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Dissolved oxygen control system in polishing unit using logic solver

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ABSTRACT

The research consists of two parts, the first one is to design the dynamic plant model of polishing unit using artificial neural network (ANN) type backpropagation, and the second one is to design a simulation of a close loop control system on Simulink consisting of logic solver, control valve and ANN polishing unit. The ANN polishing unit was trained and obtained the best model structure 4-24-3 with four inputs chemical oxygen demand (COD) influent, oil in water (OIW) influent, urea, and triple superphosphate (TSP), twenty-four hidden layer nodes, and three outputs (OIW effluent, COD effluent and dissolved oxygen (DO)). The mean square error (MSE) and root mean square error (RMSE) from ANN trained were 0.00485 and 0.06964, obtained by the second iteration. From the simulation results on Simulink by giving several scenarios in the logic solver condition table, the action is brought in the form of urea and TSP nutrition issued by the control valve. The values are used to achieve the DO setpoint (2 mg/L), among others: when COD and OIW influent exceed the quality standard, COD exceeds the quality standard, and OIW does not exceed the quality standard, and the DO error is below zero.

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1. INTRODUCTION

The side product of offshore petroleum processing is produced water which contains water, oil, and dangerous chemical pollutants [1], [2]. The increase of petroleum production also implies a higher produced water. The produced water should be treated to fill the quality standard parameters set by provision of Indonesian ministry of environment no. 19 year 2010 before it is thrown out to the sea. Prior to 2019, the unit processing the produced water was an American Petroleum Institute (API) separator, the working principle is to physically separate the oil and water content [3], [4], it causes oil which has a density smaller than water to float on the water [5]. The amount of produced water that is produced causes the API separator to be unable to treat all wastewater that still contains hazardous chemical pollutants [6], this has an impact on the quality of the wastewater to be disposed of which does not meet the quality standards that have been set. For this reason, offshore petroleum company usually added a wastewater treatment unit at the wastewater treatment plant (WWTP) called the polishing unit. Inside the polishing unit, there is biological treatment of wastewater using activated sludge. It is a waste treatment medium to utilize the aerobic microorganisms [7].

Since microorganisms need nutrients for their growth and reproduction, they must be kept alive and in a healthy condition to degrade harmful chemical pollutant compounds in the produced water [8], [9]. Based on interviews with the company, the monitoring of the condition of microorganisms carried out by operators at the polishing unit is still using the manual method, namely by taking a sample of produced water and then observing the color change in the laboratory, from this observation the operator can determine the condition of the microorganism: healthy, dying, or dead. Healthy conditions are described by brown wastewater, dying conditions are described as yellow wastewater and when microorganisms die, the color of wastewater is dark brown [10]. After knowing the condition of the microorganism, if the condition is dying or dead, then additional nutrients in the form of urea fertilizer (containing a lot of nitrogen) [11] and triple superphosphate (TSP) are added to the polishing unit in larger quantities, but none the exact number of this addition [12].

Meanwhile, if the condition of the microorganism is still healthy, the addition of nutrients is still carried out at a dose that is not too much [13]. There is no standard number that serves as a reference for adding nutrients. The addition of nutrients by paying attention to color is considered inaccurate, therefore the authors took the initiative to design the concept of automation of providing nutrition (urea and TSP) based on the values of parameters that directly affect the condition of microorganisms. In addition to observing color, we also measure wastewater parameters in each process (influent, aeration, and effluent). From this data, it can be compared with the quality standards set by the ministry of the environment. The parameter data obtained from the offshore petroleum company were further investigated by the authors to find out which parameters were the most significant in influencing the condition of microorganisms during the processing of produced water. From the parameters that were collected, we were then analyzed so that there were parameters that could be used as an indication of the condition of microorganisms in the polishing unit [14]. These parameters are arranged into a pair of input and output data for modeling the dynamics of the plant polishing unit process using an artificial neural network (ANN). The reason the author uses ANN in modeling the dynamics of the polishing unit process is because the biological process for decomposing the produced water is very complicated [15], so that it is difficult to model it in a mathematical model [16]. To maintain the operational stability of the polishing unit as a waste treatment plant for produced water, a control system is needed [17].

The polishing unit process variable that is controlled is dissolved oxygen (DO), which is a parameter that can indicate the condition of microorganisms through the large amount of DO in wastewater [18], the greater the DO value, the more microorganisms that live [19], [20], but a DO value must be maintained in a certain range of values so that value is neither more nor less. The DO value in the polishing unit was obtained from the measurement results in a portable and online analyzer in zones 1 and 2 of the polishing unit [21]. Amount of DO is measured in the aeration process which is measured in DO parameters indirectly also represents whether the produced water is feasible to be discharged into the sea because it can affect the value of effluent parameters such as oil content in water or oil in water (OIW) and chemical oxygen in wastewater or it called chemical oxygen demand (COD) [22]. indicating the quality of the wastewater [23]. So that the control system designed in this study is based on a logic solver. The logic solver as a controller can reason the DO error value as the difference between the DO set point value and the DO value measured by the online analyzer as well as the given OIW and COD influent loads [24]. The difference in the DO set point value with the measured DO value (DO error) is then used by the logic solver controller to provide an action signal to the actuator (simulation tool to determine the amount of urea and TSP to be given) so that the measured DO value on the polishing unit the next day can be calculated close to a predetermined set point range.

2. METHOD

2.1. Identification of the polishing unit parameters

The polishing unit has the following process mechanism [25]:

a. Produced water from API separator compartment 2 is channeled to the polishing unit (zones 1 and 2).
b. Before entering the polishing unit, the processing parameters are first measured such as OIW and COD influent to determine the processing load by microorganisms in processing the produced water.
c. When the water is produced in the polishing unit, aeration parameters such as DO are measured to see the amount of oxygen contained in the water. Oxygen is needed by microorganisms to degrade organic pollutants in the produced water. It is very important to know the oxygen requirements of microorganisms in produced water to keep them in a healthy condition and in controlled amounts. The measured DO is then analyzed for further action by the operator in the form of adding urea and TSP nutrients. This addition aims to keep the DO value in the desired range.
d. After processing at the polishing unit, the wastewater enters the final reservoir before being discharged into the sea. At this stage, parameters such as OIW and COD effluent are measured again to determine the decrease in value after going through the stages in the polishing unit. The schematic can be seen in Figure 1.

e. The polishing unit parameters were searched for their relationship using multiple linear regression (MLR). MLR is a regression technique that consists of more than one independent variable. MLR analysis aims to determine the extent of the relationship between the independent variables on the dependent variable [26]. The models obtained from MLR modeling between parameters are as (1)-(3) [27]:

- Effect of influent COD (X1) and OIW influent (X2) on urea (Y1):

$$Y1 = -2.947 + (0.015)X1 + (-0.009)X2 \quad (1)$$

- Effect of influent COD (X3) and OIW influent (X4) on TSP (Y2):

$$Y2 = 0.205 + (0.002)X3 + (-0{,}001)X4 \quad (2)$$

- Effect of adding urea (X5) and TSP (X6) on DO (Y3):

$$Y3 = 0.205 + (0.002)X5 + (-0{,}001)X6 \quad (3)$$

After obtaining the relationship between parameters on the polishing unit [28]. Then the pair of data record input and output of the polishing unit was taken on January 1, 2019–April 12, 2020, for the design of the ANN model. The input and output data pairs are taken with the following rules:

- Input data (COD influent, OIW influent, urea, TSP) are data on day 1-3 and so on.
- The COD effluent output data is the 3rd, 4th, 5th day data, and so on. This is based on the impact of the addition of urea and TSP on the COD effluent which can only be seen after 2 days of processing by microorganisms in the polishing unit.
- OIW effluent and DO output data are data for day 2-4, and so on. This is based on the impact of the addition of urea and TSP on the COD effluent and DO can only be seen after 1 day of processing by microorganisms in the polishing unit.
- The data records are divided into training and validation data. Data from January 01–December 29, 2019, becomes training data, while data from January 01–April 10, 2020, becomes validation data. The distribution of data for training and validation is 363 and 101 data or in a percentage close to 80%:20%.

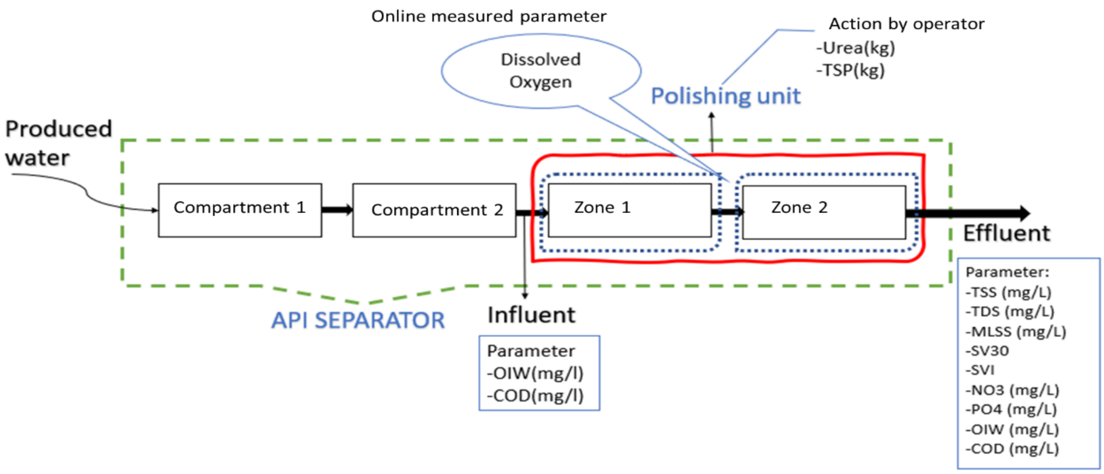

Figure 1. Schematic diagram of the produced water treatment process in polishing unit

2.2. The design and training of artificial neural network model for polishing unit

The ANN is modeled with 4 inputs (COD influent, OIW influent, urea, and TSP), 24 hidden layer nodes and 3 outputs (COD effluent, OIW effluent and DO) using a data record polishing unit. Our ANN design is shown in Figure 2. The ANN architecture that has been obtained will be trained [29]. The training is carried out using the mean square error (MSE) 0.05 training error parameter, the maximum epoch is 300 and the maximum error is 150. The training is carried out by entering the input-target data pair and the training parameters into the toolbox in MATLAB [30].

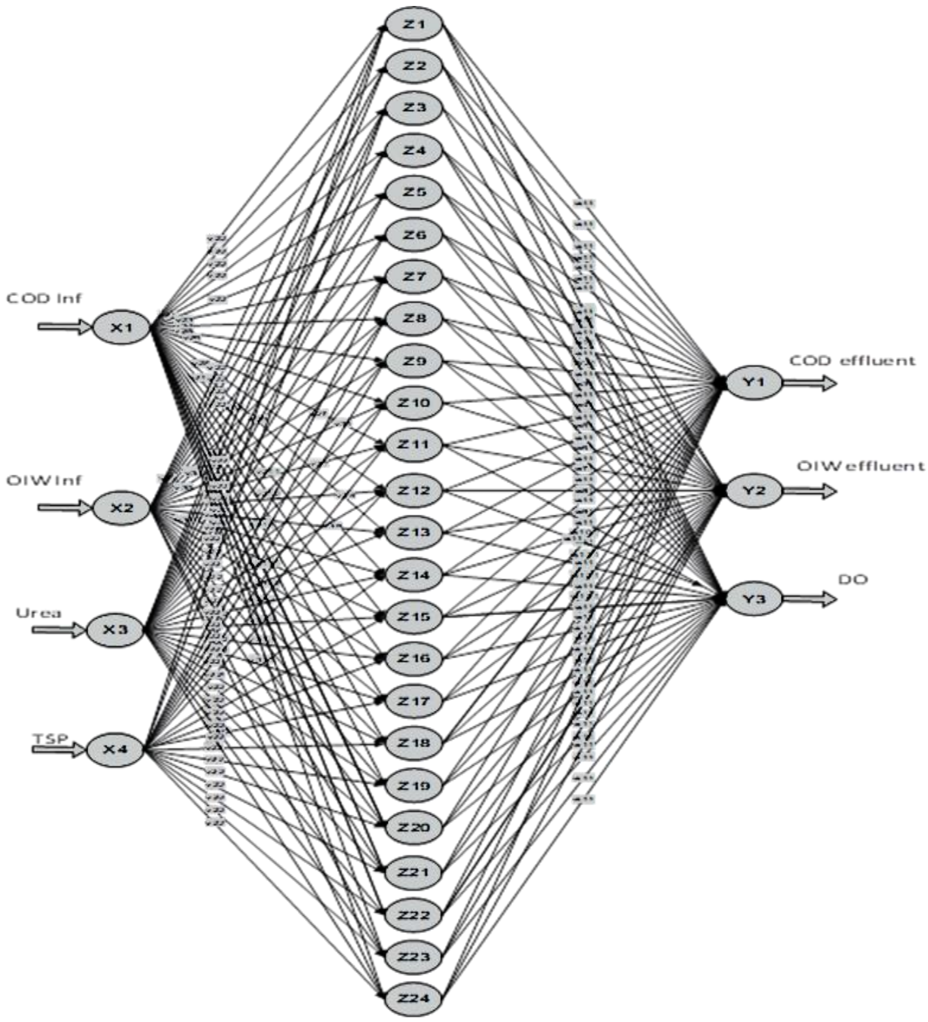

Figure 2. The ANN model of the polishing unit

2.3. The design of logic solver

Logic solver is designed by entering condition and action data in the Simulink. This condition and action data becomes the database of the logic solver in carrying out their duties. Based on the data records, the COD value is in the range of 273-1,662 mg/L while the OIW value is in the range of 8.2-170 mg/L. The quality standard according to the regulation of the Minister of the Environment for the COD parameter is 200 mg/L and for the OIW parameter it is 25 mg/L. The range of influent COD values in the data records are all above the quality standard while the influent OIW value is partly below the quality standard value and partly above the quality standard. From (1) and (2), the most influential variable on the addition of urea and TSP is the influent COD. Therefore, a logic solver database was compiled based on the influent COD range using (1) and (2). The COD and OIW influent values selected as control system test data were:

- For COD influent does not meet the quality standard and OIW influent meets the quality standard (COD=560, OIW=20)

$$Y1 = -2.947 + (0.015)X1 + (-0.009)X2$$
$$Urea = -2.947 + (0.015)560 + (-0.009)20$$
$$Urea = 5.273\ kg$$

$$Y2 = 0.205 + (0.002)X3 + (-0,001)X4$$
$$TSP = 0.205 + (0.002)560 + (-0,001)20$$
$$TSP = 1,305\ kg$$

- For COD and OIW influent does not meet the quality standard (COD=596, OIW=28)

$$Y1 = -2.947 + (0.015)X1 + (-0.009)X2$$
$$Urea = -2.947 + (0.015)596 + (-0.009)28$$
$$Urea = 5.741\ kg$$

$$Y2 = 0.205 + (0.002)X3 + (-0{,}001)X4$$
$$TSP = 0.205 + (0.002)596 + (-0{,}001)28$$
$$TSP = 1.369\ kg$$

- For COD influent does not meet the quality standard and OIW influent meets the quality standard (COD=653, OIW=22),

$$Y1 = -2.947 + (0.015)X1 + (-0.009)X2$$
$$Urea = -2.947 + (0.015)653 + (-0.009)22$$
$$Urea = 6.65\ kg$$

$$Y2 = 0.205 + (0.002)X3 + (-0{,}001)X4$$
$$TSP = 0.205 + (0.002)653 + (-0{,}001)22$$
$$TSP = 1.489\ kg$$

- For COD and OIW influent does not meet the quality standard (COD=751, OIW=29),

$$Y1 = -2.947 + (0.015)X1 + (-0.009)X2$$
$$Urea = -2.947 + (0.015)751 + (-0.009)29$$
$$Urea = 8.057\ kg$$

$$Y2 = 0.205 + (0.002)X3 + (-0{,}001)X4$$
$$TSP = 0.205 + (0.002)751 + (-0{,}001)29$$
$$TSP = 1.678\ kg$$

3. RESULTS AND DISCUSSION

3.1. Artificial neural network training results

ANN training and validation have been carried out for modeling the polishing unit process. The training was carried out using a 4-24-3 structured ANN model (4 inputs, 24 hidden layer nodes, and 3 outputs), the Levenberg-Maarquardt type of training, and the target or objective of the training was MSE. The MSE value of training using normalized data is 0.00485 which is obtained in the second iteration. This value has reached the predetermined MSE target (0.005) so that the training process has been successfully carried out. Based on the ANN training that has been carried out, the output of the ANN prediction training and the error value is obtained. These outputs and errors are obtained after returning the normalized data from the training results to their original scale. The MSE values of each output parameter of COD effluent, OIW effluent, and DO are 63.98, 0.03 and 0.15, respectively. While the MSE values for each output parameter of COD effluent, OIW effluent, and DO are 8.00, 0.18 and 0.39, respectively. When compared with the reference used (59.48) [31], the root mean square error (RMSE) value of the COD from the training results was better. Meanwhile for the DO parameter, the RMSE value when compared to the reference (0.8831) is also better.

The RMSE value is used to compare the RMSE values of the three outputs. From the table, it is found that the RMSE value of the COD effluent parameter is smaller than the OIW effluent and DO, which means that the predictions made by ANN are more accurate for the COD parameter. This shows that the ANN designed has worked quite well in modeling the process in the polishing unit plant [32], [33]. Figure 3 below is a comparison of DO results from ANN training with DO data record in polishing unit. The error range of DO ANN comparison with data record is 0.000161-2.735014. From the picture, the output of DO ANN can follow the pattern of recorded data well, but there are some data that deviate quite far, where the respective errors are 1.40, 1.42, and 2.74. This happened because the data values on that date were very different from most of the data ranges, so that ANN was not able to properly follow the desired target [34]. Overall, the data record value can be predicted by ANN well, which is indicated by the number of small error values approaching zero. In Figures 4 and 5, it can be seen the comparison of COD and OIW effluent from ANN training with COD and OIW effluent record polishing unit. From Figure 4 the COD ANN can follow the pattern of the COD data record from polishing unit. The error range for COD effluent is

0.009565-59.35001. Meanwhile in Figure 5 give us the information of the OIW effluent. Our ANN model of the OIW effluent resembling pattern with the data record of the OIW effluent from polishing unit, with error of the OIW effluent in the range of 8.6×10^{-5}-1.135028.

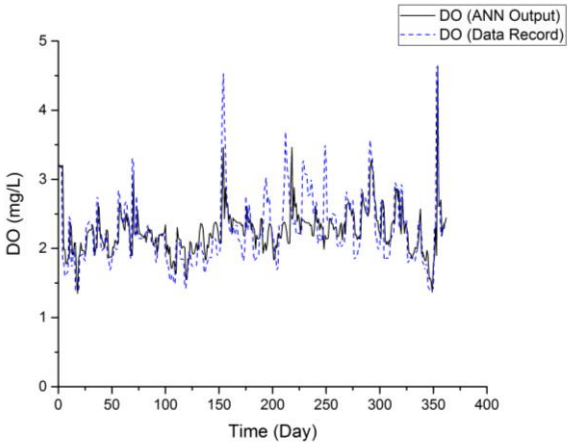

Figure 3. Comparison graph of DO ANN training with DO record in polishing unit

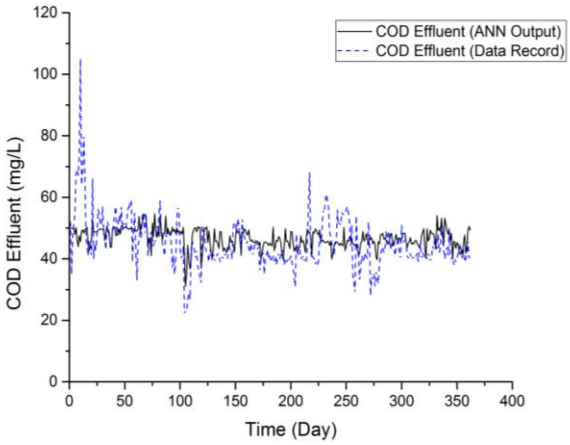

Figure 4. Comparison graph of COD effluent ANN training with COD effluent record in polishing unit

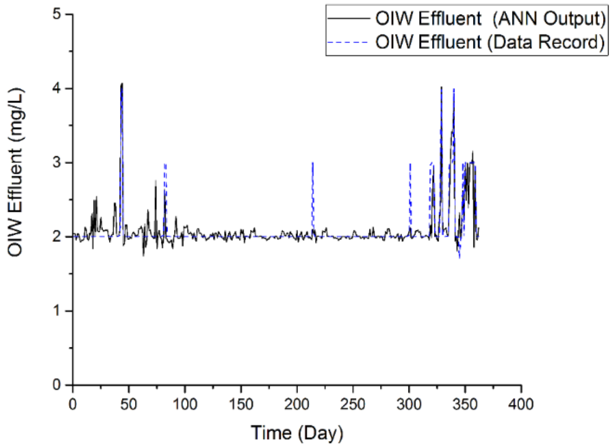

Figure 5. Comparison graph of OIW effluent ANN training with OIW effluent record in polishing unit

3.2. Artificial neural network validation results

From the ANN validation that has been done, the correlation value between the parameters is shown in Figure 6. The overall correlation coefficient (R) value is 0.80463, when compared to the source correlation (0.7594) [31]. The correlation between parameters in ANN is better, which means the network can predict a given target well with a number of input scenarios.

From the results of ANN validation using the same validation data and network as the training, the output of ANN predictions and the error values are obtained. The MSE values for each output parameter of COD effluent, OIW effluent, and DO are 22.870, 7.743 and 0.021, respectively. While the RMSE values for each output parameter of COD effluent, OIW effluent, and DO are 4.782, 2.783 and 0.470, respectively. When compared with the reference used [31], the RMSE value of COD and OIW effluent. Meanwhile for the DO parameter, the RMSE value when compared to the reference (0.8831) is also better. There is a small part of the data that has a large error and if you look back at the training RMSE for the influent OIW and DO parameters, it is greater than the validation. This can be caused by overfitting. Overfitting is a situation where the data used for the training is the "best". So that if a test is carried out using different data, it can reduce the accuracy (the results are not as expected). In this case, when given validation data, ANN cannot produce a smaller error compared with the training data [35].

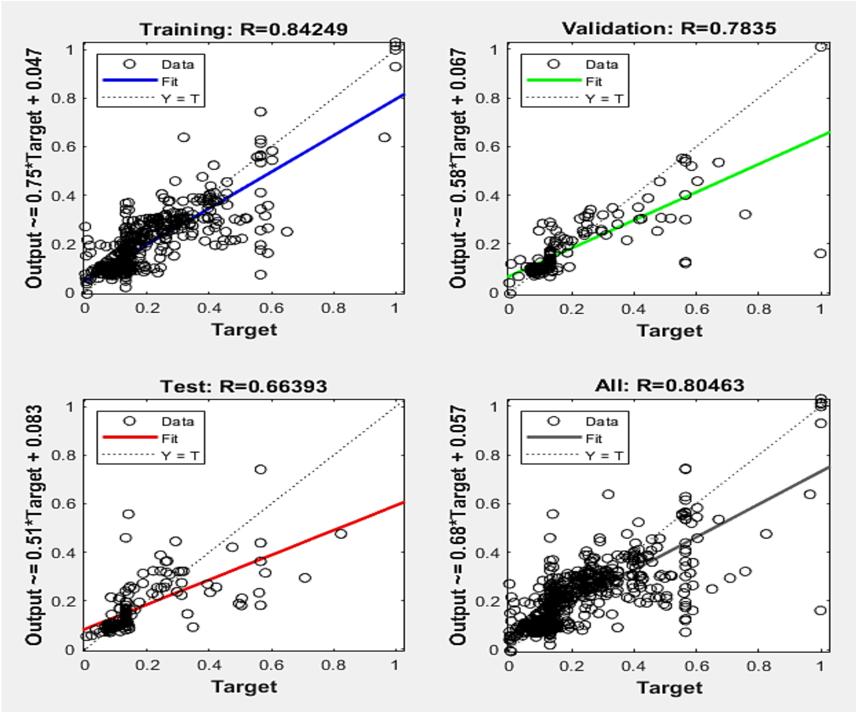

Figure 6. Correlation value of the ANN validation with twenty-four hidden layers

3.3. Artificial neural network validation with sample data in polishing unit

Sample data for validation was carried out by taking 9 data in the COD range (273–1,279) and the OIW range (10.9-40.2). The greater the COD influent value, the more urea and TSP nutrients given. The addition of more urea and TSP was followed by an increase in the DO value in the ANN output. Meanwhile in Figures 7-9 show, if the urea and TSP values increase, the OIW effluent value tends to decrease, while for the COD effluent it fluctuates (the value is unstable). From the previous explanation, ANN can follow the polishing unit work logic based on data records, namely:

- The addition of urea and TSP values is followed by a higher DO value. Which means the more nutrients provided, the more oxygen in the water and followed by an increase in the number of microorganisms.
- It is not known for certain the effect of the addition of urea and TSP on OIW and COD effluent, this is also in accordance with the data record that there is no clear relationship between urea and TSP with COD and OIW effluent. This is because the COD and OIW effluent values are heavily influenced by other factors in the polishing unit.

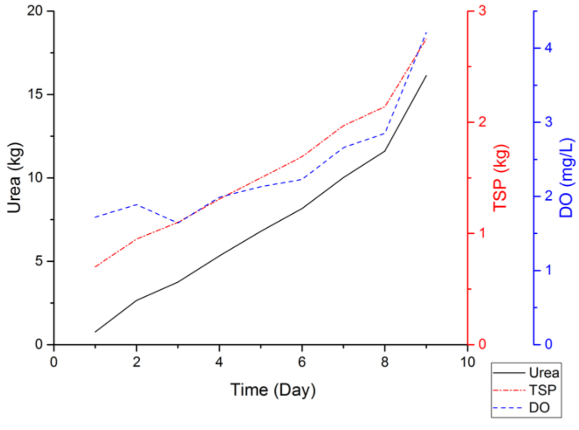

Figure 7. The relation between urea, TSP and DO of the ANN output concentration

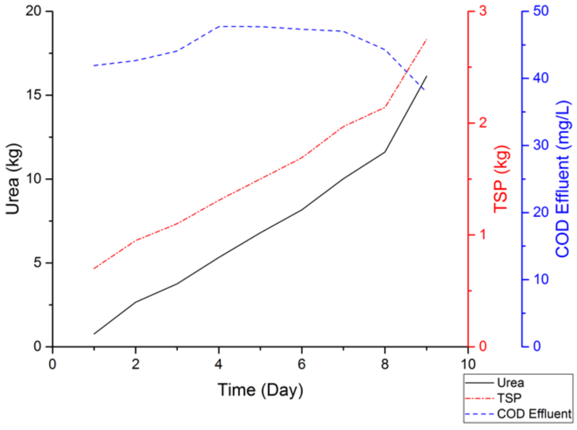

Figure 8. The relation between urea, TSP and COD of the ANN output concentration

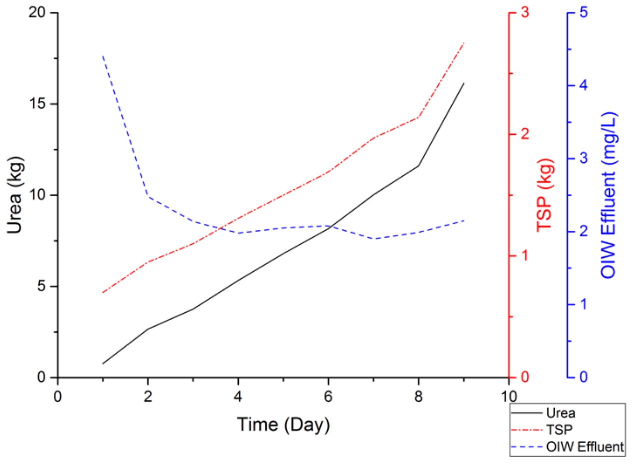

Figure 9. The relation between urea, TSP and OIW of the ANN output concentration

3.4. The test of the close loop control system

The test of the close loop control system was carried out with variations in input conditions on the polishing unit, namely manipulation of the flow rate coming out of the urea and TSP control valves and processing loads, namely OIW and COD influent parameters. The data is shown in Table 1. From Table 1, the higher of the influent COD and OIW values, implies the greater of the urea and TSP nutrition. It can also be seen in the table, to control the DO value which is close to the set point (2 mg/L) [36], different actions are given based on the existing conditions. A set point of DO (2 mg/L) [36] and a close-loop feedback control simulation is performed. From this simulation, under conditions 1-4 in Table 1, the DO values are 2,079 mg/L, 2,008 mg/L, 2,147 mg/L, 2,075, and mg/L so that the system error obtained for each condition is 0.079 (3.95%), 0.008 (0.4%), 0.147 (7.35%), and 0.075 (3.75%). From these four results, the smallest error occurs when condition 2. With these results the logic solver as a controller has worked well enough to control DO to keep it close to the set point. In addition, condition 4 reached a stable response at the twenty-third hour. This response is relatively slow, in accordance with the effect of adding urea and TSP nutrients which can be seen +/- one day later. The type of response generated is a transient overdamped response, where the value of the process variable (DO) is close to the set point.

Table 1. Control system closed loop test results

No	Set point	Condition			Action		Output		
		COD (mg/L)	OIW (mg/L)	Error DO	Urea (kg)	TSP (kg)	COD (mg/L)	OIW (mg/L)	DO (mg/L)
1	2	596	28	0.0793	5.741	1.369	31.71	2.547	2.079
2	2	560	20	0.0090	5.273	1.305	30.67	2.108	2.008
3	2	653	22	0.1473	6.650	1.489	30	2.038	2.147
4	2	751	29	0.0747	8.057	1.678	32.38	2.365	2.075

4. CONCLUSION

This research indicates that the ANN that has been designed is able to follow the logic of the process that occurred in the original polishing unit based on the data record. The DO control system is designed by using a truth table in the Simulink state flow block as the logic solver. The difference between DO and the values for the influent COD and OIW influent placed in the condition table will be analyzed by the logic solver for later determine the control signal in the action table. This reasoning takes place if the input logic solver fulfills one of the conditions in the condition table and then decides to issue an action on the action table. From the simulation results with the scenarios given several conditions, to control the DO process variable to stay close to the set point, the conditions given are that the influent COD and OIW values exceed the quality standard, the influent COD exceeds the quality standard and the OIW does not, and the DO error is less than zero. Based on this response, the performance of the designed control system is quite good based on the given scenarios of conditions.

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