Energy 278 (2023) 127831

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Incorporating air temperature into mid-term electricity load forecasting models using time-series regressions and neural networks

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ARTICLE INFO

Handling Editor: Henrik Lund

Keywords:
Load forecasting
Time series models
Neural networks
Weather
Temperature

ABSTRACT

One of the most controversial issues in the mid-term load forecasting literature is the treatment of weather. Because of the difficulty in obtaining precise weather forecasts for a few weeks ahead, researchers have, so far, implemented three approaches: a) excluding weather from load forecasting models altogether, b) assuming future weather to be perfectly known and c) including weather forecasts in their load forecasting models. This article provides the first systematic comparison of how the different treatments of weather affect load forecasting performance. We incorporate air temperature into short- and mid-term load forecasting models, comparing time-series methods and feed-forward neural networks. Our results indicate that models including future temperature always significantly outperform models excluding temperature, at all-time horizons. However, when future temperature is replaced with its prediction, these results become weaker.

1. Introduction

The literature on forecasting electricity consumption (commonly referred to as “load”) identifies three possible time horizons, each of them characterized by different methodologies and practical applications [1]. The short-term horizon is typically defined as being up to a few days ahead, and it is essential for control, power system scheduling and short-term price forecasting [2–8]. Mid-term forecasting ranges from a few days to about one year, and it informs system operation, maintenance scheduling, and the negotiation of forward contracts [9–13]. The long-term horizon can vary from one year to several decades, and it guides capacity planning [14–16].

The short-term load forecasting literature is extensive and spans several decades [17]. Mid-term forecasting has received, in comparison, less attention [10]. Arguably, one of the most controversial issues in this relatively newer literature is the treatment of weather. One of the possible explanations for this controversy is that developing accurate weather forecasts for several weeks (or months) ahead is extremely difficult, and weather projections of this sort are typically not available from weather bureaus [18,19].

Given these premises, several authors simply decide to not include weather at all in their mid-term load forecasting models [9,20–22]. Other researchers prefer to side-step the issue by including future weather data in their forecasting models [12,13,23–25]. Obviously, their forecasting performances are not genuine, because they do not consider the impact that weather forecasting errors can have on load forecasting. A third strategy is to include weather predictions (and not actual future weather) in the models for mid-term load forecasting. For instance Refs. [26–28], implement linear regression, time series models and support vector machines to forecast daily and monthly load in Italy, Chen et al. [10,18] use artificial intelligence methods to forecast one-to-twelve-months ahead load in China, and Hu et al. [29] use multi-output support vector regression and memetic algorithm to forecast interval loads up to one month in North America and Australia. This diversity of assumptions and approaches creates uncertainty not only for the development of new models, but also for comparing modelling results across different papers.

Considering this issue, the main contribution of this study is implementing a systematic comparison of the effect of the different treatments of weather on load forecasting performance at different time-horizons. Our study forecasts load in the short-to mid-term using linear regression and non-linear feed-forward neural network methods. While the importance of weather for short-term forecasting is well established (i. e., [30]; examine the impact of weather forecasts from 1 to 10 days

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https://doi.org/10.1016/j.energy.2023.127831
Received 2 January 2023; Received in revised form 21 April 2023; Accepted 13 May 2023
Available online 15 May 2023
0360-5442/

ahead), comparing the same approaches from one-day to six-months ahead is still useful in order to investigate if the conclusions drawn in short-run analyses extend to the mid-term horizon or not. In this respect, to the best of our knowledge, this is the first paper exploring this open question. Focusing on air temperature as the main weather variable for load forecasting and using daily data, we compare three groups of models: 1) specifications without temperature data, 2) specifications with actual future temperature data, and 3) specifications with predicted temperature data. In terms of techniques for forecasting, we employed the most established approaches for load forecasting. We use time series and linear regression approaches, since they are not black boxes and allow us to compare differences across models also in terms of parameters' estimates. We also use feed-forward neural networks, which are powerful non-linear modelling forecasters and are general enough in their model-building assumptions [31]. We implement our analysis on Italian Power Exchange (IPEX) day-ahead daily data from the January 1, 2016 to the December 31, 2019.

We find that models with perfect information on future temperature significantly outperform models without temperature data. This result is valid at all time horizons. However, when we replace future temperature with its prediction, results become weaker, and remain significant only for the shorter horizons. These conclusions are valid using both linear regressions and neural network models. Our results also indicate that, as expected, forecasting performance deteriorates with the time-horizon. However, this relation is highly non-linear as forecasting performance decreases significantly in the first few days and then stabilizes (i.e., forecasting one-week ahead appears to be about as hard as forecasting six-months ahead). For shorter horizons, autoregressive and moving average components provide an advantage, while for longer horizons, static models perform better. Finally, forecasts from neural network models outperform forecasts from linear regression models at all horizons; however, the difference is only significant in the short-term.

The remainder of the paper is structured as follows. Section 2 provides description of the data. Section 3 describes the models and methodology applied for estimation and forecasting. Section 4 presents the results. Finally, Section 5 concludes.

2. Data

We downloaded hourly day-ahead IPEX (Italian Power Exchange) load data in Gigawatt hour (GWh) from the European Network of Transmission System Operators for Electricity (ENTSO-E, https://www.entsoe.eu/) and converted them at daily frequency by taking the average of each day. The Italian Power exchange, the IPEX, was inaugurated in 2004, which makes it one of the youngest power markets in Europe. Short-term forecasting models for the IPEX have been developed by Ref. [32]; while mid-term load forecasting approaches are proposed by Refs. [26–28].

Terna (https://www.terna.it/) reports that in 2019–2020 the total electricity consumption in Italy was 302.75 TW-hour (TWh), and that the share of renewable energies production grew from 14% in 2005 to 35% in 2018–2019. Among fuels, the shares of natural gas, coal and biomass were around 45%, 9.3% and 9%, respectively, while other fossil fuels were responsible for about 6% of electricity generation. Furthermore, among renewable sources (RES), the shares of hydroelectric, solar and wind were about 16%, 8% and 6%, respectively. The RES are important issues for the behavior of the grid and this is crucial when predicting prices for markets with large RES size. However, energy demand is less affected by RES at short and middle horizons. The reason is that agents do not have precise information about future hourly prices, and they do not adjust their energy consumption in the short and middle term to account for stochastic behavior of the supply.

In Italy, electricity is traded in a wholesale market, organizing in day-ahead, intraday, and balancing sequential sessions [33]. In this liberalized market, the day-ahead session consists of consumption units and generators that submit bids to buy and offers to sell (both for prices and quantities) for each hour of the next day with no obligation to act. Such Day-Ahead Market is the host for most of the electricity transactions.

Regarding weather, we include what is arguably the most important driver of short- and mid-term load forecasting: air temperature [34,35]. We represent this variable for the entire country as the daily average between the temperature in Rome and in Milan (expressed in Fahrenheit degrees), downloaded from the University of Dayton weather archive (http://academic.udayton.edu/kissock/http/Weather).

Our analysis considers the period from January 1, 2016, to December 31, 2019, for total of 1461 observations. We decided to focus on the pre-COVID period, since during the coronavirus pandemic (especially during its first wave) there was a significant structural break in the dynamics of load, following the widespread lockdowns, which curtailed economic activity across Europe [36].

Fig. 1 reports the daily load time series. We observe a moderate annual seasonality, with peaks in the winter and summer months, when electricity consumption for heating and cooling is at its maximum. We also notice a pronounced weekly seasonality with demand decreasing by about 15 GWh during the weekends, when many businesses are shut down.

Fig. 2 presents the scatterplot between load and temperature, fitted using a locally estimated smoothing (loess) function. The Figure shows an asymmetric V-shaped relationship, with a minimum at about 60 °F (∼15.5 °C), in line with the load modelling literature [37,38].

Table 1 reports summary statistics and unit root tests. The average daily load ranges from about 20 GWh during Spring and Autumn weekends to 45 GWh in the summer weekdays. Average daily temperature also varies significantly, going from 28 °F (∼ −2.5 °C) to 84 °F (∼ 29 °C). The Augmented Dickey-Fuller [40] unit root tests strongly reject the null hypothesis for both series, which suggests modelling the series on the levels rather than on the first differences. In the table we report the value of the tests for the ADF with intercept and no trend, but results are robust to different specification of the test.

All our analyses are performed using the statistical software R [41] using the packages *forecast* [42], *ggplot2* [43], *lmtest* [44], *psych* [45], *sandwich* [46], and *urca* [47].

3. Methodology

3.1. Linear regression forecasting models

We compare different specifications, including linear regression, Auto-Regressive Moving Average (ARMA), and ARMA with explanatory variables (ARMAX) models. Our first model is a multiple linear regression capturing weekly and yearly seasonality effects, and the effect of public holidays. Regarding the weekly seasonality, we tested a model

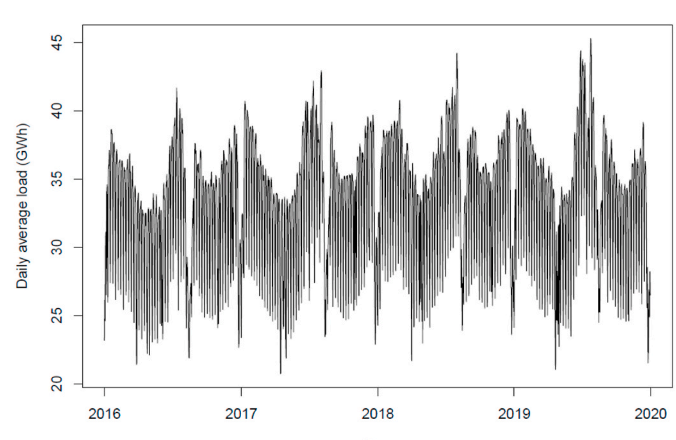

Fig. 1. IPEX daily average load.

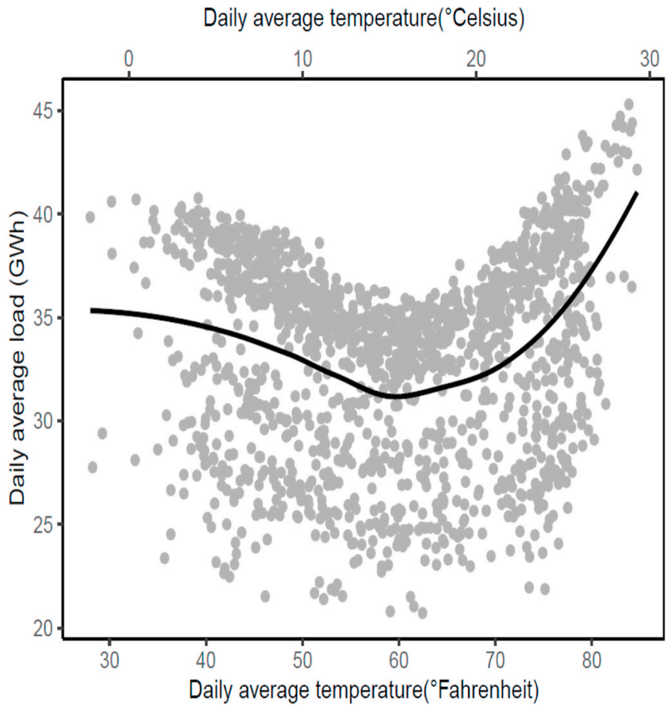

Fig. 2. Scatterplot of temperature and load
Notes: The scatterplot shows the relationship between daily average load and temperature. The line smooths the relationship using a loess function with span = 0.7 [39].

Table 1
Summary statistics.

Variables	Unit of measurement	mean	min	max	Standard deviation	ADF
Actual load	Gigawatt hour (GWh)	33.25	20.72	45.3	4.76	−23.82***
Temperature	Fahrenheit (°F)	59.27(15.5 °C)	28.00(-2.22 °C)	84.7 (29.28 °C)	12.8	−3.75***

Notes: ADF indicates Augmented Dickey Fuller unit root test with intercept and no trend and lags chosen according to the Akaike Information Criterion. Significance is indicated as: *** probability-value<0.01.

including a dummy variable for each day of the week, but the forecasting performance improved when including only Saturdays, Sundays and Mondays dummy variables and, therefore, we retained this more parsimonious specification.[1] Following previous studies (e.g. Refs. [48, 49], we capture the yearly seasonality via monthly dummy variables. They encompass the average monthly differences in weather, daylight hours and cultural practices. Finally, we include a dummy variable for public holidays [50,48]. The resulting equation is:

$$l_t = \beta_0 + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \sum_{j=1}^{11} \beta_{Mj} M_{j,t} + \beta_H H_t + \varepsilon_t \tag{1}$$

where t indicates the day, l_t is the average daily load (GWh), $W_{i,t}$ are dummy variables for Saturdays, Sundays and Mondays, $M_{j,t}$ are monthly dummy variables, H_t is a dummy variable for public holidays, β_s are the parameters to be estimated, and ε_t is the error component assumed to be white noise.

In the second model we remove the monthly variables and introduce the effect of temperature. As shown in Fig. 2, the relationship with load is non-linear and V-shaped. Following [36]; we allow such relation to be asymmetric by specifying a linear spline function, with a knot where load is at its minimum, which we define as 60 °F. The resulting equation is:

$$l_t = \beta_0 + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \beta_H H_t + \beta_{temp} temp_t + \beta_{temp'} d_{60}(temp_t - 60) + \varepsilon_t, \tag{2}$$

where $temp_t$ is the average daily temperature (°F), d_{60} is a dummy variable equal to 1 if temperature is higher or equal to 60 °F and zero otherwise, and all other symbols are defined as previously.

In the third model, we include both monthly binary variables and the non-linear effect of temperature:

$$l_t = \beta_0 + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \sum_{j=1}^{11} \beta_{Mj} M_{j,t} + \beta_H H_t + \beta_{temp} temp_t + \beta_{temp'} d_{60}(temp_t - 60) + \varepsilon_t, \tag{3}$$

All symbols are defined as previously. Our fourth model is an ARMA process, which is a widely applied benchmark for load forecasting (e.g. Refs. [51–53],:

$$\varphi(L)(l_t) = \psi(L)\varepsilon_t, \tag{a}$$

where $\varphi(L)$ and $\psi(L)$ are, respectively, the autoregressive and moving-average polynomials, which are functions of the lag operator L. After testing models up to seven lags, we selected the ARMA(1,1) as the best performing model, where $\varphi(L) = 1 - \varphi_1 L$ and $\psi(L) = \psi_0 + \psi_1 L$. This model can be written as:

$$l_t = \psi_0 + \varphi_1 l_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t, \tag{4}$$

where ψ_s and φ_1 are parameters to be estimated and all other symbols are defined as previously. We extend model 4 by including exogenous inputs in a "regression with ARMA errors" specification, defined as:

$$\varphi(L)[l_t - \psi_0 - \beta' X_t] = \psi(L)\varepsilon_t, \tag{b}$$

where X_t represents a vector of exogenous variables. In model 5, X_t includes dummy variables for days of the week, month and public holidays, creating the ARMAX version of model 1:

$$l_t = \beta_0 + \varphi_1 l_{t-1} + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \sum_{j=1}^{11} \beta_{Mj} M_{j,t} + \beta_H H_t + \psi_1 \varepsilon_{t-1} + \varepsilon_t. \tag{5}$$

By the same logic, model 6 is the ARMAX version of model 2:

$$l_t = \beta_0 + \varphi_1 l_{t-1} + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \beta_H H_t + \beta_{temp} temp_t + \beta_{temp'} d_{60}(temp_t - 60) + \psi_1 \varepsilon_{t-1} + \varepsilon_t, \tag{6}$$

Finally, model 7 is the ARMAX model corresponding to model 3:

$$l_t = \beta_0 + \varphi_1 l_{t-1} + \sum_{i=1}^{3} \beta_{Wi} W_{i,t} + \sum_{j=1}^{11} \beta_{Mj} M_{j,t} + \beta_H H_t + \beta_{temp} temp_t + \beta_{temp'} d_{60}(temp_t - 60) + \psi_1 \varepsilon_{t-1} + \varepsilon_t, \tag{7}$$

All symbols are defined as previously. We perform the in-sample estimations using the Maximum Likelihood (ML) estimator.

[1] During weekends many economic activities are suspended and, therefore, electricity load significantly decreases, while Monday is characterized by a quicker increase in demand compared to the other weekdays, at the same time, demand is typically lower during other working days [50].

3.2. Neural network forecasting

We also test the performance of Artificial Neural Networks (ANNs). We opt the multilayer feed-forward neural network (FNN) approach, which is a version of ANN with three types of layers: input, hidden, and output. The FNN is an established type of ANN in the load forecasting literature (e.g., Refs. [31,54,55]. In FNN the information goes only forward, from the input nodes, through the hidden nodes and to the output nodes [56]. The input layer takes the data and delivers them to the hidden layer using the weights between the input and the hidden layers. The neurons in the hidden layer process the data and deliver them to the output layer using the weights between the hidden and the output layers. Then, the neurons in the output layer again process the data and give the results as the output [57]. The mathematical model of the FNN can be written as:

$$y_t = f\left(b + \sum_{j=1}^{h} v_j\, g\left(b_j + \sum_{i=1}^{n} w_{ij} X\right)\right), \tag{c}$$

where y_t represents the output variable at time t, X denotes a vector of input variables including the lagged output variable as well as the exogenous variables, n represents the number of input variables, h indicates the number of neurons in hidden layer that is half of the number of input variables plus one, and $f(.) = \frac{1}{1+exp^{-f}}$ and $g(.) = \frac{1}{1+exp^{-g}}$ are the sigmoid non-linear activation functions. Furthermore, v_j and w_{ij} are the weight parameters that respectively represent the strength of the connections between the hidden nodes to the output and between the input nodes to the hidden nodes [31], and b and b_j are the bias parameters analogous to the intercept in linear models. All parameters are unknown and need to be estimated. We use four models for forecasting. In FNN1 we fit a simple model that uses as input one lag of the endogenous variable without exogenous variables, FNN2 includes the lag of load alongside monthly $(M_{j,t})$ weekly $(W_{i,t})$ and holidays (H_t) dummy variables, FNN3 includes the load lag, temperature variables ($temp_t$ and $d_{60}(temp_t - 60)$) and $W_{i,t}$ and H_t dummy variables, and FNN4 includes the load lag together with $temp_t$, $d_{60}(temp_t - 60)$, $W_{i,t}$, H_t and $M_{j,t}$. We use BFGS for optimization [58].

3.3. Forecasting setting

We compare the forecasting performance of our models at different time horizons: a) short-term: from 1 day until 7 days ahead; and b) mid-term: 1 month, 3 months and 6 months ahead. We divide our 2016–2019 dataset into two parts: we use a one-year dataset for estimation, while we compare the different models' forecasting performance on the years 2018–2019. We estimate all models using a one-year rolling window, i.e., a window going from time $t^*-364-J$ to t^*-J, where t^* indicates the day we want to forecast and J is the number of steps ahead corresponding to the forecasting horizon (e.g., $J = 1$ for day-ahead forecasts, $J = 2$ for two-days ahead forecasts, $J = 30$ for one-month ahead forecasts and so forth). For example, the models used to carry out one-day ahead forecast for 01-01-2018 are estimated on data from 01 to 01–2017 to 31-12-2017, the models to carry out the two-days ahead forecast for 01-01-2018 are estimated on data from 31 to 12–2016 to 30-12-2017, and to carry out the six-months ahead forecast for January 01, 2018, we use data from 06 to 07–2016 to 05-07-2017. By doing so, all models use the same length of the estimation window. We run recursive (iterated) multi-step ahead forecasts. Therefore, all our dynamic models (equations (4)–(7)) use previous load predictions as inputs for any forecasting horizon longer than one-day. Regarding temperature, (included in models 2, 3, 6 and 7), we compare two approaches. In the first one, we assume that we can perfectly forecast temperature, in effect estimating a lower bound for the forecasting errors of the models including this variable. In the second approach, we use some simple methods in order to predict temperature, inspired by the mid-term load forecasting literature [29]. This enables us to assess how the load forecasting performance changes at different time horizon when we use forecasted temperature instead of actual one.

We compare the price forecasting performances of our models by calculating the Root Mean Square Errors (RMSEs):

$$RMSE_k = \sqrt{\frac{\sum_{t=1}^{N}\left(\widehat{l}_{t,k} - l_t\right)^2}{N}}, \tag{d}$$

where N is the number of observations in the forecasting comparison window (years 2018–19), and $\widehat{l}_{t,k}$ is the forecasted load at time t. In total, we have $k = 1, \ldots, 212$ RMSEs for different models, methods and horizons. Furthermore, we use the RMSE and the Mean Absolute Percentage Errors (MAPEs) to evaluate temperature forecasting performance. The MAPE is defined as:

$$MAPE = \left(1 \Big/ N \sum_{t=1}^{N}\left|\frac{l_t - \widehat{l}_t}{l_t}\right|\right) \times 100, \tag{e}$$

We compare the accuracy of models by using the [59] test (D-M). We apply a one-sided test, where the alternative hypothesis indicates one forecast shows a higher accuracy than another one.

All information in this section applies to both the regressions and the neural network approaches. We represent our framework in brief in Fig. 3.

4. Results

4.1. Regression estimates

Table 2 presents the estimates for regression models 1–7 on our entire dataset, i.e., from January 1, 2016, to December 31, 2019, for a total of 1461 observations. The AR(1) and MA(1) terms are always significant at the 1% level with a positive sign. Each group of dummy variables including monthly and day of the week variables are jointly statistically significant, and the public holidays variable is also significant, all at the 1% level. Models including temperature allow us to estimate two different linear relationships connecting at 60°F. Consistent with Fig. 2, the effect of temperature before the threshold is negative, while it is positive after the threshold. These effects are highly asymmetric: in models without the ARMA terms, the impact of each degree above 60°F is about twice the effect of each degree below 60 °F, and in models including the ARMA terms, this asymmetry is even stronger, with the effect of warm temperatures being about four times that of cold temperatures. Arguably, this is because in Italy a significant share of the energy used for heating is derived by natural gas, while air cooling is all achieved via electricity consumption. Note that using a quadratic specification of temperature would have not been able to capture this asymmetry, since parabolas are symmetric.

4.2. Out of sample forecasting performance

We began the analysis by comparing the forecasting performance across regression models. We classify them in four different groups. The first group includes all models that do not contain temperature (models 1, 4, 5). The second group includes models with temperature in which temperature is represented by its future value, i.e., temperature is perfectly forecasted (models 2, 3, 6,7). The third and fourth groups also include models with temperature (models 2, 3, 6,7), but this time future temperature is replaced by its prediction for the test period. Depending on the forecasting horizon, we consider two possible approaches for predicting temperature. In the first one, we simply use the average temperature during the day in which we run the forecast as the best prediction of future temperatures, assuming that the best predictor for future values is today's value. For example, for computing one-step

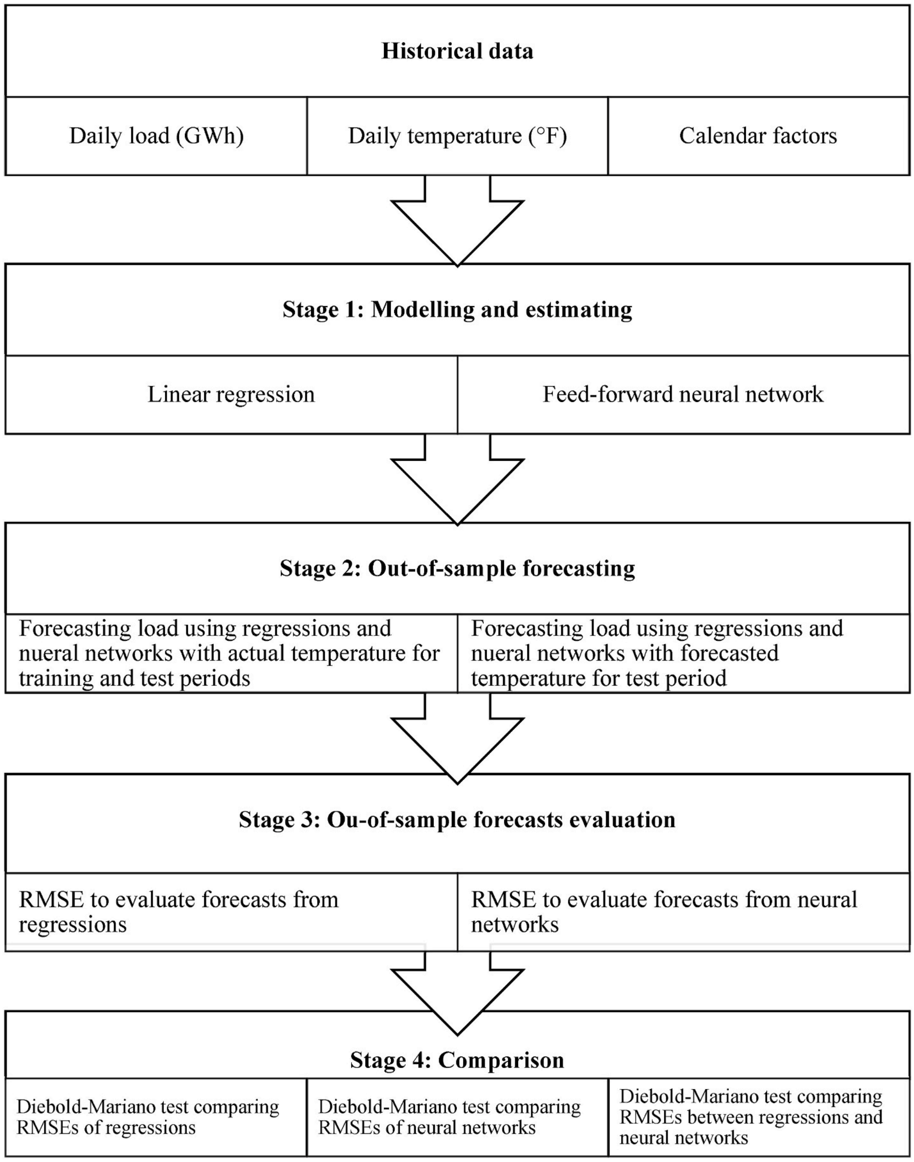

Fig. 3. Diagram of the proposed methodology.

Table 2
Model estimates on the full sample.

Dependent variable: load (GWh)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
AR(1)				0.26*** (0.03)	0.87*** (0.01)	0.86*** (0.01)	0.85*** (0.01)
MA(1)				0.60*** (0.03)	0.15*** (0.03)	0.09*** (0.03)	0.13*** (0.02)
Tempt		−0.20*** (0.02)	−0.15*** (0.02)			−0.04*** (0.01)	−0.04*** (0.01)
d60(Temp60)		0.46*** (0.04)	0.56*** (0.05)			0.22*** (0.03)	0.23*** (0.03)
Weekly seasonality	Yes	Yes	Yes	No	Yes	Yes	Yes
Holidays seasonality	Yes	Yes	Yes	No	Yes	Yes	Yes
Monthly seasonality	Yes	No	Yes	No	Yes	No	Yes
Akaike's Information Criterion	6729.43	6873.64	6416.70	7847.00	4999.90	4967.29	4952.41

Notes: The estimation covers data from January 1, 2016, to December 31, 2019, with 1461 observations. Standard errors (HAC robust standard errors for Models 1–3) are given in parentheses. Significance is indicated as: *** probability-value <0.01. The *AR(1)* and *MA(1)* represent the first order autoregressive and the first order moving average, respectively, *Temp* shows temperature (°F), *d60* indicates the dummy variable equal to 1 if temperature is higher or equal to 60 °F and zero otherwise, *Weekly seasonality* includes dummy variables for Saturdays, Sundays and Mondays, *Holidays seasonality* contains a dummy variable for public holidays and *Monthly seasonality* enters eleven dummy variables for each month of the year.

ahead forecasts, we use temperature at time *t*-1, for computing two-steps ahead forecasts, we use temperature at time *t*-2 and so forth. We consider this "random walk" approach for up to one-week ahead forecasts since it is clearly not appropriate for longer time horizons. As an alternative temperature forecasting method, we use the "climatology approach" as a simple way of forecasting temperature. This method averages temperature statistics that is accumulated over several years to make the forecast (see Ref. [60]. For instance, if we want to predict the temperature on January 1st, we would go through the temperature data that has been recorded for every January 1st in previous years and take an average. In this regard, we follow the load forecasting literature (e.g. Ref. [29], and employ the average of the temperature of the same day during the previous five years.

Table 3 compares the RMSEs and the MAPEs of the two temperature-forecasting approaches for the period from 01 to 01–2018 to 31-12-2019. Overall, our simple strategies perform well, with the MAPEs going from 3.5% to 7%, depending on the time horizon. As expected, the random-walk approach performs best in the very short term, while its performance slowly deteriorates with the increasing of the forecasting horizon. For example, the RMSE more than doubles from one-day ahead (2.5 °F) to seven-days ahead (5.1 °F). On the other hand, using historical averages gives, by construction, the same RMSE for all forecasting horizons. This second method provides performances which are superior to those provided by the random-walk from 4-days ahead onwards.

Comparison across load-forecasting models using the linear regressions is reported in Table 4. For each group of models, we highlight the best performing forecasts in bold. Furthermore, we compare best performing models across groups by using the [59] test. More precisely, at each time horizon, we test if the best performing model of each group provides significantly better forecast than the best performing model of the first group, in order to evaluate if including (future or forecasted) temperature significantly improves predictions.

In Table 4, the first column reports the RMSEs for one-day ahead forecasts. The best performing model amongst those that do not include temperature (group 1) is model 5, the ARMAX(1,1) with weekdays, holidays, and monthly dummies. ARMAX models are, in fact, the best specifications in each group at one-day-ahead predictions. As expected, including temperature significantly improves RMSEs. Not surprisingly, the best results are obtained when using future temperature (group 2). Nevertheless, using temperature at time *t*-1 provides comparable results (group 3). On the other hand, using the last five-years historical average does not generate significantly better RMSEs compared with those obtained using the best model of group 1.

The ARMAX models are the best performing ones in each group until three/four-day-ahead predictions. After that, the ARMA terms do not appear anymore in the top performing models in any of the four groups. This is consistent with the fact that AR and MA terms are useful for capturing the short-term effect of unexpected shocks. Since in these time series all shocks are mean reverting (i.e., the series are stationary), after a few lags their effects tend to fade and, therefore, the ARMA terms no longer contribute to improving predictions.

Knowing future temperature provides a considerable edge. As shown in Table 4, predictions obtained by the best performing model of group 2 are significantly better than those from group 1, at any time horizon. On the other hand, when using predicted temperatures, findings are mixed. For short leads (up to four days), using models with predicted temperature provides significantly lower RMSEs than excluding temperature.

Table 3
Temperature forecasting performance.

Time horizon	Forecast method	Forecast evaluation	
		RMSE (°F)	MAPE (%)
1-day ahead	Random walk	2.54	3.59
2-days ahead	Random walk	3.57	5.00
3-days ahead	Random walk	4.16	5.86
4-days ahead	Random walk	4.54	6.47
5-days ahead	Random walk	4.84	6.92
6-days ahead	Random walk	5.02	7.18
7-days ahead	Random walk	5.10	7.22
All horizons	Five-years average	4.27	6.08

Notes: "Five-years average" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values.

For longer leads, the gap with the models with no temperature tends to disappear and become insignificant. This is not necessarily due to the loss in precision of the temperature forecasts, since we observe this feature also in group 4, in which temperature forecasts are based on historical averages and, therefore, have the same forecasting errors at all horizons (recall Table 3).

We finally examine how the prediction accuracy deteriorates with the time horizon. Fig. 4 represents the RMSEs for all the best models of each group. Even if we assume future temperature as known, the RMSEs almost double when we go from one-day-ahead predictions to six-months-ahead ones. Interestingly, most of the increase in RSME is in the first three/four days, while the forecasting errors corresponding to one-month-ahead predictions are just slightly smaller than those pertaining to six-months-ahead ones. In other words, forecasting six-months-ahead does not appear to be much more challenging than forecasting one-month-ahead. These results do not change if we exclude temperature from our models or if we use forecasted temperature.

In Table 5, we report the results for FNN. We classify models in four groups. Group one includes models that do not contain temperature (FNN1 and FNN2). Group two includes models with temperature (FNN3 and FNN4) that is represented by its future value, i.e., temperature is perfectly forecasted. The third and fourth groups also include models with temperature (FNN3 and FNN4), but this time future temperature is replaced by its prediction for the test period. In the third group we use a random-walk temperature up to one-week ahead forecasts, and in the fourth group we employ the average of the temperature of the same day during the previous five years as the temperature forecasts.

The first column reports the RMSEs for one-day ahead forecasts. The best performing model amongst those that do not include temperature (group 1) is FNN2, which includes weekdays, holidays, and monthly dummies. In the second group, including temperature significantly improves the RMSEs, which generates the best results among the four groups. Therefore, including temperature significantly improves the RMSE. The best results are obtained when using future temperature in group 2. Nevertheless, using temperature at time *t*-1 in group 3 provides comparable results and using the last five-years historical average in group 4 also generates significantly better RMSE than those obtained by models in group 1 that do not contain temperature. This output confirms the evidence from the regression models.

In line with the linear regressions forecasts, predictions obtained by the best performing model of group 2 are significantly better than those from group 1, at any time horizon. However, when using predicted temperatures, findings are mixed. For short leads (up to three days), using models with predicted temperature provides significantly lower RMSEs than excluding temperature. For longer leads, the gap with the models with no temperature tends to disappear and become insignificant. Finally, from one-to-six months ahead models excluding temperature (group 1) outperform models including predicted temperature (group 4).

In Fig. 5 we illustrate how the prediction accuracy deteriorates with the time horizon using feed-forward neural networks. We represent the RMSEs for all the best models of each group in Table 5. Similar to the regressions forecasts, the RMSEs almost double when we go from one-day-ahead predictions to six-months-ahead ones and most of the increase in RSME is in the first few days. These results do not change if we exclude temperature from our models or if we use forecasted temperature.

These sets of findings from the linear regressions and non-linear neural network models demonstrate that comparing models assuming future temperature as known is likely to provide misleading conclusions, in particular for longer time horizons. They also showcase the importance of accurate temperature predictions for mid-term load forecasting. In our example, when we include future temperature in the models, the best regression and the best neural network models that include future temperature always generate lower RMSEs than those with no temperature, and the differences are always statistically significant at all

Table 4
The regressions forecasting performance (RMSEs).

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group1: Without temperature										
M 1: Week/Holidays/Months	2.24	2.25	2.26	**2.28**	**2.29**	**2.29**	**2.31**	**2.42**	**2.43**	**2.45**
M 4: ARMA(1,1)	3.57	4.75	4.82	4.82	4.82	4.81	4.81	4.83	4.83	4.84
M 5: ARMAX(1,1)- Week/Holidays/Months	**1.38**	**1.95**	**2.13**	2.27	2.40	2.46	2.56	3.36	3.24	3.21
Group 2: Actual temperature										
M 2: Temp/Week/Holidays	2.39	2.39	2.38	2.38	2.38	2.38	2.39	2.42	2.45	2.47
M 3: Temp/Week/Holidays/Months	2.02	2.03	2.03	**2.04*****	**2.04*****	**2.04*****	**2.05*****	**2.13*****	**2.18*****	**2.22*****
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.23*****	**1.71*****	**1.91*****	2.07	2.17	2.22	2.29	2.71	2.76	2.79
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	1.32	1.83	1.98	2.13	2.25	2.29	2.37	3.01	2.87	2.83
Group 3: Random walk temperature forecast										
M 2: Temp/Week/Holidays	2.39	2.41	2.45	2.49	2.53	2.56	2.60	–	–	–
M 3: Temp/Week/Holidays/Months	2.01	2.07	2.14	2.22	**2.28**	**2.32**	**2.36**	–	–	–
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.24*****	**1.76*****	**1.98*****	**2.16*****	2.29	2.35	2.44	–	–	–
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	1.33	1.88	2.07	2.24	2.37	2.44	2.54	–	–	–
Group 4: Five-years average temperature forecast										
M 2: Temp/Week/Holidays	2.54	2.53	2.53	2.53	2.53	2.54	2.54	2.57	2.60	2.63
M 3: Temp/Week/Holidays/Months	2.22	2.22	2.23	2.24	**2.24**	**2.25**	**2.26**	**2.37**	**2.40**	**2.41**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.33**	**1.80***	**2.00*****	**2.15*****	2.25	2.30	2.37	2.78	2.81	2.85
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	1.43	1.91	2.06	2.21	2.32	2.37	2.45	3.08	2.95	2.91

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. Asterisks (* probability-value<0.10, *** probability-value<0.01) represent the Diebold-Mariano *t*-test statistical significance comparing the smallest RMSEs in groups 2, 3 and 4 (models with temperature) to the best performing model in the first group (models without temperature). "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *M* means Model and the *ARMAX(1,1)* represents the first order autoregressive and moving average with *X* explanatory variables. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

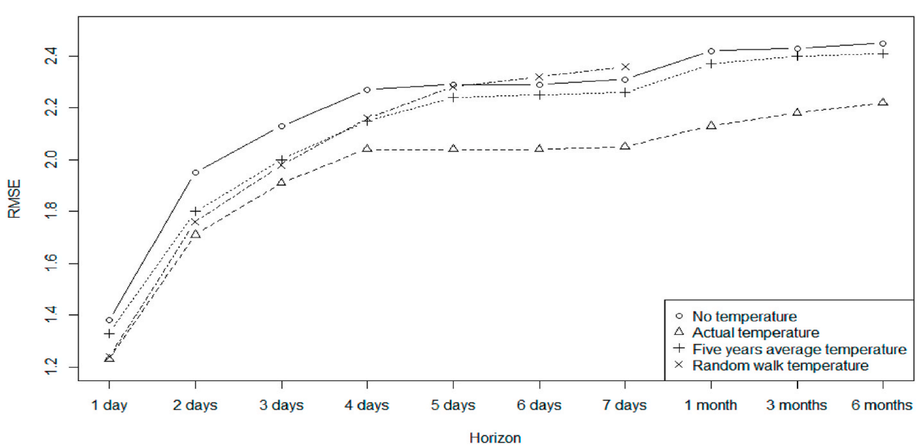

Fig. 4. The regressions best performing models at different time horizons (RMSEs)
Notes: This graph illustrates the minimum RMSE (GWh) for each forecast horizon across four groups of forecasts. "No temperature" represents the best model without temperature data. "Actual temperature" represents the best model using the future temperature data. "Five years average temperature" indicates the best model using temperature forecasted as the average of the previous five years in the same day of the year. "Random walk temperature" indicates the best model using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values.

horizons. However, when we include forecasted temperature for the test period, the best regression models that include forecasted temperature always generate lower RMSEs than those with no temperature, while this difference is not always statistically significant. Furthermore, the best forecasts using neural network models that include forecasted temperature generate lower RMSEs than those with no temperature only up to seven-days ahead forecasts and this difference is not always significant. Overall, these findings bring us to conclude that forecasted temperature should be included in the load forecasting models for all the horizons considered in our analysis specially when using linear regression models for mid-term forecasting. In the short-term load forecasting literature this conclusion is well-established, and our results indicate that it should be extended also to the mid-term.

Fig. 6 compares the performance of the regressions and the neural network models. We plot the RMSEs of the best performing model for each horizon. Overall, the neural network method outperforms the regression models for all horizons; however, the difference is only statistcally significant for two-to-seven days ahead.

4.3. Robustness

In order to assess whether increasing the sample size improves forecast performance of our models, we tested two alternative strategies for defining the sample sizes of our in-sample windows. In the first strategy, we use an expanding window (rather than the fixed, one-year, rolling window we used in our main analysis). This method has a fixed starting point and includes new data when it becomes available (i.e., the window gets bigger at each step). For example, to carry out one-day ahead forecast for 01-01-2018 we use data from 01 to 01–2016 to 31-12-2017, then to carry out one-day ahead forecast for 02-01-2018 we use data from 01 to 01–2016 to 01-01-2018, and finally to carry out one-day ahead forecast for 31-12-2019 we use data from 01 to 01–2016 to

Table 5
The neural network forecasting performance (RMSEs).

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
FNN1: FNNAR(1)	3.66	4.99	5.24	5.28	5.16	5.10	5.31	5.69	5.70	5.77
FNN2:FNNAR(1)-Week/Holidays/Months	**1.34**	**1.78**	**1.92**	**2.01**	**2.05**	**2.07**	**2.10**	**2.23**	**2.22**	**2.22**
Group 2: Actual temperature										
FNN3: FNNAR(1)-Temp/Week/Holidays	**1.15*****	**1.55*****	**1.72*****	**1.80*****	**1.88*****	**1.91*****	**1.96*****	**2.08****	2.18	2.22
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	1.30	1.74	1.89	1.98	2.03	2.01	1.99	2.08	**2.09****	**2.17*****
Group 3: Random walk temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**1.16*****	**1.59****	**1.81***	**1.95**	**2.05**	**2.13**	**2.22**	-	-	-
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	1.34	1.89	2.07	2.19	2.32	2.34	2.30	-	-	-
Group 4: Five-year average temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**1.23*****	**1.65***	**1.84**	**1.94**	**2.01**	2.07	2.12	**2.27**	**2.31**	**2.35**
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	1.41	1.84	1.96	2.05	2.04	**2.04**	**2.01***	2.51	2.43	2.43

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. Asterisks (* probability-value<0.10, ** probability-value<0.05, *** probability-value<0.01) represent the Diebold-Mariano *t*-test statistical significance comparing the smallest RMSEs in groups 2, 3 and 4 (models with temperature) to the best performing model in the first group (models without temperature). "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *FNN* means feed-forward neural network, and *FNNAR(1)* represents feed-forward neural network including the first order autoregressive term. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

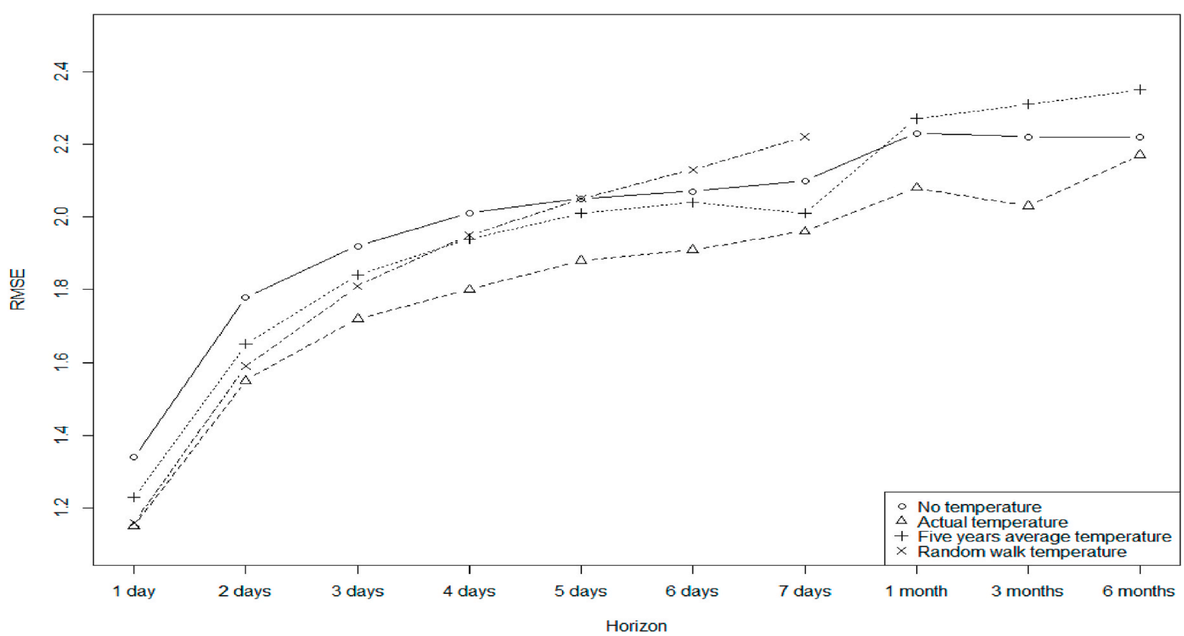

Fig. 5. The neural network best performing models at different time horizons (RMSEs)
Notes: This graph illustrates the minimum RMSE (GWh) for each forecast horizon across four groups of forecasts. "No temperature" represents the best model without temperature data. "Actual temperature" represents the best model using the future temperature data. "Five years average temperature" indicates the best model using temperature forecasted as the average of the previous five years in the same day of the year. "Random walk temperature" indicates the best model using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values.

30-12-2019. Therefore, we use all available data up to a specific point. The results are reported in the Appendix, Tables A1-A2, for the regressions and the neural network models, respectively. The outputs imply no systematic improvement in forecasts accuracies compared with the fixed one-year rolling window that we have as our main results.

In the second strategy, at each horizon we use all available data allowed by rolling window approach, with a fixed size for each specific horizon. For instance, the models used to forecast one-day-ahead for 01-01-2018 are estimated on data from 01 to 01–2016 to 31-12-2017 (i.e. 2 years of data), the models used to forecast two-days-ahead for 01-01-2018 are estimated on data from 01 to 01–2016 to 30-12-2017, and those used to forecast six-months-ahead for 01-01-2018, are estimated on data from 01 to 01–2016 to 05-07-2017. Therefore, we have bigger estimation samples size compared with the one-year sample we used in the main analysis. These windows roll on by keeping the size of the estimation sample fixed for each forecasting horizon. We use this strategy and repeat the forecasting comparison only for those models that showed the highest accuracy in each group in Tables 4 and 5 The results are reported in the Appendix, Table A3, and indicate no improvement in forecasts accuracies compared with the one-year sample window size for all horizons we have as our main results in the text.

As a robustness test, following the same forecast setting and strategy

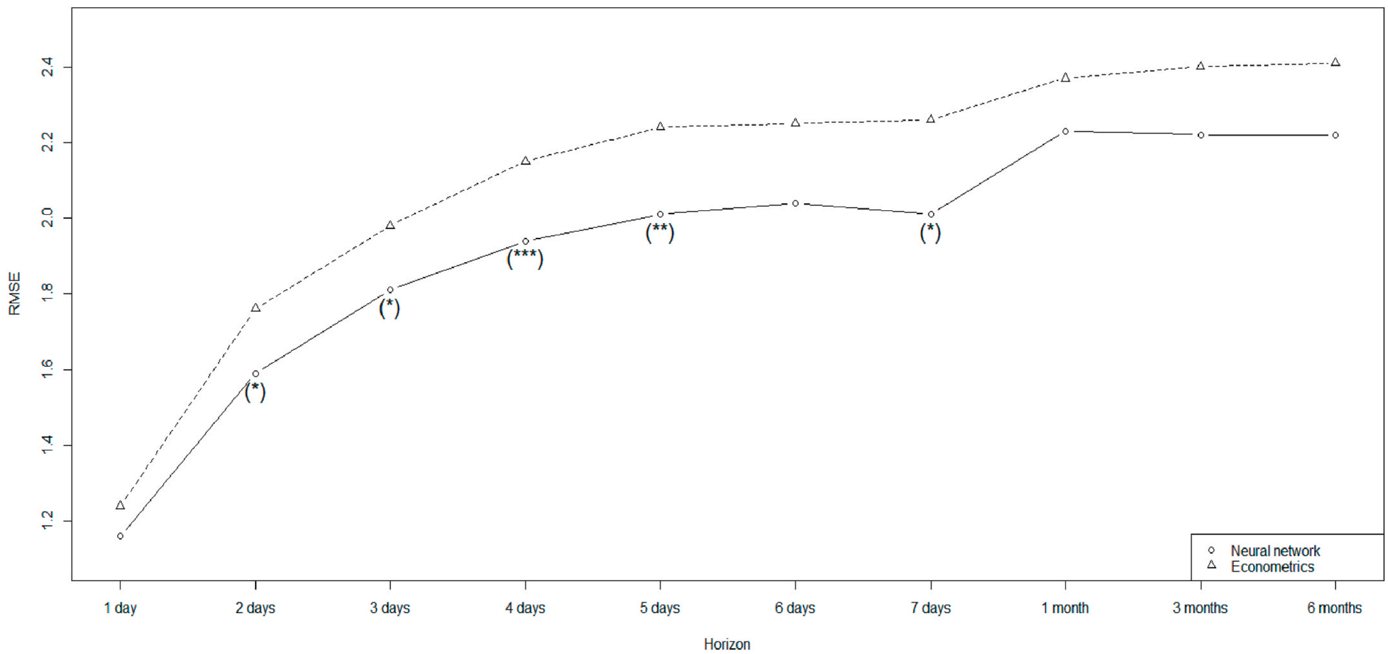

Fig. 6. Best regression model vs. best neural network model (RMSEs)
Notes: This graph illustrates the minimum RMSE (GWh) for each forecast horizon across the regressions and the feed-forward neural network models. "Neural network" represents the best models using feed-forward neural network. "Econometrics" represents the best models using the regressions. Asterisks (*probability-value<0.10, ** probability-value<0.05, *** probability value < 0.01) represent the Diebold-Mariano *t*-test statistical significance comparing the RMSEs between the best performing regression model and the best performing neural network model for each horizon.

we have in the main text, we evaluate the accuracy of load forecasts using MAPE instead of RMSE. The results in Tables B1-B2 of the Appendix indicate that the MAPEs generate conclusions that are comparable to those provided by the RMSEs.

In Tables C1-C2 of the Appendix we forecast load for the Northern region of Italy. Northern Italy is a good example of a regional study. The zone is well interconnected with foreign countries, where electricity can be imported from at lower prices. Also, the demand for electricity in this region represents almost half of the national demand [61]. We forecast load for Northern Italy and use the average daily temperature in Milan to represent weather. We achieve results that are akin to those obtained at the national level, while the RMSEs are, of course, lower.[2]

In Table D of the Appendix, we provide a nomenclature list for the abbreviations we used in the manuscript.

5. Concluding remarks

How one should include weather information in mid-term load forecasting models is arguably one of the most controversial factors in this recently growing literature. While weather is one of the most important drivers of electricity demand, weather conditions for several weeks ahead are especially hard to predict. In this paper we compared different load forecasting models with and without weather variables (represented by air temperature) at different time horizons, going from one-day to six-months ahead. Furthermore, we evaluated performance in two alternative scenarios: 1) assuming that we perfectly know future temperature and 2) using simple temperature predictions. We compared forecasts using the regressions and the neural network models and drew several conclusions that we believe should guide further mid-term load forecasting research.

First, applying both regressions and neural network methods, models with perfect information on future temperature significantly outperform models without temperature at all time horizons. In our case study, we observe an improvement in RMSEs that is between 10% and 20% depending on the specification. However, this is not a fair comparison since future temperature cannot be perfectly forecasted. When we replace future temperature with a simple prediction, results became weaker. When using the regression models, the RMSEs are still smaller for the models including forecasted temperature compared with models without temperature, but the statistical significance is retained only for short horizons, up to four-days ahead. When using the neural network models, the RMSEs are smaller for the models including forecasted temperature up to seven-days ahead, but statistical significance is preserved only for up to three-days ahead.

This leads us to draw two conclusions. First, comparisons across models should not be carried out assuming future temperature as known, as previously done in some research. Second, forecasted temperature should be included not only in short-term forecasting models (for which it is probably the most well-established driver), but also in mid-term forecasting. This output is more profound under the regressions than the neural network models. This conclusion is likely to grow in strength in the coming years, considering the constant improvement that we are witnessing in weather-prediction models [62].

Our results also clearly indicate that short-term forecasting (up to a few-days ahead) can be done much more accurately than mid-term one (one-month ahead or more). However, effects are highly non-linear with the RMSEs increasing significantly in the first few days and then stabilizing. In other words, one-day ahead load can be forecasted with much more accuracy than two-days ahead load, but one-week ahead load is not much easier to predict than one-month or even six-months ahead load. This pattern is consistent in all models (both with and without temperature) and, therefore, it is not due to weather prediction errors but, more likely, to omitted and short-living shocks. Such shocks can be captured well by AR and MA components which, in fact, provide an edge for short-term horizons (up to three or four days). However, these temporary dynamics no longer have an impact in the mid-term and, in

[2] We also try alternative approaches to forecast temperature including averages over different number of years (from two to ten) and moving averages of historical values (with 2, 3 and 7 days). Finally, we tested models which included a time trend. Our results (available upon request) remain unaffected.

fact, ARMA components disappear from the best specifications at longer horizons. From five-days ahead or more, our results tend to favor simpler, static models with only seasonal effects and other exogenous variables.

All these results hold to a series of robustness tests, including variable definitions, estimation window choices and forecasting evaluation methods. We believe that further research should investigate if our findings also hold when using more complex neural networks or other computational intelligence methods.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Niaz Bashiri Behmiri reports financial support was provided by Autonomous Province of Bolzano - South Tyrol.

Data availability

Data will be made available on request.

Acknowledgements

We acknowledge financial support from the Province of Bolzano-Bozen under the project SHE -Seasonal Hydrological Econometric Forecasting for Hydropower Optimization (grant E62F20000130003). We thank the conference participants at the EcoMod2022 International Conference on Economic Modeling and Data Science at the University of Ljubljana.

Appendix

Table A1
The regressions forecasting performance with expanding window (RMSEs)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
M 1: Week/Holidays/Months	2.43	2.45	2.47	2.48	2.49	**2.50**	**2.51**	**2.51**	**2.51**	**2.52**
M 4: ARMA(1,1)	3.57	4.78	4.86	4.87	4.87	4.87	4.87	4.89	4.88	4.89
M 5: ARMAX(1,1)- Week/Holidays/Months	**1.24**	**1.83**	**2.11**	**2.31**	**2.45**	2.54	2.66	3.19	3.14	3.13
Group 2: Actual temperature										
M 2: Temp/Week/Holidays	2.51	2.51	2.52	2.52	2.53	2.53	2.54	2.55	2.56	2.57
M 3: Temp/Week/Holidays/Months	2.19	2.21	2.22	2.23	2.24	**2.25**	**2.26**	**2.25**	**2.25**	**2.25**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.22**	**1.74**	**1.95**	**2.11**	**2.23**	2.29	2.39	2.82	2.87	2.88
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	1.23	1.76	1.99	2.17	2.29	2.37	2.47	2.79	2.77	2.76
Group 3: Random walk temperature forecast										
M 2: Temp/Week/Holidays	2.50	2.53	2.57	2.62	2.66	2.69	2.73	–	–	–
M 3: Temp/Week/Holidays/Months	2.17	2.24	2.32	2.39	2.45	2.48	**2.53**	–	–	–
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.24**	**1.79**	**2.04**	**2.22**	**2.35**	**2.42**	2.53	–	–	–
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	1.24	1.82	2.09	2.29	2.44	2.53	2.64	–	–	–
Group 4: Five-years average temperature forecast										
M 2: Temp/Week/Holidays	2.69	2.70	2.70	2.71	2.71	2.72	2.72	2.74	2.75	2.76
M 3: Temp/Week/Holidays/Months	2.45	2.46	2.47	2.49	2.49	2.50	2.51	**2.52**	**2.52**	**2.53**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**1.34**	**1.84**	**2.06**	**2.22**	**2.33**	**2.39**	**2.49**	2.92	2.95	2.97
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	1.37	1.89	2.12	2.29	2.41	2.48	2.58	2.90	2.88	2.87

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. “Five-years average temperature forecast” indicates models with temperature represented as the average of the previous five years in the same day of the year. “Random walk temperature forecast” indicates models using temperature forecasted as a random walk, i.e. using temperature at time t as the best forecast for its future values. *M* means Model and the *ARMAX(1,1)* represents the first order autoregressive and moving average with *X* explanatory variables. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

Table A2
The neural network forecasting performance with expanding window (RMSEs)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
FNN1: FNNAR(1)	3.66	5.10	5.39	5.46	5.37	5.30	5.55	6.01	6.03	6.07
FNN2:FNNAR(1)-Week/Holidays/Months	**1.16**	**1.59**	**1.84**	**1.99**	**2.10**	**2.21**	**2.29**	**2.43**	**2.43**	**2.50**
Group 2: Actual temperature										
FNN3: FNNAR(1)-Temp/Week/Holidays	1.19	1.63	1.83	1.97	2.08	2.13	2.20	2.43	2.40	2.43
FNN4: FNNAR(1)-Temp/Week/Holidays/ Months	**1.13**	**1.51**	**1.73**	**1.90**	**2.03**	**2.09**	**2.16**	**2.32**	**2.34**	**2.38**
Group 3: Random walk temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	1.21	1.69	1.95	2.17	2.33	2.41	2.50	–	–	–
FNN4: FNNAR(1)-Temp/Week/Holidays/ Months	**1.16**	**1.61**	**1.92**	**2.12**	**2.29**	**2.40**	**2.49**	–	–	–
Group 4: Five-year average temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	1.26	1.75	1.97	2.14	**2.26**	**2.34**	**2.41**	**2.64**	**2.62**	**2.66**
FNN4: FNNAR(1)-Temp/Week/Holidays/ Months	**1.22**	**1.69**	**1.95**	**2.14**	2.28	2.39	2.49	2.65	2.69	2.70

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *FNN* means feed-forward neural network, and *FNNAR(1)* represents feed-forward neural network including the first order autoregressive term. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

Table A3
Alternative sample selection (RMSEs)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Regressions										
Without temperature	1.24	1.82	2.08	2.28	2.41	2.43	2.44	2.42	2.42	2.44
Actual temperature	1.22	1.72	1.93	2.15	2.16	2.17	2.18	2.14	2.15	2.16
Random walk temperature forecast	1.24	1.78	2.01	2.20	2.36	2.40	2.45	–	–	–
Five-years average temperature forecast	1.34	1.83	2.04	2.19	2.39	2.40	2.41	2.38	2.39	2.40
Feed-forward neural network										
Without temperature	1.14	1.57	1.88	1.93	2.09	2.17	2.25	2.48	2.49	2.50
Actual temperature	1.15	1.57	1.77	1.88	1.97	2.04	2.09	2.35	2.34	2.41
Random walk temperature forecast	1.16	1.62	1.87	2.07	2.21	2.27	2.35	–	–	–
Five-years average temperature forecast	1.22	1.68	1.90	2.05	2.18	2.25	2.30	2.49	2.47	2.50

Note: In this table the RMSEs correspond to the models that had shown the smallest RMSEs in Tables 4 and 5 "Five years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. The unit of measurement for RMSE is GWh.

Table B1
The regressions forecasting performance (MAPEs)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
M 1: Week/Holidays/Months	4.73	4.80	4.85	**4.90**	**4.94**	**4.98**	**5.02**	**5.37**	**5.39**	**5.47**
M 4: ARMA (1,1)	9.24	12.46	12.54	12.49	12.49	12.47	12.44	12.5	12.54	12.59
M 5: ARMAX(1,1)- Week/Holidays/Months	**2.64**	**4.02**	**4.57**	5.00	5.29	5.47	5.69	7.90	7.64	7.62
Group 2: Actual temperature										
M 2: Temp/Week/Holidays	4.88	4.87	4.87	4.87	4.88	4.88	4.89	4.97	5.12	5.22
M 3: Temp/Week/Holidays/Months	4.17	4.22	4.25	**4.27**	**4.29**	**4.31**	**4.33**	**4.48**	**4.65**	**4.78**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**2.45**	**3.54**	**4.00**	4.33	4.54	4.67	4.88	6.09	6.24	6.36
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	2.60	3.83	4.24	4.59	4.81	4.93	5.12	6.96	6.72	6.68
Group 3: Random walk temperature forecast										
M 2: Temp/Week/Holidays	4.90	5.01	5.10	5.26	5.38	5.45	5.58	–	–	–
M 3: Temp/Week/Holidays/Months	4.19	4.4	4.55	4.71	**4.86**	**4.98**	**5.14**	–	–	–
M 6: ARMAX(1,1)-Temp/Week/Holidays	**2.44**	**3.61**	**4.18**	**4.60**	4.87	5.05	5.30	–	–	–
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	2.59	3.90	4.43	4.85	5.14	5.35	5.61	–	–	–
Group 4: Five-years average temperature forecast										
M 2: Temp/Week/Holidays	5.27	5.26	5.26	5.25	5.26	5.26	5.27	5.35	5.50	5.62
M 3: Temp/Week/Holidays/Months	4.71	4.74	4.75	4.78	4.80	4.82	**4.86**	**5.10**	**5.17**	**5.27**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**2.78**	**3.79**	**4.23**	**4.53**	**4.72**	**4.82**	5.02	8.18	6.31	6.45
M 7: ARMAX(1,1)-Temp/Week/Holidays/ Months	2.93	4.03	4.42	4.77	4.96	5.09	5.28	7.11	6.88	6.79

Notes: We report in bold the smallest MAPE for each group of models and forecasting horizon. "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *M* means Model and the *ARMAX(1,1)* represents the first order autoregressive and moving average with *X* explanatory variables. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for MAPE is %.

Table B2
The neural network forecasting performance (MAPEs)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
FNN1: FNNAR(1)	9.62	13.60	14.03	14.00	13.51	13.35	13.77	14.44	14.48	14.61
FNN2:FNNAR(1)-Week/Holidays/Months	**2.72**	**3.70**	**4.13**	**4.29**	**4.35**	**4.46**	**4.54**	**4.90**	**4.54**	**4.86**
Group 2: Actual temperature										
FNN3: FNNAR(1)-Temp/Week/Holidays	**2.28**	**3.11**	**3.47**	**3.65**	**3.73**	**3.78**	**3.84**	**4.14**	**3.84**	**4.45**

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Table B2 (*continued*)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	2.55	3.40	3.63	3.78	3.88	3.90	3.86	4.33	3.86	4.51
Group 3: Random walk temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**2.30**	**3.31**	**3.86**	**4.20**	**4.29**	**4.42**	4.67	–	–	–
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	2.64	3.79	4.20	4.37	4.62	4.72	**4.62**	–	–	–
Group 4: Five-year average temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**2.43**	**3.41**	**3.81**	**4.03**	**4.12**	**4.22**	4.33	**4.64**	**4.76**	**4.89**
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	2.85	3.78	4.06	4.18	4.17	4.23	**4.14**	5.12	5.00	5.04

Notes: We report in bold the smallest MAPE for each group of models and forecasting horizon. "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *FNN* means feed-forward neural network, and *FNNAR(1)* represents feed-forward neural network including the first order autoregressive term. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for MAPE is %.

Table C1
The regressions forecasting performance (RMSEs) for the North of Italy

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
M 1: Week/Holidays/Months	1.60	1.60	1.60	**1.61**	**1.61**	**1.61**	**1.62**	**1.68**	**1.69**	**1.70**
M 4: ARMA(1,1)	2.44	3.29	3.33	3.32	3.32	3.32	3.31	3.33	3.33	3.34
M 5: ARMAX(1,1)- Week/Holidays/Months	**0.98**	**1.39**	**1.50**	1.61	1.67	1.74	1.80	2.33	2.22	2.22
Group 2: Actual temperature										
M 2: Temp/Week/Holidays	1.79	1.79	1.79	1.79	1.79	1.79	1.79	1.81	1.83	1.85
M 3: Temp/Week/Holidays/Months	1.49	1.50	1.50	1.50	**1.50****	**1.50****	**1.51****	**1.56*****	**1.56*****	**1.58*****
M 6: ARMAX(1,1)-Temp/Week/Holidays	**0.90*****	**1.25*****	**1.38*****	**1.49****	1.56	1.59	1.64	1.93	1.94	1.97
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	0.96	1.34	1.45	1.54	1.62	1.65	1.71	2.19	2.09	2.07
Group 3: Random walk temperature forecast										
M 2: Temp/Week/Holidays	1.79	1.81	1.83	1.84	1.86	1.87	1.90	–	–	–
M 3: Temp/Week/Holidays/Months	1.48	1.52	1.56	1.59	1.62	**1.63**	**1.66**	–	–	–
M 6: ARMAX(1,1)-Temp/Week/Holidays	**0.91*****	**1.27*****	**1.42*****	**1.54**	**1.62**	1.66	1.73	–	–	–
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	0.97	1.36	1.49	1.60	1.69	1.73	1.81	–	–	–
Group 4: Five-years average temperature forecast										
M 2: Temp/Week/Holidays	1.86	1.86	1.86	1.86	1.86	1.86	1.86	1.88	1.90	1.92
M 3: Temp/Week/Holidays/Months	1.61	1.61	1.61	1.62	1.62	**1.62**	**1.63**	**1.70**	**1.70**	**1.72**
M 6: ARMAX(1,1)-Temp/Week/Holidays	**0.97**	**1.30****	**1.44*****	**1.54**	**1.61**	1.64	1.70	1.97	1.98	2.01
M 7: ARMAX(1,1)-Temp/Week/Holidays/Months	1.03	1.38	1.49	1.59	1.66	1.70	1.76	2.24	2.14	2.12

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. Asterisks (* probability-value<0.10, ** probability-value<0.05, *** probability-value<0.01) represent the Diebold-Mariano *t*-test statistical significance comparing the smallest RMSEs in groups 2, 3 and 4 (models with temperature) to the best performing model in the first group (models without temperature). "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *M* means Model and the *ARMAX(1,1)* represents the first order autoregressive and moving average with *X* explanatory variables. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

Table C2
The neural network forecasting performance (RMSEs) for the North of Italy

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 1: Without temperature										
FNN1: FNNAR(1)	2.58	3.59	3.78	3.79	3.72	3.77	3.92	4.03	4.05	4.11
FNN2:FNNAR(1)-Week/Holidays/Months	**0.92**	**1.22**	**1.34**	**1.41**	**1.49**	**1.51**	**1.57**	**1.56**	**1.64**	**1.63**
Group 2: Actual temperature										
FNN3: FNNAR(1)-Temp/Week/Holidays	**0.82*****	**1.16****	**1.34**	**1.42**	**1.45**	**1.50**	**1.51**	**1.64**	**1.57*****	**1.63**
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	0.91	1.23	1.37	1.48	1.55	1.59	1.64	1.74	1.73	1.79
Group 3: Random walk temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**0.84**	**1.17**	**1.36**	**1.50**	**1.53**	**1.55**	**1.63**	–	–	–
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	0.89	1.28	1.46	1.58	1.69	1.70	1.78	–	–	–

(*continued on next page*)

Table C2 (*continued*)

Models	One day	Two days	Three days	Four days	Five days	Six days	Seven days	One month	Three months	Six months
Group 4: Five-year average temperature forecast										
FNN3: FNNAR(1)-Temp/Week/Holidays	**0.88**	**1.21**	**1.35**	**1.44**	**1.49**	**1.55**	**1.60**	**1.68**	**1.67**	**1.72**
FNN4: FNNAR(1)-Temp/Week/Holidays/Months	0.99	1.32	1.50	1.62	1.71	1.73	1.75	1.83	1.85	1.92

Notes: We report in bold the smallest RMSE for each group of models and forecasting horizon. Asterisks (** probability-value<0.05, *** probability-value<0.01) represent the Diebold-Mariano *t*-test statistical significance comparing the RMSE to the best performing model in the first group of models (without temperature). "Five-years average temperature forecast" indicates models with temperature represented as the average of the previous five years in the same day of the year. "Random walk temperature forecast" indicates models using temperature forecasted as a random walk, i.e. using temperature at time *t* as the best forecast for its future values. *FNN* means feed-forward neural network, and *FNNAR(1)* represents feed-forward neural network including the first order autoregressive term. *Temp* indicates temperature, *Week* represents dummy variables for Saturdays, Sundays and Mondays, *Holidays* contains a dummy variable for public holidays and *Months* enters eleven dummy variables for each month of the year. The unit of measurement for RMSE is GWh.

Table D
Nomenclature list

IPEX	Italian Power Exchange
ENTSO-E	European Network of Transmission System Operators for Electricity
GWh	Gigawatt hour
TWh	Terawatt-hour
°F	Degree Fahrenheit
°C	Degree Celsius
ADF	Augmented Dickey-Fuller
ARMA	Auto-Regressive Moving-Average
l	Daily load
$\hat{l}$	Daily forecasted load
temp	Daily temperature
d60	Dummy variable equal to 1 if temperature is higher or equal to 60 °F and zero otherwise
W	Dummy variables for Saturdays, Sundays and Mondays
M	Monthly dummy variables
H	Dummy variable for public holidays
$\varphi(L), \psi(L)$	Autoregressive and moving average polynomials
L	Lag operator
β_s, ψ_s, φ_s	Parameters to be estimated
ML	Maximum likelihood
ANN	Artificial Neural Network
FNN	Feed-forward Neural Network
FNNAR(1)	Feed-forward neural network including the first order autoregressive term
BFGS	Broyden-Fletcher-Goldfarb-Shanno algorithm
y	Output variable
X	Vector of input variables
n	Number of input variables in the neural network model
$f(.)$, $g(.)$	Sigmoid non-linear activation functions
b_s	Bias parameters
v, w	Weighted parameters
h	Number of neurons in hidden layer of the neural network model
exp	Exponentiate
RMSE	Root Mean Square Errors
MAPE	Mean Absolute Percentage Errors
N	Number of observations in the forecasting comparison window
D-M	[59] test

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