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Editorial

Guest Editorial: Special Issue on Short-Term Load Forecasting 2019, Results and Future Perspectives

Antonio Gabaldón [1,*], María Carmen Ruiz-Abellón [2] and Luis Alfredo Fernández-Jiménez [3]

[1] Department of Electrical Engineering, Universidad Politécnica de Cartagena, 30203 Cartagena, Spain
[2] Department of Applied Mathematics and Statistics, Universidad Politécnica de Cartagena, 30203 Cartagena, Spain
[3] Department of Electrical Engineering, Universidad de La Rioja, 26004 Logroño, Spain
* Correspondence: antonio.gabaldon@upct.es; Tel.: +34-968-338944

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1. Introduction

In December 2018, the call for the Special Issue "Short-Term Load Forecasting 2019" of the journal *Energies* was launched. The submission deadline was in March 2020. The Special Issue followed in the footsteps of other past Special Issues devoted to methods for energy demand forecasting. The call was well received, with 27 submissions of which 13 were published: 11 research articles and 2 review articles. Short-term load forecasting (STLF) has been a topic of interest for the journal *Energies*, with numerous articles published since its inception, and is one of the themes included in the open for submission multidisciplinary topics of MDPI. All the articles of the Special Issue were published in the MDPI book with the same title in February 2021.

The scenario in which power systems operate has been undergoing major changes in recent years. Examples of these changes are the increasing integration of generation systems based on renewable energies or the appearance of new figures such as "active customers". This means that the STLF tools developed to date cannot provide the accuracy they achieved in the past. STLF tools and methods are essential for maintaining the security and stability of the power system at all levels. Precisely because of this essential role, new STLF methods, techniques or tools must address these changes. The emergence of new players on both sides of the power system, i.e., on both the generation and load sides, makes constantly balancing load and generation a much more complex task. Faced with a scenario of changing load, a question arises in the scientific community: how do we manage the availability of energy from renewable sources while allowing customers flexibility? A partial solution to the question can be provided by new STLF methods applied to both load and renewable generation estimation.

STLF has traditionally been applied to unresponsive customers, but must be adapted to deal with "active customers", that is, customers that change their demand according to technical or economic considerations. This type of customer represents a new dynamic figure in electricity markets (energy, capacity, or balance), in which they can participate alone or through load aggregators. A participation for which it is necessary to estimate demand with greater precision than has been achieved so far in order to avoid penalties for non-compliance at lower aggregation levels (under a few MW).

2. Results

Topics of interest for the call of the Special Issue included, but were not limited to:

- Short term load forecasting and distributed energy resources
- Short term load forecasting and demand aggregation levels
- Statistical forecasting models (SARIMA, ARMAX, exponential smoothing, linear and non-linear regression, and so on)
- Artificial neural networks (ANNs)

- Fuzzy regression models
- Tree-based regression methods
- Stacked and ensemble methods
- Evolutionary algorithms
- Deep learning architectures
- Support vector regression (SVR)
- Robust load forecasting
- Hierarchical and probabilistic forecasting
- Hybrid and combined models

It is worth mentioning that the published papers correspond to authors from four continents and 14 different countries, reflecting the interest in STLF worldwide.

The 11 research papers published in the Special Issue and in the book attempt to solve some of the STLF limitations, mainly by proposing new methods that improve the forecasting results with respect to those published in previous works. An important part of these articles focuses on the use of hybrid methods, whose application and analysis constitutes its main contribution. Specifically, [1] proposes a new method combining a data pre-processing technique, different forecasting algorithms, and an advanced optimization algorithm. In [2], using deep learning (deep belief network) and a phase space reconstruction, a very short-term prediction model for the bus load is developed. Classical methods based on time series also have a place in the proposed hybrid models. For instance, [3] proposes the electricity load forecasting by means of cubic splines and ARMAX models, introducing economic and weather information as exogenous variables. In [4], linear regression-based models together with spline function-based and traditional time series models are applied to analyze the two major components (deterministic and stochastic) of the electricity load. Additionally, [5] focuses on the impact of special days over the load curve of a system operator and it uses linear regression to model their effects.

The integration of STLF models into demand response (DR) actions is analyzed in two papers of the Special Issue. In [6], the authors propose a methodology combining clustering and machine learning techniques that could help power systems operators or aggregators to make up for the lack of accuracy when predicting renewable energy generation, whereas [7] provides a model based on deep learning that supports the demand response program in hybrid energy systems.

Many forecasting methods provide high accuracy at the power system level, however, the same it is not true for a single household. Two papers of the Special Issue are dealing with this topic: the method proposed in [8] is based on a deep residual neural network which extracts features from the historical load of the single household and all the ones in the dataset, whereas [9] proposes a method that can artificially enlarge the training dataset to be used later in a convolution neural network. Another typical issue in STLF is caused by a lack of historical data, which is addressed in [10] and [11]: in the former, the authors use multivariate random forest to construct a transfer learning-based model; in the latter, the authors propose an efficient and robust method for nowcasting load using machine learning techniques.

The Special Issue is completed with two review articles: the first one [12] presents a classification of STLF state-of-the-art methods based on four categories, and the second one [13] compares criteria used to tune and assess STLF methods with estimated costs caused by the forecasting errors.

The interest aroused by the articles published in the book can be estimated from the number of citations received in the scientific literature. Analyzing the data from the Scopus database obtained at the beginning of September 2022, that is, 28 months after the last paper published in the Special Issue, it can be seen that the scientific interest awakened by the articles has been remarkable. Thus, the average number of citations received per article is 16.8, with the most-cited article having received a total of 52 citations. Five of the articles of the Special Issue are in the top 10% of the most cited articles in the journal *Energies* published in 2019 and 2020. However, what is more indicative of the interest induced by these papers, the average number of full-text views registered by MDPI servers is 2090 per article, with 8156 views recorded for the most-accessed article. Taking as a reference the date of on-line publication of each article, the average number of daily full-text views of the articles is 1.92, reaching the most viewed article a value of 6.21 views per day.

3. Future Perspectives

Regardless of the effort to develop increasingly accurate and reliable STLF methods, some of the aspects that, in our opinion, should be explored in the near future include the following:

- Distributed renewable energy generation, especially in local photovoltaic (PV), has grown intensively in recent years and, because of the current energy crisis, is expected to expand further in the near future. A high level of PV penetration in low- and medium-voltage grids can cause uncertainty in the operation and management processes carried out by utilities, because most meters register the net load, i.e., the difference between the actual load and the PV power generation behind the meter. Since utilities do not have access to the PV data (capacity, type of technology, physical layout, power generation, etc.) of their customers, load forecasting is becoming much more complex. The stochastic nature of solar-based generation will be combined with a change in the consumption habits of customers who own PV systems. These customers will be more likely to shift their consumption to daylight hours. New STLF methods must be developed achieving the proper accuracy even when the value of this distributed generation behind the meter remains unknown. This problem of difficulty in forecasting the net load may increase as small-scale electricity storage systems become cheaper.
- In recent years, an important change in the means of land transport has begun. On the one hand, the development of new technologies for more powerful electric batteries has made possible the manufacture of light vehicles with technically competitive electric propulsion compared to their counterparts with combustion engines. It is foreseeable that in the near future, not only will light vehicles such as cars be electric, but also large goods and passenger vehicles. Battery-based EVs represent a source of uncertainty for the grid, since it is not known in advance when they will be charged, nor the amount of energy they need, nor the time in which they will carry out this operation [14]. On the other hand, there is the increased electrification in the transportation sector, which has been driven by environmental concerns. Both in the case of EVs with batteries, which will have to be recharged for their use, and in the case of the public transportation (buses, tramways and railways), each will have a significant influence on the change in future load patterns (e.g., faster oscillations of demand due to timetables and more frequent peaks due to the use of fast recharge stations). It will be necessary to explore new STLF methods that include explanatory variables specifically related to EV drivers, or develop methods with forecasting horizons and a granularity more adapted to the needs of the grids that facilitate these means of transport.
- The accuracy of the load forecasting depends on the data quality and the size of the load, among other factors. Results and conclusions of many papers are based on data from a specific system operator, country, region, or cover a short period of time, therefore those conclusions cannot be extrapolated to other regions or scenarios. It is necessary to create open benchmark databases, which include different load sizes and type of customers, to assess the accuracy of the forecasting methods from a more objective perspective.
- While there is considerable consensus on the use of certain measures to quantify the prediction error (e.g., RMSE or MAPE), it is also important to look more deeply into the economic or operational impact of such forecasting errors [13]. Is the MAPE the best measure of accuracy to quantify the actual cost to the system operator caused by the forecast error? New accuracy indicators may be needed. In addition, it should be

analyzed how they vary in the parameter tunning process, that is, how sensitive the forecasting method is to the selection of hyperparameters.

- It is well known that, apart from historical data, there are many factors that have a great impact on load forecasting, such as weather factors, calendar variables, electricity prices, etc. However, there is much to do in this context thanks to the current variety of data available (weather sensors, satellite images or social media platforms) with high granularity. Therefore, the analysis of new factors that can affect the load, their impact in the prediction model or even the development of reference lists of factors for each type of customer/load (residential, commercial, industrial, etc.) are worth exploring in future research papers.
- Machine learning (ML) methods are rising in many fields such as health, finances, people behavior, etc. As a result, adapting successful forecasting methods from those fields, the proposal of new ANN architectures and the development of new approaches (beyond current hybrid models) will be crucial to achieving significant progress in STLF. In this context, official competitions as well as collaborations among universities, startups, and electricity companies, represent suitable platforms for reaching a qualitative improvement in STLF.
- New STLF methods described in the literature have mostly been developed by academics, with very little involvement of industry professionals. Moreover, the proposed methods show only simulated results. The forecasting results of the proposed methods in real application scenarios, with an overview of the benefits obtained by the agent (system operator, owner, load aggregator, etc.) who uses the forecasts, the problems encountered in its implementation and the description of the solutions adopted to solve the drawbacks, would enrich the scientific contribution of the new STLF methods.
- The active customer is a cornerstone of new electricity markets, and this involves the increase in demand response levels. A fundamental requirement for the implementation and the verification of DR portfolio is the load forecasting of its participants, because DR changes the customer behavior and consequently forecasts. The improvement of STLF must have several and important advantages to engage, remain and increase the customer participation in DR. For instance, customers (and their aggregators) should obtain more stable revenues with improved customer baseline loads (CBL) that allow the right evaluation of their flexibility during DR periods. Some of these baseline attempts are based on STLF methodologies. Another consequence of the improvement of STLF is that customers, and aggregators, will be more "demand-balanced" and, in this way, they will need a fewer procurement of balance from third parties (e.g., balance service providers). Both advantages involve an improved cost-effectiveness of DR. Consequently, STLF methods aimed at DR actions should explore new explanatory variables such as the electricity price forecasts for the next hours or DR event signals triggered by operators.
- We are currently witnessing a change in the improvement of forecasting methods, where the interest of forecasting users is shifting from point to probabilistic forecasts [15]. STLF emerges as an ideal field for the development of this approach. Probability forecasting methods provide forecasts with their associated uncertainty, which allows for quantification of the risk associated with a decision based on those forecasts. Uncertainty information associated with the forecast may be presented in the form of probability functions, quantiles or prediction intervals, which represents much more complete information than the value provided by point forecasting methods. An interesting application of probabilistic STLF methods may be their integration in DR programs, enablingutilities or aggregators to select the proper program and helping to determine at what time activate it.

Although STLF has undergone a great development in recent years thanks to the use of ML techniques and new computing, it is also true that research in this field must be redirected to avoid some illusions described in [16]. The future scenario should include research into new ANN structures and new ML methods (beyond current hybrid models), along with the development of practical guidelines for forecasters. Because there is no method that outperforms the other ones, the abilities of the forecaster applying the technique are the most important aspect.

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