PREDICTION OF CHEMICAL OXYGEN DEMAND FROM THE CHEMICAL COMPOSITION OF WASTEWATER BY ARTIFICIAL NEURAL NETWORKS

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
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Approval of the Graduate School of Natural and Applied Sciences, Atılım University

Prof. Dr. Ali Kara
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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science in Chemical Engineering and Applied Chemistry, Atılım University.

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This is to certify that we have read the thesis "Prediction of chemical oxygen demand from the chemical composition of wastewater by artificial neural networks" submitted by "Basim Ahmed Saleh Alobaidi" and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

PREDICTION OF CHEMICAL OXYGEN DEMAND FROM THE CHEMICAL COMPOSITION OF WASTEWATER BY ARTIFICIAL NEURAL NETWORKS

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In our era, many technical applications and modern programs are being used and the role of artificial intelligence (AI) increases. Artificial Neural Networks (ANNs) as one of artificial intelligence tools have emerged to learn and discover a model of dynamic nonlinear behavior depending on a particular set of data through training of the network. They have high accuracy for prediction in multiple disciplines like biology, wastewater treatment and engineering.

In this study, six input parameters were taken to predict the value of the Chemical Oxygen Demand (COD) in the wastewater before and after the treatment at the North Gas Company/Kirkuk, by using the standard backpropagation algorithm. The network was trained with the 150 data collected from the quality indices of the untreated and treated waste water, such as total chloride ions Cl^{-}, nitrate ions NO_3^{-}, phosphate ions PO_4^{-3}, sulfate ions SO_4^{-2}, ammonia NH_3, Biochemical Oxygen Demand (BOD_5) to predict one element, that is the COD.

After properly training of the neural network, it was tested by using the test data, and the best results were selected by the consideration of the mean square error and the regression coefficient.

The findings of this study suggest that artificial neural networks are accurate and effective tools for predicting the COD values of treated wastewater.

Keywords: Artificial neural networks, industrial wastewater, chemical oxygen demand prediction, chemical composition.

ÖZ

ATIK SUYUN KİMYASAL BİLEŞİMİDEN KİMYASAL OKSİJEN GEREKSİNİMİNİN YAPAY SİNİR AĞLARI İLE TAHMİNİ

Basim Ahmed Saleh Alobaidi

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Çağımızda birçok teknik uygulama ve modern programın kullanılması ve yapay zekanın (AI) rolü artmaktadır. Yapay zeka araçlarından biri olan Yapay Sinir Ağları (YSA), ağın eğitimi yoluyla belirli bir veri kümesine bağlı olarak dinamik bir doğrusal olmayan davranış modelini öğrenmek ve keşfetmek için ortaya çıkmıştır. Biyoloji, atık su arıtma ve mühendislik gibi birçok disiplinde tahmin yapma konusunda yüksek doğruluk sahibidirler.

Bu çalışmada, standart geri yayılım algoritması kullanılarak, North Gas Company / Kerkük'te arıtılan atık sudaki Kimyasal Oksijen Gereksinimi'nin (COD) değerini tahmin etmek için altı girdi parametresi alınmıştır. Sinir ağı, toplam klorür iyonu Cl^-, nitrat iyonu NO_3^-, fosfat iyonu PO_4^3, sülfat iyonu SO_4^{-2}, amonyak NH_3, Biyokimyasal Oksijen İhtiyacı (BOD_5) gibi atıksu kalite indekslerinden toplanan 150 veri ile tek bir elementi yani COD'yi tahmin etmek üzere eğitilmiştir.

Sinir ağı, uygun bir şekilde eğitilmesinden sonra test verileri kullanılarak test edilmiştir ve en iyi sonuçlar ortalama kare hatası ve regresyon katsayısı dikkate alınarak seçilmiştir.

Bu çalışmada elde edilen bulgular, yapay sinir ağlarının arıtılmış atık suyun COD değerlerini tahmin etmede doğru ve etkili araçlar olduğunu göstermektedir.

Anahtar Kelimeler: Yapay sinir ağları, endüstriyel atık su, kimyasal oksijen gereksinimi tahmini, kimyasal bileşim.

DEDICATION

I would like to dedicate to my dear mother, my brothers, my sisters, and all my friends. I would like to thank my friend Younis al-Ani, Mrs. Lmyaa, Professor Dr. Amel Merzah and all those who supported me throughout my academic career. Without their moral support and encouragement to work academically, this effort would not be completed. I would like to thank all of you.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ASTM	American Society of Testing and Materials
MSE	Mean Square Error
MLR	Multiple linear regression
NN	Neural Network
NARX	Nonlinear Auto Regressive Exogenous Model
R	Regression Coefficient
R^2	Correlation Coefficient
RMSD	Root Mean Square Deviation
RMSE	Root Mean Square Error
FD	Basin with process
AD	Basin without process

CHAPTER 1

INTRODUCTION

1.1 General

The purpose of the treatment is to get a clean environment and keep the plant free of waste through processing and operation with the help of waste treatment techniques and disposal.

Waste treatment facilities comprise all equipment for treatment of wastewaters and solid wastes discharged from the central processing facilities of the plant.

1.1.1 Pollutants in Wastewater

Source of industrial wastewaters originate from industrial processes and they may contain contaminants that degrade the water quality, such as, suspended sediments, bacteria, oxygen demanding matter, and perhaps toxic substances.

Therefore, wastewater must be treated from all these contaminants, so that they are within the limits in accordance with the conditions required by laws.

Table 1.1 shows the value of each parameter in quality of water in ppm, and the properties of wastewater should be within this average.

According to the conditions, the regulations issued by the Iraqi Environmental Office and presented in Table 1.1.

Table 1.1 Quality of outgoing wastewater effluent to meet the regulations issued by the Iraqi Environmental Office

Specifications		**ppm**
PH		6.5-9.5
BOD_5		40
COD		100
TOC		2.2* BOD_5
Suspended Solids	SS	60
Lead	Pb	0.1
Arsenic	As	0.05
Copper	Cu	0.2
Nickel	Ni	0.2
Selenium	Si	0.05
Mercury	Hg	0.005
Cadmium	Cd	0.01
Zinc (divalent)	Zn	2
Chromium	Cr^{6+}	0.1
Cyanides	CN^-	0.05
Floride	F	5
Aluminum	Al	5
Barium	Ba	4
Boron	B	1
Cobalt	Co	0.5
Iron	Fe	2
Manganese	Mn	0.5
Silver	Ag	0.05
Free chlorine	Cl_2	Traces
Chloride	Cl^-	600
Phenol		0.01-0.05
Sulfate	SO_4^{-2}	400
Nitrate	NO_3^-	50
Ammonia	NH_3	5
Phosphates	PO_4^{-3}	3
Temperature		35 °C

1.1.2 Equipment Capacity

1. Oil separator is designed to treat 320 m^3/hr of oily water.
2. Equalization basin has a maximum capacity of 900 m^3.
3. Floatation basin is designed to treat 350 m^3/hr.
4. Filters A/B/C is designed to treat 350 m^3/hr.
5. Guard basin has a maximum capacity of about 1400 m^3 and is designed to hold the volume of wastewater collected during 4 hours of operation.

1.1.3 Consumption of Chemicals

Followings are the expected consumption figures. Final dosages will be established during operation to ensure optimal performance.

1.1.3.1 Aluminum Sulfate $Al_2(SO_4)_3 \cdot 14H_2O$

Dosage to coagulation pit	50 ppm
Daily consumption	400 kg

1.1.3.2 Floatation polymer (Nalco 677 SC or CH-5165)

Dosage: to flotation basin	0.5- 1 ppm
Total daily consumption	8.5 kg

1.1.4 Oil Separation

The following waste streams are collected by gravity flow in the oily wastewater basin:

- Oily wastewater from natural gasoline handling and storage facilities.
- Laboratory wastewater from control room.
- Activated carbon filter backwash water from water treatment facilities
- Boiler blow down from steam generation facilities.

The oil separator Figure 1.1 is a gravity differential type. The primary function of this process is to separate oil from water by allowing it to rise to the surface by density difference, water from the oil separator passes into equalization basin, and oil are collected by special basins and transported to places outside the station [1].

Figure 1.1 Process of separation of oil and fat from water

1.1.5 Equalization of Wastewaters

Equalization basin is provided to maintain constant water feed quantity and quality. Streams are blended by mechanical agitation using submersible agitators. This also prevents suspended solids from settling and sedimentation down the basin, the feed to the flotation pond reduces the impact of sudden changes in flow rate and composition of collected wastewater streams.

The following waste streams are collected in equalization basin by gravity flow:

- Effluent water from oil separator
- Cooling tower blow down
- Back wash water from side stream filters.

1.1.6 Floatation

The purpose of floatation (coagulation plus dissolved air floatation) is to reduce fats and suspended solid content, and to remove oil and clay from wastewater coming from the equalization basin.

We have two additions of chemicals that are aluminum sulfate and floatation aid. The aluminum sulfate is used for water purification and the floatation aid is used to adhesion of the clay to each other and deposition to the bottom of the basin and sent by gravity flow into scum storage basin

The process consists of pressurizing a recycle stream and saturating it with air, and because of release of pressure at the floatation basin inlet, it will form bubbles. These bubbles form on the surface of suspended particles and they are attracted to the particles by surface energies. Thus, an aggregate is formed having average density which is lower than that of water and which, therefore, will rise to the surface of the floatation basin Figure 1.2 Scum is scraped from the floatation basin surface and collected in the scum box, and sent by gravity flow into scum storage basin [1].

Figure 1.2 Floatation basin

1.1.7 Filtration

The purpose of the sand filters A, B, C Figure 1.3 is to efficiently remove turbidity, suspended solids and toxic metals in treated water.

The wastewater flows vertically through the sand, gravel and nozzles. In this process suspended solids and clay are removed.

During filtering operation, from the flotation basin; water enters through the filter's inlet pipe, which leads to the water distribution inside the tank. While the water flows down through the sand, the tiny sand particles catch any dirt. From the bottom of the tank the filtered water flows in to the guard basin [1].

Process flow diagram of wastewater treatment facility at North Gas Company is given in Figure 1.4 below.

Figure 1.3 Sand filters A, B, C

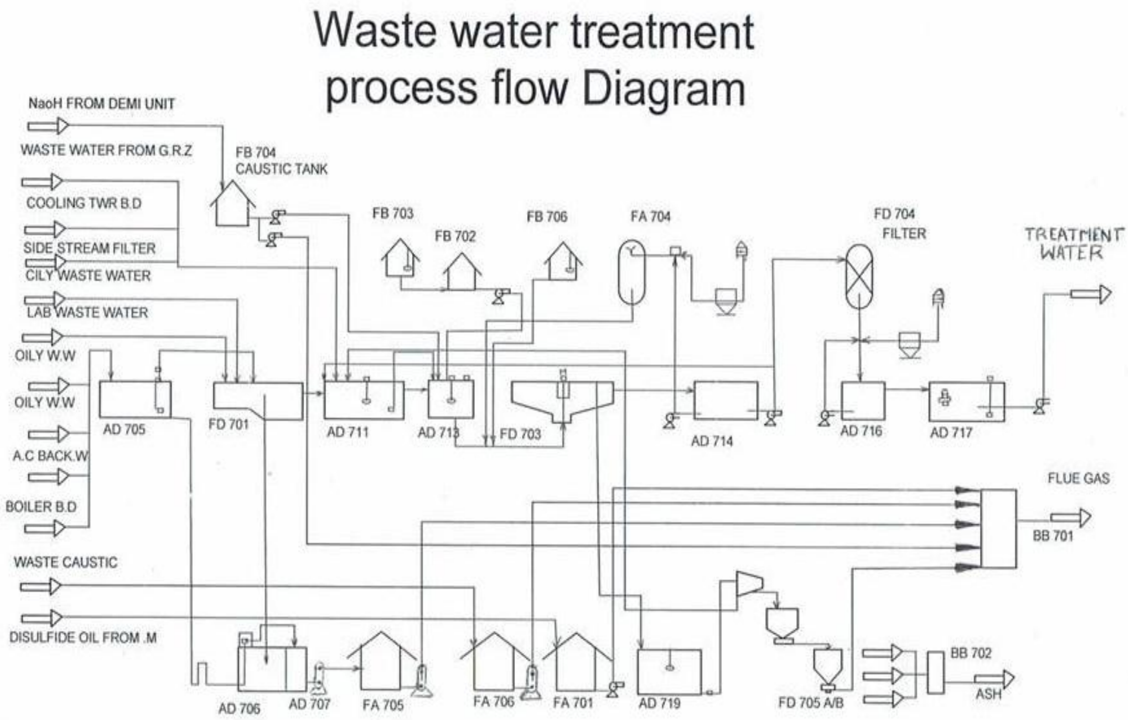

Figure 1.4 Wastewater Treatment Process Flow Diagram

1.2 Artificial Neural Networks

Artificial Neural Network (ANN) has now become a procedure model that is affected by the biological neural networks inside the human brain for information handling. Artificial Neural Networks have made a great success of excitation in machine learning, analysis and manufacture. Because of good results, clarity of vision and handling texts as much as possible, we are going to try to promote an understanding of such sort of ANN referred to as the Multi-Layer Perceptron [2].

1.2.1 What is an Artificial Neural Network?

Artificial neural networks are the programs applied in machine learning in which the neural part is brain-inspired system where it is to copy the approach that we humans learn.

Neural networks contain input and output layers and a hidden layer consisting of units that process the input into one factor or many factors that the output layer will use. They are good tools for locating patterns that are too composite or various for a human to develop information and to use them. Another development was the arrival of deep learning neural networks, which within varied layers of a multilayer network extracts various options till it will acknowledge what it's trying to find [3].

1.2.2 Why to Use Neural Networks?

With the neural networks having good capabilities, patterns can be extracted and information can be revealed by humans. Neural networks are expert in finding analysis results. This knowledge can then provide projections giving new cases of interest and answers, which include [4]:

1-Adaptive learning: Capability of knowledge and learning are good methods to do the tasks offered for this work or initial experience.

2-Self-organisation: Neural networks will produce their own system or impersonate the knowledge they receive as input information during learning time.

3-Real time operation: The artificial network accounts are applied in parallel, and simple devices are designed and made to benefit from this application.

4-Error tolerance by coding redundant information: The partial error of a network results in application degradation.

1.2.3 How does the Human Brain Learn?

Much information remains unknown about the programs but the brain has the property of knowledge, therefore theories abound. Within the human brain, neurons get signals from the other neurons with the help of their dendrites, and then they propagate their output signals to the other neurons with their axons. These signals are in the form of electrical voltage pulses. Axon conducts the signals to thousands of other microstructures called synapses. These structures convert the signal from the axon into electrical effects to trigger the activity of neuron which they are connected. The neuron sends another electrical signal output if the received signal is sufficiently huge compared with its inhibitory input. The learning procedure works by varying the synapses' effectiveness [5, 6].

1.2.4 Feedforward Neural Network

In the artificial neural networks, the first and the simplest design is the feedforward NN, where nodes are organized in layers, for example input nodes, hidden nodes, and output nodes [7]. An example of a feedforward NN is shown in Figure 1.5

A feedforward neural network may contain 3 sorts of nodes:

1. Input Nodes – Entering information to access the network, also called "input layer", where no calculation is made at any neuron of the input layer- because it is a transfer node which it transfers information only to hidden nodes.
2. Hidden Nodes – There is no connection to the hidden nodes by external information, hence it is called "hidden". It performs all calculations and also has the ability to transfer information from the input nodes to the target (output) nodes.
3. Output Nodes – The output nodes are responsible of the calculations and transmission of information from the network to the user to show the results.

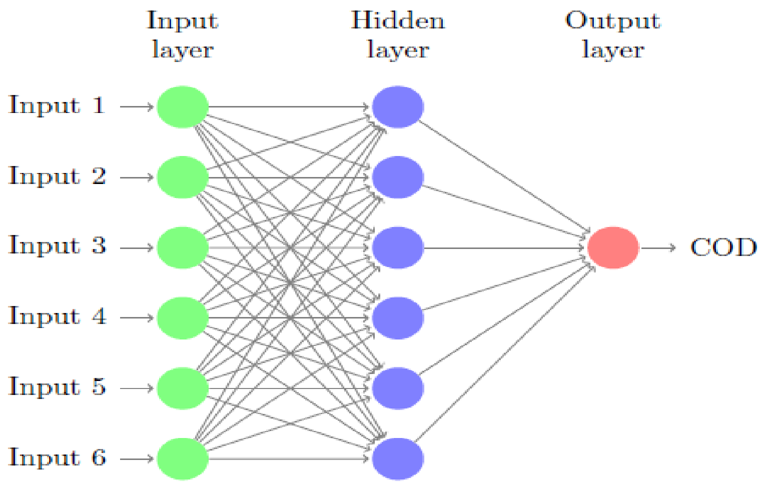

Figure 1.5 Feed forward neural network with hidden layers

1.2.5 Learning Techniques in Neural Networks

Learning processes in artificial neural networks categorized into three main groups [7]:

1. Supervised Learning

   In supervised learning, inputs and desired outputs are given to the network, and the desired outputs are tried to be obtained by adjusting the weights.

2. Unsupervised Learning

   In this learning process, only input data is provided and there is no output data available. Network consists of only an input layer and a competitive layer. This technique generally used to categorize the data into different classes. Network runs with the winner-takes-all approach.

3. Reinforcement Learning

   Learning process between inputs and outputs is performed with the help of a continuous interaction with environment to increase the performance.

   Here sometime the desired output is unknown, but the network has accessibility to the feedback that indicates whether the obtained output is true or not. Such a case is called semi-supervised learning.

   Learning happens once the weights within the network get updated when several iterations.

1.2.6 The Backpropagation Algorithm

The backpropagation algorithm is commonly employed in feed-forward artificial neural networks, so the neural neurons are orderly in layers, where, they send their signal forward and the mistakes to backwards, the network receives input data within the input layer, and then outputs the network to the output layer. There is also one layer or a many of hidden layers being introduced as network training on the output accuracy [7, 8].

The backpropagation algorithm uses supervised access information, which refers to the algorithm being stored with samples of input and output data predicted by the network [7, 8, 9].

The steps for backpropagation are as follows:

1. Model initialization: a random initialization of the model is a common practice.

2. Forward forward: once the model is initialized with the random values of weights, inputs are passed through the network layers and particular output of the model is calculated.

3. Errors are computed for the output layer neurons.

4. Backpropagation: Weight errors are computed between the output and the hidden layer.

5. Backpropagation: Weight errors are calculated between the input and the hidden layer.

6. All weights are adjusted by considering the errors obtained above.

7. The above steps are repeated until defined error is reached [10].

1.3 Thesis Objectives and Problem Statement

The objective of this study is to get the amount of the chemical oxygen demand (COD) without performing analyzes in the laboratory, because:

First: The wastage of the chemicals used. Chemical materials are used to analyze the amount of the chemical oxygen demand before treatment and after treatment. This is an expensive task for the company since it spends money on this analysis.

Second: This analysis takes approximately 4-5 hours to complete and to get the results, in addition to the effort exerted by the person in charge of this analysis. The analysis is taken place by adding the concentrated sulfuric acid and adding potassium dichromate and silver sulfate solution, and then heating the solution for two hours, then it will be cooled and a detector will be added. This process takes a long time, effort and cost. In the case of the absence of chemical materials for the analysis of the sample, or in the case of failure of the heating and the condensation device being used, we should dispense with this examination and the test will be failed.

Therefore, the artificial neural network is a way to predict the chemical oxygen demand value by previous knowledge of the amount of each water quality parameter within the wastewater samples taken from and analyzed inside the laboratory at the North Gas Company / Kirkuk. Another helpful approach is the use of the water quality parameters in an equation and multiplying each parameter by a factor obtained from the multiple linear regression models in accordance with the experimental analysis data. Hence, we can find the value of the COD without using chemical materials and analyses, and with less effort and time.

CHAPTER 2

BACKGROUND INFORMATION AND LITERATURE SURVEY

2.1 INTRODUCTION

Chemical oxygen demand (COD) is considered as a parameter that widely used to determine organic pollution in wastewater and superficial waters. Chemical oxygen demand parameter is important in the calculation of the required oxygen amount for the stabilization of present organic material to determinate of the wastewater treatment plant's performances. The measurement of COD consumes very long time to obtain the measurement results and costs more.

Artificial neural networks mostly used in engineering applications such as intense parallel systems consisting of many operation elements attached to each other with weights. Back-propagation principle is the most widely used method in artificial neural network (ANN).

Hence, many studies have been made to obtain the mean square error (MSE) and regression (R) and compare them with the results of the thesis.

2.1 Background

Areerachakul [11] used an ANN model to predict the COD from 11 sample sites in Bangkok. Water quality parameters (twelve parameters) are used as the input of the model to predict chemical oxygen demand (COD). Each record contains 13 parameters which are biochemical oxygen demand (BOD5), dissolved oxygen, temperature, pH, suspended solids (SS), hydrogen sulfide, ammonia nitrogen, nitrate nitrogen, nitrite nitrogen, total Kjeldahl nitrogen, total coliform, total phosphorous, and COD.

To represent the water quality parameters affecting COD, 12 input nodes, then 10 hidden nodes, and juts one output node is used to representing COD. Therefore, architecture of the network is used to be 12-10-1. Their findings yielded the ANN model correlation coefficient R to be 0.89 and the root mean square error to be 15.16.

Vijayan [12] used ANN models to predict wastewater treatment plant variables. This method utilizes ANNs to predict influent and effluent COD, BOD, and total suspended solids (TSS) for effluent treatment process. Feed-forward neural network with back propagation learning algorithm, was utilized to obtain BOD, COD and TSS values in the effluent. Different network architectures were tried and the best one produced an RMSE to be 0.0984 and a regression value to be 0.99959.

Abba [13] applied a feed-forward neural network model and multiple linear regression (MLR) models to predict the COD in a wastewater treatment plant in Nicosia, North Cyprus. Input parameters of ANNs are taken to be chemical oxygen demand, biochemical oxygen demand, pH, TSS, total nitrogen, total phosphates, conductivity, SS and output neuron is attributed to the COD. Findings from the ANNs model and MLR analysis were compared and the performance of the ANN model was found superior to MLR. The 8-8-1 architecture for the ANN was used. The best results appeared at epoch 203, the R^2 is equal to 0.7034 and RMSE is equal to 0.0108.

Arabameri [14] used an ANN model to predict COD from landfill leachate samples which obtained from a municipal landfill site in Shahrood, Iran. All leachate samples tested by using an ultrasonic process within 2 days after taking samples from leachate lift stations. In order to calculate the MSE and R^2 values, Levenberg–Marquardt backpropagation algorithm is applied in training. In this study, it has been found that the predicted COD results are in line with the experimental data with the R^2 which equal to 0.992, and the MSE which equal to 0.000331 at epoch 31. The sensitivity of the analysis showed that all studied variables (contact time, pH, ultrasound frequency and power) have strong effect on COD removal result. Results showed that modeling neural network can predict COD removal effectively from landfill leachate by applying ultrasonic process.

Hamada [15] used ANN models which are multi-layer perceptron (MLP) model, and radial basis function (RBF) model and also MLR model to predict three major water quality parameters in Gaza wastewater treatment plant. The obtained results of three models are compared with each other. The input parameters were temperature, pH, COD, BOD, and total dissolved solids. The output parameters were COD, BOD, and total dissolved solids. The performance of the three models was compared using the RMSE and R parameters. The architecture of the neural network model was determined as 5-10-3 after several trial and error steps but the best results obtained by 10 nodes for hidden layer. The best results in MLP to predict COD are R=0.7594 and at epoch 3 the MSE=59.48.

Parsimehr [16] studied the water quality parameters of the Gamasiab River in Iran by using ANNs. Input data includes temperature, COD, total dissolved solids (TDS), BOD, dissolved oxygen (DO), TSS, turbidity, acidity, anions, and cations. To calculate correlation between these parameters and COD, the MLP ANN model is used. The correlation was measured using correlation coefficient and regression. Results showed a good performance for MLP ANN in the modeling of the COD. The architecture of the network was 13-1-1. They obtained RMSE values between 0.09 and 0.11, and R values between 0.95 and 0.97.

2.2 Summary

Artificial neural networks were used to predict COD in all above studies. In general, this method reduces time and cost. Results can be obtained without being analyzed in the laboratory by using this method. In terms of findings, the obtained results were good in all above studies. In general, when regression results are equal to 1, means that closer relationship (fit) and when mean square error equal to zero, means that there is no error. However, all results have slight errors in all above articles.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This chapter is separated into two phases. The first one includes the work in the laboratory to measure the amount of pollutants in industrial waters, for example, nitrate ions (NO_3^-) chloride ions (Cl^-), phosphate ions (PO_4^{-3}), sulfate ions (SO_4^{-2}), ammonia (NH_3), BOD, COD and to know amount of each pollutant in industrial wastewater. In the second phase, artificial neural networks were used to predict the COD in the wastewater. The main objective of this study is to use the ANNs to predict the COD in the wastewater using the data obtained for 6 different water quality parameters. The data were obtained from industrial wastewater treatment plant in North Gas Company, Kirkuk. In general, artificial neural networks provide highly accurate predictions in finding of both linear and nonlinear relations among the data points, hence, they are considered as the main predictive tools in this study.

3.2 Analyses in Laboratory (The First Phase)

3.2.1 Analysis of Chloride ions Cl^-

The chloride ion is the important negatively charged ion in the natural water, and the salty taste is obtained, especially if Na^+ is associated with Cl^-. This taste varies by concentration and the saline taste cannot be given if it is associated with other ions such as magnesium and calcium ion. The advantage of Iraqi water is the predominance of Ca^{+2}, HCO_3^-, Cl^-, SO_4^{-2}. This indicates that mineral components of rocks and surface deposits are the predominant factor in water quality [17].

Procedure:

The following method is used when the concentration of chloride ions is more than 5 ppm

1. Take 50 ml of the sample.
2. Add 4 drops of K_2CrO_4 potassium chromate the solution becomes yellow.
3. The burette with $AgNO_3$ silver nitrate at 0.017 N concentrations.
4. The end point of the reaction is to change the color of the solution from yellow to red and takes the size of $AgNO_3$ multiply in factor.

Calculation:

Calculate the chloride ion concentration in the original sample, in parts per million, as follows:

$$Chloride, mg/liter\ (ppm) = [(V1 - V2) * N * 71000]\ /\ S$$

where,

$V1$= milliliters of standard $AgNO_3$ solution added to titrate the sample prepared.

$V2$=milliliters of standard $AgNO_3$ solution added to titrate the sample prepared.

N=normality of standard $AgNO_3$ solution,

S= Milliliters of original sample in the 50 ml test sample prepared.

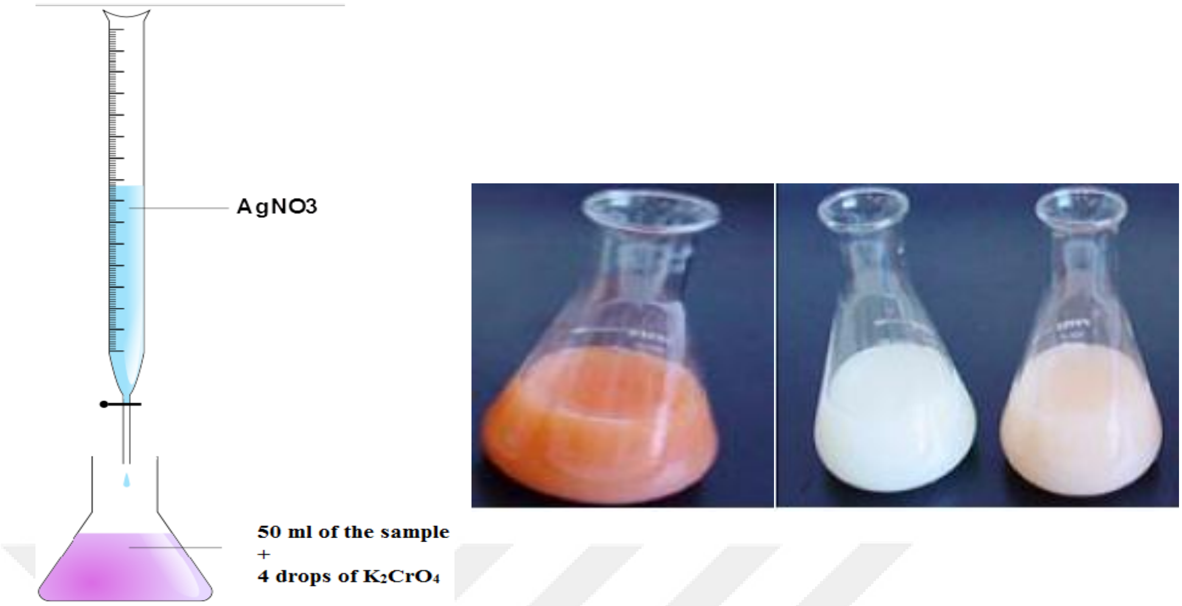

Figure 3.1 Analysis Chloride ions Cl^-

3.2.2 Chemical Oxygen Demand, COD

This method is used in industrial water models (wastewater).

The method of measuring the chemical oxygen demand is one of the accepted and good methods to express the concentration of organic matter, but it takes a long time to conduct it. This is one of the ways through which organic substances are oxidized with strong oxidant chemicals like potassium dichromate $K_2Cr_2O_7$ and concentrated sulfuric acid, and then measuring the remaining oxidant substances used to indicate the concentration of organic matter.

The chemical oxygen demand values are higher than or equal to the biochemical requirement of oxygen due to the total oxidation of all organic substances in the COD process within two hours, including even the substances that the bacteria cannot oxidize in the BOD_5 process and within days most organic matter decomposes with boiling with an increase of potassium dichromate solution and concentrated sulfuric acid, then a residual equation of potassium dichromate with Ferrous sulfate concentrate

Silver sulfate is used as an adjuvant for the analysis of aliphatic organic substances such as some types of alcohol and organic acids. Chloride is also used to reduce chloride, bromine and iodine interference when there is fat in the sample. Silver sulfate with these substances is a low oxidation residue although there is a greater interferon effect of chlorides; they can be removed by using $HgSO_4$, which converts chlorides into dissolved and low-soluble mercury chloride for the presence of nitrite in the water sample. This overlap can be avoided by adding 10 mg of Sulfonic acid per 1 mg of nitrogen the acid can be added to the potassium dichromate solution with 0.12 g of acid per liter of solution to the dichromate solution. This ratio is able to remove nitrite overlap when and in the form to a concentration of 6 mg / L [18].

Procedure:

1. Place 50 ml of the sample in a reflux flask.
2. Add 5 ml of concentrated H_2SO_4.
3. Add 25 ml of the $K_2Cr_2O_7$ solution is the consumed by the reaction.
4. Add 70 ml of sulfuric acid-silver sulfate solution (Ag_2SO_4 + H_2SO_4) this reaction is heat-reactive, the solution (Ag_2SO_4 + H_2SO_4) should be added a small amount and then cooled in the ice bath.
5. Reflex is heated for two hours.
6. Cool the sample and then complete the volume to 300 ml using distilled water.
7. Add 8-10 drops of phenanthroline ferrous sulfate solution and titrate the excess di chromate with 0.25N Ferrous Ammonium Sulfate Solution
8. The color changes at the end point will be sharp, changing from a blue-green.

9-As for Blank use 50 ml distilled water with full additives

$COD\ (ppm) = (A - B) * N * 8000 / S$

A=milliliters of Ferrous Ammonium Sulfate solution required for titration of the blank.

B=milliliters of Ferrous Ammonium Sulfate solution required for titration of the sample.

N=normality of the Ferrous Ammonium Sulfate solution.

S= milliliters of sample used for the test.


Figure 3.2 Analysis Chemical Oxygen Demand

3.2.3 Biochemical Oxygen Demand BOD_5

The amount of the dissolved O_2 required by aerobic organisms to crush organic material in water at specific conditions (such as temperature and time) is defined to be biochemical oxygen demand or biological oxygen demand (BOD).

The biochemical oxygen demand is most usually expressed in milligrams of oxygen consumed per liter of sample throughout *five days* (BOD5) of incubation at 20 °C.
The amount of oxygen required for use by microorganisms to analyze unstable organic matter present in water and turn it into a more stable and stable condition in aerobic conditions. BOD5 is used to estimate the degree of pollution of wastewater and industrial water and the ability of water bodies to absorb this polluted water, the process of technical technology of these surfaces [19].
The amount of BOD_5 is directly proportional to the amount of nitrogen and phosphate as it needs 1000 ppm of BOD_5 to (5-10 ppm nitrogen) and (1ppm of PO_4). How to read the BOD_5 using the OXITOP OCLLO WTW system:

Procedure:

1 - Wash the bottles where we put the sample.

2 - Prepare KOH solution (30%) approximated 20 ml for a total of four bottles.

3 - Using the control device attached to the system is entering the data crisis and according to the type of sample.

4 - Press the ON / OFF signal and then get the Call Up all data, Start.

5. After pressing Start, we start configuring the program.

6 - We choose the range we work to be 200ppm and from it we know the required size of the model to be analyzed.

7 - After choosing the range size of the form Press Run / Enter from which we get the list as follows: -

Type	BOD_5
Mean Rng	200mg/L
Final data	21/2/2011
ID Number	001
Start	Temp

8 - Enter the number of the form through the period ID Number and then go to the Start sign in this case should approach the control of the nozzle of the bottle at a distance of 5 cm no more and then press the Run / Enter when giving a flash in the sensitivity directed in the nozzle of this bottle indicates that the program completed and wait for 5 days to get the result.

9 - After the passage of the prescribed period we go to paragraph 4 of which we ask all values using the instructions (Call Up All Data) where the control device should be rounded for less than 40 cm. When we get the mark $\surd$ means that the program is complete and then go to the reference where we get the BOD_5 concentration.

Calculated: Another equation for calculating BOD_5:

$$BOD5 = M\ (O2)\ /\ R - TM\ *\ \{VT - VL\ /\ VL * \ TM\ /\ TO\}\ *\ \triangle P\ \ (O2)$$

where,

$M\ (O2)$ =Molecular Weight 32000 mg/mol

R= Gas constant (83.144 Mbar/mol.K)

TO=Reference Temperature (273.15 K)

TM=Measure Temperature

VT=Bottle Volume

VL=Sample Volume

R=Bunsen Absorption 0.03103

$\triangle P\ (O2)$ =difference of oxygen pressure

Figure 3.3 Analysis Biochemical Oxygen Demand

3.2.4 Analysis of Phosphate Ions PO_4^{-3}

Method: A phosphate is chemical derivative of phosphoric acid, the phosphate ions (PO_4^{-3}) is an inorganic chemical, the conjugate base that can form many different salts,

This method is based on the photometric measurement of the yellow color of molyb-dovanadophosphoric acid developed in the sample; the color intensity is proportional to the orthophosphate concentration of the sample [20].

Procedure:

1-Transfer 50 ml of a clear sample (filter if suspended matter is present) into an Erlenmeyer flask. If the sample contains more than 10 mg/liter (ppm) of phosphorus, use a correspondingly smaller sample, diluted to 50 ml with water.

2-Add 25 ml of ammonium molybdate-vanadate solution to the sample and mix well. Allow 2 min for the color development. Measure the color absorbance at 400 to 420 nm with a filter photometer or at 400 nm with a spectrophotometer, using water as the reference sample. Record the phosphorus concentration indicated by the calibration water curve prepared in accordance.

Calculation:

Calculate the concentration of orthophosphate, in milligrams per liter of phosphorus, as follows:

$Orthophosphate, mg/liter\ (ppm) = A\ x\ (50/B\ )$

where

A = milligrams per liter of phosphorus indicated by the calibration curve for the determined absorbance.

B= milliliters of sample used.

3.2.5 Analysis of Sulfate Ions SO_4^{-2}

Application: This method is intended for rapid tests for sulfate ion in industrial water, over the range of 10 to 100 mg/liter (ppm) of sulfate ion SO_4^{-2} [21].

Procedure:

1- Take 50 ml of the Sample

2-Add 10 ml of glycerol solution

3-Add 5 ml NaCl solutions.

4-Naught the device after making the above additions

5- Added with stirring 0.3 g of $BaCl_2$ 2H2O crystals continue gently stirring the solution for 1- 4 min. fill the cell sample and it is read directly of the spectrophotometer.

7-At the end of time we read the concentration of sulfate ions using a 20 mm cell and 400 nm wavelengths.

Calculation:

Convert the spectrophotometer readings obtained of the sample to mg / liter sulfate ion SO_4^{-2} by use of the calibration curve.

3.2.6 Analysis of Ammonia NH_3

Procedure: [22].

- If the sample contains turbidity, add 1 mL of $ZnSO_4$ solution to a 100-mL aliquot and mix. Add NaOH solution with gentle mixing until the pH is about 10.5. Allow to settle and filter using a water-washed, moderately-retentive filter paper, discarding the first 25 mL of the filtrate. Dilute a portion of the filtrate or clear sample, containing not more than 0.1 mg of ammonia nitrogen, to 50 mL in a Kessler tube.

-Add 2 drops of sodium potassium tartrate solution (or disodium hydrogen ethylenediamine tetraacetate) to prevent cloudy tubes, and mix. Add 1 mL of Nessler solution and measure photometrically at a wavelength of 425 nm.

- If a visual comparison method is used, select a volume containing not more than 0.04 mg of ammonia nitrogen and dilute to 50 mL Mix, add 1 mL of Nessler reagent, and remix. Compare the color developed after 10 min with the previously prepared standards. If the ammonia nitrogen concentration is below 0.008 mg (in the 50-mL tube) compare after 30 min

Calculation:

Calculate the ammonia concentration in mg/L of nitrogen in the original sample, using the following equation:

$$Ammonia\ nitrogen, \frac{mg}{L} = \left[\frac{A * 1000}{S}\right]$$

where

A = ammonia nitrogen observed, mg

S = sample, mL

Calculate the ammonia concentration in mg/L of ammonia in the original sample, using the following equation:

$$Ammonia, mg/L = E * 1.22$$

where

E = ammonia nitrogen, mg/L

3.2.7 Analysis of Nitrate Ions NO_3^-

Procedure: [22].

1- Take 5 ml of the Sample

2-Add 1 ml of Brucine -Sulfonilic Acid regent.

3-Into a second 50-ml beaker measure 10 ml of H_2SO_4.

4-Mix the contents of the two beakers by carefully adding the sample with the Brucine -Sulfonilic Acid regent.to the beaker containing the acid Pour from one beaker to the other 6- times to ensure mixing.

5-While the color is developing add 10 ml of water to the empty 50-ml beaker. After the 10 min interval, add the 10 ml of water to the sample and mix as before. Allow to cool 20 to mi 30 min in the dark.

6-Measure the absorbance of the treated sample at 410 nm against a blank treated similarly to the sample except for omitting the addition of the brucine-sulfanilic acid reagent.

7-Determine the concentration of NO_3 in the sample from a newly prepared calibration curve, read the concentration using a spectrophotometer device and a 20 mm diameters and wavelength 410 nm.

3.2.8 Spectrophotometer Device

This device is used to measure the concentration of elements and ions using spectroscopy and ultraviolet radiation. Elements and ions are read in this device based on absorption, and permeability based on the Lambert's law: (When monochromatic light passes through a solution and displays a constant cell that is directly proportional to the concentration of that solution) [23].

$A = e * b * c$

where

A= the measured absorbance

e= absorption coefficient

b= the path length

c= the analytic concentration

Where the readings are taken from the visual area of electromagnetic radiation, which have limits of wavelengths 190-1100 nm where in this region electronic transitions from external orbits and uses the area of the region ultraviolet and visible in general in the diagnosis of some metals and metal compounds in quantity and quality through electronic transitions that Where the absorption of energy to higher energy levels.

The concentrations of elements and ions are read using a spectrophotometer:

Chloride ions Cl^-

Ammonia NH_3

Phosphate ions PO_4^{-3}

Sulfate ions SO_4^{-2}

Nitrates ions NO_3^-

Figure 3.4 Spectrophotometer device

Analyses results for water quality parameters obtained from the above procedures are given in the dataset presented in the Appendix Table A and Table B.

3.3 ANN Modeling (Second Phase)

3.3.1 Introduction

ANNs are computer programs developed to simulate methods of processing in the way the human brain processes information. ANN processes the information by working on the input data, and through the training of the network with experience, weighed signals will produce the outputs of hidden layer and the output layer.

Through continuous training, communication between the units, i.e. the input layer, the hidden layer and the output layer is improved until the error in the predictions is reduced and the network reaches the required level of accuracy.

This is called network training and testing because it predicts high-precision output.

When applying artificial neural network; data collection, data processing, using numbers of hidden layers, network creation, weighting configuration, training network, and network testing, will occur [24].

3.3.2 The Basic Specification of the Model

The model to be used is a multilayer perceptron MLP.

3.3.2.1 Input Layer

It is selected the six inputs of the model and Table 3.1 indicated the input layer for samples, below.

Table 3.1 Input layer for samples

No.	Input sample
1	Chloride ion Cl^{-}
2	Biochemical of oxygen demand BOD_5
3	Ammonia ions NH_3
4	Phosphate ions PO_4^{-3}
5	Sulfate ions SO_4^{-2}
6	Nitrates ions NO_3^{-}

3.3.2.2 Output Layer

Table 3.2 Output layer for samples

No.	Output sample
1	Chemical oxygen demand (prediction of COD is the aim of this study)

3.3.3 Hidden Layer

In the ANNs, a hidden layer located between input layer and output layer, in which neurons get weighted inputs and give results through activation

.

Hidden neural network layers are supported in a lot of different method:

In firstly stages inputs are indiscriminately allotted, in second stages they're fine-tuned and labelled through a way referred to as backpropagation, either case, the artificial neuron within the hidden layer functions as a biological neuron within the brain – it obtains input signals, processes and converts them into an output comparable to a biological neuron's nerve fiber.

Description of this methodology is given by the flow chart in Figure 3.5 (before treatment and after treatment cases have the same methodology) [25].

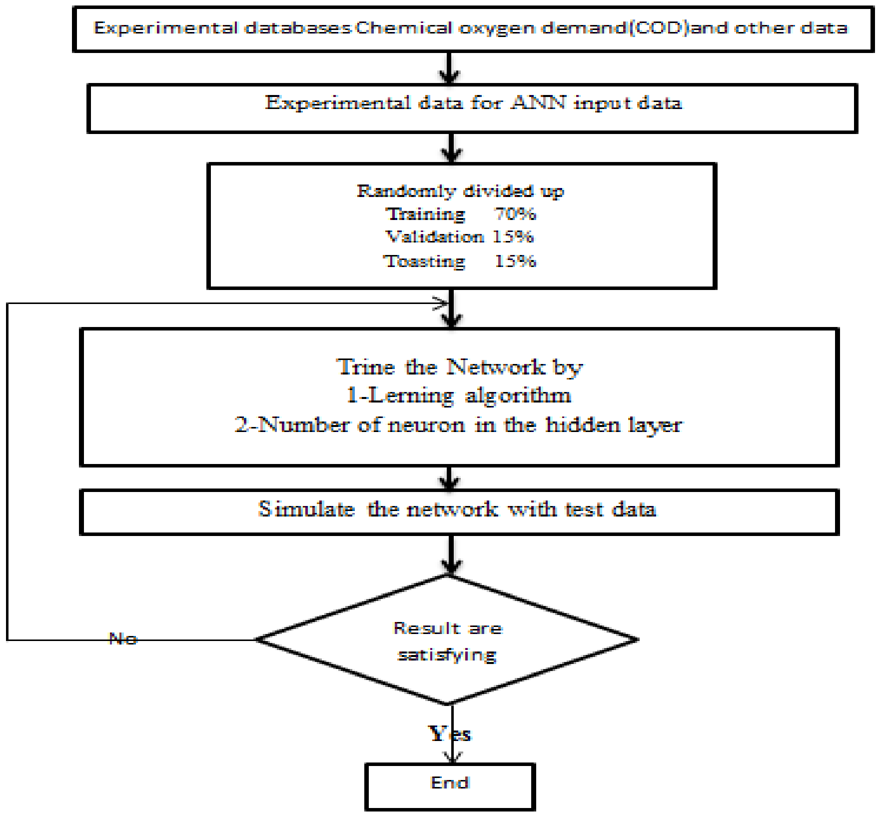

Figure 3.5 Flow chart of second phase ANN model

3.3.4 Model Design for Before Treatment

In this study, the MATLAB 2017 program and the two sets of data are used:

The inputs ‘unnamed’ are a 150x6 matrix representing static data: 150 samples of 6 elements.

The targets 'unnamed' are a 150 x 1 matrix representing static data: 150 samples of 1 element.

The data set stores samples in an aspect of rows rather than in columns, to train artificial neural network, W in the diagram indicates weights and b indicates bias units, which are parts of individual neurons, 6 inputs and corresponding weights, and 1 outputs (See Fig. 4.1 in Chapter 4 to see W and b on the ANN structure).

The hidden layer is selected from 3 to 10 layers, starting from layer 3 and according to the rule:

Input + Output / 2.

You can start the ANN by Starting GUI which in turn starts by typing the command nnstart.

After that chose the pattern recognition tool from the list to open the NN pattern recognition tool,

Then click "Next" in the welcome screen and chose "Select Data".

For the inputs select X train, and for the targets select Y train. That mean getting data from workspace input time series x (t), and target (COD) time series, and defining the desired output y (t) [29],

This form of prediction is called NARX, the formula is given below:

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{f}(\boldsymbol{x}(\boldsymbol{t}-\mathbf{1}), \dots, \boldsymbol{x}(\boldsymbol{t}-\boldsymbol{d}), \boldsymbol{y}(\boldsymbol{t}-\mathbf{1}), \dots, \boldsymbol{y}(\boldsymbol{t}-\boldsymbol{d})$$

Click "Next" and then go to "Validation, Test and Training Data". Accept the default settings and click "Next" again. This will separate the data to 104-23-23 for the training, validation and testing sets. Randomly dividing up 150 ´target time steps´ to three kinds as:

Training: the targets that are displayed on the network throughout training, its error will be modified, and the data are divided by up to 70% that's means 104 target time step.

Validating: are the targets that are utilized to measure network generalization.

Training: must be discontinued when generalization stops improving, and will be the data are divided by up to 15% that's means 23 target time step [26].

Testing: the target which has no any effect on training and providing an independent of measuring training network performances and will be the data are divided by up to 15% that's means 23 target time step.

Levenberg-Marquardt Rule

The Levenberg-Marquardt algorithm is designed to be a second-class training accuracy when the training function is in the form of totals of squares [27].

Description of Levenberg Marquart's algorithm:

It is the fastest program to train a medium-sized neural network with very high weights. In addition, the algorithm was applied in the MATLAB program, because this program gives a high result in the matrix equation, and thus its features become clearer through the MATLAB program.

In the Network Architecture", modification the worth for the amount of hidden neurons.

In the hidden layer the function is used to be sigmoid activation function. It uses the function to work out activation. The sigmoid function may be given as:

$$\mathbf{f(x) = 1/(1 + e^{-x})}$$

On the other hand, the linear function is defined as follows:

$$f(x) = x$$

Plot in the "Train Network": click the "Train" button to initialize the training and obtain results, such as regression and histogram, and performance plot to analyze network performance.

Then, the mean squared error (MSE) will be obtained. MSE is the average squared difference between targets and outputs. Lower MSE values provide better results. And the zero result means there is zero error.

The regression ´R´ value is a measure of correlation between targets and outputs.

Where R equals 1 there is a close relationship, R equals zero is random relationship.

Table 3.3 The results for before treatment

Method	Nonlinear input –output		**NN**		NARX	
Result	MSE	R	**MSE**	**R**	MSE	R
Training	597.60939	0.689562	**17.94921**	**0.992894**	1986.82630	0.258799
Validation	1047.7993	0.529208	**42.24658**	**0.976916**	2901.40912	-0.0782110
Testing	1558.7760	0.535928	**157.1701**	**0.943673**	2924.28511	-0.0938515

3.3.5 Model Design for After Treatment

You will be using the MATLAB 2017 program and the same scenario occurs in the work steps before wastewater treatment and shows the results:
Where, the Table 3.4 shows the results after wastewater treatment:

Table 3.4 The best results for after treatment

Method	Nonlinear input –output		**NN**		NARX	
Result	MSE	R	**MSE**	**R**	MSE	R
Training	31.89005	0.536108	**0.0008402**	**0.99999**	49.94740	0.207443
Validation	126.82730	-0.505833	**0.00017593**	**1**	79.04886	-0.195131
Testing	121.59570	-0.0853796	**0.00030785**	**0.99997**	68.22054	0.264173

CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, the results for before and after wastewater treatment cases are discussed.

4.1 Before Wastewater Treatment

4.1.1 Hidden Layers

In artificial neural networks, there are hidden layers between input and output layer. The artificial neural networks take inputs and give outputs via an activation function [28].

The starting number of nodes in the hidden layer is estimated by

(Input + Output) / 2

$$\text{Mean} = (6 + 1) / 2 = 3.5$$

Start point = 3 nodes.

For each number of nodes in the hidden layer, network was trained and regression coefficient between the target and output was recorded. After validation and testing results, the R was calculated for all data.

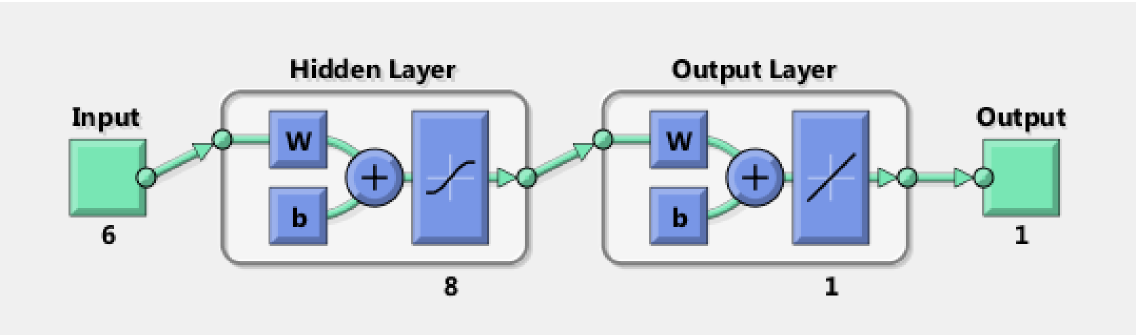

Figure 4.1 Input, hidden and output layers node numbers

The program inserted input and output layer nodes after the determination of the number of hidden nodes, and the architecture of multilayer network is shown in the Figure 4.2

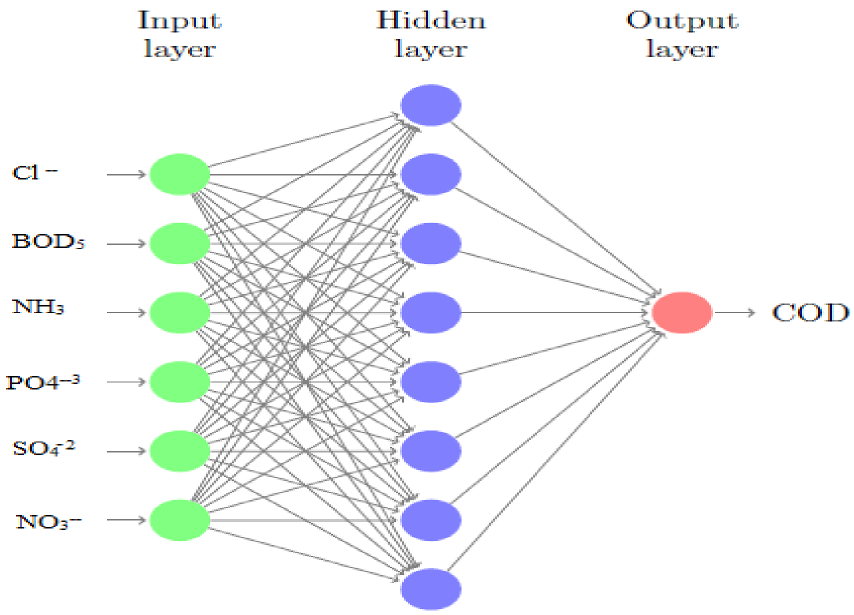

Figure 4.2 The architecture of a multilayer perceptron

Table 4.1 Hidden layer regression results before treatment

No. of Nodes	Training	Validation	Testing	All
3	0.97335	0.9835	0.95845	0.97176
4	0.93321	0.97441	0.94734	0.95165
5	0.95601	0.97277	0.96427	0.96435
6	0.94968	0.98233	0.97575	0.96925
7	0.99039	0.97339	0.95729	0.97369
8	**0.99289**	**0.97692**	**0.94367**	**0.98235**
9	0.99134	0.64839	0.98669	0.92556
10	0.98009	0.99511	0.96774	0.98098

Table 4.1 shows the regression coefficient R results from 3 to 10 nodes in the hidden layer. The results are not really well, due to choosing of the data before wastewater treatment but the hidden layer with 8 nodes has a high regression coefficient (0.98235) comparing with the others. Hence, we will choose the hidden layer with 8 nodes.

4.1.2 The Network Performance before Treatment

After finding the number of hidden nodes, the evaluation of the network performance was achieved.

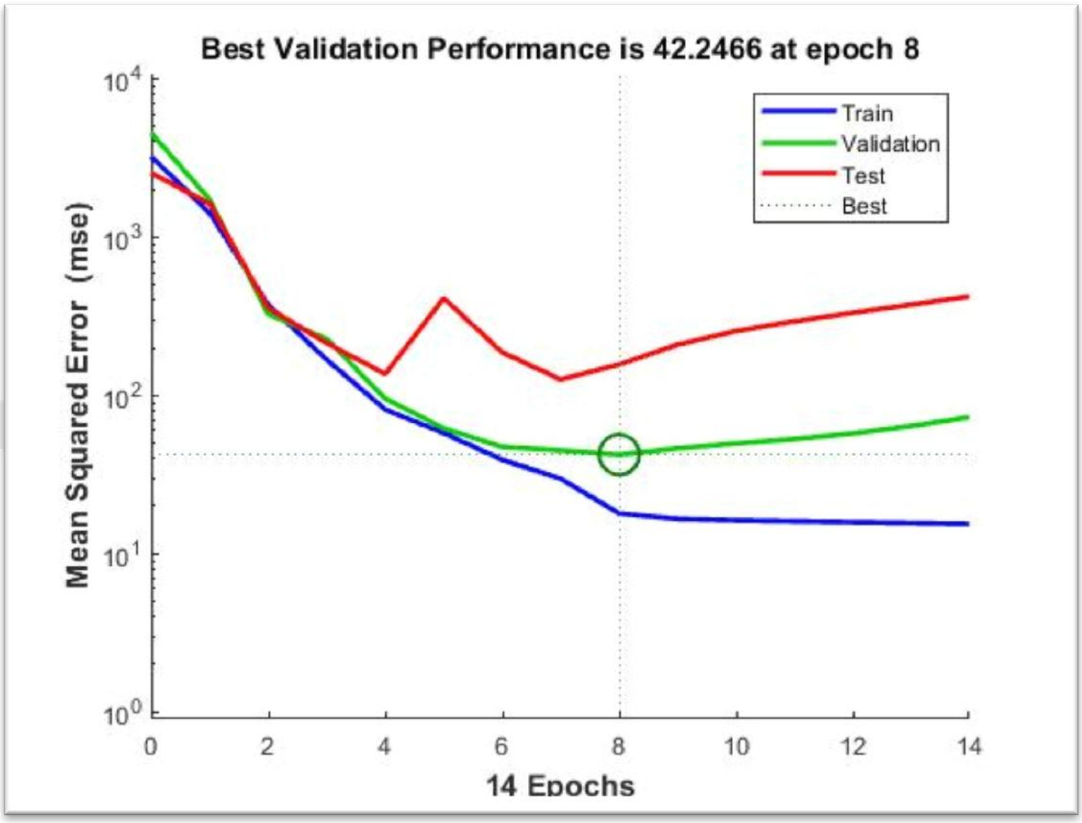

Figure 4.3 Network performance before treatment

The performance of the mean square error (MSE) has been used to evaluate the accuracy achieved while testing the ANN in the estimation of input for the given data. That means that a better prediction can be reached when MSE value is low or around zero, which means the training performance is without error. Figure 4.3 shows a plot between target values and the input values. The training performance reaches to a minimum value at the 8th iteration and the training process continues up to the iteration 14 then stops. Figure 4.3 also shows some problems for training, and the MSE performance at 42.2466 at 8th epoch is high.

4.1.3 The Regression Plots for Before Treatment

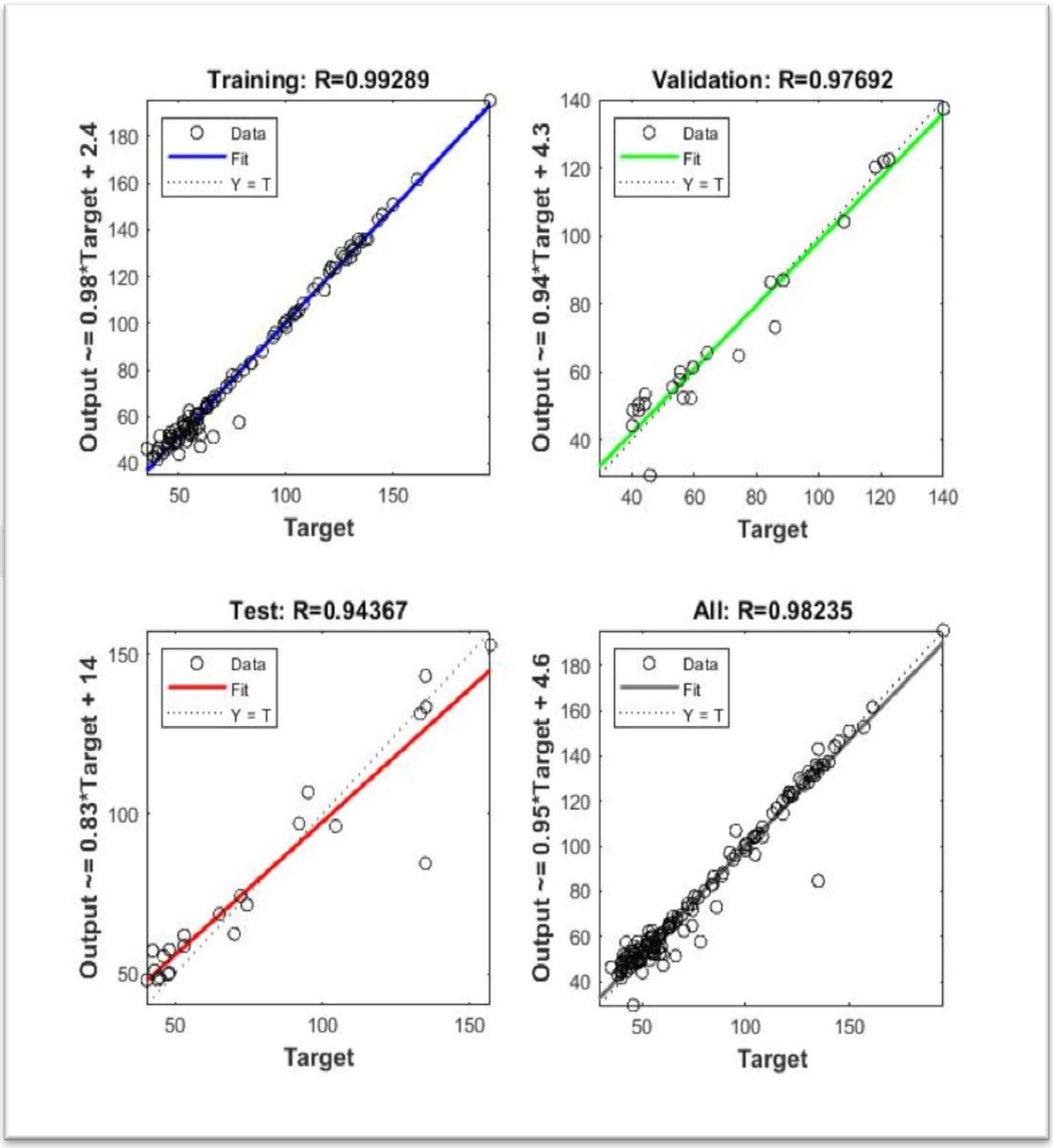

Figure 4.4 Regression plots for before treatment

Regression plots are shown in Figure 4.4, which shows the output-target values relationship.

If the training is a perfect fit, the output values and target values will be the same, and this means R=1, representing an exact linear regression between the outputs and the targets.

The regression coefficient found for all data to be 0.98235; and this finding indicates that input-output mapping obtained from the ANN is not a very good fit for this case. Therefore, it can be considered that the regression among the outputs obtained from the network and the targets (desired outputs) not exact.

4.1.4 Error Histogram of Before Treatment

The blue bars indicate to training data, the green bars indicate to validation data, and the red bars indicate to testing data in Figure 4.5. This figure exhibits the histogram that can give us an indication of outliers and the distribution of the training. Figure 4.5 clearly expresses that the validation and test errors are quite high, and the error distribution results are not reasonably well, because the most of the 150 total data are in errors, and most of the errors have fall between 48.76 and -13.24 which is a quite wide range.

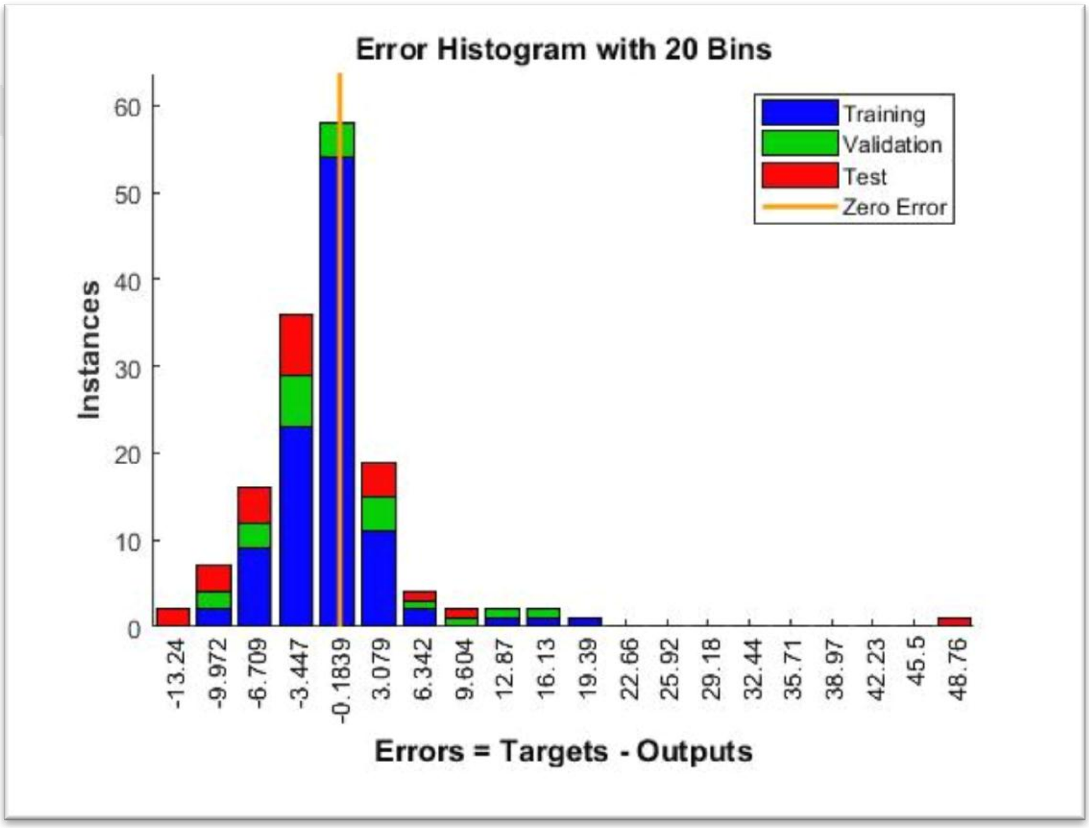

Figure 4.5 Error histogram before treatment

4.1.5 Test of Network before Treatment

The regression plots and error histogram are illustrating the network behavior with the training data.

But the best way to realize if the network performance is well or not is testing the network with more data outside of the training dataset

For this purpose, Figure 4.6 gives indication of the test network, test the network with this data and evaluate the results; therefore, 104 samples are used.

Unfortunately, the results are disappointing; the target is far away from output and the **R** and the **MSE** value are 0.98235, 43.02203 respectively, which means there is no relation between the outputs of the network and the targets.

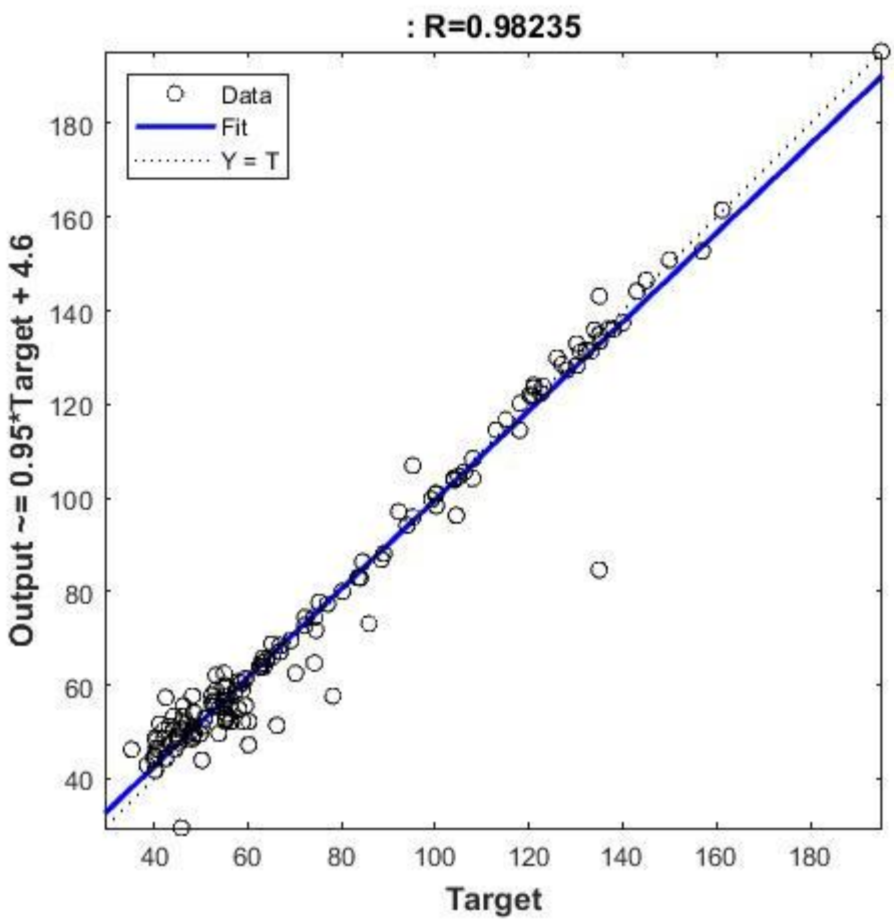

Figure 4.6 Regression plot for test Network

4.1.6 Formula for predicting the result of COD before treatment

POLYMATH 6.10 is a computer program, which is specifically designed to solve data.

The purpose of the POLYMATH program is to allow the solution of multiple linear regression systems, where the data is stored in the form of columns where each column is associated with a system variable. Program reveals the way of obtaining the simplest formula to predict the COD by producing constant factors that are multiplied by the variables of the laboratory data [29].

$$\mathbf{COD = a_1 * cl^- + a_2 * NO_3^- + a_3 * PO_4^{-3} + a_4 * SO_4^{-2} + a_5 * NH_3 + a_6 * BOD_5}$$

Where, a1, a2, a3, a4, a5, a6 are constant factors that can be determined in the regression analysis. The value of $\mathbf{R^2}$ equals to 0.87507 and the value of **RMSD** is 1.002001.

Table 4.2 Constants of the COD equation for before treatment

Variable	Value
a1	0.938811
a2	-0.2839987
a3	-0.0592047
a4	0.0221107
a5	2.061704
a6	0.8517708

4.1.7 Summary of the Results for Before Wastewater Treatment

Table 4.3 Summary of the results for before treatment

<table>
<tr><th></th><th>Training</th><th>Validation</th><th>Testing</th><th>All</th><th>Test network</th></tr>
<tr><td>R</td><td>0.992894</td><td>0.976916</td><td>0.943673</td><td>0.98235</td><td>0.982348</td></tr>
<tr><td>MSE</td><td>17.94921</td><td>42.24658</td><td>157.1701</td><td>72.45529</td><td>43.02203</td></tr>
<tr><td>Network performance of before treatment</td><td colspan="5">And the performance is 42.2466 at epoch 8 it is very high.</td></tr>
<tr><td rowspan="2">Error Histogram of before treatment</td><td colspan="5">Most errors fall between 48.76 and -13.24.</td></tr>
<tr><td colspan="5">Errors = Targets – Outputs</td></tr>
<tr><td>Simple equation to predict chemical oxygen demand MLR</td><td colspan="5">$\mathrm{COD} = 0.938811 * \mathrm{cl}^{-} - 0.2839987 * \mathrm{NO}_3^{-} - 0.0592047 * \mathrm{PO}_4^{-3} + 0.0221107 * \mathrm{SO}_4^{-2} + 2.061704 * \mathrm{NH}_3 + 0.8517708 * \mathrm{BOD}_5$
(R^2 is equal to 0.87507, RMSD is 1.002001)</td></tr>
</table>

4.2 After Wastewater Treatment

4.2.1 Hidden layers

In the same way that we followed in section 4.1.1, the simple rule to yield starting number of the nodes in the hidden layer is

(Input + Output) /2

$$\text{Mean} = (6 + 1) / 2 = 3.5$$

Start point = 3 nodes.

For each number of nodes in the hidden layer, network was trained and the regression coefficient between the target and output was recorded. After validation and testing results, the R was calculated for all data.

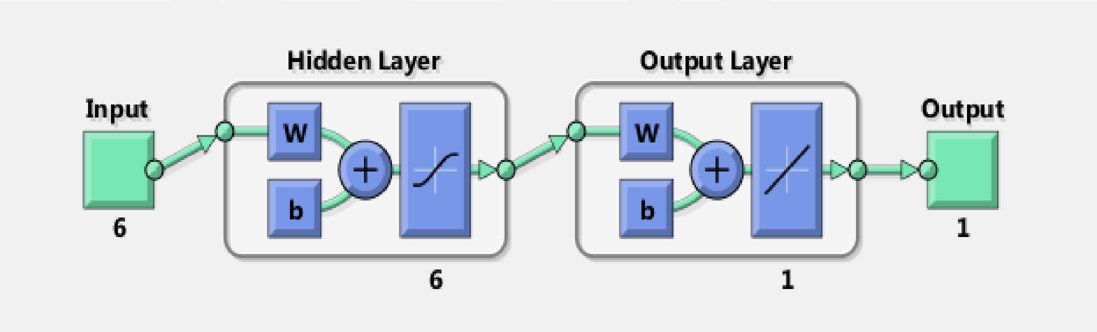

Figure 4.7 Number of input, hidden and output layers

The program inserted input layers and output layers after the calculation of the number of nodes in hidden layer, and the architecture of multilayer network is shown in the Figure 4.8

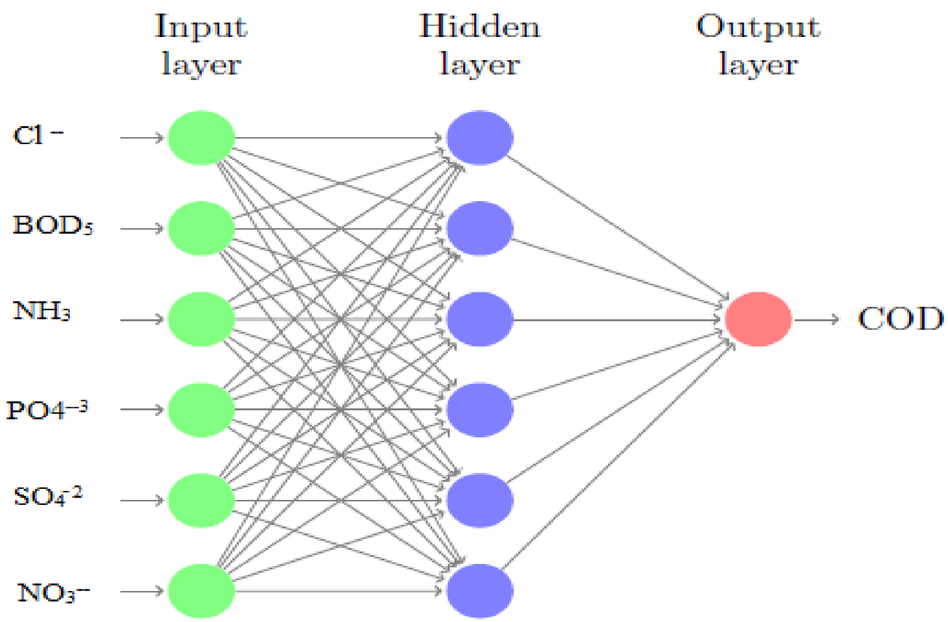

Figure 4.8 The architecture of a multilayer perceptron for after treatment case

Table 4.4 Hidden layer regression results for after treatment

No. of nodes	Training	Validation	Testing	All
3	0.99998	0.9999	0.99999	0.99989
4	0.99809	0.99765	0.99909	0.99823
5	0.99998	0.99985	0.99998	0.99995
6	**0.99999**	**1**	**0.99997**	**0.99999**
7	0.9999	0.9994	0.99336	0.9994
8	0.99997	0.98959	0.99999	0.99836
9	0.99997	0.99997	0.97171	0.99465
10	0.99999	0.9992	0.99681	0.99937

Table 4.4 shows the results obtained for hidden layer containing number of nodes from 3 to 10. The results are very good due to choosing of the data after wastewater treatment. Hidden layer with 6 nodes has a high regression coefficient, 0.99999. Therefore, it is preferred to choose a hidden layer with 6 nodes.

4.2.2 The Network Performance after Treatment

After finding the hidden nodes, the evaluation of the network performance was achieved**.**

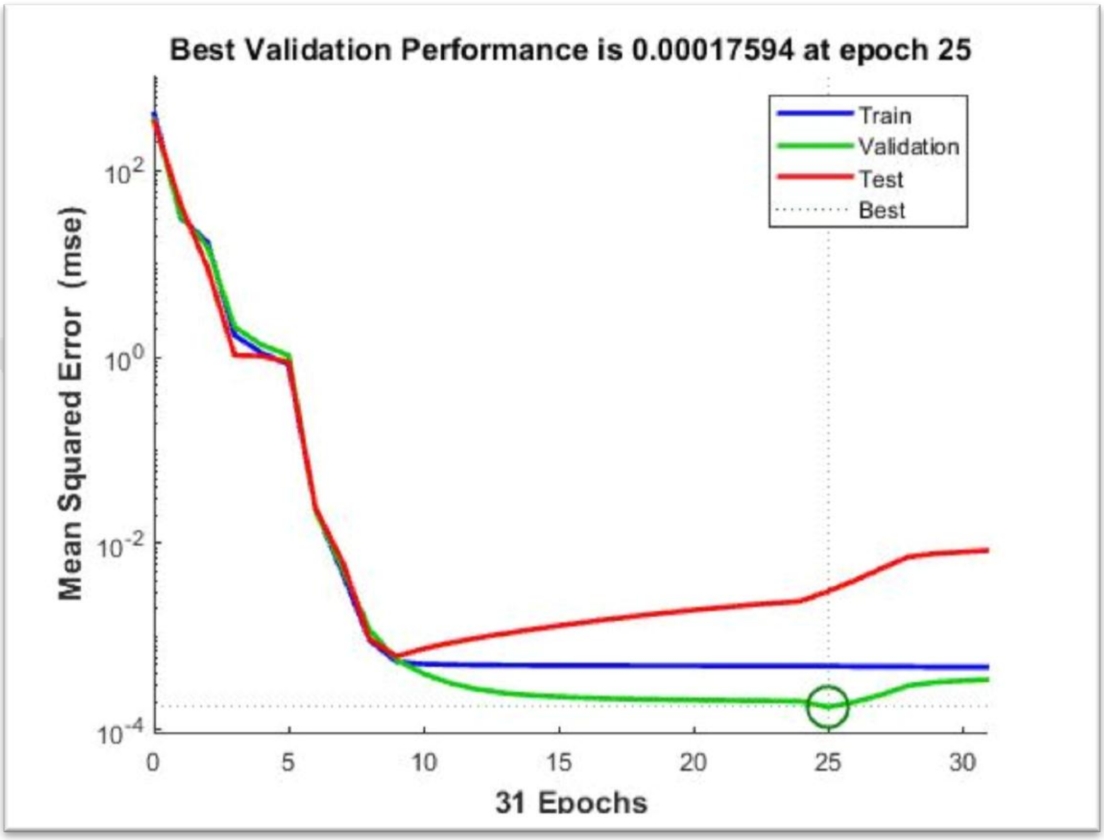

Figure 4.9 Network performance after treatment

The performance of the mean square error (MSE) has been used to evaluate the accuracy achieved while testing the ANN in the estimation of input for the given data. Figure 4.9 shows the plot between target values and the input values. The training MSE performance value reaches to the minimum at the 8^{th} iteration and then continues up to the 31^{th} iteration then stops. Figure 4.9 shows a good training performance, and the best validation performance at 25^{th} epoch is obtained to be 0.00017594 which is close to zero.

4.2.3 The Regression Plots for After Treatment

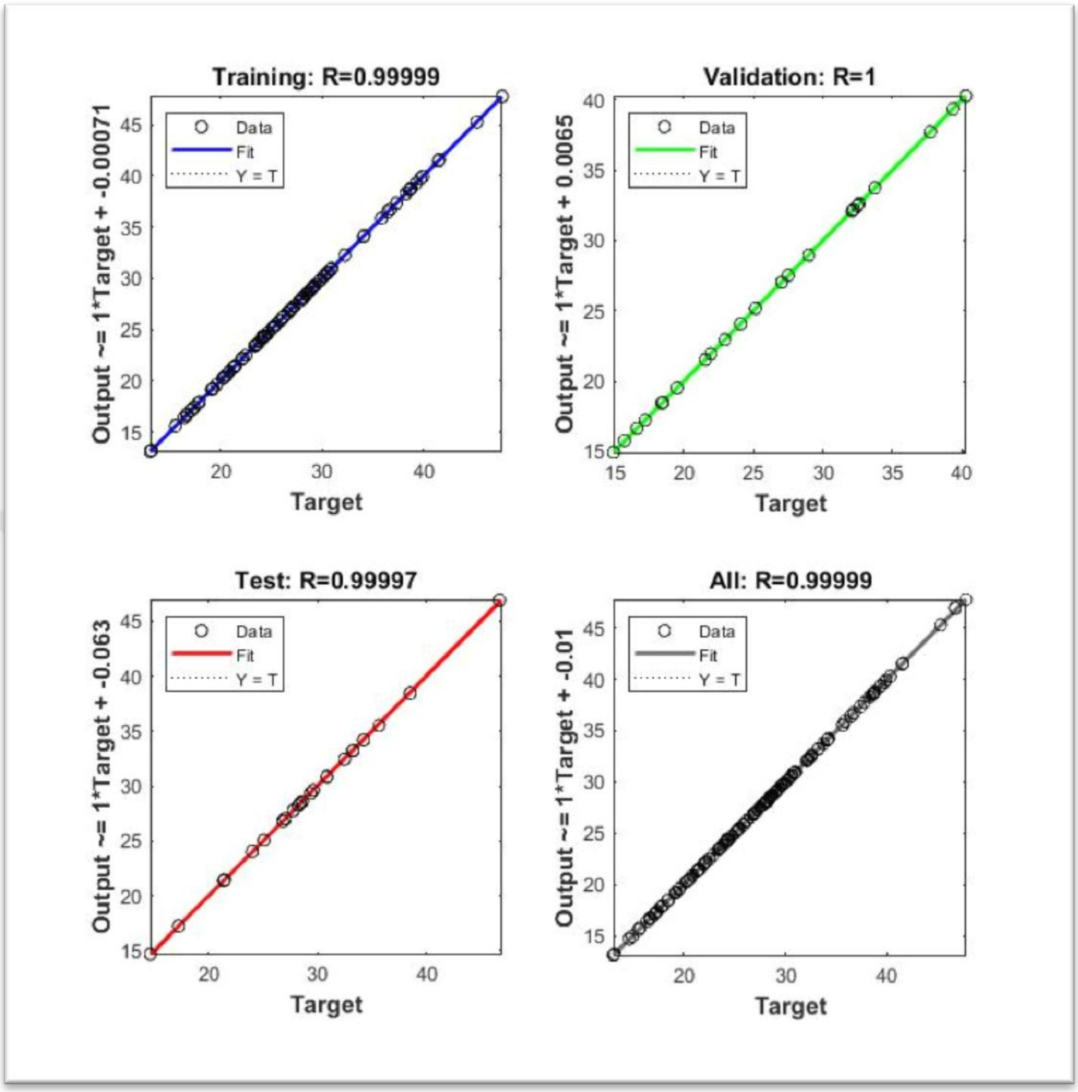

Figure 4.10 Regression plots for after treatment

The regression plots in Figure 4.10 show the relationship between the outputs of the network and the target values.

As we mentioned above, if the training is perfect fit, the output from the ANN and the target will have the same value. This means R=1, which represents an exact linear regression between the outputs and the targets.

The regression coefficient found to be 0.99999; this indicates that there is a perfect suitability of data (fit). So, it can be considered that the results are acceptable with reasonable errors and it's very close to targets, and the regression between the outputs and the targets is almost exact.

4.2.4 Error Histogram of After Treatment

Figure 4.11 gives indication of outliers and exhibits the distribution of error for training, validation and test steps. Figure 4.11 clearly expresses that the validation and test results are very well and the results for error distribution are very reasonable.

In addition, a good indication of the values of outliers is provided in this figure. However, the obtained outliers do not actually affect the performance because little errors were found out of 150 total data and most errors fall between 0.09713 and -0.2316. These errors are considered acceptable and satisfied the training distribution results.

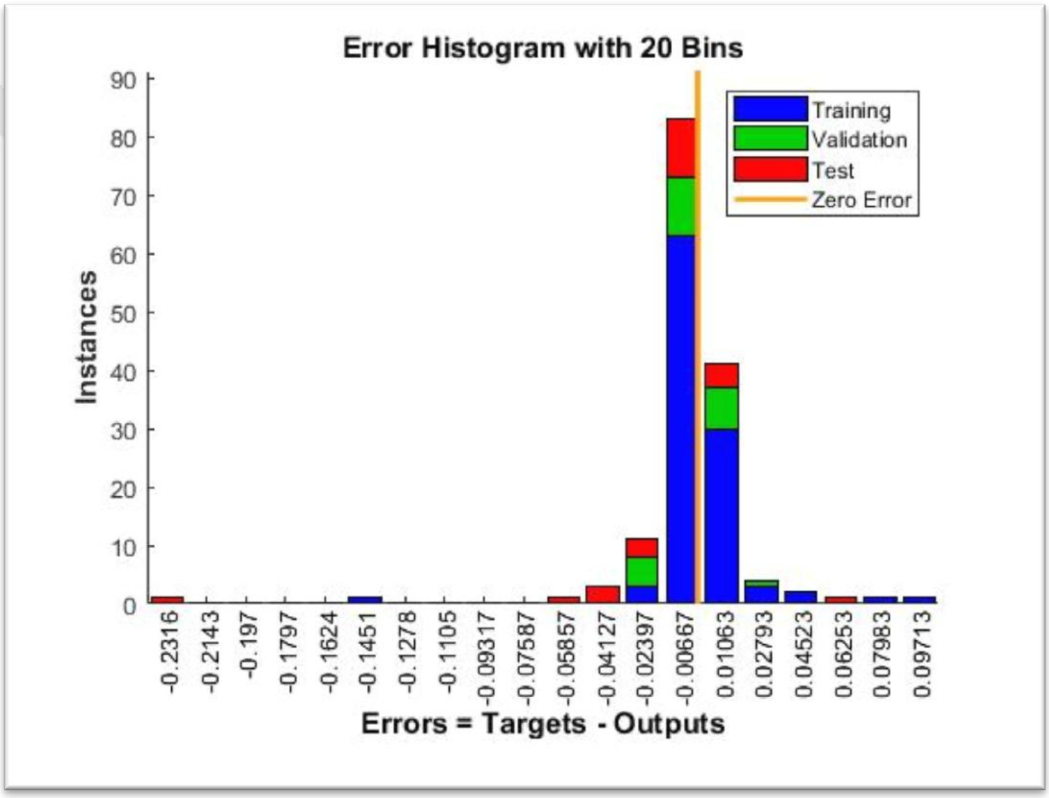

Figure 4.11 Error histogram after treatment

4.2.5 Test of Network after Treatment

Same status, the error histogram and regression plots illustrate the network behavior with training data. But the way to realize if the network performance is well or not is testing the network with more data outside of the training dataset

For this purpose, Figure 4.12 gives indication of the test network, test the network with this data and evaluate the results; therefore, 104 samples are used. Here the results are satisfactory, the outputs and the targets are so close where the **R** value is 0.99999 and **MSE** is 0.0008346 that shows good relation between the outputs of the network and the targets.

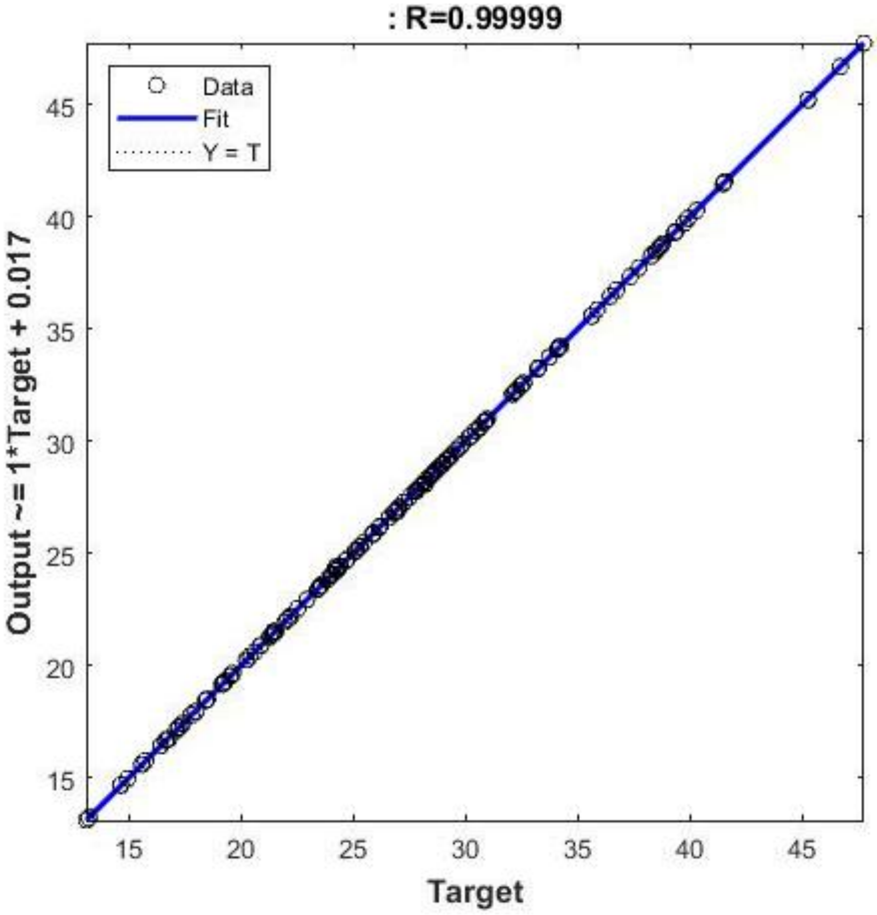

Figure 4.12 Regression plot for test Network

4.2.6 Formula for predicting the result of COD after treatment

By using POLYMATH 6.10 software, simplest formula to predict the COD to give constant factors multiplied by the variables of the laboratory data are defined as

$$\mathbf{COD = a_1 * cl^- + a_2 * NO_3^- + a_3 * PO_4^{-3} + a_4 * SO_4^{-2} + a_5 * NH_3 + a_6 * BOD_5}$$

where a1, a2, a3, a4, a5, a6 are constant factors that can be determined in the regression analysis. The value of $\mathbf{R^2}$ equals to 0.999991 and the value of **RMSD** is 0.0017172.

Table 4.5 Constants of the equation for after treatment

Variable	Value
a1	0.0104494
a2	0.2102446
a3	6.406522
a4	-0.0044695
a5	-0.4085615
a6	0.8465617

4.2.7 Summary of the Results after Wastewater Treatment

Table 4.6 Summary of the results for after treatment

	Training	Validation	Testing	All	Test network
R	0.99999	1	0.99997	0.99999	0.99999
MSE	0.0008402	0.00017593	0.00030785	0.000441	0.0008346
Network performance of after treatment	The best validation performance is 0.00017594 at epoch 25.				
Error Histogram of after treatment	Most errors fall between 0.09713 and -0.2316				
	Errors = Targets – Outputs				
Simple equation to predict chemical oxygen demand MLR	$\mathrm{COD} = 0.0104494 * \mathrm{cl}^{-} + 0.2102446 * \mathrm{NO}_3^{-} + 6.406522 * \mathrm{PO}_4^{-3} - 0.0044695 * \mathrm{SO}_4^{-2} - 0.4085615 * \mathrm{NH}_3 + 0.8465617 * \mathrm{BOD}_5$ (R^2 equals to 0.999991, RMSE is 0.0017172)				

CHAPTER 5

CONCLUSIONS

The conclusions of the present work and some considerations relating to data analysis, model performance policy, and future recommendations are presented.
The general results of this study are:

ANN is a useful tool for predicting the chemical oxygen demand. ANN units predicted chemical oxygen demand were developed with a perfect expectation based on the regression coefficient R, where R equals 1 show a close relationship (that is, they are perfectly adequate fit), R=0 a random relationship (not fit). Regression value R indicates the correlation between outputs and targets.

Mean squared error, MSE, is the average squared difference between outputs and targets, as the value of MSE goes low it will be better, and the MSE= 0 means no error.

Before wastewater treatment:

Some large errors had obtained from artificial neural network after the entering of input and output parameters, biochemical oxygen demand, ammonia NH_3, phosphates ions PO_4^{-3}, nitrates ions NO_3^-, sulfates ions SO_4^{-2} and chloride ions Cl^- and chemical oxygen demand, because these parameters had taken from the samples of the wastewater before the treatment procedures (oil separation, addition of chemicals such as aluminum sulfate and floatation aid 5165, and filtration) applied.

Regression coefficient R value was 0.98235, and the MSE value was 43.02203 when all data is considered, which is not an acceptable good performance indeed.

In addition, the validation performance obtained at epoch 8 was obtained to be 42.2466 which is a quite high value.

In the error histogram for before treatment case, most errors fall between 48.76 and -13.24. These errors are considered to be very high.

This is why the results of the equation of COD-result prediction that had developed basing on previous laboratory results that applied in polymath 6.10 program had showed errors. And the results of sampling before treatment were obtained for R^2 to be 0.87507 and for RMSD to be 1.002001.
In overall, performances of both artificial neural network modeling and multiple linear regression approach are a bit poor. The high errors in this part may originate from the unpredictable nature of the untreated wastewater since there can be some other dominating factors and parameters that affect chemical oxygen demand significantly, other than the six parameters considered here.

After wastewater treatment:

Some positive changes were found in the artificial neural networks modeling when the parameters, chemical oxygen demand, biochemical oxygen demand, ammonia NH_3, phosphate ions PO_4^{-3}, nitrate ions NO_3^-, sulfate ions SO_4^{-2} and chloride ions Cl^- had used from a sample of the wastewater after the application of treatment processes such as oil removal and passing the wastewater through the filters and other several processes of treatment mentioned before.

The straight line shows a direct relationship between the target and the output.

The regression coefficient, R, for all data is found to be 0.99999 and the mean square error, MSE, is to be 0.000441. These findings indicated that prediction results are very close to the actual values obtained from the experimental analyses.

In addition, the best performance for validation is obtained to be 0.0017594 at 25th epoch, this result is very well.

The error histogram obtained for after treatment case indicated that the most of the errors fall between 0.09713 and -0.2316. These errors are considered very low and the performance of the artificial neural network is very satisfactory.

Our multiple linear regression approach yielded the coefficients of the COD equation as a function of six variables based on the laboratory analyses, and after the evaluation of the performance of this equation it was found out that R^2 is 0.999991 and RMSD is 0.0017172. Hence, even MLR equation yields highly accurate results for the prediction of COD for after wastewater treatment case.

In summary, findings of this study suggest that artificial neural networks, as one of the artificial intelligence tools, and multiple linear regression model equation may contribute to laboratories or operators in similar industrial plants in the prediction of the value of COD by saving time, effort and money and without waste of chemicals.

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APPENDIX A

A. DATA OBTAINED FROM THE EXPERIMENTAL ANALYSES OF WASTEWATER BEFORE THE TREATMENT

No.	Cl^-	NO_3^-	PO_4^{-3}	SO_4^{-2}	NH_3	BOD_5	COD
1.	49.4	4.5	3.3	261	1.16	72	120.2
2.	32.5	3.95	2.5	263	0.13	76	108
3.	44.2	8.2	2.25	245	0.75	63	106.2
4.	45	2.82	2.77	255	1.75	74	120.8
5.	59.7	3.08	5.94	274	9.2	35	105
6.	43	1.91	7.78	246	1.94	93	138
7.	30.93	3.99	3.5	181.4	2.5	84	122.5
8.	6.53	3	5.4	163	8	75	104.5
9.	35.11	3.45	8.2	162	22.2	55	135
10.	57	5.31	8.12	167.9	8.69	32	100.2
11.	34	4.14	2.7	158	0.45	79.1	115
12.	37.4	5.5	1.63	181	0.33	10	45.8
13.	38.7	5.1	1.72	209.4	0.39	7	66.2
14.	42	6.79	2.68	218	0.16	7.3	48.2
15.	45	1.47	28	39	0.7	75	118
16.	43.1	12.6	1.74	188.1	0.8	5.3	42.2
17.	35	5.6	2.67	190	0.032	6	35.2
18.	31	5.9	3.06	198	0.055	15.8	44.2
19.	35.9	7.5	2.09	166	0.2	33.7	65.2
20.	36.3	8.5	1.88	130.6	0.19	10.1	48.22
21.	93.7	2.73	8.4	27	17	75	195.2
22.	39.1	5.2	2.2	147	0.25	3	48.2
23.	38.4	4.5	3.7	142	1.2	6	49.8
24.	32.2	4.6	2.37	143	0.021	14.2	53.8

25.	32	5.2	1.6	230	1.34	4	40.5
26.	33	12.4	1.88	212	0.11	15.3	60.2
27.	41.4	21	2.04	198.7	1.21	8	44.5
28.	38	0.64	2.34	195	5.2	11.3	53.2
29.	47	2.17	4.8	33.2	2.5	45	95.2
30.	45.1	15.2	2.02	221.4	1.13	15	53
31.	34	25	2.61	213	0.62	17	45.8
32.	34	15	1.96	120.5	0.19	12.4	40
33.	46.09	12.5	2.37	130.8	0.93	7	45.9
34.	43.5	21.4	6.04	164	1.19	9	55.2
35.	44.6	22.4	6.4	169	1.29	10	47
36.	33	10.83	4.8	167	0.12	12	38.5
37.	32.5	11.2	4.7	162	0.22	14	40.1
38.	48	2.16	30	33	2.51	45	95.2
39.	42	3.14	33	30	2.44	85	128.2
40.	46	15.78	4.19	149.7	0.06	17.1	56.2
41.	33	8.04	2.44	207	8.04	11	54.8
42.	45	15.22	4.1	2.3	2.2	14	52.3
43.	48	9.48	5.36	133	3.2	75	126
44.	53.58	19.03	2.1	124.5	0.56	3.4	45.2
45.	38	10.76	2.42	151	0.41	13.6	44.1
46.	47.8	8.39	2.04	152	5.2	85	143
47.	27	6.28	3.01	265.5	1.01	9.6	50.2
48.	44.8	8.9	3.93	243	0.93	16	52.9
49.	41	2.33	31.32	123	5.8	75	130.2
50.	38	5.13	2.5	308	0.46	15.5	48.5
51.	39	5.2	2.25	3.3	0.42	20.2	55.4
52.	34	4.46	3.12	285	0.3	18.3	58.9
53.	40.9	10.78	1.82	256.5	1.1	7	42.1
54.	34.2	7.45	5.2	296	1.54	11	40.8
55.	30	6.45	5.9	288	2	12	42.5

56.	42.76	10.46	5.01	272.35	1.32	17	56.3
57.	34.72	8.77	4.02	245	0.83	15	44.8
58.	36.3	4.67	4.89	180.16	0.85	25.4	57.3
59.	38.6	6.6	5.58	205.6	2.5	19	42.5
60.	43.9	8.73	5.58	226	3.08	20.8	62.8
61.	41.2	8.2	5.5	221	3.1	21.8	70.2
62.	35.7	8.6	4.5	236	2.24	17.7	55.4
63.	32	6.13	1.95	189	1.75	31.8	63.2
64.	55.1	14.34	2.45	181.25	1.94	25	74.2
65.	40	8.31	3.18	172.5	0.708	10.9	43.2
66.	50.2	16.86	3.49	298.8	4.29	12.6	58.8
67.	83	6.84	4.1	135	1.5	14.3	85.9
68.	54	7.4	2.4	136	0.831	6.8	55.2
69.	42	15.2	2.7	119	1.9	6	47.8
70.	44	12.2	2.9	115	2	7	50.8
71.	39.76	5.1	2.6	263	3.12	70	113
72.	34.04	1.77	2.95	224.8	0.931	66.3	100.1
73.	32.2	2.7	3.1	228	1.2	55.9	88.5
74.	33	1.5	3.5	227	2.23	50	84
75.	33.8	2.6	1.6	203.2	1.17	92	133.2
76.	42	1.6	3.6	229	2.55	55	100.2
77.	33.9	2.7	1.8	205.1	1.144	45	75.2
78.	50	7.6	3.72	229	0.7	17	58
79.	23.9	4.51	4.17	199.5	1.42	18.7	40.5
80.	41	7.32	3.27	259	2.9	15	53.2
81.	42	9.66	2.6	295	0.65	14	46.2
82.	28	6.07	2.6	232.25	0.235	29	54
83.	28.35	7.21	3.11	185.71	0.277	12.7	40.2
84.	47	1.77	4.1	120.7	2.9	26	72.2
85.	48	1.7	3.3	208	1.13	15	55
86.	44.83	3.8	4.06	160.75	0.605	46.5	89

87.	52.4	7.11	6.4	184.3	0.876	26	69.2
88.	48	9.6	2.55	292	0.994	8	48.4
89.	49	10.3	2.25	299	0.781	12	52.4
90.	47	9.6	1.9	229	2.1	8	78.2
91.	55.64	14.2	3.51	185.5	1.38	12.4	58.5
92.	65.27	22.5	3.11	268.3	1.35	47	104
93.	40.1	18	4.58	225.2	0.928	88	130.2
94.	41.5	13.2	2.19	272.6	1.27	18.3	52.5
95.	44	15.7	5.16	211	2.02	8	55.2
96.	44.2	14.8	2.55	282	1.88	18.5	48.2
97.	45	20	5	212	2	9	46.2
98.	42	15.2	2.57	296	0.354	88	127.1
99.	58.85	4	3.2	202.5	9.1	26	94
100.	52.4	3.53	8.15	232.3	1.14	85	135
101.	48	6.4	5.2	170.8	10.8	88	157
102.	40.6	22	4.5	255	3.1	80	123
103.	44	7	6.2	180	5.2	82	134
104.	41	8.2	7.5	177	4.5	90	140
105.	43	6.6	3.17	190	0.87	78.5	121
106.	88	25	3.5	180	0.88	80	161.2
107.	58.55	7.9	8.2	200	1.5	75	131
108.	36.42	12.02	8.92	191.8	1.2	44	77
109.	62	1.56	4.06	179	1.48	85	145
110.	44	14.8	8.5	213	5.2	83.2	135
111.	33	9.77	4.2	189.4	6.3	88	135.1
112.	49	2.5	2.44	279	0.53	55	99.2
113.	40	5.08	2.68	255	0.53	9.6	60.2
114.	40	5.2	3.64	427	0.3	20	58.1
115.	43.63	7.63	2.29	357.3	3.02	24.3	63.2
116.	50	8.36	3.2	200.2	3.8	35	84.5
117.	59	5.46	7.92	148.2	1.2	75.5	132.2

118.	41	2.19	19.15	59	6.56	250	150
119.	43.4	7.99	5.11	158	0.34	80	121
120.	48.2	8.2	6.2	165	1.2	89	137
121.	14	3	6	142	0.65	86.2	108
122.	34	5.75	1.83	160	0.34	14.1	41.2
123.	46	10.36	2.45	170	1.01	32	72.2
124.	37.4	7.15	2.5	205	0.3	40	72.2
125.	46.6	10.11	2.71	156	0.6	42	83.5
126.	72	14.1	1.04	143	2.03	8	74.2
127.	77	15.2	2.1	155	2.9	12	80.2
128.	41.5	6.7	1.72	150	0.799	7.6	44.2
129.	41	7	4.66	278	0.365	10	45.2
130.	29.3	14	6.2	256	1.8	18	42.5
131.	31	17.7	2.7	147	1	9	40.2
132.	29.59	8.3	2.03	197	0.209	16.9	40.2
133.	34	2.57	2.65	134	0.7	35.6	66.9
134.	57.2	7.89	3.4	166	0.55	25	74.5
135.	51.3	9.2	4.11	244	0.87	22.6	64.1
136.	42.52	16.1	3.31	322.2	0.273	17.5	48.6
137.	37.4	4.57	4.25	273	0.324	29.6	59.6
138.	37	8.66	2.75	201	1.3	18.3	59.5
139.	46.2	17.2	3.01	142	2.23	13.2	54.7
140.	47.4	3.87	8.27	198	2.7	23.2	66.9
141.	45	3.2	8.2	188	2.2	23	63.5
142.	33	1.16	4.2	231	0.55	85	118.1
143.	36.7	5.82	3.9	206	1.5	26	59.5
144.	51.33	9.66	4.9	269	1.53	19	62.5
145.	41.58	16.1	3.31	255	0.273	17.5	50.2
146.	53	21	4.77	288	0.29	15.2	56.4
147.	41	7.98	4.85	217	0.97	19	56.2
148.	59.7	3.08	5.49	274	9.2	35	104

149.	66.2	3.8	6.5	277	8.2	22	92.2
150.	45.2	4.2	3.1	268	2.1	25	65.1

A.POLYMATH REPORT BEFORE TREATMENT RELATED TO CHAPTER 4

POLYMATH Report 20 AUG 2018
Multiple linear regression

Model: C07 = a1*C01 + a2*C02 + a3*C03 + a4*C04 + a5*C05 + a6*C06

Variable	Value	95% confidence
a1	0.938811	0.1461259
a2	-0.2839987	0.3883029
a3	-0.0592047	0.4625582
a4	0.0221107	0.0235537
a5	2.061704	0.745435
a6	0.8517708	0.0671031

General
Number of independent variables = 6
Regression not including a free parameter
Number of observations = 150

Statistics

R^2	0.87507
R^2adj	0.8707321
Rmsd	1.002001
Variance	156.876

Source data points and calculated data points

No.	C01	C02	C03	C04	C05	C06	C07	C07 calc	Delta C07
1	49.4	4.5	3.3	261	1.16	72	120.2	114.3939	5.806147
2	32.5	3.95	2.5	263	0.13	76	108	100.0593	7.94074
3	44.2	8.2	2.25	245	0.75	63	106.2	99.6584	6.541601
4	45	2.82	2.77	255	1.75	74	120.8	113.5589	7.241136
5	59.7	3.08	5.94	274	9.2	35	105	109.6586	-4.658603
6	43	1.91	7.78	246	1.94	93	138	128.0194	9.980562
7	30.93	3.99	3.5	181.4	2.5	84	122.5	108.4109	14.08906

8	6.53	3	5.4	163	8	75	104.5	88.93922	15.56078
9	35.11	3.45	8.2	162	22.2	55	135	127.6955	7.30447
10	57	5.31	8.12	167.9	8.69	32	100.2	100.4087	-0.208705
11	34	4.14	2.7	158	0.45	79.1	115	102.3803	12.61971
12	37.4	5.5	1.63	181	0.33	10	45.8	46.65314	-0.853136
13	38.7	5.1	1.72	209.4	0.39	7	66.2	46.1782	20.0218
14	42	6.79	2.68	218	0.16	7.3	48.2	48.71097	-0.510968
15	45	1.47	28	39	0.7	75	118	106.3596	11.6404
16	43.1	12.6	1.74	188.1	0.8	5.3	42.2	47.10412	-4.90412
17	35	5.6	2.67	190	0.032	6	35.2	40.48754	-5.287543
18	31	5.9	3.06	198	0.055	15.8	44.2	45.19567	-0.995668
19	35.9	7.5	2.09	166	0.2	33.7	65.2	64.23697	0.9630252
20	36.3	8.5	1.88	130.6	0.19	10.1	48.22	43.43581	4.784192
21	93.7	2.73	8.4	27	17	75	195.2	186.2227	8.977283
22	39.1	5.2	2.2	147	0.25	3	48.2	41.42147	6.778526
23	38.4	4.5	3.7	142	1.2	6	49.8	45.27768	4.522324
24	32.2	4.6	2.37	143	0.021	14.2	53.8	44.08327	9.716728
25	32	5.2	1.6	230	1.34	4	40.5	39.72565	0.7743472
26	33	12.4	1.88	212	0.11	15.3	60.2	45.29422	14.90578
27	41.4	21	2.04	198.7	1.21	8	44.5	46.48424	-1.984243
28	38	0.64	2.34	195	5.2	11.3	53.2	60.01197	-6.811972
29	47	2.17	4.8	33.2	2.5	45	95.2	87.44168	7.758324
30	45.1	15.2	2.02	221.4	1.13	15	53	57.90559	-4.905592
31	34	25	2.61	213	0.62	17	45.8	45.13301	0.6669851
32	34	15	1.96	120.5	0.19	12.4	40	41.16157	-1.161569
33	46.09	12.5	2.37	130.8	0.93	7	45.9	50.35136	-4.451356
34	43.5	21.4	6.04	164	1.19	9	55.2	48.14862	7.051376
35	44.6	22.4	6.4	169	1.29	10	47	50.0445	-3.044499
36	33	10.83	4.8	167	0.12	12	38.5	41.78201	-3.282011
37	32.5	11.2	4.7	162	0.22	14	40.1	43.0126	-2.912605
38	48	2.16	30	33	2.51	45	95.2	86.90756	8.292436

39	42	3.14	33	30	2.44	85	128.2	114.6789	13.52105
40	46	15.78	4.19	149.7	0.06	17.1	56.2	56.45469	-0.254688
41	33	8.04	2.44	207	8.04	11	54.8	59.07544	-4.275442
42	45	15.22	4.1	2.3	2.2	14	52.3	54.19269	-1.892688
43	48	9.48	5.36	133	3.2	75	126	115.4743	10.52574
44	53.58	19.03	2.1	124.5	0.56	3.4	45.2	51.57602	-6.376021
45	38	10.76	2.42	151	0.41	13.6	44.1	48.24381	-4.143809
46	47.8	8.39	2.04	152	5.2	85	143	128.8538	14.14616
47	27	6.28	3.01	265.5	1.01	9.6	50.2	39.51588	10.68412
48	44.8	8.9	3.93	243	0.93	16	52.9	60.21708	-7.317081
49	41	2.33	31.32	123	5.8	75	130.2	114.5355	15.66445
50	38	5.13	2.5	308	0.46	15.5	48.5	55.03081	-6.530812
51	39	5.2	2.25	3.3	0.42	20.2	55.4	53.14827	2.251725
52	34	4.46	3.12	285	0.3	18.3	58.9	52.97568	5.92432
53	40.9	10.78	1.82	256.5	1.1	7	42.1	49.12977	-7.029769
54	34.2	7.45	5.2	296	1.54	11	40.8	48.77294	-7.972944
55	30	6.45	5.9	288	2	12	42.5	46.69576	-4.195763
56	42.76	10.46	5.01	272.35	1.32	17	56.3	60.09971	-3.799711
57	34.72	8.77	4.02	245	0.83	15	44.8	49.77174	-4.971738
58	36.3	4.67	4.89	180.16	0.85	25.4	57.3	59.83394	-2.53394
59	38.6	6.6	5.58	205.6	2.5	19	42.5	59.91721	-17.41721
60	43.9	8.73	5.58	226	3.08	20.8	62.8	67.46802	-4.668025
61	41.2	8.2	5.5	221	3.1	21.8	70.2	65.87094	4.329058
62	35.7	8.6	4.5	236	2.24	17.7	55.4	55.71942	-0.319421
63	32	6.13	1.95	189	1.75	31.8	63.2	63.0588	0.1411989
64	55.1	14.34	2.45	181.25	1.94	25	74.2	76.81243	-2.612427
65	40	8.31	3.18	172.5	0.708	10.9	43.2	49.56222	-6.362219
66	50.2	16.86	3.49	298.8	4.29	12.6	58.8	68.31716	-9.517161
67	83	6.84	4.1	135	1.5	14.3	85.9	93.99384	-8.09384
68	54	7.4	2.4	136	0.831	6.8	55.2	58.96448	-3.76448
69	42	15.2	2.7	119	1.9	6	47.8	46.61246	1.187539

70	44	12.2	2.9	115	2	7	50.8	50.29974	0.5002638
71	39.76	5.1	2.6	263	3.12	70	113	107.5964	5.403621
72	34.04	1.77	2.95	224.8	0.931	66.3	100.1	94.64212	5.457876
73	32.2	2.7	3.1	228	1.2	55.9	88.5	84.40865	4.091351
74	33	1.5	3.5	227	2.23	50	84	82.55281	1.447189
75	33.8	2.6	1.6	203.2	1.17	92	133.2	116.1667	17.03332
76	42	1.6	3.6	229	2.55	55	100.2	95.93061	4.26939
77	33.9	2.7	1.8	205.1	1.144	45	75.2	76.1755	-0.975502
78	50	7.6	3.72	229	0.7	17	58	65.54856	-7.548559
79	23.9	4.51	4.17	199.5	1.42	18.7	40.5	44.17668	-3.676678
80	41	7.32	3.27	259	2.9	15	53.2	60.70095	-7.500949
81	42	9.66	2.6	295	0.65	14	46.2	56.32025	-10.12025
82	28	6.07	2.6	232.25	0.235	29	54	54.72996	-0.729961
83	28.35	7.21	3.11	185.71	0.277	12.7	40.2	39.87829	0.3217111
84	47	1.77	4.1	120.7	2.9	26	72.2	74.17244	-1.97244
85	48	1.7	3.3	208	1.13	15	55	64.09006	-9.090062
86	44.83	3.8	4.06	160.75	0.605	46.5	89	85.17629	3.823706
87	52.4	7.11	6.4	184.3	0.876	26	69.2	74.82265	-5.622645
88	48	9.6	2.55	292	0.994	8	48.4	57.50539	-9.105385
89	49	10.3	2.25	299	0.781	12	52.4	61.38587	-8.985873
90	47	9.6	1.9	229	2.1	8	78.2	57.49233	20.70767
91	55.64	14.2	3.51	185.5	1.38	12.4	58.5	65.50349	-7.003492
92	65.27	22.5	3.11	268.3	1.35	47	104	103.4509	0.5490832
93	40.1	18	4.58	225.2	0.928	88	130.2	114.1116	16.0884
94	41.5	13.2	2.19	272.6	1.27	18.3	52.5	59.31535	-6.815354
95	44	15.7	5.16	211	2.02	8	55.2	52.18757	3.012432
96	44.2	14.8	2.55	282	1.88	18.5	48.2	63.01027	-14.81027
97	45	20	5	212	2	9	46.2	52.7473	-6.547305
98	42	15.2	2.57	296	0.354	88	127.1	117.1916	9.908442
99	58.85	4	3.2	202.5	9.1	26	94	99.30853	-5.308535
100	52.4	3.53	8.15	232.3	1.14	85	135	127.5958	7.404168

101	48	6.4	5.2	170.8	10.8	88	157	143.9362	13.06379
102	40.6	22	4.5	255	3.1	80	123	111.7725	11.2275
103	44	7	6.2	180	5.2	82	134	123.4986	10.50139
104	41	8.2	7.5	177	4.5	90	140	125.5691	14.43095
105	43	6.6	3.17	190	0.87	78.5	121	111.1655	9.83448
106	88	25	3.5	180	0.88	80	161.2	149.2441	11.95593
107	58.55	7.9	8.2	200	1.5	75	131	123.6358	7.364185
108	36.42	12.02	8.92	191.8	1.2	44	77	74.44251	2.557487
109	62	1.56	4.06	179	1.48	85	145	136.9325	8.067478
110	44	14.8	8.5	213	5.2	83.2	135	122.899	12.10097
111	33	9.77	4.2	189.4	6.3	88	135.1	120.0898	15.01024
112	49	2.5	2.44	279	0.53	55	99.2	99.25626	-0.056257
113	40	5.08	2.68	255	0.53	9.6	60.2	50.85898	9.341017
114	40	5.2	3.64	427	0.3	20	58.1	62.95533	-4.855327
115	43.63	7.63	2.29	357.3	3.02	24.3	63.2	73.48236	-10.28236
116	50	8.36	3.2	200.2	3.8	35	84.5	86.44987	-1.949875
117	59	5.46	7.92	148.2	1.2	75.5	132.2	123.4299	8.770145
118	41	2.19	19.15	59	6.56	250	150	264.5075	-114.5075
119	43.4	7.99	5.11	158	0.34	80	121	110.5088	10.49116
120	48.2	8.2	6.2	165	1.2	89	137	124.4847	12.51526
121	14	3	6	142	0.65	86.2	108	89.8386	18.1614
122	34	5.75	1.83	160	0.34	14.1	41.2	46.42689	-5.226892
123	46	10.36	2.45	170	1.01	32	72.2	73.19583	-0.995828
124	37.4	7.15	2.5	205	0.3	40	72.2	72.15496	0.0450403
125	46.6	10.11	2.71	156	0.6	42	83.5	81.17758	2.322419
126	72	14.1	1.04	143	2.03	8	74.2	77.68969	-3.489688
127	77	15.2	2.1	155	2.9	12	80.2	87.47468	-7.274681
128	41.5	6.7	1.72	150	0.799	7.6	44.2	48.39339	-4.193393
129	41	7	4.66	278	0.365	10	45.2	51.64436	-6.444364
130	29.3	14	6.2	256	1.8	18	42.5	47.86739	-5.367385
131	31	17.7	2.7	147	1	9	40.2	36.89442	3.305579

132	29.59	8.3	2.03	197	0.209	16.9	40.2	44.48367	-4.283668
133	34	2.57	2.65	134	0.7	35.6	66.9	65.76187	1.138132
134	57.2	7.89	3.4	166	0.55	25	74.5	77.35652	-2.856521
135	51.3	9.2	4.11	244	0.87	22.6	64.1	71.74359	-7.643591
136	42.52	16.1	3.31	322.2	0.273	17.5	48.6	57.74279	-9.14279
137	37.4	4.57	4.25	273	0.324	29.6	59.6	65.47866	-5.878659
138	37	8.66	2.75	201	1.3	18.3	59.5	54.82563	4.674369
139	46.2	17.2	3.01	142	2.23	13.2	54.7	57.29077	-2.590773
140	47.4	3.87	8.27	198	2.7	23.2	66.9	72.61654	-5.71654
141	45	3.2	8.2	188	2.2	23	63.5	69.1355	-5.635504
142	33	1.16	4.2	231	0.55	85	118.1	109.0447	9.055315
143	36.7	5.82	3.9	206	1.5	26	59.5	62.36399	-2.863988
144	51.33	9.66	4.9	269	1.53	19	62.5	70.44146	-7.941461
145	41.58	16.1	3.31	255	0.273	17.5	50.2	55.37447	-5.17447
146	53	21	4.77	288	0.29	15.2	56.4	63.42329	-7.023288
147	41	7.98	4.85	217	0.97	19	56.2	58.91931	-2.719313
148	59.7	3.08	5.49	274	9.2	35	104	109.6852	-5.685245
149	66.2	3.8	6.5	277	8.2	22	92.2	102.4548	-10.25485
150	45.2	4.2	3.1	268	2.1	25	65.1	72.60744	-7.507437

APPENDIX B

B. DATA OBTAINED FROM THE EXPERIMENTAL ANALYSES OF WASTEWATER AFTER THE TREATMENT

No	Cl^-	NO_3^-	PO_4^{-3}	SO_4^{-2}	NH_3	BOD_5	COD
1.	38.3	10.1	2.26	254	0.29	8.5	22.94
2.	28.7	6.3	1.7	204	0.02	5.7	16.42
3.	27.7	6.6	1.8	205	0.03	5.7	17.11
4.	42	13.5	2	389	1.05	12	24.08
5.	45.9	10.91	1.71	298	1.49	10	20.25
6.	31	8.81	1.59	252	0.31	21.1	28.97
7.	47.5	6.19	2.27	241	1.36	21	32.48
8.	34.8	6.68	2.64	216	1.5	25.4	38.61
9.	47.1	3.2	2.2	255	1.36	22	32.19
10.	46	15.3	2.26	279	1.84	18.8	32.09
11.	30	4.19	1.98	260	0.3	6.3	17.98
12.	31.3	13.2	2.69	299	0.43	6.2	24.07
13.	40.5	15.57	1.76	259	0.38	6.5	19.16
14.	40	6.7	2.34	256	0.1	6.8	21.39
15.	89	4.9	4.5	201	1.9	22	47.74
16.	38.3	12.1	1.72	242	1.2	1	13.23
17.	33	6.8	2.42	250	0.07	5.6	20.87
18.	28	6.3	1.6	180	0.01	7.3	17.23
19.	27	10	1	166	0.17	9	15.59
20.	40	12.4	2.72	213	0.17	6.2	24.67
21.	55.3	2.41	1.58	212	0.14	11	19.52
22.	44.1	2.1	2.5	211	0.145	14	27.77
23.	26	2.4	2.9	224	0.22	12	28.42
24.	33	2.8	2.3	222	0.04	17.2	29.22
25.	32	3.4	1.6	230	1.34	4	13.11
26.	28	10.2	1.1	212	0.7	10	16.77
27.	25	12	1.6	210	1.21	6	16.68

28.	22	0.81	2.4	180	0.8	8.1	21.45
29.	25	5	2.5	88	0.22	10	25.31
30.	36	23.2	1.49	241	0.54	16	27.04
31.	31	19	1.52	201	1.06	11.2	22.22
32.	33	17	1.75	228	0.38	3.9	17.25
33.	43	25	2.1	219	0.25	11.8	28.06
34.	36	18.9	2.8	155	0.72	22	39.92
35.	32	17.2	2.5	188	0.88	12	28.92
36.	30	8.3	2.4	150	0.15	26	38.71
37.	28	7.4	3.4	155	0.2	22	41.48
38.	46	12	2.4	88	0.88	25	38.79
39.	44	25	2.8	77	0.77	28	46.69
40.	45	18.2	2.58	293	0.23	11	28.73
41.	32	7.31	1.92	285	0.93	8	19.29
42.	45	18.3	2.5	293	0.23	11	28.24
43.	29	7	2.1	233	0.33	14	25.9
44.	37.2	14.3	1.55	214	1.94	4	14.96
45.	30	8.4	1.85	272	0.71	5	16.65
46.	30.2	12.54	1.79	130	0.27	16	27.27
47.	23	7.14	1.75	236	0.58	6.8	17.41
48.	40.2	9.3	2.13	252	1.45	8.5	21.49
49.	44	17.5	2.8	72	0.14	10	30.16
50.	33	5.2	1.8	240	0.47	14	23.55
51.	32	22.2	1.2	250	0.55	12	21.54
52.	30	4.5	2.3	229	0.21	14.1	26.82
53.	40.3	11.2	1.53	220	1.02	10	19.64
54.	33.5	6.71	2.27	248	1.46	12	24.75
55.	33.2	6.1	2.24	222	1.5	14	26.22
56.	40.62	10.2	2.76	260	0.6	12	29.01
57.	29.7	7.89	1.95	261	0.38	13.3	24.24
58.	32.3	7.78	1.68	285	0.74	19.7	27.84

59.	42.1	11.6	2.27	225	1.86	14	27.5
60.	44	7.57	2.27	245	0.33	10	23.83
61.	41.3	7.2	2.1	222	0.34	12	24.42
62.	33.9	5.25	1.9	270	0.122	12	22.53
63.	34	9.17	1.75	232	0.45	15.6	25.48
64.	42.22	13.6	2.42	204	1	9	25.11
65.	45	5.83	2.4	247	0.96	9.3	23.45
66.	42.1	15.16	1.8	281	0.44	2.4	15.75
67.	44	4.5	1.8	173	1.9	8.4	18.5
68.	57	9.5	2.56	220	0.466	10.7	26.87
69.	40	13.65	2.4	191	0.21	11	27.03
70.	41	12.1	1.4	222	0.55	12	20.88
71.	42.1	2.5	1.36	281	0.55	25	29.36
72.	33.45	0.12	0.62	213	1.5	22	21.41
73.	33.65	0.22	0.66	244	1.8	14	14.65
74.	34.3	1.2	1.1	178	0.66	25	27.76
75.	34	1.5	1.4	222	0.55	22	27.05
76.	39	6.4	2	281	0.11	18	28.5
77.	22.8	2.08	2.75	285	0.9	9	24.27
78.	55	1.5	2.8	295	1	25	38.27
79.	27.6	2.2	2.6	234	0.212	20	33.21
80.	26.22	5.69	2.4	261	0.23	15.5	28.7
81.	27.2	7.85	1.5	185	0.44	16	24.08
82.	39	5	2.36	254	1.55	29	39.36
83.	41.2	1.2	2.36	179	0.54	28	38.49
84.	45	4.1	2.55	205	0.23	16	30.23
85.	32	6.6	2.2	188	0.1	10	23.4
86.	45	5.2	2.1	254	0.88	15	26.22
87.	55	6.6	1.7	188	0.54	12	21.95
88.	52	11.47	2	220	1	5.7	19.22
89.	57	10.2	2.2	250	0.54	21	33.27

90.	38.8	10.5	2.7	220	0.8	14	30.45
91.	38.2	9.3	1.32	228	0.93	9.9	17.79
92.	66.9	7.5	2.42	288	0.59	14	28.21
93.	69.3	2	2.6	297	0.18	23	35.87
94.	56.2	1.62	2.1	276	0.21	25	34.23
95.	41.7	5.2	1.8	278	0.14	17	26.15
96.	44	1.9	2.5	172	2	25	36.45
97.	36.8	12.2	2	256	0.92	7.3	20.42
98.	77	7.3	2.11	289	0.29	11.3	24.01
99.	49.2	4.45	1.53	236	1.25	20.3	26.87
100.	37	9.77	2.49	255	1.59	26.8	39.29
101.	455.8	5.8	1.64	272	1.42	7	20.61
102.	39	6.18	2.3	245	0.01	9.6	23.47
103.	38	5.21	2.25	274	0.21	15	27.29
104.	44.8	12.2	2.4	298	0.04	10.4	25.86
105.	44	13	2.3	288	0.5	12	26.59
106.	41.2	9.79	2.53	241	1.36	20.2	34.16
107.	31.6	17.2	2.3	163	1.6	14	29.15
108.	54.3	6.59	1.67	272	0.74	23	30.62
109.	55.2	12.2	2.2	254	0.88	18	30.98
110.	38	5	2.9	207	0.6	12.7	29.61
111.	32	3.36	2.12	255	0.82	14.1	25.08
112.	43	7.7	2.62	279	1.28	16	30.63
113.	39.1	6.13	2.9	227	0.45	8	25.88
114.	47.9	11.05	1.77	294	0.62	15	25.29
115.	61	12.3	1.89	231	0.1	21.5	32.46
116.	49.2	3.3	2	266	1.42	20.2	29.35
117.	47.23	2	2.19	270	0.63	12.7	24.23
118.	38.9	8	2.9	299	0.7	16	32.59
119.	45	17.9	2	219	2.3	10	23.59
120.	31.87	9.2	2.35	233	0.27	14.1	28.21

121.	32.8	5.8	2.4	255	0.77	18.2	30.89
122.	36	7.54	2.85	214.5	0.55	20.9	36.73
123.	55	7.6	1.9	218	0.25	12.5	23.85
124.	53.9	6.2	2.86	266	0.17	14.1	30.86
125.	39.9	11.6	2.74	255.9	0.55	11.3	28.6
126.	35.3	5.75	2.81	232	0.81	25.4	39.71
127.	36.7	8.58	1.32	194	1.05	14.1	21.28
128.	45	16.2	2.25	146	0.25	9	25.15
129.	44.3	3.23	2.95	205	2.8	11.8	27.97
130.	42.2	4.22	2.4	208	0.44	18	30.83
131.	35.3	3.81	2.54	220	2.75	20	32.27
132.	48.4	4.02	2.1	257	2.38	11.1	22.08
133.	36.2	12.2	2.14	287	1.5	11.3	24.32
134.	51	14	2.54	230	1.71	14	29.87
135.	50	6.96	2.21	241	0.17	12	25.15
136.	24	12.2	2.48	297	0.871	24	37.34
137.	45.9	10.91	1.71	298	1.49	10.2	20.42
138.	57.2	12.5	1.87	305	2.41	18	28.09
139.	68	14.5	2.11	308	2.1	22.5	34.09
140.	61	18.2	1.92	304	1.5	27.1	37.73
141.	56	12.2	2.1	201	0.2	35	45.25
142.	25	6.2	1	298	0.55	14.2	18.43
143.	67	14.2	1.8	201	15	22.2	26.99
144.	22.2	21.2	2.64	308	2.871	11.12	28.46
145.	65.2	14.2	2.4	202	1.1	28.2	41.55
146.	35.2	12.2	1.9	100.2	1.9	31.2	40.29
147.	52	11.2	2.1	307	0.22	17.55	29.74
148.	47	14.55	2.8	221	0.87	18.21	35.62
149.	25.22	12.22	2.25	255	0.87	21.24	33.73
150.	44	15.25	1.8	247	0.45	12.2	24.27

B.POLYMATH REPORT AFTER TREATMENT RELATIVE TO CHAPTER 4

POLYMATH Report
Multiple linear regression

20 AUG 2018

Model: C07 = a1*C01 + a2*C02 + a3*C03 + a4*C04 + a5*C05 + a6*C06

Variable	Value	95% confidence
a1	0.0104494	9.723E-05
a2	0.2102446	0.0006295
a3	6.406522	0.0055878
a4	-0.0044695	4.88E-05
a5	-0.4085615	0.0026672
a6	0.8465617	0.0005126

General
Number of independent variables = 6
Regression not including a free parameter
Number of observations = 150

Statistics

R^2	0.999991
R^2adj	0.9999907
Rmsd	0.0017172
Variance	0.0004607

Source data points and calculated data points

No.	C01	C02	C03	C04	C05	C06	C07	C07 calc	Delta C07
1	38.3	10.1	2.26	254	0.29	8.5	22.94	22.94446	-0.0044649
2	28.7	6.3	1.7	204	0.02	5.7	16.42	16.42098	-0.000982
3	27.7	6.6	1.8	205	0.03	5.7	17.11	17.1057	0.0042969
4	42	13.5	2	389	1.05	12	24.08	24.08134	-0.0013426
5	45.9	10.91	1.71	298	1.49	10	20.25	20.2535	-0.0035029
6	31	8.81	1.59	252	0.31	21.1	28.97	28.97204	-0.0020436
7	47.5	6.19	2.27	241	1.36	21	32.48	32.48557	-0.0055715
8	34.8	6.68	2.64	216	1.5	25.4	38.61	38.60571	0.0042933
9	47.1	3.2	2.2	255	1.36	22	32.19	32.18829	0.0017071
10	46	15.3	2.26	279	1.84	18.8	32.09	32.09277	-0.0027746

11	30	4.19	1.98	260	0.3	6.3	17.98	17.92803	0.0519747
12	31.3	13.2	2.69	299	0.43	6.2	24.07	24.07246	-0.0024646
13	40.5	15.57	1.76	259	0.38	6.5	19.16	19.16199	-0.001989
14	40	6.7	2.34	256	0.1	6.8	21.39	21.38945	0.000548
15	89	4.9	4.5	201	1.9	22	47.74	47.73927	0.0007323
16	38.3	12.1	1.72	242	1.2	1	13.23	13.23806	-0.0080625
17	33	6.8	2.42	250	0.07	5.6	20.87	20.87305	-0.0030522
18	28	6.3	1.6	180	0.01	7.3	17.23	17.23887	-0.008867
19	27	10	1	166	0.17	9	15.59	15.59877	-0.008767
20	40	12.4	2.72	213	0.17	6.2	24.67	24.67798	-0.0079757
21	55.3	2.41	1.58	212	0.14	11	19.52	19.5143	0.0057044
22	44.1	2.1	2.5	211	0.145	14	27.77	27.7682	0.0018016
23	26	2.4	2.9	224	0.22	12	28.42	28.42288	-0.0028778
24	33	2.8	2.3	222	0.04	17.2	29.22	29.22081	-0.0008088
25	32	3.4	1.6	230	1.34	4	13.11	13.11044	-0.0004412
26	28	10.2	1.1	212	0.7	10	16.77	16.71635	0.0536545
27	25	12	1.6	210	1.21	6	16.68	16.68102	-0.0010244
28	22	0.81	2.4	180	0.8	8.1	21.45	21.50163	-0.0516314
29	25	5	2.5	88	0.22	10	25.31	25.31118	-0.0011814
30	36	23.2	1.49	241	0.54	16	27.04	27.04679	-0.0067882
31	31	19	1.52	201	1.06	11.2	22.22	22.20654	0.0134589
32	33	17	1.75	228	0.38	3.9	17.25	17.2577	-0.0076966
33	43	25	2.1	219	0.25	11.8	28.06	28.06761	-0.0076051
34	36	18.9	2.8	155	0.72	22	39.92	39.92548	-0.0054846
35	32	17.2	2.5	188	0.88	12	28.92	28.92584	-0.0058354
36	30	8.3	2.4	150	0.15	26	38.71	38.71306	-0.0030612
37	28	7.4	3.4	155	0.2	22	41.48	41.48044	-0.0004422
38	46	12	2.4	88	0.88	25	38.79	38.79045	-0.0004527
39	44	25	2.8	77	0.77	28	46.69	46.69913	-0.0091328
40	45	18.2	2.58	293	0.23	11	28.73	28.73415	-0.0041518
41	32	7.31	1.92	285	0.93	8	19.29	19.29052	-0.0005198

42	45	18.3	2.5	293	0.23	11	28.24	28.24265	-0.0026545
43	29	7	2.1	233	0.33	14	25.9	25.90409	-0.0040895
44	37.2	14.3	1.55	214	1.94	4	14.96	14.96249	-0.0024924
45	30	8.4	1.85	272	0.71	5	16.65	16.65863	-0.0086329
46	30.2	12.54	1.79	130	0.27	16	27.27	27.27336	-0.0033553
47	23	7.14	1.75	236	0.58	6.8	17.41	17.41775	-0.007752
48	40.2	9.3	2.13	252	1.45	8.5	21.49	21.49828	-0.0082829
49	44	17.5	2.8	72	0.14	10	30.16	30.16393	-0.0039301
50	33	5.2	1.8	240	0.47	14	23.55	23.55701	-0.0070054
51	32	22.2	1.2	250	0.55	12	21.54	21.5063	0.0337029
52	30	4.5	2.3	229	0.21	14.1	26.82	26.82179	-0.0017934
53	40.3	11.2	1.53	220	1.02	10	19.64	19.64343	-0.0034265
54	33.5	6.71	2.27	248	1.46	12	24.75	24.75741	-0.0074097
55	33.2	6.1	2.24	222	1.5	14	26.22	26.22682	-0.0068173
56	40.62	10.2	2.76	260	0.6	12	29.01	29.00249	0.0075122
57	29.7	7.89	1.95	261	0.38	13.3	24.24	24.39938	-0.1593768
58	32.3	7.78	1.68	285	0.74	19.7	27.84	27.8373	0.0026977
59	42.1	11.6	2.27	225	1.86	14	27.5	27.50787	-0.0078671
60	44	7.57	2.27	245	0.33	10	23.83	23.8299	0.0001017
61	41.3	7.2	2.1	222	0.34	12	24.42	24.42662	-0.0066214
62	33.9	5.25	1.9	270	0.122	12	22.53	22.53255	-0.002546
63	34	9.17	1.75	232	0.45	15.6	25.48	25.48023	-0.0002253
64	42.22	13.6	2.42	204	1	9	25.11	25.103	0.0069979
65	45	5.83	2.4	247	0.96	9.3	23.45	23.44844	0.0015558
66	42.1	15.16	1.8	281	0.44	2.4	15.75	15.75502	-0.0050236
67	44	4.5	1.8	173	1.9	8.4	18.5	18.49924	0.0007554
68	57	9.5	2.56	220	0.466	10.7	26.87	26.87817	-0.0081696
69	40	13.65	2.4	191	0.21	11	27.03	27.03618	-0.0061764
70	41	12.1	1.4	222	0.55	12	20.88	20.88332	-0.0033216
71	42.1	2.5	1.36	281	0.55	25	29.36	29.36181	-0.0018095
72	33.45	0.12	0.62	213	1.5	22	21.41	21.40632	0.0036798

73	33.65	0.22	0.66	244	1.8	14	14.65	14.65208	-0.0020799
74	34.3	1.2	1.1	178	0.66	25	27.76	27.75671	0.0032947
75	34	1.5	1.4	222	0.55	22	27.05	27.0472	0.0027999
76	39	6.4	2	281	0.11	18	28.5	28.50338	-0.0033797
77	22.8	2.08	2.75	285	0.9	9	24.27	24.27104	-0.0010381
78	55	1.5	2.8	295	1	25	38.27	38.26533	0.0046715
79	27.6	2.2	2.6	234	0.212	20	33.21	33.20666	0.0033418
80	26.22	5.69	2.4	261	0.23	15.5	28.7	28.70713	-0.0071296
81	27.2	7.85	1.5	185	0.44	16	24.08	24.08279	-0.0027919
82	39	5	2.36	254	1.55	29	39.36	39.35991	0.00009
83	41.2	1.2	2.36	179	0.54	28	38.49	38.48527	0.0047333
84	45	4.1	2.55	205	0.23	16	30.23	30.20363	0.0263695
85	32	6.6	2.2	188	0.1	10	23.4	23.40084	-0.0008413
86	45	5.2	2.1	254	0.88	15	26.22	26.22083	-0.0008335
87	55	6.6	1.7	188	0.54	12	21.95	21.95127	-0.0012727
88	52	11.47	2	220	1	5.7	19.22	19.20147	0.018528
89	57	10.2	2.2	250	0.54	21	33.27	33.27426	-0.00426
90	38.8	10.5	2.7	220	0.8	14	30.45	30.45234	-0.0023421
91	38.2	9.3	1.32	228	0.93	9.9	17.79	17.79301	-0.0030071
92	66.9	7.5	2.42	288	0.59	14	28.21	28.10328	0.1067163
93	69.3	2	2.6	297	0.18	23	35.87	35.87153	-0.0015309
94	56.2	1.62	2.1	276	0.21	25	34.23	34.22622	0.0037846
95	41.7	5.2	1.8	278	0.14	17	26.15	26.15259	-0.0025851
96	44	1.9	2.5	172	2	25	36.45	36.45371	-0.0037109
97	36.8	12.2	2	256	0.92	7.3	20.42	20.4224	-0.0024019
98	77	7.3	2.11	289	0.29	11.3	24.01	24.01313	-0.0031344
99	49.2	4.45	1.53	236	1.25	20.3	26.87	26.87138	-0.0013797
100	37	9.77	2.49	255	1.59	26.8	39.29	39.29148	-0.0014788
101	455.8	5.8	1.64	272	1.42	7	20.61	20.61903	-0.009026
102	39	6.18	2.3	245	0.01	9.6	23.47	23.46972	0.000278
103	38	5.21	2.25	274	0.21	15	27.29	27.29512	-0.005115

104	44.8	12.2	2.4	298	0.04	10.4	25.86	25.86476	-0.004763
105	44	13	2.3	288	0.5	12	26.59	26.5952	-0.0052021
106	41.2	9.79	2.53	241	1.36	20.2	34.16	34.16507	-0.005067
107	31.6	17.2	2.3	163	1.6	14	29.15	29.15105	-0.0010473
108	54.3	6.59	1.67	272	0.74	23	30.62	30.60469	0.0153105
109	55.2	12.2	2.2	254	0.88	18	30.98	30.97947	0.0005336
110	38	5	2.9	207	0.6	12.7	29.61	29.60823	0.0017726
111	32	3.36	2.12	255	0.82	14.1	25.08	25.08441	-0.0044105
112	43	7.7	2.62	279	1.28	16	30.63	30.62834	0.0016624
113	39.1	6.13	2.9	227	0.45	8	25.88	25.85035	0.0296471
114	47.9	11.05	1.77	294	0.62	15	25.29	25.29436	-0.0043619
115	61	12.3	1.89	231	0.1	21.5	32.46	32.45952	0.0004827
116	49.2	3.3	2	266	1.42	20.2	29.35	29.35247	-0.0024677
117	47.23	2	2.19	270	0.63	12.7	24.23	24.23148	-0.0014769
118	38.9	8	2.9	299	0.7	16	32.59	32.58997	2.94E-05
119	45	17.9	2	219	2.3	10	23.59	23.59375	-0.0037533
120	31.87	9.2	2.35	233	0.27	14.1	28.21	28.10742	0.1025823
121	32.8	5.8	2.4	255	0.77	18.2	30.89	30.89092	-0.0009237
122	36	7.54	2.85	214.5	0.55	20.9	36.73	36.72974	0.0002639
123	55	7.6	1.9	218	0.25	12.5	23.85	23.8505	-0.0005009
124	53.9	6.2	2.86	266	0.17	14.1	30.86	30.86757	-0.0075738
125	39.9	11.6	2.74	255.9	0.55	11.3	28.6	28.60734	-0.0073359
126	35.3	5.75	2.81	232	0.81	25.4	39.71	39.71491	-0.0049085
127	36.7	8.58	1.32	194	1.05	14.1	21.28	21.28445	-0.0044508
128	45	16.2	2.25	146	0.25	9	25.15	25.15523	-0.0052295
129	44.3	3.23	2.95	205	2.8	11.8	27.97	27.97045	-0.00045
130	42.2	4.22	2.4	208	0.44	18	30.83	30.83254	-0.0025402
131	35.3	3.81	2.54	220	2.75	20	32.27	32.26686	0.0031353
132	48.4	4.02	2.1	257	2.38	11.1	22.08	22.08043	-0.0004318
133	36.2	12.2	2.14	287	1.5	11.3	24.32	24.32377	-0.0037724
134	51	14	2.54	230	1.71	14	29.87	29.87415	-0.0041514

135	50	6.96	2.21	241	0.17	12	25.15	25.15633	-0.0063252
136	24	12.2	2.48	297	0.871	24	37.34	37.33813	0.0018694
137	45.9	10.91	1.71	298	1.49	10.2	20.42	20.42282	-0.0028152
138	57.2	12.5	1.87	305	2.41	18	28.09	28.09624	-0.0062437
139	68	14.5	2.11	308	2.1	22.5	34.09	34.08992	0.00008
140	61	18.2	1.92	304	1.5	27.1	37.73	37.73464	-0.0046429
141	56	12.2	2.1	201	0.2	35	45.25	45.25343	-0.003426
142	25	6.2	1	298	0.55	14.2	18.43	18.43583	-0.0058347
143	67	14.2	1.8	201	15	22.2	26.99	26.9842	0.0057971
144	22.2	21.2	2.64	308	2.871	11.12	28.46	28.46656	-0.0065648
145	65.2	14.2	2.4	202	1.1	28.2	41.55	41.56321	-0.0132121
146	35.2	12.2	1.9	100.2	1.9	31.2	40.29	40.29381	-0.0038089
147	52	11.2	2.1	307	0.22	17.55	29.74	29.74695	-0.0069469
148	47	14.55	2.8	221	0.87	18.21	35.62	35.56113	0.0588744
149	25.22	12.22	2.25	255	0.87	21.24	33.73	33.7332	-0.0032003
150	44	15.25	1.8	247	0.45	12.2	24.27	24.23798	0.0320196