A novel interval electricity price forecasting using deep residual neural networks

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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 bid with low risks.

A proposed new model was developed from Deep ResNet approach which it capable of spike price and price value prediction. The proposed Deep ResNet was consisting of two network layers. First neural network laver was spike prediction. The output of second neural networks layer formulated interval price forecasting by two methods; quantile regression and mean and varience estimation method. The proposed forecasting models was demonstrated with GEFCom2014 dataset where the dataset was consisting of 15 tasks for electricity price forecasting where high and spike price were included. The results were compared with benchmarkes provided by GEFCom2014, linear regression and multilayer perceptron network (MLP) methods.

The performances of forecasting models were evaluated in term of accuracy and reliablity metrics by Pinball Loss Function and Coverage Width-baed Crite-

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rion (CWC), respectively. The significant outcome of this paper was forecasting method cooperated with spike price prediction imporved the forecasting's performance in term of quaility and quantity. Moreover, increasing in confidence level could generates lower CWC values and represent high reliability's satification.

Keywords: ResNet, GEFCom2014, interval forecasting, quantile regression, mean and varience estimation

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1. Introduction

Since the transformation of the deregulation of modern power systems, electricty 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 occurences. 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 voltage control.

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

The conventional point predictions produced no information about the sampling erros and the predicition accuracy. This lead to confidence intervals (CIs) and prediction intervals (PIs). CIs and PIs were two well-know toosl for quantifying and representing the uncertainty of predicitons. 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 varience estimation which was proposed in [5]. In addition, delta technique for PI construction was presented in [6].

In computaional 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 reconigtion. There were few used on deep residual neural network in forecasting applications.

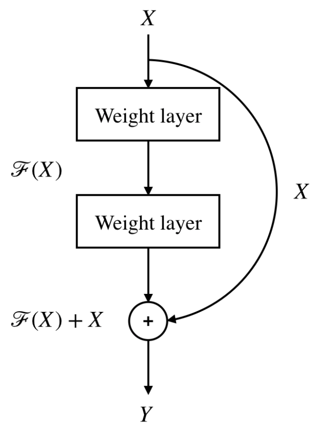

Figure 1: Basis concept of Residual Neural Network (ResNet)

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

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

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 4. Finally, conclusions are drawn in the last section of this paper.

2. Problem formulation

This section will descript construction of two proposed method; MLP and 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 electricity price forecasting with spike price prediction in 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-varience estimation metod.

2.1. Proposed Deep ResNet on interval forecasting

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

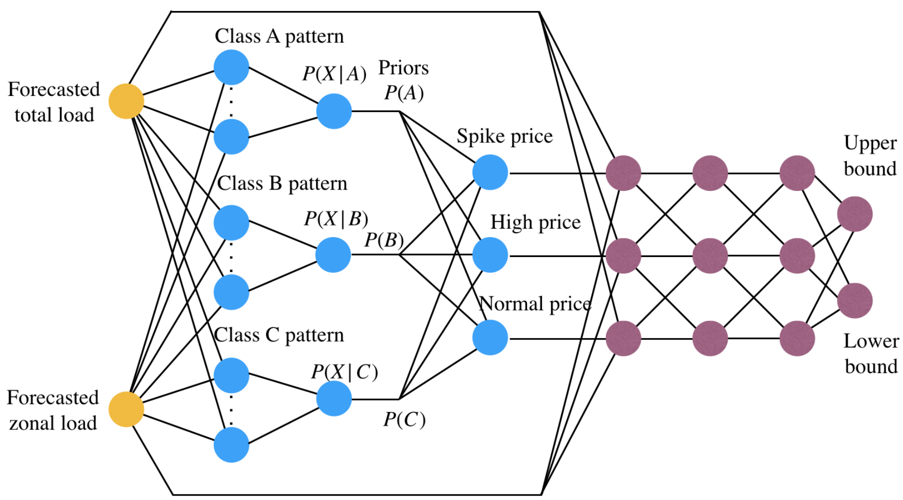

Figure 2: Proposed probabilistic Deep ResNet

The interval forecasting is formulated from two methods; lower and upper quantile regression, and mean and varianece estimation.

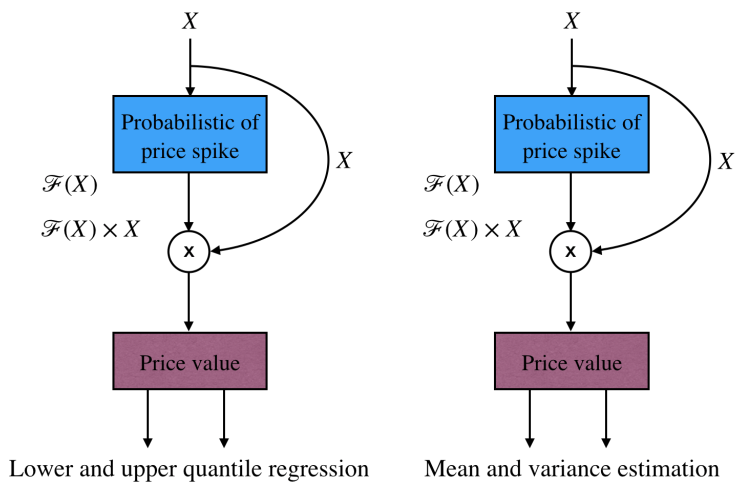

Figure 3: Upper and lower bound and mean-variance estimation

2.2. Evaluation metrics

This section will descrip evaluation metrics in accuracy and reliable point of view. In term of accuracy metric, the forecasting results will be analyzied using pinball function. The Coverage Width-baed Criterion (CWC) will take care of reliability point of view.

2.2.1. Accuracy

The widely used measurement of forecasting's accuracy is mean absoulute 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, general MAE is not satisfied in this case. Pinball loss function are proposed in [8], also be benchmark of this paper, which returns the value that can be interpreted as accuracy of mean-varience and quantile regression forecasting models. The pinball loss function is formulated as below.

$$L_\tau(y,z) = \begin{cases} (y-z)\tau if y >= z \\ (z-y)(1-\tau) if z > y \end{cases} \tag{1}$$

where $L_\tau(y,z)$ is pinball loss function at τ confidence level, y is forecasted 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.

2.2.2. Reliability

In term of reliability measurement, the performance of forecasting model is measured to ensure that the ranges of 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

$$PICP = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{2}$$

where

$$C_i = \begin{cases} 1, if t_i \in [L_i, U_i] \\ 0, if t_i \notin [L_i, U_i] \end{cases} \tag{3}$$

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 hte ith PI, repestively. The range of PICP lies between 0% (wher none of hte targets are enclosed by PI) to 100% (when all targets are enclosed by PI). Ideally, PICP should be very close or larger than the norminal 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 targetes. Therefore, a measure is resquired to check how wide the PIs are. Mean PI Width (MPIW) quantifies this aspect of PIs [9].

$$MPIW = \frac{1}{N}\sum_{i=1}^{N}(U_i - L_i) \tag{4}$$

Secondrly, 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 repectively (the new measure is called NMPIW),

$$NMPIW = \frac{NMPIW}{R} \tag{5}$$

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 probility 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 correcty or not. The Coverage Width-baed Criterion (CWC) evalutes PIs from both coverage probility and width perspectives.

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 correspomds to the nominal confidence level associated with PIs and can be set to 1-α. The design of CWC is based on two principles:

- if PICP is less than the nominal confidence level, (1-α)%, 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. γ(PICP), eliminates the 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 [10]). The aim of this competition is to forecast 15 tasks of electricity 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 electricty 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: GEFCom2014 task solution

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 estimation with pre-and-post processes[8]. These data are fed into the proposed MLP and Deep ResNet models during training section with the Levenberg-Marquardt algorithm to provent overfitting problems.

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 order to accuire more accuracy of competition task. The difficulty of forecasting in mentioned task lied in high forecasting zonal load. It is obvious that high forecasted load may trigger an electricty 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 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 generated upper and lower bound values using quantile regression and mean-varience method. Both Deep ResNet-MV and Deep ResNet-QR model performed excellent 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 comparision between MLP (non-spike price) and Deep ResNet (spike price) models.

In Figure 4, the filled area represent interval prediction of MLP-QR and Deep ResNet-QR with 5% confidence level. In cleary comarision between MLP and Deep-ResNet models, Fig 4 shows the area covered by upper and lower quantile value, with 5% confidence level, generated by those models. The Deep ResNet-QR model can forecaste the high and spike prices over task 9 data. On the other hand, MLP-QR model is unsuitable to handle price spike prediction.

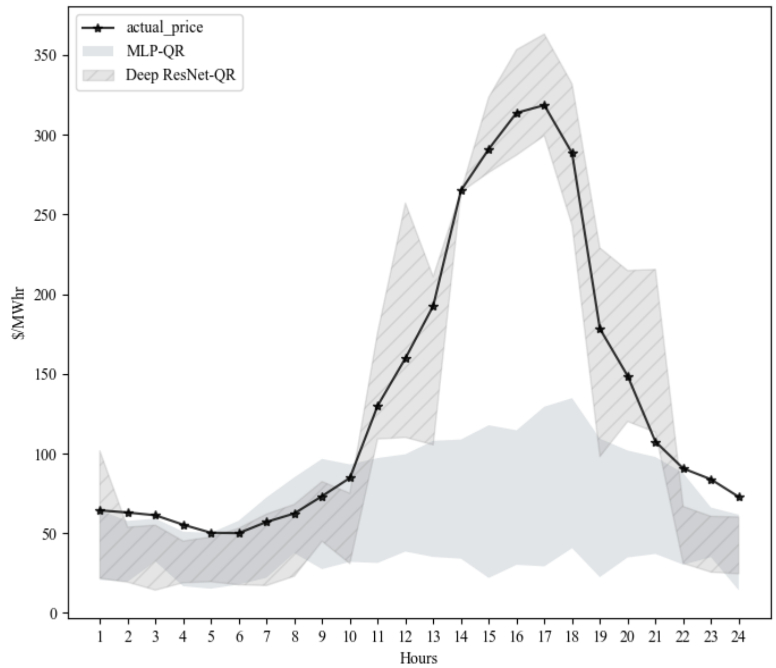

Figure 4: The results of MLP (non-spike price detection) model and Deep ResNet (spike price prediction) model with quantile regression method on confidence level ($\alpha = 5\%$ on Task 9)

Figure 5 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. Futhermore, the proposed Deep ResNet-QR model has capability of interval prediction in task 7, 8, 9 and 10.

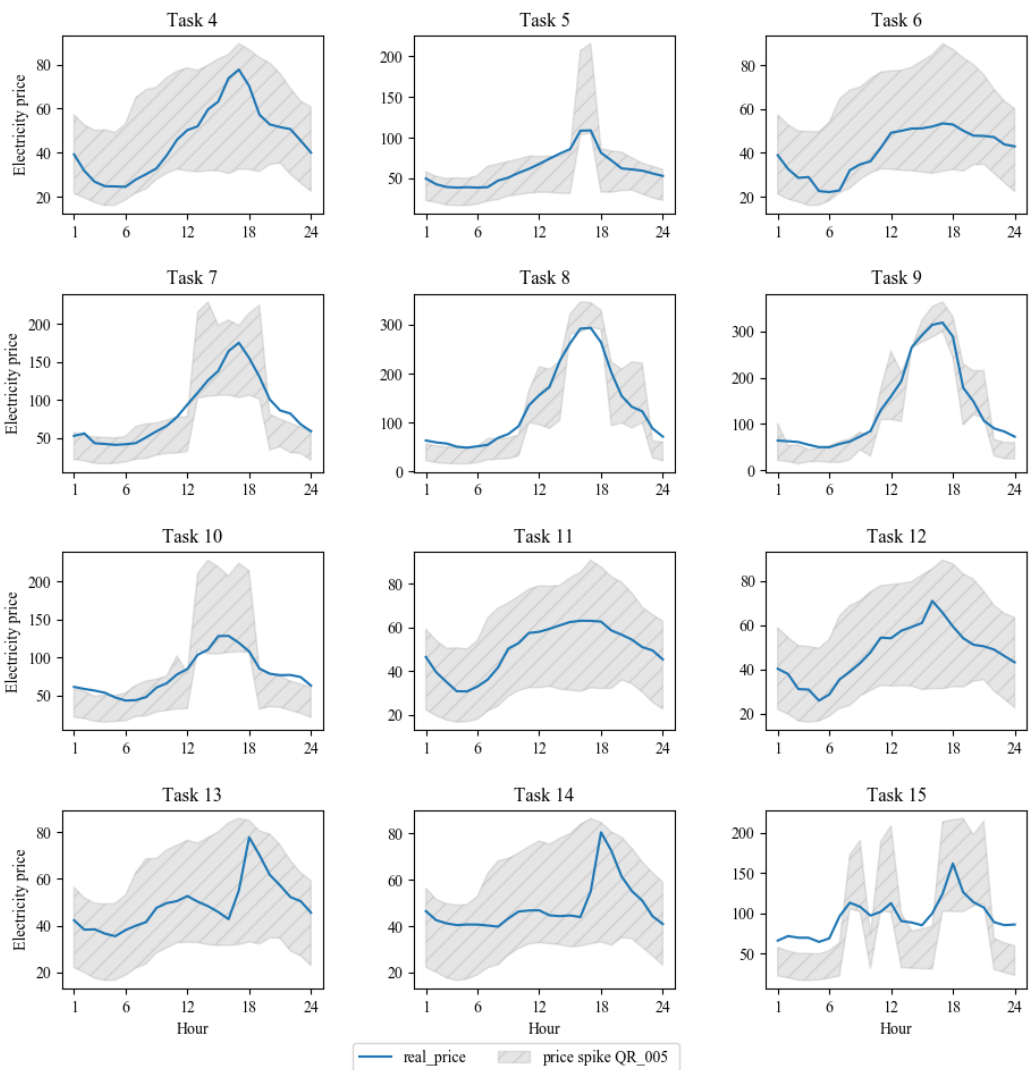

Figure 5: The results of Deep ResNet-QR with 5% confidence level in task 4-15.

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 6 illustrateds 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 perspective, the lower CWC value represents higher reliability. The Figure 6 shows 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 regression method provides higher reliabaility aspect than mean-variance method as seen in Figure 6.

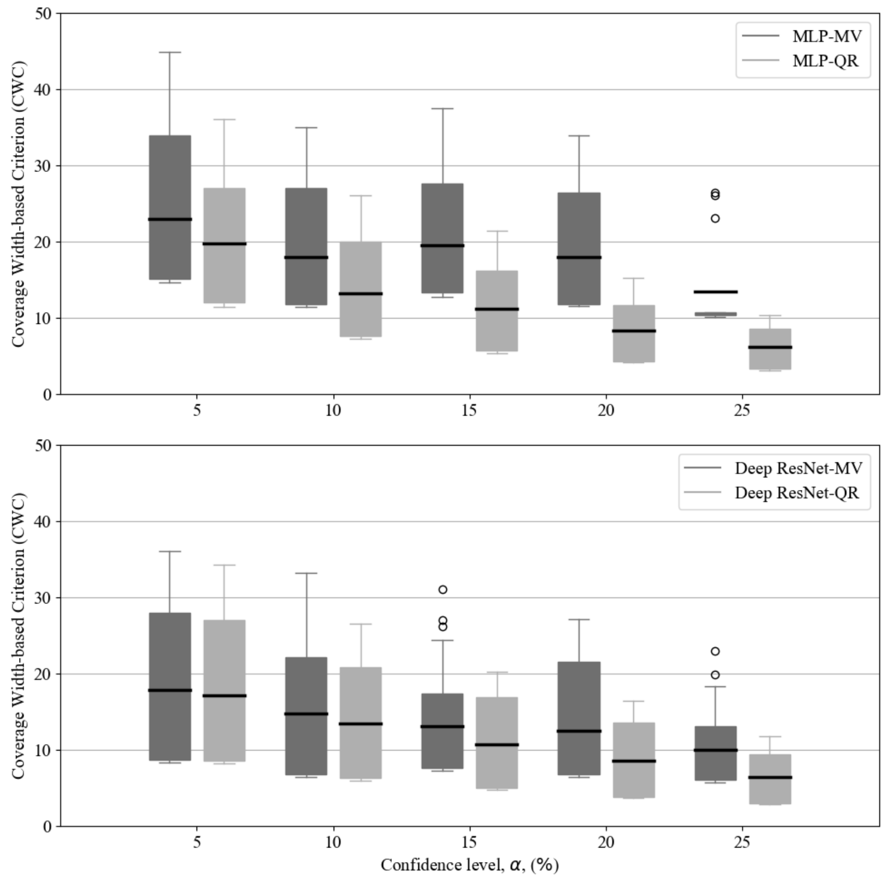

Figure 6: The results of reliability aspect are represented in CWC values. The CWC values of MLP and Deep ResNet methods with difference confidence level are shown in upper and lower figure, respectively

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 imporve reliability of forecasting model.

4. Conclusions

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

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