

A novel interval electricity price forecasting using deep residual neural networks

Pornchai Chaweewat¹, J G singh²

*Department of Energy, Environmental and Climate Change, School of Environmental,
Resource and Development, Asian Institute of Thechnology, Thailand*

Abstract

This paper proposed a novel electricity price forecasting method based on a novel Deep Residual Neural Network (Deep ResNet) for probabilistic electricity price forecasting under spike price environment. The modern electricity price became more fluctuated and generally unanticipated spike price. The use of prediction interval or probabilistic forecasting was interested due to it help market participants to submit effective bids with low risks. A proposed new model was developed from Deep ResNet approach which it capable of spike price and interval price value prediction. The proposed Deep ResNet was consisting of two network layers. First neural network layers was spike prediction. The output of second neural network layers formulated interval price forecasting by two methods; quantile regression and mean and variance estimation method. The proposed forecasting models was demonstrated with GEFCom2014 dataset. The dataset is consisting of 15 tasks for electricity price forecasting where high and spike price are included. The results were compared with benchmarks as provided by GEFCom2014, Quantile Regression Average (QRA) and multilayer perceptron network (MLP) approaches. The performances of forecasting models were evaluated in term of accuracy and reliability metrics by Pinball Loss Function and Coverage Width-baed Criterion (CWC), respectively. The significant outcome of this paper was that forecasting model cooperated with spike price

¹email: chaweewat.p@gmail.com

²email: jgsingj@ait.ac.th

prediction improved the forecasting's performance in term of accuracy and reliability aspects. Moreover, increasing in confidence level of Deep ResNet models could generates lower CWC values and represent high reliability's satisfaction.

Keywords: ResNet, GEFCOM2014, interval forecasting, quantile regression, mean and variance estimation

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. As a result of higher number of fluctuated electricity price as well as the number of the spike price occurrences. The occurrences of spike price can cause financial damage to both customers and producers. The spike prices can be reach several times to thousand times of the normal price. Spike price appears due to increasing intermittent electricity production makes electricity prices more volatile, with spikes appearing either as very high prices (due to sudden lack of available generation) or as negative prices (due to excess of renewable generation). Several evidences shows that the spike prices are around 100\$/MWhr may simply resulted from normal congestion or unexpected overload, while spike price around \$500/MWhr led by lacking of reserve. This case the day ahead clearing price was the dominant feature what indicate insufficient reserve. The spike price aboved \$1,000/MWhr should be the consequence of the outage or breakdown of the generation or transmission system. Such outage or breakdown many could came from many factors, like weather, load profile, etc [1]. [2] provided fundamental reasons of spike price which are volatility of fuel price, load uncertainty, fluctuation in hydroelectricity production, generation outage, transmission congestion, behavior of market participation and market manipulation. [3] studied on technique and economical of on centralized voltage control with high PV penetration in Portuguese network. These results illustrated that improvement in both forecasting tools and communication systems have significant impact on dedicate resources and

25 voltage control.

Over the past few decades, many powerful forecasting algorithms have been developed (for a recent comprehensive review, see [4]). The majority of empirical studies was on point forecasting (or call expected value of the spot price).

The conventional point predictions produced no information about the sampling errors and the prediction accuracy. This lead to confidence intervals (CIs) and prediction intervals (PIs). CIs and PIs were two well-know tools for quantifying and representing the uncertainty of predictions. In literature, several methods have been proposed for construction of PIs and CIs assessment. Lower Upper Bounds Estimation (LUBE) method were formulated using mean and variance estimation which was proposed in [5]. In addition, delta technique for PI construction was presented in [6].

In computational intelligent world, Deep Residual Neural Network (Deep ResNet) was 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. Deep ResNet was widely used in computer vision and pattern recognition. There were few used on deep residual neural network in forecasting applications.

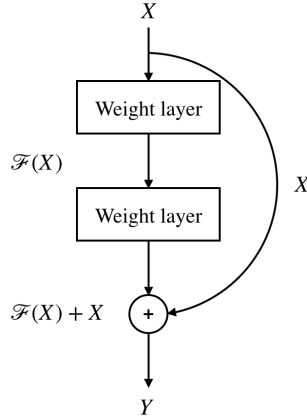


Figure 1: Basis concept of Residual Neural Network (ResNet)

Therefore, this paper seek to apply Deep ResNet in electricity price forecasting. The performance results of the Deep ResNet forecasting model were also
45 compared with linear regression and MLP techniques.

The novelty of this study is twofold. First, ResNet is first used in field of electricity price forecasting. Using this approach, the probabilistic electricity price forecasting can sastified both accuracy and reliability aspects. Second, CWC are used to evaluateate interval electricity price forecasting.

50 The remainder of the paper is organized as follows. First, the problem formulation is presented in brief in section 2. The, the main features of the ANN algorithm are presented. Next, the results after prediction in different cases of proposed method are discussed in section 3. Finally, conclusions are drawn in the last section of this paper.

55 2. Problem formulation

This section will descript construction of two proposed forecasting models; Multilayer Percepton (MLP) and Deep Residual Neural Network (Deep ResNet) model. The MPL model will represent electricity price forecasting without spike price prediction (see related work in [7]) and the Deep ResNet model will represent
60 electricity price forecasting with spike price prediction within the model. Both model will generate upper and lower bounds with respect to given confidence levels (5%, 10%, 15%, 20%, and 25%). The upper and lower bound will generate using quantile regression and mean and varience estimation metod.

2.1. Proposed Deep ResNet on interval price forecasting

65 Here is description of structure of proposed Deep ResNet

As mention eariler, this paper develop a novel Deep ResNet with spike price occurance and price value prediction. The forecasted total load and zonal load (provided in GEFCom2014) and

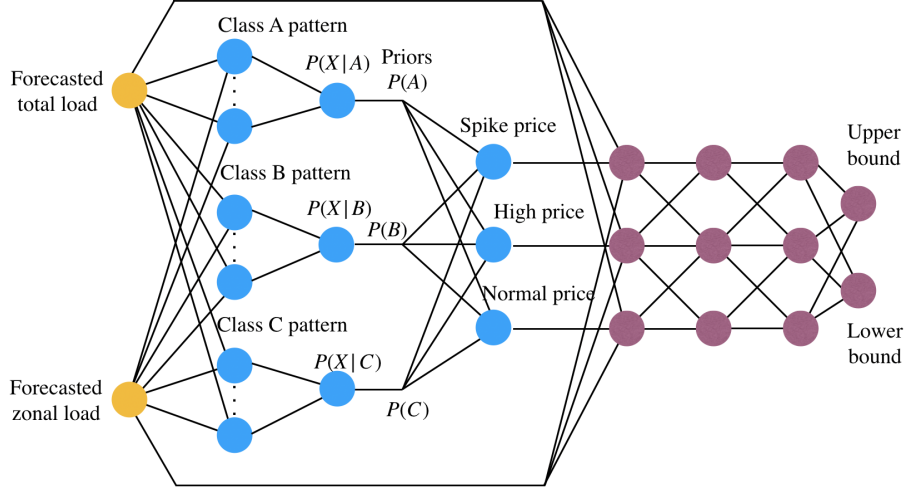


Figure 2: Proposed probabilistic Deep ResNet

Here is how to train proposed Deep ResNet These data are fed into the proposed MLP and Deep ResNet models during training section with the Levenberg-
70 Marquardt algorithm to prevent overfitting problems.

2.2. The upper and lower bound generation

The interval forecasting is formulated from two methods; lower and upper
quantile regression, and mean and variance estimation. Are express in Equa-
75 tion 1 and 2.

$$(Here is QR equation) \quad (1)$$

$$(Here is MV equation) \quad (2)$$

the figure of QR, MV is shown in Figure 3.

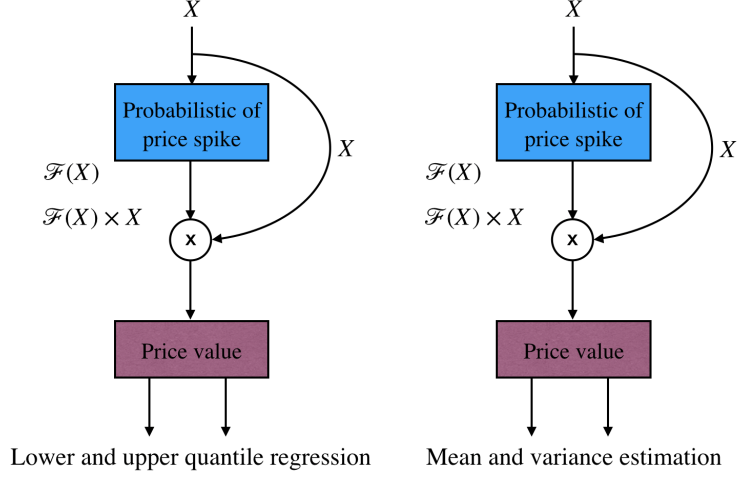


Figure 3: Quantile regression and Mean and Variance estimation picture

Figure 4 illustrates brief proposed interval price forecasting model based on Deep ResNet with quantile regression and mean and variance method or called Deep ResNet-QR and Deep ResNet-MV.

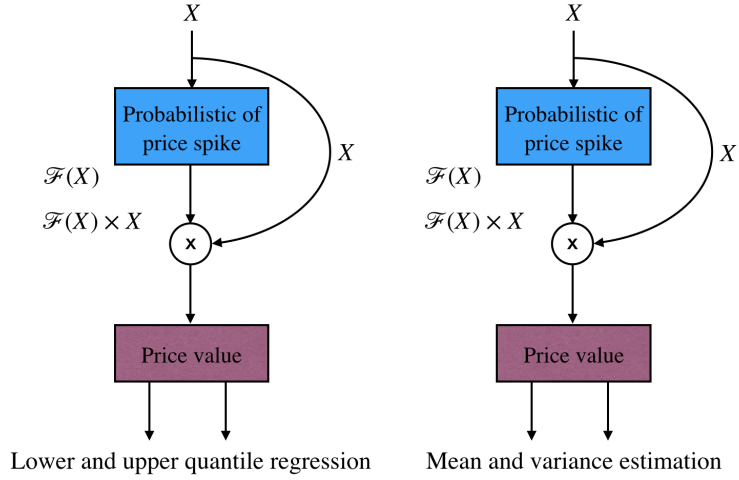


Figure 4: Upper and lower bound and mean-variance estimation

80 2.3. Evaluation metrics

This section will descript evaluation metrics on accuracy and reliable point of view. In term of accuracy aspect, the forecasting results will be analysed using pinball loss function. The Coverage Width-baed Criterion (CWC) will take care of reliability aspect.

85 2.3.1. Accuracy aspect

The widely used measurement of forecasting's accuracy is mean absolute error (MAE) which is simply and generalized method. MAE work well of point of forecasting (single value). However, this problem is to formulate upper and lower bound of forecasting which is cooperated with confidence value. Hence, 90 general MAE is not satisfied in this case. Pinball loss function are proposed in [8], also be benchmark of this paper, which returns the values or called loss values that can be interpreted as accuracy of mean-variance and quantile regression forecasting models. The pinball loss function is formulated in Equation 3.

$$L_{\tau}(y, z) = \begin{cases} (y - z)\tau & \text{if } y \geq z \\ (z - y)(1 - \tau) & \text{if } z > y \end{cases} \quad (3)$$

where $L_{\tau}(y, z)$ is pinball loss function at τ confidence level, y is forecasted 95 electricity price and z is actual electricty price. The final score of pinball loss function was computed as average L_{τ} across 24 hours for each task. The τ in this paper is 0.05, 0.10, 0.15, 0.20 and 0.25 which are represent 5%, 10%, 15%, 20% and 25% confidence levels. The important results of pinball loss function is that the lower pinball loss, the more accurate forecasting model.

100 2.3.2. Reliability aspect

In term of reliability measurement, the performances of forecasting model are measured to ensure that the ranges of interval forecasting can cover the observation values both quality and quantity.

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

$$PICP = \frac{1}{N} \sum_{i=1}^N C_i \quad (4)$$

where

$$C_i = \begin{cases} 1, & \text{if } t_i \in [L_i, U_i] \\ 0, & \text{if } t_i \notin [L_i, U_i] \end{cases} \quad (5)$$

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. Mean PI Width (MPIW) quantifies this aspect of PIs [9].

$$MPIW = \frac{1}{N} \sum_{i=1}^N (U_i - L_i) \quad (6)$$

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). The R in this paper is 10 \$/MWhr.

$$NMPIW = \frac{MPIW}{R} \quad (7)$$

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.

$$(Here is CWC equation) \tag{8}$$

Where, η and μ are two hyperparameters controlling the location and amount
 115 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
 principles:

- if PICP is less than the nominal confidence level, $(1-\alpha)\%$, CWC should be
 120 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
 exponential term of CWC when PICP is greater or equal to the nominal
 confidence level.

125 2.4. Data description

All data in this paper is provided in Global Energy Forecasting Competition
 2014 (see [10]). The aim of this competition is to forecast 15 tasks of electric-
 ity prices in term of probabilistic distribution (in quantiles). Hourly data of
 locational marginal price (LMP), zonal load forecast and system load forecast
 130 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. The summarized
 solution data set of 15 tasks is shown in table 1.

Table 1: Summary of GEFCom2014 electricity price forecasting tasks

Task	Day	Holiday	Season	Normal price	High price	Spike price
1	Sun	Yes	Summer	24	-	-
2	Mon	No	Summer	24	-	-
3	Mon	No	Summer	22	2	-
4	Thu	No	Summer	24	-	-
5	Tue	No	Summer	22	2	-
6	Sat	Yes	Summer	24	-	-
7	Tue	No	Summer	16	8	-
8	Thu	No	Summer	12	8	4
9	Fri	No	Summer	13	6	5
10	Sat	Yes	Summer	18	6	-
11	Wed	No	Summer	24	-	-
12	Thu	No	Summer	24	-	-
13	Sat	Yes	Authumn	24	-	-
14	Sun	Yes	Authumn	24	-	-
15	Tue	No	Authumn	15	9	-

The participation teams in GEFCom2014 perform electricity price forecasting method i.e.; linear regression (IR)[7], multilayer perceptron (MLP)[7], multiple quantile regression[11], hybrid quantile regression average (QRA) with pre-and-post processes[8].

3. Results

In accuracy point of view, the results were evaluated with pinball loss function and summarized in Table 2. The outcomes of benchmark and proposed approaches indicate that some tasks involves more uncertainty than others day. Benchmark-1, provided by GEFCom2014 data, is very low accuracy level, high value of pinball loss score, in Task7-12 and 15. Benchmark-2 included mixed

of ARX model, pre-filtering process, quantile estimation and post-processing in
145 order to accuire more accuracy of competition task. The difficulty of forecast-
ing in mentioned task lied in high forecasting zonal load. It is obvious that
high forecasted load may trigger an electricity spike price. The MLP-MV and
MPL-QR models were developed to ilustrate simple forecasting model without
spike price prediction. The similar work of this appoach is found in [7]. The
150 MLP models is unsuitable for task 8-9 since loss score is very high. However,
in task without spike price, the models perform quite acceptable comparing to
Benchmark-1 model.

The next result we will discuss is that the proposed Deep ResNet gener-
ated upper and lower bound values using quantile regression and mean-variance
155 method. Both Deep ResNet-MV and Deep ResNet-QR model performed excel-
lent work and provide lower losses score comparing to Benchmark-1, MLP-MV
and MLP-QR. In addition, both proposed models also provided similar losses
score with Benchmark-2 as seen in Table 2.

Table 2: The results of probabilistic electricity price forecasting compared to benchmarks

Method	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9
Benchmark-1 ^a	4.03	7.97	5.70	22.32	38.34	44.23
Benchmark-2 ^b	1.00	1.82	1.19	2.82	7.56	4.21
MLP-MV	4.19	4.33	4.18	10.48	31.57	33.35
MLP-QR	2.57	4.03	2.55	12.96	34.76	36.24
Deep ResNet-MV	2.45	3.36	2.39	5.79	8.79	6.95
Deep ResNet-QR	2.11	3.47	1.93	6.14	9.41	7.63

Method	Task 10	Task 11	Task 12	Task 13	Task 14	Task 15
Benchmark-1 ^a	18.22	31.57	42.95	2.86	3.20	22.38
Benchmark-2 ^b	2.60	1.05	1.24	4.06	1.08	3.07
MLP-MV	6.28	4.28	4.25	4.06	4.05	13.02
MLP-QR	8.83	2.51	2.49	2.47	2.62	16.81
Deep ResNet-MV	5.80	2.41	2.41	2.34	2.43	11.02
Deep ResNet-QR	6.38	1.88	1.91	2.01	2.22	11.70

Notes: The numbers are calculated according to the pinball loss function

^a benchmark data provided by GEFCom2014

^b hybrid model extending the Quantile Regression Averaging (QRA) approach provided in [8].

We will discuss more of effect of confidence levels to reliability aspect of proposed model here. First, we will discuss comparison between MLP (non-spike price) and Deep ResNet (spike price) models.

In Figure 5, the filled area represent interval prediction of MLP-QR and Deep ResNet-QR with 5% confidence level. In clearly comparison between MLP and Deep-ResNet models, Figure 5 shows the area covered by upper and lower quantile value, with 5% confidence level, generated by those models. The Deep ResNet-QR model can forecast the high and spike prices over task 9 data. On the other hand, MLP-QR model is unsuitable to handle price spike prediction.

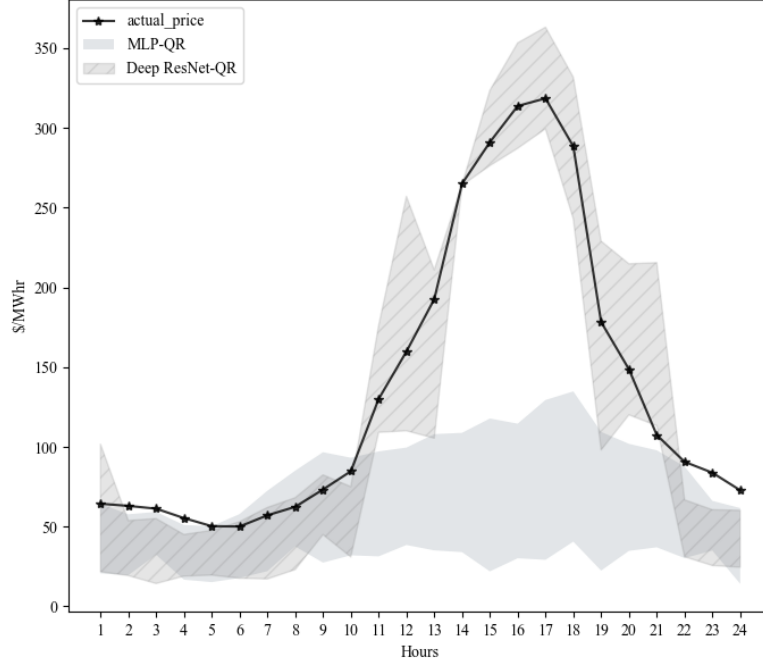


Figure 5: The results of MLP (non-spike price detection) model and Deep ResNet (spike price prediction) model with quantile regression method on confidence level ($\alpha = 5\%$ on Task 9)

Figure 6 represents that Deep ResNet-QR can perform excellent jobs in the interval prediction for non-spike price task 4, 5, 6, 11, 12, 13 and 14. Furthermore, the proposed Deep ResNet-QR model has capability of interval prediction in task 7, 8, 9 and 10.

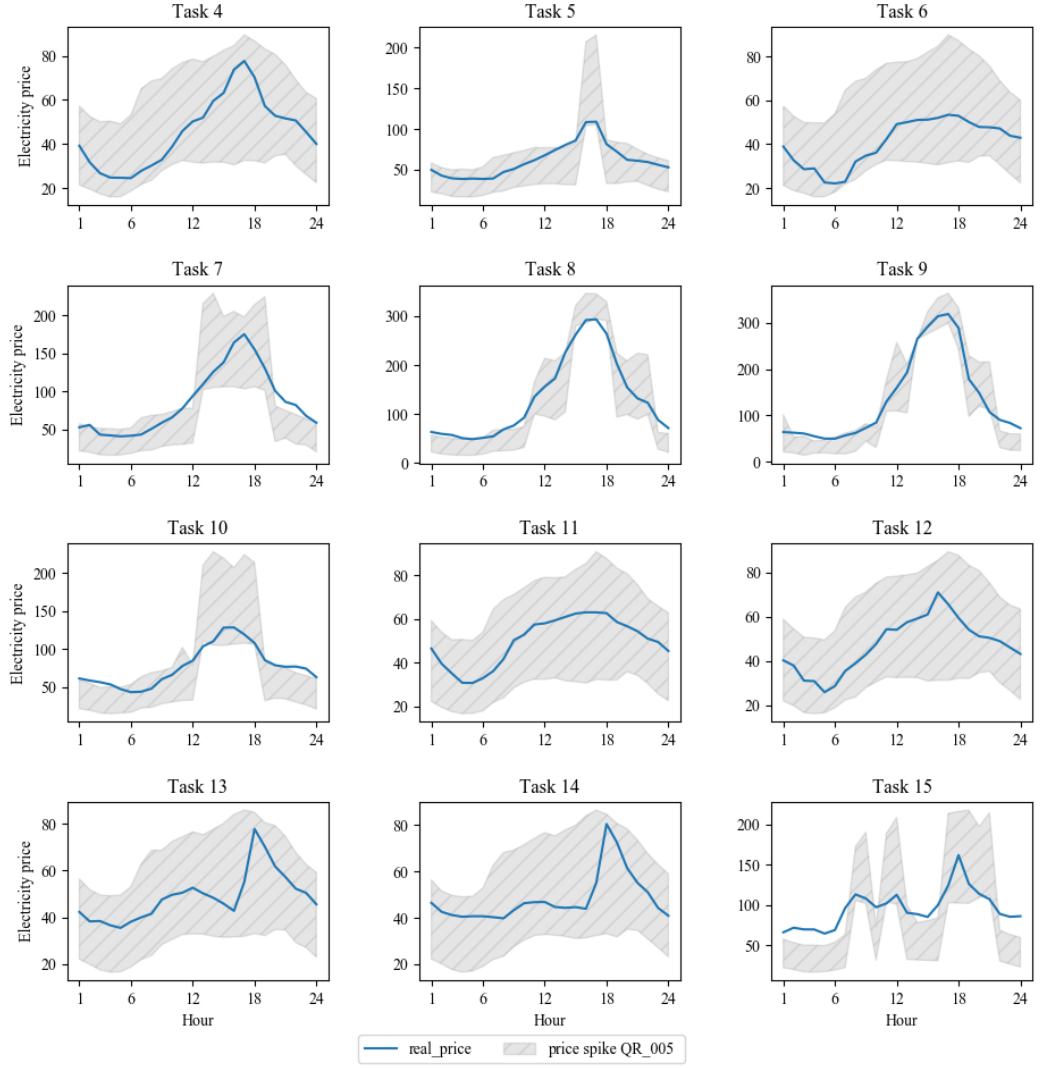


Figure 6: The results of Deep ResNet-QR with 5% confidence level in task 4-15.

Second, we will discuss more of effect of confidence levels to reliability aspect of proposed model here. All CWC values are analysed using distribution characteristic in each model at differenced confidence level. The Figure 7 illus-

175 trateds all CWC value where bold line represents average CWC values, of all
task, of particular model and confidence level. The boxes contain 50% of CWC
values. The top and buttom wiskers show highest and lowest CWC values in
each box. Since CWC value represents both coverage probility and width per-
spective, the lower CWC value represents higher reliability. The Figure 7 shows
180 that while increasing confidence level, the models could perform better in CWC
perspective. The averaged CWC value could drop below 15 while increasing
confidence level up to 15 % for Deep ResNet models. Moreover, quantile regres-
sion method provides higher reliabaility aspect than mean-variance method as
seen in Figure 7.

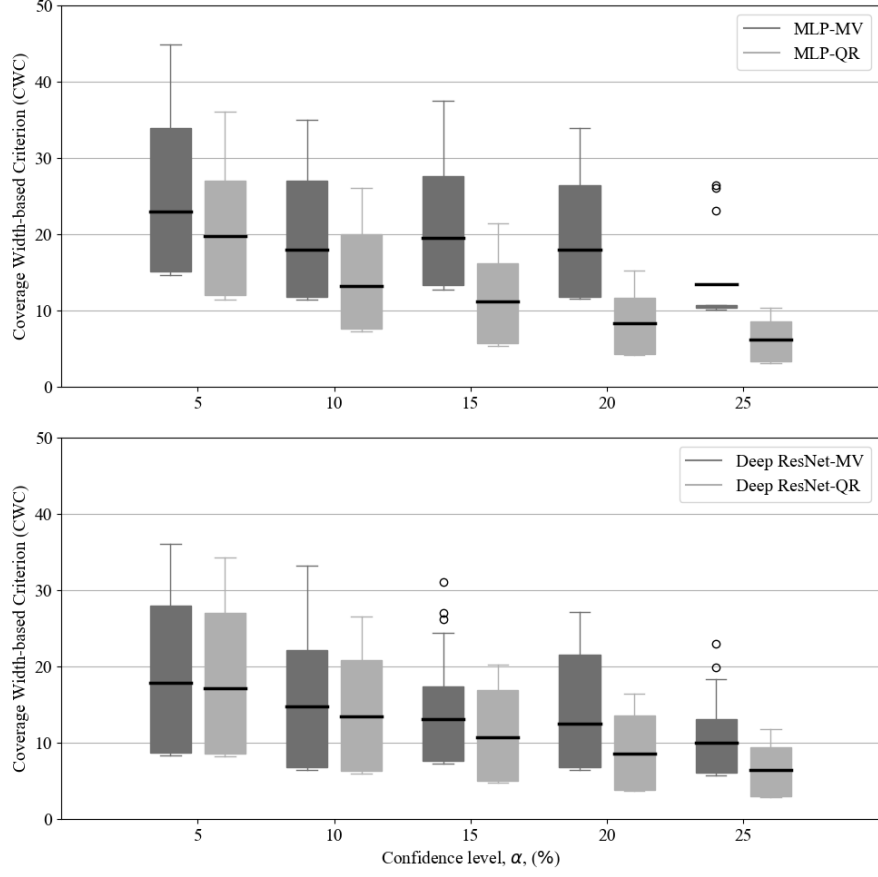


Figure 7: The results of reliability aspect are represented in CWC values. The CWC values of MLP and Deep ResNet methods with difference confidence level are shown in upper and lower Figure, respectively

185 In summary, we consider both accuracy and reliability aspects of proposed Deep ResNet models through pinball losses score and CWC values, respectively.

Consequently, the proposed Deep ResNet could improve reliability of forecasting model.

4. Conclusions

190 This paper proposes a novel application of Deep Residual Neural Network (Deep ResNet) based approach to probabilistic electricity price forecasting in term of quantile regression and mean-variance estimation. The two significant observation results were: (i)

References

- 195 [1] D. He, W. P. Chen, A real-time electricity price forecasting based on the spike clustering analysis, in: 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T D), 2016, pp. 1–5.
- [2] D. Singhal, K. Swarup, Electricity price forecasting using artificial neural networks, International Journal of Electrical Power Energy Systems 33 (3) (2011) 550 – 555.
- 200 URL <http://www.sciencedirect.com/science/article/pii/S0142061510002231>
- [3] L. Gonzalez-Sotres, P. Fras, C. Mateo, Techno-economic assessment of forecasting and communication on centralized voltage control with high pv penetration, Electric Power Systems Research 151 (2017) 338 – 347.
- 205 URL <http://www.sciencedirect.com/science/article/pii/S0378779617302419>
- [4] R. Weron, Electricity price forecasting: A review of the state-of-the-art with a look into the future, International Journal of Forecasting 30 (4) (2014) 1030–1081.
- 210 URL <https://www.sciencedirect.com/science/article/pii/S0169207014001083>
- [5] A. Khosravi, S. Nahavandi, D. Creighton, A. F. Atiya, Lower upper bound estimation method for construction of neural network-based prediction intervals, IEEE Transactions on Neural Networks 22 (3) (2011) 337–346.
- 215

- [6] D. Khosravi, A. Nahavandi, S., and Creighton, Construction of Optimal Prediction Intervals for Load Forecasting Problems, *IEEE Transactions on Power Systems* 25 (3) (2010) 1496–1503.
URL <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp={&}arnumber=5428779>
- [7] G. Dudek, Multilayer perceptron for GEFCom2014 probabilistic electricity price forecasting, *International Journal of Forecasting* 32 (3) (2016) 1057–1060.
URL <http://dx.doi.org/10.1016/j.ijforecast.2015.11.009>
- [8] K. Maciejowska, J. Nowotarski, A hybrid model for GEFCom2014 probabilistic electricity price forecasting, *International Journal of Forecasting* 32 (3) (2016) 1051–1056.
URL <http://dx.doi.org/10.1016/j.ijforecast.2015.11.008>
- [9] A. Khosravi, S. Nahavandi, D. Creighton, Construction of optimal prediction intervals for load forecasting problems, *IEEE Transactions on Power Systems* 25 (3) (2010) 1496–1503. doi:10.1109/TPWRS.2010.2042309.
- [10] T. Hong, P. Pinson, S. Fan, H. Zareipour, A. Troccoli, R. J. Hyndman, Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond, *International Journal of Forecasting* 32 (3) (2016) 896–913.
URL <http://dx.doi.org/10.1016/j.ijforecast.2016.02.001>
- [11] R. Juban, H. Ohlsson, M. Maasoumy, L. Poirier, J. Z. Kolter, A multiple quantile regression approach to the wind, solar, and price tracks of GEFCom2014, *International Journal of Forecasting* 32 (3) (2016) 1094–1102. doi:10.1016/j.ijforecast.2015.12.002.
URL <http://dx.doi.org/10.1016/j.ijforecast.2015.12.002>