Poster Abstract: Forecasting Renewable Energy at European Markets

HUN RIM, JURAJ KARDOS, Università della Svizzera italiana, Switzerland
OLAF SCHENK*, Università della Svizzera italiana, Switzerland

The ambitious energy targets, accelerated by the recent energy crisis, are driving the increase of renewable energy share in gross energy consump- tion. However, the intermittent and seasonal nature of renewable energy sources presents challenges in predicting their production capacity. The abil- ity to accurately forecast the evolution of renewable energy's stake in the dynamic and ever-evolving energy market is a critical component in the de- cision making process of policy makers, and market participants alike. This project aims to explore and evaluate the performance of well-established forecasting methods in anticipating the trends of individual renewable en- ergy components, ultimately contributing to the fostering of a balanced, sustainable, and reliable energy market in the EU. The primary focus is to assess auto-regressive forecasting methods and advanced models incorporat- ing moving-average, exploit seasonality of time series data, or those utilising the correlation with exogenous variables. The results are presented for data considering recent history of the most significant energy component at the European energy markets.

KEYWORDS

Data analytics, Forecasting for energy systems, Energy Market, Renewable energy

1 INTRODUCTION

Policymakers and other energy market participants often stress that they need the grid operational statistics faster [3], particularly the European energy supply including renewable energy components, and consumption. The goal of the project is to develop a framework for forecasting the individual energy components contributing to the overall energy balance. The framework consists of well-established forecasting methods which can be easily applied to the energy market data, compare the forecast of various methods and assess the their reliability. Staple goods such as energy has certain predictability in relation to time, and ARIMA model is one of the most widely used statistical forecasting model which can exploit this trait [2]. ARIMA is a generalized version of AutoRegressive Moving-Average (ARMA) model and difference between the two models is their ability to handle non-stationary data. Autoregression is a technique used in time series analysis that assumes temporal trend between the values in the dataset, and uncover a function of order p. In the auto-regression model, the variable regresses against itself.ARIMA model [4] improves the accuracy by factoring in the non-stationarity of the data. All these factors are combined to formularize ARIMA model as the following:

Authors' address: Hun Rim, rimh@usi.ch; Juraj Kardos, juraj.kardos@usi.ch; Olaf Schenk, olaf.schenk@usi.ch, Università della Svizzera italiana, Via Giuseppe Buffi 13, Lugano, Ticino, Switzerland, 6900.

$$\hat{L}_N^{(d)} = C + \sum_{i=1}^{p} \psi_i L_{N-i}^{(d)} + \sum_{j=1}^{q} \varphi_j \epsilon_{N-j} + \epsilon_N \tag{1}$$

EU energy market data often exhibit seasonal patterns. SARIMA is an extension that considers these seasonal patterns:

$$SARIMA = \hat{L}_N^{(d)} + \sum_{i=1}^{P} \Phi_i L_{N-im}^{D} + \sum_{j=1}^{Q} \Theta_j \epsilon_{N-jm} \tag{2}$$

The EU power sector, just like any other sector, experiences volatility due to exogenous factors such as the climate or the economy. The exogenous variable which has influence on the power sector is collected as additional indicators in the SARIMAX model.

Along with predictive statistics, deep learning (DL) is frequently used in forecasting. Especially, DL using Recurrent-Neural-Network (RNN) with Long Short-term Memory (LSTM) layers is very popular with time series forecasting [7]. RNN repeats the process of aggregation and activation unlike normal neural networks, and LSTM extends the memory of RNNs. This regression like property of RNN makes it very effective when building a forecasting model, and it would be interesting to evaluate it's performance in comparison to conventional statistical methods.

2 EXPERIMENTAL SETUP

This sections presents the setup of the forecasting methods considered in the study and presents the data that will be used to evaluate the accuracy of the approaches.

2.1 Parametrization of the Methods

The autoregressive models need to be parametrized by a set of parameters (p, d, q). Their values are determined by *auto_arima()*[8] function of Python, a built-in search algorithm from *pmdarima* library. The hyper-parameters are selected through step-wise approach using a mixture of conjugate gradient (gradient-based), and nelder-mead's (gradient-free) optimization method depending on the data. We split our data into two parts, training set and test set. We train the model using 80% of our data and assign the remaining 20% as test data set to compare it with the forecast. For training of the model, Python's functions from *statsmodels* library[6] are used. The derived order, and seasonal order are passed to the trainer functions along with the train data set. Each model has respective trainer function provided from the *statsmodels* library [5] and are configured accordingly with required training data, order of autoregression, differencing, and moving-average. Finally, the model is fitted to the passed training data. The trained model is used to make a forecast from the starting month to the ending month, in our case considering an interval of 3 months. To avoid the decrease of accuracy due to the large forecast window, forecasts are made at quarterly intervals. This approach is particularly necessary because the ARIMA model cannot incorporate new forecast errors into its formula, creating a need for iterative recalculation when the training set is updated. Therefore, we adopt the rolling horizon approach, where after each forecast, the training dataset is expanded by one month, and the model is re-trained before forecasting the future values of subsequent three months. By implementing the rolling horizon approach, the model becomes capable of incorporating real-time updates, mimics continuous learning, and avoids forecasting biases.

2.2 Analysis

The performance of forecasting method is measured in terms of the relative error between predicted and actual values using Root-Mean-Squared-Percentage-Error (RMSPE)[1]. Lower values in RMSPE indicate better performance. RMSPE measures the average percentage deviation between predicted and actual values, providing a standardized measure of prediction accuracy that is independent of the scale of the data. The data used for forecasting is not normalized and individual energy components have radically different scale. Hence, the RMSPE value provides better insight in evaluating forecasting models. Furthermore, their standard deviation values are observed to see the general precision of the models on the data.

2.3 Data

The dataset consists of monthly energy components contributing to the energy balance on the supply and demand side. The data are published by the national authorities of European countries (usually the transmission system operators or the national statistical offices) and are collected on the level of the high-voltage transmission grid. We use the time series on two different sampling frequency, one is the monthly value, while the other has the hourly resolution. The focus of this study is put on the key energy components or the components with the high level of variability, particularly electricity demand, and renewable energy generation such as wind, PV or hydro generation. Electricity demand is crucial for understanding how much power the system needs to meet consumer needs. Demand can vary significantly based on seasonal factors (heating/cooling), economic activity, and population growth. The increasing penetration of renewables significantly impacts supply dynamics. Understanding the variability of wind and solar generation, as well as the dispatchability (controllable generation) of hydro, is critical for managing grid integration challenges and optimizing renewable energy utilization. Data from the January of 2016 onwards is chosen as this period coincides with a significant ramp-up of renewable energy deployment across Europe.

3 RESULT & DISCUSSION

Forecasting model is applied to multitude of renewable energy sources of all EU countries. To ensure accurate evaluation of the forecasting model, the scope of assessment is focused on forecasting solar energy production in France. Table 1 presents the performance of the models in forecasting the solar energy production in France. Each model iteratively forecasts 3 months starting at each month within the historical data ranging from April-September 2023. The RMSPE between the test data and model's forecast is recorded. Figure 1 represents the box-plot of the data from table 1. The visualization of the data highlights accuracy, spread, and anomalies of model's performance. Forecast performance of the models showcased in figure 1 and table 1 highlights that, in general, SARIMAX model forecasting with collection of hourly data as an exogenous variable is the most accurate with all RMSPE being 3 to 5% with the median being approximately 4%. ARIMA model has second lowest median of RMSPE with the highest precision, while SARIMA has lower median but lower precision in comparison to the DL model.

Table 1: RMSPE of solar energy quarterly forecast in France

Date	Mean	ARIMA	SARIMA	DL	SARIMAX
2023-04-01	2501.90	11.52	10.35	5.31	5.17
2023-05-01	2668.51	9.18	8.78	11.96	5.04
2023-06-01	2667.33	5.12	7.97	4.93	4.20
2023-07-01	2523.00	5.18	8.15	7.79	3.20
2023-08-01	2161.00	8.89	8.11	14.82	3.13
2023-09-01	1574.33	19.80	8.74	11.45	4.46
Standard Deviation		4.95	0.98	3.64	0.80
mean		9.94	8.68	9.38	4.20

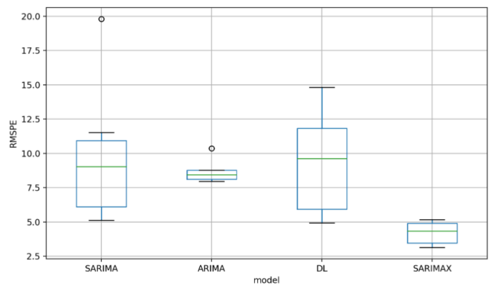


Figure 1: France solar energy production forecast performance visualization

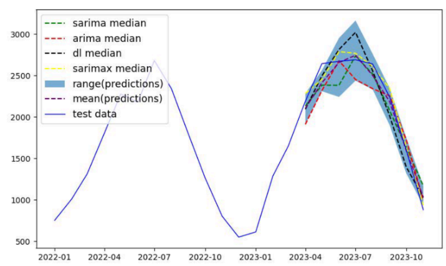
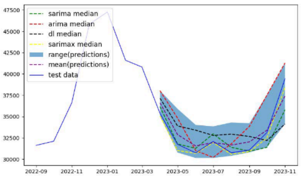
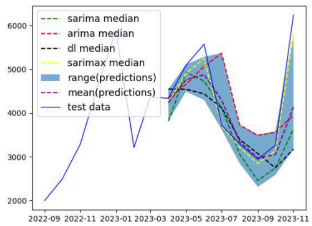


Figure 2: France solar energy production forecast

Figure 2 illustrates the median forecast values of each model against the test data. All models captured the seasonal trend of declining production from September. However, the solar energy production plateau from May to August was not forecasted correctly by any model. The models tended to predict a peak between June to July as it had occurred in the previous years. Especially the forecast made by the DL model predicted much higher peak and generally higher production of solar energy between May to August (Summer) compared to the true data. This is a reasonable expectation as the computed trend decomposition of solar energy production indicated an ascending trajectory, and in 2023, the production of solar energy surpassed that of previous years for every month until May. Although ARIMA and SARIMA models underestimated the production capacity, their accuracy was higher compared to the DL model. Possible reason for overfitting may be too many neurons in DL model, or in this case, may be due to sudden increase in residual factors which is visible from seasonal decomposition of the data. Due to seasonal component, forecasts made by SARIMA in June and July are much more accurate than ARIMA, which already started forecasting a decline in production from May. Forecast from the SARIMAX model is visibly the closest to the test data. Especially, it performs significantly better than SARIMA, its close variant. From this, we can deduce exogenous variables give significant edge to SARIMAX model, and notice the strength of well-chosen exogenous variable. However, while hourly data collection is a great exogenous variable, the time lag between availability of collection of hourly data and monthly data is very short. Hence, SARIMAX model's forecast range gets limited to the lag of the availability. As a result of combining all traits, the ensemble of forecasts accurately delineates the range within which the test data is expected to fall, as depicted by the blue highlighted region in the graphs. Furthermore, the purple dotted lines, representing a simple hybrid model averaging iterative forecasts from all models, demonstrate superior performance compared to individual models such as ARIMA, SARIMA, and DL models. In particular case such as depicted in Figure 2, the hybrid model even outperforms the SARIMAX model. Our analysis suggest that all models have unique characteristic which makes them perform better in certain scenarios. The well-established models are accurate in general, however, some models perform better than others depending on the variable. SARIMAX model promises consistently accurate and precise forecasts as it can be seen from the mean and standard deviation of SARIMAX model in the table, but it is constrained by the availability of reliable exogenous variables. Contrary to traditional models, the wisdom of artificial crowds [9] has demonstrated remarkable potential through a model that averages predictions from various models. This approach proved to be accurate, precise, and stable across all renewable energies, occasionally surpassing even the performance of the SARIMAX model. This discovery supported our belief that by tuning the wisdom of various forecasting models, it would be possible to create a hybrid model with high accuracy, precision, and consistent performance.



(a) France energy demand forecast



(b) France hydro energy production forecast

4 CONCLUSION AND FUTURE WORK

This paper has conducted an investigation into the forecasting performance of well-known statistical, and DL methods, providing insights into their strengths and limitations in forecasting demand and production capacity of various renewable energies of the EU countries. Our findings demonstrate that while conventional methods such as ARIMA, SARIMA, SARIMAX, and DL models have shown promise in modeling and forecasting renewable energy production, they have drawbacks or encounter limitations in accurately capturing rapidly shifting trend of evolving renewable energy. The conventional forecasting models showed variation in performance depending on the energy source. We realized that, for a balanced and reliable framework, there is a need for a tailor-made methodology that can better adapt to the complex dynamics of renewable energy production. During our research, we identified two promising approaches to enhance forecasting accuracy. Firstly, ensemble learning has demonstrated its effectiveness, and further development in this area could yield significant improvements. Secondly, incorporating data sources such as weather data, which have a causal relationship with renewable energy production, and utilizing their lagged correlation in the data for the SARIMAX model, could lead to better-performing frameworks. By exploiting diverse forecasting methodologies and utilising the advancements in data science, we can enhance the accuracy and reliability of renewable energy production forecasts, thus facilitating better informed decision making process of energy market participants and regulatory authorities.

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