# The research on spatial load forecasting model and method of electricity energy alternative based on cloud theory in distribution network

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**Abstract**. The research on electrical energy alternative mainly focus on alternative energy potential, expanding strategy and benefit analysis due to lack of historical data. This paper presents the total spatial load forecasting model in distribution network based on the proposed electrical energy alternative development coefficient which is generated by electricity energy objective issued by governments. To deal with fuzzy and uncertain in load forecasting for electric boiler and heater, the cloud theory and the regularity in the process of electrical energy alternative popularization are used. The component of electrical alternative spatial load forecasting is presented in sequence. The proposed method is verified in a typical case.

## 1. Introduction
China is carrying out the work on electrical energy alternative, which focuses on "substituting electricity for coal, for oil and long-distance transmission. Electric energy alternative could not only improve the economic benefits of energy utilization, but also reduce emissions of smoke, sulfur dioxide, nitrogen oxides and other pollutants, improving the living environment [1].

Because the current electrical energy alternative is in the early development stage, lacking historical data accumulation, it is difficult to forecast the electrical energy alternative load in each district by the method based on load density development regularity, as used in the spatial load forecasting of distribution network [2]. The research on electrical energy alternative mainly focuses on alternative energy potential [3] and benefit analysis [4].

However, above research lacks the spatial forecasting of electrical energy alternative in distribution network. In this paper, the total electrical energy alternative space load forecasting model in distribution network is proposed, combined with the electrical energy alternative objectives of the government. Then, various spatial loads of the electric boilers and electric heating are forecasted sequentially, based on the cloud theory and the process regularity of electrical energy alternative.

## 2. Modeling for Forecasting the Total Electrical Energy Alternative Space Load
Considering the situation of a variety of electrical energy alternative loads, the formula of total electrical energy alternative load forecasting is as follows:

$$P = \sum_{i=1}^{n} \alpha_i p_i \tag{1}$$

Where, $n$ represents the type number of electrical energy alternative in the district; $p_i$ is the predicted value of electrical energy alternative load $i$, based on the cloud theory. $\alpha_i$ is the development factor of the electrical energy alternative $i$.

The formula for the development factor of electrical energy alternative is that the government's objective $Z_i$ is divided by the sum of the predicted electrical energy alternative load values $Pi$ in distribution network.

$$a_i = Z_i / P_i = Z_i / \sum_{j=1}^{n_i} p_{i,j} \tag{2}$$

Where, $n_i$ represents the total number of all communities containing the electrical energy alternative load $i$; $p_{i,j}$ represents the electrical energy alternative load values of the community $j$ which containing the load $i$ predicted by the cloud theory.

## 3. Sequential Spatial Load Forecasting on Different Alternative Modes Based on Cloud Theory

### 3.1. Cloud Theory[9-11]

When the normal cloud model expresses linguistic values, the most commonly used mathematical expectation is:

$$C_T(x) = e^{\left[-(x-E_x)^2\right]\left[2(E_n)^2\right]} \tag{3}$$

The operation process of X-condition cloud generator, a kind of positive cloud generator, is that the cloud droplet is generated by the numerical features of the cloud under the specific value x within given domain. The algorithm steps are as follows:

(1) $E_n' = normrnd(E_n, H_e)$, where, $E_n$ represents the expectation; $H_e$ represents the standard deviation; $E_n'$ represents normal random number;

(2) Calculate the membership degree of x according to formula;

(3) Set $(x, C_T(x))$ as cloud droplets.

The steps of inverse cloud algorithm without membership information are as follows [11]:

Expectation $E_x = \dfrac{1}{n}\sum_{i=1}^{n} x_i$ ; Entropy $E_n = \sqrt{\dfrac{\pi}{2}} \times \dfrac{1}{n}\sum_{i=1}^{n}(x_i - E_x)$ ; Variance $S = \dfrac{1}{n-1}\sum_{i=1}^{n}(x_i - E_x)^2$ , hyper entropy $H_e = \sqrt{S^2 - E_n^2}$ .

### 3.2. Spatial Forecasting of Electrical Energy Alternative of Electric Boiler

According Urumqi coal-fired (oil) boiler data surveyed in 2015. The following table shows the qualitative language representation.

**Table.1** Digital features of cloudy model for vapor tons

| the qualitative language | range | expectation | entropy | Hyper entropy |
| --- | --- | --- | --- | --- |
| large | [39,70] | 50 | 8.15 | 0.027 |
| Relatively large | [20,50] | 39 | 7.51 | 0.038 |
| medium | [10,39] | 20 | 6.28 | 0.024 |
| Relatively small | [4,20] | 10 | 4.92 | 0.034 |
| Small | [0.1,10] | 4 | 3.21 | 0.03 |

The cloud uncertainty inference rules are given by the number of vapor tons for electric boiler replacement of coal-fired (oil) boiler:

1) If the number of vapor tons for coal-fired (oil) boiler is "large", then the probability of electric boiler replacement is "low";

2) If the number of vapor tons for coal-fired (oil) boiler is "relatively large", then the probability of electric boiler replacement is " relatively low ";

3) If the number of vapor tons for coal-fired (oil) boiler is "medium", then the probability of electric boiler replacement is " medium ";

4) If the number of vapor tons for coal-fired (oil) boiler is " relatively low", then the probability of electric boiler replacement is " relatively large ";

5) If the number of vapor tons for coal-fired (oil) boiler is "low", then the probability of electric boiler replacement is "large";

In the Ref. [9], the digital features of cloudy model for electric boiler replacement of boiler are as follows:

**Table.2** Digital features of probability of cloud model of coal (oil) boiler replaced by electric boiler

| qualitative language | expectation | entropy | hyper entropy |
|---|---|---|---|
| Small | 90 | 5 | 0.05 |
| Relatively small | 70 | 5 | 0.05 |
| medium | 50 | 5 | 0.05 |
| Relatively large | 30 | 5 | 0.05 |
| large | 10 | 5 | 0.05 |

The calculation formula of the replaced probability $\rho_{bz,j}$ for coal-fired (oil) boiler $j$ by the number of vapor tons is as follows:

$$\rho_{bz,j} = C_T(x_{z,j}) \tag{4}$$

The degree of membership $C_T(x_{z,j})$ is calculated by using the X condition cloud generator and inputting the number of vapor tons for electric boiler $x_{z,j}$ .

The following table shows the qualitative language representation of the cloud model.

**Table.3** Digital features of cloudy model for thermal efficiency

| qualitative language | expectation | entropy | hyper entropy | quantitative language |
|---|---|---|---|---|
| high | [87%,94%] | 91% | 2.14% | 0.15% |
| Relatively high | [80%,91%] | 87% | 2.17% | 0.13% |
| medium | [76%,87%] | 80% | 3.14% | 0.15% |
| Relatively low | [69%,80%] | 76% | 3.17% | 0.24% |
| low | [63%,76%] | 69% | 2.04% | 0.16% |

The cloud uncertainty inference rules are given by thermal efficiency is the same as vapor tons.

The digital features of cloudy model for electric boiler replacement of coal-fired (oil) boiler are shown as Table2. The calculation formula of the replaced probability $\rho_{br,j}$ for coal-fired (oil) boiler $j$ by thermal efficiency is as follows:

$$\rho_{br,j} = C_T(x_{r,j}) \tag{5}$$

Input the thermal efficiency for electric boiler $x_{r,j}$ and the degree of membership $C_T(x_{r,j})$ can be calculated by the X condition cloud generator.

Sequential spatial load forecasting of electric boiler

Combined with Eq.(4)and (5),the formula for the probability of the j-th coal (oil) boiler replaced by electric boiler is as follows:

$$\rho_{b,j} = \rho_{bz,j} \times \rho_{br,j} \tag{6}$$

According to (6), if the probability of coal (oil) boiler replaced by electric boiler in the year k is greater than the given threshold $C_b^{th}(k)$ coal (oil) boiler will be replaced by electric boiler in in parking lot $j$ ;otherwise, not.

The calculation of probability of the substitution is based on 5 inference rules from high to low, just corresponding to the 5 years of 13th Five-Year Plan, 2016 to 5th,2017 to 4th,2018,2019 and 2020

relatively to 3$^{rd}$,2$^{nd}$,1st. Thus, the probability threshold of year k is greater than that of year $k + 1$ calculated by tonnage / thermal efficiency expectations. The probability threshold of substitution in the year k is as follows:

$$C_b^{th}(k) = \rho_{br,l}(k+1) \times \rho_{bz,m}(k+1) \qquad (7)$$

Where $\rho_{br,l}(k+1), \rho_{bz,m}(k+1)$ is relatively the probability of year $k+1$, when the tonnage and thermal efficiency is equal to the expectation.

After forecasting the number of coal (oil) boiler replaced, the spatial load of replacement in community $j$ year k is presented as follows:

$$P_{z,j}^k = \beta \times \sum_{i=1}^{n_b} z_{i,j}^k \qquad (8)$$

Where $\beta$ is a coefficient, referring to Industrial steam boiler parameters series, $\beta$ =0.7; $z_{i,j}^k$ is the steam tonnage of electric boiler $i$ in community $j$; $n_b$ is total number of coal (oil) replaced in community $j$ in year $k$.

### 3.3. Spatial load forecasting of electric heating

The following table shows the qualitative language representation of the cloud model, the numerical features and number interval of heating days for each cloud model.

**Table.4** Digital features of cloudy model for heat time

| qualitative language | expectation | entropy | hyper entropy | quantitative language |
|---|---|---|---|---|
| long | [105,125] | 108 | 8.802 | 0.029 |
| Relatively long | [108,148] | 125 | 8.111 | 0.041 |
| medium | [125,170] | 148 | 6.782 | 0.026 |
| Relatively short | [148,180] | 170 | 5.314 | 0.037 |
| short | [170,183] | 180 | 3.467 | 0.032 |

The cloud uncertainty inference rules is the same as vapor tons

$\rho_{h,j}$ , the probability of substitution of unit j can be calculated as follows:

$$\rho_{h,j} = C_T(x_{h,j}) \qquad (9)$$

Input the heating days $x_{h,j}$ and the degree of membership $C_T(x_{h,j})$ can be calculated by the X condition cloud generator .

Sequential forecasting of spatial load of electric heating

According to (9),if the probability of unit j adopting electric heating in the year k is greater than the given threshold $C_h^{th}(k)$ , unit j will adopt electric heating ;otherwise, not.

The threshold value of the year k is presented as follow:

$$C_h^{th}(k) = \rho_{h,l}(k+1) \qquad (10)$$

Where $\rho_{h,l}(k+1)$ is the probability of adopting electric heating of the year $k+1$, and in its calculating process, the heating days equal to the expectation $x_{h,l}$ .

After forecasting the units adopting electric heating in the k year, the spatial load of community j of year k can calculated by the formula (11)

$$P_{h,j}^k = q \times \sum_{i=1}^{n_h} h_{i,j}^k \qquad (11)$$

Where, q is a coefficient. Referring to HVAC Common Data Manual, the value of q is equal to the Energy -saving standard for heat consumption q (W/m2) in the query table of heat consumption index in buildings energy-saving standard for heat consumption. $h_{i,j}^k$ is the construction area of community j unit i. $n_h$ is the predicted total number of electric heating units of community j in the year k.

## 4. Case study

By the method presented in this paper, the partial prediction results of Urumqi 2016 are verified and analyzed, and the load of electrical energy alternative in a region of 2016-2020 is forecasted.The residential land use planning of an area inUrumqi during 13th Five-Year is shown in Fig.1.
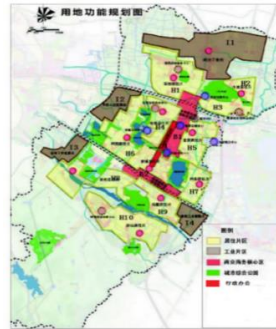


**Figure.1** Land using for an area in Urumqi from 2016 to 2020

By the method proposed, the load forecasting for electrical energy alternative of communities during 2016-2020 is acquired, and the results is shown in Table 5.

**Table.5** The electrical energy alternative forecasting load from 2016 to 2020 [unit MW]

| Num | 2016 | 2017 | 2018 | 2019 | 2020 |
|-----|------|------|------|------|------|
| I1 | 2.72 | 5.62 | 8.62 | 12.67 | 13.27 |
| I2 | 1.35 | 2.89 | 4.28 | 6.19 | 6.89 |
| I3 | 1.24 | 2.75 | 3.43 | 5.95 | 6.72 |
| I4 | 0.98 | 2.16 | 3.10 | 4.57 | 5.13 |
| O1 | 0.75 | 0.98 | 1.68 | 2.24 | 2.43 |
| B1 | 0.34 | 0.73 | 0.98 | 1.25 | 1.33 |
| B2 | 0.41 | 0.88 | 1.01 | 1.27 | 1.29 |
| H1 | 0.00 | 0.10 | 0.22 | 0.55 | 1.01 |
| H2 | 0.00 | 0.15 | 0.33 | 0.82 | 1.17 |
| H3 | 0.00 | 0.17 | 0.37 | 0.93 | 1.23 |
| H4 | 0.00 | 0.15 | 0.33 | 0.82 | 1.27 |
| H5 | 0.07 | 0.23 | 0.50 | 1.25 | 2.02 |
| H6 | 0.00 | 0.13 | 0.28 | 0.71 | 1.11 |
| H7 | 0.00 | 0.20 | 0.44 | 1.09 | 1.63 |
| H8 | 0.00 | 0.17 | 0.37 | 0.93 | 1.23 |
| H9 | 0.00 | 0.14 | 0.31 | 0.76 | 1.04 |
| H10 | 0.04 | 0.22 | 0.48 | 1.20 | 1.89 |

As seen from the above table, for Industrial land I1-I3, because the coal-fired (oil) boiler is gradually replaced by electric boilers, and the electric heating is gradually applied, the annual electricity alternative load increases linearly. By 2020 the total load of those 2 alterative modes will reach 32.01MW, accounting for 63.2% of the total electricity alternative load 50.66MW. So coal (oil) boiler and electric heating are the main modes of electricity alternative during the 13th Five-Year Plan period. For administrative office area O1 and commercial areas B1 and B2, the alternative modes are mainly electric heating and EV charging load. Because of large economic benefits of electric heating in such areas, electric heating alternative develops rather faster and by 2020, will be basically completed. For residential areas H1-H10, only H5 and H10 adopt electric heating in 2016, other areas not, that is the promotion effect in 2016 is not up to expectation. It is predicted a popularity of electric heating after 2017.

## 5. Summary

By analyzing spatial load forecasting results of electricity alternative in Urumqi, the following conclusions can be drawn:

1) Steam tonnage and thermal efficiency of coal(oil) significantly affect the probability and time that they are replaced by electric boilers, electric heating promotion are affected by the heating time;

2) We should build the cloud model of influencing factors and determine the number of cloud inference rules according to the predicted years;

3) The modified prediction error is smaller, which shows the effectiveness of the modified model.

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**References**

[1] Wang Wei,Huang Ke.The strategy of electric power alteration: opportunities,challenges and policy options[J]. Journal of North China Electric Power University (Social Sciences),2014(4):1-5(in Chinese).

[2] Wang Chengshan，Huang Chunhua，Ge Shaoyun，et al．A practical forecasting system for urban electric load density[J]．Power System Technology，1992,16(6): 41-46(in Chinese).

[3] Sun Yi, Zhou Shuang, Shan Baoguo, etc. Analysis of electrical energy alternative potential under Multi-scenario[J]. Power System Technology,2017(1) : 118-123 (in Chinese).

[4] Zheng Jincheng. Analysis on potential and environmental benefit of rural power substitute[M]. Beijing: North Electric Power University, 2015.

[5] Zhang Hongcai, Hu Zechun, Song Yonghua, et al. A prediction method for electric vehicle charging load considering spatial and temporal distribution[J]. Automation of Electric Power Systems, 2014,38(10): 13-20.

[6] GALUS M D, WARAICH R A, NOEMBRINI F，et al. Integration power systems, transport systems and vehicle technology for mobility impact assessment and efficient control[J]. IEEE Trans on Smart Grid, 2012, 3(2):934-949.

[7] TAE-KYUNG L, BAREKET Z, GORDON T, et al. Stochastic modeling for studies of real-world PHEV usage: driving schedule and daily temporal distributions [J]. IEEE Trans on Vehicular technology, 2012,61(4):1493-1502.

[8] Wen Jianfeng, Tao Shun, Xiao Xiangning, et al. Analysis on charging demand of EV based on stochastic simulation of trip chain[J]. Power System Technology，2015,39（6）：1477-1484.

[9] Liu Zifa, Pang Chengcheng, Wang Zeli, et al. Spatial load forecasting for distribution network based on cloud theory and cellular automata[J].Proceeding of the CSEE, 2013,33（10）：98-105

[10] Qiu Kaichang, Li Deyi, Li Deren. Cloudy theory and its applications in spatial data mining and knowledge discovery[J].Journal of Image and Graphics, 1999,4（11）：930-935.

[11] Yang Xueming ，Yuan Jinsha ，Wang Jianfeng，et al. A new spatial load forecasting method for distribution network based on cloud theory[J]. Proceeding of the CSEE，2006，26(6)：30-36(in Chinese) .