First Steps Towards a Systematical Optimized Strategy for Solar Energy Supply Forecasting

Robert Ulbricht[2], Ulrike Fischer[1], Wolfgang Lehner[1], and Hilko Donker[2]

[1] Technische Universität Dresden, Database Technology Group, Germany
[2] Robotron Datenbank-Software GmbH, Dresden, Germany

Abstract. The capacity of renewable energy sources constantly increases world-wide and challenges the maintenance of the electric balance between power demand and supply. To allow for a better integration of solar energy supply into the power grids, a lot of research was dedicated to the development of precise forecasting approaches. However, there is still no straightforward and easy-to-use recommendation for a standardized forecasting strategy. In this paper, a classification of solar forecasting solutions proposed in the literature is provided for both weather- and energy forecast models. Subsequently, we describe our idea of a standardized forecasting process and the typical parameters possibly influencing the selection of a specific model. We discuss model combination as an optimization option and evaluate this approach comparing two statistical algorithms in a case study. Finally, we sketch research challenges we are planning to investigate in future work.

Keywords: solar energy, energy forecast model, classification, ensemble

1 Introduction

The capacity of renewable energy sources (RES) constantly increases world-wide due to governmental funding policies and technological advancements. Unfortunately, most of the grid-connected RES installations are characterized by a decentralized allocation and a fluctuating output owed to the changing nature of the underlying powers. Coincidentally, today's available transformation and storage capabilities for electric energy are limited and cost-intensive, which is the primary reason for the increasing interference of renewable energy output with power network stability. Efficient and dedicated forecasting methods will help the grid operators to better manage the electric balance between power demand and supply in order to avoid unstable situations or even possible collapses in the near future. Respectively, a lot of research has been conducted in the past years by different communities trying to cope with this challenge. Despite of the large amount of available related work and both scientific and practical optimization ideas, there is still no straightforward and easy-to-use recommendation for a standardized forecasting strategy. Comparing the results obtained while executing different experimental approaches is difficult, as most of the presented cases are bound to a specific region where the real-world data-set originally belongs to. Further, there is no constant form of result evaluation across all publications, as different error metrics are applied to measure output quality.

In this paper, we address the problem of a systematical optimization for solar energy forecasting strategies conducting an analysis of state-of-the-art approaches. The paper is organized as follows: In Section 2 we review and classify models proposed in the literature to predict (1) weather influences and (2) the output of solar energy production units. In Section 3, the energy forecasting process is described and relevant parameter settings and exogenous influences for the model selection decision are discussed against that background. In Section 4 we evaluate the performance of an exemplary ensemble model which combines the forecast output of two popular statistical prediction methods using a dynamic weighting factor. Finally, we conclude and outline additional research directions for our future work in Section 5.

2 Energy Supply Forecasting Approaches

The prediction of energy time series is a classical application of time series analysis methods. Thus, there is a long research history related to electricity load forecasting, where a range of sophisticated high-quality models have been developed and classified (i.e. compare the work of Alfares and Nazeeruddin [2]). In contrast, the need for energy supply forecasting is a much more recent topic, as the challenge of grid-connected RES penetrating the distribution systems has emerged just a couple of years ago. Nevertheless, both energy demand and supply forecasting approaches make use of similar techniques.

2.1 Weather Forecast Models

In order to make energy supply planning rational, forecasts of RES production have to be made based on the consideration of weather conditions. As for solar energy production, the most influencing factor for output determination is the quality of the solar irradiation forecast. Consequently, the use of precise weather forecast models is essential before reliable energy output models can be generated. Although this step is orthogonal to a grid operators core activities (weather data is usually obtained from meteological services), a basic understanding of the underlying principles is helpful when choosing a specific energy output model.

Numerical Weather Prediction. Complex global *numerical weather prediction* (NWP) models are a modern and common method to predict a number of variables describing the physics and dynamic of the atmosphere, which are then being used to derive the relevant weather influences at a specific point of interest. These are e.g. the *European Center for Medium-Range Weather-Forecasts Model*[3] (ECMWF), the *Global Forecast System* (GFS) from National Centers for

[3] http://www.ecmwf.int

Environmental Prediction[4] or the *North American Mesoscale Model*[5] (NAM). As they have a coarse spatial and temporal resolution, several post-processing and correction techniques are applied in order to obtain down-scaled models of finer granularity (e.g. Model Output Statistics). A quality benchmark was conducted by Lorenz et al [13], where European ground measurement data is used to compare the performance of each NWP including different scientific and commercial post-processing approaches.

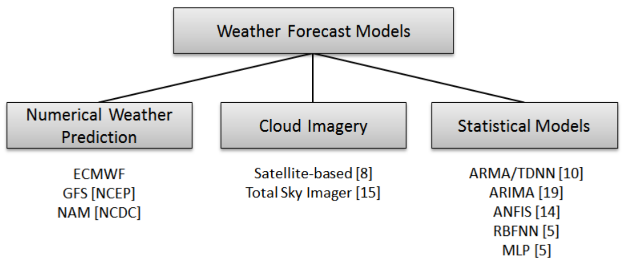

Fig. 1. Classification of weather forecasting models

Cloud Imagery. The influence of local cloudiness is considered to be the most critical factor for the estimation of solar irradiation, especially on days with partial cloudiness where abrupt changes may occur. The use of satellite data can provide high quality short-term forecasts, as geostationary satellites like METEOSAT provide half-hourly spectrum images with a resolution from 1 to 3 square kilometers. Clouds are detected by processing these images into cloud-index images. To predict the future position of a cloud over ground, two consecutive cloud-index images are interpolated using motion vectors [8]. A similar method is the use of *Total Sky Imagers*, which enables real-time detection of clouds in hemispherical sky images recorded by ground-based cameras using sophisticated analytical algorithms [15].

Statistical Models. Furthermore, there are several studies treating the forecasting of solar radiation based on historical observation data using common time series regression models like ARIMA, *Artificial Neural Networks* (ANN) or *Fuzzy-Logic* models (FL). An analysis published by Reikard shows that after comparing various regression models, ARIMA in logs with time-varying coefficients performs best, due to its ability to capture the diurnal cycle more effectively than other methods [19]. Ji and Chee [10] propose an combination of ARMA and a *Time Delay Neural Network* (TDNN). Dorvlo et al discuss the usage of two ANN-models: *Radial Basis Functions* (RBF) and *Multilayer Perceptron* (MLP) [5]. Martin et al [14] compare the performance of auto-regressive

[4] http://www.ncep.noaa.gov
[5] http://www.ncdc.noaa.gov

models (AR) against ANN and Adaptative-network-based fuzzy inference system (ANFIS). As such statistical models usually are considered being domain-neutral, their characteristics are discussed more in detail in the subsequent section.

2.2 Energy Forecast Models

Any output from the weather models described above must then be converted into electric energy output. According to the underlying methodology, the existing solutions can be classified into the categories of *physical*, *statistical* and *hybrid* methods as presented in Figure 2.

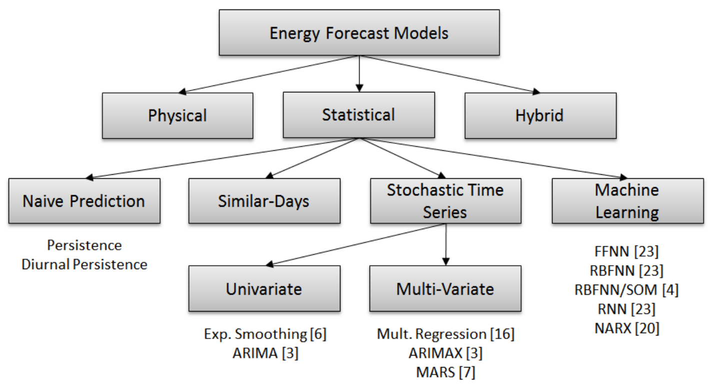

Fig. 2. Classification of energy forecasting models

Physical Models. All forecasting approaches mainly relying on a renewable power plant's technical description concerning its ability to convert the introduced meteorological resources into electrical power are summarized by the term *physical model*. Taking into account external influences derived from NWP, atmospheric conditions and local topography, once they are fitted they are accurate and do not require historical output curves. Especially the latter makes them suitable for estimating the future output of planned or recently installed RES units. Applications of physical models are more frequently found for wind power prediction, but are also used for solar energy forecasts. For example, if we consider the electrical energy P_E extracted from the NWP for global radiation G_{nwp} by a PV panel, the equation for a simplyfied model is as follows:

$$P_E = \alpha G_{nwp} A \tag{1}$$

where α is the conversion efficiency of the solar panel and A is its surface size. Improvements of this method are demonstrated by Iga and Ishihara [9] including the outside air temperature, or Alamsyah et al, using the panel temperature [1] as additional parameters. The major disadvantage of physical models is that they are highly sensitive to the NWP prediction error. Furthermore, they have to be designed specifically for a particular energy system and location. As a consequence, the usage of such models requires detailed technical knowledge about characteristics and parameters of all underlying components, thus making them more relevant for energy plant owners or producers than for grid operators.

Statistical Models. *Naive Prediction.* The most straightforward approach to determine a time series' future value denoted as P_{p+1} would be a naive guess, assuming that next periods' expected energy output will be equal to the observations of the current period P_p. This method is called *naive* or *persistent prediction*. The distinctive cycle of solar energy is expressed by choosing a period of 24 hours, which implicates *diurnal persistence*. Although very limited due to its inability to adopt to any influences and therefore providing results of low preciseness, it is easy to implement and commonly used as a reference model to evaluate the performance of concurrent, more sophisticated forecasting approaches. Using complex forecasting tools is worthwhile only if they are able to clearly outperform such trivial models.

Similar-Days Model. Based on the concept of diurnal persistence, improved forecasts can be computed by selecting similar historical days using suitable time series similarity measures. These models are very popular for load forecasts (e.g. compare [17]), where weather-awareness plays a minor part compared to the influence of consumption-cycle patterns derived from historical data. As for solar energy forecasts, such models are used whenever there is no NWP available at all or the prediction error included naturally in the NWP is estimated as too high to provide reliable energy output forecasts.

Stochastic Time Series. Depending on the number of influencing parameters, two groups of models can be distinguished: *Uni-* and *Multivariate* models. Univariate models are calculated based on the time series' history only. Well known representatives of that group are *Auto-Regressive (Integrated) Moving Average* models (ARMA/ARIMA), which can best be described as a stochastic process combining an auto-regressive component (AR) to a moving average component (MA). Dunea et al [6] propose the consideration of *Exponential Smoothing* as an effective alternative for one-period ahead forecasts. In contrast, multivariate models allow for the integration of exogenous parameters. *Multiple Regression* methods like ARIMAX (ARIMA with exogenous influences) are a popular choice whenever there is a linear correlation structure expected in two time series [16]. In the case of solar energy prediction, this is given by the dominating dependency of energy output on the global radiation values from the NWP. Historical observation data is used to derive the regression coefficients. Bacher et al demonstrate the performance of an ARIMA model using a clear-sky-normalization for short-term forecasts [3]. As an extension to linear modeling *Multivariate Adaptive Regression Splines* (MARS), a methodology developed by Friedman [7], is used in the energy domain to generate more flexible, nonlinear models.

Machine Learning. The use of machine learning methods is a common approach to forecast a time series' future values , as they are seen as an alternative to conventional linear forecasting methods. Reviewed literature shows that ANN have been successfully applied for forecasts of fluctuating energy supply. ANN learn to recognize patterns in data using training data sets. For example, the use of neural networks is proposed by Yona et all [23] due to their examination of the *Feed-Forward* (FFNN), the *Radial Basis Function* (RBFNN) and the *Recurrent Neural Network* (RNN) for solar power forecasting based on NWP input and historical observation data. A similar approach is described by Chen et al [4], where a RBFNN is combined with a weather type classification model obtained by a *Self Organizing Map* (SOM). In contrast, Tao et al compute hourly energy forecasts using an adaptive NARX network combined with a clear-sky radiation model, which allows for forecasts without including NWP data and still outperforms non-adapting regression-based methods [20].

Hybrid Models. Any combination of two or more of the above described methods is known as a *hybrid model*. The use of such hybrid approaches has become more popular as it offers the possibility to take advantage of the strongest points of different stand-alone forecasting techniques. The basic idea of combining models is to use each methods' unique features to capture different patterns in the data. Theoretical and empirical findings from other domains suggest that combining linear and non-linear models can be an efficient way to improve the forecast accuracy (e.g. [24]), so hybrid models seem to be a promising approach that can potentially outperform non-hybrid models individually. A successful application of this idea is provided e.g. by the work of Ogliari et al [18].

3 Energy Forecasting Process

As shown in the previous section, there are plenty of possibilities to compute forecasts for fluctuating energy production units. But choosing the optimal forecasting model for a given use case is an important decision to make and requires expert knowledge. Figure 3 describes the forecasting process steps: First, the specific requirements of the desired forecast have to be *analyzed*. Second is the *selection* of a suitable algorithm to best describe the observations. Next, the parameters for the chosen model have to be *estimated* before the *forecasting* task is executed. After *evaluating* the obtained results, this decision might be reconsidered in case of too high and therefore unsatisfying prediction errors. From the description of the introductory mentioned forecasting techniques, we derive that the choice of the appropriate forecasting models depends on the amount and quality of external information, the applied forecast horizon, the data aggregation level and the availability of historical observation data. Furthermore, we consider *model combination* as an optimization option, a strategy also known under the term of *ensemble prediction*. Ensembles can be created manually based on user preferences and experiences or by using machine driven optimization approaches. However, another consideration in choosing among forecasting models is their efficiency, so there is an economic preference for inexpensive and easy-to-use methods if they promise satisfying results.

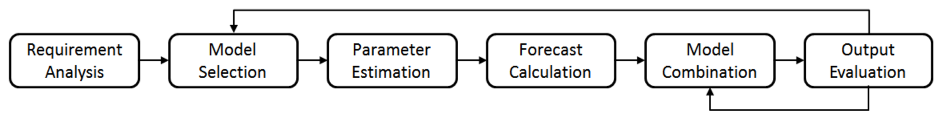

Fig. 3. Typical forecasting process steps

Context Information. The availability of weather forecasts is an essential condition for both physical and multiple-regression forecasting models, most importantly the quality of solar irradiation values. Predicted outside air temperature can be used to estimate a panels future surface temperature, as energy output is reduced significantly on hot cells. In a similar manner, wind speed can indicate cooling effects. Further, technical information like the panels inclination angle and production year (due to the fact that their conversation efficiency decreases over age) are interesting. As for environmental influences, cleaning cycles are relevant because polluted panels will produce significantly less energy, which is a considerable influence in dry and dusty areas. Also, in some regions, detected snow coverage might prevent any energy output at all.

Forecast Horizon. Studies show that the forecast horizon for which a generated model has to be applied is an important parameter while choosing an appropriate prediction approach. In the energy domain, forecast horizons are determined depending on the requirements of the underlying business process. Normally we can distinguish the following categories: now-casts (up to 4 hours ahead), short-term (up to 7 days ahead) and long-term forecasts (more than 7 day ahead). Focusing on the grid operators activities related to renewable energy integration, we find that intra-day and day-ahead horizons represent the most relevant time scales for operations [19], while long-term predictions are of special interest for resource and investment plannings.

Spatial and Temporal Aggregation. Forecast quality of statistical or physical models will vary strongly depending on the level of spatial aggregation of the underlying energy time series. Since it is well known that the overall impact of single peak values decreases with increasing size of the chosen aggregates, forecasts computed on single or disaggregated time series usually contain the risk of higher average prediction errors. In contrast, following an agglomerative or bottom-up approach by creating different aggregation levels might lead to better results on higher levels (e.g. average cloudiness in a region can be predicted more accurately than cloudiness at a particular site [12]), but complicates the integration of available context information, especially in the case of influences characterized by strong locality. The use of clustering techniques to create hierarchical aggregations of RES time series is a matter of a separate study [22] in progress. Temporal aggregation can be considered if the granularity of source time series needs to be reduced in order to obtain forecasts of lower resolution.

History Length. Stochastic approaches create a forecast model over the historical supply curves. The size of available history influences the accuracy of the forecasting result, as a longer history length might be suitable for learning repeatable patterns, while a shorter history length is more beneficial for strongly fluctuating time series. The latter requires a continuous adaption of the forecast models and, possibly, also of the history length. However, determining the best model parameters involves multiple iterations over the time series history which is an expensive process especially on large data sets. Reducing the history length can therefore significantly speed up model creation. Previous research in this area [21] proposes an I/O-conscious skip list data structure for very large time series in order to determine the best history length and number of data points for linear regression models.

4 Model Selection - A Case Study

In this section we analyze the impact of the energy model selection parameters previously described on the forecast output, including the model combination task. Therefore, we compare the forecast quality of two stochastic models belonging to the multi-variate class: (A) a simple linear model based on principal component analysis and multivariate regression from the MIRABEL project[6] and (B) a commercial library using the more complex non-linear MARS algorithm. The forecasts are compared both individually and in combination against a naive, weather-unaware reference model (REF) based on the similar-day-method.

4.1 Methodology

The Data. To cope with the recently introduced model selection criteria of spatial aggregation, we include three observed solar energy output curves into our scenario: (1) A single, disaggregated PV-installation located in central Germany denoted as DA, (2) an aggregate build of all measured PV-installations available in the same local distribution system denoted as DS and (3) an aggregate build of all PV-installations attached to the superior transmission system denoted as TS. DA and DS were provided by a cooperating distribution system operator, while TS was obtained from a public website[7]. All time series have a resolution of 15 minutes and cover the whole year 2012. Corresponding weather data including measurements of solar irradiation, air temperature and wind speed with a resolution of 1 hour is available from a weather station run by a meteorological service[8], located within the distribution networks' range. Using only observed weather data eliminates the NWP prediction error thus allowing for an evaluation of the energy model performance itself.

[6] http://www.mirabel-project.eu/
[7] http://www.50hertz.com
[8] http://wetterstationen.meteomedia.de

Experimental Setting. From our source time series, we use the first 11 months of historical data for training, and the last month for forecast evaluation. To cover both intra-day and day-ahead terms with our scenario, we define forecast horizons of 2, 12 and 24 hours ahead, starting each day at 00:15. After computing a forecast, the model building horizon is adopted by adding the forecast horizon length to the model horizon, thus extending the available history length accordingly with each completed iteration. This effect simulates the integration of newly arriving observations in the forecasting process, which can then be compared with the forecasted values and used to qualify the forecast model. Therefore, the number of forecasting models required to cover the whole month is 372 for a horizon of 2 hours, 62 (12h) and 31 (24h) respectively. In order to derive the optimal combination ratio between two analyzed algorithms A and B, we introduce the variable percentual weighting factor λ. The final energy forecast P'_t is then computed by

$$P'_t = \lambda P'_{At} + (1 - \lambda) P'_{Bt} \tag{2}$$

where P'_{At} is the forecasted value from algorithm A and P'_{Bt} is the forecasted value from algorithm B for a timestamp t.

Output Evaluation. To evaluate the quality of the forecasted values, different statistical error metrics are available. On the one hand, the *root mean square error* (RMSE) is the recommended measure and main evaluation criterion for intra-day forecasts, as is better addresses the likelihood of extreme values [11]. As the RMSE returns absolute values, we have to use a normalized form in order to compare the models performance on output curves of different aggregation scales. The *normalized root mean square error* (nRMSE) is achieved by

$$nRMSE = \frac{RMSE}{P_{max}} * 100 \tag{3}$$

with P_{max} being the maximum observed power output. On the other hand, for forecasts with day-ahead horizons or above, the percentage difference between observed and predicted power output might be more interesting. This is expressed by the *mean absolute percentage error* (MAPE). Non-daylight hours (values with timestamps before 8 am and after 4 pm) and all resting sero observation values are excluded from error calculation. The latter also implies that the effects of snow coverage or measurement failures are removed completely from the results.

4.2 Experimental Results.

Our results displayed in Table 1 show that both linear (A) and non-linear (B) models clearly outperform the similar-days reference model (REF) individually in most of the analyzed cases in terms of nRMSE. Also, in general the non-linear model shows better results than the linear model which indicates that the inclusion of historical values improves output quality. Nevertheless some constellations can be found where model combinations perform slightly better than individual models. Regarding the impact of the chosen forecast horizon, we observe that the quality of algorithm B is decreasing with longer horizons (compare Figure 4) and almost identical to model A for day-ahead periods while model A provides constant values. This can also be explained by the exponential influence of historical values, which has no effect on model A. We suspect that model A can outperform model B on short- and mid-term forecasts, which have not been covered by the presented scenario. Surprisingly, all models show the lowest pre-

REF	**λA**	**λB**	**DA2**	**DA12**	**DA24**	**DS2**	**DS12**	**DS24**	**TS2**	**TS12**	**TS24**
100%	-	-	18,46	19,97	23,99	18,72	21,42	25,69	10,56	11,76	14,33
-	100%	0%	14,77	14,77	14,77	15,86	15,86	15,86	12,08	12,08	12,08
-	80%	20%	13,98	14,28	14,79	14,97	15,39	15,80	10,84	11,41	**12,01**
-	50%	50%	13,04	13,74	14,89	14,11	15,07	15,93	9,61	**10,85**	12,13
-	20%	80%	**12,48**	13,50	15,12	13,92	15,28	16,35	9,37	10,92	12,54
-	0%	100%	12,61	**13,45**	**14,74**	**13,53**	**14,88**	**15,52**	**9,37**	11,15	12,74

Table 1. Quality of forecast results using nRMSE evaluation metric

ciseness on the DS aggregate where a better performance was expected than on the disaggregation DA. The possibly included share of self-consumption units (prosumers) may explain the reduction of correlation values, as those measurements are hidden within the observed output curve thus requiring an individual treatment (e.g. using combined energy demand and supply models) which needs to be further investigated. It is also noted that all models perform best on the highest aggregate TS (compare Figure 5). Although the correlation of weather information observed at only one location is not a representative influence on that supra-regional level, the effect of weather-awareness seems to be completely neutralized by the impact of high aggregation.

5 Conclusions

In this work we have shown that the forecasting of solar energy output is a two-step approach, typically requiring a weather- and an energy forecast model. As for the energy forecast, possible choices can be selected amongst physical, statistical and hybrid models. The selection of an appropriate model depends on various conditions and can be described as an iterative step in the forecasting process. Combining models offers additional optimization options whenever there is no model to be found that individually outperforms in all given situations, as demonstrated in the previous section against the parameters of forecast horizon and spatial aggregation. For our future work, we think that conducting a more complex and global benchmark covering most of the reviewed approaches and additional scenarios will provide useful information on how to systematically select an optimal energy model and might unlock the potential towards establishing industry standards regarding the application of forecasting strategies and output evaluation criteria.

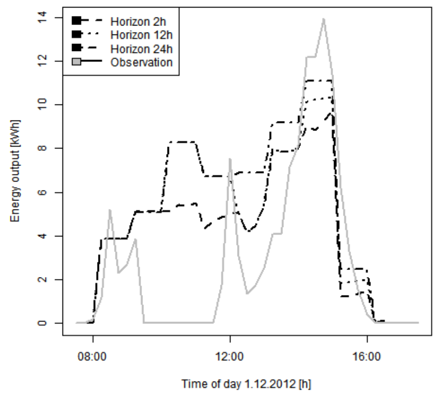

Fig. 4. Impact of chosen forecast horizon on DA level using non-linear regression (model B)

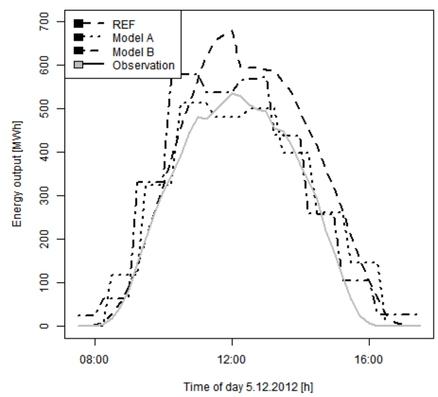

Fig. 5. Comparison of all models' performance on TS aggregation level and 12h-ahead horizon

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