1. Introduction

Marketing risks are widespread in the marketing of any business, and companies often face unpredictable factors in their production and business activities, which are often transformed into potential threat factors, thus affecting the effectiveness of the business. In modern business management, marketing management risk pretesting is a necessary process to reduce losses by comparing accounting with expected targets and using a systematic approach to prevent risks from arising before accidents occur. According to China’s current industrial structure planning, energy enterprises belong to state-owned enterprises, although there are advantages in their development, but by the limitations of traditional thinking and market changes, marketing personnel, and other uncertain factors, the current energy marketing management work in China’s energy enterprises still have a lot of problems.

The challenges brought by new energy. In recent years, not only China, almost all countries around the world are facing serious environmental problems, in this case, the state vigorously advocates the use of clean energy, such as solar energy and wind power generation. As new energy sources enter the market, the situation of exclusive operation of energy companies is broken. How energy enterprises meet the challenge has become the main task of energy marketing. However, in their work, energy companies often do not have a detailed analysis of residents’ lives, traditional marketing methods have been difficult to meet customer needs, and new energy policies and so on will have an impact on the traditional energy market.

Energy usage fee recovery is still difficult. Although most of the energy companies have adopted self-service payment methods such as bank cards and energy cards in cities, many of them still use traditional manual charges in rural areas. Many energy usage bill collectors are not responsible enough and do not have in-depth knowledge of their work, resulting in the failure to recover energy usage bills in a timely manner. In commercial use, some customers also have problems with unpaid energy bills due to cash flow difficulties. At the same time, there are also some users who have the mentality of procrastination and are unwilling to pay the energy usage fee on their own initiative, which makes the energy usage fee recovery work more difficult.

There are risks and hidden dangers in the energy marketing system. There are certain flaws in the design of the
Energy marketing management system, and today’s Internet is more complex and poses many threats to the problems of the energy system. At the same time, some staff may fail to strictly follow the system instructions in their work or even operate in violation of the rules, leading to data confusion.

The energy market risks of energy supply enterprises mainly include two aspects. First, the risk of contradiction between energy supply and demand. It should be noted that in the process of energy enterprise marketing, it will be affected by many subjective and objective factors, and there are also many uncertainties in the process of marketing, all of which will increase the risk of energy enterprises. Over the past period of time, the conflict between energy supply and demand has been greatly changed, the original energy shortage problem has been replaced by the current period of an energy shortage, and the time of energy supply tension has changed to summer or winter time, in addition, due to the construction of a large regional energy network, resulting in the failure of the energy network in a certain region will usually cause a large-scale shutdown, energy companies are facing the process of marketing. The marketing process of energy companies faces unpredictable market risks. Second is the risk of opening up the market for energy sales. With the continuous development of the market economy and the requirements of the “Opinions on Further Deepening the Reform of the Energy System,” there will be a direct purchase of energy by large users in the future. This will lead to the loss of a large number of large energy users at the county level, and a significant decline in the amount of energy sold by enterprises. The space that can be explored in the energy market is also further compressed, and it is difficult to appear a good way to make up for this loss in the short term, and the market risk is large.

2. Related Work

Energy marketing is a part of the normal production activities of energy companies and is characterized by its coherent, integral, and service nature [1]. The risk of energy marketing not only brings impact to users but also endangers energy enterprises [2]. For users, the normal supply of energy provides power for production and life, once the risk occurs will lead to normal activities that can not be carried out, such as factory shutdown, lighting system paralysis, and communication signal interruption [3]. For energy companies, the occurrence of risk can lead to problems in the recovery of funds, resulting in capital constraints affecting their own operations [4]. As the marketing of energy is service oriented, once the risk accumulates to a certain extent, it will affect the reputation of energy companies and may even bring bankruptcy risk to energy companies in the current competitive industry [5].

Energy companies face a lot of risks in the energy market and are exposed to many uncertainties in the process of selling energy [6]. By market risk, we mean that energy companies first purchase electricity resources from energy plants and then sell the resources to different users, in which there are many risk elements, including nature, supply, and demand conflicts. In recent years, with global warming, natural disasters are frequent, and floods and snowstorms are huge tests for energy companies [7]. In today’s rapid economic development, many provinces are facing energy shortages, and even have to restrict energy supply to suburban areas to meet urban energy demand. Human safety risk is also one of the huge risks for energy companies [8]. Energy companies also belong to high-risk enterprises, where employees are often associated with energy use at work, and thus accidents sometimes occur, which not only damage the physical and mental health of employees, but also cause losses to corporate interests [9]. The state will carry out macro-control according to the actual economic situation, which will lead to market price fluctuations and eventually produce risks to energy marketing [10]. In the operation of the market economy, enterprises may violate national policies in order to maximize profits, which will also have an impact on the normal operation of energy marketing [11]. Energy usage fee risk. Some energy enterprises do not check carefully in the process of meter reading, and errors may occur when entering the system, which eventually lead to problems with energy usage fees [12]. Users may refuse to pay energy usage fees when they encounter this situation, and the collection of energy usage fees will be delayed in the process of accounting determination with energy enterprises. Also, in some rural areas, some customers have the mentality of procrastination and are unwilling to pay the energy usage fee on their own initiative, which leads to the failure of energy companies to collect the energy usage fee in time. The manual meter reading method in some areas may also cause customers to be reluctant to pay energy usage charges if the meter readers fail to check the data with customers in a timely manner [13]. At the same time, problems such as inaccurate energy consumption due to aging meters can also have an impact on energy usage fee collection [14]. Although many energy companies have now introduced energy marketing systems to achieve paperless workflow, if problems occur in the system, such as attacks by network hackers and operational errors, and if the company fails to respond to these problems in a timely manner, it will have a great impact on the operation of the energy company [15].

And at this stage, energy enterprises energy marketing risk control and prevention measures, mainly market instruments. In the face of market risks in energy marketing, for example, in response to risks from natural disasters, which are objective and unavoidable, energy companies can only use the purchase of equipment insurance, innovative technologies, and other actions to reduce losses as much as possible [16]. For the contradiction between supply and demand in the energy market, on the one hand, energy companies should encourage customers to save energy as much as possible, and on the other hand, they should eliminate obsolete equipment in order to ensure that the energy load can be adjusted in a timely manner [17]. The personal injury of employees, on the one hand, is to strengthen safety education, through the standardized operation to reduce personnel injury accidents [18] and to increase the publicity of relevant laws and regulations and policies to ensure the orderly implementation of energy marketing work of energy enterprises. Second, in the process
of energy marketing, we should strengthen the legal awareness of enterprise employees and increase the legal course training, so that the process of signing contracts should be done in accordance with the law and the law. Especially for the use of energy inspectors, it is necessary to strictly follow the procedures to perform the work, when found to have determined the existence of behavior, must be video-recorded and saved, and the parties concerned issued the relevant fine documents, for the parties do not obey the decision, in accordance with legal procedures to ensure the enterprise’s own interests [19]. Policy environment means. In the face of the risks arising from macroeconomic changes, enterprises should increase the training of talents and focus on the investment of funds in the training of equipment. It is necessary to pay more attention in a timely and relative response measures according to the enterprise’s own interests [19]. Policy environment means.

3. Methodology

Bayesian networks are known as one of the most effective models for dealing with the representation and inference of uncertain knowledge at present and are very appropriate for designing marketing risk warning models for energy companies. A static Bayesian network is defined as

$$\text{BN} = \{\text{G}, \theta\},$$

where $\text{G}$ is a directed acyclic graph on the set of random variables $X = \{X_1, X_2, \ldots, X_n\}$, i.e., the network structure, and $\theta$ is a network parameter, i.e., a conditional probability table.

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)).$$

The DBN is a static Bayesian network with the addition of temporal properties, which expands the BN on the time axis to describe a stochastic process with a temporal component. The DBN consists of two parts, where $\text{BN}_0 = \{\text{G}_0, \theta_0\}$ is the initial network, $\text{G}_0$ denotes the structure of the initial network, and $\theta_0$ denotes the parameters of the initial network, which defines the joint probability distribution, $\text{G}_{\ldots}$ denotes the structure of the transfer network, and $\theta_{\ldots}$ denotes the parameters of the transfer network, which defines the probability of state transfer of the random variables between two adjacent time slices $P(X_{t+1}|X_t)$.

If $\text{BN}_0, \text{BN}_{\ldots}$ is determined, then $\text{BN}_{\ldots}$ is expanded along the time axis, and the DBN schematic is shown in Figure 1. The subscripts of the random variables in Figure 1 denote the moments and the superscripts denote the $i$th random variable.

$$P(X_1, X_2, \ldots, X_T) = P_{\text{BN}_0}(X_1) \prod_{t=1}^{T} P_{\text{BN}_{\ldots}}(X_t|X_{t-1})$$

$$= \prod_{i=1}^{N} P_{\text{BN}_0}(X_0^i|Pa(X_0^i)) \cdot \prod_{t=1}^{T} \prod_{i=1}^{N} P_{\text{BN}_{\ldots}}(X_t^i|Pa(X_t^i)).$$

3.1. Obtain the Discrete Sample Set of the Time Series. The discretization intervals and the number of clusters are highly subjective and have a great influence on the discretization results. In this paper, the number of clustering centers $k$ and the initial clustering centers is determined using the mean difference as the criterion. First, we define the sample distance, the sample mean disparity, and the mean disparity of the overall sample set.

Let the dimensionality of the sample data set $D = [x_1, x_2, \ldots, x_T]^T$, $x_i = [x_{i1}, x_{i2}, \ldots, x_{iT}]$, $D$ has the shape of $T \times L$. The Euclidean distance between two sample vectors $x_i, x_j$ is defined as

$$d(x_i, x_j) = \left[ \sum_{t=1}^{T} |x_{it} - x_{jt}|^2 \right]^{1/2}$$

$$d_i = \sum_{j=1}^{L} d(x_i, x_j)/T$$

$$M D = \sum_{j=1}^{L} d_i/T.$$ The steps to determine the initial clustering center are: first, the $\hat{d}_1$ largest samples are used as the 1st clustering center $c(1)$, and $c(1)$ is eliminated from the sample set to form a new sample set. Then find the sample with the largest $d_i$ in the new sample set, and if the difference degree of both the sample and the initial clustering center that has been selected is greater than $M D$, then the sample is used as the 2nd clustering center $c(2)$; otherwise, find the second largest sample with the average difference degree for judgment until $c(2)$ is selected. So on and so forth until the clustering center $c(q)$ satisfying the condition is screened out. After clustering, the discrete data set $D$ is obtained.

3.2. Structure Learning of DBN. Based on the discrete dataset $D$, the new network structure is obtained by the continuous operation of the above three operators, and then the new network structure is scored by the BIC scoring function, and the highest scoring network structure is taken as the result of DBN structure learning.

![DBN schematic](image-url)
3.3. Parameter Learning of DBN. After determining the DBN structure, the conditional probability table between nodes is obtained by learning the network parameters from $D$, i.e., the conditional probability table of $B_0, B_\negrightarrow$ is $\theta_0, \theta_\negrightarrow$.

The above steps lead to $B_0 = (G_0, \theta_0), B_\negrightarrow = (G_\negrightarrow, \theta_\negrightarrow)$ and thus the DBN model. As an extension of Bayesian methods, Bayesian networks can be applied to decisions that depend on multiple control factors and can be computed and reasoned about using incomplete and imprecise knowledge. The assumption of conditional independence: each node $V$ in a Bayesian network is independent of any subset of nodes consisting of the non-$V$ children given by the direct parent of $V$. This is expressed in terms of the notation

$$p(V_i | A(V_i), \prod_i (V_i)) = p(V_i | \prod_i (V_i)).$$  

In equation (4), $\prod_i (V_i)$ denotes the direct parent of $V_i$, and $A(V_i)$ denotes any child that is not a descendant of $V_i$ of $\prod_i (V_i)$.

Bayesian network model building generally consists of two parts: network structure learning and parameter learning. Among them, the network structure describes the dependency and independence relationship between variables at the qualitative level, and the network parameters portray the dependency of variables on their parents using conditional probability distribution at the quantitative level. The structure learning of Bayesian networks is to learn the network structure that fits best with the data according to the Bayesian information criterion is specified as follows. The network structure score $S$ is a function of $\mathcal{G}$ and $\theta$, and the methods are mainly classified into dependency-based statistical analysis, score-based search some measure, and the steps of model construction are as follows:

(1) Input data and do the processing
(2) Based on the two-stage method, the best combination of corresponding model factors is selected from the alternative model variables
(3) Combine the results of model factor selection to construct a Bayesian network load peak prediction model
(4) Use the constructed Bayesian network model for peak load prediction
(5) Output the peak load prediction value and the corresponding peak time

Based on the above steps, the model is constructed as follows:

$$f = B(\mathcal{G}, \theta, X),$$  

where $B$ is the Bayesian network model; $\mathcal{G}$ is the network structure; $\theta$ is the network parameter; and $X$ is the factor variable considered by the model.

And for Step 3 we have.

(1) Set the parameters of the search algorithm and the initial network solution $S_0$, such that $S_k = S_0$
(2) Calculate the current network structure score according to the Bayesian scoring criterion
(3) Determine whether the convergence criterion is satisfied, if so, output the current optimal network structure $S$; if not, continue to step (4).
(4) Determine the neighborhood of the current network structure $S$, i.e., generate candidate network structure solutions by adding an edge, changing the

$$f(X|Y) = \frac{1}{(2\pi)^{M/2}|S|^{1/2}} \exp \left\{-\frac{1}{2}(X - WY - U)^T S^{-1} (X - WY - U) \right\}.$$  

W = S_{XY}S_{XY}^{-1}, \quad S = \begin{bmatrix} S_{XX} & S_{XY} \\ S_{XY} & S_{YY} \end{bmatrix}, \quad U = [UX - WUY].$$  

Suppose there are $m$ independent and identically distributed training samples $D$. The log-likelihood function $L$ is as follows:

$$L = \log \prod_{i=1}^{m} f(X|Y, D).$$  

Then, the formula for the BIC score $S$ is formed as

$$S = L - M\ln(n(P)/2),$$  

where $M$ is the number of nodes related to the probability density function; $P$ is the number of nodes of the constructed Bayesian network [21–23].

Parameter learning of Bayesian networks is the problem of determining the parameters of the probability distribution of the network nodes with a known network. Parameter learning methods include the great likelihood estimation method and the Bayesian estimation method. The overall $P$-element normal distribution is unknown $X \sim N_P(\mu, \Sigma)$, and let $X_i = (x_{i1}, \ldots, x_{ip}) i = 1, 2, \ldots, n$ be $n$ simple random samples drawn from the overall $P$-element normal distribution $X$, i.e., $X_i$ are independently and identically distributed with the overall $X$. The mean $X$, covariance $\Sigma$, and likelihood function $L(\mu, \Sigma)$ are as follows:

$$X = \frac{1}{n} \sum_{i=1}^{n} X_i$$

$$A = \frac{1}{2} \sum_{i=1}^{n} (X_i - \bar{X})(X_i - \bar{X})$$

$$L(\mu, \Sigma) = \prod_{i=1}^{n} \frac{1}{(2\pi)^{p/2}|\Sigma|^{1/2}} \exp \left\{-\frac{1}{2} (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) \right\}.$$  

The maximum likelihood estimate of the normal distribution is calculated as $\hat{\Sigma}_{MLE} = A/n, \hat{\mu}_{MLE} = \bar{X}$, with $X = \{X_1, X_2, \ldots, X_n, X_i\}$ denoting $X_1, X_2, \ldots, X_n$ a total of 6 influencing factors and corresponding load values $X_i$, $D = \{y_1, y_2, \ldots, y_n\}$ denoting a data set, $S_k$ for the optimal Bayesian network structure, and $B_0$ for the initial Bayesian network structure.
direction of an edge, or deleting one of the edges on the basis of this network structure

(5) Determine whether the searched candidate network structure solution satisfies the contempt criterion. If yes, replace the current optimal network structure $S$ with the best candidate network structure $S_c$ that satisfies the contempt criterion, thus becoming the new optimal network structure solution and update the intelligent contraindication table with the contraindicated object corresponding to $S_c$, turning to step (3) (the contempt criterion in this study is that if there is a network structure with a better rating value than any of the previous best candidate solutions, it can be amnestied).

(6) Repeat steps (3), (4), and (5) until the convergence criterion is satisfied and then end the search

(7) Learning the network parameters using the great likelihood estimation method based on the Bayesian network structure constructed above

4. Experiments

Based on the above research object and historical data of energy companies, the training and testing samples are allocated as 6:4, 7:3, 8:2 and 9:1, and the Bayesian network model is trained by the above method. The quantitative relationships are given in Tables 1 and 2 for the connection coefficients between the nodes of the network parameters [24–26].

Based on the abovementioned Gaussian Bayesian network model, the marketing risk of energy companies is predicted and analyzed in comparison with BP neural network. Figures 2 and 3 show the prediction comparison of the magnitude of marketing risk of energy enterprises and the moment point of appearance corresponding to the marketing risk of energy enterprises, respectively.

From Figure 2, the accuracy of Bayesian network energy enterprise marketing risk is 92.98%, and the prediction accuracy of energy enterprise marketing risk is 94.88%; the prediction accuracy of BP neural network is 94.90%, and the prediction accuracy of energy enterprise marketing risk is 94.54%. From Figure 3, the time prediction error of the Bayesian network is 2.95 h; the time prediction error of the BP neural network is 4.09 h.

Compared with BP neural network prediction, the magnitude prediction accuracy of both is higher, but the time prediction error of the Bayesian network is smaller; meanwhile, the learning time of the Bayesian network model is less than 1 s, which is much smaller than the training learning time of BP model 87.64 s, indicating that the marketing risk prediction of energy enterprises based on Bayesian network has higher feasibility and effectiveness.

There are three main evaluation indicators for the interval prediction effect: PICP is evaluated from the probability that the actual observation; PINAW is evaluated from the width; AWD is evaluated from the degree of deviation when the actual observation falls outside the prediction interval, and the expressions of PICP, PINAW, and AWD are shown in equations (10)–(12).

4.1. PICP

\[
PICP = \frac{1}{N} \sum_{k=1}^{N} \epsilon_k. \tag{10}
\]

When the PICP is significantly less than the 95% confidence level, the interval prediction result is unreliable.

4.2. PINAW. The equation for PINAW is given as

\[
PINAW = \frac{1}{NR} \sum_{i=k}^{N} \left[ U_{risk} - L_{risk} \right]. \tag{11}
\]
Figure 2: The graph of forecasting.

Figure 3: The graph of time forecasting.
4.3. AWD

\[
AWD_k = \begin{cases} 
L_{t+k} - EP_{t+k} & \text{if } EP_{t+k} \leq L_{t+k} \\
U_{t+k} - L_{t+k} & \text{if } EP_{t+k} \in [L_{t+k}, U_{t+k}] \\
EP_{t+k} - U_{t+k} & \text{if } EP_{t+k} > U_{t+k} 
\end{cases}
\]

(12)

\[
AWD = \frac{1}{NR^*} \sum_{i=k}^{N} AWD_i,
\]

(13)

where \( R^* \) is used to normalize the cumulative bandwidth deviation; the smaller the value of AWD, the higher the quality of the predicted intervals.

From equations (11)–(13), it can be seen that the larger the value of PICP and the smaller the values of PINAW and AWD for interval prediction, the better the interval prediction. But such three evaluation indexes are contradictory to each other, and the integrated objective function (equation (14)) minimally optimizes the weights of KELM to achieve the accuracy prediction [27].

\[
\min F = \sum_{i=1}^{m} \left[ \gamma_i |PICE_i^{(a_i)}| + \phi_i |PINAW_i^{(a_i)}| + \lambda_i |AWD_i^{(a_i)}| \right],
\]

(14)

where \( PICE = |PICN - PICP| \) indicates the prediction interval coverage probability deviation.

\[
PICN = 100 \times (1 - \alpha_i) \%
\]

(15)

\( \gamma_i, \phi_i, \lambda_i \) denote the weight coefficients of PICE, PINAW, and AWD; \( i \) denotes the number of iterations; and \( m \) is the maximum number of iterations.

To fairly compare the prediction effects in this paper and the base method, PICP, PINAW, and AWD are used as the evaluation indexes of interval prediction to test the accuracy of interval prediction. The specific results are shown in Figures 4–7.
Figures 4–7. It can be seen that the Bayesian network-based method we used has the most accurate risk prediction effect among several methods.

5. Conclusion

The marketing business of comprehensive energy enterprises is very important in energy enterprises, and the risk prevention and control of the energy marketing business needed more attention because it is very sensitive to the influence of the general social environment. After analyzing the marketing management work of energy enterprises by using the proposed Bayesian network-based model, it is found that the marketing environment, government policies, and consumer psychological expectations all have a huge impact on energy marketing. Therefore, for energy marketing risk prevention and control, we should start from these aspects to find out the related problems. Then, the related work will be focused on risk reduction to ensure the energy marketing work performs smoothly. And the development of enterprise benefits will be further ensured. At the same time, due to the characteristics of energy, the risk prevention and control should also take into account the psychological needs of consumers. The energy market is changing rapidly, and further renovations and attention to risk management control can ensure the positive development of enterprises.

Data Availability

The dataset used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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