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Economic Impact Evaluation of Short-Term Load Forecast Errors Using A Mutative Scale Chaos Optimization Algorithm

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Abstract: -Under the circumstances of Power Market, load forecast errors directly lead to the increase of costs of dispatch and maintenance. With a mutative scale chaos optimization algorithm (MSCOA), and the next-day units bidding model as the valuation model for economy of load forecast errors, this paper quantitatively analyzes the influence of load forecast errors on the marginal prices and purchase costs of the grid. Computations give results with practical meanings: losses caused by negative load errors are larger than those caused by positive ones. The algorithm put forward is of fine convergence.

Key Words: -Power Market, Load Forecast Error, MSCOA

1 Introduction

Under the circumstances of Power Market, as biddings and dispatches of the grid rely on short-term load forecasts, the level of load forecast plays an important role in the economy of the grid, and load forecast errors will lead to the increase in dispatch and maintenance costs [1]-[6]. When load forecasts are on the high sides: excessive generators are started, costs for fuels and maintenance increase; too much expensive energy is bought, or a profitable chance to sell bulky power; hydroelectricity is not generated when it is of the most value; too expensive real-time prices occur, which lead to sag of buying market or unnecessary load limitation. When load forecasts are on the low sides: the safety restrictions of the grid can not be met; in order to satisfy unexpected load demands, units generate uneconomically, or expensive real-time energy is bought, and hence load interferences and limitations are caused; too cheap real-time price results in decreased income, et al. Therefore, how to appropriately evaluate the influence of load forecast error on economy of the grid is an essential problem for electric power corporation. Aiming at a certain power market in East China, with a mutative scale chaos optimization algorithm, and the next-day units bidding model as the economic valuation model of load forecast errors, this paper gives a quantitative analysis of the influence of load forecast errors on grid marginal and clearing prices and gives results with practical meanings.

2 Economic Evaluating Modeling of Load Forecasting Error and Algorithm

2.1 Economic Evaluating Modeling of Load Forecasting Error Margin

The objective function is to minimize the power purchase cost next day, that is

$$\min\left\{\sum_{t=1}^{T}\left[C_t L_t+\sum_{i\in G}\left[S_i(t)+H_i(t)\right]\right]\right\} \qquad (1)$$

where C_t is the system bargain price, $t=1,2,\cdots T$. T is the total bargaining period of time in one day. G is the total numbers of available generators. L_t is the grid load demand at t period. $S_i(t)$、$H_i(t)$ represent respectively the start cost and halt cost of generator i.

Constraint conditions:

(1) Active power balances

$$\sum_{i\in G} I_{t,i}P_{t,i} = L_t + P_{t,loss}$$

(2) Reserve limits

$$\sum_{i\in G} I_{t,i}P_{\max,i} \ge L_t + P_{t,loss} + R_t$$

(3) Line transfer capability limits

$$\left|X_{t,i}\right| \le \left|X_{\max,i}\right|$$

(4) Voltage limits

$$\overline{U}_{\min} \le \overline{U}_t \le \overline{U}_{\max}$$

(5) Power change limits

$$\left|\Delta P_{t,i}\right| \le \left|\Delta P_{\max,i}\right|$$

(6) The minimum running time and halting time limits

$$UT_{t,i} \ge UT_{\min,i}$$

$$DT_{t,i} \ge DT_{\min,i}$$

(7) Power generating limits

$$I_{t,i}P_{\min,i} \le P_{t,i} \le I_{t,i}P_{\max,i}$$

Where,

$I_{t,i}$ is the state of unit i at t period,1 and 0 indicate respectively unit is on and off;

$P_{t,i}$ is generating power of unit i at t period;

$P_{t,loss}$ is the system losses in t period;

R_t is reserve power at t period;

$P_{\max,i}$ and $P_{\min,i}$ are the minimum and maximum active power output genertated by unit i;

$X_{t,i}$ and $X_{\max,i}$ are the active power flow and transmission limits respectively;

$\overline{U}_{\min}$、$\overline{U}_t$、$\overline{U}_{\max}$ are the allowable minimum voltage ,voltage and maximum voltage at t period of unit i respectively;

$\left|\Delta P_{t,i}\right|$、$\left|\Delta P_{\max,i}\right|$ are the output change relative to last one period and the maximum allowable value at t period of unit i respectively;

$UT_{t,i}$、$UT_{\min,i}$ are the on time and the minimum allowable on time at t period of unit i respectively;

$DT_{t,i}$、$DT_{\min,i}$ are the off time and the minimum allowable off time at t period of unit i respectively;

Recently, there are many solutions to such model, such as priority method, dynamic programming, mixed-integer programming, branch-and-bound method, linear programming, lagrangian relaxation, simulated annealing algorithm and so on[7]-[8]. This paper adopts a mutative scale chaotic optimal algorithm to analyse economic loss due to load forecasting error margin[9].

2.2 Mutative Scale Chaos Optimization Algorithm (MSCOA)

The above problem can be defined mathematically as:

$$\begin{cases} \min \quad f(x,u) \\ s.t \quad g(x,u)=0 \\ \qquad h(x,u)\le 0 \end{cases} \tag{2}$$

Where u defines system controllable variables and x defines state variables; $f(x,u)$ defines objective function, $g(x,u)$ defines equality constraints and $h(x,u)$ defines inequality constraints.

The equation(2) changed into such forms demanded by chaotic optimal through non-differentiable precise penalty function:

$$\begin{cases} \min \quad p(x,u) = f(x,u) + \lambda \sum_{i=1}^{m} \max(0, h_i(x,u)) \\ s.t \quad u_{i,\min} \le u_i \le u_{i,\max} \quad i = 1,2,\cdots,n \end{cases} \tag{3}$$

Where λ is the penalty parameter of inequality constraint; m is the set of inequality constraints, and n is the set of controllable variables.

Because chaotic activity has many characteristics, such as catholicity, randomicity discipline and so on, chaotic activity can reach all the states non-repeatedly in some extent and jump out of partial optimal according to its own discipline, undoubtedly using such characteristics to search is superior to search random. Traditional chaotic optimal method is effective to small search range, but it is not so effective to large search range, the variable scale chaotic method can solve such problem effectively.

Considering Logistic mapping:

$$x_{n+1} = \mu x_n (1 - x_n) \tag{4}$$

Where μ is the controllable parameter, $x_n(0) \in [0,1]$.

When μ equals 4, syetem is in complete chaotic state, for any *n* initial values which have slight differences, we can get *n* chaotic variables which have different tracks.

The basic steps using variable chaotic optimization are as following:

Step1: initialization:

Assume the chaotic variable iterative marks as follows

$k = 1$, $k^{'} = 1$, $x_i(k) = x_i(0)$, $x^*{}_i = x_i(0)$, $f^* = f(0)$, $a_i(k^{'}) = a_i$, $b_i(k^{'}) = b_i$.

Step2: map the chaotic variable $x_i(k)$ to the range zone of optimal variable

$$\bar{x}_i(k) = a_i(k^{'}) + x_i(k)(b_i(k^{'}) - a_i(k^{'}))$$

Step3: search by chaotic variable

If $f(\bar{x}_i(k)) < f^*$, then $f^* = f(\bar{x}_i(k))$, $x_i^* = x_i(k)$

Otherwise continue.

Step 4: $k := k+1$ $x_i(k) := 4x_i(k)(1 - x_i(k))$.

Step 5: repeat step2 to step 4 until f^* remains unchangeable in some steps, go on next steps.

Step 6: make variable scale search in following way in order to minish search range

$$a_i(k^{'}+1) = \bar{x}^*{}_i(k) - \delta(b_i(k^{'}) - a_i(k^{'}))$$

$$b_i(k^{'}+1) = \bar{x}^*{}_i(k) + \delta(b_i(k^{'}) - a_i(k^{'}))$$

Where $\delta \in (0,0.5)$

$$x_i^* = \frac{\bar{x}_i^* - a_i(k^{'}+1)}{b_i(k^{'}+1) - a_i(k^{'}+1)}$$

Step 7: determine new chaotic variable $y_i(k)$ through equation (23), repeat step2 to step 4 until f^* remains unchangeable in some steps, go on next steps:

$$y_i(k) = (1-\beta)x_i^* + \beta x_i(k)$$

where, β is set for slight value

Step 8: let $k^{'} := k^{'} + 1$, minish β and $y_i(k)$, repeat step6 to step7 until f^* remains unchangeable in some steps, output the optimal solution f^*.

3 Economic Impact Analysis of Load Forecast Precision

3.1 The Influence of Load Forecast Errors on Grid Marginal Prices

In order to research on the influence of different load levels on grid marginal prices, three typical dairy loads and the according grid clearing prices in a certain city in East China are analyzed. Figure 1 is curves of load. Figure 2 is curves of Marginal Clearing Price. If curve 0 is set as reference, the average error of curve 1 relative to curve 0 is 0.43% and that of curve 2 is –1.3%. Concerning marginal clearing prices, the average price of curve 0 is 280.4167 Yuan/MWh, while that of curve 1 280.6074 is Yuan/MWh and curve 2 is 280.3986/MWh. It is obvious that real-time prices will increase when loads occur positive departure (forecasts are on the high sides), while they will decrease when loads occur negative departure (forecasts are on the low sides).

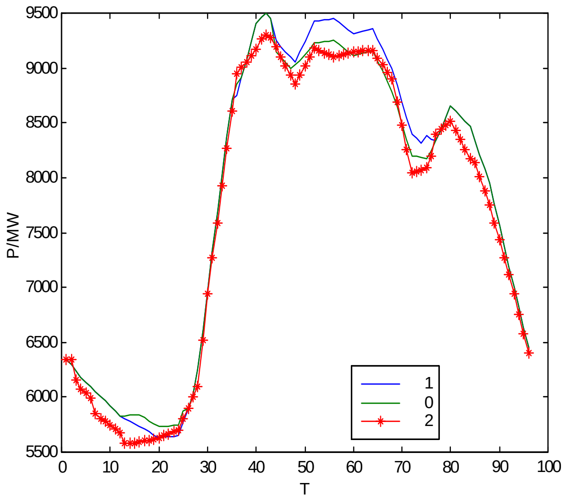

Fig 1 Curves of Load

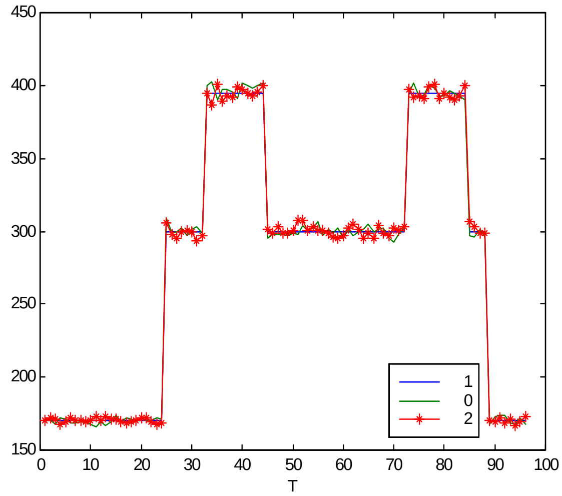

Fig 2 Curves of MCP

3.2 Impact of load forecasting error margin on grid power purchase cost

With the real load curve 0 as reference, power purchase costs and loss of charges are computed adopting the model above when the average load forecast error is in the range of [-5%, +5%] using 1% step increments.

The parameters of power plants participate in price-bidding are as follows:

Table 1 parameters of power plant

Plant No	Maximum output power (MW)	minimum output power (MW)	Ramp rate (MW/min)
1	1200	480	18
2	1200	480	17
3	1200	720	18
4	600	240	6
5	400	0	32
6	240	120	2
7	950	450	40
8	360	240	15
9	670	480	12
10	1200	480	18

When computing power purchase cost, system reserve capacity is always assumed as 10% of total loads, and the price of purchasing electricity from external grids is set to system marginal price. The loss of charges versus various errors is shown in figure 3.

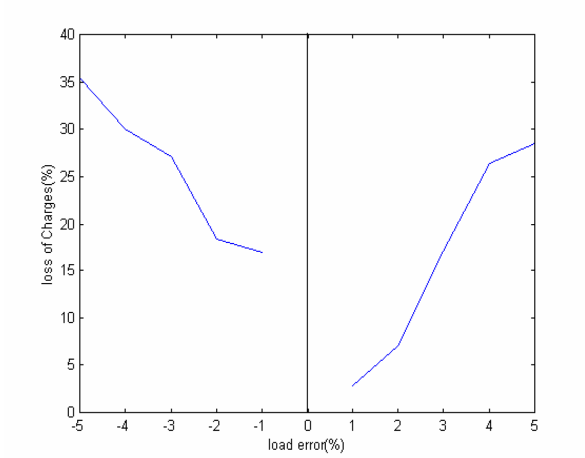

Fig 3 Loss of Charges

4 Conclusion

From the analysis in this paper, it shows that larger forecasting error will result more economic losses, which can be easily understood because larger the load forecasting error and further from optimal combination the arrangement of generator halting planning, so more the purchase cost. Meanwhile, lower load forecast results more losses then higher load forecast, for that when load forecast is lower it is necessary to add fuel units with high generating cost(or purchase expensive real energy from external grids), so more the purchase cost. It is obvious that the loss reduced by improving load forecast precision is considerable.

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