



New Dynamics of Change? AI-Led and AI-Generated Change in the Electrical Grid

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Abstract

The electrical grid is a prime example of a vast system of interconnected entities that are both empowered and challenged by artificial intelligence (AI). AI is entering this sector in two ways: as a deliberate instrument of AI-led change, enabling better forecasting, grid optimization and increasingly autonomous control approaches; and as an uninvited force of AI-generated change, driven by the enormous, spatially concentrated and rapidly evolving electricity demand of AI data centers. This demand does not arrive as an initiative or technology to be adopted, but rather as a massive load interconnection request. AI-generated change challenges some of the fundamental principles of existing literature on organizational change, such as the authorship of change, the composition of the changing unit, and the ability of the involved parties to share a joint agenda. We use the interplay between AI and the electricity sector to illustrate how authority over change is shifting toward those controlling allocation, interfaces, and architecture. The paper proposes avenues for further research into organizational change in the AI era.

Keywords

change management, technology, organizational transformation, innovation management, cooperative strategy, change

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Introduction

The synchronous electrical grid is one of the largest and most complex machines ever built. It is also, organizationally, one of the most thoroughly planned systems (Rilinger, 2025; Zweifel et al., 2017). Change in this system used to be codified by network development plans spanning decades, long-term regulatory review cycles, N-1 contingency standards, and asset lifetimes measured in 40-year increments (Glover et al., 2022). If any sector has institutionalized the classic model of coordinated and planned change, it is this one.

This model is now failing because of several developments (Doleski & Freunek, 2024; Monti et al., 2020). The core generating assets of the previously centrally planned systems, nuclear or fossil-fuel-based generators in centralized power plants, are being complemented and often replaced by renewable energy sources (RESs) like photovoltaics or wind power (Sioshansi, 2025). This shift introduces fundamental challenges to the established control system of power systems. RES are typically deployed in a distributed manner, deviating from the traditional centralized power plant scenario. RES generation is also subject to fluctuating weather conditions, leading to increased volatility in power generation and dispatch. On the demand side, today's power systems must cope with growing peak demand and less predictable consumption patterns, driven by the increasing use of electricity for mobility (e.g., electric vehicles), heating (e.g., heat pumps), and industrial manufacturing (e.g., electric arc furnaces). At the same time, installations of distributed energy storage (batteries), flexibility solutions (smart meters, etc.), and new business models (e.g., RES as an investment vehicle) are growing, adding volatility and variability to the grid (Doleski & Freunek, 2024; Robinson, 2025).

While challenging for the system, the sector's actors have been coping with similar technological and societal transformations for several decades. In organizational terms, decentralized energy generation has led the tightly coupled systems to become looser. Artificial intelligence (AI) is now adding two new dynamics of change to the sector which are, as we will argue in the following, challenging established assumptions about the relationships between actors in a network (Fiss & Zajac, 2006; Fredberg & Piller, 2011; Orton & Weick, 1990; Weick, 1976). First, AI provides the sector with new capabilities to cope with this change by offering stronger insight into grid conditions, better forecasting abilities, or faster contingency planning in case of interruptions. This aligns with the prevailing perspective on AI and organizational change in the literature (see the Special Forum in this journal in 2024, as well as this issue). We refer to this as *AI-led change* in the industry.

In addition, the electricity sector is being challenged by AI decisions taken entirely outside of it, by actors who are not its members, through a very different channel that current models of organizational change do not recognize: the exploding demand for electricity with very different load patterns created by the data centers required to operate AI at a global scale (Cheng et al., 2026; Norris et al., 2025). This demand is currently challenging the grid in ways never seen before. Hence, the most

consequential change of AI for the electrical grid has no change agent, no sponsor, no coalition, and no communication plan. It arrives as a load. We refer to this as *AI-generated change* in the industry.

In the following, we use the electrical grid as an extreme case to study a setting where the mechanisms of change imposed by AI on an established system are unusually visible because the constraints are physical. We do not claim that all sectors look like the electrical grid but rather see the grid as a leading indicator that illustrates, in an extreme, the contradictions but also synergies of AI-led and AI-generated change.

AI-Led Change in the Electricity Sector

Over the last decade, AI has reshaped grid work along a continuum between long-term planning and real-time control and operations (Blaabjerg et al., 2026; Cali et al., 2026; Heymann et al., 2024). For years, *AI-assisted predictions* of electricity demand, renewable generation, weather impacts, and price developments have been a central element of advanced grid operations (Raza & Khosravi, 2015). More recently, *AI-assisted engineering and grid planning* have emerged. This gives planners and operators an intelligent grid copilot that enables them to simulate future network states, investment and contingency scenarios, and cases of climate stress (Chaturvedi et al., 2025). This is closely connected to *AI-assisted grid optimization*. AI has recently offered new ways to optimize power flows within existing infrastructure, including improved storage dispatch, flexibility procurement, investment sequencing, and postfault restoration (Duchesne et al., 2020). At the same time, AI enables smart voltage and frequency regulation, better integration of distributed energy resources, and microgrid steering (Chen et al., 2022). Grid operators use *AI for predictive maintenance* to more efficiently detect fault patterns, grid anomalies, congestion, and slow equipment deterioration (Mahmoud et al., 2021).

The value of these applications is enormous. The International Energy Agency (IEA) estimates that AI-based tools could unlock up to 175 GW of existing transmission capacity without adding new lines, but by just using existing infrastructure in a better way (IEA, 2025). This increase in efficiency, resilience, and deferred capital expenditure is the recognizable value of a planned transformation through *AI-led change*. Despite this strong value proposition, many implementation challenges remain (Kamble et al., 2026). Some of these challenges are difficult but not novel. Much of our field's existing repertoire applies, including capability building, professional role renegotiation, legitimation, and governance design (Kanitz et al., 2023; Kulichyova et al., 2025). A utility company building an AI capability is undergoing planned radical organizational change with new technology. The change literature related to the introduction of new technologies predicts an increased need for sensemaking and learning (Argyris, 1993; Maitlis & Christianson, 2014) to clarify the system-level effects of the new technology (Orlikowski, 1992; Pasmore, 2015), and to negotiate a new power structure (Buchanan, 2008). Many utilities are following this model, using AI to cope with the changes in their industry (Kamble et al., 2026).

However, there are other challenges resulting from the interaction between AI and sector-specific contingencies of the electricity industry. Here, AI-led change challenges some of the assumptions underlying traditional change work (Fredberg & Schwarz, 2024). First, grid operators cannot follow the established playbook of AI deployment in many consumer sectors and do A/B tests on a live network. This learning-by-doing strategy that underlies AI adoption in many organizations is prohibited by the safety-criticality of the grid. Therefore, AI capabilities must be developed in simulation and transferred into operation across a validation gap. This shifts the organizational problem from experimentation to an evidence regime: Who will certify that a model is fit for control? On what basis will they do so? And what liability will they assume (Eze et al., 2025)?

Second, transmission companies operate in a deterministic and rule-bound culture (N-1, advanced risk management, defined action sequences). In contrast, machine learning is probabilistic and, in useful cases, nonobvious. When AI produces results to support decision-making without clearly explaining the logic behind the analysis, it challenges decision-makers' demand for transparency and process clarity (Fredberg & Schwarz, 2024). Asking a control-room engineer to accept an AI recommendation often creates a conflict between two legitimate professional logics about what constitutes a reason to act. Trust is not a soft variable here, but rather the binding constraint on deployment. This is consistent with our previous arguments about generative AI and trust in innovation settings (Piller et al., 2024).

Third, AI models are retrained in weeks, but the assets they control are depreciated over decades and governed by regulatory approvals that assume stable technology. Regulated organizations struggle to capitalize capabilities that obsolesce faster than the rate base. Also, when the algorithm coordinating different ends of a complex network is both obscure and difficult to define, it reduces the power of individuals and teams in an unprecedented way. While a distributed network creates more resilience, AI governing mechanisms create a much more tightly coupled network that may become more vulnerable (Perrow, 1999). An AI-augmented distribution grid needs to be designed to function securely to prevent AI algorithms from becoming single points of failure.

AI-Generated Change in the Electrical Grid

Despite these challenges, AI-led change is the smaller effect created by the new technology. AI is simultaneously the source of the sector's most acute stress. In 2024, data centers consumed roughly 415 TWh globally, accounting for about 1.5% of the world's electricity consumption. The IEA projects this figure will more than double to approximately 945 TWh by 2030, primarily due to the growth of AI. In the United States, data centers are expected to account for nearly half of all electricity demand growth by 2030 (IEA, 2025). Along with the electrification of mobility, heating, and industrial manufacturing, this reverses the long-held planning assumption that electricity demand in developed economies is flat. AI computing not only consumes

more electricity; it also changes the size, growth rate, required flexibility, location, and timing of demand (Henni & Mohammed, 2026). Three properties make this more than a volume problem:

Point loads. A traditional urban distribution grid aggregates millions of small, statistically well-understood loads. On the contrary, a single AI campus can request several hundred megawatts at one node (Brancucci et al., 2025). From a planner's perspective, this is not an incremental increase in demand; rather, it corresponds to the sudden appearance of a heavy industrial plant or even a small city. The change is a spatial problem, not a demand to manage a shifting user portfolio.

Time Asymmetries. Computing capacity is deployed in months to a few years. Transmission lines, substations, and generation take years to well over a decade to plan and implement. The two systems are coupled but operate at completely incompatible speeds. In Hughes' (1983) terms, the grid has become the reverse salient of AI expansion: the lagging component that governs the change rate of the entire system. What is new is that the reverse salient sits in a different industry, under a different regulator, and has a different cost of capital.

Non-membership. Most importantly, the actors driving this change are not members of the changing sector. They are not subject to its authority and have no obligation to its planning process. They are not adopters to be persuaded, such as consumers adopting smart meters; they are counterparties. When a utility company is confronted with a 300 MW request, it is absorbing a change that was decided elsewhere for reasons related to another sector's competitive dynamics, not managing resistance to change.

These properties illustrate the unique dynamics of *AI-generated change*. Rather than emerging from within an organization as a bold ambition or adaptation initiative, change emerges from outside the entity that must change (Burke & Litwin, 1992). This change is unowned, yet not unintentional (capital allocation by AI hyperscalers is very intentional). As we will discuss in more depth, the interconnection between the AI and energy sectors highlights the need for future research to better understand AI-generated change fully planned by individuals who are not traditional industry stakeholders.

At the same time, however, we are currently observing a unique convergence between the two perspectives. AI data centers could evolve from being the grid's biggest problem to becoming its biggest controllable load and stabilizing grid infrastructure. This is the value proposition of startups like *Emerald AI* or *GridCARE* that use advanced AI capabilities to enable "grid-aware computing." These new intermediaries locate latent capacity in existing networks and broker flexible grid interconnection rather than building anything new. They act as schedulers, shifting the focus from "What are the computing needs?" to "Where is electricity currently cheap, clean, and unconstrained?" Not all computation must occur here and now (Gu et al., 2025). AI workloads can shift in time (train two hours later), in space (run in Quebec rather than Virginia), and in intensity (temporarily throttle GPU utilization). In this design, computation follows electricity (Brancucci et al., 2025). The possible effect of this intervention is significant. An analysis of the 22 largest U.S. balancing

authorities (Norris et al., 2025) finds 76–126 GW of headroom for new loads that accept curtailment during a few hours (roughly 85 hr per year at 0.25% curtailment, 177 hr at 0.5%).

As AI data centers move from being a problem to becoming a stabilizing resource, this leads to an interesting pivot in the challenge of AI-generated change for the electricity sector. Currently, several projects, such as EnergyNet, Grid 2.0 and the EU's SAFERGrid, are developing new control architectures for the electrical grid that would allow data centers to be integrated into grid infrastructure more flexibly (Birgersson, 2026; Schwarz et al., 2026; Shelton et al., 2026). These projects have in common that they want to transfer principles of decentralized control, as established today in the communication sector with the internet protocol, to the energy sector, creating an “energy protocol.” Rather than using the synchronized architecture of the current power system, the idea is to borrow the internet's decentralized approach to utilize new actors, such as AI data centers, as local balancing resources.

Therefore, the object of change becomes an agent of change. The question is no longer simply “How do we connect enormous AI loads to today's grid?” but rather, “Could AI campuses become active, self-balancing nodes in a decentralized grid architecture?” For change scholarship, this inversion is an interesting point. The entity that must change is not the electricity utility. Rather, it is a configuration spanning a utility, a regulator, an AI hyperscaler, a chip supply chain, and a set of software schedulers. All of these actors are part of a network, and none is subordinate to any other. In the next section, we will discuss how to steer and manage this pattern of AI-generated change, even when there is no clear agent of change.

Discussion: Emerging Patterns of Steering AI-Generated Change

While the electricity sector is often seen as a peculiar, capital-intensive, highly regulated industry, the interactions between AI and this sector provide new insights into how organizational change has to respond to the economics of AI. *AI-led change* in this industry corresponds to applications of AI planned from within the sector's actors. While there are still many open issues, similar to other sectors, overseeing and managing this type of change can follow the established playbook of change scholarship. Conversely, *AI-generated change* arrives from outside (as a load), at a speed set elsewhere, through channels that were originally designed as operational principles (like queues, contracts, load forecasts), landing as a hard constraint. AI-generated change for the electrical grid is the result of a configuration spanning an entire, large sociotechnical system (Pasmore et al., 2019).

We see four patterns in the governance of AI-generated change in the electricity sector, which complement the established change-management repertoire. The first pattern describes the current state of AI-generated change. AI hyperscalers, as external actors to the sector, demand a challenging load, and the sector has to react. The second pattern occurs when an external actor perceives that the established system is unable to change

at the demanded pace and builds a parallel system. The third and fourth patterns are based on the ideas of convergence, making AI data centers an explicit part of the grid infrastructure either through the actions of external players (such as innovative startups) or through orchestrated efforts involving an expanded ecosystem of incumbents and new actors.

(1) *Change by counterparty.* When AI data centers are considered a challenging load, utilities are often unable to shoulder the investment risk of expanding the grid alone. Thus, hyperscalers become “anchor customers” by entering into power purchase agreements, long-term capacity contracts, or by directly investing in substations, storage, and generation. This materially transfers agenda-setting power to a party with no formal standing in traditional sector governance. Especially on the regional level (e.g., local politicians attracted by the idea of a data center in their region), coinvestment buys a seat at a table it was never assigned. Such action can be conceptualized as nonmarket participation (Baron, 2001) and creates an interesting area for organizational change research, as traditional dynamics and relationships are due to shift.

(2) *Change by exit.* A relatively undertheorized mechanism is the behavior of hyperscalers to become autonomous actors by taking power generation into their hands, bypassing the need for grid integration as they perceive the established system as too rigid and slow. Hence, they invest in private “behind-the-meter” generation with their own fossil or nuclear generators. This pattern is the organizational equivalent of resolving a negotiation by ceasing to be a party to it. While manufacturer-owned power plants have existed in energy-intensive industries before, this has never happened on the anticipated scale for AI. For example, Amazon recently announced plans to build a 7.65 GW gas-fired power plant in Texas (Tabuchi, 2026). Such a move carries the risk of creating a parallel, carbon-heavy power system as a side effect of interconnection delay. This development challenges existing change theory, which is based on the assumption that an organization’s members must be convinced, aligned, and engaged. These systems are interrelated yet can also alter their relationship in the short term. Rather than thinking of them as organizations, it may be more helpful to conceptualize change as an interplay between tight and loose couplings in and between networks in order to understand the resulting dynamics of change (Orton & Weick, 1990; Weick, 1976).

(3) *Change by queue.* When data centers become load-forming (steerable) infrastructure, two change paths emerge. The first is currently being developed by innovative startups outside the established energy system. These companies provide interconnection queues, capacity allocation rules, and connection cost management as new grid instruments (Brancucci et al., 2025; Norris et al., 2025). Those who set queue priority determine which loads exist, where they are located, and when they are used. This determines the industrial geography of AI. Interestingly, transformational authority is exercised by external bodies that do not see themselves as change agents and are not evaluated as such. Nevertheless, the allocation algorithms

deployed by these new players are becoming agents of change. This contrasts with established concepts of change, such as readiness, resistance, and commitment (Oreg et al., 2011), which assume the existence of human members whose attitudes can change. However, these new players provide change through algorithmic control. Investigating this new interplay could build a bridge between organizational change literature and research on interlocking systems and their governance (e.g., Perrow, 1999), making it a fascinating field for future research.

(4) Change by architecture. The second change path resulting from data centers becoming load-forming infrastructure is a new, emergent system architecture designed by established and new actors in the sector. Studying an actor's "change program" in such cases is misguided. Instead, the design of interfaces and the system's control architecture should be the focus of the analysis, for example, interconnection agreements, flexibility contracts, or balancing protocols. This is where terms are set, and change is negotiated. A similar development was the rise of the Internet Protocol, which transformed the telecommunications sector from a closed, top-down, synchronized sector into an open, decentralized ecosystem spanning many industries (Schwarz et al., 2026). Organizational change scholarship could connect here with recent research on industrial platforms (Springer et al., 2025), which investigates the emergence of new ecosystems around interconnected "smart" assets. Authority over change derives from control over interfaces, allocation, and architecture rather than from a position in a hierarchy. The functional equivalent of the change agent is closer to a referee or standards body than to the transformational leader that characterized prior change management discourse. This offers a fascinating area of study for change scholars: when one can no longer control change, how can we design the envelope within which it is allowed to happen? This also provides a different perspective on sociotechnical systems. Traditional sociotechnical systems theory emphasized how human behavior and work organization shape a technology's operation and outcomes. Therefore, it advocates the joint optimization of social and technical systems (Pasmore et al., 2019). However, with AI, some of the system's actors cease to be human and become algorithms that govern digital agents. This will have unforeseeable effects on human behavior.

In conclusion: It's tempting to view this as a case about a unique, capital-intensive, regulated industry facing a disruptive technological development. However, we believe the opposite is true. Every sector will eventually receive its own version of an interconnection request: a change authored by another sector's AI economics, arriving at a pace set elsewhere and landing as an unavoidable constraint with no counterpart to negotiate with. The electrical grid simply gets there first and in an obvious way because physics resolves what can still be settled elsewhere by rhetoric. What organizational change scholarship should take from this case is a call for further development of the field that predominantly has theorized change as being authored, bounded, and owned. The more urgent question is what remains of managing change when it is none

of these. The electricity sector suggests that the answer lies less in steering change and more in designing the envelope within which it is allowed to happen.

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Use of AI

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