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Electricity price risk management based on insurance and weather derivatives

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Abstract: In view of the risk of electricity price fluctuation in power enterprises under typhoon weather, a single risk management method is insufficient. Based on the Japanese JEPX market data from 2018 to 2023, the PSO-LSSVM model is proposed to combine insurance and weather derivatives to form a comprehensive hedging strategy, which significantly improves the risk management effect compared with a single means. The insurance hedging effect is increased by 10%, and the weather derivatives strategy effect is increased by 25%. These findings provide an efficient and comprehensive solution to the risk of electricity price fluctuation for power enterprises, and enrich the practical strategy of risk management in power market.

Keywords: Weather Derivatives; Insurance; PSO-LSSVM; Electrovalency; Risk Management

Introduction

Under frequent typhoons, power enterprises need to deal with the risk of large fluctuations in electricity prices. As the core of electricity trading, enterprises need to build a comprehensive price risk management mechanism. This includes anticipating the impact of electricity price fluctuations on revenue and diversifying strategies such as leveraging weather derivatives and insurance products to ensure long-term sound operations. Yamada Y[1] et al. combined energy and weather derivatives to verify their positive role in power trading risk hedging. Lai S [2]et al. designed catastrophe insurance and proved its effectiveness in protecting against natural disaster power trading risks. Zhang Z[3] et al. proposed deviation mutual insurance to effectively reduce the risk of energy deviation cost for retailers. At present, the single risk management method is effective, but the joint application strategy needs further study.

This paper explores the combination of insurance and weather derivatives to hedge the risk of electricity price fluctuations, especially typhoon effects. In view of the immaturity of the Chinese market, this paper analyzes the data of JEPX Tokyo Bay from 2018 to 2023 by using PSO-LSSVM model to provide a new perspective for price risk management

1. Typhoon Insurance

In order to avoid the risk, this paper introduces typhoon insurance[2]with definite deductible for power enterprises to hedge the fluctuation of electricity price.

1) Typhoon insurance loss calculation, total loss L= loss value y× risk occurrence probability $Pr(y)$ [4].

$$L = \int_0^{+\infty} yPr(y)dy \tag{1}$$

2) The loss cost of power enterprises under typhoon is the total loss C_{EE}, that is, in the typhoon duration EEP, C_{EE} is equal to the loss value multiplied by the loss probability P_{EE}.

$$C_{EE} = \sum^{EEP}(L \times P_{EE}) \tag{2}$$

3) The power enterprise's income R_{Ins} is the product of the difference between the insured quantity X_{Ins} and the compensation amount (loss cost C_{EE} - excess exc_{Ins}).

$$R_{Ins} = W_{Ins} \times X_{Ins} \times (C_{EE} - exc_{Ins}) \tag{3}$$

$$W_{Ins} = \begin{cases} 1, L > exc_{Ins} \\ 0, L < exc_{Ins} \end{cases} \tag{4}$$

4) Typhoon insurance cost C_{Ins} is the product of insurance unit price λ_{Ins} and quantity X_{Ins} .

$$C_{Ins} = X_{Ins} \times \lambda_{Ins} \tag{5}$$

$$\lambda_{Ins} = E\left[W_{Ins} \times \left(\sum^{EEP}(L \times P_{EE} - exc_{Ins})\right)\right] \times (1 + \psi_{Ins}) \tag{6}$$

$$\psi_{Ins} = \frac{\sigma\left[\left(\sum^{EEP}(L \times P_{EE}) - exc_{Ins}\right)\right]}{E\left[\left(\sum^{EEP}(L \times P_{EE}) - exc_{Ins}\right)\right]} \tag{7}$$

Here ψ_{Ins} is the net written premium surplus as a ratio of its standard deviation to the expected payout[2].

In modeling, the GAM model in reference [1] is difficult to evaluate the parameter confidence, which limits the analysis of complex data. In this paper, PSO-LSSVM combined with PSO efficient search and LSSVM modeling advantages to simplify reference and improve performance, combined with insurance and weather derivatives to hedge the risk of price fluctuations. The modeling process of GAM and PSO-LSSVM is described as follows:

2. GAM model

n literature [1], a GAM model based on international crude oil price (WTI) P_w was constructed, and two weather derivatives, solar radiation prediction error ($\varepsilon_{R,t}$ = measured value R_t -predicted value $f_R(t)$) and temperature prediction error ($\varepsilon_{T,t}$ = measured value T_t -predicted value $f_T(t)$), were taken into account to analyze their impact on corporate income under the fluctuation of electricity price. Set the electricity price per hour on day t to $S_{t,h}$ and the output power to $V_{t,h}$, then the sales revenue is $\pi_t = \sum_h S_{t,h} \times V_{t,h}$. The GAM model can be expressed as:

$$\pi_t = f(t) + \beta(t)P_w + \gamma_1(t)\varepsilon_{R,t} + \gamma_2(t)\varepsilon_{T,t} + \eta_t \tag{8}$$

Where π_t is the sales revenue on day t and η_t is the residual term with a mean of 0. $f(t)$, $\beta(t)$, $\gamma_1(t)$ is the smooth spline function of the model, which can be obtained by $\min\sum_{t=1}^{N}\{\eta_t\}^2$ optimizing the solution of the pair.

This paper intends to use typhoon insurance to hedge electricity price fluctuation risk on the basis of weather derivatives. The constructed GAM model is described as follows:

$$\pi_t = f(t) + \beta(t)P_w + \gamma_1(t)\varepsilon_{R,t} + \gamma_2(t)\varepsilon_{T,t} + \gamma_3(t)R_{Ins} + \eta_t \tag{9}$$

Where $\gamma_3(t)$ is the spline function estimated by formula (9).

This paper intends to choose VRR as the measurement tool of risk hedging effect. “1-VRR” is called “hedging effect” [1] The formula is shown in (10).

$$VRR = \frac{Var[hedge\ error\ of\ the\ target\ model]}{Var[hedge\ error\ of\ the\ base\ model]} \tag{10}$$

3. PSO-LSSVM model

3.1 LSSVM model

Least square support vector Machine (LSSVM) has the advantages of less computation, simple structure and high precision of regression fitting. The regression principle of the LSSVM model is as follows:

1) Data input, for a given training dataset $\{(x_i, y_i)\}_{i=1}^{N}$, the LSSVM model can be expressed as:

$$y(x) = w^T\phi(x_i) + b \tag{11}$$

Among them, x_i is the input data of the model, y_i is the output data, w is the weight vector, b is the bias term, $\phi(x_i)$ is a nonlinear mapping function.

2) Minimize the loss function.

$$J(w,e)=1/2\,w^T w+1/2\,\gamma\sum_{i=1}^{N}e_i^2 \qquad (12)$$

Where, e_i is the error between the predicted value $y(x_i)$ and the actual value y_i, γ is a regularization parameter to prevent overfitting. At the same time, formula (12) also needs to meet the following constraints:

$$y_i=w^T\phi(x_i)+b+e_i,\quad i=1,2,\dots,N \qquad (13)$$

3) Optimization of LSSVM model. Substitute (13) into (12) and introduce the Lagrange multiplier $\alpha_i=[\alpha_1,\alpha_2,\dots,\alpha_N]^{\mathrm{T}}$,formula (14) is obtained:

$$L(w,b,e,\alpha)=J(w,e)-\sum_{i=1}^{N}\alpha_i(y_i(w^T\phi(x_i)+b)+e_i-1) \qquad (14)$$

The partial derivative with respect to w,b,e formula (14) is obtained and set to 0, and the optimization problem is transformed into the solution of linear equations. According to Mercer condition, kernel function $K(x_i,x_j)=\phi(x_i)^{\mathrm{T}}\cdot\phi(x_j)$ is introduced into linear equations to obtain:

$$\begin{bmatrix} 0 & y_1 & N & y_n \\ y_1 & y_1y_1K(x_1,x_n)+2/\gamma & N & y_1y_nK(x_1,x_n) \\ M & M & O & M \\ y_n & y_1y_1K(x_1,x_n) & N & y_1y_nK(x_1,x_n)+2/\gamma \end{bmatrix}\begin{bmatrix} b \\ \alpha_1 \\ M \\ \alpha_n \end{bmatrix}=\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \qquad (15)$$

In order to improve the prediction accuracy of the model, the radial basis kernel function with better generalization ability is adopted in this paper, and its expression is as follows:

$$K(x_i,x_j)=\exp\left(-\|x_i-x_j\|^2/2\sigma^2\right) \qquad (16)$$

4) Using the least square method to solve the above equations, the regression model of LSSVM is obtained as follows:

$$y(x)=\sum_{i=1}^{N}\alpha_iK(x_i,x_j)+b \qquad (17)$$

3.2 Establishment of PSO-LSSVM model

Particle swarm PSO algorithm [5]-[6] adjusts the particle optimization by simulating the predation behavior of birds. In order to improve the accuracy of prediction, this paper uses the PSO-optimized LSSVM model. The specific modeling process is as follows:

1) Data preprocessing normalizes the input $\varepsilon_{R,t}$, $\varepsilon_{T,t}$, R_{Ins} data, and data of the model.

2)The position and velocity of the initializing particle swarm $X_i=\left(x_i^1,x_i^2,\dots,x_i^d\right)$, $V_i=\left(v_i^1,v_i^2,\dots,v_i^d\right)$, d is the particle population size, and i is the particle index. Set PSO algorithm parameters. The population size is 365, the maximum number of iterations is 1800, the inertia weight is set as a decreasing mode, and its range is 0.4-0.9.

3) The errors e_i and regularization parameters γ of the LSSVM model are taken as optimization targets, and the initial fitness $f(pbest_i)$ is calculated.

4) Update particle position and velocity.

$$v_i^d(t+1)=wv_i^d(t)+c_1r_1(pbest_i^d-x_i^d(t))+c_2r_2(gbest^d-x_i^d(t)) \qquad (18)$$

$$x_i^d(t+1)=x_i^d(t)+v_i^d(t+1) \qquad (19)$$

5) If i make $f(X_i(t+1))<f(pbest_i)$, update $pbest_i=X_i(t+1)$; Similar, if $f(pbest_i)<f(gbest)$, update $gbest=pbest_i$.

6) Determine whether the requirements are met or the maximum number of iterations is reached.

7) Output result: Output the optimized LSSVM parameters and train the predicted output π_t .

4. Case analysis

This paper selects Japan JEPX Tokyo Bay electricity price data from 2018 to 2023, trains PSO-LSSVM in the first four years, and forecasts in the last year. Combined with insurance and weather derivatives (solar radiation, temperature and other derivatives), typhoon losses were assessed with reference to global disaster data, and electricity price fluctuations were predicted by modeling.

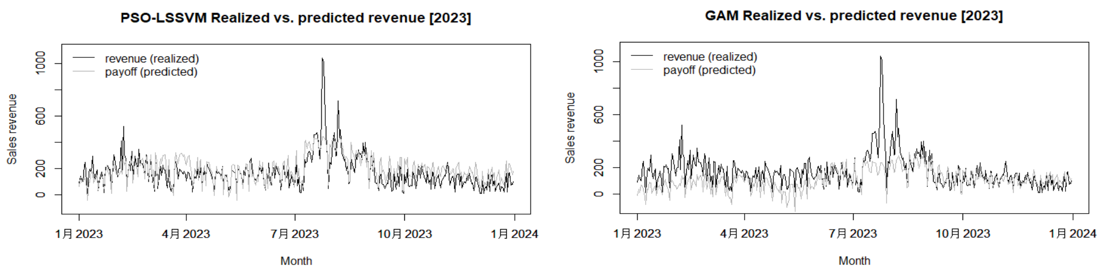

Fig.1 Plot of prediction results of PSO-LSSVM model

Figure 1 shows the prediction results of GAM and PSO-LSSVM. The comparison shows that PSO-LSSVM is more consistent with the actual data and has lower error (see Table 1). It is proved that PSO-LSSVM is more accurate and reliable in predicting electricity price fluctuation.

Tab. 1 Model error comparison

年份	RMSE		MAPE	
	GAM	PSO-LSSVM	GAM	PSO-LSSVM
2023	0.0917	0.0832	0.0681	0.0603

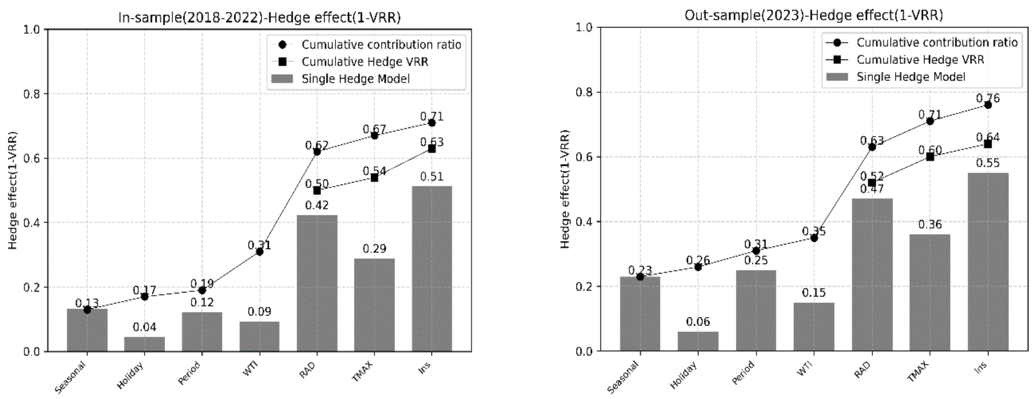

Fig.2 (PSO-LSSVM) Cumulative contribution rate and hedging effect inside (left) and outside (right) the sample

Figure 2 shows the cumulative effect of the combination of PSO-LSSVM with RAD, TMAX and Ins to hedge electricity price risk inside and outside the sample. The bar chart shows the single hedging effect, and the cumulative hedging increases significantly after the gradual introduction of the line chart.

From the perspective of cumulative hedging effect, the combined use of insurance and weather derivatives in the sample reached 0.63, far exceeding the single RAD (0.42), TMAX (0.29) or insurance (0.51), which increased by 0.21, 0.34 and 0.12 respectively. It is also better outside the sample, with a score of 0.64, which is significantly higher than that of a single measure.

The cumulative contribution rate increases steadily, strengthens the effectiveness of the joint hedging strategy to reduce the risk of electricity price fluctuations, proves that the integration of insurance and weather derivatives resources can comprehensively manage the risk of electricity price, and improves the operational robustness and market competitiveness of power enterprises。

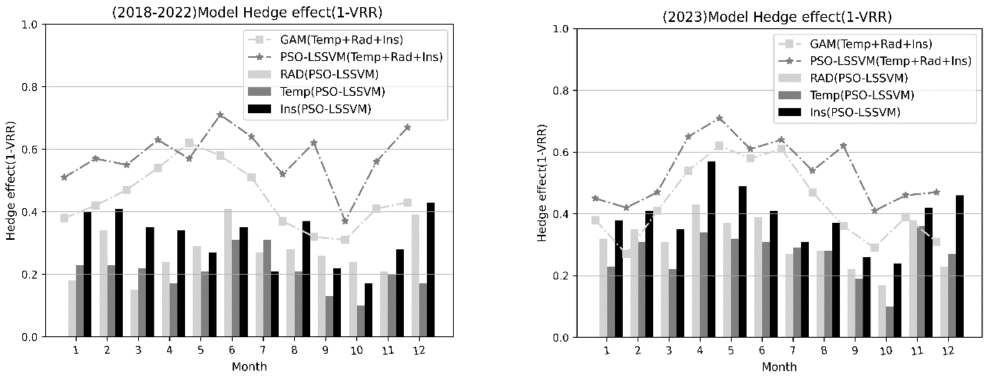

Fig.3 In-sample (left) out-sample (right) monthly hedging effect

Figure 3 shows the monthly hedging effect inside and outside the sample. The broken line is the combined hedging of insurance + weather derivatives, and the bar is the single derivative or single insurance hedging under PSO-LSSVM.

The line chart shows that in most months, the PSO-LSSVM and GAM models, combined with weather derivatives and insurance, effectively hedge the risk of price fluctuations. In particular, the PSO-LSSVM model performed better in most months, highlighting its significant advantages in forecasting and risk management.

5. Conclusion

In summary, the electricity price risk management method combined with insurance and weather derivatives shows good hedging effect both inside and outside the sample, and the PSO-LSSVM model is effective in forecasting and risk management.

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