Long-Term Electricity Consumption Forecasting in China — Based on a Combined Model of KPCA and Linear Regression

Zili Huang1*, Haochen Zhang2, Chenxi Qiu3, Jia Liu4

1 Geisel School of Medicine, Dartmouth College, Hanover, NH 03755, USA
2 School of Aerospace Engineering, Tsinghua University, Beijing, 100084, China
3 School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Shenzhen, Guangdong, 518172, China
4 Renn Consulting Company, Beijing, 100038, China

*Email: hzl163yx@163.com

Abstract. Total electricity consumption is a barometer of a country's economy. Long-term forecasting of total electricity consumption in the whole society can effectively track a country's economic development and monitor the implementation of energy conservation and emission reduction policies. How to effectively forecast the long-term total electricity consumption is an important topic in the academic and industrial fields. The combined model of kernel principal component analysis (KPCA) and linear regression (LR) proposed in this paper can accurately predict the changes in total electricity consumption over time, even if the sample size is small. Meanwhile, the model results have strong interpretability and practical value. Further, through the correlation analysis of principal components obtained from KPCA dimensionality reduction, this paper finds that the most important features affecting the total electricity consumption are the economy feature and population feature. Finally, this paper predicts that China's total social electricity consumption will reach 1.83 trillion KWH in 2035, which is more optimistic than the prediction of Oxford experts, which is consistent with the reality that China has achieved an overall victory in the fight against COVID-19.

1. Introduction

With the rapid development of China's economy, the total electricity consumption is also increasing. As the necessary energy for production and citizen's life in contemporary society, the change of total electricity consumption can indirectly measure the development in the national economy and the improvement in residents' living standards. Accurately predicting the long-term total social electricity demand could provide guidance for the country to formulate economic development strategy and carry out industrial structure transformation, as well as an important basis for the country to fulfill its international obligations of energy conservation, emission reduction and low-carbon environmental protection. Therefore, forecasting the long-term total electricity consumption accurately has been an important topic in the academic and industrial fields.

There are various methods for long-term electricity consumption prediction, and the main methods can be divided into three categories, namely econometric model, machine learning model and bottom-up subsector model. To be specific, firstly, econometric models include multivariate linear regression, time series, etc. For example, Bianco et al. forecasted electricity consumption in Italy with linear regression models [1]. Huang et al. applied AMRA model, a classic time series method, to forecast electricity consumption in Changli County, China [2]. These models are usually based on scenario...
analysis, that is, assuming that future economic, population, carbon emissions and other economic indicators change at a specific growth rate, then estimating how each major economic variable changes, and finally predicting the future value of electricity consumption based on the estimated variable. The mainstream scenario analysis method is Shared Socioeconomic Pathways (SSPs), which assumes that there are five types of economic growth modes in the future. They are green growth (SSP1)[3], a middle-of-the-road scenario (SSP2)[4], AIM (Asia-Pacific Integrated Assessment) implementation scenario (SSP3)[5], a world deepening inequality (SSP4)[6], and energy and resource-intensive scenario (SSP5)[7] respectively. SSPs have certain reference value, but due to the complexity and variability of the real world, especially in the current COVID-19 condition, SSPs may not be able to include all the possibilities of future economic situations, making electricity consumption forecast inaccurate.

Secondly, the machine learning model is also a common method to predict electricity consumption, such as neural network [8-10], support vector machine [11], random forest [12], wavelet analysis [9], etc. Specifically, Li and Lu [9] established a combined forecasting model using backpropagation neural network (BPNN) and wavelet analysis. In this model, wavelet analysis identifies important components and extracts critical information, and BPNN is used to fit the model. The authors finally obtained good prediction results. However, even though machine learning model usually has good fitting performance, it is difficult to guide production in the real world due to its “black box” feature and lack of interpretability. In addition, because many economic data are quarterly or annual, the sample sizes are usually small, which will hinder the machine learning model’s predictive performance.

Thirdly, bottom-up subsector models, like LEAP [13] or MARKAL [14], should divide the total social electricity consumption into small parts, to obtain the electricity consumption in each electricity department. By predicting the electricity consumption in different departments one by one, the total electricity consumption of the whole society can be finally obtained. However, this method requires a large amount of basic data for calculation and consumes a huge amount of computing resources, so it is not suitable for the field of private prediction.

Therefore, it is of practical significance to propose a long-term electricity consumption prediction model with high prediction accuracy, strong interpretability and small sample requirement. Hence, based on the existing electricity forecasting methods, this paper proposed a combined model of Kernel Principal Components Analysis (KPCA) with linear regression (LR) to forecast long-term electricity consumption. KPCA can reduce the sample's dimension nonlinearly, which is used to process linear inseparable data sets. KPCA has the characteristics of a classical statistical model, that is, the model is non-black-box and has a low requirement for data volume (compared with machine learning methods). In addition, KPCA increases the model complexity due to its nonlinearity and adjustable parameter, so it has a higher fitting accuracy (compared with the traditional statistical methods).

KPCA is widely used in various forecasting fields. For example, Liu et al. [8] combined KPCA and BPNN to forecast monthly electricity consumption in European countries. The authors used KPCA to reduce the complexity of the original data, then put the data after dimensionality reduction into BPNN with particle swarm optimization (PSO), and the ideal model results were finally obtained. Besides, there were applications of KPCA in face recognition [15], auxiliary driving [16], disease diagnosis [17], and so on.

In this paper, we proved that the combined model of KPCA and LR has a better result than other methods, thus providing a new feasible way for long-term electricity consumption prediction.
Figure 1. Research and modelling process.

The structure of this paper is as follows. The second chapter introduced the data. The third chapter introduced principal components analysis (PCA) and kernel principal components analysis (KPCA). The fourth chapter applied PCA and KPCA into original data for dimension reduction and got new variables, then put the new variables into the linear regression model and machine learning model. The fifth chapter analyzed and explained the optimal model results. And the sixth chapter is the conclusion. The research and modelling process of the full text is shown in figure 1.

2. Data
The data used in this paper are all from the Oxford Economics Database www.oxfordeconomics.com, which collects data from open and authoritative sources (such as the World Bank, IMF, OECD, National Statistical Offices in each country) and integrates them into a comprehensive database of the world economy. In addition, experts at Oxford University make professional forecasts for all the indicators in the database every year, so the database provides a wide range of economic data from 1980 to 2050, which is easy to use and analyze.

Table 1. Variable explanation.

| Dependent Variable | Total electricity consumption in the whole society | Abbreviation | Note                      |
|--------------------|--------------------------------------------------|--------------|---------------------------|
| Variable           | Total electricity consumption in the whole society | Elec         | Electricity feature       |
| Population growth rate | Popu                     |              | Population feature       |
| The proportion of urban population | Urban                 |              | Population feature       |
| Nominal GDP         | GDP                     |              | Economy feature          |
| Residential electricity price | ResiPri  |              | Price feature            |
| Fuel Price          | FuPri                   |              | Price feature            |
| The proportion of added value of secondary industry | SecInd |              | Industrial structure feature |
| The proportion of added value of tertiary industry | TerInd |              | Industrial structure feature |
| Per capita output value of employment | Output |              | Production efficiency feature |
According to the research results of [18,19], this paper collected the 9 China's annual economic variables from 1980 to 2035 (data in 1980-2019 is the real value, data in 2020-2035 is the predicted value by exports from Oxford). They are total electricity consumption in the whole society, population growth rate, the proportion of urban population, nominal GDP, residential electricity price, fuel prices, the proportion of added value of secondary industry, the proportion of added value of tertiary industry, per capita output value of employment. The first variable is explained variable, the rest of the variables are explanatory variables. All variables are named as shown in table 1.

In table 1, according to the characteristics of independent variables, they can be divided into five types, namely population feature, economy feature, price feature, industrial structure feature and production efficiency feature. All of these variables have a certain influence on total electricity consumption.

Visualize all the data as shown in figure 2.

![Figure 2. Visualization of all variables.](image)

Figure 2 shows that from 1980 to 2035, China's total electricity consumption, the proportion of urban population, GDP, residential electricity price, the proportion of added value of tertiary industry, per capita output value of employment displayed an upward trend. The first three variables show a steady growth rate, while the latter three variables show some jagged characteristics. The population growth rate has been decreasing over year since 1990, which is in line with the characteristics of current residents' declining desire to have children. Fuel price is growing but fluctuating over time, which is affected by the supply and demand fluctuations in international energy markets, such as the crude oil market. The proportion of added value of secondary industry presents a trend of increasing first and then decreasing. The turning point came in 2013, which reflects the transformation of China's industrial structure in recent years.

Table 2 displayed the descriptive statistics of all variables. According to table 2, the mean value of total electricity consumption and GDP is significantly greater than the median, which is consistent with their exponential growth characteristics. Skewness and Kurtosis value of most variables are different from those of standard normal distribution (Skewness equals to 0 and Kurtosis equals to 3), proving that most variables are not normal
distribution. In fact, according to Jarque-Bera test, only the proportion of added value of tertiary industry obeys a normal distribution, suggesting that all other variables changed over time.

Table 2. Descriptive statistics of all variables.

|         | Elec  | Popu | Urban | GDP       | ResiPri | FuPri | SecInd | TerInd | Output |
|---------|-------|------|-------|-----------|---------|-------|--------|--------|--------|
| Mean    | 4580.16 | 0.70 | 46.40 | 73016.98  | 0.43    | 152.76| 34.63  | 43.87  | 0.07   |
| Median  | 3362.65 | 0.60 | 45.85 | 29466.85  | 0.52    | 182.60| 36.00  | 44.10  | 0.05   |
| Maximum | 12580.20 | 1.90 | 76.60 | 308609.90 | 0.62    | 282.30| 40.70  | 57.60  | 0.20   |
| Minimum | 300.60  | -0.10| 19.40 | 480.90    | 0.17    | 14.20 | 24.80  | 28.60  | 0.00   |
| Std.Dev. | 4061.27 | 0.55 | 18.02 | 89004.00  | 0.16    | 96.86 | 5.02   | 7.38   | 0.06   |
| Skewness | 0.56   | 0.64 | 0.09  | 1.18      | -0.71   | -0.25 | -0.71  | -0.05  | 0.76   |
| Kurtosis | 1.87   | 2.56 | 1.64  | 3.21      | 1.92    | 1.43  | 2.19   | 2.55   | 2.22   |
| Observations | 56     | 56   | 56    | 56        | 56      | 56    | 56     | 56     | 56     |

3. Method

3.1. Principal Components Analysis

Principal component analysis, as a statistical method, transforms a group of potentially correlated variables into a group of linearly uncorrelated variables (called principal components, also known as factors) through orthogonal transformation. During transformation, the main information of the original variables will be retained (usually measured by variance maximization).

In all principal components, the first principal component (factor 1, $f_1$), contains the most information in the original variable and is usually chosen as the representation of the original variable. If $f_1$ contains insufficient information, factor 2 ($f_2$) will be added to jointly represent the original variable, and $\text{Cov}(f_1, f_2) = 0$, etc. The calculation process of PCA is shown below.

$$C = \frac{1}{n}X^TX$$

$$Ca_i = \lambda_i a_i$$

Where original independent variables are $X_{n*p}$, $n$ is the number of observations, $p$ is the dimension of samples, $C_{p*p}$ is the covariance matrix of $X_{n*p}$, $\lambda_i$ and $a_i$ are the eigenvalue and the corresponding eigenvectors of $C_{p*p}$ respectively.

If the first $m$ principal components are taken, the principal component matrix $F$ can be calculated as follows:

$$P = (a_{ij})_{p*m} = (a_1, a_2, \cdots, a_m)$$

$$F = XP$$

Where $P_{p*m}$ is the matrix formed by the largest first $m$ eigenvectors of $C$, $F_{n*m}$ is the principal components with $m$ dimensions.

To be specific, the $i^{th}$ principal component $F_i$ is:

$$F_i = Z(X_1) * a_{1i} + Z(X_2) * a_{2i} + \cdots + Z(X_p) * a_{pi}$$

Where $Z(X)$ represents the standardization of $X$, and $a_{1i}$ is the first element of the $i^{th}$ eigenvector.

3.2. Kernel Principal Components Analysis

Although PCA is widely used, it cannot handle linear non-fractional dataset, while KPCA can conduct nonlinear dimension reduction on dataset. The general idea of KPCA is to do the nonlinear mapping (also known as kernel function, $\phi$) on the original independent variable ($X$), and map it to a higher
dimensional space \((\phi(X))\), making the \(\phi(X)\) linearly separable, then conduct PCA dimensionality reduction in the \(\phi(X)\).

In KPCA, kernel functions play an important role, that is, by inputting two low-dimensional vectors, we can compute the inner product of the vectors in higher dimensions after some transformation. Therefore, even though there are various KPCA methods, the difference between various KPCA methods mainly lies in the different kernel functions selected.

Not all functions can be used as a kernel function. A simple way to judge whether a function satisfies the kernel criterion is Mercer's Condition [20], that is, any semi-positive definite symmetric function can be used as a kernel function.

Common kernel functions mainly include radial basis function kernel (RBF), polynomial kernel (poly), sigmoid kernel, and cosine kernel. Their definitions are as follows.

Radial basis function kernel:

\[
    k(x, y) = \exp(-\gamma \|x - y\|^2)
\]  

(6)

Polynomial kernel:

\[
    k(x, y) = (x^T y + c)^d, \quad d \in \mathbb{N}, c \geq 0
\]  

(7)

Sigmoid kernel:

\[
    k(x, y) = \tanh(\alpha x^T y + \gamma)
\]  

(8)

Cosine kernel:

\[
    k(x, y) = \frac{x^T y}{\|x\|_2 \|y\|_2}
\]  

(9)

Among them, \(c\) and \(d\) in poly, \(\gamma\) in RBF, \(\alpha\) and \(\gamma\) in sigmoid are all adjustable parameters.

It can be proved that the above kernel functions all satisfy Mercer's Condition. Since the model parameters of KPCA are tunable, the model effect has a larger space for optimization. This paper will use the above four kernel functions to conduct dimensional reduction on the original data.

4. Modelling Process

First, this paper calculated the Pearson correlation coefficients between all variables to analyze the relationships between all variables, and the heat map of the correlation matrix was drawn in figure 3.
According to figure 3, the relationship among all variables is close. In fact, the average for the absolute value of the correlation coefficient of the whole correlation matrix is as high as 0.81. Among them, the absolute value of correlation coefficient between **Elec** and **Urban**, **GDP**, **TerInd**, **Output** is more than 0.9, and that between **Elec** and **Popu**, **ResiPri**, **FuPri** is more than 0.8. Therefore, it is necessary to conduct dimensionality reduction on independent variables. Otherwise, the assumption of independent and identical distribution (i.i.d.) of variables in statistical regression cannot be satisfied.

In order to deeply dig the relationship structures inside each variable and to obtain better model fitting effect, PCA and KPCA (RBF, poly, sigmoid, cosine) were respectively conducted in this paper to reduce the sample dimension. Based on multiple experiments, this paper set KPCA's parameters as follows, $\gamma = 0.125$, $\alpha = 1$, $c = 1$, $d = 3$. And we retain the first three principal components.

Next, new variables obtained by PCA and KPCA methods were put into different regression models respectively, and data from 1980 to 2009 were taken as training set, data from 2010 to 2019 as validation set, and data from 2020-2035 as forecasting set. The mean squared error (MSE) of the three sets was calculated separately, and the optimal model was selected based on MSE. Two things need to be noted. One is that the value of total electricity consumption from 2020 to 2035 comes from experts' predictions. Therefore, if a model's MSEs in training set and validation set are both small, but in forecasting set is large, the model is still considered to be ideal. Second, the prediction results of the model should be in line with the practical situation. For example, if a model predicts that the total electricity consumption will gradually decrease in 2020-2035, even though the MSE of its training set and validation set are small, we still think that the model is not ideal, because it is generally believed that the total electricity consumption should increase gradually in the future.

Table 3 compared the fitting performances of various dimensional reduction methods combined with different regression models.

In table 3, we find the optimal model with small MSE in training set and validation set, as well as no downward trend in forecasting set. Therefore, two combinations are selected as the optimal model, that is the combination of polynomial KPCA and LR and cosine KPCA and LR. We respectively assign 50% weights to each combination, and add the two together to obtain the final model's forecast result of total electricity consumption in 2020-2035.

![Figure 3. Correlation coefficients of all variables.](image)
Table 3. Summary of MSE for all combined regression models.

| Mean Squared Error | Linear Regression | Random Forest | Neural Network | GBDT | SVM |
|--------------------|------------------|---------------|----------------|------|-----|
| No PCA             |                  |               |                |      |     |
| Training           | 0.0000           | 0.0000        | 0.0023         | 0.000| 0.0069|
| Validation         | 0.0009           | 0.1124        | 0.0717         | 0.0936| 0.1942|
| Forecasting        | 0.1538           | 1.0572        | 0.4650         | 0.9805| 1.4492|
| No downward        | No               | Yes           | Yes            | Yes  | Yes  |
| PCA                |                  |               |                |      |     |
| Training           | 0.0003           | 0.0001        | 0.0034         | 0.000| 0.0059|
| Validation         | 0.0183           | 0.1996        | 0.3097         | 0.1768| 0.1569|
| Forecasting        | 0.9034           | 1.3748        | 1.6304         | 1.3715| 1.3835|
| No downward        | Yes              | Yes           | No             | No   | No   |
| RBF                |                  |               |                |      |     |
| Training           | 0.0001           | 0.0000        | 0.0061         | 0.000| 0.0057|
| Validation         | 0.0218           | 0.1327        | 0.2844         | 0.0996| 0.1723|
| KPCA Forecasting   | 2.7322           | 1.4663        | 1.3966         | 1.3482| 1.4127|
| No downward        | No               | No            | Yes            | No   | No   |
| Poly               |                  |               |                |      |     |
| KPCA Forecasting   | 1.2267           | 1.2300        | 1.7098         | 1.1337| 1.3582|
| No downward        | Yes              | No            | No             | No   | No   |
| Sigmoid            |                  |               |                |      |     |
| KPCA Forecasting   | 0.0316           | 0.1043        | 0.4038         | 0.0883| 0.1359|
| No downward        | No               | Yes           | No             | No   | No   |
| Cosine             |                  |               |                |      |     |
| KPCA Forecasting   | 0.4828           | 0.9423        | 1.6553         | 0.8984| 1.0819|
| No downward        | Yes              | No            | No             | No   | No   |
| Cosine             |                  |               |                |      |     |
| KPCA Forecasting   | 0.0007           | 0.0001        | 0.0059         | 0.000| 0.0069|
| No downward        | Yes              | No            | No             | No   | No   |

Note: We use multilayer perceptron (MLP) as the neural network method; GBDT is the abbreviation of Gradient Boosting Decision Tree. No downward means the model's forecast value in the forecasting set is not in the downward trend. If a model's No downward is Yes, it means the model's forecast result is in accordance with common sense, because the total electricity consumption should increase gradually in the future.

The comparison of model's forecast value and Oxford expert's forecast value is shown in figure 4.

Figure 4. Comparison between model forecast result and experts forecast result.
According to figure 4, in 2019, the total electricity consumption in China is 721.24 billion KWH, and in 2035, our model predicts that the total electricity consumption will reach 1827.85 billion KWH. However, experts from Oxford predict that the value is only 1258.02 billion KWH, which shows that the prediction of the model is relatively optimistic. To be specific, cosine KPCA's forecast was lower than that of experts, while poly KPCA's forecast was higher than that of experts. Therefore, these two predictions could be regarded as the lower and upper bounds of China's total electricity consumption in 2035, which is 973.71 billion KWH and 2681.98 billion KWH respectively.

Although the forecast value of the model is much higher than that of the experts, we think the prediction is reasonable to some extent. In effect, the past 40 years of reform and opening up have witnessed China's super-fast economic growth, while experts around the world had underestimated China's economic growth rate at that time. At present, with the continuous improvement of China's urbanization and the advancement of RMB internationalization, the future growth rate of China's economy is still immeasurable. Especially in 2020, China has achieved great success in the fight against COVID-19. Therefore, China's future development potential should not be underestimated.

To sum up, the model's optimistic estimate of China's total electricity consumption has a certain realistic basis.

5. Analysis of Model Results
To interpret the meaning of KPCA, this paper drew the line chart of three principal components \(f_1, f_2, f_3\) and the total electricity consumption after standardization \((y)\), as shown in figure 5.

![Figure 5. Three principal components and total electricity consumption line diagram.](image)

Note: This figure consists of two parts, poly KPCA is the left subfigure and cosine KPCA is the right subfigure. Standardized total electricity consumption is in right hand side, and \(f_1, f_2, f_3\) are in left hand side.

According to figure 5, the first principal component of both poly KPCA and cosine KPCA showed a relatively stable growth trend, indicating that the total electricity consumption was continuously increasing. The other two principal components show alternate characteristics of growth and decline, which are used to describe the fluctuation in the evolution of electricity consumption. The above three principal components can better represent the characteristics of electricity consumption spiraling in real life, so a better fitting effect can be achieved.

Further write the regression equation:

\[ y = 1.157 + 0.580 * f_1 - 0.578 * f_2 - 0.879 * f_3 \]  
(10)

\[ y = 1.157 + 6.055 * f_1 + 5.692 * f_2 + 0.435 * f_3 \]  
(11)

Where (10) was the regression equation of poly KPCA, and (11) was about cosine KPCA. All the coefficients in the equations are significant at \(p < 0.01\).

The correlation coefficients between all principal components and all original variables are calculated in table 4.

As can be seen from table 4, poly KPCA's \(f_1\) has the closest correlation with nominal GDP and per capita output value of employment, and \(f_2\) has the closest correlation with the proportion of added
value of secondary industry. And cosine KPCA’s $f_1$ has the closest correlation with population growth rate and residential electricity price, while $f_2$ still has the closest correlation with nominal GDP and per capita output value of employment. In general, the important features that affect total electricity consumption can be divided into three groups. The first group is economy feature and production efficiency feature. The second group is population feature and price feature. The third group is industrial structure feature. Among them, the economy feature and production efficiency feature have the most critical impact on China's long-term electricity consumption, which is basically consistent with China's current national conditions.

### Table 4. Correlation coefficients between principal components and original variables.

| Corr. Coef. | Poly KPCA | Cosine KPCA |
|-------------|-----------|-------------|
| F1          | F2        | F3          | F1        | F2        | F3        |
| Dep. Var.   | Elec      |             |           |           |           |
| Popu        | 0.94      | -0.29       | -0.15     | 0.74      | 0.67      | 0.05      |
| Urban       | -0.77     | 0.54        | -0.20     | **0.94**  | -0.24     | 0.07      |
| GDP         | 0.99      | -0.47       | -0.05     | 0.86      | 0.51      | 0.03      |
| Ind. Var.   | ResPri    | 0.70        | -0.66     | 0.23      | **0.97**  | 0.17      | -0.14     |
| SecInd      | 0.16      | **0.91**    | 0.36      | 0.87      | 0.33      | -0.12     |
| TerInd      | 0.89      | -0.38       | 0.04      | 0.85      | 0.44      | 0.24      |
| Output      | **0.97**  | -0.22       | -0.13     | 0.70      | **0.69**  | 0.07      |

### 6. Conclusion

In order to accurately predict the long-term electricity consumption under the premise of scarce sample size, a combination model of KPCA and linear regression was proposed in this paper. Empirical results show that the combined models achieve higher fitting accuracy, and the results are consistent with the reality. By visualizing the three principal components obtained through KPCA, we found that the first principal component can represent the long-term growth of electricity consumption, while the other two principal components can represent the long-term fluctuation of electricity consumption. Through the correlation analysis between the original variables and principal components, we found that the features that have a significant impact on the total electricity consumption can be divided into three groups, and the first group of features, that is the economy feature and production efficiency feature, are of the most importance. What’s more, this paper predicted that China’s total social electricity consumption will reach 1.83 trillion KWH in 2035, which is higher than 1.26 trillion KWH predicted by Oxford experts. The model is more optimistic about China's future economic prospects, which is consistent with China's rapid economic growth and the fact that China has achieved an overall victory in the fight against COVID-19.

### References

1. Bianco V, Manca O and Nardini S. Electricity consumption forecasting in Italy using linear regression models 2009 Energy 34 1413–21
2. Huang Z, Li Z, Zhang Y and Guo K. Forecasting on electricity consumption of tourism industry in Changli County 2019 Int. C. Data Serv. 77–87
3. Vuuren D et al. Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm 2017 Global Environ. Chang. 42 237–50
4. Stemmer J and Graul J. The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century 2001 J. Cryst. Growth 222 701
5. Fujimori S et al. SSP3: AIM implementation of shared socioeconomic pathways 2017 Global Environ. Chang. 42 268–83
[6] Calvin K et al. The SSP4: A world of deepening inequality 2017 Global Environ. Chang. 42 284–96
[7] Kriegler E et al. Fossil-fueled development (SSP5): an energy and resource intensive scenario for the 21st century 2017 Global Environ. Chang. 42 297–315
[8] Liu Z et al. Midterm power load forecasting model based on kernel principal component analysis and back propagation neural network with particle swarm optimization 2019 Big Data 7 130–38
[9] Li A and Lu J. Forecasting monthly runoff using wavelet neural network model 2011 IEEE Comput. Soc. 2177–80
[10] Ekonomou L. Greek long-term energy consumption prediction using artificial neural networks 2010 Energy 35 512–17
[11] Kavaklioglu K. Modeling and prediction of Turkey's electricity consumption using Support Vector Regression 2011 Appl. Energ. 88 368–75
[12] Ahmad T and Chen H. Nonlinear autoregressive and random forest approaches to forecasting electricity load for utility energy management systems 2019 Sust. Cit. Soc. 45 460–73
[13] Mirjat N, Uqaili M, Harijan K, Walasai G, Mondal M and Sahin H. Long-term electricity demand forecast and supply side scenarios for Pakistan (2015–2050): A LEAP model application for policy analysis 2018 Energy 165 512–26
[14] Jaskólski M. Modelling long-term technological transition of Polish power system using MARKAL: Emission trade impact 2016 Energ. Policy 97 365–77
[15] Wang Q. Kernel principal component analysis and its applications in face recognition and active shape models 2012 preprint arXiv:1207.3538
[16] Xie L, Tao J, Zhang Q and Zhou H. CNN and KPCA-Based automated feature extraction for real time driving pattern recognition 2019 IEEE Acc. 7 123765–75
[17] Alam S and Kwon G. Alzheimer disease classification using KPCA, LDA, and multi-kernel learning SVM 2017 Int. J. Imag. Syst. Tech. 27 133–143
[18] Lin B. Structural changes, efficiency improvement and electricity demand forecasting 2003 Econ. Res. 5 57–65
[19] He X, Liu X and Lin Y. China's electricity demand forecast under urbanization process 2009 Econ. Res. 1 118–30
[20] Hofmann T, Scholkopf B and Smola A. Kernel methods in machine learning 2008 Ann. Stat. 36 1171–1220