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## Focus on monitoring and control of complex supply systems

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**Abstract**

The ongoing rapid transformation of our energy supply challenges the operation and stability of electric power grids and other supply networks. This focus issue comprises new ideas and concepts in the monitoring and control of complex networks to address these challenges.

**1. Introduction**

Supply networks are vital to our society, providing electric power, natural gas, water, heating and cooling to private and industrial customers. The electric power grid is the backbone of almost all technical infrastructures, as nearly every technical system depends on the supply of electric power. Furthermore, power grids are among the most complex systems ever built by mankind, connecting millions of power plants, wind turbines, photovoltaic panels and customers. A stable operation is enabled by sophisticated monitoring and control systems, ensuring that power generation and demand are always balanced and no device gets ever overloaded.

Many supply systems are facing enormous challenges during the transition to a sustainable energy production. Electric power systems are rapidly evolving, as power plants based on fossil fuels are replaced by renewable sources, in particular wind and solar power [1]. These sources are typically distributed and inherently uncertain, requiring novel methods of monitoring and control. Different systems and networks are being integrated, for instance via Power-To-Gas or Power-To-Heat technologies [2]. This integration facilitates decarbonization and provides flexibility, but further increases the overall system complexity.

Mastering these challenges requires an interdisciplinary collaboration [3], where physicists are increasingly contributing. Ideas from statistical physics, nonlinear dynamics and complexity science may lead to new insights and methods in engineering and applied sciences [1]. This Focus Issue addresses four aspects in the monitoring and control of complex supply systems: the inference of network structures and its relation to network control [4–6], the inference of models of supply networks [7, 8], the prediction of critical events [9], and the role of fluctuations and correlations [10, 11]. Most contributions focus on electric power systems due to their enormous technical and societal importance.

**2. Statistical inference and control of complex networks**

Controlling a system requires some knowledge about it, both about its current state through monitoring, or about the system itself through system inference. One of the paradigms in network and interactions inference is to perform a detailed statistical analysis of the measured time series. The most intuitive (and maybe a bit naive) approach would be to infer the existence of an edge in the interaction network if the trajectories of its two end nodes are ‘sufficiently’ correlated. However, it is now well-established that simple correlation is not

enough, and that it often leads to spurious inference. Over the last decades, a variety of statistical tools have been adapted to network and interaction inference, all of them with pros and cons that need to be balanced.

In [4], De Lellis *et al* propose an evaluation of *Intrinsic Mutual Information (IMI)* for the inference of pairwise directed interactions. Through a simple toy model, they show analytically, that IMI cannot perform better than a combination of two (more common) statistical quantities: *time-delayed MI* and *Transfer Entropy (TE)*. The power of their approach relies in that they analyze a very simple model, allowing for a full analytical proof.

In a similar spirit, Das and Porfiri [5] elegantly illustrate the limitations of TE for the inference of bidirectional interactions through a simple example of two interacting agents. More precisely, they show how the intrinsic dynamics of the agents can influence TE and lead to spurious inference. To overcome this limitation, they introduce the *Controlled TE* and the *Fully Controlled TE*. These two statistical measures leverage the knowledge of the agents' past trajectory to isolate the contribution of the interaction on their TE, allowing a more accurate interaction inference.

Putting themselves at odds with the inference approach, Hellmann *et al* [6] show that a full knowledge of the system is not necessary to meet specifications. Indeed, specifications are usually imposed on the outputs of the system, which are typically of lower dimension than the actual system's state. Providing a rather general framework, Hellmann *et al* [6] show that a sampling approach allows to keep a complex system within specifications without requiring a full knowledge thereof.

These three contributions clarify the performance of inference techniques and the amount of information needed to keep a supply systems within some specifications. Both are important to ensure a reliable operation of complex supply systems.

### 3. Inference and modelling of supply networks

Understanding supply networks is essential for their safe and efficient operation. Such understanding relies on a detailed model to be available, both in terms of a simulation environment and by estimating key parameters. Two contributions of this Focus Issue have shed further light on various aspects of supply network inference and modelling. While these two contributions investigated power grids, i.e. electrical supply networks, the methods developed and discussed could also be of use in power supply networks.

Onsaker *et al* [7] address the importance of modelling, forecasting, and understanding the dynamics of power grids, particularly in smaller systems such as islands. By examining power grid frequency measurements from European islands, including the Faroe Islands, Ireland, the Balearic Islands, and Iceland, the study compares their predictability to the reference Nordic power system. Adequate data, typically 2–4 weeks, is identified as crucial for accurate predictions.

Meanwhile, Gorjão and Maritz [8] investigate the non-Gaussian behavior observed in power-grid frequency recordings within the South African grid. Through a Fokker–Planck approach, the study establishes a direct relationship between model parameters and non-parametric estimations obtained from frequency recordings. Two potential explanations are proposed for the non-Gaussian leptokurtic distributions observed in South Africa: multiplicative noise or scheduled/unscheduled load shedding.

Summarizing, these two papers contribute valuable insights to the inference and modelling of supply networks, with a specific focus on power grids. From predicting power grid frequency dynamics to exploring non-Gaussian behavior and developing synthetic power grid models, the studies enhance our understanding of complex supply networks.

### 4. Inference and prediction of critical events in power grids

The increasing penetration of renewable sources is aggravating the fluctuations in power generation. It is paramount for grid operators to better understand the odds of their systems to undergo a stability deterioration in order for them to plan or react accordingly, by reinforcing their infrastructure, changing their operational practice or monitoring even more diligently their systems.

In this Focus Issue, one article tackles this problem [9] using a stochastic extended version of the standard swing equations. In particular, a noise term which explore beyond the usual Gaussian white noise is considered. This is a crucial point because most of the existing literature, for lack of better understanding or for sake of simplicity, falls into using Gaussian white noise, but more and more evidence shows that fluctuations of renewables have longer (of the order of several minutes) and complex correlations. Ritmeester and Meyer-Ortmanns [9] mainly investigates the loss of stability. There are two elementary ways for this to happen: the system can be driven by the noise to a bifurcation point, leading to the loss of synchrony or the noise can disturb the system out the current fixed point's basin of attraction.

Ritmeester and Meyer-Ortmanns [9] use different techniques rooted in theoretical physics to obtain closed-form expressions of the mean escape time, i.e. the expected time before loss of synchrony, for a split system. This extends previous theoretical works and shows that, under slightly weaker and thus more realistic assumptions, one obtains different asymptotic behaviours. This is a strong reminder of the fact that, when seeking for close-form expressions, it is important to check the validity of the assumptions that were made in the process.

This promising early work is still far from being applicable on a full-scale system and acknowledges that further investigation and developments must be carried out. Especially, it will be essential to show the ‘scalability’ of the methods, as this preliminary work was performed on case studies with single digit number of buses.

## 5. Fluctuations and correlation in supply networks

Supply networks such as gas pipelines or electric power grids, are vital to various human activities. Therefore, the accurate assessment of their stability and robustness to external perturbations is of primal importance to ensure reliable operations. To achieve such a task, one relies on models of the system’s dynamics and external perturbations, which both have to reach the adequate level of precision. Two contributions to this Focus Issue [10, 11] present refinement in the modelling of electric power grids subjected to external perturbations.

Tyloo *et al* [11] consider the propagation of non-Gaussian noise in high-voltage transmission grids, originating from renewable energy sources such as solar panels and wind turbines. Based on this more realistic description of the input noise, they investigate how the statistics of the voltage angle deviations are affected across the whole grid for different correlation times. For long correlation times, they analytically show that non-Gaussianity originating from a single source of noise propagates to every buses in the grid, while in the case of multiple sources of noise, non-Gaussianity essentially disappears due to a Berry–Esseen theorem.

Thümler and Timme [10] investigate a more detailed model of the swing equations taking into account the dynamics of the amplitude of the voltages, known as the third-order model. As for the second-order model neglecting voltage amplitude dynamics, it is shown numerically that three regimes are displayed by the system: a bulk or zero mode response that is homogeneous amongst the buses, a resonant response that is heterogeneous for frequencies within the system’s time-scales, and a localized response for fast frequencies. The authors also find that for the third-order model, the amplitude of the response decreases slower with the shortest path distance from the source compared to the second-order model.

These two contributions deepen our understanding of disturbance propagation in electric power grids, by taking into account the realistic statistical properties of the noise inputs from renewable energy sources, and increasing the number of degrees of freedom accounted for in the modelling of the grid’s dynamics.

## 6. Conclusion

The safe and efficient operation of supply systems generally requires an adequate monitoring and control. Important examples and applications cases are found in power engineering: transmission system operators record the grid frequency to control the operation of power plants and battery electric storage systems to maintain the balance of generation and load. They apply state estimation algorithms to infer the value of unknown state variables from measurements to ensure a stable operation of the grid. A classic text book example is the inference of voltage angles from measurements of real power flows using maximum likelihood. Many techniques have been used and refined for decades. Yet, the ongoing rapid transformation of our energy system requires novel techniques and algorithms.

Against this context, we highlight two major challenges: (1) Inference: Power grids and other supply systems are getting more distributed, heterogeneous and interconnected. A simple state estimation will no longer be sufficient; we will need a new comprehensive inference of system parameters and network structures or even complete dynamic models from data. (2) Statistics: Future energy systems will be dominated by fluctuating and uncertain renewable power sources. Future control methods must reflect this uncertainty, which requires a careful quantification of fluctuations and correlations.

The articles in this Focus Issue contribute new ideas and provide new methods for the monitoring and control of complex supply systems. All articles are intrinsically interdisciplinary, combining ideas from statistical physics and complexity science with models and methods from engineering and computer science. We believe that this interdisciplinary approach is material to solve the great challenges discussed above.

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