

Prediction interval using quantile regression and mean variance based on ANN

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Abstract

Here is abstract What we do? - This paper proposes a electricity price forecasting approach based on a novel residual neural network for probabilistic electricity price forecasting under price spike environment for GEFCom2014.

Keywords: Here are keywords

1. Introduction

Since the transformation of the deregulation of modern power systems, electricity price forecasting has become more important process to energy market's participants at planning and operation levels.

5 (talk about point of forecasting, 1 method, 2 measurement, 3 problems) Over the past few decades, many powerful forecasting algorithms have been developed (for a recent comprehensive review, see [1]). The majority of empirical studies are on point forecasting (or call expected value of the spot price).

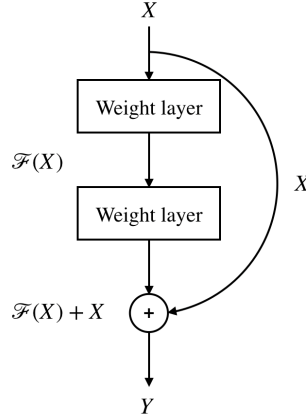
(mention about problems of poing of forecasting, introduct to interval forecasting)
10

(mention on used of deep residual neural network and why we use this method) Deep residual network is modified from deep Feed Forward Neural Networks (FFNNs) with extra connections (or called skip connections), passing input from one layer to a late layer as well as the next layer as shown in figure 1.

[☆]Fully documented templates are available in the elsarticle package on CTAN.

15 DRN is widely used in computer vision and pattern reconigition. There are few
used on deep residual neural network.

Figure 1: Basis DRN



(proposeal) Therefore, this paper seeks to apply

(structure) The remainder of the paper is organized as follows. First, the
problem formulation is presented in brief in section 2. The, the main features
20 of the ANN algorithm are presented in section 3. Next, the results after predic-
tion in different cases of proposed method are discussed in section 4. Finally,
conclusions are drawn in the last section of this paper.

2. Problem formulation

2.1. Interval forecasting

25 2.2. Measurement

The performance of the proposed model need to be assessed in term of the
quaility of of prediction interval, namely converage probability and PI width.
First, PI converage probility (PICP) refers to the ability of the constructed PIs
to capture the actual target variables. PICP can be methematically stated as

$$PICP = \frac{1}{N} \sum_{i=1}^N C_i \quad (1)$$

30 where

$$C_i = \begin{cases} 1, & \text{if } t_i \in [L_i, U_i] \\ 0, & \text{if } t_i \notin [L_i, U_i] \end{cases} \quad (2)$$

where N is the number of samples in the test set, t_i represents the actual target, and L_i and U_i are lower and upper bounds of the i th PI, respectively. The range of PICP lies between 0% (when none of the targets are enclosed by PI) to 100% (when all targets are enclosed by PI). Ideally, PICP should be very close or larger than the nominal confidence level associated to the PIs. PICP has a direct relationship with the width of PIs. A satisfactorily large PICP can be easily achieved by widening PIs from either side. However, such PIs are too conservative and less useful in practice, as they do not show the variation of the targets. Therefore, a measure is required to check how wide the PIs are.

40 Mean PI Width (MPIW) quantifies this aspect of PIs [2].

$$MPIW = \frac{1}{N} \sum_{i=1}^N (U_i - L_i) \quad (3)$$

Secondly, MPIW shows the average width of PIs. Normalizing MPIW by the range of the underlying target, R , allows us to compare PIs constructed for different datasets respectively (the new measure is called NMPIW),

$$NMPIW = \frac{MPIW}{R} \quad (4)$$

Both PICP and NMPIW, are representing quality and width of PIs, evaluate the quality of PIs from one aspect. A combined index is required for the comprehensive assessment of PIs from both coverage probability and width perspectives. The new measure should give a higher priority to PICP, as it is the key feature of PIs determining whether constructed PIs are theoretically correct or not. The Coverage Width-based Criterion (CWC) evaluates PIs from both coverage probability and width perspectives.

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Where, η and μ are two hyperparameters controlling the location and amount of CWC jump. These measures can be easily determined based on the level of confidence associated with PIs. μ corresponds to the nominal confidence level

associated with PIs and can be set to $1-\alpha$. The design of CWC is based on two
55 principles:

- if PICP is less than the nominal confidence level, $(1-\alpha)\%$, CWC should be large regardless of the width of PIs (measures by NMIPW),
- if PICP is greater than or equal to its corresponding confidence level, then NMPIW should be the influential factor. $\gamma(\text{PICP})$, eliminates the
60 exponential term of CWC when PICP is greater or equal to the nominal confidence level.

2.3. Data description

All data in this paper is provided in Global Energy Forecasting Competition 2014 (see [3]). The aim of this competition is to forecast 15 tasks of electric-
65 ity prices in term of probabilistic distribution (in quantiles). Hourly data of locational marginal price (LMP), zonal load forecast and system load forecast are provided. The participants receive historical data and forecast for next day electricity price. In total, the price forecasting track involves about three years of locational marginal price, zonal and system load forecast. Where, table 1
70 summarizes top four team's method.

Table 1: Summary of the methods used by the top four teams of the price forecasting track.

Techniques		Spike preprocessing	Forecast combination
Tololo	(1) Quantile regression, generalized additive models; (2) autoregressive models, random forest regression, gradient boosting machine; (3) Kernel based quantile regression.	Preprocessed spikes for some of the models.	ML-Poly aggregation
Team Poland	Autoregressive models with exogenous variables; filtering; quantile regression; judgmental forecasting	Three filtering methods: day type filtering, similar load profile filtering and expected bias filtering	Arithmetic average
GMD	Feed forward neural network	None	None
C3 Green Team	Quantile regression; radial basis function network; k-means algorithm; alternating direction method of multipliers; Autoregressive models with exogenous variables	None	None

3. Proposed probabilistic deep residual network

As mention earlier,

Figure 2: Upper and lower bound and mean and variance estimation

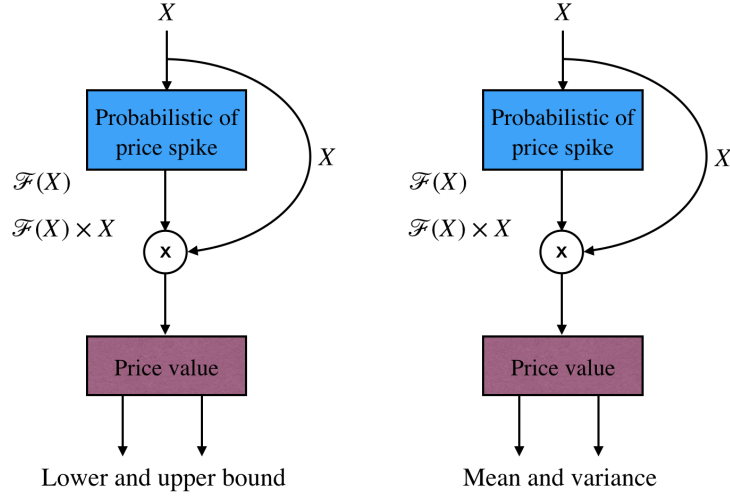
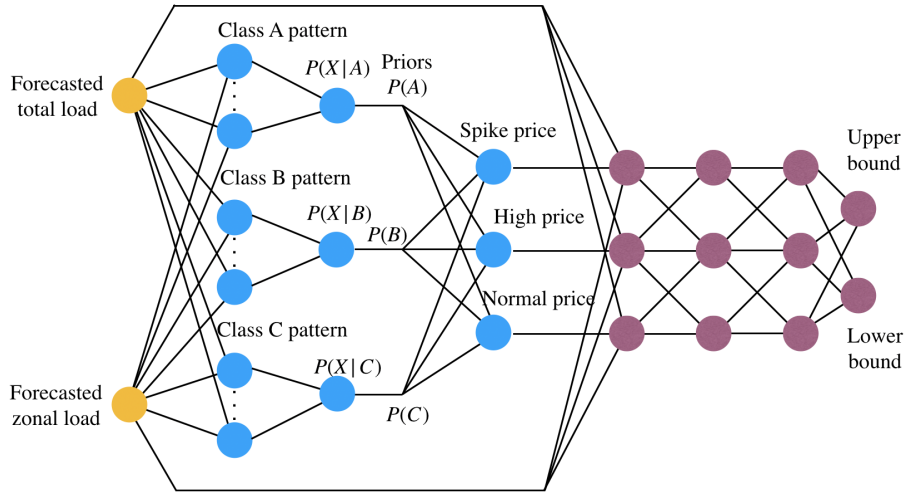


Figure 3: Proposed probabilistic deep residual network



4. Conclusions

This paper proposes a novel application of residual neural network based
75 approach to probabilistic electricity price forecasting.

References

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