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Dealing with Uncertainty: An Empirical Study on the Relevance of Renewable Energy Forecasting Methods

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Abstract. The increasing share of fluctuating renewable energy sources on the world-wide energy production leads to a rising public interest in dedicated forecasting methods. As different scientific communities are dedicated to that topic, many solutions are proposed but not all are suited for users from utility companies. We describe an empirical approach to analyze the scientific relevance of renewable energy forecasting methods in literature. Then, we conduct a survey amongst forecasting software providers and users from the energy domain and compare the outcomes of both studies.

Keywords: Renewable energy forecasting · Practical relevance · Machine Learning

1 Introduction

As much as for any industry, forecasting time series is traditionally an important issue in the energy domain. In corporate areas like distribution or pricing, many decisions always had to be made based on uncertain data. Nowadays, the capacity of renewable energy sources like solar and wind power constantly increases world-wide and with this the necessity of conducting pre-dispatch studies is created. Although this is a standard procedure for conventional power plants where the future energy output can be calculated based on the available fossil resources, the fluctuating nature of renewable energy sources causes additional uncertainty about the expected amount of produced energy and therefore challenges the electric balance between power demand and supply. To allow for their better integration into the power grids and energy markets, the development of precise forecasting approaches for the supply side emerged as a relatively young research topic compared to the long history of energy demand forecasting. With this, interesting new problems arise for researchers and are currently treated by

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a multitude of very active communities. Their results are then implemented in commercial software solutions, brought back to the energy industry and, if successful, adopted by the market. As usual, one problem remains: How to identify the optimal solution propositions for implementation? There are numerous literature reviews available for solar (e.g. Glassley et al. [3] or Yadav and Chandel [12]) and wind power prediction (e.g. Monteiro et al. [8], Colak et al. [2] or Tascikaraoglu and Uzunoglu [10]) and they do give a good overview on the topic or draw attention to recent research trends, but usually few things are said about the overall significance of the discussed approaches within the related research field or in practice. Another alternative is forecasting competitions like *GEFCom*[1], as they try to bridge the gap between the worlds of science and industry by offering interesting technical challenges to the community. Although such competitions provide well comparable results because all general conditions are pre-defined, the insights published by Hong et al. [4] show the limitations with the simulation of real-world situations, where for example forecasts have to be provided on a rolling basis for intra-day or day-ahead periods. Apparently, there seems to be no serious option beside the classical trial-and-error-approaches. The present work aims at reducing the necessary efforts by providing answers to the following questions: (1) How strong is the current scientific interest in renewable energy forecasting methods, (2) which methods are the preferred research topics, and (3) can the most promising directions be identified? This is then compared to the industry view where we analyze the methods currently implemented in the available software products (4), the quality evaluation criteria commonly used (5) and the users' expectations of such solutions (6).

In this paper, we describe an empirical approach to analyze the current state-of-the-art for forecasting methods used to predict the output of fluctuating renewable sources. The paper consists of 4 sections, the first being this introduction. In Sect. 2, we describe the methodology applied for the empirical review of scientific publications and the obtained results. Section 3 contains a report on a survey conducted among forecasting software providers and users from the energy industry. Finally, we summarize our findings in Sect. 4.

2 Scientific Relevance

In this section, we analyze the scientific relevance of renewable energy forecasting methods based on reviewed literature. We describe the applied methodology before we present and discuss the results. Thereby we differentiate between quantitative and qualitative aspects.

2.1 Methodology

Our first step is to determine a representative population for the analysis. We search the *IEEE*, *ScienceDirect*, *SpringerLink* and *WileyOpenLibrary* online

[1] Global Energy Forecasting Competition, http://www.gefcom.org.

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databases for relevant articles published during the last decade (2005 to 2015), thus covering the most common publication channels like scientific journals, books and conference proceedings. For the search queries, we combine the keywords *error*, *forecasting*, *renewable*, *wind*, *solar* and *method* while we exclude *demand* and *production* in order to increase the relevance for our purposes while reducing the total amount of possible hits. This will provide us with an overall idea of the research activity for the target domain across all involved communities.

In the next step, out of the numerous query results obtained, we define a smaller sample data set which is better usable for the in-depth analysis. In order to reduce the risk of getting less relevant or low quality results, we restrict the sample to the most important renewable energy journals according to the *SCImago Journal Rank Indicator* (SJR): Only the highest two quantiles (Q1 and Q2) of journals offering full-text online access are included, which covers the most relevant 50% of all ranked sources. The list of included journals is shown in Table 1. Furthermore, we consider only articles published during the last 6 years (2010 to 2015) thus reflecting the most recent research trends. Finally, all abstracts are manually revised to filter out all topics possibly not relevant for our study. We do explicitly exclude journals originating from other domains, like for example statistical journals. Although offering valuable contributions to the forecasting community, their natural preference for domain-specific approaches (e.g. statistical methods) could lead to biased results.

Table 1. List of relevant journals and number of articles found

Rank	Symbol	Title	SJRQ	SJR	Articles
6	RSER	Renewable and Sustainable Energy Reviews	Q1	3.273	9
7	TSTE	IEEE Transactions on Sustainable Energy	Q1	2.826	8
10	SE	Solar Energy	Q1	2.291	27
11	RE	Renewable Energy	Q1	2.256	27
13	IET	IET Renewable Power Generation	Q1	2.178	1
19	ECM	Energy Conversion and Management	Q1	1.801	12
29	ER	International Journal of Energy Research	Q2	1.106	1
32	EPP	Energy Sources, Part B: Economics, Planning and Policy	Q2	0.856	0
35	WEIA	Journal of Wind Engineering and Industrial Aerodynamics	Q2	0.791	5
42	EPSE	Environmental Progress and Sustainable Energy	Q2	0.629	1
47	RSE	Journal of Renewable and Sustainable Energy	Q2	0.472	2

2.2 Quantitative Analysis

First, we have a look at some quantitative aspects. According to the search criteria previously described in Sect. 2.1, we find a total number of 839 relevant publications. The most important channels in terms of published articles are scientific journals with a share of 47.1%, followed by conference papers with 37.8%, while book chapters are under-represented with 15.1%. Figure 1 demonstrates

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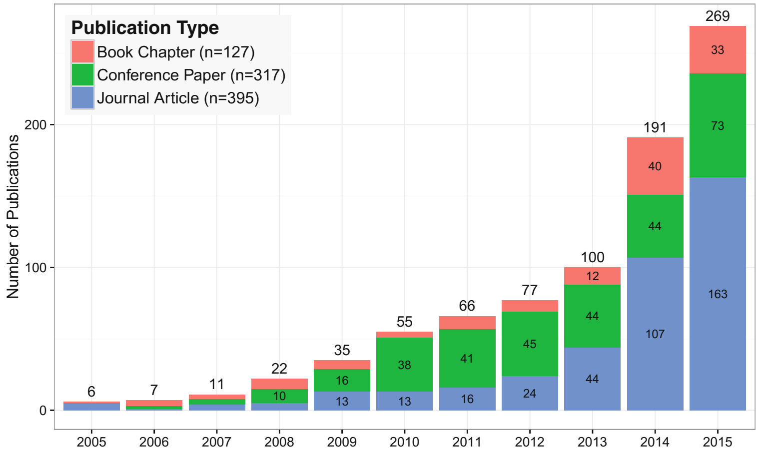

Fig. 1. Evolution of yearly renewable energy forecasting publications

the evolution of the yearly publication frequency for all searched publication types. We observe a steadily increasing number of publications with an average growth of 48.8% p.a. reaching a peak of 269 relevant publications in 2015, the last year considered for the study. This shows a clear trend of the rising and unbroken scientific interest in renewable energy forecasting methods especially during the last 2 years. However, compared to the results we obtain by searching for energy demand (5106 hits) and price forecasting literature (1869 hits) in the same databases, it becomes obvious that renewable energy forecasting still represents only a small subset of less than 11% of the published forecasting activities in the energy domain.

The following results are derived from the reduced sample data set. Out of the 93 filtered articles from the journal search, 83 remain after manual revision. This means that a 10% of the defined population (which still might include less relevant results, as no manual refinement is applied) are represented by the sample. Amongst them, forecasting methods aiming at solar energy are notably over-weighted compared to wind energy with 57.8% vs. 38.6% respectively, and only 3.6% propose methods applicable to both energy sources.

Figure 2 shows the distribution of proposed forecasting methods for solar or wind energy production. According to previous work [11], methods can be classified based on the nature of the underlying modeling technique and the combination type. For example a Neural Network is a Machine Learning technique (ML), while ARIMA is an univariate Stochastic Time Series model (STS) but both of them are statistical models, as they make use of historical observations which is not the case for Physical models. All of them can appear either as a stand-alone method or as part of a combined model. As a consequence, whenever two or more stand-alone methods are combined they cannot be classified unless considering such approaches as a model class on its own, the Hybrid models. Some articles

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also propose more than one method as stand-alone solution. From a total of 87 methods proposed in that articles, the most common classes are Machine Learning (30%), followed by Hybrid models (29%) and multivariate Stochastic Time Series models (23%), while Physical models (11%) and univariate STS models (5%) play a subordinate role. A similar result is reflected from a closer inspection of the Hybrid models, as again ML (40%) and multivariate STS methods (34%) are the most popular elements of combined models, but Physical models (20%) are much more often used here than they are as a stand-alone method.

Model Class / Combination Type	Physical Model	Statistical Model							Hybrid Model	Σ
		Stochastic Time Series					Similar-Days	Machine Learning		
		Univariat				Multivariat				
		Naive Prediction	Least Squares	Exponential Smoothing	Others					
Stand-alone Model	12	1	1	0	2	20	0	26	25	87
Part of Hybrid Model	10	0	1	1	0	17	1	20	x	50
Σ	22	1	2	1	2	37	1	46	25	137

Fig. 2. Proposed forecasting methods according to model class and combination type

The evolution of the model classes' proportions on the total number of proposed stand-alone models (compare Fig. 3) shows that there are no significant changes in popularity during the observation period. ML and multivariate STS models alternate each other, while only Physical models gain a slightly but constantly increasing share of scientific attention during the last two years covered by this study.

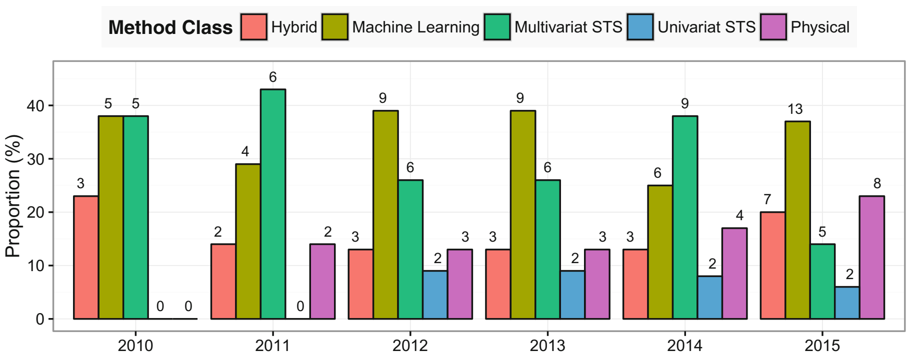

Fig. 3. Temporal evolution of proposed stand-alone model classes. The total yearly publications are shown with discrete values while the bars display the corresponding proportion for each class.

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2.3 Qualitative Analysis

After the view on quantitative aspects, the next step to follow in order to determine the most successful forecasting methods is a qualitative analysis of the sample data. This is problematic to the extent that quality determination for the commonly used point forecasts is mostly reduced to the accuracy dimension, sometimes combined with the model's robustness or technical performance. However, the selection of appropriate statistical metrics to measure the accuracy of forecasts is an independent research topic (compare e.g. Chen and Yang [1] or Hyndman and Koehler [5]). For renewable energy forecasts, the foundations of a standardized performance evaluation protocol were defined by Madsen et al. [7] more than a decade ago. As a minimum set of measures, they propose the use of normalized *Mean Bias Error* (MBE), *Mean Absolute Error* (MAE), *Root Mean Square Error* (RMSE) and improvement factors like the *Skill Score* (SS) for comparison between concurring methods and against simple predictors like the *Persistence Model* (PM).

Indeed, as shown in Fig. 4, the most frequently used error measures in the sample data set are RSME (65.1%), MAE (47.0%) and MBE (27.7%). In contrast, only 8 publications (9.6%) make use of all three of them, and this value decreases to 3 (3.6%) when SS is included. The number of simultaneously used accuracy measures reaches from 0 to 8 among all articles with an average value of 2.6 per article. The most frequent combinations are RMSE-MBE and RMSE-MAE with 24.1% and 22.9% respectively, followed by RMSE-MAPE with 14.5%. A 26% make use of normalized source data or error values. We also find that 32% do include a simple benchmark predictor (usually represented by the PM), which all of them outperform. Additionally, there are numerous individual accuracy measures normally seldom found in energy forecasting literature like e.g. *NashSutcliffe Equation*, *Scutter Index* or *Legates-McCabe's Coefficient of Efficiency*. These tailor-made criteria along with all undefined error measures are denoted as 'Others'. Considering the present variety it is not surprising that in the end only one out of the 83 analyzed publications matches all criteria derived from the evaluation protocol described above.

In addition to the problem previously discussed, the qualitative comparability of methods is further delimited by (1) the underlying use case and (2) the operational framework applied in the experiments. Evaluations are conducted on dissimilar data sets, so they do always vary in aspects like measurement quality and completeness, the available input features and history length of the target time series, and individual characteristics like signal-to-noise ratio or aggregation level. The geographical origin of the data also matters, as for example the output from solar energy sources located in northern Europe is less predictable than from sites in the south due to usually less stable weather conditions. Of course, providing access to sensitive real-world data is always problematic but there are alternatives: From the studied articles, 8.4% make use of the publicly available solar or wind data sets offered by the *National Renewable Energy Laboratory* (NREL) [9], which might be a first step towards more homogeneity in use cases. As for the experiments, parameters like forecasting horizon, the ratio of training and evaluation

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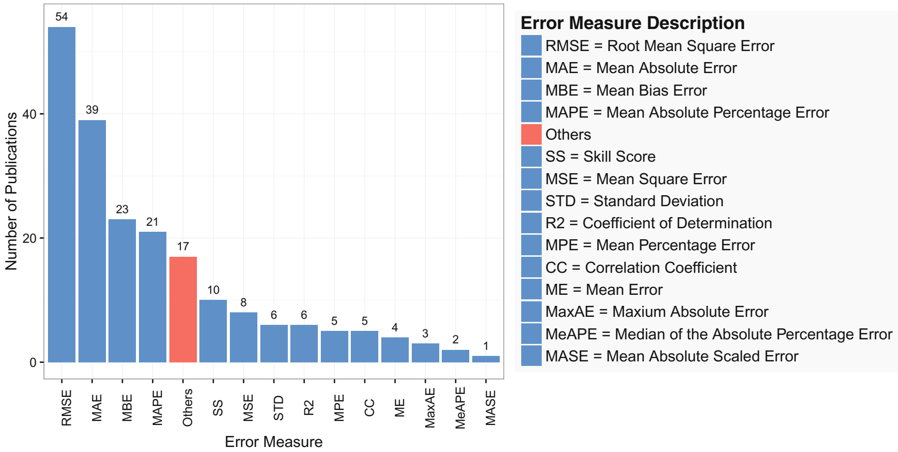

Fig. 4. Variety of applied forecast performance evaluation criteria.

data and any additional pre- or post-processing procedures influence the results. Finally, conclusions can also suffer from the authors' somehow 'personal' point of view. Experimental results may be optimized towards the desired findings by using only very few and specific test cases or compared against too simple baselines, so incredibly low errors or high improvement factors are achieved but will hardly be reproducible in different environments. However, recently published related work proves that such standardization problems still remain unsolved for wind [2] and solar energy [6] alike. Unfortunately, we can not derive reliable statements concerning the performance of the proposed methods for that reason.

3 Practical Relevance

In this section, we analyze the practical relevance of renewable energy forecasting methods for the energy industry. Due to the natural lack of publications in that area, we conduct a brief study of the German energy market to identify possibly relevant target companies and carry out a survey among software providers and users before we compare and discuss the results.

3.1 Methodology

First, we examine the web presences of energy software providers based in Germany and listed in the market reports regularly published by EMW[2]. We verify two simple criteria: (1) The target company offers an energy forecasting software product and (2) the product supports renewable energy supply forecasts. Those companies not providing sufficient information online are contacted directly. Out

[2] http://www.emw-online.com.

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of 56 revised companies, 6 match both criteria, while 23 match the first criteria only thus giving us a total of 29 potential targets for the survey. We design a questionnaire with 14 questions aiming at obtaining the following information: (1) For which appliance the forecasts are computed, (2) the underlying energy source, (3) the used algorithm classes, (4) additional parameters of interest like forecasting horizon, applied evaluation criteria, pre- or post-processing procedures and (5) some characteristics of the participating company.

For the user questionnaire, we contacted 65 companies from the utility sector, 41 of them located in Germany. This time, we only used 8 questions asking for (1) market role, (2) forecast appliance, (3) underlying energy source, (4) output evaluation criteria and (5) additional parameters like forecasting horizon and weather data sources. We also contacted 13 associations and public organizations belonging to the energy domain and placed posts in energy related news groups to reach as many participants as possible. The surveys were conducted during a period of two months, from August to October 2015.

3.2 Feeback from Software Providers

From the contacted software companies, a total of 19 answers were obtained but only 7 questionnaires are complete and were used. The participants belong to 6 companies, making for a response rate of 21%. Although low in number, if we consider the fact that the focus of our study is a very specialized topic usually treated only by a few corporate experts and may concern sensitive information for potential competitors, having any answer at all is a satisfying result.

According to the answers received, the most common application areas for the commercial software are energy demand and -price forecasting (37.5% each), while only 25% state that the solution is also suitable for energy supply forecasts. No difference is made between the prediction for supply from conventional and renewable energy sources, as all answers state that both can be handled by the software. This indicates that the implemented forecasting algorithms seem to be more general solutions and none of the companies offer a product portfolio explicitly specialized for the renewable energy domain. Furthermore, there is no difference concerning the forecasting horizon as all software products are equally suited for short- (e.g. intra-day or day-ahead) and long-term forecasts. Unfortunately, it remains unclear if the used methods provide a robust result quality during all stages of the target time series and if so, how this is obtained.

Concerning the characteristics of the implemented forecasting methods based on the classification previously introduced in Sect. 2.2, 21 methods are mentioned: With 29% the most common method is the Similar-Days approach, followed by Machine Learning and Stochastic Time Series models with 24% each. Hybrid (14%) and physical models (10%) seem to be of less significance for the software providers. Hereby, no difference is made between stand-alone methods or methods used as part of hybrid models. Beside the model class, some participants provide additional information as they specify *Multi-variate Regression* (5 times), *Neural Networks* (4 times), *k-nearest Neighbors* (2 times) and *Support Vector Machines* (1) as the underlying algorithms of their product. Figure 5 compares

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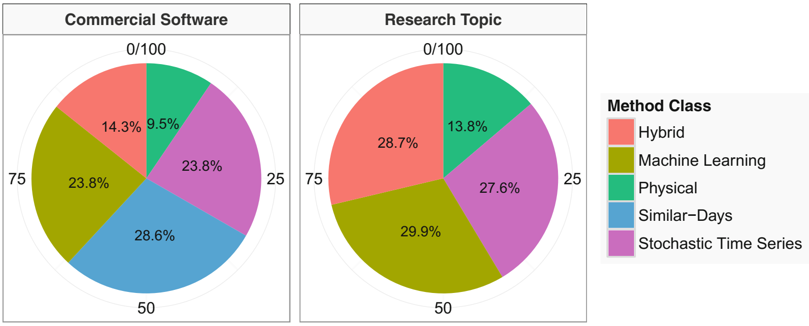

Fig. 5. Comparison of scientific and practical relevance of stand-alone method classes. Showing the proportions of methods implemented in commercial software on the left and corresponding research topics (compare Fig. 2) on the right side.

these results to the values obtained from the scientific literature: While STS and ML models show an almost identical relevance and dominate both areas, it is noted that the practical interest in hybrid and physical models is much inferior. On the other hand, the similar-days method plays a much more significant role in industry but is irrelevant for scientists.

Further, 50% of the participants state that data pre-processing procedures are applied, 40% mention data post-processing procedures and almost half (42%) use both of them. All answers claim that the provided solution can handle seasonal influences. Concerning the applied evaluation criteria, a 25% uses Standard Deviation (SD), while 21% use each RMSE (respective nRMSE) and MAPE and only 13% use MAE. Other mentioned error measures are BIAS, WMAE and U-Theil.

3.3 Feeback from Software Users

For the user questionnaire, we obtain 14 completed and 35 partially completed responses. From the latter 6 could be used as they contain sufficient pieces of information for our purposes, making for a response rate of 21.5% or 30% respectively. Concerning the participant's market roles, 25% of the companies classify as transmission system operators (TSO), each 20% as energy suppliers and -generators and 10% as distribution network operators (DSO), while 15% classify as others (e.g. energy planning &construction, independent energy procurer) and 10% do not classify.

A 42.9% of the participants state that they are already using energy forecasting software, while 38.1% do not. The almost equal distribution of the results indicates a still unsaturated market and thus a promising potential for such solutions. Those using the software tools say that their application focus is the prediction of future energy demand (50%), energy supply (30%) and energy prices (20%). Supply forecasts are mainly computed for renewable energy sources by 73%, and only by 28% for conventional energy production.

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Table 2. Importance of positive effects expected from supply forecasts. Values are obtained by dichotomous distribution from 5-level scales.

Factor	Important	Irrelevant	Abstention
Increased supply security	76.5%	5.9%	17.6%
Avoidance of overproduction	64.7%	17.6%	17.6%
Use of smart grid applications	35.3%	41.2%	23.5%
Improved demand-site management	58.8%	23.5%	17.6%
Balancing energy cost estimation	70.6%	17.6%	11.8%
Production site analysis	64.7%	23.5%	11.8%

Among a variety of qualitative aspects which may be achieved by implementing reliable and accurate forecasting technology (compare Table 2), the majority of the participants considers an increased supply stability, a better possibility of balancing cost estimations and the identification of possible renewable energy production sites as the most important benefits. Surprisingly, only 35.3% see an importance of supply forecasts for smart grid applications while 41.2% oppose and 23.5% abstain. The most important user requirements for such solutions are the availability of appropriate statistical output evaluation measures, the robustness of the models in terms of their flexibility when adapting to changing situations and the necessary maintenance efforts (compare Table 3).

Table 3. Importance of quality aspects for forecasting software. Values are obtained by dichotomous distribution from 5-level scales.

Requirement	Important	Irrelevant	Abstention
Statistical error measures	92.9%	7.1%	0.0%
Technical performance	85.8%	7.1%	7.1%
Robustness/adaptability	92.9%	7.1%	0.0%
Application usability	71.4%	21.4%	7.1%
Maintenance efforts	92.9%	7.1%	0.0%
Graphical result representation	64.3%	35.7%	0.0%
Manual output pre-processing	71.4%	21.4%	7.1%

Regarding the forecast evaluation criteria preferences, the most important error measures for the users are the *Mean Absolute Percentage Error* (MAPE) with 24% and *Standard Deviation* (SD) with 20%, followed by MAE and RMSE with 16% each while 20% abstained. A comparison to the results obtained from literature review and software providers is shown in Table 4: MAPE and SD seem to be more suited for the industry, while researchers prefer to use RMSE and MAE. The absence of the MBE measure in the industry is surprising, because

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this means that differences between over- and underestimations are not considered as such important.

Table 4. Comparison of error measures used as forecast evaluation criteria in science and industry.

Scientific literature	Software providers	Software users
65% RMSE	25% SD	24% MAPE
47% MAE	21% MAPE	20% SD
28% MBE	21% RMSE	16% RMSE
25% MAPE	13% MAE	16% MAE
20% Others	13% Others	2% Others

4 Summary

Based upon the results presented in Sects. 2 and 3 we conclude that the scientific interest on renewable energy forecasting methods is unabated for more than one decade, making it a small but increasing research field among other popular forecasting topics related to the energy domain. Machine learning, hybrid- and multivariate time series regression models are the most frequently proposed solutions in the last 6 years covered by our study. Physical models are still under-represented but are advancing as part of hybrid models, while univariate methods do not have much significance. Commercial solutions mostly follow that direction with some exceptions, while their application areas are not explicitly restricted to the renewable energy domain. Although a method's quality is commonly considered as output accuracy and the RMSE is the dominating accuracy measure, the qualitative comparison of concurring methods remains difficult due to the lack of widely respected evaluation standards or reference models. Furthermore, the preferences for error measures differ between science and industry.

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Appendix: List of Reviewed Journal Articles

Journal	Article	Year
SE	A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid connected PV plant at Trieste, Italy	2010
SE	A benchmark of statistical regression methods for short-term forecasting of photovoltaic electricity production. Part II: Probabilistic forecast of daily production	2014
SE	A hybrid model (SARIMA-SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant	2013
RE	A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks	2012
RE	A hybrid strategy of short term wind power prediction	2013
ECM	A new approach to very short term wind speed prediction using k-nearest neighbor classification	2013
ECM	A new wind speed forecasting strategy based on the chaotic time series modelling technique and the Apriori algorithm	2014
WEIA	A novel wind speed modeling approach using atmospheric pressure observations and hidden Markov models	2010
RSER	A review of measure-correlate-predict (MCP) methods used to estimate long-term wind characteristics at a target site	2013
RSER	A review of solar energy modeling techniques	2012
RE	A statistical approach for sub-hourly solar radiation reconstruction	2014
WEIA	A statistical method to merge wind cases for wind power assessment of wind farm	2013
TSTE	A Unified Approach for Power System Predictive Operations Using Viterbi Algorithm	2014
TSTE	A Weather-Based Hybrid Method for 1-Day Ahead Hourly Forecasting of PV Power Output	2014
ECM	Aggregated wind power generation probabilistic forecasting based on particle filter	2015
ECM	An adaptive model for predicting of global, direct and diffuse hourly solar irradiance	2010
RE	Bayesian adaptive combination of short-term wind speed forecasts from neural network models	2011
SE	Clear-sky irradiance predictions for solar resource mapping and large-scale applications: Improved validation methodology and detailed performance analysis of 18 broadband radiative models	2012
SE	Cloud motion and stability estimation for intra-hour solar forecasting	2015
ECM	Comparison of four Adaboost algorithm based artificial neural networks in wind speed predictions	2015
ECM	Comparison of new hybrid FEEMD-MLP, FEEMD-ANFIS, Wavelet Packet-MLP and Wavelet Packet-ANFIS for wind speed predictions	2015
SE	Daily global solar radiation prediction based on a hybrid Coral Reefs Optimization Extreme Learning Machine approach	2014
RE	Data mining and wind power prediction: A literature review	2012
TSTE	Determination Method of Insolation Prediction With Fuzzy and Applying Neural Network for Long-Term Ahead PV Power Output Correction	2013
SE	Embedded nowcasting method using cloud speed persistence for a photovoltaic power plant	2015
RE	Environmental data processing by clustering methods for energy forecast and planning	2011
SE	Estimation of solar radiation using a combination of Hidden Markov Model and generalized Fuzzy model	2013
WEIA	Estimation of wind speed: A data-driven approach	2010
SE	Evaluation and improvement of TAPM in estimating solar irradiance in Eastern Australia	2014
RSER	Evaluation of hybrid forecasting approaches for wind speed and power generation time series	2012
RE	Evolutive design of ARMA and ANN models for time series forecasting	2012
RSE	Feasibility study of a novel methodology for solar radiation prediction on an hourly time scale: A case study in Plymouth, United Kingdom	2014
SE	Forecasting solar radiation on an hourly time scale using a Coupled AutoRegressive and Dynamical System (CARDS) model	2013
SE	Genetic programming for photovoltaic plant output forecasting	2014
TSTE	Geostrophic Wind Dependent Probabilistic Irradiance Forecasts for Coastal California	2013
SE	Hourly solar irradiance time series forecasting using cloud cover index	2012
SE	Hybrid intra-hour DNI forecasts with sky image processing enhanced by stochastic learning	2013
SE	Hybrid solar forecasting method uses satellite imaging and ground telemetry as inputs to ANNs	2013
ER	Improved synthetic wind speed generation using modified Mycielski approach	2012
RE	Improved wind prediction based on the Lorenz system	2015
EPSE	Improving solar energy prediction in complex topography using artificial neural networks: Case study Peninsular Malaysia	2015
ECM	Intelligent optimization models based on hard-ridge penalty and RBF for forecasting global solar radiation	2015
RE	Local models-based regression trees for very short-term wind speed prediction	2015
TSTE	Model of Photovoltaic Power Plants for Performance Analysis and Production Forecast	2012
SE	Model output statistics cascade to improve day ahead solar irradiance forecast	2015
SE	Modeling global solar radiation using Particle Swarm Optimization (PSO)	2012
RE	Neural network approach to estimate 10-min solar global irradiation values on tilted planes	2013
ECM	Neural network based method for conversion of solar radiation data	2013
ECM	Observation and calculation of the solar radiation on the Tibetan Plateau	2012
RE	On the role of lagged exogenous variables and spatiotemporal correlations in improving the accuracy of solar forecasting methods	2015
SE	Online 24-h solar power forecasting based on weather type classification using artificial neural network	2011
RE	Online multi-step prediction for wind speeds and solar irradiation: Evaluation of prediction errors	2014
SE	Post-processing of solar irradiance forecasts from WRF model at Reunion Island	2014
ECM	Probabilistic wind power forecasting with online model selection and warped gaussian process	2014
SE	PV power forecast using a nonparametric PV model	2015
RE	Quaternion-valued short-term joint forecasting of three-dimensional wind and atmospheric parameters	2011
RE	Real-time prediction intervals for intra-hour DNI forecasts	2015
RSER	Selection of most relevant input parameters using WEKA for artificial neural network based solar radiation prediction models	2014
SE	Short-mid-term solar power prediction by using artificial neural networks	2012
RE	Short-term predictability of photovoltaic production over Italy	2015
RE	Short-term prediction of wind power with a clustering approach	2010
RE	Short-term solar power prediction using a support vector machine	2013
TSTE	Short-Term Wind Power Prediction Using a Wavelet Support Vector Machine	2012
WEIA	Simultaneous nested modeling from the synoptic scale to the LES scale for wind energy applications	2011
SE	Solar irradiance forecasting using a ground-based sky imager developed at UC San Diego	2014
SE	Solar irradiance forecasting using spatio-temporal empirical kriging and vector autoregressive models with parameter shrinkage	2014
TSTE	Solar Power Prediction Using Interval Type-2 TSK Modeling	2012

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Journal	Article	Year
RSER	Solar radiation forecasting with multiple parameters neural networks	2015
RSER	Solar radiation prediction using Artificial Neural Network techniques: A review	2014
RE	Solar radiation variability in Nigeria based on multiyear RegCM3 simulations	2015
SE	Stochastic approach for daily solar radiation modeling	2011
ECM	Stochastic models for wind speed forecasting	2011
IET	Study of forecasting renewable energies in smart grids using linear predictive filters and neural networks	2011
RE	The impact of large scale atmospheric circulation patterns on wind power generation and its potential predictability: A case study over the UK	2011
SE	The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data	2010
TSTE	Time Adaptive Conditional Kernel Density Estimation for Wind Power Forecasting	2012
RSER	Validation of direct normal irradiance predictions under arid conditions: A review of radiative models and their turbidity-dependent performance	2015
SE	Very short term irradiance forecasting using the lasso	2015
RE	Very short-term wind speed forecasting with Bayesian structural break model	2013
RE	Wind power forecasting based on principle component phase space reconstruction	2015
WEIA	Wind power prediction based on numerical and statistical models	2013
RE	Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA-ANN model	2010
RE	Wind speed forecasting using a portfolio of forecasters	2014

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