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Sustainability as a challenge in complex systems dynamics

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Mehrnaz Anvari[1,2,5] & Marc Timme[3,4,5]

Environmental, social and economic challenges antagonize sustainable development. Understanding the emergent collective dynamics of the underlying complex interconnected systems is key to predicting processes and preventing failures. This requires integrating data-driven methods, computational modeling and conceptual theoretical progress as well as specific insights from a variety of different fields. Here we review recent advances in analyzing collective dynamics of infrastructure systems, focusing on electric energy supply and sustainable mobility. Key phenomena include flow disruptions, supply fluctuations and non-equilibrium states emerging through distributed demand—highlighting the need for cross-disciplinary tools to guide sustainable system design.

Humanity faces a growing number of severe environmental, social and economic challenges and crises that antagonize the sustainability of a range of complex systems that fundamentally underlie our daily lives. Examples include the climate system, global and local economies, as well as energy supply, mobility and transportation systems. Pressing challenges change boundary conditions and system parameters, act as external drivers, and imply perturbations of the systems' overall dynamics, often with the potential to disrupt normal operation and cause systemic failure. Societal transformations and technical innovations help address some aspects of these challenges and simultaneously catalyze others, yet often create ever more tightly interacting complex systems and thereby facilitate unexpected and sometimes undesired collective dynamics.

Collective phenomena underlie all of these challenges. They refer to the behavior of a complex system as a whole that emerges without central organization, from the interactions among its individual units. Complex systems consist of many units or agents that interact in nonlinear ways. Their dynamics self-organizes to create novel, collective forms of behavior that are not immediately foreseeable from analyzing their individual units in isolation[1–4].

All complex systems of immediate socio-economic relevance are dynamically driven by multiple structural changes and external dynamical influences, perturbations and fluctuations on various timescales, including technical and regulatory boundary conditions, the activities of individuals, and physical fluctuations. Such external disturbances cause—sometimes transient, sometimes persistent—changes of system states over time. Topical research thus strives to understand and constrain the dynamics of complex systems although these are typically heterogeneously interconnected, nonlinear, high-dimensional networked systems with multiple external driving signals impinging on them.

Since the turn of the century, energy supply networks and mobility systems have received major attention owing to their rapid restructuring and their critical functional roles in the economy and in society. Emerging new boundary conditions and new modes of operations substantially affect these systems' collective dynamics. For instance, the increasing share of renewable energy sources (RES), such as wind and solar, makes supply more variable, originating from a larger number of smaller units compared with conventional power plants, and more distributed, requiring adaptation of infrastructures and technologies. Similarly, digitally enabled, increasingly networked new modes of mobility have emerged, inducing novel forms of collective behavior.

In this Review, we focus on two types complex infrastructure system—electric power grids and transportation networks (Fig. 1). We have selected these systems for several reasons. First, for their major ongoing transformations with immediate socio-economic relevance;

[1]Fraunhofer Institute for Algorithms and Scientific Computing, Sankt-Augustin, Germany. [2]Potsdam Institute for Climate Impact Research, Potsdam, Germany. [3]Chair for Network Dynamics, Institute of Theoretical Physics, Center for Advancing Electronics Dresden (cfaed), and Center Synergy of Systems (SynoSys), TUD Dresden University of Technology, Dresden, Germany. [4]Lakeside Labs, Klagenfurt, Austria. [5]These authors contributed equally: Mehrnaz Anvari, Marc Timme. e-mail: mehrnaz.anvari@scai.fraunhofer.de; marc.timme@tu-dresden.de

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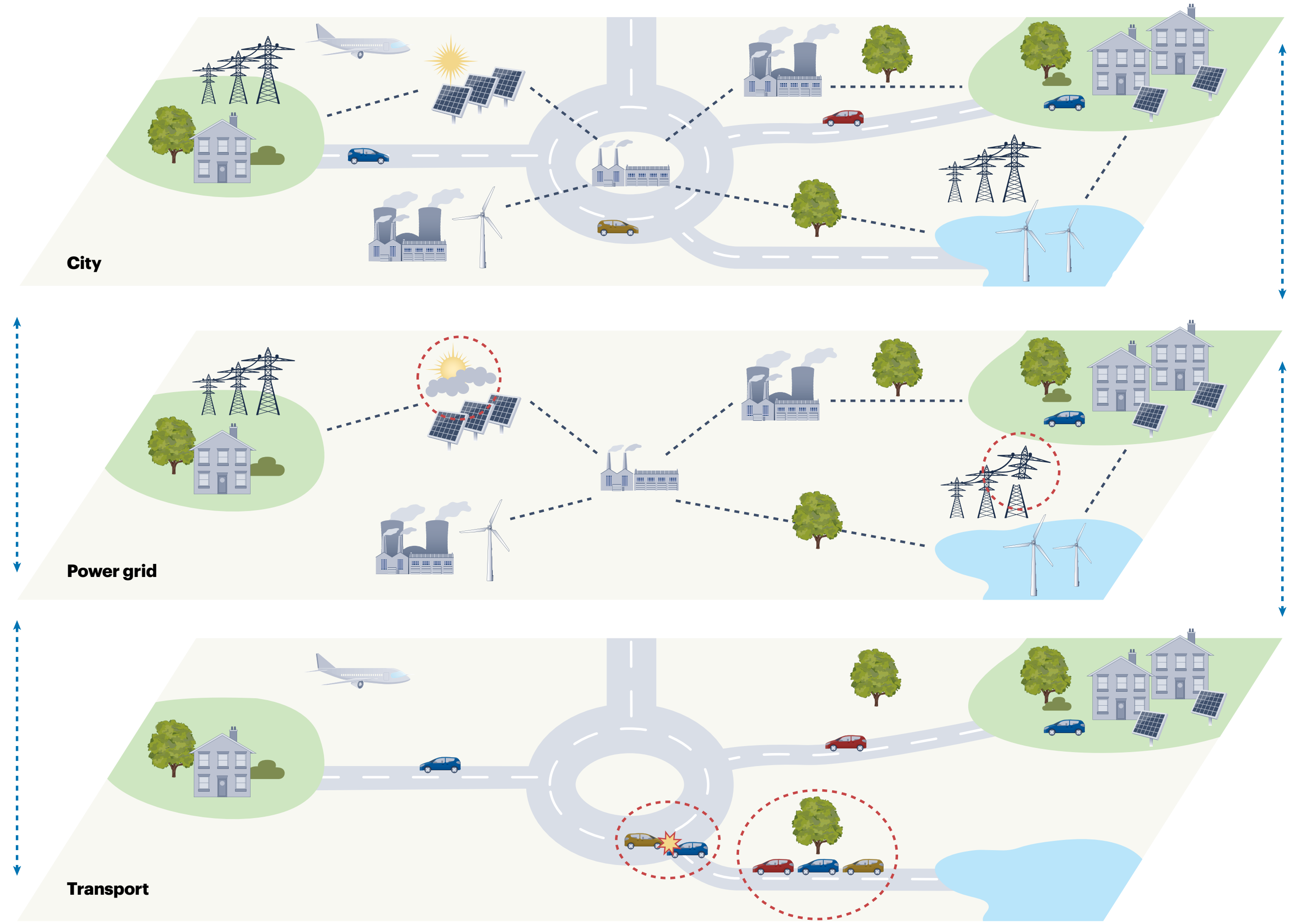

Fig. 1 | Disentangling complex systems and understanding their collective dynamics. A typical city (top layer) comprises industrial, residential and commercial areas. In a first step, features present in parallel need to be studied individually, for example, electricity flows in power grids (middle layer) and mobility on street networks (bottom layer). Different perturbations and external influences (red dashed circles) impinge on the systems at different layers. Understanding the collective nature of the dynamics of complex systems individually already requires to broadly collaborate across many disciplines and to closely integrate methods and tools, especially data-driven approaches, computational modeling and simulation, as well as mathematical concepts and theory. In later steps, results from the different 'layers of complexity' are reintegrated, for instance, coupling the dynamics of electric vehicles that support human mobility with charging infrastructure and thus electric power grids that support the supply of energy.

second, for the availability of time-series data along with fundamental dynamical systems models about their collective network phenomena; and third, because the two systems share certain collective phenomena and associated concepts, emphasizing a certain degree of transferability of approaches across different complex systems.

To emphasize the phenomena rather than the specific systems, and to thereby highlight the perspective of complexity science taken in this article, we also arrange the article by phenomena of roughly increasing complexity.

With core examples from the realms of power grids and street traffic, we explain features of collective dynamics and illustrate their analysis on four levels of complexity. First, we highlight how to characterize collective properties for stationary states, for example, in systems exhibiting temporally constant traffic flows or electric power flows and cover the influence of structural changes upon dynamics. Second, we characterize fluctuating driving signals such as fluctuating electric power feed-in and fluctuating demand. Third, we consider the impact of such fluctuations on the collective response dynamics, resulting in non-equilibrium conditions that these complex systems are exposed to. Fourth, we explain why ride-sharing systems constitute an extreme form of non-equilibrium dynamics, underlining how their dynamics is entirely induced from outside the system itself, solely by the customer requests for trips, and argue why this type of driving induces strong, long-range spatio-temporal correlations. We do not discuss here the reintegration of the individual complex systems' layers (power supply grid, street traffic flows) into higher-order complex systems, for example, at city level. The resulting interdependent networks form systems of a new level of complexity and have a key role in today's world with multiple infrastructure networks interacting. However, research on their collective dynamics is still nascent, as discussed toward the end of this article.

We specifically review recent work that has catalyzed progress by integrating theoretical, modeling and data-driven methods toward a more overarching understanding of possible complex systems dynamics. We zoom in on specific examples of the dynamics of electric power supply and demand with a high share of renewable energies and on paths toward sustainable human transport.

Stationary supply networks and Braess's paradox

Supply networks mediate the transport of people, electricity, water, gas, food, goods and related entities, all essentially underlying every aspect of our life. These networks require dedicated infrastructures to provide services and distribute goods to end-users and need to respect certain operating constraints. Several types of collective dynamics

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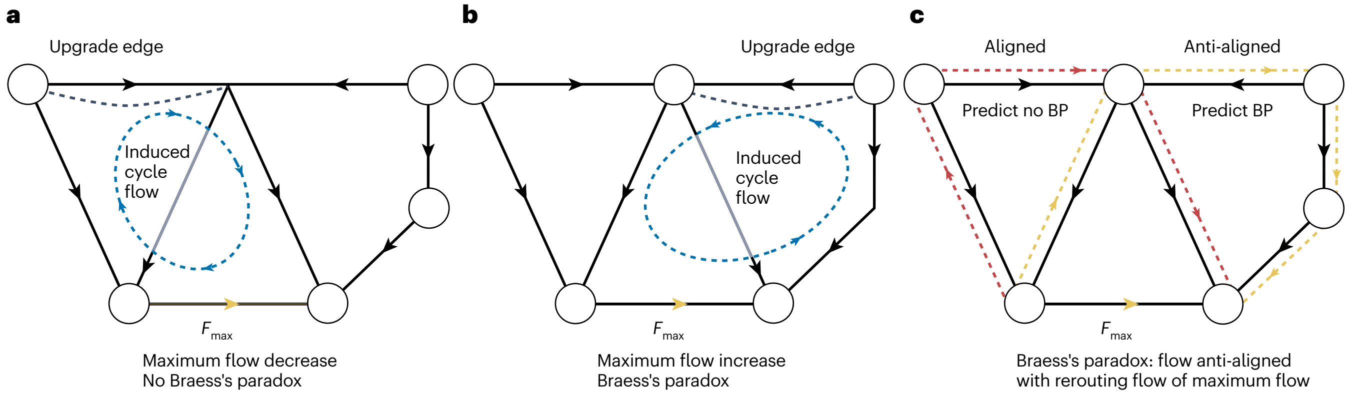

Fig. 2 | Identifying Braessian edges whose upgrade causes Braess's paradox. a, For certain edge upgrades, induced additional (cyclic) flows anti-align with the maximally loaded edge such that the maximum flow in the network decreases and no Braess's paradox (BP) emerges. The upgraded edge is not Braessian. **b**, In contrast, upgrading another edge, the induced cycle flow aligns with the maximally loaded edge and the maximum flow (F_{max}) in the network increases. Braess's paradox occurs and the upgraded edge is Braessian. **c**, In planar networks, such basic alignment properties accurately (but not perfectly) predict which edges are Braessian and which are not. Figure adapted from ref. 13, CC BY 4.0.

emerge similarly across different types of supply network. For instance, both electric power grids and street networks enable stationary flows, either of electric energy or of humans or goods.

What happens if infrastructural elements change, for example, a transmission line or a street is newly built or removed? The new collective dynamics on the systemic level may or may not satisfy the operating constraints. Ordinarily, adding new supply links to a supply network is thought of as strengthening the system's robustness of operation against overload or other failures. However, already in the 1968, Dietrich Braess observed what is known today as Braess's paradox[5]: that adding streets to a street network may worsen its performance or, equivalently, closing streets may improve overall traffic flow.

How and under which circumstances does this collective phenomenon come about? The mathematician Braess initially pinned down the paradox in a mathematical model of traffic flow where some streets, such as highways, have fixed travel times, while for others, such as smaller city streets, the travel time and thus throughput strongly depend on the street's traffic load. He observed that upon adding a fast shortcut street to an existing network, all cars eventually needed longer—in contrast to common intuition. Furthermore, from a game theoretic perspective, this system-wide 'slow' state constitutes a Nash equilibrium[6]. In such a state, if any single driver decides to take an alternative route, she is worse off, that is, even slower, although such an alternative is faster if all drivers switch[7]. Over the decades, theoretical work as well as small-scale lab experiments have established the existence of Braess's paradox across vastly different systems, including more complicated traffic systems, mechanical systems of masses coupled by springs, the direct-current (DC) electric circuit of a Wheatstone bridge and microfluidic circuits[8–11].

For models of alternating-current (AC) power grid dynamics, theoretical work[12] has not only shown that Braess' paradox may emerge upon upgrading the grid, that is, adding new transmission lines or strengthening existing ones (Fig. 2). It has also revealed that the relations between phase deviations relative to the overall grid's time evolution, as determined by the grid frequency (typically 50 Hz or 60 Hz), need to satisfy topological constraints. Each new line induces an additional constraint. For certain lines, Braessian edges, the set of all constraints becomes unsatisfiable, causing the loss of the desired operating state (collective phase-locking, with pairwise phase differences constant in time across all lines). The theoretical approach has thus identified a mechanism underlying Braess's paradox, yet it remained open whether the paradox is actually relevant in the real world.

A long-term cross-disciplinary study[13] that joined engineering experiments, physics-based ideas, mathematical analysis and computational evaluation of grid extension scenarios took a first step toward closing this gap. It analyzed a laboratory-size AC grid of both physical synchronous generators[14] characteristic of traditional fossil fuel power plants such as coal or gas power plants and of hydropower plants, as well as virtual synchronous machines that become increasingly important to imitate inertia in inertia-free renewable power generation[15–17]. In such grids realized in hardware, the study experimentally demonstrated the emergence of Braess's paradox in AC grids under conditions akin to large-scale power supply networks. Moreover, it computationally evaluated stationary flow patterns resulting from various originally planned scenarios of actual extensions of the European grid in Germany and found evidence that Braessian edges exist in real-world power grids as well.

Recent progress has highlighted that most of the Braessian edges whose addition causes Braess's paradox may be straightforwardly detected computationally by exploiting an approximate theory of the influence of effective network dipoles, pairs or connected network nodes with net power supplied through and taken out at the other node[18]. Moreover, intriguing recent modeling work uncovered a second mechanism causing Braess's paradox, observed through extensive direct simulations as a function of initial conditions in state space[19]. The authors found a change in non-local stability properties that implies a diminishing probability of returning to the desired operating state with increasing line strengths. They thus discovered a new kind of Braess's paradox in which a given operating state continues to exist but becomes less robust to perturbations if lines are upgraded.

Supply-and-demand fluctuations in power grids

The collective dynamics of supply networks is typically characterized by fluctuations that arise from variations in supply and demand on different timescales. Robust networks need to tolerate all of those fluctuations. During the energy transition, the share of variable RES is increasing while the pattern of electricity consumption is changing due to the exploitation of RES in other sectors, digitalization, the increased use of smart devices and other factors.

May such fluctuations enable the emergence of new nonlinear collective dynamics in supply networks and may they disrupt normal network operations? To address these questions, we first need to better understand the characteristics of fluctuations of supply-and-demand patterns, which we explore in this section.

Supply-side power fluctuations

Among the RES, wind and solar power are sources inherently time-varying on scales from seconds to seasons[20,21]. This irregular,

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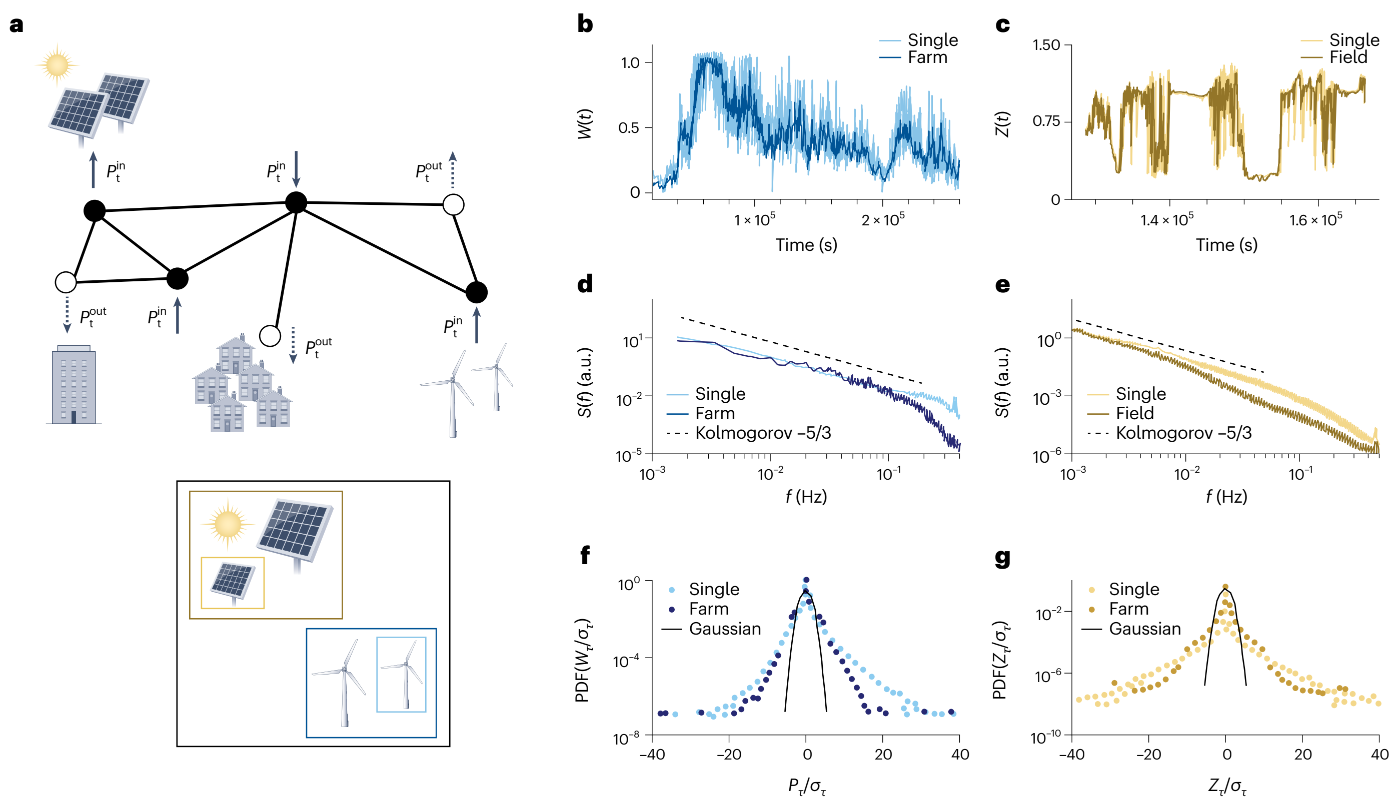

Fig. 3 | Supply fluctuations and extreme events impacting electric power grids. **a**, Direct feed-in (solid arrows) of RES fluctuations to the power grid. The framed box at the bottom illustrates a single solar panel (yellow) versus a solar field (dark yellow) and a single wind turbine (blue) versus a wind park (dark blue). At each grid node, feed-in provides fluctuating input power P_t^{in} through external supply while power consumtion causes power fluctuations P_t^{out} **b**, Wind power fluctuations (blue) for a single wind turbine and a wind farm (averaged over 12 turbines) based on data analyzed in ref. 25, where $W(t)$ represents scaled wind power $P_{wind}(t)/P_r$, with P_r the rated or maximum power output of a wind turbine. **c**, Solar power fluctuations (yellow) for a single solar panel and a solar field (averaged over 16 small panels of area 0.13 m^2 each)[25]. Here $Z(t) = P_{solar}(t)/P_{clearsky}$ represents the power standardized by the clear-sky index, that is, the ratio of the measured solar power $P_{solar}(t)$ to its theoretical prediction under clear-sky conditions $P_{clearsky}$. **d**,**e**, Fourier power spectra, illustrating slow power-law decay. **f**,**g**, PDF (that is, histogram) of wind and solar power increments for a time interval of 1 second, indicating that extreme events of several standard deviations (σ_τ) occur many orders of magnitude more frequently than if the increments were Gaussian (black solid fit). **b**–**g**, Data from ref. 25.

hardly predictable and often extreme variability may constitute serious threats for power grid stability (Fig. 3a–c).

Recent data analysis[22–25] found that the (Fourier) power spectra $S(f)$ of high-frequency recordings of time-series data of wind- and solar power feed-in $x(t)$ as a function of time t algebraically decays as $S(f) \approx f^{-\gamma}$ for small and moderate frequencies $f < 0.1$ Hz with an exponent of $\gamma \approx -5/3$ close to the Kolmogorov exponent known for turbulent flows[26] (Fig. 3d,e). A second characteristic of turbulence is its intermittency[26], such that the flow exhibits repeated and randomly timed rapid switches among different states, such as sunny and cloudy or windy and low-wind states[24,25].

The probability distribution function (PDF) of wind and solar power increments is capable of revealing whether RES fluctuations are indeed intermittent.

The analysis demonstrates that these PDFs decay exponentially for large increments $x_\tau = x(t + \tau) - x(t)$ after a time difference τ and thus strongly depart from the normal (Gaussian) distribution, supporting the hypothesis of intermittent power feed-in (Fig. 3f,g). Intermittency is a common phenomenon emerging in complex systems where its collective dynamics alternates between regular periods and periods of irregular or chaotic behavior. In wind power systems, for instance, intermittent power feed-in may be induced by periods that are dominated by laminar, low-power winds interrupted by periods of higher-power wind gusts that causes turbulent, chaotic behavior[27,28].

The finding of intermittency and thus broadly distributed power feed-in is relevant also for computational modeling of power grid feed-in that often assumes Gaussian fluctuations with a characteristic scale that does not exist in intermittent dynamics (see, for example, International Electrotechnical Commission: IEC 61400-1[29]). Extreme events may occur as power drops to nearly zero within a few seconds, happening at several time intervals during a single day, contrasting much fewer of such events in a Gaussian time series. These extreme events may impede stable operation of power grids in the absence of sufficiently fast control systems and ready back-up energy sources.

Wind turbulence explains the intermittency in wind power time series on short timescales, so that the nonlinear relation of wind speed u and wind power P_{wind} (that is $P_{wind}(t) \propto u^3(t)$) results in the power output of wind turbines being even more intermittent than wind speed itself[24]. As for solar power in general and photovoltaics in particular, the dynamics of clouds and their size distributions cause intermittent characteristics of the respective time series. The on/off pattern of the rapid succession of direct sunlight exposure and cloud shadow coverage of a fixed location thereby induces many extreme events of large amplitude ramps and jumps in solar irradiance (see, for example, Woyte et al.[30] and Lohmann et al.[31]).

Importantly, time-series data from installations of wind and solar fields aggregated country-wide still exhibit non-Gaussian statistics, including intermittent fluctuations[25] (Fig. 3). One major reason is long-range correlations of the wind velocity and cloud size distribution that are approximately 600 km and 1,200 km, respectively[32,33]. However, combining statistical physics theory with large-scale data analysis uncovered a critical phase transition of the stochasticity from jumpy, that is on/off type, to a persistent stochastic process, depending on the spatial size over which the renewable energies are harvested[25]. Indeed, spatially averaging across sufficiently many feed-in units, jumps cease to exist ($\xi = 0$ in equation (1)), yet the process still remains intermittent.

Intrinsic fluctuations of RES directly transfer to the electric power fed in to the grid. Studying the footprint of the RES intermittency on the recorded power grid frequency has indicated[34] that the large increments in the German power grid frequency occur when large amounts of wind power are fed in.

The aforementioned statistical analyses are complemented by studying the nonlinear temporal evolution of the wind and solar power dynamics. Such studies may reveal which dynamical features may induce large increments and how these vary with the geographical size of a wind or solar field. In this way, the jumpy and diffusive stochastic behaviors of RES may be separated.

To model both jumpy and diffusive behavior of these sources, in particular, solar power, a non-parametric stochastic model, the jump–diffusion equation, was introduced in Anvari et al.[35]. It is a modified Langevin equation[24] for modeling discontinuous processes that include jumps. This process is characterized by the jump rate and jump amplitude, drift, and diffusion coefficients, where all of the parameters and functions can be calculated non-parametrically, that is, directly from measurement datasets. The jump–diffusion equation

$$\mathrm{d}x(t) = D^{(1)}(x,t)\mathrm{d}t + \sqrt{D^{(2)}(x,t)}\mathrm{d}w(t) + \xi \mathrm{d}J(t), \tag{1}$$

characterizes the time evolution of the wind or solar power (or even solar irradiance) $x(t)$, where $D^{(1)}(x,t)$ and $D^{(2)}(x,t)$ are the drift and diffusion coefficients, respectively, $\{w(t); t \geq 0\}$ is a Wiener process (scalar Brownian motion), ξ is a jump size taken to be normally distributed random number, that is, $\xi \approx N(0;\sigma_\xi)$. The σ_ξ is called the jump amplitude. Finally, $J(t)$ is a time-homogeneous Poisson jump process with jump rate λ per unit time. Another stochastic model that mimics the stochastic characteristics of wind force is introduced in Schmietendorf et al.[36].

These stochastic models allow the construction of RES time series that are statistically identical to those of measured ones. The parameters of these models can be directly calculated from the recorded time-series data from a single wind turbine or solar panel, as well as wind or solar fields (see, for instance, Milan et al.[24] and Anvari et al.[35]). Importantly, these parameters are adjustable individually such that computational modeling is capable of revealing their impact on power grid dynamics[36–38]. As these stochastic time series can be generated indefinitely, they constitute a practical solution to the lack of real training datasets. Large datasets are required for computational models to learn stochastic fluctuations and to detect the fast transitions between system states, such as the jumpy behavior of solar energy between cloudy and sunny states. Recently, the combination of deep learning and stochastic differential equations, such as neural jump stochastic differential equations[39,40] has become a topic of great interest, where the time series obtained from equation (1) can be used as training sets, and maybe offer a suitable solution for predicting short-term fluctuations in RES.

Demand-side fluctuations

To maintain the balance between energy provided and consumed it is equally essential to estimate the typical variations in electricity demand. Variations over the course of a day yield what is known as the load profile (of energy consumers)[41,42]. Classically, two main model classes exist to calculate the household load profile: (1) top-down and (2) bottom-up models[43]. Top-down models estimate the total electricity consumption of multiple households along with macro-variables, such as the total residential sector electricity consumption, the structural characteristics of the dwellings, the number, age, sex, race/ethnicity, income and so on, to model the dynamics of load profiles for households[44]. Bottom-up models require as input many micro-parameters, such as the number of active occupants, each appliance's energy demand, usage time and so on, as an input. Sometimes, top-down and bottom-up techniques are combined to construct load profiles, known as hybrid modeling[45].

In Germany, for instance, a top-down model has been used to help the electricity providers to forecast their customer's yearly electricity consumption[41]. Specifically, the consumption data of 332 houses recorded between 1960s and 1990s with 15- and 60-minute time resolution were selected. After upsampling all data to 15 minutes and including characteristics of seasons such as temperature, as well as week days and weekend days, the first methodologically systematic German household load profile, known as the H0 standard load profile (H0 SLP), was developed in 1999. It has been used as a guide without alterations since then in at least Germany and Austria[46].

Although the topic of developing load profiles goes back to at least the 1940s[43], finding a precise, high-resolution load profile is still challenging, and it is becoming increasingly urgent. The reasons are manifold and include, for instance: the continuous increase in electricity consumption—due to increased energy consumption and increased electrification—along with the increase in the share of variable RES; the replacement of the traditional consumers with the prosumers who simultaneously produce and consume energy[47,48], for instance, through roof-top photovoltaics; and the movement toward power-to-X technologies, in particular for making use of the surplus of RES electricity in other sectors, such as for mobility, heating and gas production[49].

The recent statistical analyses of recorded high-resolution demands demonstrate that the loads are far from constant across times and locations[50–53], and similar to RES, they are intermittent (Fig. 4b). Specifically, the electricity consumption ramps up and down quickly much faster than revealed by 15- and 60-minute time resolution underlying the current standard load profile. Extreme consumption spikes are of particular importance to lower-voltage distribution grids, where coincident consumption may dominate the consumption patterns locally or on a country scale due to, for instance, synchronized activity during major (for example, sports) events, such as TV pick-up in Britain[54]. At present, only a few demand analysis models use a high temporal resolution (down to seconds) to generate daily residential electricity load profiles[44] and those require many micro-parameters, which still leaves us with the need for an accurate, high-resolution, easy-to-use data-driven load profile to be developed. Recently, a generally applicable data-driven modeling framework was introduced[53] that follows the dynamics of residential electricity consumption. In that work, the baseline demand dynamics over the course of a day, an average load profile (ALP) (Fig. 4c), has been disentangled from the fluctuations on top of that baseline, a stochastic fluctuation profile (SFP) (Fig. 4e). To obtain the ALP, the empirical mode decomposition (EMD)[55] has been used to split the dataset into multiple modes and, thereby, separate the long-term trends (low-frequency modes) from the short-term fluctuations (high-frequency modes). The sum of low-frequency modes up to some maximum frequency yields the ALP. The sum of the remaining modes yields the SLP. To re-generate the intermittent SLP with similar statistic and stochastic characteristics, a superstatistical model[53,56,57] has been applied. Eventually, by combining the EMD-based trend of the demand with the stochastic fluctuation model, a data-driven load profile (DLP) is obtained (Fig. 4f).

Taking into account available microscopic data, such a DLP is capable of characterizing (1) the demand of already moderately sized sets of consumers with (2) high time resolution. It moreover is (3) applicable to a range of data, including those to be recorded in the future. Together, these features and capabilities open up a new direction of research beyond what the SLP offers. Moreover, the DLP does not require microscopic parameters for consumer behaviour, consumer appliances, house infrastructures or other features that other models depend on.

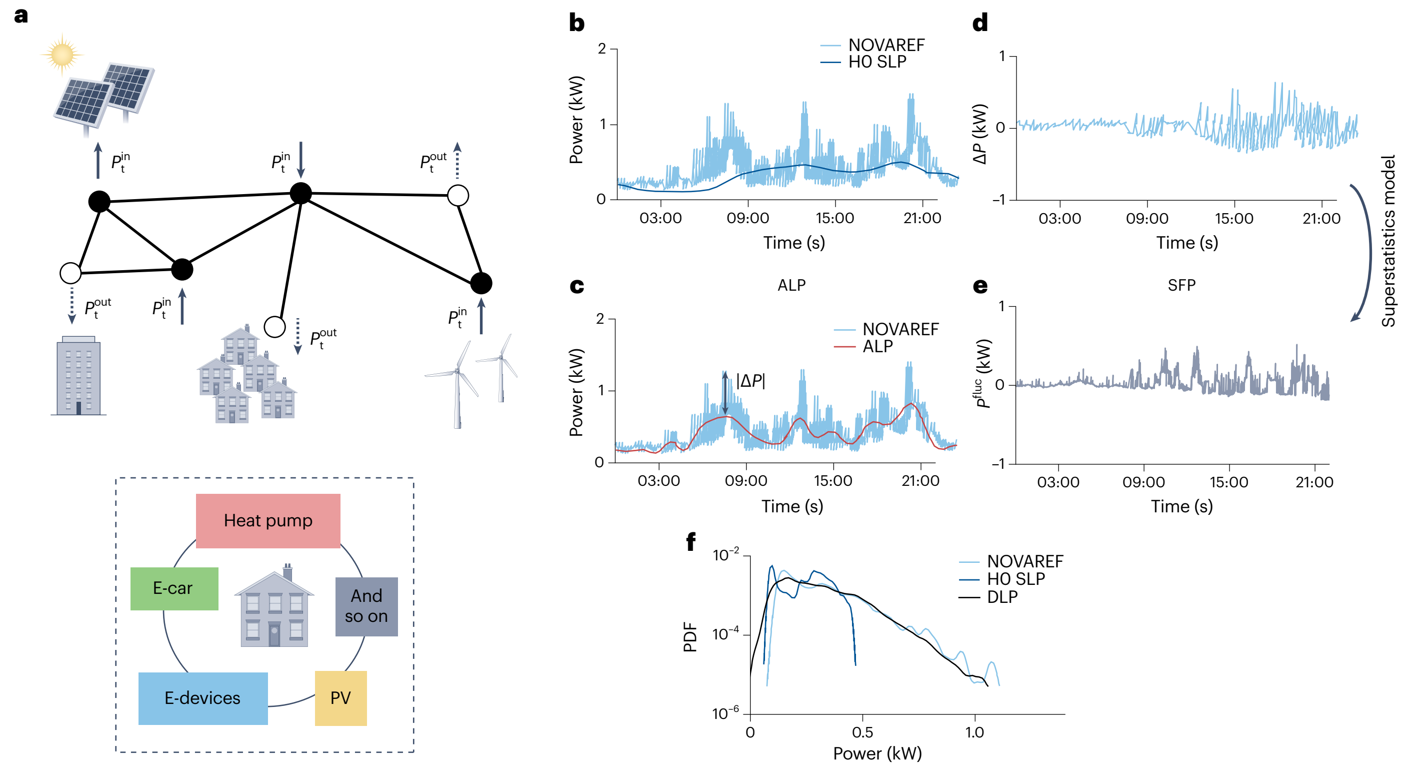

Fig. 4 | Demand fluctuations and extreme events impacting electric power grids. **a**, Fluctuations on the demand side (dashed gray arrows) influence the power grid dynamics. The dashed-framed box at the bottom illustrates various residential consumers and producers (prosumers) that include electric cars and consumption devices as well as supply devices such as photovoltaic (PV) arrays. **b**, Time series of 1-day empirical power consumption dynamics associated with the NOVAREF project[129], which includes 12 households, shown with the H0 standard load profile (SLP). **c**, The average load profile (ALP) more closely follows slow demand variations than the H0 SLP. **d**, Subtracting the ALP from the empirical data time series yields the stochastic components ΔP of the fluctuations. **e**, A superstatistics model best-fitting empirical sample data $\Delta P(t)$ generates similar fluctuations. **f**, Combining the ALP and the stochastic fluctuation profile (SFP) yields the data-driven load profile (DLP) with its PDF closely matching the empirical data PDF, also at larger power magnitudes. In contrast, the PDF of the H0 SLP is far from the empirical data at larger power magnitudes. **b**–**f**, Data from ref. 130.

The introduced data-driven model for the demand time series, similar to the stochastic model introduced for the RES time series, is applicable for computational modeling of power grid consumption and, thereby, the power dispatch design, considering the non-Gaussian SLP instead of assuming a Gaussian demand time series[58]. In addition, the time series of demand generated indefinitely by the data-driven model are useful for machine learning techniques to accurately predict the required demand during a day, to be provided by energy providers[39,40].

Besides temporal fluctuations, the spatial variability of demand as quantified through cross-sectional data is also key to planning grid infrastructure and may impact the resulting dynamics. Basic approaches of linear regression models (see, for example, Salisu and Ayinde[59]) assumed linear relationships between electricity demand and income, population density, the size of industrial complexes, and other factors to help estimate spatial variations in demand as well as long-term changes. Multiple linear regression, which generalizes linear regression to simultaneously incorporate several explanatory variables, helps to better capture the multi-factored nature of electricity demand. Relevant factors may range from household size to electric vehicle ownership to regional climate conditions, all of which vary spatially. For instance Li et al.[60] used multiple linear regression as a baseline for cross-sectional analysis of load demand across different smart grid zones. Moreover, recent research by Hamann et al.[61] suggests that insights from such cross-sectional data analysis may help integrate advanced machine learning techniques into modeling varying demand in space and time. All of these approaches in particular address spatial variations that impact grid planning and stable operation quantitatively yet often do not change the collective dynamical states qualitatively.

Fluctuating responses of supply networks

Electric power grids and other supply networks often operate near but not at specific operating points. Recent advances combining observed frequency data, mathematical analysis and direct numerical model simulations have revealed how such networks respond to instantaneous or continuing external signals that may arise from demand (consumer)-side fluctuations, perturbations due to line outages, input fluctuations due to renewable energy feed-in, as well as load shedding or voltage drops at network nodes[62]. We here review recently developed analysis and modeling approaches. We also briefly cover the analysis of perturbation spreading patterns for networks that can give rise to undesirable collective dynamics in the system.

Spreading and propagation phenomena were originally analyzed in simple models of network dynamical systems. For instance, Motter and colleagues[63] investigated failure cascades in basic threshold models while Radicchi and Meyer-Ortmanns[64] characterized the continuous response dynamics of regular networks of phase oscillators with one unit driven as a pacemaker. As a main finding with broader implications, the latter study found that the influence of the (perturbed) pacemaker-like unit decays exponentially with the distance on the connectivity graph. Zanette[65] analyzed how local perturbations to a unit distribute in a sparse network of oscillators and how that depends on the frequency content of the perturbation. Hens et al.[66] revealed that perturbations that permanently change the state of one unit in a network generate responses that exhibit only a few types of universal spatio-temporal propagation pattern[67]. They arrived at this conclusion by combining mathematical asymptotic analysis[68] with direct numerical simulations of spreading patterns across networks of various interaction topologies and dynamics. Recent work picking up on the question has revealed that network motifs, small substructures of the network, determine the type of propagation pattern[69].

Such fundamental pieces of research lay the conceptual ground for understanding more system-specific questions about how fluctuations and other external perturbations or signals induce distributed collective response dynamics in both energy supply networks and networked mobility systems.

Yang et al.[70] studied the vulnerability of power grid transmission lines to cascading failures. They combined large-scale data about the North American power grid at various snapshots (different years, seasons, and supply-and-demand setting) with extensive load-flow calculations[14]. Initial perturbations may cause additional failures of system components upon which load flows are recalculated. The evolution of cascades has been modeled based on a cascading model to investigate how line overloads and outages are distributed in the grid. A main finding is that only small sets of lines that are highly vulnerable contribute most to cascades. Such approaches to cascading processes on networks implicitly assume a discrete dynamics of the flows as they iteratively re-adapt to each new failure in the system. Schäfer et al.[71] in contrast studied cascading as a hybrid process of the shorter-term continuous-time dynamics, that is, interrupted by discrete time events in the form of discrete line outages. A related study suggested a more general perspective for analyzing tipping cascades across networked systems of hybrid form[72].

Extreme weather events such as hurricanes or floods may damage key elements of electric power grids, in particular, transmission lines, and thereby cause local power outages or large-scale system blackouts. Recent studies[73,74] combined spatio-temporal wind-speed data from major historic hurricanes with a mathematical network model for the power transmission grid of Texas and a probabilistic line fragility model to investigate how single line failures caused by extreme wind events induce cascades and larger outages. They found that protecting only 1% of lines from failing may reduce the number of major outages caused by extreme wind events by an order of magnitude.

A broad, non-Gaussian power grid frequency distribution has been consistently observed across several countries[75,76]. The broadness is jointly caused by several factors such as fluctuating RES feed-in, fluctuating demand, as well as trading and regulatory actions[75–77]. The time evolution of power grid frequency may be partially predicted based on past time-series patterns[78], potentially integrating RES variability.

To better understand how power fluctuations on the supply and demand sides translate to grid-intrinsic frequency fluctuations and how ongoing fluctuating signals distribute across power grids, Zhang et al.[79,80] and Kettemann and co-workers[81] developed and evaluated a linear response theory for network models of power grid dynamics[82]. The theory mathematically approximates the response to fluctuating input signals to first order in the amplitude of the driving signal. Besides a regime of responses that are localized topologically near the network node of signal inputs at high driving frequencies, there is a bulk regime at low frequencies as well as a regime of complex resonance patterns at intermediate frequencies (Fig. 5a,d).

A comparison with direct numerical simulations suggests that the linear approach faithfully reproduces model response dynamics not only for small but also for moderate signal amplitudes. However, the prediction error becomes large for strong driving signals that induce responses near overloads and thus poses risks to grid operation. Recent work also estimated realistic propagation velocities in grids with frequency and voltage dynamics and offered a measure to quantify responses across networks[83].

Interestingly, taking into account dynamically varying voltage variables revealed a novel, genuinely nonlinear response property (Fig. 5e) that is not at all captured by linear response theory[84]. The recent study uncovered that the average response of externally driven power grids typically is non-vanishing, such that the response voltage does not fluctuate around the original operating state but is shifted with respect to it. Moreover, if the driving amplitude becomes large, the response ceases to be close to the original operating state and the system crosses a tipping point, exhibiting qualitatively different dynamics beyond a critical driving amplitude.

A proposed non-standard perturbative technique[84] may help to predict such nonlinear responses as well as the location of tipping points. Such approximate mathematical information becomes valuable in particular for systems with many parameters. As parameters are never exactly known, the only alternative for predicting such responses would be to numerically simulate long-time system trajectories for all, typically exponentially many, combinations of parameters, a task often computationally expensive or even practically infeasible.

From traffic flow to demand-induced ride-pooling dynamics

We now turn to the collective dynamics of ride-pooling that represents an active type of dynamics that only emerges because customers request rides. Before we go into details, we set the stage by providing a perspective on different levels of model street traffic that, similar to modeling power grids, starts from stationary states with temporally constant flows.

Stationary street traffic and fluctuations

A traditional basic model of the dynamics of street traffic considers traffic flow in terms of the number of vehicles (or passengers) passing a given point of a street segment per time. Implicitly, evaluating flows models an average, overall and stationary dynamics of traffic, not individual vehicles. Computational modeling is thus relatively simple as it evaluates standard flows given street networks as well as sources and sinks of traffic. The fundamental diagram of traffic flow constitutes one core example of this perspective[85]. It quantifies the flows of vehicles as a function of traffic density, with below-maximal flows beyond a certain density and thus inefficient, congested, economically and ecologically unsustainable traffic states.

Basic and increasingly complex computational agent-based models, starting with the Nagel–Schreckenberg model[86–90], in contrast, take into account varying properties, behaviors and boundary conditions of drivers, vehicles and infrastructures. The resulting intrinsic heterogeneities and time-dependent behaviors thereby induce fluctuations in such models.

Fluctuations, in turn, may cause collective phenomena such as congestion. For instance, fluctuations in driving speed may result in heterogeneously distributed distances between one vehicle (or person) driving (or walking) behind another. Such heterogeneity in inter-vehicle distances may induce a suboptimal[91] throughput capacity of street segments and thereby congestion emerging below what pure flow-based analysis may suggest. Kühne et al.[91] have characterized such traffic breakdown by analysis of a stochastic process mathematically modeling the phenomenon whereas individual realizations of such breakdowns are typically found via agent-based simulations[90]

Interestingly, such heterogeneity and implied congestion also emerges in the absence of initial velocity differences, purely due to stochastic fluctuations of the number of vehicles that enter a street segment per time. Treiber and Kesting[89] have generally characterized stochasticity-induced instabilities of traffic states. Andreotti et al.[92] found that fluctuations by random route choices may induce congestion in the absence of other factors whereas Kim et al.[93] found traffic breakdown due to weather conditions in combination with the time of day. Finally, recent work by Kerner[94] suggests that bottlenecks may act as major causes for traffic slowing and congestions and Krall et al.[95] explained congestion that emerges from pure number fluctuations even for average flows that are subcritical.

Demand-initiated non-equilibrium dynamics

Ride-pooling systems exhibit additional, non-local mechanisms of stochasticity that go beyond such locally induced randomness. First,

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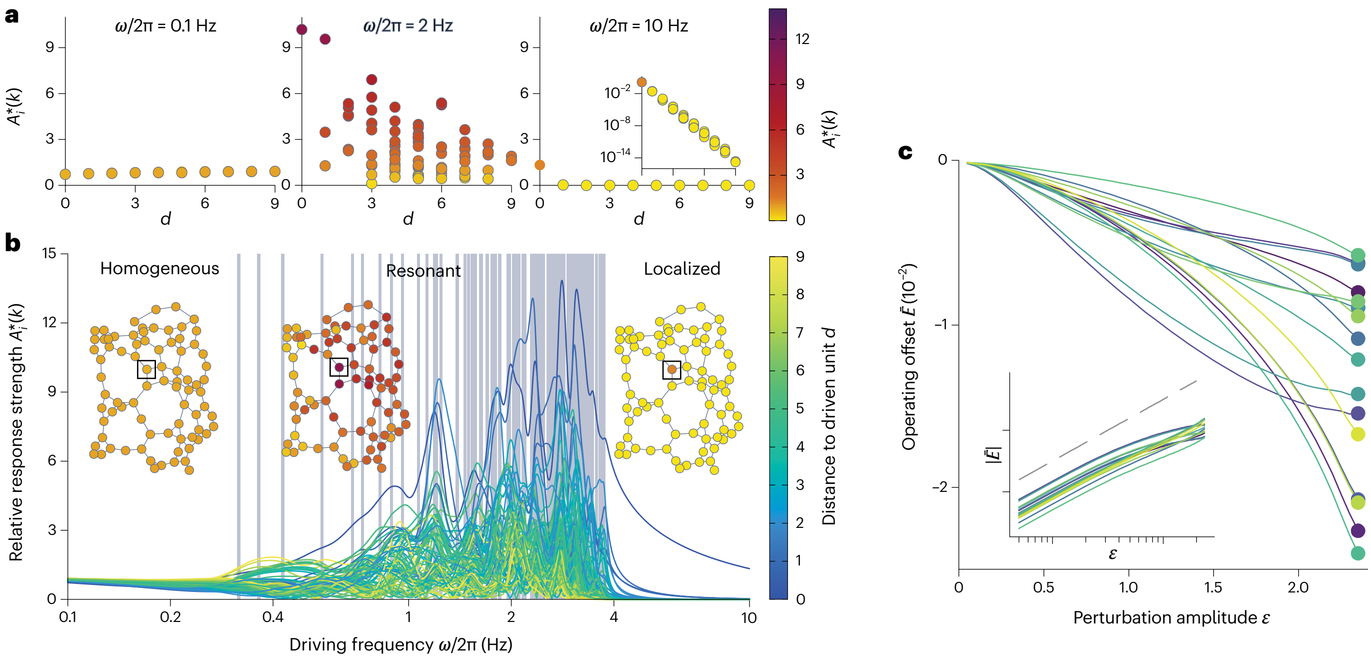

Fig. 5 | Complex collective fluctuation-response dynamics of electric power grids. a,**b**, For power grid models driven by a signal of the form sin(ωt) impinging on one node, the AC phase frequencies of all network nodes respond in dependence of the system parameters, the driving frequency and the network's topology of interactions, in particular, the distance *d* between driven node *k* and responding node *i*. The resulting response amplitude $A_i(k)$ at node *i* depends on the which node *k* is driven and on the driving frequency ω. Depending on the driving frequency ω, the network responds with three qualitatively different forms of collective dynamics. **a**, Left: at low driving frequencies ω, the network responds essentially as one and all nodes respond with approximately the same amplitude. Middle: at intermediate driving frequencies, the system responds with resonances that depend on the details of the network topology and the underlying base operating state the system is perturbed from. Right: at high driving frequency, the responses are localized near the driven node, decaying also with increasing frequency. **b**, All these responses are well characterized by linear response theory[82] such that fluctuation responses to driving signals containing multiple frequencies and impinging on several network nodes are well described by the superposition of individual responses. **c**, Intriguingly, the local voltage variables E_n respond in a genuinely nonlinear fashion, with the average offset of the fluctuating response from the base operating point $\bar{E}_n$ scaling nonlinearly (initially quadratically; dashed line in inset) with the perturbation amplitude ε. Ever stronger offsets ultimately are not viable and induce tipping (colored disks) at a certain driving amplitude above which the grid ceases to operate normally. Panels adapted with permission from: **a**,**b**, ref. 82, APS; **c**, ref. 84, Elsevier.

in on-demand ride-pooling systems, vehicles drive only in response to (essentially random) transportation requests, so there is no dynamics of the vehicles at all in the absence of requests.

Moreover, the ad hoc customer ride requests make the dynamics of ride-pooling systems non-local in space and time.

Specifically, in ride-pooling systems, individuals request to be transported between personally defined origin and destination locations within a desired time window, similar to a conventional taxi service (see, for example, Santi et al.[96]).

In contrast to taxi services, however, two or more individuals accomplish their trips by sharing rides on one vehicle, therefore increasing vehicle efficiency and sustainability. Because requests need to be assigned to vehicles and vehicles need to be routed accordingly, and because the assigned vehicle an individual requests implies a pair of additional stops, the motion of individual vehicles and thus of a fleet of ride-pooling vehicles becomes strongly correlated in time and space (Fig. 6). As a consequence, it remains highly challenging to efficiently assign requests, to understand the joint implications of request patterns and (street) network topologies, and assignment and routing for fleet efficiency, and to computationally model and analyze such systems in other aspects. We briefly mention key recent progress with a focus on heuristics.

Alonso-Mora et al.[97] have discussed the potential benefits of ride-sharing services and proposed a scalable algorithm capable of matching large groups of riders to a fleet of shared vehicles in real time. The algorithm was experimentally validated using historic, that is, pre-recorded, data of New York City taxi rides and a simulated shared vehicle fleet with passenger capacities of up to ten. The results showed that a fleet of 2,000 such vehicles may serve 98% of the requests, delaying trips due to rider waiting times and vehicle detours by approximately 3.5 minutes on average compared with direct taxi rides. The algorithm can also dynamically generate optimal routes with respect to online demand and vehicle locations and incorporates rebalancing of idling vehicles to areas of high demand. The framework is general and may be transferred to many real-time multi-vehicle, multi-task assignment problems. The findings suggest that ride-sharing services may at least algorithmically provide efficient and sustainable mobility by ride sharing in urban areas. The algorithm is capable of optimizing fleet size, capacity, waiting time, travel delay and operational costs for low- to medium-capacity vehicles such as taxis and minibuses.

Research extending those results[98] offers a design of an on-demand ride-sharing system where users may be required to walk to nearby pick-up and drop-off locations with the purpose of improving overall efficiency. The optimization problem contains two sub-problems that extend the set-cover problem of combinatorics, and the authors provide a general formulation and specific heuristics that can solve it over large instances. Simulations again using New York City taxi trips showed that average walks of about 1 minute may reduce the number of rejections by more than 80%. Vazifeh et al.[99] have introduced the notion of a 'vehicle-sharing network' that efficiently combines requests for rides that are spatio-temporally close. It enables an optimal, computationally efficient solution to the problem of identifying a minimal fleet of ride-sharing vehicles.

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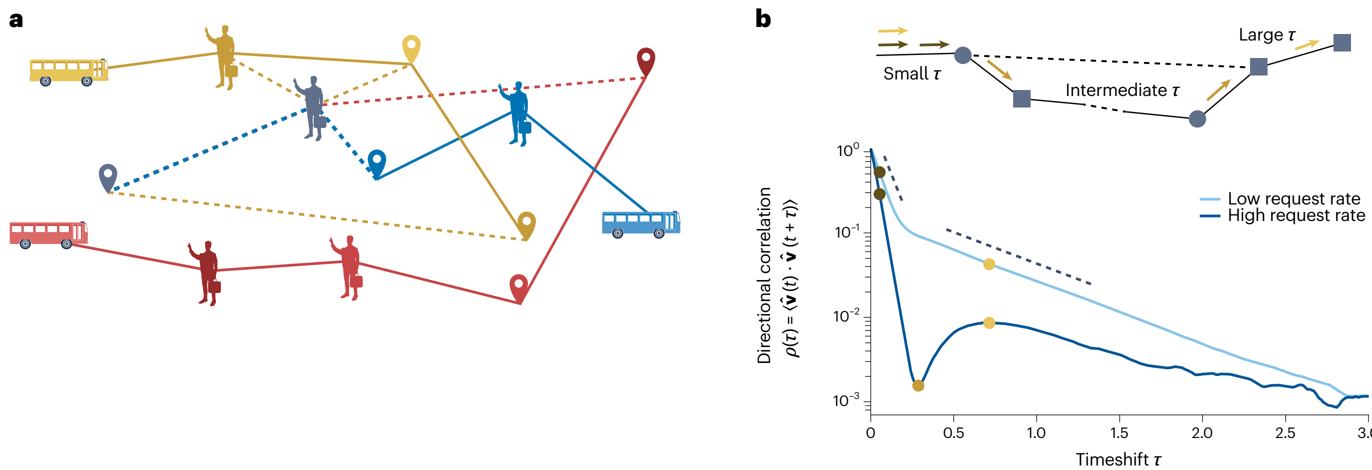

Fig. 6 | External requests create non-equilibrium dynamics and non-local correlations in ride-pooling systems. In ride-pooling systems, on-demand service requests entirely create system dynamics. Without any requests, there is no need for vehicles (minibuses) to drive at all. **a**, Scheme illustrating requests from origins (person icons) to destinations (pin icons) to be served by three vehicles (colored, solid lines indicate planned route, dashed lines indicate future route options); the latest passenger request (gray) is so far unscheduled and may be scheduled to any of the three vehicles. Riders and vehicles interact on the system's level: for instance, if one ride request is associated to one vehicle (blue), it changes that vehicle's route by adding detours and provides a larger option spaces for the other vehicles (red, green). **b**, Directional correlations $\rho(\tau)$ of a vehicle's velocity direction vectors $\hat{\mathbf{v}}$ indicate three characteristic timescales. One short time duration on which vehicles drive essentially shortest (straight) paths, one intermediate on which detours occur to pick up or drop off passengers, and one long timescale over which the overall driving direction of a vehicles stays roughly the same. Figure adapted with permission from ref. 131, APS.

Recently, Jung and Manik have provided a detailed simulation framework[100] for ride-pooling systems for the purpose of modeling collective dynamics emerging from external transport requests. Within that framework, the dispatching algorithm as well as other features such as the topology of the underlying street network, can be freely adapted.

Theoretical research by Molkenthin et al.[101] has proposed an observable that quantifies the efficiency of a ride-sharing service based on the overall collective fleet dynamics and showed that it exhibits a universal scaling law. For a given dispatcher algorithm, the efficiency observable, with suitable rescaling, collapses across qualitatively different topologies of model networks and empirical street networks from cities, islands and rural areas. A basic mean-field analysis uncovered the characteristic number of buses at which the average waiting time matches the system-intrinsic timescale as the single scaling parameter. It jointly captures the influence of network topology and demand distribution. Zech et al.[102] generalized this work by mapping fleets with vehicles of different passenger capacities to effective fleet sizes. Such results further our conceptual understanding of the collective dynamics of ride-sharing fleets and may support the adaptation of ride-sharing services to new boundary conditions or regions. Overall, much of recent progress simultaneously highlights challenges in uncovering the factors controlling service efficiency, including efficient service adoption by the riders[101,103–106].

Indeed, short-term fluctuations such as requests for rides and usage of specific routes may strongly influence the efficiency and thus sustainability of modern mobility systems by impacting their collective dynamics.

In summary, collective dynamics that emerge from signals with short-term fluctuations may support more sustainable mobility services. One example is improved efficiency: by suitably matching requests with service vehicles in ride-sharing systems, the usage of vehicles may become more efficient, and waiting, delivery and service times may be reduced, thereby improving real and perceived service quality. Another is improved accessibility and adoption: by using data on requested demands, vehicle supply options, street networks and the the usage of specific routes, mobility systems, not only ride-sharing systems, may be optimized for improved accessibility and adoption.

Overall, fluctuations and non-equilibrium responses and also long-term adaptions have crucial roles in making modern mobility systems more sustainable. Combining various data-driven, computational modeling and theoretical approaches, these systems may be designed and possibly optimized to promote more sustainable transportation modes and their co-action, thereby improving the environmental and societal impact of the mobility sector.

Outlook

Collective dynamics of infrastructure systems as a complex systems challenge

We have illustrated on different levels of dynamical complexity that integrating data-driven, computational and theoretical approaches is necessary to better understand, predict and ultimately control the collective dynamics of complex (infrastructure) systems. However, such integration does not follow any one overarching framework or recipe because what exactly and how to integrate very strongly depends on the question whose relevance in turn strongly varies with the particular phenomenon and system setting.

For instance, one example above demonstrated how fluctuations in input power to electricity grids that are observed from time-series data support theoretical model building about generic features of input fluctuations (such as power-law scaling and extreme events), which in turn feed a computational model for analyzing collective grid responses in specific scenarios. In another example, simulations of ride-pooling systems gave rise to generic features of directional correlations that yield a qualitative theoretical prediction that may be tested experimentally with empirical data. Both examples are similar in that computational, theoretical and data-driven approaches come together and that theory building is enabled by data (either observed in the real world or simulated). However, there are also marked distinctions between these approaches. While the first goes from real data to theory to a computational model, the second goes from computational modeling (via artificial data) to theory and potentially on to tests against empirical data.

From the perspective of phenomena, several of the collective dynamics presented above exemplify that certain insights about one particular system are at least partially transferable to very different systems because the mechanisms underlying the collective phenomena are closely related. For instance, Braess's paradox and other collective transport phenomena emerge across flow networks, independent of whether the flow is generated by moving vehicle traffic on street networks or electricity in power grids (or water, gas or other supply networks). At the same time, the different systems also exhibit marked differences in their dynamics, for instance, regarding their fluctuations (individual driving vehicles respond distinctly different from individual electrons to deviations from average flows). In general, the more detail a complex systems model covers, the less universal their dynamical properties become and the more of the differences between specific systems come to light.

Emerging technologies, data and boundary conditions

Recent research points to a wide spectrum of research areas that are currently opening up either due to technological progress, increasingly available and increasingly complex data, or changing external boundary conditions, such as the impact of climate change itself on infrastructure function.

For instance, climate change influences the statistics of power fed into power grids. Besides short-term fluctuations and extreme weather events impacting RES as discussed above, fluctuations on longer timescales occur increasingly frequently. These include dark clams (no wind, no solar inputs) as well as drought events of increasing duration and intensity[107–109]. One essential future research topic is thus to identify faster and more reliable optimization methods[110] to estimate the back-up energy[111] required to overcome energy shortages during dark clams or droughts for a power grid with a high share of RES. More recently, bright breezes, situations where simultaneously solar and wind power generation far exceeds demand, is equally catching research attention. Furthermore, establishing models that integrate both short- and long-term fluctuations into the dynamics of the power grid is essential for developing a better control system to maintain grid stability, as discussed in ref. 112.

In general, extreme weather events happen increasingly often at increasing intensity due to climate change, with strong impact also on the collective responses of energy systems. Intriguingly, a recent combination of data analysis and computational modeling[74] suggests the counterintuitive possibility of a positive impact of an increased number of failures of system components. For instance, during extreme wind events such as hurricanes, the simultaneous damage of two or more transmission lines in the same grid may induce smaller power outages and thereby less overload in the remaining functional part of the grid than the damage of only one line in the same part of the grid. As for Braess's paradox introduced above, the counterintuitive character emerges on the collective level of the dynamics of the entire system and cannot be explained by considering the parts of the system individually (compare, refs. 13,113). How to identify its mechanistic origin and estimate its probability of occurrence is still unknown so far.

Equally, technological progress may create open questions and challenges as it changes system boundary conditions or creates new interactions. Any strategy under discussion, for example, for upgrading the existing power grid and the formation of virtual power plants[114], for introducing new storage capacities, intelligent smart grid concepts[115] or power-to-X technologies[49], will further increase the complexity of the existing systems. Planning and operating decisions should be based both on the detailed knowledge of the dynamics of these renewable energy system components and on the emerging collective dynamics[62].

In the mobility sector, for instance, the surge of electric car usage[116] does not only induce novel forms of collective dynamics in the form of congestion, such as charging congestion patterns[117] that travel along the driving direction, not against it, as common for normal street congestion[85,86,89]. The scale of electric vehicle adoption may also influence the overall demand for electric power and its temporal distribution, thereby modifying how power grid systems are driven on the consumer side. Finally, electric cars often come with newly installed local 'home' battery systems that may in turn be used additionally to stabilize power grid dynamics.

Towards integrating artificial intelligence

Techniques from machine learning and artificial intelligence have recently seen a surge in applications, also regarding the collective dynamics of complex systems relevant for sustainability. For instance, explainable artificial intelligence has helped to identify which out of a broad range of demographic, geographic, political and socio-economic features play key roles in influencing electricity prices, which in turn act as driving signals to time-dependent power flows in power grids. In particular, a recent work[118] pinned down the roles of wind and solar power in the residual load and quantified the impact of generation ramps, emphasizing the importance of feature interactions in understanding price fluctuations.

Complex systems often are simultaneously characterized by a large number of dynamical variables, a large number of parameters and a wide range of influences from outside the system (such as wind power fluctuations impinging on power grid dynamics) or from agents acting as part of the system (such as drivers of vehicles). Moreover, the collective dynamics of complex systems emerges on different spatial and temporal scales. Identifying their effective, lower-dimensional dynamics thus helps to understand, predict and control such systems. Recent progress focusing on this general complex systems' challenge has, for instance, suggested how to learn effective models to enable multiscale simulations, proposed new control strategies for complex networks and ways to effectively control a complex system based on different machine learning techniques that guide data-driven modeling (see, for example, Vlachas et al.[119] and D'Souza et al.[120] for more details). Effective models and control schemes guided by such models and schemes are finding applications in the various settings discussed above, from understanding responses in flow networks to tackling huge multi-agent systems. We believe that perspectively, such learning and artificial intelligence approaches will support the prediction and control of most complex systems relevant to infrastructures that enable a sustainable world. We would thus need to understand how to train artificial intelligence to analyze and make decisions about unprecedented new types of collective dynamics, a task that may turn out to be a major challenge.

Collective dynamics of interdependent networks

The interdependence of multiple different complex systems is currently becoming increasingly important, and their stable and resilient collective dynamics are vital for their reliable operation and use. For example, with the increasing electrification and digitization of transportation and other infrastructures, the underlying infrastructure networks have become increasingly interconnected, making it essential to ensure their joint stable dynamics. On the one hand, the electricity needed for transportation must be factored into the daily load profiles of power grids and the energy supply must match this extra demand. On the other hand, electric vehicles may act as additional storage systems for power grids, buffering the temporally variable RES, such as wind and solar, and utilizing surplus energy generated during the day. Such advancing mutual influences highlight the interdependence of the electricity and transportation networks and the necessity of also analyzing the collective nonlinear dynamics of interdependent networks more generally. However, past work has strongly focused on structural aspects of interdependent networks[121,122]. In the broad majority of research on sector coupling[123], different sectors (such as energy, transportation, water supply and so on) are only treated as low-dimensional subsystems, so the network character has mainly been taken care of for the interactions between sectors. The fact that the individual supply systems themselves are also typically networked was often not taken into account for understanding their collective dynamical properties[123–125]. Internal details of the individual sectors and, above all, their important dynamic properties are largely lost in such modeling approaches, but can be decisive for the response dynamics and thus the resilience of interdependent networks. Where network topologies of different coupled systems have been taken into account, the focus was on sets of discrete events impinging from one network onto another, for instance, inducing cascades[70,71], not on their continuously ongoing collective dynamics.

Overall, research on the temporally continuous collective dynamics of externally driven interdependent networks is still in its infancy. The sector coupling between gas and electric power networks or the coupling between electric mobility and electric supply networks mentioned above are just two instances in this broadly open research landscape. Further examples include communication networks that enable regulatory actions of power grids, both supporting operation and posing risks in case of failure. Even entirely virtual networks such as echo chambers in online social networks may influence the functioning of physical infrastructure. They may, for example, induce vandalism through reinforced misinformation. A recent study[126] exemplifies several related influence schemes from online dynamics to physical infrastructures. More generally, the vast range of fields from multilayer, hierarchical and interdependent to higher-order network structures (with three-point or multi-point rather than pairwise interactions) offers an intriguing challenge for research on the collective nonlinear dynamics of complex systems relevant to a socially, economically and environmentally sustainable future (see, for example, refs. 127,128).

Robust design of collective dynamics

Taken together, designing and operating sustainable energy and mobility systems—as well as many other infrastructure systems underlying a sustainable world—frequently requires us to consider them as complex systems with different potential collective dynamics, some of which are undesirable. For power grids, for example, there is only one type of desired collective dynamics—synchronization in the form of phase-locking. Indeed, all controls and system parameters in the power grid are set to keep it synchronized at 50 Hz (or at 60 Hz in some grids).

Realizing the desired collective dynamics of complex systems is sometimes hard, for example, due to unpredictable external driving signals as different as rapid changes in renewable energy supply, strong excursions of electricity consumption or unusual ride-sharing demands. The examples above on future-compliant forms of electricity and mobility systems have illustrated that understanding these dynamics needs a combined approach that integrates data-driven analysis, theoretical conceptualization and mathematical modeling, as well as direct numerical simulations and computational analyses.

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M.T. and M.A. contributed equally to the design, writing and preparation of this work.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to Mehrnaz Anvari or Marc Timme.

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