Predicting Grid Demand with Variable Renewable Energy

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INTRODUCTION

Load following has given natural gas an economic edge over nuclear power because unlike nuclear, natural gas plants can follow grid demand and even shut off when renewable penetration makes the price of electricity go negative [1]. Advanced reactor designs, like Molten Salt Reactors (MSR), promise strong load following capabilities due to harder neutron spectra and faster Xe-135 burnup [2]. Unfortunately, the most mature MSR designs are at least a decade away from obtaining a commercial license in the United States. The climate crisis is too urgent to wait this long for nuclear power to become fully competitive with natural gas. Renewable energy has also challenged the base load electricity production that nuclear provides by introducing unpredictable variability in grid demand. Nuclear energy can be more economically feasible by relaxing the strong load following requirements with improved predictions of renewable energy production several hours or days in advance. If reactor operators knew in advance how much electricity will be produced by renewable energy they can slowly and accurately ramp reactor power to meet demand rather than operate continuously at full power and risk paying to export electricity. Thus improving nuclear energy's comptetitiveness against natural gas and strengthening nuclear's ability to couple with renewable energy. This work examines machine learning algorithms for accurate medium term predictions of spatio-temporal dynamic systems, such as weather and, by extension, renewable energy production.

BACKGROUND

Echo State Networks (ESN), a flavor of reservoir computing, are a modern machine learning algorithm that enables accurate short to medium term predictions. Pathak et. al demonstrated that reservoir computing can be used to accurately predict the evolution of a chaotic system up to seven Lyapunov times in the future [3, 4]. A Lyapunov time is the timescale on which a dynamic system expresses chaos due to small deviations in initial conditions. Conventional predictions succumb to chaos after one Lyapunov time and thus become useless. The Lyapunov time for a weather system is on the order of a few days but depends on regional environment. Electricity production from solar and wind are tightly coupled to regional weather. Electricity demand exhibits some seasonal regularity but is still subject to stochasticity. Combining accurate demand predictions with reliable renewable energy predictions will enable an artificially intelligent reactor operator to adjust power in a relaxed manner. Additionally, reservoir computing is relatively computationally inexpensive and fast to train. This is owed to its sparse network architecture [3, 4, 5].

METHODOLOGY

This work consists of three parts, data generation model training, and prediction. To generate data needed for training our RC model we used the `TrainARMA` functionality in the `RAVEN` tool from INL to generate synthetic histories. These scenarios are passed to the RC model for training and testing.

Training Data Generation

In this work we use the scenario generation method described in Baker et. al using the `RAVEN` framework [6]. The algorithm for producing synthetic histories is:

1. Create a "typical year" from historical data.
2. Fit an Autoregressive Moving Average (ARMA) model using `TrainARMA`.
3. Use Monte Carlo sampling to generate synthetic histories from ARMA model.

We perform this process for three datasets: Electricity demand, wind generation, and solar generation. This allows us to train an RC model to predict generation from wind and solar farms and to predict the net demand profile given by

$$D_{net} = (D_{total} - P_{wind} - P_{pv})_h \ \forall \ h \text{ in } [0, 8759] \tag{1}$$

Where D_{total} is the total demand at a given hour, h, of a synthetic demand profile from the ARMA model.

Reservoir Computing Model

Unlike a typical feed forward neural network, an "echo state network" (also called a "liquid state machine") is a type of recurrent neural network that uses a single layer of many neurons called a "reservoir". The reservoir has an adjacency matrix $\boldsymbol{A}$ that is

1. sparsely populated
2. connected by uniformly random weights centered at zero
3. has a large number of neurons

A reservoir computer also satisfies the *echo state property* [3, 7]. This property ensures that a system's state has a decaying influence on future states (like an echo of sound or ripples on water). This property is satisfied in most cases when the spectral radius (the absolute value of the greatest eigenvalue of $\boldsymbol{A}$)[7] is,

$$\rho(\boldsymbol{A}) < 1. \tag{2}$$

However, the echo state property can still be satisfied for a spectral radius greater than unity [8].

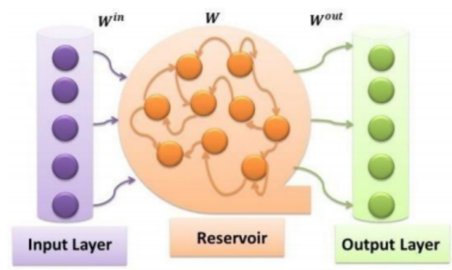

Fig. 1: A basic reservoir computer or echo state network. Image taken from [9]. The connections in the reservoir are given by $\boldsymbol{A}$

Figure 1 gives an visual representation of a basic ESN. An input vector of length K is mapped to the reservoir layer by an input weight matrix $\boldsymbol{W_{in}}$. The state of the reservoir is mapped to an output layer of length N with an output weight matrix $\boldsymbol{W_{out}}$. In this work, the input vector is a function of time, $\boldsymbol{u}(t)$, and the output vector is the next state of the system, $\boldsymbol{u}_p(t + \Delta t)$. Ideally, the difference between the prediction, $\boldsymbol{u}_p$, and the actual, $\boldsymbol{u}_a$, is minimized. During training, the output weight matrix is trained through backpropagation using a loss function like cross entropy [3, 10].

Hyperparameter Search

Due to the architecture of ESNs the weights and connections inside the reservoir do not need to be trained and, in our choice of implementation, cannot be. This dramatically reduces the training time because only the linear output layer needs to be trained. One drawback of this approach is its sensitivity to hyperparameters, which must be carefully chosen before running the network. Here, we perform grid searches over a variety of networks to establish which combination of hyperparameters minimizes the mean squared error of the model,

$$MSE = \frac{1}{N}\sum_{i}^{N}(\hat{y} - y_i)^2 \tag{3}$$

where

$$\hat{y} = \text{the average value of the ouput.}$$

RESULTS

Current results include the generation of time series data to be used in training the RC model. Shown in Figure **??**, Figure **??**, and Figure **??**.

Additionally, we have some preliminary predictions from a simple ESN in Figure 5 and Figure 6

CONCLUSIONS

In this work we demonstrated the `RAVEN` tool's scenario generation capability. Ott et. al and others have shown that

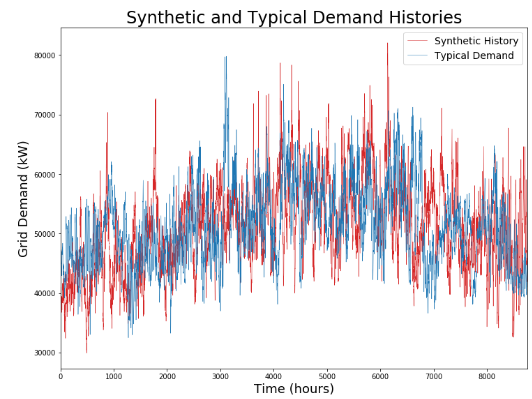

Fig. 2: The typical year of hourly grid demand in kW at UIUC.

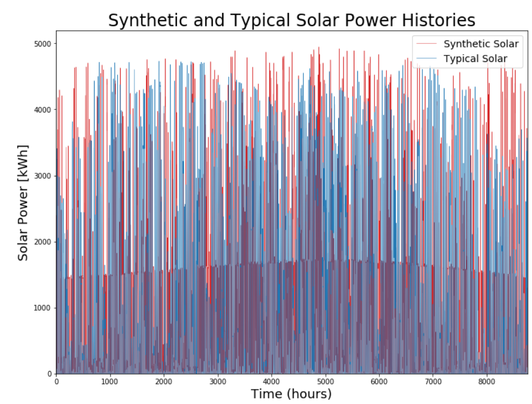

Fig. 3: The typical year and a synthetic year of hourly solar electricity generation in kWh per hour at UIUC. Data from [11]

Echo State Networks can be a powerful method for predicting the evolution of dynamic, chaotic, systems [3, 4, 12]. Accurate predictions of chaotic systems, like wind energy production, will enable nuclear power plants to maintain their economic feasibility. Knowledge, in advance, of renewable electricity generation will enable operators to ramp the reactor power within the constraints given by reactor physics.

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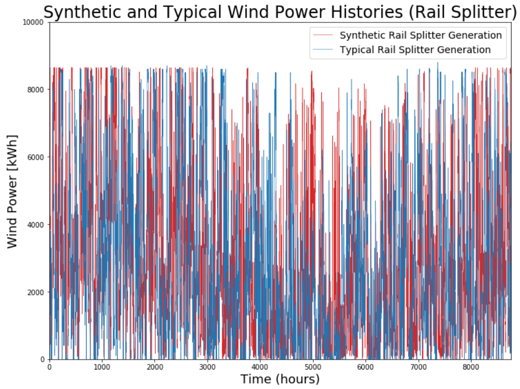

Fig. 4: The typical year and a synthetic year of hourly power produced by the UIUC wind power purchase agreement with Railsplitter Wind Farm.

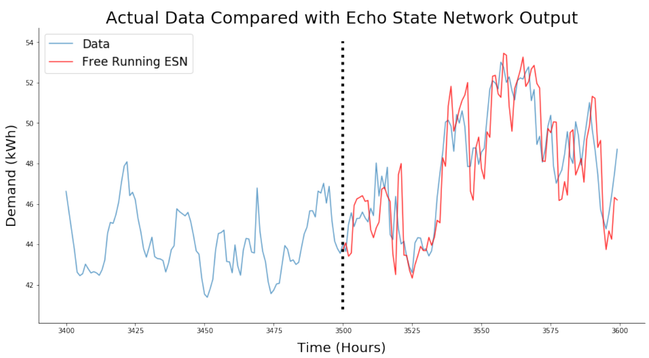

Fig. 5: A simple ESN with a prediction of 100 hours into the future.

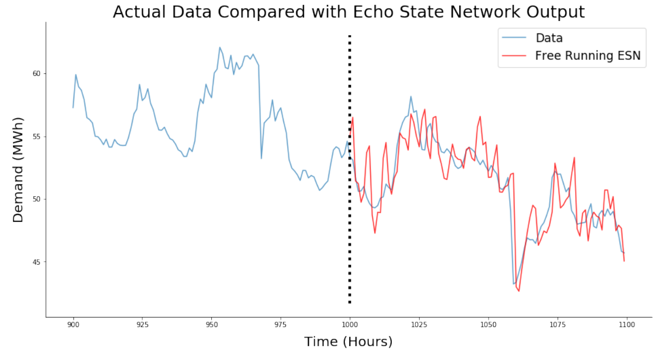

Fig. 6: A simple ESN with a prediction of 100 hours into the future.

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