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ARTICLE

Research on Condenser Deterioration Evolution Trend Based on ANP-EWM Fusion Health Degree

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ABSTRACT

This study presents a proposed method for assessing the condition and predicting the future status of condensers operating in seawater over an extended period. The aim is to address the problems of scaling and corrosion, which lead to increased loss of cold resources. The method involves utilising a set of multivariate feature parameters associated with the condenser as input for evaluation and trend prediction. This methodology offers a precise means of determining the optimal timing for condenser cleaning, with the ultimate goal of improving its overall performance. The proposed approach involves the integration of the analytic network process with subjective expert experience and the entropy weight method with objective big data analysis to develop a fusion health degree model. The mathematical model is constructed quantitatively using the improved Mahalanobis distance. Furthermore, a comprehensive prediction model is developed by integrating the improved Informer model and Markov error correction. This model takes into account the health status of the equipment and several influencing factors, including multivariate feature characteristics. This model facilitates the objective examination and prediction of the progression of equipment deterioration trends. The present study involves the computation and verification of the field time series data, which serves to demonstrate the accuracy of the condenser health-related models proposed in this research. These models effectively depict the real condition and temporal variations of the equipment, thus offering a valuable method for determining the precise cleaning time required for the condenser.

KEYWORDS

Condenser; health degree; improved Mahalanobis distance; GC-Informer model; Markov error correction

1 Introduction

In the preceding thirty years, the secondary loop systems of nuclear power plants have encountered diverse levels of degradation and deterioration in their crucial equipment. Hence, conducting research on the health status of nuclear power unit equipment carries significant importance [1]. The condenser, being a crucial heat exchange apparatus within the conventional island of nuclear power plants, has a direct influence on the safety of the turbine unit by ensuring its proper and steady operation. The extended exposure of condensers to seawater might result in the occurrence of scaling and corrosion. Presently, the prevailing method for cleaning condensers involves the utilisation of conventional online rubber ball cleaning equipment in order to uphold cleanliness and optimise heat transfer efficiency. Nevertheless, the utilisation of rubber balls for cleaning purposes incurs a substantial financial burden, while inadequate cleaning intervals, whether too prolonged or excessively brief, can lead to unnecessary energy consumption [2,3]. The determination of condenser cleaning time holds considerable importance in enhancing the operational dependability of the condensing system and the economic efficiency of the turbine unit. Therefore, it is important to conduct monitoring and analysis of the condenser's status in order to determine the appropriate timing for cleaning the condenser equipment. This can be achieved by quantitatively assessing the degree of equipment health.

For the purpose of successfully cleaning the condenser, it is essential to accurately evaluate its overall condition. Currently, the predominant approach employed to assess the condition of the equipment is based on the notion of health degree. Nevertheless, the concept of a "healthy degree" lacks quantifiability and necessitates the identification and analysis of pertinent aspects that contribute to its attainment. The establishment of a scientifically valid assessment approach for determining the status of equipment is deemed required [4,5]. The assessment methods can be broadly categorised into subjective weighting methods and objective weighting methods. Subjective weighing methods are predominantly exemplified by two prominent approaches, namely the Analytic Hierarchy Process (AHP) and the Fuzzy Comprehensive Evaluation method (FCE). The literature employs the use of AHP [6,7] in order to establish an evaluation model that is based on scientific principles. This approach presents the benefits of a straightforward procedure and yielding intuitive outcomes. Nevertheless, the susceptibility of this phenomenon to subjective factors, such as expert knowledge and experience, should be acknowledged. As a result, it is possible that this could result in inaccuracies when evaluating the outcomes. The FCE [8] methodology employs fuzzy mathematics in order to thoroughly evaluate a wide range of criteria that pose challenges in terms of quantitative assessment. In their study, Hassan et al. [9] utilised a Fuzzy Analytic Hierarchy Process (FAHP) methodology to evaluate the level of satisfaction among borrowers. Nevertheless, their methodology exclusively facilitates a thorough fuzzy assessment, without immediately offering a quantitative depiction of the level of health of the item. The Principal Component Analysis (PCA) and the Entropy Weighting Method (EWM) are the primary objective weighting approaches. In their study, Giorgi et al. [10] employed an enhanced Principal Component Analysis (PCA) technique to extract the feature parameters that carry the most relevant information for the purpose of monitoring the health status of engines. Nevertheless, the use of PCA involves the conversion of correlated indicators into principle components, hence resulting in the potential loss of certain information. This loss of information can subsequently lead to the wrong determination of weights. In their study, Erkhembaatar et al. [11] employed the entropy weighting approach to ascertain the significance coefficients of indicators. In their study, Zavadskas et al. [12] utilised the Entropy Weighting Method to evaluate alternative solutions. Their objective was to identify the most optimal alternative solution by identifying the most suitable criteria. In their study, Gorgij et al. [13] employed the Exponential Weighted Moving Average (EWM) technique to construct a model for evaluating groundwater quality. The researchers evaluated the weights of pertinent factors in order to assess the water quality level of 21 groundwater samples. This model is well-suited for scenarios that involve several indications, since it has the capability to objectively reflect the significance of these indicators based on big data analysis. Nevertheless, it is worth noting that this issue can be delicate, potentially resulting in the inefficiency of parameters. Hence, there is a need for a more precise approach to ascertain the weights of feature parameters in order to quantify the degree of equipment health. By integrating the benefits of subjective weighting methods and objective weighting methods, a more comprehensive depiction of equipment health status can be attained through mutually reinforcing approaches.

The assessment of the operational condition and estimation of the cleaning duration of the condenser are crucial tasks in evaluating the health status of the equipment, as per the healthy degree model. In their study, Ma [14] focused on the determination of the equipment health index and its status after a one-year period. This was achieved by establishing a functional link between the equipment health index and the failure rate. Furthermore, Alinejad et al. [15] proposed a complete approach to determine the equipment health index by employing the Monte Carlo method. Nevertheless, the aforementioned approaches solely consider the past health condition, neglecting the influence of previous running parameters on the future condition of the equipment. On the other hand, deep learning techniques facilitate the implementation of multilayer nonlinear transformations, hence enhancing the ability to extract and discern correlations among input parameters. The utilisation of layer-by-layer coding networks and Deep Neural Networks (DNN) for condition monitoring of wind turbine main bearings and gearboxes has been proposed in references [16,17]. The operational data of condensers comprises multidimensional time series, wherein there exists temporal dependence between the current and historical moment data. The modelling methods mentioned above have limitations due to their reliance on single time point input and their inability to account for time series dependencies. In recent times, there has been an increase in the utilisation of LSTM techniques by researchers for the purpose of forecasting the operational condition of nuclear power plants. In their study, Zhang et al. [18] employed a Long Short-Term Memory (LSTM) neural network to forecast the pressure of steam generators by utilising a fusion technique for multi-sensor signals. The experimental outcomes provided confirmation of the LSTM model's effectiveness in predicting the operational condition of nuclear power plants. Babu et al. [19] employed a Long Short-Term Memory (LSTM)-based neural network to estimate the state of water health. Similarly, Tuerxun et al. [20] utilised LSTM to predict renewable energy generation in wind farms. However, it should be noted that the training pace of this model is relatively slow while achieving comparable prediction accuracy. In comparison to alternative deep learning approaches, the Informer model is employed for the purpose of extracting time connections between input sequences, resulting in superior accuracy in temporal prediction. In their study, Bommidi et al. [21] put out the utilisation of the Informer model for the prediction of wind speed indicators characterised by intricate uncertainties. Li et al. [22] introduced a novel approach for predicting the Remaining Useful Life (RUL) of rolling bearings. This method combines multiscale degradation metrics with the Informer model, addressing the limitations of traditional prediction models in terms of slow runtime and limited reliance on long time series data. However, it is important to note that the generalisation of this approach still requires improvement, particularly when handling feature parameters with varying probability distributions. In response to the variability in condenser performance caused by external factors, certain scientists have proposed integrating error correction techniques with predictive models as a means to improve the resilience and adaptability of these models. The researchers in the study conducted by Theocharides et al. [23] utilised linear regression as a method to address the prediction bias associated with solar radiation angles. This approach resulted in improved accuracy of day-ahead forecasts for photovoltaic power generation. The aforementioned model possesses the merits of being straightforward and exhibiting a notable degree of computational efficacy. Nevertheless, the performance of this method is influenced by the distribution of data and the underlying assumptions of the model, limiting its ability to capture non-linear correlations. Zou et al. [24] employed a Markov chain methodology to rectify the prediction outcomes pertaining to China's Gross Domestic Product (GDP). The present model incorporates the empirical data collected throughout a specific historical timeframe, effectively accounting for the cumulative effects of inaccuracies. This study aimed to examine the progression of condenser health status. This paper presents a novel approach by integrating the Informer model with the MC error correcting method to estimate the health of condensers, taking into account the natural state transition patterns in health evolution. This methodology enables enhanced precision in forecasting the condition of equipment, particularly within the framework of extensive data settings.

In order to effectively schedule the cleaning time of equipment and optimise the monitoring of condenser health status, as well as accurately predict the equipment's deterioration trend, this paper proposes two models: a fusion health degree model utilising high-dimensional Mahalanobis distance, and a combined prediction model that incorporates this health degree. The initial step involves utilising a collection of multivariate feature parameters associated with health degree as the input. This input is then utilised to construct a fusion health degree model, employing high-dimensional Mahalanobis distance. The fusion model integrates both subjective Analytic Network Process (ANP) and objective Entropy Weight Method (EWM), and is commonly referred to as ANP-EWM. In this study, we propose the utilisation of a refined Informer model in conjunction with a Markov error correction technique referred to as Generalised Correntropy-Informer-Markov Error Correction (GC-Informer-MEC). The Informer model utilises the generalized correlation entropy as its loss function to enhance the correlation between feature data and the sequential correlation of time-series data. This approach addresses the issue of low prediction accuracy observed in Informer models when handling non-Gaussian probability distribution parameters. Furthermore, the issue of unpredictability in the process of predicting the level of health degree is mitigated through the implementation of enhanced error correcting techniques. This research shows that the condenser's calculated health degree using the proposed approach is congruent with its real health condition based on the examination of field time-series data. The provided analysis delivers a quantitative assessment of the equipment's health status based on its running time. This analysis effectively forecasts the future trend of the condenser and provides a dependable reference for selecting the optimal cleaning time for the condenser.

2 Building of Weight Fusion Health Degree Model Based on High-Dimensional Mahalanobis Distance

Let $\boldsymbol{X} = [x_1, x_2, x_3, \ldots, x_m]$ be a multidimensional vector composed of m features, then the Mahalanobis distance between the ith step feature vector $\boldsymbol{X}_i$ and the health feature $\boldsymbol{X}_0$ can be expressed as [25]:

$$D_M(\boldsymbol{X}_i, \boldsymbol{X}_0) = \sqrt{(\boldsymbol{X}_i - \boldsymbol{X}_0)\,\boldsymbol{\Sigma}^{-1}\,(\boldsymbol{X}_i - \boldsymbol{X}_0)^{\mathrm{T}}} \tag{1}$$

where $\boldsymbol{X}_i = [x_{i1}, \cdots, x_{ik}, \cdots, x_{im}]$, x_{ik} denotes the k eigenparameter value in the ith step of monitoring; $\boldsymbol{X}_0 = [x_1, \cdots, x_k, \cdots, x_{\mathrm{m}}]$, x_k represents the k eigenparameter value when the equipment is in full health; Σ is the covariance matrix of the multidimensional variables $\boldsymbol{X}_i$ and $\boldsymbol{X}_0$.

Taking into account the varying degrees of influence that each characteristic parameter within the multivariate characteristic parameters has on the equipment's health status, we introduce weights to enhance their significance in determining the health degree. Thus, the fusion healthiness model can be formulated as follows:

$$H(\boldsymbol{X}_i, \boldsymbol{X}_0) = 1/\left[1 + \sqrt{\boldsymbol{W}(\boldsymbol{X}_i - \boldsymbol{X}_0)\,\boldsymbol{\Sigma}^{-1}\,(\boldsymbol{X}_i - \boldsymbol{X}_0)^{\mathrm{T}}}\right] \tag{2}$$

where $H(X_i, X_0)$ represents the health degree of step i, and the health degree range is defined as [0,1]; The weight vector, denoted as W, is derived by integrating the analytic network process incorporating subjective experience and the entropy weight method based on objective big data analysis.

2.1 Calculation of W_1 Based on Analytic Network Process

The Analytic Network Process (ANP) is a hierarchical multi-criteria decision-making method that builds upon the AHP method. ANP takes into account the multi-level structure and the interdependencies among numerous indicators, resulting in an enhanced approach [26]. This study focuses on the condenser as the subject of investigation, employing a thermodynamic mechanism analysis. The primary objective is to develop a health evaluation system comprising four distinct characteristic factors. The comprehensive evaluation of the condenser equipment's performance can be achieved to a certain extent by considering the overall heat transfer coefficient and cleaning coefficient. Condensate subcooling degree $X_{\Delta tgl}$, circulating water temperature rise $X_{\Delta t_{xhs}}$, circulating water pump motor current $X_{I_{sb}}$ and end difference $X_{\Delta t_{dc}}$ all have certain influence on heat transfer coefficient and cleaning coefficient. Analyzing the working principle of the condenser, it can be obtained that there is a coupling relationship between the four characteristic parameters [27]. Establishing a health assessment framework for the condenser requires analyzing the extent to which its characteristic parameters affect overall performance. This involves calculating the weights of different characteristic parameters in the evaluation of equipment health. The use of the analytic network process allows for the comprehensive consideration of the interrelationships among these characteristic parameters. It facilitates the development of a multi-criteria weight calculation method, enabling accurate assessment of the impact of different characteristic parameters on equipment health degree. The diagram in Fig. 1 illustrates the hierarchical structure of the algorithm applied in the analytic network method.

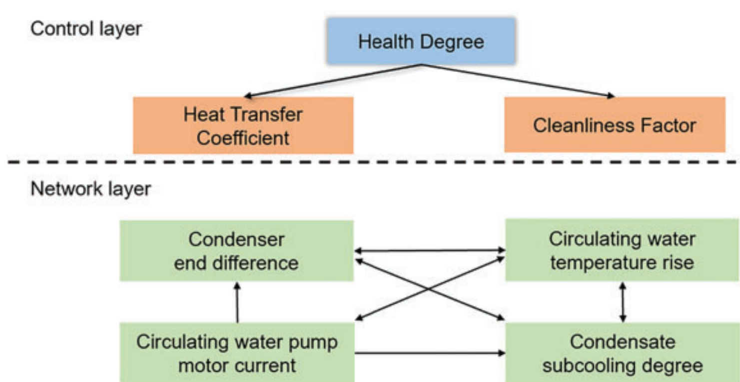

Figure 1: The hierarchical structure of analytic network process

Based on the above hierarchical structure, with the control layer as the main criterion and the four characteristic parameters in the network layer as the secondary criterion, the elements are compared in pairs to build an initial unweighted supermatrix W_s:

$$W_s = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \tag{3}$$

where the column vector of $\boldsymbol{W}_{ij}$ represents the indirect dominance degree comparison of the influence of the elements in element group i on the elements in element group j with the elements in element group j as sub-criteria:

$$\boldsymbol{W}_{ij} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix} \tag{4}$$

Taking the overall heat transfer coefficient and the overall cleaning coefficient as the secondary criterion, a judgment matrix is established by pairwise comparison, and then the weight supermatrix $\boldsymbol{A}_s$ is obtained:

$$\boldsymbol{A}_s = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{5}$$

On the basis of formulas (3) and (5), the weighted supermatrix $\boldsymbol{W}_{as}$ shown in formula (6) is constructed:

$$\boldsymbol{W}_{as} = \boldsymbol{A}_s \boldsymbol{W}_s \tag{6}$$

Finally, the weight is obtained by calculating the limit weighted supermatrix, and the priority of the feature variable is determined:

$$\boldsymbol{W}_1 = \lim_{k \to \infty} \boldsymbol{W}_{as}^{w} \tag{7}$$

where $\boldsymbol{W}_1$ is the weight vector calculated by the ANP.

2.2 Calculation of W_2 Based on Entropy Weight Method

According to the above four characteristic parameters and the data set of n groups of samples, an evaluation matrix $\boldsymbol{M} = \left(m_{ij}\right)_{n\times 4}$ is built. In instances when the initial evaluation matrix comprises values that are equivalent to zero, it indicates that these characteristic parameters do not contribute to any loss of information in the health assessment. As a result, the entropy values associated with these parameters reach a state of zero, hence causing a proportional augmentation in their respective weights. This phenomenon has the potential to induce bias into the outcomes of health assessments. In real-world scenarios, feature parameters may face instances of zero values as a result of measurement mistakes and various other factors. In order to mitigate any bias in the weights, this study proposes the incorporation of a little perturbation when employing the Entropy Weight Method (EWM) to calculate weights, particularly in cases when zero values are present. The purpose of this perturbation is to reduce the potential influence of zero values on the process of determining weights. Subsequently, m_{ij} is standardized to obtain a standard evaluation matrix $\boldsymbol{V} = \left(v_{ij}\right)_{n\times 4}$ [28].

The entropy value e_j of the jth feature parameter can be expressed as:

$$e_j = -k \sum_{j=1}^{n} h_{ij} \ln h_{ij}, k = 1/\ln n \tag{8}$$

where $h_{ij} = v_{ij} / \sum_{i=1}^{n} v_{ij}, i = 1, 2, \cdots, n; j = 1, 2, \cdots, 4$ denotes the weight of the ith sample value under the jth characteristic parameter.

Further, the weight vector calculated by the entropy weighting method is obtained as [29]:

$$\boldsymbol{W}_2 = \left[\omega_1, \cdots, \omega_j, \cdots, \omega_4\right]^{\mathrm{T}} \tag{9}$$

where $\boldsymbol{W}_2$ is the weight vector calculated by entropy weight method, $\omega_j = \partial_j / \sum_{j=1}^{4} \partial_j, j = 1, 2, \cdots, 4$.

2.3 Health Degree Model of Weight Fusion

To enhance the precision of assessing the health degree, the health degree model is constructed by incorporating the high-dimensional Mahalanobis distance. Additionally, a fusion weighting method is employed, which combines both subjective and objective weighting methods, to determine the weights assigned to the characteristic parameters that represent the health degree. This methodology circumvents the inherent subjectivity associated with the ANP and addresses the computational bias resulting from the limited data available in the EWM. $\boldsymbol{W}$ is a linear combination of $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$. Due to the subjective sources of representing health degrees using the ANP and the objective sources of representing health degrees using the EWM, this study considers both subjective and objective sources, each contributing equally to the composite weight, to characterize equipment health degree. The proposed model for determining the fusion weight of health degree is as follows:

$$\begin{cases} H\left(\boldsymbol{X}_i, \boldsymbol{X}_0\right) = 1 / \left[1 + \sqrt{\boldsymbol{W}\left(\boldsymbol{X}_i - \boldsymbol{X}_0\right) \boldsymbol{\Sigma}^{-1} \left(\boldsymbol{X}_i - \boldsymbol{X}_0\right)^{\mathrm{T}}}\right] \\ \boldsymbol{W} = \alpha \boldsymbol{W}_1 + \beta \boldsymbol{W}_2 \end{cases} \tag{10}$$

where α and β are the proportions of the weights calculated by the ANP and the EWM in the comprehensive weight, respectively.

3 Combined Prediction Model Based on GC-Informer and Markov Error Correction

Various aspects in the operational environment of nuclear power plants have an impact on the operating parameters of the condenser. The equipment parameter data in this context generally follows a non-Gaussian distribution. The health degree time-series data is subject to the influence of the equipment operating environment and many characteristics, resulting in a non-Gaussian distribution. In order to further understand the deterioration trend of the condenser and improve the stability and accuracy of the health degree prediction model, aiming at the problem that the Informer model has low prediction accuracy for non-Gaussian distribution parameters, an improved combination prediction model of Informer and MEC is established. By changing model loss function and increasing the error correction amount to achieve the purpose of accurately predicting the health degree of the condenser. This model comprehensively takes into account the impact of historical running data on health status. It utilizes various time series as input variables in order to forecast the health degree of the condenser.

3.1 GC-Informer Model

The GC-Informer prediction model obtains the temporal dependence of the five-dimensional feature parameter set including the historical health degree of the condenser through the encoder, and generates the health prediction result through the decoder. Considering the significance of time in health degree prediction, before inputting the model, time stamp encoding is used to encode the year, month, day, hour, minute and other information in the data to improve the predictive ability of the model in long-term series. The operation is as follows:

$$PE(\mathrm{pos},\, 2\mathrm{i}) = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{\mathrm{model}}}}}\right) \tag{11}$$

$$PE(\mathrm{pos}{,}2i+1) = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{\mathrm{model}}}}}\right) \tag{12}$$

3.1.1 Encoder

The encoder is mainly composed of multi-head probsparse self-attention mechanism modules and distillation modules. It takes the historical running data $\mathbf{X}^{\mathrm{t}} = [\mathbf{X}^{\mathrm{t}}_{\Delta \mathrm{tgl}}, \mathbf{X}_{\Delta t_{xhs}}, \mathbf{X}^{\mathrm{t}}_{\mathrm{Isb}}, \mathbf{X}^{\mathrm{t}}_{\Delta \mathrm{t_{dc}}}, \mathbf{H}^{\mathrm{t}}(\mathbf{X}, \mathbf{X_0})]$ of the condenser as input and uses the multi-head sparse self-attention mechanism to extract long-term dependencies in the temporal data. The attention distillation mechanism is then applied to reduce the temporal dimension by half for each individual layer's features. The feature dimension is further compressed and essential information is extracted using a 1D convolutional neural network [30]. The distillation process from j layer to $j+1$ layer is illustrated by Eq. (14), enhancing the model's capability to handle long time series data.

$$X^{t}_{j+1} = \mathrm{MaxPool}\left(\mathrm{ELU}\left(\mathrm{Convld}\left(\left[X^{t}_{j}\right]_{\mathrm{ATTENTION}}\right)\right)\right) \tag{13}$$

Among them, $\left[X^{t}_{j}\right]_{\mathrm{ATTENTION}}$ represents the processing process in the multi-head probsparse self-attention mechanism, Convld represents the one-dimensional convolution operation on the time-series, and ELU$(\cdot)$ is the activation function. After applying a max-pooling layer, the dimension of X^{t} is reduced by 1/2. The dimension of the self-attention block is also reduced by 1/2 compared to the previous one, thereby reducing the memory footprint and runtime of the encoder. The encoder structure is shown in Fig. 2.

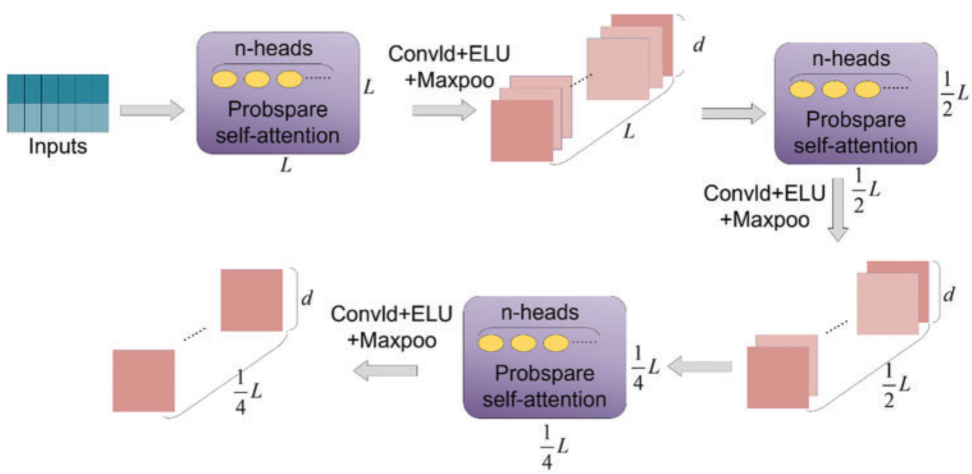

Figure 2: Encoder structure

3.1.2 Multi-Head Probsparse Self-Attention Mechanism

The self-attention mechanism assigns weight coefficients by calculating the similarity between the Query and Key [31]:

$$\text{Attention}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \text{Softmax}\left(\frac{\mathbf{Q}\boldsymbol{K}^{\mathrm{T}}}{\sqrt{d}}\right)\boldsymbol{V} \tag{14}$$

where $\boldsymbol{Q} \in R^{L_Q \times d}, \boldsymbol{K} \in R^{L_K \times d}, \boldsymbol{V} \in R^{L_V \times d}$ is the feature matrix obtained by linear transformation of the input feature variables, d is the input dimension, and S$oftmax(\cdot)$ is the activation function. To further discuss the self-attention mechanism, let the ith row of $\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}$ be $\boldsymbol{q}_i, \boldsymbol{k}_i, \boldsymbol{v}_i$, respectively. The attention coefficient of the ith row of Query is defined as a kernel smoother in the probabilistic form:

$$\text{Attention}\left(\boldsymbol{q}_i, \boldsymbol{K}, \boldsymbol{V}\right) = \sum_j \frac{k\left(\boldsymbol{q}_i, \boldsymbol{k}_j\right)}{\sum_l k\left(\boldsymbol{q}_i, \boldsymbol{k}_l\right)} v_j = E_{p\left(k_j q_i\right)}\left[\boldsymbol{v}_j\right] \tag{15}$$

where $p\left(\boldsymbol{k}_j \mid \boldsymbol{q}_i\right) = k\left(\boldsymbol{q}_i, \boldsymbol{k}_j\right) / \sum_l k\left(\boldsymbol{q}_i, \boldsymbol{k}_l\right),\ k\left(\boldsymbol{q}_i, \boldsymbol{k}_j\right) = \exp\left(\boldsymbol{q}_i \boldsymbol{k}_i^{\mathrm{T}} / \sqrt{d}\right)$. The GC-Informer model sparsifies the attention mechanism by distinguishing high-importance queries based on the similarity between distributions p and q, using KL divergence to measure the similarity.

$$M\left(\boldsymbol{q}_i, \boldsymbol{K}\right) = \ln \sum_{j=1}^{L_K} e^{\frac{q_i \boldsymbol{k}_j^{\mathrm{T}}}{\sqrt{d}}} - \frac{1}{L_K} \sum_{j=1}^{L_K} \frac{\boldsymbol{q}_i \boldsymbol{k}_j^{\mathrm{T}}}{\sqrt{d}} \tag{16}$$

where the first term is the Log-Sum-Exp (LSE) of $\boldsymbol{q}_i$ on all Keys, and the second term is their arithmetic mean. If the ith row of Query obtains a larger $M\left(\boldsymbol{q}_i, \boldsymbol{K}\right)$, the dot product has a larger contribution to attention. The probsparse self-attention mechanism is implemented by allowing each Key to focus only on the Query with higher importance, thus reducing the model computational complexity.

$$\text{Attention}\ (\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \text{Softmax}\left(\frac{\overline{\mathbf{Q}}\boldsymbol{K}^{\mathrm{T}}}{\sqrt{d}}\right)\boldsymbol{V} \tag{17}$$

3.1.3 Decoder

The input to the decoder is a five-dimensional data sequence, including the historical health index of the condenser, along with a segment of zeros that is equal to the prediction step length. Zeros are used as placeholders for the predicted values to prevent the model from accessing future sequence information during training. The input vector is represented as shown in Eq. (19).

$$\boldsymbol{X}^{\boldsymbol{t}}_{\text{decoder}} = \text{Concat}\left(\boldsymbol{X}^{\boldsymbol{t}}_{\text{token}}, \boldsymbol{O}^t\right) \tag{18}$$

Within the decoder, the input time series data is first calculated by the masked multi-head probsparse self-attention mechanism module, and then the sparse self-attention operation is performed with the feature map output by the encoder. The resulting computation is then passed through a fully connected layer to obtain the prediction result $\boldsymbol{Y} = [y^{t+1}, y^{t+2}, \cdots, y^{t+m}, \cdots, y^{t+n}]$. The prediction results are compared with the actual values to calculate the loss function, which is used to continuously optimize the model based on the errors. In order to address the probability distribution characteristics of the running parameters in the subject of this study, the generalized correntropy function is applied as the loss function for training the Informer prediction model. The mathematical formula for the GC is shown in Eq. (20):

$$\begin{aligned} L_{\text{GCloss}}\left(y^{r+m}, H^{r+m}\right) &= G_{\alpha,\beta}(0) - V_{\alpha,\beta}\left(y^{r+m}, H^{r+m}\right) \\ &= G_{\alpha,\beta}(0) - \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} G_{\alpha,\beta}\left(y^{r+m}, H^{r+m}\right) \\ &= \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)} - \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)} \exp\left(-\left|\frac{y^{r+m} - H^{r+m}}{\beta}\right|^{\alpha}\right) \end{aligned} \tag{19}$$

where y^{r+m} is the predicted value, H^{r+m} samples the true value, N is the number of data, $\alpha > 0$ is the shape parameter of the generalized Gaussian distribution, $\beta = \sigma\sqrt{\frac{1/\sigma}{3/\sigma}}$, σ is the Gaussian kernel parameter, and $\Gamma(\bullet)$ is the gamma function. Input the test data set into the trained GC-Informer model, and output the health degree prediction result. Its overall structure is shown in Fig. 3.

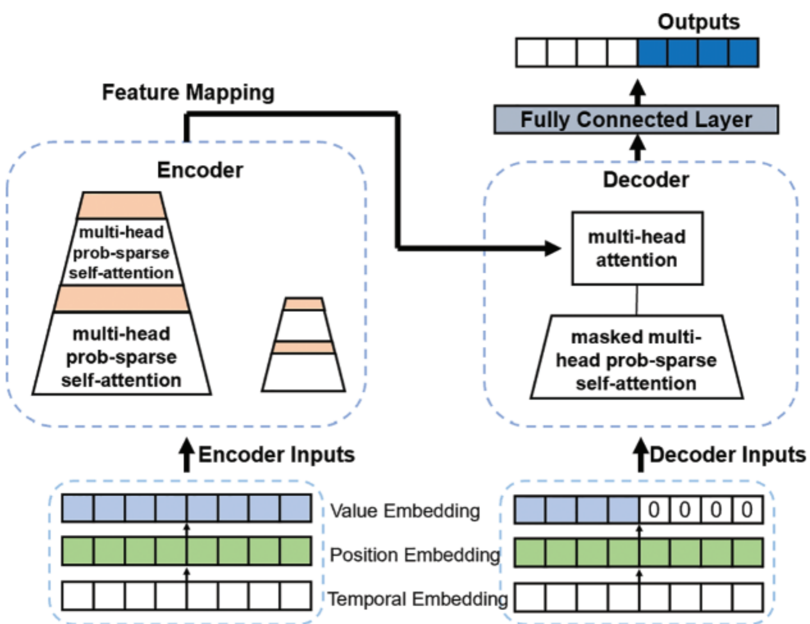

Figure 3: Informer model structure

3.2 Markov Error Correction

Considering the presence of randomness in the prediction process and aiming to enhance the prediction accuracy of condenser health degree, a Markov chain is applied to partition the development pattern and potential outcomes of condenser health into different states. The transition rules between different states are studied to modify the predicted results of condenser health degree. Characterized by the transition matrix, in the process of solving the state probability, the states are divided into n types (namely $S_1, S_2, \cdots, S_n$) through the analysis of the condenser health degree prediction error sequence, and the state division is based on the following [32]:

$$n = \mathrm{EVEN}\left(\frac{d}{\sigma}\right) \tag{20}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\varepsilon_j - \bar{\varepsilon}_i\right)^2} \tag{21}$$

where the EVEN($\cdot$) function is the nearest even number taken along the direction of increasing absolute value, ε is the sequence of residuals, and d is the difference between the maximum and minimum residuals. Next, based on the statistics of health prediction errors, the transition probabilities between states are calculated. Specifically, the probability of relative error transitioning from state S_i to state S_j over k time steps is given by:

$$P_{ij}(k) = \frac{M_{ij}(k)}{M_i} \tag{22}$$

where $M_{ij}(k)$ represents the number of times state S_i transitions to state S_j after k time steps, and M_i represents the number of occurrences of relative error in state S_i. The matrix form is:

$$\boldsymbol{P} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{23}$$

Assuming that the current state is S_i, in the ith row of the transition probability matrix, P_{ij} is the maximum value in this row, then the possibility of the state S_j appearing at the next moment is the greatest, and it is taken as the corresponding prediction result.

Finally, an error correction value e^{t+m} is taken for each state to modify it, resulting in the predicted health degree. The correction basis is as follows:

$$e^{t+m} = \left[\left(\Delta_{\max} + \Delta_{\min}\right)/2\right] y^{t+m} \tag{24}$$

where $\Delta_{\max}$ and $\Delta_{\min}$ are the upper and lower limits of the relative error state interval, respectively, and y^{t+m} is the predicted health degree of GC-Informer model.

3.3 Establishment of GC-Informer-MEC Combined Prediction Model

Based on the above theories, this paper combines GC-Informer and MEC to establish a combined predicting model that improves Informer and Markov error correction. The input of the prediction model is $\mathbf{X^t} = [\mathbf{X}^{\mathrm{t}}_{\Delta\mathrm{tgl}}, \mathbf{X}_{\Delta t_{xhs}}, \mathrm{X}^{\mathrm{t}}_{\mathrm{Isb}}, \mathbf{X}^{\mathbf{t}}_{\Delta \mathrm{t_{dc}}}, \mathbf{H}^{\mathrm{t}}(\mathbf{X}, \mathbf{X_0})]$. The inputs of the model are presented in Table 1. The historical time-series data of the condenser's characteristic parameters include the condensate subcooling degree $X_{\Delta tgl}$, circulating water temperature rise $X_{\Delta t_{xhs}}$, circulating water pump motor current $X_{I_{sb}}$ and end difference $X_{\Delta t_{dc}}$. Additionally, the historical time-series data of the condenser's health degree is represented by the health degree. One instance of variable data at a particular moment (row) can be observed as [0.4977, 7.1874, 0.5846, 6.7075, 0.9571]. The time-series data, which consists of five dimensions, is divided into segments for the composite prediction model. The segmentation is achieved by utilising a sliding time-series window with a length of 200. In every iteration of the model, a matrix with dimensions of 200 $*$ 5 is employed as input data, which is segmented using the sliding window technique.

Table 1: The inputs of the GC-Informer-MEC combined prediction model

No.	Symbol	Name
1	Δt_{gl}	Condensate subcooling degree
2	Δt_{xhs}	Circulating water temperature rise
3	I_{sb}	Circulating water pump motor current
4	Δt_{dc}	End difference
5	$H(\boldsymbol{X}, \boldsymbol{X}_0)$	Historical health degree

In order to enhance the reliability of predicting outcomes, the data utilised for the model is divided into three distinct sets: training datasets $\mathbf{X}_1^t$, validation datasets $\mathbf{X}_2^t$, and testing datasets $\mathbf{X}_3^t$. These sets are allocated in a ratio of 6:2:2, respectively. The training dataset $\mathbf{X}_1^t$ and validation dataset $\mathbf{X}_2^t$ are used to train the model, and the testing dataset $\mathbf{X}_3^t$ is fed into the trained GC-Informer model for health degree prediction. The first part of the proposed combined prediction model is the GC-Informer prediction model. This model compares the Informer method's predicted results against actual values using the training and validation datasets, calculating the GC loss function. Continuous optimization of the model is achieved through error minimization, resulting in a well-trained GC-Informer model. Using the testing dataset $\mathbf{X}_3^t$, the trained GC-Informer model generates predictions. The latter half of the combined prediction model applys the Markov Error Correction algorithm to calculate errors between the GC-Informer predicted results and actual values. It subdivides the error state space and calculates the state transition matrix, obtaining error correction values. The final prediction of the model is a combination of GC-Informer predictions and MC correction values. The overall process is illustrated in Fig. 4.

$$H^{t+m} = y^{t+m} + e^{t+m} \tag{25}$$

4 Example Verification

This paper utilizes an example dataset comprising 12,960 sets of field operation data from January to March 2022 of a domestic 1000 MW nuclear power plant unit for validation and analysis. Using four characteristic parameters $X_{\Delta tgl}$, $X_{\Delta t_{xhs}}$, $X_{I_{sb}}$, and $X_{\Delta t_{dc}}$, the health degree $H(\boldsymbol{X}, \boldsymbol{X}_0)$ of the condenser is determined. In addition, the computed condenser health degree is utilised in conjunction with these four distinctive factors to forecast the trajectory of changes in the health degree of the condenser. In order to improve the quality of the data, several procedures were adopted during the processes of data collecting and conversion. The missing data were resolved by employing the mean fill approach, and the outliers were managed with the plural fill method.

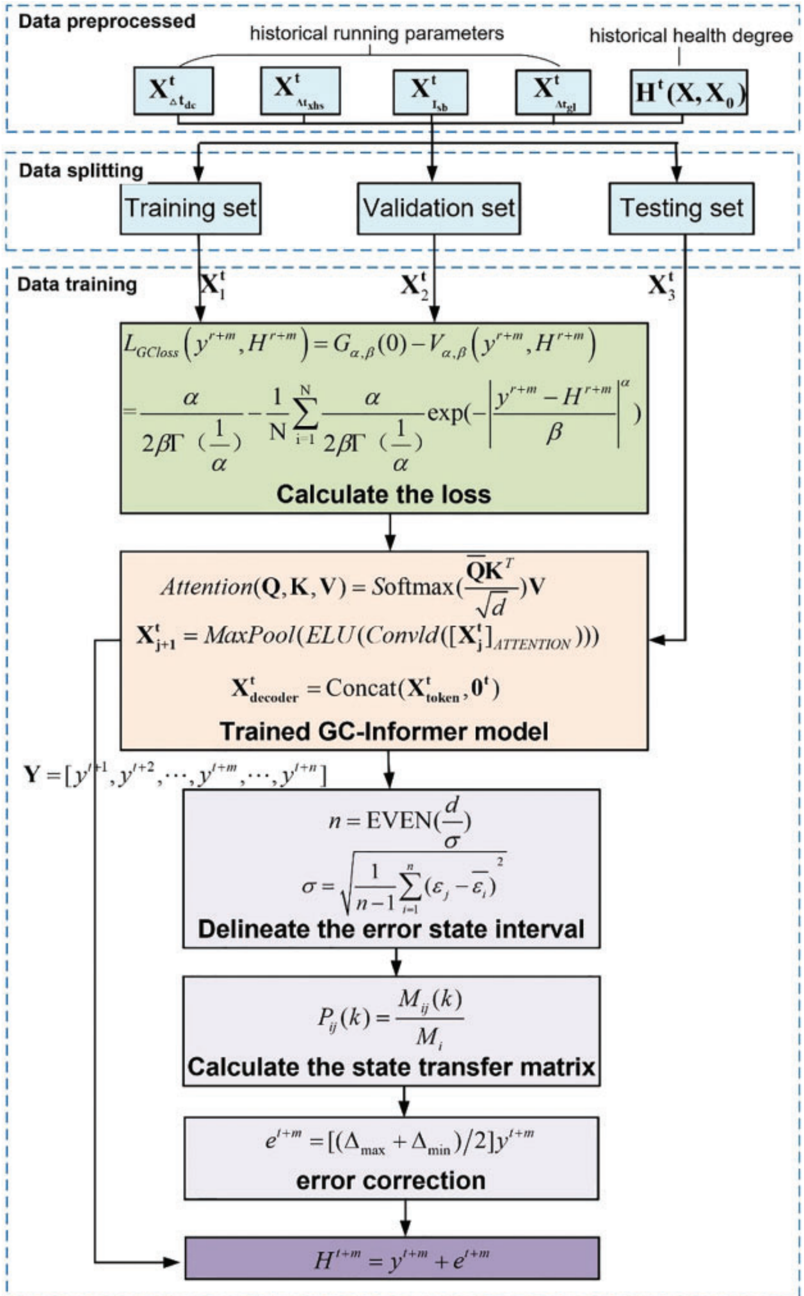

Figure 4: GC-Informer-MEC model

4.1 Calculation of Condenser Health Degree

Through the hierarchical analysis of the fusion health degree model, the overall heat transfer coefficient and the overall cleanliness coefficient are taken as the determining factors, and the initial unweighted supermatrix for the control layer health degree indicator is obtained as follows:

$$\mathbf{W}_s = \begin{bmatrix} 0 & 0.25 & 0.1365 & 0.25 & 1 & 0 & 0 & 0 \\ 0.25 & 0 & 0.2385 & 0.75 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0.75 & 0.75 & 0.625 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0.1047 & 0.1169 & 0.25 \\ 0 & 1 & 0 & 0 & 0.1667 & 0 & 0.1998 & 0.75 \\ 0 & 0 & 1 & 0 & 0 & 0.2582 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.8333 & 0.6370 & 0.6833 & 0 \end{bmatrix} \tag{26}$$

Using the overall heat transfer coefficient being superior to the overall cleanliness coefficient as a sub-criterion, the weight supermatrix is obtained as:

$$\boldsymbol{A}_s = \begin{bmatrix} 0.6667 & 0.3333 \\ 0.3333 & 0.6667 \end{bmatrix} \tag{27}$$

The weighted supermatrix $\boldsymbol{W}_{as}$ is obtained according to Eq. (6):

$$\boldsymbol{W}_{as} = \begin{bmatrix} 0 & 0.1667 & 0.091 & 0.1667 & 0.3333 & 0 & 0 & 0 \\ 0.1667 & 0 & 0.159 & 0.5 & 0 & 0.3333 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.3333 & 0 \\ 0.5 & 0.5 & 0.4167 & 0 & 0 & 0 & 0 & 0.3333 \\ 0.3333 & 0 & 0 & 0 & 0 & 0.0698 & 0.0779 & 0.1667 \\ 0 & 0.3333 & 0 & 0 & 0.1111 & 0 & 0.1332 & 0.5 \\ 0 & 0 & 0.3333 & 0 & 0 & 0.1722 & 0 & 0 \\ 0 & 0 & 0 & 0.3333 & 0.5556 & 0.4247 & 0.4556 & 0 \end{bmatrix} \tag{28}$$

Ultimately, the weight vector of the feature parameters based on the analytic network process according to Eq. (7) is:

$$\boldsymbol{W}_1 = [0.1734, 0.3454, 0.0713, 0.4099]^{\mathrm{T}} \tag{29}$$

The weight vector $\boldsymbol{W}_2$ of the feature parameters calculated based on the entropy weight method is:

$$\boldsymbol{W}_2 = [0.1771, 0.2509, 0.2543, 0.3177]^{\mathrm{T}} \tag{30}$$

Weighting was performed using the fusion weighting method based on Eq. (11). The subjective AHP and objective EWM based weighting methods contributed to proportions α and β, respectively, in the comprehensive weight, with both being 0.5. The final weights of each feature parameter are presented in Table 2. The weights of the health feature parameters were substituted into the fusion health degree model Eq. (11), resulting in the health degree values of the condenser at each time step.

4.2 Validation of Condenser Health Degree Trend Prediction

On the basis of the fusion health degree model, the health degree of the condenser is predicted in multiple steps with 12960 sets of data in the example data set, and then the deterioration evolution trend of the condenser can be judged. Next, based on Eqs. (21) and (22), the training set data were used to partition the error state space. By considering the relative error, the error sequence was divided into four state intervals, which are defined as follows: $S_1(-0.059, -0.005)$, $S_2(-0.005, -0.001)$, $S_3(-0.001, 0.005)$, $S_4(0.005, 0.047)$. The state transition matrix $\boldsymbol{P}$ is obtained by counting the state transition as follows:

$$\boldsymbol{P} = \begin{bmatrix} 0.3552 & 0.4352 & 0.2411 & 0.1321 \\ 0.4564 & 0.1432 & 0.1618 & 0.1334 \\ 0.4352 & 0,2641 & 0.1642 & 0.1424 \\ 0.2443 & 0.1617 & 0.2815 & 0.2514 \end{bmatrix} \tag{31}$$

Table 2: Feature weight coefficient

No.	Characteristic parameters	weight
1	Δt_{gl}	0.1753
2	Δt_{xhs}	0.2981
3	I_{sb}	0.1628
4	Δt_{dc}	0.3638

In order to demonstrate the improvement in the accuracy of condenser health degree prediction achieved by the multidimensional inputs GC-Informer-MEC combination prediction model proposed in this paper, predictions were made using only one-dimensional time-series data consisting of historical health information as the model input. These health prediction results were then compared with the approach presented in this paper, as depicted in Fig. 5. The image depicts three curves: green, blue, and orange. These curves correspond to the actual health degree, health degree forecasts derived from five-dimensional time-series data as input, and health degree predictions derived from one-dimensional time-series data as input, respectively. The graphic illustrates three vertical dashed lines, where the black line represents the commencement of the prediction, and the two red lines represent the anticipated condenser cleaning times for the multi-input and single-input scenarios, respectively.

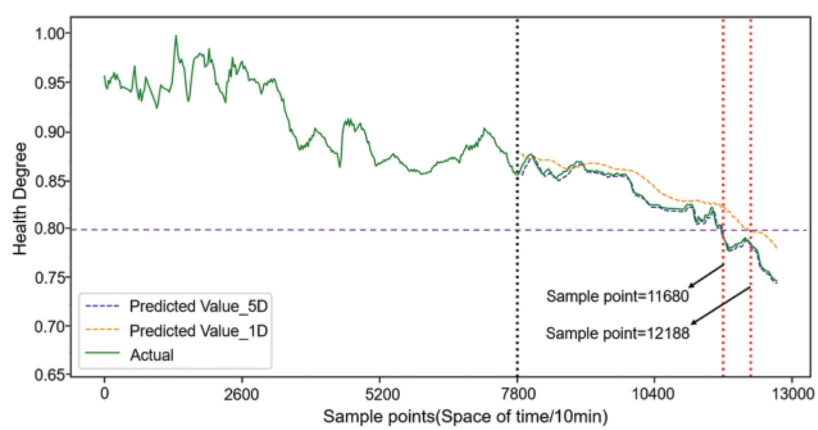

Figure 5: GC-Informer-MEC model prediction results

Upon careful examination of Fig. 5, it becomes apparent that the utilisation of both historical running parameters and historical health degree as inputs to the model regularly results in projected health degrees that closely coincide with the genuine degree. This alignment demonstrates a notable level of accuracy and few discrepancies. In contrast, employing a solitary metric of previous health degree for the purpose of predicting future health outcomes results in diminished levels of accuracy. In this study, the determination of the optimal time point for condenser cleaning is based on the application of a health degree threshold of 0.8. The single-input prediction model exhibits a delay of 508 sample points, each representing a 10-minute interval, compared to the multi-input prediction model in predicting the cleaning time point. As a result, the single-input prediction model indicates a cleaning time point that is approximately 84 h later than that of the multi-input prediction model. The delay has the potential to have a negative impact on the operational quality of the equipment, resulting in extended operation of the condenser at a reduced efficiency level. This, in turn, can lead to a decline in the economic efficiency of the secondary loop. When the condenser operates below a health degree of 0.8, performing timely cleaning can increase its efficiency by 1%. Based on the thermal calculation of a 1000 MW unit with a coal consumption of 320 grams per kWh, it can be determined that the impact of this timely condenser cleaning on coal consumption is:

$$B = 84\ \text{h} \times 1000\ \text{MW} \times 320/\text{KW} \cdot \text{h} \times 1\% = 268.8\ \text{T} \tag{32}$$

When calculated at 460 RMB per metric ton of standard coal, utilizing the multi-input prediction model for timely cleaning of the condenser equipment can result in a cost saving of 123,648 RMB.

The prediction errors are presented in Table 3. The analysis table illustrates that incorporating numerous data inputs significantly improves the predictive accuracy of the model. Furthermore, it indicates that the selected historical running parameters of the condenser have a certain impact on the forecast of the health degree. When solely utilising health degree time series data as the primary input for the prediction model, there is a notable discrepancy in the projected health outcomes, despite the approximate alignment of the predicted trend with the actual health progression. This approach provides an impartial reflection of the anticipated future evolution trend of condenser equipment. The predictive model demonstrates strong performance in accurately projecting future trends for a single time-series. In situations when exactitude is not the primary concern, a solitary indicator may be employed to forecast the forthcoming condition of the apparatus. In scenarios where the precise prediction of equipment condition is of utmost importance, the construction of multi-dimensional time series allows for more accurate forecasts of the health level. This, in turn, aids operators in effectively monitoring the health status of the condenser equipment and facilitates the development of a well-informed cleaning schedule for the condenser.

Table 3: Predictive errors under multiple indicators

Input parameters	MAPE
Five-dimensional time-series data containing health degree	0.077%
Historical health degree time series data	1.147%

In order to assess the enhanced efficacy of the GC-Informer-MEC prediction model in comparison to utilising a solitary model, three commonly applied prediction models, specifically Informer, Long Short-Term Memory (LSTM), and Deep Neural Network (DNN), were chosen as control experimental groups for the purpose of comparing their respective prediction performances. The sample data for this study consists of 12,960 sets of field operating data obtained from a 1000 MW unit of a nuclear power plant. To create a training set, the historical data from the prior 7,800 sets at the projected time were picked. The comparative analysis of the projected outcomes derived from the utilisation of multi-source time-series data is presented in Fig. 6.

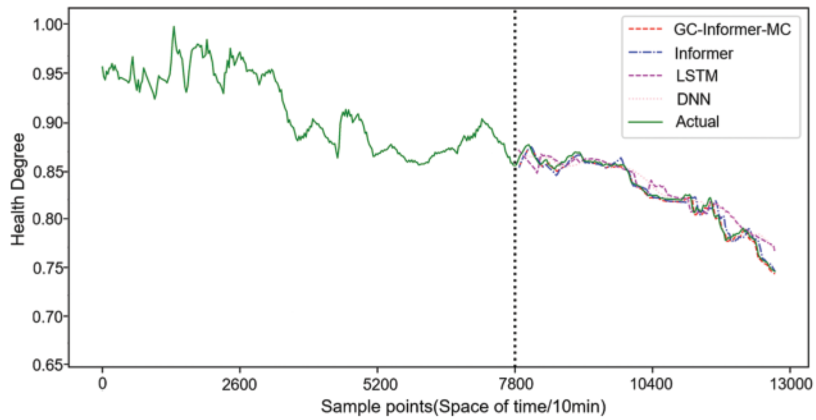

Figure 6: Comparison of prediction results of different models

Upon examination of Fig. 6, it becomes apparent that the chosen prediction models, namely Informer, LSTM, and DNN, demonstrate differing levels of accuracy in forecasting the future trend of the health degree. These models closely align with the progression of the actual health degree. Nevertheless, the efficacy of forecasting future health outcomes varies based on the selected predictive model. The present study highlights the effectiveness and accuracy of the suggested GC-Informer-MEC combined prediction model, as evidenced by the results presented in Fig. 6. Table 4 displays the discrepancies observed in the forecast outcomes across several prediction models.

Table 4: Error results from multiple predictive models

Predictive model	MSE	MAE	MAPE
GC-Informer-MEC	1.23e-06	0.00071	0.077%
Informer	8.47e-06	0.00224	0.241%
LSTM	2.09e-05	0.00405	0.437%
DNN	1.10e-04	0.00798	0.867%

5 Conclusion

Aiming at the problem of determining the cleaning time for condensers, this paper proposes a fusion health degree model based on improved Mahalanobis distance. On the basis of the fusion health degree model, a combined prediction model based on GC-Informer-MEC is established to predict the health degree of the condenser, and then the state trend of the deterioration and evolution of the condenser can be judged. Applying the above method to an example, the following conclusions are obtained:

The improvement of the Mahalanobis distance is achieved by the utilisation of a weighting method that combines the analytic network process and the entropy weight method. This approach allows for the integration of expert knowledge and objective observations, enabling a quantitative assessment of the actual status of the condenser's health. The GC-Informer-MC combination prediction model is constructed based on the health degree, utilising past running parameters and historical health degree data. In contrast to a single-input model, the combined model has the capability to anticipate condenser deterioration durations at 508 sample locations, hence facilitating prompt equipment cleaning and resulting in an estimated cost savings of roughly 123,648 RMB. In contrast to a singular prediction model, the utilisation of this approach yields a more refined forecast and study of the degradation pattern exhibited by the condenser. Consequently, it furnishes a more precise benchmark for ascertaining the optimal timing for equipment cleaning.

Health indicators, which are derived from the measurement of health status, are extensively utilised in various industrial processes. However, further enhancements are needed in order to get a more precise depiction of equipment status through the utilisation of health degree indicators. In our future research, we aim to improve the health degree model by employing optimisation methods. Additionally, we plan to implement online weight updates for the subjective and objective source weights, denoted as α and β respectively, which are used to quantify the health degree. This approach is expected to enhance the accuracy of equipment status quantification.

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Availability of Data and Materials: The data used this study was obtained from the actual operation records of the condenser at Fangchenggang Nuclear Power Plant from January to March 2022. Due to safety and confidentiality requirements of the nuclear power plant, this data cannot be released.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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