

# Renewable Energy Forecasting with Echo State Networks

Samuel G. Dotson<sup>a,\*</sup>, Kathryn D. Huff<sup>a</sup>

<sup>a</sup>*Dept. of Nuclear, Plasma, and Radiological Engineering, University of Illinois at Urbana-Champaign, Urbana, IL 61801*

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## Abstract

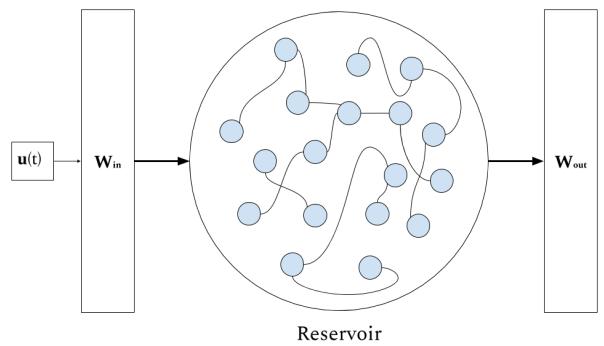
The abstract goes here. As a general guide, you should provide a concise (150-250 words) summary of your article - introduction, methodology, results, and conclusion. Avoid using abbreviations and acronyms unless the abbreviation/acronym is used repeatedly in the abstract. There should be no references in the abstract.

*Keywords:* FIXME, key words, go here, like:, simulation, spent nuclear fuel

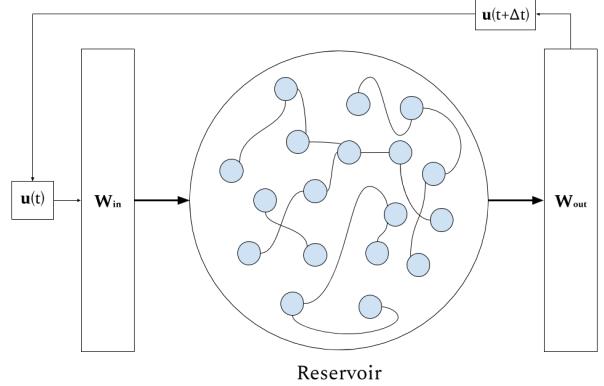
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## 1. Introduction

Reducing carbon emissions has become a priority for many countries in response to the rising threat of climate change. The goal set by the 2015 Paris Agreement is to prevent the global temperature from rising more than 1.5 °C above pre-industrial levels [1]. Virtually all current plans to reduce carbon emissions depend on increasing the share of energy production by renewable and clean energy sources, especially solar and wind energy [2, 3]. While solar and wind are low-carbon sources, these forms of electricity generation are variable and unpredictable. This variability is found to be major cause of black-outs and power system failures [4]. Further, even modest penetrations of renewable energy negatively affect the economics of other types of clean energy, such as nuclear power [2, 5]. There has been some work done to quantify the economic benefit of improving forecasts of renewable energy [6, 7, 8]. Some of the benefits of improving forecasts are: 1) It is often cheaper than building storage devices [6]. 2) Would reduce curtailment and allow for efficient use of non-renewable sources [7]. 3) Enable a slight, but important, amount of load-following from nuclear and bio-mass generators which are not designed for rapid load following [8].



(a) Training Flow



(b) Predicting Flow

Figure 1: Reservoir behavior in the training and predicting phases.

## 2. Methodology

### 2.1. Echo State Networks

An Echo State Network (ESN), sometimes called a “reservoir computer,” [9, 10, 11] is a type of recurrent neural network that replaces the many hidden layers of a conventional feed-forward neural network with a reservoir that is

1. sparse.
2. connected by uniformly random weights, centered at zero.
3. large (i.e. has many neurons).

The reservoir is therefore a randomly instantiated adjacency matrix,  $\mathbf{W}$ , of size  $N \times N$ . The input vector,  $U(t)$ , of  $K$  units is mapped onto the reservoir by an input matrix,  $W^{in}$  of size  $N \times K$ . The activation states of the reservoir are calculated by

$$x(t) = \tanh(W^{in} \cdot U(t) + \mathbf{W}x(t-1)) \quad (1)$$

Where  $x(t)$  is the collection of reservoir activations [12, 10, 13]. The output is read by an output weight matrix,  $W^{out}$ .

$$y(t) = (W^{out})^T \cdot x(t) \quad (2)$$

In the training phase, the output,  $U(t + \Delta t)$ , is discarded and the next training input passed to the network. During the prediction phase, the output is kept and used as the next input. This behavior is shown in Figure 1. The speed of ESNs is owed to this structure; only  $W^{out}$  has tunable weights. Everything else is fixed. In this work, we adapted the open source Python package pyESN [14] to construct and train the network.

### 2.2. Hyper-parameter Optimization

ESNs are fast because the hidden layer in a conventional feed-forward neural network is replaced by a large reservoir that does not require training. The trade off is that ESNs are sensitive to various hyper-parameters that need to be optimized [13]. These hyper-parameters are summarized in Table 1. The spectral radius ( $\rho$ ) should satisfy the “echo state property” which means that previous reservoir activations have a decaying influence on future states. This is usually guaranteed for  $\rho < 1$ , but this is not a requirement [13].

The hyper-parameters are optimized by performing a grid search over the test values specified in Table 1. The following steps were taken for each prediction task:

1. Select a hyper-parameter or pair of parameters.
2. Generate ESN prediction with the specified parameters.
3. Calculate and record the RMSE.
4. Continue until last entry in the parameter set is reached.
5. Set the network parameters to hyper-parameter value that minimizes the RMSE.

This algorithm generates an error surface where the coordinates of the absolute minimum correspond to the indices of values in the hyper-parameter test sets that minimized the RMSE.

### 2.3. Prediction Tasks

We first performed a benchmarking task by making a prediction for the Lorenz 1963 model [15]. Then we optimized predictions for univariate time-series representing total demand, solar energy, and wind energy 4-hours ahead and 48- hours ahead. Finally, those same six tasks are repeated with an additional predictor. The tasks are summarized in Table 2.

### 2.4. Data Selection and Processing

All data predicting demand, wind energy, and solar energy on the University of Illinois at Urbana-Champaign (UIUC) campus are from the UIUC Solar Farm 1.0 dashboard [16] and proprietary data shared with us courtesy of the UIUC Facilities and Services Department. All data had hourly resolution. Weather data was retrieved from the National Oceanic and Atmospheric Administration (NOAA)[17] for two locations: Champaign, IL, where UIUC is located, and Lincoln, IL, where Rail-splitter Windfarm is located. UIUC has a power purchase agreement with Railsplitter Windfarm [18]. In the case of UIUC solar data, significant portions were missing due to instrument failure. In order to fill in this missing data, we calculated the theoretical solar energy production based on irradiance data from OpenEI [19]. The solar output is given by [20]

$$P = G_T \eta_{ref} \tau_{pv} A [1 - \gamma(T - 25)] \quad [W] \quad (3)$$

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\*Corresponding Author  
Email address: sgd2@illinois.edu (Samuel G. Dotson)

Table 1: Description of Model Hyper-parameters

| Hyper-parameter | Purpose                                    | Tested Values  |
|-----------------|--|--|
| <b>noise</b>    | Neuron regularization                      | [0.0001, 0.0003, 0.0007, 0.001, 0.003, 0.005, 0.007, 0.01] |
| $\rho$          | Spectral radius                            | [0.5, 0.7, 0.9, 1, 1.1, 1.2, 1.3, 1.5]                     |
| $N$             | Size of reservoir, $\mathbf{W}$            | [600, 800, 1000, 1500, 2000, 2500, 3000, 4000]             |
| <b>sparsity</b> | The density of connections in $\mathbf{W}$ | [0.005, 0.01, 0.03, 0.05, 0.1, 0.12, 0.15, 0.2]            |
| Training Length | Size of the training set before prediction | $L \in [5000, 25000]$ , step size = 300                    |

Table 2: Summary of Prediction Tasks

| Target       | Future         | Additional Predictor                           |
|--------------|----------------|--|
| Total Demand | 4 hours ahead  | None   |
| Solar Energy | 48 hours ahead | Solar Elevation<br>Humidity<br>Pressure        |
| Wind Energy  |                | Wet Bulb Temp.<br>Dry Bulb Temp.<br>Wind Speed |

where

$$G_T = P_{DNI} * \cos(\beta + \delta - lat) + P_{DHI} * \left( \frac{180 - \beta}{180} \right) \left[ \frac{W}{m^2} \right] \quad (4)$$

where

$$\delta = 23.44 \sin \left( \left( \frac{\pi}{180} \right) \left( \frac{360}{365} \right) (N + 284) \right) \text{ [degrees]} \quad (5)$$

$\eta, \tau, \gamma$  are solar panel properties

$P_{DNI}$  is the direct normal irradiance

$P_{DHI}$  is the diffuse horizontal irradiance

$\beta$  is the tilt angle of the solar panels

The solar elevation angle,  $\alpha$ , was also calculated [21, 22] using coordinates for the UIUC solar farm.

$$\alpha = \sin^{-1} [\sin(\delta) \sin(\phi) + \cos(\delta) \cos(\phi) \cos(\omega)] \quad (6)$$

where

$\delta$  is the declination angle

$\phi$  is the latitude of interest

$\omega$  is the hour angle

Finally, we normalized all of the data using the infinity norm

$$\|\mathbf{x}\|_\infty \equiv \max |x_i|. \quad (7)$$

This is useful because it simplifies the comparison of our results between tasks whose training data have vastly different magnitudes.

### 2.5. Error Metric

We measure the accuracy of the model using two error metrics: Mean absolute error and root mean squared error. These are defined as

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (8)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (9)$$

## 3. Results

Below we show the best prediction for each task.

### 3.1. Benchmark: Lorenz 1963

We first verified that our choice of implementation for ESNs produces similar results to those found

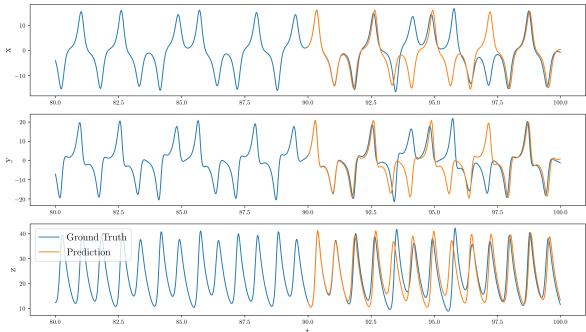


Figure 2: Using an ESN to replicate the climate of the Lorenz Attractor.

in the literature [9]. The hyper-parameters that minimized the RMSE of the model can be found in Table 3. Our optimized values are somewhat different from the literature, but we are satisfied that our ESN implementation successfully replicated the climate of the Lorenz Attractor similar to Pathak et. al 2017.

Table 3: Hyper-parameters for the Lorenz 1963 Model

| Parameter       | This paper | Literature [9] |
|-----------------|------------|----------------|
| $N$             | 2000       | 300            |
| $\rho$          | 0.9        | 1.2            |
| sparsity        | 0.1        | 0.1            |
| noise           | 0.001      | 0              |
| Training Length | 3200       | Not Specified  |

#### 4. Acknowledgments

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#### References

- [1] The paris agreement | UNFCCC. URL <https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement>
- [2] C. Cany, C. Mansilla, G. Mathonnière, P. da Costa, Nuclear contribution to the penetration of variable renewable energy sources in a french decarbonised power mix 150 544–555. doi:10.1016/j.energy.2018.02.122. URL <http://www.sciencedirect.com/science/article/pii/S0360544218303566>
- [3] J. Chilvers, T. J. Foxon, S. Galloway, G. P. Hammond, D. Infield, M. Leach, P. J. Pearson, N. Strachan, G. Strbac, M. Thomson, Realising transition pathways for a more electric, low-carbon energy system in the united kingdom: Challenges, insights and opportunities 231 (6) 440–477, publisher: IMECE. doi:10.1177/0957650917695448. URL <https://doi.org/10.1177/0957650917695448>
- [4] H. Haes Alhelou, M. E. Hamedani-Golshan, T. C. Njenda, P. Siano, A survey on power system black-out and cascading events: Research motivations and challenges 12 (4) 682, number: 4 Publisher: Multidisciplinary Digital Publishing Institute. doi:10.3390/en12040682. URL <https://www.mdpi.com/1996-1073/12/4/682>
- [5] J. H. Keppler, C. Marcantonini, O. N. E. Agency, O. for Economic Co-operation {and} Development, Carbon pricing, power markets and the competitiveness of nuclear power, Nuclear development, Nuclear Energy Agency, Organisation for Economic Co-operation and Development.
- [6] Q. Wang, C. B. Martinez-Anido, H. Wu, A. R. Florita, B.-M. Hodge, Quantifying the economic and grid reliability impacts of improved wind power forecasting 7 (4) 1525–1537, conference Name: IEEE Transactions on Sustainable Energy. doi:10.1109/TSTE.2016.2560628.
- [7] E. V. Mc Garrigle, P. G. Leahy, Quantifying the value of improved wind energy forecasts in a pool-based electricity market 80 517–524. doi:10.1016/j.renene.2015.02.023. URL <http://www.sciencedirect.com/science/article/pii/S0960148115001135>
- [8] C. Brancucci Martinez-Anido, B. Botor, A. R. Florita, C. Draxl, S. Lu, H. F. Hamann, B.-M. Hodge, The value of day-ahead solar power forecasting improvement 129 192–203. doi:10.1016/j.solener.2016.01.049. URL <http://www.sciencedirect.com/science/article/pii/S0038092X16000736>
- [9] J. Pathak, Z. Lu, B. R. Hunt, M. Girvan, E. Ott, Using machine learning to replicate chaotic attractors and calculate lyapunov exponents from data 27 (12) 121102. arXiv:1710.07313, doi:10.1063/1.5010300. URL <http://arxiv.org/abs/1710.07313>
- [10] J. Pathak, B. Hunt, M. Girvan, Z. Lu, E. Ott, Model-free prediction of large spatiotemporally chaotic systems from data: A reservoir computing approach 120 (2) 024102, publisher: American Physical Society. doi:10.1103/PhysRevLett.120.024102. URL <https://link.aps.org/doi/10.1103/PhysRevLett.120.024102>
- [11] P. R. Vlachas, J. Pathak, B. R. Hunt, T. P. Sapsis, M. Girvan, E. Ott, P. Koumoutsakos, Backpropagation algorithms and reservoir computing in recurrent neural networks for the forecasting of

## Demand Prediction with ESN

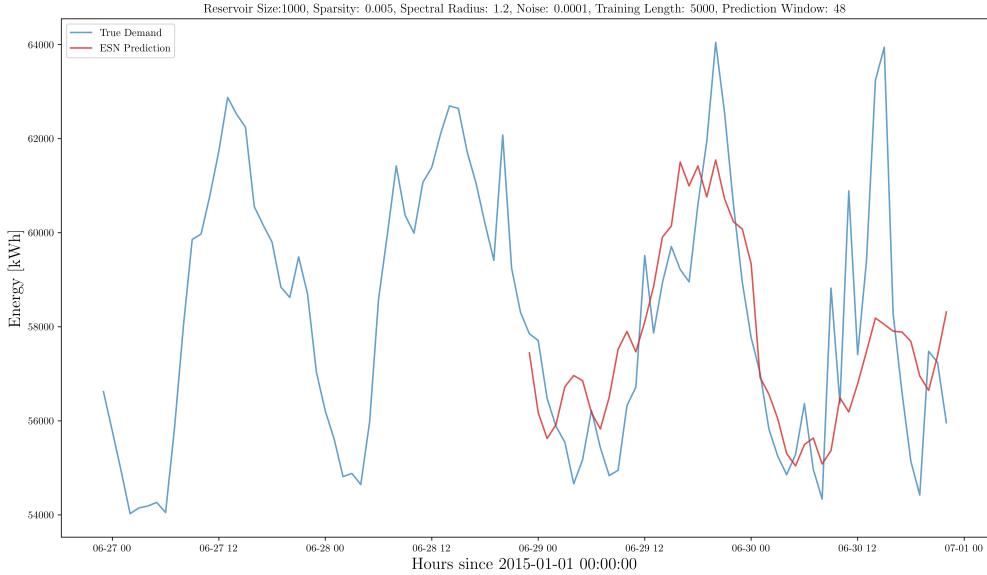


Figure 3: The optimized 48-hour ahead demand prediction with pressure as a meteorological predictor.

Table 4: Tabulated error for 48-hour ahead total electricity demand forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting electricity demand alone.

| Scenario                | MAE      | RMSE     | Improvement MAE (%) | Improvement RMSE (%) |
|-------------------------|----------|----------|---------------------|----------------------|
| Total Demand            | 0.018892 | 0.024137 | [ - ]               | [ - ]                |
| Demand + Sun Elevation  | 0.013375 | 0.022893 | -29.20              | -5.15                |
| Demand + Humidity       | 0.048357 | 0.063544 | +155.96             | +163.26              |
| Demand + Pressure       | 0.009329 | 0.017334 | -50.62              | -28.18               |
| Demand + Wet Bulb Temp. | 0.033473 | 0.039922 | +77.18              | +65.40               |
| Demand + Dry Bulb Temp. | 0.031866 | 0.040409 | +66.67              | +67.42               |
| Demand + Wind Speed     | 0.051045 | 0.074966 | +170.19             | +210.58              |

complex spatiotemporal dynamics 126 191–217.  
doi:10.1016/j.neunet.2020.02.016.

185 URL <http://www.sciencedirect.com/science/article/pii/S0893608020300708> 205

[12] G. Shi, D. Liu, Q. Wei, Energy consumption prediction of office buildings based on echo state networks 216 478–488. doi:10.1016/j.neucom.2016.08.004.

190 URL <http://www.sciencedirect.com/science/article/pii/S0925231216308219> 210

[13] M. Lukoševičius, A practical guide to applying echo state networks, in: G. Montavon, G. B. Orr, K.-R. Müller (Eds.), Neural Networks: Tricks of the Trade: Second Edition, Lecture Notes in Computer Science, Springer, pp. 659–686. doi:10.1007/978-3-642-35289-8\_36.  
URL [https://doi.org/10.1007/978-3-642-35289-8\\_36](https://doi.org/10.1007/978-3-642-35289-8_36)

200 [14] C. Korndörfer, pyESN.  
URL <https://github.com/cknd/pyESN> 220

[15] E. N. Lorenz, Deterministic nonperiodic flow 20 (2) 130–141, publisher: American Meteorological Society

Section: Journal of the Atmospheric Sciences. doi: 10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2.

URL [https://journals.ametsoc.org/view/journals/atsc/20/2/1520-0469\\_1963\\_020\\_0130\\_dnf\\_2\\_0\\_co\\_2.xml](https://journals.ametsoc.org/view/journals/atsc/20/2/1520-0469_1963_020_0130_dnf_2_0_co_2.xml)

[16] AlsoEnergy, University of illinois solar farm dashboard, <http://s35695.mini.alsoenergy.com/Dashboard/2a5669735065572f4a42454f>

URL <http://go.illinois.edu/solar>

[17] N. C. for Environmental Information, Find a station | data tools | climate data online (CDO) | national climatic data center (NCDC).

URL <https://www.ncdc.noaa.gov/cdo-web/datatools/findstation>

[18] S. Breitweiser, Wind power: University of illinois at urbana-champaign.

URL [https://www.fs.illinois.edu/docs/default-source/news-docs/newsrelease\\_windppa-factsheet.pdf?sfvrsn=43aaffea\\_0](https://www.fs.illinois.edu/docs/default-source/news-docs/newsrelease_windppa-factsheet.pdf?sfvrsn=43aaffea_0)

[19] National solar radiation data base - NSRDB viewer - OpenEI datasets.

### Demand Prediction with ESN

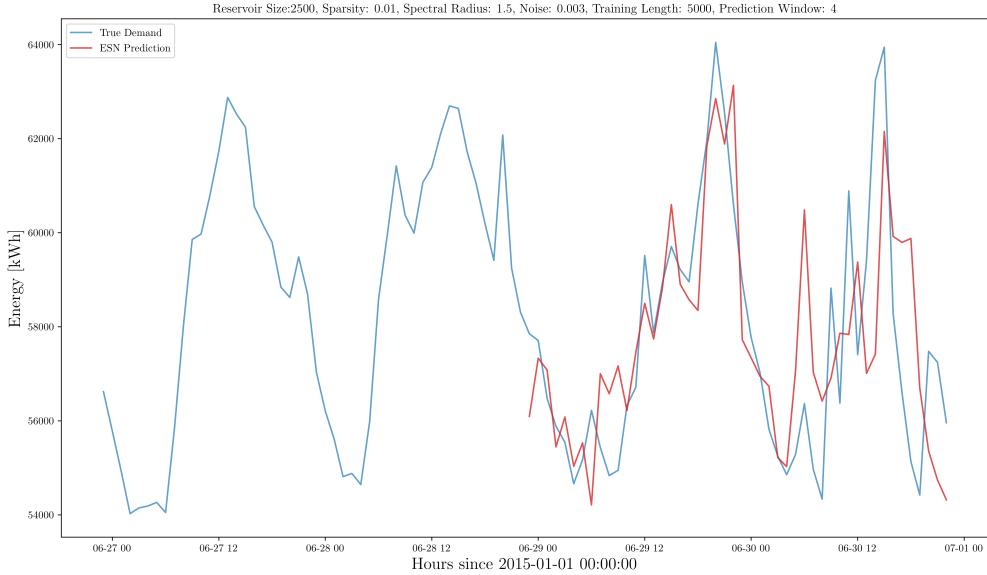


Figure 4: The optimized 4 hour ahead demand prediction with solar angle as an additional predictor.

Table 5: Tabulated error for 4-hour ahead total electricity demand forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting electricity demand alone.

| Scenario                | MAE      | RMSE     | Improvement MAE (%) | Improvement RMSE (%) |
|-------------------------|----------|----------|---------------------|----------------------|
| Total Demand            | 0.019343 | 0.026322 | [-]                 | [-]                  |
| Demand + Sun Elevation  | 0.009869 | 0.016928 | -48.98              | -35.69               |
| Demand + Humidity       | 0.054772 | 0.073056 | +183.16             | +177.54              |
| Demand + Pressure       | 0.009754 | 0.019314 | -49.57              | -26.62               |
| Demand + Wet Bulb Temp. | 0.020932 | 0.026979 | +8.21               | +2.50                |
| Demand + Dry Bulb Temp. | 0.026577 | 0.039963 | +37.40              | +51.82               |
| Demand + Wind Speed     | 0.042534 | 0.067427 | +119.89             | +156.16              |

URL <https://openei.org/datasets/dataset/national-solar-radiation-data-base/resource/b2074dd9-36a4-4382-a12f-e795b578404c>

- [20] H. E. Garcia, J. Chen, J. S. Kim, M. G. McKellar, W. R. Deason, R. B. Vilim, S. M. Bragg-Sitton, R. D. Boardman, Nuclear hybrid energy systems regional studies: West Texas & northeastern Arizona. doi:10.2172/1236837.

URL <https://www.osti.gov/biblio/1236837-nuclear-hybrid-energy-systems-regional-studies-west-texas-northeastern-arizona>

- [21] N. US Department of Commerce, ESRL global monitoring laboratory - global radiation and aerosols.

URL <https://www.esrl.noaa.gov/gmd/grad/solcalc/calcdetails.html>

- [22] J. Meeus, Astronomical Algorithms, 2nd Edition, Willmann-Bell, Inc.

### Solar Generation Prediction with ESN

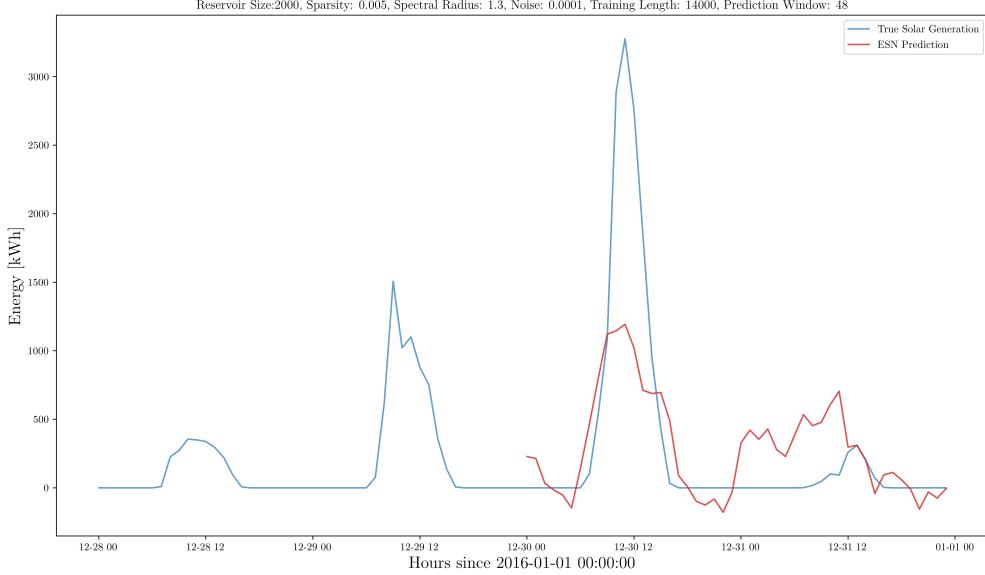


Figure 5: The optimized 48-hour ahead solar energy prediction with humidity as a meteorological predictor.

Table 6: Tabulated error for 48-hour ahead solar energy forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting solar energy alone.

| Scenario               | MAE      | RMSE     | Improvement MAE (%) | Improvement RMSE (%) |
|------------------------|----------|----------|---------------------|----------------------|
| Solar Energy           | 0.143276 | 0.206162 | [ - ]               | [ - ]                |
| Solar + Sun Elevation  | 0.200627 | 0.292516 | +40.02              | +41.88               |
| Solar + Humidity       | 0.086920 | 0.111476 | -39.33              | -45.93               |
| Solar + Pressure       | 0.098554 | 0.152672 | -31.21              | -25.94               |
| Solar + Wet Bulb Temp. | 0.114157 | 0.167503 | -20.32              | -18.75               |
| Solar + Dry Bulb Temp. | 0.079036 | 0.123783 | -44.84              | -39.96               |
| Solar + Wind Speed     | 0.147270 | 0.191722 | +2.788              | -7.004               |

Table 7: Tabulated error for 4-hour ahead solar energy forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting solar energy alone.

| Scenario               | MAE      | RMSE     | Improvement MAE (%) | Improvement RMSE (%) |
|------------------------|----------|----------|---------------------|----------------------|
| Solar Energy           | 0.061426 | 0.095794 | [ - ]               | [ - ]                |
| Solar + Sun Elevation  | 0.033263 | 0.060048 | -45.85              | -37.32               |
| Solar + Humidity       | 0.054951 | 0.078739 | -10.54              | -17.80               |
| Solar + Pressure       | 0.046862 | 0.089294 | -23.71              | -6.78                |
| Solar + Wet Bulb Temp. | 0.038104 | 0.053419 | -37.97              | -44.24               |
| Solar + Dry Bulb Temp. | 0.044104 | 0.073112 | -28.20              | -23.68               |
| Solar + Wind Speed     | 0.070293 | 0.099912 | +14.44              | +4.30                |

### Solar Generation Prediction with ESN

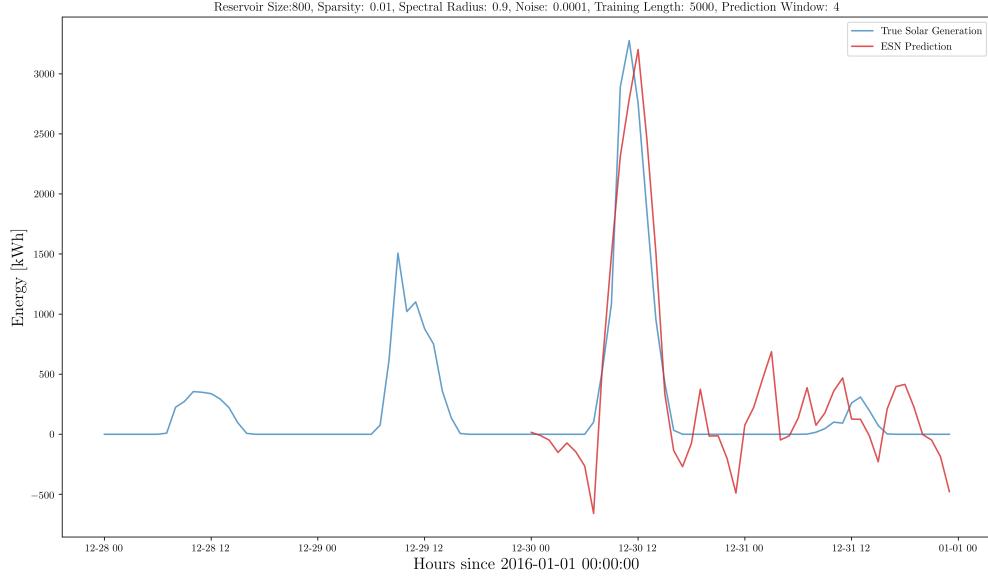


Figure 6: The optimized 4 hour ahead solar energy prediction with wet bulb temperature as a meteorological predictor.

### Wind Generation Prediction with ESN

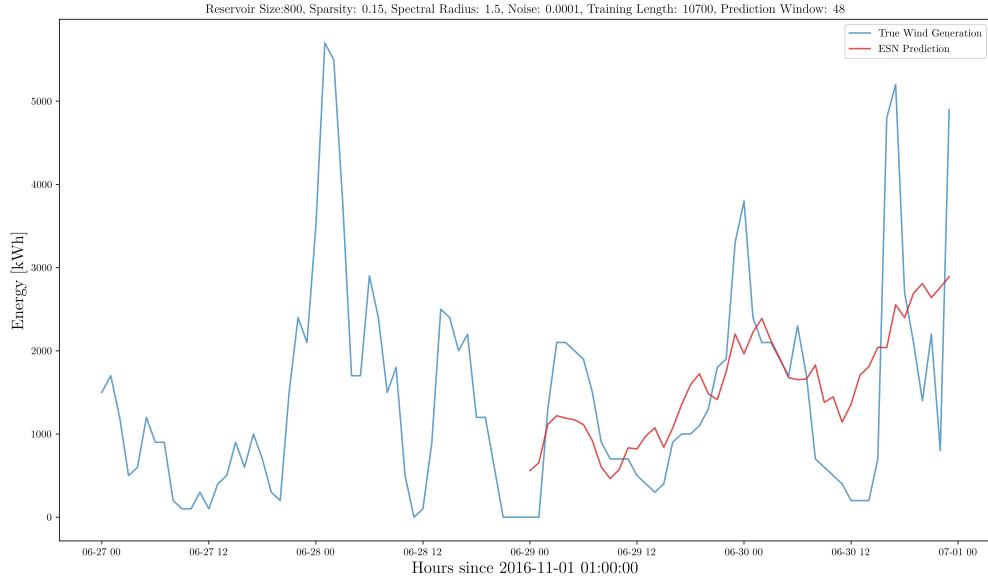


Figure 7: The optimized 48-hour ahead wind energy prediction with solar angle as an additional predictor.

Table 8: Tabulated error for 48-hour ahead wind forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting wind energy alone.

| Scenario              | MAE      | RMSE     | $\frac{1}{\text{MAE}} (\%)$ | Improvement<br>RMSE (%) |
|-----------------------|----------|----------|-----------------------------|-------------------------|
| Wind Energy           | 0.103516 | 0.130848 | [ - ]                       | [ - ]                   |
| Wind + Sun Elevation  | 0.051899 | 0.081339 | -49.82                      | -37.84                  |
| Wind + Humidity       | 0.091975 | 0.112054 | -11.15                      | -14.36                  |
| Wind + Pressure       | 0.054388 | 0.097670 | -47.46                      | -25.36                  |
| Wind + Wet Bulb Temp. | 0.074085 | 0.097004 | -28.43                      | -25.86                  |
| Wind + Dry Bulb Temp. | 0.081268 | 0.105289 | -21.49                      | -19.53                  |
| Wind + Wind Speed     | 0.100880 | 0.122271 | -2.5464                     | -6.555                  |

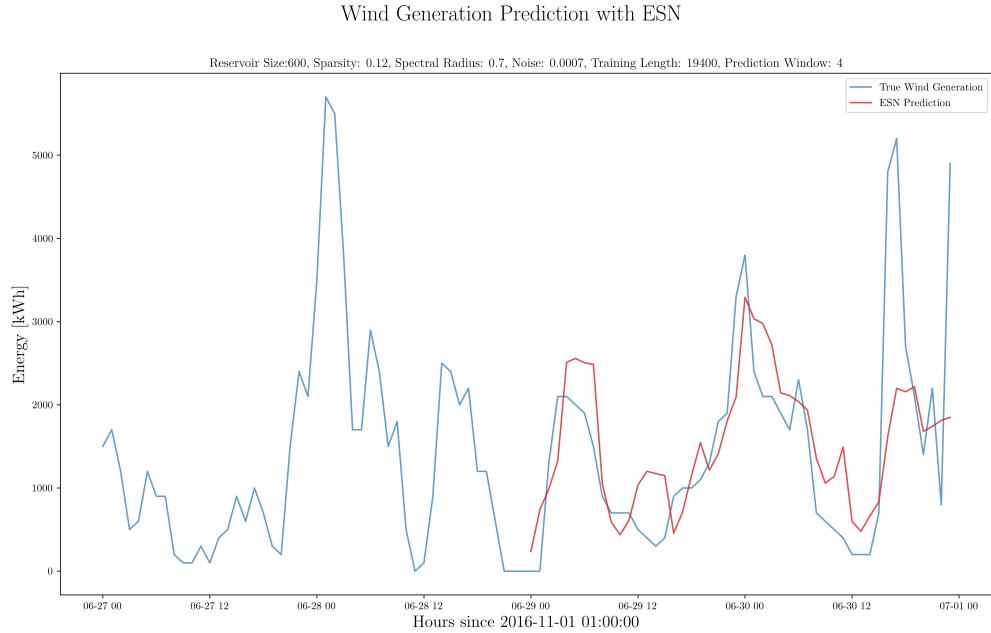


Figure 8: The optimized 4 hour ahead wind energy prediction with wet bulb temperature as a meteorological predictor.

Table 9: Tabulated error for 4-hour ahead wind forecasts with various coupled quantities. Improvement indicates the percentage improvement over the base case of forecasting wind energy alone.

| Scenario              | MAE      | RMSE     | Improvement<br>MAE (%) | Improvement<br>RMSE (%) |
|-----------------------|----------|----------|------------------------|-------------------------|
| Wind Energy           | 0.090266 | 0.124303 | [ - ]                  | [ - ]                   |
| Wind + Sun Elevation  | 0.039248 | 0.083134 | -56.52                 | -33.12                  |
| Wind + Humidity       | 0.064131 | 0.096310 | -28.95                 | -22.52                  |
| Wind + Pressure       | 0.043739 | 0.087981 | -51.54                 | -29.22                  |
| Wind + Wet Bulb Temp. | 0.044447 | 0.077770 | -50.76                 | -37.44                  |
| Wind + Dry Bulb Temp. | 0.050536 | 0.083151 | -44.01                 | -33.11                  |
| Wind + Wind Speed     | 0.063456 | 0.088157 | -29.70                 | -29.07                  |