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Energy forecasting: A review and outlook

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Energy Forecasting: A Review and Outlook

Tao Hong, Pierre Pinson, Yi Wang, Rafał Weron, Dazhi Yang, and Hamidreza Zareipour

***Abstract*—Forecasting has been an essential part of the power and energy industry. Researchers and practitioners have contributed thousands of papers on forecasting electricity demand and prices, and renewable generation (e.g., wind and solar power). This paper offers a brief review of influential energy forecasting papers; summarizes research trends; discusses importance of reproducible research and points out six valuable open data sources; makes recommendations about publishing high-quality research papers; and offers an outlook into the future of energy forecasting.**

***Index Terms*—Energy forecasting, load forecasting, electricity price forecasting, wind forecasting, solar forecasting**

I. INTRODUCTION

FORECASTING is an integral part of business decision processes. The energy industry relies on forecasters to forecast load, generation, and prices, etc. These forecasts are being used by all segments of the energy industry, for planning and operations of both power systems and business entities.

While energy forecasting could be interpreted as forecasting kWh usage, we adopt a broader definition of energy forecasting in this paper, which is forecasting in energy industry. Specifically, we focus on subjects around power systems, including electricity demand and prices, and wind and solar power generation. Although oil and gas forecasting is also an important subdomain of energy forecasting, it is out of the scope of this review.

One way to structure a review of a wide field is to dissect the review by subdomain, dedicating each section to a subdomain of interest [1]. We, however, believe readers of this paper could have been better served by domain specific reviews, of which some are highlighted in Section II. Considering the energy forecasting problem as a whole, in this paper, we examine the common developments and concerns among the subdomains, together with their connections and joints. This paper aims at offering a holistic view of the entire field to promote collaborations among different research communities.

The rest of this paper is organized as follows: Section II presents a bird's eye view of the literature, including highlighted review articles in each subdomain, as well as bibliometric analysis; Section III discusses several emerging problems in the frontiers of energy forecasting research; Section IV emphasizes the importance of reproducible research to the advancement of the field, and introduces six valuable data sources for researchers and practitioners; Section V makes recommendations about publishing high quality papers; Section VI concludes the paper with a look back at a historical forecast and an outlook of future research directions.

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II. A BIRD'S EYE VIEW

Thousands of energy forecasting papers have been published during the past few decades, including many influential review articles and original research papers. In this section, we highlight several worth-reading reviews in each specific domain for interested readers to continue the exploration. We also provide a brief bibliometric analysis of the recent 10 years.

A. Selected Reviews

Long-term load forecasts have been used for planning purposes for over a century [1]. Spatial load forecasting, which offers when, where and how much electricity demand would grow, was heavily used for transmission and distribution planning in the late 20th century. The tutorial review by Willis and Northcote-Green covered many spatial load forecasting methods at that time, of which some are still being used in today's industry [2]. As power companies started to pursue operational excellence, short-term load forecasting gradually attracted attention of researchers and practitioners. The review article by Gross raised many practical issues the field in 1980s, of which many are still challenges to today's industry [3]. From 1990s to 2000s, load forecasters tried many forecasting techniques, among which artificial neural networks (ANN) were quite popular. An exemplary technique-focused review took a rational look at the hype of ANN for load forecasting in 1990s, while pointing many critical issues in theory and practice [4]. In the recent decade, probabilistic load forecasting becomes a popular topic. A tutorial review on probabilistic load forecasting connected the point load forecasting literature developed earlier to probabilistic load forecasting methods developed through mid 2010s [5]. One load forecasting problem often overlooked by the power engineering community is building load forecasting. As the footprints of smart meters continue to grow, forecasting the loads at premise level is becoming a common interest of both building engineers and power engineers. A review of building load forecasting can be found in [6].

Since 1980s, due to the deregulation and rise of electricity markets, electricity price forecasting has been attracting more and more attention from the industry and academia. Many early electricity price forecasting papers were devoted to short term forecasting. Zareipour's review [7] illustrated salient features of short term electricity prices, and presented a data-driven approach to price modeling and forecasting. A more comprehensive review of electricity price forecasting, which is also the highest cited price forecasting article in recent years, is Weron's [8]. Recent advances in probabilistic electricity price forecasting can be found in [9].

Wind speed is a dominant driving factor of wind power generation. A review of wind power and wind speed forecasting methods across different forecast horizons ranging from a few seconds to a week ahead can be found in [10]. Another review focused on three decades of short term wind power forecasting literature through mid 2000s [11]. Among the four major domains of energy forecasting, wind power forecasting has been leading the maturity on probabilistic forecasting methods and applications, largely due to the interactions between wind forecasters and meteorologists. A review on probabilistic wind power forecasting can be found in [12]. The wind forecast uncertainty was also discussed in [13], as an effort to introduce wind forecasting to the statistics community. Over a period of more than a decade, academics and practitioners have seen two parallel approaches (recently again discussed by [14]) to wind power forecasting, coined physical and statistical. Today they have come together and it does not make sense anymore to separate them, since state-of-the-art approaches to wind power forecasting have to incorporate both physical and statistical (possibly machine learning) considerations.

Modern solar forecasting started in early 2010s. In 2013, the typology of solar-specific forecasting methods was set forth in the first major, and now the most cited, review of the domain [15]. In that review, camera-based, satellite-based, and NWP-based solar forecasting were associated to intra-hour, intra-day, and day-ahead horizons, respectively. After a booming 5 years, a text-mining based review was conducted in 2018, in which 1000 references based on the top Google Scholar search results were analyzed [16]. Hundreds of important concepts of solar forecasting, obtained from text mining, were annotated and interpreted by five editors of SOLAR ENERGY, the journal publishing the most solar forecasting papers to date. As a fast-advancing field, solar forecasting desperately needs reconciliation and standardizing the best practices. Hence, the ROPES guideline, abbreviation for reproducible, operational, probabilistic and physically-based, ensemble and skill, was proposed in [17]. These characters jointly mark most salient features of irradiance to be considered for solar forecasting.

Although many review articles have been published in the energy forecasting literature, there are still some areas that deserve to be reviewed in detail. Industrial load forecasting is an important part of load forecasting. Although the literature included many solid studies such as [18]–[20], we have not yet seen a notable review paper on this topic. Reviews on camera-based and NWP-based solar forecasting would be beneficial to the community, particularly because that topics such as 3D cloud construction and dynamical weather modeling are essential to solar forecasting but not very well understood by solar forecasters. In addition, reviews of data sources and their use would be great for promoting reproducible research as well.

B. Bibliometric Analysis

Fig. 1 shows the growth of energy forecasting literature during the past 10 years. Load forecasting papers take about half of the energy forecasting literature. The increasing trend can be observed across all four sub-domains. The growth of renewable forecasting literature has been stronger than load and price forecasting, which may be largely attributed to the worldwide renewable integration efforts in the recent decade.

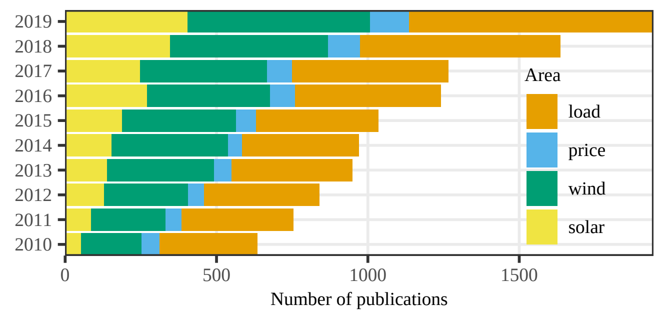

Fig. 1. Number of publications in load, price, wind and solar forecasting returned by respective Scopus search.

In each subdomain, we have picked the top 10 journals that publish most forecasting papers of that subdomain over the last 10 years. These journals are considered the major publication outlets for energy forecasting papers. The list includes 22 journals in total, because some are ranked top 10 in terms of publication quantity across multiple subdomains. In Fig. 2, we rank these journals by the ratio of energy forecasting papers to the total publications of each journal. The counts for energy forecasting papers published by each journal have been labeled next to the journal title, so that interested readers may find out which journals publish the most papers of the sub-domain of their interest. Some journals, such as WIND ENGINEERING, SOLAR ENERGY, IEEE TRANSACTIONS ON SUSTAINABLE ENERGY and ENERGY ECONOMICS, are mostly dedicated to one or two sub-domains, while several other journals, such as INTERNATIONAL JOURNAL OF FORECASTING, IEEE TRANSACTIONS ON POWER SYSTEMS and IEEE TRANSACTIONS ON SMART GRID publish a wide range of energy forecasting papers. Caution should be applied when interpreting this figure, as publication quantity does not imply quality. More discussions about issues with today's publication process will be presented in Section V.

III. RESEARCH FRONTIERS

Energy forecasting has evolved way beyond standard implementations of existing forecasting methods onto "new" problems. Hence, for a researcher or practitioner entering the field, there are many papers and studies to read before one can build an accurate model or publish his/her own papers. Sturgeon's law suggests that *90% of everything is crap*, so it is wise to avoid wasting time on published works that are not classic nor on the research frontiers. In what follows, we outline several emerging research topics. Nonetheless, we clarify that these topics are by no means to be comprehensive. Some emerging problems cannot be covered by this review due

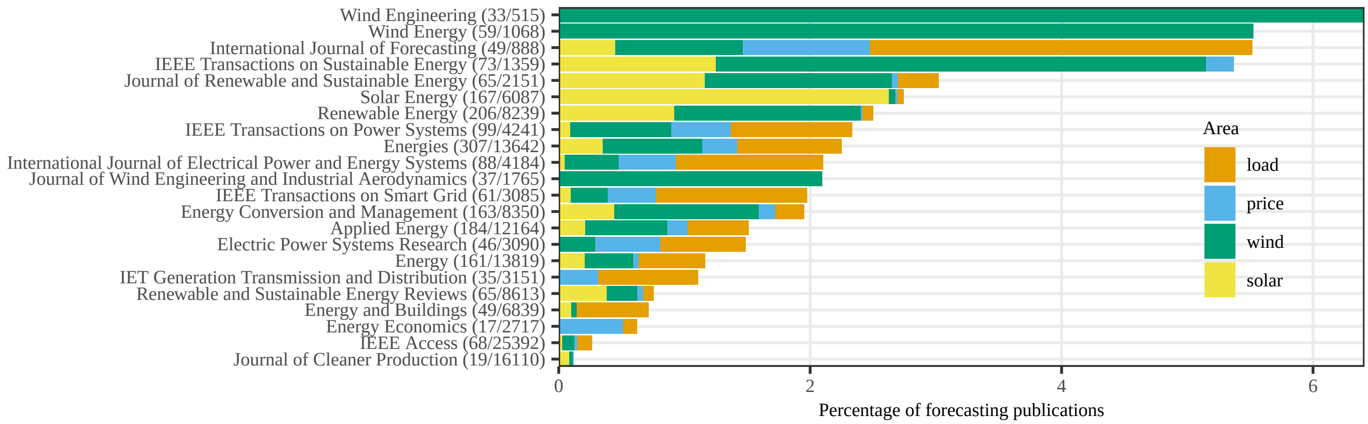

Fig. 2. Percentage of energy forecasting publications. Only the top 10 journals with the most forecasting publications in each area are considered; some are ranked top 10 across multiple subdomains. Numbers of forecasting publications and total publications for each journal are shown beside journal names.

to page limit. Some classical problems are certainly important, which should be better served by more specific review articles.

A. Artificial Intelligence and Machine Learning

The fundamental assumption of forecasting is to assume the future repeats the history in some way. Discovering the patterns or hidden information from historical data is a key to accurate forecasts. The development of artificial intelligence (AI) and machine learning (ML) techniques certainly benefits the advancement of energy forecasting. In fact, AI/ML techniques have been adopted for energy forecasting for over three decades [21]–[23].

In recent years, the field of AI/ML is experiencing another hype largely due to the advancement of computing technologies. Various advanced AI/ML techniques such as deep learning [24], [25], reinforcement learning [26], and transfer learning [27], have been adopted in energy forecasting.

A downside of deep learning is that its training process is much more complex and time consuming than of regression models. It is not only the sheer number of parameters (weights) to estimate, but also the optimization of the hyper-parameters (network structure, activation functions, stopping conditions, regularization, etc.) [28]. The applications of deep learning techniques rely on the constant increase of both computing power and collected data.

It should be emphasized that machine learning based methods for load, wind, solar, and price forecasting have to be informed of the physical characteristics of the processes involved, both for modelling and variable selection. Utilizing exogenous data does not mean the simple inclusion of unprocessed weather variables into machine learning models. Instead, we should dive deeper and investigate the intrinsic properties, salient features, and limitations of these data.

B. Forecast Combination and Ensemble Forecasting

The two terms share the same meaning and can be used interchangeably. While the former is frequently used by statisticians and econometricians, the latter is favored by meteorologists. Combining forecasts has been widely recognized as one of the best practices in forecasting. Benefits of forecast combination were formally discussed in 1969 [29]. Many empirical studies were published later to show positive and negative effects of combining forecasts. Some notable reviews can be found in [30]–[32]

Success of forecast combination strategies can be easily found in the energy forecasting literature. For instance, a homogeneous combination was found to be effective in point load forecasting [33], where the authors tested 11 combination algorithms on the so-called sister forecasts generated by a family of regression models. The same regression models were found to be good input to generate probabilistic load forecasts via quantile regression averaging [34]. Ensemble forecasting methods have also been applied to smart meter data [35] and other subdomains of energy forecasting, such as price forecasting [36]–[38]. Empirical results show that for both point and probabilistic forecasts the quality of predictions can be significantly improved if combined, even when forecasts of the same model are averaged just across a few short and a few long calibration windows [39], [40].

An alternative approach to ensemble forecasting is via exploitation of the data space and parameter space to quantify the uncertainty associated with a forecasting model. Considering the dynamical ensemble used in weather forecasting, where the initial analysis is perturbed and evolved separately, different trajectories of the same future event can be projected. This is typified by the 51-member ECMWF Ensemble Prediction System, which is one of (if not) the best numerical weather prediction (NWP) models to date. Ensemble wind speed and irradiance forecasts are particularly important in wind and solar forecasting, whereas the temperature forecasts widely benefit load forecasting. The reader is referred to [41] for an overview on ensemble weather forecasting.

C. Hierarchical Forecasting

Energy forecasting often encounters time series that have aggregation constraints due to temporal or geographical groupings. For instance, sum of the loads at distribution feeders should equal to the load at the corresponding transmission minus losses, which are typically a small percentage. In these scenarios, hierarchical forecasting, which reconciles base forecasts generated individually at different levels of a hierarchy, becomes important. Hierarchical forecasting has two distinct advantages over conventional forecasting. Firstly, the final forecasts in a hierarchy are coherent. In other words, the sum of lower level forecasts equals to the corresponding upper level forecast. Secondly, the reconciled forecasts are often, if not always, more accurate than base forecasts.

Recent advances of hierarchical forecasting were mostly contributed by Hyndman's research group [42]. Over several publications, computation issues that hinder the large-scale applications of hierarchical forecasting have been addressed [43]–[45]. Due to the generality of the framework, hierarchical forecasting has been applied to energy forecasting, particularly in load and solar forecasting, e.g., [46]–[48]. In fact, the load forecasting track of GEFCom2012 was designed to be a hierarchical load forecasting problem, but none of the contestants took advantage of the hierarchy [49]. GEFCom2017 was dedicated to hierarchical probabilistic load forecasting [48], but the use of hierarchy was rather modest. Among the 12 finalists selected from the qualifying match, only four used the hierarchy, though none of them ranked Top 6 in the qualifying match. Hierarchical reconciliation applies to both point and probabilistic forecasting. However, there is not yet any consensus on the definition of coherence, especially in a probabilistic sense.

D. Probabilistic Forecasting

The nature is stochastic. Forecasting, by nature, is a stochastic problem. The frequently used point forecasts, or single-valued forecasts, are simply presenting summary statistics, mostly expected values, of a subject during different time periods. In weather forecasting, it has long been known that a forecast is essentially five-dimensional, spanning the three-dimensional space, time and probability [50]. To that end, generating probabilistic forecasts is never a choice, but a reflection on a forecaster's understanding on basic subject matters. The reader is referred to the seminal review on probabilistic forecasting [51].

Probabilistic forecasting can be issued in forms of parametric, semiparametric, or nonparametric predictive distributions, predictive quantiles, or prediction intervals. The aforementioned ensembles, where several forecasters issue a (point or probabilistic) component prediction, can be also viewed as a special form of probabilistic forecasts. Regardless of which form a probabilistic forecast is issued, methods converting from one form to another are available. Additionally, probabilistic forecasts can be summarized into point forecasts following the guidelines proposed in [52].

Probably the most important step in the recent history of energy forecasting is the transition from a deterministic to a probabilistic view. Wind power forecasting certainly takes a lead w.r.t. probabilistic forecasting. This may largely due to the close collaborations between wind power forecasters and meteorologists in the early days.

Many have proposed alternative approaches to probabilistic wind power forecasting, explained how to use such forecasts as input to decision-making, as well as showed the benefits from placing oneself in a probabilistic framework. Parametric approaches have been proposed, relying on various types of distributions e.g. truncated Gaussian for wind speed [53] and generalized logit-Normal for wind power [54]. Instead of formulating assumptions about predictive densities, some have proposed nonparametric approaches most often relying on quantile regression e.g. [55]–[57]. An alternative consists in using meteorological ensemble forecasts, which can then be dressed and calibrated with kernel-based methods [58]. In a more general framework, the transformation from meteorological forecast information to power may be thought of in a Bayesian framework (hence relying on stochastic power curves) e.g. through conditional kernel density estimation [59]. All these methods aimed at obtaining predictive marginal densities, i.e., informing about forecast uncertainty for each location and lead time individually. This is while it may also be of relevance to look at those in a multivariate framework more generally so as to also inform about spatial and temporal dependencies. The main approach that was proposed builds on the use of copulas for coupling predictive marginal densities [60]. Alternatively, modern machine learning approaches can be employed e.g. using generative adversarial networks [61].

Developing probabilistic load forecasts can be dated back to 1970s [5]. However, the formal adoption of proper skill measures for probabilistic load forecasts did not start until GEFCom2014 [49]. From the perspective of system theory, a point forecasting system can be dissected into three parts, i.e., input (e.g., features), modeling, and output (e.g., forecasts). We can adopt these three parts to construct a probabilistic forecasting process. The three parts have been formally studied in the recent probabilistic load forecasting literature, such as scenario generation on the input side [62], quantile regression neural networks on the modeling side [63] and variable selection methods [64], and residual simulation on the output side [65].

The overarching principle of generating good probabilistic forecasts is to minimize sharpness subject to calibration [66]. To that end, various post-processing techniques, such as ensemble model output statistics [67] or forecast combination [68], are used to calibrate and sharpen the initial forecasts. That said, combining probabilistic forecasts is an underrepresented topic, despite its long history [69]. Methods for combining predictive distribution, quantiles and intervals also may differ [70]–[72]. Some specific examples can be found in the area of load forecasting. Researchers have proposed various forecast combination strategies to generate and improve probabilistic load forecasts [34], [73], [74]. One of them, quantile regression averaging, first proposed for probabilistic price forecasting in [38], is particularly worth highlighting, because it was also shown to be effective in probabilistic load forecasting [34], [73].

IV. Reproducible Research

Replicating existing models and methods in the energy forecasting literature is not only good for researchers just entering the field, but also a must to further advance the state of the art. Unfortunately, most papers can never be replicated, because the data have never been published. In this section, we first take a brief look at energy forecasting competitions, which stimulated many major breakthroughs. We then introduce six useful data sources for energy forecasting research.

A. Forecasting Competitions

Forecasting competitions, if set up properly, are a great way to compare various forecasting models, techniques and methods, to recognize the effective ones, and to stimulate novel ideas. Some competitions have released the data and/or had contestants publish their methods, which help promote reproducible research, hence advancing the research progress.

The first notable energy forecasting competition in the literature can be traced back to early 1990s. The competition was focusing on day-ahead load forecasting, hosted by Puget Sound Power and Light Company. The Pudget Sound Competition included ten participants with various models, such as neural network models, state space models, and multiple regression models. A multiple regression model was considered the best performing one among 14 competitive models [75]. A participant of this competition later further developed their models into a commercial solution for load forecasting [76], [77].

In 2001, EUNITE network organized a competition to forecast daily load for a period of one month. The winning entry was mainly based on support vector machine (SVM), which was known as the first successful application of SVM in load forecasting [21]. The lead author of the paper was also the author of several SVM libraries including LIBSVM of MATLAB.

Driven by the idea of promoting reproducible research and recognizing effective methods, Hong and his collaborators organized a series of Global Energy Forecasting Competitions, a.k.a. GEFCom2012, GEFCom2014 and GEFCom2017 [48], [49], [78]. The competitions were financially sponsored by IEEE Power and Energy Society. The INTERNATIONAL JOURNAL OF FORECASTING was the publication sponsor to collect the papers that describe winning methodologies and to publish the competition data. These competitions cover a wide range of topics, such as electricity demand and price forecasting, wind and solar power forecasting, hierarchical forecasting, and probabilistic forecasting. With hundreds of contestants from more than 60 countries worldwide, the Global Energy Forecasting Competitions (GEFComs) are considered the largest energy forecasting competitions and one of the largest forecasting competitions to date.

Over the past few years, more and more energy companies started to organize forecasting competitions for various purposes, such as selecting software vendors and recruiting student interns. However, the outcome of these competitions, such as the data and winning methods, has not been well documented in the academic literature.

B. Open Data

Seasoned researchers may find many data in the public domain to support their research projects. Here we highlight six important data sources for energy forecasting research.

1) Data published with ties to research papers: Some scholarly journals encourage authors to submit data and code as an effort to promote reproducible research. INTERNATIONAL JOURNAL OF FORECASTING published papers introducing all three GEFComs, which also include the data released to the contestants as supplementary files [48], [49], [78]. SOLAR ENERGY recently launched a Data Article initiative to publish papers that introduce datasets [79]. Other than publishing the code and data with journals, some researchers may upload their code to public repository, such as GitHub [80]. Some choose to go a step further to develop packages in free software environment, such as the R project. For instance, an improved version of the models proposed in [81] is now in an R package `MEFM`.

2) ISO/RTO data: Independent systems operators (ISOs) and Regional Transmission Operators (RTOs) are another frequently used data sources, especially for load and price data. The length, variety, and quality of data published by these ISOs/RTOs vary. Many ISOs do not publish weather information, which is an important driver of load, which influences the prices. ISO New England is one of those organizations that make their data archive easily accessible. As a result, it is a frequently cited organization in energy forecasting case studies. The qualifying round of GEFCom2017 also used ISO New England Data [48]. Electricity markets in Europe are also frequently studied by the load and price forecasters, thanks to the data availability.

3) Smart meter projects: Several notable smart meter projects have released valuable datasets to the scientific community. One of the frequently used dataset is the Irish data [82]. Pecan Street and Low Carbon London are two other frequently used data sources in the scientific literature. A recently published review of smart meter data analytics has covered these datasets, as well as several other useful datasets [83], where the reader can find a more comprehensive list.

4) In situ weather data: In situ measurements of weather variables come from ground-based weather stations, buoys, and radiosondes. Subject to proper instrument calibration, these measurements are the most accurate weather data. However, *in situ* data are rare and come from autonomous sources. Therefore, when sourcing these measurements for forecasting purposes, the quality-control procedures must be placed with high priority.

5) Remote-sensed data: Since ground-based measurements are not available everywhere, gridded weather data obtained by remote sensing becomes important in weather forecasting. These remote-sensed data could either come from instruments onboard geostationary weather satellites or those onboard polar orbiters. Geostationary satellites have a fixed field-of-view, and thus are able to perform continuous monitoring over various disk areas that jointly cover all parts of the world from $\pm 65^\circ$ in latitude. On the other hand, polar orbiters measure weather variables in swaths along their paths. Remote-sensed data generally comes at a lower accuracy than ground-based data, but is advancing fast.

6) NWP and reanalysis data: NWP data are generated by national weather centers, and are available for worldwide locations for free or for pay. Although these datasets are hosted on different data servers maintained by different weather agencies, anyone with basic computer literacy is able to download and use these data, as long as the exact links are known. A special case of NWP data is reanalysis, which is essentially a re-run of a weather model using a consistent assimilation scheme. The two most recent global reanalyses are MERRA-2 and ERA5, which both offer thousands of atmospheric variables on an hourly scale from 1980 to now.

V. Publishing Quality Papers

Sitting on the editorial boards of many elite journals that publish energy forecasting papers, we have handled thousands of manuscripts during the past decade. Most of those manuscripts share the same issues that prevent them from being published by top journals. In this section, we will discuss some common issues with energy forecasting papers in the literature. We will also make some recommendations about publishing quality papers. One mission of this review is to point the readers to quality sources. To keep the reference list concise and immune from substandard papers, we do not name individual papers as counterexamples. We also acknowledge that many high quality papers are not on our reference list due to page limitations.

A. Common Issues

First and foremost, a super majority of the energy forecasting models in the literature are evaluated using unique and limited datasets, such as short time periods, one single location, and datasets never used in any other study. This makes comparisons with models proposed earlier in the literature problematic, if possible at all.

Secondly, the evaluation metrics are often inadequate. For instance, Mean Aboslute Percentage Error (MAPE) is used for close to zero load, prices or renewable power generation. Sometimes authors tend to pick the error measures in favor of their proposed method but hide the results from other error measures. When the obtained differences in errors are close to zero, the statistical significance tests are seldom performed. Similar issues were already discussed in the context of price forecasting [8]. Although the average level of price forecasting studies has improved since 2014, it is still not to a satisfactory level.

Thirdly, many papers avoid direct comparisons with classic, established, and state-of-the-art models. Some even skip comparisons with naive models. Many papers draw a small circle in the case study section by only comparing with the models within the immediate family. Sometimes the parameters are manipulated, so that the competing models are being dominated by the proposed ones. A hypothetical example could be proposing a hybrid model of neural networks, wavelet, and particle swarm optimization for wind power forecasting, while the competing model is a neural network model with an arbitrary structure and poorly tuned parameters.

Last but not least, the use of forecasting terminology is inconsistent from one paper to another, which often leads to ambiguous description of forecasting models, methodologies and processes. Sometimes a new term was invented to make the proposed idea look novel. Such practices typically make the article hardly noticeable through search engines, unless the idea was really groundbreaking, which makes the newly invented term widely recognized.

B. Recommendations

To help create a healthy environment for current and future researchers to publish quality papers at the right venues, we would like to make the following five recommendations tailored for energy forecasting research.

1) Literature review: The reviewers and editors expect authors to present *high quality* references *relevant* to properly set the stage for their proposed research. The reference list should prioritize state-of-the-art methods as well as the classical ones. The coverage density of the literature may reduce as the area goes further away from the core proposal. For example, if the proposed idea is long term probabilistic load forecasting using XYZ method, the reference list should prioritize other long term probabilistic load forecasting papers and other papers that use XYZ method, followed by long term load forecasting and probabilistic load forecasting papers, followed by load forecasting papers and probabilistic forecasting papers in other energy forecasting subdomains, followed by general forecasting papers. After assembling the list of references, citing references in bulk should be avoided. Instead of citing more than a handful of references at the end of one sentence, a better presentation is to discuss each reference separately or in small groups, which requires the authors to sight what they cite.

2) Forecasting terminology: Authors should refrain from introducing jargon into the field. Most problems and processes can be clearly explained by following existing terminology precisely. We would encourage energy forecasters to trace back to the forecasting, statistics and machine learning literature for the original and formal terminologies, such as out-of-sample tests [84] and cross validation [85]. An important concept in energy forecasting is forecast horizon, which refers to the length of time into the future for which forecasts are to be prepared. Although many subdomains of energy forecasting use “short”, “long”, and their variants to characterize forecast horizons, the definitions are often ambiguous. Authors are encouraged to use precise language to describe their forecasting process. For instance, day-ahead forecasting refers to forecasts issued sometime today for the 24 hours of the following calendar day, which is different from 24-hour ahead forecasting. In solar forecasting, researchers are moving away from using short, medium and long to describe forecast horizons. Instead, they use intra-hour, intra-day and day-ahead.

3) Comparative study: To propose a new idea, one has to compare it with the existing ones, preferably the state-of-the-art methods or something well established in the literature. If the proposal is to a new problem without well-established solutions, comparison to naive methods is required. When evaluating point or probabilistic forecasts, proper measures of errors or skills ought to be selected [51], [86]. When different models have almost identical values in the selected error measures, significance tests, such as the Diebold-Mariano test, ought to be performed. For a discussion in the price forecasting context, see [8], [9]. Sometimes a manuscript presents astonishingly good results showing dominance of the proposed method over its counterparts, which is, more often than not, too good too be true. If exaggerating results are obtained, authors are advised to perform a sanity check and see if future information has been used during parameter estimation, model selection, or tuning of hyper-parameters. The authors are also encouraged to check whether or not a core step in the forecasting process is easily replaceable. If so, explore the variations to offer a complete picture of the proposed method.

4) Enhance reproducibility: Most experienced editors and reviewers understand the importance of reproducible research. Therefore, they may favor the papers that are easily reproducible. Authors may enhance the reproducibility of their research by using public data, or publishing their data and code. Sometimes, research sponsors may not allow the authors to publish the data or code. In those situations, clearly explaining the proposed methodology using formal terminology is a must.

5) Finding the right venue: Not every manuscript can eventually appear in the top journals.To avoid wasting publication time and review resources, authors are encouraged to look for the right journals to publish their research. For example, among 22 major publication outlets for energy forecasting papers in Fig. 1, the ones being called out in Section II-B would be unlikely to accept papers rejected by other journals. Instead, they are mostly looking for research with high archival value, groundbreaking ideas, and solid technical solutions to novel problems. Some journals, such as IEEE Transactions, may require five or more reviewers for each paper. Some journals, such as INTERNATIONAL JOURNAL OF FORECASTING, only requires two reviewers, but their reviewers usually give comprehensive comments that may lead to major revisions. If authors are looking for an easy review process, they may want to seek other venues. Some journals, such as SOLAR ENERGY, strongly favor reproducible research. Authors who are willing to publish their code and data may consider such venues.

VI. OUTLOOK

Right after GEFCom2014, the competition organizers joined forces to make a 10-year ahead forecast of energy forecasting, which was later published in 2016 [49]. In this section, we conclude our review by taking another look at that historical forecast, followed by a discussion of two challenging problems that deserve rigorous investigation for the next decade.

A. A Historical Forecast

The forecast made by GEFCom2014 organizers included 12 predictions on a wide range of topics around energy forecasting [49]. Looking back at those predictions, five of them have become true:

1) Solar power forecasting: Solar power forecasting research has seen flourish indeed. As shown in Fig. 1, the amount of solar forecasting papers have been increasing rapidly over the past 5 years. The growing trend is expected to continue.

2) High resolution data: The recent energy forecasting literature has seen an increased use of high resolution data, temporally, spatially and conceptually.

3) Forecasting methodologies: Several energy forecasting methodologies have been adopted across different subdomains. For example, the 24 solar terms were originally used as input features for load forecasting in [87]. This idea was then applied for wind forecasting in [88]. As another example, copulas were first applied in wind power forecasting [89], and then found its effectiveness in solar power forecasting [80].

4) Energy forecasting subjects: A diversification of energy forecasting subjects was predicted five years ago. Since then, we have seen forecasting studies for wave energy forecasting [90], reactive power [20], demand response capacity forecasting [91], which were rarely studied before.

5) Forecasting competitions: Many large and small forecasting competitions have been organized Since GEFCom2014. GEFCom2017 is just an example [48]. As the benefits of competitions are being recognized by the community, we expect more and more competitions to be hosted in the future.

Six other predictions made in [49] are well on track:

6) Connecting point and probabilistic forecasting: An attempt was made in load forecasting to investigate whether the variables selected to minimize point forecasting error measures can also be the best model to minimize the quantile scores [64]. How the forecasting residual is conditional on point forecasts and related factors was studied in [92], which verified that a better point forecast helps produce a better probabilistic forecast. More exploration is needed along this direction, not just for load forecasting, but also other subdomains of energy forecasting.

7) Energy forecasting problems: When the forecast was made back in 2015, net load forecasting was a particular example raised for the fusion of energy forecasting problems. At that time, there were few studies on behind-the-meter solar estimation and net load forecasting. Five years later, several solid studies on this topic have appeared in the literature [93]–[96]. Load and LMP are deeply coupled. How to derive probabilistic LMP forecasts by considering load uncertainties was studied in [97]. We expect the diversification of energy forecasting problems would continue to grow in the coming years.

8) Interdisciplinary collaborations: Collaborations among different subdomains of energy forecasting, between the energy forecasting community and other scientific communities, and between industry and academia, have been growing over the past few years, and will be growing in the future.

9) Regular conferences: Although a regular conference in energy forecasting has not been established yet, we did have the first International Symposium on Energy Analytics (ISEA) in 2017. Two years after that in 2019, the International Symposium on Forecasting for the first time hosted a full track of energy presentations, covering more than 30 talks in three days.

10) Scholarly journal: We do not yet have a dedicated publication outlet for energy forecasting. Nevertheless, most, if not all, major venues listed in Fig. 2 have appointed at least one editor or associate editor to handle energy forecasting papers. In 2019, INTERNATIONAL JOURNAL OF FORECASTING, the leading journal in forecasting, appointed Pierre Pinson, an IEEE Fellow for his contribution in wind power forecasting, as its Editor-in-Chief.

11) Professional society: The IEEE Working Group on Energy Forecasting (WGEF) took a leading role to move the state of the art forward in 2010s. In 2019, WGEF extended its scope from forecasting to analytics and changed its name into IEEE Working Group on Energy Forecasting and Analytics (WGEFA). Also in 2019, the International Institute of Forecasters launched SWEET, Section for Water, Energy and EnvironmenT. SWEET offers networking and collaboration opportunities to forecasters from energy and its surrounding areas. While WGEFA continues its activities with a focus on electric power, SWEET brings researchers and practitioners from a wider range of communities. Tackling the energy forecasting problem from different angles, the two organizations are expected to complement each other and continue growing the community and advancing the research progress in the future.

One of the 12 predictions in [49] has not seen much development yet:

12) Practical error measures for probabilistic energy forecasting: The development of practical error measures for probabilistic energy forecasting has not seen much progress yet. In fact, developing measures to properly reflect the value of energy forecast errors in general is an area worth looking into. We leave an in-depth discussion of this item in Section VI-C.

No forecasts are perfect. The hype of AI/ML and its applications in energy forecasting is a major trend completely missed by this historic forecast in [49]. In this paper, We have devoted Section III-A to AI/ML.

B. Close-loop Forecasting

In practice, forecasts are being produced, so that decision makers can take actions to optimize the future outcomes. For example, a large industrial load might cut back on its consumption in response to expected high prices. similarly, a battery storage facility may decide to recharge in response to expected low prices due to high wind generation at night or high solar generation during a sunny day. Such actions would change load profiles. If the change is significant, a supposedly accurate load forecast may become inaccurate comparing with the actually observed load due to decision makers' reaction to the original forecast. The shift in load profiles would also change the underlying price formation process, thus change the price. Forecasting change of load due to demand response was mentioned in [48] as a future research direction.

Post-forecast actions made by the users or receivers of forecasts had not been accounted for when the original load and price forecasts were released. Therefore, the forecasting models are blind-sighted. Observed load and prices may end up very different than anticipated. In other words, typical forecasting models are 'open-loop' whereas the process is inherently 'closed-loop'. This issue is arguably affecting electricity price more than forecasting of load, wind and solar, because the are too many factors that influence the prices. An in-depth discussion of this concept in the context of electricity price forecasting can be found in [98].

Another auxiliary issue around close-loop forecasting is the change in historical data. For example, in response to an anticipated high price during a hot summer day, power companies may activate their demand response programs to shed or shift the anticipated annual peak load. If the shifted load profiles are being used for future modeling activities without proper treatment, forecasting models would tend to underestimate how load profiles respond to high temperatures. As a result, the models would be under estimating the "organic" or "uncontrolled" peak load, or peak load without intervention of demand response programs. The same analogy is applicable to other subdomains of energy forecasting as well.

In economics, elasticity is the measurement of the (proportional) change of a variable in response to a change in another. Considering the growth of price-responsive market participants resulting from smart grid initiatives around the world, new models should be designed to account for this price elasticity.

C. Valuation of Forecasts

The typical error measures that are well-understood by the energy forecasting community may not necessarily reflect the economic value of reducing forecast errors. As argued in [99] for load forecasting, from a short-term unit commitment perspective, *a 1% reduction in forecasting error for a 10,000 MW utility can save up to $1.6 million annually*. The savings at a similar scale were derived in a more recent study [100] with considerations of several factors, such as the size of company, areas affected by forecasting models, and so forth. However, accurate valuation of energy forecasts is quite difficult, if ever possible, to accomplish. This is because the energy forecasts are used to influence or guide the decision making process. How forecasts are being used would affect the valuation of forecast errors. Depending upon the business applications, the cost functions may be asymmetric on the positive and negative errors.

It was demonstrated in [101] that measuring the economic value of improving electricity price forecasting errors is rather complex. In other words, a model that yields lower errors may not always point to a more effective model for forecast users. It is thus important to tie the evaluation measures to the users' characteristics and define alternative metrics that better capture the strengths and weaknesses of competing price forecasting models. Attempts at tackling this issue include proposing simple bidding strategies based on a comparison of the actual prices and their forecasts [102], [103] or using measures popular in financial portfolio analysis, like the Sharpe ratio [104], [105]. A recent study demonstrated that during volatile market periods, and for micro-grid energy management, a moving horizon deterministic model with point price forecasts led to significantly lower operation costs, compared to more complex stochastic and robust models [106]. Definitely, more research has to be done in this respect. Proper valuation of energy forecasts can also lift the recognition of forecasters in their organizations as well as the energy industry.

D. Working Together

Fig. 3 shows the main generation sources (conventional, wind, solar), system-wide load and wholesale electricity prices (day-ahead, intraday) in June 2019 in Germany. Note the spike in ID prices on June 25th (Tuesday) at 20:00 due to relatively high demand and low wind power generation (apparently unexpected a day earlier – the price in the DA market was 'normal'). Also note the negative prices on June 8th (Saturday) and 30th (Sunday), when very large wind and solar generation brought the demand for conventional power to monthly lows [107]. A picture like this perfectly speaks for the necessity of having energy forecasters working across subdomains. More and more influential research will be from interdisciplinary collaborations.

This paper serves as an energy forecasting primer for current and future researchers and practitioners interested in energy forecasting. The review does not mean to be exhaustive nor comprehensive. We primarily focus on influential papers published in the recent 20 years, as well as classical review articles and original research papers in the late 20th century. Interested readers may find the list of references a quality source of papers to read. We believe reproducible research is what the community need to to pursue as a whole, while interdisciplinary collaborations can lead to groundbreaking research outcomes.

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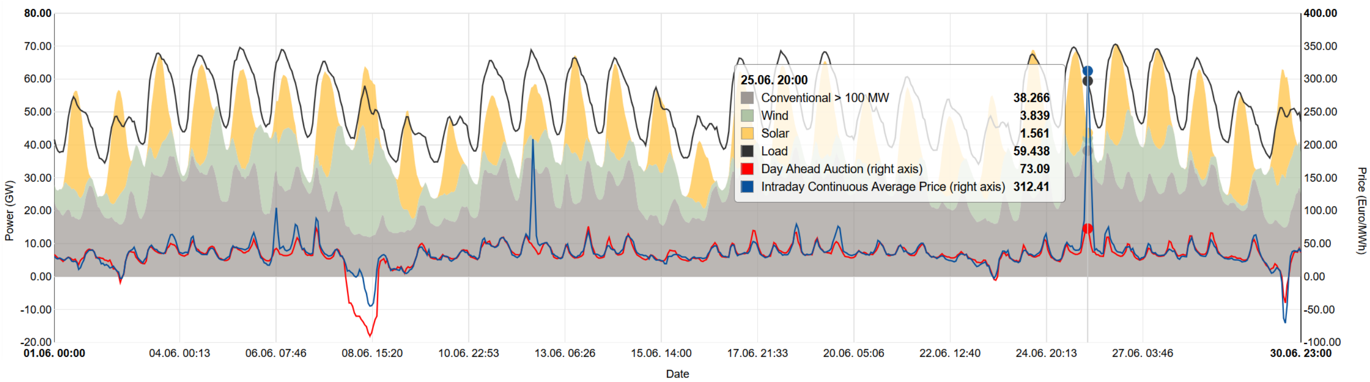

Fig. 3. One month (July 2019) of power generation, demand and prices in Germany. Source: [107].

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