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Effluent prediction of chemical oxygen demand from the astewater treatment plant using artificial neural network application

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Abstract

Chemical oxygen demand (COD) has been utilized to determine the content of organic matter of bath water, wastewater and natural water, due to the time consuming of biological oxygen demand (BOD) test, COD became an alternative in controlling the treatment process. For the oxidation of both organic and inorganic matter COD may be expressed as one of the demand parameters. In this paper, the Artificial neural network (ANNs) was employed to develop and estimate the effluent COD model from the wastewater treatment plant (WWTP), to evaluate the model, the daily recorded data sets were obtained from the new Nicosia WWT, the input parameters of ANNs are inlets COD, BOD, pH, Conductivity, Total Nitrogen (T-N), Total Phosphates (T-P), Total suspended solid (TSS), Suspended solid (SS) and the effluent COD were considered as an output neuron of ANN. The ANN performance has been evaluated using statistical techniques (Determination coefficient, RMSE, Correlations), the result of ANNs model was compared with the Multilinear regression analysis (MLR) and the efficiency revealed that ANNs model showed the prominent accuracy and better performance in predicting the effluent COD over the MLR model.

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Keywords: Chemical oxygen demand; artificial neural aetwork; wastewater treatment plant; multilinear regression analysis.

1. Introduction

Municipal wastewater is one of the major sources of polluting the environment, due to the amount of various types of chemicals released. Therefore, in order to estimate the effluent performance, the need for a reliable model is

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paramount, for controlling the complex process in wastewater treatment plant (Dogan et al., 2015). COD is one of the most widely use parameters of indicating organic pollution applied to both waste water and surface water. It is defined as the oxygen requires for microorganisms to carry out biological decomposition of dissolved solids or organic matter in wastewater under standard temperature. Being an alternative to BOD, the measurement of COD may be used for the following purposes: determine the size of wastewater treatment facilities, the strength of sewage and efficiency of some treatment plant(Jain, 2014). COD is an imperative parameter in analysing the quality of water parameter, since it gives an index to assess the impact of discharge on the receiving water body. The more the COD level the higher the oxidation in an organic compound in the sample, which will eventually reduce the dissolved oxygen (DO) levels. The subsequent reduction in DO can further lead to anaerobic condition, which is harmful to aquatic life(Jain, 2014).

The effluent quality of wastewater treatment plant (WWTP) becomes more important due the serious concern on environmental and public health issues (Hamed et al., 2004). The characteristic of wastewater treatment plant is quite dynamic and involves several complex and nonlinear processes, which are difficult to predict or explain by linear statistical or mathematical model. However, convenient modelling process plays an essential role in describing the general interactions taking place in the system(Hamed et al., 2004). Rapid increase in population growth caused the development of urbanization, agricultural and an industrial activity as well as outstanding improvement in wastewater has increased water pollution level. Thus, making the provision of water quality very hard and resourcing consuming(Nourani et al., 2013). To improve effluent quality and meet the regular standard, from the wastewater treatment plant while reducing the costs of operation and maintenance, the priority of adopting the advance technologies needs to be put in place. Most of the deterministic and numerical models used for accessing effluent quality cannot be predicted accordingly, under this situation(Pai et al., 2011;Goyal et al.,2015). Due to the complicated nature of the treatment process, this requires high precision in reaching the desire standard limits of different physical and biochemical parameters, as the major challenge in attaining effluent quality. Meanwhile, the expensive nature and time consuming in evaluating the quality of water by experimental model becomes an urgent to address. As such, soft computational techniques now have been applied to deal with the uncertainty concept and overcome the shortage of experimental model(Nourani et al., 2013).

Thus, A neural network method hasacquired significant consideration in modellinghydrology and wastewater treatment processes, in recent years, ANNs were adopted as an approaches for effectively predicting, controlling, monitoring, forecasting, classification and model simulation of non-linear interaction. The ability of ANNs to consider multi-input and output parameters, self–learning, work on parallel processing, self-adaptive in complex functional relationship have made its implementation in any application(Bagheri et al., 2015;Nourani et al., 2013;Dursun, 2010). Many researchers have succeeded in employing an ANN model to predict, classify or optimize the various water quality parameters. Reference(Dogan et al., 2015)estimated biological oxygen demand from wastewater treatment inlet using ANN. Reference (Nourani et al., 2015) used the artificial neural network to modelled the ground water. Reference (Areerachakul et al., 2011;Djeddou and Achour, 2015) utilized ANN for the prediction of sludge volume index in municipal wastewater treatment plants.

The study is purposely used to determine the efficiency and performance of ANNs in predicting the COD of Nicosia wastewater treatment plant in comparison with experimental model, to come out with a feasible model that can be utilized as a general model for quality monitoring and performance of the treatment plant.

2. Material and Method

2.1. Basic of ANNs

ANNs is a device designed to simulate the functions of the human brain. It's a massively, parallel, distribute processor, which has the ability to store the huge experimental data and making it available for use. The most common applications are feature extraction, pattern recognition and classification(Kuo et al.,1995). ANNs are nonlinear mathematical and statistical modelling tools; that is useful in solving problem in various engineering fields. It consists of a large number of highly processors and interconnected element (neurons), working simultaneously to overcome the problem of large amount dynamic data (Hamed at al., 2004;Dogan at al.,2015).

ANNs composed of nodes as the basic unit. These nodes, which are connected each other by synapse (links) receive the input data, which are processed to produce the output. The process of adjusting and updating the synaptic weight and biases in such a way that for a given input the desired output is achieved is known as a learning process (algorithm), which is used to reduce the errors between, observed and predicted target. Among the various classifications of ANNs, feed-forward neural network (FFNN) is the most common one, in which data flow from input layer, through the hidden layer (middle layer) to the output layer, it is usually drawn from left to right or bottom to top. The present work employed the FFNN with a back propagation training algorithm (BP) (Nourani et al., 2009;Gaya et al., 2014;Nourani et al., 2013). Learning in the context of FFNN is generally associated with back propagation algorithms, which is also known as, Multi-layer Perceptron (MLP). The main concept of BP is based on finding the total weights at each neuron which would generate the target; the actual target is compared to a desired target. The difference between the two is called an error, which is propagated back into the input layer(Gaya et al., 2014;Nourani et al., 2013). As indicated in Fig. 1, the architecture of ANNs,(*i , j ,k*) where, *i , j , and k* nodes represent input, middle and output layers respectively, are considered in the present work is MLP, which has been applied to solve numbers of different problems for demonstrating the non –linear function between the input and target.

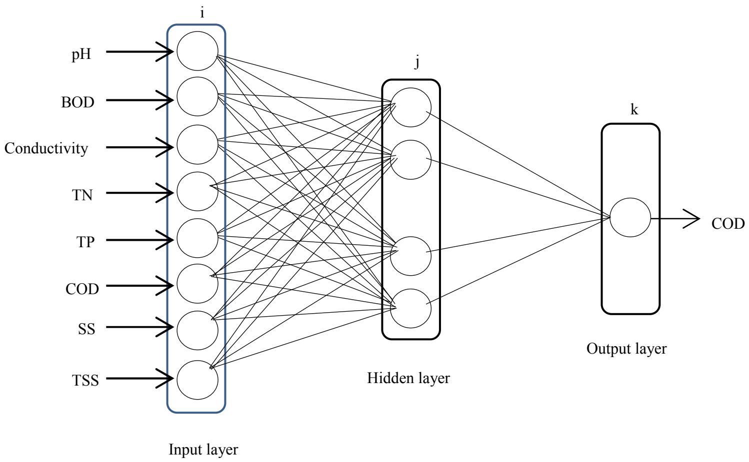

Fig. 1: The architect of a MLP

2.2 Training and Performance Evaluation of ANNs

In ANN there are no exact available formulas to decide the effective structure of ANN and which training algorithm will solve a given problem, the best solution is to obtain by trial and error. In such a case the knowledge of selecting the input variables is highly essential for ANNs modelling. The important and key parameter should be considered first and avoid the unnecessary one's in the model. In this work, sensitivity analysis is considered, in order to find out the significance of the parameters and determine the key parameters. Insignificant variables over the desired target should be avoided for better performance of ANN (Nourani, 2012;Dogan et al., 2015). Table 1 shows the statistical analysis of the each parameter.

For a neural network to produce a desired output that is as approximately as the target output, a training or learning process need to be undergoes(Kuo et al.,1995). The input and output data are used in an ANN training, the techniques of assigning, updating and adjusting the weight and bias connection, until learning is achieved is referred to as learning process. The initial weight are normally assigned randomly during the simulation process, the larger the data both in quality and quantity the better the training, as lack of enough data may create over fitting (over learning), which is one of the major problem occur in learning, in addition lack of suitable number of hidden neurons and inappropriate epoch (iteration) can also lead to over fitting, small nodes can also result in under fitting while many nodes can lead to over fitting in the hidden layers(Dogan et al.,2015; Dursun ,2010; Sharifi et al.,2009).

However, each layer is composed of neurons, which are interconnected with others by weights; an activation function is introduced in each neuron in order to convert the linear function to non- linear function which is a mathematical function. This function applies to processing neuron and defined how that neuron is activated; it also accepts the input from the previous layers and produce output to the next layers. The activation function used for the purpose of this work is a sigmoid activation function, defined in equation (1); which is continuing non-linear exponential function that switches between 0 and 1 gradually(Dogan et al.,2015; Nourani et al., 2015).

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

In this paper, the multilayer perceptron model is trained by the algorithms Lavenberg-Marquardt techniques due to its outstanding performance in different literature of hydrology (Kuo et al.,1995; Sharifi et al., 2009). Using equation (2), generally, the data were normalized from the range of 0 and 1, at the initial stage before training of the model. The normalization is done in order to reduce the data redundancy and increase data integrity. To employed and ANNs model for estimating COD in wastewater treatment the FFNN method and Back Propagation error algorithm were used in which the training and testing were categorized in to seventy percentage (70%) and thirty percentage (30%) respectively.

$$X'_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Where "X'_i" is the normalized quantity, "x_i" is un- normalized quantity, "x_{min}", "x_{max}" are minimum and maximum quantity of data, respectively.

The criteria used to determine the efficiency and performance of the model development depend on the specific problems, the statistical performance evaluation used are Determination coefficient (D or $R^{2)}$ and the root mean square (RMSE) . The RMSE and R^2 shown the differences between the measured and computed value, for the best network, both the D and RMSE value should be high in training and validation, the higher the D the lower the RMSE under normal condition. The following equations (3) and (4) are used in determining the parameters (Nourani and Sayyah, 2012 ; Pai et al., 2011).

$$D = 1 - \frac{\sum_{i-n}^{N}(COD_O - COD_P)^2}{\sum_{i-n}^{N}(COD_P - \overline{COD_O})^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i-n}^{N}(COD_O - COD_P)^2}{N}} \tag{4}$$

Where, COD_O , COD_P , and $\overline{COD_O}$, are measured data, estimated values and means of N measured values respectively. The RMSE is a criteria used in order to evaluate the effectiveness of models and their ability to make a precise prediction and decision, it provides the best fit between the measure and computed values when the RMSE is towards the zero value. It ranges from zero for a best estimate and differences between predicted and measured turned out to be increasingly larger (Nourani et al., 2013).

2.3 Nicosia wastewater Treatment Plant and Sensitivity Analysis

The New Nicosia Wastewater Treatment Plant was designed to serve up to 270,000 inhabitants for stage 1 with the design horizon year 2025. In order to avoid extensive capacity surcharge for the consumer for unused capacity, implementation staged at 1 and 2. In stage1 established with a capacity of 30,000 m^3/day and stage 2 will be implemented l to reach the final capacity 45,000 m^3/day. New Plant based on Membrane Bioreactor (MBR) technology. Membrane technology developed essentially within the last couple of years. It is a state- of- art technology for wastewater treatment and new plant has been designed as a MBR plant with Advance Biological Nutrient Removal (ABMR).It is now the second largest wastewater treatment plant in Europe to use membrane technology(UNDP, 2013).

In this research, the daily wastewater data of Nicosia wastewater treatment plant were obtained from the municipal wastewater Board of Nicosia for the years 2014 to 2016, data processing and mining were carried out to remove the noisy and unrecorded data set, the data contained 312 records and each record consist of eight parameters.

2.4 Multi-linear regression (MLR) Analysis

In regression one variable is assumed as dependent parameters Y and the other one as independent variables X in which the linear equation is considered for the relationship. The multilinear regression equation can be considered as in in equation (5)

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots \beta_n x_n \quad (5)$$

Where,
$\alpha, \beta_1, \beta_2 \dots \beta_n$, are regression coefficients.

y shows the predicted values of Y variables when $X_1 = x_1, x_2, x_3 \dots x_n$.
We need to consider our predicted value (P-value) and exclude all the insignificant values in any multilinear regression analysis(Dogan et al.,2015).

Table1. The Statistical Analysis of Data Set of each input parameter

Parameters	Mean	Max	Min	Variance	Standard deviation	Correlation with COD
pH	3.1019	8.2	5.6	0.0684	0.2616	-0.1576
BOD(mg/l)	53.7660	616	105	7945.68	89.138	0.1793
COD(mg/l)	961.3846	1463	385	24706.49	157.183	1.000
T-N(mg/l)	3.5406	143	30.54	707.646	26.6016	0.2478
T-P(mg/l)	1.0801	14	8	0.916129	0.9571	0.2578
SS (mg/l)	7.0047	100	3.37	67.3643	8.2075	0.2604
TSS(mg/l)	20.8205	660	70	24952.17	157.9625	0.1969
Conductivity(mmho/cm)	1.3685	4	2	0.1810	0.4255	0.1704

3. Results and Discussion of ANN

3.1 FFNN and MLR result

The eight different input variables were checked using various types of model, to design the most appropriate model with a single target variable. With the reference result of sensitivity analysis another four input parameters were used for the application of a FFNN model on a data set as shown in Table 3, to have a precise comparison between the initial inputs and effective sensitivity analysis inputs, which are SS, COD, T-P, and T-N, Table 4 shows the model combination of the four parameters. The performance criteria and comparison of measured and estimated values used in this study that are coefficient of determination and root mean square error were tabulated in Table 2 and Fig2 to 7, respectively. The paper aimed at determining an alternative model in predicting the effluent COD_{eff} as output of the model, the network was trained at different numbers of iteration (epoch) and finally the 203 epoch was considered as the appropriate range.

Table2. Determination of the best result of trained ANN architecture

Model Type	ANN Structure	Epoch No.	R^2	RMSE
ANN I	(8 - 8 - 1)	203	0.7034	0.0108
ANN II	(8 - 8 - 1)	180	0.6706	0.0987
ANN III	(8 - 9 - 1)	150	0.6092	0.3417
ANN IV	(8 - 10 -1)	50	0.6268	0.0470
ANN V	(8 - 10 -1)	80	0.6968	0.1074
ANN VI	(8 - 11 -1)	150	0.6064	0.1334

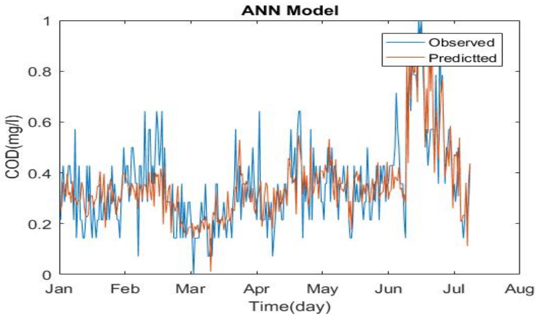

Fig.2 ANN model type I of observed and predicted value of COD_{eff}

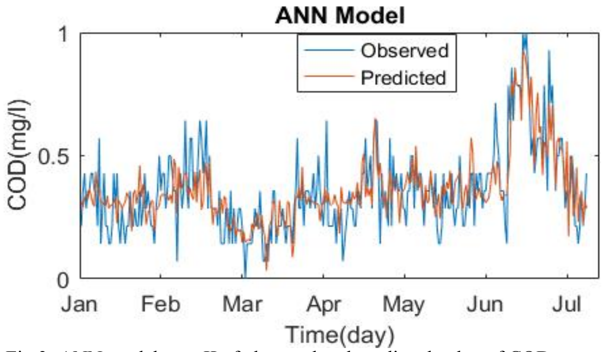

Fig.3: ANN model type II of observed and predicted value of COD_{eff}

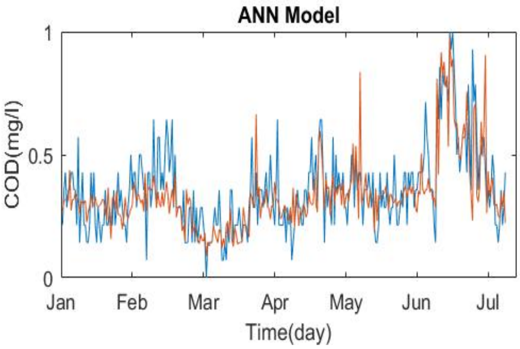

Fig.4: ANN model type III of observed and predicted value of COD_{eff}

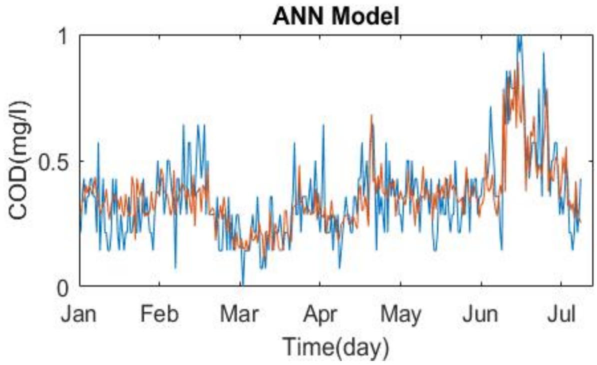

Fig.5: ANN model type IV of observed and predicted value of COD_{eff}

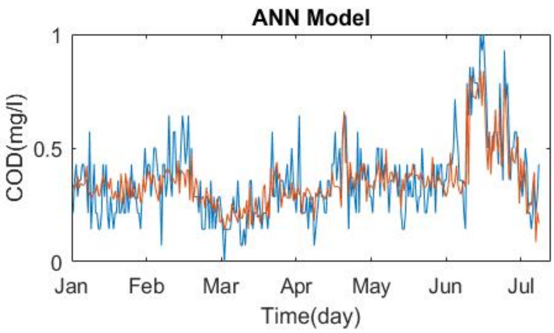

Fig.6: ANN model type V of observed and predicted value of COD_{eff}

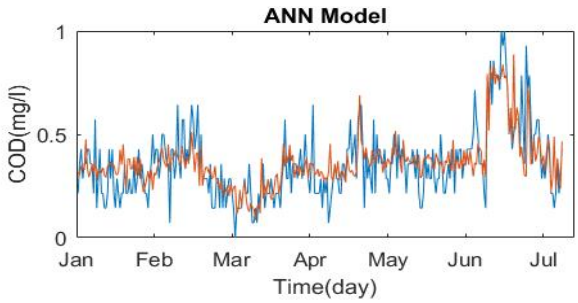

Fig.7: ANN model type VI of observed and predicted value of COD_{eff}

Table 3. Performance evaluation of four parameters

S/N	Model Structure	Epoch	Performance Evaluation R^2	RMSE
1	(4 -6 -1)	100	0.4142	0.1997
2	(3- 3- 1)	130	0.3137	0.0064
3	(2- 2-1)	80	0.2241	0.1013

Table 4. Model combination of parameters

S/N	Model Architecture	Inputs Model
1	(2- 2-1)	COD_{inff} + T-N_{inff}
2	(3- 3- 1)	COD_{inff} + T-N_{inff} + T-P_{inff}
3	(4 -6 -1)	COD_{inff} + T-N_{inff} + T-P_{inff} + SS_{inff}

Base on the ANN and MLR application, the cleared comparative performance of various ANN models was given in Table 2, which the value of the D and RMSE varies in the range of 0.6064 to0.7034and 0.0108 to 0.3417, respectively. The best performing model is ANN I with the values of D and RMSE as0.7034and 0.0108 respectively, for the best network, the higher the D value the lower the RMSE for both training and verification of ANN model. As demonstrated in Table 3, the least number of input variables the less the performance of the model. Thus, the result of this study indicates that the model with the optimum number of input parameters, optimum epoch and least hidden layers, as indicated in Table 2 and Figure 2. The outcome of multilinear regression analysis (MLR) in estimating the COD_{eff} is determined and the performance of the MLR base on D and RMSE are 0.3421 and 0.0121, respectively. In comparison with the other model it was indicated that the ANN I model provides better outcomes in terms of D and RMSE values due to its ability to deal with the nonlinearity complex process.

4. Conclusion

In this paper, the application of FFNN model was used to predict the COD_{eff} in Nicosia municipal wastewater treatment plant, for the comparison MLR model was also adopted. The sensitivity analysis was conducted using various statistical performance tools. For determination of effectiveness of the parameters, the result demonstrated that, COD_{eff} is more effective for all the eight input parameters than considering the four input parameters after sensitivity analysis. According the results the determination coefficient and root mean square error was found to be 0.7034and 0.1018, respectively, which on the basis of comparing the result, the ANNs turned to be high in term of performance and efficiency to the MLR for modelling the wastewater treatment plant. It was also revealed from the analysis that, other water quality indices and experimental model could not produce a better prediction of COD_{eff} in this wastewater treatment plant. The outcomes also suggested that, for the application of this model in the real world, the uncertainty phenomena need to address as such, the others artificial intelligence tool should be introduced and compared, such Adaptive Neuro-fuzzy inference system (ANFIS), Fuzzy tool and etc.

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