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*Research Article*

# Application of AHP and EIE in Reliability Analysis of Complex Production Lines Systems

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It is necessary to grasp the operation state of the production system for scientific scheduling, process improvement, fault analysis, equipment maintenance, or replacement. The matter-element information entropy is proposed to evaluate the health index of the product line, and the parameter self-optimization support vector machine is used to predict the future health index. A new type of three-dimensional cross compound element is established by synthesizing the operation state of equipment, energy consumption, production efficiency, and human factors. The subjective, objective, and joint weights are determined by the analytic hierarchy process (AHP) method, entropy, and the combination weighting method, respectively. The health index is calculated by complex element correlation entropy. The calculations of the beer filling production line show that the combined weighting method is an effective method on the health index calculation and can accurately reflect the actual operation state of the production. Support vector machine (SVM) optimized by multiparameters is established to predict the health index; the simulation shows that Least Squares Support Vector Machine (LSSVM) based on radial basis function (RBF) has prominent prediction effect. It can provide accurate data support for the production and management of enterprises.

## 1. Introduction

In recent years, the organizational reliability analysis of the production system, the human reliability analysis, and the system reliability analysis under the dynamic environment have become one of the most concerned hot issues in the industrial engineering and other scientific circles [1].

Health index is one of the main indexes to measure the reliability of the system. Health assessment refers to relying on advanced testing methods, combining reliable and effective assessment methods using complete operation data to analyze, predict, and judge; thus, it can effectively improve the system maintenance support capability and reduce maintenance costs and save spare parts [2, 3]. The research of its evaluation method is mainly concentrated on two directions: one is system modeling and analysis. However, the modeling of the system is difficult and the adaptability of the method is not strong. The other is the data-driven method. The method is flexible and adaptable, with the maturity of machine learning and statistical analysis methods; data-driven method becomes the mainstream algorithm for system health assessment [4, 5].

Reddy proposed a stochastic fuzzy reliability analysis method, which effectively improved the overall system reliability of mining production system [6]. Soualhi et al. proposed an artificial ant colony clustering method to classify the degraded state of HMM. By using the adaptive fuzzy neural method, the determination of the degenerate state of the bearing and the prediction of the remaining life are realized [7]. Dong et al. proposed a hidden semi-Markov model (HSMM) to predict the residual life of deteriorating equipment. This method only obtains the expected value of residual life and is not used to analyze and apply in the health management of equipment [8]. Yu Shui proposed a novel approach by combining the extreme value moment method and the improved maximum entropy method, which can efficiently estimate the time-variant reliability accounting for multiple failure modes and temporal parameters at

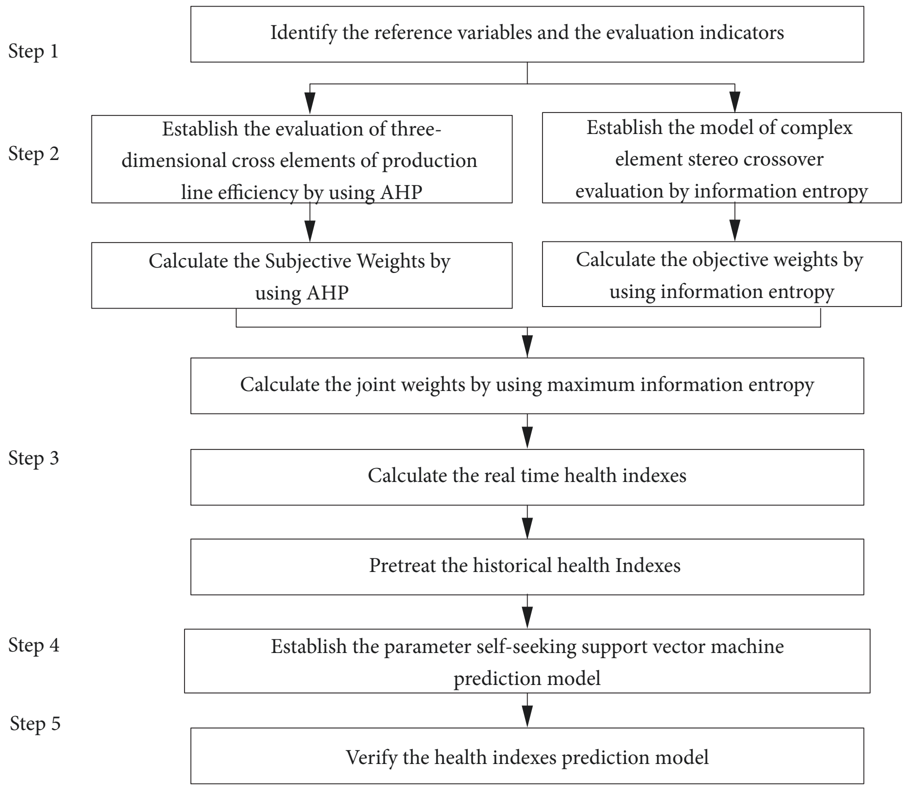



Figure 1: The flowchart of health calculation and prediction for beer filling production line.

the same time. In the same year [9], he also proposed a method based on fault process decomposition to improve computational efficiency and ensure computational accuracy [10]. Li Fangyi proposed a sequential sampling method based on the hybrid model of probability and convex set to solve the reliability-based design optimization problem [11]. Qiu Na proposed the simple uncertainty quantification method is for numerical uncertainty (noise) and surrogate model uncertainty (error) in the optimization process [12].

Beer filling production is the main link of beer production. The system has the characteristics of large scale, multi-equipment, high energy consumption, and complex coupling relations, so the line reliability is difficult to be guaranteed. At present, the key performance indicator (KPI) is commonly used to evaluate the efficiency of filling production line. The rules of this method are simple; the adaptability is not strong [13, 14]

Combining the energy consumption, real time output, raw material consumption, alcohol loss, and key performance index (KPI) in beer filling production, the three-dimensional cross compound element is established. The quantitative calculation of the health index of the filling production line is designed by AHP, combined weights, and the compound matter-element correlation entropy.

According to historical health index, LSSVM is adapted to model and predict the future health index of the production line; thus a new method of the overall evaluation of the operation of the line is formed to predict the future health index of the line. The detailed calculation flowchart is shown in Figure 1.

## 2. Theoretical Calculation of Health Index

In this section, we illuminate the details of using AHP to establish the compound matter-element model of the beer filling production line and calculate the theoretical weights of the health index.

*2.1. Problem Statement.* AHP is a method that makes use of less amount of information and makes the decision-making process digitized. It is suitable for the situation, which is artificial qualitative judgment of its subjective role and measures the results directly and accurately, it has the characteristics practicability, systematicness, simplicity, and so on [15–19]. So, a compound element model of beer filling production line is established by AHP, and the theoretical weights of each decision index affecting the health index are calculated.

*2.2. Establishment of Compound Matter-Element Hierarchical Structure Model.* The compound matter-element hierarchical structure model reflects the interrelationship between the target level, the standard layer, and the decision level. The target layer is the health index of the beer filling production line, the standard layer consists of energy consumption index, productivity index and KPI, and the decision layer consists of beer consumption, unit energy consumption, unit time capacity, unit time raw material consumption, total asset utilization, wool production rate, total equipment utilization, and line efficiency.

*2.3. Construction of Judgment Matrix.* In the AHP method, the target layer weight matrix A and the index layer weight matrix B are established. The square root method is used to calculate the maximum feature value $\lambda_{\max}$ of the judgment matrix. Its corresponding normalized eigenvector $W = (\omega_1, \omega_2 \cdots \omega_n)^T$ and $AW = \lambda_{\max} W$. The judgment matrix of the target layer and the criterion layer are calculated by the same method.

*2.4. Consistency Test.* (a) Calculate the consistency index $C.I.$:

$C.I. = (\lambda_{\max} - n)/(n-1)$. In the formula, n is the order of the judgment matrix.

(b) Calculate the average random consistency index $RI$.

(c) Calculate the conformance ratio $C.R.$:

$C.R. = CI/RI$. If $CR \le 0.1$, it is considered that the consistency of the judgment matrix is acceptable.

*2.5. Calculation of Influence Weight of the Target Layer.* Calculate the weight of each layer, that is, the impact weight of the scheme layer on the target layer.

$$\omega' = W_C \times W_A \tag{1}$$

where, $W_C = [\omega_{C1}, \omega_{C2}, \cdots \omega_{Cn}, ]$ is the eigenvector of each decision parameter; $W_A = [\omega_{A1}, \omega_{A2}, \cdots \omega_{An}]^T$ is the eigenvector of the target layer.

## 3. Information Entropy and Joint Weights of Stereoscopic Cross Compound Matter Element

The "entropy" is a measurement to systemic confusion extent, which can objectively reflect the utility value of system information [20]. For the various decision data of the beer filling production line at different time, the compound matter element is set up, and the objective weights of the health index are calculated by using the maximum discrete entropy of the compound matter element.

*3.1. Establishment of the Stereoscopic Cross Compound Element.* Matrix $R_{mn}$ is the stereoscopic cross composite element matrix with m∗n.

$$R_{mn} = \begin{bmatrix} & M_1 & M_2 & \cdots & M_m \\ C_1 & x_{11} & x_{12} & \cdots & x_{1m} \\ C_2 & x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_n & x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{2}$$

$M_i$ is the $i$-th operation state of filling production line; $C_j$ is the $j$-th evaluation index of the stereoscopic cross scheme; $x_{ij}$ is the corresponding $j$-th index value of the $i$-th operation state.

*3.2. Standardization of the Stereoscopic Cross Matter Element.* It is necessary to standardize the evaluation index. Formula (3) will be used to standardize the one who has the propelling effect on the evaluation index. Formula (4) will be used to standardize the one who can weaken the evaluation index

$$\delta_{ij} = \frac{\left(x_{ij} - \min_{1\le i\le n} x_{ij}\right)}{\left(\max_{1\le i\le n} x_{ij} - x_{ij}\right)} \quad \left(i = 1, 2, \cdots, n;\ j \in J^+\right) \tag{3}$$

$$\delta_{ij} = \frac{\left(\max_{1\le i\le n} x_{ij} - x_{ij}\right)}{\left(\max_{1\le i\le n} x_{ij} - \min_{1\le i\le n} x_{ij}\right)} \quad \left(i = 1, 2, \cdots, n;\ j \in J^-\right) \tag{4}$$

After standardized, the stereoscopic cross matter element is set up as $R_{mn}$; it is shown in formula (5).

$$R_{mn} = \begin{bmatrix} & M_1 & M_2 & \cdots & M_m \\ C_1 & \delta_{11} & \delta_{12} & \cdots & \delta_{1m} \\ C_2 & \delta_{21} & \delta_{22} & \cdots & \delta_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_n & \delta_{n1} & \delta_{n2} & \cdots & \delta_{nm} \end{bmatrix} \tag{5}$$

*3.3. Determination of Correlation Function and Weights Coefficient of Evaluation Indexes for Interchange Schemes.* The weights of evaluation index directly affect the evaluation results, and the objective weights coefficients of each index are determined by correlation entropy method. Firstly, the correlation function $\boldsymbol{y_j} = \max_{1\le \boldsymbol{i} \le \boldsymbol{m}} \boldsymbol{\delta_{ij}}$, $(\boldsymbol{j} = 1, 2, \cdots, \boldsymbol{n})$ is determined, and the ideal reference series is $\boldsymbol{Y} = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots \boldsymbol{y_n}\}$. According to the maximum discrete entropy theory [21], the entropy is maximum when the occurrence probability of each symbol is equal and the value is $\boldsymbol{H}_{\max} = \ln \boldsymbol{n}$. The correlation function of the first index of the complex element is shown in formula (6):

$$\zeta_{ij} = \frac{\min_i \min_j \left|\delta_{ij} - y_j\right| + 0.5 \max_i \max_j \left|\delta_{ij} - y_j\right|}{\left|\delta_{ij} - y_j\right| + 0.5 \max_i \max_j \left|\delta_{ij} - y_j\right|} \tag{6}$$

The entropy values of the $j$-third index of the stereoscopic cross are

$$\boldsymbol{F_j} = \boldsymbol{K} \sum_{\boldsymbol{i}}^{\boldsymbol{m}} \boldsymbol{f_{ij}} \ln \boldsymbol{f_{ij}} \tag{7}$$

In formula (7), $\boldsymbol{K} = -(\boldsymbol{H}_{\max})^{-1} = -(\ln \boldsymbol{n})^{-1}$, $\boldsymbol{f_{ij}} = \boldsymbol{\zeta_{ij}} / \sum_{\boldsymbol{i}=1}^{\boldsymbol{m}} \boldsymbol{\zeta_{ij}}$, $\boldsymbol{j} = 1, 2, \cdots, \boldsymbol{n}$, $\boldsymbol{F_j} \in [0, 1]$.

The weight coefficient of the index $c_j$ is shown as follows:

$$\omega'' = \frac{e_j}{\sum_{j=1}^{n} e_j} \tag{8}$$

The deviation degree of entropy value is shown as follows:

$$e_j = 1 - F_j \tag{9}$$

*3.4. Determination of the Joint Weights.* Considering the shortcomings of the subjective and objective weights, the joint weights are determined by the combined empowerment method, and the weights of the AHP method and information entropy are integrated with the additive integration method. The formula is shown as follows:

$$\omega_j = \alpha\omega_j'' + (1-\alpha)\,\omega_j' \tag{10}$$

where $\omega_j''$ is the objective weight of the j index calculated by AHP, $\omega_j'$ is the subjective weight of the *j* index calculated by AHP, $\omega_j$ is the joint weight of the *j* index calculated by AHP, and $\alpha$ is the undetermined coefficient, calculated by formula (11):

$$\alpha = \frac{1}{n-1} G_{AHP} \tag{11}$$

where $\boldsymbol{G_{AHP}}$ is the difference coefficient of each index in AHP.

$$G_{AHP} = \frac{2}{n}\left(1p_1 + 2p_2 + \cdots + np_n\right)\frac{n+1}{n} \tag{12}$$

where $\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p_n}$ are the ascending sorting values of subjective weight $\omega_j'$ (see the values in Table 2) in AHP; n is the number of indexes. The weight matrix of evaluation indexes is shown as follows:

$$R_{\omega j} = \begin{bmatrix} & C_1 & C_2 & \cdots & C_n \\ \omega_j & \omega_1 & \omega_2 & \cdots & \omega_n \end{bmatrix} \tag{13}$$

*3.5. Calculation of Health Index.* The compound correlation entropy matter element $\underset{Hi}{R}$ based on the comprehensive evaluation of M beer filling production line can be constructed by formulas (5)-(11).

$$\underset{Hi}{R} = \begin{bmatrix} & M_1 & M_2 & \cdots & M_i & \cdots & M_m \\ H_i & H_1 & H_2 & \cdots & H_i & \cdots & H_m \end{bmatrix} \tag{14}$$

$$H_i = -\sum_{j=1}^{n} P\left(\omega_j \delta_{ij}\right) \ln P\left(\omega_j \delta_{ij}\right) \tag{15}$$

$$\boldsymbol{P}\left(\omega_j \delta_{ij}\right) = \omega_j \delta_{ij}\left[\sum_{j=1}^{n} \omega_j \delta_{ij}\right]^{-1} \tag{16}$$

$$\boldsymbol{i} = 1, 2\cdots \boldsymbol{m},\ \boldsymbol{j} = 1, 2, \cdots, \boldsymbol{n}$$

From the definition of entropy, the bigger the entropy is, the better operation state of the production line is. Therefore, sort the health index of the beer filling production line according to the entropy value. According to the sort situation combined with the demand of production, reasonably and scientifically arrange the production scheduling. This method provides theoretical and data support for production line maintenance and technological improvement.

## 4. Health Index Calibration and Analysis

*4.1. Experimental Data.* In order to scientifically and comprehensively assess the operation state of beer filling production lines, in addition to taking into account traditional key performance indicators KPI (total asset utilization rate, linear gross yield rate, total equipment utilization rate, and line efficiency), the experimental data also include unit beer consumption, unit energy consumption, unit time production capacity, and unit raw material consumption. Energy consumption, alcohol loss, production, and raw materials consumption data come from the energy metering management system; KPI data come from the filling shop control system. All data are collected in the filling workshop of China Resources Snow Beer Tonghua Co. Ltd. The first line of filling production line works for 19 days in June, 10 days in November, 23 days in June, and 12 days in November 2016. The line 1 is the old one and the line 3 is the new one. The normalized KPI data coming from beer filling production lines are shown in Figure 2.

*4.2. Experiments Based on Theories 1 and 2 and Data Analysis*

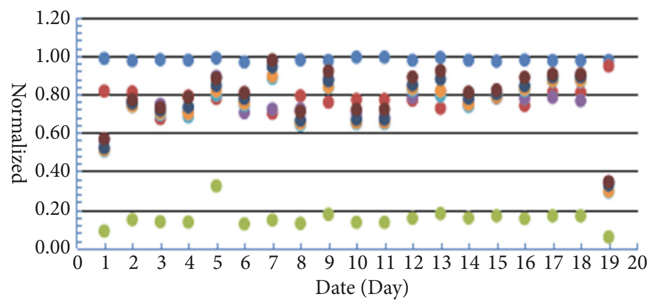
*4.2.1. Composite Element Structure of Beer Filling Production Lines.* Using AHP to establish a three-dimensional cross complex element for evaluating the health status of beer filling production lines, the target layer A is the health index of beer filling production lines; the standard layer is the indexes affecting the health index, such as energy consumption ($B_1$), capacity ($B_2$), and KPI ($B_3$). The decision layer includes beer consumption ($C_1$), unit energy consumption ($C_2$), unit time production capacity ($C_3$), unit time raw material consumption ($C_4$), and KPI($C_5$-$C_8$). The structure and interrelationships are shown in Figure 3.

According to the incidence relation between different levels of the hierarchical structure model, the 1-9 scaling method [22] is used to construct the AHP weight matrixes of the target layer matrix A and the index layer matrixes $B_1$, $B_2$, and $B_3$. The value of each element in the matrix refers to the method of material accounting, heat accounting, and parameter weight relation reflected by KPI calculation formula; after calculation, the matrix is shown in formulas (17)-(20).

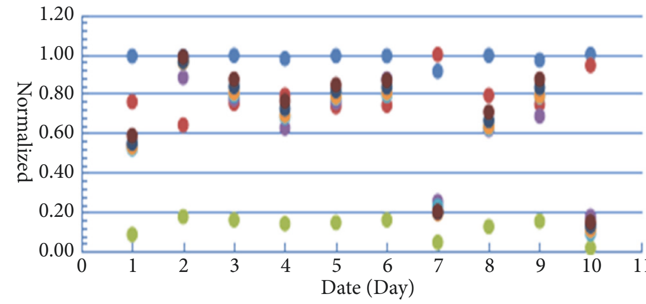
$$A = \begin{bmatrix} A & B_1 & B_2 & B_3 \\ B_1 & 1 & \frac{1}{2} & \frac{1}{2} \\ B_2 & 2 & 1 & \frac{1}{2} \\ B_3 & 2 & 2 & 1 \end{bmatrix} \tag{17}$$

$$B_1 = \begin{bmatrix} B_1 & C_1 & C_2 \\ C_1 & 1 & \frac{1}{2} \\ C_2 & 2 & 1 \end{bmatrix} \tag{18}$$

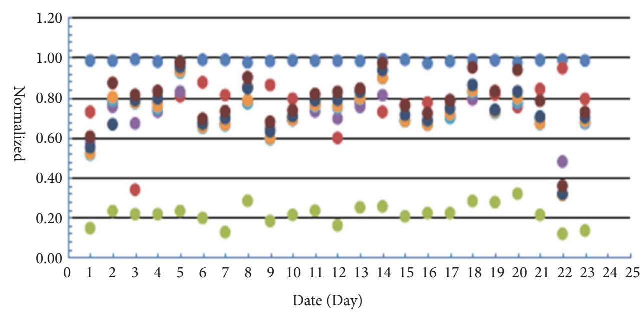
$$B_2 = \begin{bmatrix} B_2 & C_3 & C_4 \\ C_3 & 1 & 3 \\ C_4 & \frac{1}{3} & 1 \end{bmatrix} \tag{19}$$



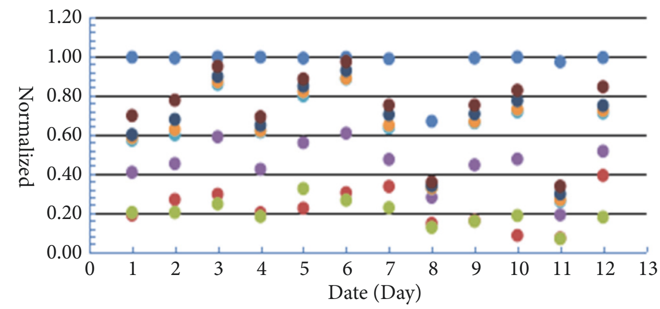
(a) Production data of line 1 in June 2016



(b) Production data of line 1 in November 2016



(c) Production data of line 3 in June 2016



(d) Production data of line 3 in November 2016

FIGURE 2: KPI data coming from beer filling production lines. (i) Beer consumption ($C_1$); (ii) unit energy consumption ($C_2$); (iii) unit time production capacity ($C_3$); (iv) unit time raw material consumption ($C_4$); (v) total asset utilization rate ($C_5$); (vi) linear gross yield rate ($C_6$); (vii) total equipment utilization rate ($C_7$); (viii) line efficiency ($C_8$).

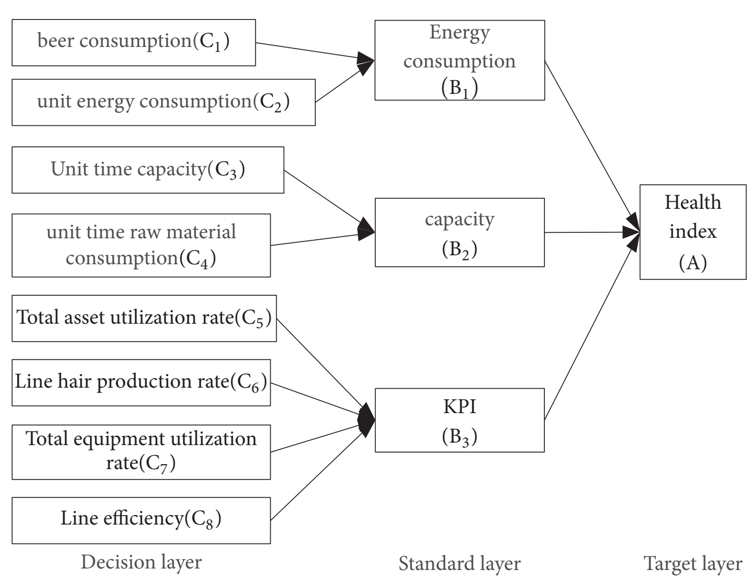



FIGURE 3: Structure diagram of complex elements.

$$B_3 = \begin{bmatrix} B_3 & C_5 & C_6 & C_7 & C_8 \\ C_5 & 1 & \frac{2}{3} & \frac{1}{2} & \frac{2}{5} \\ C_6 & \frac{3}{2} & 1 & \frac{1}{2} & \frac{1}{3} \\ C_7 & 2 & 2 & 1 & \frac{1}{2} \\ C_8 & \frac{5}{2} & 3 & 2 & 1 \end{bmatrix} \quad (20)$$

The consistency check is carried out for each judgment matrix. The RI value is 1.12. The average random consistency index obtained after calculating 1000 times is shown in Table 1.

The CR value, which is the result of the total level of sorting, is far less than 0.1, with satisfactory consistency.

*4.2.2. Calculation of AHP Weights.* Through the calculation of the hierarchical single sorting and hierarchical total

Table 1: Consistency verification each parameter value.

| Judgment matrix | $\lambda_{max}$ | CI | RI | CR |
|---|---|---|---|---|
| A | 3.054 | 0.0268 | 1.12 | 0.024 |
| $B_1$ | 2 | 0 | 1.12 | 0 |
| $B_2$ | 2 | 0 | 1.12 | 0 |
| $B_3$ | 4.054 | 0.017 | 1.12 | 0.015 |

Table 2: Theoretical weight calculations.

| Index | Weights | Sub indexes | Relative weights | $\omega'$ |
|---|---|---|---|---|
| $B_1$ | 0.1958 | $C_1$ | 0.3333 | 0.0653 |
| | | $C_2$ | 0.6667 | 0.1305 |
| $B_2$ | 0.3108 | $C_3$ | 0.75 | 0.2331 |
| | | $C_4$ | 0.25 | 0.0777 |
| $B_3$ | 0.4934 | $C_5$ | 0.1358 | 0.067 |
| | | $C_6$ | 0.1584 | 0.0782 |
| | | $C_7$ | 0.2651 | 0.1308 |
| | | $C_8$ | 0.4407 | 0.2174 |

ordering of the matrix, the AHP weight $\omega'$ can be calculated; the calculations are shown in Table 2.

*4.2.3. Calculation of Information Entropy Weights and Joint Weights.* Using test data from different production lines each month to build composite element matrix $R_{mn}$, in 8 decision indicators, alcohol loss energy consumption and material consumption per unit time are low; the higher the efficiency, the higher the other variables, but the other variables are high, so, the energy consumption, alcohol loss, and unit consumption are standardized by formula (3), and other variables are standardized by formula (4). The deviation $e_j$ and weight $\omega_j''$ for each evaluation indicator are calculated by formulas (7), (8), and (9); the calculations are shown in Table 3.

The joint weight $\omega_j$ for each evaluation indicator is calculated by formulas (10), (11), and (12); the calculations are shown in Table 4.

*4.3. Calculation and Sorting of Health Index.* For the old and new production lines, based on the data collected and calculated in Sections 3 and 4, when the objective weights and joint weights, respectively, and the health index are calculated by formula (15) and (16), the calculations are shown in Figures 4–7.

From Figures 4, 5, 6, and 7, the trend of health index calculated under subjective, objective, and joint weights is the same, the change trend of the health index curves calculated under the objective weights is eased, and it indicates that there is little difference in information state in a short time. The health index curves calculated under subjective weights change dramatically; it indicates that subjective weights preference trends to certain evaluation indicators. Small changes in relevant evaluation indicators lead to drastic changes in health index. The joint weight synthesizes the advantages of subjectivity and objectivity and not only reflects the change of objective information but also reflects the fluctuation of experts' preferences, which increases the reliability of health assessment and reflects the change of production line operation more accurately. The average monthly health index of each filling production line is shown in Table 5.

In actual production, under the same month, the new production line has less output downtime, less wine loss, good thermal insulation, and less energy consumption, so the production efficiency is better than the old one. June is the peak season for production. The equipment has a long continuous running time, high ambient temperature, good KPI parameters, low energy consumption, and high production efficiency. November is an off-season and production is intermittent. So the production line is healthier in June than

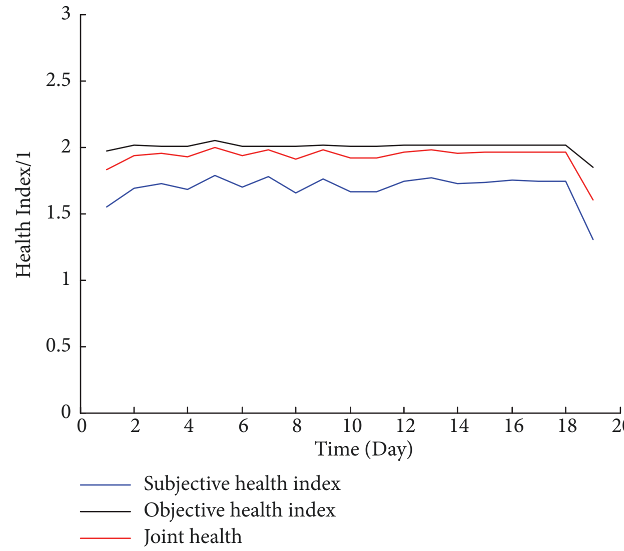



Figure 4: Health index curves of line 1 in June 16.

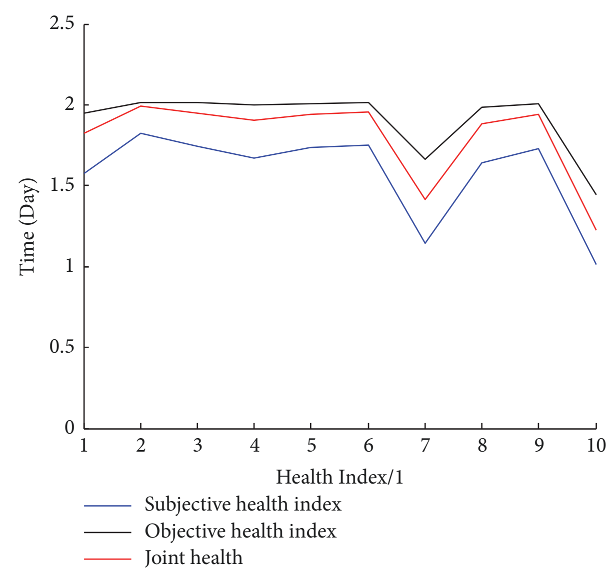



Figure 5: Health index curves of line 1 in November 16.

Table 3: Weights of each evaluation indicator.

| Evaluation indicators | Production Line 1 June | | Production Line 1 November | | Production Line 3 June | | Production Line 3 November | |
|---|---|---|---|---|---|---|---|---|
| | $e_j$ | $\omega''$ | $e_j$ | $\omega''$ | $e_j$ | $\omega''$ | $e_j$ | $\omega''$ |
| $C_1$ | 0.416 | 0.1278 | 0.1067 | 0.1446 | 0.5078 | 0.1271 | 0.1818 | 0.1274 |
| $C_2$ | 0.412 | 0.1265 | 0.0993 | 0.1346 | 0.5 | 0.1251 | 0.1848 | 0.1295 |
| $C_3$ | 0.412 | 0.1267 | 0.1051 | 0.14236 | 0.5042 | 0.1262 | 0.1897 | 0.1329 |
| $C_4$ | 0.406 | 0.1248 | 0.0863 | 0.11696 | 0.5018 | 0.1256 | 0.1825 | 0.1279 |
| $C_5$ | 0.402 | 0.1235 | 0.0858 | 0.11626 | 0.4964 | 0.1242 | 0.1825 | 0.1207 |
| $C_6$ | 0.402 | 0.1236 | 0.0854 | 0.1157 | 0.4963 | 0.1242 | 0.1825 | 0.1203 |
| $C_7$ | 0.402 | 0.1235 | 0.085 | 0.1152 | 0.4954 | 0.124 | 0.1825 | 0.1205 |
| $C_8$ | 0.402 | 0.1236 | 0.0845 | 0.1145 | 0.4938 | 0.1236 | 0.1825 | 0.1207 |

Table 4: Joint weights of each evaluation indicator.

| evaluation indicators | $\omega$ (AHP) | Production Line 1 June | | Production Line 1 November | | Production Line 3 June | | Production Line 3 November | |
|---|---|---|---|---|---|---|---|---|---|
| | $\omega'$ | $\omega''$ | $\omega_j$ | $\omega''$ | $\omega_j$ | $\omega''$ | $\omega_j$ | $\omega''$ | $\omega_j$ |
| $C_1$ | 0.1645 | 0.1278 | 0.1461 | 0.1446 | 0.1545 | 0.1271 | 0.1458 | 0.1274 | 0.1459 |
| $C_2$ | 0.3289 | 0.1265 | 0.2275 | 0.1346 | 0.2315 | 0.1251 | 0.2268 | 0.1295 | 0.2290 |
| $C_3$ | 0.2331 | 0.1267 | 0.1798 | 0.1424 | 0.1876 | 0.1262 | 0.1795 | 0.1329 | 0.1829 |
| $C_4$ | 0.0777 | 0.1248 | 0.1013 | 0.117 | 0.0974 | 0.1256 | 0.1017 | 0.1279 | 0.1029 |
| $C_5$ | 0.0266 | 0.1235 | 0.0752 | 0.1163 | 0.0716 | 0.1242 | 0.0755 | 0.1207 | 0.0738 |
| $C_6$ | 0.031 | 0.1236 | 0.0774 | 0.1157 | 0.0734 | 0.1242 | 0.0777 | 0.1203 | 0.0758 |
| $C_7$ | 0.0519 | 0.1235 | 0.0878 | 0.1152 | 0.0836 | 0.124 | 0.0880 | 0.1205 | 0.0863 |
| $C_8$ | 0.0863 | 0.1236 | 0.1050 | 0.1145 | 0.1004 | 0.1236 | 0.1050 | 0.1207 | 0.1035 |

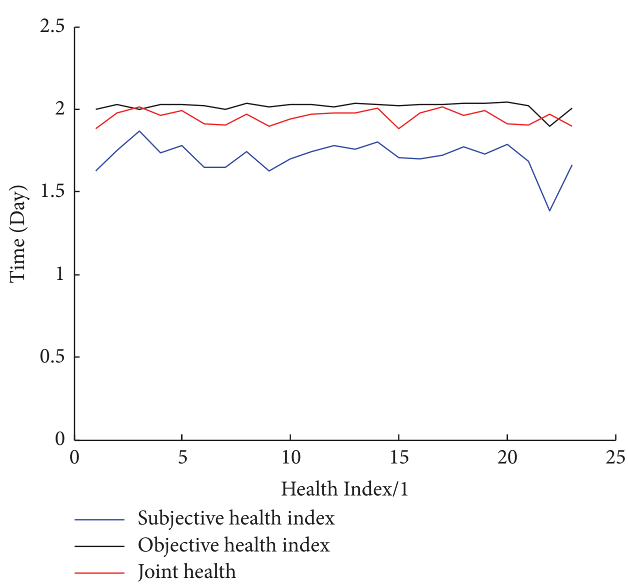



Figure 6: Health index curves of line 3 in June 16.

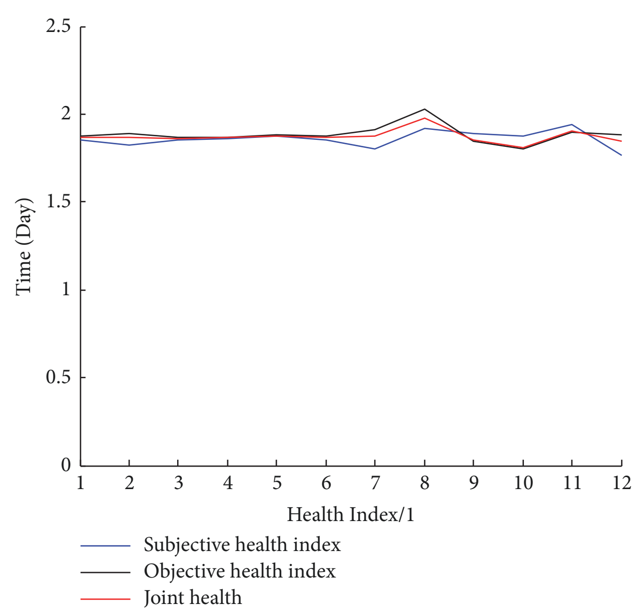



Figure 7: Health index curves of line 3 in November 16.

in November. From Table 5, it is shown the average health index of the calculation of the method is consistent with the actual situation, which proves that the scheme is reasonable and accurate, and the health index is quantified, which has a certain practical reference value.

## 5. Health Index Prediction

*5.1. Forecast Modeling Method.* In practical applications, predicting the future health index of production lines is more

Table 5: Average monthly health index.

| production line | Line 1 | | Line 3 | |
|---|---|---|---|---|
| month | June | Nov | June | Nov |
| Average health index | 1.926 | 1.802 | 1.943 | 1.872 |

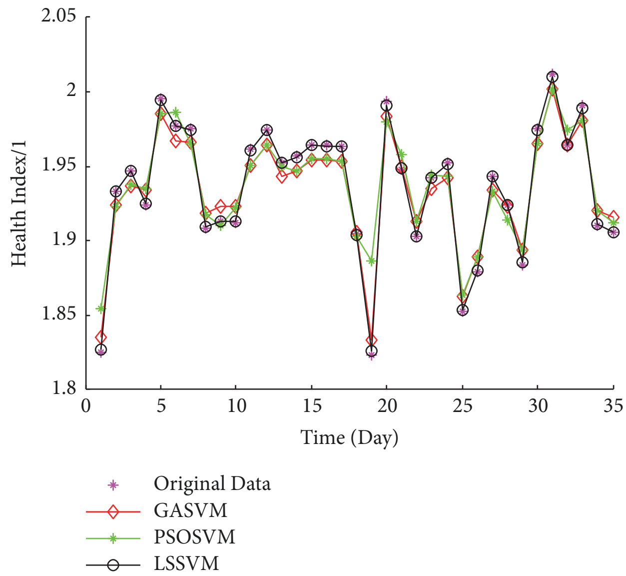



Figure 8: Health index training set fitting curves.

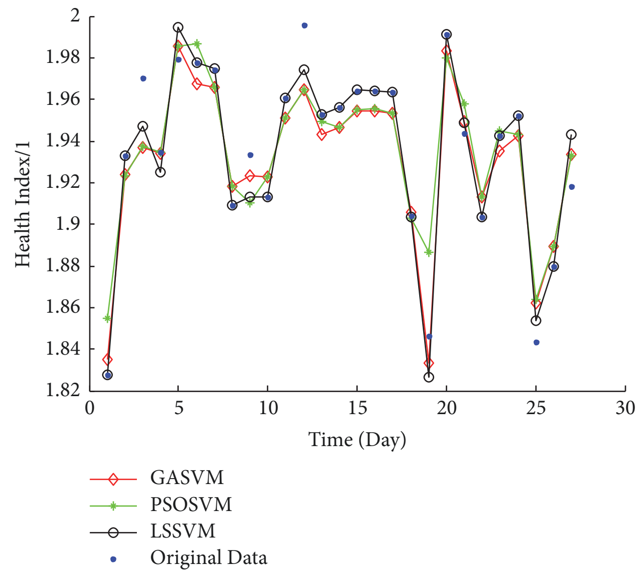



Figure 9: Health index testing set regression curves.

valuable for production schedule and equipment maintenance [23–27]. According to the data of 65 samples calculated in Section 4.3, 25 samples are taken as the testing set and 40 samples are used as the training set, the input to the LSSVM is time/day, and the output is the health index, by the MATLAB 7.11.0 development software, using the LSSVM lab toolbox developed by K Pelekmans, J.A.K, and Suykens to establish an optimal model.

For the same training set, the regression model is established by using LSSVM optimized by Grid-search with cross validation and epsilon-SVM algorithm optimized by genetic algorithm and particle swarm algorithm; these are abbreviated as LSSVM, GASVM, and PSOSSVM, respectively. The decision function $f(x) = \sum_{i=1}^{n} W_i K(x, x_i) + b$ is looked as the final health index expression, where $W_i$ are support vector coefficients, $x_i$ are support vectors, $x$ are the inspected samples, n is the number of support vectors, $b$ is constant, and $K(x, x_i)$ is a scalar radial basis kernel function computed as $K(x, x_i) = \exp(-g\|x - x_i\|^2)(g > 0)$. The fitting curve is shown in Figure 8. The testing set validation curve is shown in Figure 9.

*5.2. Comparison of Performance of Three Modeling Methods.* The best prediction model for the health index of the beer filling production line should be one with high fitting degree, the best correlation coefficient, and the least prediction error. The performances ($c, g, \sigma^2, \gamma$, Train-MSE, Train-R, Test-MSE, Test-R) of the three modeling methods are shown in Table 6. $c$ and g are the penalty parameter and the span coefficient of RBF function in SVM, $\sigma^2$and $\gamma$ are the kernel parameter

Table 6: Performances comparison.

| Performance | GASVM | PSOSVM | LSSVM |
|---|---|---|---|
| Optimal parameters | $c$= 13.5401 | $c$= 15.7359 | $\sigma^2$= 0.5875 |
| | $g$ = 1.3132 | $g$ =1.5760 | $\gamma$ = 343.67 |
| Train-MSE | 0.0093 | 0.0107 | 0.0094 |
| Train-R | 0.9396 | 0.9398 | 0.9506 |
| Test-MSE | 0.0131 | 0.0129 | 0.0106 |
| Test-R | 0.9210 | 0.9152 | 0.9227 |
| TIME | 9.718s | 17.57s | 0.037s |

and the normalized parameter in LSSVM, and Train-MSE and Train-R are the error and correlation coefficient in fitting. Test-MSE and Test-R are the error and correlation coefficient when testing is verified.

From Table 6, in the GASVM model, the fitting error and correlation coefficient are 0.0093/93.96%, the predicted error and correlation coefficient are 0.0131/92.10 %, and in the PSOSVM model, the fitting error and correlation coefficient are 0.0107/93.98 %, respectively. The forecast error and correlation coefficient are 0.0129/91.52 %. The prediction effect in the LSSVM model is better, the fitting error and correlation coefficient are 0.0094/95.06 %, respectively, and the predicted error and correlation coefficient are 0.0106/92.27 %, which can meet the needs of the production line health index prediction.

## 6. Conclusion

Aiming at the problem of health index evaluation and prediction of complex production lines, a new data mining method based on extension matter-element entropy and support vector machine is designed. A new method for evaluating the health of the beer filling production line is put forward, which integrates energy utilization, raw material consumption, production efficiency, beer loss, and equipment operation state. AHP and matter-element information entropy are used to determine subjective and objective weights; the combination weighting method is used to calculate joint weights, which improves the reliability of information entropy weights. Quantitative calculations of the health index are consistent with the actual qualitative analysis results. Using the optimized support vector machine algorithm to construct the health index prediction model, the experiment proves that the health index calculation is reasonable and the forecast accuracy is satisfactory. This method provides data support for beer filling process improvement, equipment overhaul, and production scheduling.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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