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An Approach for The Electricity Consumption Prediction based on Artificial Neural Network

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Abstract: This paper studies the day-ahead prediction of electricity consumption for power supply-demand balance in electric power networks. To handle the uncertainties in weather forecast and the nonlinearity relation between the electricity consumption and the weather conditions, this paper proposes a Radial Basis Function like Artificial Neural Network (RBF-like ANN) model with temperature, humidity, and sampling times as inputs. Then the Least Absolute Deviation, i.e., the L_1 norm condition, is employed as the optimization cost which is minimized in the model training process. To solve the L_1 optimization problem, two approaches, namely least square (L_2) based and alternating direction method of multipliers (ADMM), are utilized and compared. The simulations on real data collected in California shows that the latter approach performs better, and the number of neurons does not affect much to the prediction performance of the latter approach while it does influence on that of the former approach. Further, the proposed RBF-like ANN model equipped with ADMM solving approach provides reasonably good prediction of the electricity consumption in spite of the imprecise weather forecast.

Keywords: Electricity Demand Prediction, Machine Learning, Artificial Neural Network, L_1 Optimization, ADMM.

1. INTRODUCTION

Power supply-demand balance is one of the most fundamental and crucial problems for electric power networks because an imbalance between the power supply and demand causes the frequency fluctuation leading to power outage if it is out of an allowed working region. It is therefore necessary, especially for power utility companies, to predict the electricity demand so that the supply can be properly adjusted.

Basically, power demand forecast can be separated into two major groups namely short-term (hourly, three hourly, one day, few days, and a week) and long-term (monthly, and yearly) in [1]. The former is able to supply future information to the electricity companies to plan for generation and distribution appropriately. The latter can be referred to estimate the material inputs such as water, coal, and nuclear, for generators, or to install photovoltaic cell and wind turbine in case of renewable energy. In this research, we focus on the day-head electricity consumption prediction.

The authors in [2] investigated people's habits in using modern devices, which is not related with the environmental conditions to forecast the electricity demand. Additionally, several factors, e.g. temperature, humidity, gross domestic product (GDP), population, types of households and their correlation coefficients, and user behaviors moderately impacting consumption have been also considered to find the relationship between them and power demand.

On the contrary, many environmental conditions such as the season, amount of rain, temperature, humidity, and solar radiation also influence consumption significantly. The model ZABES (Zone Air Building Energy Simulation) was applied to solve the energy and mass balance equations of the zone air to calculate a building envelope model in [3]. The authors in [4] described the relationship between incomplete data and energy consumption by using a grey model. One of the most popular method applied to predict the electricity consumption is Artificial Neural Network (ANN) because the nonlinear relationship between major factors and demand can be accounted for.

The monthly average temperature and electric consumption from April 2013 to September 2014 in 1100 households in Japan was investigated by [6] to apply the Fourier transform and Gaussian process (time series) to forecast the future electricity consumption. Because individuals tend to use energy unstably, two methods should be used to predict the aggregated consumption based on the collected consumption in both short and long periods. Moreover, these methods are able to characterize data based on time and magnitude to make similar groups. The Gaussian process can indicate clearly changes in small intervals while the Fourier transform causes a large error. The authors in [7] employed the support vector regression and fuzzy based on PSO algorithm to predict the short-term demand in South Korea. ANN was applied to predict both the aggregated and individual electricity consumption in [8] because this method can analyze highly nonlinear systems. Although fuzzy logic may show the relationship between input and output, this method also cannot separate historical data into small groups. Both approaches need a large number of data and much time to train their networks to find unknown parameters of

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hidden layer. The study in [9] used a two-layer perceptron neural network to predict the electricity consumption with six inputs including the population, GDP per capita, inflation percentage, unemployment percentage, and winter/summer average temperature. To improve the accuracy, the author also forecast the future population which depends on many factors, leading to large error of this method. The authors in [10] proposed an electricity consumption regression model based on the linear combination of the GDP and the population or the GDP per capita.

In order to predict the electricity consumption, temperature is generally chosen as input to calculate the future demand in almost of the existing works, while relative humidity, one of the most important weather factor impacts human comfort may be ignored. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [11] proposed several standards for the indoor comfort zones, i.e. people feel comfortable when temperature and humidity are in this zones. These standards have been researched and further investigated in many studies, e.g., [12, 13]. Several methods such as ANNs, autoregressive variants, fuzzy control, and hybrid models were employed to manage the thermal comfort in [14].

In this paper, a Radial Basis Function like Artificial Neural Network (RBF-like ANN) model is proposed to predict the day-ahead hourly electricity consumption, which includes a known first layer and an unknown second layer. This model has three inputs, vectors of sampling times, temperature, and humidity. The unknown parameters of the second layer is sought by minimizing the error of model output and the past consumption where an optimization problem with L_1 cost function is solved. At each step, the cost function is solved by the least square (L_2) based method or by the ADMM method [18].

We then introduce two methods to generate the prediction interval, i.e., the boundary of the prediction value. In reality, the electricity manufacturer needs the envelope of prediction to generate and distribute appropriately to avoid lack or redundancy. The standard deviation of past data at each time zone can be used to create the prediction interval of future consumption. Besides, the bootstrap method is also employed to generate the envelope, in that partial number of considered days is randomly picked up to train the proposed model to predict future consumption, which is iterated in many times to obtain mean, maximum, and minimum line.

The following notations and symbols will be used in the paper. The notation $x_{[i],j}$ denotes the variable x for the j-th input in the i-th layer of the RBF-like ANN. Then $X_{[i],j}(k)$ is the k-th element of a vector $x_{[i],j}$, and $X(i,k)$ denotes the (i,k)-th element of a matrix X. Next, $\mathbb{R}$ stands for the set of real numbers, while $\mathbf{1_n}$ is used for the vector having n elements equal to one. Last, $|\bullet|$ stands for the absolute operator.

2. DESCRIPTION OF THE PROPOSED MODEL

In this section, Table1 shows the correlation of temperature, humidity and electricity consumption using the realistic data in California [16, 17] to explain reason why temperature and humidity are chosen as two in three inputs of our model though there are many other weather parameters, which affect the electricity consumption. These data will also be utilized in the test cases to validate our proposed approach. The closer to 1 the absolute value of the correlation is, the more related to the electricity consumption the associated parameter will be.

Table 1 Correlation between weather parameters and the electricity consumption from 4 September 2018 to 28 September 2018 in California

Parameters	Correlation value
temperature	0.82
relative humidity	-0.55

Obviously, temperature is most related to the electricity consumption in California while humidity is also an important factor, during the period of collected data. Similar observations can also be seen from the data in other places, but in this work we choose California because its hourly electric consumption data is available to the public.

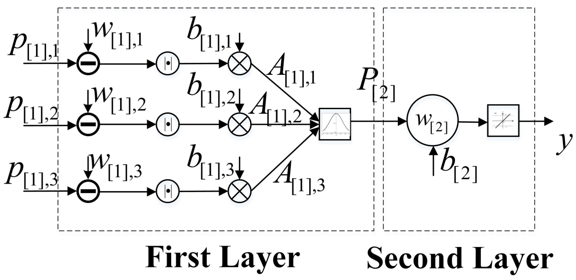

Fig. 1 Description of the employed RBF-like ANN.

Subsequently, we describe the proposed RBF-like ANN model used in this research with an illustration in Figure 1. This RBF-like ANN composes of two layers. The first layer has m neurons whose outputs are fed to a nonlinear Gaussian function while the second layer is a pure linear function with bias.

The input vector to the RBF-like ANN consists of three components $p_{[1],1}, p_{[1],2}$, and $p_{[1],3}$, in which $p_{[1],1}$ is the vector of time indexes (hours), $p_{[1],2}$ is the historical temperature (^oC), and $p_{[1],3}$ is the historical humidity (%). The dimensions of the variables are as follows. The inputs $p_{[1],j} \in \mathbb{R}^N$ for $j = 1,2,3$, and the output matrix of the first layer $A_{[1],j} \in \mathbb{R}^{m\times N}$, where N is the number of hours at which the historical data is collected. $w_{[1],j} \in \mathbb{R}^m$ and $b_{[1],j} \in \mathbb{R}^m$ are the weight and bias vector; respectively. Consequently, $P_{[2]} \in \mathbb{R}^{3m\times N}$ is the input matrix to the second layer. The output vector and the target vector of historical electricity consumption, are denoted by $y \in \mathbb{R}^N$ [10 MWh] and $t \in \mathbb{R}^N$ [10 MWh]. Finally,

$w_{[2]} \in \mathbb{R}^{3m}$ and $b_{[2]} \in \mathbb{R}$ are the weight vector and the bias in the second layer.

$$A_{[1],j}(i,k) = \left| p_{[1],j}(k) - w_{[1],j}(i) \right| b_{[1],j}(i) \tag{1}$$

$$A_{[1]} = \left[A_{[1],1}^T, A_{[1],2}^T, A_{[1],1}^T \right]^T \tag{2}$$

$$P_{[2]} = radbas(A_{[1]}) \tag{3}$$

$$y = P_{[2]}^T w_{[2]} + b_{[2]} \mathbf{1_N} \tag{4}$$

where *radbas* stands for the Gaussian function. Employing this model and the historical data on electricity consumption, temperature, and humidity, the model parameters are trained so that $y \to t$, i.e., the estimated model for the existing data is derived. Then the obtained model parameters in the estimated model are used to predict the future electricity consumption based on the forecast of hourly temperature and hourly humidity.

3. TRAINING APPROACHES

The RBF-like ANN is usually equipped with an L_2 cost function,

$$\begin{aligned} J_2 &= \sum_{k=1}^{N} [y(k) - t(k)]^2 = (y-t)^T (y-t) \\ &= \left(P_{[2]}^T w_{[2]} + b_{[2]} \mathbf{1_N} - \mathbf{t} \right)^T \left(P_{[2]}^T w_{[2]} + b_{[2]} \mathbf{1_N} - \mathbf{t} \right) \end{aligned} \tag{5}$$

and the least-square method is utilized to find the model parameters to fit the model output y to the existing data t. Denote

$$x \triangleq \begin{bmatrix} w_{[2]} \\ b_{[2]} \end{bmatrix}, \; U \triangleq \begin{bmatrix} P_{[2]} \\ \mathbf{1_N^T} \end{bmatrix} \tag{6}$$

Then Eq. (5) can be rewritten as

$$J_2 = \left(U^T x - t \right)^T \left(U^T x - t \right) \tag{7}$$

of which the optimal solution is

$$x^* = \left(U U^T + \rho I \right)^{-1} U t \tag{8}$$

The small term $\rho > 0$ is added to Eq. (8) because UU^T may not be invertible. For the considering RBF-like ANN, the above optimal solution gives us all parameters of the second layer while the parameters of the first layer are fixed *a priori*.

Nevertheless, in this research we propose to use the following L_1 cost function

$$J_1 = \sum_{k=1}^{N} |y(k) - t(k)| \tag{9}$$

The L_1 cost function Eq. (9) is employed because it is known to be more robust to outliers than the L_2 cost function [18, Chapter 6], which is important to the estimation and prediction problems because of the possible inaccuracies on the temperature and humidity forecast.

In the following, we present two approaches for solving the L_1 cost function Eq. (9) to train the parameters in the second layer of the proposed RBF-like ANN.

3.1. L_2-based Approach for Solving Eq. (9)

In this subsection, we introduce an iterative method to solve Eq. (9) based on the least-square solution Eq. (8) obtained from solving Eq. (5). To do so, rewrite Eq. (9) as follows,

$$J_1 = \sum_{k=1}^{N} \frac{1}{|y(k) - t(k)|} [y(k) - t(k)]^2 \tag{10}$$

At the l-th iteration ($l > 1$), we set

$$J_1(l) = \sum_{k=1}^{N} \frac{1}{|y_l(k) - t(k)|} [y_l(k) - t(k)]^2 \tag{11}$$

where $y_l(k)$ is the k-th element of vector y at the l-th iteration. Given a tolerance $\varepsilon > 0$, this iterative algorithm is stopped, i.e., $y_l \to y^* \triangleq \operatorname{argmin} J_1$, if

$$\| y_l - y_{l-1} \|_2 \le \varepsilon \tag{12}$$

Since y_l is unknown at the l-th iteration, Eq. (11) is approximated as follows,

$$J_1(l) = \sum_{k=1}^{N} \frac{1}{|y_{l-1}(k) - t(k)|} [y_l(k) - t(k)]^2 \tag{13}$$

Denote

$$\begin{aligned} \alpha_l(k) &\triangleq \frac{1}{|y_{l-1}(k) - t(k)|}, \\ \Lambda_l &\triangleq diag\left(\alpha_l(1), \alpha_l(2), ..., \alpha_l(N) \right) \end{aligned} \tag{14}$$

Substituting $\alpha_l(k)$ and Λ_l into Eq. (13) gives us

$$J_1(l) = (y_l - t)^T \Lambda_l (y_l - t) \tag{15}$$

The optimal solution of Eq. (15), similar to Eq. (8), is

$$x_l^* = \left(U \Lambda_l U^T + \rho I \right)^{-1} U \Lambda_l t \tag{16}$$

Subsequently, the following steps are presented to summarize the iterative process for solving the L_1 cost function Eq. (9).

Algorithm 1: L_2-based approach to solve the L_1 optimization problem Eq. (9)**.**

- Step 1: Set $l = 1$ and select the tolerance ε. Then set $y_l = \mathbf{1_N}$.
- Step 2: Set $l = l + 1$. Calculate Λ_l from Eq. (14) and find x_l^* from Eq. (16).
- Step 3: Find vector $w_{[2]}$ and $b_{[2]}$ from Eq. (6).
- Step 4: Compute y_l.
- Step 5: Examine Eq. (12). If true, going to step 6, otherwise go back to step 2.
- Step 6: Obtain the optimal solution y_l.

3.2. ADMM Approach for Solving Eq. (9)

In order to use the ADMM approach, the optimization problem, whose objective function is the L_1 cost function Eq. (9), is rewritten in the ADMM form as follows,

$$\min \; J_1 = \|z\|_1 \tag{17}$$

$$s.t. \; U^T x - z = t \tag{18}$$

Define an augmented Lagrangian associated with the above problem as follows,

$$L_{\rho}(x,z,\mu) = \|z\|_1 + \frac{\rho}{2}\|U^T x - z - t + \mu\|_2^2 \quad (19)$$

where $\rho > 0$ is a scalar penalty parameter and $\mu \in \mathbb{R}^N$ is called the scaled dual variable or scaled Lagrange multiplier [18]. Following the approach in [18, Chapter 6], Eq. (17) will be solved iteratively where the variables x, z, and μ are sequentially updated by the following formulas,

$$x_{l+1} = \left(UU^T\right)^{-1} U\left(t + z_l - \mu_l\right) \quad (20)$$

$$z_{l+1} = S_{1/\rho}\left(U^T x_{l+1} - t + \mu_l\right) \quad (21)$$

$$\mu_{l+1} = \mu_l + U^T x_{l+1} - z_{l+1} - t \quad (22)$$

where $S_{1/\rho}$ denotes the soft thresholding operator defined by

$$S_{1/\rho}(X) = \begin{cases} X - 1/\rho & if \quad X > 1/\rho \\ X + 1/\rho & if \quad X < -1/\rho \\ 0 & otherwise \end{cases} \quad (23)$$

This ADMM algorithm is terminated if the following stopping criteria are satisfied [18]:

$$\begin{aligned} &\|r_{l+1}\|_2 \leq \varepsilon^{pri} \\ &\|s_{l+1}\|_2 \leq \varepsilon^{dual} \end{aligned} \quad (24)$$

where

$$s_{l+1} = \rho U\left(z_{l+1} - z_l\right) \quad (25)$$

$$r_{l+1} = U^T x_{l+1} + z_{l+1} - t \quad (26)$$

$$\varepsilon^{pri} = \sqrt{N}\varepsilon^{abs} + \varepsilon^{rel} max\left\{\left\|U^T x_l\right\|_2, \|z_l\|_2, \|t\|_2\right\} \quad (27)$$

$$\varepsilon^{dual} = \sqrt{3m+1}\varepsilon^{abs} + \varepsilon^{rel}\|U\mu_l\|_2 \quad (28)$$

This algorithm is summarized below.

Algorithm 2: ADMM approach to solve the L_1 optimization problem Eq. (9).

- Step 1: Set $l = 1$ and select the tolerance λ. Then set $x_l = \mathbf{1_N}$, $\mu_l = 0.01 * \mathbf{1}_N$, and $z_l = U^T x_l - t$.
- Step 2: Calculate x_{l+1} from Eq. (20) and $X_{l+1} = U^T x_{l+1} - t + \mu_l$.
- Step 3: Examine X_{l+1} at Eq. (23) to update z_{l+1} from Eq. (21) and μ_{l+1} from Eq. (22).
- Step 4: Examine Eq. (24). If true, going to step 6, otherwise $l = l + 1$ and go back to step 2.
- Step 5: Obtain the optimal solution x_l.

3.3. Prediction Error

After the parameters of the second layer is found, the predicted consumption y_{pre} can be obtained by putting the prediction input p_{pre}. The Mean Absolute Percentage Error (MAPE) coefficient Eq. (29) is selected to evaluate the error between the real data and the estimated value or the predicted value.

$$MAPE = \frac{100\%}{N}\sum_{k=1}^{N}\left|\frac{t(k) - y(k)}{t(k)}\right| \quad (29)$$

Next, because the weather forecast including that for temperature and humidity is not precise and there are uncertainties on end-user behaviors, the prediction of electricity consumption in reality is often required in form of a prediction interval. Therefore, we introduce in the following two methods to generate an envelope of the predicted electricity consumption for a given probability of exactness. In the first method, the upper bound and lower bound of this envelope can be calculated as follows:

$$y_{up} = y_{pre} + z^{\alpha}\sigma \quad (30)$$

$$y_{low} = y_{pre} - z^{\alpha}\sigma \quad (31)$$

where z^{α} and σ are 100α percentile of a normal deviation and the standard deviation of the actual electricity consumption; respectively, for example $z^{0.8} = 1.282$. During working days, usually the electricity consumption largely varies where the consumed energy in the late evening and early morning (from 10 pm to 7 am) is far less than that in the the other hours. Therefore, the standard deviation σ can be calculated to generate the envelope of the prediction interval at each hour in a day.

In the second method, the envelope of the predicted electricity consumption is generated by the well-known bootstrap method (see e.g., [19]). A fixed number of days in the historical data will be randomly picked up to derive the parameters of the RBF–like ANN model, and then the obtained model will be utilized to predict the electricity demand in the future. This process is repeated many times to generate the set of predicted demand curves, i.e., an estimation of the prediction interval. Afterward, the mean of those demand curves is set to be the predicted electricity demand, while the maximum and minimum of 90% of this set will create the boundaries of the predicted envelope for the electricity demand.

4. NUMERICAL EXAMPLES

The historical temperature and humidity data of California are collected on [16] for working days *between 4 September and 28 September 2018*. The historical hourly electricity consumption in California is found on [17]. In order to show the effective performance of ADMM method, the number of neurons will be selected as $m = 20$ or $m = 100$. Lastly, $\varepsilon = 0.1$, $\rho = 10^{-3}$, $\varepsilon^{abs} = 10^{-4}, \varepsilon^{rel} = 10^{-5}$.

The parameters of the second layer in the RBF-like ANN is found by minimizing the cost function (9) with collected data of weather and electricity consumption. Consequently, the day-ahead prediction for the electricity consumption on *1 October 2018* is obtained using the day-ahead forecast of temperature and humidity. In fact, we could not have the weather forecast on *1 October 2018* but only the real weather data on that day, so we assume that the weather forecast is deviated from the real weather data as in (32). The real data and assumed forecast on the

Table 2 Comparison of two training approaches

	L_2-based approach		ADMM approach	
	20 Neurons	**100 Neurons**	**20 Neurons**	**100 Neurons**
Computational Time (s)	8.54	42.35	0.29	6.23
MAPE Estimation (%)	1.76	1.74	1.65	1.57
MAPE Prediction (%)	4.14	3.89	3.92	3.87

temperature and humidity are then shown in Figures 2–3.

$$p_{[1],2}^{predicted} = p_{[1],2}^{real} \pm 2^oC$$
$$p_{[1],3}^{predicted} = p_{[1],3}^{real} \pm 6\% \qquad (32)$$

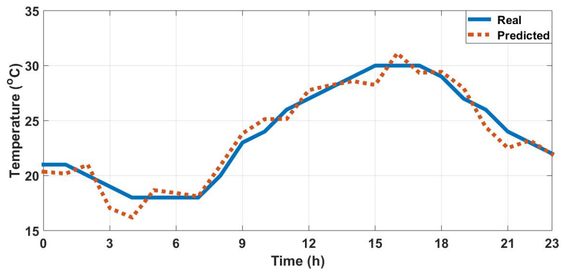

Fig. 2 Prediction of temperature on 1 October 2018.

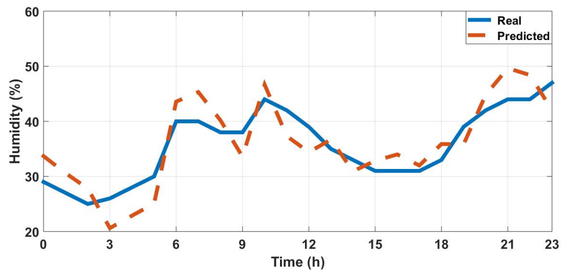

Fig. 3 Prediction of humidity on 1 October 2018.

Based on the assumed weather forecast, the prediction result of the electricity consumption on *October 1 2018* is exhibited in Figure 4 which shows the comparison of four two proposed approaches with different number of neurons utilized. It can be seen that the prediction by using ADMM method is better than that by utilizing L_2-based approach. Further, the ADMM-based predictions with 20 and 100 neurons are similar. A more detailed comparison between the L_2-based approach and the ADMM approach is shown in Table 2, which reveals that the computational time of the latter approach is much faster than the former one while the accuracy of the latter approach is also better than the former one.

Next, the envelopes of prediction employing ADMM method are displayed in Figures 5–6 based on the historical value the calculation in (30). We can observe that the obtained envelope when using 20 neurons is almost similar to that derived when utilizing 100 neurons.

On the other hand, the prediction envelope using the bootstrap method is shown in Figure 7, which is generated by randomly picking up 10 days from 19 days of data to find the parameters of RBF-like ANN and then to predict the demand in 1000 runs. It is clear that this envelope

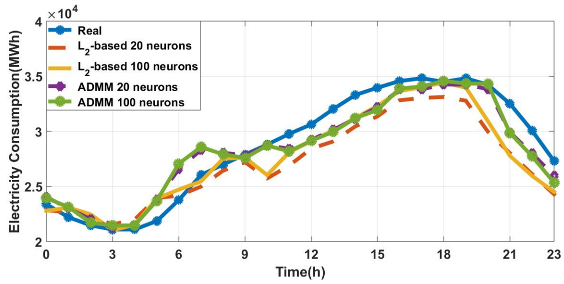

Fig. 4 Prediction result for the electricity consumption on 1 October 2018.

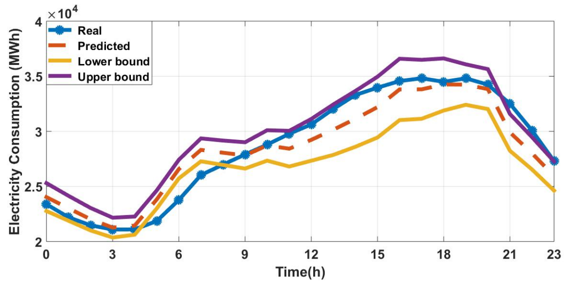

Fig. 5 The prediction interval obtained from ADMM approach with 20 neurons using the standard deviation of the past data.

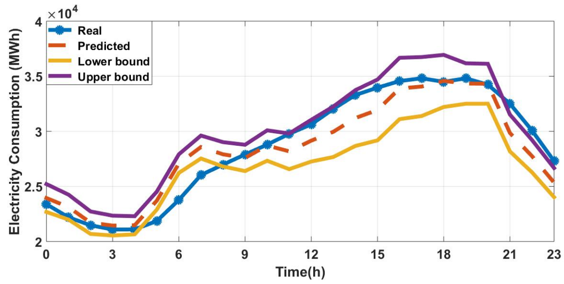

Fig. 6 The prediction interval obtained from ADMM approach with 100 neurons using the standard deviation of the past data.

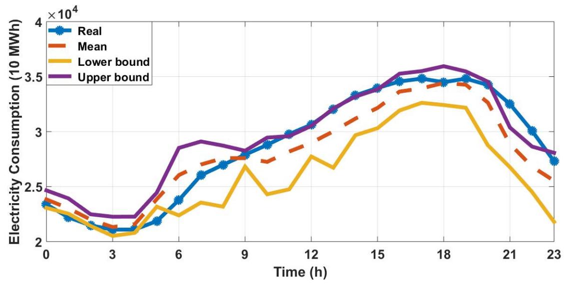

Fig. 7 The prediction interval obtained from ADMM approach using bootstrap method.

generated by many predicted lines has more meaningful than that by the standard deviation and may give better prediction interval than that using the standard deviation method.

5. CONCLUSIONS

In this paper, an RBF-like ANN is proposed to predict the day-ahead electricity consumption using the weather forecast on the temperature and humidity, where the ANN parameters are trained using the past data on temperature, humidity, and electricity consumption. Moreover, the L_1 cost function is used for model training instead of the L_2 cost in the traditional RBF-ANN. Subsequently, two approaches based on the least square and ADMM approaches are employed to solve the L_1 optimization problem. It then turns out that ADMM-based prediction is better than least square based prediction. Additionally, the prediction interval using the standard deviation and bootstrap methods are also studied, which show reasonably good match with the real consumption.

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