Renewable Energy Forecasting with Echo State Networks

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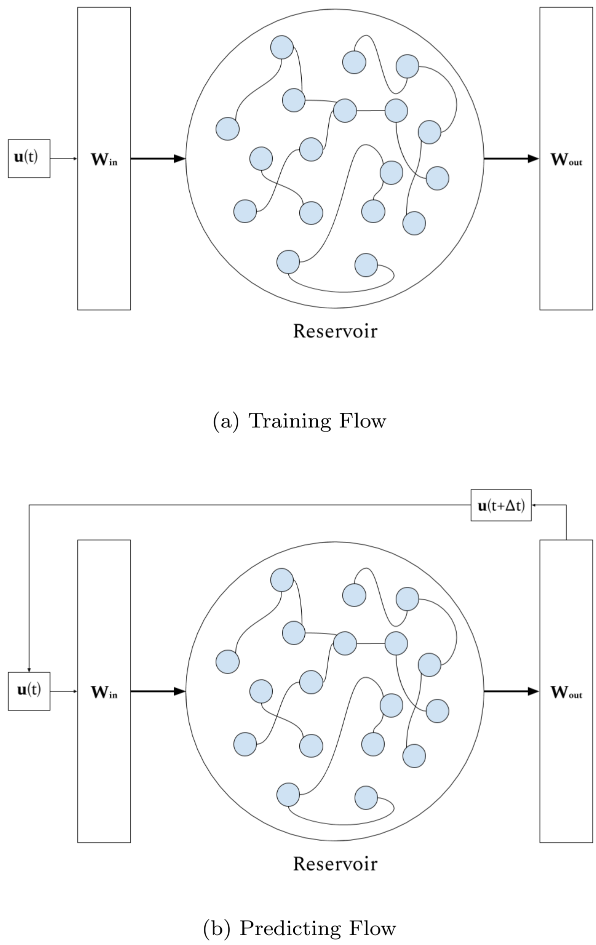
Abstract

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

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 “reservoir computing,” 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, $\boldsymbol{W}$, 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 output is read by an output weight matrix, W_{out}. This output matrix functions like a single layer feed-forward neural network. 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.

3. Results

4. Acknowledgments

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Table 1: 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	1 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

Table 2: 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

Table 3: 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 4: 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

Table 5: 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

Table 6: 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