Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Electric load forecasting based on Long-Short-Term-Memory network via simplex optimizer during COVID-19

Li Xiaole, Wang Yiqin, Ma Guibo, Chen Xin, Shen Qianxiang, Yang Bo

PII: S2352-4847(22)00605-9
DOI: https://doi.org/10.1016/j.egyr.2022.03.051
Reference: EGYR 3483

To appear in: Energy Reports

Received date: 8 February 2022
Accepted date: 8 March 2022

Please cite this article as: X. Li, Y. Wang, G. Ma et al., Electric load forecasting based on Long-Short-Term-Memory network via simplex optimizer during COVID-19. Energy Reports (2022), doi: https://doi.org/10.1016/j.egyr.2022.03.051.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2022 Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
Electric Load Forecasting Based on Long-Short-Term-Memory Network via Simplex Optimizer during COVID-19

Li Xiaole\textsuperscript{a}, Wang Yiqin\textsuperscript{a}, Ma Guibo\textsuperscript{a}, Chen Xin\textsuperscript{a}, Shen Qianxiang\textsuperscript{b}, Yang Bo\textsuperscript{b}\textsuperscript{*}

\textsuperscript{a}Fuxin Electric Power Supply Company, State Grid Liaoning Electric Power Co. Ltd, Fuxin, Liaoning 123000, China
\textsuperscript{b}Shenyang EPIC Technology Co., Ltd, Shenyang, liaoning 110004, China

Abstract

Electric load forecasting is a challenging research, which is of great significance to the safe and stable operation of power grid in epidemic period. In this paper, Long-Short-Term-Memory (LSTM) model with simplex optimizer is proposed to forecast the electric load for an enterprise during the COVID-19 pandemic. The forecasting process consists of data processing, LSTM network construction and optimization. Firstly, some data processing steps includes information quantifying, electric load data cleaning, correlation-coefficient-based medical data filtering, clustering-based medical data and electric load data filling. Then LSTM-Based electric load forecasting model of enterprise is established during the COVID-19 pandemic. On this basis, LSTM network is trained and parameters are optimized via simplex optimizer. Finally, an example of the electric load forecasting of an enterprise during the COVID-19 pandemic is investigated. The forecasting results show that the reduced number of iterations is about 25\% and the improved forecasting accuracy is about 5.6\%. These results can be used as a reference for resuming production of enterprises and planning of electric grid.

1. Introduction

At the end of 2019, COVID-19 broke out worldwide, which had a serious impact on the global economy [1]. Enterprises shut down, materials damaged, industrial chain shut down, and people cannot cross the region. Because of COVID-19, productions of enterprises and people's life have been greatly impacted, so that the electric load in power system has also been significantly changed. As an important reference index of economic development, electric load can reflect the economic situation of the society. Changes of electric load during the COVID-19 pandemic have become complicated. Accurate electric load forecasting can ensure the normal operation of the society, effectively
reduce the operation cost of the power system, ensure the economic benefits of the power grid and improve the social stability.

Generally, the purpose of electric load forecasting is to guide the planning of electric energy production and distribution [2]. Due to robustness and self-regulation ability of the power grid, the electric energy fluctuations caused by local equipment failures and electric load changes will not make a serious impact on the power grid. Therefore, these small faults and disturbances can be ignored in conventional forecasting, and the forecasting results are basically consistent with the reality. At present, more and more intelligent algorithms are used to forecast electric load [3,4]. Deep learning algorithm has attracted much attention because of its strong learning ability and adaptability [5-7]. Various neural networks are also designed to meet the special needs of electric load forecasting in different environments [8-10]. However, unlike meteorological events, holidays and other periodic events, COVID-19 epidemic is an aperiodic emergency. Moreover, the influence of COVID-19 on electric load takes a long time. Depending on the severity of COVID-19 and the countermeasures adopted, the influence may last for several months or even a year. The training for electric load forecasting model depends on a large number of sample data under normal conditions. And the trained forecasting model is insensitive to an aperiodic emergency and has no memory ability, so it is obviously not suitable for forecasting the electric load of enterprise during the COVID-19 pandemic. Since the influence of COVID-19 on electric load is not a short period of time, it requires that the forecasting model should remember information passed through a long period of time. The ordinary recurrent neural network (RNN) cannot deal with the data with long-term dependence and is only suitable for the forecasting of short change period. As a special kind of RNN, Long Short Term Memory (LSTM) neural network can solve this problem well [11], so it is more appropriate to use LSTM neural network to forecast electric load of enterprise during the COVID-19 pandemic. This problem has been described in [12-14]. In [12], in order to study the changing trend of hourly electric load over a long period of time, fourteen years’ real data are used to train the LSTM neural network forecasting model, and ideal forecasting results are obtained. In [13], a forecasting model based on LSTM is established to study the influence of seasonal factors on wind power generation. In [14], LSTM neural network is established to forecast energy prices in the electricity market, taking into account the long-term impact caused by changes in energy utilization rate and user demand. Therefore, LSTM neural network is very suitable for solving the forecasting task with many influencing factors and long influencing time, because it can selectively retain the memory data of a long time ago.

However, a large number of sample data and quite a few iterations are needed to train conventional LSTM neural networks if desired training results are ideal. During COVID-19 period, it is impossible to obtain medical data with an interval of less than an hour, so it is difficult to obtain enough medical data to train the LSTM neural network. In order to forecast electric load of enterprise during the COVID-19 pandemic, an LSTM electric load forecasting model combined with simplex optimizer is proposed. When the LSTM model is trained, its training parameters are optimized by simplex optimizer, and updated at appropriate time, so that the training can be completed with less iteration. Compared with conventional LSTM model, the novel LSTM model combined with simplex optimizer requires less training data and less iteration, and can achieve the same or even higher forecasting accuracy.

In order to deal with COVID-19, a novel LSTM model is used to forecast the electric load of an enterprise and the problem of insufficient historical data is solved. The main contributions of this paper are as follows: ① A series of data processing is carried out to make the data more suitable for forecasting electric load of enterprise during the COVID-19 pandemic. ② The electric load forecasting model based on LSTM is established. ③ In view of the lack of data for model training, simplex optimizer is used to optimize training parameters, which reduced the amount of data required. ④ The electric load forecasting model of enterprise during the COVID-19 pandemic is verified by a example. The remainder of the paper is organized as follows. Section 2 analyzes the electric load characteristics of enterprise during COVID-19 period and section 3 describes data processing. Section 4 firstly presents electric load forecasting model based on LSTM, and then optimizes training parameters of model by simplex optimizer. Section 5 analyses forecasting results for electric load of an example. Section 6 concludes the paper.

2. Analysis of electric load characteristics

Under normal circumstances, the electric load of enterprises has periodic changes due to the influence of air temperature, time of day, season, public opinion and official policy [15], and also shows regularity on weekends and holidays. Not just that, the historical data of electric load of enterprises is sufficient. These characteristics make the electric load forecasting method of enterprise very mature. However, compared with the normal situation, it is difficult
to forecast the electric load of enterprise due to the loss of experience guidance when emergencies occur. If there is a model that can quickly respond to events and give high precision forecasting results, the power system's ability to deal with emergencies will be greatly improved.

Electric load of enterprise during the COVID-19 pandemic is not only affected by conventional factors such as air temperature, public opinion, official policy and time of day, but also affected by medical data [16]. In addition, incomplete data resulted in a lack of sample data that could be used for model training.

In this paper, in order to more clearly describe the impact of COVID-19 on the forecasting results of electric load, ignoring the influence factors such as temperature, official policy and public opinion, the historical data of electric load and local medical data are highlighted. Meanwhile, LSTM model is used to forecast electric load and model parameters optimized by simplex optimizer in the training process, so the forecasting model is effectively trained by less sample data. The realization process of electric load forecasting of enterprise during the COVID-19 pandemic will be described in detail below.

3. Data processing

3.1. Electric load data cleaning and medical data filtering

Different from the conventional factors that affect electric load of enterprise, the influence of COVID-19 on electric load tends to be more rapid, more complex, less regular and aperiodic. In order to make the relationship between medical data and of enterprise more obvious and more relevant, firstly, the enterprise historical data of electric load is cleaned. That is, the epidemic factors are retained and other factors that have a great impact on the electric load are removed. Then, several medical data with high correlation with historical data of electric load are filtered according to correlation coefficient. Therefore, the influencing factors of electric load are removed by setting the weight of these factors. It can be considered that the historical data of electric load after cleaning is only related to medical data. When using these processed data to train LSTM neural network, it can reduce the computational complexity and solve the problem of poor forecasting accuracy caused by a variety of factors.

Many studies have shown that electric load of enterprise is mainly affected by air temperature and time, but also by public opinion and official policies. Since the time is periodic and definite, it will not interfere with the influence of epidemic factors. The air temperature, public opinion and official policies are random changes which need to be removed. Since the collected public opinions and official policies are all text information, they need to be quantified first. The quantified data of public opinion is defined as vector $D_{op}$, and the quantified data of official policy is defined as vector $D_{po}$, so the daily quantitative criteria of single public opinion information meet the table 1 and the quantitative criteria of official policies meet the table 2.

| Table 1. Public opinion quantification table |
|----------------------------------------------|
| Daily page views | <0.1k | 0.1k~0.5k | 0.5k~1.5k | 1.5k~3k | 3k~6k | 6k~10k | 10k~20k | >20k |
| Quantitative numerical | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |

| Table 2. Official policy quantification table |
|-----------------------------------------------|
| Administrative level | Township level | County level | Prefecture level | Provincial level | National level |
| Quantitative numerical | 1 | 2 | 3 | 4 | 5 |

Each element in $D_{op}$ is the sum of all quantified values of public opinion in a day, and each element in $D_{po}$ is the sum of quantified values of all official policy that remain in effect in a day. After the quantification of public opinion and official policy information is completed, the historical data of electric load of enterprise begin to be cleaned. First, the temperature data is defined as vector $W$, where the element is daily average temperature, and the historical data of electric load of enterprise is defined as vector $Y$. Therefore, the correlation coefficient between temperature data, public opinion data, official policy data and electric load data can be calculated as the correlation weight when the influencing factors are removed. If the correlation coefficient of the two variables is $R$, it can be calculated as follows:
\[ R = \frac{E(ab) - E(a)E(b)}{\sqrt{E(a^2) - E(a^2)}} \] (1)

Where, \( a, b \) are two variables, and \( E(.) \) is the expectation function. Suppose \( R_w \) is the correlation coefficient between temperature and electric load. \( R_{\text{zy}} \) is the correlation coefficient between public opinion and electric load. \( R_{\text{zy}} \) is the correlation coefficient between official policies and electric load. They can be calculated by (1). Next, the negligible thresholds for temperature, public opinion, official policy are \( Q_w, Q_{\text{zy}}, Q_{\text{zy}} \), respectively. These thresholds are the empirical expectations of various influencing factors in actual production, which are quantified by actual production experience. When the value of influencing factors is equal to the negligible threshold, the effect of these factors can be ignored. If the historical data of electric load after cleaning is represented by vector \( \mathbf{Y} \), it can be obtained as follow:

\[
\mathbf{Y}' = R_w (Q_w \mathbf{E} - \mathbf{W}) + R_{\text{zy}} (Q_{\text{zy}} \mathbf{E} - \mathbf{D}_{zy}) + R_{\text{zy}} (Q_{\text{zy}} \mathbf{E} - \mathbf{D}_{zy}) + \mathbf{Y}
\] (2)

Where, \( \mathbf{E} \) is the unit vector. The processed historical electric load data \( \mathbf{Y}' \) is only related to medical data and time after the data is calculated by (2). Since time is a deterministic quantity, only considering the impact of medical data on electric load, a large deviation will not be caused in the forecasting results.

In order to achieve effective model training and electric load forecasting, medical data should be filtered according to correlation coefficients. Currently, there are nine kinds of medical data that can be collected, such as new deaths, new cases, new confirmed cases, new suspected cases, cumulative deaths, cumulative cures, cumulative confirmed cases, existing confirmed cases and existing suspected cases. These nine kinds of data are expressed as vectors \( \mathbf{N}_{\text{sw}}, \mathbf{N}_{\text{zy}}, \mathbf{N}_{\text{zy}}, \mathbf{L}_{\text{zy}}, \mathbf{L}_{\text{zy}}, \mathbf{L}_{\text{zy}} \), and \( \mathbf{X}_{\text{zy}} \), respectively. Their correlation coefficients with \( \mathbf{Y}' \) are \( R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}}, R_{\text{zy}} \), respectively. The correlation degree comparison is shown as table 3.

| Coefficient range | Very weak | Weak | Normal | Strong | Highly strong |
|-------------------|-----------|------|--------|--------|--------------|
| Degree of correlation | 0.0–0.2 | 0.2–0.4 | 0.4–0.6 | 0.6–0.8 | 0.8–1 |

According to table 3, two variables with correlation coefficient greater than 0.6 are considered to have strong correlation, so the medical data with correlation coefficient greater than 0.6 are selected from the nine kinds of medical data. It is considered that these medical data have a great impact on the electric load of enterprise. If these medical data are used for model training, electric load forecasting can achieve ideal results.

3.2. Data filling in sample set

In data processing, a small amount of data is missing in the collection process due to various reasons. In order to further improve the accuracy and reliability of electric load forecasting, a data clustering method is adopted to fill the missing data in sample set. When using the clustering method to complete the historical electric load data, the complete data vector is clustered, and then the incomplete data vector is classified. By constructing a characteristic fitting vector in each data vector and scaling this vector in equal proportion, the missing data can be covered, so as to realize data filling. The historical data filling process of electric load is illustrated as follows.

In the cleaned historical data of electric load, \( \mathbf{Y}_{(d, t)}' \) is defined the data at the sampling time point \( t \) of the day \( d \). Assuming that \( m \) days of data have been collected and the number of sampling time points in a day is \( n \), the daily electric load vector of the enterprise on the day \( d \) can be expressed as \( \mathbf{Y}_d' = [\mathbf{Y}_{(d, 1)}', \mathbf{Y}_{(d, 2)}', \ldots, \mathbf{Y}_{(d, n)}'] \). The historical data matrix of electric load is \( \mathbf{Y}' = [\mathbf{Y}_1', \mathbf{Y}_2', \ldots, \mathbf{Y}_m'] \). Set daily average electric load \( \overline{\mathbf{Y}}_d \) is

\[
\overline{\mathbf{Y}}_d = \left( \frac{\sum_{i=1}^{n} \mathbf{Y}_{(d, i)}'}{n} \right)
\] (3)

Then, the domain between values \( \max \{ \overline{\mathbf{Y}}_d, \mathbf{Y}_d' \} \) and \( \min \{ \overline{\mathbf{Y}}_d, \mathbf{Y}_d' \} \) of daily average electric load is called the range of average electric load data. \( k \)-means clustering is used to performed on all daily electric load
vectors. That is, the range of average electric load data is divided into $k$ parts of equal length, and all daily electric load vectors are classified according to the range of average value of each part. In order to obtain an appropriate number of $k$, the centroid vector of class $i$ is defined as $M_i$, which satisfies

$$M_i = \left( \sum_{d=x_i} \mathbf{v}_d \cdot \mathbf{y}_d \right) / \sum_{d=x_i} \mathbf{v}_d = \left[ M_{i(1)} \ M_{i(2)} \ldots M_{i(n)} \right]^{T}$$

(4)

Where, $M_{i(a)}$ is element in vector. $X_i$ is the set that contains all the daily electric load vectors of class $i$. According to the centroid vector of each class in $k$-means clustering, the total eccentric distance $Z(k)$ of electric load data under $k$-means clustering can be calculated as follows:

$$Z(k) = \sum_{i=1}^{k} \sum_{d=x_i} \left( \sum_{t=1}^{n} \left( y_{i(t)} - M_{i(t)} \right)^2 \right)$$

(5)

In (5), $Z(k)$ is used as the index to measure the clustering effect. The smaller $Z(k)$ is, the more obvious the clustering effect is. However, if $Z(k)$ is reduced by increasing $k$ blindly, the amount of calculation will be greatly increased. Therefore, appropriate $k$ should be selected to achieve obvious clustering effect and the $k$ is as small as possible. In data filling process, the value of $k$ satisfies $Z(k) - Z(k+1) < 0.01(Z(1) - Z(2))$.

After the $k$ value is determined, $k$ centroid vectors can be obtained, and then each daily electric load vector with missing data can be classified. If daily electric load vector of day $d$ has missing data, the Euclidean distance between it and the centroid vector of class $i$ is defined as $\rho_i$. Minimum Euclidean distance $\min\{\rho_1, \rho_2, \ldots, \rho_k\}$ corresponds to the class which is belonged to the incomplete daily electric load vector. The centroid vector of incomplete daily load vector class is taken as a characteristic fitting vector, and the missing part is filled, as shown in Fig.1.

![Schematic diagram of missing data clustering filling](image)

Fig. 1. Schematic diagram of missing data clustering filling

In Fig.1, the curve is generated by a vector, and each data point on the curve corresponds to each element in the vector. The $x$-axis is the position of the element in the vector, and the $y$-axis is the value of the $x$-th element. The curve to be completed $y_i(x)$ is generated according to the incomplete vector. It is assumed that $n$ data are missing from data $a$ to data $b$ on $y_i(x)$. The characteristic fitting curve $y_{\tilde{i}}(x)$ is generated according to the characteristic fitting vector of the corresponding class. The values $y_{\tilde{1}}(a)$ of $a$-th data, $y_{\tilde{1}}(b)$ of $b$-th data, $y_{\tilde{2}}(a)$ of $a$-th data, $y_{\tilde{2}}(b)$ of $b$-th data are all known, then the filling value $y_i(i)$ of $i$-th data missing by incomplete vector can be calculated as follows:

$$y_i(i) = y_{\tilde{1}}(i) + (i-a) \times \frac{y_{\tilde{1}}(a) - y_{\tilde{1}}(b) + y_{\tilde{2}}(a) - y_{\tilde{2}}(b)}{n+1}$$

(6)

Where, $y_{\tilde{2}}(i)$ is the data value at the same position as the missing data in the characteristic fitting curve.

Therefore, (6) can be used to fill the missing data in $Y^\prime$ and filtered medical data. Since the sampling points of medical data are less than those of electric load data, two adjacent known data are used to linearly fill the missing data.
4. Modeling and optimization of electric load forecasting

4.1. Modeling of electric load forecasting

In order to forecast the electric load of enterprise during the COVID-19 pandemic, a forecasting model based on LSTM network is established. Its schematic diagram of the time-order expansion is shown as Fig. 2. In Fig 2, a LSTM unit of the forecasting model is mainly composed of four gate structures, such as forgetting gate, updating gate, input gate and output gate. This unit has four inputs, namely, the memory value $c_{t-1}$ retained at the last moment, the output value $x_t$ at the last moment, the input value $x_t$ at the current moment and the network parameter $p_t$ at the current moment. LSTM network can realize long-term memory of data features by controlling retention and forgetting of memory $c$. Where forgetting gate is used to control how much information in $c_{t-1}$ is saved into $c_t$, its memory retention degree function $w_f$ can be expressed as follows:

$$w_f = \sigma(W_f [s_{t-1}, x_t] + b_f)$$ (7)

Where, $W_f$ is the forgetting gate weight matrix. $b_f$ is the forgetting gate bias. $\sigma(\cdot)$ is the sigmoid activation function. When $w_f$ is equal to 1, it means that the output of the last moment is completely retained. The input gate is used to control how much information in $x_t$ is saved into $c_t$, and its input reservation degree function $i_t$ and preinput function $\tilde{c}_t$ can be expressed as follows:

$$i_t = \sigma(W_i [s_{t-1}, x_t] + b_i)$$ (8)
$$\tilde{c}_t = \tanh(W_c [s_{t-1}, x_t] + b_c)$$ (9)

Where, $W_i$ is the input retention weight matrix. $b_i$ is the input retention bias. $W_c$ is the input gate weight matrix. $b_c$ is the input gate bias. $\tanh(\cdot)$ is the $\tanh$ activation function. When $X$ is equal to 0, the current input is completely forgotten. The update gate is used to update the current memory, so the current memory $c_t$ can be expressed as:

$$c_t = c_{t-1} \times w_f + i_t \times \tilde{c}_t$$ (10)

Finally, the output gate is used to control how much information in current memory $c_t$ is output. Its output degree function $o_t$ and unit output $s_t$ at this moment can be expressed as follows:

$$o_t = \sigma(W_o [s_{t-1}, x_t] + b_o)$$ (11)
$$s_t = o_t \times \tanh(\tilde{c}_t)$$ (12)

Where, $W_o$ is the weight matrix of the output gate. $b_o$ is the bias of the output gate.

The model of electric load forecasting is composed of LSTM units connected in a time sequence. Each unit receives the memory information of the previous unit and selectively passes it to the next unit, so as to achieve the long-term memory effect on the impact of COVID-19. Its structure is shown in Fig. 2.

![Fig. 2. Structure of LSTM model for electric load forecasting](image)

4.2. Optimization of model parameters

Due to the specific nature of the COVID-19 pandemic, sample data that can be used for training forecasting model are insufficiency. In this way, a simplex optimizer is used to continuously optimize the training parameters in the training process, so that the error can converge faster and meet the training requirements with less iteration, thus the requirement of sample number for model training is reduced. The structure of model parameter optimization module for electric load forecasting is shown in Fig. 3. In Fig.3, $p_i$ is an array containing 2 parameters. One is the number of hidden neurons; the other is the learning rate of the network. $F_0$ is the optimization objective function. $f_{test}$ is the
reflection module. \( f_{\text{exp}} \) is the expansion module. \( f_{\text{comp}} \) is the contraction module. \( f_{\text{comp}} \) is the compression module. \( \phi_1, \phi_2, \phi_3, \phi_4, \phi_5\) and \( \phi_6 \) are all judgment modules with different judgment behaviors, respectively. Before the model training, three arrays of different initial training parameters were set, and the objective function value of each array of parameters is calculated after ten iterations. The three arrays of parameters are used to form the initial simplex. The two parameter values of an array are used as the two components of a point coordinate, and the three points formed a triangle. The point with the smallest objective function value is the reference point \( P_{\text{low}} \). The point with the largest objective function value is the worst point \( P_{\text{high}} \). The remaining point is the target point \( P_{\text{goal}} \). The module processes the simplex by four actions: reflection, expansion, contraction, and compression, so that all points in the simplex approach the reference point. The module has three inputs, namely, the current input value \( x_t \), the current output value \( o_t \) and the current training parameters \( p_t, x_t \) and \( o_t \) are input into the optimization objective function \( F_0 \), which is shown as follows:

\[
F_0 = \sum_{i=1}^{3} e_1 + \sum_{i=1}^{3} e_2 + \sum_{i=1}^{3} e_3
\]  
(13)

Where, \( e_1, e_2, e_3 \) are the first type error, the second type error and the third type error respectively, which are defined as follows:

\[
e_1(t) = x_t - o_t
\]  
(14)

\[
e_2(t) = e_1(t) - e_1(t - 1)
\]  
(15)

\[
e_3(t) = e_2(t) + e_3(t - 2) - 2e_3(t - 1)
\]  
(16)

After ten iterations and updating the objective function value, the current training parameters are substituted to form a new simplex \( S \), \( S \) needs to be judged in \( \phi_6 \). It is to determine whether the sum of the absolute values of errors is greater than 0.01. This error is difference value between the objective function value at each point and the objective function value at the worst point on the parametric simplex. And it is to determine whether the absolute value of errors between the objective function value after this iteration and the last one is greater than 0.001. If both two conditions are true, optimization will be carried out; otherwise, the iterative training will continue with unchanged parameters. After starting the optimization, the reflection point \( P_{\text{refl}} \) is calculated by \( f_{\text{refl}} \).

\[
P_{\text{refl}} = (1 + \alpha)P_{\text{cen}} - \alpha P_{\text{high}}
\]  
(17)

Where, \( P_{\text{cen}} \) is the midpoint between \( P_{\text{low}} \) and \( P_{\text{goal}} \), \( \alpha (\alpha > 0) \) is the reflectance coefficient. The training parameters are updated by the parameters of the reflection point for a new round of iteration and the objective function value of the reflection point is calculated. Next, the judgment module \( \phi_2 \) is carried out. In judgment module \( \phi_2 \), if the reflection point function value is less than the reference point function value, the reflection point will be expanded. The expansion point \( P_{\text{exp}} \) is calculated by \( f_{\text{exp}} \).

\[
P_{\text{exp}} = \beta P_{\text{refl}} + (1 - \beta)P_{\text{cen}}
\]  
(18)

Where, \( \beta (\beta > 1) \) is the expansion coefficient. After completion of expansion, the parameters of the expansion point are used to update the training parameters for a new round of iteration and the objective function value of the expansion point is calculated. Next, the judgment module \( \phi_3 \) is carried out. In judgment module \( \phi_3 \), if the objective function value of the extension point is smaller than that of the reference point, the extension point is used to replace the worst point to form a new simplex for a new round of optimization; otherwise, the reflection point is used to replace the worst point for a new round of optimization. When the judgment module \( \phi_2 \) is in progress, if the reflection point objective function value is greater than that of the reference point, the judgment module \( \phi_3 \) is carried out. When the judgment module \( \phi_3 \) is in progress, if the objective function value of the reflection point is greater than that of the target point, the judgment module \( \phi_4 \) is carried out; otherwise, the reflection point is used to replace the worst point for optimization again. In judgment module \( \phi_4 \), if the objective function value of the reflection point is greater than that of the worst point, the contraction shall be carried out; otherwise, the reflection point is replaced by the worst point, then the contraction shall be carried out. The contraction point \( P_{\text{comp}} \) is calculated by \( f_{\text{comp}} \).

\[
P_{\text{comp}} = \gamma P_{\text{high}} + (1 - \gamma)P_{\text{cen}}
\]  
(19)

Where, \( \gamma (0 < \gamma < 1) \) is the contraction coefficient. After the contraction, the training parameters are updated with the parameters of the contraction point for a new round of iteration, and then the objective function value of the contraction point is calculated. Next, the judgment module \( \phi_5 \) is carried out. In judgment module \( \phi_5 \), if the objective function value of the contraction point is less than that of the worst point, the contraction point is used to replace the worst point for optimization again; otherwise the compression is carried out. The compression point \( P_{\text{comp}} \) is calculated by \( f_{\text{comp}} \).
\[ P_{\text{comp}} = \eta P_i + (1-\eta)P_{\text{low}} \]  

(20)

Where, \( P_i \) is the worst point or target point. \( \eta (0<\eta<1) \) is the compression coefficient. After the worst point and target point are compressed, the original worst point and target point are replaced respectively. The objective function value is obtained through one round of iteration and then a new simplex is formed for the next round of optimization. At this point, a whole round of training parameter optimization is completed. In this way, in the training process of electric load forecasting model, the training parameters are continuously optimized until the model training is completed.

5. Results analysis of electric load forecasting

In order to illustrate the electric load forecasting during the COVID-19 pandemic, a forecasting system based on LSTM model is studied. The system can realize information quantification, historical electric load data cleaning, medical data filtering, data filling, model training and electric load forecasting. The flow chart of the forecasting system is shown in Fig.4.

![Flow chart of electric load forecasting system](image)

In this example, electric load of an automobile manufacturing enterprise in Shenyang is forecasted. The historical data of electric load were collected by Power Acquisition System of Liaoning State Grid Electric Power Company from January 1, 2020 to April 15, 2020. The data of the first 75 days are used as the training sample data, and the last 30 days are used to verify the accuracy of the model forecasting results. Firstly, the collected public opinion data and official policy data are quantified. The correlation coefficients of temperature, public opinion, official policy and electric load data are respectively calculated as \( R_w = -0.382 \), \( R_{op} = 0.477 \) and \( R_{pc} = 0.413 \) according to (1). The curve of influencing factors during COVID-19 pandemic is shown in Fig.5. The comparison of data before and after the cleaning is shown in Fig.6.

![Quantization weighted curve of influencing factors of historical electric load](image)

![Comparison of historical data of electric load before and after cleaning](image)

In Fig.5, the historical electric load data of the enterprise are cleaned through the quantitative weighted data of influencing factors. In Fig.6, the influence of factors on historical data of electric load is shown that when COVID-19 is serious, influencing factors have a reduction effect on electric load, and after the epidemic ease off, influencing factors have a promotion effect on electric load.

As the influence of temperature, public opinion and official policy after the cleaning is ignored, the relationship between historical data of electric load and medical data is stronger. The medical data collected in this example include new deaths, new cures, new confirmed cases, new suspected cases, cumulative deaths, cumulative cures, cumulative confirmed cases, existing confirmed cases and existing suspected cases. The correlation coefficients between them
and historical electric load data are as follows: 
\[ R_{N-sw} = -0.2067, \quad R_{N-zy} = -0.1693, \quad R_{N-qz} = -0.1487, \quad R_{N-ys} = -0.2009, \]
\[ R_{C-sw} = 0.6652, \quad R_{C-zy} = 0.6882, \quad R_{C-qz} = 0.6068, \quad R_{E-qz} = -0.238, \quad R_{E-ys} = -0.2039. \]
It can be seen that cumulative deaths, cumulative cures and cumulative confirmed cases are strongly correlated with historical electric load, while the other data are weakly correlated or very weakly correlated. Therefore, cumulative deaths, cumulative cures and cumulative confirmed cases are selected for model training. These medical data are shown in Fig. 7. Due to data missing in historical data of electric load, it is necessary to fill data of electric load after cleaning, and the filling result is shown in Fig. 8.

The model is trained with the processed historical data of electric load and medical data. In order to illustrate the effect of simplex optimizer on LSTM model training, a conventional LSTM model in [17] and LSTM model with simplex optimizer are trained respectively. The electric load of the enterprise in the next 30 days is forecasted by two models respectively. The normalized error curve of training conventional LSTM model is shown in Fig. 9(a). The normalized error curve of training LSTM model with simplex optimizer is shown in Fig. 9(b). Under the same number of iterations, it is obvious that the normalized error of LSTM model training with simplex optimizer can drop to the allowable range of error faster, and the training can be completed when the number of iterations is 2750. However, the normalized error of conventional LSTM model training still does not drop to the allowable error range after 3750 iterations. The number of iterations is reduced by more than 25%.
Next, the two LSTM models after training are used respectively to forecast the electric load of the automobile manufacturing enterprise from March 16 to April 14, 2020, and their actual values and forecasted values are shown in Fig. 10 and Fig. 11. Considering the Mean Absolute Percentage Error (MAPE) as the evaluation index of each forecasting model, the MAPE between the actual value and the forecasted value in Fig. 10 is about 8.95%, and the MAPE between the actual value and the predicted value in Fig. 11 is about 3.31%. It can be observed that the improved forecasting accuracy is about 5.6% based on the LSTM model with simplex optimizer.

6. Conclusion

In order to provide guidance and reference for the electric energy planning of the power system, and the shutdown and resumption plans of various industries during the COVID-19 pandemic, a LSTM model via simplex optimizer is established for electric load forecasting. Through comparing with the conventional LSMT model and forecasting example verification for electric load, the proposed model is very suitable for electric load forecasting under the conditions of the lack of training data samples, and ideal forecasting results can be obtained by fewer training iterations. The forecasting results show that the proposed model is effective and high accuracy during the COVID-19 pandemic.

Acknowledgements

This paper is funded by the science and technology project of State Grid Liaoning Electric Power Company Co. Ltd, namely Deep Learning-Based Power Consumption Demand of Work Resumption of Industries and the Model of Correlated Work Resumption between Industries. (2021 YF-28)

References

[1] J. Liu. (2020) “Statistical analysis on the change of economic condition in China under the influence of COVID-19.” 2020 International Conference on Big Data Economy and Information Management (BDEIM) (2020): 95-100.

[2] I. Baric, R. Gribi and E. K. Nyarko. (2019) “Short-term forecasting of electricity consumption using artificial neural networks - an overview.” 2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO) (2019): 1076-1081.

[3] S.N. Fallah, M. Ganjkhani, S. Shamshirband, K. W. Chau. (2019) “Computational intelligence on short-term load forecasting: a methodological overview.” MDPI 12,3 (2019): 393-414.

[4] J. Chen, Y. Wu, Z. Lin, L. Zhao, Q. Wang, H. Hou, X. Deng. (2021) “Medium term load forecasting in distribution systems based on multi-linear regression & principal component analysis: A novel approach.” 2021 6th Asia Conference on Power and Electrical Engineering (ACPEE) (2021): 340-344.

[5] B. S. Kwon, R. J. Park, K. B. Song. (2019) “Weekly peak load forecasting for 104 weeks using deep learning algorithm.” 2019 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC) (2019): 1-4.

[6] B. Masoud, R. K. Ashkan. (2020) “Forecasting electric load by aggregating meteorological and history-based deep learning modules.” 2020 IEEE Power & Energy Society General Meeting (PESGM) (2020): 1-5.

[7] R. Mina, T. Dama. (2020) “Residential appliance-level load forecasting with deep learning.” 2020 IEEE Global Communications Conference, GLOBECOM 2020 - Proceedings (2020): 1-6.

[8] N. Gautam, A. S. Mayal, V. S. Ram and A. Priya. (2019) “Short term load forecasting of urban loads based on artificial neural network.” 2019 2nd International Conference on Power and Embedded Drive Control (ICPEDC) (2019): 46-51.

[9] J. Zhang, S. Yan, Y. Liu, W. Zhu, Z. Zhao. (2021) “A novel wavelet neural network load forecasting algorithm with adaptive momentum factor.” 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (2021): 1673-1678.

[10] Z. Zheng, L. Feng, X. Wang, R. Liu, X. Wang, Y. Sun. (2021) “Multi-energy load forecasting model based on bi-directional gated recurrent unit multi-task neural network.” ESS Web of Conferences 256(2021): 2032-2038.

[11] A. T. Bayrak, A. A. Aktaş, O. Susuz and O. Tunali. (2020) “Churn prediction with sequential data using long short term memory.” 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (2020): 1-4.

[12] R. Akter, J. -M. Lee and D. -S. Kim. (2021) “Analysis and prediction of hourly energy consumption based on long short-term memory neural network.” 2021 International Conference on Information Networking (ICOIN) (2021): 732-734.

[13] D. Dong, Z. Sheng and T. Yang. (2018) “Wind power prediction based on recurrent neural network with long short-term memory units.” 2018 International Conference on Renewable Energy and Power Engineering (REPEN) (2018): 34-38.

[14] A. Ioanq and R. Timovin. (2019) “Energy price prediction on the Romanian market using long short-term memory networks.” 2019 54th International Universities Power Engineering Conference (UPEC) (2019): 1-5.
[15] X. Zhao, J. Hu and J. Yang. (2008) “Empirical analysis of electricity consumption affected by structural changes of China’s heavy energy industries.” 2008 4th International Conference on Wireless Communications, Networking and Mobile Computing (2008):1-4.

[16] R. Ruensukon, N. Tephiruk and K. Hongesombut. (2021) “Effects of COVID-19 on electrical energy demand based on spatial analysis–A case study of Phetchaburi, Thailand.” 2021 9th International Electrical Engineering Congress (iEECON) (2021): 137-140.

[17] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu and Y. Zhang. (2019) “Short-term residential load forecasting based on LSTM recurrent neural network.” IEEE Transactions on Smart Grid 10,1(2019): 841-851.
Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: