Stochastics for Energy Distribution Systems

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Goal of this talk

Present three problems in energy distribution systems that are relevant to Stochastica.

These are topics we are actively working on, for which data is available that can be shared. If you are interested in any of these topics, feel free to reach out.

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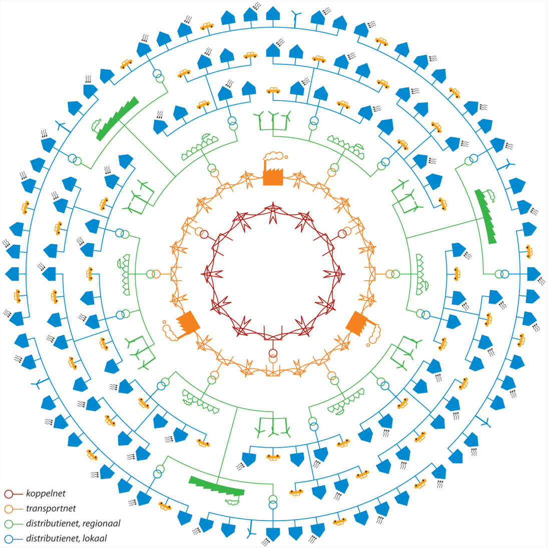
Introduction

The Energy Transition

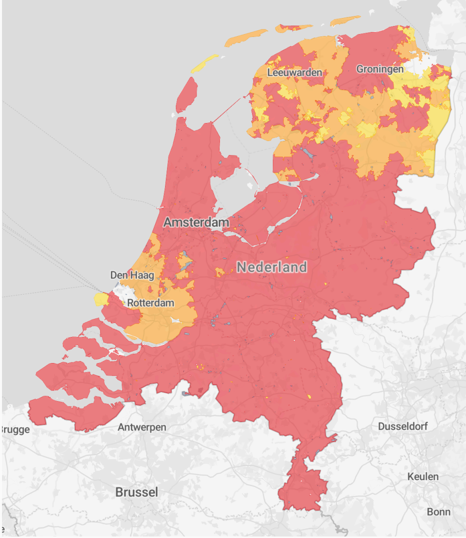
Global shift from fossil fuel-dominated energy systems to renewable, electrified systems to reduce carbon emissions.

Paris Climate Agreement (2015): EU-countries targeting net-zero emissions by 2050.

The Dutch Power Network.



Complication: Grid Congestion



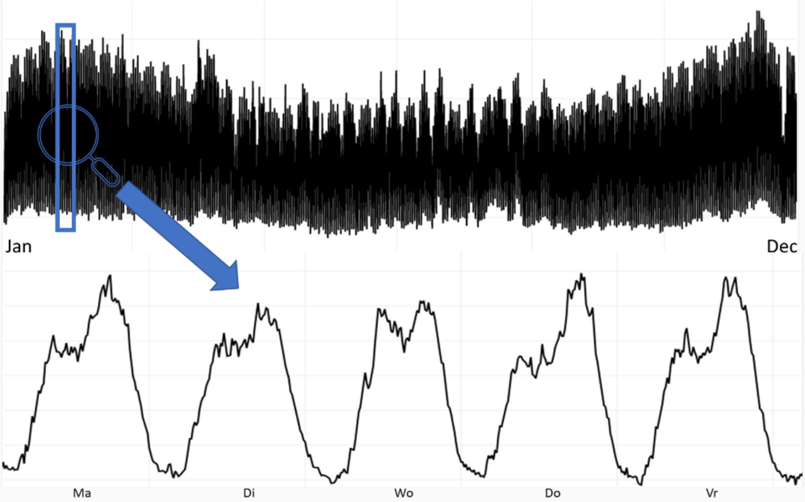
At the same time: 99.99% uptime.

Load forecasting

Different time horizons important for different processes

- **Short term (operational)**: real-time - 2 days ahead. Managing congestion and activation of flexibility.
- **Medium term (tactical)**: 1 - 5 years ahead. Customer intake: flexibility, temporary solutions, and grid reinforcement.
- **Long term (strategic)**: 10 - 40 years. Grid planning, investment decisions. Mostly scenario based, not discussed in this presentation.

Yearly load profiles



Notations

We consider a set of **loads** $P_i(t)$ with $i = 1, \dots n$ over a finite time horizon $t \in [0, T]$.

Let $\mathcal{I}_0$ be known information at $t = 0$. This can be historical loads, customer data, weather predictions, energy market prices, or other covariates.

Let $S(t) = \sum_i P_i(t)$ be the aggregate load.

The peak load is denoted by the random variable:

$$M = \max_{t \in [0,T]} S(t).$$

Problem description

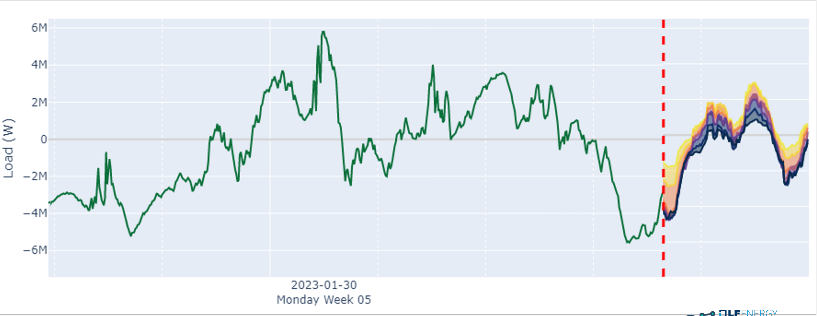
Estimating the peak load M is not sufficient. Need to determine:

- The **peak distribution** $\mathcal{L}(M \mid \mathcal{I}_0)$. For example to estimate peak loads during extreme events such as an extremely cold winter evening.
- The **overload probability** $\mathbb{P}(M > C \mid \mathcal{I}_0)$ where C is the capacity of the grid.
- The **frequency and duration** of peak and overload events over the time horizon.

Short term forecasting using OpenSTEF

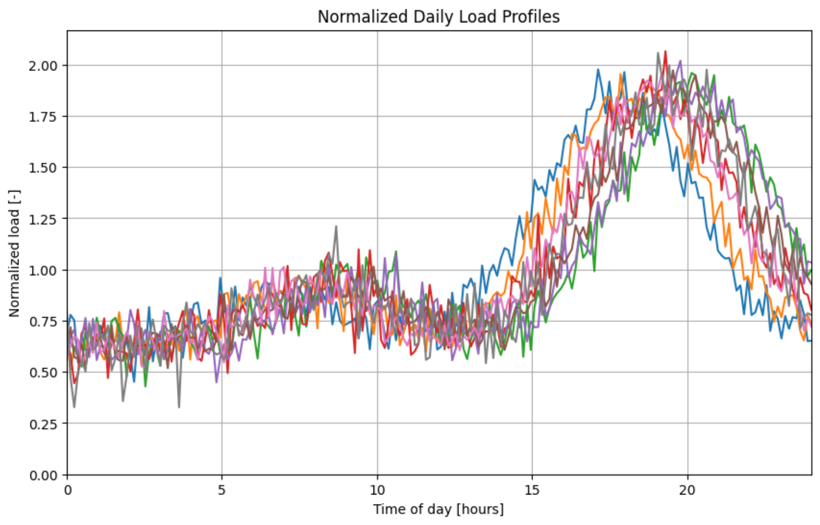
Open source platform using gradient boosted trees (machine learning) for quantile regression.

Stochastic / equation-based alternatives?



LF ENERGY OpenSTEF

Medium term forecasting for residential customers



Peak load estimation

Traditional approach (**Velander**):

$$M \approx k_1 E + k_2 \sqrt{E}$$

where $E = \sum_{i=1}^{n} E_i$ is the aggregated consumption.

- Aggregation effects and dependence are implicitly captured in k_1, k_2.
- Peak loads are often overestimated.
- Does not model temporal behavior and extreme events.

Stochastic models for load estimation

High-resolution data such as **smart meter data** is now available. This enables stochastic modeling of loads.

What should such models capture?

- Mean-reversion around baseline profile.
- Periodicity at different timescales (days, weeks, year).
- Time dependent volatility, different regimes.
- Non-Gaussian noise: heavy tails.

References

S. Shi, J. Heres, and S. H. Tindemans, "Scalable quantile predictions of peak loads for non-residential customer segments," in *Proc. IEEE PES ISGT Europe*, 2025.

S. Shi, E. A. Cator, J. Heres, and S. H. Tindemans, "Extreme value distributions of peak loads for non-residential customer segments," arXiv preprint, 2025.

Thermal modeling and the inverse problem

What determines the capacity of the grid?

- Grid operators typically define grid capacity as the maximum **steady-state** load such that grid components (cable, line, transformer) operate at their maximum allowed **temperature**.
- This steady-state assumption leads to a highly conservative estimate of grid capacity.
- By combining accurate, transient thermal modeling with robust uncertainty quantification, grid capacity can be increased by 20 to 30%.

The stochastic heat equation

Heat diffusion is governed by the parabolic stochastic PDE

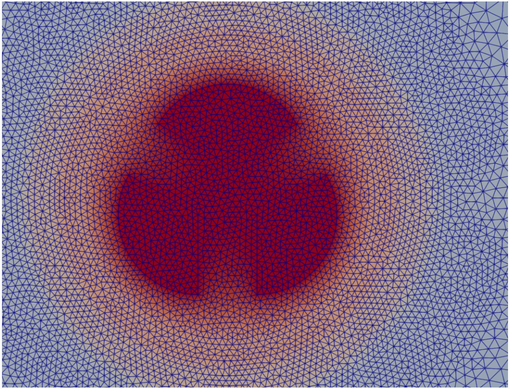
$$c\frac{\partial u}{\partial t} = \nabla \cdot (\sigma \nabla u) + P$$

where the terms

- u : temperature
- c : thermal capacity
- σ : thermal conductivity
- P : stochastic forcing (load)

all depend on $\mathbf{x}$ and t.

Modeling transient cable temperature



Inverse problem

Soil properties are uncertain and difficult to measure directly, motivating an inverse approach.

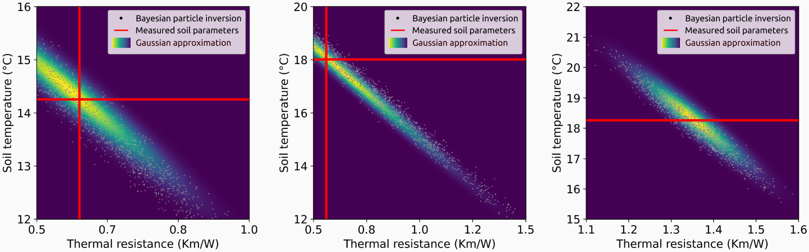
Given:

1. Prior distributions for soil parameters.
2. Cable burial depth, geometry, material properties.
3. Temperature measurements in time at specific location(s).
4. Load profile (forcing).
5. Forward model for temperature (FEM).

Problem: infer the posterior distribution of the soil thermal resistivity and soil temperature over time.

References

S. Rieken, W. van Harten, D. Heldens, L. Scarabosio, and G. Lord,
"Application of particle-based Bayesian inversion to underground medium voltage cables in the Netherlands,"
in *Proc. CIRED*, 2025.

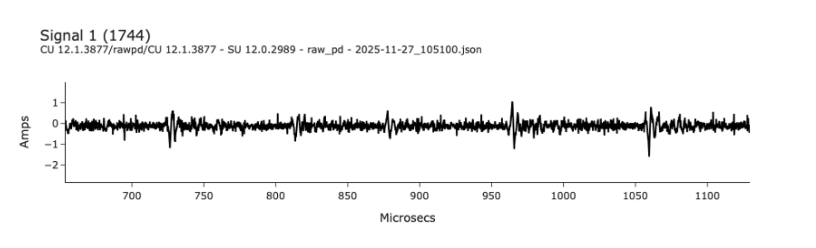


Asset degradation and optimal replacement

Partial discharges

Partial discharges (PD) are small sparks in the insulation of a cable system that often precede failures.

Problem: how can we reliably identify the partial discharge events from noise in time-resolved measurement data?



Wave propagation model

The current $I(z,t)$ along a transmission line satisfies the Telegrapher's equation:

$$\frac{\partial^2 I}{\partial z^2} - LC\frac{\partial^2 I}{\partial t^2} - (RC + LG)\frac{\partial I}{\partial t} - RG\, I = 0.$$

The measured current can be decomposed as

$$I(z,t) = S(z,t) + N(z,t),$$

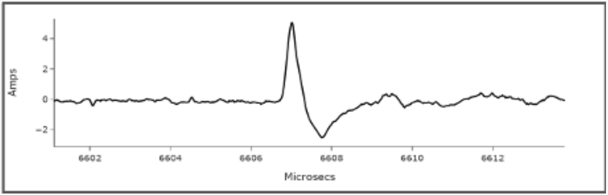
where S is the signal (e.g. PD events) and N is noise.

Time domain characteristics of partial discharges

These characteristics distinguish PD signals from noise:

- Short-duration pulse.
- Fast rise time.
- Decaying tail and/or damped oscillation.
- Can have either polarity

Observed waveforms also depend on sensor, bandwidth, and propagation path.

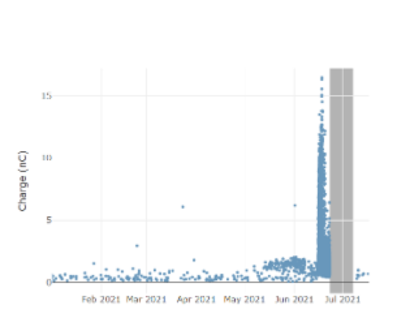


Remaining lifetime prediction from PD data

Goal: Estimate the remaining lifetime of a component from its PD time series

Using: Population-level PD and failure data for calibration.

PD activity is used as a proxy for insulation degradation.



References

R. van Dinter, S. Rieken, B. Tekinerdogan, and C. Catal, "Estimating optimal replacement time for systems with two-state degradation and technological obsolescence," *Int. J. Electrical Power & Energy Systems*, vol. 172, 2025.