International Journal of GEOMATE, April, 2020, Vol.18, Issue 68, pp. 87 - 93
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2020.68.5703
Special Issue on Science, Engineering and Environment

EVALUATING HABITABILITY OF WATER ENVIRONMENTS FOR FIREFLIES WITH AN ARTIFICIAL INTELLIGENCE MODEL

*Shengping Zhang[1] and Jie Qi[2]

[1]Professor, Meijo University, Japan; [2] Professor, Utsunomiya University, Japan

*Corresponding Author, Received: 15 June 2019, Revised: 20 Dec. 2019, Accepted: 11 Feb. 2020

ABSTRACT: This study constructs an artificial intelligence (AI) model to evaluate water environments, and applies an artificial neural network system to this AI model construction. This AI model has been tested in a real urban river basin. The evaluation results based on the model reveal that most parts of the river do not meet its management goal of being suitable for fireflies to inhabit. Therefore, a sensitivity analysis based on the AI Model is carried out to select and rank the river environment improvement measures in terms of the effectiveness of improvement. This study has shown that an AI Model is able to reveal and simulate the complicated relationships between river management goals and diverse river environment factors and also is able to make the sensitivity analysis and the selecting of effective river environment improvement measures much more convenient and reliable. This study will contribute to establishing a more reliable river environment planning and management methodology.

Keywords: Water Environment, Artificial Intelligence (AI), Firefly Habitability, Sensitivity Analysis

1. INTRODUCTION

Water environment evaluation is neccessery not only for water environment planning but also for selecting the most effective and most efficient water environment improvement measures. The traditional water environment evaluation methods can be classified into three groups [1-3].

The most-widely applied water environment evaluation method is the one based on the physical, chemical or biochemical indexes of river water quality, such as PH, Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), and total coliforms. Objectivity is considered to be the most significant and most important character of this method which, however, also leads to critiques that relatively subjective resident/human demands for water environments have not been taken into consideration with this method. Furthermore, this method has only evaluated water bodies with no consideration on the spaces around water bodies, which is why it usually classified as a water quality evaluation method.

In order to maximize the utility of the residents in a river basin, the water environment evaluation method based on the satisfaction of all residents has been applied quite frequently, particularly in urban river planning in which resident satisfaction is the main water environment management goal. Questionnaire survey is the central tool of this method.

The third common method for water environment evaluation is based on the biodiversity of the water environment, which takes the perspective that the water environment is not only for human beings but also for the entire ecosystem.

Every method is suitable for some specific water environment planning goals, and there are no particular standards or characteristics that can be used to distinguish one from the others as good or bad. But there is one very strong common critism which applies to all three methods [3]: each method has only evaluated the final water quality/environment. No direct connections between evaluation results and the causes or related environmental factors inside the river basins have been taken into any consideration in all of the methods although water environment is neccessarily considered as a whole system.

Artificial intelligence (AI) has achieved great successes in a broad range of fields such as image recognition, automatic driving, and gaming due to AI's strong capability to identify causal relations [3, 4]. An AI model is expected to be a powerful analytic tool for water environment evaluation when the water environment of a specific river is considered to be a result caused by all possible water-environment-related factors in the river basin. This study will construct an AI model specifically for water environment evaluation and establish a more reliable methodology for river environment planning and management.

2. ARTIFICIAL INTELLIGENCE MODEL

An artificial intelligence model, specifically a neural network model has been adopted to compose a water environment evaluation method for evaluation or prediction problems due to the suitability of neural network models [4, 5].

2.1 Structure of A Neural Network

A neural network is a network system constructed artificially by idealizing the neurons (nerve cells), and consists of a number of nodes and lines that are called *units* and *connections* (or *links*) respectively. Based on the differences in network structures, neural networks generally are classified into two types: layered networks and interconnected networks. It has been shown that a layered network is suitable for evaluation/prediction problems due to its abilities in learning (self-organization) and parallel processing of information.

Figure 1 shows the structure of a typical layered neural network, which has a layer of input units at the top, a layer of output units at the bottom, and a number of hidden layers between the input layer and the output layer. Connections exist only between the units in the adjacent layers, and connections within a layer or from a higher to lower layers are forbidden.

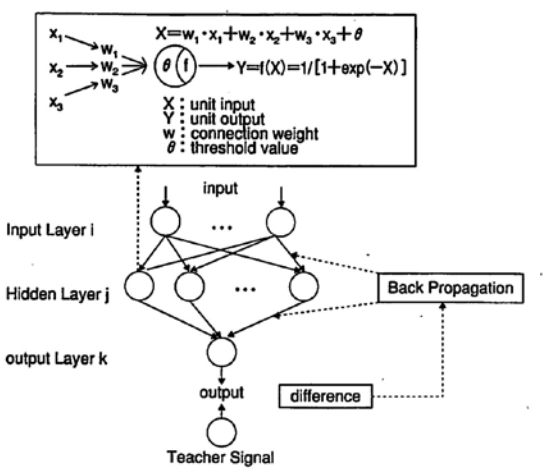


Fig. 1 Structure of a layered neural network.

2.2 Modelling A Neural Network

For the sake of simplicity, consider a neural network consisting of three layers.

Let the unit numbers of the input layer, hidden layer and output layer be N, M, and 1, respectively. When an input $\{I_i,\ i = 1,2,\cdots,\ N\}$ is given to the units of the input layer, the inputs and outputs of the hidden layer units as well as the output layer units are represented as follows.

$$Y_j = f(X_j),\ \ j = 1,2,\cdots,M \tag{1}$$

$$X_j = \sum_{i=1}^{N} w_{ij} I_i + \theta_i \quad ,\quad j = 1,2,\cdots,M \tag{2}$$

$$O = f(Z) \tag{3}$$

$$Z = \sum_{j=1}^{M} w_j Y_j + \theta \tag{4}$$

Where Y_j : output from the unit j of the hidden layer.
X_j : input the unit j of the hidden layer.
$f(\cdot)$: unit output function.
w_{ij}: connection weight between the input layer unit i and hidden layer unit j.
θ_j : threshold value of the hidden layer unit j
O : output from the output layer unit.
Z : input to the output layer unit.
w_j: connection weight between the hidden layer unit j and the output layer unit.
Θ : threshold value of the hidden layer unit j

For the unit output function $f(\cdot)$, some expressions have been proposed. The following Sigmoid function has been applied frequently. However, it is not necessarily the best one in terms of learning efficiency. A testing process for different output functions is strongly suggested.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Theoretically, the neural network model expressed by Eqs. (1) through (5) is able to approximate any non-linear relationship between inputs and outputs with any degree of accuracy by using enough hidden layer units and setting connection weights and thresholds to be appropriate through proper learning processes [5].

2.3 Learning Process of Neural Network Model

For a neural network model, the process of setting the connection weights unit thresholds is called *learning*. The term *learning* here means the self-organization process through which the neural network model automatically adjusts all the parameters (i.e. all the connections and thresholds) to the appropriate values, when a series of samples of input-output data (called teacher data or teacher signals) are shown to the model. If we consider the information processing in a neural network model as a transformation of input data to output data, then model learning can be considered to be a process through which the neural network model gradually becomes capable of imitating the transforming patterns represented by the teacher data.

A lot of learning algorithms have been proposed, and among them the Error Back Propagation Algorithm is the most widely used and most successful algorithm. The following is the summary of the Error Back Propagation Algorithm [6].

Suppose T sets of teacher data are given.

$$\left\{I_1^{(t)}, I_2^{(t)}, \cdots, I_N^{(t)}, O^{(t)};\ t = 1,2,\cdots,T\right\} \tag{6}$$

Notice that the teacher data consists of two parts: the input part $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t = 1, 2, \cdots, T\right\}$ and the output part $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$.

Now consider an initial value

$$w_{ij}^{[k]}, w_j^{[k]}, \theta_j^{[k]}, \theta^{[k]}\ \ ,\ k = 0 \tag{7}$$

for each of the connection weights and threshold values, respectively. Notice that the superscript [k] indicates the number of learning iterations and [k=0] means the initial values for all the parameters directly preceding the start of the learning process. Then the outputs corresponding to the inputs of the teacher data $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t = 1, 2, \cdots, T\right\}$ can be obtained from Eq. (1) ~ Eq. (5). Let these outputs be $\left\{U^{[k](t)};\ t = 1, 2, \cdots, T\ and\ k = 0\right\}$. Clearly, $\left\{U^{[k](t)};\ t = 1, 2, \cdots, T\ and\ k = 0\right\}$ are different from the outputs of the teacher data $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$, and an error function can be defined with the two different kinds of outputs as follows.

$$R^{[k]} = \sum_{t=1}^{T}\left(O^{(t)} - U^{[k](t)}\right)^2,\ \ k = 0 \tag{8}$$

Obviously, $R^{[k]}$ is a function of connection weights and threshold values because $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$ are calculated after all $w_{ij}^{[k]}$, $w_j^{[k]}, \theta_j^{[k]}\ and\ \theta^{[k]}$ are given.

The Error Back Propagation Algorithm makes use of the connection weights and threshold values that minimize the above error function $R^{[k]}$. Usually a non-linear programming method is required to solve the optimization problem along with an iteration process in order to obtain the optimal (but possibly suboptimal) connection weights and threshold values. The final iteration procedures derived from a non-linear programming method known as the Method of Gradient Descent are as follows.

$$w_j^{[k+1]} = w_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot Y_j^{[k](t)}\right) \tag{9}$$

$$\theta^{[k+1]} = \theta^{[k]} - \eta \cdot \sum_{t=1}^{T}\delta^{[k](t)} \tag{10}$$

$$w_{ij}^{[k+1]} = w_{ij}^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)} \cdot I_i^{(t)}\right) \tag{11}$$

$$\theta_j^{[k+1]} = \theta_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)}\right) \tag{12}$$

where the superscript [k] indicates the number of learning iterations as mentioned earlier, and η is a small positive number that indicates the step size of the Method of Gradient Descent for optimization iteration process, and we have set $\eta = 0.25$ in this study. The other variables which occurred in the final learning procedures are defined as follows.

$$\delta^{[k](t)} = (O^{(t)} - U^{[k](t)}) \cdot O^{(t)} \cdot (1 - O^{(t)}) \tag{13}$$

$$\gamma_j^{[k](t)} = Y_j^{[k](t)} \cdot \left(1 - Y_j^{[k](t)}\right) \tag{14}$$

In order to avoid the overfitting (or over-learning) problem, a criterion is usually required to make a judgement when the iterative learning process should be terminated. In this study the learning process will be stopped when the Mean Relative Error (MRE) of the outputs is less than a specified relative error expectation for prediction/evaluation results, which is a common treatment for a learning process of teacher data with random errors (i.e. white noise). In this study we have set the error expectation to 2%, which is considered an accuracy that is good enough for the expected result in this study. Needless to say, this error expectation should be set according to the required accuracy of the problem which is being dealt with.

2.4 Verification of Neural Network Model

The proposed neural network model has been verified by applying it to an urban daily water demand prediction problem [7], which has been studied with several different models, and for which there is clarity regarding what is a good or an acceptable prediction for daily water demand. We will examine whether the proposed neural network model is able to predict daily water demand with the same or even higher accuracy by using the same information as the other prediction models used.

Specifically, the neural network model has been compared with three different prediction models: Multiple Regression Model [8], ARIMA (Auto-Regressive Integrated Moving Average) Model [9, 10] and Kalman-Filtering Model [10]. All the models used the same daily water delivery records from April 1982 to March 1990 for a city in Japan, the weather information during the same time period and each day's characteristics (weekday or weekend/ national holiday) to calibrate or identify the model parameters. This historical data is used because the comparison models are composed with these data. For the neural network model, these records are used as the teacher data to train the model. As for the weather information, the records of daily high temperature, weather (sunny, cloudy or rainy) and daily precipitation are included.

Three accuracy indexes have been applied to compare the models to identify which model is able to give the most accurate prediction for daily water demands. Mean Relative Error (MRE, %) is a very straight index: the smaller the Mean Relative Error is, the better the predictions are. Correlation Coefficient (CC) between predictions and records indicates how good the predictions are: the predictions are perfect when CC=1.0, and the predictions are totally random when CC=0. Relative Root Mean Square Error (RRMSE) are similar to CC and reflect how good the predictions are: RRMSE=0 for perfect predictions and RRMSE=1 when all the predictions are equal to the mean of the records.

Table 1 shows the prediction accuracies of daily water demands over the course of a year for the same city from April 1991 to March 1992 by different models. The neural network model gave the best predictions by far in terms of all the three accuracy indexes. The improvement magnitudes of prediction accuracy in each index show the reliability and the potential of the neural network model.

Table 1 Prediction accuracy comparison of different models.

Model	MRE(%)	CC	RRMSE
Multiple Regression Model	2.90	0.764	0.659
ARIMA Model	2.80	0.794	0.623
Kalman Filtering Model	2.69	0.808	0.599
Neural Network Model	2.13	0.877	0.483

In order to understand the error structure of the predictions given by the neural network model, the prediction error distribution is shown in Table 2, and the possible causes have been examined for the 5 days which have a prediction relative error greater than 10%, which is shown in Table 3. Per Table 3, the largest prediction error was yielded when important information that affected daily water demands was missed. In other words, prediction accuracy is expected to be further improved when this missed information, such as typhoon, continuous rain periods, extreme weather events or atypical days, are taken into consideration by including all of them into the teacher data for neural network training. This demonstrates that careful teacher data hunting is important in artificial intelligence application research.

Based on these results, it is reasonable to conclude that the proposed neural model is a reliable and capable tool in information processing of data. In the next section we will apply this neural network model to river environment evaluations and predictions in order to provide better information for water environment planning and management.

Table 2 Relative error distribution of the predictions made by the Neural Network Model

Relative Error Range (%)	No. of Days	Composition (%)
[0.0, 3.0)	278	76.2
[3.0, 5.0)	61	16.7
[5.0, 8.0)	19	5.2
[8.0, 10.)	2	0.5
[10. , ∞)	5	1.4

Table 3 The possible causes for the days with a relative error more than 10%.

Date	Demand prediction (m^3/day)	Delivery record (m^3/day)	Relative error (%)	Possible causes
May 5	354.5	320.0	10.8	The last day of Japanese holiday “Golden Week” and sunny after a rainy week.
Sept. 17	364.9	319.5	14.2	Hit by typhoon.
Oct. 5	362.9	315.0	15.2	Heavy rain. (105.5mm/day)
Oct. 7	361.4	404.4	10.6	Sunny after 5 continuous rainy days.
Jan. 2	358.5	315.0	13.8	New Year Holiday and sunny.

3. TRAINING OF NEURAL NETWORK MODEL

3.1 Teacher Data

The neural network model proposed above is now ready to be applied to a water environment evaluation problem, which is the purpose of this study. As for the water environment evaluation index, the habitability of a water environment to Genji fireflies (*Luciola cruciate*) is adopted. Genji fireflies are highly prized in Japanese culture, and are widely regarded as a symbol for a good water environment. Firefly habitability has even been adopted as a river environment management goal in many urban river basins in Japan.

As for the factors that affect the habitability of fireflies, five highly critical factors have been selected to be included in the teacher data although there are many factors that impact firefly habitability [11]. Additionally, these five factors have been selected because they are the main changeable factors through common river environment improvement measures. The five factors are 1) Concentration of Dissolved Oxygen (DO), 2) Brightness of lighting during nighttime, 3) Inflow of sewage, 4) Riverbed situation, and 5) Type of revetment construction.

3.2 Quantification of Habitability and Factors

Firefly habitability and related factors have been quantified by utilizing information and knowledge about Genji fireflies from existing research [11, 12].

First, firefly habitability is treated as a continuous variable which ranges from 0.0 (for extremely unlivable water environments) to 1.0 (for an idealistic water environment). Then, all the factors are categorized although most are usually measured quantitatively as a continuous figure. This resolves the issue that the same number can mean different things for different rivers. For example, the sewage inflow rate 1.0 *ton/hour* is an extremely strong pollution source for small urban rivers, but could mean almost nothing for a river with a flow rate of more than 100 m^3/s.

As an example, Concentration of Dissolved Oxygen (DO) is categorized as 1 for a DO saturated situation, 0 for the DO concentration above 6.8 *mg/l* (which means a livable environment for fireflies), and -1 for the DO concentration below 6.8 mg/l (which means an undesirable/deadly living environment). In the same way, the other four factors are also categorized as shown in Table 4.

Table 4 Factor Quantification

Factor	Category	Meaning
Concentration Of Dissolved Oxygen (DO)	1	DO saturated
	0	≥6.8*mg/l*, livable
	-1	<6.8*mg/l*, undesirable
Inflow of sewage	1	No sewage inflow
	0	A small amount of inflow
	-1	Constant inflow
Brightness Of lighting	1	Dark (no artificial light)
	0	Relatively dark
	-1	Bright
Riverbed situation	1	Natural riverbed with soil, sands or pebbles
	-1	Artificial riverbed
Type of revetment construction	1	Natural
	0	Partially natural
	-1	Artificial

Table 5 Teacher data samples.

Concentration of DO	Inflow of sewage	Brightness of lighting	Riverbed situation	Type of revetment	Habitability
0	1	1	1	0	0.915
-1	1	1	1	0	0.000
1	0	1	1	0	0.875
0	0	1	1	0	0.865
-1	0	1	1	0	0.000
1	-1	1	1	0	0.000
1	1	1	1	1	1.000

The firefly habitability and the five related factors together make the teacher data. Samples of teacher data which are used in this study are shown in Table 5. 162 teacher data have been collected from a variety of research references on Genji firefly habitability [11, 12].

3.3 Training of Neural Network Model

The neural network model has been trained (put under a learning process) with the collected teacher data. The training process is based on the learning procedures as explained before, but it is still a process of trial and error because there are still a lot of details that remain undecided, such as a suitable step size of optimization, a suitable output function, an efficient order to present the teacher data to the neural network model, and a proper initial network size (layers and units in each layers). An experienced AI engineer may be able to assist in accelerating the learning process.

Figure 2 shows the reproduction accuracy of the teacher data with the trained neural network model. Here the reproduction accuracy is represented by the absolute error between the habitability in the teacher data and the habitability generated with the trained neural network model. Based on the results in Fig. 2, there are only 6 out of 162 teacher data that have the same order of absolute error as the smallest significant figure (±0.001) of habitability, and all the 156 teacher data have an error less than the smallest significant figure, which means that the trained neural network model is able to reproduce the teacher data with almost no errors. In the next section, this well-trained neural network model will be used to evaluate the firefly habitability of an urban river.

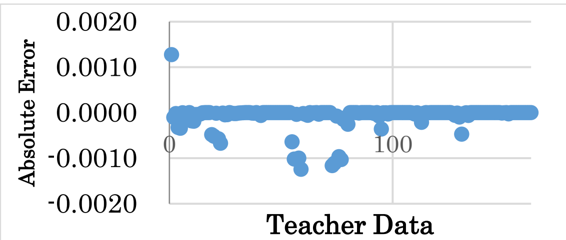


Fig. 2 Reproduction accuracy of teacher data

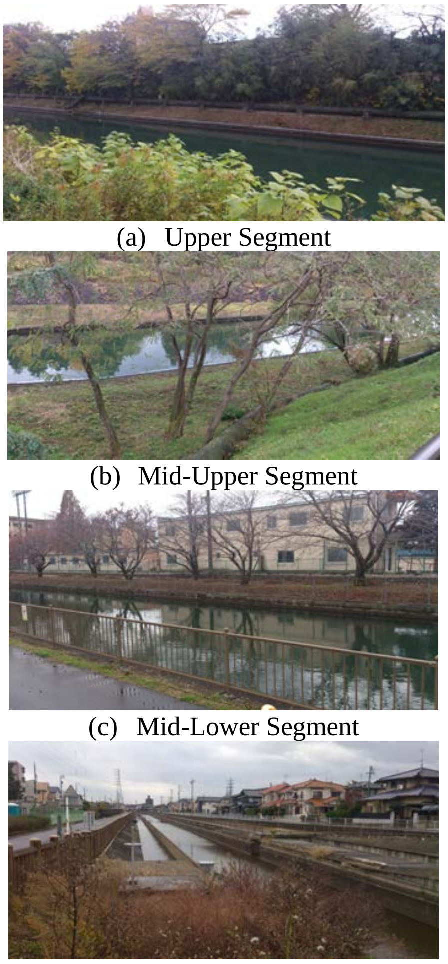
4. WATER ENVIRONMENT EVALUATION

4.1 Firefly Habitability of Aise River

The trained neural network model has been applied to evaluate the firefly habitability of Aise River. Aise River passes through Inuyama City in Aichi prefecture, Japan, and is a typical urban river which receives sewage and urban drainage. Aise River also receives fresh water inflow at its uppermost location from Kisogawa River, a regional water supply source with a high flow rate. The fresh water from Kisogawa River has improved the water environment of Aise River in its upper segments significantly, but the improvement effects have been gradually cancelled out by the constant sewage inflow when the river runs downstream. In this study, Aise River has been divided into four segments according to the present water environment: upper, mid-upper, mid-lower and lower. Fig. 3 shows the images of the four segments of Aise River.

The present water environment factors of Aise River and its firefly habitability yielded by the trained neural network model are shown in Table 6. The evaluation results can be summarized as follows.

- The upper segment of Aise River is a habitat very suitable to Genji fireflies.
- The habitability has decreased sharply downstream.
- The mid-lower and the lower segments of Aise River are no longer habitable to Genji fireflies.



(a) Upper Segment

(b) Mid-Upper Segment

(c) Mid-Lower Segment

(d) Lower segment

Fig. 3 Images of Aise River

The above conclusions derived from the evaluation results that are given by the trained neural network model match well with the observation that there are no fireflies during summer along the mid-lower and lower segments of Aise River for many years.

Table 6 The firefly habitability of Aise River

Location	Concentration of DO	Inflow of Sewage	Brightness of lighting	Riverbed situation	Type of revetment	Habitability
Upper	1	1	1	1	1	0.999
Mid-Upper	1	1	0	1	0	0.874
Mid-Lower	1	0	0	1	-1	0.471
Lower	1	-1	-1	-1	-1	0.003

4.2 Sensibility Analyses of Factors

The trained neural network model has also been used to carry out a sensibility analysis for all the factors related to firefly habitability. The sensibility coefficient of a factor is defined as the partial derivative of the habitability regarding the factor as follows.

$$S_i = \frac{\partial O(X_1, X_2, \cdots, X_N)}{\partial X_i} \Big|_{present\ factor\ values} \qquad (15)$$

S_i is the sensitivity coefficient of factor X_i at the present factor values. For all the factors, the sensitivity coefficients have been calculated and shown in Table 7. The whole number 0 means a coefficient value less than the smallest significant figure.

Table 7 Sensibility coefficients of factors.

Location	Concentration of DO	Inflow of Sewage	Brightness of lighting	Riverbed situation	Type of revetment
Upper	0.0003	0.0042	0.0016	0.0002	0.0016
Mid-Upper	0.0749	0.0585	0.4608	0.1195	4.4079
Mid-Lower	0.0010	0	0.0002	0.0002	0.0011
Lower	0	0	0	0	0

For the upper segment of Aise River, all the factors have a relatively small sensibility coefficient, which is because the present values of all the factors are good enough and there is no room for further improvement.

For the mid-lower and lower segments, all the factors also have a relatively small sensibility coefficient, which is because the present values of all the factors are so poor that a small improvement will not make a meaningful change in firefly habitability along these river segments.

For the mid-upper segment, the revetment has a large sensitivity coefficient, this indicates that improving the present revetment (partially natural) will increase the firefly habitability significantly. The brightness factor also has a large sensitivity coefficient, which means that removing all the artificial lighting will improve the firefly habitability. The other three factors all have a relatively small sensitivity coefficient, which is because the present values of these factors are already good, and there is no need for further improvement.

4.3 Selecting Improvement Measures

The evaluation results of firefly habitability along with the sensibility analysis results have drawn a clear picture about the most effective water environment improvement measures, which can be summarized as follows.

- For the upper segment, no improvement measures are necessary because the present situation is already good enough.
- For the mid-upper segment, changing the revetment into natural revetment and removing all the artificial lighting are expected to raise firefly habitability significantly.
- For the mid-lower and lower segments, significant improvement for all factors are necessary because a small change for either factor is not expected to cause any meaningful improvement in firefly habitability due to the poor situation at present.

5. CONCLUSIONS

With the purpose of developing a better methodology for water environment planning and management, a neural network model has been proposed for water environment evaluation in this study.

The neural network model was tested with the daily water demand prediction problem, a well-studied problem suitable for testing. The test has shown the reliability and potential of an artificial intelligence model.

The verified neural network model was applied to a water environment evaluation problem, specifically the Genji firefly habitability problem. The application results have shown that, with a neural network model, not only can the environment of an urban river be evaluated with a high level of accuracy and detail, but also that the most effective environment improvement measures can be clearly identified. These results demonstrate that artificial intelligence is an effective and efficient tool for water environment evaluation.

The firefly habitability was studied with only select critical factors in this study, which is insufficient for genuine habitability research because there are many other factors which affect firefly habitability. The factors were limited to the critical ones due to the limitations of data hunting. This illustrates that one of the significant challenges of practical research on artificial intelligence applications will be the gathering of teacher data. In spite of these difficulties, artificial intelligence is a promising tool for water environment planning and management.

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