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Research paper



Prediction of Blue Water Footprint Accounting for Water Treatment Plants in Kuantan River Basin

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Abstract

Water treatment plants (WTPs) in Kuantan river basin abstracts water from the blue water source, which is the Kuantan river. Therefore, by accounting the blue water footprint (WFb), the overall water consumption for all five WTPs namely; Sungai Lembing, Bukit Sagu, Panching, Semambu, and Bukit Ubi can be obtained. In order to predict the value, Backpropagation method is the best method to be used due to the historical data obtained from the WFb accounting for all five WTPs above. The objective of this study is to predict the overall blue water consumption for water treatment plants located along Kuantan river basin using Backpropagation method in artificial neural network. In this study, WFb has been accounted throughout all water treatment plants by using reference from water footprint manual. Then, the WFb will undergo a series of testing using application in MATLAB software in order to predict the future value based on historical data from 2015 until 2016. As a result, the total WFb accounting obtained was 190,543,378.2 m^3/day, while the total maximum capacity of the WTPs was 189,654,000 m^3/day. Hence, the prediction value that kept increasing will not be able to cater the future demand due to unstoppable urbanization.

Keywords: *Water Supply, Water Resources Management, Water Footprint, Backpropagation Method*

1. Introduction

In Malaysia, most water sources come from blue water resources, which are either groundwater or surface water, and mostly are from the river [1]. Water resources are involved in the abstraction process; water abstraction is increasing remarkably and globally due to increasing demand of water and therefore, this will contribute to the imbalanced ecosystem and its function [2]. Moreover, the sustainability of water resources is believed to be dependent on the availability of water resources from the intake [3]. Water resources are part of the ecosystem and the sustainability of ecosystem is defined as when the ecosystem is able to meet human needs without causing any harm to the environment [4]. Due to that, there are many studies done in terms of environmental sustainability of water supply. Among them are the effects of human intervention and climate change to water resources [5], the effects of climate change to the water resources in Yellow river basin in China [6], sustainable urban water resources management by considering the Life Cycle Assessment (LCA) in terms of uncertain water utilization [7], and a modelling study of future water resources for food production in the involved river basin in South Asia [8].

Currently, the water intake, water discharge and all volumes of water along the conventional Water Treatment Plants (WTPs) are recorded. However, the type of water involved in the process is not well defined. In Water Footprint (WF), water is categorized into three types, namely; Blue WF, Green WF and Grey WF. As water resources in Malaysia are dependent on surface water sources such as rivers and reservoirs [9], some places in Malaysia are dependent on groundwater resources but it is not Malaysia's main water source [1]. Thus, better management of water resources is essential to ensure the continuous presence of clean water. Since the use of water has created good and bad effects, thus the WF concept is introduced to the public, especially to promote awareness. More significantly, it can be said that WF assessment is a holistic approach to an efficient use of the resource as water is an imperative resource for human and ecosystem health.

Generally, Water Footprint (WF) is defined as the amount of water used to produce a product or service in a country [10]. Several studies have revealed that most researches in WF has also emphasized the use of water in wastewater treatment plant [11], citrus production [12], olive growing system [13], iron and steel industry [14], potato production [15], energy production and supply [16], winemaking industry [17], transport fuels [18], a pair of jeans [19], ethanol production [20], paddy rice system [21], coffee and tea consumption [22], farm animal products [23], humanity [24], tourism in Spain [25], food waste [26], bioenergy [27], crops and derived crops products [28], and for the service sector of water scarce in gaming industry of Macao [29]. As stated, most of the researches were conducted on product-basis and according to Hoekstra, by using WF approach, researcher would be able to assess sustainable water allocation [3].

Previously, several reports have shown that the ANN application is useful in hydrology field, especially in forecasting and predicting parameters [30]. Applications of ANN by researchers in analyzing water-based cases are quite enormous and directly related to one of our biggest challenges in managing the water issues, that is the water quality. ANN applications are playing a major role in

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predicting water quality parameters [31] and in the prediction of the groundwater recovery cost for drinking use based on the quality of water resources. One of the interesting findings is the development of prediction modelling by using ANN to predict the monthly values of two parameters for water quality of Delaware River, Pennsylvania [32]. Other than that, ANNs can also predict solar radiation accurately when compared with conventional methods [33].

Moreover, a research is done to create a model that allows the prediction of the flow of "Tomebamba" river at any specific day of a year [34], and to predict a variety of ocean water quality parameters [35] by using ANN. In addition, ANN was used in predicting the water quality of polluted aquifer [36]. Commonly, in time series prediction, which is basically describing a future value based on the current and historical data, is called as the backpropagation method. Recently, ANN has been massively used by many researchers due to its less-complex process, such as in predicting the NOx emission of diesel engine by improving the linear and nonlinear auto-regressive model [37]. Other than that, real-time damage detection can also be analyzed using time varying auto-regressive model and recursive principal components [38].

Backpropagation (BP), or also known as propagation of error is one of the methods with the ability to teach artificial neural network to perform tasks that are instructed to them. It was initially portrayed by Arthur E. Bryson and Yu-Chi Ho in 1969, and on 1986, this method was recognized by David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams through their work, thus becoming popular in ANN research [39]. Hence, this method will be used in time series tool of prediction in ANN. However, before uploading a historical data, a problem need to be selected based on what prediction is to be analyzed.

Hence, this study aims to predict the overall blue water consumption for water treatment plants located in Kuantan river basin using backpropagation method in artificial neural network based on overall WFb accounting.

2. Methodology

Firstly, total blue water consumption is calculated by using water footprint manual to get the total WFb for each WTP from year 2015 to 2017. Secondly, WFb for each WTP is predicted for the next three years' trend in order to know the rate of changes.

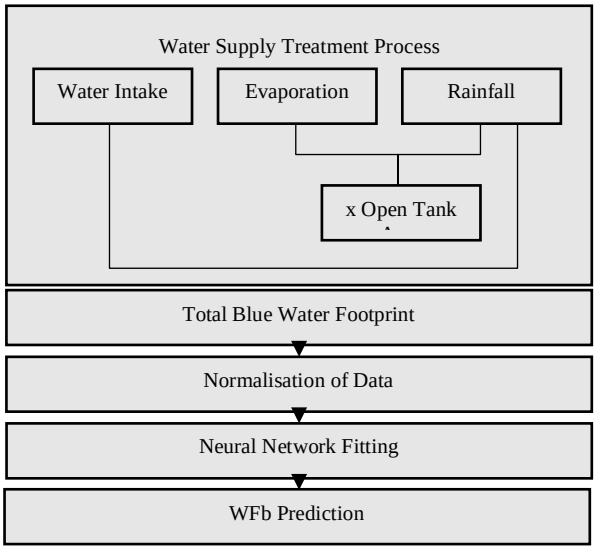


Fig. 1: Flow of Methodology

2.1. Blue Water Footprint Accounting

Blue water footprint (WFb) is the amount of surface water and groundwater required (evaporated or directly used) in each stage of the water treatment process. The method of blue water footprint calculation is expressed in Equation (1):

$$WF_{blue} = \text{water intake} + [ET_0 \times \text{Area}] + [\text{Rainfall} \times \text{Area}] \quad (1)$$

Definition 2.1: ET_0 is reference evapotranspiration in m^3/day, p is mean daily percentage of annual daytime hours, T is mean daily temperature (°C), rainfall is amount of precipitation within the WTP area, and Area is open tank area that is exposed to precipitation and evaporation.

Definition 2.2: ET_0 is the rate of blue water evaporation calculated using Blaney-Criddle method. The formula of Blaney-Criddle method are expressed as in Eq. (2).

$$ET_0 = P(0.46\,T\,\text{mean} + 8) \quad (2)$$

The formula to calculate T_0 mean is expressed in Eq. (3). Meanwhile, Table 1 is used to determine the value of p. To be able to determine the p value, it is essential to know the approximate latitude of the area and the number of degrees north or south of the equator. In this study, all WTPs are located in Latitude 3.0.

Table 1: p Value

LATITUDE	**NORTH**	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUNE**
	South	July	Aug	Sept	Oct	Nov	Dec
5		.27	.27	.27	.28	.28	.28
0		.27	.27	.27	.27	.27	.27
LATITUDE	North	July	Aug	Sept	Oct	Nov	Dec
	South	Jan	Feb	Mar	Apr	May	June
5		.28	.28	.28	.27	.27	.27
0		.27	.27	.27	.27	.27	.27

$$T_{mean} = \frac{T_{min} + T_{max}}{2} \quad (3)$$

Since the latitude of intake and plant station are not stated in the table of mean daily percentage of annual daytime hours for different latitude, thus, the interpolation must be done by using Eq. (3). After all total WFb for all WTPs involved have been accounted for, those values will be compared with the capacity of all WTPs in order to know whether the actual amount of water used in the process is still under the capacity of WTP or not. This method must be made before predicting the trend for the future.

2.2. Normalization of Data

The extreme value of data set in this study were normalized by using min-max method. Min-max normalization performs a linear transformation on the original data. This method helps to reduce the effects of outliers, i.e. extreme values in the input as well as output data (total blue water footprint), and makes the scaled data easier to be modelled in ANN. The formula for data normalization is:

$$V_n = \frac{V\text{-}min_a}{max_a - min} \quad (4)$$

Definition 2.3: Vn is the value of normalization, in order to get the normalized value, current value needs to be subtracted by minimum value of the data, then, the data is divided by maximum value minus the minimum value of the data set.

2.3. Prediction using Backpropagation Method

In this study, predicted data will be obtained by undergoing a series of historical data from 2015 until 2016 for all WTPs. This method is named backpropagation method, total WFb accounts for three years period undergo a series of testing after all the data have been taken and the amount of daily WF for three years have been accounted, the value will be listed and used as training elements in order to get the predicted value of WF in the future. Neural Fitting Application in ANN will be used because the result that will be obtained is a numeric value. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (fitnet) can fit multi-dimensional mapping problems arbitrarily well, given the consistent data and enough neurons in its hidden layer. The network will be trained with scaled-conjugate backpropagation algorithm because this algorithm requires less memory. Training automatically stops when generalization stops improving, as indicated by an increase in the mean squared error of the validation samples. The WF value for two years period will be inserted in this application to obtain the prediction value. The Neural Fitting app helps select the data, create and train a network, and evaluate its performance using mean squared error and regression analysis. The input variables are presented in Table 2

Table 2: Input Variables for ANN

CATEGORY	VARIABLES
INPUT VARIABLES	Daily Water Intake
	Rainfall
	Evaporation
OUTPUT VARIABLE	Total Water Footprint

3. Results and Analysis

The 3.1 sub-topic will be presenting the total blue water footprint WFb in all WTPs in Kuantan river basin. Meanwhile, sub-topic 3.2 will be presenting the prediction of all WFb in Kuantan River basin.

3.1. Total Blue Water Footprint for each WTP in Kuantan River Basin

3.1.1 Sungai Lembing Water Treatment Plant

Sungai Lembing Water Treatment Plant supplies treated water for Sungai Lembing and Panching Utara area. The WTP is located at 3.561, 103.47, and it is expected to cover almost 88,616.53 ha of land use with the capacity of 250 m^3/hour and can reach to $2.19x10^6$ m^3/year, where it benefits almost 7,500 population. Fig. 2 is the graph for total WFb of this WTP from 2015 to 2016.

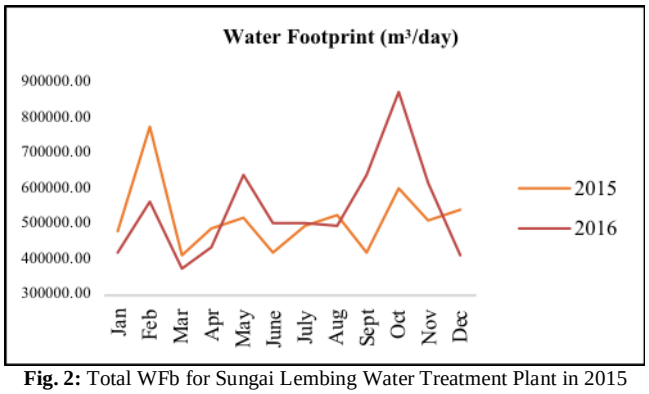


Fig. 2: Total WFb for Sungai Lembing Water Treatment Plant in 2015

As seen in Fig. 2, based on the graph of total WFb for Sungai Lembing Water Treatment Plant for 2015, the graph shows a great fluctuation throughout the year. In January, the value of WFb was 482,384.745 m^3/month, which then increased greatly to 777,125.987 m^3/month in February, where the highest reading for year 2015 was obtained. In March, the reading dropped to the lowest value, which was 413,146.967 m^3/month. This low value might be due to the less amount of rainfall for that particular month. The data of total WFb increased again in April and May and dropped again to 420,460.275 m^3/month in June. This trend continued until the end of the year, where the WFb decreased and increased alternately for every month starting July to December.

Meanwhile, by referring to the total WFb graph plotted for Sungai Lembing Water Treatment Plant in 2016 in Fig. 2, it can be seen that the pattern of WFb is almost similar to the pattern in 2015. Great fluctuation had occurred in 2016. The lowest value was 377,707.101 m^3/month, which was obtained in March. This is similar to the water footprint in March 2015, where less rainfall occurred in the same month. The value of water footprint increased in April and May, but then had a slight drop starting from June until August. However, it increased greatly in October, with a value of 876,205.542 m^3/month, which might be caused by the monsoon that increased the amount of rainfall for the respective month. The reading decreased again in November and December, which indicates less rainfall had occurred during these two months compared to one that eventuated in October.

The total WFb for the whole year were 6,211,895.80 m^3/year in 2015 and 6,485,405.187 m^3/year in 2016. Those values are greater than the total capacity of this WTP, which is 2.19 x 10^6 m^3/year. Since Sungai Lembing is located in the upstream area of Kuantan river basin and covered with hillside and forestry, the amount of rainfall also greater than other WTPs. Therefore, the amount of total WFb is greater than the capacity of the WTP due to this condition. Moreover, there were two WTPs that were closed in this area, which are Pasir Kemudi Water Treatment Plant and Bukit Goh Water Treatment Plant, therefore, the burden is passed to Sungai Lembing Water Treatment Plant. However, there was a planning to divert the supply for this area to Panching Water Treatment Plant since that WTP has a higher capacity than that of the Sungai Lembing Water Treatment Plant.

3.1.2 Bukit Sagu Water Treatment Plant

Bukit Sagu Water Treatment Plant is located at 3.5456, 103.1032 and has a capacity of 900 m^3/hour and at maximum, it can reach to 7.88 x 106 m^3/year. This capacity could be said to be sufficient enough to cater the bauxite mining industry in that area. Along with the Panching and Semambu Water Treatment Plants, Bukit Sagu Water Treatment Plant is only focusing on supplying the water to a small area of Felda Bukit Sagu.

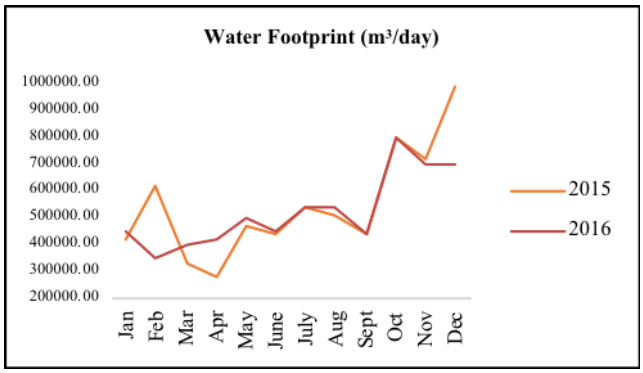


Fig. 3: Total WFb for Bukit Sagu Water Treatment Plant in 2016

From the data presented in the table above, the values for WFb at Bukit Sagu Water Treatment Plant in 2015 fluctuated greatly throughout the year. In January, the value of water footprint was 419,957.571 m^3/month. It then increased to 615,896.637 m^3/month in February, which might be caused by the heavy rainfall and dropped substantially in March and April. However, the values of WFb increased gradually from May towards September, and started to increase greatly in October with an increment of 354,474.012 m^3/month. Bukit Sagu Water Treatment Plant achieved the highest value of WFb for year 2015 in December, with a value of 987,006.943 m^3/month. This proves that the

Northeast Monsoon had taken place and given a major effect on the value of water footprint.
In 2016, the values of WFb in Bukit Sagu Water Treatment Plant was almost consistent from January until August. There was a gradual increase from February, where the value of water footprint is 346,471.96 m^3/month until August (535,037.844 m^3/month). The highest data for water footprint was achieved in October due to heavy rainfall from the monsoon that occurred during that month, with a value of 794,664.05 m^3/month. The monsoon plays a big role in determining the changes of pattern of water footprint. It can be seen that the value of water footprint was then consistent in both November and December, with a slight difference between these two months.
The total WFb for 2015 in Bukit Sagu Water Treatment Plant was 6,523,952.217 m^3/year, and 6,271,712.715 in 2016. Both values are still under the capacity, which is 7.88 x 10^6 m^3/year and this is due to the purpose of this WTP, which is to supply for Felda Bukit Sagu area only.

3.1.3 Panching Water Treatment Plant

Kuantan River has become the source of water intake for Panching Water Treatment Plant. It is the second bigger WTP in Kuantan district and located at 3.5020, 103.1238, where the areas of water supply are both for Penur and Kualan Kuantan. The capacity of 7,000 m^3/hour and expected to be 6.13 x 10^7 m^3/year will be able to sufficiently provide 389,000 people with treated water including the residential area and as well as 5600 ha of industrial area.

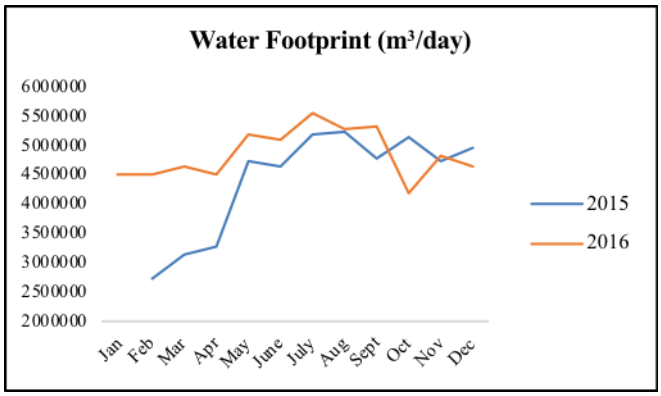


Fig. 4: Total WFb for Panching Water Treatment Plant

In February 2015, the graph shows the lowest result of water footprint with the value 2,760,322 m^3/month. The value that was shown might be due to the beginning of operation of Panching Water Treatment Plant, which started their operation in February 2015. In the beginning of the operation, there was no backwash thus this was also the factor of lower amount of WFb at the beginning. Then, the value of WFb gradually increased from February until April and increased greatly in May with a value of 4,750,800.6 m^3/month. By referring to the graph, it can be seen that the water footprint increased gradually until August and became constant until the end of the year.
Based on the plotted graph as shown in the above, the values of WFb at Panching Water Treatment Plant in 2016 were consistent from January until September. Starting from January until April, there were minor differences of value for water footprint, where the values of water footprint are 4,524,827.526 m^3/month, 4,508,682.468 m^3/month, 4,669,823.352 m^3/month and 4,522,155.315 m^3/month, respectively. In May, WFb increased to 5,224,373.347 m^3/month and decreased slightly to 5,092,312.577 m^3/month in June. This trend of minor increase and decrease continued until September and dropped significantly in October with a value of 4,198,732.457 m^3/month. This occurrence happened due to less rainfall throughout this month.
The total WFb for 2015 in Panching Water Treatment Plant was 53,098,640.29 m^3/year, while 58,431,711.23 m^3/year in 2016. Therefore, both values were still under the capacity, which is 6.13 x 10^7 m^3/year.

3.1.4 Semambu Water Treatment Plant

Sub-districts of Sungai Karang and Beserah has received treated water from the Semambu Water Treatment Plant. Although located at 3.521, 103.2016 and 18 km away from the intake location, it is recognized as the biggest WTP's capacity with 12,000 m^3/hour and will increase to 1.05 x 10^8 m^3/year. The average population of 92,800 occupied in areas of 30,300 ha benefited from this water treatment plant. Residential area of Kotasas and industrial park of Semambu and Gebeng has become the major receiver of treated water.

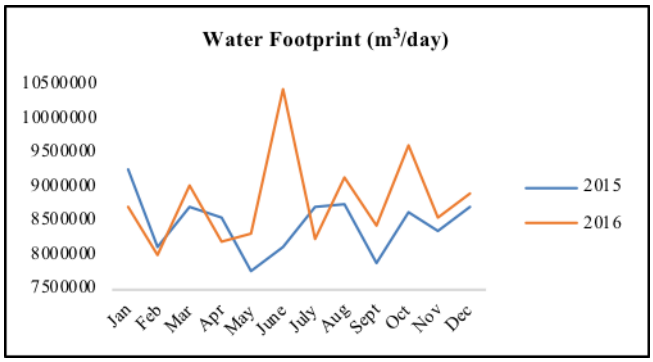


Fig. 5: Total WFb for Semambu Water Treatment Plant

The WFb accounting of Semambu Water Treatment Plant has highest values compared to other WTPs in this study. From the graph that was plotted, it can be seen that the trend of WFb in this WTP is showing not much changes throughout the year. In January, the WFb value was 9,253,289.64 m^3/month and decreased to 8,124,504.96 m^3/month in February; this is due to the decreasing amount of rainfall in that month. Meanwhile, 8,722,423.39 m^3/month, 8,536,409.97 m^3/month, and 7,755,509.67 m^3/month were the values from March to May. The lowest value for 2015 is in May. The values increased from June to August which were 8,131,937.36 m^3/month, 8,692,609.30 m^3/month, and 8,759,547.2 m^3/month. Then, the value decreased in September, which was 7,877,043.34 m^3/month, and increased back in October which was 8,614,167.41 m^3/month, decreased back in November, which was 8,333,557.07 m^3/month and increased back in December, which was 8,706,333.65 m^3/month. The uncertainties of rainfall results in the fluctuation in WFb for 2015.
By referring to the graph of Water Footprint Accounting 2016, it can be observed that the lowest data of water footprint at Semambu Water Treatment Plant was in February with a value of 7,997,701.05 m^3/month compared to January, which was 8,709,836.45 m^3/month. This is due to the lowest amount of water intake in February compare to other months. The value increased in March, which was 9,010,409.29 m^3/month. However, the highest value recorded in June, which was 10,419,952.75 m^3/month. This is due to the increasing amount of rainfall and water intake for that month. The trend of WFb fluctuated until the end of the year, where a minor decrease and increase occurred every month.
The total WFb for Semambu Water Treatment Plant in 2015 was 101,507,333 m^3/year, while 105,542,873.8 m^3/year was recorded in 2016. The capacity of Semambu Water Treatment Plant is 1.05 x 10^8 m^3/year, thus, for 2016, the total WFb was exceeded. There was a planning of constructing a new phase, which is third phase of this WTP to cater the future demand.

3.1.5 Bukit Ubi Water Treatment Plant

The treated water supply for commercial area in Kuala Kuantan is being covered by the one and only, Bukit Ubi Water Treatment Plant. Located at 3.4920, 103.1973 at the centre of the town area, the maximum area of water distributed to that particular commer-

cial area is 1500 m^3/hour and with an exponential growth of 1.31 x 10^7 m^3/year.

The Water Footprint Accounting for Bukit Ubi Water Treatment Plant in 2015 can be seen as shown in the table and graph above. Based on the data that was shown, the reading for the first month of the year was 1,082,303.571 m^3/month. The reading escalated greatly to 1,976,360.637 m^3/month in February, where the highest value for year 2015 was obtained. The WFb value decreased back to 1,109,095.373 m^3/month in March and had a consistent value towards August. However, there was a significant drop in September, where the lowest value of water footprint for year 2015 was obtained at a value of 970,476.599 m^3/month. This might be due to lack of water intake at the WTP, as well as smaller number of rainfall. The value increased again in October and gradually decreased until the end of the year. The trend of Water Footprint Accounting at Bukit Ubi Water Treatment Plant in 2016 is similar to the discussed WFb in 2015. This can clearly be seen by comparing the two graphs plotted for year 2015 and 2016. In January 2016, the water footprint value was 1,097,918.969 m^3/day, and rose greatly to 1,917,772.966 m^3/day in February. The highest value of water footprint in February indicates frequent rainfall that occurred during that particular month. The value decreased again in March and April, where the lowest value of water footprint for year 2016 was obtained in April with a value of 901,133.992 m^3/month. In May, the water footprint value started to increase gradually towards the end of the year.

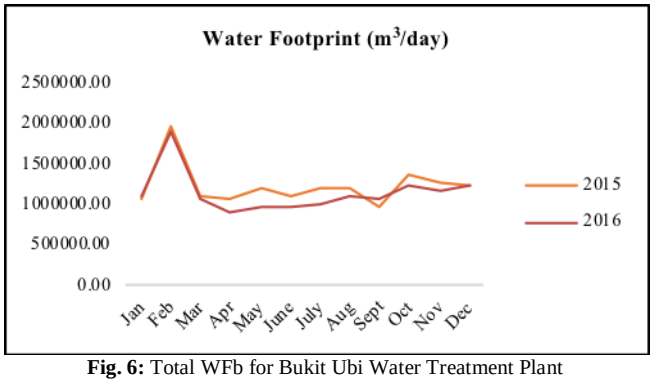


Fig. 6: Total WFb for Bukit Ubi Water Treatment Plant

Therefore the total WFb for 2015 in Bukit Ubi Water Treatment Plant was; 14,866,252.61 m^3/year, and 13,811,675.29 in 2016. The capacity of this WTP is 1.31 x 10^7 m^3/year; therefore, the value of WFb recorded in 2016 was exceeded the capacity value. Rainfall amount was the main factor of the increment however, water demand due to urbanization is also a consideration factor due to the area of supply within the town area is occupied with commercial buildings and offices.

3.2. Comparison between Total Blue Water Footprint and WTPs Capacity in Kuantan River Basin

In this section, total WFb is analyzed based on the overall capacity of all WTPs located in Kuantan river basin and abstracted water from Kuantan river. Therefore, Fig. 7, 8 and 9 are the graphs of total WFb of all WTPs in Kuantan river basin versus the capacity of the same WTPs for 2015, 2016 and 2017.

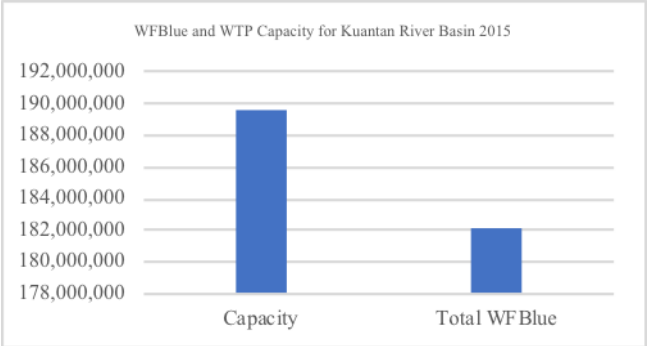


Fig. 7: *Total WF and WTP Capacity for Kuantan District 2015*

The graph above shows the Water Footprint and Capacity of Kuantan WTPs in 2015. It can be said that the total water footprint accounting did not exceed the maximum capacity of all WTPs. The total capacity of Kuantan WTPs (Sungai Lembing, Bukit Sagu, Panching, Semambu and Bukit Ubi) is 189,654,000 m^3/year, whereas the total water footprint for all WTPs was only 182,208,073.92 m^3/year for the year 2015. This indicates that the WTPs can work effectively if the water footprint produced were still within its capacity limit.

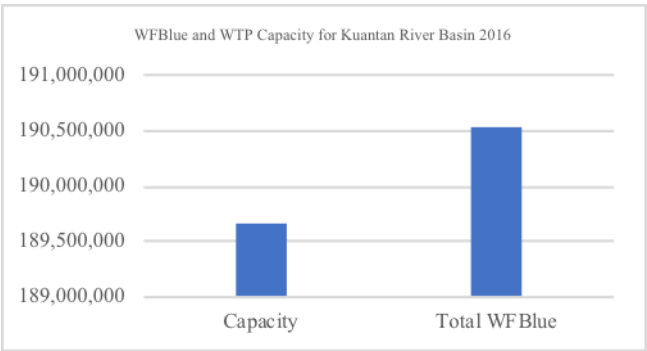


Fig. 8: *Total WF and WTP Capacity for Kuantan District 2016*

In 2016, the total water footprint accounting of WTPs at Kuantan (Sungai Lembing, Bukit Sagu, Panching, Semambu, and Bukit Sagu) exceeded the capacity limit of the total capacity of the WTPs in Kuantan. The total water footprint accounting obtained was 190,543,378.2 m^3/day, while the total maximum capacity of the WTPs was 189,654,000 m^3/day. However, there are many plans of opening new phase of treatment in certain treatment plant but new river water intake must be taken into consideration as it is uncertain whether Kuantan River basin can act as river water intake for all WTPs in the years to come. As in South Africa WF Assessment was used as a method to inform water management and policy making [40]. This can also be adapted in Malaysia especially to face future water stress due to urbanization.

3.3. WFb Prediction for Kuantan River Basin

For the purpose of finding the optimal architecture of the ANN model to prevent over-fitting of data, several numbers of hidden layers have been tested in this study. The connection between input and output layer is included in the testing and training. The minimum value of the Root Mean Square Error (RMSE) for the training and prediction set were used as a basis for the determination of parameter variations. In the process of optimization, the number of

hidden neurons were tested from 1 to 10. The increase in number of neurons result in different RMSE values for given by the network for training and testing data set. Table 3 shows the RSME values for training and testing data as a function of the number of hidden layers.

Table 3: Analysis of error and correlation coefficient for training data set as a function of hidden neuron

HIDDEN NEURON	RMSE
1	0.0402776
2	0.0432995
3	0.0412190
4	0.0334191
5	0.0316944
6	0.0330238
7	0.0320120
8	0.0312778
9	0.0155078
10	*0.0111246*
11	0.0113411
12	0.0134016
13	0.0154110
14	0.0169620
15	0.0195835

As seen in Table 3, the RMSE for training data of the network was much higher for the lower hidden neuron. As an increasing number of hidden layers were tested, the RMSE value decreases until no of hidden neuron of 10. After that, the RMSE values fluctuated with only a small difference between the number of hidden layers. The same observation was obtained for the RMSE of the test data. With 11 hidden neurons, the RMSE reached its minimum value of 0.0111246 for training of data. Hence, the neural network containing 10 hidden neurons was chosen to develop the optimal ANN architecture for training data set. Please note that all previous data calculated have been inserted in normalization formula before being used in the ANN application by using formula as stated in sub-section 2.2.
Therefore, Fig. 9 represents the comparison between calculated data and prediction trend value based on normalized data of total WFb based on hidden neuron chosen for training data in ANN.

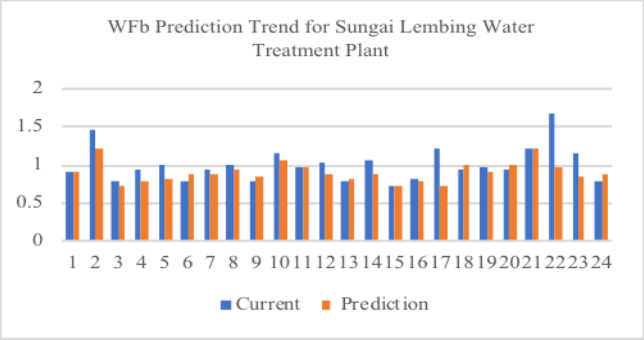


Fig. 9: Prediction of Total WFB for Sungai Lembing Water Treatment Plant

As seen in Fig. 9, most of WFb is predicted to decrease from the current trend in Sungai Lembing Water Treatment Plant. The capacity for this WTP is 2.19 x 10^6 m^3/year; therefore, based on this prediction, the need of opening new treatment plant can be on hold for Sungai Lembing because the predicted and current trends were still under its capacity.

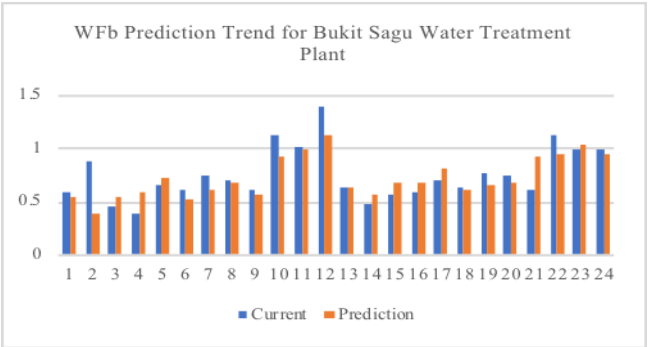


Fig. 10: Prediction of Total WFb for Bukit Sagu Water Treatment Plant

Meanwhile, in Bukit Sagu Water Treatment Plant, most of prediction trend are increasing, as shown in Fig. 10. However, as this WTP has yet to exceed its capacity, therefore, the increment in prediction will not affect the main function of this WTP, which is to supply water to FELDA Bukit Sagu.

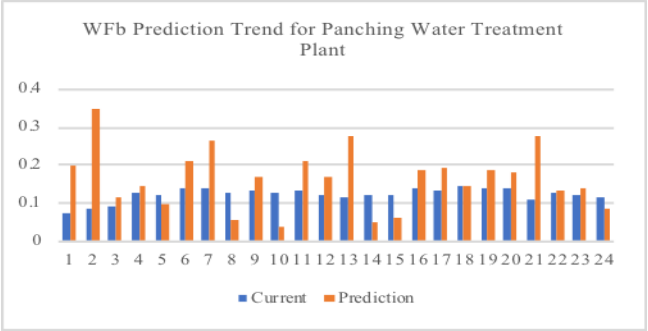


Fig. 11: Prediction of Total WFb for Panching Water Treatment Plant

In Panching Water Treatment Plant, prediction value of WFb showed that an increasing trend from current trend then decreasing. This will not affect the function of this WTP as the capacity of this WTP is still broad and can cater more water for consumer in the future. Despite that, Panching Water Treatment Plant is new compared to other WTPs and is expected to be able to cater the demands for more years to come.

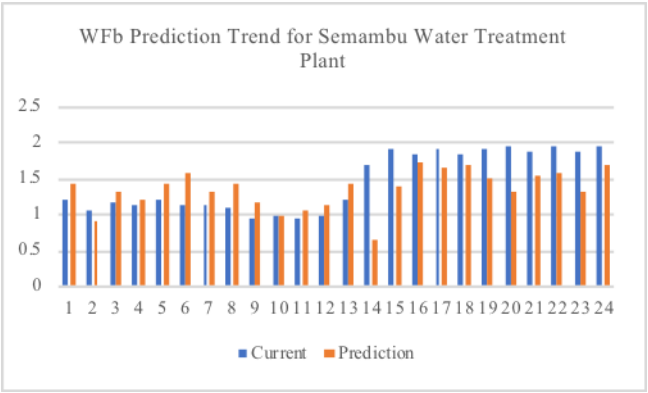


Fig. 12: Prediction of Total WFb for Semambu Water Treatment Plant

As shown in Fig. 12, although the current value has exceeded the capacity of Semambu Water Treatment Plant, but predicted value showed trend that the amount of total WFb will decrease below than its capacity. This is after certain times of training in the ANN, variables that had contributed to the amount of total WFb have been normalized in the process and the result is shown, as in Fig. 12.

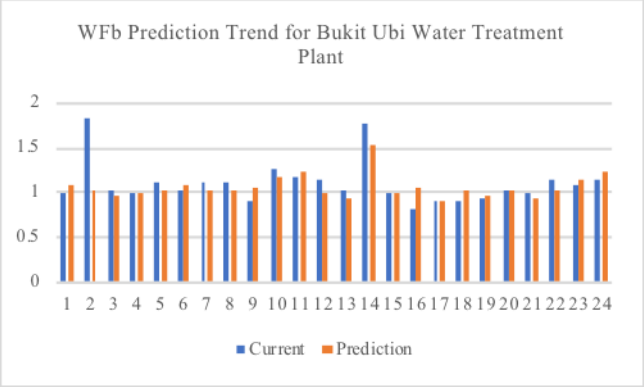


Fig. 13: Prediction of Total WFb for Bukit Ubi Water Treatment Plant

Meanwhile, for Bukit Ubi Water Treatment Plant, the predicted trend is increasing and although the maximum trend is still below the current trend, the current WTP has been recorded to exceed the capacity of WTP. Therefore, mitigation measures such as finding new plant and water intake must be taken into consideration.

4. Conclusion

In summary, the determination of blue water footprint for water treatment process in Kuantan river basin can be determined by calculating the blue water footprint (WFb) at each WTP that is involved in this study through the design of water treatment process while considering certain parameters. The dependencies of the parameters such as water intake, rainfall intensity towards the uncertainty in many aspects like weather shall be specifically addressed in the accounting of blue water footprint. Thus, WFb has been calculated and the highest is recorded in 2016, that is at 190,543,378.22 m^3/year. Therefore, WFb in Kuantan river basin is increasing by the year due to the increase in local population that subsequently leads to urbanization and also uncertainties of monsoonal changes (rainfall intensity).

After comparing total WFb of Kuantan river basin with the capacity of all WTPs within the same river basin, it showed that some of the WTPs were not be able to stay below the capacity such as in Sungai Lembing Water Treatment Plant, Semambu Water Treatment Plant and Bukit Ubi Water Treatment Plant . Hence, mitigation planning to cater the need of water and to ensure the amount of water intake will be sustainable for more years to come must be implemented. Although those WTPs are currently still able to supply treated water to consumers, however, the actual amount of water involved in the process as accounted by using water footprint approach has shown negative impact. This is because water footprint accounting is the most accurate approach in calculating the total amount of water utilized in process in producing goods and services [41].

Next objective is to predict the sustainability of water supply treatment process by using series of modelling called Artificial Neural Network (ANN) – an Artificial Intelligence (AI) application tools in MATLAB–a software to develop patterns of changes in water footprint in the future with regards to some factors that are to be considered. Prediction values were found to have increased in certain WTPs, especially in Panching Water Treatment Plant as Panching Water Treatment Plant recorded an increasing data in each month throughout the year due to increasing water-use activities, especially urbanization process that use Panching as the source of supply. Since Panching Water Treatment Plant capacity is broad, there are also much planning in taking this WTP to supply for new area. Therefore, it is important to consider new intake rather than clinging to the Kuantan river basin.

5. Recommendation

Generally, these findings provide a notable implications for better understanding towards maintaining sustainable resources to the future generations of this country. Benefits of this study shall be extended to the next research findings, where some improvements can and should be taken up in order to produce better and accurate results. For the WFb accounting, the development of technologies in this era should be fully implemented, especially when it comes to the centralization of data among local authorities. A manual or way of collecting data nowadays is partially relevant to the current technologies that exist. Therefore, a better management would be the best way to cater the problem while this study is being conducted.

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