Artificial Intelligence and Electrical & Electronics Engineering: AIEEE Open Access

PRIME OPEN ACCESS

Volume 2, Issue 3

Review Article

Date of Submission: 21 Jul, 2026
Date of Acceptance: 02 Sep, 2026
Date of Publication: 16 Sept, 2026

# Scientific Machine Learning for Power Grids

## M. Temple-Raston*

Decision Machine and Fides et Ratio, New York, NY, USA

**Corresponding Author:**
M. Temple-Raston, Decision Machine and Fides et Ratio, New York, NY, USA. mtempler@decision-machine.com

**Citation:** Temple-Raston, M. (2026). Scientific Machine Learning for Power Grids. *Art Intelligence and Ele & Electronics Eng: AIEEE Open Access, 2*(3), 01-07.

## Abstract
Power grid operators need real-time situational awareness under conditions where historical training data does not reliably predict what is coming next. With renewable variability and demand shifts there is simply no time to retrain models. Scientific machine learning (sml) is the analytical solution to the science-of-counting (in units) that produces a set of scientific (thermodynamic) measurements for any time-series, available immediately, with no training, as a cloud-based "multi-meter". The measurements are presented for power consumption data (New York State, industrial grid in MWhs, monthly, 2010-2026). The measurements are then used as unbiased evidence to investigate hypotheses in non-equilibrium dynamics for power consumption data in NYS. Balance and control strategies are understood and developed with access to scientific time-series measurements.

### Introduction
The scientific foundation for the theory of electricity in the $19^{th}$ century was the science-of counting(-in-units) (soc). We see this in the definition of electric current: the number of units of electric charge passing a point per second. By measuring in units, that is, count up to "the last full measure" and refuse any rounding, then the input data is exact. Counting becomes pure objective experience. In addition, when measurements can be expressed exactly as functions of the input data, then the output is exact as well!

By looking at many exact measurements, it is clear that time-series data usually does not behave statistically, because often there is energy entering or exiting the system. In the 19th and 20th century we could rely on stable and reliable power generation (supply). With renewable energies, the design principle for supply must be revisited. By only counting, the complete Theory of Electricity is regained, so that the strain (supply) is animated, and at the same level of analysis as the demand, as a sibling.

In the Science-of-Counting every time-series counts both units, $n$, and the rate of change of units, $\dot{n}$, in a unit time-interval, so that the Lagrangian for the science-of-counting is given by eq. (1) (see reference [1], Chapter 11):

$$\begin{aligned} \mathrm{L}(n, \dot{n}) &= H - \lambda < n > - \sigma < \dot{n} >, \\ &= - \mathbf{p} . \ln \mathbf{p} - \lambda\, \mathbf{n} . \mathbf{p} - \sigma\, \dot{\mathbf{n}} . \mathbf{p}. \end{aligned} \tag{1}$$

By counting in units our input will be always exact, and the math transforms into combinatorics. The expected values for n and $\dot{n}$ are denoted by $< n >$ and $< \dot{n} >$, respectively.

The Lagrange multipliers, $\lambda$ and $\sigma$, enforce the counts as self-coupling constraints. The probability distribution, is given by p, so that each state i in p has probability $p_i$, and the probabilities add to one, $\Sigma\, p_i = 1$. The information entropy is given by

$H = - \mathbf{p} . \ln \mathbf{p}$.

When $<\dot{n}>= 0$, the system is in equilibrium, that is, the system is just as likely to go up, as to go down, or, equivalently, energy does not enter or exit the system on average. The system dynamics is greatly simplified in equilibrium. However, as stated above, most of the time energy is not constant and the system is not in equilibrium. The Lagrangian for the science-of-counting defines dispersion relations—how energy, speed, momentum, and so on, must fit together. The dispersion relation can be written as $E = pv$.[1]

The normaized momentum, $p(\lambda, E) = < \mathbf{p} >$, obtained from the Lagrangian eq. 1 for the science-of-counting, is also a solution to the exact sequence:

$$0 \longrightarrow \underline{\mathrm{N}} \hookrightarrow -\ln p(\lambda, E) \xrightarrow{d} A \xrightarrow{d^A} F^A \xrightarrow{d^A} 0 \tag{2}$$

The input data for the science-of-counting are natural numbers ∈ N times the unit—there is no need to truncate digits. The time-stamps and the counts are together a time-series in $\underline{\mathrm{N}}$. the input vector of user measurements. The (Ehresmann) connection, A, in (2) defines a discrete geometric line bundle with curvature, $F^A$. The Lagrangian (1) and the exact sequence (2) define Scientific Machine Learning. The topology also tells us we are on the right track. When N is given the discrete topology, then N is a locally compact abelian group under addition and is Hausdorff, conditions that allow us to regain the action-angle variables and invariant tori when the energy entering or exiting is zero.

In previous papers  classes of practical business and life applications were investigated: Open System Allocations, Inventory Levels, and Supply Chain Optimization [2,3]. This paper instead reflects on Machine Learning as a decision architecture that integrates real-time data for critical decision making. SML is illustrated using power consumption time-series, [4] and placed in the context of recent SciML activity for power grids in the next section.

**Related Work**

Recent SciML activity for power grids clusters into four largely disjoint paradigms, each of which retains a trained or fitted model as its core computational object.

**Physics-informed neural networks (PINNs).** The dominant paradigm augments a conventional neural network with a physics-consistency term in the loss function, $L = L_{\text{pred}} + \lambda L_{\text{reg}} + \gamma L_{\text{phys}}$, so that governing equations (power flow, swing dynamics) constrain but do not replace statistical training [5,6]. Applications span state estimation [7], distribution-system voltage prediction, and optimal power flow [8]. The physics term regularizes; it does not eliminate the need for a training set or the assumption that future data resembles past data.

**Graph neural networks (GNNs).** A second line exploits the grid's topology directly, using graph convolution or graph-attention architectures for state estimation, cascading-failure prediction, and EV charging demand GNNs improve on feed-forward PINNs by encoding network structure, but remain supervised, trained models subject to the same train/test-distribution assumption [9,12].

**Foundation models.** A recent and growing direction pretrains large models on grid time-series at scale, aiming for transferable representations across utilities and forecasting horizons [10]. This inherits, at larger scale, the same core assumption: a model fit to historical data is deployed forward in time.

**Stochastic-dynamics approaches.** A smaller body of work departs from feed-forward point-prediction architectures, coupling stochastic differential equations to grid frequency dynamics via a Fokker–Planck formulation [11]. However, the SDE parameters in this approach are themselves the output of a feed-forward neural network trained via maximum likelihood on a historical corpus, mapping techno-economic features to dynamical parameters – the train/deploy split is preserved one level up, not eliminated. This is instructive: even the SciML literature's closest departure from black-box regression retains an offline-fit, historically-trained component.

**Empirical departures from Gaussian/equilibrium statistics.** Closest in spirit to the present work is an empirical finding, not a modeling framework: Schäfer et al. [14] analyzed measured power-grid frequency time-series directly and found that fluctuations follow non-Gaussian, Levy-stable statistics better described by superstatistics than by the Gaussian, near-equilibrium assumptions underlying standard grid stability analysis. This is direct empirical evidence, from measured data rather than simulation, that the equilibrium/Gaussian assumption implicit in conventional risk and stability analysis does not hold in practice – the same conclusion the Non-Equilibrium Hypothesis (Section 5) reaches for grid demand. Unlike the present paper, this result is descriptive rather than the basis of a deductive measurement scheme; it establishes the empirical motivation independently, from a different data source and a different physical quantity (frequency rather than demand).

**Positioning:** What distinguishes SML from the paradigms above is not how its parameters are obtained – SML has no fitted parameters at all. In PINNs, GNNs, foundation models, and physics-informed SDEs alike, some component

[1] The functional form of E = pv is proprietary and is presented as a challenge problem, suitable for college seniors and graduate students in physics.

(network weights, an FFNN mapping features to SDE parameters, an attention mechanism) is fit by optimizing a loss or likelihood over a historical corpus, and then deployed forward under the assumption that future data resembles that corpus. In SML, $\lambda$, $E$, and $p$ are not fit; they are computed by direct functional evaluation on the incoming time-series (Section 6), in the same way that the arithmetic mean or entropy is computed rather than estimated by optimization. There is no corpus, no loss function, no optimizer, and consequently no train/deploy split for these quantities to inherit an implicit stationarity assumption from. Section 3 specifies the functional forms disclosed here and the one that is not.

**Scope and Disclosure**

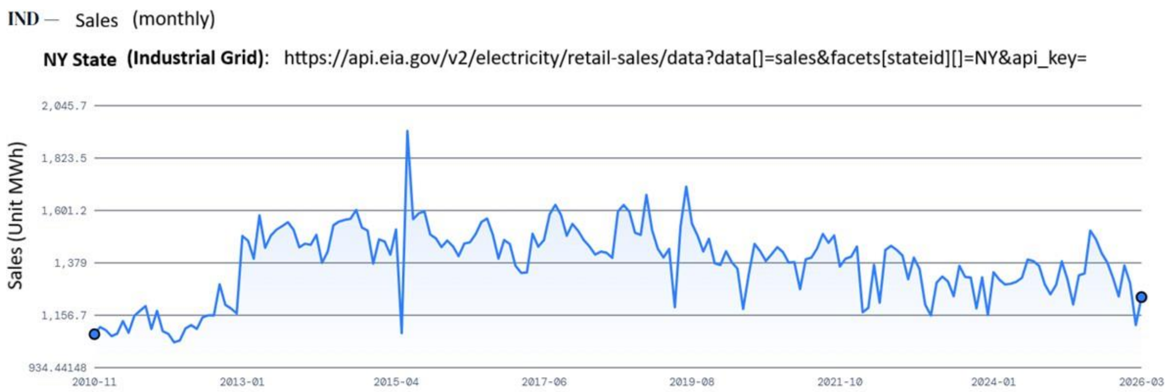
The governing structure of Scientific Machine Learning applied to power grids is given here in full: the Lagrangian (eq. 1), the dispersion relation E = pv, the exact sequence defining the measurement and geometry (eq. 2), and the balance equations (eq. 3). These equations couple E, p, v, and λ: the functional form of any one determines the rest. The Theory of Electricity therefore reduces to a single undisclosed function – the closed-form realization of p($\lambda$, E) used in production – and disclosing it would recover the other three as well.

What is given above is sufficient to verify the framework's internal consistency, reproduce the commutative diagrams of Section 4, and evaluate the Non-Equilibrium Hypothesis qualitatively against the New York State data (Figure. 4). It is not sufficient to reproduce the quantitative measurements in Fihures. 1–2 exactly, which is why p($\lambda$, E) is withheld. The measurement equipment is made available as a service.

**Real-Time Measurements**

In the science-of-counting everything that is counted, material or immaterial, whether it serves a purpose or not, produces a set of scientific measurments that define the thermodynamic state of what has been counted. From scientific measurement (below) it is immediately apparent that the thermodynamic environment affects the behavior of the time-series consequentially, and that we in turn affect the environment, often to our own detriment. The energy entering or exiting the system is an example of an SML measurement See the data dictionary in [15].

Time-series is counting with a cadence, that is, a list of time-stamps and counted values in appropriate units. From the time-series below, SML counts the up and down states (binary) and then evaluates functions to give the scientific measurements, which are all returned together. In the plots below (Fig. 1 and 2), SML ingests monthly power consumption (MWh) data for New York State's industrial energy grid, and returns scientific measurements that define the thermodynamic state of the time-series. For clarity, adapted coordinates are introduced. The displacement energy, $E$, is the total energy of the system minus the statistical binary equilibrium energy (zero offset). Displacement energy is either entering ($E > 0$), exiting ($E < 0$), or, in statistical equilibrium ($E = 0$). The displacement momentum, $p$, is the inertia to perpendicular deflection from statistical mechanics, generalizing the mechanical momentum. As the displacement momentum, $p$, increases, the resistance to deflection from statistical mechanics increases (inertia). For Figure 2 double-sided plots (two y-axis) are used to demonstrate the thermodynamic energy cycle.



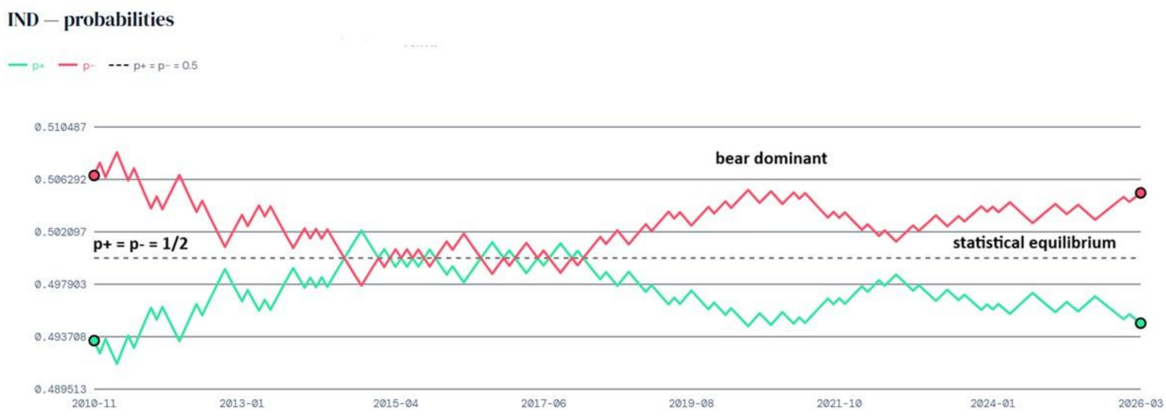




**Figure 1: The Monthly Power Consumption (MWh) For New York State, Industrial Grid (2010 to 2026), Top Plot: Input to SML. SML Returns Scientific Measurements (2: Probabilities, 3: Energy). Measurements Show Time-Series behavior is Generally not Statistical, Due To Energy That Enters or Exits the Time-Series. Bear Dominance (p− > 1/2) in probabilities is Caused by Energy, E, Exiting the System. Probabilities Behave Statistically when p+ = p− = 1/2, E = 0**

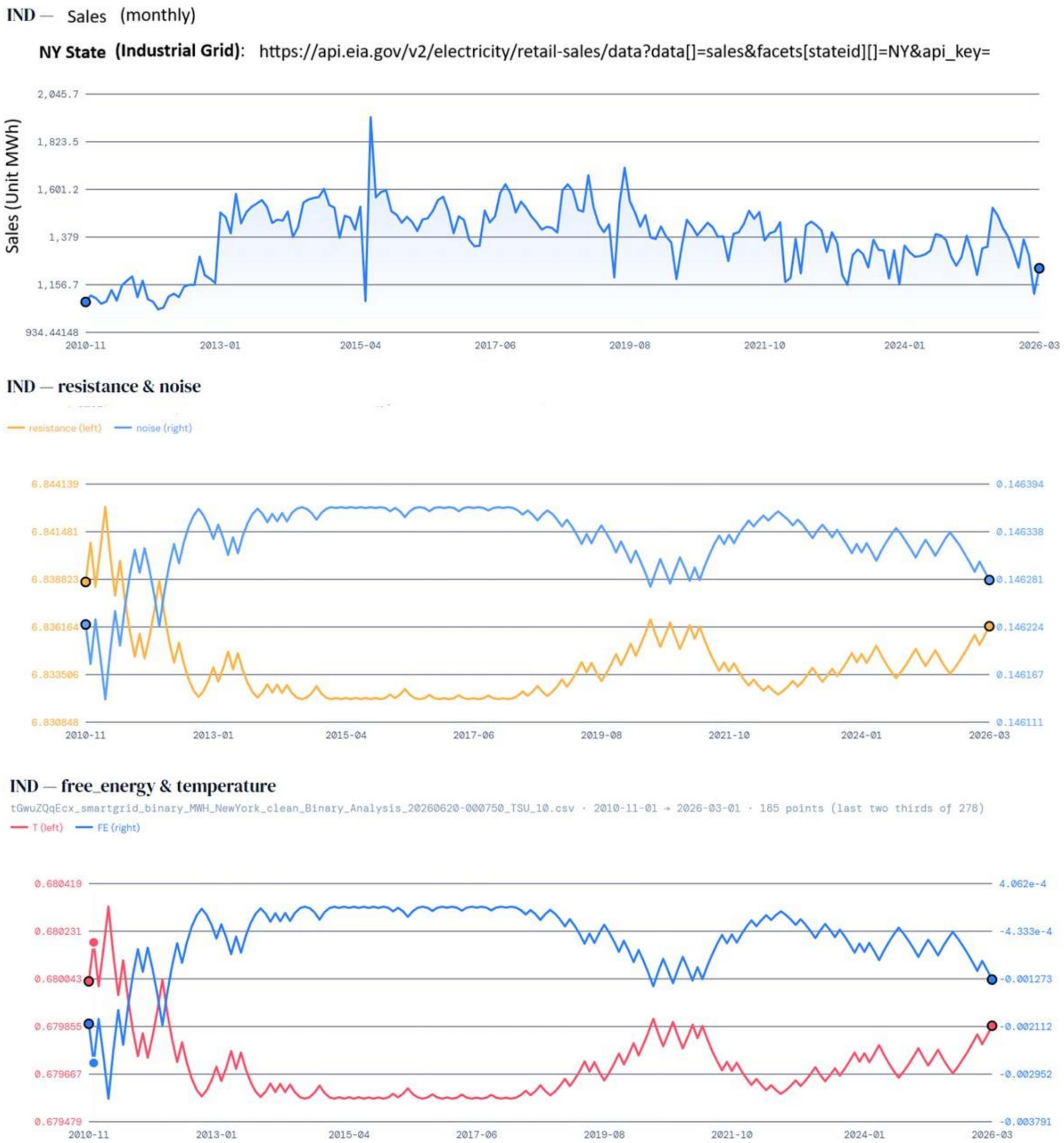



**Figure 2: The Monthly Power Consumption (MWh) For New York State, Industrial Grid (2010to 2026), Top plot: Input to SML. SML Returns Scientific Measurements (2: Noise (light blue) and Resistance (Orange), 3: Free Energy (dark blue) and Temperature (red)) as Double-Sided Plots. Noise and Free Energy are Observed to be Greatest at Statistical Equilibrium. Noise and Free Energy Drop with Separation From Statistical Equilibrium, while Resistance and Temperature Increase**

### Free Energy Cycle

The battery of measurements that are returned by SML can be used to identify patterns that favor one dynamic behavior over another. The energy cycle, for example, can tell whether there is the free energy available to do value-work, and as value-work is done, the free energy falls and generates heat that increases the temperature, to dissipate heat forever lost to the system. A dissipative structure is a Free Energy Cycle oscillating round thermal equilibrium (not statistical equilibrium).

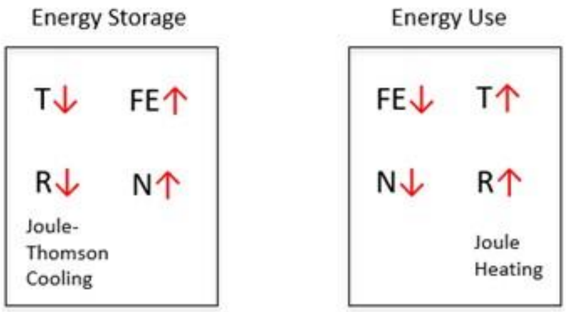
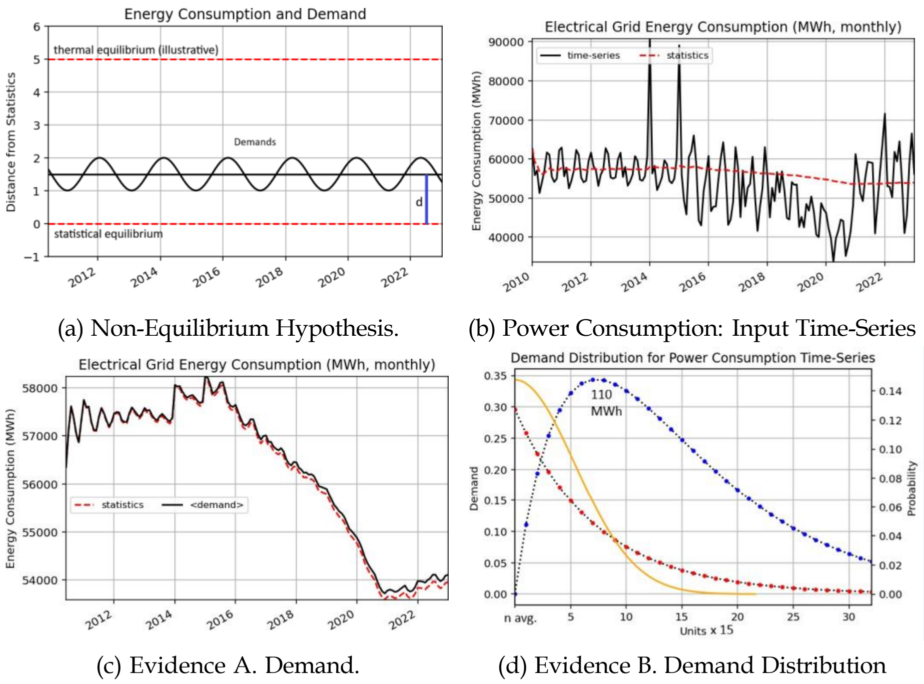



**Figure 3: Energy Cycle. Look at the last Two Plots (c,d) In Figure 2 Together. Free Energy (FE) Is by Definition the Energy Available for value-work, Equivalently, the Total Energy Of The System Minus Heat Dissipation (FE = E − TS). In the Measurements in Figure. 2 d, it is Observed that as value-work is Done, the Free Energy Decreases and the Stored Energy in the Noise Also Decreases. At the same time, the temperature (T) of the time-series is seen to Increase As The work is Done, and in lockstep with Resistance (R) That also Increases, Thereby Increasing the Temperature (Joule Heating), And That in turn increases the heat Dissipation Until There Is No Free Energy left to do value-work. The Tank is Empty. As the Time Series Temperature Cools, However, the Free Energy is Replenished Automatically**

### Hypothesis Investigation

With access to unbiased scientific measurements, investigations into non-equilibrium power grids start with hypotheses. The most hopeful is the Non-Equilibrium Hypothesis, that as power consumption moves away from statistical equilibrium, an operationally easier environment is created, where fluctuations are reduced and stability easier to maintain.




(a) Non-Equilibrium Hypothesis. (b) Power Consumption: Input Time-Series

(c) Evidence A. Demand. (d) Evidence B. Demand Distribution

**Figure 4: Non-Equilibrium Hypothesis: The Operating Environment Between Statistical and Thermal Equilibriums is easier to manage Than when in statistical equilibrium. As the system Moves Away From Statistical Equilibrium, There is Evidence That Fluctuations are Reduced and Stability Easier to Maintain. Power Consumption (Input) Data is Plotted in Figure 4 b. Figure 4 c,d, Ingests Power Consumption Time series and Plots the Expected Demand (Black), $< \eta >$, And The Arithmetic Mean for Statistics (dashed red). Figure 4 c : After 2017 a separation is Observed Between Demand and Statistical Equilibrium that Persists Over many years, and we observe that the power fluctuations when the gap is present are Much Smaller Compared to the Fluctuations when $< \eta > \sim < n >$, Preceding 2016. Figure 4 d: an exact Discrete Demand Distribution, at the right-hand edge of Figure 4b. The Cap is not Circular; Some Distortion to a Pure Sinusoid is Expected. The Corresponding "Bell Curve" For The Same Data Set is Plotted in Orange. In soc, The Gaussian Always Simplifies To The Exponentially Decreasing Probability Distribution**

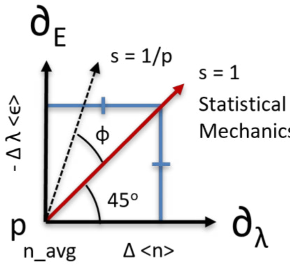
## Balance and Control

The exact sequence in the introduce (2) uses the Chain Rule on $-\ln p(\lambda, E)$ to define both the expected value, $-\partial_\lambda \ln p = < n >$, and the expected strain, $-\partial_E \ln p = \lambda < \epsilon >$, for a time-series. Both value and strain must be managed together. In addition to scientific measurements for time-series (Section 4), useful patterns in the measurements can be found. The simplest pattern is the balance equation (first eq. in (3)): the ratio of the expected value and the expected strain, equals the momentum, $p > 0$. An interesting relationship, however, for balance to prove useful it should be sustained for some duration. A momentary balance is "uncontrolled". If the momentum, $p$, is maintained from one time-stamp to the next, then the net forces necessarily vanish and balance is achieved (second eq. in (3)).

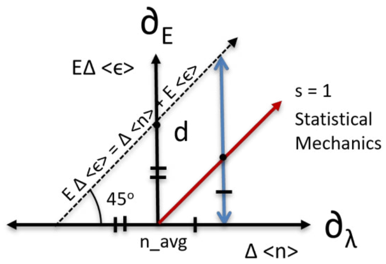
$$\frac{< n >}{-\lambda < \epsilon >} = p = \frac{\Delta < n >}{\Delta(-\lambda < \epsilon >)}. \tag{3}$$

The geometry of the balance equation is summarized in Figure 5 a below.

A sailboat is a familiar "steady-state" non-equilibrium system that also balances expected value and expected strain. Energy enters as wind fills the sails and increases strain as the sailboat heels (tilts). With increasing strain/heel, displacement energy is both viscuously dissipated in seawater, and stored as potential energy with the keel (or "Sailors") as counterweight. A constant value for the tilt means that the lateral forces are balanced (net force zero), and that the path travelled has constant momentum. Finally, like the wind that drives a sailboat, there may be no control over the wind, with unpredictable lulls and gusts of energy, like renewable energies that enter a power grid. While we cannot direct the wind, we can trim the sails.




(a) Balance Equation.




(b) State Equation.

**Figure 5: Control Strategies. a) The Balance Equation (First Eq. in (3)) Tells us That The Ratio of the expected value and the expected strain, equals the momentum, p > 0. The x-axis is the Change in the Expected value, Δ < n >, in units of MWh Measured from the Average, n̄. In the Special Case when The Increment of Expected value Equals the Increment of Expected strain, Δ < n > = Δ(−λ < ϵ >), So That p = 1, Statistical Equilibrium is Regained with Δ < n > = Δ(−λ < ϵ >) = 0. But This Control Path is not Sustainable, Because as the Path Continues away from statistical equilibrium, greater energy input is required to maintain the Path. b) A More Realistic Control Strategy is Presented in Figure 5 b, where the displacement Momentum Runs Parallel to Statistical Mechanics. A State-Equation is Derived from the Commutative diagram 5 below. This particular control strategy creates conditions for the Non-Equilibrium Hypothesis Figure 4 Investigated in Section 5. By Setting a Desired Distance, d = EΔ < ϵ >, from Statistical Equilibrium, the State Equation is the Equation of a Straight line. The Balance Equation in a) is Used Here to Create a Ramp up to the Distance d, And That Maintains the Slope of the Path Parallel to Statistics**

To see how to "trim the sails", return to the fundamental dispersion relation, $E = pv$. When system balance is maintained ($p$ is constant), then the dispersion relation at each time-step simplifies to:

$$E_n = p\, v_n, \tag{4}$$

so that balance produces a proportionality relationship and control law between $E_n$ and $v_n$. Once a time-series is ingested, given one, the other becomes known. Examples. Control $E_n$ (spill or tighten wind) to generate reliable $v_n$. Ask for a desired $v_n$, and the system energy required to achieve $v_n$ is returned.

To complete the control analysis, a state-equation can be derived from the following commutative diagram (used previously without mention to define the expected value and expected strain):

$$\begin{array}{ccc} -\ln p(\lambda, E) & \xrightarrow{\partial_\lambda} & < n > \\ \downarrow{\scriptstyle \partial_E} & & \downarrow{\scriptstyle \partial_E} \\ \lambda < \epsilon > & \xrightarrow{\partial_\lambda} & E\Delta < \epsilon > = \Delta < n > + E < \epsilon > . \end{array} \tag{5}$$

Using current time-series meaurements the distance from statistical equilibrium can be calculated, $d = E\,\Delta < \epsilon >$, And we see that the state equation is the equation of a straight line (Figure 5 b). The balance equation in a) is used to create a ramp up to $d$, and maintains the correct slope of the path parallel to statistics. The control strategy 5 b creates conditions to further investigate the Non-Equilibrium Hypothesis Figure 4.

## Conclusion

In this paper a universal scientific program for time-series analysis is introduced as scientific machine learning (sml). This paper focuses on power grids because sml appears to be "native", both historically and structurally, with both supply and demand present and coupled (non-linearly). Our principle design hypothesis is that the power grid can be operated as a steady-state non-equilibrium system that stores energy, and then uses it to stabilize variable power flows. The combinatorial equations of motion that balance (steady state) defines a very restrictive set of allowable paths that are consistent with observed measurements that suggest that better operational behavior might be achieved away from statistical equilibrium. Scientific equipment to measure time-series is available in the cloud [15].

## References


1. Jaynes, E. T., & Bretthorst, G. L. (2003). Probability theory: The logic of science (Vol. 1, No. 10.1017). Cambridge: Cambridge university press.
2. Temple-Raston, M. (2026). Scientific Machine Learning. Art Intelligence and Ele & Electronics Eng: AIEEE Open Access, 2(2), (2026). DOI:10.66311/3069–0706.
3. Temple-Raston, M. (2026). Machine Learning and Applications: An International Journal (MLAIJ) Vol.13, No.1, March 2026. DOI:10.5121/mlaij.2026.13101
4. US Energy Information Administration (2026).
5. Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422-440. DOI: https://doi.org/10.1038/s42254-021-00314-5
6. Huang, B., & Wang, J. (2022). Applications of physics-informed neural networks in power systems-a review. IEEE Transactions on Power Systems, 38(1), 572-588. DOI: 10.1109/TPWRS.2022.3162473
7. Zamzam, A. S., & Sidiropoulos, N. D. (2020). Physics-aware neural networks for distribution system state estimation. IEEE Transactions on Power Systems, 35(6), 4347-4356. DOI: 10.1109/TPWRS.2020.2988352
8. Mohammadian, M., Baker, K., & Fioretto, F. (2023). Gradient-enhanced physics-informed neural networks for power systems operational support. Electric Power Systems Research, 223, 109551. DOI: 10.1016/j.epsr.2023.109551
9. Ngo, Q. H., Nguyen, B. L., Vu, T. V., Zhang, J., & Ngo, T. (2024). Physics-informed graphical neural network for power system state estimation. Applied Energy, 358, 122602. DOI: https://doi.org/10.1016/j.apenergy.2023.122602
10. Hamann, H. F., Gjorgiev, B., Brunschwiler, T., Martins, L. S., Puech, A., Varbella, A., ... & Sobolevsky, S. (2024). Foundation models for the electric power grid. Joule, 8(12), 3245-3258. DOI: https://doi.org/10.1016/j.joule.2024.11.002
11. Kruse, J., Cramer, E., Schäfer, B., & Witthaut, D. (2023). Physics-informed machine learning for power grid frequency modeling. PRX energy, 2(4), 043003. DOI: https://doi.org/10.1103/PRXEnergy.2.043003
12. Wang, S., Li, Y., Shao, C., Wang, P., Wang, A., & Zhuge, C. (2025). An adaptive spatio-temporal graph recurrent network for short-term electric vehicle charging demand prediction. *Applied Energy*, 383, 125320. DOI: https://doi.org/10.1016/j.apenergy.2025.125320
13. Schäfer, B., Beck, C., Aihara, K., Witthaut, D., & Timme, M. (2018). Non-Gaussian power grid frequency fluctuations characterized by Lévy-stable laws and superstatistics. Nature Energy, 3(2), 119-126. DOI: https://doi.org/10.1038/s41560-017-0058-z
14. Witthaut, D., Hellmann, F., Kurths, J., Kettemann, S., Meyer-Ortmanns, H., & Timme, M. (2022). Collective nonlinear dynamics and self-organization and Data Dictionary, in decentralized power grids. Reviews of modern physics, 94(1), 015005. DOI: https://doi.org/10.1103/RevModPhys.94.015005
15. SML-Training Application and Data Dictionary, 2026. (Sign-up: https://fides-ratio.com) mtempler@decision-machine.com