

MOTIVATIONS

Electricity demand forecasting is essential for proper electricity market operation.

Due to growing network sizes, developing better electricity demand forecasting systems has become essential. Such algorithms can

- allow smooth and efficient power control and transmission
- keep electricity prices less volatile
- prevent wastage and allow cheaper operation of electrical power systems.

There are mainly two paradigms for forecasting electricity demand time series, namely statistical methods and machine learning methods.

Machine Learning methods can map non-linear patterns well, but may suffer from overfitting (high variance) due to too many learnable parameters.

We have introduced a new machine learning architecture which has much fewer number of learnable parameters than existing algorithms, while not sacrificing the accuracy of the model.

CONCLUSIONS

We have introduced a new architecture that improves upon the existing architecture **DeepESN**. The new method has fewer learnable parameters than DeepESN, while preserving the performance of the DeepESN. Upon optimizing with PSO, the proposed architecture gives a much improved result than DeepESN.

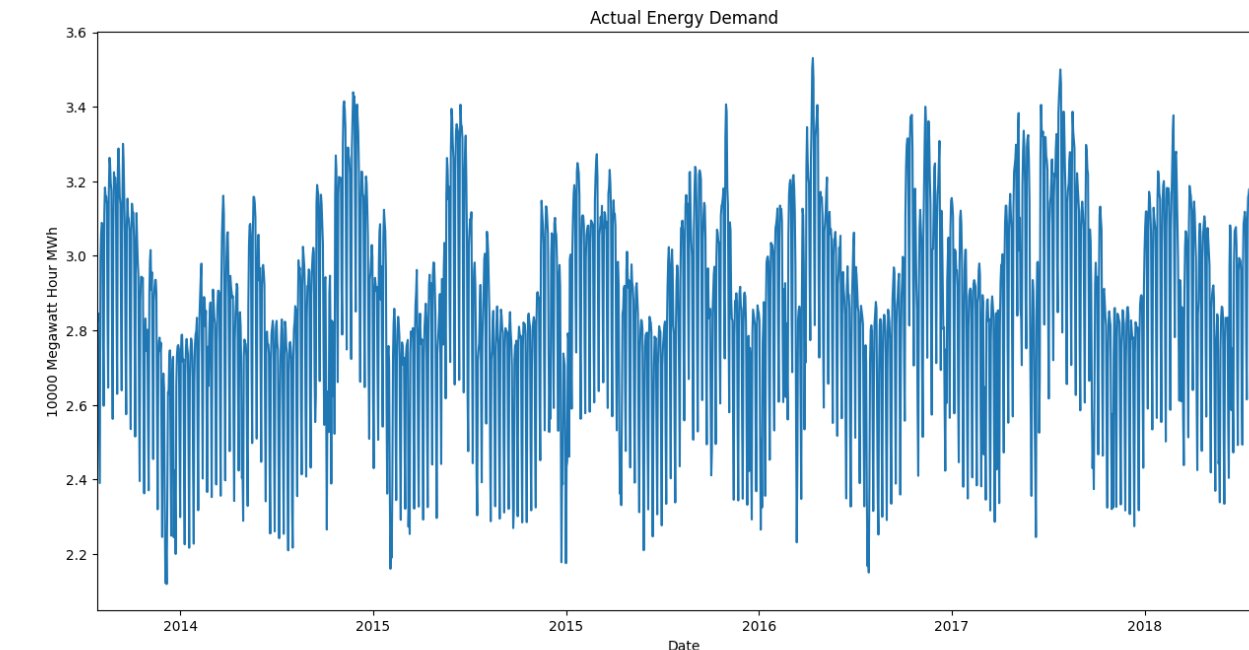
In future, we plan to extend the Echo State Network (ESN) model to handle time series with more nonlinearities. We also hope to be able to incorporate the various components of the time series (trend, seasonality, etc.) into our forecasting model.

REFERENCES

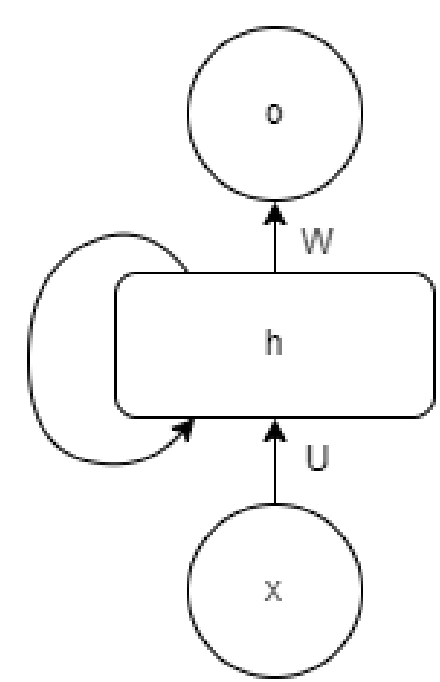
- [1] Jaeger, H., and Harald H., Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication. *Science* (2004)
- [2] Gallicchio, C., Alessio M., and Luca P., Deep reservoir computing: A critical experimental analysis. *Neurocomputing* 268 (2017): 87-99.
- [3] Crisostomi, E., Claudio G., Alessio M., Marco R., and Mauro T. Prediction of the Italian electricity price for smart grid applications. *Neurocomputing* 170 (2015): 286-295.
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BACKGROUND

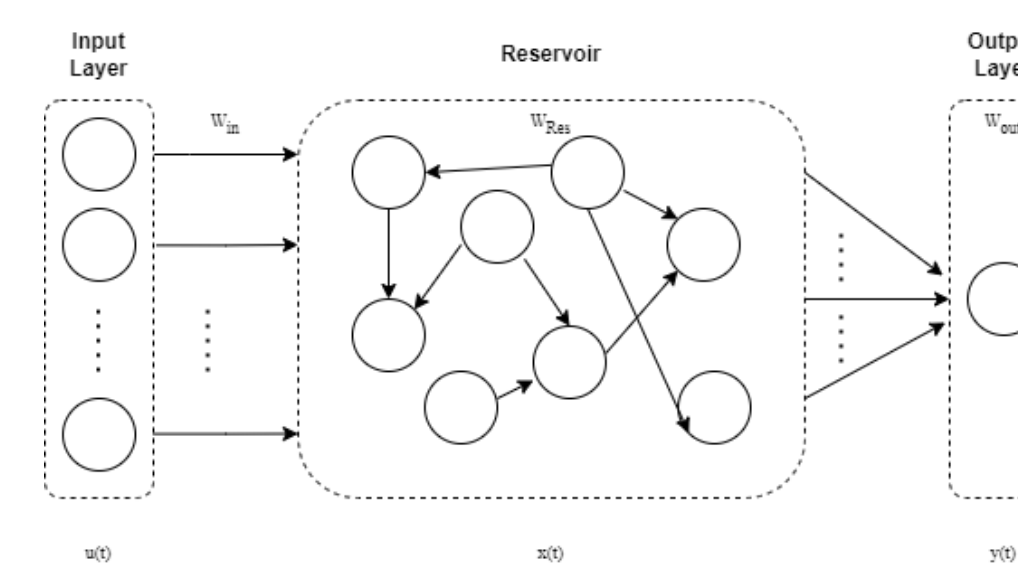
The electricity demand time series is a highly non-stationary series with multiple components such as trend, seasonality, irregular, etc.



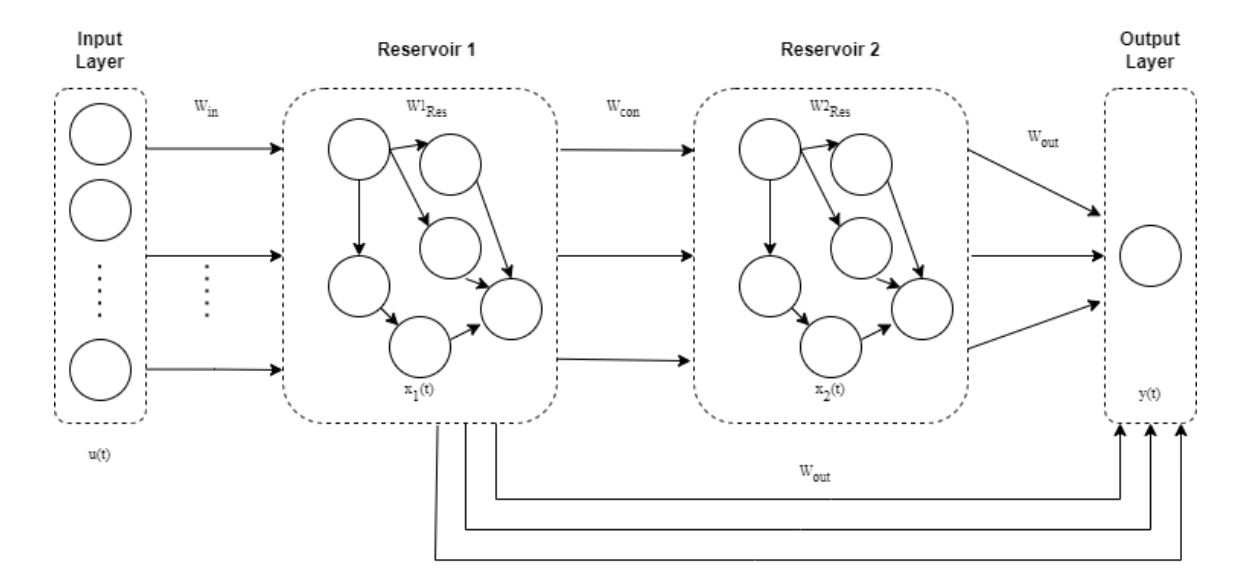
Some commonly used machine learning models are:



Vanilla RNN



Echo State Network



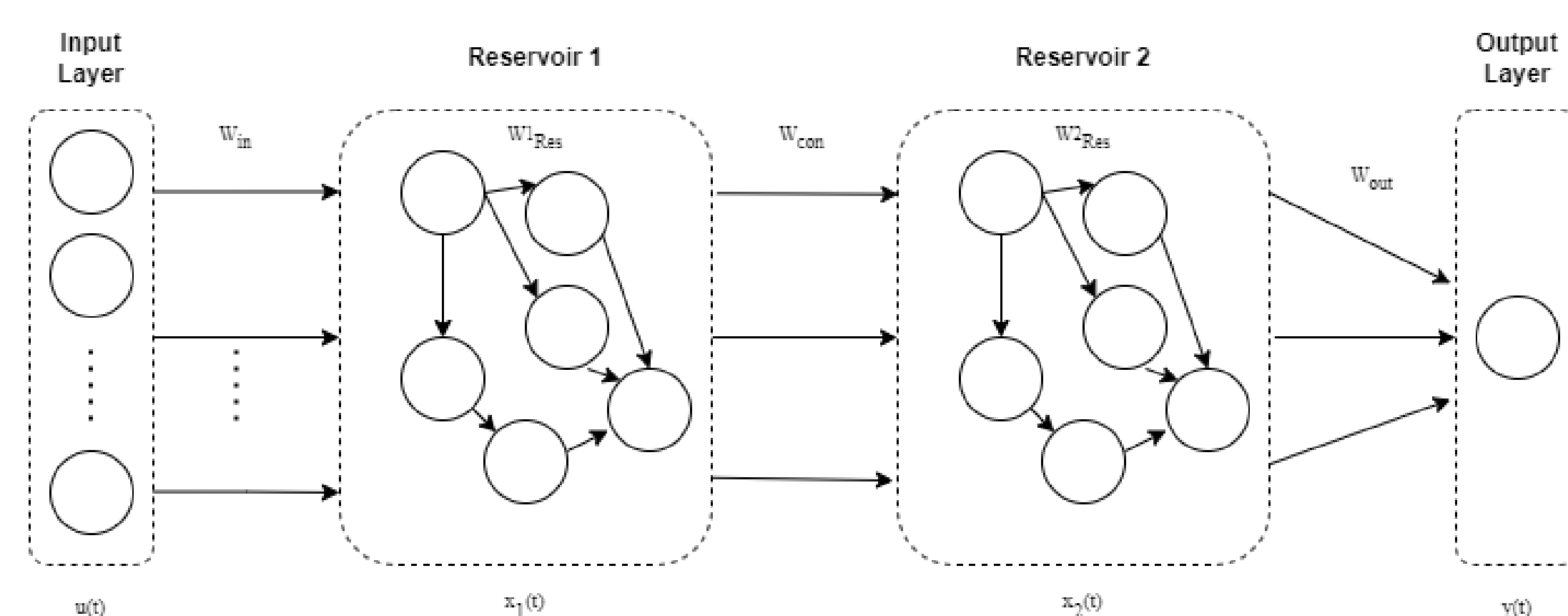
Deep Echo State Network

The **Echo State Network** (ESN) has been used successfully for demand forecasting. An Echo State Network consists of three layers, namely the input layer, the reservoir, and the output layer. The weights of the input and the reservoir layers are randomly set, while the weights for the output layer are learned via linear regression. The **Deep Echo State Network** (DeepESN) makes the ESN deep, thereby getting improved performance.

OUR CONTRIBUTION

Our proposed method improves upon the extant DeepESN model.

The output is disentangled from each reservoir, thus reducing the total number of learnable parameters. It also makes the DeepESN architecture more scalable.



Proposed Architecture

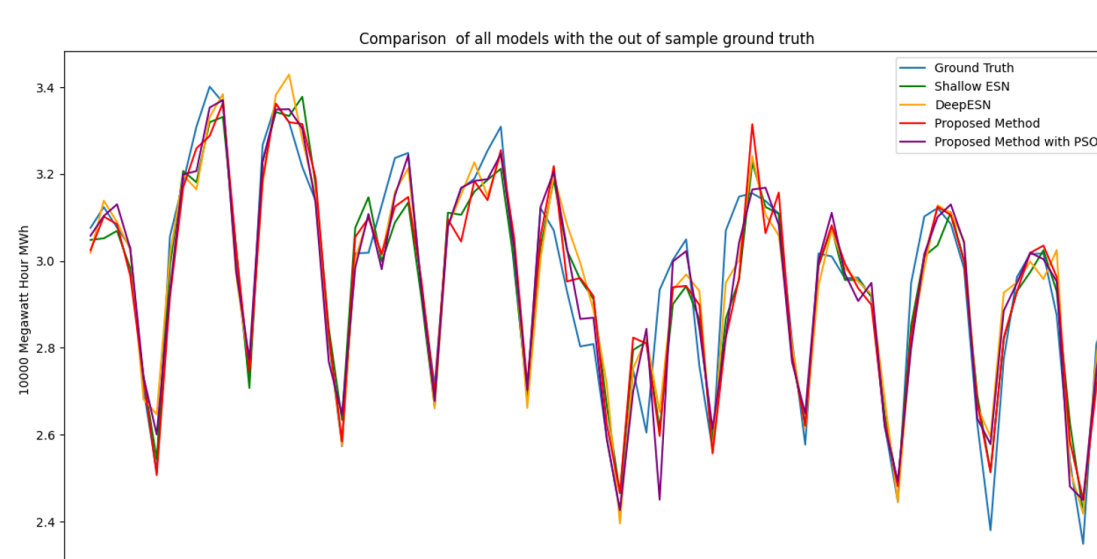
We use the *MAPE* ($MAPE = \left(\frac{100}{n}\right) \sum_{i=1}^n \left|\frac{y_i - x_i}{y_i}\right|$) metric to compare the performance of the models on the Spanish daily electricity demand time series.

MAPE comparison

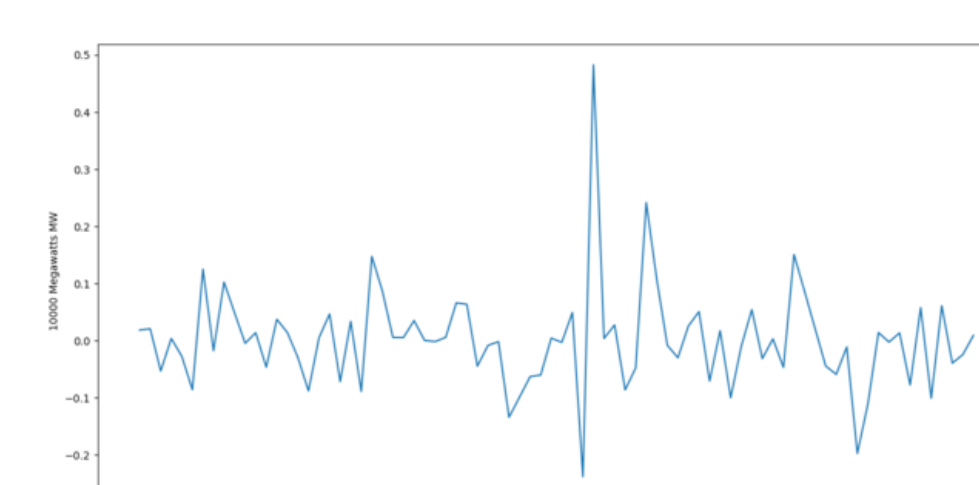
Models Used	Mean Absolute Percentage Error (MAPE)
Naive Forecasting Method	0.0802
Autoregression (AR)	0.0290
Echo State Network	0.0303
Deep Echo State Network	0.0276
Proposed Method	0.0276
Proposed Method with PSO	0.0251

We also optimized the internal parameters of our architecture using **Particle Swarm Optimization (PSO)**.

Results



Comparison of Forecasts



Error and Error Autocorrelation for proposed method with PSO

