and I cannot see how something like this will not be relevant in the future."*
Both experts highlighted **temporality** as a central strength, seeing the interface as a tool to understand change and evaluate plans over time rather than at fixed points.

"It feels a bit like weather radar."
The lead engineer drew an analogy between the timeline and the experience of watching weather patterns evolve: *"It feels a bit like Buienradar, where can make your own interpretion of incoming rain by scrubbing the timestamps to see how clouds are moving."*
This reflection captures how the timeline interaction allows operators to visualise uncertainty dynamically. Rather than freezing decisions in a single snapshot, it provides a means to explore how forecasts and strategies interact as the situation develops.

"The report manager is still a bit unclear."
The control-room researcher noted that the **report management panel** remains esthetically and thus conceptually confusing. While its function of connecting forecasts, optimisation reports, and plans makes logical sense, it *"puts focus on a system feature that is not directly relevant to decision-making."*
He suggested that the feature should be less forward in the design and clarified to distinguish between reports, plans, and strategies. *"The waterfall feature makes sense,"* he said, *"but it currently looks like these are iterations or strategies already; it should be clearer that these are just for data manging reports and adding some monitoring capabilties."*
This insight reinforces that the hierarchy of information needs to prioritise decision-relevant content while still enabling structuring and traceability.

"Optimisation tools should ideally do a perfect job on their own once properly constrained."
The lead engineer questioned the degree of operator

control in the design, expressing that the optimisation process should ideally run autonomously once parameters are defined.
This discussion highlights a recurring **tension between automation and human agency**: whether future systems should fully automate strategy generation or continue to include human oversight and iteration.
In response, this feedback underlines the need to advocate for **human-centred collaboration**, ensuring that as automation increases, operators remain in the loop as evaluators and interpreters of system output.

"It takes a more dashboard-like approach."
Several comments concerned the alignment between the proposed interface and the existing collaboration patterns. The lead engineer observed that *"this version takes a more dashboard-like approach, requiring active interaction, whereas our earlier work leaned more towards guided workflows."*
He also noted that some functionalities intentionally designed into the current system were *"put in limp mode,"* emphasising that while the concept is promising, it will require deeper software-engineering integration to realise its full potential.
This raises the question of how to **encourage operator engagement**, designing interaction that feels rewarding and purposeful rather than demanding extra effort.

"We have succeeded in making a feasible, tangible collaborative interface."
The control-room researcher concluded that the project successfully created *"a feasible, tangible collaborative interface that enables the intended collaboration patterns and integrates many relevant ideas."* He noted that while the final product may eventually take a different form, *"this provides something concrete that we can start discussions from."*
Both experts agreed that the interface serves as an **evolution of GridOptions** and the **incorporation of collaborate decision making**, therefore extending its familiar design language and core functions to support proactive, collaborative work.

Despite critical discussions on technical details and workflow emphasis, both reviewers confirmed that the design is **feasible, forward-looking, highly relevant and bringing a fresh persepective** to the future of control-room operation. The feedback collectively validates that the design translates collaboration theory into practice, providing a realistic and valuable direction for further development and testing.

Summary of expert insights
The evaluation confirmed three main points of validation. First, the introduction of **temporality** was recognised as an essential step toward understanding and managing uncertainty in future operations. Second, the interface successfully demonstrated how **collaboration between humans and AI** can be structured through transparent, interactive tools that preserve operator agency. Third, the concept was considered **technically feasible** and well aligned with ongoing development efforts, offering a tangible foundation for future iterations. Together, these insights position the design as both a credible and forward-looking contribution to the evolution of controlroom interfaces, setting the stage for further refinement and empirical testing in collaboration with operators.

Reflections
Working closely with domain experts throughout this project provided invaluable depth and accuracy, but it also came with its own challenges. Immersion in expert knowledge can gradually blur the outsider perspective that often drives innovation.
When every decision is shaped by feedback from people deeply embedded in the system, it becomes difficult to step back, question assumptions, and establish your own interpretation of what might be possible.

At times, it felt challenging to find the balance between absorbing technical understanding and maintaining enough creative distance to propose new directions. This experience, however, also showed the value of design as a translational discipline, where we move between perspectives, interpreting technical realities while imagining what they could become.

DISCUSSION

1. Interface design in collaborative congesiton remediation

This discussion addresses the main research question — *how interface design can support the evolution of collaborative congestion management in power-grid control operations* — by translating the conceptual findings of the earlier chapters into practical design understanding. It also responds to the three sub-questions that guided this research: (1) identifying the principles from existing theory that inform the Hypervision concept; (2) analysing how current decision-making and human-machine interactions shape control-room practice; and (3) translating this understanding into concrete design implications for future collaborative human–AI operations.

In this thesis, current congesiton manangement tools move from assistive role to a to collaborative environment. The interface becomes the shared place where operator and AI work on the same facts, see the same history, and shape the same plans. Initiative passes cleanly between them: operators pose hypotheses, set constraints, and request studies; the AI explores options at speed, exposes rationale and uncertainty, and stays interruptible. A single temporal spine links forecasts, remedial options, plans, and observed effects so each decision carries its implications on the state of the grid in a visual manner. This shifts identification of congestion forward in time and makes proactive decision management the default. Collaboration then reads as a tight loop of guidance, testing, and revision with transparency and control preserved at every step.

These ideas synthesise insights from existing research on joint cognitive systems, shared situational awareness, and mixed-initiative control, as discussed in Chapters 2 and 3, and turn them into concrete design principles to make GridOptions more collaborative and move towards a future Hypervision environment. At the same time, they respond to the observation that current tools are largely assistive, providing isolated recommendations without supporting iterative reasoning or shared understanding (Chapter 3). Building on these limitations, the following sections outline three design implications that define how collaboration can be realised within future human–AI operations.

Three essential elements

1. Co-iteration of plans and strategies as goals and conditions evolve.
2. Mixed human and AI initiative from element level to framing level, enabling hypothesis-led exploration.
3. Timeframe-aware collaboration that respects operational goals and uses complementary strengths across scenarios.

Co-iteration of plans and strategies

In this thesis we put collaborative iteration at the centre of human-AI capabilities. The focus for this thesis is the Grid Options strategy optimisation tool and the forecasts that precede it. In an effort to move towards proactive congestion management, the operator needs to be in control over upcoming issues by implementing plans and strategies. Finding the best strategies is ultimately the task of the operator. Inherently, AI results lack human judgement and situational awareness, and thus we need both to achieve a better final outcome; A cornerstone of collaboration being that the capabilities of the human-AI team exceeds the capabilities of either individual.

Finding the best strategies is not done with the press of a button; it requires an optimisation process in which the AI and the human play a role. Thus we want the human and the AI to iterate together to increase the performance of the team in congestion management. As time progresses towards real time, forecasts are bound to change, and so the impact of our collaboratively generated plans changes as well. We therefore assume continuous adjustment and iteration of plans throughout the entire congestion remediation process. This means the human needs to be able to put their input into iterations as well.

Mixed initiative and hypothesis-led exploration

Besides input in iterations, the system should align with human cognitive needs for motivation and learning by being able to test hypotheses. Mixed initiative means alignment with human cognitive needs of hypothesis testing, of ideating with the tool, and of using feedback to come to a better result. In the current version it is only the AI that can take initiative by prompting periodic update reports with suggested strategies. Making this process collaborative means that the human can request a specific strategy based on new ideas, but also iterate on current and existing ideas by expanding on them. Here we leverage human experience and contextual awareness to judge AI outcomes and steer them towards a more optimised direction.

Collaboration across timeframes

These aspects of co-iteration of strategies and mixed initiatives need to happen in the context of situational goals, challenges, and tasks. We have clearly laid out in Chapter 4 how different operational timeframes require different approaches to congestion management. We see that in the short term, in reactive congestion management, we want to resolve issues quickly. In the medium term we want to find sets of strategies that align with our goals of maintaining a safe grid state at all times. This means finding redundant strategies with different trade-offs and making decisions for their implementation. We can see that this doesn't work in the long term. Forecasts have a high level of uncertainty in the later intraday and day-ahead timeframe, meaning that robust strategisation can be wasteful as the situation is likely to change, making our plans obsolete. Instead, this timeframe demands exploring uncertainties in forecasts and relating them to patterns and trends to identify them early.

2. From recommendation to sense-making

Through the development of Hypervision we noticed that by creating a tool for proactive congestion remediation, we had in fact built a proactive sense-making environment. The interface no longer functions as a system that merely recommends actions or displays information; it becomes a medium for forming understanding. By allowing operators to follow the evolution of congestion over time, relate their actions to outcomes, and interpret emerging patterns, the tool shifts from decision support to also offering situational awareness support.

The temporal dimension is central to this transformation. When congestion forecasts are seen as static snapshots, the operator's ability to interpret their characteristics remains limited. By introducing the ability to move through time, patterns can be followed as they grow, merge, or disappear. This temporal continuity helps the operator connect cause and effect, recognise recurring conditions, and anticipate what might come next. It turns the forecast from a stationary map of risk into a dynamic story of system behaviour.

The same principle extends to the plans and strategies created within the environment. Each plan carries with it a temporal footprint that shows when it was proposed, how it developed, and how effective it proved over time. Seeing these traces side by side with live forecasts turns the platform into a place of reflection. Operators can evaluate how their earlier assumptions hold up, where their interventions were effective, and how those actions influenced subsequent system states.

This constant interplay between observation and reflection increases situational awareness for both the human and the AI. The tool becomes a shared environment for mutual awareness where both sides learn from the unfolding system and from each other's actions. In this process, action and understanding merge: operators monitor not only the grid but also their own reasoning as it interacts with the system's feedback.

3. Anticipation to reduce cognitive load

Forecasting is becoming more necessary, not less. The grid is more dynamic, markets move faster, and the consequences of late discovery are higher. The interface should not pretend that forecasts are certainties. It should help operators make sense of uncertainty. This is where the hypothetical becomes powerful. Let the system study multiple futures at once, and tie each to assumptions, constraints, and candidate actions. Planning for the worst is not pessimism. It is the practical way to ensure that when a situation escalates there are prepared options and fallbacks that can be executed without panic. This is highlighted well in collaboration pattern 2 of chapter 4, where it not only provides redundancy in case of emergency, but also allows the operator to tailor the intervention to the situational needs as congestion escalates is de-escalates.

4. Opportunities in inter team collaboraiton

Control room work spans more than one team. There is the operator on shift, the senior who oversees risk and priorities, and colleagues in other regions whose actions can change the picture in seconds. Today much of this coordination happens through ad hoc chat, calls, and personal memory. The opportunity is to make collaboration through the interface. Plans are now registred entries in a connected system. Operators can work on the same issues, iterate together or request an extra set of eyes. The system, effectively logging all interactions, plans and decisions could also create logs to update coleaques for takeover at the end of the shift.

4. Design and operational implications

The outcomes of this project reveal several implications for both design and operation. While the concepts explored in Hypervision remain speculative, they point toward concrete directions for how human–AI collaboration can be embedded in future control-room practice. These implications concern how tools are designed, how work is organised, and how decision-making unfolds in time.

Designing for continuity in decision-making

One of the clearest implications is the need to treat decision-making as a continuous, evolving process rather than a series of discrete moments. The ability to track and refine plans over time means that the interface must preserve the history of ideas and the reasoning behind them. Design should therefore support versioning, comparison, and rollback not as technical features but as integral parts of operational thinking. This continuity of reasoning allows operators to revisit assumptions, validate earlier decisions, and build confidence in long-term strategies.

Embedding temporal awareness in the interface

The temporal dimension of the grid, how situations evolve and how uncertainty reduces as time progresses, must be made explicit in interface design. Operators should be able to move smoothly between the day-ahead, intraday, and real-time horizons, seeing how patterns develop and how plans interact across them. The concept of "scrubbing through time", developed during this project, illustrates how the interface can support reflection on past actions and anticipation of future ones. A real world parallel would be the weather radar animations that help make sense of weather trend and bring nuance and meaning to weather reports. This temporal coherence strengthens situational awareness and helps bridge planning and execution.

Integrating learning into daily operation

A further implication lies in the potential of collaborative tools to turn everyday operations into opportunities for learning. Each decision, plan, and outcome can serve

as feedback for improving both human expertise and algorithmic performance. Future systems could capture this data to refine models, detect recurring conditions, and support reflective practice among operators. This approach moves training from separate sessions into the flow of work itself, aligning with the idea of continuous adaptation that defines collaborative systems. This element is also crucial to potentially move towards an automated future.

Folding and unfolding complexity

Another implication concerns how complexity is revealed in the interface. Hypervision must balance its dual role as both a monitoring dashboard and an analytical workspace. During regular operation, operators need a clear overview that communicates system health and emerging risks at a glance. To achieve this, information should be folded into a high-level view showing indicators of status, performance, and the effectiveness of ongoing plans over time. These summaries allow the operator to maintain situational awareness without being overwhelmed by detail.

When deeper understanding is required, the interface should allow the operator to unfold information selectively. Behind every indicator lies a layer of reasoning, data sources, and plan dependencies that can be accessed on demand. This layered structure ensures that the system remains legible at all levels: simple enough to monitor at a glance, but rich enough to analyse when context requires it. Folding and unfolding thus becomes a design mechanism for managing cognitive load while preserving transparency. It keeps the interface light for monitoring yet deep enough for reflection, supporting both immediate awareness and informed decision-making within the same environment.

5. Reflection on method

The methodological approach of this project combined conceptual exploration with empirical grounding. Rather than beginning from predefined requirements, we developed understanding through continuous engagement with the domain. This iterative process of moving between observation, synthesis, and design, proved essential to keeping the work relevant to real control-room practice. It also exposed the limits of conventional user testing for a context as complex and safety-critical as the power grid.

Our method can be seen as a form of situated design research: insights were generated not by isolating variables but by observing the interplay between people, tools, and organisational structures. Early observations revealed how current systems are primarily assistive, providing fragments of information without enabling joint reasoning. These findings shaped the conceptual direction of Hypervision, steering it towards collaboration rather than automation. Through this process we developed new principles for Hypervision that place the human perspective at the centre of system design. Rather than focusing on one-way assistance or even bi-directional communication between operator and AI, we aimed for a more integrated form of collaboration where both contribute to a shared understanding of the situation. This meant designing not only for information exchange but for mutual sense-making: the human interprets system output, the AI adapts to human intent, and both learn from the outcomes of their combined actions.

Close collaboration with domain experts played a decisive role. Working alongside control-room specialists and researchers within TenneT's Control Room of the Future programme allowed us to verify assumptions continuously and anchor ideas in operational reality. This iterative feedback loop replaced the traditional boundary between research and evaluation. The experts' insights guided the abstraction level of our design work, ensuring that it remained usable and technically plausible while still pushing conceptual boundaries.

At the same time, the method had clear constraints. Direct involvement of operators during live operations was limited due to safety regulations and the experimental nature of the concepts. As a result, our validation relied on expert reasoning and theoretical alignment rather than quantitative performance metrics. The strength of this approach lies in its ability to reveal patterns and design opportunities; its weakness lies in the absence of empirical testing under real operational pressure.

Looking back, this balance between conceptual and empirical work allowed us to move beyond surface-level interface design toward a more systemic understanding of human–AI collaboration. The process itself mirrored the principles we advocate: iterative, reflective, and collaborative. It demonstrated that designing for the future of control-room work requires methods that can adapt to complexity rather than simplify it.

6. Rethinking collaboration towards the future

Throughout this journey, the ambitions behind Hypervision continually pointed toward opportunities for higher-level pattern recognition on both the AI's and the human's side, similar to how humans engage with conversational AI systems to gain new insights through reframing and reinterpretation. In theory, collaboration is defined by shared goals and shared situational awareness. Yet the AI explored in this thesis is not an autonomous teammate but a preprogrammed optimisation algorithm that supports goal achievement. The human remains responsible for defining the goal and making the final decision. One could imagine an AI recommending a particular strategy, but does that elevate the interaction to true collaboration? Perhaps only if the AI can propose strategies that are not merely optimal in performance terms but also meaningful within the operational context. Such alignment would correspond to higher-level goal sharing, as described in the Joint Control Framework (Level 5).

However, perhaps the answer is more nuanced. If collaboration were defined solely by producing outcomes superior to what either actor could achieve alone, then almost any computational tool would qualify as collaborative. Does the essence of collaboration lies instead in the joint shaping of problem understanding and action, where human and system iteratively adapt to one another's reasoning. Within this view, there remains significant potential to expand AI capabilities at higher abstraction levels. Yet designing for these capabilities directly would risk detaching the system from real operational practice. This is why the stripped-down, foundational interaction patterns developed in this thesis are valuable: they capture the core of human–system collaboration as it currently exists, providing a grounded basis for future enhancement as AI capabilities evolve.

While this work did not yet evaluate collaboration at these higher abstraction levels, it has laid the groundwork for doing so. The identified interaction patterns, role allocations, and decision-making structures form the necessary foundation upon which more advanced, co-interpretative AI functions can be built and studied in future iterations of Hypervision.

A final limitation lies in the underexplored potential of hypothesis-driven collaboration. While the current work focused on defining foundational interaction patterns, future iterations of Hypervision could extend these by enabling operators to formulate and test hypotheses directly within the system. Granting operators constraining and targeting functions would give them full operational flexibility to explore "what-if" conditions and alternative strategies. At higher abstraction level though, this capability could evolve further as the AI begins to recognise recurring patterns, trends, or anomalies in historical and simulated data, offering hypotheses of its own. Such a feedback loop would turn the collaboration into a shared reasoning process, where both human and system generate, test, and refine ideas in pursuit of deeper situational understanding.

6. Future workand limitations

This project established the conceptual and design foundation for collaborative human-AI operation within power-grid control. Yet many of its ideas still need to be tested, refined, and expanded. The following directions outline how future research and design work could continue to evolve the Hypervision concept toward practical implementation.

Iteration and feedback integration

The next step is to iterate on these concepts together with the interface designers and researchers across TenneT. The evaluation of the design outcome pointed to slight missallignment of top level design intentions. This doesn't mean our proposed design missed its marks, but rather that there should be high level in depth allignment with all relevant stakeholder. This review should assess how their current design deliberations align with, extend, or challenge the principles outlined in this project. Once this internal round of iteration has been completed, the refined concepts can be brought to operators for evaluation. Scenario-based sessions will be key for gathering end-user feedback, observing how operators interact with the system, and identifying where assumptions about workflow, trust, or cognitive load diverge from real practice.
These iterations will help validate whether the envisioned collaboration model holds under operational reasoning and will guide how the system can be incrementally introduced in future control-room contexts.

Exploring the strategic middle timeframe

Our findings indicate that the strategic middle timeframe, the period between roughly one and four hours ahead, remains underexplored. This horizon sits between our definition of intraday remediation and real-time remediation, yet it is where most collaborative decision-making could occur.

Arguing on the general statement that uncertainty decreases towards realtime, we can assume that somethere between realtime and "a couple of hours ahead" lies the optimal time to make a decision. The current distinction of 3 timeframe, with one being reactive and two far ahead leaves this time frame understudied.
Operators in this window must choose the level of depth and granularity in staggered strategies, deciding which actions to commit to and which to leave flexible. Understanding how operators balance these choices, and how the system can best support them in doing so, is an important area for further study. Future work should dig deeper into this strategic middle ground to identify design opportunities for supporting dynamic planning and confidence assessment.

Integrating maintenance and redispatch into congestion remediation

Another important extension lies in connecting congestion remediation with maintenance planning and redispatch/curtailment. Throughout this project, maintenance was treated as an external process, yet it strongly influences system flexibility and operational risk. Integrating maintenance scheduling into the GridOptions environment could reveal how planned work interacts with congestion forecasts and available strategies. This would allow operators to simulate combined impacts, anticipate potential conflicts, and evaluate mitigation options earlier in the planning cycle. Exploring this link would help bridge proactive grid operation with long-term asset management.

A side note here is the opportunity for automation of these procedural and time time consuming tasks. Following the principles of hypervision would mean that this function should be integrated into the remediation tools. Moving toward a fully operational version of Hypervision requires deeper integration with existing tools and data systems. In the mock-up interface we already included the ability to adjust parameters and compare different forecasts. Future iterations could expand this integration by linking directly to systems such as GOPAX for redispatch coordination or curtailment requests.

Beyond Decision-Making: Opportunities in Monitoring and Sense-Making

Another limitation is the scope of this research within the control-room workflow. The focus was placed on decision-making and congestion remediation, yet according to Endsley's model of situation awareness, these processes are preceded by perception and comprehension—stages where operators construct their mental model of the grid. The potential of AI to enhance these earlier monitoring and sense-making stages repeatedly emerged during the project but ultimately remained outside the defined scope. Connected AI capabilities could play an important role here, for example by checking alignment between data sources, relating alarms to their underlying causes and system-wide implications, or detecting inconsistencies in network behaviour. Some of these speculative functions are outlined in Appendix 3, while Appendices 4 and 5 show how the described collaboration patterns could apply to scenario-based examples.

CONCLUSION

Conclusion

This thesis set out to explore how human–AI collaboration can support power grid operators in managing congestion under increasing complexity and uncertainty. By combining theoretical frameworks with empirical insights from control-room observations, the research demonstrated that the current systems at TenneT still operate in an assistive mode, offering information and recommendations without true collaboration. The work identified how interaction design can help transition toward shared decision-making that preserves human expertise while using AI to enhance foresight and adaptability.

Collaboration between human and AI is most effective when both contribute complementary strengths. Humans provide contextual judgement, intuition, and adaptability, while AI contributes analytical power and speed. Integrating AI into critical decision support requires true human–AI teaming, where collaboration is grounded in shared situational awareness built within a shared environment. Such an environment must enable mutual initiative and co-iteration, allowing both agents to leverage their strengths to optimise outcomes. In this thesis, this principle guided the enhancement of an optimisation tool for congestion remediation. Interactive capabilities and hypothesis-based exploration enable proactive congestion management, allowing operators to test scenarios, evaluate trade-offs, and build foresight rather than react to events. By supporting proactive planning for intraday and day-ahead timeframes, the system can help form robust plans under uncertainty, strengthening situational awareness across the forecast horizon.

Across operational timeframes, collaboration changes in character. In real-time reactive contexts, the system must enable quick and targeted decision-making, grounded in reliable insights and supporting fast implementation. In intraday operations, collaboration should facilitate continuous sense-making, helping operators interpret shifting grid conditions and update strategies. For day-ahead planning, it should promote exploration to facilitate early identification of diverging scenarios and support transparent reasoning under uncertainty. Designing for these shifts requires acknowledging that collaboration is dynamic, shaped by uncertainty, time pressure, data availability, and operational intent.

Research has shown that fully automating such processes or relegating humans to an oversight role leads to deskilling, reduced motivation, and loss of operational insight. This thesis therefore reaffirms that the human must remain central in the decision-making model. Humans possess superior situational awareness and intuition, which are essential for managing uncertainty and ethical complexity. Remaining actively involved also preserves operators' engagement, expertise, and sense of agency, ensuring that collaboration enhances, rather than replaces, human capability.

Through enabling collaboration across timeframes within a unified interface, operators and AI systems can co-iteratively reach better outcomes by anticipating challenges and planning ahead with staggered and robust sets of actions. This design approach allows congestion to be prepared for and prevented rather than merely mitigated, marking a shift from reactive to proactive congestion management. The resulting paradigm redefines the role of both human and machine, each contributing their strengths in a shared process of reasoning and adaptation, demonstrating how effective collaboration can extract the best from the team to achieve resilient and foresight-driven grid operation.

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