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# ESTIMATION THE BOD OF WASTEWATER BY USING THE NEURAL NETWORKS (ANN)

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**Abstract -** Now days Artificial Neural¥ Networks (ANNs¥) have been operated rapidly to predict water resources. Using Feed-forward ¥ neural network modeling method is the most frequently used ANN style in wastewater uses. The main goal of this paper is to examine the abilities of an (ANNs) model to develop the accuracy of the biological oxygen demand (BOD) prediction. Many of the water quality variables such as Chemical oxygen demand (COD), dissolved oxygen (DO) and (TOC) that will affect biological oxygen demand concentrations were collected at 698 sampling sites in treatment plant of the industrial city of Jeddah 2014-2017. Evaluation of outcomes reveals that the ANN ¥ model presents reliable result for the BOD prediction. The results shown that, According this model, it was found R for (training = 0,93, test = 0,87 and validation = 0.83). In this case, the network response is satisfactory and both ANN and MLR evaluations follow the consequent experimentally calculated data with a considerably high R value of training 0.93 and R of validation 0.83, R of test 0.87 and R of all 0.91, individually. Additionally ANN statistically outperforms MLR in terms of BOD assessment. It is concluded that, ANN¥ supplies an effective analyzing and identifying tool to understand and simulate the plant, and is used as a appreciated performance valuation tool for plant machinists and decision makers

## 1. Introduction

Industrial and municipal wastewaters are main infection foundations of aquatic biota, accounting for numerous thousand categories of chemicals discharged into the environment. Consequently, the importance of realizing efficient observing and control methods for wastewater treatment procedures is well known. A reliable pattern for any wastewater treatment plant is fundamental in order to supply a tool for predicting its performance and to form a source for controlling the process of the procedure. This procedure is complicated and attains a high amount of nonlinearity due to the presence of bio-organic constituents that are hard to model by using mechanistic tactics. Predicting the plant's operational parameters using conventional experimental methods, is also an inefficient step and an obstacle in the way to a resourceful control of such processes.

Biochemical€ oxygen demand€ (BOD) is one€ of the main factors for wastewater management and planning. It is an estimated measure of the quantity of biochemical degradable organic matter current in a water sample. It is described as the amount of oxygen necessary for the aerobic microorganisms present in the sample to oxidize the organic material to a stable organic form. The oxygen consumption from degradation of biological material is normally determined as biochemical oxygen demand (BOD) and chemical oxygen demand (COD), so around is an significant relation among them. Presenting the test for BOD demands significant time and commitment for arrangement and analysis. This procedure requires five days, with data collection and assessment occurring on the last day (1).

Some water quality patterns such as traditional mechanistic methods have been progressed in order to achieve the best practices for conserving the characteristic of water. Most of these patterns need numerous different input data, which are not simply accessible and make it a very expensive and time-consuming procedure.

Artificial€ neural networks (ANNs) are computer techniques that attempt to simulate the functionality and decision-making procedures of the human brains. In the previous few periods, ANNs€ have been generally used in a large variety of engineering applications. Recently, ANNs€ have been progressively functional in modeling water value. ANNs[ have been effectively used in hydrological procedures, water resources, water value prediction, and reservoir process (2) (3). They have been used specifically for the forecasting of water quality parameters and estimating nutrient attentiveness from pollution foundations of watershed (4) (5).

The research presented in this study is interested by a require to explore the potential of ANN estimation of biochemical oxygen demands (BODs) of the input stream of a biochemical wastewater management plant. Various of the water characteristic variables such as Chemical oxygen demand (COD), dissolved oxygen (DO) and (TOC) that will assume biological oxygen demand concentrations were assembled from 698 sampling sites in treatment plant of the industrial city of Jeddah 2014-2017. Comparison of outcomes reveals that the ANNs models gives reliable result for the BOD prediction.

The ANN would be preferably suited for assessing inlet BOD owing to its facility to provide good generalization implementation in capturing nonlinear regression relationships among predictors and the predicted. The implementation of the ANNs standard are compared with multiples linear regression (MLR€). Evaluation of the results shows that the ANN standard is statistically greater to the MLR standard (6).

## 1.1 An Artificial Neural Network (ANNs)

An Artificial Neural Networks (ANNs¥) is a mathematical pattern that attempts to simulate the assembly and functionalities¥ of biological neural¥ networks. Elementary structure block of each artificial¥ neural networks (ANNs¥) are artificial neuron, that is, a simple mathematical pattern (function). Such a pattern has three simple sets of rules: multiplications, summations and activations. At the access of artificial neuron, the inputs data are weighted which means that each inputs values is multiplied with separate weight. In the central section of artificial neuron is sum function that calculations all weighted inputs and bias. At the exit of artificial neuron the sum of previously weighted inputs and bias is delivering through activation function that is also named transfer function ( **Error! Reference source not found.**) (7).

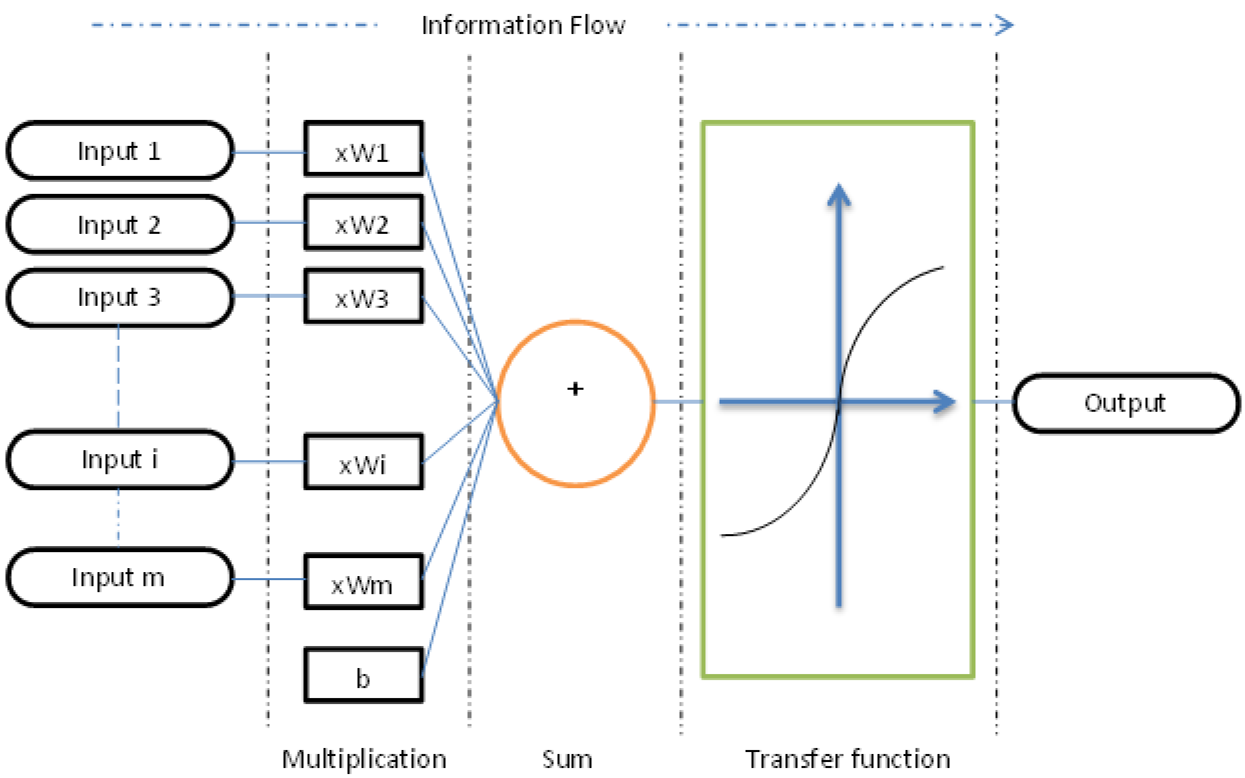


Figure 1 AN principle working

While the AN principles working and simple set of procedures of artificial neuron (AN) looks similar nothing unusual the full potential and estimation power of these patterns approach to life once we beginning to intersect them into artificial€ neural networks (ANNs) ( Figure 1 . Example of simple ANN ). These artificial€ neural networks (ANNs) use simple detail that difficulty can grow out of simply few intricate and simple rules (8) (9).

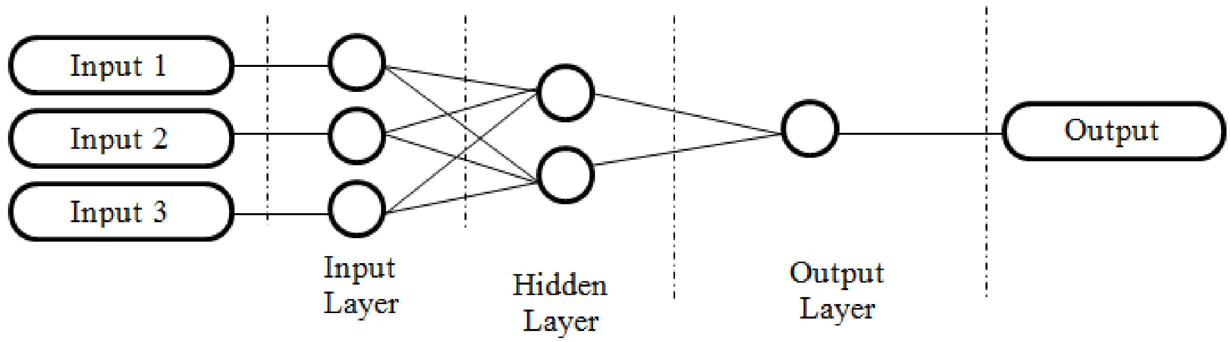


**Figure 1 . Example of simple ANN**

In order to completely produce the benefits of mathematical complication that can be accomplished during interconnection of separate artificial¥ neurons and not just creating system complicated and unmanageable. We frequently do not intersect these artificial¥ neurons randomly. In the early, investigators have come up with numerous "standardized" features of artificial¥ neural networks. These predefined features can assistance us with simpler, quicker and more helpful problem solving. Another types of artificial¥ neural network features are matched for solving different types of difficulties. After concluding the type of assumed problem we necessity to decide for topology of artificial¥ neural network, we are successful to use and then perfect it. We essential to perfect fine-tune the topology itself and its factors (10) (11).

Perfect-tuned topology of artificial€ neural network does not require which we can beginning using our artificial€ neural network, it is only a requirement. Before we can use our artificial¥ neural network, we essential to teach it solving the kind of assumed problem. Just as biological neural€ networks can study their behavior / replies on the foundation of inputs which they get from their background of the artificial¥ neural networks can do the similar. There are three main learning models: managed learning, unmanaged learning and reinforcement learning. We indicate learning model similar as we chose artificial€ neuron network topography€ - based on the problem we are attempting to solve. While learning paradigms are different in their rules that they all have one object in common; on the foundation of "learning data" and "learning rules" (selected cost function) artificial¥ neural network is attempting to realize proper output response in agreement of input indications (12).

Subsequently selecting topology of an artificial€ neural network, perfect-tuning of the topology and after artificial€ neural networks have learn a proper behavior, we may beginning using it for solving assumed problem. Artificial € neural networks have been in application for some time now and we may discovery them working in regions such as process controls, chemistry, gaming, radar systems (RS), automotive industry (AI), space industry (SI), astronomy, genetics , banking, fraud detection, etc. and solving of difficulties like corresponding approximation, regression analysis, time series prediction, classification, pattern recognition, decision making, data processing, filtering, clustering, etc., naming a few (13) (14).

## 2. Methodology

### 2.1 Data collection

Artificial€ Neural Network ANN model was progressed to simulate of EL AGAMY WWTP€. This plant is a sequencing secondary treatment systems use a biological process located Jeddah Industrial city that serve the industrial area with a design capacity of 2500,000 m3/d and achieves a secondary treatment to meet the General Authority for Meteorology and Environmental Protection (GAMEP) effluent-standards for the treated sewage. Measurements of the COD, BOD, TOC, S.S,PH, and TSS were collected over a 3-year period. This period was acceptable as it faces all possible seasonal differences in the reviewed variables.

**Table 1 wastewater characteristics in Al-AGAMY WWTP**
**(source: American public health association (APHA))**

| Kind | characteristics |
|---|---|
| **Color** | Gray |
| **Odor** | Musty |
| **Dissolved oxygen (DO)** | > 1.1 mg/L |
| **pH** | 6.4 – 9.1 |
| **TSS** | 100 - 350 mg/L |
| **BOD5** | 150 - 350 mg/L |
| **COD** | 250 - 550mg/L |
| **Total Nitrogen** | 25 - 95 mg/L |
| **Total Phosphorus** | 7 - 22 mg/L |
| **Fecal Coliform** | 400,000 - 3,000,000 MPN/100 mL |

### 2.2 Parameters of Network

The neural network prototype was examined in MATLAB version 2004. Import, create, use, and export neural networks data was open on MATLAB Toolbox. The Network properties are as following below:

- Network inputs: TOC, S.S, pH, COD, BOD and TSS.
- Network outputs: BOD.
- Network type: Feed-Forward Back Propagation.
- Training€ function: TRAINLM.
- Adaption€ learning function: LEARNGDM€.
- Performance function€: MSE.
- Number of hidden layers: 2,3,4 used respectively
- Input Layer Transfer function: logsig, purelin and tansig
- Output Layer Transfer function: purelin

The design or architecture of an ANN model is classified by quantity of layers and number of neurons for each layer. In this study it was used diverse numbers of hidden layers and neurons in each hidden layer to catch out the greatest proper model. For getting best result on ANN model in this case a trial and error method of nine different architectures was used. The structures considered present a similar number of neurons in each shrouded layer, extend from seven to eleven. These structures as takes below:

with two concealed layer were [5-7-7-1], [5-8-8-1], [5-9-9-1] and [5-10-10-1];

with three shrouded layers were [5-7-7-7-1], [5-8-8-8-1], [5-9-9-9-1] and [3-10-10-10-1]

with four shrouded layers were [5-7-7-7-7-1], [5-8-8-8-8-1],[5-9-9-9-9-1] and [3-10-10-10-10-1].

In request to estimate the performance of each architecture the correlation coefficient (R¥) was used.

Results & Discussion

Artificial Neural Network technique, which is formerly used in several modeling researches, is used in this study for estimating BOD values of influent wastewater in ICDOC WWTP. MATLAB program was used for performing the process. trainlm - Levenberg–Marquardt function model were used for training. The MATLAB software randomly divides input variables and target samples into three groups. 60 % of the experiments are assumed to the training sets 20¥ % to the validation set, and 20¥ % to the¥ test set. Several changed functions such as "logsig", "tansig", and "purelin" were used in the experiment for testing as transfer function for hidden layer and "purelin" function was used as the output layer (harvest) transfer function.

**Table 2 Summary of training and transfer functions used for removal efficiency**

| Transfer Functions | Training Functions | training | validation | test | all |
|---|---|---|---|---|---|
| Logsig | 7 | 0.84041 | 0.90573 | 0.85013 | 0.85474 |
| Purelin | | 0.68798 | 0.7707 | 0.59576 | 0.68726 |
| Tansig | | 0.90558 | 0.8264 | 0.84072 | 0.88469 |
| Logsig | 8 | 0.86861 | 0.83954 | 0.70483 | 0.84237 |
| Purelin | | 0.69372 | 0.67492 | 0.57523 | 0.67187 |
| Tansig | | 0.90169 | 0.88648 | 0.77962 | 0.88191 |
| Logsig | 9 | 0.85754 | 0.66459 | 0.68727 | 0.80134 |
| Purelin | | 0.69942 | 0.56202 | 0.72703 | 0.68564 |
| Tansig | | 0.86759 | 0.89342 | 0.83952 | 0.86805 |
| Logsig | 10 | 0.89112 | 0.80119 | 0.86002 | 0.87203 |
| Purelin | | 0.66816 | 0.71986 | 0.72076 | 68423 |
| Tansig | | 0.84589 | 0.77228 | 0.85117 | 0.83754 |

Learngdm function was controlled as the alteration learning function and (R) was operated as the performance function. The network models used with different neurons (7-10), handover functions and number of ANN configuration mentioned section 2. The correlation coefficient (R) values related to these unlike ANN configuration's the marks and result values are presented in Tables (Table 2 Summary of training and transfer functions used for removal efficiency) (Table 3 Summary of training and transfer functions used for removal efficiency) (

Table 4 Summary of training and transfer functions used for removal efficiency) in details.

Models were aimed to generate the maximum correlation coefficient (R) values with 7-10 neurons¥ in hidden layers and tansig, logsig and purelin transfer functions.

The proper training algorithm at dissimilar layers, the number of hidden layers and number of neurons¥ determination of the transfer and training functions are highly responsive parameters in the design of artificial¥ neural networks¥. Different ANN¥ architectures were tried for best result.

The optimal network size was selected from the one which resulted in maximum R to training and test data sets and the architecture of the best ANN models for the prediction of the TSS of the ICDOC is shown in

Table 4 Summary of training and transfer functions used for removal efficiency. According this model, it was found R for ( training = 0,93, test = 0,87 and validation = 0.83). In this case, the network response is satisfactory.

**Table 3 Summary of training and transfer functions used for removal efficiency**

| Transfer Functions | Training Functions | training | validation | test | all |
|---|---|---|---|---|---|
| Logsig | 7 | 0.85552 | 0.76425 | 0.82941 | 0.83598 |
| Purelin | | 0.73374 | 0.71441 | 0.66057 | 0.71765 |
| Tansig | | 0.8434 | 0.87102 | 0.71022 | 0.82873 |
| Logsig | 8 | 0.91278 | 0.85105 | 0.79016 | 0.88322 |
| Purelin | | 0.71488 | 0.73539 | 0.72449 | 0.71894 |
| Tansig | | 0.89129 | 0.81898 | 0.74868 | 0.86308 |
| Logsig | 9 | 0.84925 | 0.75853 | 0.79685 | 0.82789 |
| Purelin | | 0.71139 | 0.74379 | 0.73889 | 0.71787 |
| Tansig | | 0.92521 | 0.84001 | 0.72857 | 0.88129 |
| Logsig | 10 | 0.91462 | 75039 | 0.80059 | 0.87154 |
| Purelin | | 0.67871 | 0.78668 | 0.81643 | 0.71833 |
| Tansig | | 0.87427 | 0.82074 | 0.82621 | 0.85937 |

Table 4 Summary of training and transfer functions used for removal efficiency

| Transfer Functions | Training Functions | training | validation | test | all |
|---|---|---|---|---|---|
| Logsig | 7 | **0.92629** | **0.83239** | **0.87219** | **0.90545** |
| Purelin | | 0.73399 | 0.64165 | 0.71493 | 0.71562 |
| Tansig | | 0.81576 | 0.18326 | 0.73943 | 0.80149 |
| Logsig | 8 | 0.892002 | 0.7623 | 0.85706 | 0.86294 |
| Purelin | | 0.73007 | 0.67814 | 0.68602 | 0.71674 |
| Tansig | | 0.85063 | 0.85816 | 0.74921 | 0.83622 |
| Logsig | 9 | 0.84105 | 0.79559 | 0.83903 | 0.83229 |
| Purelin | | 0.7036 | 0.7421 | 0.76387 | 0.71952 |

| | | | | | |
|---|---|---|---|---|---|
| **Tansig** | | 0.90832 | 0.80954 | 0.85093 | 0.88361 |
| **Logsig** | 10 | 0.8419 | 0.77886 | 0.70045 | 0.82109 |
| **Purelin** | | 0.762727 | 0.59231 | 0.58608 | 0.71352 |
| **Tansig** | | 0.87054 | 0.86912 | 0.76717 | 0.85499 |

The implementation of the selected neural¥ network model and MLR¥ in predicting BOD¥ is established in Figure 3 for the test data set. As can be seen from Figure 3, both ANN and MLR evaluations follow the consequent experimentally calculated data with a considerably high R value of training 0.93 and R of validation 0.83, R of test 0.87 and R of all 0.91, individually. Additionally ANN statistically outperforms MLR in terms of BOD assessment.

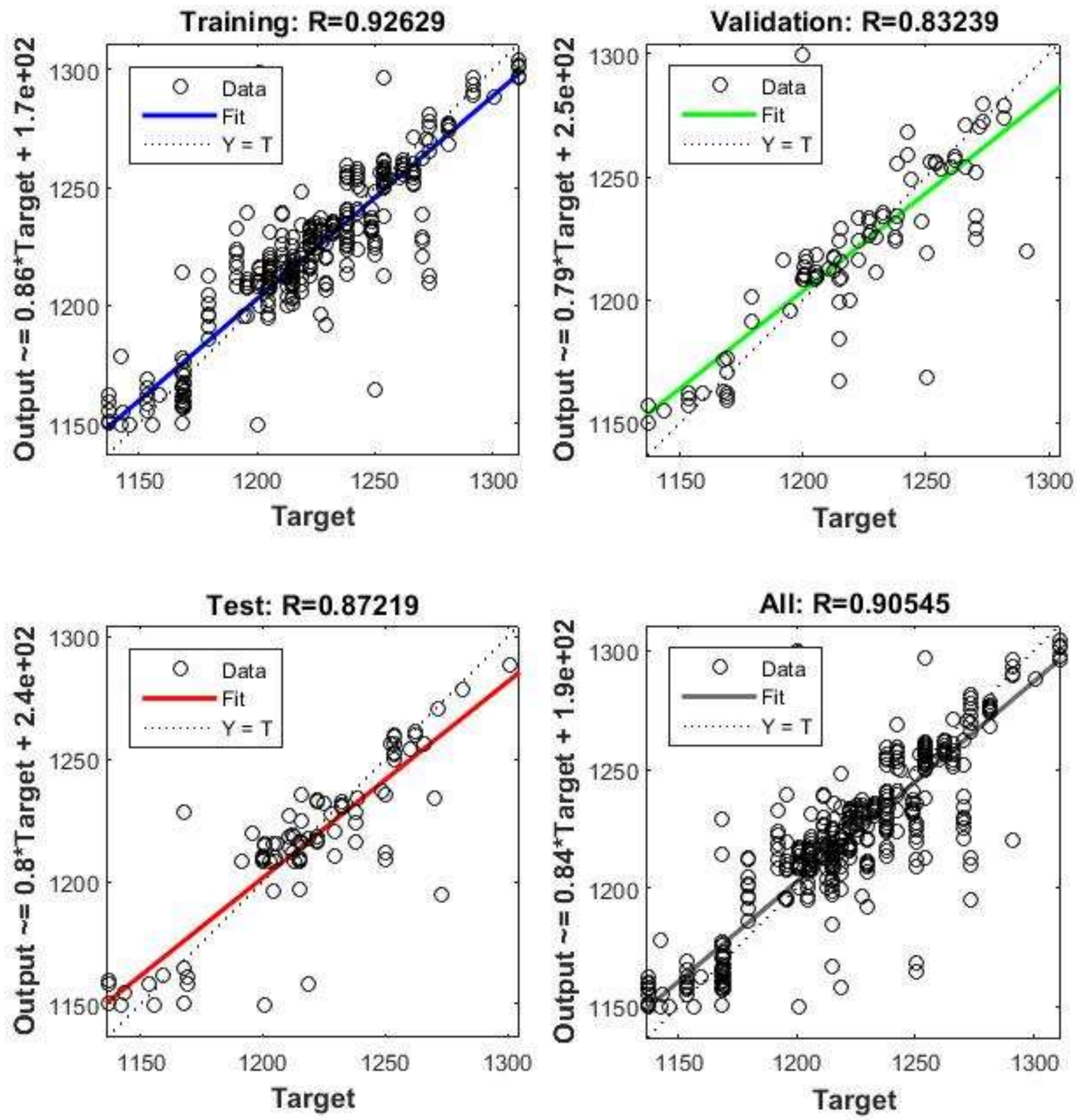


**Figure 2 The observed and estimated of BOD**

## 3. Conclusions

The outcomes of this study presented maximum correlation¥ coefficient (R¥) among the calculated and predicted output variables, accomplishment up to 0.93. Therefore, the model established in this work has an satisfactory outcome and accuracy. As a result, the neural¥ network modeling could successfully predict the performance of ICDOC.

It is concluded that, ANN¥ supplies an effective analyzing and identifying tool to understand and simulate the plant, and is used as a appreciated performance valuation tool for plant machinists and decision makers.

This signifies which all these variables are necessary for improved BOD¥ modeling. The MLR¥ model was similarly used for predicting BOD¥. However, the effectiveness of the objective parameters was presented through the sensitivity analysis

MLR¥¥ model does not reflect water discharges' effect. It is a drawback for the MLR¥. On the foundation of the comparison outcomes, the ANN¥ system was found to be greater to the MLR¥ system.

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