Edge Computing in Water Management: A KPCA-DeepESN and HOA-Optimized Framework for Urban Resource Allocation

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***Abstract*—This paper presents a novel approach to optimizing urban water resource allocation by integrating Kernel Principal Component Analysis (KPCA) with a Deep Echo State Network (DeepESN), further optimized using the Hiking Optimization Algorithm (HOA). The proposed model addresses the issue of achieving an optimal balance between water supply and demand in urban environments, utilizing advanced machine learning techniques to enhance prediction accuracy and allocation efficiency. KPCA is employed to reduce the dimensionality of key water resource indicators, capturing nonlinear relationships in the dataset. DeepESN, a deep recurrent neural network model, is then applied to predict water consumption trends. HOA, a meta-heuristic algorithm inspired by hiker behavior, is used to fine-tune the DeepESN network parameters, ensuring faster convergence and higher accuracy. The experimental setup includes water resource data from January 2010 to December 2023, divided into training, testing, and validation sets. The model's performance is compared with other approaches, such as PCA-DeepESN and standalone DeepESN. Results show that the KPCA-HOA-DeepESN model achieves the lowest prediction error and fastest convergence, making it a superior solution for urban water management. Optimized network parameters include a reservoir size of 140, a spectral radius of 0.3, an input scaling factor of 0.22, and a reservoir sparsity degree of 0.72. This study demonstrates the applicability of distributed computing techniques in water resource management by utilizing cloud-based data processing and real-time predictions. The proposed approach not only improves resource allocation but also showcases the potential for edge computing to enhance the responsiveness of water management systems.**

Keywords*—KPCA Method; water supply and demand equilibrium; allocation of resources in urban water environment; optimization strategy for hiking; DeepESN

I. Introduction

Water, being an essential natural resource for the existence of humans, is intricately linked to both social stability and economic progress [1]. The fast expansion of civilization and population increase have resulted in an uneven distribution of water resources and pollution produced by human activities. This has led to a crisis in water resources, which is a pressing problem for every country and industry. In recent years, professionals and academics in the area have paid attention to the evaluation of water resources usage efficiency, recognizing its importance in the best allocation of water resources [2]. Studying objective and accurate approaches for optimizing the allocation of urban water resources may assist the water resources management department in enhancing the efficiency of water resource utilization and improving the precision of water usage solution control [3]. The analysis of water resources encompasses the evaluation of water resource utilization efficiency, the examination of water resource policies and regulations, the creation and implementation of water resource management strategies, the study of variables that influence water resources, and the evaluation of water resource utilization efficiency [4]. The efficient distribution of water resources is a crucial aspect of water resources analysis. The use of water resources is assessed by identifying key areas for review and employing data analysis methods to construct mathematical models that optimize resource distribution.

Presently, the water resource optimal allocation techniques encompass the fuzzy comprehensive assessment method, Tobit regression analysis method, machine learning algorithms, neural networks, deep learning networks, and other approaches [5]. Aghu and Reddy [6] employ an enhanced fuzzy set and fuzzy comprehensive evaluation method to assess and analyze the carrying capacity of water resources. The principal component analysis technique is combined with the particle swarm optimization algorithm, using an improved projection tracing model method, to evaluate the hierarchical water resources carrying capacity [7]. The inefficient use of urban water resources is simulated and analyzed using the least squares method and the Tobit regression model [8]. Lv et al. [9] examine the problem of water resource sustainability through a multi-level fuzzy comprehensive evaluation model and provides relevant water use measures. In literature [10], the random forest algorithm is utilized to predict and analyze water balance and forecast data. Lastly, Mangal et al. [11] introduces a deep echo state network based on a multi-layer self-coder and applies it to the evaluation of urban water resources. While there have been significant achievements in researching the best way to allocate urban water resources both domestically and internationally, there are still certain limitations and flaws in the methodologies used for water resource analysis. Firstly, the analysis method relies on subjective evaluation, which can easily compromise the objectivity of the results. Additionally, relying solely on evaluation or allocation methods can impact the accuracy of the results. Moreover, the optimization model used for water resources allocation in the local area fails to adequately reflect equilibrium and does not contribute to enhancing the overall utilization rate of water resources [12].

This study utilizes the hiking optimization algorithm and deep echo state network to address the issue of optimal allocation of urban water resources, with the aim of analyzing the current research situation. The structure of this paper is:

- Examine the problem by considering water resources analysis and water resources optimization.
- Design the appropriate index parameters and optimize the parameters of the deep echo state network using the hiking optimization algorithm.
- Develop a method for optimizing and allocating urban water resources based on the HOA-DeepESN model.
- Suggested approach is utilized in the examination of data about the allocation of urban water resources.
- Contrasted with alternative models in order to confirm its superiority and correctness.

II. Water Allocation Challenges

A. *Examination of Water Resources*

Water resources analysis is the application of systems analysis techniques to comprehensively examine the design, planning, management, and challenges related to water resources. Its aim is to develop a scientifically sound and rational program. The analysis of urban water resources typically involves the selection of indicators, processing without dimensions, finding a solution for weighting, calculating a comprehensive score, and analyzing the efficiency of the city's water benchmarking by considering spatial and temporal differences. Additionally, a seven-step analysis is conducted to assess the potential for water conservation, as depicted in Fig. 1.

Regarding indicator selection, this paper opts for four urban water resources analysis indicators: 10,000 RMB GDP water consumption A, 10,000 RMB industrial output value water consumption B, per capita comprehensive water consumption C, and per capita living water consumption D [13], as depicted in Fig. 2.

Furthermore, this study uses Z-score methodology to standardize the analysis indicators for urban water resources. It utilizes principal component analysis to determine the weights of the indicators and develops complete assessment indicators using the weighted average approach.

B. *Efficient Distribution of Water Resources*

1) Guidelines for efficient distribution of water resources: To achieve the best allocation of water resources, it is recommended to utilize the comprehensive score obtained from analyzing urban water resources as an explanatory variable. Additionally, select the influencing factors of each field at each level as explanatory variables and employ the regression algorithm to construct the water resources allocation model. The water resource optimization allocation process involves many key processes, including indicator selection, correlation analysis, building of an allocation model, and optimization of the allocation model [14]. These steps are illustrated in Fig. 3.

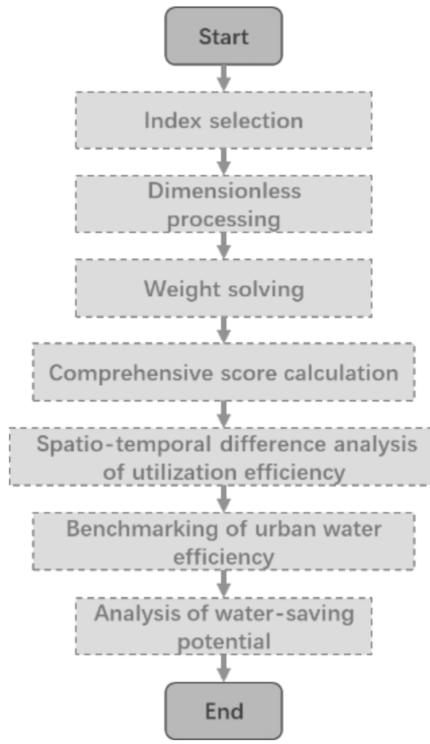


Fig. 1. Sequential process of assessing urban water resources.

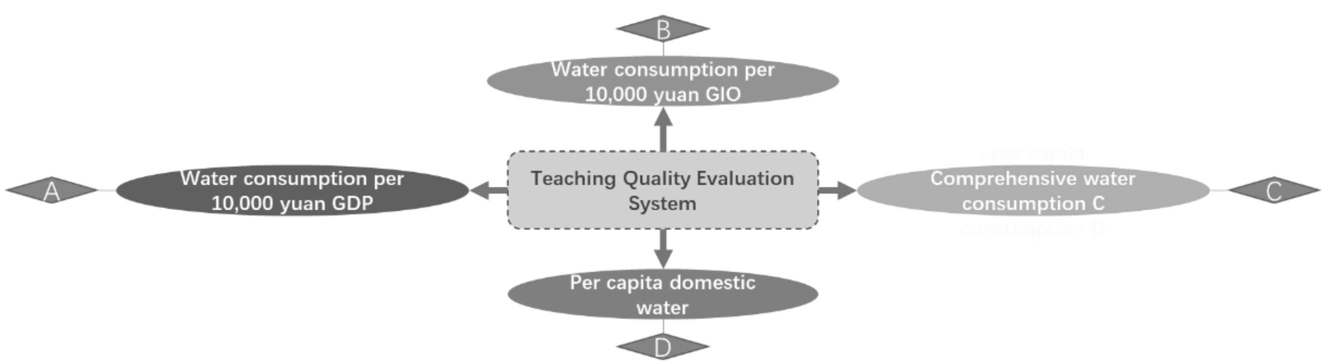


Fig. 2. Indicators used to analyze urban water resources.

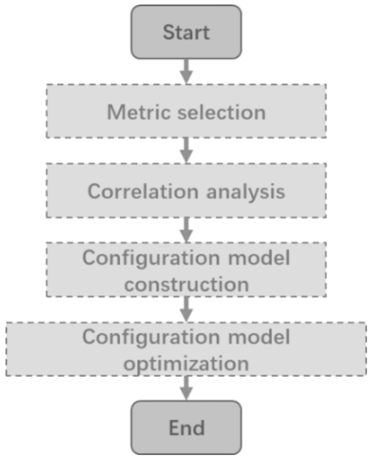


Fig. 3. Steps for optimal allocation of urban water resources.

2) Choosing appropriate indicators for efficient distribution of water resources: Several variables influence the efficiency of water resource consumption, such as natural factors, economic considerations, scientific and technological factors, and the organization of industrial water use. Hence, this article chooses water resource optimization indicators based on four viewpoints: natural factors, economic aspects, scientific and technical considerations, and industrial water usage structure [14]. 1) Natural factors indicators consist of total annual water supply (S1), per capita water possession (S2), and per capita regional gross domestic product (S3). 2) Economic factors indicators include the proportion of the first industry (J1), the proportion of the second industry (J2), and the proportion of the third industry (J3). 3) Scientific and technological factors indicators include the investment cost of wastewater treatment (K1). 4) Industrial investment cost of wastewater management (K1) is also an indicator of scientific and technological factors. 5) Indicators of industrial water use structure include agricultural water use (C1), industrial water use (C2), domestic water use (C3), and ecological water use (C4). Fig. 4 shows selection of indicators for optimal allocation of urban water resources.

3) Optimal allocation modeling of water resources: Water resource optimization and allocation model construction is the use of machine learning algorithms or mathematical agent model analysis training to construct a nonlinear mapping relationship between the water resource optimization and allocation indicators and the comprehensive score of water resource utilization efficiency. In this paper, we propose to use the deep learning algorithm to construct the water resources optimization model, and at the same time, we adopt a meta-heuristic optimization algorithm inspired by the hiker's travel experience to optimize the parameters of the deep learning algorithm to optimize the prediction accuracy of the water resources optimization model, which is shown in Fig. 5.

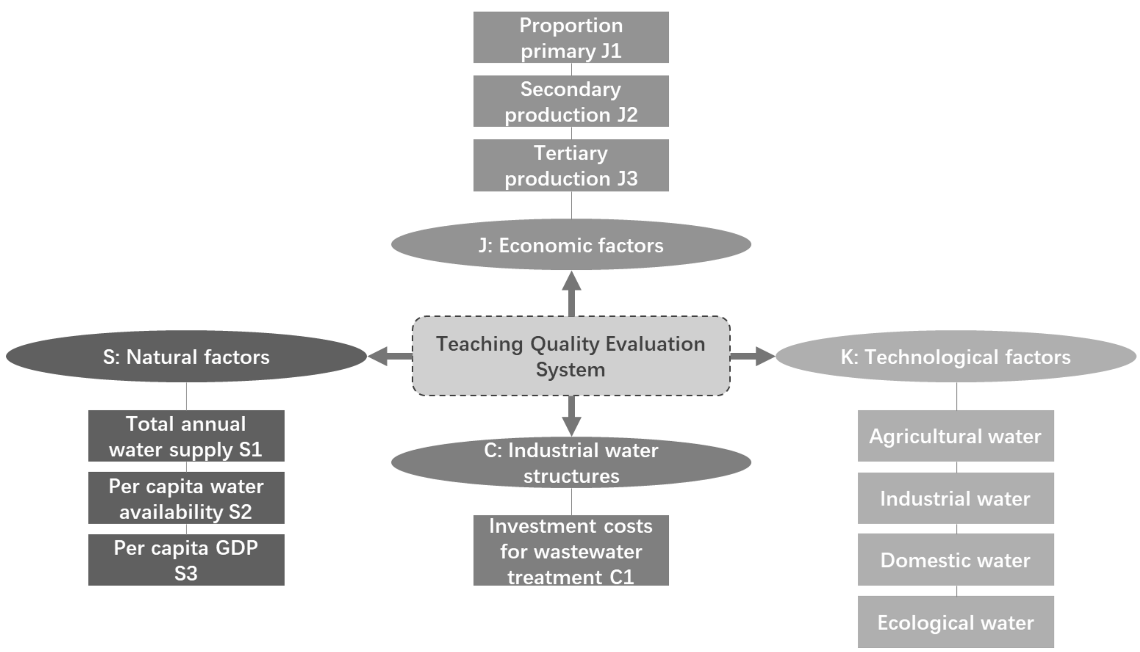


Fig. 4. Selection of indicators for optimal allocation of urban water resources.

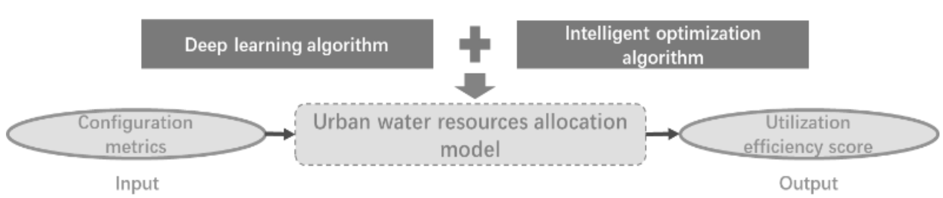


Fig. 5. Model construction of optimal allocation of urban water resources.

III. Risk Assessment Problems

A. Kernel Principal Component Analysis (KPCA)

Kernel Principal Component Analysis (KPCA) [15] is an enhanced version of Principal Component Analysis (PCA) [16] that addresses nonlinear data structures by transforming the data into a feature space with a higher dimensionality. KPCA, unlike classic PCA, does not directly calculate the covariance matrix and eigenvectors in the original data space. Instead, it employs a kernel function to transform the data into a new feature space and then calculates the principal components in this transformed space. Some frequently employed kernel functions include the linear kernel, Gaussian kernel (also known as radial basis function), polynomial kernel, and others. KPCA effectively captures the non-linear characteristics of the data and is particularly useful for datasets that cannot be accurately represented using linear approaches in their original form. Fig. 6 provides a schematic representation of the precise structure.

The fundamental procedures of KPCA are as follows: 1) Choose a suitable kernel function, such as the radial basis function; 2) Calculate the kernel matrix; 3) Center the kernel matrix; 4) Perform eigenvalue decomposition; 5) Normalize the eigenvectors; 6) Select the principal components; 7) Compute the nonlinear principal components; 8) Reconstruct the data.

KPCA is mostly employed in pattern recognition, image processing, bioinformatics, and fault detection, as seen in Fig. 7. It aids researchers in identifying intricate patterns in data, decreasing data dimensionality, and enhancing the efficiency and precision of future analysis.

B. HOA-DeepESN Network

1) Algorithm for optimizing hiking: The Hiking Optimization method (HOA) [17] is a meta-heuristic optimization method that draws inspiration from the act of hiking. Hikers consciously or unconsciously consider the incline of the land when they try to reach the top of mountains, hills, or rocks. This activity is a well-liked recreational pursuit that acknowledges the resemblance between the search landscape of an optimization problem and the rugged terrain that hikers navigate, as depicted in Figure. The number 9. The mathematical model of HOA is based on the Tobler hiking function, which considers the height of the terrain and the distance walked to calculate the walking pace of the hiker (agent). During the optimization phase, the Tobler hiking function (THF) is employed to ascertain the precise whereabouts of the hiker.

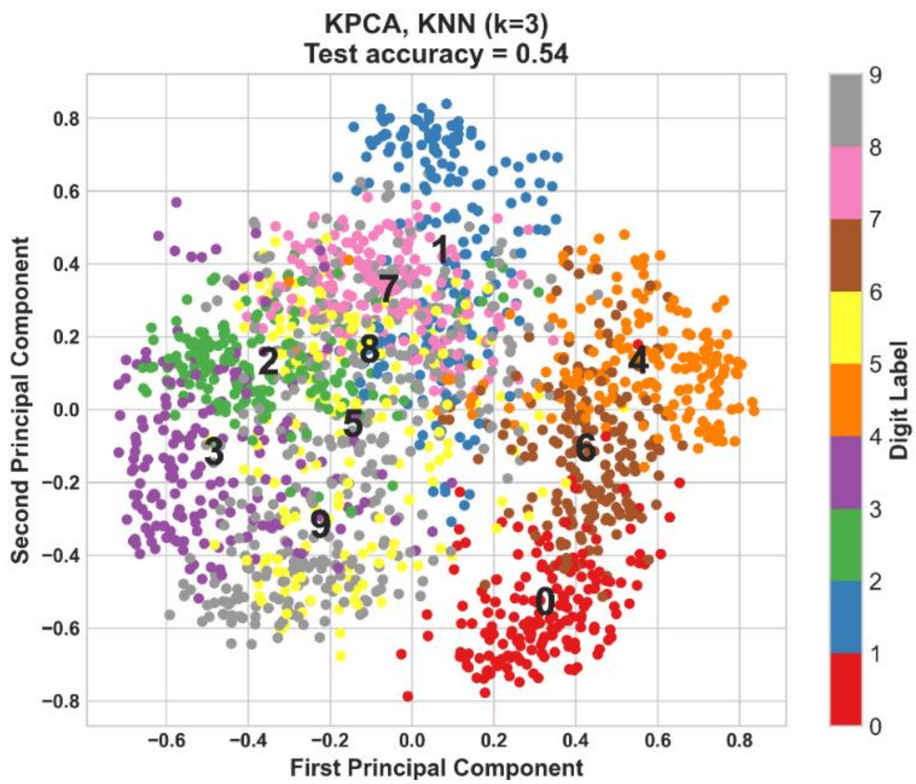


Fig. 6. KPCA structure.

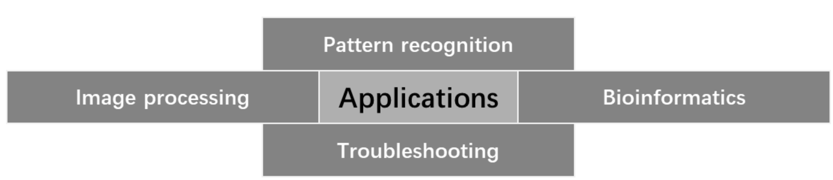


Fig. 7. Types of machine learning algorithms.

a) Principles of Homeowners Association (HOA): The mathematical basis of HOA is derived from the renowned Tobler Hiking Function, initially introduced by Waldo Tobler, a Swiss-American geographer and cartographer. The Tobler Hiking Function is an exponential function that calculates the velocity of a hiker, considering the incline or slope of the terrain or path. The precise mathematical model of the THF is as follows:

$$W_{i,t} = 6e^{-3.5|S_{i,t}+0.05|} \tag{1}$$

Where, $W_{i,t}$ denotes the speed of hiker i in km/h; and $S_{i,t}$ denotes the slope of the terrain, which is calculated as follows:

$$S_{i,t} = \frac{dh}{dx} = \tan\theta_{i,t} \tag{2}$$

Where, dh is the hiker elevation gradient, dx is the difference in hiker distance, and θ denotes the angle of terrain inclination, typically at [0, 50°].

HOA algorithms hikers as a group for the benefit of social thinking and individual hikers for the benefit of their personal cognitive abilities. The updated or actual speed of a hiker is a function of the initial speed determined by the THF, the position of the leading hiker, the actual position of the hiker, and the sweep factor. Thus, the current speed of hiker i is calculated as follows:

$$W_{i,t} = W_{i,t-1} + \gamma_{i,t} \cdot \left(\beta_{best} - \alpha_{i,t}\beta_{i,t}\right) \tag{3}$$

where $\gamma_{i,t}$ is a uniformly distributed random number; β_{best} is the position of the lead hiker; $\alpha_{i,t}$ is the scan factor SF for hiker i, which lies between 1 and 3; SF ensures that hikers do not stray too far from the lead hiker so that they can see the direction of the lead hiker and receive signals from the lead hiker.

The location update for hiker i is calculated as follows:

$$\beta_{i,t+1} = \beta_{i,t} + W_{i,t} \tag{4}$$

In addition, the HOA algorithm initializes the hiker population as follows:

$$\beta_{i,t+1} = \phi_j^1 + \delta_j\left(\phi_j^2 - \phi_j^1\right) \tag{5}$$

where δ_j is a uniform distribution and ϕ_j^1 and ϕ_j^2 denote the upper and lower bounds of the jth dimension of the optimization problem.

The exploratory and exploitative tendencies of the HOA algorithm are influenced by the SF parameter. When the SF range increases, the HOA algorithm tends to the developmental stage; when SF decreases, the HOA algorithm enters the exploratory stage.

b) Sequential progression of the HOA algorithm: Table I displays the pseudo-code for the hiking optimization method.

TABLE I. HIKING PSEUDO-CODE

Algorithm 1: Hiking Optimization Algorithm

```
Nout upper and lower limits, Max_iter, Np, d;
Intislize hikers' position randomly;
Calculate fitnss and output best fitness;
For t = 1:Max_iter
    Determine best fitness of hikers;
    Determine trail/terrain angle of elevation;
    Compute the slope;
    Determine the actual velocity of hiker;
    Update hiker's position;
    Bound position using upper and lower limits;
    Update best hiker position;
End
Output best solution.
```

2) DeepESN network: The Deep Echo State Network (DeepESN) [18] is a customized deep recurrent neural network designed for the processing of temporal data. The model is an expansion of the Echo State Network (ESN) [19]. DeepESN is an advanced technique used to create recurrent neural networks that are trained efficiently. It involves combining multiple recurrent layers to create a network that can represent temporal information at different time scales. This makes DeepESN more effective at processing data that changes over time. The precise configuration is illustrated in Fig. 8.

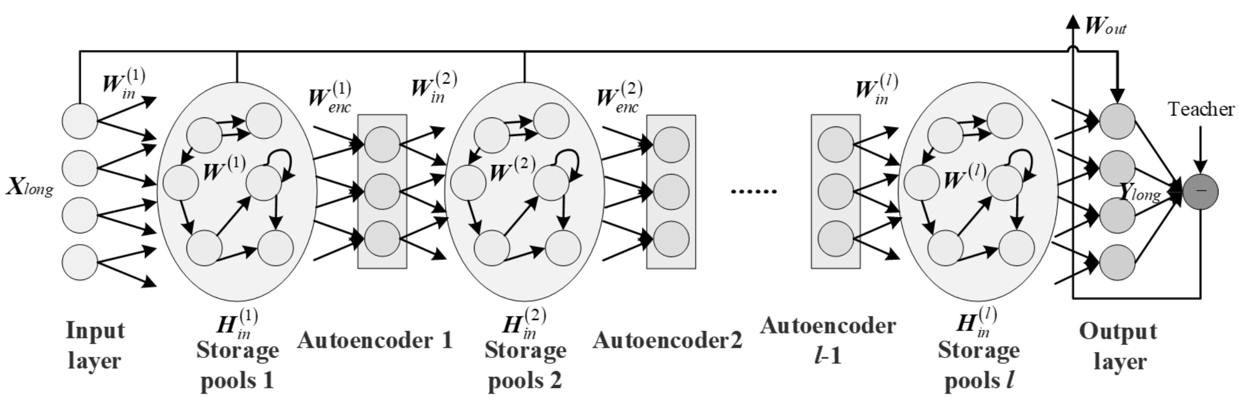


Fig. 8. DeepESN structure.

DeepESN is a variant of Echo State Networks (ESNs) that enhances the depth of the reservoir by employing a self-encoder mapping. In the DeepESN network architecture, the preceding reservoir echo state is compressed to lower dimensions using an Autoencoder (AE). This compressed state is then fed into the subsequent reservoir pool, and the process continues until reaching the last layer. In the final layer, all the echo states are organized and the ultimate result is outputted to the network. The mathematical model is precisely defined as follows:

$$\boldsymbol{H}_{in}^{(l)}(t)=\boldsymbol{W}_{in}^{(l)}\boldsymbol{X}_{in}^{(l)}(t)+\boldsymbol{W}^{(l)}\boldsymbol{H}^{(l)}(t-1) \tag{6}$$

$$\boldsymbol{X}_{in}^{(l)}(t)=\begin{cases}\boldsymbol{X}_{long}(t), l=1\\ f_{enc}\left(\boldsymbol{W}_{enc}^{(l-1)}\boldsymbol{H}^{(l-1)}(t)\right), l>1\end{cases} \tag{7}$$

$$\boldsymbol{H}^{(l)}(t)=\left(1-SD^{(l)}\right)\boldsymbol{H}^{(l)}(t-1)+SD^{(l)}\tanh\left(\boldsymbol{H}_{in}^{(l)}(t)\right) \tag{8}$$

$$\boldsymbol{Y}_{long}(t)=g\left(\boldsymbol{W}_{out}\boldsymbol{H}(t)\right) \tag{9}$$

Where, $\boldsymbol{H}_{in}^{(l)}(t)$ denotes the weighted input data of storage pool in layer *l* at moment *t*, $\boldsymbol{W}_{in}^{(l)}$ denotes the connection weight from input to storage pool in layer *l*, $\boldsymbol{X}_{in}^{(l)}(t)$ denotes the input in layer *l* at moment *t*, $\boldsymbol{W}^{(l)}$ denotes the state feedback weight of storage pool in layer l, $\boldsymbol{H}^{(l)}(t-1)$ denotes the state of storage pool in layer *l* at moment t-1, $\boldsymbol{W}_{enc}^{(l-1)}$ denotes the projection weight of the self-encoder in layer l-1 at moment t, $f_{enc}(\cdot)$ denotes the activation function of the self-encoder, $\boldsymbol{X}_{long}(t)$ denotes the input variable at moment t, $\boldsymbol{H}^{(l)}(t)$ denotes the state value of storage pool in layer l at moment t, and denotes the degree of sparsity of storage pool in layer l at moment t. represents the state value of storage pool in layer *l at* time t, and $SD^{(l)}$ is the sparsity degree of storage pool in layer *l*. The state value of storage pool in layer l at time t is the state value of storage pool in layer l. $\boldsymbol{H}(t)$ The vector formed for the states of all storage pools is denoted as $\left[\boldsymbol{H}^{(1)}(t),\boldsymbol{H}^{(2)}(t),\cdots,\boldsymbol{H}^{(l)}(t)\right]$; $g(\cdot)$ denotes the activation function of the output layer. The DeepESN neural network training process is generally solved by regularized ridge regression.

The core strength of DeepESN is its deep structure, which allows the network to learn features on different time scales. Its cascading structure not only helps to achieve multi-timescale representations, but also improves unsupervised reservoir adaptation and network design. Application scenarios for DeepESN [20-25] include environmentally-assisted living, medical diagnosis, speech and music processing, weather forecasting, energy prediction, transportation forecasting, and financial market forecasting (Fig. 9).

3) DeepESN network model based on hiking optimization algorithm: In order to increase the design effect of the optimal urban water resources allocation scheme, this paper takes the parameters of DeepESN network (storage pool size N_r , spectral radius SR , input scale factor IS , storage pool sparsity SD) as the optimization decision variables, HOA algorithm hiker optimization strategy as the optimization method, and MAPE error value as the fitness function, and the specific process steps are shown in Table II.

TABLE II. HOA-DEEPESN PSEUDO-CODE

Algorithm 2: DeepESN based on HOA	
1	Determine optimized variables, including Nr, SR, IS, SD;
2	Set HOA algorithm parameters;
3	Encode hikers population;
4	Calculate fitness using MAPE, and update best hiker;
5	For i = 1:Np
6	Updated hiker velocity
7	Updated hiker position
8	End
9	Output best parameters of DeepESN;
10	Build HOA-DeepESN model.

C. Application of KPCA and HOA-DeepESN

This study utilizes the KPCA (Kernel Principal Component Analysis) and HOA-DeepESN (Higher Order Autoregressive-Deep Echo State Network) algorithms to identify the main factors affecting urban water resources allocation. The aim is to enhance the effectiveness and precision of water resources optimization and allocation. The specific procedure is illustrated in Fig. 10. The urban water resources optimization allocation method consists of five main components: water resources analysis, extraction of water resources allocation index, principal component analysis of allocation index, preprocessing of allocation index data, and construction of optimal allocation model. These components are based on the KPCA and HOA-DeepESN method.

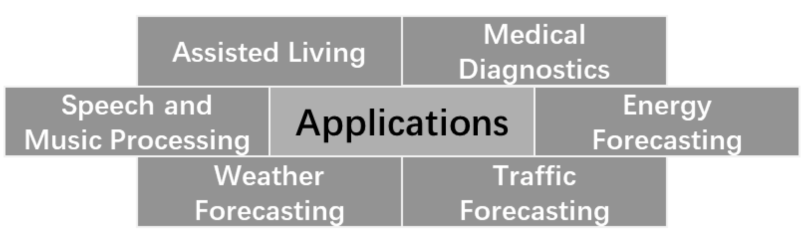


Fig. 9. DeepESN application.

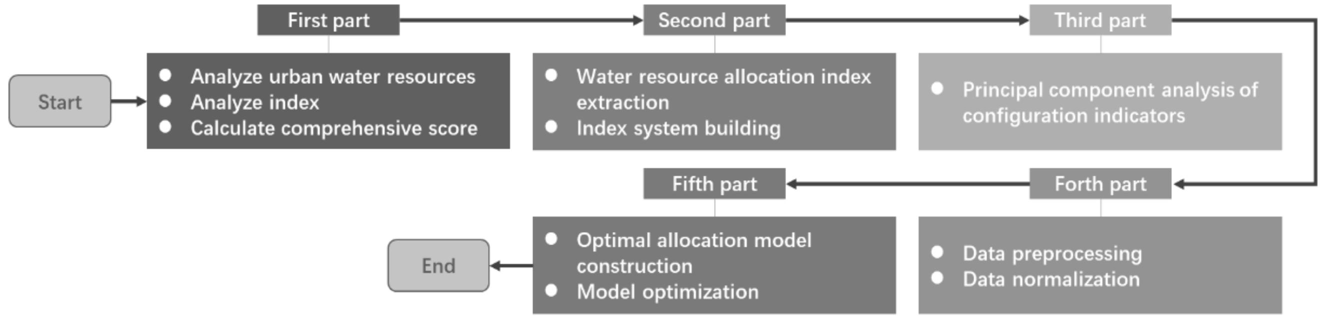


Fig. 10. KPCA with HOA-DeepESN algorithm application.

IV. Case Study

The operating system on which the instance analysis program operates is Windows 10, and the software utilized for the analysis technique is Matlab 2019b. The experiment will utilize the urban water environment resource-related index data from January 2010 to December 2023. The data will be divided into training, test, and validation sets in a ratio of 7:2:1. To analyze the impact of the principal components of the KPCA technique, we will compare the performance of DeepESN, PCA-DeepESN, and KPCA-DeepESN. The specific configurations for these models are described in Table III.

TABLE III. Parameter Settings of the Comparison Algorithm

No.	Algorithms	Descriptions
1	DeepESN	SD=0.7, Nr=100, SR=0.2, IS=0.25, 3layers of AE with 50 nods per layer of AE
2	PCA-DeepESN	PCA technique, 3 layers of AE with 50 nodes in each layer.
3	KPCA-DeepESN	Kernel Principal Component Analysis (KPCA) technique, Radial Basis Function (RBF) was selected, three layers of AE with 50 nodes per layer
4	KPCA-HOA-DeepESN	Kernel Principal Component Analysis (KPCA) technique, Radial Basis Function(RBF) selection, Three layers of AE with 50 nodes per layer, HOA algorithm to optimise DeepESN parameters

This paper aims to validate the effectiveness of the HOA algorithm in enhancing the efficiency of urban water environment resource allocation using the DeepESN network. To achieve this, the SCA, BBO, KMA, and QIO algorithms are employed to optimize the DeepESN network and the HOA algorithm. A comparative analysis of the specific algorithm parameter settings can be found in Table IV. The dimensions of the storage pool, the spectral radius, the input scale factor, and the range of sparsity parameters for the storage pool are displayed in Table V.

TABLE IV. Parameter Settings of Intelligent Optimization Algorithm for Optimizing DeepESN Network

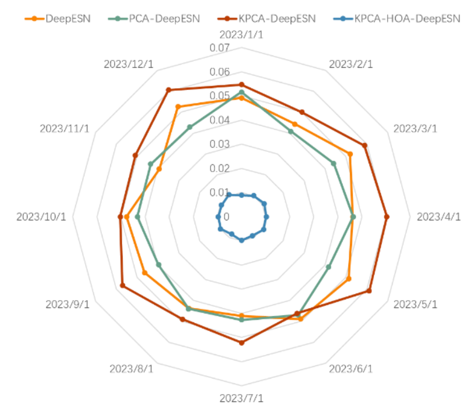
No	Algorithms	Parameter Settings
1	SCA-DeepESN	A reduce linearly 2 to 0
2	BBO-DeepESN	Probability of modifying a habitat is 1
3	KMA-DeepESN	Mlipir rate=0.5, Female mutation rate=0.5, Female mutation radius=0.5
4	QIO-DeepESN	No
5	HOA-DeepESN	Angle of inclination is [0,50], SF=[1,3]

TABLE V. Decision Range Settings for Parameters to be Optimized in the DeepESN Network

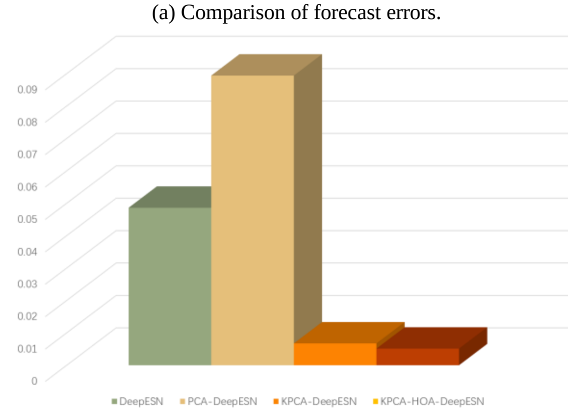
No	Variables	Range Settings
1	Nr	[50,300]
2	SR	[0.4,0.9]
3	IS	[0.1,0.8]
4	SD	[0.1,0.5]

A. Evaluation of the Impact of using the KPCA Approach

This article examines the efficiency of resource allocation in the urban water environment for four models: DeepESN, PCA-DeepESN, KPCA-DeepESN, and KPCA-HOA-DeepESN. The particular connections between these models are illustrated in Fig.11.



(a) Comparison of forecast errors.



(b) Comparison of projected time consumption.

Fig. 11. Comparison of urban water resources prediction error and time-consuming results of different algorithms.

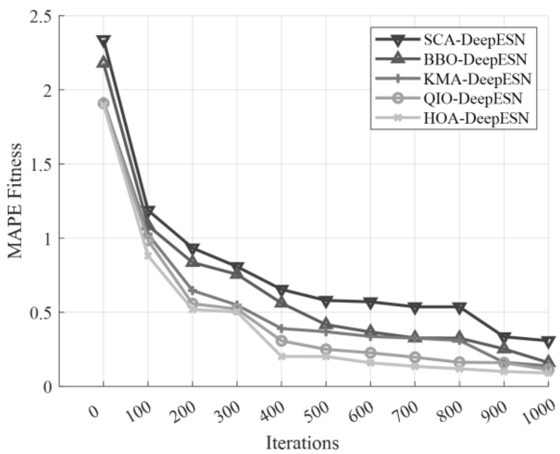
Fig. 11 presents the prediction error and time consumed for urban water allocation for the four algorithms. From Fig. 11, it can be seen that KPCA-HOA-DeepESN has the lowest prediction error among the 12-month prediction errors of the test set; KPCA-DeepESN is compared with PCA-DeepESN, which indicates that the principal component analysis method of KPCA is more effective; and the prediction time consumed by KPCA-HOA- DeepESN is the lowest.

B. *Analysis of the Effectiveness of the Water Resources Optimization Model*

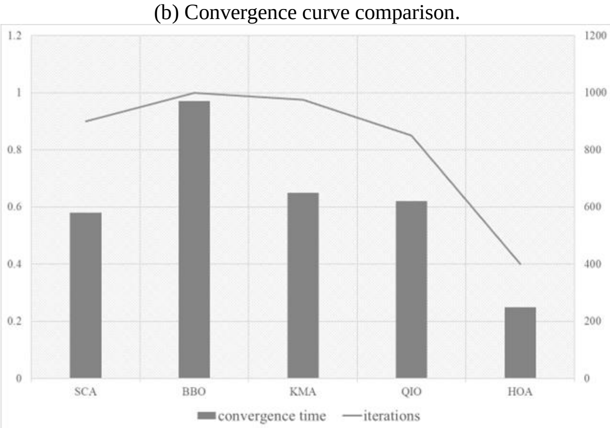
The water resources optimization configuration data is used as input to optimize the DeepESN network parameters using SCA, BBO, KMA, QIO, and HOA algorithms. The optimization results, convergence curves, and speeds are obtained and shown in Fig. 12(a)-(c). According to the Fig. 12, it is evident that the HOA algorithm enhances the optimization of DeepESN network parameters by achieving quicker convergence speed and greater convergence accuracy. The resulting optimized parameters are Nr=140, SR=0.3, IS=0.22, and SD=0.72.

No.	Parameters	SCA-DeepESN	BBO-DeepESN	KMA-DeepESN	QIO-DeepESN	HOA-DeepESN
1	Nr	103	120	145	120	140
2	SR	0.19	0.27	0.33	0.3	0.3
3	IS	0.21	0.26	0.29	0.24	0.22
4	SD	0.79	0.7	0.65	0.7	0.72

(a) Comparison of Optimal DeepESN Network Parameters.



(b) Convergence curve comparison.



(c) Convergence time vs. number of iterations.

Fig. 12. Comparison of optimization results of different algorithms.

V. CONCLUSION AND FUTURE WORK

The HOA-DeepESN method, which integrates KPCA and deep learning techniques, effectively addresses the urban water balance resource allocation problem and enhances the efficiency of the allocation model. This paper begins by examining the optimal allocation problem, taking into account the equilibrium between the supply and demand of water resources. We then use the optimal allocation model to establish a method for urban water resources allocation based on the HOA-DeepESN network. The objective function is defined as the minimum of MAPE, and the optimization decision vector consists of the DeepESN network structure parameters. The proposed method is simulated and analyzed using urban water environment resource data from January 2010 to December 2023. The following conclusions are drawn: (1) The use of the KPCA technique improves the model training, testing, and prediction time. (2) Optimizing the parameters of the DeepESN network using the HOA algorithm enhances the prediction accuracy of the optimal allocation model. (3) The optimal values for the storage pool size, spectral radius, input scale factor, and storage pool sparsity are 140, 0.3, 0.22, and 0.72, respectively.

The study also has several limitations: The model is tested on urban water resource data from a specific period and location. Its performance may vary across different regions or under different environmental conditions. The choice of water resource indicators, though based on widely accepted criteria, may not capture all relevant factors, especially in more complex ecosystems.

Based on the above analysis, we look forward to future research directions, which can be started from the following three aspects: 1), Future studies could apply the KPCA-HOA-DeepESN approach to other geographic locations or sectors to validate its generalizability. 2), Integrating real-time data streams, such as satellite observations or sensor data, could further enhance the precision of the model in dynamic environments. 3), exploring other meta-heuristic optimization algorithms or combining HOA with other methods, like genetic algorithms or particle swarm optimization, could lead to even more robust models for resource allocation.

ACKNOWLEDGMENT

This work is supported by Precision Teaching and Students' Innovative Ability Driven by Data. Teaching Reform Research Project of Hunan General Higher Education Institutions Grant No.HNJG-2231216.

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