Cleaner Production Assessment for Wastewater Treatment Plants Based on Backpropagation Artificial Neural Network

Fang He*, Jian Wang, Wei Chen

ABSTRACT

This paper aims to create a rational standard for cleaner production (CP) in wastewater treatment plants (WWTPs). To this end, a cleaner production assessment system was established for WWTPs in light of relevant theories on cleaner production review; then, the analytic hierarchy process (AHP) and the artificial neural network (ANN) were combined into an AHP-based BP-ANN model for CP assessment of WWTPs. In the proposed model, the AHP evaluation results are taken as the network inputs, and trained and tested via backpropagation artificial neural network (BP-ANN). Then, the proposed model was verified through a case study on several WWTPs in Central China. The verification results show that the model fully absorbs the tacit knowledge and experience of expert scoring, and reduces the arbitrariness of subjective evaluation. With high accuracy, sound feasibility and controllable error, the proposed method boasts a great potential in the cleaner production evaluation of WWTPs.

Key Words: Artificial Neural Network (ANN), Analytic Hierarchy Process (AHP), Backpropagation Artificial Neural Network (BP-ANN), Evaluation Index, Wastewater Treatment Plant (WWTP), Cleaner Production (CP)

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Introduction

Cleaner production (CP) is a preventive strategy to eliminate or minimize the negative environmental impacts of production processes and products. The strategy has been widely adopted across the globe to suppress the contribution of industrial activities to global warming. The implementation of cleaner production can enhance resource utilization, reduce or stop pollutant generation, and protect and improve the environment.

Artificial neural network (ANN). Inspired by the neural interaction in the human brain, the ANN is an artificial intelligent method for information transmission and processing (Gonçalves, 2017). This adaptive and nonlinear network combines the merits of bioscience and computer science. Compared to traditional artificial intelligence methods, the ANN overcomes the intuitive errors in unstructured information processing. It has been applied in various fields thanks to its strong ability of reasoning and simulation.

Literature Review

General studies on cleaner production

Luken *et al.*, (2016) introduces the framework of global cleaner production programme, advises to elevate the framework from the standard for inhouse assessment and training to national strategy on green industry, and lauds its great potential in resource efficiency and environmental management. References (Yong *et al.*, 2016; Severo *et al.*, 2017; Placet *et al.*, 2005) investigate the relationship between the conditions for sustainable product innovation,

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discusses the correlation between cleaner production and environmental management, and realize sustainable product innovation via structural equation modelling (SEM). Considering the moderation effect of company size, Reference Guimar~aes *et al.*, (2017) explores the relationship between strategic drivers (SDR), cleaner production success (CPS) and project management maturity (PMM), and discloses the significant correlations between SDR and CPS and between PMM and CPS. Relying on descriptive statistics, Bhupendra and Sangle, (2016) weighs the relative importance of different influencing factors of cleaner production strategy in Indian companies, revealing that the vision of top management and the ability of risk control are essential to the implementation of cleaner production strategy. Severo *et al.*, (2015) proves that cleaner production methods contribute to the productivity, flexibility, health and safety of companies.

Sakr and Sena, (2017) analyses the empirical data on CP from Egypt, and provides insights into the design of future cleaner production programmes. During the research, Egypt, a victim of energy crisis, was pursuing sustainable economic growth through innovative methods for cleaner production. Focusing on China's CP policies, Peng and Liu (2016) discovers the strong associations between cleaner production and audit, implementation and environmental production. Silva *et al.*, (2013) integrates high-quality tools into a standard CPmethod through the analysis of nine theoretical and empirical methods, and overcomes existing problems in CP implementation, especially the limited use of systematic techniques and tools. Wen *et al.*, (2016) explores the best available techniques (BATs) for cleaner production of coal gasification, and determines the ELECTRE-II method, a popular outranking method for multi-criteria decision-making, as the optimal option. The research findings lay a scientific basis for BATs formulation, and provide a valuable reference for assessing alternatives. To reduce the Cans Loss Index (CLI) of a company, Silva *et al.*, (2017) implements a cleaner production programme through the plan-do-check-act (PDCA) method, and includes the following actions into the implementation: training on standards, review of maintenance plans, segmented control, design of responsibility matrix, alignment of services, and equipment maintenance.

Evaluation systems of cleaner production

Govindan *et al.*, (2016) evaluates the common barriers to remanufacturing by interpretive structural modelling (ISM) and fuzzy analytic network process (ANP). Specifically, the ISM was employed to analyse the relationship and dependency among the barriers, and the fuzzy ANP was adopted for a case study on the barriers to the remanufacturing of essential auto parts. Jia *et al.*, (2014) assesses the cleaner production in vanadium extraction industry by fuzzy analytic hierarchy process (AHP) model, and verifies the model through quantitative calculation and qualitative assessment. The fuzzy AHP model sheds new light on the feasibility assessment of CP plans. To quantify the CP effect in stone processing industry, Bai *et al.*, (2015) proposes a cleaner production evaluation system based on AHP and fuzzy membership analysis, and proves that the system is of guiding importance to implementing CP in the said industry. Dan *et al.*, (2013) describes the original drivers of compulsory CP assessment in key companies in China, identifies the analysis indices for the assessment, and regresses the effects of external factors (e.g. provincial economic level, pollution pressure and staff training) on the assessment. To disclose the competitive relationship among iron and steel enterprises (ISEs), Gong *et al.*, (2017) constructs a nonlinear programming model through evidential reasoning (ER) and the cross-efficiency of data development analysis (DEA), and applies the model to obtain the optimal weight and utility, aggregate the evaluation data, and rank the ISEs by cleaner production performance.

Dong *et al.*, (2012) develops a system dynamics model for simulating cleaner production in electroplating industry, and implements the model to analyse the effects of policy parameters on cleaner production investment decisions in a typical electroplating company in Shenzhen, China. The research reveals that the promotion of cleaner production in underdeveloped countries hinges on rational industry water price, accurate standards, and sufficient economic incentives. Basappaji and Nagesha (2014) creates a fuzzy logic model for assessing the cleaner production level, and applies the model to 22 cashew processing units. The level of cleaner production was assessed against influencing factors like process efficiency, environmental degradation and sustainability. Through the assessment, various dimensions were identified and measured for each influencing factor. The research results have positive implications on the promotion of cleaner production initiatives. Daylan *et al.*, (2013) evaluates the cleaner production of zinc electroplating process through onsite plant audit and mass balance analysis, reveals the possible cleaner production applications in the selected zinc electroplating plant via input-output evaluation based on flow and material balances, and evaluates the environmental benefits and economic feasibility of selected cleaner production opportunities. Using emergy and money-based indices, Reference (Zhang *et al.*, 2015; Lim and JongMoon, 2009; Brown *et al.*, 2009) measure the performance change of a large wastewater treatment plant (WWTP) through the implementation of a cleaner production measure. The results show across-the-board improvement in resource efficiency and environmental performance.

Overall studies on the ANN

The ANN is a popular tool of evaluation and prediction. El-Abbasy *et al.*, (2014) collects the historical inspection data from 3 offshore oil-gas pipelines in Qatar, and sets up three ANN-based models to evaluation and forecast the pipeline conditions (e.g. corrosion). Priyadarshinee *et al.*, (2017) analyses the data collected from 660 professional experts using the SEM and ANN, and builds a two-stage SEM-ANN model to predict the motivators behind the proliferation of cloud computing services in Indian private companies. Lazakis *et al.*, (2018) projects the upcoming exhaust gas temperatures of all main engine cylinders by the ANN. The ANN-based projection method consists of two steps. First, the critical systems/components were identified through reliability modelling; Second, the physical parameters of these systems/components were monitored with the ANN.

From the above review, it can be seen that the cleaner production has rarely been applied in WWTPs, despite its popularity across different industrial sectors. The WWTPs, as essential municipal infrastructure, belong to the scope of the mandatory cleaner production audit in China. Nevertheless, there is no national or professional standard on cleaner production in WWTPs. To make up for the gap, this paper develops a comprehensive evaluation index system of cleaner production in WWTPs, and applies the AHP and the backpropagation artificial neural network (BP-ANN), a typical ANN, to the cleaner production evaluation in WWTPs.

Mathematical Model

AHP

Considering the numerous and multi-level influencing factors of cleaner production in WWTPs, the decomposition-coordination method of large scale systems was introduced to allocate these factors into different layers, forming a continuous hierarchal structure. As shown in Figure 1, our evaluation index system of cleaner production in WWTPs consists of five dimensions, namely, process unit, pollutant, energy consumption, resource reuse and product.

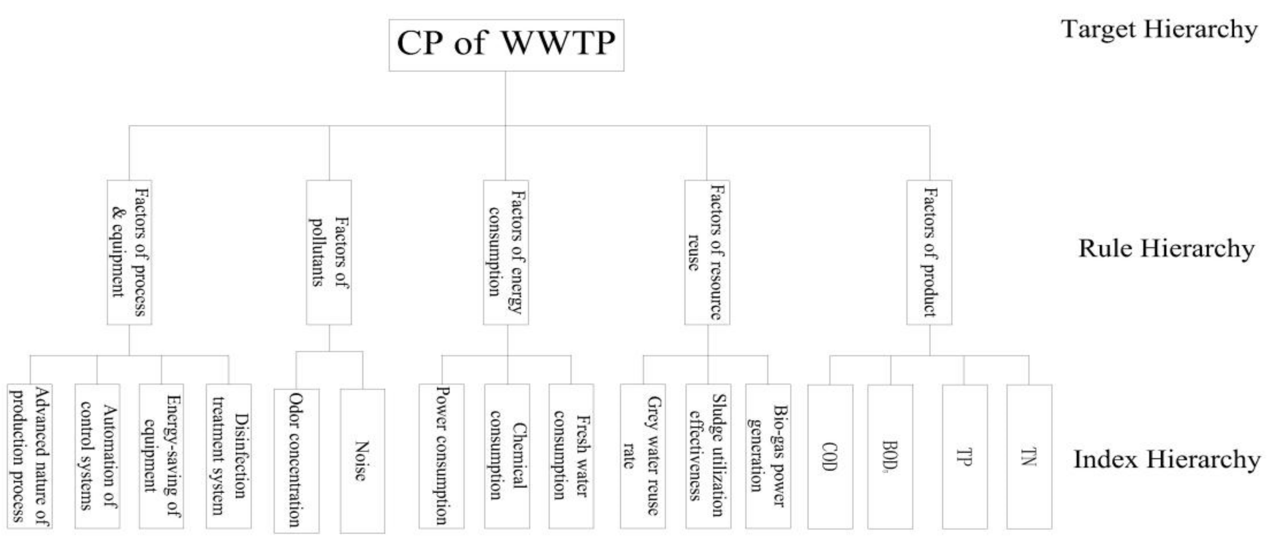

Figure 1. Proposed evaluation index system of cleaner production in WWTPs

The proposed evaluation index system has 5 primary indices in the criteria layer and 16 secondary indices in the alternative layer. The first step is to determine the weight of the indices on each layer. Several experts in wastewater treatment industry were invited to rate the indices against a 9-point scale, and fill their ratings in a form. Based on the expert scores, the judgement matrix of each layer was established against a 9-point scale. Then, the eigenvector corresponding to the λmax of each judgement matrix was solved and normalized to derive the weight of each evaluation index. Finally, a consistency test was performed for each level. The comprehensive weight of a level was determined after that level passed the consistency test. The specific steps are as follows:

(1) Decompose the evaluation indices into interrelated elements, and build a hierarchy to indicate the relationship between different layers.

(2) Make judgement according to the features of the evaluation object. Perform pairwise comparison between the elements on the same layer, and assign values to these elements against a 9-point scale, forming pairwise judgement matrices.

(3) Find the eigenvector of each judgement matrix by mathematical method. After normalization, obtain the importance, i.e. weight, of an element in one layer relative to another element in the superior layer.

(4) Perform consistency test on each judgement matrix. If the matrix fails the test, adjust the elements in that layer, and repeat the above steps.

(5) Calculate the total ranking weight of the elements in a layer relative to the system goal, and rank the different layers to provide a decision plan.

BP-ANN model

The BP-ANN algorithm can establish a structure of artificial neurons similar to the information reception and processing architecture of the biological brain. The established structure receives external information through sensors, analyses the object information in the “nerve centre” of numerous artificial neurons, and recognises the activities of the object. The construction of a BP-ANN model consists of the following two steps.

(1) Determining network topology

a. Determining the number of network layers: The BP-ANN can handle complex nonlinear problems at ease if it has a complicated structure. However, such a complex network requires an excessively long training time. By contrast, the network training will face difficulty in convergence if the BP-ANN has an oversimplified structure. In a closed interval, any continuous function can be approximated by a BP-ANN with a hidden layer. Therefore, the network topology was determined as a three-layer BP-ANN with one hidden layer. The network structure is shown in Figure 2.

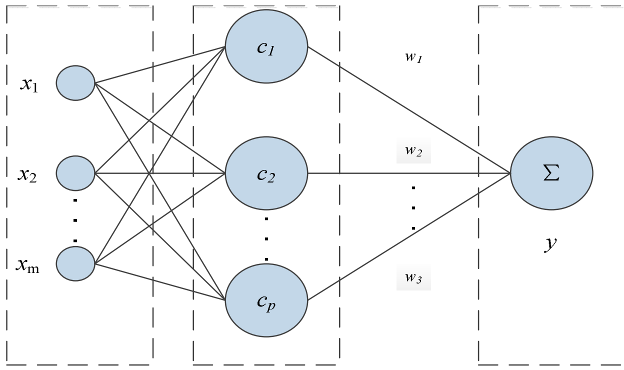

Figure 2. Structure of the 3-layer BP-ANN

b. Determining the number of nodes in each layer: According to the evaluation index system for cleaner production of WWTPs, the 16 secondary indices were taken as the input neurons of the network (i.e. the number of input layer nodes m=16), and the evaluation score of cleaner production as the network output (i.e. the number of output layer nodes *l*=1). There should be a sufficient number of hidden layer nodes, as per the universal approximation theorem. If the number is too big, however, there will be an excessive amount of connections, leading to reduced network generalization ability. Hence, the author firstly determined the range for the number of hidden layer nodes, and then chose the maximum value in that range. Here, the said range is determined as $\sqrt{ml} \le p \le \sqrt{m(l+3)}+1$.

c. Selecting the excitation function for each layer: *tansig* function was selected as the excitation function of the hidden layer; *purelin* linear transformation function was selected as the excitation function of the output layer; *trainbr* function was selected as the training function, such that the network was trained with Bayesian normalization method for better generalization performance.

(2) Training of BP-ANN model

a. Determination of initial network parameters: Currently, there is no universally accepted method for selecting initial weights. In general, the initial weights are randomly chosen from the interval [-1, 1], while thresholds of the hidden layer and the output layer are generated randomly or set to certain values from the interval [0, 1]. Here, the initial weights and thresholds are all randomly generated.

b. Selection of sample data: The quantitative index data were obtained through actual survey; the qualitative index data were acquired through expert scoring. The scores fell in the interval [0, 1]. The importance of an index is positively correlated with its final score, which equals the average of the scores given by all experts to the index. The same weight applies to all the experts.

c. Data pre-processing: Before BP-ANN training, the sample data were standardized to enhance the training efficiency and generalization ability of the network. The standardization involves two steps: First, the mean vector of the sample data was adjusted to zero; Second, the data were normalized such that the standard deviation of the input data vector was 1.

If the assessed quality is positively correlated with the index value: $x^*=(x_i-x_{imin})/(x_{imax}-x_{imin})$;

If the assessed quality is negatively correlated with the index value: $x^*=1-(x_i-x_{imin})/(x_{imax}-x_{imin})$.

where x^* is the standardized value of index x_i; x_{imin} and x_{imax} are the minimum value and maximum value of the pre-set i-th value, respectively; i is the number of evaluation indices.

d. Network training and testing: The sample data were divided into the training sample and the test sample. The former was used to train the network until reaching the required accuracy; the latter was used to test the trained network. The post-training network should be deemed as mature, if the maximum relative error between the output value and the expected value falls within the acceptable range. The parameters of the trained BP-ANN should be saved, so that the results can be obtained in the next assessment simply by inputting the standardized index values.

Case Study

This case study targets 15 WWTPs in a central province of China. The raw data on the indices of Figure 1 were obtained through a survey on these WWTPs. Considering the relative importance of the attributes of these indices, the judgement matrix A for primary indices were established through expert scoring against a 9-point scale (Table 1).

Table 1. Judgement matrix A for primary indices

A	A_1	A_2	A_3	A_4	A_5
A_1	1	1/2	3	1	2
A_2	2	1	5	3	2
A_3	1/3	1/5	1	1/2	1/3
A_4	1	1/3	2	1	2
A_5	1/2	1/2	3	1/2	1

The maximum eigenvalue of the judgement matrix was calculated as λ_{max}=5.1249, below the critical value of a matrix of order 5 λ'_{max}=5.45. This means the matrix passes the consistency test. Thus, the eigenvector equals weight of each primary index: $\omega_i=(0.2124, 0.3867, 0.0693, 0.2124, 0.1192)^T$, where $i=1,2,3,4,5$. The weight of each secondary index was determined in a similar manner:

$\omega_{1j}=(0.1464, 0.4393, 0.3107, 0.1036)^T$, $j=1,2,3,4$;

$\omega_{2j}=(0.6, 0.4)^T$, $j=1,2$;

$\omega_{3j}=(0.1429, 0.7143, 0.1429)^T$, $j=1,2,3$;

$\omega_{4j}=(0.6482, 0.2297, 0.1220)^T$, $j=1,2,3$;

$\omega_{5j}=(0.5303, 0.3061, 0.0985, 0.0678)^T$, $j=1,2,3,4$.

The graded specific gravity method was employed to determine the membership function index, and provide the standardized score of each WWTP index (Table 2).

The raw data of each index was normalized and weighted by the AHP. Then, the WWTP comprehensive score was obtained based on the index weights (Table 3). Considering the cleaner production grades of WWTPs and the objects of this case study, the cleaner production was divided into five levels: excellent (comprehensive score: [0.9~1]), good (comprehensive score: [0.8~0.9]), medium (comprehensive score: [0.7~0.8]), qualified (comprehensive score: [0.6~0/7]), and unqualified (comprehensive score: below 0.6).

The assessment results may lack some objectivity, as the weights were determined by expert scoring in AHP. To solve the problem, the BP-ANN was introduced to freely adjust the weights and thresholds. The main functions of the BP-ANN toolbox were adopted to establish a three-layer BP-ANN with a hidden layer, such that the assessment could be performed on the BP-

Table 2. Standardized scores of secondary indices in CP assessment of WWTPs

		P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
	A_{11}	0.89	0.98	0.96	0.76	0.86	0.80	0.81	0.76	0.86	0.89	0.86	0.87	0.86	0.86	0.98
A_1	A_{12}	0.55	0.64	0.64	0.91	0.73	1.00	0.89	0.60	0.64	0.55	0.64	0.78	0.82	0.64	1.00
	A_{13}	0.82	0.90	0.87	0.77	0.80	0.73	0.80	0.63	0.67	0.80	0.78	0.83	0.77	0.67	0.93
	A_{14}	0.88	0.94	0.89	0.83	0.76	0.75	0.80	0.77	0.79	0.89	0.90	0.80	0.83	0.79	0.97
A_2	A_{21}	0.89	0.96	0.92	0.82	0.85	0.83	0.84	0.76	0.82	0.90	0.80	0.85	0.81	0.82	0.95
	A_{22}	0.90	0.90	0.94	0.81	0.73	0.75	0.86	0.78	0.71	0.84	0.88	0.75	0.85	0.71	0.93
A_3	A_{31}	0.64	1.00	1.00	0.73	1.00	0.70	0.89	0.80	0.73	1.00	0.82	0.55	1.00	0.73	0.91
	A_{32}	1.00	1.00	1.00	0.87	1.00	1.00	0.87	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00
	A_{33}	0.73	0.82	0.91	0.70	0.91	0.82	0.89	0.70	0.73	0.89	0.64	1.00	0.73	0.73	1.00
A_4	A_{41}	0.91	1.00	1.00	0.91	0.73	0.82	1.00	0.90	0.73	0.78	1.00	0.78	1.00	0.73	1.00
	A_{42}	0.89	0.98	0.96	0.76	0.86	0.80	0.81	0.76	0.86	0.89	0.86	0.87	0.86	0.86	0.98
	A_{43}	0.88	0.94	0.89	0.83	0.76	0.75	0.80	0.77	0.79	0.89	0.90	0.80	0.83	0.79	0.97
A_5	A_{51}	0.89	0.98	0.88	0.87	0.86	0.82	0.84	0.71	0.86	0.84	0.82	0.93	0.86	0.86	0.94
	A_{52}	0.91	0.98	0.84	0.84	0.84	0.85	0.86	0.82	0.75	0.86	0.76	0.88	0.78	0.75	0.95
	A_{53}	0.87	0.98	0.90	0.79	0.84	0.84	0.78	0.72	0.80	0.89	0.80	0.90	0.83	0.80	0.94
	A_{54}	0.64	0.82	0.91	0.73	1.00	0.90	0.78	0.89	0.87	0.49	0.64	0.55	1.00	0.87	1.00

Table 3. Comprehensive scores of the WWTPs

WWTP	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
Comprehensive score	0.8558	0.9234	0.9013	0.8334	0.8062	0.8257	0.8633	0.7694
Level	good	excellent	excellent	good	good	good	good	medium
WWTP	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	
Comprehensive score	0.7678	0.8293	0.8388	0.8249	0.8540	0.7678	0.9649	
Level	medium	good	good	good	good	medium	excellent	

Table 4. Network training results

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
T-0	0.8558	0.9234	0.9013	0.8334	0.8062	0.8257	0.8633	0.7694	0.7678	0.8293
T-0.0001	0.8567	0.9161	0.8985	0.8346	0.8079	0.8220	0.8633	0.7691	0.7677	0.8291
T-0.0002	0.8567	0.9129	0.8963	0.8349	0.8084	0.8200	0.8632	0.7689	0.7676	0.8291

Table 5. Network simulation results

	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
SR-T_1	0.8546	0.8166	0.8815	0.7678	0.9381
SR-T_2	0.8517	0.8229	0.8746	0.7677	0.9344
SR-T_3	0.8496	0.8255	0.8712	0.7674	0.9321
Expert scores-T	0.8388	0.8249	0.8540	0.7678	0.9649
level	good	good	good	medium	excellent

ANN according to the evaluation index system for cleaner production in WWTPs. The number of hidden layer nodes was determined by checking the assessment ability of the model. The number of output layer nodes (i.e. tertiary indices), hidden layer nodes and output layer node was set to 16, 16 and 1, respectively, forming a topology of 16-16-1. Next, the evaluation index system for cleaner production in WWTPs was trained by the method in Section 2.2. From Table 2, the $S_1=\{P_1, P_2, ..., P_{10}\}$ was selected as the network training sample, and $S_2=\{P_{11}, P_{12}, ..., P_{15}\}$ as the network simulation sample. The network trainings were conducted at three different target errors: goal=0, goal=0.0001 and goal=0.0002. The training results are recorded in Table 4.

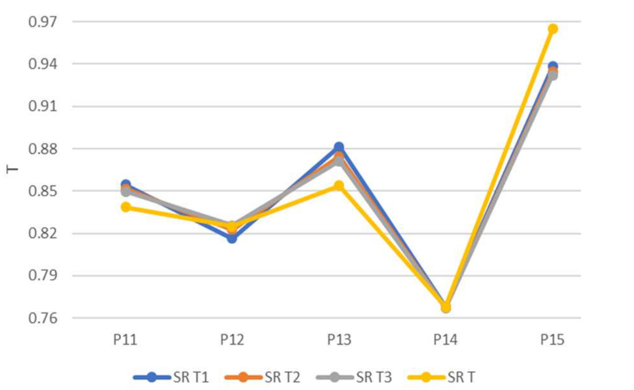

Figure 3. Comparison between simulation results and expert scores

The untrained five test sets were reserved for network simulation. The simulation results are shown in Table 5. The simulation results at three different error conditions were contrasted with the expert scores (Figure 3).

It can be seen that the simulation results always agree with expert scores at any required accuracy. Thus, the proposed network model is suitable for cleaner production assessment of the WWTPs.

Conclusions

The WWTP is essential municipal infrastructure for urban development. The CP of the WWTP directly bears on its performance in energy saving, consumption reduction and comprehensive utilization of resources. In light of this, an AHP-based BP-ANN cleaner production assessment method was presented for WTPPs. Specifically, the BP-ANN model structure was determined through the training of the sample data of the target WWTPs. The proposed system manages to satisfy any accuracy requirement through continuous BP-ANN learning of the sample data, and achieves dynamic tracking and assessment with the increase in sample size and training time.

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