# Energy Forecasting Tools and Services

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**Abstract**

The increasing complexity of the power grid and the continuous integration of volatile renewable energy systems on all aspects of it have made more precise forecasts of both energy supply and demand necessary for the future Smart Grid. Yet, the ever increasing volume of tools and services makes it difficult for users (e.g., energy utility companies) and researchers to obtain even a general sense of what each tool or service offers. The present contribution provides an overview and categorization of several energy-related forecasting tools and services (specifically for load and volatile renewable power), as well as general information regarding principles of time series, load, and volatile renewable power forecasting.

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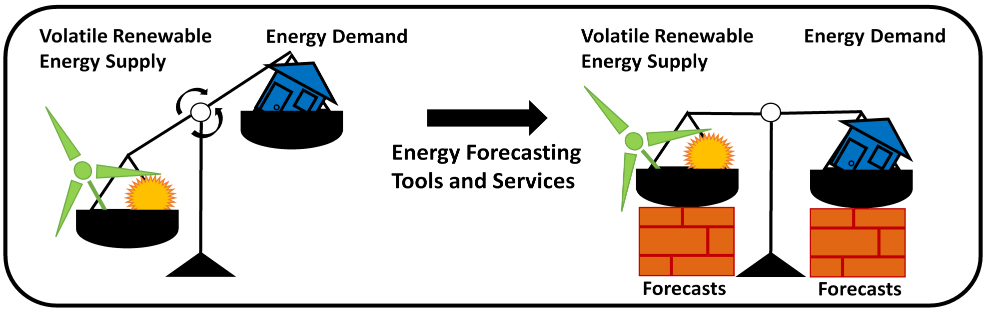


Forecasts provide the only option for the correct planning and scheduling of the power grid. The ever increasing volume of forecasting tools and services makes it difficult to obtain even a general sense of what each tool or service offers. The present contribution provides an overview and categorization of several energy-related forecasting tools and services.

# INTRODUCTION

The transition from traditional power generation systems (e.g., coal-fired power plants) to "greener" power generation has increased the complexity of the power grid. This increase in complexity calls for further integration of information and communication technologies (ICT) into the power grid, i.e. the development of the so-called Smart Grid[1,2]. Accurate demand and supply forecasts are part of these necessary ICTs. The shift towards "greener" power generation is exemplified by Germany, which has been following a path of continuously increasing the share of renewables in its primary energy demand, and has plans – outlined in the "Energiewende" – of augmenting the share further to 50 or even 100 percent in the next 30 years.[3] Yet, the power generated by some renewable energy systems, like wind and photovoltaic (PV) power plants, is completely dependent on the weather. By nature, the power generated by these systems is intermittent and volatile. Such volatility complicates the necessary balancing of electricity demand and supply.[4] Forecasts provide the only option for obtaining insight into future volatile renewable power generation as well as electrical load and thereby enable the correct planning and scheduling of the electrical grid;[5] for example, by using a demand side management (DSM) approach. [1] Not only do electrical grids benefit from forecast information, natural gas and district heating grids also require load forecasts to ensure their stability and good performance.[7,8] In addition, both heating and gas grids can be fed with excess renewable electricity through conversion technologies like "Power to Gas"[9] and "Power to Heat".[10,11] Yet such integration, increases the need for accurate volatile renewable power forecasts. Furthermore, load forecasts are an important tool for energy utility companies (especially in competitive energy markets[12]), because they depend on such information to conduct relevant decisions, like electricity generation and purchasing, as well as infrastructure planning.[13,14]

The ever-increasing number of energy-related forecasting tools and services available is reflective of the importance of energy forecasts. However, the sheer volume of tools and services available make understanding the differences among them a complicated task. To address

[1]Some DSM concepts for guaranteeing the correct electrical demand and supply balancing – in the presence of renewable energy – are presented by Müller et al.[6]

this challenge, the present contribution briefly describes and categorizes several energy forecasting tools and services found online. Additionally, to allow a better understanding of what each tool and service presented offers, general information about time series, as well as load and volatile renewable power forecasting is provided.

The present contribution is divided into four parts. First, background information on time series forecasting is given. Second, energy-related forecasting aspects are described, including specific properties of energy time series, as well as more specific information regarding load and volatile renewable power forecasting. Thereafter, the energy forecasting tools and services selected for review, as well as the criteria utilized to describe them, are presented. Lastly, a conclusion outlining the present works' findings is offered.

# FORECASTING BACKGROUND INFORMATION

Energy load and volatile renewable power generation are typically represented as time series, therefore, the present section provides background information on general aspects of time series forecasting.

The goal of a time series forecasting model is the obtainment of unknown future information of a desired time series at a forecast horizon $H \geq 1$ utilizing available information. For example, a forecasting model for a future value of a time series $y$ (whose time steps are given as $k \in [1, K]$) using current and past values (from timesteps $k$ to $k - H_1$, with $H_1$ being the used time lags) of the desired time series and from several exogenous time series contained in the vector $\mathbf{u}$ is described by the functional relation

$$\hat{y}[k + H] = f(y[k], .., y[k - H_1], \mathbf{u}^T[k], .., \mathbf{u}^T[k - H_1]; \boldsymbol{\theta}); k > H_1 \ . \tag{1}$$

In this equation the vector $\boldsymbol{\theta}$ contains the model's parameters.

This equation shows that a forecasting model maps a given input to an approximation of a desired output, which is the definition of a regression according to Fayyad.[15] Therefore, the generalization of a forecasting model's obtainment to a regression problem is possible.

According to Hyndman and Athanasopoulos,[16] both the exponential smoothing and the auto-regressive integrated moving average (ARIMA) models are the most common approaches in forecasting the future developments of a time series. A simple exponential smoothing model – with $\hat{y}[1+H] = y[1]$ as initialization – is given by the equation[2]

$$\hat{y}[k+H] = \sum_{i=0}^{k-2} \alpha(1-\alpha)^i y[k-i] + (1-\alpha)^{k-1} y[1]; k > 1 \ , \tag{2}$$

with $\alpha \in [0,1]$ being the so-called smoothing parameter. As it can be seen, the forecast is a weighted average of the desired time series' past values, whose weights decay exponentially as the observations get older, hence giving the most recent observations a greater influence.[5,16] The state of the art in exponential smoothing techniques, including more complex and non-linear variants, can be found in the article presented by Gardner.[17]

The ARIMA model is a generalization – for non-stationary time series – of the autoregressive moving average (ARMA)[18] model that is comprised of an auto-regressive (AR) and a moving average part (MA) (in which it can be further simplified). Such models are based on the premise that time series are realizations of a stochastic process.[19] Furthermore, ARIMA and all its simplifications allow the inclusion of exogenous time series, which is denoted by the letter X at the end of their names (e.g., ARIMAX).[20] For example, a linear forecasting model can be given as an ARX model:

$$\hat{y}[k+H] = \sum_{i=0}^{H_1} a_i y[k-i] + \sum_{j=0}^{H_1} \mathbf{b}_j^T \mathbf{u}[k-j]; k > H_1 \ , \tag{3}$$

or as an ARIMAX model of first order difference:

$$\begin{aligned} \hat{y}[k+H] = \hat{y}[k+H-1] &+ \sum_{i=0}^{H_1} a_i \Delta y[k-i] + \sum_{j=0}^{H_1} \mathbf{b}_j^T \mathbf{u}[k-j] \\ &+ \sum_{l=0}^{H_1} c_l \epsilon[k-l]; k > H_1 + 1 \ , \\ \text{with } \Delta y[k] &= y[k] - y[k-1] \\ \text{and } \epsilon[k] &= \hat{y}[k] - y[k] \ . \end{aligned} \tag{4}$$

In this instance, $a_i$, $\mathbf{b}_j$ and $c_l$ are the models' parameters. Further information regarding ARIMA(X), including its simplifications and more complex variants, can be found in Brockwell[18] or Shumway.[21]

[2]Equation (2) only provides suitable forecasts for $H > 1$, if $y$ has no trend or seasonal component.

Time series can be decomposed into different parts, which can be added or multiplied to form the original time series. Hyndman and Athanasopoulos[16] separate a time series in three distinct components:

- **Trend-Cycle Component**: This component contains long-term increases or decreases in the time series (trend) and rises and falls in non-fixed periods of time (cycle). Sometimes it is only referred to as the trend component.

- **Seasonal Component**: This component contains the parts of the time series that change in fixed and known periods of time due to seasonal (periodic) effects (e.g., day and night cycles or summer and winter cycles in PV power times series, changes in heating and non-heating periods in heat load time series).

- **Remainder**: This component includes anything else in the time series.

Information about the components can be used to create forecasting models, such as the Holt-Winters model[17] (expands the traditional exponential smoothing technique in order to approximate a trend and a seasonality) or the seasonal ARIMA(X) model (SARIMA(X)). For the sake of illustration, a SARX model with $S$ seasons – each represented by their number of timesteps $H_{p_s}$ with $s \in [1, S]$ – is given by the equation:

$$\begin{aligned}\hat{y}[k+H] = &\sum_{s=1}^{S} d_s y[k+H-H_{p_s}] + \sum_{i=0}^{H_1} a_i \left( y[k-i] - \sum_{s=1}^{S} d_s y[k-i-H_{p_s}] \right) + \\ &\sum_{j=0}^{H_1} \mathbf{b}_j^T \mathbf{u}[k-j]; k > H_1, \forall H_{p_s} : H_{p_s} \geq H, H_{p_s} < k+H, H_{p_s} < k-H_1 \ .\end{aligned} \tag{5}$$

with $a_i$, $\mathbf{b}_j^T$, and $d_s$ being the parameters of the SARX model.

As linear models can be insufficient for some real-world applications,[19] non-linear techniques have also been found useful in forecasting. Two common non-linear techniques include artificial neural networks (ANN) and support vector machines (SVM). ANNs are constructs which try to emulate certain aspects of the biological nervous system.[5] They are formed by interconnecting several basic building blocks, called neurons, in a series of different layers. Through a training algorithm, all the free parameters inside the neurons (i.e., weights and biases) are changed, in order to approximate the relation between input values and desired outputs in an optimal manner.[22] SVMs (also called Support Vector Regressions (SVR) when applied in regression problems) map the original data into a high-dimensional feature space and calculate a linear hyper-plane, which when transformed into the original dimensions represents an approximation of the desired functional relation.[23,24] Depending on their utilized input values, models obtained by non-linear techniques (like the ones described above) can be classified as NARIMA(X) models, with the non-linearity denoted by the letter N at the beginning of the model's name. For example, Equation (1) can also be used to describe a NARX model obtained from an ANN.

For more information regarding time series forecasting approaches, including state space models, autoregressive conditional heteroscedasticity (ARCH) models, generalized ARCH (GARCH) models, etc., refer to the article written by De Gooijer and Hyndman.[19] Additionally, examples of novel forecasting approaches that have caught the interest of researchers, as e.g., deep learning, Gaussian process regression (in geostatistics commonly referred to as Kriging[25]), and techniques using compressed sensing can be found in the works of Sun et al.,[26] Tascikaraoglu and Sanandaji,[27] Yang et al.,[28] and Zhao et al.[29]

Forecasting models can be separated into three different types:

- **White-Box Models**: These models use known relations, expert knowledge, etc. (e.g., physical models for volatile renewable power forecasting) to define the relation between the utilized inputs and the future of the time series of interest.

- **Black-Box Models**: These models infer the relation between used inputs and future time series values through the application of data mining techniques on available data.

- **Gray-Box Models**: These models are a combination of white and black-box models.

Figure 1 depicts the types of time series forecasting models.

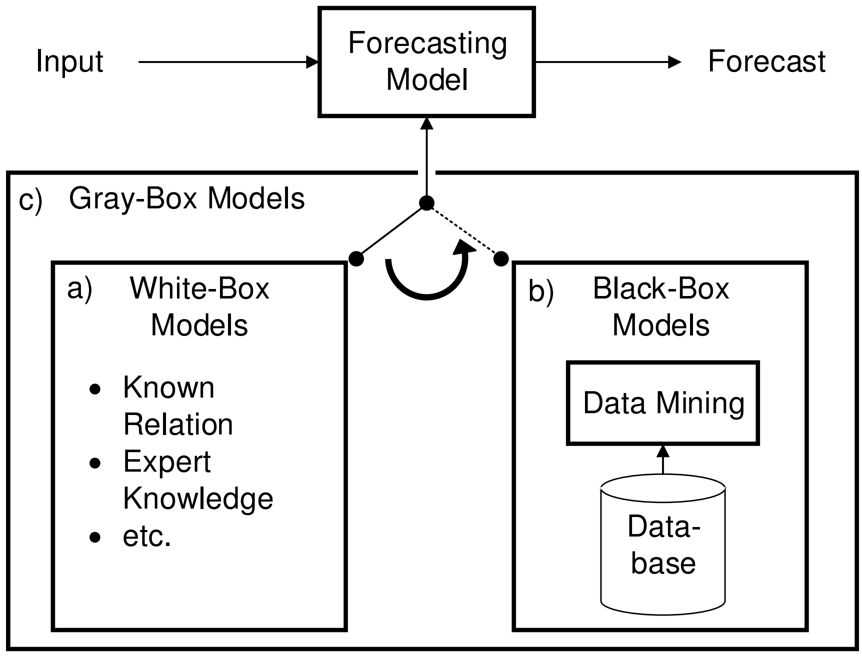


Figure 1: Different forecasting model types. a) White-Box Models: created using known relations, expert knowledge, etc.; b) Black-Box Models: created utilizing pure data mining techniques; c) Gray-Box Models: created through the combination of white and black-box models

Furthermore, for the obtainment of black-box models many data mining tools exist, several of which are presented in the article of Mikut and Reischl.[30]

## POINT VS. PROBABILISTIC FORECASTING

Most forecasting models deliver a so-called point forecast;[31] a single value that according to the models criteria is to be expected. The predominance of point-forecasting models is common in energy-related forecasting.[32–35] However, point-forecasting models are unable to provide information about the forecast uncertainty, which is of interest for several cases (e.g., model predictive control). A method of quantifying such uncertainty is by conducting probabilistic forecasts.[36–38] General principles of probabilistic forecasts are presented in the article written by Gneiting and Katzfuss.[39] Due to the increasing interest towards probabilistic forecasting, several articles tackling their obtainment for both load and volatile renewable power forecasting models are presented in the next sections. Nonetheless, a thorough description of probabilistic forecasting models and their application for energy-related tasks is beyond the scope of the present work and hence will be omitted.

## ENERGY-RELATED FORECASTING

The present section provides a summary of energy-related forecasting, for both load and volatile renewable power, alongside state-of-the-art examples of point energy forecasting.[3] Even though the information contained in the following sections mostly relates to point forecasting models, Figure 2 illustrates the state of maturity, according to Hong et al.,[33] of different point and probabilistic energy forecasting research fields.

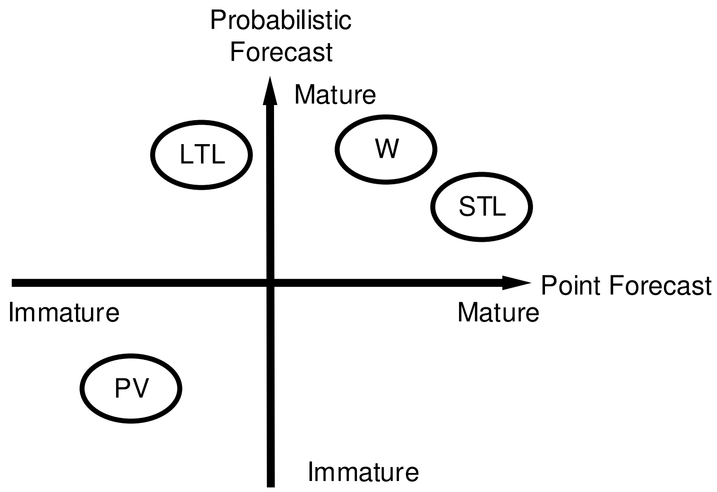


Figure 2: Maturity of energy-related point and probabilistic forecasting based on the figure presented by Hong et al.[33] STL: short-term (two weeks ahead or shorter) load forecasting; LTL: long-term (a few months to a few decades ahead) load forecasting; PV: photovoltaic power forecasting; W: wind power forecasting

A common issue that arises when looking at forecasting approaches in the literature is the utilization of proprietary data that complicates the comparison between approaches. Therefore, the present contribution recommends the utilization of free available benchmark

[3]For a thorough description of each approach, it is recommended to look into the original research articles.

data for the creation and testing of future energy-related forecasting models. Examples of free, available data sources include the Global Energy Forecasting Competitions of 2012 (GEFCom12)[40] and 2014 (GEFCom14),[33] the Open Power System Data (OPSD) project's website (open-power-system-data.org), and the Australian Solar Home Electricity dataset[41] provided by Ausgrid (ausgrid.com.au).

**Note**:

Load and generated power are not the only values, whose forecast is relevant in an energy-related context. For example, the forecast of energy prices is relevant for energy trading decisions (e.g., purchase and sales strategies).[42] However, it is not the main focus of the present contribution and thus it is not discussed further. Nonetheless, information regarding energy price forecasting and the influence that prices have on load time series forecasts in demand response scenarios can be found in the articles by Aggarwal et al.,[43] Klaiber et al.,[44] Waczowicz et al.,[45] and Weron.[46] Another interesting case, which is not discussed further, is the forecast of time series formed by a combination of both generation – via renewable energy systems – and load (e.g., time series measured at a low voltage substation). An example of such energy time series forecasting is presented by Kummerow et al.[47] In this work separate forecasting models for generation and load components are created, with the combination of their outputs forming the forecast result.

## ENERGY TIME SERIES' SPECIFIC PROPERTIES

The forecasting of energy time series is highly influenced by certain properties which differentiate them from many other time series. A clear example is the dependency of volatile renewable power on certain weather parameters, such as the solar irradiation in the case of photovoltaic power[48] and wind speed in the case of wind power.[49] The dependency of solar power on solar irradiation – and temperature – is clearly seen in the Osterwald equation; a commonly utilized equation to estimate the maximal power that can be obtained by a given PV cell.[50,51] The Osterwald equation is described as

$$P = \frac{P_{stc}}{G_{stc}}(1 - \gamma(T_c - 25°\text{C}))G \ , \tag{6}$$

in which $P$ [W] is the maximal generated cell power, $P_{stc}$ [W] is the maximal cell power under standard conditions, $G$ [$\mathrm{W\,m^{-2}}$] is the cell's incident solar irradiation , $G_{stc}$ [$\mathrm{W\,m^{-2}}$] is the standard conditions' solar irradiation, $T_c$ [°C] is the cell/module temperature, and $\gamma$ [$\mathrm{°C^{-1}}$] is the power temperature coefficient. The dependency of wind power on wind speed is demonstrated by the fundamental wind power equation[52]

$$P = c_w \frac{1}{2} \rho A w_s^3 \ , \tag{7}$$

with $P$ [W] being the power obtained by a wind turbine, $c_w$ its power coefficient, $\rho$ [$\mathrm{kg\,m^{-3}}$] the air density, $A$ [$\mathrm{m^2}$] the wind turbine's swept area, and $w_s$ [$\mathrm{m\,s^{-1}}$] the hub height wind speed. The relation of how wind speed changes with height has to be considered when determining $w_s$ due to the fact, that wind speed is normally measured at a reference height instead of at the turbines' hub height.[53]

Weather dependencies can also be seen in load time series, most notably in heat load time series, which are highly dependent on ambient temperature.[54] Load's weather dependency can be attributed to human behavior. Furthermore, human behavior not only influences load depending on the weather, but also affects it differently depending on the time of day and the day of the week. These variations are visualized in Figure 3, which shows heat maps displaying normalized averages of household's daily electrical loads separated into months and weekdays. The data is from the FIXED price group households in the Olympic Peninsula Project.[55]

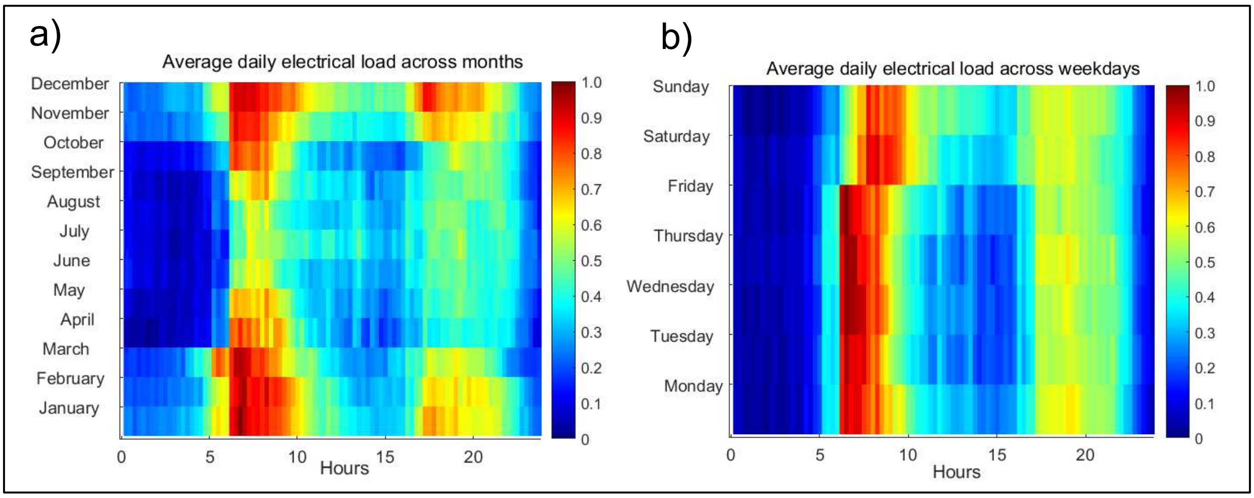


Figure 3: Heat maps depicting a) average daily household electrical loads across several months; b) average daily household electrical loads across the different weekdays

As seen in Figure 3, electrical load time series possess seasonal components, a property that they share with PV power time series and that can be utilized to increase the accuracy of a given forecasting model. For example, a PV power seasonal AR forecasting model for a forecast horizon, $H$, and a single season, $H_{p_1}$, equal to the number of timesteps representing 24 hours can be described as (the equation and its variables are consistent with the example presented in Equation 5; with $H_1 = 0$):

$$\hat{P}[k+H] = (a_1 + d_1)P[k] + a_1 d_1 P[k - H_{p_1}] \ . \tag{8}$$

This equation approximates the power to be generated 24 hours in the future as a weighted average of the previous two days. While the daily seasonality of generated PV power is ruled by the earth's day and night cycle, the daily, weekly, and yearly seasonal components of load strongly depend on people's routines and their reactions in response to external factors (e.g., the four seasons of the year).

In addition to explicitly modelling the seasonality, as in Equation (8), the repeating nature of PV power and load time series can be utilized to generate time series that, when utilized as further input values,[56] may increase the models' accuracy.

Moreover, repeating behaviors in non-fixed periods of time can be estimated through exogenous time series. For example, a forecast can be conducted by averaging the power or load of previous days whose conditions are similar according to the exogenous time series values (e.g., weather, day of the week). An example of such an approach is presented in the article by Zhang et al.[57]

## LOAD FORECASTING

Though several categorizations of load forecasting approaches exist, the most common is based on the forecast horizon. Depending on their horizon, the forecasting approaches are normally categorized as short-, medium-, or long-term. Table 1 offers examples of such categorization present in the literature.

<table>
<tr><th rowspan="2">Author</th><th colspan="5">Forecast Horizon</th></tr>
<tr><th>$\mathbf{H \leq 1d}$</th><th>$\mathbf{1d < H \leq 1w}$</th><th>$\mathbf{1w < H \leq 1M}$</th><th>$\mathbf{1M < H \leq 1Y}$</th><th>$\mathbf{1Y < H}$</th></tr>
<tr><td>Ahmad[58]</td><td colspan="2">Short</td><td colspan="2">Medium</td><td>Long</td></tr>
<tr><td>Feinberg[13]</td><td colspan="2">Short</td><td colspan="2">Medium</td><td>Long</td></tr>
<tr><td>Hahn[59]</td><td colspan="2">Short</td><td colspan="2">Medium</td><td>Long</td></tr>
<tr><td>MCSharry[37]</td><td colspan="2">Short</td><td>Medium</td><td>Medium & Long</td><td>Long</td></tr>
<tr><td>Raza[22]</td><td colspan="2">Short</td><td>-</td><td>Medium</td><td>Long</td></tr>
<tr><td>Ghiassi[60]</td><td colspan="2">Short</td><td>-</td><td colspan="2">Medium</td></tr>
<tr><td>Alfares[61]</td><td>Short</td><td colspan="3">Medium</td><td>Long</td></tr>
<tr><td>Takiyar[14]</td><td>Short</td><td colspan="3">Medium</td><td>Long</td></tr>
<tr><td>Almeshaiei[62]</td><td>Short</td><td>Short & Medium</td><td colspan="2">Medium</td><td>Long</td></tr>
<tr><td>Metaxiotis[63]</td><td>Short</td><td>Medium</td><td colspan="2">Medium & Long</td><td>Long</td></tr>
</table>

Table 1: Categorization of load forecasting approaches regarding their forecast horizon $H$.
**Forecast Horizon:** hour (h), day (d), week (w), month (M), year (Y)

As shown in Table 1, the categorization based on forecast horizons varies considerably. So, even though some consensus seem to appear from the presented articles, the concepts of short-, medium-, and long-term are not going to be utilized further. Instead, the forecast horizons are going to be given explicitly. Figure 4 shows the applications load forecasts can have based on their forecast horizon. The depicted applications correspond to forecasts at an energy transmission level, whose integration in energy systems is crucial for an optimal system operation. Furthermore, the importance of load forecasts at the lower distribution level is currently increasing, as exemplified by the work of Sun et al.[64]

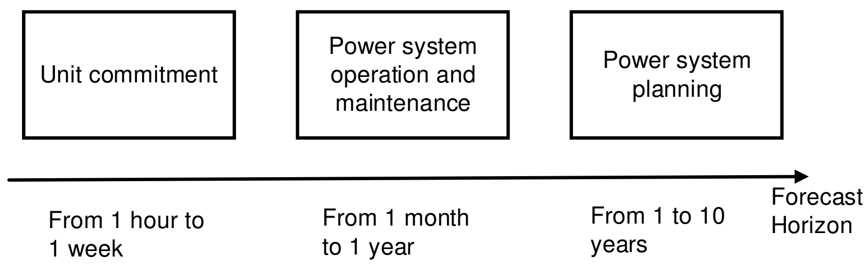


Figure 4: Examples load forecasting models' applications depending on their forecast horizon. The figure is based on the article given by Raza et al.[22]

The difference in forecast horizons plays an important role in the selection of the approach and data utilized to conduct the forecasts. According to Feinberg,[13] the approaches commonly used for forecast horizons of up to a day are: ANNs, SVMs, and time series models (e.g., ARIMA, regression models). For greater horizons end-use, econometric models, and their combination are mostly utilized. End-use models estimate the future load by utilizing extensive information about the users and their equipment, while econometric models link energy demand with macro-economic variables. An example of end-use models can be found in the article of Asare-Bediako et al.,[65] in which future residential load profiles are estimated by considering photovoltaic systems installations, electrical vehicle charging, etc. More information regarding econometric models can be found in the review presented by Suganthi and Samuel.[66] The utilization of end-use and econometric models reflects a property that differentiates load forecasting from volatile renewable power forecasting: the influence that human behavior has on energy consumption. Due to such influence, calendar functions (used to differentiate between weekdays, weekends, and holidays) are commonly utilized as an additional input for load forecasting models.[67] Similarly, Ghiassi et al.[60] argue that variables representing socioeconomic growth in regions whose socioeconomic conditions could rapidly change should be included as input for monthly and yearly forecasts. Likewise, weather data, such as temperature, have also been defined as key inputs in most load forecasting models. For forecast horizons of up to a week, forecast weather data can be easily obtained from weather services, while for greater forecast horizons other methods of obtaining future weather data are required.[68] The fact that large uncertainties might be present in weather forecasts for great forecast horizons (e.g. one month or more) needs to be considered before their utilization. In addition, a priori knowledge of substantial maintenance, expansions or dismantling of large industrial complexes, planned urban changes, etc. must also be taken into account for forecasting accuracy.

Table 2 contains general information of several point forecasting approaches found in the literature, including: the author of the respective article, the utilized technique, the forecast load type (electrical (E), heat (H) or gas (G)), the forecast horizon, the temporal resolution in which the forecasts are given, and the utilized input data.

| Author | Technique | Load Type | Forecast Horizon | Resolution | Input |
|---|---|---|---|---|---|
| Bacher[69] | Adaptive linear Time Series Model | H | 1-42h | 1h | $T_a, \hat{T}_a, w_s, \hat{w}_s, G, \hat{G}$, Hour |
| Ding[70] | ARMAX, ANN, SVR | E | 15min, 30min, 1h | 15min, 30min, 1h | Autoregressive, Activity Information, Hour, Day |
| Dotzauer[7] | Time Series Model | H | 1w | 1h | $\hat{T}_a$, Social Component |
| Ghiassi[60] | Dynamic ANN | E | 1M, 3M, 6M, 1Y | 1M | Autoregressive, Monthly Cooling Degree Days |
| Hong[24] | SVR with Immune Algorithm | E | 1Y | 1Y | Autoregressive |
| Idowu[54] | SVR | H | 1h, 3h, 6h, 12h, 18h, 24h | 1h | Autoregressive, $T_a$, $\hat{T}_a$, Hour, Supply Temperature, Flow Rate, Supply and Return Temperature Difference |
| Kandil[71] | Knowledge-Based Expert System | E | 1Y | 1Y | Knowledge Base |
| Liu[72] | Least Squares SVM | G | 1M | 1d | Autoregressive, $\hat{T}_a$, Calendar Function |
| Senjyu[73] | Autoregressive ANN | E | 1h | 1h | Autoregressive, $T_a$ |
| Taylor[74] | ANN with Ensemble Weather Predictions | E | 1-10d | 1d | Autoregressive, Effective Temperature, Effective Illumination, Cooling Influence of Wind, Calendar Function |
| Yu[8] | Genetic Algorithm and ANN | G | 1d | 1d | Autoregressive, maximum, minimum, and average $T_a$, Future Weather Conditions, Calendar Function |

Table 2: Examples of point forecasting approaches found in the literature.

**Forecast Horizon & Resolution:** minutes (min), hour (h), day (d), week (w), month (M), year (Y)

**Input Description:** Autoregressive: Past Load Values, $T_a$: Ambient Temperature, $\hat{T}_a$: Forecast Ambient Temperature, $w_s$: Wind Speed , $\hat{w}_s$: Forecast Wind Speed, $G$: Solar Irradiation, $\hat{G}$: Forecast Solar Irradiation

The small sample of articles contained in Table 2 reflect the fact, that point forecasting models whose horizons are shorter than a week have attracted greater interest from the research community than forecasting models for greater forecast horizons.[60,68]

Thorough reviews describing the state-of-the-art in load forecasting (specifically electrical load forecasting) are provided by Alfares and Nazeeruddin,[61] Raza and Khosravi,[22] and by Suganthi and Samuel.[66] However, these reviews, like the examples found in Table 2, focus on point forecasting approaches. The review presented by Hong and Fan[34] is recommended for information regarding current developments in probabilistic load forecasting.

## VOLATILE RENEWABLE POWER FORECASTING

Just as with load, volatile renewable power forecasting approaches can be categorized by forecast horizons. Table 3 contains examples of categorizations given in the literature, for both PV and wind power forecasting.[4]

| | **Forecast Horizon** | | | | |
|---|---|---|---|---|---|
| **Author** | **$H \leq 1d$** | **$1d < H \leq 1w$** | **$1w < H \leq 1M$** | **$1M < H \leq 1Y$** | **$1Y < H$** |
| Foley[75] | Short | Short & Medium | - | | |
| Monteiro[76] | Short | Short & Medium | - | | |
| Wan[77] | Short & Medium | | Long | | |
| Soman[78] | Short & Medium | Long | | | |
| Wang[79] | Short | Long | - | | |
| Huang[80] | Short | | Long | | - |
| Ogliari[81] | Short | | Medium | | Long |
| Kostylev[82] | OD | | Medium | | Long |

Table 3: Categorization of power forecasting approaches with respect to their forecast horizon $H$ (OD: other definitions).
**Forecast Horizon:** hour (h), day (d), week (w), month (M), year (Y)

The examples in Table 3 show the formation of a small consensus, which defines short- and medium-term forecasting approaches as those, whose horizons range from less than a

[4]Some authors categorize forecasting approaches further into very short-term forecasts, but in the present contribution such a categorization is considered part of the short-term category.

day up to a week. Furthermore, both Foley et al.[75] and Monteiro et al.[76] – with articles regarding wind power forecasting – avoid defining the forecasts of which horizons are greater than a week, while Wan et al.[77] – whose article is specifically about PV power forecasting – defines all those forecasts as long-term. Additionally, other authors avoid using classical terms and instead opt to utilize terms like intra-hour or intra-day forecasts, as shown by Antonanzas et al.[32] Ultimately, a classification of volatile renewable power forecasting approaches based on their forecast horizons remains vague and inconsistent. Therefore, the forecast horizons of volatile power forecasting approaches are explicitly mentioned, herein. Figure 5 shows examples of different applications of PV power forecasting models depending on their horizons.

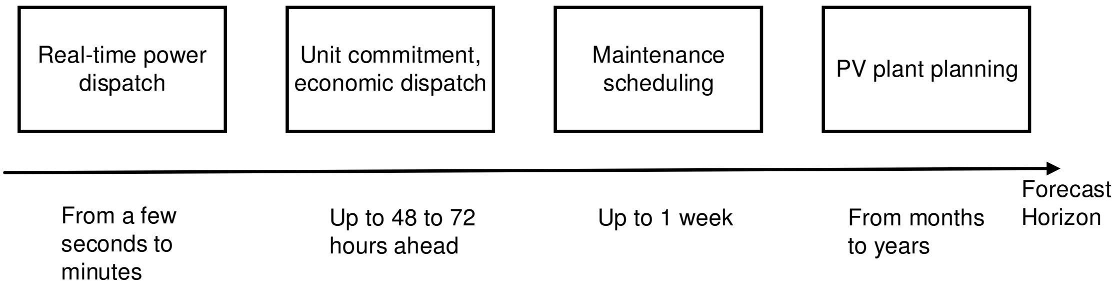


Figure 5: Examples of PV power forecasting models' applications depending on their forecast horizon, based on a depiction by Wan et al.[77]

Volatile renewable power forecasting approaches can be divided into physical and statistical (in the present contribution referred to as data-driven) approaches,[76,83,84] with the models of the former being white-box models, while those of the latter being black-box models. Of course, a combination of both types to form a gray-box model is also possible.[32] Duran et al.[85] argues that pure data-driven approaches are more effective at forecasting (wind power) values at short horizons, while approaches that use more physical information are better for longer horizons. Nonetheless, it is important to note that Duran et al.[85] do not offer a clear definition of short and long horizons in their work.

Physical approaches take forecast weather data, like numerical weather predictions (NWP) such as solar irradiation for PV power[48] and wind speed for wind power,[49] and transform it through an intermediate step into values, which directly influence the volatile renewable power generation (e.g., solar irradiation on the PV modules and wind speed at the wind turbines). This information is then converted into a power forecast by utilizing models based on physical relations, such as a power curve (cf. Equation 7) in the case of wind power, or a PV model (cf. Equation 6) in the case of PV power. An example of a physical approach can be found in the article of Lange et al.,[86] which presents the wind power forecasting system "Previento". The fact that physical models allow the obtainment of volatile renewable power forecasts without the utilization of historical data show the possibility of conducting forecasts prior to the construction of a renewable energy system.[32] Yet, it can be argued that forecasting approaches based on physical models are not true forecasting techniques, as the forecasting effort lays in calculating the forecast weather data.

Data-driven approaches, such as ANNs, SVMs, and ARIMA(X), use past generated power data and/or other possible inputs like historical NWP data[76,79,84] to develop models which directly transform those inputs into power forecasts. An advantage of utilizing data-driven models over physical models is that specific properties of the renewable energy system in question do not need to be modeled explicitly, as this information is implicitly contained in the data. Some of these properties include:

- **PV power**:
  - local shadowing effects caused by neighboring buildings and/or vegetation
  - PV modules aging
  - reduced generation capacity, due to snow and/or dirt
  - power line losses
- **Wind power**:
  - the influence of the geographical location on production
  - the wind turbines mutual influence
  - relation between the wind speed measured at a reference height or the one from the NWP data and the corresponding hub height wind speed
  - power line losses

The high correlation between the volatile renewable power and certain weather parameters have made weather data, and specifically forecast weather data, a common utilized input. However, Pelland et al.[84] argue that accurate PV power forecasts for short horizons can be obtained through pure autoregressive models. Pedro and Coimbra[87] and González Ordiano et al.[88] show evidence of such fact, for horizons of one and two hours and 24 hours correspondingly. Pure autoregressive models can also be used to forecast wind power generation, as shown by Catalãou et al.,[89] nonetheless according to Monteiro et al.[76] for horizons greater than three to six hours NWP data should be used as input. Autoregressive approaches for forecast horizons larger than a couple of hours come with certain quality restrictions. For example, if a PV power forecast for the next 24 hours is obtained using historical power data of the previous days, whose weather happened to be completely different to that of the forecast day, then the forecast is most certainly incorrect. Additionally, a priori information of the expansion or maintenance of the volatile renewable power systems helps to assure the accuracy of the utilized models.

Table 4 outlines volatile renewable power point forecasting approaches found in the literature including: the author of the respective article, the used technique, the type of forecast power (photovoltaic (PV) or wind (W)), the forecast horizon, the temporal resolution, and the input data.

| Author | Technique | Power Type | Forecast Horizon | Resolution | Input |
|---|---|---|---|---|---|
| Bouzerdoum[90] | Hybrid SARIMA SVM Model | PV | 1h | 1h | Autoregressive |
| Catalãou[89] | ANN, Wavelet Transform | W | 3h | 15min | Autoregressive |
| Chaouachi[91] | ANN Ensemble | PV | 1d | 1h | $G$, $T_a$, Vapor Pressure, Humidity, Cloud Coverage, Sunshine Duration |
| Duran[85] | AR and ARX | W | 6,12,24h | 1h | Autoregressive, $\hat{w}_s$ |
| Gonzalez Ordiano[88] | Polynomial Regression, ANN | PV | 24h | 15min | Autoregressive, Hour |
| Li[92] | ARMAX | PV | 1d | 1d | Autoregressive, Daily Average of $\hat{T}_a$, Highest and Lowest $\hat{T}_a$, $\hat{w}_s$, $\hat{w}_d$, Forecast Values of: Dew Temperature, Precipitation Amount, Humidity, Insolation Duration, Air Pressure |
| Lin[93] | Evolutionary Seasonal Decomposition Least-Square SVR | PV | 1M | 1M | Autoregressive |
| Mellit[94] | ANN Ensemble with Day-Type Classification | PV | 1d | 1h | Autoregressive, $\hat{G}$, $\hat{T}_a$ |
| Sideratos[95] | ANNs with Fuzzy Logic | W | 1-48h | 1h | Autoregressive, $\hat{w}_s, \hat{w}_d$, Hour |
| Tao[96] | NARX ANN | PV | 1d | 1h | Autoregressive, Highest and Lowest $\hat{T}_a$, Day-Type index, Forecast Clear Sky Radiation |
| Yang[97] | SVR with Vector Quantization using Self-Organizing Maps | PV | 1d | 1h | Autoregressive, $G$, $T_a$, Month, Weather Description, Precipitation Probability |

Table 4: Examples of point forecasting approaches found in the literature.

**Forecast Horizon & Resolution:** minutes (min), hour (h), day (d), week (w), month (M), year (Y)

**Input Description:** Autoregressive: Past Power Values, $T_a$: Ambient Temperature, $\hat{T}_a$: Forecast Ambient Temperature $\hat{w}_s$: Forecast wind speed, $\hat{w}_d$: Forecast Wind Direction, $G$: Solar Irradiation, $\hat{G}$: Forecast Solar Irradiation

The small sample of research articles contained in Table 4, show a lack of interest in the creation of volatile renewable power forecasting models for long forecast horizons. Such is reflected in the thorough PV power forecasting review presented by Antonanzas et al.[32] in which only 6 of the 86 presented research articles (contained in Table 2 by Antonanzas et al.[32]) deal with forecast horizons equal or longer than 3 days. Furthermore, Foley[75] argues that wind power forecasting approaches with horizons ranging from a few seconds to seven days receive a major focus, as power systems operations, such as unit commitment and scheduling, are conducted within these horizons.

Current trends in wind power forecasting are provided in the literature reviews given by of Foley et al.,[75] Lei et al.,[49] Monteiro,[76] Soman et al.,[78] and Wang et al.[79] Trends in PV power forecasting are provided in the articles of Antonanzas et al.,[32] Kostylev and Pavlovski,[82] Pelland et al.,[84] and Wan et al.[77] Though, point forecasting approaches are most abundant in the literature, probabilistic forecasts have gained interest[33]. Examples of probabilistic wind power forecasting approaches can be found in the articles of Bremnes[36] and Nielsen et al.,[98] while probabilistic PV power forecasting approaches are described in the articles of Join et al.,[99] Juban et al.,[100] and Zhang et al.[57]

# ENERGY FORECASTING TOOLS & SERVICES

The present section provides an overview of energy forecasting tools and services, with tools and services differentiated as:

- **Tools:** Software users can interact with to conduct forecasts.
- **Services:** Services from which users can receive useful forecasts, either by sending the service provider their data, or by allowing the service provider to conduct forecast utilizing data already in their possession.

Many energy providers use self-created forecasting solutions. However, information regarding those solutions is not publicly available. For such reason, the present section focuses only on tools and services publicly available on the internet.

## CATEGORIZATION CRITERIA

In order to differentiate forecasting tools and services, a systematic categorization is necessary. In the present contribution, such a categorization is conducted using seven criteria (with one criterion for tools only and another for services only). These criteria include:

1. **Horizon:**

   The forecast horizon represents how far in the future the tools and services are able to deliver a forecast. The following abbreviations are utilized for time values: minutes (min), hour (h), day (d), week (w), month (M), and year (Y).

2. **Resolution:**

   Indicates the temporal resolution in which the forecasts are given. For example, a service delivering a forecast for an horizon of 24h can provide results with a daily resolution, one value for each day, in an hourly resolution, 24 different values are provided each day, or in any other variant.

3. **Forecast Value:**

   Specifies the type of value that a tool is able to forecast, or which forecast values are offered by a service. The load values are abbreviated as E for electrical, H for heat, and G for gas, while the volatile renewable power is abbreviated as PV for photovoltaic and W for wind.

4. **Probabilistic Forecast:**

   This criterion indicates if the tool or service is capable of quantifying the forecast uncertainty via a probabilistic forecast.

5. **Approach:**

   This criterion applies to forecasting services only. It describes the type of approach used to conduct the forecast: physical (P), data-driven (DD),[5] or both.

[5] Data-driven approaches include methods normally referred to as statistical (e.g., ARIMA(X)), as well as methods often referred to as artificial intelligence approaches (e.g., ANN).

6. **User Models:**

   This criterion applies to forecasting tools only. It indicates whether the tool allows for the creation and usage of forecasting models designed by its user, or if it only enables forecasts using predefined models.

7. **License:**

   Indicates if the tool or service is available free of charge (F) or liable to pay costs (C).

In addition to the previous criteria, other considerations are applied to the information contained in the next sections:

1. The description of the tools and services comes directly from the websites on which they are profiled.

2. The presented information about the tools and services is readily accessible online, without requiring the contact with someone at the corresponding company.

3. Only tools and services, whose descriptions explicitly states their ability to forecast energy time series or whose companies are specialized in energy forecasting, are presented.

4. If a company offers the possibility of obtaining forecast for different values as a service, but does not differentiate the forecast of each value as separate services with distinctive names, then the forecast of those values is considered to be part of a single service.

5. If information about one of the utilized criteria is not found or mentioned by the tools or service providers, the abbreviation NIA (no information available) is used.

6. If it is explicitly mentioned that various forecast horizons and resolutions are possible, but no specifics are given, the word "variable" is going to be used.

7. If the type of load being forecast by a tool or service is not mentioned, it is assumed that it forecasts the electrical load.

**Note**:

All the information that is presented in the next sections is available in a table that can be found in dropbox.com/sh/4ebiyfrdrolhnrr/AAAm8ZK-5Z8qbecHDRtbbFpfa?dl=0. The table is going to be constantly updated by the authors of the present contribution. Furthermore, the reader of the present contribution is encouraged to test the information presented in this table and to contact the authors if further updates and/or corrections are required.

## ENERGY FORECASTING TOOLS

Examples of energy forecasting tools available online are provided in Table 5. Two of the presented tools are available free of charge, the first is the web-based tool called *RENES* developed at the Technical University of Crete (*TUC*). *RENES* utilizes forecast weather data available online as well as specific parameters of the renewable energy systems to conduct PV and wind power forecasts. Wind power forecasts are obtained by applying forecast wind speed data to a wind turbine's power curve[101] (i.e. a physical approach). The specifics of how the PV power forecasts are conducted can be found in the article by Panagopoulos et al.[101] Even though the tool's website and the article written by Panagopoulos et al.[101] state the possibility of obtaining short- to medium-term forecasts for any region in Europe, the specific forecast horizons are not given. In addition, a temporal resolution of one hour was observed when visualizing some forecast examples obtained by *RENES*.

The second tool available free of charge, is a tool tailored for PV energy forecasting. It was developed by the American National Renewable Energy Laboratory (*NREL*) and is named the *PVWatts Calculator*. The calculator's user is able to select a specific region on the globe and to specify the properties of the PV system (e.g., module type, tilt of the PV modules, inverter efficiency) for which the forecast is desired. After doing so, the calculator delivers an estimation of the energy which is going to be produced in each month of a given year (the forecasts are always from January to December, not for the next 12 months). According to the tool's website, the main goal of the calculator is to estimate the performance of potential grid-connected PV installations. Moreover, the website mentions that the forecasts are obtained by analyzing approximately 30 years of historical weather data. Interestingly, the *PVWatts Calculator* is not only implemented on its own website, but is also available on an open-source platform called the Global Atlas of Renewable Energy (irena.masdar.ac.ae). The Atlas possesses an interface called Geographic Information System (GIS), whose goal is to progressively integrate tools to allow for the assessing of technical and economical potential of renewable energy systems around the world. GIS integrates, in addition to the *PVWatts Calculator*, other free tools. Nonetheless, it is important to note that the additional tools are not necessarily forecasting tools (e.g., the Global Wind Atlas, globalwindatlas.com).

The remaining tools contained in Table 5 are created and sold by private companies. For example, *AleaSoft* provides the tool *AleaModelizer*, which offers its users several techniques (e.g., seasonal ARIMA (SARIMA), ANNs) for the creation of energy-related forecasting models with many exogenous variables, as well as variable resolutions. Yet, the possible forecast horizons are not explicitly mentioned. Even though there is no information - on the tools website - stating that the tool is specialized for energy-related forecasts, it is assumed that the creation of electrical load, gas load, PV power, and wind power forecasting models is possible.[6] Unlike *AleaSoft*, *ENFOR* offers a series of separate tools to forecast values at different horizons. Each of these tools is customized to forecast a different value, for example, electrical load (*LOADFOR*), heat load (*HEATFOR*), PV power (*SOLARFOR*) or wind power (*WINDFOR*). Furthermore, the option of running all the tools on servers managed by *ENFOR*, instead of locally, is mentioned on *ENFOR*'s website.

Tools lacking a description of their possible horizons and resolutions are *Escoware*'s Demand Forecasting System (*DFS*) and *DNV GL*'s *Synergi Forecaster*. The former is only briefly described as a cloud-based software solution for the forecasting of electrical load, while *DNV GL* describes the latter as a set of energy demand forecasting models (e.g., ARIMA, ANN) and features, but does not specify the kind of load (electrical, gas, heat) which can be forecast by the tool. *Escoware* offers another software called *PipeOps*, which includes a gas load forecasting tool. *Fraunhofer IOSB*'s *EMS-EDM Prophet* tool is able to forecast electrical, gas, and heat load for variable forecast horizons using a number of

[6]The assumption is made, due to the fact, that AleaSoft is specialized at forecasting those values, as their available services presented in the next section demonstrate.

different models (e.g., AR, ARX, ANN). Nonetheless, its properties description is only reserved to a PDF on its website, in which information regarding the temporal resolution and the possibility of user-created models using the available model structures is unavailable. The tool, *Nominator*, provided by *Matrica* also has a limited description. Its website only states that the tool is capable of forecasting electrical and gas load, as well as renewable energy generation (it is assumed that renewable encompasses PV and wind power) utilizing ANNs. The Germany-based company *Metalogic* offers a tool, *mpEnergy*, able to forecast electrical, gas, and heat load as well as PV and wind power. *Metalogic* describes this tool as able to deliver short-, medium, and long-term forecasts with different time resolutions, yet, explicit horizons or resolutions are not provided. An interesting feature of *mpEnergy* is its interfaces for 3$^{rd}$ party software integration (such as SAP, ORACLE). Another interesting tool is *GMDH-Shell*, described as a "forecasting software for your business" (i.e. inventory forecasts), yet also described as being able to forecast electrical load. The tool creates a forecasting model, based on the group method of data handling,[102] which complicates itself iteratively, until the forecast error stops decreasing. However, details regarding the user's involvement in the model's obtainment process are missing. Furthermore, *GMDH Shell* is offered free of charge for academic research. A further available tool is contained in *Etap*'s Power System Monitoring and Simulation (*PSMS*) software, which offers, in addition to monitoring tools, energy accounting tools, etc., a load forecasting tool. The forecasting tool can provide values up to seven days ahead, nonetheless, the possible resolutions are not mentioned. *Itron* is one of the companies, which offers the most information about its forecasting tool, *MetrixND*. This tool contains techniques like exponential smoothing, ARIMA, ANNs, etc., and is able to work with Excel spreadsheets, SQL Servers, and other media. *Reuniwatt*'s *Soleka* is specialized in PV power forecasting with three different forecast horizons (30min, 1h, and 1d), however, information regarding the models behind the forecasts as well as the resolution in which they are given is not provided. The German company *KISTERS* offers a tool able to create forecasting models for any type of value using a variety of methods (e.g. ANNs, ARMAX, exponential smoothing). Even though the possibility of obtaining forecast with different temporal resolutions is stated on the tool's website, no information regarding the possible forecast horizons is given.[7] Lastly, *SAS Energy Forecasting* is described as being able to deliver hourly forecasts for horizons ranging from one hour to 50 years ahead. Interestingly, the tool is supposed to allow the user to select the level of automation in the forecasting process. Moreover, customized forecasting solutions for individual energy providers are possible.

Finally, it is important to point out that only five of the 21 presented tools explicitly state the ability to provide probabilistic forecasts.

[7] The possibility of obtaining short-, medium-, and long-term forecast is only explicitly mentioned for energy sales forecast.

| Provider | Tool | Website | Horizon | Resolution | Forecast Value | | | | | Probabilistic Forecast | User Models | License |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Load | | | PV | W | | | |
| | | | | | E | G | H | | | | | |
| *Aiolos Forecast Studio* | *Vitec* | vitecsoftware.com | Variable | Variable | X | X | X | X | X | NIA | X | C |
| *AleaSoft* | *AleaModelizer* | aleasoft.com | NIA | Variable | X | X | - | X | X | NIA | X | C |
| *DNV GL* | *Synergi Forecaster* | dnvgl.com | NIA | NIA | X | - | - | - | - | NIA | NIA | C |
| *ENFOR* | *HEATFOR* | enfor.dk | NIA | NIA | - | - | X | - | - | NIA | - | C |
| *ENFOR* | *LOADFOR* | enfor.dk | NIA | NIA | X | - | - | - | - | X | - | C |
| *ENFOR* | *SOLARFOR* | enfor.dk | Variable | Variable | - | - | - | X | - | X | - | C |
| *ENFOR* | *WINDFOR* | enfor.dk | Variable | Variable | - | - | - | - | X | X | - | C |
| *Escoware* | *DFS* | escoware.com | NIA | NIA | X | - | - | - | - | NIA | NIA | C |
| *Escoware* | *PipeOps* | escoware.com | Variable | NIA | - | X | - | - | - | NIA | NIA | C |
| *Etap* | *PSMS* | etap.com | up to 7d | NIA | X | - | - | - | - | NIA | NIA | C |
| *Fraunhofer IOSB* | *EMS-EDM Prophet* | edm-prophet.de | Variable | NIA | X | X | X | - | - | NIA | NIA | C |
| *GMDH Shell* | *GMDH-Shell* | gmdhshell.com | Variable | NIA | X | - | - | - | - | NIA | NIA | C/F |
| *Itron* | *MetrixND* | itron.com | Variable | Variable | X | - | - | - | - | X | X | C |
| *KISTERS* | *BelVis Pro* | kisters.eu | NIA | Variable | X | X | X | X | X | X | X | C |
| *Matrica* | *Nominator* | matrica.co.uk | NIA | NIA | X | X | - | X | X | NIA | NIA | C |
| *Metalogic* | *mpEnergy* | metalogic.de | Variable | Variable | X | X | X | X | X | NIA | NIA | C |
| *NREL* | *PVWatts Calculator* | pvwatts.nrel.gov | 1Y | 1M | - | - | - | X | - | - | - | F |
| *PSI* | *PSIcontrol* | psienergy.de | NIA | NIA | X | - | - | X | X | NIA | NIA | C |
| *Reuniwatt* | *Soleka* | reuniwatt.com | 30min, 1h, 1d | NIA | - | - | - | X | - | NIA | NIA | C |
| *SAS* | *SAS Energy Forecasting* | sas.com | 1h-50Y | 1h | X | - | - | - | - | NIA | X | C |
| *TUC* | *RENES* | intelligence.tuc.gr | NIA | 1h | - | - | - | X | X | - | - | F |

Table 5: Energy forecasting tools.

## ENERGY FORECASTING SERVICES

Table 6 offers an overview of several forecasting services found on the internet. The table reveals that most companies offer different services depending on their forecast value. For example, *AleaSoft* provides a series of distinct forecasting services: four for load, one for PV power, and one for wind power. Each of *AleaSoft*'s first three load forecasting services (*AleaDemandShort*, -*Mid*, -*Long*) is for different forecast horizons and resolutions, as shown in Table 6. In addition, *AleaSoft* mentions that the forecasts are tailored for specific consumer types (e.g., households, industry). However, if forecasts for a costumer's portfolio containing different types are required, *AleaSoft* offers its *AleaDemandRetail* service, which can provide forecasts for various horizons. *AleaSoft* also offers PV and wind power forecasting services called *AleaSolar* and *AleaWind*. According to *AleaSoft*'s website, modeling tools based on ANNs, genetic algorithms, and statistics are utilized. Pattern Recognition Technologies (*PRT*) similarly offers three separate services for each of the considered forecast values. According to the services' description, the forecasts are obtained through an ensemble of intelligent system based models, capable of capturing non-linear relationships. Both the load (gas and electrical) and wind power forecasting services offer their forecast in hourly and sub-hourly resolutions. However, the specific sub-hourly resolutions supported are not explicitly mentioned, hence only the one hour resolution is given in Table 6. Additionally, *PRT* offers only for the case of electrical load, medium- and long-term forecasts for forecasts horizons of up to five years in an hourly or daily resolution. Like *AleaSoft* and *PRT*, *Vaisala* offers two separate services based on data-driven techniques. The first, *Premium Wind Forecasting*, is able to deliver wind power forecasts for several horizons (1h, 1d, and 1w). The second, provides hourly PV power forecasts for a forecast horizon of two and a half days.

Interestingly, only five of the presented services utilize physical approaches to obtain their results. Two of them are offered by *energy&meteo systems* and are called *Suncast* and *Previento*. They utilize, as classical physical approaches do, NWP data to work, but also implement a process called Kombi-Box in which different prediction models are combined, with the most accurate one weighted the strongest, to obtain, according to their website, a more accurate forecast. From the five services with physical models, three of them combine their physical methods with data-driven techniques in order to refine their forecasts. *EWC*'s *Solar* and *Ventus* services combine their physical approaches with techniques like deep neural networks, while *Scirocco* uses – in addition to the physical models – an error back-propagation scheme to adjust several unknown variables.

Outside of the previous examples, the majority of services gathered rely on pure data-driven approaches to obtain their forecasts. For example, the Spain-based *Nnergix* conducts its forecast – in both its *EOforecast* and *PVforecast* services – via data driven methods, referred by them as artificial intelligence technologies through data mining processes. The Germany-based company *KISTERS* mentions in their *BelVis Pro* tool product sheet that forecasts can also be delivered as a service by email or file transfer protocol (FTP). Nonetheless, the product sheet only states the possibility of obtaining intraday, short-, medium-, and long-term load (i.e., electricity, gas, heat, and water) forecasts. *Vortex* offers in a wide range of formats (e.g., TXT, CSV, XML) wind power, wind speed, and wind direction forecasts for seven to 10 days horizons in hourly or higher resolutions, which can be updated several times a day. However, the utilized techniques are not described further. *TESLA, Inc.* offers another interesting service, which utilizes the so-called Tesla Model to obtain forecasts for load (electrical, gas, and steam (i.e. heat)), PV power, and wind power. The Tesla Model is described as being formed by two parts: a stratified non-linear regression and an error correction filter. Furthermore, *TESLA, Inc.* explicitly states that for PV and wind power only forecasts with short forecast horizons are possible, whereas for load medium and long horizons are available. However, the details on the available forecast horizons are not given. *DNV GL* provides not only a previously described tool, but also a forecasting service for PV and wind power forecast with an hourly resolution and a maximal horizon of 15 days, yet again, specifics on the forecasting methods are not given. Lastly, *AWS Truepower* offers forecasts of volatile renewable power at variable forecast horizons (no specifics are given), accessible via web-based interface.

It is important to note that none of the presented services is freely available, and only 10 of the 24 explicitly offer probabilistic forecasts.

| Provider | Service | Website | Horizon | Resolution | Forecast Value | | | | | Probabilistic Forecast | Approach | | License |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Load | | | PV | W | | P | DD | |
| | | | | | E | G | H | | | | | | |
| *Aeolis* | *Scirocco* | windknowhow.com | Variable | NIA | - | - | - | - | X | NIA | X | X | C |
| *AleaSoft* | *AleaDemandShort* | aleasoft.com | 10d | 1min,15min, 30min,1h | X | X | - | - | - | X | - | X | C |
| *AleaSoft* | *AleaDemandMid* | aleasoft.com | 3Y | 1h | X | X | - | - | - | X | - | X | C |
| *AleaSoft* | *AleaDemandLong* | aleasoft.com | 15Y | 1M | X | X | - | - | - | X | - | X | C |
| *AleaSoft* | *AleaDemandRetail* | aleasoft.com | Variable | NIA | X | X | - | - | - | NIA | - | X | C |
| *AleaSoft* | *AleaSolar* | aleasoft.com | 1-10d | 1h | - | - | - | X | - | NIA | - | X | C |
| *AleaSoft* | *AleaWind* | aleasoft.com | 1-10d | 1h | - | - | - | - | X | NIA | - | X | C |
| *AWS Truepower* | - | awstruepower.com | Variable | NIA | - | - | - | X | X | NIA | NIA | | C |
| *DNV GL* | - | dnvgl.com | up to 15d | 1h | - | - | - | X | X | X | NIA | | C |
| *enercast GmbH* | *enercast* | enercast.de | up to 10d | PV: 15min, W: NIA | - | - | - | X | X | NIA | - | X | C |
| *energy&meteo systems* | *Previento* | energymeteo.de | up to 10d | 5min-1h | - | - | - | - | X | X | X | - | C |
| *energy&meteo systems* | *Suncast* | energymeteo.de | up to 10d | 5min-1h | - | - | - | X | - | NIA | X | - | C |
| *EWC* | *Solar* | weather-consult.com | up to 14d | 15min | - | - | - | X | - | NIA | X | X | C |
| *EWC* | *Ventus* | weather-consult.com | up to 14d | 15min | - | - | - | - | X | X | X | X | C |
| *KISTERS* | - | kisters.eu | Variable | NIA | X | X | X | - | - | NIA | NIA | | C |
| *Nnergix* | *EOforecast* | nnergix.com | 6h-10d | 1h | - | - | - | - | X | X | - | X | C |
| *Nnergix* | *PVforecast* | nnergix.com | 6h-10d | 1h | - | - | - | X | - | X | - | X | C |
| *PRT* | *e-AccuWind* | prt-inc.com | up to 7d | 1h or less | - | - | - | - | X | NIA | - | X | C |
| *PRT* | *e-LoadForecast* | prt-inc.com | E & G: up to 15d E: up to 5Y | E & G: 1h or less E: 1h,1d | X | X | - | - | - | NIA | - | X | C |
| *PRT* | *e-solarForecast* | prt-inc.com | up to 7d | 1h | - | - | - | X | - | NIA | - | X | C |
| *TESLA, Inc.* | - | teslaforecast.com | Variable | NIA | X | X | X | X | X | X (only for Load) | - | X | C |
| *Vaisala* | *Premium Wind Forecasting* | vaisala.com | 1h, 1d, 1w | NIA | - | - | - | - | X | NIA | - | X | C |

| Provider | Service | Website | Horizon | Resolution | Forecast Value | | | | | Probabilistic Forecast | Approach | | License |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Load | | | PV | W | | P | DD | |
| | | | | | E | G | H | | | | | | |
| *Vaisala* | - | vaisala.com | 2.5d | 1h | - | - | - | X | - | NIA | - | X | C |
| *Vortex* | *Forecast* | vortexfdc.com | up to 7-10d | 1h or less | - | - | - | - | X | X | - | X | C |

Table 6: Energy forecasting services.

# CONCLUSIONS

As of today, a great variety of energy-related forecasting options exists. The sheer number of these options reflected by the here presented tools and services, will continue to increase in coming years, and will continue to play an increasingly important role in the future Smart Grid. For such reason, a clear understanding of general aspects of energy-related forecasting and the properties of forecasting tools and services currently available, such as, their forecast horizons, resolutions, their type of models, etc., is necessary. The present contribution offers brief summaries regarding the basics of time series forecasting as well as energy-related forecasting. Additionally, an overview of energy forecasting tools and services that can be found online – for both load and volatile renewable power – is presented. These tools and services are categorized to allow for comparisons and a better understanding of what each one of them offers. Moreover, the present contribution advocates for the creation of a competition, of sorts, in which the tools and services providers test their approaches on a benchmark dataset, to offer a comparison of forecast accuracy. This assessment is certainly relevant, but was not possible to include at the time of writing. Such a competition would provide relevant information for users and researchers, as well as for providers looking at making their forecasting tools and/or services more competitive.

It can easily be concluded that the majority of forecasting tools and services come from private companies and that free options to obtain energy-related forecasts are not broadly available. Furthermore, there seems to be an imbalance between the forecasting tools and services, with the former focusing on load forecasting, while the latter focusing on volatile renewable power forecasting.

Finally, as stated earlier, the readers of the present contribution are encouraged to contact the authors regarding needed corrections and updates on the energy forecasting tools' and services' provided, in order to keep the online table[8] current and as precise as possible.

[8]Found under dropbox.com/sh/4ebiyfrdrolhnrr/AAAm8ZK-5Z8qbecHDRtbbFpfa?dl=0

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