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Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms

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HIGHLIGHTS

- A novel deep learning framework to forecast electricity prices is proposed.
- The framework leads to accuracy improvements that are statistically significant.
- The largest benchmark to date in electricity price forecasting is presented.
- 27 state-of-the-art methods for predicting electricity prices are compared.
- Machine learning models are shown to, in general, outperform statistical methods.

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ABSTRACT

In this paper, a novel modeling framework for forecasting electricity prices is proposed. While many predictive models have been already proposed to perform this task, the area of deep learning algorithms remains yet unexplored. To fill this scientific gap, we propose four different deep learning models for predicting electricity prices and we show how they lead to improvements in predictive accuracy. In addition, we also consider that, despite the large number of proposed methods for predicting electricity prices, an extensive benchmark is still missing. To tackle that, we compare and analyze the accuracy of 27 common approaches for electricity price forecasting. Based on the benchmark results, we show how the proposed deep learning models outperform the state-of-the-art methods and obtain results that are statistically significant. Finally, using the same results, we also show that: (i) machine learning methods yield, in general, a better accuracy than statistical models; (ii) moving average terms do not improve the predictive accuracy; (iii) hybrid models do not outperform their simpler counterparts.

1. Introduction

Because of the liberalization of the electricity markets in the past decades, the dynamics of electricity prices have become a complex phenomenon with rare characteristics and important consequences. In particular, when compared with other commodities, electricity trade displays a set of attributes that are quite uncommon: constant balance between production and consumption [1]; dependence of the consumption on the time, e.g. hour of the day, day of the week, and time of the year; load and generation that are influenced by external weather conditions [2]; and influence of neighboring markets [3]. Due to these characteristics, the dynamics of electricity prices have become very complex, e.g. highly volatile prices with sudden and unexpected price peaks [2].

In recent years, with the increasing penetration of *renewable energy sources* (RES), the described behavior has aggravated. In particular, while there are no questions regarding the contribution of RES to build a more sustainable world, several concerns have been raised regarding their influence on electricity prices and grid stability. More specifically, as the penetration of RES increases, so does the dependence of electricity production w.r.t. to weather conditions and, in turn, the volatility in electricity prices. This relation has been largely identified in the literature: [4] studied the effect of wind power penetration on the New England electricity market and concluded that price volatility increases with increasing wind penetration. Similarly, [5] carried out a similar study for the Texas market and also concluded that price volatility increased with increasing wind penetration. Looking at the penetration of solar power, [6] indicated that price spikes are expected to occur more

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Acronyms

AR	autoregressive
ARIMA	autoregressive integrated moving average
ARMA	AR with moving average terms
ARX	autoregressive with exogenous inputs
CNN	convolutional neural network
DL	deep learning
DM	Diebold-Mariano
DNN	deep neural network
DR	dynamic regression
DSARIMA	double seasonal ARIMA
DSHW	double seasonal Holt-Winter
EPEX	European power exchange
fARX	full-ARX
fARX-EN	fARX regularized with an elastic net
fARX-Lasso	fARX regularized with Lasso
GARCH	generalized autoregressive conditional heteroscedasticity
GRU	gated recurrent unit
IHMARX	Hsieh-Manski ARX
LSTM	long-short term memory
MA	moving average
MAPE	mean absolute percentage error
MLP	multilayer perceptron
RBF	radial basis function
ReLU	rectifier linear unit
RES	renewable energy sources
RF	random forest
RNN	recurrent neural network
sMAPE	symmetric mean absolute percentage error
SNARX	smoothed nonparametric ARX
SOM-SVR	SVR with self-organizing maps
SVR	support vector regressor
TARX	threshold ARX
TBATS	exponential smoothing state space model with Box-Cox transformation, ARMA errors, trend and seasonal components
TF	transfer function
WARIMA	wavelet-ARIMA
XGB	extreme gradient boosting

frequently as the share of PV increases in the California system. Likewise, looking at the effect of increasing wind penetration in UK for the year 2020, [7] reported that prices are expected to be more volatile than at present.

Due to this effect, as the increasing integration of RES increases the volatility of prices, the behavior of market agents becomes naturally more unpredictable, sudden drops in generation and consumption are more likely to occur, the imbalances between production and consumption increase, and the electrical grid becomes more unstable.

In order to tackle the problems mentioned above, electricity markets together with electricity price forecasting have become a central point of research in the energy sector. In particular, by improving the forecasting accuracy, the negative effects of price uncertainty can be mitigated, the grid can be stabilized, and economic profits can be made.

1.1. Electricity price forecasting

The electricity price forecasting literature is typically divided into five areas: (i) game theory models, (ii) fundamental methods, (iii) reduced-form models, (iv) statistical models, and (v) machine learning methods [2]. Since statistical and machine learning methods have showed to yield the best results [2], they are the focus of this review, and in turn, of the benchmarking experiment that will be performed in this paper.

Common statistical methods are: *autoregressive* (AR) and *autoregressive with exogenous inputs* (ARX) models [8], *double seasonal Holt-Winter* (DSHW) models [9], *threshold ARX* (TARX) models [10], *autoregressive integrated moving average* (ARIMA) models [11,12], semi/non-parametric models [8,13], *generalized autoregressive conditional heteroscedasticity* (GARCH) based models [14–16], or *dynamic regression* (DR) and *transfer function* (TF) models [17]. In addition, hybrid versions of the previous models are also common, e.g. wavelet-based models [12,18,19].

A pitfall of statistical models is that they are usually linear forecasters, and as such, they might not perform good in data where the frequency is high, e.g. hourly data with rapid variations. In particular, while they show a good performance if the data frequency is low, e.g. weekly patterns, the nonlinear behavior of hourly prices might become too complicated to predict [20]. To address this issue and predict the nonlinear behavior of hourly prices, different machine learning methods have been proposed. Among them, *multilayer perceptrons* (MLPs) [21–24], *support vector regressors* (SVRs) [25,26] and *radial basis function* (RBF) networks [27] are the most commonly used.

While the academic literature comprises a much larger collection of approaches, e.g. see [2,28], a complete review falls outside of the scope of this paper.

1.2. Deep Learning

In the last decade, the field of neural networks has experienced several innovations that have lead to what is known as *deep learning* (DL). In particular, one of the traditional issues of neural networks had always been the large computational cost of training large models. However, that changed completely when [29] showed that a deep belief network could be trained efficiently using an algorithm called greedy layer-wise pretraining. As related developments followed, researchers started to be able to efficiently train complex neural networks whose depth was not just limited to a single hidden layer (as in the traditional MLP). As these new structures systemically showed better results and generalization capabilities, the field was renamed as deep learning to stress the importance of the depth in the achieved improvements [30, Section 1.2.1].

While this success of DL models initiated in computer science applications, e.g. image recognition [31], speech recognition [32], or machine translation [33], the benefits of DL have also spread in the last years to several energy-related applications [34–39]. Among these areas, wind power forecasting is arguably the field that has benefited the most: [34] shows how, using a deep belief network and quantile regression, probabilistic forecasting of wind speed can be improved. Similar to [34], [39] proposes a deep feature selection algorithm that, in combination with a multi-model framework, improves the wind speed forecasting accuracy by 30%. In the same area of research, [37] proposes an ensemble of *convolutional neural networks* (CNNs) to obtain more accurate probability forecasts of wind power.

In addition to wind power applications, DL has also shown success in other energy-related fields. In the context of load forecasting, [36] proposes a deep autoencoder in combination with an *extreme gradient boosting* (XGB) model and shows how they forecast building cooling load more accurately than alternative techniques; within the same research paper, a *deep neural network* (DNN) to accurately forecast building cooling load is also proposed. For a different application, [38] proposes a DL model to detect islanding and to distinguish this effect from grid disturbances; based on the obtained simulation results, [38] indicates that the DL model can detect islanding with a very high accuracy. In addition, [35] proposes a DL strategy for time series forecasting and shows how it can be used successfully to forecast electricity