Characterizing of water-energy-emission nexus of coal-fired power industry using entropy weighting method

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ABSTRACT

The coupled relationships among water, energy, and emission, i.e., water-energy-emission nexus (WEEN), are found to be spatial-temporally characterized. This research is aimed at evaluating the spatial-temporal characteristics of the WEEN of the selected 227 coal-fired power plants in China from 2012 to 2014 by employing the entropy weighting method. Firstly, the WEEN performances (the sub-indicators, i.e., the emissions, water for cooling, water for pollutant removal, energy for electricity generation, and energy for pollutant removal) of the plants are computed. Then, each sub-indicator of the WEEN performances is compared at plant level. Finally, the entropy weighting factor is introduced to evaluate the overall performances of WEEN (defined as the WEEN indicator). The results show that NOx and SO2 removal sub-indicators were with the highest entropy weights. Overall, the WEEN indicator improves significantly from 0.21 (2012) to 0.37 (2014), which means the increases of pollutant removal were more significant than the changes in water and energy inputs. The power plants located in Northern China and Central China grids show more significant improvement. This is mainly contributed by the improvement of the three emission sub-indicators and the larger amount of removed pollutants. By evaluating the improvement of WEEN indicators, the overall performances of WEEN with the simultaneous consideration of water, energy and emission are quantitatively addressed, which reflect the technology improvement and the strict policies and regulations behind it. This research provides a quantifiable and integrated way to evaluate and compare the various aspects of WEEN at the plant level.

1. Introduction

The water-energy nexus has been widely discussed in the past decades (Schnoor, 2011; Wang et al., 2019a). The water is needed mainly for cooling in the electricity generation processes (Ma et al., 2018; Wu and Chen, 2017). Moreover, studies have identified that emissions (such as SO2, NOx, and greenhouse gases (GHGs)) are closely linked with the water-energy nexus (Agrawal and Kumar, 2018), as emissions are mainly caused by energy combustion (Liu et al., 2019a), and water/energy is needed for emission reduction (Gingerich et al., 2017; Wang et al., 2019a). The coupled interactions among water, energy, and emission are defined as water-energy-emission nexus (WEEN) (Sun et al., 2020; Wang et al., 2018a; Wang et al., 2017). The concept of WEEN has been applied in several industrial sectors, such as coal-fired power industry, steel-making industry, petrochemical industry. This study specifically focuses on the WEEN performances (i.e., the water consumption/energy consumption/emission) of electricity generation due to the significant amount of water use (35% of total industrial water consumption), energy consumption (65% of total industrial energy consumption), and emissions (33%, 51%, and 15% of total industrial SO2, NOx, and dust emissions) among all the industrial sectors (MEE (Ministry of Ecology and Environment), 2015).

Studies prove that significant spatial and temporal variations exist in the WEEN performances of electricity generation. Peer and Sanders (2018) demonstrate that the decrease of cooling water withdrawal and consumption mainly occurred in middle and east water basins 2008 and 2014 in the U.S., which could be explained by a combination of various factors such as the technology adoption (e.g., cooling technologies), and operational efficiency, spatial-temporal changes in the magnitude of electricity demand, and the added and retired power plants (Peer and Sanders, 2018). At regional level and provincial level, great spatial variations of water for energy were also
analysed, respectively. Zhang et al. (2016) identified that the north China, northeast China, and coastal city clusters where the baseline water stress exerted by thermal power generation were comparatively significant (Zhang et al., 2016). Strong spatial variations of water for energy sector were found at provincial level in China, e.g., water for energy sector in Sichuan (middle China) was 48 times higher than that of Hainan (south China) (Chu et al., 2019).

Analogous to the water-energy nexus, the emissions are also found to be with spatial-temporal characteristics (Jaramillo and Muller, 2016; Liu et al., 2016, 2015; Tian et al., 2014). For instance, the SO2 emission of coal-fired power industry in China was estimated to be 4.9 Tg/yr in 1990, increased to 16.7 Tg/yr in 2005, and then decreased to 7.7 Tg/yr in 2010. These up-and-down changes over the years were caused by several reasons, such as coal quality improvement (e.g., sulfur content in the coal decreased from 1.07% in 1990 to 0.95% in 2010), increase of coal-fired electricity generation, and high-efficient desulfurization technology adoption (e.g., the penetration rate of FGD, which is high-efficient desulfurization technology, increased from 0.1% in 1990 to 85.6% in 2010) (Liu et al., 2015).

The changes in emissions and water use (water withdrawal and consumption) of electricity generation are not synchronized, spatially and temporally. From the temporal perspective, it is estimated that the water withdrawal decreased by 20%, the water consumption doubled, and the NOx and SO2 emissions increased greatly between 2000 and 2010 in Hai River Basin in China; from the spatial perspective, the national total water use and emissions increased during this period, yet the water use in some basins (e.g., Hai River, Huai River, Southeastern Rivers) remained to be stable or decreased (Liu et al., 2015; Zhang et al., 2018). These spatial-temporally unsynchronized changes are caused by facts that water and energy are often required for pollutant removal, which means that there are trade-offs between water/energy saving and lower emissions.

Given the various aspects of WEEN performances and great spatial-temporal changes of WEEN, researchers attempt to quantitatively evaluate to what extent the WEEN performances have been improved across spatial and temporal. Efforts have been made to quantify and compare the WEEN performances of electricity generation at various scales, e.g., plant (Dong et al., 2018; Jiang and Ramaswami, 2015), city (Li et al., 2019; Zhang et al., 2017a), region (Larsen and Drews, 2019; Stokes-Draut et al., 2017), country (Lee et al., 2018; Lim et al., 2018; Mouratiadou et al., 2018), global (Lohmann et al., 2019; Spang et al., 2014), etc. Based on plant-level reported data, the average water use for electricity generation mix in the U.S. was estimated to be approximately 2.2 L/kWh, while the water uses for thermal power and hydropower were in ranges of 0.2-2.0 L/kWh and 0.7-1194 L/kWh (Lee et al., 2018).

Although implemented approaches vary in different studies, their results are comparable to some degree (Dai et al., 2018; Macknick et al., 2012). These comparisons are usually made in terms of a single aspect of WEEN performances (e.g., only water consumption for electricity generation). A new index is also proposed for comparison. For instance, the water consumption of energy production index (WCEP) is developed to quantify and compare the water consumption for various types of energy production, globally (Spang et al., 2014).

The introduced comparisons methods mentioned above could only be conducted for a single aspect of WEEN performances (Islam et al., 2017), mainly due to data unit differences (e.g., water consumption for electricity generation is quantified in volume unit (e.g., m³/kWh), while the electricity generation related emission is quantified in mass unit (e.g., mg/kWh)). The evaluations of the overall performances of WEEN in terms of all the WEEN performances are barely done.

Thus, the contrary changes in water, energy, and emissions raise a question of how to evaluate the plant with higher water/energy consumption but lower emissions. In this regard, several aspects of the WEEN with different units and meanings, e.g., water for energy, energy for water, water for SO2 removal, energy for SO2 removal, should be considered simultaneously to depict a full configuration of the WEEN system. Given the significant variations in the temporal-spatial characteristics of the WEEN, it is crucial to developing/utilizing an approach that could address the overall WEEN performances across different spatial-temporal scales, and various WEEN performances.

The spatial-temporal variances of the WEEN performances are defined as the diversity of WEEN. This study aims at proposing an indicator to evaluate the overall WEEN performances and associated spatial-temporal diversities, which would provide valuable insights into the diversity of WEEN. Considering the data availability, the coal-fired electricity industry in China from 2012-2014 is selected as the case study to depict the evaluation of WEEN performances and associated diversity. Individual power plant is set as the model unit for evaluation due to the fact that great variations of technology utilization and the resulting WEEN performances exist among the plants. The structure of this study is organized as follows: (1) Section 2 introduces the method selection and data sources used in this study; (2) Section 3 illustrates the evaluation results of WEEN sub-indicators, namely three emission-related 7 sub-indicators (i.e., the SO2 removal, NOx removal, and dust removal), two water-related sub-indicators (i.e., water for cooling and water for pollutant removal), and two-energy related sub-indicators (i.e., energy for electricity generation and electricity for pollutant removal), and the overall WEEN indicators of all the evaluated coal-fired power plants. Also, the related policies that may cause the variances of the WEEN are analysed. (3) Section 4 provides conclusions, limitations, and future work.

2. Methods

2.1. Data description

In total, 227 coal-fired power plants, covering around 53% of the total thermal electricity generation (NBSC, 2015) in China from 2012 to 2014, are analysed in this study. The power plants in Tibet are excluded due to data limitations. Detailed information, including electricity generation, coal consumption, water withdrawal intensity, combustion technologies, cooling types, water sources, pollutant removal technologies, and associated efficiency for each power plant, is collected from China Electricity Council (CEC, 2015). This study employs the mathematical material flow analysis approach for the WEEN (WEEN model), which is developed by Wang et al. (2018a), to calculate the WEEN.

Table 1

<table>
<thead>
<tr>
<th>Sub-indicators</th>
<th>Emissions (C1)</th>
<th>Water (C2)</th>
<th>Energy (C3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SO2 removal</td>
<td>NOx removal</td>
<td>Dust removal</td>
</tr>
<tr>
<td></td>
<td>(S1)</td>
<td>(S2)</td>
<td>(S3)</td>
</tr>
<tr>
<td></td>
<td>mg/kWh</td>
<td>mg/kWh</td>
<td>mg/kWh</td>
</tr>
<tr>
<td></td>
<td>mg/kWh</td>
<td>mg/kWh</td>
<td>L/kWh</td>
</tr>
<tr>
<td>Unit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>5555.3</td>
<td>470.5</td>
<td>75341.8</td>
</tr>
<tr>
<td>2013</td>
<td>4520.4</td>
<td>1366.1</td>
<td>72116.3</td>
</tr>
<tr>
<td>2014</td>
<td>3961.8</td>
<td>1799.1</td>
<td>69352.7</td>
</tr>
</tbody>
</table>

Note: The value of each sub-indicator in this table is the average value of the 227 coal-fired power plants for a given year. Detailed information of the sub-indicators for 227 coal-fired power plants is provided in the Supporting Information (S1).
performances at plant level. The outcomes consist of seven sub-indicators (S1-S7) classified into three types (i.e., emissions, water, energy, labeled as C1-C3) (c.f., Table 1).

2.2. Method selection

The 7 sub-indicators are the multi-criteria for the WEEN performance evaluation, which could be considered as a multi-criteria decision making (MCDM) problem. MCDM is a branch of operational research dealing with finding optimal results in complex scenarios including various indicators, conflicting objectives and criteria (Kumar et al., 2017). MCDM has been successfully applied in various fields, such as the economy (Banasik et al., 2018), environment (Diaz-Balteiro et al., 2017), transportation (Mardani et al., 2016), etc. The techniques used for MCDM could be divided into 3 types: elementary methods, methods in unique synthesizing criteria and outranking methods (Wang et al., 2009). Based on a review study of MCDM techniques used in the sustainability field, Analytical Hierarchy Process (AHP) and Weighted Arithmetic Mean (WAM) are found to be most frequently used (Diaz-Balteiro et al., 2017). The AHP is one of the subjective-based methods that highly rely on experts’ judgments. WAM is regarded as an objective-based elementary method that uses a weighted sum of criteria for evaluation. The weighting factors are obtained from numbers of objective-based techniques, such as entropy weighting method, least square method, min-max deviation method, etc. Those various techniques do not necessarily result in the same conclusion for a specific case study (Bian and Yang, 2010).

Through thoroughly comparing the pros and cons of these weighting techniques (Zardari et al., 2014), the entropy weighting method, one of the objective-based methods that are theoretically valid, is chosen in this study. The entropy weighting method can adequately consider the information of values all the units provided to balance the relationship among numerous evaluating criteria, which can weaken the bad effect from some abnormal values and make the result of evaluation more accurate and reasonable. It can retain valuable information in the preprocessed data by giving the higher weights if the data are more diverse for a special attribute or smaller weights if the data are more similar/closer to across units for a special attribution (Hainmueller, 2012). The greater the value of the entropy corresponding to a special attribution, which imply the smaller attribution’s weight, the less the discriminate power of that attribute in decision making process (Lotfi and Fallahnejad, 2010).

Entropy is a measure of the disorder degree of a system, and the entropy weight reflects the amount of useful information carried and transported by each index of the system. That is, the higher the amount of useful information carried and transported by an index, the higher the index’s entropy weight, and vice versa (Tang, 2015; Wang et al., 2018a). Among the large group of entropy weighting methods, the one based on Shannon information theory (Shannon Entropy) is widely employed (Li et al., 2011). It has been applied in urban ecological security evaluations (Han et al., 2015), environmental risk assessment (Jozí et al., 2012), sustainability development evaluation (Fedajev et al., 2019; Liu et al., 2019a; Wang et al., 2015), industrial plant operational performance comparison (Wu et al., 2018a), evaluation of material flow analysis (Liu et al., 2018; Velázquez Martínez et al., 2019), etc. The Shannon information entropy is a measure of the variances of a given system. Generally, if the value of information entropy is higher, the given system is considered to be a more balanced structure with less variation; otherwise, if the value of information entropy is lower, the given system is regarded to have a more unbalanced structure and greater variation (Tang, 2015). Hence, this study employs the entropy information to obtain weighting factors for exploring the coupling relationships and associated spatial-temporal changes among the various WEEN performances.

2.3. Entropy weighting method

Normalisation

Before normalization, two cases should be considered: the positive indicators and negative indicators. The positive indicators mean that the larger the values are (e.g., the more SO2 removed per unit electricity generation), the better the WEEN performances they have. The negative indicators mean that the smaller the values are (e.g., the less water for cooling per unit electricity generation), the better the WEEN performance they have. Hence, all 3 emission-related sub-indicators (S1-S3) should be regarded as positive indicators; all 4 water/energy-related sub-indicators (S4-S7) should be regarded as negative indicators. The normalization procedure is conducted as Eq. (1):

\[
\begin{align*}
\text{Positive: } S'_{ij} & = \frac{S_{ij} - \min(S_i)}{\max(S_i) - \min(S_i)} \\
\text{Negative: } S'_{ij} & = \frac{\max(S_i) - S_{ij}}{\max(S_i) - \min(S_i)}
\end{align*}
\]

where, \( S_{ij} \) is the normalized value of the sub-indicator \( i \) for power plant \( j \); \( S_{ij} \) is the original value of the sub-indicator \( i \) for power plant \( j \); \( \max(S_i) \) and \( \min(S_i) \) are the maximum and the minimum values of the sub-indicator \( i \) among all the plants, respectively.

The entropy of each sub-indicator

\[
e_i = -k \sum_{j}^{m} \left( \frac{S'_{ij}}{\sum_{j}^{m} S'_{ij}} \right) \ln \left( \frac{S'_{ij}}{\sum_{j}^{m} S'_{ij}} \right)
\]

where, \( e_i \) is the entropy of the evaluated sub-indicator \( i \); \( k \) refers to a coefficient, i.e., \( 1/\ln(m) \); is the number of the evaluated plants (i.e., 227 in this study).

The redundancy of the entropy of each sub-indicator

\[
d_i = 1 - e_i
\]

The entropy weight factor of each sub-indicator

\[
W_i = d_j \sum_{i}^{n} d_i
\]

where, \( n \) is the number of sub-indicators, i.e., 7 in this study.

The entropy of each sub-indicator type

\[
c_{tij} = \sum_{i}^{k} \left( w_i \times \frac{S'_{ij}}{\sum_{j}^{m} S'_{ij}} \times \ln \left( \frac{S'_{ij}}{\sum_{j}^{m} S'_{ij}} \right) \right)
\]

where, \( C_{tij} \) is the entropy of the sub-indicator type \( t \) of power plant \( j \); \( k \) is the number of the sub-indicators which belong to the same type (i.e., emission, energy, and water).

(1) The WEEN indicator

\[
I_j = \frac{1}{l} \times \sqrt{\frac{\sum_{p=1}^{l} \left( \frac{C_{pj} - C_{qj}}{\max(C_{pj}, C_{qj})} \right)}{f}}
\]

where, \( I_j \) is the WEEN indicator of power plant \( j \); \( l \) is the number of sub-indicator types (i.e., 3 in this study); \( C_{pj} \) and \( C_{qj} \) are the combinations of any two sub-indicator types \( p \) and \( q \) of power plant \( j \); \( f \) is the number of combinations of any two sub-indicator types.

3. Results and discussion

The average level of emissions, water consumption, and energy consumption of the evaluated 227 plants for a given year are tabulated in Table 1. Overall, the WEEN performances show decrease trends over the 3 years. Detailed information about the WEEN performances of the 227 power plants is provided in Supporting Information (SI).
According to the concept of Shannon Entropy, the larger the entropy weight factor is, the more information this sub-indicator includes. This means that there exist more considerable differences in the sub-indicator among the 227 power plants. The entropy weight factors of these seven sub-indicators are calculated using the equations in Section 2, and the results are illustrated in Fig. 1.

It can be inferred that NOx and SO2 removal were the two sub-indicators (the entropy weight factors are larger than 0.31) with far more substantial differences (i.e., 2.5-46 times higher) than the rest five sub-indicators (entropy weights are smaller than 0.15). This means that SO2 and NOx removal changed significantly from 2012-2014. Further exploring the estimated SO2 and NOx generation and emission, it is found that more SO2 and NOx were removed in 2014 than 2012. This is in line with the fact that the denitrification technologies and associated NOx removal efficiency and desulfurization efficiency were more widely adopted in 2014 than 2012 (Chang et al., 2016; Song et al., 2018). Nationally, the denitrification technology penetration rate almost tripled during this period (Chang et al., 2016). The desulfurization rate increased mainly thanks to the synergic desulfurization effect brought by the denitrification technology (Wang et al., 2018a; Wu et al., 2018a), given that the desulfurization technology penetration rate barely increased during this period.

The water-(C2) related sub-indicators (S4-S5) and energy-(C3) related sub-indicators (S6-S7) were significantly less “disordered” and had fewer variations as their weight factors were smaller than 0.1 (c.f. Fig. 1). This fact indicates that compared to the three emission-(C1) related sub-indicators (S1-S3), these four sub-indicators (S4-S7) showed relatively more similar performances among the 227 power plants from 2012 to 2014. This is probably due to two reasons: (1) no significant changes in water-saving and energy-saving technologies for major water and energy consuming processes, such as the cooling technology and coal-combustion technology, occurred over the three years, which lead to the water for cooling and energy for electricity generation to be stable (Zhang et al., 2018); (2) the differences of pollutant removal technology-associated water and energy consumptions (i.e., water for pollutant removal and energy for pollutant removal) are significantly lower than the pollutant removal efficiency (Wang et al., 2018a).

3.2. The WEEN indicator

After normalization (c.f., Eq. (1)), all the sub-indicators are transformed to be positive. As calculated based on the normalized sub-indicators, the overall WEEN indicator (I) turns out to be positive as well.
Therefore, the larger the WEEN indicator (Ij) is, the better the plant is performing.

Based on the computed absolute values of the WEEN indicators for the 227 power plants during 2012-2014, the indicators are classified into 4 levels and illustrated with different colors in Fig. 2. Each dot represents one power plant, and the background is the geographic boundary of the 6 electricity grids in China (i.e., Northeast China (NEC), North China (NC), East China (EC), Central China (CC), South China (SC), and Northwest China (NWC), Tibet is excluded). The indicators in the ranges of 0-0.2 (dark green), 0.2-0.4 (light green), 0.4-0.6 (orange), and 0.6-1.0 (red) are considered to be fair, good, better, and best WEEN performance, respectively.

In general, the WEEN indicator improved significantly from 2012 to 2014, as the average of WEEN indicators of the 227 power plants increased from 0.21 to 0.37 (c.f., Table 2). These improvements of WEEN indicators reflect the improvement of overall WEEN performances. It should be noted that a higher WEEN indicator of a specific plant or the regional WEEN indicator improvement does not mean that the specific power plant/region emits fewer pollutants, consumes less water, and consumes less energy simultaneously, as there are tradeoffs between pollutants removal and water/energy consumption. The entropy weights of each sub-indicator (emissions, water consumption, and energy consumption) quantitatively reveal how significant/small these changes are. Hence, the improvement of WEEN indicator could be interpreted as the power plant/region achieves larger pollutant removal at less cost of water and energy inputs.

Four power plants labeled as red (i.e., WEEN indicators are larger than 0.6) in Fig. 2(c) should be noted as their WEEN indicators were much higher than the rest ones (i.e., WEEN indicators were smaller than 0.6). Further exploration of the technologies applied in these plants, it could be found that they were equipped with high-efficient pollutant removal technologies, seawater/recycled water-cooling technologies. These result in higher water/energy use efficiency and (or) fewer emissions. Therefore, these power plants could be set as role models from the perspective of the overall WEEN performances.

Distinguishing the WEEN indicators by electricity grids can provide deeper insights into the WEEN performances from the view of spatial variation (c.f., Fig. 3 and Table 2). The results imply that all these six grids have been significantly improved over 2012-2014. Stated alternatively, it can be concluded that the WEEN indicator improved significantly from 2012 to 2014 in these two grids, and was mainly contributed by the emission sub-indicator, i.e., more pollutants were removed in 2014 than in 2012. The higher pollutant removal rate was due to the increase in the penetration rate of high-efficient pollutant removal technologies in regions like Hebei, Henan, Sichuan, Hubei, Hunan, which belong to the NC and CC grids (Cao et al., 2019). This result (i.e., the high-efficient pollutant removal technologies were widely adopted) sides with the conclusions obtained from existing research about such as studies focusing on the technologies applied in the coal-fired power industry and their spatial distribution (Liu et al., 2016).

The variations of the three sub-indicator types in the CC grid were smaller than the NC grid, inferred from the distribution curve shape in Fig. 4. This means that the power plants in NC had more considerable differences, and some of them might be far behind the “role models” in terms of the WEEN (sub-)indicators.

### 3.3. Policy discussions

Such significant improvements in emissions were driven by the launched policies regarding the emissions control of the coal-fired power industry (Cui, 2014; Zhao et al., 2017). Even the national emission control policies were initiated early in 9th Five Year Plan (FYP) (1995-2000) and further specified in the 10th FYP (2000-2005), but the implementation and results were failures. Since 2006, China implemented strict emission and energy control policies; during the 12th FYP (2011-2015), these policies were maintained and extended (Jin et al., 2016). The control of the coal-fired power industry became stricter, followed by rigorous emission standards (Kaplus et al., 2018), such as ultra-low emission standards (NEA, 2014).

A review of energy-saving and emission control policies in China indicates that the number of issued policies sharply increased and peaked in 2010 (Zhang et al., 2017a). Our study focuses on the coal-fired industry during 2012-2014, which benefits from the 11th FYP due to time lag and was further constrained by the policies in 12th FYP. Key policies include: (1) the strict emission standards (GB 13223-2011) of the coal-fired power industry launched in 2011 (MEE, 2011); (2) the 12th FYP of energy-saving and emission control released in 2012, in which the goals of the energy efficiency, SO2 and NOx emission in the thermal power industry were set. Also, the small-scale coal-fired power

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**Table 2**

<table>
<thead>
<tr>
<th></th>
<th>Central China (CC)</th>
<th>East China (EC)</th>
<th>North China (NC)</th>
<th>Northeast China (NEC)</th>
<th>Northwest China (NWC)</th>
<th>South China (SC)</th>
<th>National total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>0.20</td>
<td>0.22</td>
<td>0.20</td>
<td>0.19</td>
<td>0.19</td>
<td>0.22</td>
<td>0.21</td>
</tr>
<tr>
<td>2013</td>
<td>0.35</td>
<td>0.33</td>
<td>0.32</td>
<td>0.28</td>
<td>0.28</td>
<td>0.30</td>
<td>0.32</td>
</tr>
<tr>
<td>2014</td>
<td>0.46</td>
<td>0.34</td>
<td>0.41</td>
<td>0.28</td>
<td>0.35</td>
<td>0.34</td>
<td>0.37</td>
</tr>
<tr>
<td>2012-2014 improvement</td>
<td>130%</td>
<td>55%</td>
<td>105%</td>
<td>47%</td>
<td>84%</td>
<td>55%</td>
<td>76%</td>
</tr>
<tr>
<td>Number of power plants</td>
<td>37</td>
<td>54</td>
<td>63</td>
<td>25</td>
<td>18</td>
<td>30</td>
<td>227</td>
</tr>
</tbody>
</table>

Note: The “2012-2014 improvement” is calculated as the difference between 2014 and 2012, and then divide by 2012.

Overall, the NC and CC grids are with the most significant improvement as their WEEN indicator doubled from 0.20 to 0.41 (105% higher) and 0.20 to 0.46 (130% higher), respectively (c.f., Table 2). This means the overall performances (weighted values of all 7 sub-indicators) in these two grids have been significantly improved over 2012-2014. Further, these two grids have been significantly improved over 2012-2014. Further, these two grids have been significantly improved over 2012-2014.
plants were forced to phase out by the end of 2015 (NEA, 2012); (3) the 12th FYP of air pollution control in key regions issued in 2012, in which the coal-fired power industry was listed as one of the 5 key industries (MEE, 2012); (4) the announcement on the implementation of special emission limits for air pollutants carried out in 2013, which regulates the air emissions of coal-fired power industry as well as other 5 industries in 19 provinces and 47 cities (MEE, 2013); (5) the ten measures of action plan for air pollution control policy in 2013 (State Council, 2013).

Great achievements have been made shortly after the issue of those policies, which led to the significant decreases in emissions. For instance, small-scale coal-fired power plants with the capacity of 26.9 MW were phased out during 2011-2014, which was 6.9 MW more than the 12th FYP of energy-saving and emission control. It is proved that the small-scale coal-fired power plants were less efficient in emission control, energy savings than the large-scale ones (Zhao et al., 2008).

Focusing on the NC and CC, it could be found that provinces in these two grids were specifically targeted to implement these policies on emissions control of coal-fired power industry or even stricter policies. For example, four (i.e., Sichuan, Chongqing, Hunan, and Hubei) of the five provinces in CC grid and five (Hebei, Beijing, Tianjin, Shandong, and Shanxi) out of the six provinces in NC grid were listed in as key regions to implement the special emission limits (MEE, 2013). The key provinces (Beijing, Tianjin, and Hebei) in NC were forced to reduce at least 5% more air pollutants than the national average required by the ten measures of action plan for air pollution control policy (State Council, 2013). In 2012, the State Council provided guidelines on cleaning industry development, such as prohibiting the entry of high energy consumption and emission companies, when promoting the development in central China (State Council, 2012). This national strategy contributed to the significant decrease in CC during 2012-2014.

In general, the WEN indicator improvement reflects the technology improvement and the strict policies and regulations behind it. The overall improvement of WEN performance shows that the issued policies and applied technologies have led to significant increases in emission removal and less significant increases in water and energy inputs. Alternatively speaking, the changes in the costs of energy and water inputs are less significant than the increases in emission removal. In this sense, the WEN indicator could be regarded as a way to evaluate the policies and associated technologies and outcomes.

4. Conclusions

This study proposes a quantifiable method, i.e., entropy weighting method, to evaluate the spatial-temporal characteristics of WEN performances of the 227 coal-fired power plants in China from 2012 to 2014. Precisely, the results of this study imply that the emission-related sub-indicators had significantly larger variances as their weights were larger than water/energy-related sub-indicators. Based on the concept of the overall WEN indicator, four power plants were set as the role models due to their higher WEN indicators. Averagely, the WEN indicator improved significantly from 2012 to 2014, as it increases from 0.21 to 0.37 (76% higher), reflecting the upgrading WEN performance of the 227 coal-fired power plants in China. The 100 power plants located in Northern China grid (37 power plants) and Central China grid (63 power plants) show more significant improvement (with an increase of 105% and 130%, respectively) than the remaining 127 power plants in East China grid, Northeast China grid, Northwest China grid, and South China grid. These high increases were mainly contributed by the improvement of the three emission-related sub-indicators (SO2 removal, NOx removal, and dust removal), i.e., more pollutants were removed in 2014 than 2012 in these two grids. The WEN indicator improvement could be used to address and evaluate the policy-oriented technology changes in these grids.

This comprehensive indicator provides a doable and easy way to compare individual plants within a given industry/system. The results can help to distinguish the most significant variances among the various aspects of WEN, or which factors would have the most significant impact on the overall performance of WEN. It can find out the very plant with the highest indicator score and set it as the role model for other plants. It could also be used as a way to evaluate the policies and
associated technologies and outcomes in terms of various aspects of WEEN. For the coal-fired power industry, a larger improvement of WEEN indicator reflects that the increases of pollutant removal are more significant than the changes in water and energy inputs. The WEEN indicator in the selected industry can be mirrored in other industries with similar coupled relationships among water, energy, and emissions. Last but not least, combining with other weighting methods that consider the local environment, economics, etc., this indicator can be used to provide more sophisticated policy-making suggestions.

Further work remains to be done: (1) More comprehensive results and analysis could be conducted with higher power plant data cover rate (temporal-spatially) and better data quality. The power plants dataset we adopt in this study covers 227 power plants from 2012-2014, which was only 38% of the national total coal-fired electricity generation. The results will be more accurate and robust if a more comprehensive dataset, consisting of information on technologies, locations, water sources, coal types of individual power plants, is available. Besides, the changes in the WEEN performances over a more extended period (e.g., 2000-2018) could be more significant than our current study (2012-2014) as technologies improved greatly in recent years comparing to the early 2000s. (2) The comparisons of the WEEN performance using the entropy weighting method among different industries could be carried out. The entropy weighting method can eliminate the unit obstacles among various WEEN aspects and industries, and keep the information (e.g., variances) of the (sub-) indicators. The cross-sector comparisons and evaluation could identify the target industry with regard to the value of the overall WEEN indicator and associated variances. It could shed light on more precise technology-related promotion instructions for the targeted industry.

Author statement


Declaration of Competing Interest

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

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Supplementary materials

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References


