

Evaluation of Weather Parameters for Renewable Energy Forecasting with Echo State Networks

Samuel G. Dotson^{a,*}, Kathryn D. Huff^a

^a*Dept. of Nuclear, Plasma, and Radiological Engineering, University of Illinois at Urbana-Champaign, Urbana, IL 61801*

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

1. Introduction

1.1. Motivation

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, 4, 5]. 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 blackouts and power system failures [6]. Further, even modest penetrations of renewable energy negatively affect the economics of other types of clean energy, such as nuclear power [2, 7, 8]. This may force nuclear plants to shutdown prematurely, at the precise moment clean sources of energy are most needed. There has been some work done to quantify the economic benefit of improving forecasts of renewable energy [9, 10, 11]. Some of the benefits of improving forecasts are: 1) It is often cheaper than building storage devices [9]. 2) Would reduce curtailment and allow for efficient use of non-renewable sources [10]. 3) Enable a slight, but important, amount of

load-following from nuclear and bio-mass generators which are not designed for rapid load following [11]. Most proposed forecasting improvements involve new algorithms or machine learning techniques. However, one of the simplest approaches to improving forecasts is to improve the training data for such algorithms. There is a veritable zoo of weather parameters that can supplement target training data and we don't know *a priori* which of these parameters will be helpful or detrimental to model performance. In this paper, we evaluate several common parameters for use in renewable energy forecasting with Echo State Networks (ESNs).

1.2. Why Echo State Networks

ESNs have several appealing features. They are simple, consisting only of a large sparse reservoir and a single output layer [12]; flexible and generalizable where other network architectures require significant fine tuning [13]; and fast, due to their simple structure and very few trainable weights relative to other neural networks. Additionally, ESNs have been shown to outperform other prediction techniques [14, 15, 16, 17, 18].

Classical ESNs have previously been used to forecast demand, wind energy, and solar energy [19, 15, 18]. ESNs are typically used to make very short term predictions, on the order of seconds or minutes [20, 21, 17], one-hour ahead [16], up to a single day ahead [19]. Forecasts need to be multiple-hours to a couple of days ahead to aid unit commitment and grid-scale energy economy [9, 10, 11].

*Corresponding Author

Email address: sgd2@illinois.edu (Samuel G. Dotson)

In this work we use a classic ESN architecture to
60 forecast total demand, wind production, and solar production, 4-hours and 48-hours ahead.

There has been a lot of work to improve the forecasting capability of the basic ESN. Approaches include adding multiple reservoirs [18, 22, 23, 24];
65 including non-linear units [25, 17]; combining with other network architecture [20, 26]; and using a particle swarm approach [27, 21]. Some works mention that including weather parameters may be useful for renewable energy forecasting [28, 17] but none
70 have demonstrated the effect each parameter has on model performance. The primary goal of this work is to fill that gap.

1.3. Contributions

In this work, we use ESNs for three main prediction tasks: Total electricity demand, wind energy production, and solar energy production. We split these tasks into further sub tasks; predicting four hours ahead, and 48- hours ahead. These predictions are useful for scheduling and grid planning because
75 current market rules put renewable energy on the grid first, forcing conventional power generators to work around this variability [9]. Using ESNs to make predictions two-days ahead is unique this paper since the longest predictions by ESNs in the literature is only one-day ahead [19]. Finally, we repeat these
80 tasks with several commonly used weather parameters and evaluate their effect on model performance. The need to consider exogenous meteorological inputs has been noted previously. Surprisingly, using sun elevation as a correlated quantity for energy demand and wind power is absent from the literature.
85

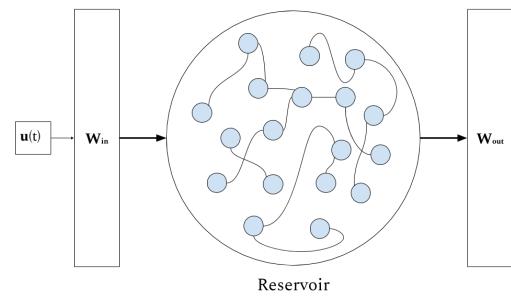
The structure of the paper is as follows. In section 2, we discuss how data was selected, processed, and review ESNs. Section 3 shows a benchmarking
90 exercise for our ESN implementation and presents the results. We discuss the results and future implications in section 4.

2. Methodology

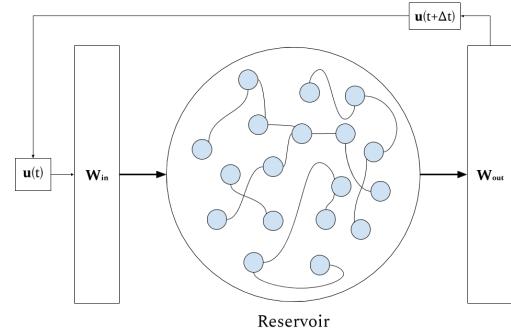
2.1. Echo State Networks

An ESN, sometimes called a “reservoir computer,”[29, 30, 31] 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
100

105 1. sparse.



(a) Training Flow



(b) Predicting Flow

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

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 [16, 30, 12]. The output is read by an output weight matrix, W^{out} .

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

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 [32] 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 [12]. These hyper-parameters are summarized in Table 1. The spectral radius (ρ) 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 is not a requirement [12].

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 [33]. 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 [34] 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)[35] 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 Rail-splitter Windfarm [36]. 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 [37]. The solar output is given by [38]

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

where

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

where

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

η, τ, γ are solar panel properties

P_{DNI} is the direct normal irradiance

P_{DHI} is the diffuse horizontal irradiance

β is the tilt angle of the solar panels

Table 1: Description of Model Hyper-parameters

Hyper-parameter	Purpose	Tested Values
noise	Neuron regularization	[0.0001, 0.0003, 0.0007, 0.001, 0.003, 0.005, 0.007, 0.01]
ρ	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]
sparsity	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 Humidity Pressure
Wind Energy		Wet Bulb Temp. Dry Bulb Temp. Wind Speed

The solar elevation angle, α , was also calculated [39, 40] using coordinates for the UIUC solar farm.

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

where

δ is the declination angle

ϕ is the latitude of interest

ω is the hour angle

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

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

The infinity norm is equivalent to normalizing by the system capacity. This is useful because it simplifies the comparison of our results between tasks whose training data have vastly different magnitudes.

160 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 in the literature [29]. 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 our ESN implementation successfully replicated the climate of the Lorenz Attractor similar to Pathak et. al 2017.

4. Discussion

The forecast accuracy of our ESN for the Lorenz model does not persist for quite as long as in other

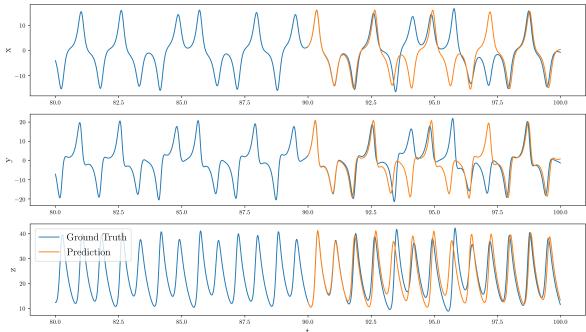


Figure 2: Using an ESN to replicate the climate of the Lorenz Attractor.

Table 3: Hyper-parameters for the Lorenz 1963 Model

Parameter	This paper	Literature [29]
N	2000	300
ρ	0.9	1.2
sparsity	0.1	0.1
noise	0.001	0
Training Length	3200	Not Specified

works [29]. However, our model successfully replicates the environment that produces the Lorenz Attractor. Further, optimal parameters may be unique for each randomly instantiated reservoir. It is impossible to replicate the exact conditions of other works without information about a seed for the random state. We have included this information for future work to compare with our results.

For each target variable, demand, wind, and solar, we found that air pressure was the only meteorological factor that improved the forecast error in every case. Solar elevation angle also decreased the error in most cases with one exception, 48-hour ahead solar production. One possible reason for the improved performance from adding air pressure is that the data may contain implicit information about weather dynamics. For example, air pressure typically changes throughout the day due to solar heating and has close relationship to air temperature [41], thus it contains implicit information about both the amount of solar energy reaching the ground and the ambient temperature which influences electricity demand and solar energy generation. Similarly, the height of the sun in the sky has a strong influence on ambient weather and thus on demand and the production of renewable energy. Elevation angle lacks information about how much solar energy reaches the ground, which is perhaps why air

pressure performed better in some cases. Using the solar angle to improve forecasting has a couple of important advantages over measured weather data. First, it can be calculated accurately within a minute time-resolution [39]. Second, because solar angle can be calculated deterministically, it reduces the amount of data processing required. Based on this, we recommend using solar elevation as a simple first attempt at improving forecasts.

The forecast lengths were decided based on the requirements for improved economics and planning mentioned in the literature [9, 10, 11]. The ESN model performed reasonably well at predicting four hours ahead but is not an improvement over the state-of-the-art [9, 42]. The model did not perform well at the 48-hour ahead forecasts. This could be due to the lack of higher resolution data. ESNs are known for their ability to predict highly non-linear systems [43, 44] yet using hourly data could add superfluous complexity [45] that confounds the model.

5. Acknowledgments

This work was made possible with the support from the people at UIUC Facilities & Services. In particular, Morgan White, Mike Marquissee, and Mike Larson. It was also aided by other members of the Advanced Reactors and Fuel Cycles (ARFC) group, in particular Nathan Ryan. This work is supported by the Nuclear Regulatory Commission Fellowship Program. Prof. Huff is supported by the Nuclear Regulatory Commission Faculty Development Program (award NRC-HQ-84-14-G-0054 Program B), the Blue Waters sustained-petascale computing project supported by the National Science Foundation (awards OCI-0725070 and ACI-1238993) and the state of Illinois, the DOE ARPA-E MEITNER Program (award DE-AR0000983), and the DOE H2@Scale Program (Award Number: DE-EE0008832)

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>

Demand Prediction with ESN

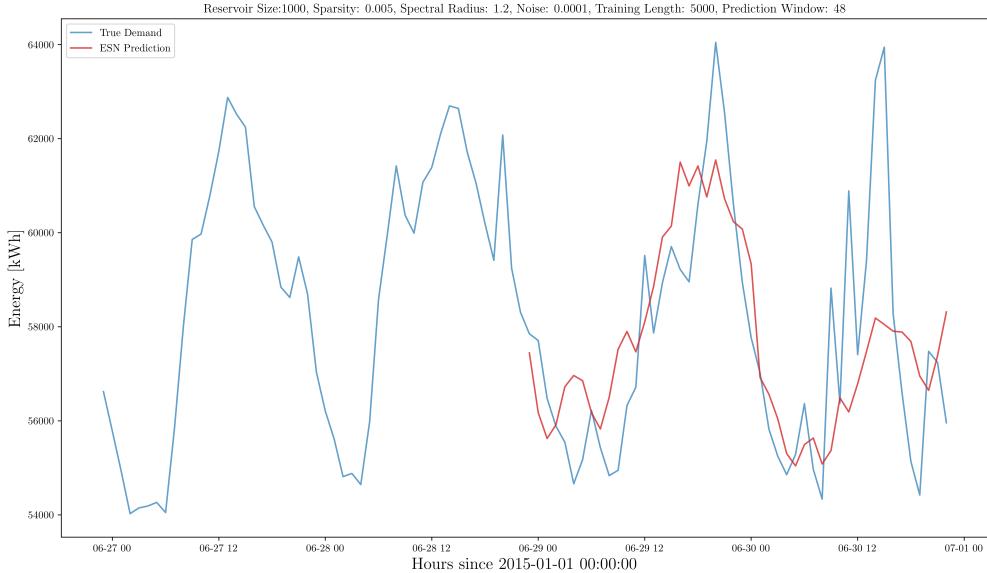


Figure 3: The optimized 48-hour ahead demand prediction with pressure as a meteorological predictor.

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

- [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] 99th General Assembly, Illinois general assembly - full text of SB2814.
URL <http://www.ilga.gov/legislation/fulltext.asp?DocName=&SessionId=88&GA=99&DocTypeId=SB&DocNum=2814&GAID=13&LegID=96125&SpecSess=&Session=>
- [5] iSEE, Illinois climate action plan (iCAP).
URL <https://sustainability.illinois.edu/campus-sustainability/icap/>
- [6] 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>

- [7] 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.
- [8] Illinois Commerce Commision (ICC), I. P. A. (IPA), I. E. P. A. (IEPA), I. D. of Commerce and Economic Opportunity (IDCEO), Potential nuclear power plant closings in illinois.
URL http://www.ilga.gov/reports/special/Report_Potential%20Nuclear%20Power%20Plant%20Closings%20in%20IL.pdf
- [9] 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)

Demand Prediction with ESN

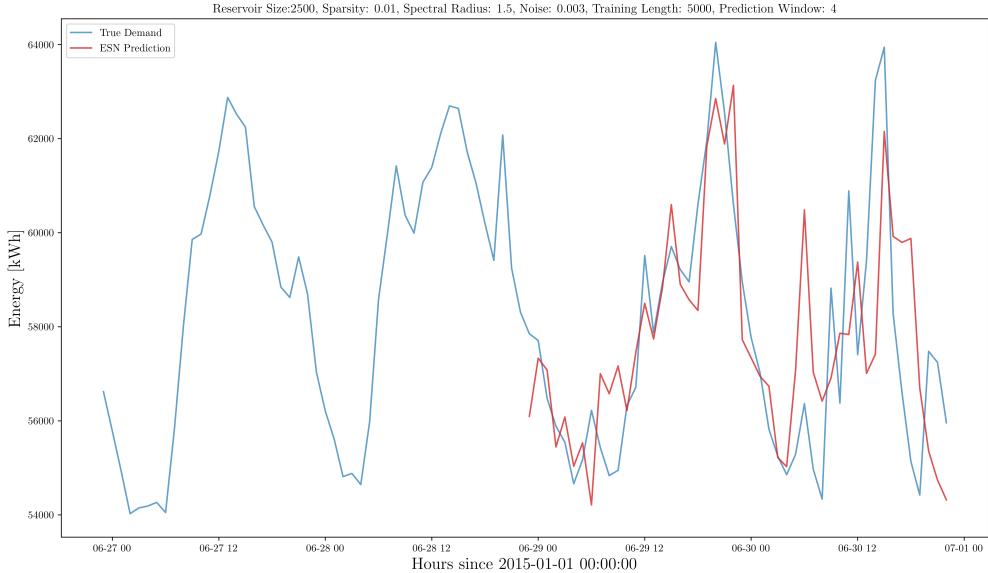


Figure 4: The optimized 4 hour ahead demand prediction with solar angle as an additional predictor.

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

- 1525–1537, conference Name: IEEE Transactions on Sustainable Energy. doi:10.1109/TSTE.2016.2560628.
- [10] 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>
- [11] 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>
- [12] 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
- [13] Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods 195 328–345, publisher: Pergamon. doi:10.1016/j.enconman.2019.05.020. URL <http://www.sciencedirect.com/science/article/pii/S0196890419305655>
- [14] I. Jayawardene, G. K. Venayagamoorthy, Comparison of echo state network and extreme learning machine for PV power prediction, in: 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), pp. 1–8, ISSN: 2326-7690. doi:10.1109/CIASG.2014.7011546.
- [15] I. Jayawardene, G. Venayagamoorthy, Comparison of adaptive neuro-fuzzy inference systems and echo state networks for PV power prediction 53 92–102. doi:10.1016/j.procs.2015.07.283.
- [16] 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. URL <http://www.sciencedirect.com/science/article/pii/S0925231216308219>
- [17] M. A. Chitsazan, M. S. Fadali, A. Tryznadlowski, Wind speed and wind direction forecasting using echo state network with nonlinear functions 131 879–889, publisher: Pergamon. doi:10.1016/j.renene.2018.07.060.

Solar Generation Prediction with ESN

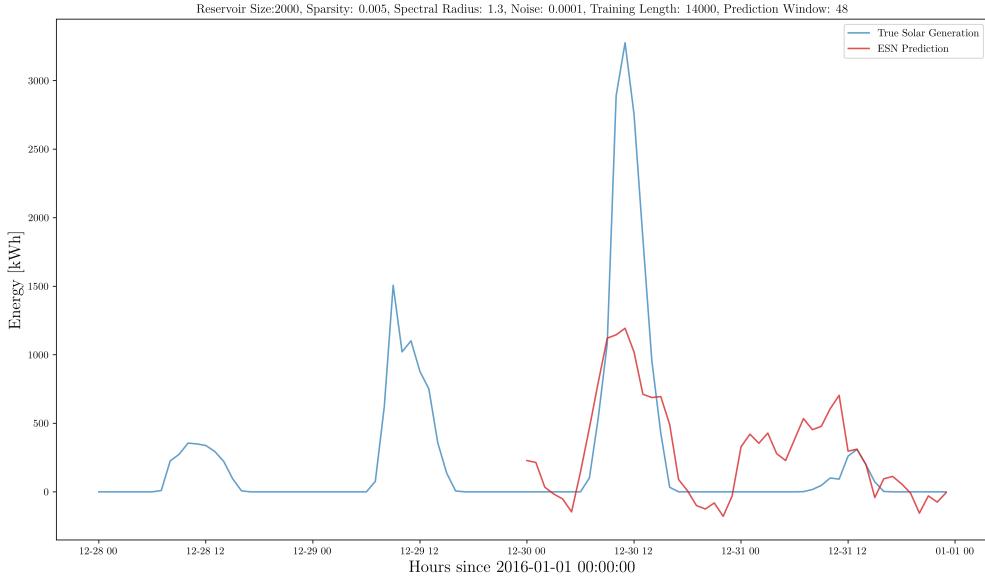


Figure 5: The optimized 48-hour ahead solar energy prediction with humidity as a meteorological predictor.

Table 5: 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

- URL <http://www.sciencedirect.com/science/article/pii/S0960148118308577>
- 340 [18] H. Hu, L. Wang, S.-X. Lv, Forecasting energy consumption and wind power generation using deep echo state network 154 598–613. doi:10.1016/j.renene.2020.03.042. URL <http://www.sciencedirect.com/science/article/pii/S0960148120303645>
- 345 [19] A. Deihimi, H. Showkati, Application of echo state networks in short-term electric load forecasting 39 (1) 327–340. doi:10.1016/j.energy.2012.01.007. URL <https://linkinghub.elsevier.com/retrieve/pii/S0360544212000126>
- 350 [20] Y. Chen, Z. He, Z. Shang, C. Li, L. Li, M. Xu, A novel combined model based on echo state network for multi-step ahead wind speed forecasting: A case study of NREL 179 13–29. doi:10.1016/j.enconman.2018.10.068. URL <https://linkinghub.elsevier.com/retrieve/pii/S0196890418311968>
- 360 [21] H. Wang, Z. Lei, Y. Liu, J. Peng, J. Liu, Echo state network based ensemble approach for wind power forecasting 201 112188. doi:10.1016/j.enconman.2019.112188. URL <http://www.sciencedirect.com/science/article/pii/S019689041931194X>
- 365 [22] C. Gallicchio, A. Micheli, Deep echo state network (Deep-ESN): A brief survey arXiv:1712.04323. URL <http://arxiv.org/abs/1712.04323>
- 370 [23] X. Yao, Z. Wang, H. Zhang, A novel photovoltaic power forecasting model based on echo state network 325 182–189. doi:10.1016/j.neucom.2018.10.022. URL <http://www.sciencedirect.com/science/article/pii/S0925231218312104>
- 375 [24] Q. Li, Z. Wu, R. Ling, L. Feng, K. Liu, Multi-reservoir echo state computing for solar irradiance prediction: A fast yet efficient deep learning approach 95 106481. doi:10.1016/j.asoc.2020.106481. URL <https://linkinghub.elsevier.com/retrieve/pii/S1568494620304208>
- [25] G. Holzmann, H. Hauser, Echo state networks with filter

Solar Generation Prediction with ESN

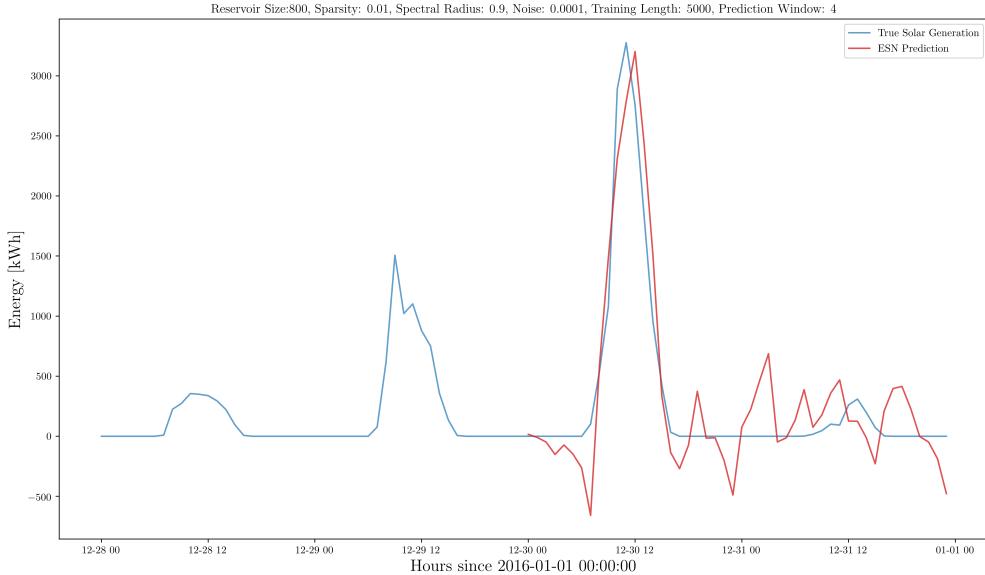


Figure 6: The optimized 4 hour ahead solar energy prediction with wet bulb temperature as a meteorological predictor.

Table 6: 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

and a delay&sum readout.

- [26] E. López, C. Valle, H. Allende, E. Gil, H. Madsen, Wind power forecasting based on echo state networks and long short-term memory 11 (3) 526, number: 3 400 Publisher: Multidisciplinary Digital Publishing Institute. doi:10.3390/en11030526.
URL <https://www.mdpi.com/1996-1073/11/3/526>
- [27] N. Chouikhi, B. Ammar, N. Rokbani, A. M. Al-405 imi, PSO-based analysis of echo state network parameters for time series forecasting 55 211–225. doi:10.1016/j.jasoc.2017.01.049.
URL <https://linkinghub.elsevier.com/retrieve/pii/S1568494617300649>
- [28] Q. Li, Z. Wu, R. Ling, M. Tan, Echo state network-based spatio-temporal model for solar irradiance estimation 158 3808–3813, publisher: Elsevier. doi:10.1016/j.egypro.2019.01.868.
URL <http://www.sciencedirect.com/science/article/pii/S1876610219309105> 415
- [29] 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>
- [30] 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>
- [31] 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 complex spatiotemporal dynamics 126 191–217. doi:10.1016/j.neunet.2020.02.016. URL <http://www.sciencedirect.com/science/article/pii/S0893608020300708>
- [32] C. Korndörfer, pyESN.

Wind Generation Prediction with ESN

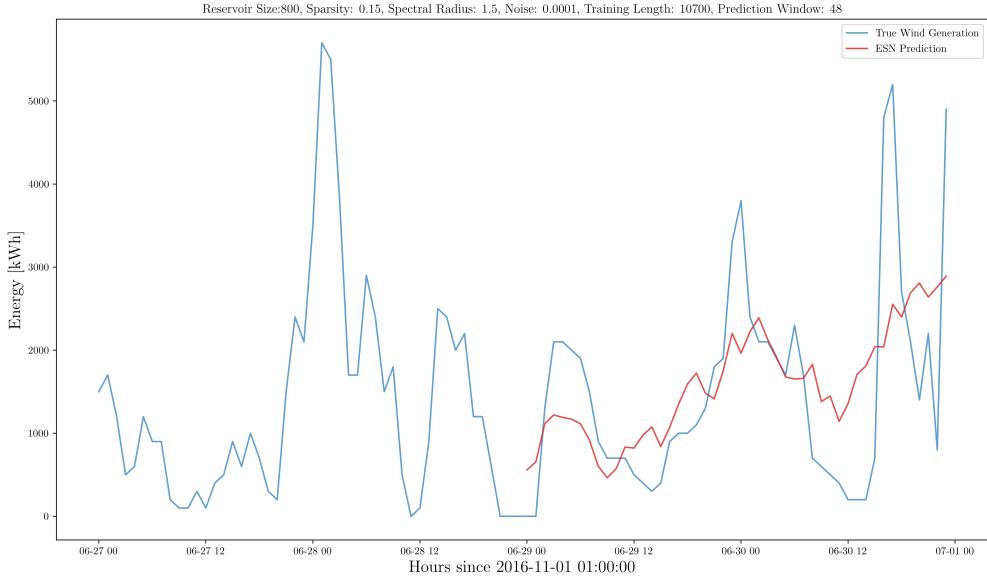


Figure 7: The optimized 48-hour ahead wind energy prediction with solar angle as an additional predictor.

Table 7: 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	Improvement MAE (%)	Improvement 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

- URL <https://github.com/cknd/pyESN>
- [33] E. N. Lorenz, Deterministic nonperiodic flow 20 (2) 130–141, publisher: American Meteorological Society 420 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
- [34] AlsoEnergy, University of illinois solar farm dashboard, <http://s35695.mini.alsoenergy.com/Dashboard/2a5669735065572f4ad2d541a77917d1d3dWest%20texas%20&%20northeastern%20arizona>
- [35] 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>
- [36] S. Breitweiser, Wind power: University of illinois at urbana-champaign. URL https://www.fs.illinois.edu/docs/default-source/news-docs/newsrelease_windppa___.aspx?sfvrsn=43aaffea_0
- [37] National solar radiation data base - NSRDB viewer - OpenEI datasets. URL <https://openei.org/datasets/dataset/national-solar-radiation-data-base/resource/b2074dd9-36a4-4382-a12f-e795b578404c>
- [38] 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 425 445 450 455 460 465 470 475 480 485 490 495 500 505 510 515 520 525 530 535 540 545 550 555 560 565 570 575 580 585 590 595 600 605 610 615 620 625 630 635 640 645 650 655 660 665 670 675 680 685 690 695 700 705 710 715 720 725 730 735 740 745 750 755 760 765 770 775 780 785 790 795 800 805 810 815 820 825 830 835 840 845 850 855 860 865 870 875 880 885 890 895 900 905 910 915 920 925 930 935 940 945 950 955 960 965 970 975 980 985 990 995 1000 1005 1010 1015 1020 1025 1030 1035 1040 1045 1050 1055 1060 1065 1070 1075 1080 1085 1090 1095 1100 1105 1110 1115 1120 1125 1130 1135 1140 1145 1150 1155 1160 1165 1170 1175 1180 1185 1190 1195 1200 1205 1210 1215 1220 1225 1230 1235 1240 1245 1250 1255 1260 1265 1270 1275 1280 1285 1290 1295 1300 1305 1310 1315 1320 1325 1330 1335 1340 1345 1350 1355 1360 1365 1370 1375 1380 1385 1390 1395 1400 1405 1410 1415 1420 1425 1430 1435 1440 1445 1450 1455 1460 1465 1470 1475 1480 1485 1490 1495 1500 1505 1510 1515 1520 1525 1530 1535 1540 1545 1550 1555 1560 1565 1570 1575 1580 1585 1590 1595 1600 1605 1610 1615 1620 1625 1630 1635 1640 1645 1650 1655 1660 1665 1670 1675 1680 1685 1690 1695 1700 1705 1710 1715 1720 1725 1730 1735 1740 1745 1750 1755 1760 1765 1770 1775 1780 1785 1790 1795 1800 1805 1810 1815 1820 1825 1830 1835 1840 1845 1850 1855 1860 1865 1870 1875 1880 1885 1890 1895 1900 1905 1910 1915 1920 1925 1930 1935 1940 1945 1950 1955 1960 1965 1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025 2030 2035 2040 2045 2050 2055 2060 2065 2070 2075 2080 2085 2090 2095 2100 2105 2110 2115 2120 2125 2130 2135 2140 2145 2150 2155 2160 2165 2170 2175 2180 2185 2190 2195 2200 2205 2210 2215 2220 2225 2230 2235 2240 2245 2250 2255 2260 2265 2270 2275 2280 2285 2290 2295 2300 2305 2310 2315 2320 2325 2330 2335 2340 2345 2350 2355 2360 2365 2370 2375 2380 2385 2390 2395 2400 2405 2410 2415 2420 2425 2430 2435 2440 2445 2450 2455 2460 2465 2470 2475 2480 2485 2490 2495 2500 2505 2510 2515 2520 2525 2530 2535 2540 2545 2550 2555 2560 2565 2570 2575 2580 2585 2590 2595 2600 2605 2610 2615 2620 2625 2630 2635 2640 2645 2650 2655 2660 2665 2670 2675 2680 2685 2690 2695 2700 2705 2710 2715 2720 2725 2730 2735 2740 2745 2750 2755 2760 2765 2770 2775 2780 2785 2790 2795 2800 2805 2810 2815 2820 2825 2830 2835 2840 2845 2850 2855 2860 2865 2870 2875 2880 2885 2890 2895 2900 2905 2910 2915 2920 2925 2930 2935 2940 2945 2950 2955 2960 2965 2970 2975 2980 2985 2990 2995 3000 3005 3010 3015 3020 3025 3030 3035 3040 3045 3050 3055 3060 3065 3070 3075 3080 3085 3090 3095 3100 3105 3110 3115 3120 3125 3130 3135 3140 3145 3150 3155 3160 3165 3170 3175 3180 3185 3190 3195 3200 3205 3210 3215 3220 3225 3230 3235 3240 3245 3250 3255 3260 3265 3270 3275 3280 3285 3290 3295 3300 3305 3310 3315 3320 3325 3330 3335 3340 3345 3350 3355 3360 3365 3370 3375 3380 3385 3390 3395 3400 3405 3410 3415 3420 3425 3430 3435 3440 3445 3450 3455 3460 3465 3470 3475 3480 3485 3490 3495 3500 3505 3510 3515 3520 3525 3530 3535 3540 3545 3550 3555 3560 3565 3570 3575 3580 3585 3590 3595 3600 3605 3610 3615 3620 3625 3630 3635 3640 3645 3650 3655 3660 3665 3670 3675 3680 3685 3690 3695 3700 3705 3710 3715 3720 3725 3730 3735 3740 3745 3750 3755 3760 3765 3770 3775 3780 3785 3790 3795 3800 3805 3810 3815 3820 3825 3830 3835 3840 3845 3850 3855 3860 3865 3870 3875 3880 3885 3890 3895 3900 3905 3910 3915 3920 3925 3930 3935 3940 3945 3950 3955 3960 3965 3970 3975 3980 3985 3990 3995 4000 4005 4010 4015 4020 4025 4030 4035 4040 4045 4050 4055 4060 4065 4070 4075 4080 4085 4090 4095 4100 4105 4110 4115 4120 4125 4130 4135 4140 4145 4150 4155 4160 4165 4170 4175 4180 4185 4190 4195 4200 4205 4210 4215 4220 4225 4230 4235 4240 4245 4250 4255 4260 4265 4270 4275 4280 4285 4290 4295 4300 4305 4310 4315 4320 4325 4330 4335 4340 4345 4350 4355 4360 4365 4370 4375 4380 4385 4390 4395 4400 4405 4410 4415 4420 4425 4430 4435 4440 4445 4450 4455 4460 4465 4470 4475 4480 4485 4490 4495 4500 4505 4510 4515 4520 4525 4530 4535 4540 4545 4550 4555 4560 4565 4570 4575 4580 4585 4590 4595 4600 4605 4610 4615 4620 4625 4630 4635 4640 4645 4650 4655 4660 4665 4670 4675 4680 4685 4690 4695 4700 4705 4710 4715 4720 4725 4730 4735 4740 4745 4750 4755 4760 4765 4770 4775 4780 4785 4790 4795 4800 4805 4810 4815 4820 4825 4830 4835 4840 4845 4850 4855 4860 4865 4870 4875 4880 4885 4890 4895 4900 4905 4910 4915 4920 4925 4930 4935 4940 4945 4950 4955 4960 4965 4970 4975 4980 4985 4990 4995 5000 5005 5010 5015 5020 5025 5030 5035 5040 5045 5050 5055 5060 5065 5070 5075 5080 5085 5090 5095 5100 5105 5110 5115 5120 5125 5130 5135 5140 5145 5150 5155 5160 5165 5170 5175 5180 5185 5190 5195 5200 5205 5210 5215 5220 5225 5230 5235 5240 5245 5250 5255 5260 5265 5270 5275 5280 5285 5290 5295 5300 5305 5310 5315 5320 5325 5330 5335 5340 5345 5350 5355 5360 5365 5370 5375 5380 5385 5390 5395 5400 5405 5410 5415 5420 5425 5430 5435 5440 5445 5450 5455 5460 5465 5470 5475 5480 5485 5490 5495 5500 5505 5510 5515 5520 5525 5530 5535 5540 5545 5550 5555 5560 5565 5570 5575 5580 5585 5590 5595 5600 5605 5610 5615 5620 5625 5630 5635 5640 5645 5650 5655 5660 5665 5670 5675 5680 5685 5690 5695 5700 5705 5710 5715 5720 5725 5730 5735 5740 5745 5750 5755 5760 5765 5770 5775 5780 5785 5790 5795 5800 5805 5810 5815 5820 5825 5830 5835 5840 5845 5850 5855 5860 5865 5870 5875 5880 5885 5890 5895 5900 5905 5910 5915 5920 5925 5930 5935 5940 5945 5950 5955 5960 5965 5970 5975 5980 5985 5990 5995 6000 6005 6010 6015 6020 6025 6030 6035 6040 6045 6050 6055 6060 6065 6070 6075 6080 6085 6090 6095 6100 6105 6110 6115 6120 6125 6130 6135 6140 6145 6150 6155 6160 6165 6170 6175 6180 6185 6190 6195 6200 6205 6210 6215 6220 6225 6230 6235 6240 6245 6250 6255 6260 6265 6270 6275 6280 6285 6290 6295 6300 6305 6310 6315 6320 6325 6330 6335 6340 6345 6350 6355 6360 6365 6370 6375 6380 6385 6390 6395 6400 6405 6410 6415 6420 6425 6430 6435 6440 6445 6450 6455 6460 6465 6470 6475 6480 6485 6490 6495 6500 6505 6510 6515 6520 6525 6530 6535 6540 6545 6550 6555 6560 6565 6570 6575 6580 6585 6590 6595 6600 6605 6610 6615 6620 6625 6630 6635 6640 6645 6650 6655 6660 6665 6670 6675 6680 6685 6690 6695 6700 6705 6710 6715 6720 6725 6730 6735 6740 6745 6750 6755 6760 6765 6770 6775 6780 6785 6790 6795 6800 6805 6810 6815 6820 6825 6830 6835 6840 6845 6850 6855 6860 6865 6870 6875 6880 6885 6890 6895 6900 6905 6910 6915 6920 6925 6930 6935 6940 6945 6950 6955 6960 6965 6970 6975 6980 6985 6990 6995 7000 7005 7010 7015 7020 7025 7030 7035 7040 7045 7050 7055 7060 7065 7070 7075 7080 7085 7090 7095 7100 7105 7110 7115 7120 7125 7130 7135 7140 7145 7150 7155 7160 7165 7170 7175 7180 7185 7190 7195 7200 7205 7210 7215 7220 7225 7230 7235 7240 7245 7250 7255 7260 7265 7270 7275 7280 7285 7290 7295 7300 7305 7310 7315 7320 7325 7330 7335 7340 7345 7350 7355 7360 7365 7370 7375 7380 7385 7390 7395 7400 7405 7410 7415 7420 7425 7430 7435 7440 7445 7450 7455 7460 7465 7470 7475 7480 7485 7490 7495 7500 7505 7510 7515 7520 7525 7530 7535 7540 7545 7550 7555 7560 7565 7570 7575 7580 7585 7590 7595 7600 7605 7610 7615 7620 7625 7630 7635 7640 7645 7650 7655 7660 7665 7670 7675 7680 7685 7690 7695 7700 7705 7710 7715 7720 7725 7730 7735 7740 7745 7750 7755 7760 7765 7770 7775 7780 7785 7790 7795 7800 7805 7810 7815 7820 7825 7830 7835 7840 7845 7850 7855 7860 7865 7870 7875 7880 7885 7890 7895 7900 7905 7910 7915 7920 7925 7930 7935 7940 7945 7950 7955 7960 7965 7970 7975 7980 7985 7990 7995 8000 8005 8010 8015 8020 8025 8030 8035 8040 8045 8050 8055 8060 8065 8070 8075 8080 8085 8090 8095 8100 8105 8110 8115 8120 8125 8130 8135 8140 8145 8150 8155 8160 8165 8170 8175 8180 8185 8190 8195 8200 8205 8210 8215 8220 8225 8230 8235 8240 8245 8250 8255 8260 8265 8270 8275 8280 8285 8290 8295 8300 8305 8310 8315 8320 8325 8330 8335 8340 8345 8350 8355 8360 8365 8370 8375 8380 8385 8390 8395 8400 8405 8410 8415 8420 8425 8430 8435 8440 8445 8450 8455 8460 8465 8470 8475 8480 8485 8490 8495 8500 8505 8510 8515 8520 8525 8530 8535 8540 8545 8550 8555 8560 8565 8570 8575 8580 8585 8590 8595 8600 8605 8610 8615 8620 8625 8630 8635 8640 8645 8650 8655 8660 8665 8670 8675 8680 8685 8690 8695 8700 8705 8710 8715 8720 8725 8730 8735 8740 8745 8750 8755 8760 8765 8770 8775 8780 8785 8790 8795 8800 8805 8810 8815 8820 8825 8830 8835 8840 8845 8850 8855 8860 8865 8870 8875 8880 8885 8890 8895 8900 8905 8910 8915 8920 8925 8930 8935 8940 8945 8950 8955 8960 8965 8970 8975 8980 8985 8990 8995 9000 9005 9010 9015 9020 9025 9030 9035 9040 9045 9050 9055 9060 9065 9070 9075 9080 9085 9090 9095 9100 9105 9110 9115 9120 9125 9130 9135 9140 9145 9150 9155 9160 9165 9170 9175 9180 9185 9190 9195 9200 9205 9210 9215 9220 9225 9230 9235 9240 9245 9250 9255 9260 9265 9270 9275 9280 9285 9290 9295 9300 9305 9310 9315 9320 9325 9330 9335 9340 9345 9350 9355 9360 9365 9370 9375 9380 9385 9390 9395 9400 9405 9410 9415 9420 9425 9430 9435 9440 9445 9450 9455 9460 9465 9470 9475 9480 9485 9490 9495 9500 9505 9510 9515 9520 9525 9530 9535 9540 9545 9550 9555 9560 9565 9570 9575 9580 9585 9590 9595 9600 9605 9610 9615 9620 9625 9630 9635 9640 9645 9650 9655 9660 9665 9670 9675 9680 9685 969

Wind Generation Prediction with ESN

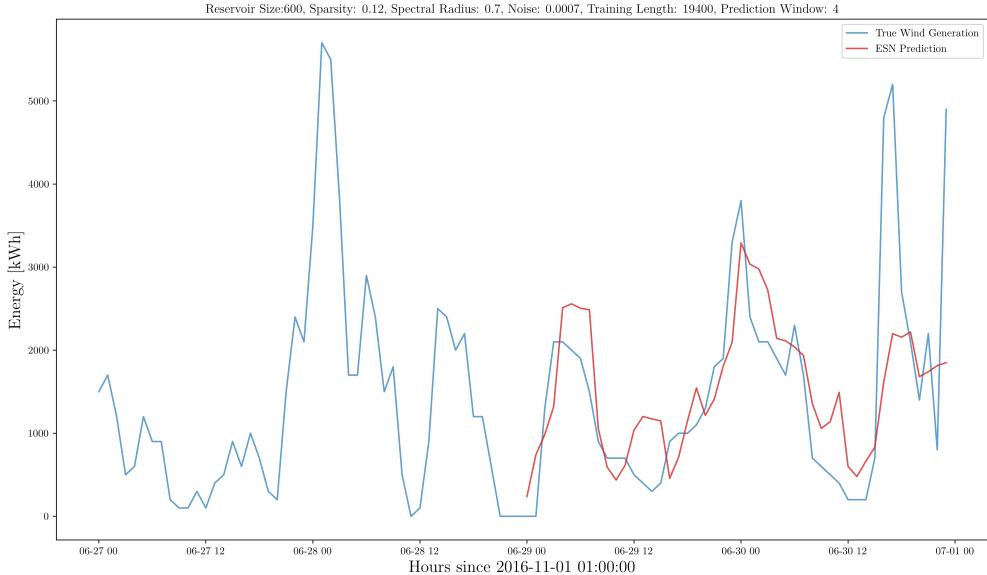


Figure 8: The optimized 4 hour ahead wind energy prediction with wet bulb temperature as a meteorological predictor.

Table 8: 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 MAE (%)	Improvement 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

temperature and pressure change in different regions of antarctica, in: M. B. India, D. L. Bonillo (Eds.), Detecting and Modelling Regional Climate Change, Springer, pp. 215–228. doi:10.1007/978-3-662-04313-4_19. URL https://doi.org/10.1007/978-3-662-04313-4_19

[42] J. G. Powers, J. B. Klemp, W. C. Skamarock, C. A. Davis, J. Dudhia, D. O. Gill, J. L. Coen, D. J. Gochis, R. Ahmadov, S. E. Peckham, G. A. Grell, J. Michalakes, S. Trahan, S. G. Benjamin, C. R. Alexander, G. J. Dimego, W. Wang, C. S. Schwartz, G. S. Romine, Z. Liu, C. Snyder, F. Chen, M. J. Barlage, W. Yu, M. G. Duda, The weather research and forecasting model: Overview, system efforts, and future directions 98 (8) 1717–1737, publisher: American Meteorological Society Section: Bulletin of the American Meteorological Society. doi: 10.1175/BAMS-D-15-00308.1. URL <https://journals.ametsoc.org/view/journals/bams/98/8/bams-d-15-00308.1.xml>

[43] H. Jaeger, Harnessing nonlinearity: Predicting chaotic

systems and saving energy in wireless communication 304 (5667) 78–80. doi:10.1126/science.1091277.

URL <https://www.science.org/lookup/doi/10.1126/science.1091277>

[44] M. Lukoševičius, H. Jaeger, Reservoir computing approaches to recurrent neural network training 3 (3) 127–149. doi:10.1016/j.cosrev.2009.03.005.

URL <http://www.sciencedirect.com/science/article/pii/S1574013709000173>

[45] J. Garland, R. James, E. Bradley, Model-free quantification of time-series predictability 90 (5) 052910, publisher: American Physical Society. doi:10.1103/PhysRevE.90.052910.

URL <https://link.aps.org/doi/10.1103/PhysRevE.90.052910>