Expert Systems With Applications 299 (2026) 130029

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

An enhanced hybrid deep neural network method for adjusted industrial time series prediction with variable operating states

Meifang Zhang [a], Jing Bi [a], Haitao Yuan [b,*], Ziqi Wang [c], Jia Zhang [d], Rajkumar Buyya [e]

[a] College of Computer Science, Beijing University of Technology, 100124, Beijing, China
[b] School of Automation Science and Electrical Engineering, Beihang University, 100191, Beijing, China
[c] School of Software Technology, Zhejiang University, 315100, Ningbo, China
[d] Department of Computer Science, Lyle School of Engineering at Southern Methodist University, 75205, Dallas, TX, USA
[e] Cloud Computing and Distributed Systems (CLOUDS), School of Computing and Information Systems, University of Melbourne, 3010, Melbourne, VIC, Australia

ARTICLE INFO

Keywords:
Process modeling
Process industry
Time series prediction
Identification of operating mode
Deep learning

ABSTRACT

In industrial production, dynamic nature of working conditions and reliance on manual judgment introduces significant hurdles for accurate prediction models. Despite commendable performance of contemporary Deep Learning techniques in time series prediction (TSP), they frequently overlook crucial impact of human intervention. Moreover, the subjective nature of operational condition labeling and the scarcity of comprehensive experimental datasets further hinder the efficacy of predictive systems. This work proposes an Enhanced Hybrid Deep Neural Network (EH-DNN) framework to tackle these issues. It achieves robust classification and prediction of working conditions by integrating the multi-dimensional features of set values and observation time series. The data preprocessing phase encompasses feature extraction and feature fusion, ensuring the model acquires the essential information intrinsic to the production process. A novel two-step prediction methodology is employed during the training phase, incorporating pre-classification to enhance TSP, achieving an accuracy of 94%. EH-DNN mirrors intricate dynamics of industrial production and aligns seamlessly with real-world application scenarios, demonstrating substantial practical utility. By integrating this methodology, the industrial sector can anticipate a significant leap in automation levels and production efficiency, bridging the gap between theoretical models and practical implementation.

1. Introduction

Industrial production processes are inherently variable, influenced by equipment wear, raw material inconsistencies, and environmental fluctuations. Operators are required to continuously monitor and adjust parameters through manual interventions to stabilize production. While indispensable, these human adjustments introduce subjectivity and imprecision, hindering the consistency of control strategies and complicating the accurate modeling of industrial dynamics. Anticipating operating states is thus critical not only for optimizing efficiency but also for enabling proactive maintenance and safeguarding product quality.

In practice, data collected by Distributed Control Systems (DCS) manifest as Industrial Time Series (ITS). Predicting such time series has been widely addressed with machine learning and deep learning approaches (Bertolini et al., 2021; Bi et al., 2025), including Convolutional Neural Networks (CNNs) (Jin et al., 2019), Recurrent Neural Networks (RNNs) (Liu et al., 2020), Autoencoders (AEs) (Wu et al., 2020), Restricted Boltzmann Machines (RBMs) (Wang et al., 2020a), Attention Mechanisms (Wang et al., 2023), and Graph Neural Networks (GNNs) (Chen et al., 2022c). These methods are effective at capturing nonlinear temporal dependencies. However, existing studies largely assume stable operating conditions and rely on pre-labeled datasets (Yuan et al., 2025), which rarely exist in real industrial contexts. Simplifications such as binary "normal vs. abnormal" classifications fail to represent the richness of real operating states. Moreover, conventional univariate time-series prediction (TSP) neglects interactions among variables and overlooks the non-stationary behavior arising from external disturbances and human intervention.

The core research gap, therefore, lies in how to perform accurate TSP under variable operating states that are strongly influenced by manual settings and adjustments. Conventional forecasting frameworks are limited in two aspects.

1. Inadequate modeling of manual interventions. Operator-defined set values, though central to PID-based control, are seldom incorporated as explicit features. Their randomness, timing, and fuzziness directly

* Corresponding author.
E-mail address: yuan@buaa.edu.cn (H. Yuan).

https://doi.org/10.1016/j.eswa.2025.130029
Received 19 March 2025; Received in revised form 27 August 2025; Accepted 12 October 2025
Available online 15 October 2025

affect process dynamics but remain underutilized in predictive modeling.
2. Failure to adapt to dynamic operating states. Industrial time series exhibit concept drift caused by shifts in equipment conditions, fuel quality, or operator expertise. Without adaptive segmentation and state-specific learning, long-term predictions quickly lose reliability.

To address these challenges, this paper proposes Enhanced Hybrid Deep Neural Network (EH-DNN) framework. This framework achieves robust classification and prediction of working conditions by integrating multidimensional features of Setting Values and observed time series. The EH-DNN framework introduces feature extraction and feature fusion techniques in the data preprocessing stage to ensure that the model can obtain key information inherent in the production process. During the training phase, a novel two-step prediction method is adopted to enhance the accuracy of TSP through pre-classification. The experimental results show that the framework achieved an accuracy of 94% in industrial TSP, significantly better than existing methods. EH-DNN can reflect the complex dynamics of industrial production and seamlessly integrate with practical application scenarios, demonstrating significant practicality. By integrating this method, the industrial sector is expected to achieve significant improvements in automation level and production efficiency, bridging the gap between theoretical models and practical applications.

The main contributions of this work are summarized as:

1. Adaptive Operating State Identification: An approach for detecting shifts in operational states through concept drift detection has been suggested, employing sliding window techniques to observe real-time variations in the operational states of industrial processes.
2. Predicting Features Beyond Numbers: A multidimensional feature extraction and fusion method was designed, which combines the set values with time-domain and frequency-domain features to enhance feature expression ability. Moving beyond traditional numerical forecasting, it emphasizes feature prediction by using Deeo Learning to uncover intrinsic properties and non-linear relationships in ITS, offering valuable insights into industrial process dynamics.
3. EH-DNN Framework: An innovative two-step prediction approach was developed to greatly enhance the precision of time series predictions by utilizing pre-classification and detailed regression forecasting. EH-DNN incorporates operational state evaluations and model improvements, taking into consideration operational changes and human interventions, leading to accurate TSP and a new approach to modeling industrial processes.

This research offers both a novel approach to forecasting industrial time series and theoretical backing along with practical advice for realizing intelligent, automated industrial processes. The structure of the remaining sections is as follows. Section 2 reviews related work on operation state identification and time series prediction (TSP) methods. Section 3 explains motivation of this research and proposes overall design. Section 4 provides a detailed introduction to the core methods of the EH-DNN framework. Section 5 demonstrates the effectiveness of EH-DNN. Finally, Section 6 wraps up the study.

2. Related work

2.1. Operation state identification

Operation state identification in industrial processes has been widely studied, with methods ranging from clustering-based approaches (K-means (Huang et al., 2016), Fuzzy C-Means Time Series (FCM-TS) (Lu et al., 2014)) to supervised and semi-supervised learning. While effective in simple settings, these methods require prior assumptions (*e.g.*, number of clusters) and are less capable of capturing temporal dynamics. Recent advances attempt to incorporate concept drift detection to address non-stationary behavior in industrial systems. For example, Uchiteleva et al. (2021) proposed a drift-aware prediction approach for IIoT data, while adaptive sliding window methods such as Adaptive Sliding Window (ADWIN) have been applied in financial forecasting (Chou & Nguyen, 2018) and seizure detection (Wang et al., 2013). Liu et al. (2019) convert time series data into a three-dimensional tensor to allow convolution operations to explore local interactions and temporal dependencies. In the industrial domain, more recent studies integrate online drift detection with deep learning to dynamically retrain models (Arena et al., 2024), but such methods are rarely extended to state segmentation and labeling. This highlights a gap between drift detection and practical operating state identification in complex production environments.

2.2. Time series prediction

Traditional data-driven methods combine feature extraction (*e.g.*, TSFresh (Sala et al., 2018), Empirical Mode Decomposition (EMD) (Zheng et al., 2021), Wavelet Decomposition (WD) (Bi et al., 2024b; Zheng et al., 2022)) with regression models such as Vector-Autoregressive (VAR) (Coyle et al., 2005) or Support Vector Regression (SVR). However, they struggle with noise sensitivity and non-stationarity. In recent years, there has been a notable increase in deep learning methods: CNNs and LSTMs for capturing spatial–temporal dependencies (Chadha et al., 2019; Guo et al., 2018). Hybrid models integrating Deep Learning with probabilistic methods, *e.g.*, LSTM + Gaussian Process for battery life prediction (Liu et al., 2021). Attention mechanisms and Transformer-based models (Bi et al., 2024a; Wang et al., 2023, 2024; Zhang et al., 2021) that effectively capture long-term dependencies. Graph Neural Networks (GNNs) for multivariate industrial processes (Chen et al., 2022b). Very recently, lightweight architectures such as TSMixer (Ekambaram et al., 2023) have emerged to address scalability issues in multivariate forecasting.

Despite these advances, two critical limitations persist:

- Neglect of manual interventions: Operator-defined set values, which directly affect control decisions, are rarely incorporated as model input.
- Lack of adaptation to variable operating states: Most Deep Learning models assume stationarity, and while some studies include noise or disturbances, they rarely handle systematic shifts in operational modes caused by raw material quality, environmental changes, or human adjustments.

2.3. Summary of existing studies

In summary, existing research demonstrates substantial progress in industrial time series prediction through advanced feature extraction, deep learning, and drift-aware techniques. However, the following gaps remain:

- Insufficient integration of operator knowledge: Few methods incorporate human-set control values, despite their central role in process dynamics.
- Weak adaptability to dynamic operating states: Current models perform poorly when frequent state changes or concept drift occur.
- Limited unification of classification and regression: Most approaches treat state identification and forecasting separately, missing the opportunity to exploit their interdependence.

Therefore, a unified framework is needed that adaptively identifies operating states under concept drift, fuses multidimensional features including manual interventions, and combines pre-classification with state-specific regression. This paper's EH-DNN framework directly addresses these issues by bridging the gap between theoretical advances in Deep Learning and the realities of industrial operations.

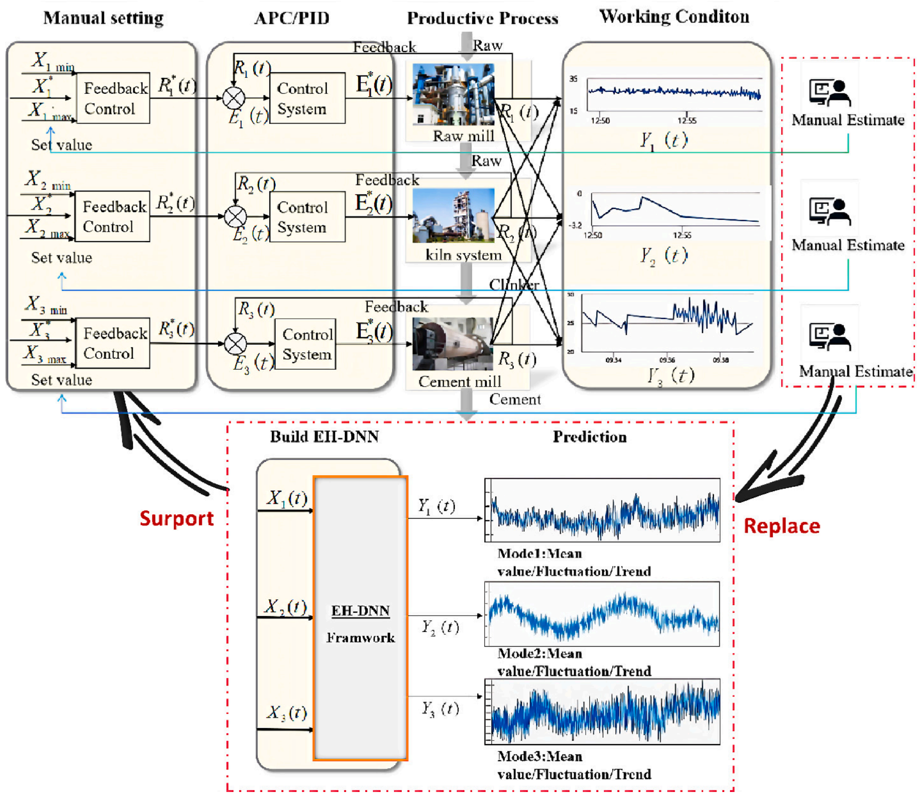


Fig. 1. Change from experience-based manual control process to data-driven online prediction.

Table 1
Labels of variables in Fig. 1.

Tag	Var Name	Tag	Var Name	Tag	Var Name
X1	Temp Setting	E1	Tail Oil Flow	R1	Calciner Outlet Temp
X2	Pressure Setting	E2	Fan Speed	R2	Kilin Head Pressure
X3	Raw Feed Setting	E3	Flow Value	R3	Raw Feed

3. Research motivation and proposal design

This section introduces the research motivation and the design of the EH-DNN framework. Firstly, taking cement production as an example, the value of operational data in the industrial field and the importance of manually setting and observing values in the production process are explained. Furthermore, in response to the complexity of industrial time series data and the limitations of traditional methods, the design concept of EH-DNN framework is proposed, aiming to optimize the production process through data-driven methods, reduce manual intervention, and improve prediction accuracy.

3.1. Research motivation

The industrial realm has amassed a substantial volume of operational data, containing valuable insights into the interplay between production operations and process parameters. Take cement manufacturing, for instance, where DCS stands as a pivotal technology, harnessing computer-based control and micro-controllers to oversee real-time production processes, ensuring their smooth operation. By capturing key parameters within the cement production process, DCS system furnishes essential reference and control mechanisms for central controllers. This study aims to delve into the intricate relationship between operational variables and conditions, using the cement industry as a focal point and leveraging data from DCS system to drive technical inquiry.

In this investigation, manually adjusted process parameters are denoted as “Setting Values,” typically established by experts based on their experience to meet production objectives. The Proportional-Integral-Derivative (PID) control process, facilitated by these set values, orchestrates adjustments to uphold production process stability and efficiency. The variables of the PID adjustment process, as depicted in Fig. 1, are elucidated in Table 1. For instance, manipulating the opening of the $E3$ valve to regulate the feed speed of $R3$ or setting the target temperature of $X1$ to modulate the oil supply from $E1$ facilitates precise control over the temperature of $R1$. Typically, PID control operates within two levels, allowing for attainment of the final target value in most scenarios. This study specifically excludes aberrant situations and does not encounter any anomalies related to PID during the data collection process. Therefore, the provided quantity values act as input variables for operational behavior, while the observed values serve as parameters monitored by operators throughout industrial operations, forming the identification variable of the working situation, $Y = \{Y(k) \mid k = 1, 2, \ldots, n\}$.

However, due to the complex and unpredictable nature of production processes, as well as the inability to measure certain external factors (such as output requirements, fuel type, power consumption demands, product specifications, and quality criteria), achieving complete automation and control throughout the entire process is still difficult to attain. Therefore, central control operators must constantly monitor and make necessary adjustments to observed variables at all times in order to assure uninterrupted production progress.

This paper proposes a process modeling approach that is based on historical operation records as a remedy to this difficulty. By analyzing previous operational data, experts can extract valuable insights that allow for the automatic identification and forecast of operational circumstances. This methodology not only improves production efficiency and product quality, but also reduces the workload of central control operators. By doing so, this study introduces novel concepts and methodologies for optimizing production processes within the cement sector through the extraction of valuable insights from operational data.

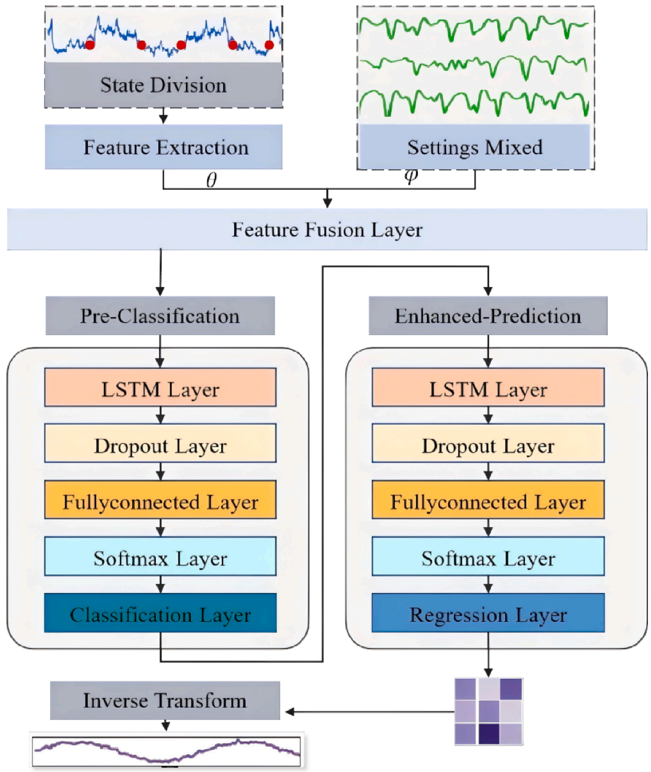


Fig. 2. EH-DNN framework.

Although the attainment of fully automated end-to-end control remains a persistent challenge, advancements towards intelligent and automated production processes can be achieved through the application of process modeling and the consolidation of expert knowledge.

3.2. Problem description and proposal design

When dealing with multidimensional ITS, the primary challenge lies in transforming heterogeneous data, comprising operator-defined setting values and observed process variables, into reliable operational models. Traditional methods often fail to manage large volumes of redundant information, strong non-stationarity, and human interventions, significantly altering the dynamics of ITS. Consequently, accurate prediction requires not only feature extraction, but also adaptive modeling of variable operating states.

To overcome these challenges, we design the Enhanced Hybrid Deep Neural Network (EH-DNN) framework, whose core components are illustrated in Fig. 2 and described as follows.

1. Operating-State Pre-Classification Module
   - Purpose: Detect and segment data streams into consistent operational states.
   - Methods: A drift-aware operating state identification mechanism is used, using dual sliding windows to capture statistical differences in distributions. This enables adaptive segmentation under changing raw material quality, combustion efficiency, or operator interventions.
   - Contribution: Provides a stable basis for training by ensuring that subsequent regression is performed under homogeneous states rather than on globally mixed data.
2. Feature Extraction and Fusion Module
   - Time–frequency features: Extracted *via* wavelet decomposition with energy normalization, capturing both local and global signal dynamics at multiple scales.
   - Manual setting values: Processed through setting values granulation (SVG), which reduces dimensionality while preserving the uncertainty and fuzziness inherent in human adjustments.
   - Fusion: The two feature sets are combined into an integrated feature matrix, serving as a comprehensive representation of both system dynamics and operator influence.
3. Two-step Prediction Strategy
   - Step 1: State-specific Classification. A deep neural network classifier is trained to identify the operational state of incoming data.
   - Step 2: Regression Prediction. For each identified state, a regression sub-model is applied to predict the future trajectory of process variables. This design allows the model to adapt prediction parameters to specific operating conditions.
4. Adaptive Learning Mechanism

   EH-DNN incorporates a feedback-driven mechanism to adjust prediction parameters whenever concept drift or state transitions occur.This ensures that the framework maintains robustness under non-stationary industrial environments and remains reliable during long-term operation.

Overall, EH-DNN integrates state-aware segmentation, multidimensional feature fusion, and a dual-phase prediction strategy into a unified framework. By doing so, it directly addresses the limitations of conventional TSP methods, which either ignore manual interventions or fail to adapt to shifting operational states. This design not only improves predictive accuracy but also reduces reliance on operator experience, moving toward more intelligent and automated production processes.

4. Proposed methods under EH-DNN framework

This section provides a detailed introduction to the core methods of the EH-DNN framework. Firstly, a sliding window based operation state detection method is proposed, which identifies state changes through concept drift analysis. Subsequently, the multidimensional feature extraction and fusion techniques were elaborated, including wavelet decomposition and fuzzy granulation of set values. Finally, the EH-DNN architecture design was introduced, which significantly improved the accuracy and robustness of industrial time series prediction through a two-step strategy of pre classification and regression prediction.

4.1. Detection of operating state changes through drift analysis

There is a significant link between shifts in operating state and drift in concept. Changes in operating state involve modifications to factors such as equipment status, environmental situations, and material composition in industrial processes. Concept drift describes alterations in data distribution or how data is generated over time. Modifications in operating state may affect data distribution or the link between data and target variables, resulting in concept drift.

To monitor changes in the operational state during working process, Operating State Identification (OSI) approach is introduced. OSI method identifies concept drift by analyzing the statistical traits in two separate data windows. It utilizes dual sliding windows: one for the most recent data samples and another for historical data samples. Through the comparison of statistical properties between these windows, OSI assesses the occurrence of concept drift. OSI calculates a test statistic by computing the mean and variance from both windows. A bilateral test technique is applied to check if this statistic surpasses a predefined threshold. If the threshold is crossed, it indicates a shift in the operating state, depicted in Fig. 3. The comprehensive steps are outlined in Algorithm 1.

4.2. Feature extraction and feature fusion

This study aims to translate the operator's skills into quantifiable knowledge to minimize reliance on individual expertise and experience, thereby increasing the standardization and automation of the

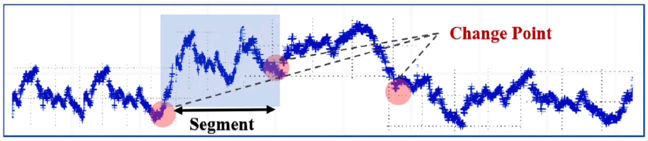


Fig. 3. Operating state change detection.

Algorithm 1 OSI.

Input: ITS (dataStream)
Output: Indices of detected change points

Initialize parameters: minimum window size (min), maximum window size (max), change detection threshold (θ)
for each data point ρ at index i in dataStream **do**
  Append ρ to $dataWindow$
  if len $(dataWindow)$>max **then**
    $mean \leftarrow mean(dataWindow)$
    $v \leftarrow variance(dataWindow)$
    $sd \leftarrow sqrt(v)$
    $d \leftarrow |\rho - mean|$
    if $d > \theta \times sd$ **then**
      $changeDetected \leftarrow True$
      Append i to $changePoints$
      % record the index of the change point
      Decrease window-size by 1, ensuring it bigger than min
    else
      $changeDetected \leftarrow False$
    end if
    Increase window size by 1, ensuring it does not exceed max
  else
    $changeDetected \leftarrow False$
  end if
end for
Return $changePoints$

operating process. Achieving this involves establishing a set of operational patterns. The dataset $\{X_k(i) \mid i = 1, 2, \dots, n\}$ consists of preset values selected by the operator for equipment parameters at specific time points. These presets are based on the operators' knowledge of equipment performance and process needs, along with historical operational data analysis. The dataset $\{Y(k) \mid k = 1, 2, \dots, n\}$ contains observed values recorded during actual operations. This dataset can verify the correctness of the preset values and provide data for optimization processes. Through comparing and analyzing these preset and observed values, one can detect patterns and deviations in the operation process. Furthermore, developing various operational modes can guide future operations, reduce human errors, and improve operational efficiency and product quality.

EH-DNN addresses the challenge of multivariate and multidimensional feature exaction shown in Fig. 4. First, single-variable ITS ($\{Y(k) \mid k = 1, 2, \dots, n\}$) is decomposed to extract time-frequency dual-channel features of operating parameters. Unlike deep learning techniques like CNNs, it is essential to accurately capture statistical features to effectively represent the time-frequency characteristics of signals. Due to varying ITS lengths as described in Section 4.1, to deal with unequal length data, features at different scales are extracted through energy-normalized WD for unequal length data.

Subsequently, to effectively capture the combinations of values in the industrial setting ($\{X_k(i) \mid i = 1, 2, \dots, n\}$) and the impacts of manual intervention, setting values granulation is incorporated. Manual adjustments can occur at any moment, with their sequence and timing differing among individuals. In the processes of human reasoning and developing concepts, information granules often manifest as fuzzy (f-granular) rather than precise (c-granular). Fuzzy information granulation addresses this ambiguity and uncertainty by utilizing fuzzy sets and fuzzy logic to articulate and manage these granules. For instance, in time series analysis, granulation can segment data into fuzzy time intervals, thus more effectively encapsulating the dynamic variations of the data. Finally, the features from both steps are combined into an eigenvalue matrix.

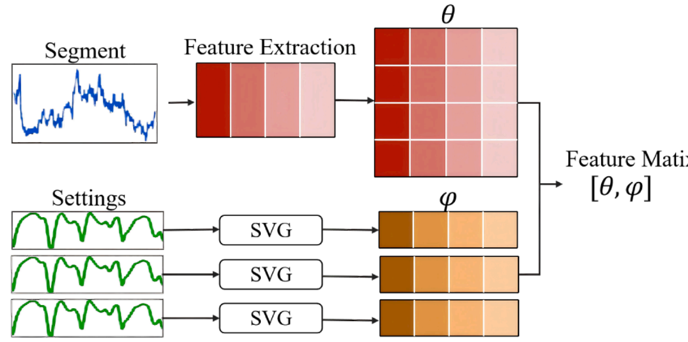


Fig. 4. ITS feature exaction and feature fusion process.

4.2.1. *Energy normalized WD of unequal length scales*

Unlike the Fourier transform, WD provides localized transformations in both time and frequency domains, making it more effective for extracting information from signals. Through scaling and translation, WD enables multiscale analysis, addressing the limitations of the Fourier transform. EH-DNN employs WD to extract features across various time and frequency scales from raw, noisy data, enhancing traditional single-variable TSP in industrial processes. This approach captures hidden non-linear relationships by incorporating these extracted features into a Deep Learning-based model, resulting in more reliable and accurate predictions.

In the discrete wavelet transform (DWT), a signal is decomposed into approximation coefficients (cA) and detail coefficients (cD) through convolution with low-pass and high-pass filters. This process is shown as follows.

Approximation Coefficients (Low-frequency component):

$$cA_j[n] = \sum_k x[k] \cdot h[2n - k] \tag{1}$$

where $x[k]$ represents the signal, $h[k]$ is the low-pass filter, and $cA_j[n]$ is the approximation coefficient at level j. After the convolution, downsampling is performed, keeping only the even-indexed coefficients, where n is the index after downsampling.

Detail Coefficients (High-frequency component):

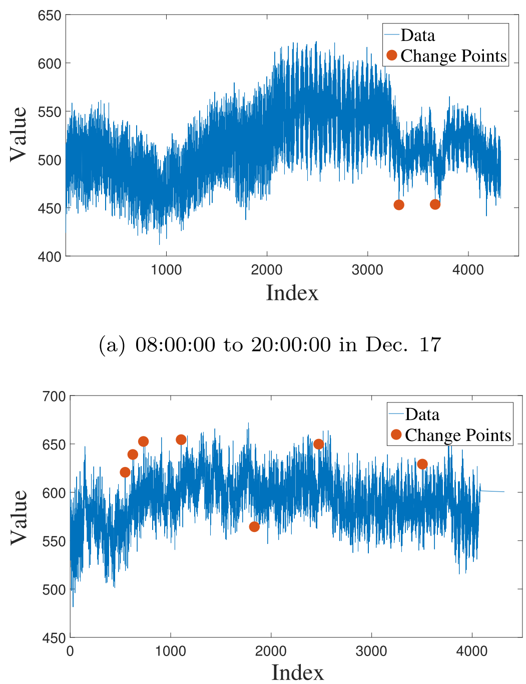
$$cD_j[n] = \sum_k x[k] \cdot g[2n - k] \tag{2}$$

where $g[k]$ is the high-pass filter, and $cD_j[n]$ is the coefficient at level j. Similarly, convolution is followed by downsampling.

Assuming the initial signal is $x(t)$, the wavelet decomposition at level j is expressed as:

$$x(t) \xrightarrow{Decomposition} \left(cA_j, cD_j\right) \tag{3}$$

In Section 4.1, ITS is adaptively segmented in the first stage of the ITS window, resulting in inconsistent segment lengths. After extracting wavelet coefficients, it is necessary to normalize them based on each segment's time scale, such as by calculating the energy proportion for each scale or the relative intensity of frequency components. Energy normalization scales the energy of different features relative to the total signal energy, making it useful for comparing features from signals



(a) 08:00:00 to 20:00:00 in Dec. 17

(b) 08:00:00 to 20:00:00 in Dec. 18

Fig. 5. Cases of KC state change detection with OSI.

with varying lengths or amplitudes. A step-by-step description of how to perform energy normalization:

For each feature or component (*e.g.* wavelet coefficients), calculate its energy, which is typically the sum of the squared values of the coefficients.

$$E_i = \sum_k |C_i[k]|^2 \tag{4}$$

where $C_i[k]$ represents the k-th coefficient in the i-th component (*e.g.* wavelet detail or approximation coefficients), and E_i is the energy of the i-th component.

Add the energies of all components together to calculate the total energy of the signal.

$$E_{\text{total}} = \sum_i E_i \tag{5}$$

For each component, divide its energy by the total energy. This step scales the energy of each component to be relative to the overall energy of the signal.

$$\tilde{E}_i = \frac{E_i}{E_{\text{total}}} \tag{6}$$

where $\tilde{E}_i$ is the normalized energy of the i-th component.

4.2.2. Setting values granulation

Setting values refers to the adjustments of the control operator's parameters to intervene in the production process. To reduce data dimensionality while preserving key information, SVG is used.

SVG consists of two steps: window division and fuzzification. First, ITS is segmented into operational windows. Then, each window is converted into a fuzzy set, reducing data volume while retaining critical features. A general definition of SVG utilizes fuzzy sets, which can be described as follows.

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in U\} \tag{7}$$

where $\mu_{\tilde{A}}(x) \in [0,1]$ represents the membership degree. Commonly used fuzzy processing forms include triangle, trapezoid, and symmetrical Gaussian. The Gaussian function is used as the membership function, and it is defined as follows.

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{8}$$

where $\mu(x)$ represents the membership of element x to the fuzzy set, c is the center point of the Gaussian function, and σ is the parameter that controls the smoothness of the Gaussian curve in the system.

Table 2
Classification performance result.

Tasks	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
KC	95.12 ± (1.33)	92.94 ± (2.03)	95.76 ± (1.89)	90.22 ± (3.79)
COP	92.01 ± (1.87)	90.68 ± (3.12)	93.33 ± (2.09)	88.31 ± (4.74)
COT	93.99 ± (2.06)	91.09 ± (2.56)	92.82 ± (2.64)	89.58 ± (5.10)

5. Performance evaluation

5.1. Experimental design and dataset

The complexity of industrial production processes, along with unknown disturbances, complicates accurate state adjustments. Operators must modify input amounts based on fluctuations in process parameters to stabilize the system. The cement production industry is selected for experiment, utilizing data from the DCS system with a collection frequency of 3 seconds. The training data set spans from December 9, 2023, to January 1, 2024, excluding downtime. Online data is taken from 12 hours of actual production. The predictions of the model are compared to actual data to assess the accuracy of the prediction. Key operating parameters monitored include Kiln Current (KC), Calciner Outlet Pressure (COP), and Cyclone1 Outlet Temperature (COT). In addition, eight frequently adjusted settings are selected as fusion feature sources. The experimental process follows six steps.

1. Preprocessing: Apply state labeling through the OSI method (Section 4.1), resample uniformly at 10s intervals, and segment operating states adaptively.
2. Feature extraction and fusion: Conduct wavelet decomposition with energy normalization for time–frequency features, and fuzzy granulation for setting values.
3. Model training: Train the EH-DNN framework in two stages: classification pre-training for operating states, and state-specific regression forecasting.
4. Comparative evaluation: Benchmark EH-DNN against representative baseline and state-of-the-art models with identical training/test splits.
5. Performance metrics: Evaluate prediction using MAE and R^2 across operating scenarios. Each experiment is repeated five times, reporting mean (%) ± standard deviation (%).

5.1.1. Preprocessing

Data statistical traits alter with changes in the operational state. The initial step EH-DNN undertakes is to segment states based on operating state parameters, thereby identifying the training state. As the data set records observational variables every 3 s/time, but this is not consistent, the ITS is first resampled uniformly at 10 s/time. Subsequently, the operating state detection method OSI from Section 4.1 categorizes the operational state parameters into distinct states. Each subfigure in Fig. 5 illustrates the operating state labeling results for KC data spanning December 17 to 20. Experimentally, the window size is configured to 30, with a threshold of 2.6. The threshold's value is adjustable, depending on the desired granularity in state segmentation.

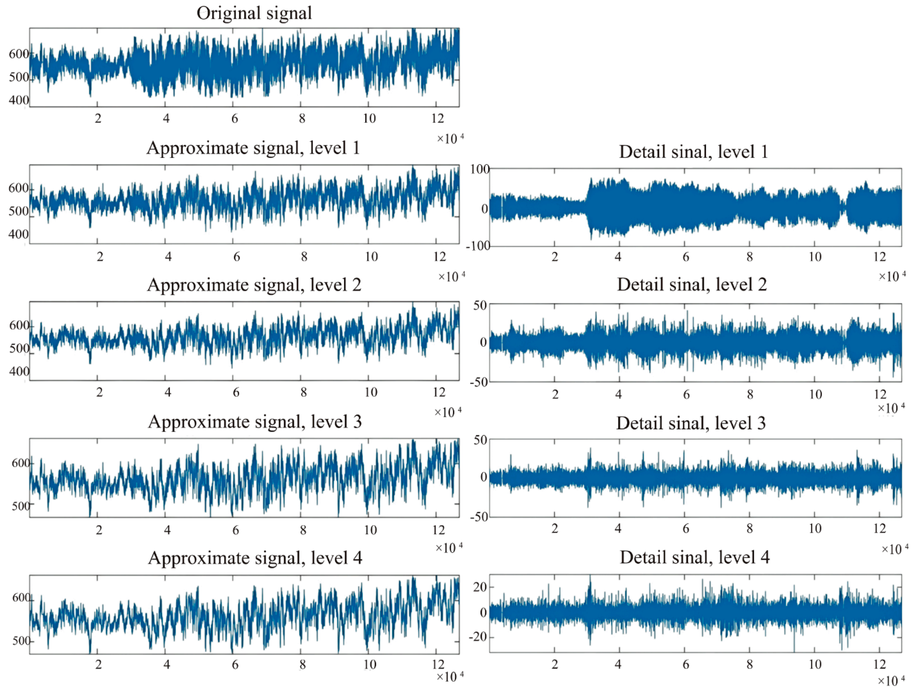
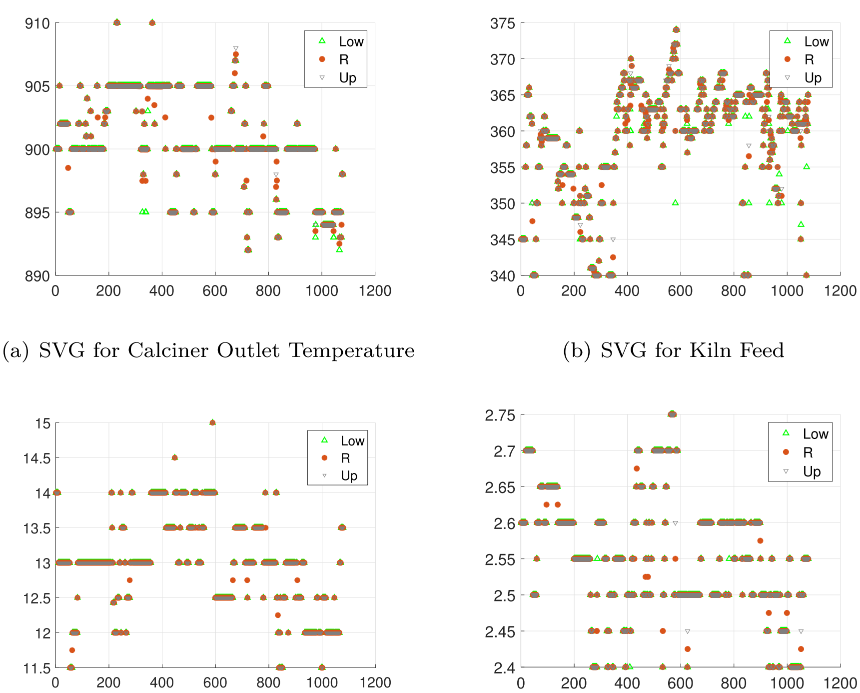


Fig. 6. Result of operating state feature exaction using WD.



(a) SVG for Calciner Outlet Temperature (b) SVG for Kiln Feed

(c) SVG for Cooler Speed (d) SVG for Kiln Speed

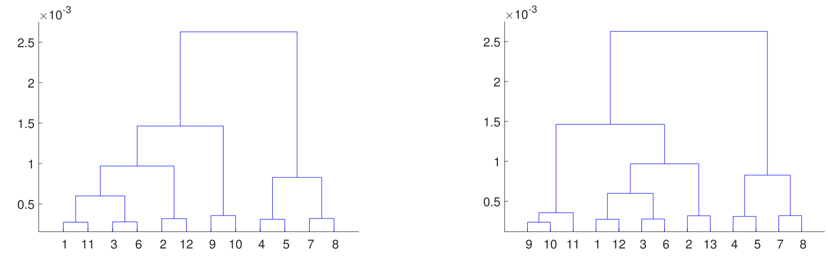
Fig. 7. Feature Extraction of Setting values with SVG.

5.1.2. Feature extraction and fusion

It is essential to go into the extraction of characteristics following the state labeling process. At this stage, the Daubechies wavelet function is a practical basis for a detailed decomposition of the primary data. This decomposition is meticulously carried out at a depth of three levels, and the result example is shown in Fig. 6. The resultant matrix, composed of approximate and detailed decomposition coefficients, serves as the backbone for regression analysis. Concurrently, the normalized energy output is harnessed for classification tasks, while the aforementioned feature matrix is dedicated to enhancing regression accuracy.

5.1.3. ITS feature fusion process

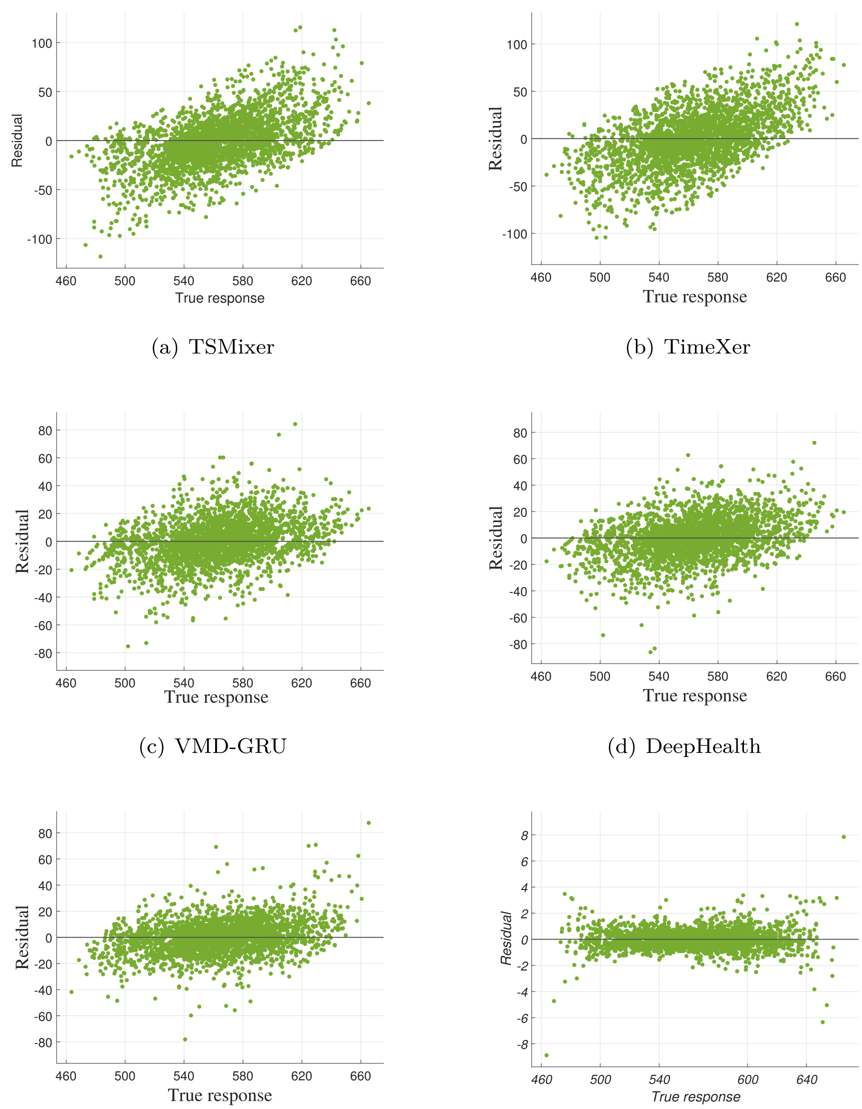
To supplement the influence of set values in the actual production process, the experiment fuses the set value matrix φ with the operating state feature matrix θ. Supposing that manual adjustment is the key reason for the alteration of working conditions, it is considered that a set of



(a) 12-levels

(b) 13-levels

Fig. 8. Hierarchical clustering tree diagram.



(a) TSMixer

(b) TimeXer

(c) VMD-GRU

(d) DeepHealth

(e) GCN-Attention

(f) EH-DNN

Fig. 9. Prediction residual plot under different models.

set-value matrices can be retrieved under identical working conditions. However, manual intervention is random in actual production, and a small amount of adjustment does not necessarily bring about a state change. Therefore, the set value within a specific operating state period is not ideal. SVG processing is chosen for approximate substitution of the setting process. The size of the fuzzy set is set to 10 minutes for dimensionality reduction. Due to space constraints, this article displays the results for three configuration settings in Fig. 7.

5.1.4. Model training

Step 1: Classification Pre-training After segmenting the operating state, although the state transition points can be identified, it is impossible to consider states in different periods as distinct. Without classification labels for the same state, it becomes impossible to identify identical states from historical data and make predictions. The working conditions of various states are hierarchically clustered after state segmentation. A weighted average distance approach is used to determine

Table 3
Prediction for Each Operating Scenario.

Prediction index		KC			COP			COT		
Feature component		I	II	III	I	II	III	I	II	III
TXMixer	MAE	13.266	8.694	10.256	5.847	8.886	11.334	4.232	12.365	6.306
	R^2	0.744	0.867	0.843	0.717	0.720	0.700	0.758	0.645	0.832
TimeXer	MAE	12. 399	15.399	16.328	11.721	11.589	13.090	14.785	15.231	15.789
	R^2	0.655	0.643	0.617	0.758	0.744	0.708	0.638	0.792	0.808
VMD-GRU	MAE	11.233	10.699	10.259	9.923	9.876	10.254	9.129	10.840	10.431
	R^2	0.756	0.792	0.758	0.809	0.808	0.778	0.816	0.854	0.840
DeepHealth	MAE	1.059	1.771	1.344	**0.895**	**0.903**	1.224	0.771	**1.155**	1.399
	R^2	0.896	0.808	0.826	0.819	0.897	0.849	0.816	0.891	0.834
GCN-Attention	MAE	1.233	1.699	**1.259**	1.923	1.876	1.254	**0.129**	2.840	3.431
	R^2	0.856	0.892	0.858	0.809	0.808	0.878	0.816	0.854	0.840
EH-DNN (ours)	MAE	**0.489**	**0.392**	1.431	1.265	2.399	**0.872**	0.834	1.389	**1.007**
	R^2	**0.988**	**0.992**	**0.972**	**0.918**	**0.906**	**0.908**	**0.913**	**0.930**	**0.922**

Table 4
Ablation study results for EH-DNN core modules.

Model	MAE(KC)↓	MAE(COP)↓	MAE(COT)↓	R^2(KC)↑	R^2(COP)↑	R^2(COT)↑	Δ MAE(avg)	ΔR^2(avg)
EH-DNN(full)	0.49	1.27	0.83	0.99	0.92	0.91	-	-
EH-DNN-1(w/o Feature Extraction)	11.09	8.86	12.01	0.79	0.86	0.74	+10.1	-0.13
EH-DNN-2(w/o State Classification)	1.06	0.90	0.77	0.90	0.92	0.92	+0.25	-0.05
EH-DNN-3(w/o Both)	19.04	30.53	25.99	0.40	0.26	0.39	+24.0	-0.55

the distance between two combined data points. For every cluster merging, the ideal merge is identified by calculating the average distance between all points in the two clusters. An excessive number of clusters would lead to shorter distances between neighboring clusters and worse classification accuracy. As illustrated in Fig. 8, twelve categories are used for labeling in the experiment since the cluster distances are closer when KC is divided into thirteen categories. The goal of this labeling stage is to improve the accuracy of the subsequent phase's predictions. A DNN is subsequently trained using the classification model, and the performance outcomes are displayed in the Table 2. Performance results are expressed in the form of mean (%) ± standard deviation (%).

Step 2: state-specific regression forecasting Before modeling, it is necessary to reconstruct training samples. Feature fusion refers to taking the previous step's classification prediction results as the training data's dimension input. The parameter settings of EH-DNN are carefully adjusted by cross-validating the reconstructed samples. EH-DNN specifically selects a 6-layer neural network and uses the Adaptive Moment Estimation (Adam) solver, and the learning rate range is [0.01, 0.40].

5.2. Comparison methods

To highlight the advantage of EH-DNN, we compare it with both classical and latest research models.

1. TSMixer: Lightweight MLP-Mixer for multivariate time series forecasting (Ekambaram et al., 2023).
2. TimeXer: Transformer-based forecasting framework incorporating exogenous variables (Wang et al., 2024).
3. DeepHealth: A self-attention-based predictive maintenance framework for industrial IoT (Zhang et al., 2021).
4. GCN-Attention – Graph convolutional networks with attention for multivariate prediction (Chen et al., 2022a).
5. VMD-GRU: Variational Mode Decomposition combined with GRU for short-term industrial time series forecasting (Wang et al., 2020b).

In addition, three ablation variants of EH-DNN are implemented to evaluate the contribution of its core modules:

1. EH-DNN-1 (without Feature Extraction): Removes wavelet decomposition and fuzzy granulation.
2. EH-DNN-2 (without State Classification): Trains regression on unsegmented data.
3. EH-DNN-3 (without Both): Simplified baseline without feature extraction or classification.

5.3. Results and analysis

5.3.1. Comparison with baseline models

Table 3 summarizes experimental results comparing EH-DNN to similar models, with the best performances highlighted in bold. A residual plot effectively illustrates the impact of various models on predictions, as depicted in Fig. 9. Each procedure is replicated five times to reduce the effects of random variables, and the metrics are averaged for balanced representation of each method's effectiveness. In this analysis, "I" represents wavelet approximation coefficients, "II" refers to primary-level wavelet detail coefficients, and "III" indicates secondary-level coefficients. MAE denotes the Mean Absolute Error, reflecting the difference between estimated and actual values. "R^2" measures the variance explained by models relative to total variability in the dataset. The results show the following.

- TSMixer and TimeXer achieve R^2 values between $0.64 - 0.87$, reflecting their ability to capture temporal dependencies. However, their performance degrades under frequent operating state changes.
- VMD-GRU benefits from signal decomposition, achieving R^2 above 0.75, but it lacks adaptability to manual interventions.
- DeepHealth and GCN-Attention demonstrate improved capacity for long-term dependencies and relational modeling, with R^2 around $0.80 - 0.85$, but still underperform in non-stationary industrial settings.
- EH-DNN consistently outperforms all baselines, achieving R^2 above 0.90 and MAE reductions by $5 - 10\times$. This demonstrates that integrating operator set values with adaptive state classification yields advantages unattainable by general-purpose models.

5.3.2. Ablation study analysis

Table 4 presents the results of the ablation experiments designed to evaluate the contribution of the core modules in EH-DNN. In this table, ΔMAE(avg) indicates the increase in the model's average MAE relative to the Full EH-DNN. ΔR^2(avg) indicates the decrease in the model's average R^2 relative to the Full EH-DNN.

The following insights can be drawn:

1. Impact of Feature Extraction and Fusion (EH-DNN-1)
 Removing wavelet decomposition and setting-value granulation leads to a dramatic performance drop (average ΔMAE + 10.1, ΔR^2 − −0.13). This indicates that raw ITS alone cannot adequately represent the dynamics of industrial processes. The incorporation of both time–frequency features and fuzzy-granulated set values is therefore crucial for capturing the intrinsic characteristics of process dynamics and operator interventions.
2. Impact of Operating State Pre-classification (EH-DNN-2)
 When the pre-classification stage is skipped, the model shows moderate degradation (average ΔMAE + 0.25, ΔR^2 − −0.05). While regression models can still capture partial dependencies, they struggle to remain stable across variable operating states. The results confirm that adaptive state identification improves robustness and reduces forecasting uncertainty in dynamic production environments.
3. Impact of Removing Both Modules (EH-DNN-3)
 The simplified baseline without feature extraction and state classification performs the worst (average ΔMAE + 24.0, ΔR^2 − −0.55). This suggests that a “black-box” DNN cannot generalize under nonstationary, operator-driven processes, underscoring the necessity of combining domain-inspired feature engineering with state-aware modeling.
4. Full EH-DNN
 The complete model achieves the highest accuracy across all operating scenarios, with MAE values below 1.5 and ΔR^2 consistently above 0.90. This demonstrates the synergistic effect of feature extraction, state classification, and regression prediction. Each module contributes complementary strengths, and together they provide a robust solution for industrial time series prediction under variable operating states.

5.3.3. Overall findings

EH-DNN not only surpasses classical and recent baseline models but also proves that its performance stems from a carefully designed architecture.

- Adaptive state identification ensures stability across varying conditions.
- Feature extraction and fusion capture both system dynamics and operator influence.
- Two-step prediction strategy provides accurate and robust forecasting.

Thus, EH-DNN bridges the gap between theoretical advances in deep learning and the realities of industrial production under variable operating states with manual interventions.

6. Conclusions and future work

In industrial manufacturing, traditional predictive frameworks are tied to critical metrics. In that case, they often fail to grasp the nuanced interplay of factors embedded within production systems, especially when faced with many variables that resist straightforward analysis. To address this difficulty, the Enhanced Hybrid Deep Neural Network (EH-DNN) explores the amalgamation of deep learning within industrial environments. Weaving Deeo Learning architectures into the tapestry of real-world manufacturing creates a groundbreaking time series prediction (TSP) model. This model acknowledges the variability of operational states and incorporates manual settings as pivotal attributes, thereby deepening the portrayal of production intricacies during the data preparation stage. It adopts a classification pre-training strategy to reinforce the framework of the deep neural network (DNN), markedly enhancing its capability to distill features when dealing with fluctuating operational data. The remarkable accuracy of the model in TSP 94% is confirmed by empirical data, emphasizing the importance of feature extraction and condition identification in improving forecast accuracy in general.

Future work aims to expand the scope of the research, tackling the existing gap in status data availability during the start, shutdown, and malfunction phases. In addition, further exploration may focus on incorporating essential constraints, such as considering energy use and carbon footprint, into prediction algorithms, aiming to optimize the regulation of industrial operations. This research pathway promises to augment the utility and industrial relevance of the model and promote greener and more efficient smart manufacturing.

CRediT authorship contribution statement

Meifang Zhang: Conceptualization, Methodology, Software, Validation, Writing – original draft; **Jing Bi:** Methodology, Data curation, Supervision, Project administration, Funding acquisition; **Haitao Yuan:** Resources, Investigation, Data curation; **Ziqi Wang:** Formal analysis, Methodology, Validation, Visualization; **Jia Zhang:** Investigation, Writing – review & editing; **Rajkumar Buyya:** Resources, Investigation, Writing – review & editing.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Haitao Yuan reports financial support was provided by National Natural Science Foundation of China. Jing Bi reports financial support was provided by National Natural Science Foundation of China. Haitao Yuan reports financial support was provided by Beijing Natural Science Foundation. Jing Bi reports financial support was provided by Beijing Natural Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This work was supported by the National Natural Science Foundation of China under Grants 62173013 and 62473014, the Beijing Natural Science Foundation under Grants L233005 and 4232049.

References

Arena, S., Florian, E., Sgarbossa, F., lvsberg, E. S., & Zennaro, I. (2024). A conceptual framework for machine learning algorithm selection for predictive maintenance. *Engineering Applications of Artificial Intelligence*, *133*, 108340.
Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). *Machine Learning for industrial applications: A comprehensive literature review*, *175*, 114820.
Bi, J., Guan, Z., Yuan, H., & Zhang, J. (2024a). Improved network intrusion classification with attention-assisted bidirectional lstm and optimized sparse contractive autoencoders. *Expert Systems with Applications*, *244*, 122966.
Bi, J., Wu, X., Yuan, H., Wang, Z., Wei, D., & Wu, R. (2025). Stmf: A spatio-temporal multimodal fusion model for long-term water quality forecasting. (pp. 1–1).
Bi, J., Yuan, H., Li, S., Zhang, K., Zhang, J., & Zhou, M. (2024b). Arima-based and multiapplication workload prediction with wavelet decomposition and savitzky-golay filter in clouds. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *54*(4), 2495–2506.
Chadha, G. S., Krishnamoorthy, M., & Schwung, A. (2019). Time Series Based Fault Detection in Industrial Processes Using Convolutional Neural Networks, IECON 2019 - 45th Annual Conference of the (vol. 1). IEEE Industrial Electronics Society.
Chen, Y., Ding, F., & Zhai, L. (2022a). Multi-scale temporal features extraction based graph convolutional network with attention for multivariate time series prediction. *Expert Systems with Applications*, *200*, 117011.
Chen, Y., Ding, F., & Zhai, L. (2022b). Multi-scale Temporal Features Extraction Based Graph Convolutional Network with Attention for Multivariate Time Series Prediction, Expert systems with Applications (vol. 200).
Chen, Z., Xu, J., Peng, T., & Yang, C. (2022c). Graph convolutional networkbased method for fault diagnosis using a hybrid of measurement and prior knowledge. *IEEE Transactions on Cybernetics*, *52*(9), 9157–9169.

Chou, J.-S., & Nguyen, T.-K. (2018). Forward forecast of stock price using sliding-window metaheuristic-optimized machine-learning regression. *IEEE Transactions on Industrial Informatics*, *14*(7), 3132–3142.
Coyle, D., Prasad, G., & Mcginnity, T. M. (2005). A time-series prediction approach for feature extraction in a brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *13*(4), 461–467.
Ekambaram, V., Jati, A., Nguyen, N., Sinthong, P., & Kalagnanam, J. (2023). TSMixer: Lightweight MLP-Mixer Model for Multivariate Time Series Forecasting, Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining.
Guo, L., Lei, Y., Li, N., Yan, T., & Li, N. (2018). *Machinery Health Indicator Construction Based on Convolutional Neural Networks Considering Trend Burr*, *292*, 142–150.
Huang, X., Ye, Y., Xiong, L., Lau, R., Jiang, N., & Wang, S. (2016). Time series k-means: A new k-means type smooth subspace clustering for time series data. *Information Sciences*, *367*, 1–13.
Jin, X., Yu, X., Wang, X., Bai, Y., Su, T., & Kong, J. (2019). Prediction for time series with cnn and lstm. *Proceedings of the 11th International Conference on Modelling, Identification and Control*, *582*, 631–641.
Liu, C., Hsaio, W., & Tu, Y. (2019). Time series classification with multivariate convolutional neural network. *IEEE Transactions on Industrial Electronics*, *66*(6), 4788–4797.
Liu, K., Shang, Y., Ouyang, Q., & Widanage, W. D. (2021). A data-driven approach with uncertainty quantification for predicting future capacities and remaining useful life of lithium-ion battery. *IEEE Transactions on Industrial Electronics*, *68*(4), 3170–3180.
Liu, Y., Gong, C., Yang, L., & Chen, Y. (2020). Dstp-rnn: A dual-stage two-phase attention-based recurrent neural network for long-term and multivariate time series prediction. *Expert Systems with Applications*, *143*, 113082.
Lu, W., Yang, J., Liu, X., & Pedrycz, W. (2014). The Modeling and Prediction of Time Series Based on Synergy of High-order Fuzzy Cognitive Map and Fuzzy C-means Clustering, Knowledge-Based Systems (vol. 70).
Sala, D. A., Jalalvand, A., Deyne, A., & Mannens, E. (2018). Multivariate time series for data-driven endpoint prediction in the basic oxygen furnace. In *th ieee international conference on machine learning and applications (icmla)* Orlando, FL, USA (pp. 1419–1426).
Uchiteleva, E., Primak, S. L., Luccini, M., Hussein, A. R., & Shami, A. (2021). The trils approach for drift-aware time-series prediction in iiot environment. *IEEE Transactions on Industrial Informatics*, *18*(10), 6581–6591.
Wang, G., Qiao, J., Bi, J., Jia, Q., & Zhou, M. (2020a). An adaptive deep belief network with sparse restricted boltzmann machines. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(10), 4217–4228.
Wang, R., Li, C., Fu, W., & Tang, G. (2020b). Deep learning method based on gated recurrent unit and variational mode decomposition for short-term wind power interval prediction. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(10), 3814–3827.
Wang, S., Chaovalitwongse, W. A., & Wong, S. (2013). Online seizure prediction using an adaptive learning approach. *IEEE Transactions on Knowledge and Data Engineering*, *25*(12), 2854–2866.
Wang, Y., Qian, C., & Qin, S. (2023). Attention-mechanism based dipls-lstm and its application in industrial process time series big data prediction. *Computers & Chemical Engineering*, *176*, 108296.
Wang, Y., Wu, H., Dong, J., Liu, Y., Zhang, H., Wang, J., & Long, M. (2024). TimeXer: Empowering Transformers for Time Series Forecasting with Exogenous Variables. https://doi.org/10.48550/arxiv.2402.19072
Wu, K., Liu, J., Liu, P., & Yang, S. (2020). Time series prediction using sparse autoencoder and high-order fuzzy cognitive maps. *IEEE Transactions on Fuzzy Systems*, *28*(12), 3110–3121.
Yuan, H., Hu, Q., Wang, M., Wang, S., Bi, J., & Buyya, R. (2025). Data-filtered prediction with decomposition and amplitude-aware permutation entropy for workload and resource utilization in cloud data centers. *IEEE Internet of Things Journal*, *12*(12), 19189–19201.
Zhang, W., Yang, D., Xu, Y., Huang, X., Zhang, J., & Gidlund, M. (2021). Deephealth: A self-attention based method for instant intelligent predictive maintenance in industrial internet of things. *IEEE Transactions on Industrial Informatics*, *17*(8), 5461–5473.
Zheng, J., Su, M., Ying, W., Tong, J., & Pan, Z. (2021). Improved uniform phase empirical mode decomposition and its application in machinery fault diagnosis. *Measurement*, *179*, 109425.
Zheng, Y., Wang, S., Dong, C., Li, W., Zheng, W., & Yu, J. (2022). Urban road traffic flow prediction: A graph convolutional network embedded with wavelet decomposition and attention mechanism. *Physica A: Statistical Mechanics and its Applications*, *608*, 128274–128284.

Meifang Zhang received her M.E. degree in Software Engineering from Beijing Institute of Technology. She is currently a Ph.D. student in the College of Computer Science, Beijing University of Technology, Beijing, China. Her research interests include industrial modeling, big data analysis, artificial intelligence, deep learning and performance optimization. She received the Best Application Paper Award in the 21st IEEE ICNSC. And she has received the Industry Technology Innovation Award, participated in the formulation of national standards and national research projects during her work in CNBM Group Co., Ltd.

Jing Bi received her B.S. and Ph.D. degrees in Computer Science from Northeastern University, Shenyang, China, in 2003 and 2011, respectively. From 2013 to 2015, she was a Post-doc researcher in the Department of Automation at Tsinghua University, Beijing, China. From 2011 to 2013, she was a research scientist at the Beijing Research Institute of Electronic Engineering Technology in Beijing, China. From 2009 to 2010, she was a research assistant and participated in research on cloud computing at IBM Research, Beijing, China. From 2018 to 2019, she was a Visiting Research Scholar with the Department of Electrical and Computer Engineering, New Jersey Institute of Technology, Newark, NJ, USA. She is a Professor at the College of Computer Science, Beijing University of Technology, Beijing, China. She has over 150 publications in international journals and conference proceedings. Her research interests include distributed computing, cloud computing, large-scale data analytics, machine learning, and performance optimization.

Haitao Yuan received the Ph.D. degree in Computer Engineering from New Jersey Institute of Technology (NJIT), Newark, NJ, USA in 2020. He is currently a Deputy Director in the Department of Strategic Development, Wenchang International Aerospace City, Hainan, China. He is currently an Associate Professor at the School of Automation Science and Electrical Engineering at Beihang University, Beijing, China, and he is named in the world's top 2% of Scientists List. His research interests include the Internet of Things, edge computing, deep learning, data-driven optimization, and computational intelligence algorithms. He received the Chinese Government Award for Outstanding Self-Financed Students Abroad, the 2021 Hashimoto Prize from NJIT, the Best Work Award in the 17th ICNSC, and the Best Student work Award Nominees in 2024 IEEE SMC. He is an associate editor for IEEE Trans. on Systems, Man, and Cybernetics: Systems, IEEE Internet of Things Journal, and Expert Systems With Applications.

Ziqi Wang is currently pursuing the Ph.D. degree with the School of Software Technology, Zhejiang University, China. Before that, he received the B.S. degree in Internet of Things in 2022 and the M.S. degree in Software Engineering in 2025, both from Beijing University of Technology, China. His research interests include mobile edge computing, task scheduling, intelligent optimization algorithms, and deep learning. He received the Best Paper Award in 2024 ICAIS & ISAS and the Best Application Paper Award in the 21st IEEE ICNSC.

Jia Zhang received a Ph.D. degree in computer science from the University of Illinois at Chicago. She is the Cruse C. and Marjorie F. Calahan Centennial Chair in Engineering and a professor of the Department of Computer Science in the Lyle School of Engineering at Southern Methodist University. Her research interests emphasize applying machine learning and information retrieval methods to tackle data science infrastructure problems, with a recent focus on scientific workflows, provenance mining, software discovery, knowledge graphs, and interdisciplinary applications of all these interests in earth science.

Rajkumar Buyya is a Redmond Barry Distinguished Professor and Director of the Cloud Computing and Distributed Systems (CLOUDS) Laboratory at the University of Melbourne, Australia. He received a B.E and M.E in Computer Science and Engineering from Mysore and Bangalore Universities in 1992 and 1995, respectively, and a Ph.D. in Computer Science and Software Engineering from Monash University, Melbourne, Australia, in 2002. He was a Future Fellow of the Australian Research Council from 2012 to 2016. He has authored over 800 publications and seven textbooks. He is one of the highly cited authors in computer science and software engineering worldwide, with over 164,286 citations and an h-index of 175. He was recognized as a "Web of Science Highly Cited Researcher" from 2016 to 2021 by Thomson Reuters.