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# Prediction of Biochemical Oxygen Demand in a Wastewater Treatment Plant by Artificial Neural Networks

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In this study, output biochemical oxygen demand concentration of Kayseri advanced biological wastewater treatment plant was defined with the daily input data of 2004-2007 belonging to the same facility and this data was estimated rapidly and confidently by training with multi layered artificial neural networks model. In the establishment of the artificial neural networks model temperature, total nitrogen, total phosphorus, suspended solids, chemical oxygen demand and total dissolved solids parameters were used as input while biochemical oxygen demand parameter was used as output. The structure yielding the best result was obtained by training the artificial neural networks structure with 5 inputs, two hidden layers by Levenberg-Marquardt algorithm. In this structure, it was found that mean square error 0.45, mean absolute error 0.445 and $R^2$ = 0.915.

**Key Words: Artificial neural networks, Biochemical oxygen demand, Kayseri, Wastewater treatment plant, Modeling, Prediction.**

## INTRODUCTION

Biochemical oxygen demand ($BOD_5$) is a parameter widely used for determining organic pollution in wastewater and superficial waters. Biochemical oxygen demand parameter carries importance in the calculation of the required oxygen amount for the stabilization of present organic material, for the determination of the wastewater treatment plant's performances, for the determination of pollution potential of the receptor environment and assimilation capacity[1,2].

But the measurement of this crucial parameter is difficult and it takes a long time as 5 d to obtain the measurement results. The difficulty of the measurements and that they take much time increases the cost of the measurements at the same time[3]. When wastewater treatment facilities is taken into consideration the mathematical models developed for performance evaluation is useful for defining biological processes and to control system operation. But these models can be efficient because the wastewater treatment facilities have a number of complex variables and the linear relationships between these parameters are not explicit[4-7].

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When this situation is taken into consideration, computer operated modeling systems can be taught the defined measurements recorded in the past, can make parameter estimation using the present data and strengthening the decision making mechanism[8]. High accurate estimation ability and applicability on various subjects brings artificial neural networks (ANN) to the foreground among computer operated modeling[9,10].

Artificial neural networks which have found many applications on different issues in engineering field was also used successfully in the evaluation of performance and analysis of refining facility[11,12], in the forecast of rain input in the entrance of the refining facility[13], in the control of methane gas amount in anaerobic digestion[14], in the control of industrial wastewater treatment plant[15], in the chloride prediction in treatment facility disinfection unit[16], in the control of consecutive intermittent reactor's nitrogen and phosphorous removing[17] and in many similar subjects. Under the scope of this study, daily $BOD_5$ amount estimation in the wastewater treatment plant's exit by using multi-layered artificial neural networks.

**Overview of artificial neural network (ANN):** Multilayer neural networks (MNN) mostly preferred and used in engineering applications are intense parallel systems consisting of many operation elements connected to each other with weights. The most widely used one among ANN methods is the one that operates according to the back-propagation principle[18]. Fig. 1 shows the architecture of three layered neural networks used in this study.

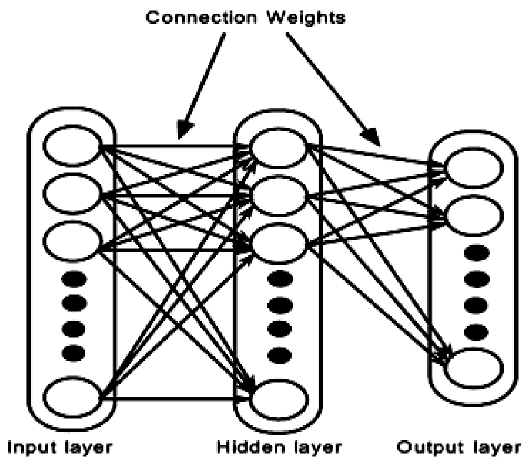


Fig. 1. Schematic diagram of a multi-layer neural network

The weight values assigned randomly at the beginning are changed continuously by comparing the estimated outputs in the training process and the real output values and until the connection weight values that minimize the errors are fixed the errors are spread backwards[19]. To balance the weights in this study Levenberg-Marquardt method was used[20].

In Fig. 1, it was shown that how each cell in the entrance, intermittent and exit layers perceived the NET weighted total outputs as inputs. NET value is calculated by eqn. 1:

$$NET_{pj} = \sum_{i=1}^{D} A_{ij} C_{pi} + \theta_j \quad (1)$$

Here D is the dimension of the entrance vector, $\theta_j$ is the bias constant, $A_{ij}$ is the set of weights between entrance and intermittent layers, $C_{pi}$ is the exit set of entrance layer for sample p. This transfer function used commonly is expressed as follows:

$$f(NET) = \frac{1}{1 + e^{-NET}} \quad (2)$$

In the training phase, total error for sample p, Hp is calculated by eqn. 3 depending on the difference of the squares between estimated and actual outputs.

$$H_p = \sum_{k=1}^{N} (G_{pk} - C_{pk})^2 \quad (3)$$

Here, N is the iteration coefficient and $G_{pk}$ and $C_{pk}$, respectively are the actual and estimated output values for sample p. Each connection weight is renewed by eqn. 4:

$$A_{ij}^{new} = A_{ij}^{old} - \left[J^T J + \mu I\right]^{-1} J^T H_p \quad (4)$$

Here J, is the Jacobian matrix including derivatives of the errors according to the weights; $J^T$, transpose of the Jacobian matrix; I, the unit matrix and μ is a parameter expressing divergence speed.

When μ value increases the equation turns to slope decreasing algorithm and when it decreases equation turns to Gauss-Newton algorithm[21].

## EXPERIMENTAL

In the study, daily for pre-sedimentation tank output data between 2004-2007 of advanced biological wastewater treatment plant operated by Kayseri Metropolis Municipality were used. The capacity of the facility was selected as to purify 110,000 $m^3$/d wastewater and 800,000 equivalent populations at the first level[22].

Unlike from the domestic wastewater treatment plants, Kayseri advanced biological wastewater treatment plants is treated with domestic wastewater coming from the city and 20,000 $m^3$/d industrial wastewater coming from Kayseri organized industrial region. The facility, in which the process scheme is given in Fig. 2, operates with a yield of 90 % by making nitrogen and phosphorous removal as well as carbon[22,23]. In accordance to the data received from the facility training and testing grouping of the data was made priorly. 910 of total 1215 data set were used training and the remaining 305 data set were used as test set for the evaluation of performance of the program to the actual values. And then statistical analysis of the entrance values was made and the correlation relationship between the $BOD_5$ parameter to be estimated and other entrance parameters were evaluated.

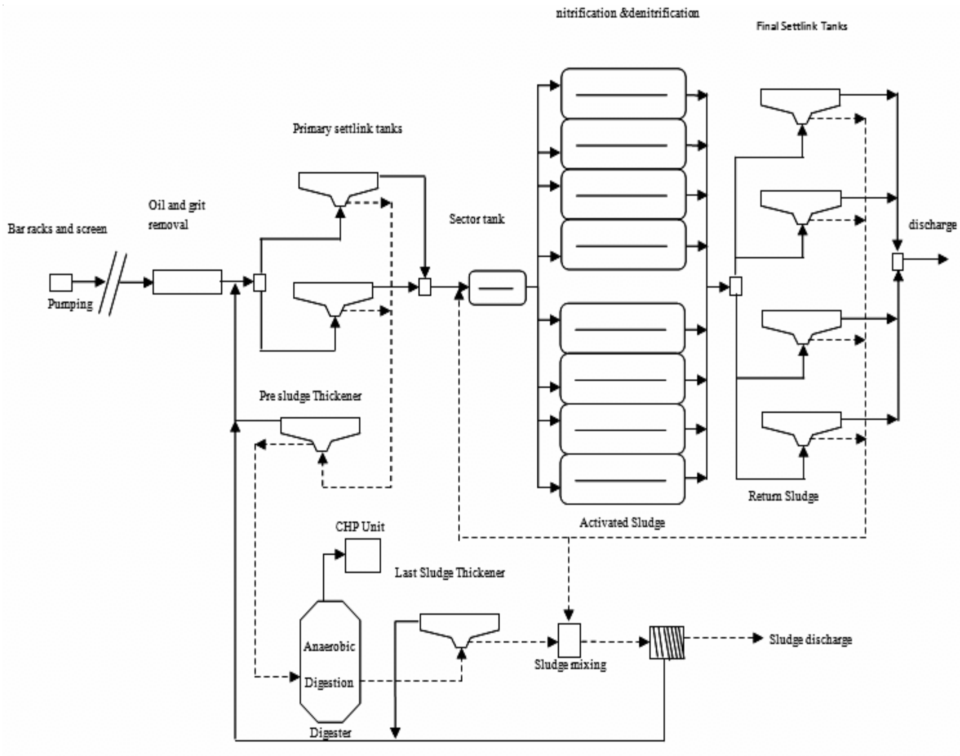


Fig. 2. Process scheme

Table-1 shows the average ($x_{ort}$,) minimum ($x_{min}$), maximum ($x_{mak}$) and standard deviation ($S_x$) values of each data set, respectively. Besides again on the same table, correlations of the entrance values used in the study with the $BOD_5$ concentration. When the statistics data are examined, it is clearly seen that the linear dependence between the parameters is not high. The information obtained before gives us the idea that in the facilities making domestic wastewater treatment correlation of $BOD_5$ with chemical oxygen demand (COD) moves linearly and these two parameters has high linearity with each other.

TABLE-1
STATISTICAL EVALUATION OF ENTRANCE DATA

| Parameter | Avg | Min | Max | Sx | Correlation with $BOD_5$ |
|---|---|---|---|---|---|
| Temperature (ºC) | 19 | 11 | 25 | 3.68 | 0.040 |
| SS (mg/L) | 357 | 122 | 1132 | 124.70 | 0.511 |
| COD (mg/L) | 687 | 329 | 2118 | 153.30 | 0.679 |
| TDS (mg/L) | 7 | 0 | 26 | 2.59 | 0.514 |
| Total N (mg/L) | 53 | 21 | 250 | 9.54 | 0.227 |
| Total P (mg/L) | 10 | 4 | 18 | 1.59 | 0.312 |
| $BOD_5$ (mg/L) | 369 | 121 | 1100 | 1.76 | 1.000 |

But in this study it is considered that with the relatively low value of $BOD_5$ and COD correlation as 0.679, unlike from conventional treatment facilities Kayseri wastewater treatment plant, industrial wastewater are treated as well as domestic wastewater. This encountered situation delayed the learning process of ANN models and depending on this made it relatively harder to accurately estimate the $BOD_5$ value. From the data obtained from purification facility three different input combinations was formed. These are: (1) temperature + total phosphorus + total nitrogen, (2) suspended sludge + COD + total dissolved solids, (3) suspended sludge + COD + total dissolved solids + total nitrogen + total phosphorus.

In the ANN models prepared under the scope of the combinations shown above, entrance layer includes 3 and 5 pieces; output layer includes 1 piece of neuron, respectively. The models in which $BOD_5$ concentration is estimated are trained with Levenberg-Marquet (LM) learning algorithms which have higher learning speed and yield healthier results than other algorithms[24,25]. Iteration number and intermittent layer cell numbers were obtained after many trials and errors and logarithmic sigma training activation function was used in all ANN models.

Using the weights obtained as a result of the training ANN models were tested for all input combination and the ANN structure yielding the best result was determined. As comparison criteria, mean square error (MSE), mean absolute error (MAE) and significance coefficient ($R^2$) was used. The mean square error (MSE) and mean absolute error (MAE) formulas used in the study are given below:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{Yi}_{\mathrm{observed}} - \mathrm{Yi}_{\mathrm{predicted}})^2 \quad (5)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{Yi}_{\mathrm{observed}} - \mathrm{Yi}_{\mathrm{Predicted}}\right| \quad (6)$$

Here N states the total data number Yi the value of $BOD_5$. For different input combinations MSE, MAE and $R^2$ values of ANN models at the test stage is given on Table-2.

TABLE-2
MSE, MAE AND $R^2$ VALUES OF ANN MODELS AT TEST STAGE

| Input | Intermittent layer cell number | ANN | | |
|---|---|---|---|---|
| | | MSE | MAE | $R^2$ |
| 1 | 2 | 2.798 | 7.301 | 0.540 |
| 2 | 1 | 0.574 | 0.876 | 0.735 |
| 3 | 2 | 0.451 | 0.445 | 0.915 |

When the first combination is examined with the trial of temperature, total phosphorus and total nitrogen as entrance it is clearly seen that the maximum MSE = 2.798 and MAE = 7.301. When we look at the second combination by adding COD, suspended sludge (SS) and total dissolved sludge (TDS) which has better correlation with $BOD_5$ compared to other data as the entrance data it is seen that the estimation yields better results.

In the last combination all the data we have except for the temperature was used as an entrance to the ANN model. In this model when the test set $BOD_5$ estimations are compared with $BOD_5$'s it is seen that the estimations yield results closer to the observed values.

When minimum MSE (0.451), MAE (0.445) and maximum $R^2$ (0.915) values are compared with other entrance combinations, it is again seen that it is calculated in this structure. In the 3 different combination set determined, being independent of the model architecture, it was seen that the error value remained fixed after 500 iteration steps. Therefore, it is observed that increasing the iteration step does not affect training performance in general, $R^2$ and MSE value changes in this stage stems from differences in model architecture. In Figs. 3a-b, 4a-b and 5a-b test stage estimation graphics of ANN structures is displayed.

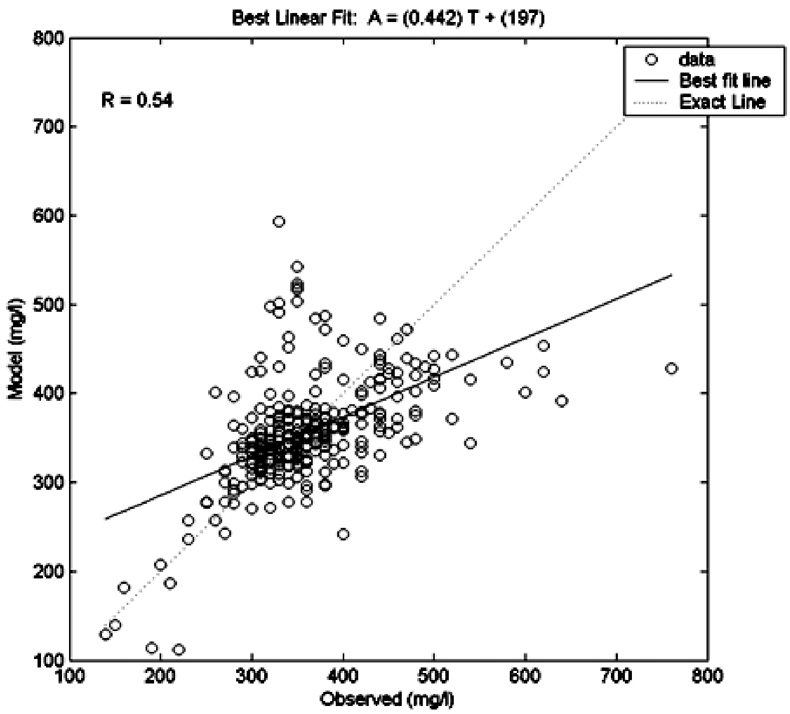


Fig 3a. Comparison of estimated and measured values of $BOD_5$ exit variable of number 1 combination at the test stage

As it is seen in the graphics the correlation coefficient obtained for test set at the last combination was found as 0.915. The obtained results suggest that ANN algorithm defines the relationship between input and output parameters well and the output parameters are estimated with high accuracy.

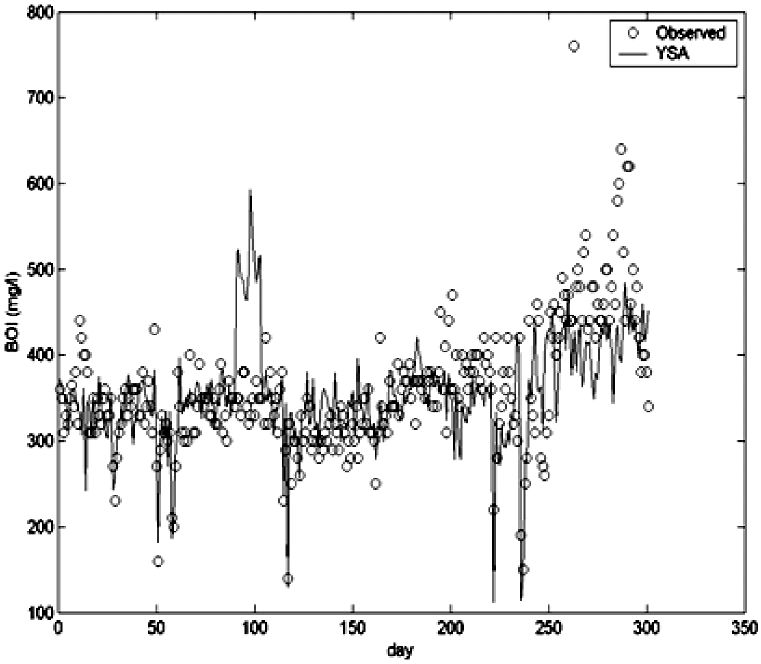


Fig. 3b. Change of estimated and measured values over time

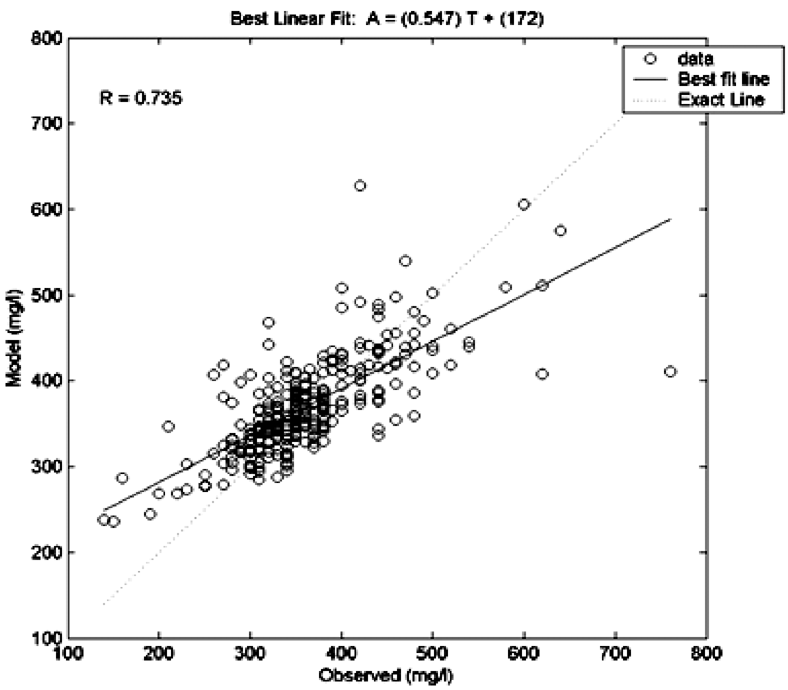


Fig. 4a. Comparison of estimated and measured values of $BOD_5$ exit variable of number 2 combination at the test stage

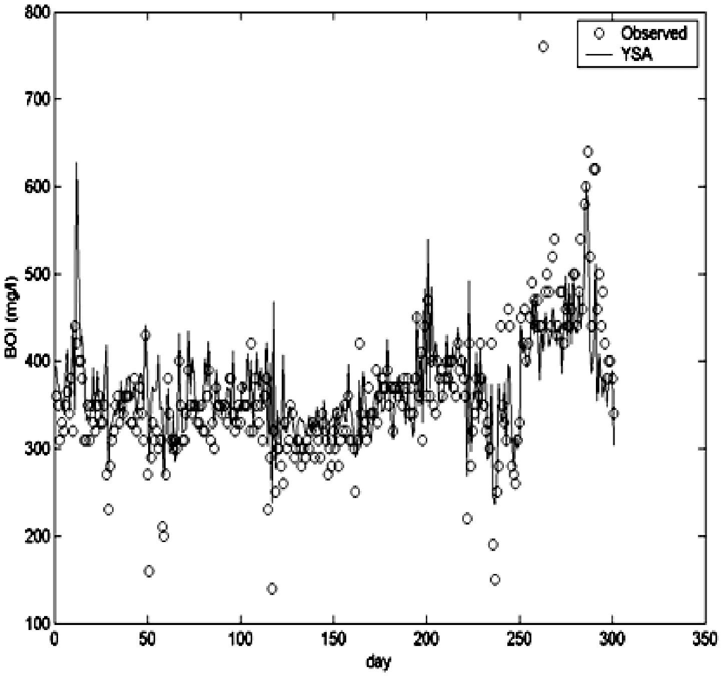


Fig. 4b. Change of estimated and measured values over time

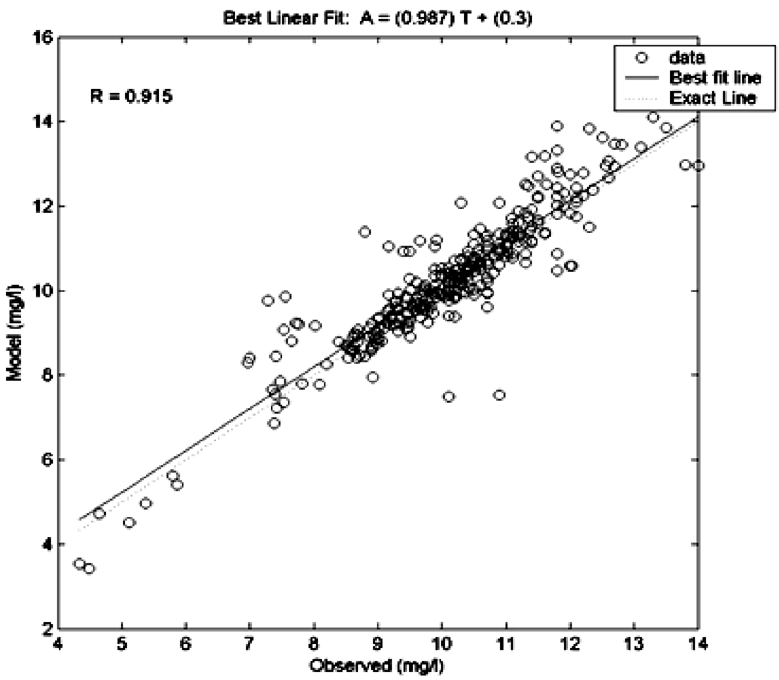


Fig. 5a. Comparison of estimated and measured values of $BOD_5$ exit variable of number 3 combination at the test stage

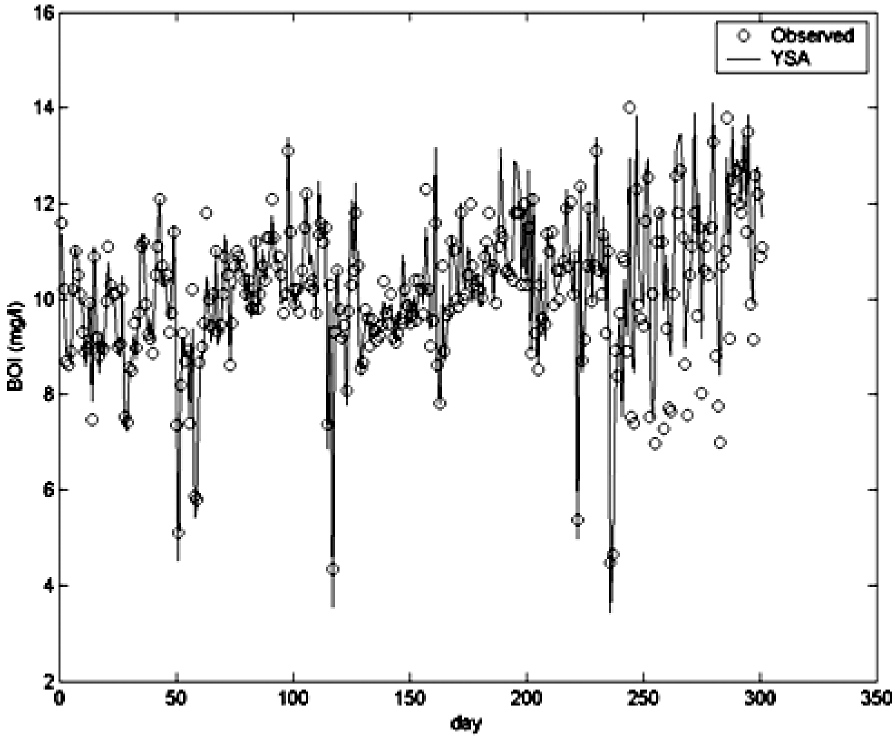


Fig. 5b. Change of estimated and measured values over time

## RESULTS AND DISCUSSION

In this study exit $BOD_5$ parameter in Kayseri biological wastewater treatment facility where nitrogen and phosphorus removal where pollution load consists of 30 % mixed industrial wastewater was estimated by multi layered ANN. Three different entrance combination was tried to form ANN model. It was seen that SSM, COD, TDS, total nitrogen and total phosphorus were used as entrance and ANN trained with Levenberg-Marquet algorithm yielded the best result.

The relationship between these parameters and $BOD_5$ parameter was determined with ANN at this facility dimension. The model is simple in terms of structure. However the calculation speed is so high. Therefore by estimating the $BOD_5$ parameter that takes an analysis period of 5 d with ANN the evaluation of the facility's performance and calculation of the pollution load at the exit of the facility can be actualized faster and economical.

## ACKNOWLEDGEMENT

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