Use Cases for the AI-empowered Smart Grid

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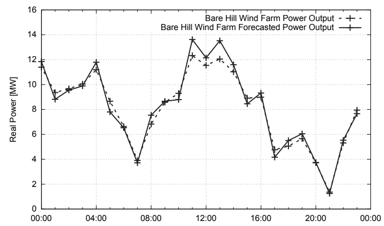
The notion of the smart grid is nowadays almost always connected with a high share of renewable energy sources, i.e., the smart grid enables us to integrate a large number of volatile energy sources. In order to still provide a reliable supply of power, grid operation relies on more planning, based on reliable forecasting, models to predict or estimate the state of the grid at a certain point in time, and a distributed intelligence for automatic, fine-tuned voltage control.

1 Forecasting Real Power

Purpose Create a forecast of real power generation or consumption on a node.

Methodology Use Recurrent Neural Networks to forecast a time series. The RNN architecture captures the concept of a series of data with interdependencies, but has no representation of absolute time values. The inputs at $t-n, \ldots, t-1, t$ are used to forecast P_{t+1}. Valid input data are the previous power generation/consumption as well as other useful features, such as barometric pressure.



(Veith, 2017)

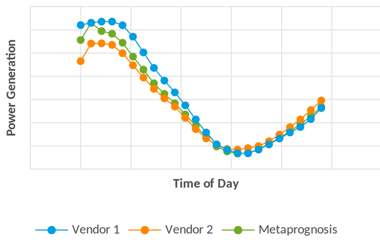
Pros This technique allows forecasting even for renewable energies without meteorological model with an accuracy suitable for distribution grids. It requires constant refinement and re-training.

Cons An intelligent data storage is needed to keep the pattern set bounded. The RNN can hardly forecast unknown weather phenomena.

2 Meta-Prognosis for Distributed Renewables

Purpose Algorithmically merge the weather-based power regeneration prognosis for a portfolio of renewables.

Methodology The output forecasted by different vendors' prognoses are compared against the actual power generation of a wind farm or PV installation. Different meteorological models weight the available features differently and are thus not optimized for a specific renewables portfolio. Neural networks can be trained to learn the error of each model, thus creating a meta-prognosis.



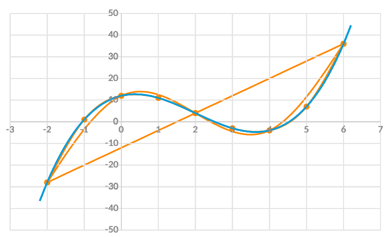
Pros Reduces need for after-market trade of undersupply, which is comparatively expensive.

Cons The meta-prognosis does not capture real weather phenomena; features are hidden in the meteorological model that creates the input data.

3 Surrogate Models

Purpose Replace a simulation (or a part thereof) that is computationally or memory expensive with an approximation derived from artificial neural networks in order to reduce compute time.

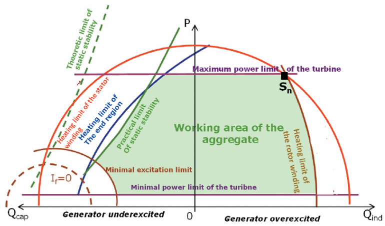
Methodology The artificial neural network is trained as a surrogate model that replaces another, more expensive, computation, such as a power flow study or a network state estimation. For a given network, example states are used for training and validation; the neural network can afterwards replace the actual model and computation for different states.



Pros Dramatically quicker evaluation time, making the surrogate model suitable for on-line usage.

Cons Every surrogate model is just an approximation; the neural network can learn the errors of the surrogate model and not the representation of the surrogated original. Also, using the surrogate model makes sense only when the model it replaces is sufficiently large to make a difference.

4 Power Factor Correction in Non-Linear Loads



(Ilic et al., 2011)

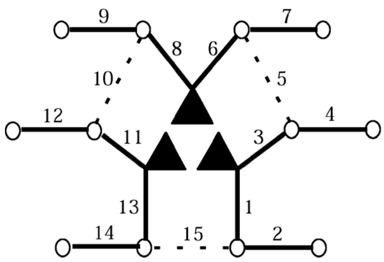
Purpose Reactive power management in the distribution grid helps to keep voltage within safe levels while driving generators powered by renewable energy sources as efficient as possible.

Methodology Devices that measure the phase angle (ϕ) are mostly deployed in the transmission grid, while most wind farms are connected to the distribution grid. The non-linear voltage drop makes it desirable to integrate them into the power factor correction (i.e., correction of $\cos\phi$). Wind farms and PV installations currently have a fixed $\cos\phi$ or fixed characteristic curve. Artificial neural networks can be used to derive the desired power factor correction for installed renewables, even if no extensive installation of Phase Measurement Units (PMUs) is available.

Pros The artificial neural networks solve an optimization problem with constraints: Optimal real power generation and providing ancillary services through power factor correction that helps to sustain the grid while keeping within own operational limits and those of the grid.

Cons As with the usage of surrogate models, the application of artificial neural networks provides an approximation, not an exact solution.

5 Distribution System Loss Minimum Reconfiguration



(Inoue et al., 2014)

Purpose Open and close switches in a distribution system in such a way as to minimize line loss while remaining within safe operating parameters.

Methodology An artificial neural network learns, for different load situations, which switches to open and which to close, and is then able to re-configure the grid for optimal power flow and low line losses.

Pros Fast reconfiguration of a distribution system leads to nearly minimal line loss for all time periods.

Cons Highly unusual or fault situations can cause the neural network to suggest erroneous switch configurations, which damage the grid.

References

Bhosekar, A. and Ierapetritou, M. (2018). Advances in surrogate based modeling, feasibility analysis, and optimization: A review. *Computers and Chemical Engineering*, 108:250–267.

Chen, Z. and Spooner, E. (2001). Grid power quality with variable speed wind turbines. *Energy Conversion, IEEE Transactions on*, 16(2):148–154.

Deshmukh, S., Natarajan, B., and Pahwa, A. (2012). Voltage/VAR control in distribution networks via reactive power injection through distributed generators. In *IEEE Transactions on Smart Grid*, volume 3, pages 1226–1234.

Ilic, I., Viskovic, A., and Vrazic, M. (2011). User P-Q diagram as a tool in reactive power trade. In *2011 8th International Conference on the European Energy Market (EEM)*, pages 580–584.

Inoue, T., Takano, K., Watanabe, T., Kawahara, J., Yoshinaka, R., Kishimoto, A., Tsuda, K., Minato, S.-i., and Hayashi, Y. (2014). Distribution Loss Minimization With Guaranteed Error Bound. *IEEE Transactions on Smart Grid*, 5(1):102–111.

Kirby, B. J. (2004). Frequency Regulation Basics and Trends. Technical Report December, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tennessee 37831-6283.

Manitsas, E., Singh, R., Pal, B. C., and Strbac, G. (2012). Distribution system state estimation using an artificial neural network approach for pseudo measurement modeling. *IEEE Transactions on Power Systems*, 27(4):1888–1896.

Nara, K., Shiose, A., Kitagawa, M., and Ishihara, T. (1992). Implementation of Genetic Algorithm for Distribution Systems Loss Minimum Re-Configuration. *IEEE Transactions on Power Systems*, 7(3):1044–1051.

Simpson, T. W., Peplinski, J. D., Koch, P. N., and Allen, J. K. (2001). Metamodels for computer-based engineering design: Survey and recommendations. *Engineering with Computers*, 17(2):129–150.

Veith, E. M. (2017). *Universal Smart Grid Agent for Distributed Power Generation Management*. Logos Verlag Berlin, Berlin, Germany.