Probabilistic forecasting of nodal high-voltage electric loads using a variational autoencoder

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High-voltage electric power grids face an increasing amount of uncertainty in their operating state. Aside from component failures, there is growing uncertainty in the in and outflows at grid nodes, caused by fluctuating renewables, electric vehicles, intra-day trading, unscheduled foreign transit flows and more. As these in and outflows depend on complicated human and economic interactions, a data-driven forecasting approach is natural, which can subsequently be combined with the known physics of power flow to form a full probabilistic forecast of the grid state.

This work uses a variational autoencoder (VAE) [1, 2] to learn the joint probability density of hourly nodal loads in the Swiss transmission grid, as a function of time and weather features. The VAE learns a Bayesian network representation of the joint density, making it possible to use ancestral Monte Carlo sampling of complete and coherent 'load snapshots' for a given context.

The benefits of this approach are multiple. Firstly, the load distributions are highly correlated and non-Gaussian: the VAE makes it possible to learn flexible marginal distributions depending in a non-linear way on the context, and to model the correlations by sampling the load snapshots for the grid as a whole. Secondly, the ancestral sampling approach makes it possible to form a picture of uncertainty given how much is known at the time: unknown inputs can be sampled, for example from an external probabilistic weather forecast, leading to a wider picture of uncertainty that narrows over time. Lastly, the resulting sampled load snapshots can directly be used in a power flow analysis, leading to a joint distribution over the line flows that can be used to obtain risk measures: examples include the probability of exceeding the thermal limit of a line, and if exceeded, the expectation value of by how much.

[1] Kingma, D. P., and Welling, M. (2013). Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.
[2] Kingma, D. P., and Welling, M. (2019). An introduction to variational autoencoders. arXiv preprint arXiv:1906.02691.