forecasting

Editorial

Editorial for Special Issue: “Feature Papers of Forecasting 2021”

Sonia Leva

Department of Energy, Politecnico di Milano, 20156 Milano, Italy; sonia.leva@polimi.it

The human capability to react or adapt to upcoming changes strongly relies on the ability to forecast them. Forecasting and its applications are increasingly important because they allow to improve decision-making processes by providing useful insights about the future. Scientific research is giving unprecedent attention to forecasting methods and applications, with a continuously growing number of articles about novel forecast approaches being published.

In this Special Issue, as well as in the one published in 2020 [1], high-quality papers in *Forecasting* spread into topics such as power and energy forecasting, forecasting in economics and management, forecasting in computer science, weather and forecasting and environmental forecasting have been selected and published. In particular, in this Special Issue, the most recent and high-quality research about forecasting is collected. Eleven papers are selected to represent a wide range of research fields where forecasting applications are playing a crucial role.

Nikolaidis et al. [2] propose a dynamical forecaster capable of estimating the required spinning reserves on the basis of a real-time load forecast. A neural network is trained via non-linear regression to accurately predict the load ahead starting from eight predictors, divided into constant and variable inputs by exploiting a model predictive control. The results provided demonstrate that the adoption of the proposed dynamical forecaster allows for significant improvements in terms of decreasing operating reserve requirements: Based on real-time updates, the load forecasting can achieve lower costs while the system security is preserved.

Ramos et al. [3] present a methodology designed for office buildings and aimed at improving the accuracy in electricity consumption forecasting on a 5-min time interval, providing proper support to decisions related to energy management towards higher efficiency. The prediction, based on data measured by different devices including presence, temperature, consumption and humidity, is carried out by means of two different forecasting algorithms, namely, Artificial Neural Network (ANN) and K-Nearest Neighbor (KNN) algorithms. The present research demonstrated that in order to achieve the maximum forecast accuracy in different periods of the day, hence in different contexts regarding consumption patterns, different forecasting algorithms must be used.

Chaiton et al. [4] present the outcomes of simulations forecasting the impact of five possible Tobacco Endgame policies on smoking prevalence and on tax revenues in Ontario by 2035. The Ontario SimSmoke simulation is exploited for modeling the expected effect of the first four strategies, namely: plain packaging, free cessation services, decreasing the number of tobacco outlets and increasing tobacco taxes. On the other hand, different models are involved in the evaluation of the impact of increasing the minimum required age to legally purchase tobacco to 21 years. Simulations predict that an increase in tobacco taxes will determine the greatest decrease in smoking prevalence, and that reducing smoking prevalence to “less than 5 by 35” by combining non-tax interventions and excise tax increase will result in a minimal impact on tax revenues.

Petropoulos et al. [5] focus on univariate time series forecasting and provide an overview of five different approaches allowing an improvement in the performances achievable with standard extrapolation methods. In further detail, the Theta method (manipulation of local curvatures), Multiple Temporal Aggregation (MTA), bootstrapping,

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Forecasting with Sub-seasonal Series (FOSS) and forecasting with multiple starting points are discussed and compared in terms of how information is extracted from data, the computational cost and the performance. Moreover, the concept of the "wisdom of the data" is presented, explaining how a proper data manipulation can translate into improved forecast accuracy by combining forecasts carried out from different perspectives on the same data.

Watson et al. [6] investigate how the quality of weather data derived from thunderstorm simulations influences the outcome of power outage models. A comparative analysis is conducted using two different Numerical Weather Prediction (NWP) systems with various levels of data assimilation, determining how outage models trained on these different sets of weather data differ in terms of performance. It is demonstrated that erroneous estimations in weather simulations propagate into the outage models in specific and quantifiable ways, suggesting how improved weather representations can possibly improve the quality of the power outage insights obtained.

Nespoli et al. [7] propose a preliminary forecast procedure with the objective to predict a family of batteries which is suitable, from both a technical and a financial point of view, for coupling with a certain PV plant configuration. The procedure is applied to hypothetical plants aimed at fulfilling the energy requirements of a commercial and an industrial loads. The amount of energy produced by the PV system is estimated on the basis of a performance analysis carried out on real plants with similar characteristics, while the battery operations are determined by two distinct control logics regulating charge and discharge, respectively. Finally, an unsupervised clustering based on k-means algorithm applied to all possible PV+BESS (Battery Energy Storage System) configurations allowed the researchers to identify the family of feasible solutions which, as expected, was characterized by a low payback time and a low number of residual cycles.

Boudhaouia et al. [8] describe a novel web-oriented data analysis platform capable of forecasting water consumption in real-time by exploiting Machine Learning techniques. The prediction is carried out with no prior and contextual information, relying only on past water consumption data recorded by smart meters as unevenly spaced time series with high-resolution and based on two different algorithms, namely, a Long Short-Term Memory (LSTM) and a Back-Propagation Neural Network (BPNN). The two models are tested on forecasting the water consumption in a private building: By evaluating their performance, it is observed that LSTM outperforms BPNN, providing more accurate predictions. According to the authors, the developed model can even be generalized to different types of consumption, such as electricity and gas.

Bas et al. [9] introduce a novel time series forecasting approach based on the Holt method modified by using time-varying smoothing parameters instead of fixed ones. Holt's smoothing parameters are obtained for each observation exploiting first-order autoregressive models whose parameters, in turn, are assessed through a Harmony Search Algorithm (HSA). The proposed method is tested on Istanbul Stock Exchange datasets covering the years between 2000 and 2017: The forecasts are obtained with a subsampling bootstrap approach, and different test lengths are considered during this analysis.

Wu et al. [10] deal with the topic of forecasting volatility from econometric datasets, a crucial task in finance. First, they assess the robustness of state-of-art Normalizing and Variance-Stabilizing (NoVaS) methods for long-term time-aggregated predictions, addressing the lack of experimental results in current NoVaS-related studies. Then, they develop a novel model-free method that, after an extensive analysis, demonstrated improved and more stable performance with respect to state-of-art NoVaS and standard GARCH-type methods in both the short and long term, regardless of whether simulation or real-world data are used.

Ali et al. [11] propose a novel approach aimed at predicting ocean currents by means of deep learning. In detail, a LSTM model is applied to the prediction of the three-dimensional tensors representing water column velocity. The proposed method is tested on estimating the Loop Current (LC) measured in the Gulf of Mexico between 2009 and 2011 at multiple spatial and temporal scales, where an RMSE (Root Mean Square Error) lower than 0.05 cm/s and a correlation coefficient of 0.6 were presented. Moreover, the model presented a useful forecast period, hence the time interval after which the forecast significantly diverges from the observed motion field, larger than 4 days.

Vega et al. [12] face the challenge of forecasting the number of new COVID-19 infections in the short and medium term by proposing the SIMLR model, incorporating Machine Learning (ML) into the epidemiological SIR model. By combining these two components, it is substantially possible to reduce the amount of data required by Machine Learning in order to produce accurate predictions and to estimate the time-varying parameters of a SIR model to produce forecasts with an advance of one to four weeks. The proposed SIMLR model is applied to study cases from Canada and the United States, demonstrating state-of-the-art forecasting performance with the additional advantage of providing probabilistic and interpretable outcomes. The authors expect this approach to be involved not only in COVID-19 modeling and for other infectious diseases as well.

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References

1. Leva, S. Editorial for Special Issue: “Feature Papers of Forecasting”. *Forecasting* **2021**, *3*, 135–137. [CrossRef]
2. Nikolaidis, P.; Partaourides, H. A Model Predictive Control for the Dynamical Forecast of Operating Reserves in Frequency Regulation Services. *Forecasting* **2021**, *3*, 228–241. [CrossRef]
3. Ramos, D.; Khorram, M.; Faria, P.; Vale, Z. Load Forecasting in an Office Building with Different Data Structure and Learning Parameters. *Forecasting* **2021**, *3*, 242–254. [CrossRef]
4. Chaiton, M.; Dubray, J.; Guindon, G.E.; Schwartz, R. Tobacco Endgame Simulation Modelling: Assessing the Impact of Policy Changes on Smoking Prevalence in 2035. *Forecasting* **2021**, *3*, 267–275. [CrossRef]
5. Petropoulos, F.; Spiliotis, E. The Wisdom of the Data: Getting the Most Out of Univariate Time Series Forecasting. *Forecasting* **2021**, *3*, 478–497. [CrossRef]
6. Watson, P.L.; Koukoula, M.; Anagnostou, E. Influence of the Characteristics of Weather Information in a Thunderstorm-Related Power Outage Prediction System. *Forecasting* **2021**, *3*, 541–560. [CrossRef]
7. Nespoli, A.; Matteri, A.; Pretto, S.; De Ciechi, L.; Ogliari, E. Battery Sizing for Different Loads and RES Production Scenarios through Unsupervised Clustering Methods. *Forecasting* **2021**, *3*, 663–681. [CrossRef]
8. Boudhaouia, A.; Wira, P. A Real-Time Data Analysis Platform for Short-Term Water Consumption Forecasting with Machine Learning. *Forecasting* **2021**, *3*, 682–694. [CrossRef]
9. Bas, E.; Egrioglu, E.; Yolcu, U. Bootstrapped Holt Method with Autoregressive Coefficients Based on Harmony Search Algorithm. *Forecasting* **2021**, *3*, 839–849. [CrossRef]
10. Wu, K.; Karmakar, S. Model-Free Time-Aggregated Predictions for Econometric Datasets. *Forecasting* **2021**, *3*, 920–933. [CrossRef]
11. Ali, A.M.; Zhuang, H.; Vanzwieten, J.; Ibrahim, A.K.; Chérubin, L. A Deep Learning Model for Forecasting Velocity Structures of the Loop Current System in the Gulf of Mexico. *Forecasting* **2021**, *3*, 934–953.
12. Vega, R.; Flores, L. SIMLR: Machine Learning inside the SIR Model for COVID-19. *Forecasting* **2022**, *4*, 72–94. [CrossRef]