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New probabilistic price forecasting models: Application to the Iberian electricity market

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ABSTRACT

This article presents original Probabilistic Price Forecasting Models, for day-ahead hourly price forecasts in electricity markets, based on a Nadaraya–Watson Kernel Density Estimator approach. A Gaussian Kernel Density Estimator function is used for each input variable, which allows to calculate the parameters of the probability density function (PDF) of a Beta distribution for the hourly price variable. Thus, valuable information is obtained from PDFs such as point forecasts, variance values, quantiles, probabilities of prices, and time series representations of forecast uncertainty. A Reliability Indicator is also introduced to give a measure of "reliability" of forecasts. The Probabilistic Price Forecasting Models were satisfactorily applied to the real-world case study of the Iberian Electricity Market. Input variables of these models include recent prices, power demands and power generations in the previous day, power demands in the previous week, forecasts of demand, wind power generation and weather for the day-ahead, and chronological data. The best model, corresponding to the best combination of input variables that achieves the lowest MAE, obtains one of the highest Reliability Indicator values. A systematic analysis of MAE values of the Probabilistic Price Forecasting Models for different combinations of input variables showed that as more types of input variables were considered in these models, MAE values improved and Reliability Indicator values usually increased.

1. Introduction

1.1. Context of this research related to the day-ahead electricity price forecasting

In the last 25 years the transition from monopolistic power sectors to competitive ones has led to the trade of electricity under market rules. In the market paradigm, the economic operation of the power system is based on price signals that are holistically influenced by all the market agents, which try to achieve their economic interests. These price signals are mainly generated in the day-ahead market, which influences all the remaining market prices (e.g., intraday markets, derivative product markets, and bilateral markets). Knowing in advance the prices that will be settled by the day-ahead electricity market is essential for the price-makers' agents, guiding the bidding decision-making process in order to maximize their economic profit.

Furthermore, knowing the prices in advance is even important for the least relevant agents (those who, due to their low volume of trading operations, do not influence the price value), who can evaluate the risk of anomalous prices in advance and, consequently, respond to high or low price forecasts by managing their electricity consumption and/or their self-power generation.

Therefore, a significant effort has been made in recent years to develop Day-Ahead Electricity Price Forecasting models (DAEPF models). Most of the published DAEPF models are focused on point (spot) forecasts, that is, they provide the values of forecasted hourly electricity prices without any additional information. However, these DAEPF models that only give point forecasts can be inadequate for trading purposes because they do not show the uncertainty associated with the price forecasts, which is essential for risk-based market decisions. Point (spot) forecasts do not offer information to support trading associated with market risks. Market decisions based on point forecasts are suitable when the economic impact of the deviation (between forecast value and real value) is linearly dependent on the absolute value of the deviation. However, probabilistic price forecasting models are able to provide information regarding the uncertainty of the price forecasts. They have become essential models for making proper risk-based decisions when the magnitude of the price (or magnitude of the deviation) has a higher relative impact on more extreme price values, that is, when it is imperative to know the probability of occurrence of

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Nomenclature

Abbreviations

PPFM	Probabilistic Price Forecasting Model
DAEPF	Day-Ahead Electricity Price Forecasting
NW-KDE	Nadaraya–Watson Kernel Density Estimator
PDF	probability density function
MAE	Mean Average Error
RI	Reliability Indicator
SVM	Support Vector Machine
MIBEL	Iberian Electricity Market
OMIE	Market Operator of the MIBEL
TSO	Transmission System Operator
REE	Spanish Transmission System Operator
REN	Portuguese Transmission System Operator
NWP	Numerical Weather Prediction
GFS	Global Forecast System

Variables

x	explanatory price variable
y	electricity price variable
$x_{v,new}$	explanatory price variable for dimension v for future hour (*new*)
$x_{v,p}$	explanatory price variable for dimension v for past instant p
$\{x_{1,new}, \ldots, x_{v,new}, \ldots, x_{m,new}\}$	generic case for future hour (*new*)
x_{new}	explanatory price variable for future hour (*new*)
x_v	explanatory price variable for dimension v
y_{new}	electricity price variable for future hour (*new*)
y'_{new}	standardized electricity price variable between 0 and 1 corresponding to y_{new}
y_p	electricity price variable for instant p
y'_p	standardized variable between 0 and 1 corresponding to y_p

Elements

$[Y_{new}]$	element associated with y_{new}
$[Y'_{new}]$	element associated with y'_{new}
$[X_{new}]$	set of elements associated with explanatory variables $x_{v,new}$

Numerical values

n	number of cases of the historical dataset
m	number of price explanatory variables
$x_{new,\max}$	highest limit value for x_{new}
$x_{new,\min}$	lowest limit value for x_{new}
$x_{v\_\max}$	maximum value of x_v of the historical dataset of cases
$x_{v\_\min}$	minimum value of x_v of the historical dataset of cases
$y_{new,\max}$	the highest limit value for y_{new}
$y_{new,\min}$	the lowest limit value for y_{new}
$n\text{-}new,\min$	number related to $y_{new,\min}$
$n\text{-}new,\max$	number related to $y_{new,\max}$
bl_a	basic level of activation
bl_{a_std}	standardized basic level of activation
F_{chg}	factor between 0 and 1
N_p	minimum number of activated points from the historical dataset
NQ	total number intervals
N	number of elements in the out-sample dataset

Parameters

h_v	bandwidth for dimension v
α_{new}	parameter α of PDF of a Beta distribution for future hour (*new*)
β_{new}	parameter β of PDF of a Beta distribution for future hour (*new*)
$(\alpha_{new}, \beta_{new}, y_{new,\min}, y_{new,\max})$	parameters of a PDF of a Beta distribution for future hour (*new*)
$(\alpha_{new\_q}, \beta_{new\_q}, y_{new\_q,\min}, y_{new\_q,\max})$	parameters of a PDF of a Beta distribution for new case q

Functions

$K_v(x_{v,p};x_{v,new}, h_v)$	kernel density estimation function
$F_{new}\ (\alpha_{new}, \beta_{new}, y_{new,\min}, y_{new,\max})$	Beta cumulative distribution function for future hour (*new*)
$f\,(y'_{new};\alpha_{new}, \beta_{new})$	PDF of a Beta distribution, in [0; 1], for y'_{new}
$f_{new}\ (y_{new;}\ \alpha_{new}, \beta_{new}, y_{new,\min;}\ y_{new,\max})$	PDF of a Beta distribution for future hour (*new*)
$F_{new\_q}\ (y_q;\ \alpha_{new\_q}, \beta_{new\_q}, y_{new\_q,\min}, y_{new\_q,\max})$	Beta cumulative distribution function for new case q for future hour (*new*)

Frequencies

$f_{obs,i}$	observed frequencies in the interval i
$f_{tar,i}$	target frequency in the interval i

Data for application of PPFM models to MIBEL

$p_{D\text{-}6,h}$	price for hour h of day D-6
$p_{D,h}$	price for hour h of the day D
w_{D+1}	week
$\widehat{T}_{D+1,h\mid D,t}$	regional weighted forecasted hourly temperature for hour h of day D + 1, obtained at hour t of the day D
$\widehat{I}_{D+1,h\mid D,t}$	regional weighted forecasted hourly irradiations for hour h of day D + 1, obtained at hour t of the day D
$\widehat{v}_{D+1,h\mid D,t}$	regional weighted forecasted hourly wind speeds for hour h of day D + 1, obtained at hour t of the day D
$HG_{D\text{-}1,h}$	hydropower generation for hour h of day D-1
$SG_{D\text{-}1,h}$	solar power generation and power cogeneration for hour h of day D-1
$CG_{D\text{-}1,h}$	coal power generation for hour h of day D-1
$CCG_{D\text{-}1,h}$	combined cycle power generation for hour h of day D-1
$WG_{D\text{-}1,h}$	wind power generation for hour h of day D-1
$NG_{D\text{-}1,h}$	nuclear power generation for hour h of day D-1
$LD_{D\text{-}1,h}$	power demand for hour h of day D-1
$LD_{D\text{-}6,h}$	power demand for hour h of day D-6
$\widehat{W}G_{D+1,\,h\mid D,\,t}$	wind power generation forecast for hour h of day D + 1, obtained at hour t of the day D
$\widehat{L}D_{D+1,h\mid D,t}$	power demand forecast for hour h of day D + 1, obtained at hour t of the day D
P_{real_T}	real hourly price value for the hour T

Forecasts from the application of PPFM models to MIBEL

$\widehat{p}^{\,d}_{D+1,\,h\mid D,\,t}$	day-ahead hourly price forecast for hour h of day D + 1, obtained at hour t of the day D
$P_{forecast\_T}$	expected value of hourly price of a PPMF model for the hour T