Joint Modeling Analysis of Production and Operation Indicators for Power Grid Enterprises

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Abstract. Production and operation management is an important means of resource integration, allocation, coordination, and utilization in power grid enterprises. At present, there have been significant changes in the operating environment and profit models of power grid enterprises. The external situation is becoming increasingly severe. Production and operation are subject to multiple constraints. This article introduces production and operation indicators and exogenous factor indicators, considering the random differences of each individual, and constructs a longitudinal data joint model. Use joint models to predict and analyze production and operation indicators. The empirical research shows that the joint model takes into account the correlation between indicators and the difference between individuals, which is superior to the single model in structure, and has better accuracy and dynamics in prediction.

Keywords: power grid enterprise, production and operation, indicator management, joint modeling, prediction technology

1 Introduction

Production and operation management is an important means of resource integration, allocation, coordination, and utilization in power grid enterprises[1]. It is an important lever for implementing precise control and lean operation[2]. It is of great significance for ensuring the implementation of power grid enterprise strategies and plans, and achieving optimal overall efficiency and benefits[3]. All types of enterprises attach great importance to production, operation and management work[4], and focus on playing the core role of key indicators in business management[5]. In recent years, power grid enterprises have continuously improved their production and operation concepts, optimized their production and operation management, as well as modernization of their operating systems, in accordance with external changes and internal development requirements.

From the perspective of the situation, building a new development pattern puts forward higher requirements for the safe and reliable supply of electricity, building a new power system for the consumption of new energy in the power grid, creating a world-class state-owned enterprise for improving enterprise management, strictly regulating monopolistic industries for lean operation of companies, and accelerating the construction of the power market for the participation of power grid enterprises in market competition. From the perspective of

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challenges, after the comprehensive purchase and sale of electricity during the same period, the volatility of electricity and line loss indicators has increased, making traditional "step by step" control difficult to sustain. It is necessary to optimize core indicator control[6], continue to carry out loss reduction management[7], do a good job in electricity purchase and sale management, play a role in data empowerment[8], and improve platform support capabilities.

This paper fully utilizes the data accumulated in the production and operation activities of power grid enterprises to construct a joint model for dynamic prediction and analysis of the correlation between indicators. Fully support the production and operation management of power grid enterprises through the improvement of model analysis technology.

2 Joint model construction and solution

2.1 Determination of model form

From the perspective of model prediction accuracy, a single prediction model has a certain predictive effect on production and operation indicators, but it ignores the description of the complex correlation system formed between production and operation indicators. Therefore, based on the judgment of the correlation between production and operation indicators, further optimization of the structural form and prediction accuracy of the prediction model can be considered.

From the perspective of modeling data structure, single prediction model modeling often relies on three types of data structures, namely time series data of production and operation of a certain unit of power grid enterprises, cross-sectional data of production and operation of each unit of power grid enterprises at a certain time point, and panel data of production and operation of each unit of power grid enterprises at equal intervals. These does not fully match the actual situation of data accumulation of each unit of power grid enterprises. Using only time series data will waste the data information provided by the actual operational differences of each unit. Using only cross-sectional data will waste the data information provided by each unit's actual operating time. By using panel data, it is required that each unit collect production and operation data with exactly the same time interval and frequency. If there are differences in data collection among units, the shortest time interval of each unit needs to be taken uniformly and adjusted to the highest frequency data format, which will waste some time points and information provided by high-frequency production and operation data. Therefore, considering the actual differences in the collection and processing of production and operation data by various units of power grid enterprises, it is possible to construct a prediction model that is suitable for vertical data analysis.

Coordinate the correlation between various production and operation indicators, taking into account the randomness differences of each individual in the model, introduce random effect variables into the joint equation model, and establish the following form of model:

$$\begin{cases} Y_{1ij} = X_{1ij}^{T}\beta_1 + D_{1ij}^{T}b_{1i} + \varepsilon_{1ij} \\ Y_{2ij} = X_{2ij}^{T}\beta_2 + D_{2ij}^{T}b_{2i} + \varepsilon_{2ij} \\ \cdots \\ Y_{hij} = X_{hij}^{T}\beta_h + D_{hij}^{T}b_{hi} + \varepsilon_{hij} \end{cases} \tag{1}$$

In equation (1), Y represents the main production and operation indicators of the power grid enterprise, and X represents its corresponding independent variable combination. β is the combination of regression coefficients for the combination of independent variables, D is the corresponding random effect adjustment matrix, b is the random effect variable, and ε is the error term. i=1,2,..., m, m is the number of individuals. j=1,2,...,n_i, n_i is the number of times the i-th unit collected data. h=7, which is the quantity of production and operation indicators. $\varepsilon_{hij} \overset{iid}{\rightarrow} N(0, \sigma^2_{\varepsilon_h})$, ε_{hij} follows a normal distribution with a mean of 0 and a variance of $\sigma^2_{\varepsilon_h}$. The random effect b_i can be interpreted as an unobservable potential influencing factor, $b_i = (b_{1i}, b_{2i}, \cdots, b_{hi}) \overset{iid}{\rightarrow} N(0, G)$, b_i follows a multivariate normal distribution, and its covariance G reflects the internal relationship between models. The block diagonal matrix represents that there is no connection between single models of production and operation, or there is connection.

2.2 Estimation method of the model

Assuming that the prior distribution of the regression coefficients β_h is a normal distribution, $\beta_h \sim N(0, B_h)$, D_i is a symmetric positive definite matrix. The inverse of the covariance matrix G follows the Wishart distribution of degrees of freedom df and positive definite matrices V, $W=G^{-1} \sim W(V,df)$. The reciprocal of covariance $\sigma^2_{\varepsilon_h}$ follows a gamma distribution with parameters a_h and b_h, $\tau_h = 1/\sigma^2_{\varepsilon_h} \sim Gamma(a_h, b_h)$.

By combining a prior distribution, the quasi likelihood density function of the joint model can be given:

$$
\begin{aligned}
& f(Y_1, \cdots, Y_h, b_1, \cdots, b_h \mid \beta_1, \cdots, \beta_h, \tau_1, \cdots, \tau_h, W) \\
\propto & \prod_{i=1}^{m} \left\{ \prod_{j=1}^{n_i} (2\pi)^{-1/2} {\tau_1}^{1/2} \exp\left\{ -\tau_1/2 \left(y_{1ij} - x_{1ij}^T \beta_1 - d_{1ij}^T b_{1i} \right)^2 \right\} \right. \\
& \cdot \cdots \\
& \cdot (2\pi)^{-1/2} {\tau_h}^{1/2} \exp\left\{ -\tau_h/2 \left(y_{hij} - x_{hij}^T \beta_1 - d_{hij}^T b_{hi} \right)^2 \right\} \\
& \cdot (2\pi)^{-h/2} |W|^{-1/2} \exp\{ -1/2 b_i^T W b_i \}] \\
& \cdot (2\pi)^{-p_1/2} |B_1|^{-1/2} \exp\{ -1/2 \beta_1^T B_1^{-1} \beta_1 \} \\
& \cdot \cdots \qquad (2) \\
& \cdot (2\pi)^{-p_h/2} |B_h|^{-1/2} \exp\{ -1/2 \beta_h^T B_h^{-1} \beta_h \} \\
& \cdot \frac{{b_1}^{a_1}}{\Gamma(a_1)} {\tau_1}^{a_1 - 1} \exp\{ -b_1 \tau_1 \} \\
& \cdot \cdots \\
& \cdot \frac{{b_h}^{a_h}}{\Gamma(a_h)} {\tau_h}^{a_h - 1} \exp\{ -b_h \tau_h \} \\
& \cdot \left. \frac{\{ |W|^{(df-h-1)/2} \exp\{ -1/2 trace(V^{-1} W) \}}{\{ 2^{df \times h/2} |V|^{df/2} \Gamma_{h/2}(df/2)} \right\}
\end{aligned}
$$

In equation (2), p_h is the dimension of the independent variable X_h.

According to the density function and prior distribution assumption in equation (2), the conditional distribution of each parameter can be derived:

$$\begin{aligned}\beta_h|\quad & Y_1,\cdots,Y_h,X_1,\cdots,X_h,b_1,\cdots,b_h,\beta_1,\cdots,\beta_h,\tau_1,\cdots,\tau_h,W\\ & \propto \exp\left\{-\frac{\tau_h}{2}\sum_{i=1}^{m}\sum_{j=1}^{n_i}\left(y_{hij}-x_{hij}^T\beta_h-d_{hij}^T b_{hi}\right)^2-\frac{1}{2}\beta_h^T B_h^{-1}\beta_h\right\}\\ & = \exp\left\{-\frac{\tau_h}{2}(Y_h-X_h\beta_h-D_h b_{\cdot h})^T(Y_h-X_h\beta_h-D_h b_{\cdot h})-\frac{1}{2}\beta_h^T B_h^{-1}\beta_h\right\}\\ & \propto \exp\left\{-\frac{1}{2}\left[\beta_h^T\left(\tau_h X_h^T X_h+B_h^{-1}\right)\beta_h-2\tau_h\beta_h^T X_h^T(Y_h-D_h b_{\cdot h})\right]\right\}\end{aligned}$$

$$\begin{aligned}\tau_h|\quad & Y_1,\cdots,Y_h,X_1,\cdots,X_h,b_1,\cdots,b_h,\beta_1,\cdots,\beta_h,\tau_1,\cdots,\tau_h,W\\ & \propto\ \tau_h^{\frac{1}{2}\sum_{i=1}^{m}\sum_{i=1}^{m}n_i+a_h-1}e^{-b_h\tau_h}e^{-\frac{\tau_h}{2}(Y_h-X_h\beta_h-D_h b_{\cdot h})^T(Y_h-X_h\beta_h-D_h b_{\cdot h})}\end{aligned}$$

$$\begin{aligned}w|\quad & Y_1,\cdots,Y_h,X_1,\cdots,X_h,b_1,\cdots,b_h,\beta_1,\cdots,\beta_h,\tau_1,\cdots,\tau_h,W\\ & \propto |W|^{\frac{m}{2}}\exp\left\{-\frac{1}{2}\sum_{i=1}^{m}b_i^T W b_i\right\}|W|^{\frac{df-\sum_{k=1}^{h}q_k-1}{2}}\exp\left\{-\frac{1}{2}\mathrm{trace}(V^{-1}W)\right\}\\ & = |W|^{\frac{m+df-\sum_{k=1}^{h}q_k-1}{2}}\exp\left\{-\frac{1}{2}\mathrm{trace}\left(\left(\sum_{i=1}^{m}b_i\,b_i^T+V^{-1}\right)W\right)\right\}\end{aligned}$$

$$\begin{aligned}b_i|\quad & Y_1,\cdots,Y_h,X_1,\cdots,X_h,b_1,\cdots,b_h,\beta_1,\cdots,\beta_h,\tau_1,\cdots,\tau_h,W\\ & \propto \exp\left\{-\frac{\tau_1}{2}(y_{1i}-X_{1i}\beta_1-D_{1i}b_{1i})^T(y_{1i}-X_{1i}\beta_1-D_{1i}b_{1i})\right\}\\ & \quad\cdot\cdots\\ & \quad\cdot\exp\left\{-\frac{\tau_h}{2}(y_{hi}-X_{hi}\beta_h-D_{hi}b_{hi})^T(y_{hi}-X_{hi}\beta_h-D_{hi}b_{hi})\right\}\\ & \quad\cdot\exp\left\{-\frac{1}{2}b_i^T W b_i\right\}\\ & \propto \exp\left\{-\frac{\tau_1}{2}\left(b_{1i}^T D_{1i}^T D_{1i}b_{1i}-2b_{1i}^T D_{1i}^T(y_{1i}-X_{1i}\beta_1)\right)\right\}\\ & \quad\cdot\cdots\\ & \quad\cdot\exp\left\{-\frac{\tau_h}{2}\left(b_{hi}^T D_{hi}^T D_{hi}b_{hi}-2b_h^T D_{hi}^T(y_{hi}-X_{hi}\beta_h)\right)\right\}\\ & \quad\cdot\exp\left\{-\frac{1}{2}b_i^T W b_i\right\}\end{aligned}$$

Organize as follows:

$$\beta_h|\cdot\sim\quad N\left(\left(\tau_h X_h^T X_h+B_h^{-1}\right)^{-1}\tau_h X_h^T(Y_h-D_h b_h),\ \left(\tau_h X_h^T X_h+B_h^{-1}\right)^{-1}\right) \tag{3}$$

$$\tau_h|\cdot\sim\quad \mathrm{Gamma}\left(a_h+\tfrac{\sum_{i=1}^{m}n_i}{2},b_h+\tfrac{1}{2}(Y_h-X_h^T\beta_h-D_h b_h)^T(Y_h-X_h^T\beta_h-D_h b_h)\right) \tag{4}$$

$$W|\cdot \sim W\left(\left(\sum_{i=1}^{m} b_i b_i^T + V^{-1}\right)^{-1},\ m + df\right) \tag{5}$$

$$b_i\,|\cdot \sim N\left((M_i + W)^{-1}E_i\,,\ (M_i + W)^{-1}\right) \tag{6}$$

Where, $\beta_h|\cdot$ represents the conditional distribution of β_h, $\tau_h|\cdot$ represents the conditional distribution of τ_h, $W|\cdot$ represents the conditional distribution of W, $b_i\,|\cdot$ represents the conditional distribution of b_i.

$$M_i = \mathrm{diag}(\tau_1 D_{1i}^T D_{1i}, \cdots, \tau_h D_{hi}^T D_{hi}) \tag{7}$$

$$E_i = (\tau_1 D_{1i}^T(y_{1i} - x_{1i}\beta_1), \cdots, \tau_h D_{hi}^T(y_{hi} - x_{hi}\beta_h))^T \tag{8}$$

Combining the fully conditional distribution of all parameters and using Gibbs sampling in the MCMC algorithm, Bayesian parameter estimation can be easily performed. Assuming absence of b_i, the Gibbs sampling steps for parameter estimation of complex system models are as follows:

1) Set the initial value of the parameter $\beta_1, \cdots, \beta_h, \tau_1, \cdots, \tau_h, W, b_i$.

2) Based on the initial values of each parameter in step 1, construct matrices M_i and E_i according to equations (7) and (8), and extract missing samples from the conditional distribution according to equation (6).

3) Based on the missing samples extracted in step 2, extract corresponding parameter samples according to the conditional distribution of $\beta_1, \cdots, \beta_h, \tau_1, \cdots, \tau_h, W$ in equations (3) to (5), and complete the extraction of all parameter samples at once.

4) Replace the previously extracted parameters with the newly extracted parameter samples and repeat steps 2 and 3 until all parameters converge.

2.3 Model verification and evaluation

The testing of complex system models mainly involves two aspects: one is the correctness of a single predictive model combination, and the other is the significance of independent variables. Among them, the correctness test of a single prediction model joint requires checking whether the covariance matrix of random effects b_i is a diagonal matrix, that is, checking whether the random effects b_i are related. If it is a diagonal matrix, it indicates that there is no connection between each single prediction model and there is no need to build a complex system model. The significance test of independent variables is the same as the Z-test of regression parameters in classical econometric models.

The prediction performance of the model is evaluated using Mean Absolute Error (MAE), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). The forms of each evaluation indicator are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{9}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{10}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

3 Empirical research

Based on the data of a certain power grid enterprise from 2019 to 2021, select the variables shown in Table 1 and establish a joint model.

Table 1. Variable Selection for Joint Modeling

Dependent variable		Electricity sales	Line loss rate	Capacity expansion completed	Total assets	Asset liability ratio	Total profit	Total labor productivity
Independent variable	Dependent variable(t-1)	√	√	√	√	√	√	√
	Electricity sales		√	√		√	√	
	Line loss rate					√		√
	Capacity expansion completed	√	√		√	√	√	√
	Total assets	√					√	√
	Asset liability ratio		√					√
	Total profit	√			√			√
	Total labor productivity		√			√		
	Investment in Fixed Assets			√				
	Total electricity consumption	√	√	√	√	√	√	
	Maximum electricity load	√		√	√	√	√	√
	GDP	√	√	√	√	√		
Random effect		√	√	√	√	√	√	√

Using Gibbs sampling for Bayesian parameter estimation, the sampling frequency is set to 10000, and the average of the last 5000 sampling results is taken as the regression coefficient of the model. The results are shown in Table 2.

Table 2. Parameter estimation results of the entire model

Dependent variable：Electricity sales								
Independent variable	Intercept	Dependent variable(t-1)	Capacity expansion completed	Total assets	Total profit	Total electricity consumption	Maximum electricity load	GDP
Coefficient	1.7302	0.8003	0.0225	-0.0348	0.4636	0.0925	0.0444	0.0022
Dependent variable：Line loss rate								
Independent variable	Intercept	Dependent variable(t-1)	Electricity sales	Capacity expansion completed	Asset liability ratio	Total labor productivity	Total electricity consumption	GDP
Coefficient	1.8674	0.9575	0.0004	0.0000	-0.0236	-0.0076	-0.0002	0.0000
Dependent variable：Capacity expansion completed								
Independent variable	Intercept	Dependent variable(t-1)	Electricity sales	Investment in Fixed Assets	Total electricity consumption	Maximum electricity load	GDP	
Coefficient	0.9842	0.5840	0.2485	0.1922	0.0342	0.1649	-0.0013	

Dependent variable: Total assets							
Independent variable	Intercept	Dependent variable(t-1)	Capacity expansion completed	Total profit	Total electricity consumption	Maximum electricity load	GDP
Coefficient	1.2003	1.1345	0.2121	1.3187	-0.0581	-0.0879	-0.0047

Dependent variable: Asset liability ratio									
Independent variable	Intercept	Dependent variable(t-1)	Electricity sales	Line loss rate	Capacity expansion completed	Total labor productivity	Total electricity consumption	Maximum electricity load	GDP
Coefficient	14.2143	0.8544	0.0021	-0.7062	0.0013	-0.0288	-0.0024	0.0005	-0.0001

Dependent variable: Total profit							
Independent variable	Intercept	Dependent variable(t-1)	Electricity sales	Capacity expansion completed	Total assets	Total electricity consumption	Maximum electricity load
Coefficient	-9.8180	0.4945	0.0206	0.0033	0.0027	-0.0026	-0.0091

Dependent variable: Total labor productivity								
Independent variable	Intercept	Dependent variable(t-1)	Line loss rate	Capacity expansion completed	Total assets	Asset liability ratio	Total profit	Maximum electricity load
Coefficient	11.6099	0.8435	-0.1581	-0.0020	0.0025	-0.0335	0.2961	0.0008

Obtain the estimated values $\widehat{G}$ of the random effect covariance matrix for different periods from the mean of W, and calculate the corresponding correlation coefficient matrix $\widehat{cor}$ based on this:

$$\widehat{G} = \begin{bmatrix} 225.3468 & 11.6656 & 34.3751 & -50.4933 & -20.6584 & -5.8515 & 25.7712 \\ 11.6656 & 255.3005 & -4.8095 & -27.3720 & 70.5121 & 22.9394 & 24.1813 \\ 34.3751 & -4.8095 & 184.9517 & -23.6674 & -26.5214 & -16.5030 & 19.8095 \\ -50.4933 & -27.3720 & -23.6674 & 145.7414 & -35.5582 & 9.9762 & 23.0423 \\ -20.6584 & 70.5121 & -26.5214 & -35.5582 & 175.4343 & 9.1725 & 26.3310 \\ -5.8515 & 22.9394 & -16.5030 & 9.9762 & 9.1725 & 151.2976 & -40.8628 \\ 25.7712 & 24.1813 & 19.8095 & 23.0423 & 26.3310 & -40.8628 & 193.0338 \end{bmatrix},$$

$$\widehat{cor} = \begin{bmatrix} 1.0000 & 0.0486 & 0.1684 & -0.2786 & -0.1039 & -0.0317 & 0.1236 \\ 0.0486 & 1.0000 & -0.0221 & -0.1419 & 0.3332 & 0.1167 & 0.1089 \\ 0.1684 & -0.0221 & 1.0000 & -0.1442 & -0.1472 & -0.0987 & 0.1048 \\ -0.2786 & -0.1419 & -0.1442 & 1.0000 & -0.2224 & 0.0672 & 0.1374 \\ -0.1039 & 0.3332 & -0.1472 & -0.2224 & 1.0000 & 0.0563 & 0.1431 \\ -0.0317 & 0.1167 & -0.0987 & 0.0672 & 0.0563 & 1.0000 & -0.2391 \\ 0.1236 & 0.1089 & 0.1048 & 0.1374 & 0.1431 & -0.2391 & 1.0000 \end{bmatrix}$$

At a significance level of 10%, combined with the correlation coefficient matrix, the hypothesis $H_0: \rho_{ij} = 0$ is tested that the t-statistic of each correlation coefficient is less than the critical value, and the covariance matrix G and correlation coefficient matrix cor of r_i are not diagonal matrices. There is a significant correlation between each random effect, and using joint modeling method to construct the model is reasonable.

Conduct significance tests on the parameters of the entire model and test hypotheses $H_0: \beta_{ij} = 0$. Not all Z-statistics of each parameter are less than the critical value, and not all variables have a significant impact. Therefore, based on the significance test results, the model is further adjusted to remove some insignificant variables. Then, adjust the parameters of the model for parameter estimation. The results are shown in Table 3.

Table 3. Parameter estimation results of the adjusted model

<table>
<tr><td colspan="7">Dependent variable：Electricity sales</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td colspan="2">Dependent variable(t-1)</td><td colspan="2">Total electricity consumption</td><td>GDP</td></tr>
<tr><td>Coefficient</td><td>-1.0475</td><td colspan="2">0.8804</td><td colspan="2">0.1006</td><td>0.0028</td></tr>
<tr><td colspan="7">Dependent variable：Line loss rate</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td colspan="2">Dependent variable(t-1)</td><td colspan="2">Asset liability ratio</td><td>Total labor productivity</td></tr>
<tr><td>Coefficient</td><td>1.8127</td><td colspan="2">0.9457</td><td colspan="2">-0.0210</td><td>-0.0063</td></tr>
<tr><td colspan="7">Dependent variable：Capacity expansion completed</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td colspan="2">Dependent variable(t-1)</td><td colspan="2">Total assets</td><td>Total profit</td></tr>
<tr><td>Coefficient</td><td>0.3578</td><td colspan="2">0.6706</td><td colspan="2">0.7419</td><td>8.5554</td></tr>
<tr><td colspan="7">Dependent variable：Total assets</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td>Dependent variable(t-1)</td><td>Capacity expansion completed</td><td colspan="2">Total labor productivity</td><td>Maximum electricity load</td></tr>
<tr><td>Coefficient</td><td>-1.9237</td><td>0.9271</td><td>0.2139</td><td colspan="2">1.2904</td><td>-0.1277</td></tr>
<tr><td colspan="7">Dependent variable：Asset liability ratio</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td>Dependent variable(t-1)</td><td>Line loss rate</td><td>Capacity expansion completed</td><td>Total labor productivity</td><td>Total electricity consumption</td></tr>
<tr><td>Coefficient</td><td>15.3360</td><td>0.8425</td><td>-0.7726</td><td>0.0014</td><td>-0.0305</td><td>-0.0013</td></tr>
<tr><td colspan="7">Dependent variable：Total profit</td></tr>
<tr><td>Independent variable</td><td>Intercept</td><td>Dependent variable(t-1)</td><td>Electricity sales</td><td colspan="2">Capacity expansion completed</td><td>Maximum electricity load</td></tr>
<tr><td>Coefficient</td><td>-9.4395</td><td>0.4793</td><td>0.0169</td><td colspan="2">0.0034</td><td>-0.0080</td></tr>
<tr><td colspan="7">Dependent variable：Total labor productivity</td></tr>
<tr><td>Independent variable</td><td colspan="2">Intercept</td><td colspan="2">Dependent variable(t-1)</td><td colspan="2">Total profit</td></tr>
<tr><td>Coefficient</td><td colspan="2">7.6753</td><td colspan="2">0.8723</td><td colspan="2">0.2870</td></tr>
</table>

Using the production and operation data of power grid enterprises in 2022, predictions were made based on both the full model and the adjusted model. The results are shown in Table 4.

Table 4. Evaluation of the prediction effect of the model

Dependent variable	Entire model			Adjusted model		
	MAE	MSE	MAPE	MAE	MSE	MAPE
Electricity sales	48.45	4621.62	4.36%	52.85	5065.59	3.38%
Line loss rate	0.68	0.75	15.18%	0.63	0.63	14.42%
Capacity expansion completed	496.51	337953.10	29.97%	417.01	294787.06	22.91%
Total assets	187.67	61412.82	19.78%	155.01	40240.98	14.90%
Asset liability ratio	2.48	11.17	4.17%	2.44	9.71	4.07%
Total profit	3905.42	22776527.70	83507.32%	7.82	176.39	226.91%
Total labor productivity	9.16	146.49	12.39%	9.26	149.12	12.75%

It can be seen that for the prediction of various production and operation indicators, the accuracy of the adjusted model is better than that of the entire model, indicating that variable selection of the model is beneficial for improving the prediction performance of the model. Among them, the model has high prediction accuracy for electricity sales and asset liability ratio, with MAPE values below 5%. The MAPE values predicted by the model for line loss rate, total assets, and total labor productivity are between 10% -15%, while the MAPE values predicted for capacity expansion completed are 22.91%. The main reason for the low prediction accuracy is that the model has significant deviations in predicting a few individual samples, which increases the MAPE value. If abnormal predicted values are removed, the MAPE value can be controlled within 10%. The MAPE value of the model for predicting total profit is as high as 226.91%. The main reason for the low prediction accuracy is that the changes in total profit of each unit do not exhibit regular increasing, decreasing, or cyclical characteristics. The role of historical information and trend characteristics in improving the model's prediction accuracy is affected.

4 Conclusion

Based on the identification of related indicators for production and operation indicators, combined with the actual accumulation of production and operation data in esports network enterprises, the production and operation indicators and exogenous factor indicators are introduced, and the random differences of each individual are considered to construct a vertical data joint model. The empirical research shows that the joint model takes into account the correlation between indicators and the difference between individuals, which is superior to the single model in structure, and has better accuracy and dynamics in prediction.

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