

Zhang, Jian; Wen, Jianzhou; Lu, Zhen; Qian, Jiang; Wei, Ning

Article

Investment allocation method for distribution networks based on a panel data model and an incentive-penalty mechanism

Amfiteatru Economic

Provided in Cooperation with:

The Bucharest University of Economic Studies

Suggested Citation: Zhang, Jian; Wen, Jianzhou; Lu, Zhen; Qian, Jiang; Wei, Ning (2025) : Investment allocation method for distribution networks based on a panel data model and an incentive-penalty mechanism, Amfiteatru Economic, ISSN 2247-9104, The Bucharest University of Economic Studies, Bucharest, Vol. 27, Iss. 69, pp. 656-673,
<https://doi.org/10.24818/EA/2025/69/656>

This Version is available at:

<https://hdl.handle.net/10419/319830>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

INVESTMENT ALLOCATION METHOD FOR DISTRIBUTION NETWORKS BASED ON A PANEL DATA MODEL AND AN INCENTIVE–PENALTY MECHANISM

Jian Zhang¹, Jianzhou Wen², Zhen Lu³, Jiang Qian^{4*} and Ning Wei⁵
¹⁾²⁾³⁾⁴⁾⁵⁾ State Grid Shanxi Electric Power Company Yuncheng Power Supply
Company, Yuncheng City, China

Please cite this article as:

Zhang, J., Wen, J., Lu, Z., Qian, J. and Wei, N., 2025. Investment Allocation Method for Distribution Networks Based on a Panel Data Model and an Incentive–Penalty Mechanism. *Amfiteatru Economic*, 27(69), pp. 656-673.

DOI: <https://doi.org/10.24818/EA/2025/69/656>

Article History

Received: 21 December 2024

Revised: 15 November 2024

Accepted: 5 February 2025

Abstract

The scale of distribution network construction is huge and the differences in construction areas are significant. The accuracy of investment strategies would directly affect the effectiveness of upgrading distribution networks. In response to the current subjectivity and lack of precision in the distribution network investment allocation process, this study proposed a method to allocate the investment amount to distribution networks based on a panel data model and an incentive–penalty mechanism. First, the type of panel data model was selected using the joint hypothesis test and the Hausman test. Second, the initial allocation of the investment amount was calculated based on the selected panel data model. Third, investment productivity in each region in recent years was calculated using the data envelope analysis model. Given the variations in the importance of information during different periods, the concept of time degree was introduced to establish a time degree model. The weights of the model during different periods were assigned to the investment productivity and then the sum was calculated separately to obtain the comprehensive investment productivity of each distribution network. The final allocation of the investment amount for each distribution network was obtained based on its initial allocation of the investment amount and the comprehensive investment productivity. The case study showed the following points. (1) The differences among the distribution networks were significant and, thus, the fixed effects model could be employed to effectively compute the investment scale. (2) Given the differences in the construction and investment productivity of various distribution networks, the proposed method to calculate the complete investment productivity could be used to adjust the allocation of the investment amount and achieve an optimal allocation of funds. The research results exhibited practical significance in improving the investment allocation strategy of distribution networks.

* Corresponding author, **Jiang Qian** – e-mail: ycqianjiang@sina.com



This is an Open Access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. © 2025 The Author(s).

Keywords: distribution network investment, investment allocation, panel data model, time-degree model, incentive–penalty mechanism.

JEL Classification: C01, C33, C53

Introduction

The economy of China has experienced rapid growth in recent years. Consequently, the demand for electricity has also been increasing. Therefore, the construction of distribution networks as key links in power transmission has become a crucial task in the power industry. In particular, with the significant advancements in new energy and smart grid technology, a distribution network must not only undertake traditional power transmission and distribution, but must also have the ability to integrate new energy and optimise its allocation (Lu et al., 2022; Lu, Lin and Dabić, 2024). Therefore, a scientific and rational investment strategy for distribution networks is directly related to the sustainability of the national economy, social development, and the environment.

At present, the allocation of investment amounts to distribution networks is based largely on construction projects proposed by various regions. This method is highly subjective and lacks a theoretical basis, and thus ensuring the rationality and balance of investment amount allocation is difficult during the construction of distribution networks. Consequently, national funds are not only wasted, but the development of regional power grids and the economy are also affected. Research on investment allocation in distribution networks encompasses two principal classifications. In the initial classification, the required investment amount for each region is determined by establishing predictive models (Wang et al., 2022; Wu et al., 2022). In the second classification, project optimisation is performed to determine the investment amount allocated to each region, with the maximisation of one or more indexes as the objective function and known total investment amount as one of the constraints (Gao, Zhao and Li, 2022; Garifi et al., 2022; Farah and Andresen, 2024). In the first type of method, the electricity demand related directly to the construction of distribution networks is used as the input of the model to estimate the investment amount of a distribution network, avoiding the drawbacks of traditional methods that rely largely on experience. However, the prediction results of the model are easily affected by data; moreover, a model based on the construction of distribution networks and regional economic characteristics cannot be established by utilising commonly used prediction models, such as grey models and neural networks (Chen et al., 2020; Xu et al., 2021). Insufficient consideration of regional differences leads to unreasonable investment allocation. In the second type of method, the optimisation of projects is performed in the entire research area, and thus, the investment amount cannot be accurately estimated, resulting in unreasonable allocation with excessive or insufficient investment in some regions.

Taking into account the aforementioned issues, in-depth research on investment models for distribution networks is carried out and an investment allocation method is proposed based on a panel data model and an incentive–penalty mechanism in the current study. The suitable panel data model for regional characteristics is selected through the joint hypothesis test and the Hausman test and is used to construct the investment allocation model for distribution networks. Data envelope analysis (DEA) and the time degree model are introduced to

quantify regional differences, and thus accurate allocation of investment amount to the construction of distribution networks can be obtained.

1. Literature review

Existing investment allocation methods can be broadly categorised into two groups. The first group involves detailed planning reports and unit price of the equipment. The amount of investment can be divided into several sections, and formulas based on planning reports and unit prices of equipment are proposed for each section to calculate its investment amount. The amount of investment is divided into rigid, economic, actual and planned investments based on project data in the planning reports. Yu et al. (2017) provided detailed calculation methods for each type of investment amount. However, these methods must be based on detailed planning reports and the requirement for initial data is strict, making them less applicable in practical situations.

The second group involves macro-level investment allocation in the absence of planning reports. Currently, these methods include mainly evaluation and prediction. An evaluation method involved establishing an investment index system evaluation, collecting relevant index data, assigning weights to each index through a weighting method, and then using relevant evaluation models for evaluation (Sengul et al., 2015; Koponen and Le Net, 2021; Zafar et al., 2016; Sha et al., 2021). This method is simple and convenient, but establishing an investment index evaluation system is difficult. Many related studies had directly used an evaluation index system for distribution networks as an evaluation index system for investment, resulting in a lack of a scientific basis and accuracy. In contrast, the relevant factors that influence the allocation of investment amount were selected and the functional relationships between them were studied in a prediction method. Essentially, a prediction method was a modified evaluation method. The mathematical relationship between evaluation results and investment amount allocation was not thoroughly explored in an evaluation method, but it was examined using fitting functions in a prediction method, and thus accuracy was improved.

The investment amount was allocated at the macrolevel and the calculation was optimised using the particle swarm algorithm. Xu et al. (2020) calculated the investment amount required for the distribution network in each region based on its evaluation result. Li et al. (2021) and Zhang et al. (2021) predicted the investment amount to be allocated based on investment and electricity demand by using the panel data model. These methods involved the general prediction of the investment amount to be allocated, resulting in a significant improvement in rationality and accuracy compared to evaluation methods.

Based on the aforementioned studies, the current work presents an allocation method for the investment amount based on a panel data model and an incentive–penalty mechanism. The panel data model was used to determine the investment amount of each region, accurately reflect the situation of the regional power grids, and achieve the initial allocation of the investment amount. The incentive–penalty mechanism based on DEA and the time-degree model was introduced to adjust the initial allocation of investment amount to each region and, thus, fully utilise the investment advantages of all regions.

The structure of the rest of this paper is described below. The third part briefly describes the establishment of the panel data model, the DEA, and the time-degree model. Then it analyses

the allocation methods and the processes of the investment amount for distribution networks. The fourth part examines the advantages and effectiveness of the panel data model and the incentive–penalty mechanism in the allocation of investment amounts to distribution networks through a numerical example. The fifth part summarises the research results and provides the relevant conclusions.

2. Methodology

The panel data model is commonly used to analyse data distribution in two dimensions: time and space; it obtains more information than a single-section data model (Lee and Yu, 2012; Briseño and Rojas, 2020; Hill et al., 2020; Zhou and Wang, 2022; Salamaga, 2023). The investment amount is distributed in the time and region dimensions, and thus, it is a common type of panel data. The panel data model is introduced in this study to establish the allocation model for the amount of investment in the distribution networks.

2.1. Establishment of the panel data model

(1) Basic panel data model

The fundamental representation of a panel data model is expressed as:

$$y_{it} = \beta x_{it}^T + u_i + \varepsilon_{it} \quad (1)$$

where:

i – represents the region, and $i = 1, 2, \dots, n$ (n : number of regions);

t – represents time, and $t = 1, 2, \dots, T$ (T : evaluation duration, number of years here);

y_{it} – is the value of the dependent variable in the it th region and the t th year;

x_{it} – is a vector of explanatory variables;

$\beta = [\beta_1, \beta_2, \dots, \beta_l]$ – is the vector of parameters to be estimated;

l – number of explanatory variables;

ε_{it} – is a random error term with zero mean, same variance, and independent distribution; and u_i is an intercept term. Here, the panel data model includes three categories.

1) Mixed effects model

The model is appropriate for situations wherein data in the time dimension are significantly different, but data in the region dimension are not considerably different. That is, data from different regions can be mixed and considered in the actual regression process. The mixed effects model can be expressed as:

$$y_{it} = \beta_{ME} x_{it}^T + u_0 + \varepsilon_{it} \quad (2)$$

where:

β_{ME} – is the set of parameters that require estimation.

2) Fixed effects model

The model is appropriate for situations where the data in the time and region dimensions are significantly different. Data from different regions must be considered separately to reflect differences among regions. The intercept term u_i expresses the individual effect of each region, and thus, it is correlated with the explanatory variables. The fixed effects model can be expressed as:

$$y_{it} = \beta_{FE} x_{it}^T + u_i + \varepsilon_{it} \quad (3)$$

where

β_{FE} – is the set of parameters that require estimation.

3) Random effects model

The model is appropriate for situations wherein data in the time and region dimensions are significantly different, and the intercept term u_i bears no correlation with the explanatory variables and is used to represent random interference that reflects the characteristics of unobservable random information. The model can be expressed as:

$$y_{it} = \beta_{RE} x_{it}^T + u_i + \varepsilon_{it} \quad (4)$$

where:

β_{FE} – is the set of parameters that require estimation.

(2) Recognition of data feature

The joint hypothesis test and the Hausman test are used to select a panel data model from the three types using the specific data in this study.

1) Joint hypothesis test

The joint hypothesis test is also called the F test. For the mixed effects model and the fixed effects model, the essence is to determine the importance of the disparity between the intercept terms u_i to be estimated. The null hypothesis is:

$$H_0 : u_1 = u_2 = \dots = u_n \quad (5)$$

where:

n – represents the number of regions.

If the test results reject the null hypothesis, then the intercept terms u_i to be estimated are significantly different, and thus, the fixed effects model should be selected. Conversely, if the test results accept the null hypothesis, then the difference between the intercept terms u_i to be estimated is within the acceptable range, and thus, the mixed effects model should be selected. The F statistic is defined as:

$$F = \frac{(SSE_r - SSE_u)/(n-1)}{SSE_u/(nT - n - l)} \quad (6)$$

where:

SSE_r – represents the aggregated squared residuals from the mixed effects model;

SSE_u – represents the aggregated squared residuals from the fixed effects model;

n – is the number of regions;

T – is the evaluation duration;

l – is the number of explanatory variables.

If the value of the F statistic is greater than the value of $F(n-1, nT-n-l)$ at a given significance level, then the null hypothesis is rejected and the fixed effects model should be selected. Conversely, the null hypothesis is accepted and the mixed effects model should be selected.

2) Hausman test

This test is primarily employed to select between the fixed effects model and the random effects model. It essentially judges whether the intercept term u_i is related to the explanatory variables. If u_i is associated with the explanatory variables, then the fixed effects model should be selected. If u_i is unrelated to the explanatory variables, then the random effects model should be selected. The null hypothesis is:

$$H_0 : Cov(u_i, x_{it}) = 0, \text{ for all } t \quad (7)$$

The statistic can be calculated as:

$$W = \frac{(\beta_{FE} - \beta_{RE})(\beta_{FE} - \beta_{RE})^T}{Var(\beta_{FE} - \beta_{RE})} \quad (8)$$

where:

β_{FE} – is the dispersion ordinary least squares (OLS) estimators of the parameters in the fixed effects model;

β_{RE} – is the feasible generalised least squares estimators of the parameters in the random effects model;

Var – denotes variance.

If the value of W surpasses the value of $\chi^2(l-1)$ at a given significance level, then the null hypothesis is rejected. That is, u_i is related to the explanatory variables, and the fixed effects model should be selected. Conversely, the null hypothesis is accepted and the random effects model should be selected.

2.2. Establishment of the incentive–penalty mechanism

(1) Evaluation of the investment productivity based on the DEA model

DEA is a mathematical programming-based technique for evaluating the relative performance of organisations (Yan, 2019; Akbarian, 2020; Kuosmanen and Johnson, 2020; Tohid, Mohammad and Sajad, 2020; Pouralizadeh, 2020; Yilmaz, 2023). In DEA, the organisational units are called decision-making units (DMUs). To enable its application to a wide variety of activities, the term DMU is used to refer to any object that is to be evaluated in terms of its ability to convert input into output. The Charnes–Cooper–Rhodes (CCR) model is a type of DEA. Suppose m DMUs, DMU_i , $i = 1, 2, \dots, m$, and the input and output index vectors for DMU_i are E_i and O_i , respectively. Thus,

$$E_i = (e_{i1}, e_{i2}, \dots, e_{ip}) \quad (9)$$

$$O_i = (o_{i1}, o_{i2}, \dots, o_{iq}) \quad (10)$$

where:

p – is the number of input indices;

q – is the number of output indices.

In accordance with the CCR model, the optimisation model for the relative efficiency of DMU_i can be established as follows:

$$\begin{cases} \max h_i = \frac{gO_i^T}{\mu E_i^T} \\ s.t. \begin{cases} h_i \leq 1, i \in [1, m] \\ \mu_r \geq 0, r \in [1, p] \\ g_j \geq 0, j \in [1, q] \end{cases} \end{cases} \quad (11)$$

where $\mu = (\mu_1, \mu_2, \dots, \mu_r, \dots, \mu_p)$, $g = (g_1, g_2, \dots, g_j, \dots, g_q)$, μ_r ($r = 1, 2, \dots, p$) is the weight coefficient of e_{ir} ($r = 1, 2, \dots, p$), and g_j ($j = 1, 2, \dots, q$) is the weight coefficient of o_{ij} ($j = 1, 2, \dots, q$). By using the Charnes–Cooper transformation:

$$t_i = \frac{1}{\mu E_i^T} \quad (12)$$

$$\omega_i = t_i \mu \quad (13)$$

$$\zeta_i = t_i g \quad (14)$$

where:

$$\omega_i = (\omega_{i1}, \omega_{i2}, \dots, \omega_{ir}, \dots, \omega_{ip});$$

$$\zeta_i = (\zeta_{i1}, \zeta_{i2}, \dots, \zeta_{ij}, \dots, \zeta_{iq}).$$

Eq. (11) can be transformed into a linear programming problem, as follows:

$$\left\{ \begin{array}{l} \max h_i = \frac{gO_i^T}{\mu E_i^T} = \zeta_i O_i^T \\ s.t. \left\{ \begin{array}{l} \frac{gO_i^T}{\mu E_i^T} = \frac{\zeta_i O_i^T}{\omega_i E_i^T} \leq 1, i \in [1, m] \\ \omega_i E_i^T = 1, i \in [1, m] \\ \omega_{ir} \geq 0, i \in [1, m], r \in [1, p] \\ \zeta_{ij} \geq 0, i \in [1, m], j \in [1, q] \end{array} \right. \end{array} \right. \quad (15)$$

Eq. (15) can be reduced to

$$\left\{ \begin{array}{l} \max h_i = \zeta_i O_i^T \\ s.t. \left\{ \begin{array}{l} \omega_i E_i^T - \zeta_i O_i^T \geq 0, i \in [1, m] \\ \omega_i E_i^T = 1, i \in [1, m] \\ \omega_{ir} \geq 0, i \in [1, m], r \in [1, p] \\ \zeta_{ij} \geq 0, i \in [1, m], j \in [1, q] \end{array} \right. \end{array} \right. \quad (16)$$

If the optimal solution to Eq. (16) is $h_i = 1$, then the investment productivity of DMU_i (the i th evaluation object) is the highest.

(2) Time degree model

The DEA allows for the assessment of each region's investment productivity in recent years. Evidently, investment productivity that is closer to the current time plays a greater role, that is, it should be assigned a greater weight; hence, the time degree model (Yager, 1988) is introduced to measure investment productivity in the current study. Time degree can fully reflect the following characteristic: the effect of the new information outweighs that of the old one; that is, the difference in importance among information during every period can be reflected by different time degree values. The time degree values and their corresponding meanings are provided in table no. 1.

Table no. 1. Values of time degree and their corresponding meanings

Values of Time Degree	Meaning
0.1	Extremely value new information
0.3	Comparatively, value new information
0.5	Value both new information and old information
0.7	Comparatively value old information
0.9	Extremely value old information

Source: Yager R. R., 1988, p. 183-190.

As indicated in Table no. 1, the greater the time degree value, the less emphasis is placed on new information and the greater emphasis is placed on old information. Conversely, a lower time degree value indicates a greater emphasis on new information compared to old information. When the time degree values are 0.2, 0.4, 0.6, and 0.8, their corresponding importance of information is between the importance of the corresponding information of adjacent values in Table no. 1.

The time degree α is defined as:

$$\alpha = \sum_{t=1}^T \frac{T-t}{T-1} \tau_t \quad (17)$$

where:

T – is the total number of years during which investment productivity is to be evaluated;

τ_t ($\tau_t \in [0,1]$) – is the investment productivity weight of the t th year that is determined by information entropy I and time degree α in this study.

$$I = - \sum_{t=1}^T \tau_t \ln \tau_t \quad (18)$$

As the value of I decreases, the fluctuation over time diminishes. To obtain a set of investment productivity weights that are most stable in evaluation during every period, an optimisation model is established as

$$\begin{cases} \max I = - \sum_{t=1}^T \tau_t \ln \tau_t \\ s.t. \begin{cases} \alpha = \sum_{t=1}^T \frac{T-t}{T-1} \tau_t \\ \sum_{t=1}^T \tau_t = 1 \end{cases} \end{cases} \quad (19)$$

The objective function of Eq. (19) is nonlinear, but the relevant constraints are linear. In this study, the interior point method is used to solve Eq. (19) for weight τ_t by using the time degree value.

2.3. Allocation method for the investment amount

The allocation method for the amount of investment in distribution networks based on the panel data model and the incentive–penalty mechanism involves the following steps.

(1) The main factors that affect the allocation of the investment amount for the regression are used.

Total annual power consumption, regional gross domestic product (GDP), maximum social load, and the status quo evaluation of distribution network construction are selected as the major factors (explanatory variables) that affect the allocation of investment amount (independent variable) to make a regression.

(2) The panel data model is selected using the F test and the Hausman test.

Eqs. (5) and (6) are employed to determine whether to choose the mixed effects model or the fixed effects model. Eqs. (7) and (8) are employed to decide between the fixed effects model and the random effects model. Then, a suitable panel data model is determined.

(3) The selected type of panel data model is used for the initial proportion of investment amount allocation for each distribution network.

The initial allocation of their investment amount for the following year is calculated by substituting the explanatory variables, that is, the total annual power consumption, regional GDP, maximum social load, and status quo evaluation of distribution network construction for each distribution network for the following year, into the selected type of panel data model.

(4) The annual investment productivity of each region in recent years is calculated based on DEA and the annual investment productivity weight based on the time degree model.

Eq. (16) is solved for the optimal solution from which the annual investment productivity in recent years is obtained. Eq. (19) is solved for the annual investment productivity weight in recent years by setting the appropriate time degree value from table no. 1 and using the interior point method.

(5) The comprehensive investment productivity of each region is calculated.

The weight of annual investment productivity is assigned to the corresponding annual investment productivity of each distribution network in recent years. Their sum is calculated individually, followed by normalisation of the results to derive their respective comprehensive investment productivity.

(6) The final allocation proportion of the investment amount is computed using the complete investment productivity and the initial allocation proportion of the investment amount.

Let P_f , P_b , and E_c denote the final allocation proportion of the investment amount, the initial allocation proportion of the investment amount, and the comprehensive investment productivity, respectively. Thus,

$$P_f = k_1 E_c + k_2 P_b \quad (20)$$

where: k_1 and k_2 are the coefficients $k_1=0.1$ and $k_2=0.9$ in this study.

The flow chart of the allocation method for the investment amount is shown in figure no. 1.

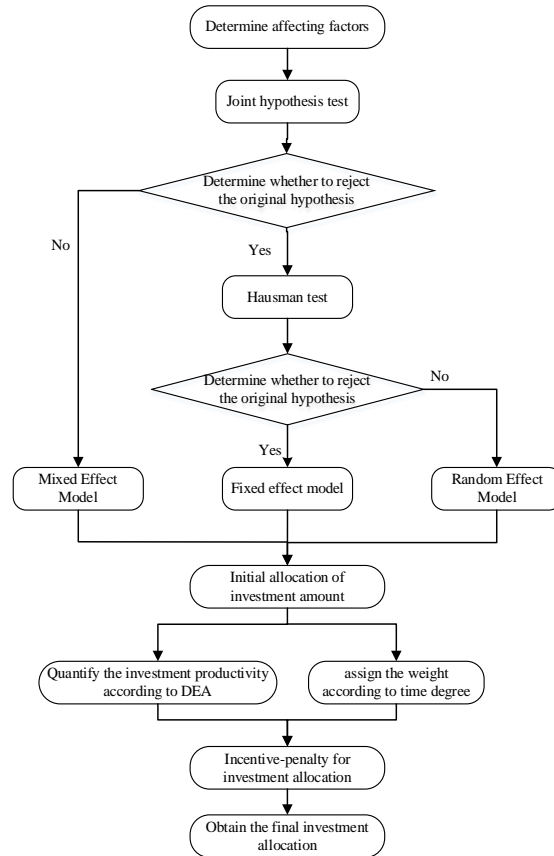


Figure no. 1. The flowchart of allocation of investment amount

4. Results and discussion

The allocation of investment amounts for the distribution networks of nine cities in a province of China is used to verify the proposed method.

The total annual power consumption, regional GDP, maximum social load, and the status quo score of the distribution network construction of the nine cities in the period 2018–2021 are selected as affecting factors. Hence, the number of objects to be evaluated $n = 9$, the number of years $T = 4$, and the number of explanatory variables $l = 4$.

The marginal effect occurs during the investment process and, thus, the logarithm of the variables in Eqs. (2), (3), and (4) are considered to reduce the order of magnitude and fluctuation ranges of total power consumption and other data. Evidently, the monotony of the logarithm ensures that the data are not distorted.

The values of the related statistics of the F test, as indicated in Table no. 2, can be obtained by using Eq. (6). From the F distribution table, the value of $F(8, 23)$ is 2.37 at a significance level of 5%.

Table no. 2. Values of related statistics of F test

Related statistics	SSE_r	SSE_u	F	$F(8,23)$
Value	554.3305	232.3459	5.8896	2.37

Source: Authors' calculations

The values of the W statistic of the Hausman test, as indicated in table no. 3, can be obtained using Eq. (8). From the chi-square distribution table, the value of $\chi^2(3)$ is 7.815.

Table no. 3. Values of related statistics of the Hausman test

Related statistics	W	$\chi^2(3)$
Value	10.54	7.815

Source: Authors' calculations

From Table no. 2, the calculation result of the F statistic exceeds the value of $F(8,23)$, and thus, the null hypothesis is rejected. From table no. 3, the calculation result of the W statistic exceeds the value of $\chi^2(3)$, and thus, the rejection of the null hypothesis is also confirmed. A conclusion is drawn from the above judgment results that the fixed effects model should be selected; hence, the difference among regional distribution networks is marked.

Substituting the dispersion OLS estimators $\beta_{FE1} = 3.5140$, $\beta_{FE2} = 2.8533$, $\beta_{FE3} = -3.2660$, and $\beta_{FE4} = -13.1946$ into Eq. (3) and taking the logarithm of the variables yield

$$\ln y_{it} = u_i + 3.5140 \ln x_{1it} + 2.8533 \ln x_{2it} - 3.2660 \ln x_{3it} - 13.1946 \ln x_{4it} + \varepsilon_{it} \quad (21)$$

where:

x_{1it} — is the total annual power consumption for the tth year;

x_{2it} — is the regional GDP for the tth year;

x_{3it} — is the maximum social load for the tth year;

x_{4it} is the status quo evaluation of distribution network construction for the tth year.

Investment amount is positively correlated with total annual power consumption and regional GDP; that is, power grid investment should meet the needs of social and economic development and investment amount should be increased in regions with faster economic growth. Meanwhile, the investment amount is negatively correlated with maximum social load and the status quo score of distribution network construction, because the ratio of input to output is relatively low for a mature power grid during construction, and thus, the investment in such a power grid should be reduced appropriately.

The dispersion OLS estimators $\mu_i (i = 1, 2, \dots, 9)$ for $\mu_i (i = 1, 2, \dots, 9)$ are provided in table no. 4.

Table no. 4. Values of $\mu_i (i = 1, 2, \dots, 9)$ corresponding to 9 distribution networks

No. of City	City1	City2	City3	City4	City5	City6	City7	City8	City9
μ_i	7.1278	15.4285	12.7183	17.6034	18.5317	14.5630	15.5796	22.0212	20.0288

Source: Authors' calculations

Hence,

$$\ln y_{it} = \mu_i + 3.5140 \ln x_{1it} + 2.8533 \ln x_{2it} - 3.2660 \ln x_{3it} - 13.1946 \ln x_{4it} + \varepsilon_{it} \quad (22)$$

Substituting the values of the total annual power consumption, regional GDP, maximum social load, and status quo score of distribution network construction of the nine cities in 2022 in Eq. (22) yields the initial allocation results of the investment amount, as indicated in table no. 5.

Table no. 5. Initial allocation of investment amount of 9 distribution networks in 2022

No. of City	City1	City2	City3	City4	City5	City6	City7	City8	City9
Initial investment amount/100 Million CNY	14.45	12.69	8.35	3.56	10.15	8.68	7.95	11.31	8.03

Source: Authors' calculations

From Table no. 5, the expected investment amount is 8518 million yuan in 2022. Therefore, the initial allocation proportions of the investment amount of the distribution networks of the nine cities in 2022 are obtained, as indicated in Table no. 6.

Table no. 6. Initial allocation proportion of investment amount of 9 distribution networks in 2022

No. of City	City1	City2	City3	City4	City5	City6	City7	City8	City9
Initial allocation proportion	0.1697	0.1489	0.0980	0.0418	0.1192	0.1019	0.0933	0.1328	0.0943

Source: Authors' calculations

With an urban distribution network as the DMU, the investment amount of each region is employed as the input, while the score and its increment of each distribution network and the increment in power consumption are taken as the output, the annual investment efficiencies of the distribution networks of the nine cities in the period 2018–2021 are evaluated using Eq. (16). The results are presented in Table no. 7 and Figure no. 2.

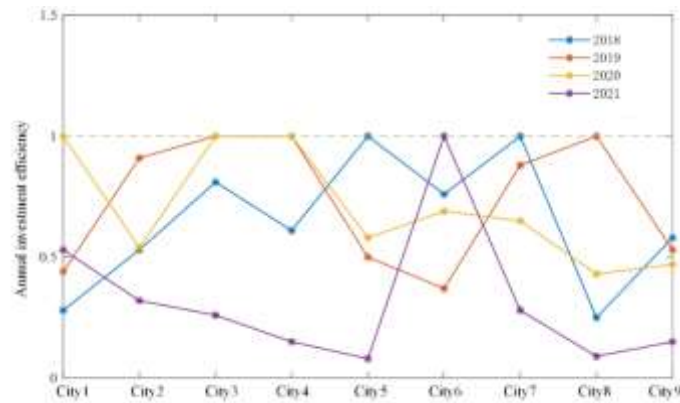


Figure no. 2. Annual investment productivity of 9 distribution networks in the year 2018-2021

Table no. 7. Annual investment productivity of 9 distribution networks in the year 2018-2021

Year	City1	City2	City3	City4	City5	City6	City7	City8	City9
2018	0.28	0.53	0.81	0.61	1.00	0.76	1.00	0.25	0.58
2019	0.44	0.91	1.00	1.00	0.50	0.37	0.88	1.00	0.53
2020	1.00	0.54	1.00	1.00	0.58	0.69	0.65	0.43	0.47
2021	0.53	0.32	0.26	0.15	0.08	1.00	0.28	0.09	0.15

Source: Authors' calculations

The time degree value is set as 0.4 here, and the annual investment productivity weights of the nine distribution networks in the period 2018–2021 (as provided in table no. 8) are obtained by solving Eq. (19).

Table no. 8. Annual investment productivity weight of 9 distribution networks in the year 2018-2021

Year	2018	2019	2020	2021
Annual investment productivity weight	0.1671	0.2133	0.2722	0.3474

On the basis of tables no. 7 and no. 8, the comprehensive investment efficiencies of the nine distribution networks, as indicated in table no. 9, are obtained by assigning the weight of the annual investment productivity to the corresponding annual investment productivity of the nine distribution networks in the period 2018–2021, calculating their sum separately and normalising the results.

Table no. 9. Comprehensive investment productivity of 9 Distribution Networks

No. of City	City1	City2	City3	City4	City5	City6	City7	City8	City9
Comprehensive investment productivity	0.1168	0.1058	0.1389	0.1254	0.0898	0.1450	0.1230	0.0790	0.0763

Source: Authors' calculations

In accordance with Eq. (20), the final allocation proportions of the investment amount of the nine distribution networks in 2022 are provided in table no. 10.

Table no. 10. Final allocation proportion of investment amount of 9 distribution networks in 2022

No. of City	City1	City2	City3	City4	City5	City6	City7	City8	City9
Final allocation proportion	0.1644	0.1446	0.1021	0.0502	0.1163	0.1062	0.0963	0.1274	0.0925

Source: Authors' calculations

The final and initial allocation proportions of the investment amount of the nine distribution networks in 2022 are shown in Figure no. 3.

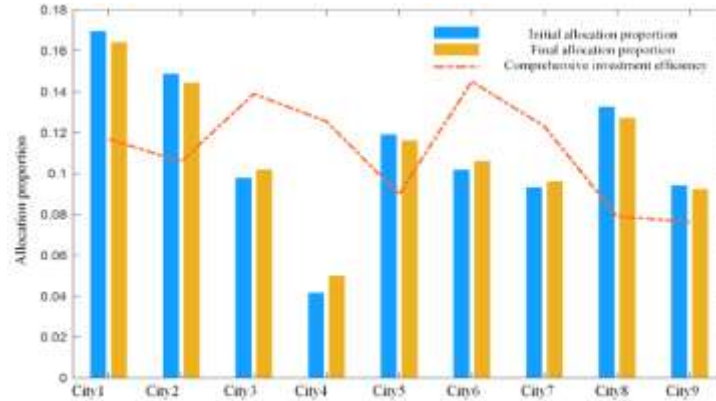


Figure no. 3. The final proportion and initial one of allocation of the investment amount of 9 distribution networks in 2022

From this figure, given that the comprehensive investment efficiencies (dotted line) of the distribution networks of City3, City4, City6, and City7 are high, their final allocation proportion of investment amount (yellow) is also higher than their initial one (blue) to a certain extent. However, the case is contrary to the distribution networks of the remaining cities.

Conclusions

This study presents an allocation method for the amount of investment in distribution networks based on a panel data model and an incentive–penalty mechanism. The main conclusions drawn are as follows.

- (1) In general, the fixed effects model exerts a good regression effect on the allocation of investment amount for distribution networks, and therefore it can be used for the allocation of investment amount.
- (2) The DEA and the time degree model can reflect the investment productivity of each region; therefore, they can be used to adjust the initial allocation of the investment amount as a type of incentive–penalty mechanism.
- (3) The approach suggested in this research can mirror the characteristics of the distribution networks in each region, fully utilising regional investment advantages and effectively achieving a reasonable allocation of the investment amount for the distribution networks.

In the allocation of the investment amount, the basic scale and investment productivity of a distribution network are considered comprehensively in this study. However, minimal attention is paid to factors related to the geographical adjacency and interconnection of distribution networks. Linkage effects caused by developments in the adjacent regional distribution network may potentially influence the analysis of investment benefits. Therefore, these factors should be considered in the optimisation of the follow-up of the allocation of investment amount to distribution networks.

Acknowledgement

This work is supported by the Science and Technology Project of State Grid Shanxi Electric Power Company “Research and Application of Precise Investment Decision-Making in Distribution Networks under the Background of ‘Dual Carbon’ and New Power Systems” (5205M0230002).

References

- Akbarian, D., 2020. A new DEA ranking system based on interval cross efficiency and interval analytic hierarchy process methods. *International Journal of Management and Decision Making*, 19(3), p.344. <https://doi.org/10.1504/IJMDM.2020.108641>.
- Briseño, H. and Rojas, O., 2020. Factors associated with electricity losses: a panel data perspective. *International Journal of Energy Economics and Policy*, 10(5), pp.281-286. <https://doi.org/10.32479/ijee.9599>.
- Chen, S., Jiang, Q., He, Y., Huang, R., Li, J., Li, C. and Liao, J., 2020. A BP Neural Network-Based Hierarchical Investment Risk Evaluation Method Considering the Uncertainty and Coupling for the Power Grid. *IEEE Access*, 8, pp.110279-110289. <https://doi.org/10.1109/ACCESS.2020.3002381>.
- Farah, S. and Andresen, G.B., 2024. Investment-based optimisation of energy storage design parameters in a grid-connected hybrid renewable energy system. *Applied Energy*, 355, art. no. 122384. <https://doi.org/10.1016/j.apenergy.2023.122384>.
- Gao, L., Zhao, Z.-Y. and Li, C., 2022. An Investment Decision-Making Approach for Power Grid Projects: A Multi-Objective Optimization Model. *Energies*, 15(3), art. no. 1112. <https://doi.org/10.3390/en15031112>.
- Garifi, K., Johnson, E.S., Arguello, B. and Pierre, B.J., 2022. Transmission Grid Resiliency Investment Optimization Model With SOCP Recovery Planning. *IEEE Transactions on Power Systems*, 37(1), pp.26-37. <https://doi.org/10.1109/TPWRS.2021.3091538>.
- Hill, T.D., Davis, A.P., Roos, J.M. and French, M.T., 2020. Limitations of Fixed-Effects Models for Panel Data. *Sociological Perspectives*, 63(3), pp.357-369. <https://doi.org/10.1177/0731121419863785>.
- Koponen, K. and Le Net, E., 2021. Towards robust renewable energy investment decisions at the territorial level. *Applied Energy*, 287, art. no. 116552. <https://doi.org/10.1016/j.apenergy.2021.116552>.
- Kuosmanen, T. and Johnson, A.L., 2021. Conditional Yardstick Competition in Energy Regulation. *The Energy Journal*, 42(1_suppl), pp.1-26. <https://doi.org/10.5547/01956574.42.S12.tkuo>.

- Lee, L. and Yu, J., 2012. Spatial panels: random components versus fixed effects. *International Economic Review*, 53(4), pp.1369-1412. <https://doi.org/10.1111/j.1468-2354.2012.00724.x>.
- Li, N., Li, C., Zhou, J., Gao, Y., Hong, Y. and You, W., 2021. Investment Allocation for Medium-Voltage Distribution Networks Considering Investment Equilibrium and Benefits. *Electric Power*, 54(12), pp.143-149.
- Lu, J., Lin, W. and Dabić, M., 2024. Coevolution Analysis of the Sustainable Development Systems of Energy Firms From a Strategic Philanthropy Perspective. *IEEE Transactions on Engineering Management*, 71, pp.6887-6902. <https://doi.org/10.1109/TEM.2023.3244500>.
- Lu, J., Rong, D., Lev, B., Liang, M., Zhang, C. and Gao, Y., 2023. Constraints affecting the promotion of waste incineration power generation project in China: A perspective of improved technology acceptance model. *Technological Forecasting and Social Change*, 186, art. no. 122165. <https://doi.org/10.1016/j.techfore.2022.122165>.
- Pouralizadeh, M., 2020. A DEA model to sustainability improvement of the electricity supply chain in presence dual-role factors and undesirable outputs: a case on the power industry. *AIMS Energy*, 8(4), pp. 580-614. <https://doi.org/10.3934/energy.2020.4.580>.
- Salamaga, M., 2023. Study on the influence of foreign direct investment on innovations in enterprises in Poland using the ECM panel model. *Argumenta Oeconomica*, 50(1), pp.119-136. <https://doi.org/10.15611/aoe.2023.1.06>.
- Sengul, U., Eren, M., Shiraz, S. E., Gezder, V. and Sengul, A.B., 2015. Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. *Renewable Energy*, 75, pp. 617-625. <https://doi.org/10.1016/j.renene.2014.10.045>.
- Sha, Y., Li, W., Yan, J., Li, W. and Huang, X., 2021. Research on investment scale calculation and accurate management of power grid projects based on three-level strategy. *IEEE Access*, 9, pp. 67176-67185. <https://doi.org/10.1109/ACCESS.2021.3077481>.
- Tohid, F., Mohammad, R.J.O. and Sajad, N.R., 2020. Multi-objective modelling of day ahead scheduling of MMG-based distribution networks accompanied by DEA considering economics, emissions and power quality. *International Journal of Ambient Energy*, 41(5), pp. 588-599. <https://doi.org/10.1080/01430750.2018.1467310>.
- Wang, Q., Yang, X., Pu, D. and Fan, Y., 2022. Sustainable investment forecasting of power grids based on the deep restricted boltzmann machine optimized by the lion algorithm. *CMES-Computer Modeling in Engineering and Sciences*, 130(1), pp. 269-286. <https://doi.org/10.32604/cmes.2022.016437>.
- Wu, Y., Li, X., Zhang, L., Liu, C., Zhao, W. and Zhang, T., 2022. Machine learning driven deduction prediction methodology for power grid infrastructure investment and planning. *Frontiers in Energy Research*, 10, article no. 893492. <https://doi.org/10.3389/fenrg.2022.893492>.
- Xu, B., Ma, J., Liu, H., Chen, Q., Liu, J. and Hu, P., 2020. Investment allocation method based on distribution network evaluation. *Engineering Journal of Wuhan University*, 53(03), pp. 248-254. <https://link.cnki.net/doi/10.14188/j.1671-8844.2020-03-009>.
- Xu, X., Peng, L., Ji, Z., Zheng, S., Tian, Z. and Geng, S., 2021. Research on substation project cost prediction based on sparrow search algorithm optimized bp neural network. *Sustainability*, 13(24), article no. 13746. <https://doi.org/10.3390/su132413746>.

- Yager R.R., 1988. On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Trans on Systems Man and Cybernetics*, 18(1), pp. 183-190.
- Yan, J., 2019. Spatio temporal analysis for investment efficiency of China's rural water conservancy based on DEA model and Malmquist productivity index model. *Sustainable Computing, Informatics and Systems*, 21, pp. 56-71.
- Yilmaz, I., 2023. A Hybrid DEA-Fuzzy COPRAS Approach to the Evaluation of Renewable Energy: A Case of Wind Farms in Turkey. *Sustainability*, 15(14), article no. 11267. <https://doi.org/10.3390/su151411267>.
- Yu, S., Wu, Y., Wang, Z. and Zhang, M., 2017. Models and Strategies of Distribution Network Investment Allocation. *Power System and Clean Energy*, 33(12), pp. 28-36.
- Zafar, T., Zafar, K., Zafar, J. and Gibson, A., 2016. Integration of 750MW renewable solar power to national grid of pakistan – an economic and technical perspective. *Renewable and Sustainable Energy Reviews*, 59, pp. 1209-1219. <https://doi.org/10.1016/j.rser.2016.01.073>
- Zhang, Y., Chen, L., He, M., Pan, L., Yu, X., Li, Z., Zhang, T., Jiang, Z. and Hu, P., 2021. Investment optimization method of a distribution network based on shadow price and a spatial error panel data model. *Power System Protection and Control*, 49(04), pp. 133-140. <https://link.cnki.net/doi/10.19783/j.cnki.pspc.200575>.
- Zhou, X. and Wang, J., 2022. Panel semiparametric quantile regression neural network for electricity consumption forecasting. *Ecological Informatics*, 67. <https://doi.org/10.1016/j.ecoinf.2021.101489>.