Edge-cloud cooperation-driven smart and sustainable production for energy-intensive manufacturing industries

Shuaiyin Ma, a,b,c,d Yuming Huang, a,b,c,d Yang Liu, e,f,* Xianguang Kong, g,* Lei Yin, g Gaige Chen, h

a School of Computer Science and Technology, Xi’an University of Posts and Telecommunications, Xi’an, 710121, China
b Shaanxi Key Laboratory of Network Data Analysis and Intelligent Processing, Xi’an University of Posts and Telecommunications, Xi’an, 710121, China
c Xi’an Key Laboratory of Big Data and Intelligent Computing, Xi’an, 710121, China
d Shaanxi Union Research Center of University and Enterprise for 5G+ Industrial Internet Communication Terminal Technology, Xi’an University of Posts and Telecommunications, Xi’an, 710121, China
e School of Management and Engineering, Shenzhen University, Shenzhen, 518060, China
f School of Information Science and Technology, Xi’an Jiaotong University, Xi’an, 710049, China
g School of Mechatronic Engineering, Xi’an University of Science and Technology, Xi’an, 710071, China
h School of Communications and Information Engineering & School of Artificial Intelligence, Xi’an University of Posts and Telecommunications, Xi’an, 710121, China

HIGHLIGHTS

• An edge-cloud cooperation-driven sustainable manufacturing strategy is proposed.
• A KPCA algorithm is used for data processing.
• An improved TOPSIS-AISM algorithm is established for data mining.
• The effectiveness of the models and the management implications are discussed.

ABSTRACT

Energy-intensive manufacturing industries are characterised by high pollution and heavy energy consumption, severely challenging the ecological environment. Fortunately, environmental, social, and governance (ESG) can promote energy-intensive manufacturing enterprises to achieve smart and sustainable production. In Industry 4.0, various advanced technologies are used to achieve smart manufacturing, but the sustainability of production is often ignored without considering ESG performance. This study proposes a strategy of edge-cloud cooperation-driven smart and sustainable production to realise data collection, preprocessing, storage and analysis. In detail, kernel principal component analysis (KPCA) is used to decrease the interference of abnormal data in the evaluation results. Subsequently, an improved technique for order preference by similarity to ideal solution (TOPSIS) based on the adversarial interpretative structural model (AISM) is proposed to evaluate the production efficiency of the manufacturing workshop and make the analysis results more intuitive. Then, the architecture and models are verified using real production data from a partner company. Finally, sustainable analysis is discussed from the perspective of energy consumption, economic impact, greenhouse gas emissions and pollution prevention.

Keywords: Edge-cloud cooperation; Energy-intensive manufacturing industries (EIMIs); Environmental, social and governance (ESG); Kernel principal component analysis (KPCA); Technique for order preference by similarity to ideal solution (TOPSIS); Adversarial interpretative structural model (AISM)

Abbreviations: AISM, Adversarial interpretative structural model; EIMIs, Energy-intensive manufacturing industries; GDP, Gross domestic product; IoT, Internet of Things; KPCA, Kernel principal component analysis; MRCMCP, Manufacture of raw chemical materials and chemical products; PANISD, Positive and negative ideal solutions distance; PPCP/NF, Processing of petroleum, coking and processing of nuclear fuel; SPFM, Smelting and pressing of ferrous metals; TOPSIS, Technique for order preference by similarity to ideal solution; EIS, Energy-intensive industries; ESG, Environmental, social and governance; GHG, Greenhouse gas; ISM, Interpretative structural model; MNMP, Manufacture of non-metallic mineral products; PANGCD, Positive and negative grey correlation degree; PANRS, Positive and negative reference sequence; PSEPHP, Production and supply of electric power and heat power; SPNM, Smelting and pressing of non-ferrous metals.

* Corresponding authors at: Department of Management and Engineering, Linköping University, SE-581 83 Linköping, Sweden (Y. Liu).+ Corresponding authors at: Department of Management and Engineering, Linköping University, SE-581 83 Linköping, Sweden (Y. Liu).

E-mail addresses: yang.liu@liu.se (Y. Liu), kongxianguang@xidian.edu.cn (X. Kong).

https://doi.org/10.1016/j.apenergy.2023.120843
Received 24 December 2022; Received in revised form 27 January 2023; Accepted 9 February 2023
Available online 1 March 2023
0306-2619/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
local computing services to analyse production data timely [9]. Mean-10- effectively respond to the challenge of massive data mining and analysis transmission delay, improve data security and mine information and while, cloud computing enables businesses to use computational tools [7]. Edge-cloud cooperation provides a new strategy to solve these heterogeneous data are collected using the IoT. The advanced technologies support for cleaner production [6]. A framework for EIMIs-energy consumption [5]. Moreover, based on Cyber-Physical System production by using a decision support system [4]. A framework for EIMIs was proposed with digital twins to save energy and reduce emissions and energy consumption [3]. Moreover, based on Cyber-Physical System technology, a qualitative and quantitative collaborative analysis model of material, energy and information flow was proposed, which provided support for cleaner production [6].

With the development of smart factories, massive multi-source heterogeneous data are collected using the IoT. The advanced technologies facilitate the realisation of smart and sustainable production but cannot effectively respond to the challenge of massive data mining and analysis [7]. Edge-cloud cooperation provides a new strategy to solve these problems [8]. Edge computing is applied to information terminals such as production lines, robots and sensors, which can provide distributed local computing services to analyse production data timely [9]. Meanwhile, cloud computing enables businesses to use computational tools that can be deployed and scaled rapidly, reducing the need for huge upfront investments in the server setup. Edge-cloud cooperation combines the advantages of edge and cloud computing, which can reduce transmission delay, improve data security and mine information and knowledge. Firstly, the edge node is used to realise data preprocessing, which can reduce transmission delay and submit the production data to the cloud computing platform in a timely manner. Secondly, cloud computing confirms that the production data cannot be leaked and lost even if the local computer is damaged or subjected to network attacks. Thirdly, the high-speed computational capability of cloud computing provides support for mining information and knowledge [10]. Then, the analysis results can be timely feedback to the enterprise management terminal.

The application of mining information and knowledge from multi-source heterogeneous data to production has become a concern of enterprise managers [11]. Many comprehensive evaluation models have been proposed to achieve smart and sustainable production. For example, based on the technique for order preference by similarity to ideal solution (TOPSIS), selecting industrial arc welding machines method has been proposed to improve product quality and economic efficiency [12]. However, this method does not consider the production disruption caused by equipment failure. Maintenance factors affecting manufacturing are evaluated based on fuzzy TOPSIS and AHP methods [13]. Although this method provides a reference for equipment maintenance, it ignores the demand for enterprises to realise energy saving and emission reduction [14]. In conclusion, these methods improve production intelligence and economic efficiency but ignore production sustainability.

The adversarial interpretative structural model (AISM) is introduced based on the improved TOPSIS algorithm; it can detect operation conditions, evaluate operational efficiency, and perform timely maintenance [15]. Firstly, a production data acquisition network is established based on smart factories and IoT. Then, the data preprocessing is realised using edge nodes, which can reduce the data to be transmitted. Secondly, the data are uploaded to the cloud server and kernel principal component analysis (KPCA) is used to filter anomalies and noises [16]. Finally, the TOPSIS-AISM models are used for data mining and analysis to carry out benefit evaluations for EIMIs based on multi-source heterogeneous data, which can promote and achieve smart and sustainable production [17].

The improved TOPSIS-AISM provides an analytical method for energy-intensive enterprises to improve production efficiency and realise energy saving and emission reduction [7]. However, this method does not consider the social and governance implications. Fortunately, environmental, social and governance (ESG) was proposed by the UN global compact in 2004, which helps enterprises realise cleaner production and green manufacturing from the environment, society and governance. At present, more investors and enterprises attach importance to ESG related to environmental and ecological protection. Therefore, the combination of ESG and analysis results of the proposed TOPSIS-AISM can facilitate energy-intensive manufacturing enterprises to improve production smart and sustainable.

In the era of Industry 4.0, edge-cloud cooperation, energy, comprehensive evaluation, ESG, and manufacturing intersect one another, which are no longer independent disciplines, thus forming some new crossed research areas. As shown in Fig. 1, our research in this paper is the centre of the interdisciplinary.

The remainder of the study is organised as follows. Section 2 explains the structure of edge-cloud cooperation-driven smart and sustainable production for EIMIs. In Section 3, the KPCA and improved TOPSIS-AISM are introduced. In Section 4, the proposed architecture and models are verified according to a case study. Section 5 discusses the sustainability analysis for energy saving, economic impact, greenhouse gas emissions and pollution prevention. In Section 6, the proposed architecture and models are further analysed based on the managerial implication for ESG and effectiveness in theory and practice. In Section 7, conclusions, limitations and future research directions are discussed.

2. Edge-cloud cooperation-driven smart and sustainable production for EIMIs

As shown in Fig. 2, this section will introduce an edge-cloud cooperation-driven smart and sustainable production architecture for EIMIs [18], providing a set of feasible tools to reduce energy consumption and improve productivity [19]. The right side of Fig. 2 shows the analysis process of the architecture from bottom to top. Firstly, the fundamentals
of the proposed architecture are the data capture based on edge-cloud cooperation, which provides data support for intelligent analysis. Secondly, data can be converted into knowledge using intelligent analysis, thereby providing a basis for making energy-saving decisions [20]. Meanwhile, the equipment and infrastructure of the edge-cloud cooperation are updated iteratively according to the analysis results. Finally, the parameters of the intelligent processing algorithm are feedback adjusted according to the application results, which can realise the long-term objective of carbon neutral and carbon peak for EIMIs.

2.1. Data capturing layer based on edge-cloud cooperation

The sensors and smart meters are used to capture and collect production data in manufacturing workshops. Then, the collected production data are preprocessed by edge computing [21], which reduces network bandwidth pressure and transmission delay. Subsequently, the preprocessed data can be uploaded to cloud computing platforms using 5th-generation mobile communication technology and other data transmission technologies to achieve data security and high-speed transmission. The cloud server can support further data analysis and mining based on data storage. Finally, the production data can be quickly analysed by the high computing capability of the cloud server. In summary, the production data of EIMIs are collected and analysed based on edge-cloud cooperation, providing data support for further analysis and mining [22].

2.2. Energy-saving decision layer based on intelligent analysis

The preprocessed data of the edge node is uploaded to the cloud platform. Then, the data are analysed using algorithms to mine valuable information and knowledge according to the requirements of enterprise managers [23]. At present, multidimensional scaling, isometric mapping, grey correlation and data envelopment analysis have been proposed for data mining [24]. The correlation between samples and various indicators to evaluate production efficiency can be measured using grey correlation analysis [25]. Data envelopment analysis has been performed to study the input and output indexes [26]. The data mining methods can be used to mine valuable information and transform it into knowledge [27], which can support enterprise benefit evaluation and energy governance. For example, abnormal production can be found and warned timely, the operation efficiency of the equipment can be evaluated, and the equipment is maintained on time [28].

2.3. Service application layer based on management implications

The collected data are processed and mined into information and knowledge, which provides management implications to the actual production of the enterprise [29]. The application layer of the architecture and models are proposed to provide a set of feasible methods, strategies and tools to realise the cooperative management of ESG. Firstly, the architecture can help EIMIs reduce the discharge of waste gas, waste water and waste residue in the environment [30]. Secondly, scientific decision-making can be provided to undertake environmental protection responsibility for enterprises in terms of the social level. Finally, the traditional factory and shop inspection can be replaced to save the labour cost of the enterprise in terms of governance [31]. In the service application layer, the mined information and knowledge can help EIMIs to achieve smart and sustainable production [32], accelerate
Fig. 3. An improved TOPSIS-AISM model.

Fig. 4. Normalised energy consumption in Company HD from 2017 to 2020.
Fig. 5. Normalised energy consumption of the No.2 factory from 2017 to 2020.

Fig. 6. Kernel matrixes of energy consumption data in Company HD from 2017 to 2020.
the transformation to ESG and achieve the strategic goal of carbon neutral and carbon peak [33].

3. Improved TOPSIS-AISM model

With the development of IoT applied in smart factories, production data can be collected using smart meters, RFID and soft sensor technologies [34]. Edge computing can verify and preprocess the collected data, and the preprocessed data is uploaded to the cloud computing platforms using encrypted data links [35]. The cloud platform is responsible for data storage and mining. The mining results can be timely returned to the enterprise management terminal.

Some redundant and abnormal data are inevitable due to random and uncertain equipment failures [36]. The original data need to be filtered and screened to improve the data quality and achieve more accurate analytical results. PCA algorithm is widely used for data dimension reduction; it measures the distribution of data projected in all directions by variance and selects effective dimensional directions [37]. However, the definition of PCA is unclear when the sign of factor loading of principal components is positive or negative. Fortunately, KPCA has been proposed to avoid these problems [38]. The KPCA projects the data into the high-dimensional feature space using nonlinear mapping and reduces the data dimension in the high-dimensional feature space [39]. Therefore, the KPCA is proposed for data preprocessing to weaken abnormal data’s impact.

The comprehensive evaluation model of the improved TOPSIS-AISM is proposed [40], which transforms the data into information and knowledge to guide enterprise production. The comprehensive evaluation methods have been widely used with some restrictions [41]. For example, the preference ranking organisation method for enrichment evaluations may lead to the loss of information and results [42]. The evaluation result of the analytic hierarchy process can be affected by subjective factors [43]. Fortunately, the improved TOPSIS solves the impact of uncertainties by introducing grey correlation analysis, which enhances the approach objectivity of the assessment [44]. In addition, the weighted matrix should be constructed in the improved TOPSIS algorithm. Objective weights are influenced by personal knowledge and preferences. Therefore, the weight is determined using the entropy
weight method in the objective weight [45].

The interpretative structural model (ISM) is used to solve the hierarchy process from the Pareto optimal to the Pareto worst [46]. AISM introduces the concept of adversarial contention in generative adversarial networks to ISM [47]. The results of the AISM show the advantages and disadvantages of the evaluation objects at the confrontation level based on the topology diagram [48]. The confrontation level based on the topology diagram extends the evaluation result of the improved TOPSIS from the ranking result. In conclusion, this section establishes the AISM method based on the improved TOPSIS algorithm [49], which intuitively observed the advantages and disadvantages of the evaluation objects. The establishment process of the model is as follows:

### 3.1. Kernel principal component analysis model

**Step 1:** The original data $x_{ij}$ should be standardised, and the calculation process of the standardised index variable $\tilde{x}_j$ is shown in Eqs. (1-3):

$$\mu_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij},$$  

(1)

$$s_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \mu_j)^2}, j = 1, 2, 3, \ldots, m,$$  

(2)

$$\tilde{x}_j = \frac{x_{ij} - \mu_j}{s_j}, j = 1, 2, 3, \ldots, m,$$  

(3)

where $x_{ij}$ is the $j$-th evaluation index of the $i$-th analysis object, $\mu_j$ and $s_j$ are the sample mean and standard deviation, respectively.

**Step 2:** According to the selected kernel function, the kernel matrix $K$ is shown in Eq. (4):

$$K_{ij} = \kappa(x_i, x_j),$$

where $\kappa$ is the kernel function.
\[ k(\tilde{x}_i, \tilde{x}_j) = e^{-\frac{||\tilde{x}_i - \tilde{x}_j||^2}{2\sigma^2}}, \quad (4) \]

where \( \tilde{x}_i \) and \( \tilde{x}_j \) are standardised index variables, and \( \sigma \) is the parameter of the Gaussian kernel function.

**Step 3:** The kernel matrix \( K = (k_{ij})_{m \times m} \) is centralised, and the modified kernel matrix \( \tilde{K} = (\tilde{k}_{ij})_{m \times m} \) is shown in Eq. (5):

\[ \tilde{k}_{ij} = k_{ij} - \frac{1}{m} \left( \sum_{i=1}^{m} k_{ii} + \sum_{j=1}^{m} k_{jj} \right) + \frac{1}{m^2} \sum_{i,j=1}^{m} k_{ij}, \quad (5) \]

where \( m \) is the index number of samples. The modified kernel matrix \( \tilde{K} \) consists of \( \tilde{k}_{ij}, i, j = 1, 2, \ldots, m \).

**Step 4:** The eigenvalues and eigenvectors of the modified kernel matrix \( \tilde{K} \) are calculated in Eqs. (6-7):

\[
\begin{align*}
  y_1 &= u_{11}\tilde{k}_1 + u_{12}\tilde{k}_2 + \cdots + u_{1m}\tilde{k}_m, \\
  y_2 &= u_{21}\tilde{k}_1 + u_{22}\tilde{k}_2 + \cdots + u_{2m}\tilde{k}_m, \\
  \vdots & \quad \vdots \\
  y_m &= u_{m1}\tilde{k}_1 + u_{m2}\tilde{k}_2 + \cdots + u_{mm}\tilde{k}_m, \\
  \lambda u &= \tilde{k} u \quad (7)
\end{align*}
\]

where \( \lambda \) is the eigenvalue of the modified kernel matrix \( \tilde{K} \), \( u_i \) comprises \( m \) new index variables, \( y_i \) represents the \( i \)-th principal component, \( i = 1, 2, \ldots, m \).

**Step 5:** The information contribution rate is calculated according to the eigenvalues is shown in Eq. (8):

\[ b_j = \frac{\lambda_j}{\sum_{k=1}^{m} \lambda_k}, \quad (8) \]

where \( b_j \) is the information contribution rate and \( j = 1, 2, \ldots, m \).

**Step 6:** The contribution rate is accumulated according to the eigenvalues is shown in Eq. (9):

\[ a_p = \sum_{j=1}^{p} b_j, \quad (9) \]

where the cumulative contribution rate of the principal components \( y_1, y_2, \ldots, y_p \) is \( a_p \). The first \( p \) principal components are selected to replace the original data when \( a_p \) is close to 0.85, 0.90 and 0.95.

High-quality data can be provided for data processing methods by KPCA; the influence of abnormal and missing values can be attenuated on data mining results [50]. Then KPCA can provide an effective basis to achieve smart and sustainable production for EIMIs [51]. Sections 3.2 and 3.3 propose an improved TOPSIS-AISM comprehensive evaluation model for data mining.
3.2. Improved TOPSIS algorithm

**Step 1:** The normalisation matrix \( B = (b_{ij})_{m \times n} \) is calculated in Eq. (10):

\[
b_{ij} = \begin{cases} 
\frac{\text{max}_i x_{ij} - x_{ij}}{\text{max}_i x_{ij} - \text{min}_i x_{ij}} & \text{(Benefit indices)} \\
\frac{x_{ij} - \text{min}_i x_{ij}}{\text{max}_i x_{ij} - \text{min}_i x_{ij}} & \text{(Cost indices)}
\end{cases}.
\]

(10)

where \( X = (x_{ij})_{m \times n} \) is the sample matrix. \( m \) and \( n \) represent the number of evaluation objects and indicators, respectively; \( i = 1, 2, \ldots, m \).
Table 3
Reference sequence constituted a reference sequence in 2020.

<table>
<thead>
<tr>
<th>Factory</th>
<th>Positive reference sequence</th>
<th>Negative reference sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.1</td>
<td>0.239</td>
<td>0.498</td>
</tr>
<tr>
<td>No.2</td>
<td>0.187</td>
<td>0.674</td>
</tr>
<tr>
<td>No.3</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>No.4</td>
<td>0.266</td>
<td>0.404</td>
</tr>
<tr>
<td>No.5</td>
<td>0.192</td>
<td>0.537</td>
</tr>
<tr>
<td>No.6</td>
<td>0.240</td>
<td>0.468</td>
</tr>
<tr>
<td>No.7</td>
<td>0.039</td>
<td>0.966</td>
</tr>
<tr>
<td>No.8</td>
<td>0.204</td>
<td>0.600</td>
</tr>
<tr>
<td>No.9</td>
<td>0.000</td>
<td>1.400</td>
</tr>
</tbody>
</table>

\(j = 1, 2, \ldots, n\).

Step 2: The weight matrix \(C = (c_{ij})_{m \times n}\) is calculated in Eq. (11):

\[
c_i = w_i b_{ij},
\]

where \(b_{ij}\) is a member of the normalised matrix \(B\) and \(w_i\) is the index weight determined by the entropy weight method.

Step 3: The positive ideal solution \(C^+ = (c_{i1}^+, c_{i2}^+, \ldots, c_{ij}^+)\) and the negative ideal solution \(C^- = (c_{i1}^-, c_{i2}^-, \ldots, c_{ij}^-)\) are considered. The selection process for \(C^+\) and \(C^-\) is shown in Eq. (12):

\[
c_{ij}^+ = \max_{i} c_{ij} (\text{Benefit indices})
\]

\[
c_{ij}^- = \min_{i} c_{ij} (\text{Cost indices})
\]

where \(c_{ij}^+\) is the \(j\)-th variable of the positive ideal solution \(C^+\). When \(j\)-th variable is the benefit indicator, \(c_{ij}^+ = \max c_{ij}\), \(j\) is the cost indicator, \(c_{ij}^- = \min c_{ij}\). The positive and negative ideal solutions are the opposite.

Step 4: \(s_i^+\) and \(s_i^-\) in Eqs. (13-14) represent the distance from the index value of each evaluation object to the positive and negative ideal solution, respectively.

\[
s_i^+ = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_{ij}^+)^2},
\]

\[
s_i^- = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_{ij}^-)^2},
\]

where \(c_{ij}^+\) is the positive ideal solution and \(c_{ij}^-\) is the negative ideal solution; \(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\).

Step 5: The distance of positive and negative ideal solutions is normalised. \(NS^+ = (ns_1^+, ns_2^+, \ldots, ns_m^+)\) and \(NS^- = (ns_1^-, ns_2^-, \ldots, ns_m^-)\) in Eqs. (15-16) represent the normalised distance vectors of positive and negative ideal solutions, respectively.

\[
s_i^+ = \frac{\max s^+ - s_i^+}{\max s^+ - \min s^+},
\]

\[
s_i^- = \frac{\max s^- - s_i^-}{\max s^- - \min s^-},
\]

Step 6: The positive grey correlation coefficient \(\zeta_{ij}^+\) and the negative grey correlation coefficient \(\zeta_{ij}^-\) of \(j\)-th indicators of the \(i\)-th sample are calculated in Eqs. (17-18):

\[
\zeta_{ij}^+ = \frac{\min|c_{ij} - c_{ij}^+| + \rho \max|c_{ij} - c_{ij}^-|}{|c_{ij} - c_{ij}^+| + \rho \max|c_{ij} - c_{ij}^-|},
\]

\[
\zeta_{ij}^- = \frac{\min|c_{ij} - c_{ij}^-| + \rho \max|c_{ij} - c_{ij}^+|}{|c_{ij} - c_{ij}^-| + \rho \max|c_{ij} - c_{ij}^+|},
\]

where \(c_{ij}^+\) is the positive ideal solution and \(c_{ij}^-\) is the negative ideal solution, \(\rho\) is the resolution coefficient and \(\rho \in [0, 1]\). The resolution coefficient is selected as 0.5 in practical application; it can also be adjusted according to the analysis results [52], \(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\).

Step 7: \(f_i^+\) and \(f_i^-\) in Eqs. (19-20) are the positive and negative grey correlation degrees of the \(i\)-th sample, respectively.

\[
f_i^+ = \frac{1}{n} \sum_{j=1}^{n} \zeta_{ij}^+,
\]

\[
f_i^- = \frac{1}{n} \sum_{j=1}^{n} \zeta_{ij}^-,
\]

Step 8: The normalised vector \(NF^+ = (nf_1^+, nf_2^+, \ldots, nf_m^+)\) and \(NF^- = (nf_1^-, nf_2^-, \ldots, nf_m^-)\) in Eqs. (21-22) are the positive and negative grey correlation degrees, respectively. They are calculated as follows.

\[
nf_i^+ = \frac{f_i^+ - \min f^+}{\max f^+ - \min f^+}, \quad i = 1, 2, \ldots, m,
\]

\[
nf_i^- = \frac{f_i^- - \min f^-}{\max f^- - \min f^-}, \quad i = 1, 2, \ldots, m,
\]

Step 9: The reference sequence \(G_i^+\) of the positive ideal solution and \(G_i^-\) of the negative ideal solution are obtained by combining the distance between positive and negative ideal solutions and the grey correlation degree in Eqs. (23-24):

\[
G_i^+ = a ns_i^+ + \beta nf_i^+,
\]

\[
G_i^- = a ns_i^- + \beta nf_i^-,
\]

where \(s_i^+\) and \(s_i^-\) are the normalised distances of the \(i\)-th sample of the positive and negative ideal solutions, respectively. Then, \(f_i^+\) and \(f_i^-\) are the normalised grey correlation degree of the \(i\)-th sample of the positive and negative ideal solutions, respectively. \(a\) and \(\beta\) are determined according to the trend of the data curve and the importance of different algorithms; and \(a + \beta = 1\).

Step 10: The benefit coefficient \(H_i\) of the sample is calculated, and the specific calculation process is shown in Eq. (25):

\[
H_i = \frac{G_i^+}{G_i^+ + G_i^-},
\]

where \(H_i\) is used to measure the benefit of the \(i\)-th evaluation object. The larger value of \(H_i\) indicates better benefit of the \(i\)-th evaluation.
object. Otherwise, the benefit of the \( i \)-th evaluation object is worse. The benefit level of each evaluation object is ranked according to the score of the benefit coefficient.

### 3.3. Adversarial interpretative structural model

**Step 1:** The relational matrix \( A = (a_{ij})_{m \times m} \) is shown in Eq. (26):

\[
a_{ij} = \begin{cases} 
1 & \text{Better}(j \rightarrow i) \\
0 & \text{Worse}(j \rightarrow i) 
\end{cases}
\]  

(26)

where \( m \) refers to the number of evaluation object. Relational matrix \( A \) is constructed from decision matrix \( D \). The matrix \( D \) refers to the positive and negative reference sequence calculated according to Eqs. (23-24). The evaluation object \( j \) is superior to evaluation object \( i \), which is called \( \text{Better}(j \rightarrow i) \) in this study; otherwise, it is called \( \text{Worse}(j \rightarrow i) \). The relational matrix \( A \) is constructed according to the following rules in Eqs. (27-28):

\[
\begin{cases} 
\forall d(i, p_1) \leq d(j, p_1) \\
\forall d(i, p_2) \leq d(j, p_2) \\
\vdots \\
\forall d(i, p_m) \leq d(j, p_m) 
\end{cases}
\]  

(27)

\[
\begin{cases} 
\forall d(i, n_1) \geq d(j, n_1) \\
\forall d(i, n_2) \geq d(j, n_2) \\
\vdots \\
\forall d(i, n_m) \geq d(j, n_m) 
\end{cases}
\]  

(28)

where \( p_1, p_2, p_3, \ldots, p_m \) and \( n_1, n_2, \ldots, n_m \) are positive and negative indicators, respectively, in decision matrix \( D \). \( m \) refers to the number of indicators in the decision matrix. The positive indexes of evaluation objects \( i \) and \( j \) accord with Eq. (23), and the negative indexes of evaluation objects \( i \) and \( j \) accord with Eq. (24). Therefore, evaluation object \( j \) is superior to evaluation object \( i \), which is called \( \text{Better}(j \rightarrow i) \) in this study; otherwise, it is called \( \text{Worse}(j \rightarrow i) \).

**Step 2:** The skeleton matrix \( S \) and multiplication matrix \( B \) are calculated in Eqs. (29-31):

\[
B = A + I, 
\]  

(29)

\[
B^{+1} \neq B \quad B^{+1} = R, 
\]  

(30)

\[
S = R - (R - I)^{-1} - I, 
\]  

(31)

where \( R \) is the reachable matrix and \( I \) is the identity matrix. The matrices are square matrices of \( m \) dimensions. The proof of Eq. (30) is in Appendix A.
Step 3: The Boolean matrix $L$ is defined in Eq. (32), and the confrontation level based on the topology diagram is described as follows:

$$L = S + I.$$  (32)

Firstly, the reachable set $R$, antecedent set $Q$ and common set $T$ are obtained according to the Boolean square matrix $L$. The evaluation object with row value 1 corresponding to the evaluation object $i$ in matrix $L$ is denoted as $R(e_i)$. The evaluation object with column value 1 corresponding to the evaluation object $i$ in matrix $L$ is denoted as $Q(e_i)$. When $R(e_i) \cap Q(e_i)$, the evaluation object is denoted as $T(e_i)$. Secondly, the objects are extracted when the reachable and common sets are identical.
The extracted objects are placed on top of the up-directed hierarchical topology. The object is extracted when the antecedent and common sets are the same. The extracted objects are placed at the bottom of the up-directed hierarchical topology. Finally, the ranking of each node is provided according to the level of the hierarchy, and the evaluation objects at the top and bottom levels are Pareto optimal and the worst, respectively.

The analysis process of the improved TOPSIS-AISM models is shown in Fig. 3. Initially, KPCA is used to reduce the dimensionality of the original data. Then, the objective weight of the index is calculated according to the entropy weight method. Finally, the improved TOPSIS-AISM models enhance the analysis results’ reliability by introducing the grey correlation and the AISM. Meanwhile, the proposed architecture and models based on edge-cloud cooperation provide an efficient and reliable technical route for multi-source heterogeneous data mining and analysis [53].

4. Case study

The proposed architecture and models are proved based on the actual production data presented in this section, which was provided by Company Huida (hereafter Company HD) from Northern China. To satisfy the requirements of a listed company, Company HD issued a prospectus in 2017, which provides data support for this section [54]. The company is a sanitary ceramic manufacturing enterprise, and the business scope includes toilets, cisterns, squatting pans, basins, tiles and other sanitary ceramic products. Company HD consumed 840 thousand cubic meters of gas, 9.9 million kWh of electricity and 130 thousand cubic meters of water in 2021. Therefore, Company HD is a typical energy-intensive enterprise conforming to this study’s proposed architecture and models.

4.1. Data capture and edge-cloud cooperation

The data acquisition networks based on IoT are established to achieve data acquisition. The data acquisition nodes comprise smart sensors, meters and other IoT equipment. Then, the real-time production

The analysis process of the improved TOPSIS-AISM models is shown in Fig. 3. Initially, KPCA is used to reduce the dimensionality of the original data. Then, the objective weight of the index is calculated according to the entropy weight method. Finally, the improved TOPSIS-AISM models enhance the analysis results’ reliability by introducing the grey correlation and the AISM. Meanwhile, the proposed architecture and models based on edge-cloud cooperation provide an efficient and reliable technical route for multi-source heterogeneous data mining and analysis [53].

4. Case study

The proposed architecture and models are proved based on the actual production data presented in this section, which was provided by Company Huida (hereafter Company HD) from Northern China. To satisfy the requirements of a listed company, Company HD issued a prospectus in 2017, which provides data support for this section [54]. The company is a sanitary ceramic manufacturing enterprise, and the business scope includes toilets, cisterns, squatting pans, basins, tiles and other sanitary ceramic products. Company HD consumed 840 thousand cubic meters of gas, 9.9 million kWh of electricity and 130 thousand cubic meters of water in 2021. Therefore, Company HD is a typical energy-intensive enterprise conforming to this study’s proposed architecture and models.

4.1. Data capture and edge-cloud cooperation

The data acquisition networks based on IoT are established to achieve data acquisition. The data acquisition nodes comprise smart sensors, meters and other IoT equipment. Then, the real-time production

The analysis process of the improved TOPSIS-AISM models is shown in Fig. 3. Initially, KPCA is used to reduce the dimensionality of the original data. Then, the objective weight of the index is calculated according to the entropy weight method. Finally, the improved TOPSIS-AISM models enhance the analysis results’ reliability by introducing the grey correlation and the AISM. Meanwhile, the proposed architecture and models based on edge-cloud cooperation provide an efficient and reliable technical route for multi-source heterogeneous data mining and analysis [53].

4. Case study

The proposed architecture and models are proved based on the actual production data presented in this section, which was provided by Company Huida (hereafter Company HD) from Northern China. To satisfy the requirements of a listed company, Company HD issued a prospectus in 2017, which provides data support for this section [54]. The company is a sanitary ceramic manufacturing enterprise, and the business scope includes toilets, cisterns, squatting pans, basins, tiles and other sanitary ceramic products. Company HD consumed 840 thousand cubic meters of gas, 9.9 million kWh of electricity and 130 thousand cubic meters of water in 2021. Therefore, Company HD is a typical energy-intensive enterprise conforming to this study’s proposed architecture and models.

4.1. Data capture and edge-cloud cooperation

The data acquisition networks based on IoT are established to achieve data acquisition. The data acquisition nodes comprise smart sensors, meters and other IoT equipment. Then, the real-time production

The analysis process of the improved TOPSIS-AISM models is shown in Fig. 3. Initially, KPCA is used to reduce the dimensionality of the original data. Then, the objective weight of the index is calculated according to the entropy weight method. Finally, the improved TOPSIS-AISM models enhance the analysis results’ reliability by introducing the grey correlation and the AISM. Meanwhile, the proposed architecture and models based on edge-cloud cooperation provide an efficient and reliable technical route for multi-source heterogeneous data mining and analysis [53].

4. Case study

The proposed architecture and models are proved based on the actual production data presented in this section, which was provided by Company Huida (hereafter Company HD) from Northern China. To satisfy the requirements of a listed company, Company HD issued a prospectus in 2017, which provides data support for this section [54]. The company is a sanitary ceramic manufacturing enterprise, and the business scope includes toilets, cisterns, squatting pans, basins, tiles and other sanitary ceramic products. Company HD consumed 840 thousand cubic meters of gas, 9.9 million kWh of electricity and 130 thousand cubic meters of water in 2021. Therefore, Company HD is a typical energy-intensive enterprise conforming to this study’s proposed architecture and models.

4.1. Data capture and edge-cloud cooperation

The data acquisition networks based on IoT are established to achieve data acquisition. The data acquisition nodes comprise smart sensors, meters and other IoT equipment. Then, the real-time production

Fig. 16. Confrontation level based on the topology diagram in 2020.

Fig. 17. Energy consumption of EIIs throughout China in 2019.
Fig. 18. GDP throughout China in 2019.

Fig. 19. Million tons (Mt) of GHG emissions throughout China in 2019.
data generated by the device are uploaded to the edge node that is responsible for preprocessing data to reduce the pressure for bandwidth. The production data can be uploaded to the cloud server and further analysed and mined.

To ensure the confidentiality of production data in Company HD, the data presented are standardised according to Eq. (33):

\[ y_i = \frac{x_i - \mu}{\sigma} \]  

(33)

where \( x_i \) is the original data, \( \mu \) is the average of each energy consumption, \( y_i \) is the standardised data, and \( i \) is the number of evaluation objects.

4.2 Data processing and intelligent analysis

In this subsection, the production data in Company HD are used to verify the proposed models. The data can be transformed into information and knowledge, providing management implications for production. Company HD is divided into nine factories and other production workshops according to the different manufacturers of sanitary ware ceramics and production processes. The No.9 factory is responsible for the secondary processing of the defective products produced by other factories to reach the standard of qualified products. Meanwhile, kilns are divided into shuttle kilns and tunnel kilns according to the structure and operating mechanism. With the increasing market demand, the No.6 shuttle kiln was inaugurated into production in 2018. In 2020, Company HD has six shuttle kilns and nine tunnel kilns. The energy consumption of Company HD from 2017 to 2020 is shown in Fig. 4. In 2018, the No.6 shuttle kiln in the No.2 factory was put into production, which caused an increase in natural gas and coal consumption. Then, the energy consumption decreased from 2019 to 2020. The reason is that the circular on printing the comprehensive control plan for air pollution of industrial furnaces was issued by the Ministry of Ecology and Environment of the People’s Republic of China in 2019 [55]. Therefore, the energy consumption structure of Company HD has changed since 2019. Electricity consumption was increased to reduce waste gas and solid waste generation.

The score of each principal component is calculated according to Eq. (6). The analysis results in Fig. 7 confirm that the four principal components are selected to replace the original data. Principal component scores from 2017 to 2020 are shown in Fig. 9.

4.3 Data mining and service application

In this section, the dimensionality reduction data of KPCA are further analysed and mined using the improved TOPSIS-AISM models. Data mining results are connected with the production status to provide management implications for enterprises to realise smart and sustainable production.

Table 1 shows the positive and negative ideal distance and grey correlation degree in 2020. The No.3 factory’s positive and negative ideal solutions distance are the smallest and largest, respectively, indicating that the No.3 factory has better production efficiency. The positive and negative grey correlation degrees are the largest and smallest, respectively, confirming the analysis of the positive and negative ideal solutions distance. However, the comprehensive evaluation result of the No.9 factory is opposite to that of the No.3 factory. Therefore, the positive and negative ideal solution distance and grey correlation degree results of the No.3 and No.9 factory corroborate each other, indicating that the evaluation results of the model have high reliability.
According to Eqs. (13-24), the positive and negative ideal solutions distance (PANISD), grey correlation degree (PANGCD) and the reference sequence (PANRS) are calculated, where PANISD and PANRS are the results of original and improved TOPSIS algorithms, respectively. The original and improved TOPSIS algorithms are compared in Fig. 10. The highest three points in Fig. 10 (d) represent the parameters of the No.9 factory. PANISD of the No.9 factory is the largest and smallest, respectively. Grey relational analysis is introduced into the original TOPSIS algorithm to form the improved TOPSIS. PANGCD of the No.9 factory is the smallest and largest, respectively. PANRS of the No.9 factory is the minimum and the maximum, respectively, indicating that the production benefit of the No.9 factory is poor. The improved TOPSIS does not change the definition of the original TOPSIS and has no adverse impact on the evaluation results, thereby solving the influence of uncertainty factors and improving the credibility of the algorithms.

The highest and lowest average coal consumption in Company HD is 78 and 30 tons, respectively. The coal consumption is small and only consumed in the production of specific factories, which cannot serve as a general indicator to compare with the energy consumption of other factories. Therefore, coal consumption will not be shown in the following analysis. Table 2 shows the ranking by benefit coefficient from 2017 to 2020. The No.3 factory ranked first, consistent with the author’s previous paragraph analysis. As shown in Fig. 11, the product yield of the No.3 factory has always been the highest amongst other factories. Meanwhile, as the product yield increases, the consumption of energy and resources increases, leading to the growth in electricity and water consumption in the No.3 factory. Compared with coal gas, natural gas has great advantages in terms of price and environmental friendliness. Therefore, natural gas gradually replaced coal gas in industrial production, increasing natural gas consumption. In summary, the No.3 factory has a high product yield and balanced energy consumption structure, and the production situation can be reflected using the ranking. The No.3 factory has better production efficiency. The authors suggest that the equipment parameters in the No.3 factory should be applied to the equipment in other factories to achieve sustainable production.

As shown in Table 2, the ranking of the No.9 factory has remained at the bottom. Fig. 11 shows that the product yield of the No.9 factory is low, the energy consumption of coal gas and natural gas is high, and water is not consumed. The reason is that the No.9 factory is responsible for backburning defective products. The authors suggest that the high energy consumption equipment should be operated by frequency conversion given the task particularity of the No.9 factory. Equipment should be stopped to save energy and reduce the operation cost when defective products are not processed.

Since 2018, the ranking of the No.5 factory has continued to decline. According to Fig. 12, the No.5 factory’s energy consumption and product...
### Pareto optimality

<table>
<thead>
<tr>
<th>Step</th>
<th>R((e_i))</th>
<th>Q((e_i))</th>
<th>T((e_i))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>1st,5th,6th</td>
<td>1st,2nd</td>
<td>1st</td>
</tr>
<tr>
<td>2nd</td>
<td>1st,2nd</td>
<td>2nd,8th</td>
<td>2nd</td>
</tr>
<tr>
<td>3rd</td>
<td>3rd</td>
<td>3rd,4th</td>
<td>3rd</td>
</tr>
<tr>
<td>4th</td>
<td>4th,5th</td>
<td>4th,5th</td>
<td>4th</td>
</tr>
<tr>
<td>5th</td>
<td>5th</td>
<td>5th</td>
<td>5th</td>
</tr>
<tr>
<td>6th</td>
<td>6th</td>
<td>6th</td>
<td>6th</td>
</tr>
<tr>
<td>7th</td>
<td>7th,8th</td>
<td>7th,9th</td>
<td>7th</td>
</tr>
<tr>
<td>8th</td>
<td>2nd,8th</td>
<td>2nd,8th</td>
<td>2nd</td>
</tr>
<tr>
<td>9th</td>
<td>7th,9th</td>
<td>9th</td>
<td>9th</td>
</tr>
</tbody>
</table>

### Pareto worst

<table>
<thead>
<tr>
<th>Step</th>
<th>R((e_i))</th>
<th>Q((e_i))</th>
<th>T((e_i))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>1st,5th,6th</td>
<td>1st,2nd</td>
<td>1st</td>
</tr>
<tr>
<td>2nd</td>
<td>1st,2nd</td>
<td>2nd,8th</td>
<td>2nd</td>
</tr>
<tr>
<td>3rd</td>
<td>3rd</td>
<td>3rd,4th</td>
<td>3rd</td>
</tr>
<tr>
<td>4th</td>
<td>4th,5th</td>
<td>4th,5th</td>
<td>4th</td>
</tr>
<tr>
<td>5th</td>
<td>5th</td>
<td>5th</td>
<td>5th</td>
</tr>
<tr>
<td>6th</td>
<td>6th</td>
<td>6th</td>
<td>6th</td>
</tr>
<tr>
<td>7th</td>
<td>7th,8th</td>
<td>7th,9th</td>
<td>7th</td>
</tr>
<tr>
<td>8th</td>
<td>2nd,8th</td>
<td>2nd,8th</td>
<td>2nd</td>
</tr>
<tr>
<td>9th</td>
<td>7th,9th</td>
<td>9th</td>
<td>9th</td>
</tr>
</tbody>
</table>

---

**Fig. B3.** The calculation process of the confrontation level based on topology diagram in 2018.
However, the distribution situation in 2020 is different. In 2020, the production plan of some factories should be further adjusted and optimized, indicating that the operation of each factory is normal and the regular inspection and maintenance should be carried out to the abnormal operating status of equipment. The authors suggest that gas consumption increased. The reason is that coal gas and natural gas-...nly the No.3 factory is less affected by the COVID-19 pandemic. Most of the production benefit of the No.3 factory is good, and the No.5 factory is smaller than that of the No.8 factory. Therefore, the relationship between the No.5 and No.8 factories cannot be judged according to the positive and negative reference sequences.

Fig. 15 shows the calculation process of the confrontation level based on a topology diagram in 2020 calculated according to Eq. (32). The calculation process for the remaining years is shown in Appendix B. Pareto optimality is obtained by the result preference extraction, which is the Pareto optimal start. Pareto worst is obtained by the cause preference extraction, which is the Pareto worst start. According to these rules, the evaluation object extracted from Pareto optimality is placed at the top level, and the evaluation object extracted from Pareto worst is placed at the bottom level. The confrontation level based on the topology diagram in Fig. 16 is formed.

As shown in Fig. 16, the relationship between the advantages and disadvantages of each factory can be intuitively explained using AISM. The results are represented by the up and down directed topological hierarchy diagrams, and the production efficiency of each factory decreases from top to bottom. The production efficiency of the No.3 factory is the best, and the No.9 factory is the worst. Based on the previous analysis of Table 3, the production benefit of the No.3 factory is good, with high product yield and low energy consumption. The factories located at the up, such as the No.3, No.4 and No.6 factories, have high product yield and low energy consumption, reflecting good production efficiency. On the contrary, the No.2, No.7, and No.9 factories are at the bottom, with high energy consumption and low product yield. In conclusion, low energy consumption and high product yield can achieve high production benefits. The requirements for energy conservation and emission reduction cannot be satisfied, making up for the shortcomings of development as soon as possible. For example, optimising production strategies, updating production technology, and the scheduling efficiency of energy and resources can be improved to achieve the strategic goal of smart and sustainable production.

4.4. Results

In Sections 4.2 and 4.3, the production data of Company HD are used to verify and analyse the proposed architecture and models, and the conclusions are as follows. Firstly, a data acquisition network is established based on IoT, which can preprocess the collected heterogeneous production data, and KPCA is used to reduce the influence of abnormal data. Secondly, the improved TOPSIS solve the influence of uncertain factors in the system, and the credibility and objectivity of the evaluation results can be improved. Thirdly, the analysis result of improved TOPSIS is further analysed and mined using AISM. The confrontation level is based on the topology diagram to make the analysis results more efficient and intuitive. Fourthly, the proposed architecture and models can help EIMIs coordinate the relationship between reducing environmental pollution and improving production efficiency, thereby providing a decision basis for enterprises to detect equipment faults and refine the production technique. For example, the not commonly used high energy consumption equipment changed to frequency conversion. The heat generated by the kiln is recycled for winter heating and other production processes. Abnormal equipment can be found in times, which can improve the sustainability of
production. In conclusion, the proposed architecture provides EIMIs with an integrated management platform from equipment monitoring and maintenance to production efficiency [56], thereby providing scientific production guidance for the entire manufacturing process.

5. Sustainability analysis for energy-intensive industries in China

Sustainability is essential to evaluate the development potential of companies. Energy consumption, environment and economy have become important indicators of sustainable analysis. In China, energy consumption per unit GDP (Gross domestic product) is 144 g of standard oil equivalent per dollar [57]; it is 1.5 times the average value throughout the world [58]. In addition, EIIs account for 49.93% of the total energy consumption in China; it has become the focus of sustainable production [59]. Therefore, sustainability analysis for EIIs in China is representative. In detail, the remainder of this section describes the sustainability analysis for EIIs to make energy-saving decisions from

<table>
<thead>
<tr>
<th>Step</th>
<th>R(ei)</th>
<th>Q(ei)</th>
<th>T(ei)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>1st,1st,3rd</td>
<td>1st,3rd,4th</td>
<td>1st,3rd,4th</td>
</tr>
<tr>
<td>2nd</td>
<td>2nd,4th,6th</td>
<td>2nd,9th,7th</td>
<td>2nd,9th,7th</td>
</tr>
<tr>
<td>3rd</td>
<td>3rd,5th,6th</td>
<td>3rd,7th,8th</td>
<td>3rd,7th,8th</td>
</tr>
<tr>
<td>4th</td>
<td>4th,5th,6th</td>
<td>4th,7th,8th</td>
<td>4th,7th,8th</td>
</tr>
<tr>
<td>5th</td>
<td>5th,6th,7th</td>
<td>5th,8th,9th</td>
<td>5th,8th,9th</td>
</tr>
<tr>
<td>6th</td>
<td>6th,7th,8th</td>
<td>6th,9th,10th</td>
<td>6th,9th,10th</td>
</tr>
<tr>
<td>7th</td>
<td>7th,8th,9th</td>
<td>7th,9th,10th</td>
<td>7th,9th,10th</td>
</tr>
<tr>
<td>8th</td>
<td>8th,9th,10th</td>
<td>8th,9th,10th</td>
<td>8th,9th,10th</td>
</tr>
<tr>
<td>9th</td>
<td>9th,10th,11th</td>
<td>9th,10th,11th</td>
<td>9th,10th,11th</td>
</tr>
</tbody>
</table>

Fig. B5. The calculation process of the confrontation level based on topology diagram in 2019.
vigorously develop the clean energy industry [61]. Conversely, the government should rely on abundant sunlight at high altitudes to oriented mechanism [64]. From the perspective of enterprises, the economic benefits, environmental pollution and social governance to find solutions and environmental pollution. Subsequently, Inner Mongolia and Shanxi have rich coal reserves and developed thermal power generation [68]. The government should accelerate the development of the coal deep processing industry, improve the conversion efficiency of coal calorific value and reduce GHG emissions [69].

5.3. Sustainability analysis for greenhouse gas (GHG) emissions

The total GHG emission throughout China in 2019 is shown in Fig. 19 [67]. The name of provinces with higher GHG emissions is marked in red. The GHG emission in Shandong is the highest, followed by Hebei, Jiangsu, Inner Mongolia, Guangdong and Shanxi. In detail, Shandong, Hebei, Jiangsu, and Guangdong are economically developed areas with large populations and advanced industrial systems, resulting in large amounts of GHG emissions by industrial production and people’s livelihood. EILs should accelerate the use of clean energy to replace fossil fuels, develop tertiary and high-tech industries, and introduce advanced production and pollution treatment technologies to reduce GHG emissions and environmental pollution. Subsequently, Inner Mongolia and Shanxi have rich coal reserves and developed thermal power generation [68]. The government should accelerate the development of the coal deep processing industry, improve the conversion efficiency of coal calorific value and reduce GHG emissions [69].

5.4. Sustainability analysis for pollution prevention

EILs include the following: smelting and pressing of ferrous metals (SPFM), smelting and pressing of non-ferrous metals (SPNM), manufacture of raw chemical materials and chemical products (MRCPM), processing of petroleum, coking and processing of nuclear fuel (PPCPNF), manufacture of non-metallic mineral products (MNMP), and production and supply of electric power and heat power (PSEPHP) [5]. The total energy consumption of the six EILs is shown in Fig. 20(a). The SPFM has the highest total energy consumption, and PSEPHP has the least energy consumption [70]. Coal is the primary energy source for thermal power generation; it produces considerable pollution. Then, the coal consumption of EILs is analysed in Fig. 20(b), the proportion of coal consumption in total energy consumption differs. The coal consumption of PSEPHP is higher than the total energy consumption. The reason is that generated electricity and heat are supplied to other industries, and the coal consumption is counted by the entire industries [71]. In SPFM, coal is used to heat a furnace that melts metals, leading to higher coal consumption. The reason for the high coal consumption in PPCPNF is that coal is used as raw material and fuel for processing by distillation and retorting [72]. According to the level of energy consumption, SPFM and PSEPHP can be selected for pollution prevention analysis. These industries have great potential for the recovery and utilisation of waste. SPFM produces considerable waste residue with a wide range of applications in many fields [30]. For example, the waste residue is refined into metal and then used as accessories for glass glazing and building materials [73]. However, it is difficult for enterprises to easily select a waste residue treatment method that considers the economic benefits and environmental pollution. The proposed strategy considers the economic benefits, environmental pollution and social governance to find an optimal waste disposal scheme [74].

As shown in Fig. 20, the SPFM has the highest coal consumption. The reason is that China relies on burning coal for electricity and heat, thereby producing considerable waste gas and cinder. The proposed
strategy can improve the production equipment by analysing the entire production process to increase the combustion rate and reduce waste gas generation. In addition, the cinders can be recycled by cement plants [75], reducing the pollution of cinders to the environment [76].

6. Discussion

6.1. Effectiveness of the proposed architecture and models

EIMIs use lean, Six Sigma production and other advanced measures to improve the efficiency of energy saving and emission reduction [77]. However, as the production scale and equipment intelligence continues to expand, the production process becomes more complex for EIMIs. These measures cannot easily solve the problems of high energy consumption and pollution of EIMIs [78]. This study provides a feasible technical route and production guidance for EIMIs to transform into smart and sustainable production [79]. The effectiveness of the proposed architecture and models are shown in the following.

The proposed architecture establishes a multi-source heterogeneous data acquisition network based on IoT [80]. Multi-source heterogeneous data can be collected using edge nodes for preprocessing and uploaded to the cloud server for storage and processing [81]. Then, real-time data are evaluated and analysed using the proposed architecture. The problems such as the evaluation of equipment efficiency and timely warning of equipment anomalies can be solved by analysing and mining the evaluation results.

The proposed models use KPCA for data dimensionality reduction, where abnormal data can be filtered from large multi-source heterogeneous data [51]. The amount of data to be analysed is reduced using KPCA, which can speed up the analysis and reduce the impact of abnormal data on evaluation results. The grey relational degree analysis is introduced based on the TOPSIS algorithm [49], which solves the influence of uncertain factors in the system. The improved TOPSIS-AISM models evaluate and analyse each producer object in the multi-source heterogeneous production data. The advantage of this model is that the managers of enterprises do not require a base of professional knowledge [82]. The evaluation results can be intuitively displayed to the managers and provide scientific guidance for production using AISIM analysis [48].

6.2. Managerial implication for ESG

Recently, more and more investors and enterprises have attached importance to ESG [83], which is critical to achieving green production, energy conservation and emission reduction [84]. The managerial implication for ESG can be summarised to achieve smart and sustainable production for EIMIs, which is an important measure of green innovation and sustainable development [85].

- Environmental: In terms of the ecological environment, realising clean production, green manufacturing, and comprehensive sustainable development has become a global consensus [86]. The proposed architecture and models can help enterprises find high-energy equipment and conduct targeted optimisation to reduce unnecessary energy consumption, thereby optimising the carbon ratio and reducing carbon emissions. This study provides a feasible strategy and technical route for manufacturing industries to coordinate the relationship between production efficiency and energy consumption, helping enterprises transform into smart and sustainable production [87].

- Social: In social, enterprises assume legal responsibilities and take responsibility for consumers, communities and the environment [88]. The proposed architecture can help enterprises to find equipment with high production efficiency and provide a reference for parameter adjustment of other high-energy consumption equipment [89]. The model can provide scientific decision-making basis for enterprises to promote environmental protection technology. This study helps enterprises improve product quality, reduce environmental pollution and actively assume social responsibility.

- Governance: In business governance, managers’ primary problem is reducing production costs and improving production efficiency [90]. The traditional factory inspection can be replaced using the proposed architecture, saving many labour costs for enterprises [91]. The equipment used in the EIMIs production process is characterised by high energy and resource consumption [92]. Therefore, a tremendous amount of energy and materials are wasted when equipment fails. This study based on edge-cloud cooperation can solve the above problem, which provides technical support to monitor the operational efficiency of equipment, [93] equipment failure warning and equipment maintenance [94].

7. Conclusions

In industry 4.0, big data, artificial intelligence and other advanced technology play an essential role in facilitating EIMIs to achieve smart and sustainable manufacturing. However, it is still in the early stages of integrating edge-cloud cooperation and smart and sustainable manufacturing. Therefore, using edge-cloud cooperation technology to mine manufacturing data and information for EIMIs, and summarising the implications of sustainability analysis and ESG management are important topics that require further study.

This study illustrates an architecture of edge-cloud cooperation-driven smart and sustainable production for EIMIs to address these challenges. Firstly, the edge-cloud cooperation-driven smart and sustainable production can provide an efficient and reliable decision-making basis for EIMIs. This study can help EIMIs to achieve clean production and green manufacturing and accelerate the transformation to smart and sustainable production. Secondly, KPCA is used for data dimensionality reduction and filters abnormal data in large mult-source heterogeneous data. KPCA can reduce the amount of data to be processed; it can analyse and reduce the impact of abnormal data on evaluation results. Thirdly, the impact of uncertain factors can be solved by the improved TOPSIS algorithm. The AISM has been used for data mining to make the analysis results more intuitive, improving the algorithm’s research connotation and effectiveness. The proposed architecture can help enterprises actively undertake environmental and social responsibilities to obtain broader development prospects. In conclusion, this study can help EIMIs coordinate the relationship between production efficiency and energy consumption and provide a scientific decision-making basis for enterprises to implement equipment transformation and process technology improvement.

This study provides a feasible technical route for EIMIs to implement sustainable analysis and ESG. However, the proposed improved TOPSIS-AISM model uses KPCA for data dimensionality reduction, which inevitably causes certain information loss. To solve this problem, data dimensionality reduction algorithms can be used to ensure the integrity of the information, and advanced data transmission equipment and technology can be used to ensure the accuracy of the data. The authors will further study the comprehensive evaluation algorithm to mine the hidden information and knowledge in the data, which can provide management implications for EIMIs to realise smart and sustainable production.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.
Acknowledgements

The authors are grateful to the Huida Ceramics Group for providing the data sets for this work and the helpful information on their utilisation. The authors would like to acknowledge the Youth Innovation Team of Shaanxi Universities “Industrial Big Data Analysis and Intelligent Processing”. This study is supported by the Special Construction Fund for Key Disciplines of Shaanxi Provincial Higher Education, the financial support of the Natural Science Basic Research Plan in Shaanxi Province of China (2022JQ-37), the Scientific Research Program Funded by Shaanxi Provincial Education Department (22JK0567), the Project of National Natural Science Foundation of China (62271390, 51905399) and the Postgraduate Innovation Fund of Xi’an University of Posts and Telecommunications (CXXJDL2022012).

Appendix A

The proof of reachable matrix R in Eq. (30):

\[ R = I + A + A^2 + \cdots + A^{n-1}, \]  
(A.1)

\[ (I + A)^3 = (I + A) \times (I + A) = I + A + A^2 \]  
(A.2)

\[ (I + A)^n - 1 = (I + A)^{n-2} \times (I + A) = I + A + A^2 + \cdots + A^{n-1}, \]  
(A.3)

where \( A \) is the relation matrix and \( I \) is a Boolean matrix. Eq. (A.1) defines the reachability matrix \( R \). \( A \) is a Boolean matrix, and the elements in \( A \) are defined as 1 when they are greater than 0. According to Eqs. (A.1-A.2), Eq. (A.3) becomes the following:

\[ (I + A)^3 = (I + A)^{3+1}, \]  
(A.4)

The existence of \( k \in n - 1 \) makes Eq. (A.4) hold.

\[ (I + A)^n = (I + A)^{n+k} \]  
(A.5)

According to Eq. (A.5), there exists a constant \( k \) such that \( B = (I + A) \) and \( B^{n-1} = B^k = R \) are valid.

Appendix B.


References


S. Ma et al.
Deng F, Xu L, Fang Y, Gong Q, Li Z. PCA-DEA-tobit regression assessment with
Liu S, Sun W. Attention mechanism-aided data- and knowledge-driven soft sensors
Chen J, Zhang Z, Wu F. A data-driven method for enhancing the image-based
product-service systems solution design based on CPS and IoT. Adv Eng Informatics
recommendation approach for knowledge aided intelligent process planning with
Yang, J. Zhi, H. Zhi, Liu, H. Zhi, Feng, X. Urban and rural energy sustainability
Mardani A, Zavadskas E, Streimikiene D, Jusoh A, Khoshnoudi M. A comprehensive
Ning H, Li Y, Shi F, Yang L. Heterogeneous edge computing open platforms and
Gan X, Chang R, Zuo J, Wen T, Zillante G. Barriers to the transition towards off-site
construction in China: An interpretive structural modeling approach. J Clean Prod
Zhou T, Ming X, Chen Z, Miao R. Selecting industrial IoT platform for digital
servitization: A framework integrating platform leverage practices and cloud
00207543.2020.1707519.
Huida sanitary ware co. L. Huida sanitary ware co, LTD prospectus 2017. https://
g.stock.sohu.com/newpdf/201726011321.pdf. [accessed in 23 October, 2022,
China].
Ministry of ecology and environment of the people’s republic of China. Circular
on printing and distributing the comprehensive control plan for air pollution
201907/t20190712_709309.html; [accessed in 25 July 2022, in Chinese].
attention mechanism: A dynamic domain adaptation method for rotary
machine fault diagnosis under different working conditions. Knowledge-Based Syst
China minineng bank. Development comparison between China and the world’s
cmbc.com.cn/gymd/mndy/jbyj/index.htm. [accessed in 24 October, 2022,
China].
People’s daily. China reduced energy consumption per unit of GDP by 13.5%
cn/xinxwen/2021-08/10/content_5630408.htm; [accessed in 24 October, 2022,
China].
efficiency of energy-intensive industries in China from the perspective of shared
resources: Dynamic change and improvement path. Technol Forecast Soc Change
Standardisation administration of China. General rules for calculation of the
aei.2022.101799.
China ‘s daily. China reduced energy consumption per unit of GDP by 13.5%-
cn/xinxwen/2021-08/10/content_5630408.htm; [accessed in 24 October, 2022,
China].
Zhao C, Zhao M, Wu X, Feng J, Shi J. Machine learning for condition monitoring
of steelmaking ladles in an iron and steel plant: An improved approach based on
feature fusion-based deep learning approach for machining condition monitoring.
IEEE Trans Cybern 2022;1:–. https://doi.org/10.1109/TCYB.2021.3178116.
Zhang G, Zhou G, Li J, Chang F, Ding K, Ma D. A multi-access edge computing
enabled framework for the construction of a knowledge-sharing intelligent
10.1016/j.jmsy.2022.11.015.
Lu G, Wu Y, Xu H, Yang H, Zou J. Deep multimodal learning for municipal solid
S1143-2101(19)30729-4.
Chen J, Zhang Z, Wu F. A data-driven method for enhancing the image-based
decision-making oriented collaborative cross-organisation knowledge sharing blockchain
for exploring CO2 emissions of the iron and steel industry: An integrated material-
Liu, S, Sun W. Attention mechanism-aided data- and knowledge-driven soft sensors
Securing data in transit using data-in-transit defender architecture for cloud
3005001-009528-6.
Zhou B, Li J, Li X, He B, Bao J. Leveraging on causal knowledge for enhancing the
root cause analysis of equipment spot inspection failures. Adv Eng Informatics
Deng F, Xu L, Fang Y, Gong Q, Li Z. PCA-DEA-tobit regression assessment with
carbon emission constraints of China’s logistics industry. J Clean Prod 2020;271:
Anagnostou F, Sadoou S, Selim B. Conceptual and empirical comparison of
dimensionality reduction algorithms (PCA, KPCA, LDA, MDS, SVD, LLE, ISOMAP,
Nayi M, Menkin D, Nadoofi M. Sensor fault detection and isolation of an industrial
Lin S, Shen S, Zhang N, Zhou A. Comprehensive environmental impact evaluation
for concrete mixing station (CMS) based on improved TOPSIS method. Sustain
Li Y, Li Z, Yang L, Liu J, Liu Y. Comprehensive evaluation on the ‘maturity’ of
wind power station site selection using a PROMETHEE method under intuisionistic
seawater desalination projects based on an integrated fuzzy comprehensive
evaluation and analysis hierarchy process model. Desalination 2020;478:114286.