Research on Environmental Performance and Measurement of Smart City Power Supply Based on Non Radial Network DEA

Ying Sun[1], JiaJia Huang[2], Fusheng Wei[1], Yanzhe Fu[3] and LiangZhao He[4,*]

[1]*Guangdong Power Grid Corporation, Guangzhou, 510180, Guangdong, China*
[2]*Shaoguan Power Supply Bureau of Guangdong Power Grid, Shaoguan, 512099, Guangdong, China*
[3]*CSG Electric Power Research Institute Co., Ltd, Guangzhou, 510700, Guangdong, China*
[4]*LongShine Technology Group Co., Ltd, Guangzhou, 510000, Guangdong, China*
E-mail: heliangzhao@longshine.com
[*]*Corresponding Author*

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Abstract

The continuous development of smart cities has put forward higher requirements for the supply of power systems. In response to the constraints in the environmental performance and measurement of smart city power supply, this paper proposes a research model for smart city power supply environmental performance and measurement based on non-radial network DEA based on the characteristics of DEA model and distance function. This model can combine different stages of power supply to conduct more reasonable statistics and analysis of efficiency in different regions. In addition, correlation coefficients were analyzed for the impact of efficiency factors on the phase ratio in the production and sales stages of the power supply system.

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The research results indicate that there is a positive correlation between the output value and power generation of electricity sales and the efficiency of the electricity sales stage, with correlation coefficients of 0.57 and 0.092, respectively; The length of newly added lines, capacity of new equipment, and line loss rate are all negatively correlated with their efficiency, with correlation coefficients of −0.42, −0.12, and −0.46, respectively. Based on the above analysis, this study provides more theoretical support for the study of environmental performance and measurement of smart city power supply.

Keywords: Smart city, electricity supply, non-radial, network DEA, environmental efficiency.

1 Introduction

With the continuous deepening of industrialization in society and the continuous development of technology, the urgency of people's demand for ecological civilization construction is becoming stronger, and the concept of green and sustainable development is receiving greater attention. The public is increasingly aware of the importance of respecting natural laws, and the development model is paying more attention to efficiency and efficiency; At the same time, there is also greater emphasis on the construction of smart cities [1, 2]. Continuous reform and adjustment have been carried out on industries and enterprises with high investment, high consumption, high pollution, and low efficiency, emphasizing green and efficient development methods. The development concept has undergone significant changes, and has also provided more support for the construction of smart cities.

The concept of green development and the construction requirements of smart cities have also put forward new requirements for enterprises in terms of environmental pollution and protection. Enterprises should place themselves in an organization that considers the social and ecological environment to seek a more long-term and efficient development path. Under the development concept of the new era, enterprises should keep up with the times, transform management concepts, adhere to national environmental protection policies, uphold sustainable development concepts, improve production quality and efficiency to achieve long-term development of the enterprise [3, 4]. Under the concept of green development, the consumption and impact of environmental resources should also be considered by enterprises, and management work should not only focus on data-driven financial information, but also consider the impact of enterprise activities on the ecological environment. Environmental accounting, as a branch of accounting, is becoming increasingly important in its theoretical and practical research [5–8].

One of the important constraints faced by the construction of smart cities at present is to combine practical conditions, analyse the current structure of the power industry and integrate its complex structural relationships, use cutting-edge evaluation tools, and expand them to achieve objective environmental efficiency evaluation of the power industry, and ultimately provide analysis of the industry's current situation and policy recommendations at the government level. This article is based on the actual situation of the power industry and uses the network environment DEA (Data Envelopment Analysis) to model it. The network DEA method used can open the black box of traditional single stage DEA models and provide efficiency improvement suggestions with more reference value [9, 10]. In terms of environmental performance evaluation and measurement research, this article assumes weak disposability for unexpected outputs under the condition of variable returns to scale. By expanding Kuosmanen's thinking and adopting weak disposability modelling methods, Kuosmanen is applied to network DEA, which can more efficiently meet the needs of environmental performance and measurement requirements for power supply in smart city construction. In addition, based on the actual situation of the power industry, the status of two sub stages in the smart city power supply chain was analysed. Based on this, the impact relationship between the two stages was further determined and integrated into network DEA modelling, making the analysis results of the model constructed in this article more in line with the current development status of the power industry in modern smart cities [11–13].

Based on the evaluation results of the development efficiency of the power supply chain in each province, it is possible to analyse the development of power supply between different provinces, propose targeted improvement strategies, provide suggestions for the balance of internal development of the power supply chain, and provide suggestions for the development of the power supply chain from an overall perspective. In addition, by calculating the failure degree of each input and output variable through a model, each evaluated power supply chain unit can be more truly improved, thereby providing support for the performance and measurement research of the smart city power industry.

2 Smart City Power Supply Environmental Performance and DEA Theory

2.1 Smart City Power Supply Environmental Performance

Traditional corporate performance refers to the business results achieved by a company during a certain operating period, often measured by financial indicators. However, based on the application of green development concepts in the field of smart cities, the environmental management work of enterprises is becoming increasingly important. Therefore, traditional corporate financial performance should not be solely considered, but also the environmental performance of enterprises. Enterprise environmental performance refers to the establishment, implementation, maintenance, and improvement of environmental management behaviours in various stages of operation, driven by certain goals and standards. The environmental management results obtained comprehensively reflect the environmental behaviour and consequences of the enterprise [14].

Environmental performance evaluation can serve as an important tool for analysing and studying whether the effectiveness of environmental management in enterprises or regions has met established standards. By using environmental performance evaluation, it can be determined whether the enterprise or region has met relevant policy requirements, and at the same time, it can provide more decision-making basis for decision-makers. In the process of building a smart city, it is inevitable to involve the environmental performance evaluation of enterprises. It is necessary to establish a complete evaluation system, determine evaluation standards, indicators, and methods around the evaluation objectives, and finally obtain evaluation results and feedback [15, 16]. The evaluation objective is the significance of environmental performance evaluation in the construction of smart cities. Including providing strategic adjustment plans for internal enterprises or providing environmental management information for external enterprises; The evaluation standard is a comprehensive evaluation basis for the evaluation object; Evaluation indicators are concrete and quantifiable comprehensive indicators that reflect the objective level of the evaluation object, and are the quantitative carrier of the evaluation content; The evaluation method is to use mathematical and other methods to process quantitative data.

In terms of environmental performance and measurement research on power supply in smart cities, enterprise environmental performance evaluation is mainly used for internal and external stakeholders of the enterprise. For internal enterprises, it is necessary to adjust the enterprise strategy based on the results of environmental performance evaluation, and actively optimize the enterprise management plan [17]. For external enterprises, relevant decisions need to be made based on the level of enterprise environmental management. In short, enterprise environmental performance evaluation is beneficial for improving the level of environmental management work and improving the efficiency of environmental management work.

2.2 DEA Basic Theoretical Model

Due to its inherent characteristics, the DEA model has gradually deepened its application in industries such as finance and education, and has also gained the attention of industrial technology practitioners. It has good applicability for the development of the smart city power industry, and can promote the continuous improvement and improvement of power supply environmental performance and measurement work, it has become one of the mainstream models for performance and econometric analysis in the smart city power industry. From the research results of existing scholars in different industries, it can be seen that the DEA model is widely used in the field of power supply environmental efficiency and measurement research in smart cities [18]. At the same time, the DEA model can also serve as a convenient tool for evaluating comparable organizational performance of the same type. Therefore, this article combines the characteristics of smart city power supply environmental performance and measurement research, and combines non-radial distance functions to construct a method for evaluating the efficiency of smart city power supply institutions based on non-radial network DEA model.

A certain organization, region, or research field can be considered as a unit, and the input and output of these units are quantitative. Although the specific form and content of these activities vary, the goal of the activities is to obtain maximum benefits, and these units are called Decision Making Units (*DMUs*). In the process of application in the field of smart city power supply, *DMU* can be a concept that covers the research field. Units with the same target task, external environment, and input/output indicators can be considered as *DMUs* of the same type. Sometimes the same *DMU* can also be considered as the same type of *DMU* at different time periods. In most cases, researchers are accustomed to conducting research on *DMUs* of the same type or with the same attributes [19–21]. As shown in Figure 1, a weight chart of the input and output quantities and indicators of the decision-making unit is presented.

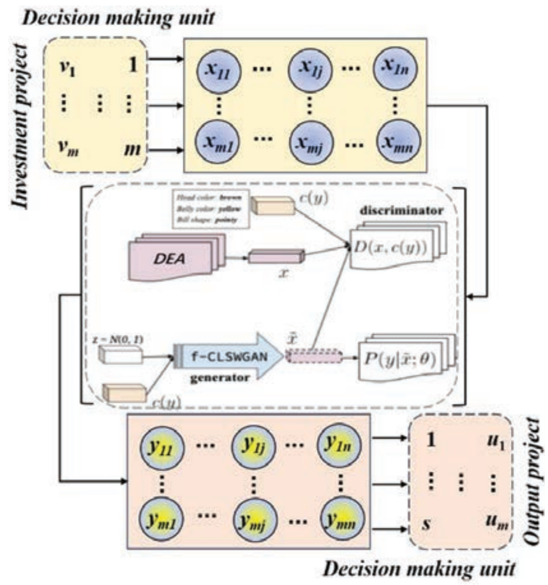


Figure 1 Weight chart of input and output volumes and indicators of decision units.

Assuming a decision-making unit (DMU_k) named K has inputs and outputs of $x_1, x_2, x_3, \ldots, x_t$ and $y_1, y_2, y_3, \ldots, y_\mathrm{s}$ in a certain activity, denote the input vector as $x = (x_1, x_2, x_3, \ldots, x_t)^\mathrm{T}$ and the output vector $y = (y_1, y_2, y_3, \ldots, y_\mathrm{s})^\mathrm{T}$. At this point, all production activities (x, y) of the unit are represented.

If there are n decision-making units with $DMU_j = (1 \leq j \leq n)$, each decision-making unit has m input elements and s output elements. The input vector and output vector corresponding to DMU_j are shown in formulas (1) and (2), respectively:

$$Input\ vector \quad x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^\mathrm{T} 0 j = 1, 2, \ldots, n \tag{1}$$

$$Input\ vector \quad y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^\mathrm{T} 0 j = 1, 2, \ldots, n \tag{2}$$

Each decision-making unit DMU_j has a corresponding efficiency evaluation index, and appropriate weight coefficients v and u can be selected to make $h_j < 1$, where h_j is given by formula (3):

$$h_j = \frac{u^T y_i}{v^T x_i} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \quad j = 1, 2, \ldots, n \tag{3}$$

If the efficiency of the j0th decision-making unit is evaluated, generally speaking, a larger h_{j0} indicates that DMU_{j0} can use fewer inputs to obtain more outputs. If we want to evaluate the performance of DMU_{j0} at this time, we will look at whether this h_{j0} is relatively optimal among these n DMU_s. At this point, we can examine the maximum value of h_{j0} through weights.

Taking the efficiency index of the j_0-th decision-making unit as the target and constraining all decision-making units as the efficiency index, a model can be constructed as shown in formula (4):

$$\begin{cases} \max h_{j_0} = \dfrac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} \\ s.t. \dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \\ v = (v_1, v_2, \ldots, v_m) \\ u = (u_1, u_2, \ldots, u_s) \end{cases} \tag{4}$$

By performing Charnes Cooper changes, the above model can be transformed into a linear programming model, as shown in formula (5):

$$p \begin{cases} max h_{j_0} = \mu^{\mathrm{T}} y_0 \\ s.t. w^{\mathrm{T}} x_j - \mu^{\mathrm{T}} y_j \geq 0, j = 1, 2, \ldots, n \\ w^{\mathrm{T}} x_0 = 1 \\ w \geq 0, \mu \geq 0 \end{cases} \tag{5}$$

From the above model, for formula (5), its dual model can be represented by formula (6):

$$D' \begin{cases} \min \theta \\ s.t. \sum_{i=1}^{n} \lambda_j x_j \leq \theta x_0 \\ \sum_{j=1}^{n} \lambda_j y_j \geq y_0 \\ \lambda_j \geq 0, j = 1, 2, \ldots, n \end{cases} \tag{6}$$

3 Construction of Smart City Power Supply Environmental Performance and Measurement Model Based on Non-Radial DEA

3.1 DEA Model in Environmental Performance and Measurement of Power Supply

3.1.1 Non radial distance function

The distance function assumes that the distance from the production unit to the leading edge is the efficiency value of the unit, but this distance may become unique due to directional uncertainty, so it is necessary to apply a certain direction to adjust the efficiency of the unit's input and output simultaneously in this direction. If the distance is zero, it indicates that the unit is effective, otherwise it is invalid. The breakthrough of this idea also includes its negation of the traditional DEA's radial evaluation of all inputs and outputs, and its ability to incorporate both inputs and outputs into efficiency evaluation, thus having groundbreaking value [22–24]. Researchers have extended the advantages of this model to environmental efficiency evaluation, using non expected output as a variable that needs to be reduced, achieving simultaneous evaluation of input expected output and non-expected output. Formula (7) provides the basic form of the distance function containing non expected outputs (where x, p, y represents inputs, non-expected outputs, and expected outputs, respectively):

$$\vec{D}(x, p, y, \vec{g}) = \max\{\beta : (x - \beta\vec{g}_x, y + \beta\vec{g}_y, p - \beta\vec{g}_z) \in T\} \tag{7}$$

However, the traditional distance function model mentioned above has some shortcomings: the model measures all variables according to a unified adjustment degree variable, which will result in significantly higher evaluation results than the actual value. For the evaluated unit located below the leading edge, the direction variable adjusted by the distance function model is represented by the direction vector in the second quadrant. If measured in this direction, the point will be projected onto the leading edge, Not the optimal efficiency projection point.

For this defect, the non-expected output can be integrated into the distance function method and its non-radial form can be proposed, as shown in formula (8):

$$N\vec{D}(X, Y, P; \vec{g}) = \max\{\partial\beta : [(x, y, p) + \vec{g} \cdot diag(\beta)] \in T\} \tag{8}$$

3.1.2 Weak disposability theorem

In order to further discuss the applicability of weak disposability in the performance and measurement of smart city power supply environment, this study combines its basic characteristics to analyze the application performance of weak disposability. Researchers have proposed the weak disposability hypothesis based on observations of real-world production environment phenomena. This idea is since if an industry wants to reduce its non-expected output emissions, it must pay the cost of reducing its expected output. It is believed that the production possibility set in DEA environmental assessment needs to meet this condition [25, 26]. Therefore, adjustments can be made to the DEA production possibility set containing non expected outputs. The relevant theorem content can be expressed as follows (where X refers to input, P and Y respectively refer to non-expected output and expected output): If $(p, y) \in S_1$, then under the assumption that non expected output is weakly disposable, there exists $0 \leq \theta \leq 1$, so that $(\theta P, \theta y) \in S_1$. Based on this theorem, it can be inferred that in real production activities, if an unexpected output is to be reduced, the subject must pay a cost, and the proportion of the cost reduction should be the same as the proportion of the unexpected output reduction. The production possibility set applied to the study of environmental performance and measurement of smart city power supply can be expressed in the form shown in formula (9):

$$T = \left\{ X, P, Y \,\middle|\, \sum_{m=1}^{M} \lambda_m \, X_m^b \leq X_m^o, \sum_{m=1}^{M} \lambda_m P_m^t = P_m^o, \sum_{m=1}^{M} \lambda_m Y_m^r \geq Y_m^o \right\} \tag{9}$$

It is precisely due to the modelling method of weak disposability that the weak disposability theorem can be combined with DEA models, providing more analytical methods for the environmental performance and measurement research of smart city power supply. The discussion of the weak disposability theorem is already very sufficient, but it is not common for scholars to extend this theorem to DEA models of network structures [27–29]. In the network structure, there exists a variable with the special property of intermediate output, which can serve as both the output of the first stage and the input of the second stage. The idea of the above model is to apply emission reduction factors to the output side. Therefore, for network DEA, there are some limitations in applicability and universality (such as intermediate output including both expected and non-expected outputs). This structure is not commonly seen, so it cannot be directly applied to the power industry structure in this article [30]. Therefore, this article will combine the integration of weak disposability under network structure and DEA model to provide a foundation for the research on environmental performance and measurement of smart city power supply.

3.2 Construction of Environmental Performance and Measurement Model for Smart City Power Supply

Through the process of integrating unexpected output with distance function method mentioned above, a smart city power supply environmental performance and measurement research model based on non-radial network DEA can be constructed. Based on the research and analysis of the environmental performance and measurement of power supply in smart cities, as shown in Figure 2, a visual diagram of the power industry structure in smart cities and the variables involved in this article are presented. Assuming that there are M independent power supply chains that need to be evaluated in the research process of smart city power supply. The power generation stage of each supply chain produces R expected outputs and T unexpected outputs by consuming B inputs. The different evaluation methods of network DEA under cooperative and non-cooperative scenarios discussed in the game DEA theory method require first evaluating the efficiency of the leader in the non-cooperative game scenario, and then substituting the results obtained from the leader's efficiency into the efficiency evaluation model of the follower to obtain the efficiency value of the follower. This article will study the leadership and follower relationship in the smart city power supply system based on the above logic.

In addition, under the condition of variable returns to scale in smart cities, the production possibility set needs to remove the cone-shaped assumption,

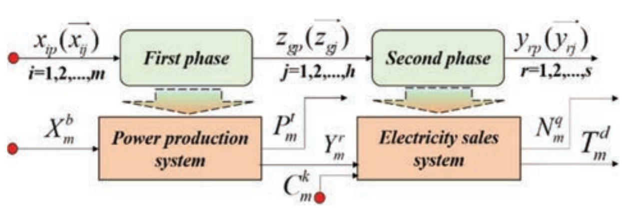


Figure 2 Visual diagram of power industry structure and variable relationships in smart cities.

and in the actual production process, the returns to scale can change in line with the actual production scenario. Assuming there is n decision units $DUM_0(o = 1, 2, \ldots, n)$, each DUM_0 decision unit contains two stages $(k = 1, 2)$. $x_o^k(o = 1, 2, \ldots, n; k = 1, 2)$ represents the *o-th* input variable of DUM_0 in the stage; $y_o^k(o = 1, 2, \ldots, n; k = 1, 2)$ represents the *o-th* output variable of DUM_0 in stage k; $z_o^{(1,2)}(o = 1, 2, \ldots, n)$ represents the o intermediate variable between the first and second stages. Therefore, the definition of the production set $(x^k, y^k, z^{(k,h)})$ of DUM_o is shown in formula (10):

$$\begin{cases} x^k \geq \sum_{o=1}^{n} x_o^k y_o^k (k = 1, 2) \\ y^k \leq \sum_{o=1}^{n} y_o^k \lambda_o^k (k = 1, 2) \end{cases} \tag{10}$$

In addition, the input in the middle of node 1 and the output in the middle of node 2 are further given through formulas (11) and (12):

$$z^{(1,2)} = \sum_{o=1}^{n} z_o^{(1,2)} \lambda_o^1 \quad \forall (1, 2) \tag{11}$$

$$z^{(1,2)} = \sum_{o=1}^{n} z_j^{(1,2)} \lambda_j^1 \quad \forall (1, 2) \tag{12}$$

Based on the production set shown in the above equation, the input-output oriented efficiency evaluation model of DUM_o is shown in formula (13):

$$\rho_o^* = \min_{\lambda^k, s^{k-}, s^{k+}} \frac{\sum_{k=1}^{2} w^k \left[1 - \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k}\right]}{\sum_{k=1}^{2} w^k \left[1 + \frac{1}{r_k} \sum_{r=1}^{r_k} \frac{s_i^{k+}}{y_{ro}^k}\right]} \tag{13}$$

When $\rho o^* = 1$, it is considered that DUM_o has overall investment efficiency; When the objective function $\rho_o^* 1$ is used, it is considered that DUM_o has efficiency loss and does not have overall investment efficiency. Among them, s_i^{k-} represents the input relaxation variable, and s_i^{k+} represents the output relaxation variable. The calculation process of x_{io}^k and y_{ro}^k is respectively given by formula (14):

$$\begin{cases} x_o^k = X^k \lambda^k + s^{k-} \quad (k = 1, 2) \\ y_o^k = Y^k \lambda^k + s^{k+} \quad (k = 1, 2) \end{cases} \tag{14}$$

4 Model Demonstration and Result Analysis

4.1 Indicator Selection and Regional Division

4.1.1 Indicator selection

In order to analyse and demonstrate the evaluation effect of the model constructed in this article on the environmental performance and econometric research of smart city power supply, based on basic data of power supply in some provinces in China, efficiency comparisons and evaluations will be conducted for the sustainability of power supply chains in different regions. Through data analysis of the power industry in different regions, it can be found that the structural characteristics of China's power industry are reflected in the construction of power supply systems with provinces as the main body. Therefore, the analysis process of smart city power supply environmental performance and measurement model results based on non-radial network DEA studied in this article will default to each province as a power supply system evaluation unit.

Firstly, it is necessary to determine the indicator system for the performance and econometric research model of smart city power supply environment based on non radial network DEA. The determination of clearance related indicators can provide assurance for the prediction efficiency and accuracy of non radial network DEA models. Previous research is often based on a single stage of analysis. This article combines the availability of indicator data and analyses the actual situation of the smart city power supply environment to construct the following indicators: for the research process of the power generation stage system, this study selected four indicator variables as input variables, one indicator variable as expected output, and one indicator variable as non-expected output variable. The selection of relevant indicators is as follows: newly added production capacity for power supply construction; Power plant power generation equipment capacity of 5000 kW and above; Average utilization hours of power generation equipment; Coal consumption rate for power generation; Power generation and carbon emissions of related power enterprises.

Secondly, for the electricity sales stage of smart city power supply, this study selects two indicator variables as additional inputs, one indicator variable as its expected output, and one indicator variable as its unexpected output. The above two indicators are selected as: the capacity of newly added 220 kV and above substation equipment in the power grid and the length of newly added 220 kV and above transmission lines in the power grid; The electricity sales revenue of relevant power enterprises and the line loss rate

Table 1 Division and distribution of provinces by region

Region	Amount	Provinces Included
Eastern China	7	Beijing, Jiangsu, Guangdong, Zhejiang, Tianjin City, Hebei, Shandong
Central China	6	Shanxi, Anhui, Hunan, Henan, Jiangxi, Hubei
Western China	8	Guangxi, Guizhou, Qinghai, Yunnan, Gansu, Shaanxi, Sichuan, Inner Mongolia
Northeast China	3	Liaoning, Jilin, Heilongjiang

in the power system. Among them, the power generation in the first stage is also used as the input in this stage, and can also become intermediate output, with the line loss rate counted in percentage.

4.1.2 Regional division

In order to analyse the performance of the power supply chain in different regions and combine the development situation of each province, 24 provinces were selected and divided into 4 main regions for investigation. Among them, the eastern region of China includes 7 provinces; The central region of China includes 6 provinces; The western region of China includes 8 provinces; The Northeast region of China includes three provinces. The specific division and distribution of provinces in each region are shown in Table 1.

In addition, in order to further compare the distribution of provinces in different geographical regions more intuitively, as shown in Figure 3, the distribution and division of provinces in each region are presented. From the figure, the determination of provinces involved in analysing the environmental performance and measurement of smart city power supply is a comprehensive consideration of their geographical location and economic development.

4.2 Result Analysis

In order to analyse the performance of the smart city power supply environment performance and measurement research model based on non-radial network DEA proposed in this article, combined with the basic data collected, the traditional BCC radial model and the non-radial DEA model proposed in this article were used to compare the analysis results, and then analyse the differences in performance between different models. By comparing different models, as shown in Figure 4, the efficiency scores of different models in

Figure 3 Division and distribution of performance regions in the power supply chain.

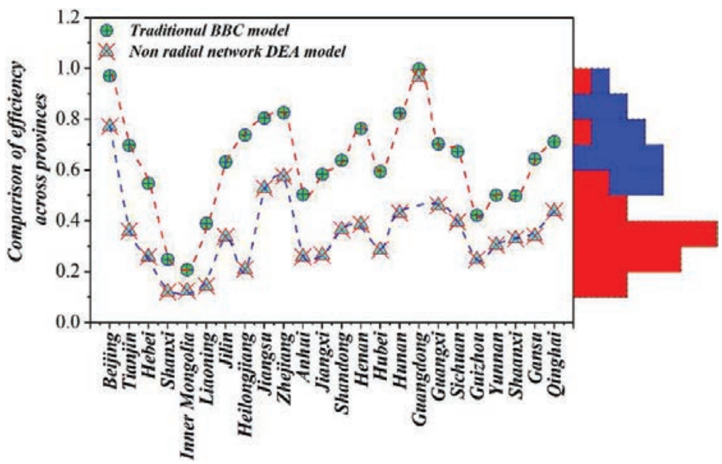
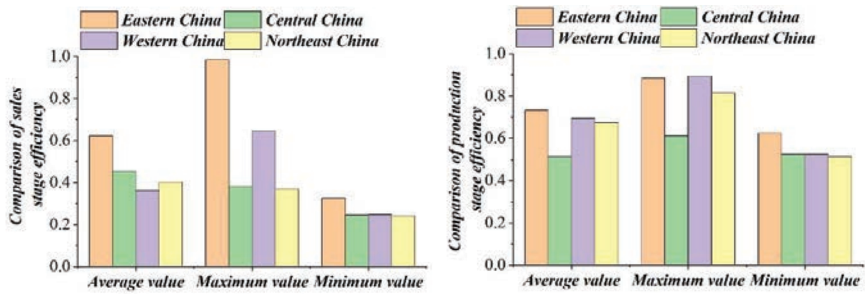


Figure 4 Scoring of efficiency of different models in different provinces.

each province are presented. From the figure, it can be seen that under the same scale of returns, after comprehensive analysis of the five variables in the electricity sales stage of the power supply system in smart cities, it is evident that the smart city power supply environmental performance and measurement model based on non-radial network DEA has obvious advantages, that is, the average efficiency score of each province obtained



a) Power Production System b) Electricity Sales System

Figure 5 Statistical analysis of regional efficiency scores at different stages.

by this model is lower than the efficiency score of the traditional BBC radial model. Among them, the average efficiency of the model in this article is about 37.8%, while the efficiency of the traditional BBC radial model is about 63.0%. The province efficiency calculated by this model can make each province have greater room for improvement, that is, the non-radial network DEA model has higher efficiency identification and greater advantages.

In order to more intuitively compare the performance of the power supply environment in four regional smart cities, a non-radial network DEA based smart city power supply environment performance and econometric research model was developed. Furthermore, the efficiency of two different stages of power production and sales was analysed and compared. As shown in Figure 5, the efficiency results of the power generation and sales systems in the power supply environment of smart cities in different provinces and regions are presented. Through comparison, it can be seen that in the four different regions studied, whether it is the power generation system or the power sales system, the performance of the eastern region of China is at the highest level among the four regions, with the average scores of 0.73 and 0.62, respectively. The scores of the region are also in line with its economic development level; In the power production system, the performance of the western region is closely followed, with an average score of about 0.69. Therefore, it can be found that compared to the central and northeastern regions of China, the efficiency performance of the power generation system in the smart city power supply environment in the western region of China is more advantageous. At the same time, it can be seen that the overall performance of various provinces in the central and northeastern regions of China is relatively insufficient to a certain extent. Therefore, the smart cities in these two provinces need to further improve their technological level in the power production system and enhance their comprehensive management capabilities. Through the continuous improvement of relevant management elements and parameters, the comprehensive power supply management capabilities of smart cities can be gradually improved, and the performance gap with the other two regions can be continuously narrowed.

In terms of the average score in the power sales system, after the provinces in the eastern region, the central region has a more obvious advantage compared to other regions, with a score of about 0.45. The average scores for the western and northeastern regions are 0.36 and 0.40, respectively. Therefore, compared to the eastern and western regions, the central and northeastern regions need to further improve their sales competitiveness in the process of building their own smart cities through the power sales system.

In addition, different influencing factors will also have varying degrees of impact on the production and sales processes of the power supply system in smart cities. In order to analyse the impact of relevant influencing factors on the performance of power supply, we first combined the impact of efficiency in the power production stage. Based on this, this article combines relevant data to study the impact of changes in factors such as power generation, equipment usage time, and newly added equipment capacity on efficiency; Then further combine the impact of coal consumption rate, power generation capacity, and carbon dioxide emissions involved in the power production stage on the efficiency of the power production stage. In the analysis process, in order to achieve unified comparative analysis, the relevant data was normalized. As shown in Figure 6, the relationship between different influencing factors and the efficiency of smart city power production stage is presented. Among them, in the power production stage, only the adoption of new power production equipment has a positive correlation with its efficiency, with a correlation coefficient of about 0.34. Other influencing factors show varying degrees of negative correlation, with a correlation coefficient ranging from -0.18 to -0.35.

According to the analysis of the non-radial network DEA model, there are certain differences in the correlation coefficients between different influencing factors and the efficiency of each stage. For the power sales stage in the smart city power supply system, as shown in Figure 7, the correlation coefficient changes of various influencing factors on the power grid stage of the power system are presented. As shown in the figure, there is a positive correlation between the output value and generation of electricity sales and the efficiency of the electricity sales stage, with correlation coefficients of 0.57 and 0.092; The length of newly added lines, capacity of new equipment,

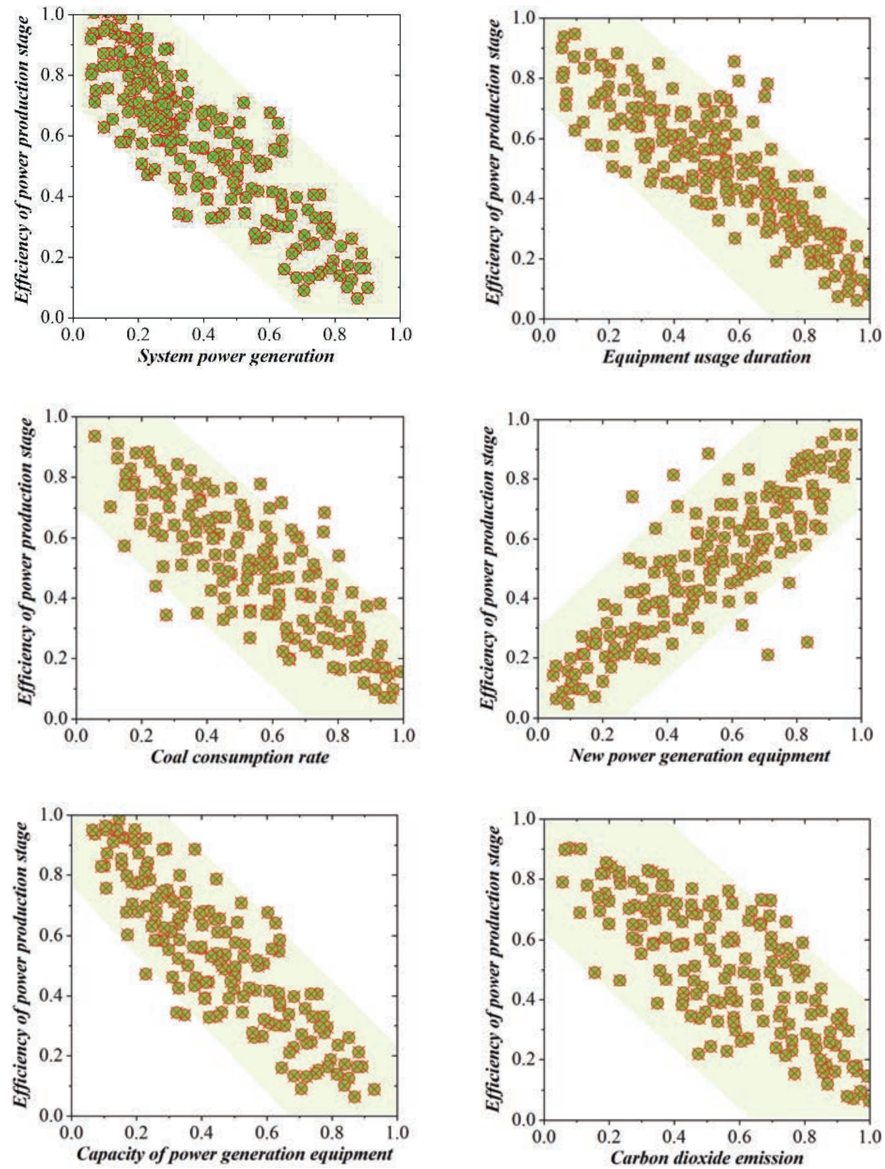


Figure 6 Correlation coefficient of impact of different influencing factors on efficiency of power production stage.

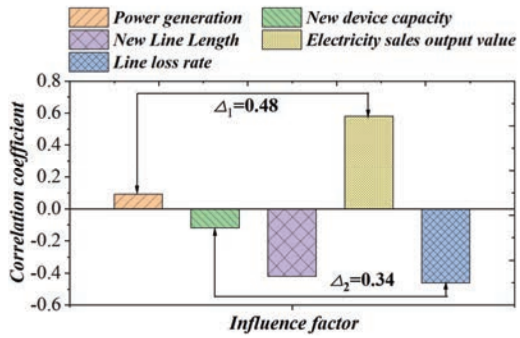


Figure 7 Correlation coefficient of impact of different influencing factors on efficiency of power grid stage.

and line loss rate are all negatively correlated with their efficiency, with correlation coefficients of −0.42, −0.12, and −0.46, respectively.

5 Conclusions

The continuous development of smart cities has made research on the environmental performance and measurement of power supply a key focus in the field of renewable energy. Based on the application characteristics of the DEA model, unexpected outputs were integrated into the distance function method and its non-radial form was proposed. A smart city power supply performance and measurement model based on non-radial network DEA was constructed, and the performance of the model was compared and analysed with relevant data. The main conclusions are as follows:

(1) Through the application of distance function, a DEA model based on non-radial networks was constructed, and the constructed model showed better overall performance compared to the analysis of environmental performance and measurement of smart city power supply. Through comprehensive analysis of data, the efficiency of this model in the smart city power supply system is about 0.36, providing guidance for further improvement of system efficiency; In the production and sales systems of different regions, the performance of the eastern region of China is the highest, with an average score of 0.73 and 0.62, respectively.

(2) The relationship between different influencing factors and the efficiency of smart city power production stage indicates that in the power production stage, only the adoption of new power production equipment shows

a positive correlation with its efficiency, with a correlation coefficient of about 0.34. The correlation coefficients of other influencing factors range from −0.18 to −0.35; For the power sales stage in the power supply system, the correlation coefficients between the output value and generation of electricity sales and the efficiency of the power sales stage are 0.57 and 0.092, respectively. Other influencing factors exhibit a negative correlation characteristic.

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Biographies

Ying Sun graduated from Harbin Institute of Technology with a doctoral degree in Information and Communication Engineering. After graduation, I worked at Guangdong Power Grid Co., Ltd. My main research direction was advanced measurement in the power grid. The current professional title is Senior Engineer.

JiaJia Huang graduated from North China Electric Power University with a bachelor's degree in Electrical Engineering and Automation. After graduation, I worked at Shaoguan Power Supply Bureau of Guangdong Power Grid, with a main research focus on electricity. The current professional title is Senior Economist.

Fusheng Wei graduated with a master's degree from South China University of Technology. Guangdong Power Grid Corporation. A senior engineer with a research focus on electricity metering.

Yanzhe Fu graduated from South China University of Technology with a master's degree. After graduation, I worked at Southern Guangdong Power Grid Co., Ltd. My main research direction is energy metering. The current professional title is Senior Engineer.

LiangZhao He graduated from Sun Yat sen University with a bachelor's degree in Microelectronics. After graduation, I worked at LongShine Technology Group Co., Ltd. with a main research focus on electricity. The current professional title is Senior Engineer.