DETERMINATION AND PREDICTION OF BLUE WATER FOOTPRINT AT SUNGAI LEMBING, BUKIT SAGU AND BUKIT UBI WATER TREATMENT PLANT

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Thesis submitted in fulfillment of the requirements
for the award of the
B. Eng (Hons.) Civil Engineering

Faculty of Civil Engineering and Earth Resources

UNIVERSITI MALAYSIA PAHANG

MAY 2019

ACKNOWLEDGEMENTS

Praise to Allah SWT for the blessing passing all obstacles and finish this thesis on time. I would like to express my special thanks of gratitude to those who contribute, guide, and support me throughout the research.

A million thanks to my supervisor Dr Edriyana A.Aziz for the continuous support, advice and guidance for my study. Also my sincere thanks goes En Syazwan Nizam bin Moni, lectures and all my friends in Faculty of Civil Engineering and Earth Resources. Without all the help and support, this thesis would not be possible and I shall eternally be grateful for all the assistance.

Not to be forgotten, I would express appreciation names of my dear friends Siti Fazlina Suhaimi and Ruziana Kamarzaman for all the idea and support to keep me going on my path to success. All the memories we create in UMP will be the most beautiful memories that I will remembered forever.

I am highly indebted and extremely grateful to my parents Noor Hazlim Mamat and Nuzah Awang for their love, prayers, caring and sacrifices for educating and preparing me for my future. This would not be possible without their unwavering love and support given to me at all times.

Finally, my thanks go to all the people who have supported me to complete the research work directly or indirectly. Thank you for all your kindness.

ABSTRAK

Sebahagian besar bumi dilindungi oleh air, tetapi hanya sedikit peratusan jumlah itu tersedia untuk digunakan sebagai air bersih. Pada masa ini, satu pertiga penduduk dunia menghadapi kekurangan air. Oleh itu, penilaian jejak air biru (WFb) akan membantu dalam mengkaji penggunaan air secara keseluruhan untuk tiga loji rawatan air yang berbeza di lembangan sungai Kuantan. Makalah ini menggambarkan ramalan jejak air biru Loji Rawatan Air (WTP) Sungai Lemping, Bukit Sagu dan Bukit Ubi sepanjang tahun 2015 hingga 2017. Antara parameter yang dipertimbangkan dalam kajian ini adalah pengambilan air, intensiti hujan dan penyejatan. Dalam kajian ini, manual jejak air digunakan untuk merakam jejak air biru di semua loji rawatan air. Untuk membuat ramalan, Bayesian Networks (BN) dan Rangkaian Neural Buatan (ANN) digunakan sebagai algoritma untuk melatih hasilnya. Oleh itu, trend ramalan untuk tiga rawatan air yang berbeza telah dapat dihasilkan dengan menggunakan perisian WEKA. Hasilnya, jumlah jejak kaki air biru untuk Loji Rawatan Air (WTP) Sungai Lembing, Loji Rawatan Air (WTP) Bukit Sagu dan Loji Rawatan Air (WTP) Bukit Ubi bagi tahun 2015 hingga 2017 masing-masing adalah 4,905,076 m^3, 5,924,203 m^3 dan 26,400,519 m^3. Hasilnya membuktikan bahawa (ANN) adalah algoritma terbaik untuk semua loji rawatan air (WTP) kerana ia menghasilkan nilai yang lebih rendah daripada kesilapan akar min (RMSE) berbanding dengan Rangkaian Bayesian (BN).

ABSTRACT

The majority of the earth is covered by water, but only a small percentage of that amount is available for use as clean water. Currently, one-third of the world populations are facing the water shortages. Therefore, accounting blue water footprint (WFb) will help in assessed overall water consumption for three different water treatment plant in Kuantan river basin. This paper illustrates the prediction of blue water footprint of Sungai Lembing, Bukit Sagu and Bukit Ubi WTPs throughout year 2015 to 2017. The parameters considered in the study were water intake, rainfall intensity and evaporation. In this study, water footprint manual was used to account blue water footprint throughout all water treatment plants. In order to make a prediction, Bayesian Networks (BN) and Artificial Neural Network (ANN) were used as an algorithm to train the result. Thus, prediction trend for three different water treatments has been able to be produced by using WEKA software. As a result, total blue water footprints for Sungai Lembing WTP, Bukit Sagu WTP and Bukit Ubi WTP for 2015 to 2017 were 4,905,076 m^3, 5,924,203 m^3 and 26,400,519 m^3 respectively. Results proved that ANN is the best algorithm for all WTPs as it produced lower value of root mean square error (RMSE) compared to Bayesian Network.

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m^3	Meter cube
m^3/month	Meter cube per month

LIST OF ABBREVIATIONS

ANN	Artifial neural network
BN	Bayesian networks
BWF	Blue water footprint
CSV	Comma separated value
WTP	Water treatment plant
JPS	Jabatan Pengairan dan Saliran Pahang
MMD	Malaysian Meteorological Department
PAIP	Pengurusan Air Pahang Berhad
RMSE	Root mean square error

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Water is absolutely essential for the existence, growth and preservation of all human life, making it an important commodity in the world. All human life including plants and animals must have water to survive. If there was no water there would be no life on earth. The increasing world population, improving living standards, changing consumption patterns, and expansion of irrigated agriculture are the main thrust for the rising global demand for water. This leads to the water shortages all around the world. Currently, one-third of the world population are facing the water shortages (Kummu *et al.*, 2016).Water shortage and the degradation of water quality in river basin are among the major issues addressed by water resources management authorities (Li *et al.*, 2018). Now days, water are very important in life as it is a used for every purpose in daily activity. Water is not essential for human beings, but also for animals, plants and all other living beings. In India, ensuring water security is a way to guarantee good food quality and nutritional as well as economic security (Salome, 2018).

According to the United States Environmental Protection Agency the average American family uses more than 300 gallons of water at home daily. The water uses seems like a really high number. There are many important of the water in life. One of them is water used in most of the domestic sector. For instant, water is used for drinking, washing, cleaning, cooking, shower and growing food. Besides, water usage is even contributing more to the industry for generating electricity, manufacture products, and transport people and goods. All of the water that exists around the world comes from local lakes, rivers, streams or underground aquifers, depending on the city and state. As the water is very close to human including animal and plants, it is important to keep supplying the good quality of water resources to all.

Now days, there are many problems regarding the water resources. One of them is water pollutant. Pollution of water sources by organic and inorganic chemical toxins is a priority concern worldwide. Water pollution is the contamination of water bodies such as lakes, rivers, oceans, aquifers and groundwater usually as a consequence of human activities. For instance, liberate insufficient treated wastewater into natural water bodies can lead to degradation of aquatic ecosystems. The lack accessibility of clean water leads to numerous waterborne diseases causing the death of millions of people yearly and obstruct the development of society (WHO and UNICEF, no date).

The majority of the earth is covered in water, but only a small percentage of that amount is available for use as clean water. Currently, the increasing water scarcity has two main reasons. It causes by the high demand and low availability (de Almeida Castro *et al.*, 2018). Water demand is growing mainly due to population growth and economic development, which contribute to the formation of new industries and irrigated districts (WWAP, 2015). This will becoming worst for the developing country with the high population compared to other country. Improving the water crises positively will affects the development of a country. As in result, it helps to provide safe water to the communities.

The water footprint is a measure the quantity of water used to produce each of the goods and services used. Water footprint across global supply chains at the international level can be used to investigate water flows and the equity of water resources distribution across nations. The connection between consumption behaviors, trade activities, and anthropogenic water use can also be evaluating (Zhan-Ming and Chen, 2013). In conclusion, it is useful to use to the study as can predict the blue water footprint in water treatment plants in Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin.

1.2 Problem statement

Between mid-October and the end of March the climate at the eastern side of the peninsula is affected by the rainy season or monsoon season. Weather usually is very rough in these months. During the monsoon period it can sometimes rain for days. Not all other parts of Malaysia are affected by this monsoon, for example Penang, Langkawi and many other places on the western side. Since the study area is in Kuantan which is capital city of Pahang located at the peninsular Malaysia, it is more likely exposed to the changes in climate for every certain month. This leads to uncontrolled of water stream flow in the selected water treatment plants.

The problem at the study area which is Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin is that the water management is still using the old version of management. In overall, there is no data of water recorded that include with the rainfall and evaporation. In order to update to management of the water, it data is needed to predict the blue water footprint. The researcher find hard in order to do the prediction due to the missing data. As a result, the study is conduct to help in order to calculate and do the prediction.

Day by day, there has been an increasing in water consumption due to growth of population. This would make sense to the shortage of water if it continues to grow. This results to the high demand of the water consumption due to the population growth. Stream flow plays a vital resources management such as assessing the impact of past, ongoing and future climate or land use change. Besides, it integrated with the model such as designing flood.

Urban development without a proper plan often results in environmental issues, for example, deterioration of water quality of rivers, lakes, and reservoirs. In other words, the urban development causes human population and activities to increase and surrounding environment to be polluted (Lee *et al.*, 2017). The outstanding of the past, present and future changes of water stream flow are very significant in preparing the long term effectiveness management of water resources. Therefore, the study is conducted and helping in many future development soon.

The water footprint illustrates the extent of water use in relation to consumption of people. The water footprint of a country is outlined as the volume of water needed for the production of the goods and services consumed by the population of the country (Hoekstra and Chapagain, 2007). By using water footprint, the blue water footprint in Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin can be estimated and the problem regarding the management of the water resources can easily be solve.

1.3 Objectives

The main objectives of the study are outlined as follows:

i. To calculate total blue water footprint for Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin for 2015-2017.
ii. To predict the trend of water blue water footprint for Sungai Lembing, Bukit Sagu and Bukit Ubi in water treatment plant Kuantan river basin.
iii. To compare the best algorithm between Bayesian Network and Lavenberg Marquardt in blue water footprint prediction.

1.4 Scope of study

The study is focused on total blue water footprint for Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants (WTP) in Kuantan river basin over the year of 2015-2017. The calculation of the blue water footprint is only covered within the water treatment plant with is from the abstraction to the final before distributing to the community. By doing this, the exact quantity of the water used by the user in order to get the prediction of blue water footprint can be determine. As the result, the prediction of blue water footprint within the Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plant in Kuantan river basin can be estimated at the end of the research. The reason of calculating the blue water footprint is because to know the amount of surface water and groundwater required (evaporated or used directly) to produce an item in the WTPs in Kuantan river basin.

The study only covered Sungai Lembing, Bukit Sagu and Bukit Ubi water treatments plants in Kuantan river basin for year of 2015-2017. The location was selected because there are many water problems there but the water management is still using the old system which cause water overflow and resulting in floods. The sample was only taken within the WTPs area. Subsequently, rapid urbanization occurred in the area affecting the stream of water. Besides, the study is conduct to predict the trend of water blue water footprint for Sungai Lembing, Bukit Sagu and Bukit Ubi in water treatment plant Kuantan river basin as we can estimate the pattern of blue water footprint in WTPs in Kuantan river basin.

There are many formula called algorithms created by the researcher in order to calculate the blue water footprint. But for this study, the Bayesian Network and Lavenberg Marquardt are selected as a method in order to calculate the blue water footprint as it is commonly used algorithm by the researcher in their study. The study used existing equation and formula instead of created another formula in order to finding the prediction. Two different algorithm between Bayesian Network and Lavenberg Marquardt will be compared in order choose the best algorithm and the best one will be selected to use for the study in blue water footprint prediction.

1.5 Significance of study

This study is significant endeavor in the prediction of the total blue water footprint as it can be used to calculate the total blue water footprint for Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin for 2015-2017. As already known, the blue water footprint is the amount of surface water or groundwater resources such as lakes, rivers, wetlands and aquifers that required the evaporating or used directly to produce the product. The study helps to know the pattern of blue water footprint in WTPs selected in Kuantan river basin. As a result, the water management efficiency in Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin can be improve.

With the changing in climate, the water levels of the rivers become fluctuated. Thus, this data analysis is important for the authorities to know the total blue water footprint and estimate the pattern in the future. There are several benefits and the significant of the study. First, water management can be managed properly. Next, the design of the future plan water footprint model prediction can be done. Besides, it helps to determine the trend or pattern of the blue water footprint for the future improvement. As a result, problem regarding water such as the overflow of the water that result in flooding can be avoid.

Generally, the aim evaluating water footprint is to trace on how the human activity or particular product connect with the issues of water shortage and pollution. Besides, to see on how the activities and products can become more sustainable to the water perspectives. As the world population is increasingly, the demand of fresh water is also high. The study is important to take the measurement of the water footprint level. Otherwise, it will be running short of fresh water soon. By doing this study, such a thing will be avoided.

CHAPTER 2

LITERATURE REVIEW

2.1 Water Consumption

Water consumption is the amount of water use that is not returned to the original water source after being distributed. Referring to World Resources Institute, water utilize is the amount of water extricate from it sources to be utilized to deliver a good or services and to carry an activities (World Resouces Institute, 2013). The national utilization water impression is defined as the entire amount of fresh water utilized to create the products and services consumed by the individuals of the nation. People use lots of water for drinking, cooking and washing, but significantly more for producing things such as food, paper and cotton clothes. Water covers 70% of the planet, and it is simple to think that water will continuously be abundant. However, only 3% of the world's water is fresh water and two-thirds is tucked absent in solidified ice sheets or else unavailable for uses and utilization. This leaves less than one per cent of the global water resources as freshwater accessible

However, freshwater is a renewable which implies that it is persistently renewed through precipitation over land. Renewable does not mean that supply is unlimited. The availability of freshwater is primarily limited by the replenishment rate and not by the existing stocks. At present, roughly 1.2 billion people live in areas wherein water is scarce and 1.6 billion people facing an economic water scarcity (UN OCHA, 2010). Meanwhile, the United Nations estimates that the domestic water utilization of developing nations is anticipated to extend by over 50% since of advancements in water supply, living standards, and water appliances (DSE, 2016). There are about millions of people all over the world do not have access the water resources or the water is unable to be used thus it lead to water shortage all around the world. Water shortage, implies that a circumstance where lack of a access to adequate amounts of water for human and environmental uses, whereas destitute water resources administration categorize beneath economic water shortage The most important components influencing water shortage in local and worldwide accessibility of fresh water resources not only contamination and climate change but also increasing of world population and an expanding water demand (Rosegrant, Cai and Cline, 2002). For example, China has been experiencing a dramatic economic development that lead to increasing of water use in the last decades (Xu, Li and Lu, 2017).

Figure 2.1 Water scarcity

(Sources: http://www.sociallyconsciousliving.com/causes/clean-water-scarcity-crisis/)

In addition, calculation of overall water consumption is simpler than finding the arrangement to uneven water distribution. Water consumption can be estimate on water accessibility after the human activity. By 2008, 28% of total water consumption in crop areas in China served the production of crops for trade to other districts and normal, 35% of the crop-related WF of a Chinese consumer was exterior its own area (L, Mekonnen and Hoekstra, 2016). Total of water consumption can be calculated by total amount of water taken from the sources which can also called water intake have and minus by the amount of water returned. In order to avoid further inefficient water use, water footprint concept had been developed (Aldaya *et al.*, 2011). The water footprint (WF) of a product or process was introduced for the primary time in 2003 and is characterized as the volume of freshwater expended and contaminated to create an item (Hoekstra and Hung, 2002). The WF not only account for the direct water utilize of a consumer or producer but also for indirect water utilize, which depends on the water footprint of the activities related to the examined item or process that goes past the boundary of the process (Hoekstra and Mekonnen, 2012). Generally, Water Footprint (WF) is characterized as the amount of water utilized to deliver a product or service in a country (Aldaya *et al.*, 2011).

The WF can be divided into three components: blue, green and grey WFs (Morera *et al.*, 2016). Blue water footprint is amount of surface water or groundwater that required in specifically utilized or evaporated of water treatment plant for each stage involved (Moni *et al.*, 2018). Meanwhile, grey water footprint is characterized as the volume of freshwater that is required to assimilate the load of pollutants based on common background concentrations and existing encompassing water quality standards (Aldaya *et al.*, 2011). In addition, green water footprint is characterized as the utilization of water from precipitation that's stored within the soil and does not run off or energize the ground water and thus accessible for evapotranspiration of plants (Morera *et al.*, 2016).

Some places in Malaysia are subordinate on groundwater assets but it is not Malaysia's primary water source (Huang *et al.*, 2015). Thus, proper management of water supply can be executed in future by using WF Approach in order to produce better water supply management in the future. Thus, this study used water footprint approach was used as a tool in order to calculate overall water consumption in Sungai Lembing, Bukit Ubi and Bukit Sagu water treatment plants in Kuantan River Basin.

2.2 Blue Water Footprint

2.2.1 What is Blue Water Footprint?

The water footprint (WF) of a product or process was introduced for the primary time in 2003 and is characterized as the volume of freshwater expended and contaminated to create an item (Hoekstra and Hung, 2002). According to the Hoekstra (2005), the principle of water footprint has been presented in relationship to the environmental impression concept as was introduced by William Rees within the 1990s. Water footprint is an integrated measurement indicator for total water consumption, including green, blue and grey water (Hoekstra and Mekonnen, 2012). In addition, water footprint of a country is characterized as the volume of water required for the generation of the goods and services expended by the occupants of the country (Hoekstra and Chapagain, 2007) .

Water footprint can be categorized into three types, which are blue WF, green WF and grey WF. Blue water footprint refer to amount of surface water or groundwater that required in specifically utilized or evaporated of water treatment plant for each stage involved (Moni *et al.*, 2018). Blue water footprint evaluation is a process measuring the sustainability of water utilization and set up ideal activities in order to have sustainable footprint. Besides, it defined as volume of surface and groundwater consumed as a result of the generation of a good or service.

Consumption refers to the volume of freshwater utilized and evaporated or consolidated into a product. Consumptive water use does not define that the water was loss, because water still within the cycle and always return in other catchment areas. It also incorporates water abstracted from surface or groundwater in a catchment and returned to another catchment or the ocean. Besides, the amount of water abstracted from groundwater or surface water that does not return to the catchment from which it was withdrawn (Aldaya *et al.*, 2011). Moreover, blue water footprint helps in order to determined overall water consumption in country.

2.2.2 Previous study used Blue Water Footprint Application

Water Footprint (WF) concept has been essentially utilize in numerous sort of field and activities which related to the human uses of water. The concept of water footprint related to the virtual water concept. Virtual water is defined as the amount of water utilized in order to deliver an items or services. Idea of virtual water concept will be used as a tool to release the issue on the barely accessible residential water resource. Several studies and researches have been done, particularly in applications of WF for agricultural and productions food industry.

A study by Veettil & Mishra (2016) utilizing blue and green water footprints based the quantitative assessment of water security. Water footprints approach can progress water resources management from local up to regional scale. The ecological footprint defined as the total land required in order to provide a sufficient area demand by population or the region of productive land and marine ecosystem needed to produce the resources used and to integrate the wastes that is produced. Besides, (Li and Gao, 2017) study the utilize of water in wastewater treatment plant.

Wastewater treatment plants (WWTPs) play an imperative part in the urban water cycle in securing accepting waters from untreated discharges. However, WWTPs processes will also affect the environment. In order to assess the effect of direct releases from WWTPs and indirect emissions related to vitality or chemical production, life cycle assessment, life cycle evaluation has customarily been utilized (Li and Gao, 2017). Thus water footprint study by (Li and Gao, 2017) helps to give complementary information to assess the effect of a WWTP with respect to the utilize of freshwater.

The common equation to evaluate the water footprint of a WWTP in which is the volume of water consumed amid a period of time and incorporates the blue water footprint (WFblue), green water footprint (WFgreen) and grey (WFgrey) water footprints that expressed as follows:

$$WF = WF_{blue} + WF_{grey} + WF_{green} \qquad \dots (1)$$

Eq (1) General equation for the water footprint calculation of a WWTP

Moreover, (Li and Gao, 2017) presents that the appropriation of the Water Footprint Assessment technique by considering both blue and grey water footprint in order to evaluate the utilization of water resources in WWTPs. Study by (Morera *et al.*, 2016) stated that Wastewater treatment plants (WWTPs) have an essential part in securing received water from untreated discharges. Besides that, wastewater is treated in wastewater treatment plants (WWTPs), which has the vital part within the urban water cycle to make strides the water quality before being returned into the natural ecosystem. In WWTPs, the blue water footprint accounts for the water which evaporates during wastewater treatment and the water utilized for all forms related to the different WWTP unit operations such as chemicals, energy utilization, build-up administration, transportation and slime treatment which incorporated into the final product (Li and Gao, 2017).

More recently, study by Hogeboom et al. (2018) estimate the blue water impression of the world artificial supply based on their economic esteem to the point hydroelectricity era, residential and mechanical water supply, water system water supply and surge security based on their economic esteem. Besides, (Chouchane *et al.*, 2013) study about the evaluation and examine the blue water footprint within Tunisia by analysing the blue water footprint into the setting of blue water accessibility, survey economic water and land productivities that related to crop generation for flooded and rain-fed horticulture, appraise the financial profit related to send out and the economic costs related in order to import per unit of water virtually traded and estimate the external water footprint beside water dependency of Tunisian consumption.

Moreover, (Mekonnen *et al.*, 2014) assess the natural sustainability of the WF by comparing the blue WF to blue water accessibility per river basin by assessing the increasing utilize of land and green water assets for horticulture at the cost of normal vegetated regions. Previous study by (Ercin, Mekonnen and Hoekstra, 2012) assess the water footprint assessment for Switzerland from a consumption perspective. The assessment focuses on the investigation of the external water footprint of Swiss utilization in order to obtain a total full idea of how national utilization interprets to water utilize which not only Switzerland but also in Swiss.

2.3 Algorithm

2.3.1 What is algorithm?

An algorithm is a method of solving a problem. It is commonly utilized for data handling, evaluation and other related computer and numerical operations. It is utilized to control information in different ways, such as embedding a new information item, searching for a specific item or sorting an item. In addition, algorithm is considered to be the most significant in public life as it plays progressively essential in selecting the information or data needed.

In addition, algorithms can perform calculation, information handling, robotized thinking, and other errands. An algorithm is expressed as an effective method in a limited sum of space and time and in a well-defined formal language for evaluation a function A study by (Maier *et al.*, 2014) express that researches had updated the algorithms and their application in numerous regions such as calibration of demonstrate, water dispersion system, administration of groundwater, planning and management of river-basin.

A different advantage is provides by the function of algorithm. The algorithm functions by providing an arrangement to any given task which it is able to understand. Algorithm is work by providing an order to make it function. It is designed to function automatically according to the order even though with no human treatment or observation when activated.

There are various algorithms that can be used in accomplishing any given tasks by entering an appropriate data into the system. Moreover, algorithm been widely utilized all through each data innovation divisions. It is utilized to provide information in numerous ways where it can be by embedding unused information sets, finding a specific thing or classifying an item.

The criteria of algorithm are the input must be zero or more provided the output must be created at least one. Besides, definiteness which the clear instruction, the limit is when the instruction of the algorithm is followed out, the past step of the calculation is end and the final criteria is the adequacy where each instruction must be basic and fundamental.

2.3.2 How to choose algorithm towards different roles

Choosing the right machine learning algorithm depends on several factors such as data size, quality and diversity. Moreover, other additional considerations includes accuracy, training time, parameters, data points and many more also need to give attention. However, a compiled machine learning algorithm will help in finding the most appropriate one for the problem. Machine learning is an application of artificial intelligence (AI) that gives frameworks the capacity to consequently learn and progress from encounter without being unequivocally modified. . In addition, according to some algorithmically defined policies, regulate certain aspects of our daily human activities or certain aspects of society (Cities *et al.*, 2018)

Machine learning focuses on the advancement of computer programs that can access information and utilize it learn for themselves. There are two type of machine learning as supervised or unsupervised. Supervised machine learning algorithms can apply what has been learned within the past to new data utilizing such as prediction to predict future events unsupervised machine learning algorithms are used when the data utilized to prepare is neither classified nor labelled. Besides, it studies how frameworks can gather a work to describe a hidden structure from unlabelled information. Thus, machine learning enables analysis of enormous quantities of data.

The algorithm selection competitions can offer assistance users to create the choice which framework and approach to utilize, based on a reasonable comparison over an assorted range of different spaces (Lindauer, Rijn and Kotthoff, 2019). However, large number of diverse approaches and application domains makes it troublesome to compare different algorithm choice systems, which presented users with a really practical algorithm determination issue.

2.4 Artificial Neural Network (ANN) Algorithm

2.4.1 What is ANN?

Artificial Neural Networks (ANN) is a framework of various machine learning algorithms patterned after the operation of neurons that inspire by human brain. ANN is not an algorithm, but a system for different machine learning calculations which prepare any complex information sets. In addition, ANN is an arithmetic model based on the structure and functions of biological neural networks. Ordinarily, the biological neural framework is shaped by a few layers compose by a enormous number of neurons that can produce data in parallel (Kuan, 2000). ANN is based on a group of associated data called artificial neurons. Each association can transmit a signal from one neuron to another neuron.

Typically, a neural organize is initially trained or encouraged huge amounts of information. Training consists of giving input and assesses the network that the output should appear. Each input is accompanied by the coordinating identification. The input layer receives information or independent variables from the exterior meanwhile the output layer produce the results of the ANN. For this study, the input was water intake, rainfall intensity and evaporation. Typically, artificial neurons are amassed into layers. It described in term of depth including several layers that exist between the input and output that called as hidden layers. Different layers may perform diverse sorts of changes on their inputs.

Hidden layers described by the number of hidden nodes demonstrate or in terms of numerous inputs and outputs each node has. Variations on the neural arrange plan allow different forms of forward and backward propagation of data among tiers. In common ANN usage, the signal at an association between artificial neurons may be a genuine number and the output of each artificial neuron is computed by a few non-linear work of the whole of the inputs Furthermore, signal is produced by the recipient neuron that helps to connect between neuron to another neuron.

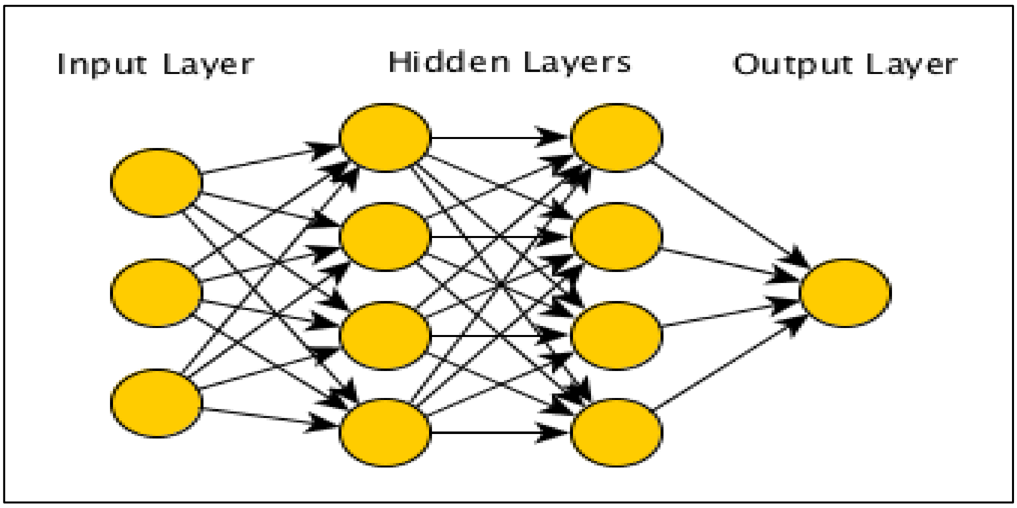


Figure 2. 2 A simple neural network with two hidden layers and one output variable (Sources: https://technology.condenast.com/story/a-neural-network-primer)

Figure 2 illustrates a simple neural network. This network has three input neurons, two hidden layers with four neurons each, and one output neuron. The neuron computes a linear combination of the inputs, weighted by the weights and biased. This output will pass thru a nonlinear activation function before being propagated downstream through the network. Hence, the total output of the neuron will appear.

2.4.2 Previous study that used ANN application

ANN is a segment in artificial intelligence (AI) which works as a device for investigation because it is competent to illuminate non-linear work estimation, information sorting, design location, optimization, clustering and simulation (Yadav and Chandel, 2014). Many researches used ANN application in analysing water based cases. Few reports have appeared that the ANN application is valuable tools in hydrology field, particularly in determining and predicting parameters (Silverman and Dracup, 2013). The major roles in ANN application was predicting the water quality parameter (Najah *et al.*, 2013).

The most widely used in ANN types are the feed-forward neural network, multilayer perceptron (MLP), or back-propagation network. Moreover, multilayer was organized as layers of computing elements, known as neurons that were connected between layers (Najah *et al.,* 2013).

There are many applications using ANN such as controlling the machine, prediction of time series, recognition of handwritten and many more (Olawoyin and Chen, 2018). Moreover, ANN application also can anticipate sun powered radiation precisely when compared with routine strategies (Yadav and Chandel, 2014). A study by Kalogirou (2009) has reviewed the use of ANN in renewable energy systems applications. ANN procedures have become alternative strategies to conventional strategies and are utilized in a number of solar vitality applications.

In addition, Ascione (2017) has proposed a modern approach utilizing artificial neural systems (ANN) to anticipate the utilization of essential vitality and the warm consolation of the tenants for any part of a building lesson. Result appears an awfully satisfactory reliability of ANNs because the values of relative errors and relapse coefficients obtained are comparable to those gotten in past studies on utilize of ANNs to estimate vitality execution within the building industry. Besides that, a study by (Danandeh Mehr *et al.*, 2015) investigated the forecast on successive-station month to month stream flow utilizing different artificial neural network.

One of our greatest challenges by researchers in analysing using ANN application which water based cases that are quite colossal and specifically related in managing the water issues is water quality (Moni *et al.*, 2018). Moreover, numerous researcher has been enormously utilize ANN due to the less-complex plan, such as in anticipating the NOx outpouring of diesel engine by moving forward the coordinate and nonlinear auto-regressive appear (Ma *et al.*, 2016).

For displaying early testimony of silt in unbending boundary channels, Safari, Aksoy & Mohammadi (2016) compared three diverse ANN procedures which is feed-forward back propagation (FFBP), generalized regression (GR) and radial basis function (RBF). Parameter used for this research are flow discharge, channel bed slope, hydraulic radius, flow depth, median size of sediment particles and relative specific mass of sediment. Thus, the result shown that FFBP was found to be better compared other ANN and all regression models.

2.5 Bayesian Networks (BN) Algorithm

2.5.1 What is BN?

Bayesian Networks is a probabilistic graphical show which represents a set of variables and their conditional conditions that are presented by directed acyclic graph (DAG). DAG is coordinated graph that contains a topological requesting, a sequence of the vertices such that each edge is coordinated from earlier to afterward within the arrangement. It is an idea of taking occurred and predicting the probability of several possible known for the causes was the contributing factor that affects the output. In this study, possible causes that contributing as the factor to the output was water intake, rainfall intensity and evaporation rate.

Briefly, BNs are probabilistic graphical models in which the conditional dependencies of the variables relevant to a particular study are encoded within directed acyclic graphs (DAGs). Each node of the graph is associated with one variable of the dataset. The directed links connecting the nodes represent informational or cause-effect relationships. These dependencies are quantified by the conditional probability tables (CPTs), which represent the extent to which one node is likely to be affected by the others. Thus, BNs facilitate common features causal chains and network approaches (Requejo-Castro, Giné-Garriga and Pérez-Foguet, 2019).

Bayesian networks are a type of probabilistic graphical model that can be utilized to construct models from data or expert opinion. A Bayesian Network is a solid probabilistic inference model consists of two types (Jackson and Mosleh, 2016). First type is a graphical structure specifying a set of connections of reliance and autonomy between the factors. Another type is a set of dispersions of conditional probability measuring the qualities of the connections. In addition, Bayesian Networks is widely used for a wide range of tasks including prediction, anomaly detection, diagnostics, automated insight, reasoning, time series prediction and decision making under uncertainty.

Moreover, Bayesian Networks consists of nodes that represent as a variable and links which represent a dependency relation. The nodes and links form the structure of the Bayesian Network. Links are added between hubs in order to demonstrate that one node directly dependent influences the other nodes. If there is no link exists between two different nodes, it indicates that nodes are completely independent. However nodes, become dependent or independent depending on the evidence that is set on other nodes.

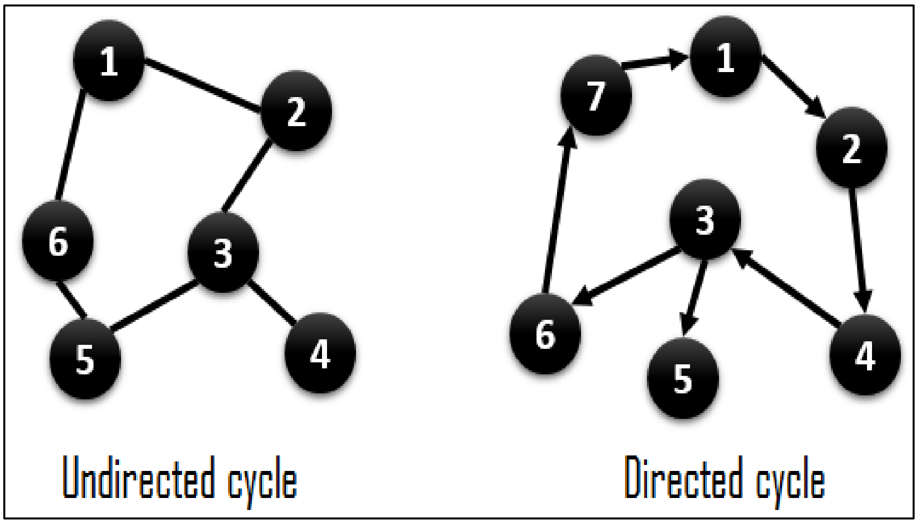


Figure 2.3 Undirected and directed cycle in Bayesian Networks
(Sources: http://alexvolov.com/2015/02/detecting-cycle-graph/)

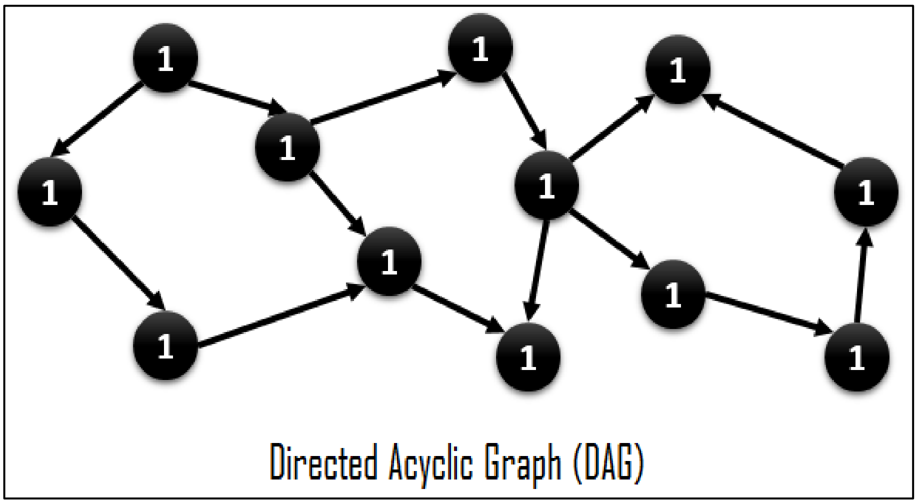


Figure 2.4 Directed acyclic graph (DAG)

(Sources: http://alexvolov.com/2015/02/detecting-cycle-graph/)

Table 2.3 shows an undirected cycle and directed cycle in Bayesian Networks. Directed graph that has no cycles is called directed acyclic graph or DAG. DAG utilized as a compact representation of sequence data such as the directed non-cyclic word chart representation of a collection of strings or the binary decision chart representation of sequences of double choices.

2.5.2 Previous study that used BN application

Bayesian Networks (BN) is probabilistic models that have been effectively applied in a huge variety of domains. A study by (Song, Semakula and Fullana-i-Palmer, 2018) have too been utilized Bayesian Networks to recognize the key variables that impact aspects of interest. It is used to understand household waste generation and reduction possibilities. Besides that, (Tang and Huang, 2019) had proposes a Bayesian organize (BN) method for seismic vulnerability assessment of an urban street organize by considering spatial seismic hazard with distinctive levels of ground movement power defencelessness of the components and impact of basic harm of components inside the street organize to the network functionality. It is established based on transportation network analysis.

In addition, Bayesian Network are progressively being exploited to evaluate WaSH issues and to support arranging and decision-making processes (Requejo-Castro, Giné-Garriga and Pérez-Foguet, 2019). WaSH is standing for the term water, sanitation and hygiene (WaSH) sector. The study was aim to evaluate the validity, reliability and feasibility of BNs in replicating an existing CI-based conceptual framework. Besides, While BNs have been successfully applied to address environmental issues and water issues (Phan *et al.*, 2016). The study was reviews of Bayesian Networks applications with regard to spatial components, water spaces, and the thought of climate alter impacts.

Moreover, (Cronk and Bartram, 2018) applied Bayesian Networks to define the factors that influence 24 hours water service availability and to explore which variable was more influential in water discontinuity. In the study, he Bayesian networks predicted that great condition framework and year-round water source accessibility were more compelling on the accessibility of 24 hours benefit than administration factors such as the accessibility of outside specialized bolster and stores to restore the framework.

Study by (Hobold and da Silva, 2019) show that machine learning calculations can precisely induce boiling warm exchange administrations from visualization, and proposes the utilization of Bayesian measurements to be able to identify the move from nucleate to film bubbling with self-assertively expansive certainty inside seconds. Results propose that the exact detection can be possibly done in future than ordinary temperature estimation sensors such as commercial thermocouples and RTDs.

Besides, (Azzimonti, Corani and Zaffalon, 2019) propose a novel approach for progressing parameter estimation in Bayesian systems, based on various levelled Bayesian displaying. The proposed hierarchical model yields a major performance improvement in classification with Bayesian networks compared to traditional models. The study also introduces a hyper-prior in the Multinomial Dirichlet model, traditionally used for conditional distribution estimation in Bayesian networks. In addition, motivated by a real case think about, the progressive show is connected to the estimation of Bayesian systems parameters by borrowing quality from related spaces. Thus, it show that Bayesian network are widely used in the previous study for various cases.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The methodology of water footprint introduced by Water Footprint Network can be used to in the way to calculate the total of blue water footprint in order to make the prediction and impacts on water used by human activities (Delgado et al., 2004). This study can be used to improve the water management at the water treatment plants for the better management system in future. There are three type of water footprint which is blue water footprint, grey water footprint and green water footprint. Water footprint assessment is essential to calculate the water resource requirements by the consumers for the products and services (Hogeboom, Knook and Hoekstra, 2018). Water footprint for each stage of the water treatment is identify by referring to “The Water Assessment Manual” that introduced by Arjen Y. Hoekstra in 2011. This study will be only focusing on blue water footprint assessment. Generally, blue water footprint is the amount of surface water or groundwater that required in directly used or evaporated of water treatment plant for each stage involved (Moni et al., 2018).

There is several input of blue water footprint that will be calculated in this assessment which is total water intake, rainfall intensity and amount of water evaporated in the tank for each process involves. In this study, most of the tank using an open tank instead using closed tanks. This lead to the water to evaporated to atmosphere. Therefore, amount of evaporated will also be calculated. The blue water footprint of water treatment process is defined as total summation of the water consumed in every stages of water supply treatment process and can be formed as the water footprint formula:

$$WF_{blue} = Total\ Water\ Intake + (Rainfall\ Intensity\ x\ Area) + (ET_o\ x\ Area)$$

In this study, the first activity involved in the scope is setting phase which include preliminary study. This activity involved the background of study, identifying the problem statements that lead to the research study, the objectives and scope, significance of study and the literature review. Next the calculation of total blue water footprint and prediction of the trend will be analysed using WEKA software and both algorithms: Artificial Neural Network and Bayesian Network and will be compared in order to choose the best one.

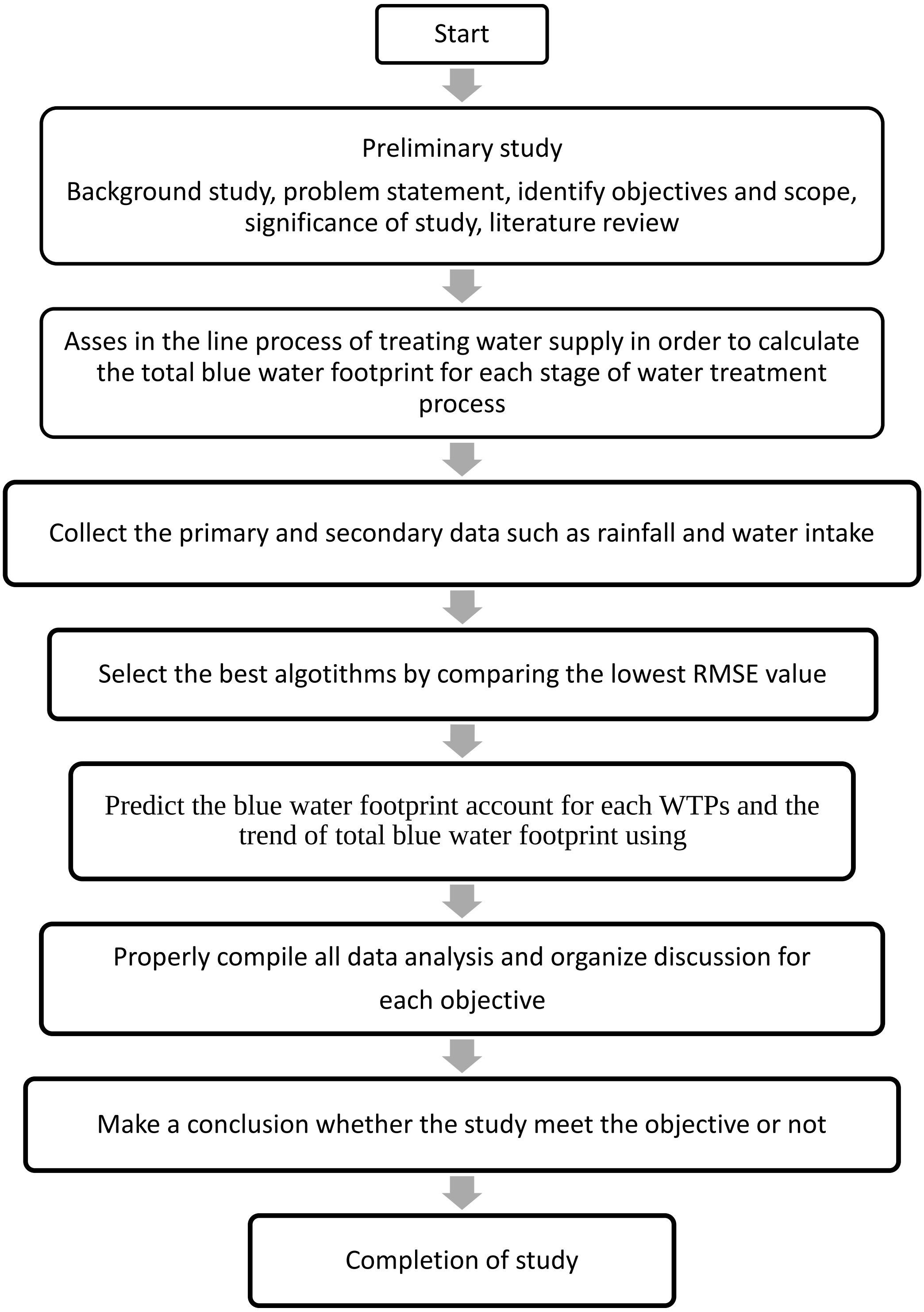
There are several departments involved to collect the data directly or indirectly throughout the study such as Pengurusan Air Pahang Berhad (PAIP), Jabatan Pengairan dan Saliran (JPS) Pahang for the rainfalls and Malaysian Meteorological Department (MMD) to get the data for the temperature. The area for each WTP will be calculated manually at the site which involves Sungai Lembing, Bukit Sagu and Bukit Ubi WTPs.

Then, blue water footprint accounting will be obtained. Then, it will be asses in the line process of treating water supply in order to calculate the total blue water footprint for each stage of water treatment process. Next, the result will be analysed in WEKA software in order to choose the best algorithm and predict the blue water footprint account for each water treatment plant and produce trend of total blue water footprint using the Artificial Neutral Network (ANN) and Bayesian Networks (BN).

The trend for the predicted graph will be compared with the actual graph. The parameter which is root mean square error (RMSE) is used for the prediction in order to choose the best algorithm between Artificial Neural Networks and Bayesian Network. The best algorithm will be determined by lower value of RMSE as the lower value indicates the lower error that result to the best choice of the algorithm. Then the study will be proceeding by using the best algorithm in order to make the prediction in future.

3.2 Flow Chat

The following figure below shows the flow chart to explain in detail the step that involve throughout the study period in order to fulfilling the objective of the study.



3.3 Study Area

The study area is located at the Kuantan River Basin covered only Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants (WTP) in Kuantan River Basin over the year of 2015 to 2017. Kuantan River Basin is located at Kuantan District area which its capital state is Pahang. This study is to determine the total blue water footprint for three main water treatment plants in Kuantan which is Sungai Lembing, Bukit Sagu and Bukit Ubi Water Treatment Plants. All WTPs water intake are freshly from Kuantan river basin

The location was selected because there are many water problems there but the water management is still using the old system. This problem will lead to water scarcity if it is continues and not be solve in a few years. The purpose of the study is to upgrade the new water system management in order to supply the best quality and services to the consumer. There are total 80 water treatment plants in Pahang. But this study only cover three water treatment plants which only located at Kuantan River Basin. There are Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants (WTP). Sungai Lembing WTP is the smallest water treatment plant which only supply for the small area population that cover around Sungai Lembing area.

The location of Sungai Lembing WTP is located at (3.9337132, 103.0501850). Meanwhile, Bukit Sagu water treatment plant is located at (3.9111174, 103.1666351). For Bukit Ubi water treatment plant it only covers the treated water supply to the Kuala Kuantan commercial area and it is located at (3.8325003, 103.2606332) in the center of the municipality of Permatang Temesu. All WTPs are manage to fulfilled the water demand for Kuantan which around 500 000 number of population. The treated fresh water will then be distributed to the consumer for their daily uses such as drinking, cooking, washing, carrying away wastes and other domestic needs. Therefore, water treatment is very important in order to ensure that the distributed water is clean and safe.

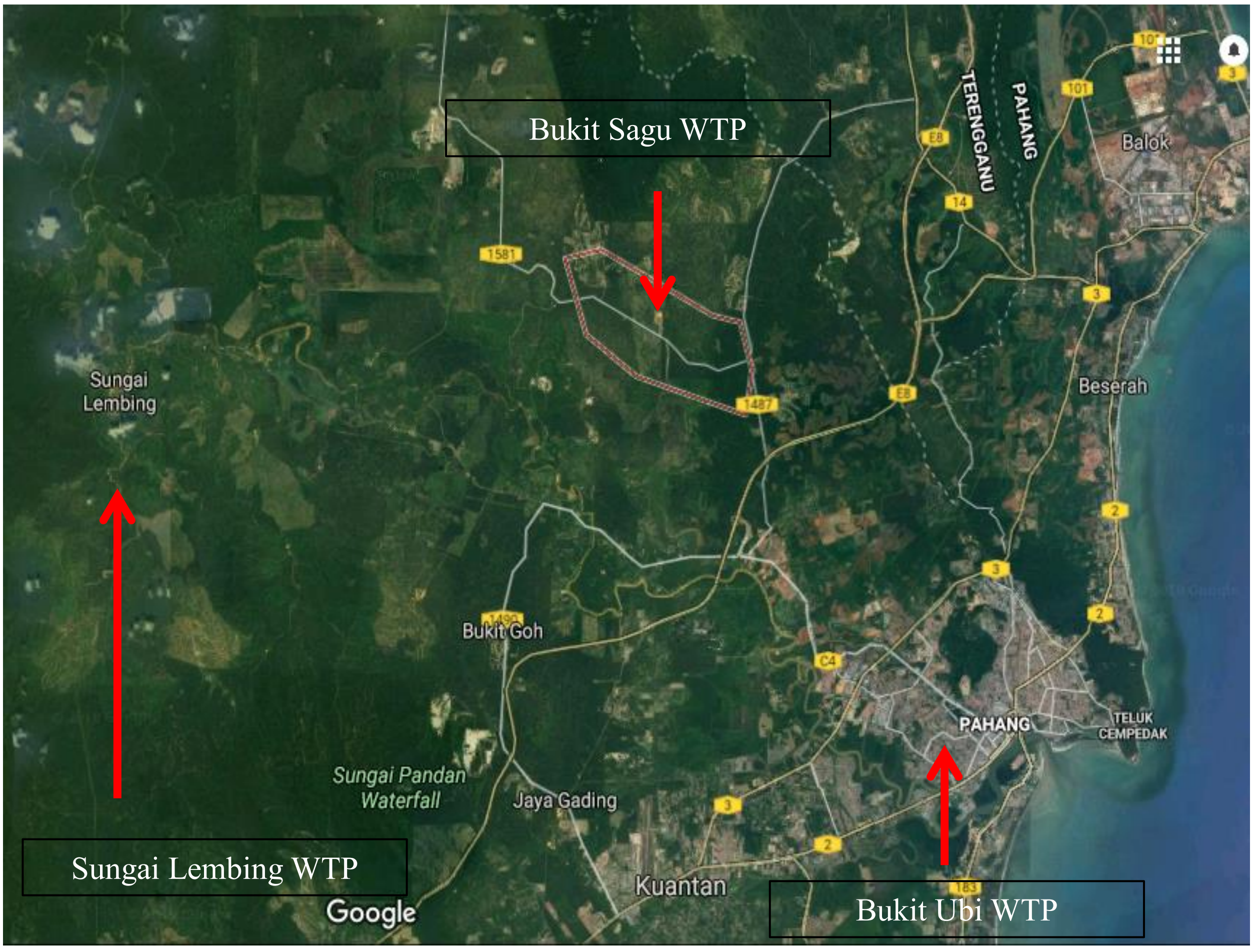


Figure 3.1 Location of Study

(Source: https://www.google.com/maps)

3.4 Data Collection

There are several departments involved to collect data directly or indirectly throughout the study. The table below shows the list of data collection and departments involved throughout the study period.

Table 3.0.1 List of data collection and department Involved

Data	Department
Water Intake	Pengurusan Air Pahang Berhad (PAIP)
Rainfall	Jabatan Pengairan dan Saliran (JPS) Pahang
Temperature	Malaysian Meteorological Department (MMD)
Area of WTPs	Calculated Manually

3.5 Site Visit

In this study, the visit will be involved for each stage of water treatment plants of Sungai Lembing, Bukit Sagu and Bukit Ubi WTPs. The data collection during the visit will be used for making the prediction. With help of site visit, the information regarding the site or the area around the site can be easily recorded and collected. By performing the site visit, the clear view of the water treatment condition can be experienced. The observation can carry throughout the visit. For example, the process for each steps involved in the treatment of water will be easily be observed and learn during the visit.

In addition, site visit is very helpful in order to have more understanding about the whole process involved during the treatment. By doing the treatment, clean and safe water can be produce before distributed to the consumer. Other than that, it helps to experience the real environment at the water treatment plants as it is differ with the other site. As in result, better management system will

All water treatment plants still using conventional water treatment process which some stages of the treatment process tanks still exposed to the surface without any cover. The probability of rainfall to enter the tanks is high. Besides, there will be evaporation of water to atmosphere due to open tanks. Hence total blue water footprint calculation is important to identify the missing information in order to know total amount of water that been consumed along the process.

3.6 Treatment of Missing Data

Missing data occurs in almost all research and attempts a number of solutions no matter how researcher tries to handle all sources of data loss in the survey or how well the experiments are designed but there will be a case of missing data. In blue water footprint accounting, rainfall intensity and amount of water evaporated through the process of water treatment need to be measured in order to obtained total blue water footprint. In this study, rainfall intensity will undergo a treatment of missing data due to missing rainfall in certain places for certain date.

There are many methods in order to determine the missing data for rainfall such as arithmetic average method, normal ratio method and quadrant method. For this study, arithmetic average method was used in order to obtain the missing data for rainfall. This is the simplest method of computing the average rainfall over a basin. The arithmetic mean method formula represented as below:

$$P_x = \frac{1}{n} \sum_{i=1}^{i=n} P_i \tag{2}$$

Where:

P = Precipitation

N = Normal annual precipitation

Result was obtained by the division of the sum of rain depths recorded at different rain gauge stations of the basin by the number of the stations. By using this method, the result obtained will be quite satisfactory and not differ much than those obtained by other methods as the rain gauges are uniformly distributed over the area and the rainfall varies in a very regular manner. In addition, this method can be used for the storm rainfall, monthly or annual rainfall average computations.

3.7 Water Supply Treatment Process Identification

This study is carried out at water treatment plant of Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plant. All water treatment plants were used conventional method which involves in process of water intake, aeration, coagulation, flocculation, sedimentation, filtration, disinfection and water distribution. The aim for all water treatment process is to eliminate the existing in the water, and improving for subsequent use in order to supply the clean and safe water to the consumers. Below is illustration of standard water supply treatment process in Malaysia.

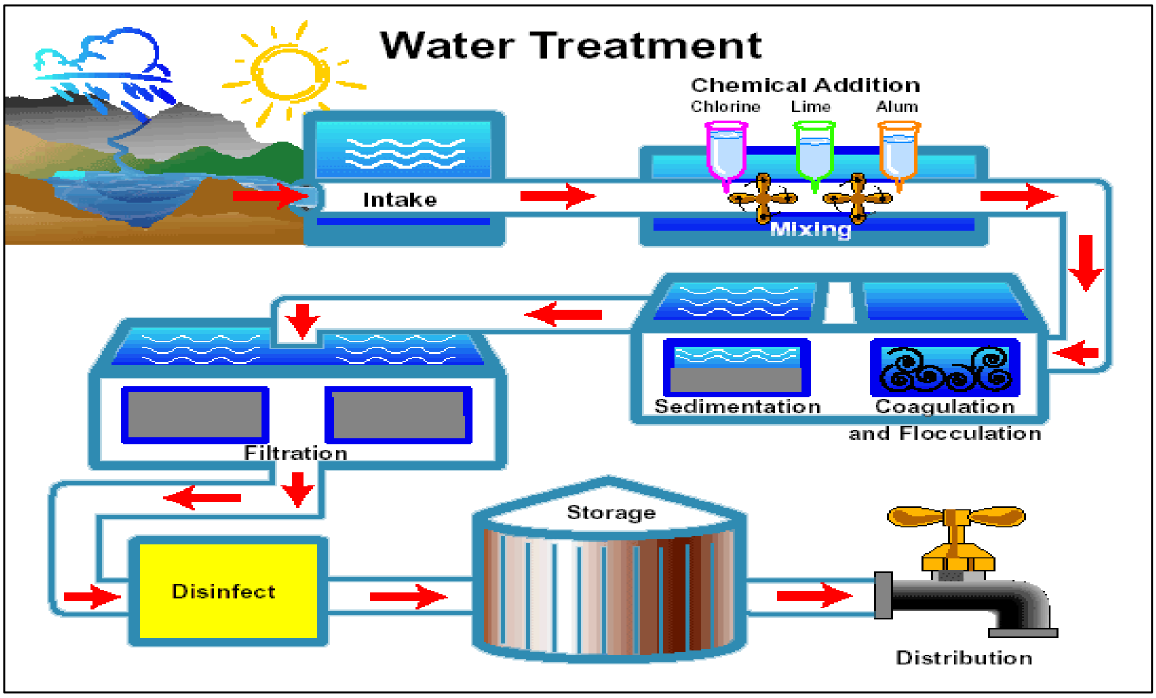


Figure 3.2 Water treatment process
(Source: https://www.ecwa.org/treatmentprocess)

3.7.1 Stages in Water Supply Treatment Process

1. Water Intake

   Water is taken from a source such as a lake or river. The aim of water intake is to provide an adequate and sufficient water supply for the consumers in their best quality.

2. Aeration

   Process whereby the water and air brought to eliminate the unneeded dissolved gases.

3. Coagulation

   Chemicals added to the water cling to particles already in the water.

4. Flocculation

   Process of adding and slow mixing of chemical and particles to remove the suspended material settle out of water.

5. Sedimentation

   Process of remove suspended solids from water under the effect of gravity.

6. Filtration

   Process of passing the water through porous medium to remove suspended.

7. Disinfection

   To eliminate the pathogenic microorganism including bacteria, parasites and viruses that harmful to the consumers

3.8 Water Footprint Accounting

There are three type of water footprint accounting which is blue water footprint (WFblue), green water footprint (WFgreen) and grey water footprint (WFgrey). In this study, it will be focusing on the blue water footprint assessment. The blue water footprint is the is the amount of surface water or groundwater that required in directly used or evaporated of water treatment plant for each stage involved (Moni et al., 2018). There is several input of blue water footprint that will be calculated in this assessment which is total water intake, rainfall intensity and amount of water evaporated in the tank for each process involves. The blue water footprint of water treatment process is defined as total summation of the water consumed in every stages of water supply treatment process. The formula of blue water footprint was presented as below:

$$WF_{blue} = Total\ Water\ Intake + (Rainfall\ Intensity\ x\ Area) + (ET_o\ x\ Area) \tag{3}$$

Where:

WF_{blue} = Blue water footprint

ET_o = Evaporation for every tank [m^3/ day]

Area = Area of each tank

ET_0 is equal to the rate of blue water evaporation calculated using Blaney-Criddle method.

Since most of the tank in all water treatment plants was in rectangular shape, thus the area to calculated the tank was used normal formula which is length multiple by width. In addition, most of the tank in all three water treatment plants were used an open tank instead using closed tanks. This lead to the water to evaporated to atmosphere. Therefore, amount of evaporated will also be calculated. Thus Blaney-Criddle method equation that was empirical simplistic formula for calculating evapotranspiration was chosen since the available data just only the temperature. The formula of Blaney-Criddle method is expressed below:

$$ET_0 = p\,[(0.457 \times Tmean) + 8.128] \qquad (4)$$

Where:

ET_0 = Evapotranspiration [m^3/ day]

p = Mean daily percentage of annual daytime hour

T_{mean} = Mean daily temperature [°C]

Below is use of the Blaney-Criddle method:

Step 1: Determined the mean daily temperature, T_{mean}

$$T_{mean} = \frac{T_{mean} + T_{max}}{2} \qquad (5)$$

Step 2: Determination of the ρ value in table Mean Daily Percentage of Annual Daytime Hours for Different Months. Approximate latitude of the study area and the number of degree north or south of the equator was identified before using the table.

Step 3: Calculate ET_0 by using formula:

$$ET_0 = p\,[(0.457 \times Tmean) + 8.128 \qquad (6)$$

Table 1.15 Mean Daily Percentage of Annual Daytime Hours, P, by Month for Different Northern and Southern Latitudes

Latitude North South[a]	Jan. July	Feb. Aug.	Mar. Sept.	Apr. Oct.	May Nov.	June Dec.	July Jan.	Aug. Feb.	Sept. Mar.	Oct. Apr.	Nov. May	Dec. June
60°	0.15	0.20	0.26	0.32	0.38	0.41	0.40	0.34	0.28	0.22	0.17	0.13
58°	0.16	0.21	0.26	0.32	0.37	0.40	0.39	0.34	0.28	0.23	0.18	0.15
56°	0.17	0.21	0.26	0.32	0.36	0.39	0.38	0.33	0.28	0.23	0.18	0.16
54°	0.18	0.22	0.26	0.31	0.36	0.38	0.37	0.33	0.28	0.23	0.19	0.17
52°	0.19	0.22	0.27	0.31	0.35	0.37	0.36	0.33	0.28	0.24	0.20	0.17
50°	0.19	0.23	0.27	0.31	0.34	0.36	0.35	0.32	0.28	0.24	0.20	0.18
48°	0.20	0.23	0.27	0.31	0.34	0.36	0.35	0.32	0.28	0.24	0.21	0.19
46°	0.20	0.23	0.27	0.30	0.34	0.35	0.34	0.32	0.28	0.24	0.21	0.20
44°	0.21	0.24	0.27	0.30	0.33	0.35	0.34	0.31	0.28	0.25	0.22	0.20
42°	0.21	0.24	0.27	0.30	0.33	0.34	0.33	0.31	0.28	0.25	0.22	0.21
40°	0.22	0.24	0.27	0.30	0.32	0.34	0.33	0.31	0.28	0.25	0.22	0.21
35°	0.23	0.25	0.27	0.29	0.31	0.32	0.32	0.30	0.28	0.25	0.23	0.22
30°	0.24	0.25	0.27	0.29	0.31	0.32	0.31	0.30	0.28	0.26	0.24	0.23
25°	0.24	0.26	0.27	0.29	0.30	0.31	0.31	0.29	0.28	0.26	0.25	0.24
20°	0.25	0.26	0.27	0.28	0.29	0.30	0.30	0.29	0.28	0.26	0.25	0.25
15°	0.26	0.26	0.27	0.28	0.29	0.29	0.29	0.28	0.28	0.27	0.26	0.25
10°	0.26	0.27	0.27	0.28	0.28	0.29	0.29	0.28	0.28	0.27	0.26	0.26
5°	0.27	0.27	0.27	0.28	0.28	0.28	0.28	0.28	0.28	0.27	0.27	0.27
0°	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27

Note: Appendix B details methodology and equations for computing daytime hours and *P* to facilitate computer application of this table.
[a] Southern latitudes: apply 6 month difference as shown.

Figure 3.3 Mean daily percentage of annual daytime hours

3.9 The Best Algorithm for Prediction

There are two algorithms that will be used for the prediction of blue water footprint which is Artificial Neural Network and Bayesian Networks. Both algorithms will be compared in order to select the best one. WEKA software was used to run both algorithms. The best algorithm was determined by the lower value of RMSE envision in WEKA software. Root Mean Square Error (RMSE) was frequently used to measure the differences between predicted value by a model or an estimator with the values observed. In addition, it measures value error between two data sets. In other words, it compares a predicted value and an observed. The lower the value of RMSE, the best the graph as it indicates the least error that been made by the algorithm. Thus, the best algorithm can be determined at the end and will be used for the prediction of blue water footprint.

3.10 Prediction of Blue Water Footprint Accounting

All accounted blue water footprint was uploaded in WEKA software. WEKA is a group of learning algorithms for data mining activities. It contains appliances for data clustering, regression, classification, visualization and preparation. The software was chosen because it is user friendly and easy to handle compared to other software such as MATLAB. The data was organized based on the input output before proceed with the software. The inputs for the study were water intake, rainfall intensity and evaporation while total blue water footprint for three different water treatment plants was the output. The input was chooses due to complete data and same unit which is m^3.

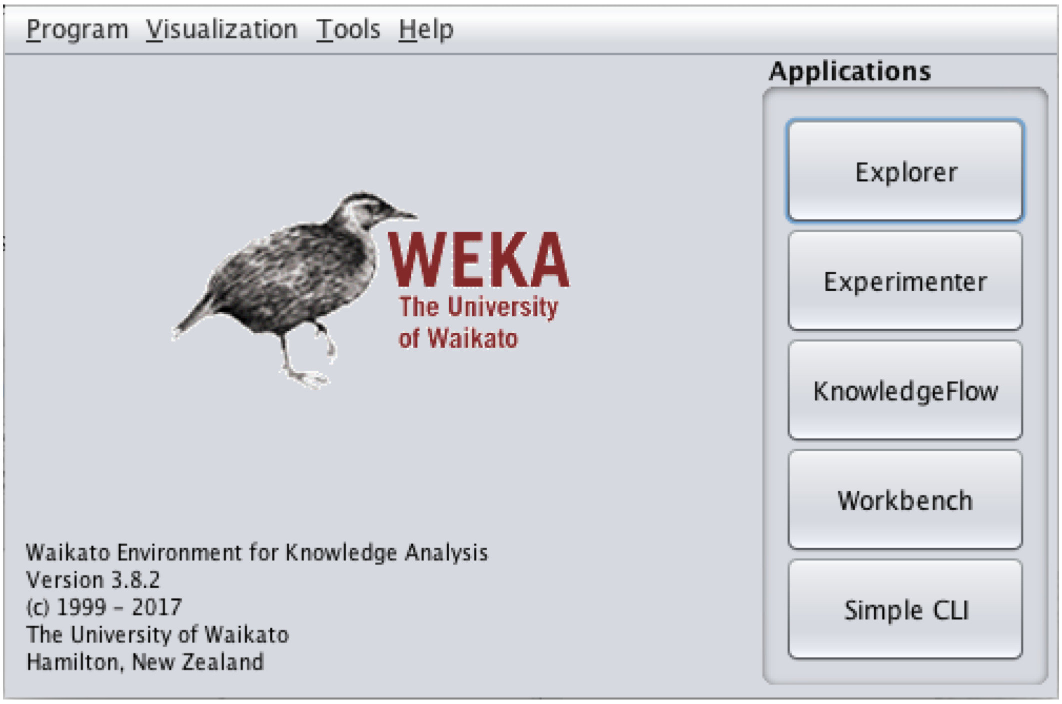


Figure 3.4 WEKA software

Before proceed with the prediction of blue water footprint, pre-processing data was carried out in order to determine the best algorithm selection. The data will undergo cleaning process before uploading into WEKA software. Besides, cleaning processes included by removing the outliers. Next, process was continued with data normalization. The data normalization process was used within range 0 to 1 to standardize between the different ranges of values. Then, process proceeded by removing the outliers. The outliers are the value that is very different from the other data set. Outlier can skew the results. Hence, it has significant effect on the mean data. The data will tabulate using Microsoft Excel for systematically organized. Then the excel will converted to Comma Seperated Value (CSV) before inserted into Weka software to be run. The same methods were applied for both algorithms.

The prediction of blue water footprint will be determined after the total blue water footprint was obtained. Two different algorithms between Artificial Neural Network and Bayesian Networks were compared in order to choose the best algorithm. The selecting was based on the lowest root mean square error (RMSE) value. The trend shown for the predicted graph should be slightly same with the actual data. Thus, predicted amount of blue water footprint for 2018 to 2020 was obtained at the end of study.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The purpose of this chapter is to analyse and discuss the result obtained from the study based on three objectives given. The result data will include the total of blue water footprint, the comparison to choose the best algorithm between Bayesian Networks (BN) and Aritificial Neural Network (ANN) and the prediction trend of blue water footprint for Sungai Lembing WTP, Bukit Sagu WTP and Bukit Ubi WTP in 2015 to 2017.

4.2 / Total Blue Water Footprint Accounting

Water treatment process at Sungai Lembing, Bukit Sagu and Bukit Ubi WTP, blue water footprint calculations involve only from water abstraction to final step filtration before being distributed to all consumers. Based on the result obtained, high value of total blue water footprint is due to value of water intake for each water treatment plant while lowest value of total blue water footprint is also due to the lowest value water intake in all water treatment plant for each year. Rainfall intensity and evaporation were only contributing less in the value of blue water footprint accounting. Hence, value of total blue water footprint is depends on value water intake for each day.

For the calculation of blue water footprint, the amount of water intake, rainfall and evaporation was added to get the total of blue water footprint. The backwash water was not consider as a lost and included in blue water calculation is because basically backwash water returned back to the same river basin. Overall rainfall intensity for each day and water evaporated been multiplied with the total area for all the tanks in each water treatment plants. Then, rainfall intensity and water evaporated been added with the amount of water intake in order to determine the total blue water footprint.

Table 4.0.1 Area of each tank at Sungai Lambing, Bukit Sagu and Bukit Ubi WTPs

Tank	Sg Lembing WTP (m^2)	Bukit Sagu WTP (m^2)	Bukit Ubi WTP (m^2)
Aeration	10.89	-	3.60
Flocculation	60.00	105.93	244.10
Sedimentation (Phase 1)	200.00	110.75	39.06
Sedimentation (Phase 2)	-	-	62.78
Sedimentation (Phase 3)	-	-	450.00
Sedimentation (Phase 4)	-	-	167.20
Filtration (Phase 1)	60.72	59.34	200.00
Filtration (Phase 2)	-	-	111.69
Filtration (Phase 3)	-	-	102.60
Total area	331.610 m^2	276.02 m^2	1381.05^2

4.2.1 Sungai Lembing Water Treatment Plant

Table 4.0.2 Total blue water footprint at Sungai Lembing WTP in 2015

Month	Water Intake (m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	140771	60.519	57.340	140888.858
February	132244	32.332	50.983	132327.315
March	132090	30.674	58.035	132178.709
April	131880	40.788	57.545	131978.333
May	130610	73.283	55.844	130739.127
June	144987	30.840	56.154	145073.993
July	137022	57.203	57.839	137137.042
August	137063	75.441	58.207	137196.648
September	123030	39.130	55.188	123124.318
October	140722	57.700	57.000	140836.700
November	134982	73.120	54.116	135109.236
December	134666	95.504	55.928	134817.432

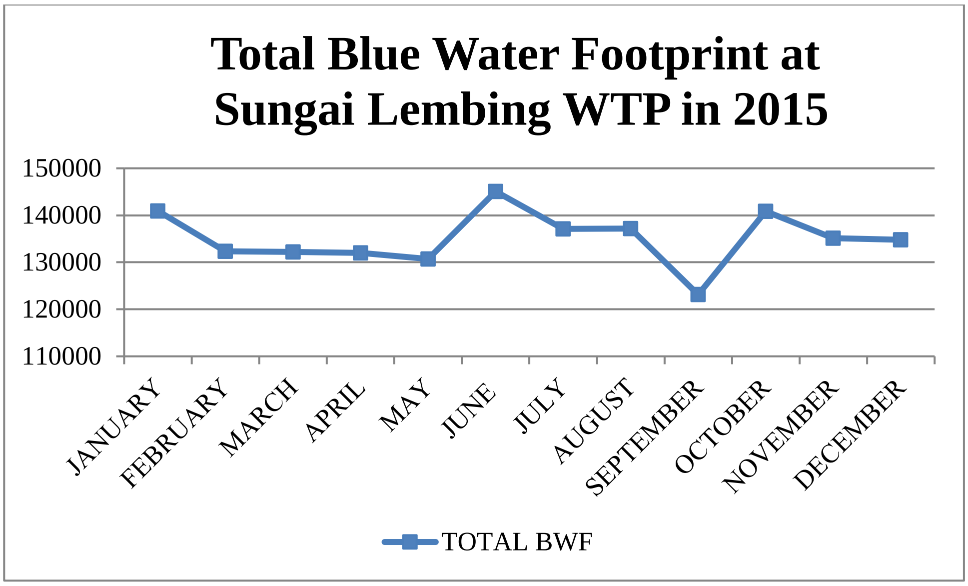


Figure 4.1 Total blue water footprint at Sungai Lembing WTP in 2015

Table 4.1 shows the total blue water footprint from January to December 2015 at Sungai Lembing WTP. In January, the amount of blue water footprint was 140888.858m³/month. The value was decrease in February with 132327.315m³/month. March recorded 132178.709m³/month while April shows 131978.333m³/month. In May, amount of blue water footprint was 130739.127m³/month. June shows an increasing in total blue water footprint with 145073.993m³/month. Meanwhile, for July and August the amount of blue water footprint was 137137.042m³/month and 123124.318m³/month respectively. There was increase in total amount of blue water footprint in October with 140836.700m³/month. Meanwhile November and December shows decreasing back in total blue water footprint with only135109.236m³/month and 134817.432m³/month respectively. The highest value of blue water footprint obtained was in June with 145073.993m³/month due to the high water intake for that month. Meanwhile, the lowest value was in September which 123124.318m³/month. The factor lead to the lowest value of blue water footprint was due to the lower amount of water intake. From the figure 4.1, it shows that the trend of was uniform to the end of the year with the highest value in June and lowest value in September due to amount of water intake

Table 4.0.3 Total blue water footprint at Sungai Lembing WTP in 2016

Month	Water Intake (m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	139797	34.322	57.340	139891.000
February	137474	105.651	52.791	137633.000
March	145912	10.280	58.035	145984.000
April	142697	19.731	57.545	142776.000
May	142529	105.116	55.844	142691.000
June	141245	66.985	56.154	141371.000
July	145328	63.835	57.839	145452.000
August	145319	59.690	58.207	145439.000
September	140691	122.364	55.188	140871.000
October	145572	114.074	57.000	145744.000
November	131254	118.219	54.116	131428.000
December	137431	95.006	55.928	137582.000

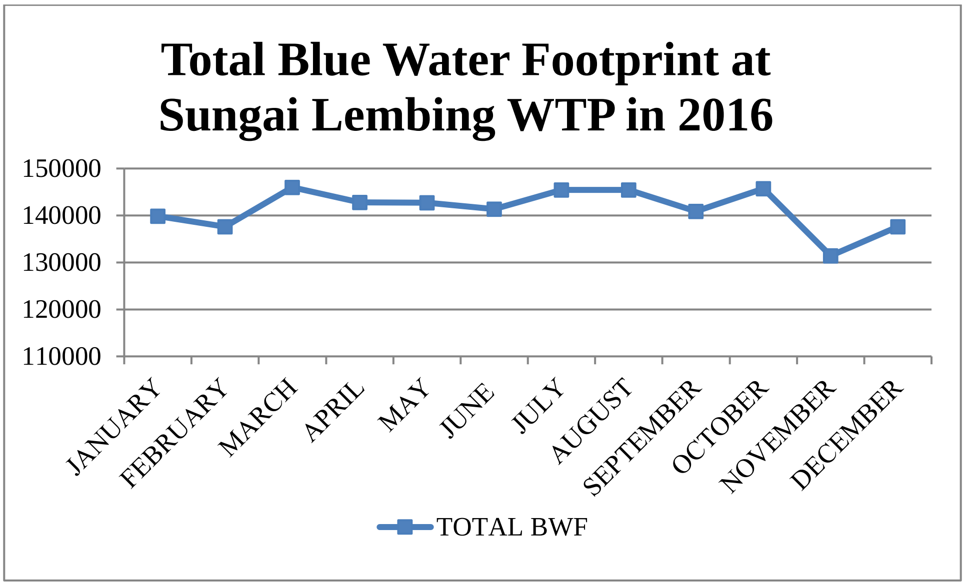


Figure 4.2 Total blue water footprint at Sungai Lembing WTP in 2016

From figure 4.2, it shows that there was a decreasing in early and end month of total blue water footprint at Sungai Lembing in year 2016. In January, the amount of blue water footprint was 139891m³/month. The value was decrease in February with 137633m³/month. March recorded 145984m³/month while April shows

142776m³/month. In May, amount of blue water footprint was 142691m³/month. June shows an increasing in total blue water footprint with 145073.993m³/month. Meanwhile, for July and August the amount of blue water footprint was 141371m³/month and 145439m³/month respectively. There was increase in total amount of blue water footprint in October with 145744m³/month. Meanwhile November and December shows decreasing back in total blue water footprint with only131428³/month and 137582m³/month respectively. This is due to high value of rainfall intensity even though the water intake was low. The lowest amount was obtained in November with 131428.00m³/month. This is due to lower water intake compared to other month. In the middle month, the trend was seen to be uniform from March to October. In addition, water intake amount gives big impact in calculating overall total blue water footprint.

Table 0.4 Total blue water footprint at Sungai Lembing WTP in 2017

Month	Water Intake (m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	137058	183.878	57.340	137301.000
February	127596	101.108	52.227	127752.000
March	138383	57.899	58.035	138501.000
April	132031	52.560	57.545	132139.000
May	140134	86.630	54.685	140274.000
June	134837	46.757	56.154	134941.000
July	136232	39.029	56.728	136332.000
August	126076	65.730	57.074	126200.000
September	132501	82.239	55.188	132640.000
October	129128	106.655	55.869	129291.000
November	122821	138.447	54.116	123013.000
December	128219	147.401	56.487	128422.000

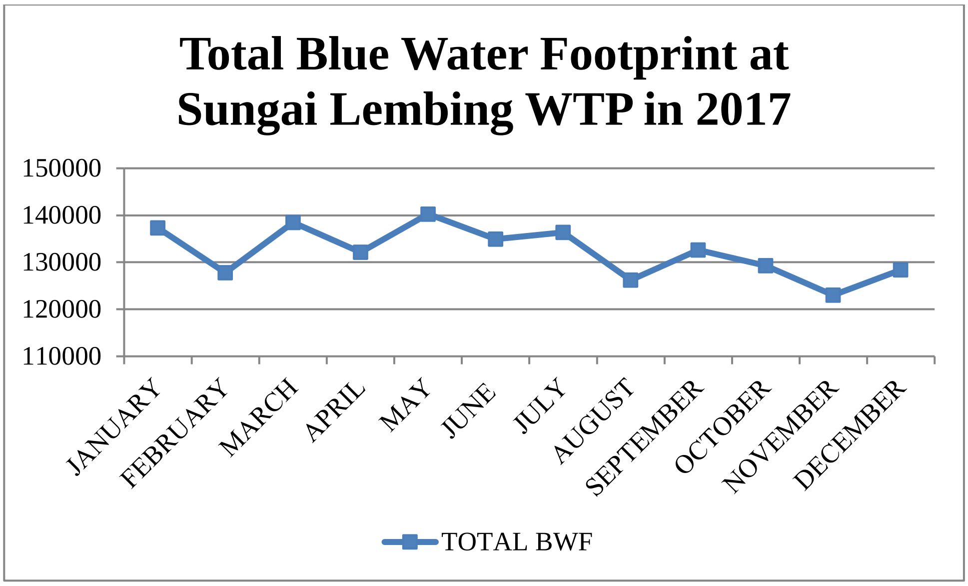


Figure 4.3 Total blue water Footprint at Sungai Lembing WTP in 2017

From the data presented in table 4.4 and figure 4.3 above, the value of blue water footprint at Sungai Lembing water treatment plant in 2017 was fluctuation throughout the year. In January, the amount of blue water footprint was 137301.00m³/month. It then decrease to 127752.00m³/month in February which caused by lower water intake compared to January. From March to July, the trend was rise and fall due to uneven amount of water intake. It then starts to decrease steadily on August to the end year due to lower water intake for that month. Low water intake was basically due to dry season, where the water abstracted must be lemmatized because it is afraid more sediment will be abstracted rather than raw water, and this will result in damaging the treatment plant or more alum needed and more costing will be added. This proves that the water intake value plays big roles in trend of blue water footprint.

Table 4.0.5 Total blue water footprint analysis at Sungai Lembing WTP

Month	Total Blue Water Footprint (m^3)		
	2015	2016	2017
January	140889	139891	137301
February	132327	137633	127752
March	132179	145984	138501
April	131978	142776	132139
May	130739	142691	140274

June	145074	141371	134941
July	137137	145452	136332
August	137197	145439	126200
September	123124	140871	132640
October	140837	145744	129291
November	135109	131428	123013
December	134817	137582	128422
Total Blue Water Footprint	1621408	1696862	1586806

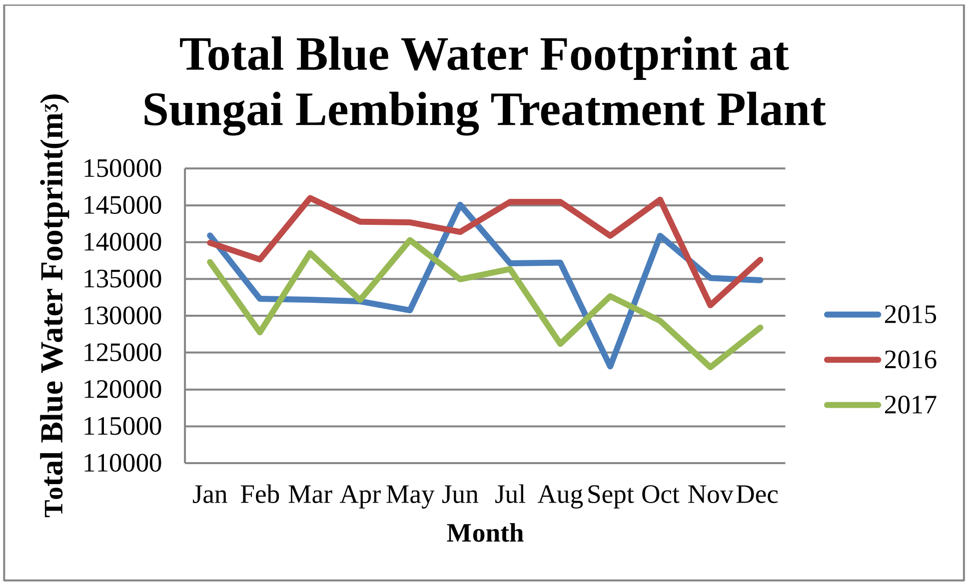


Figure 4.4 Total blue water footprint analysis at Sungai Lembing WTP

From Figure 4.4, based on the graph of total blue water footprint for Sungai Lembing Water Treatment Plant for 2015, the graph shows a slightly drop in September which around 123,124 m^3/month. The value was increasing back in October by 140,837m^3/month. For year 2016, the value was remaining uniform until September but then slightly decrease in November with total blue water footprint was 131,428m^3/month. By referring to the graph of blue water footprint in 2017, it can observe that the lowest value was on November with blue water footprint of 123,013m^3/month. This might due to the less amount of water intake for that month.

Usually the less amount of water intake is due to smallest area of water treatment plants that produce water to consumer.

4.2.2 Bukit Sagu Water Treatment Plant

Table 4.0.6 Total blue water footprint at Bukit Sagu WTP in 2015

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	158596	67.211	47.727	158710.938
February	130032	34.088	42.436	130108.525
March	108600	27.878	48.306	108676.184
April	56511	22.772	47.898	56581.670
May	142890	36.297	49.287	142975.584
June	144219	37.677	46.740	144303.375
July	161347	44.439	48.143	161439.582
August	157940	68.453	48.449	158057.266
September	107800	20.563	45.936	107866.500
October	185606	58.102	47.445	185711.547
November	190668	59.758	45.044	190772.589
December	164508	82.944	46.552	164653.528

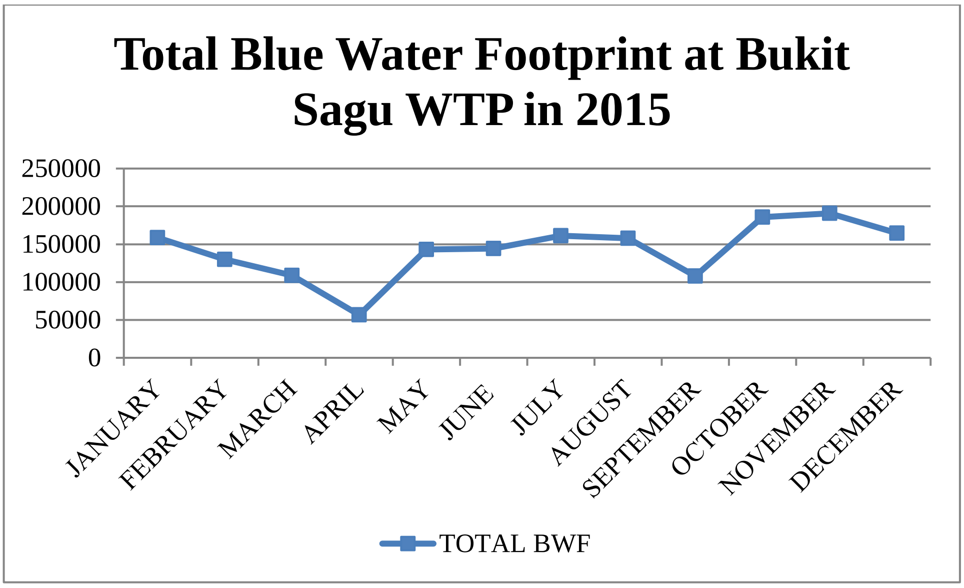


Figure 4.5 Total blue water footprint at Bukit Sagu WTP in 2015

Table 4.6 shows the total blue water footprint amount from January to December 2015 at Bukit Sagu WTP. In January, the amount of blue water footprint was 158710.938m^3/month. The value was decrease in February with 130108.525m^3/month. March recorded only 108676.184m^3/month while April shows 56581.670m^3/month. In May, amount of blue water footprint was increase to 142975.584m^3/month. June shows an increasing in total blue water footprint with 144303.375m^3/month. Meanwhile, for July and August the amount of blue water footprint was 144303.375m^3/month and 158057.266m^3/month respectively. There was increase in total amount of blue water footprint in October with 185711.547m^3/month. Meanwhile November and December shows also an increasing in total blue water footprint with 190772.589^3/month and 164653.528m^3/month respectively. In April, the total amount of blue water footprint is the lowest with the value 56581.67 m^3/month due to the low amount of water intake. Moreover, the rainfall intensity in that month is also one of the lowest throughout the year that will affect the amount of blue water footprint. Figure 15 shows the amount of blue water footprint is the highest in November with the value 190772.59 m^3/month.

Table 4.0.7 Total blue water footprint at Bukit Sagu WTP in 2016

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	183521	28.568	47.727	183596.979
February	175338	65.720	43.965	175447.827
March	180958	0.138	48.306	181006.632
April	198369	4.278	47.898	198420.768
May	175839	49.822	49.287	175937.643
June	154990	27.602	46.740	155064.117
July	169601	64.313	48.143	169713.335
August	157940	55.894	48.449	158044.707
September	161407	58.240	45.936	161511.190
October	186284	85.014	47.445	186415.984
November	171159	93.709	45.044	171297.675
December	179090	84.600	46.512	178752.736

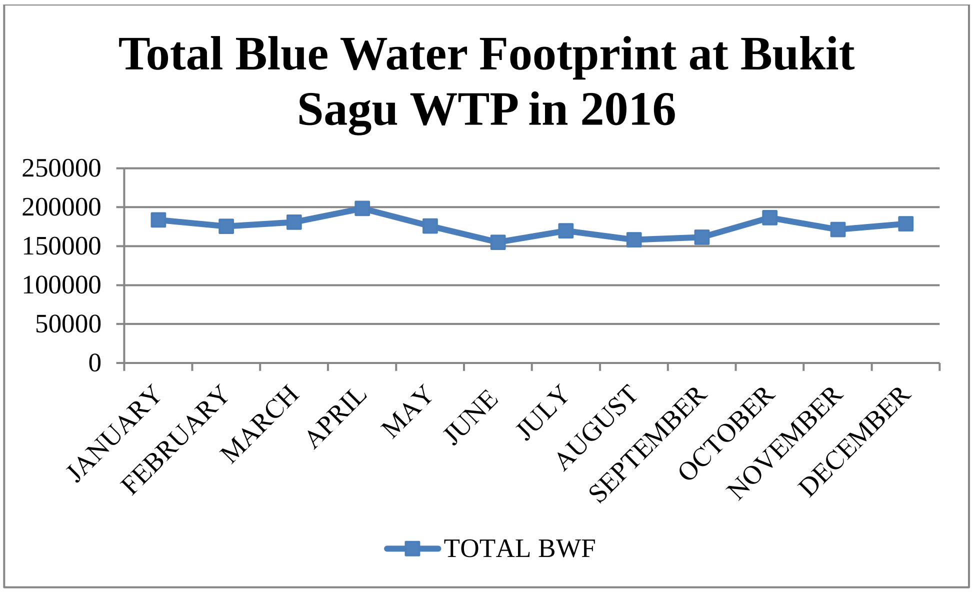


Figure 4.6 Total blue water footprint at Bukit Sagu WTP in 2016

By referring to table 4.7, the total amount of blue water footprint was in range 150,000 m^3 to 200,000 m^3 per month. This is due to moderate temperature rate evaporation throughout the year. In January, the amount of blue water footprint was 183596.979m^3/month. The value was decrease in February with 175447.827m^3/month. March recorded an increasing amount of blue water footprint with 181006.632m^3/month while April shows 198420.768m^3/month. In May, amount of blue water footprint was decrease to 175937.643m^3/month. June also shows decreasing in total blue water footprint with 155064.117m^3/month. Meanwhile, for July and August the amount of blue water footprint was 169713.335m^3/month and 158044.707m^3/month respectively. There was increase in total amount of blue water footprint in October with 186415.984m^3/month. Meanwhile November and December shows decreasing in total blue water footprint with 171297.675^3/month and 178752.736m^3/month respectively. Based on figure 6, the highest amount of blue water footprint was recorded in April with 198420.77m^3/month. Meanwhile, the lowest value of total blue water footprint was in June only 155064.12 m^3/month. Overall, the trend for blue water footprint in Bukit Sagu for year 2016 was uniform thought out the year.

Table 4.0.8 Total blue water footprint at Bukit Sagu WTP in 2017

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	178913	134.422	47.727	179094.818
February	154280	80.736	42.436	154402.847
March	171011	63.485	47.326	171121.920
April	157438	35.055	47.898	157520.953
May	188703	58.516	49.287	188810.354
June	167765	64.037	46.740	167876.059
July	172947	33.674	48.143	173028.817
August	175688	40.299	48.449	175776.748
September	189535	54.928	45.936	189635.864
October	186824	76.458	47.445	186947.902
November	185342	112.892	45.044	185499.936
December	189251	121.311	47.017	189419.328

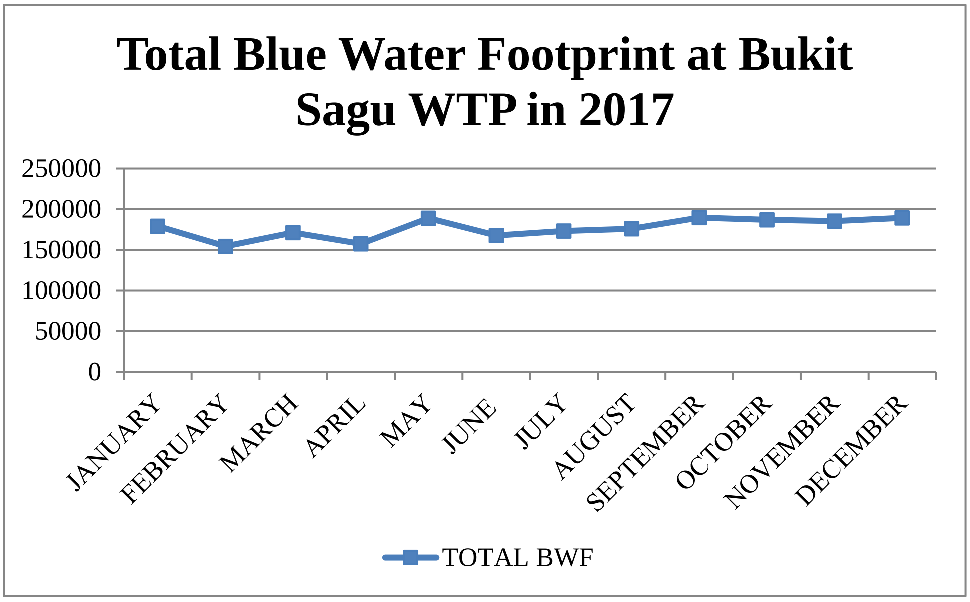


Figure 4.7 Total blue water footprint at Bukit Sagu WTP in 2017

Figure 4.7 shows the total blue water footprint at Bukit Sagu for year 2017. In January, the amount of blue water footprint was 179094.818m3/month. The value was decrease in February with 154402.847m3/month. March recorded an increasing amount of blue water footprint with 171121.920m3/month while April shows

157520.953m^3/month. In May, amount of blue water footprint was increase to 188810.354m^3/month. June shows decreasing in total blue water footprint with 167876.059m^3/month. Meanwhile, for July and August the amount of blue water footprint was 173028.817m^3/month and 175776.748m^3/month respectively. There was decreasing in total amount of blue water footprint in October with 186947.902m^3/month. Meanwhile November and December shows decreasing in total blue water footprint with 185499.936^3/month and 189419.328m^3/month respectively. The highest amount of blue water recorded in May by 188810.35m^3/month. Meanwhile, the lowest value was in April which only 157520.95 m^3/month. This is due to lower water intake compared to other month. In 2017, total blue water footprint is just in the range of 150,000 m^3 to 200,000 m^3 per month. From June to the December, the blue water footprint shows increasing in the amount of blue water footprint. The overall trend of blue water footprint at Bukit Sagu in 2017 was uniform thought out the year.

Table 4.0.9 Total blue water footprint analysis at Bukit Sagu WTP in 2015 to 2017

Month	Total Blue Water Footprint (m^3)		
	2015	2016	2017
January	158711	183597	179095
February	130109	175448	154403
March	108676	181007	171122
April	56582	198421	157521
May	142976	175938	188810
June	144303	155064	167876
July	161440	169713	173029
August	158057	158045	175777
September	107866	161511	189636
October	185712	186416	186948
November	190773	171298	185500
December	164654	178753	189419
Total Blue Water Footprint	1709857	2095210	2119136

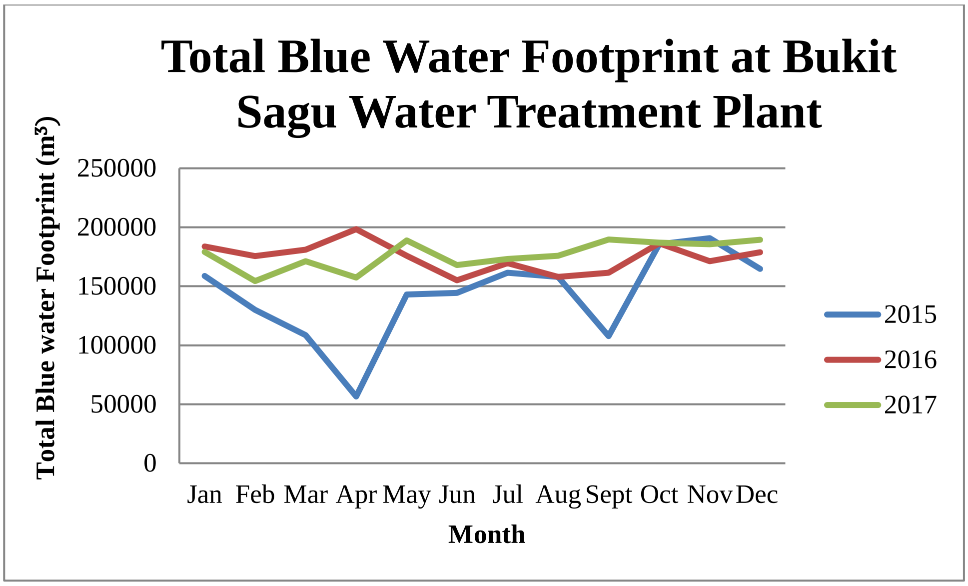


Figure 4.8 Total blue water footprint analysis at Bukit Sagu WTP in 2015 to 2017

The blue water footprint accounting of Bukit Sagu water treatment plant has the lowest value during year 2015 with the total blue water footprint of 56, 582 m^3/month compared to the other WTPs. The value was increased gradually after April but then decreased back to 107,867m^3/month in September. The decrease amount of blue water footprint was due to the lower amount of water intake. Low basically due to dry season, where the water abstracted must be lemmatized because it is afraid more sediment will be abstracted rather than raw water, and this will result in damaging the treatment plant or more alum needed and more costing will be added. Meanwhile, the pattern for year 2016 and 2017 was slightly same with the total blue water footprint for 2016 was 2,095,210m^3/month and 2,119,136m^3/month respectively. The highest reading recorded for Sungai Lembing water treatment plant was in year 2016 with total blue water footprint of 198,421m^3/month.

4.2.3 Bukit Ubi Water Treatment Plant

Table 4.0.10 Total blue water footprint at Bukit Ubi WTP in 2015

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	820942	308.665	238.801	821489.466

February	810264	167.798	212.327	810644.125
March	890007	55.933	241.698	890304.631
April	864985	100.817	239.656	865325.472
May	892342	168.488	246.606	892757.094
June	819897	81.482	233.862	820212.305
July	838374	80.101	240.880	838694.981
August	822331	577.279	242.414	823150.693
September	638764	152.606	229.840	639146.532
October	771577	234.088	237.387	772048.475
November	742431	412.243	225.376	743068.634
December	744268	490.963	232.922	744991.554

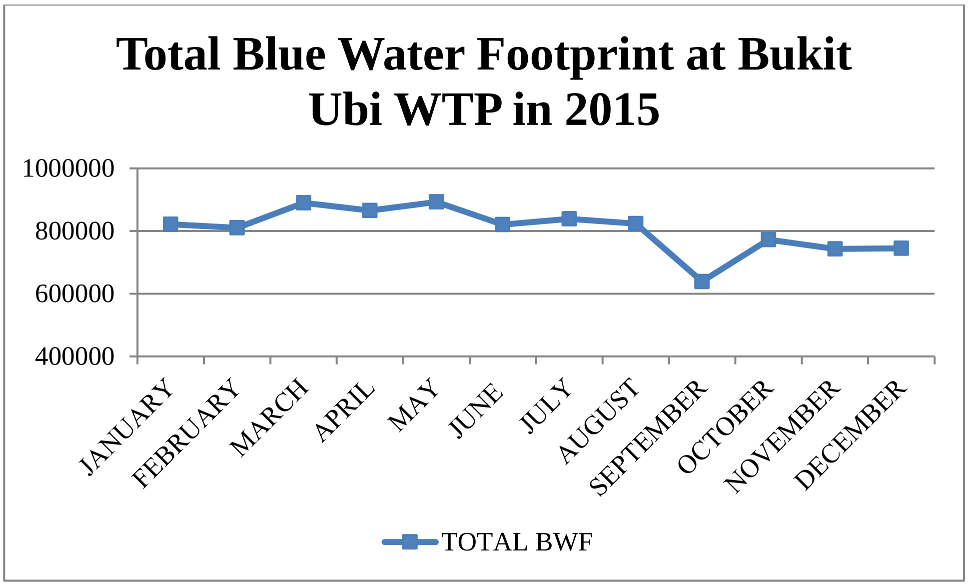


Figure 4.9 Total blue water footprint at Bukit Sagu WTP in 2015

From table 4.10, the total blue water footprint at Bukit Ubi in 2015. . In January, the amount of blue water footprint was 179094.818m^3/month. The value was decrease in February with 154402.847m^3/month. It started to increase starting from March to May and decrease in June towards the end of the year. The lowest was obtained in September 639,146.53m^3/month. Meanwhile, the highest value of total blue water footprint was in May compared to other month. This is due to the higher value of water intake in May. Figure 4.9 shows total blue water footprint trend started to increase in the early of the year until May and being decrease in June to the end of the year with most decreasing amount was in September.

Table 4.0.11 Total blue water footprint at Bukit Ubi WTP in 2016

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	750266	246.517	238.801	750751.527
February	685829	225.213	219.403	686273.256
March	840969	39.360	241.698	841250.449
April	698715	13.811	239.656	698968.480
May	697130	94.602	246.606	697471.298
June	661397	273.448	233.862	661904.237
July	725026	60.766	240.880	725327.477
August	714131	435.721	242.414	714809.584
September	638764	345.263	229.840	639339.188
October	654469	419.839	237.387	655126.605
November	700367	510.989	225.376	701103.193
December	753920	615.948	232.922	754768.868

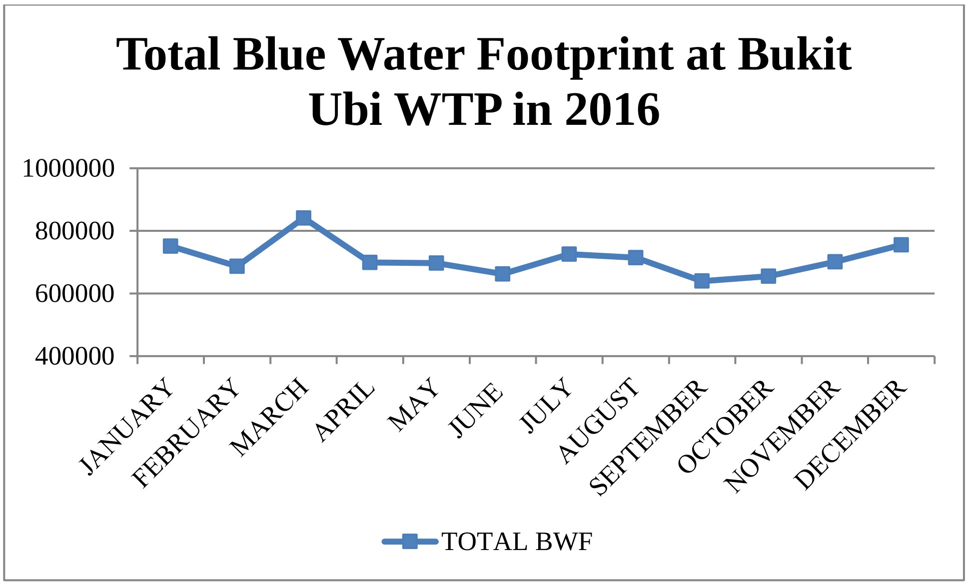


Figure 4.10 Total blue water footprint at Bukit Ubi WTP in 2016

Table 4.11 shows the total blue water footprint amount from January to December 2016 at Bukit Ubi WTP. In January, the amount of blue water footprint was 750751.527m^3/month. The value was decrease in February with 686273.256m^3/month. March recorded an increasing amount of blue water footprint with 841250.449m^3/month while April shows 698968.480m^3/month. In May, amount of blue water footprint was decreasing to 697471.298m^3/month. June also shows decreasing in total blue water footprint with 661904.237m^3/month. Meanwhile, for July and August the amount of blue water footprint was 725327.477m^3/month and 714809.584m^3/month respectively. There was decreasing in total amount of blue water footprint in October with 655126.605m^3/month. Meanwhile November and December shows decreasing in total blue water footprint with 701103.193^3/month and 754768.868m^3/month respectively. The highest amount of blue water footprint was in March while the lowest is in October with the value of 841,250.45m^3/month and 655,126.61m^3/month respectively. Meanwhile, in figure 14, there is slightly increase of blue water footprint between July and August due to the increasing in the amount of water intake but decrease back in September. The total evaporation along the year is almost the same due to the uniform value of temperature rate for that month.

Table 4.0.12 Total blue water footprint at Bukit Ubi WTP in 2017

Month	Water Intake(m3)	Total Rainfall (m3)	Total Evaporation (m3)	Total BWF (m^3)
January	707184	458.160	238.801	708549.858
February	573744	268.614	212.327	574225.063
March	676610	134.652	241.698	676986.710
April	688857	95.292	239.656	689191.948
May	709201	211.991	246.606	709659.418
June	744940	243.755	233.862	745417.731
July	755195	305.212	240.880	755741.092
August	731105	169.179	242.414	731516.093
September	722299	354.239	229.840	728701.080
October	686801	287.258	237.387	687325.145
November	556141	423.982	225.376	556790.358
December	646759	492.344	235.248	647486.593

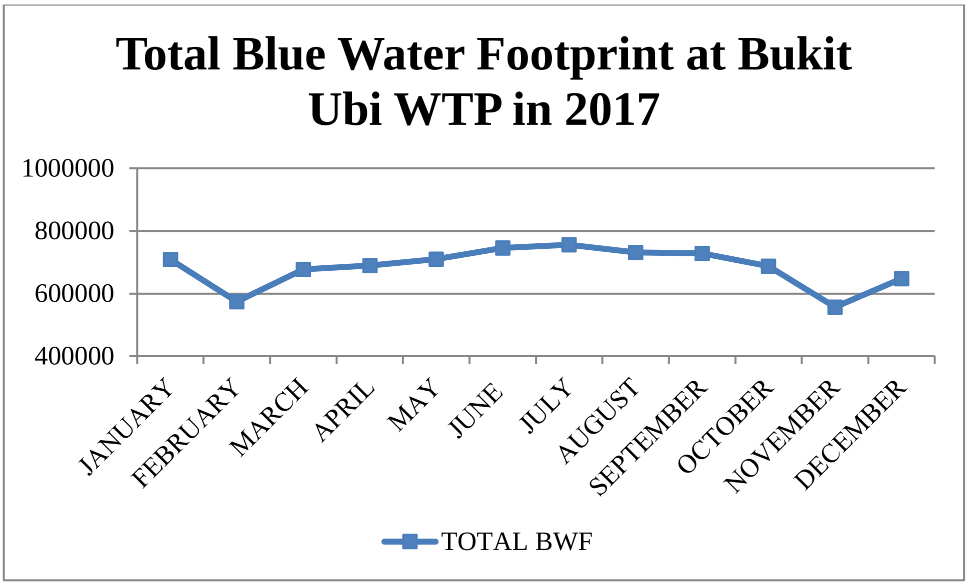


Figure 4.11 Total blue water footprint at Bukit Ubi WTP in 2017

Table 4.12 shows the total blue water footprint amount from January to December 2017 at Bukit Ubi WTP. In January, the amount of blue water footprint was 708549.89m^3/month. It then decrease to 574225.063m^3/month in February which caused by lower water intake compared to January. From March to July, the trend was rise due to high amount of water intake. It then starts to decrease steadily on September to the end year due to lower water intake for that month. There was decreasing in total amount of blue water footprint in October with 687325.145m^3/month. Meanwhile November and December shows decreasing in total blue water footprint with 556790.358^3/month and 647486.593m^3/month respectively. This was due to the lower water intake for that month. Low water intake basically due to dry season, where the water abstracted must be lemmatized because it is afraid more sediment will be abstracted rather than raw water, and this will result in damaging the treatment plant or more alum needed and more costing will be added. This proves that the water intake value plays big roles in trend of blue water footprint. The total blue water footprint recorded at Bukit Ubi WTP for year 2017 was 8211591m^3.

Table 4.0.13 Total blue water footprint analysis at Bukit Ubi WTP in 2015 to 2017

Month	Total Blue Water Footprint (m^3)		
	2015	2016	2017
January	821489	750752	708550
February	810644	686273	574225
March	890305	841250	676987
April	865325	698968	689192
May	892757	697471	709659
June	820212	661904	745418
July	838695	725327	755741
August	823151	714810	731516
September	639147	639339	728701
October	772048	655127	687325
November	743069	701103	556790
December	744992	754769	647487
Total Blue Water Footprint	9661834	8527094	8211591

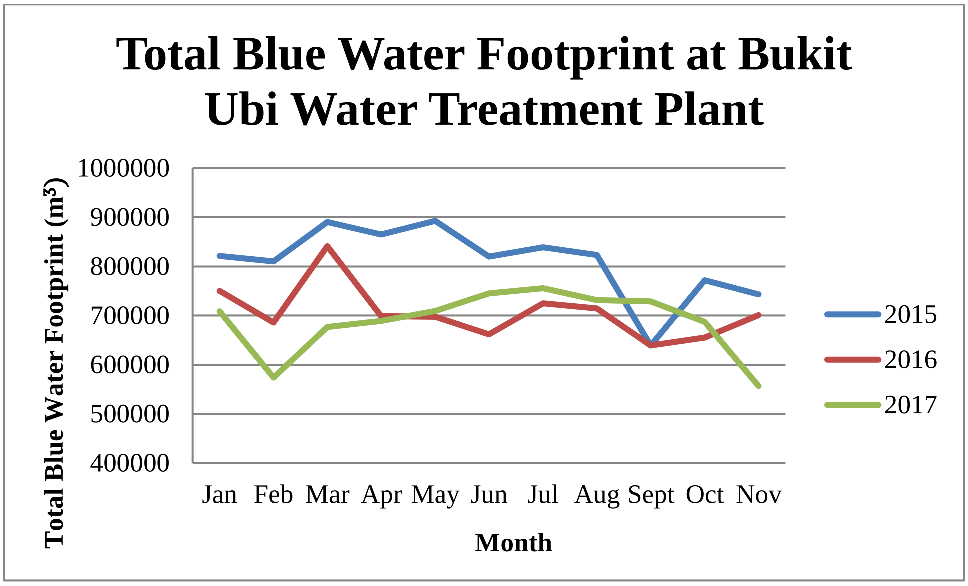


Figure 4.12 Total blue water footprint analysis at Bukit Ubi WTP in 2015 to 2017

By referring to the figure 4.12 of blue water footprint accounting for 2015, it shows that the lowest data was recorded in September 2015 at Bukit Ubi water treatment plant with a value of 639,147m^3/month. However the value increased back on October until December. The value of blue water footprint of Bukit Ubi in 2016 has the highest value in March with 841,250 m^3/month but then starts to fluctuate continuously until September increase back to December. Accounting at Bukit Ubi Water Treatment Plant in 2017 was having two lowest values in February and November.

4.3 Prediction of Blue Water Footprint

4.3.1 Sungai Lembing Water Treatment Plant

4.3.1.1 Artificial Neural Network Algorithm

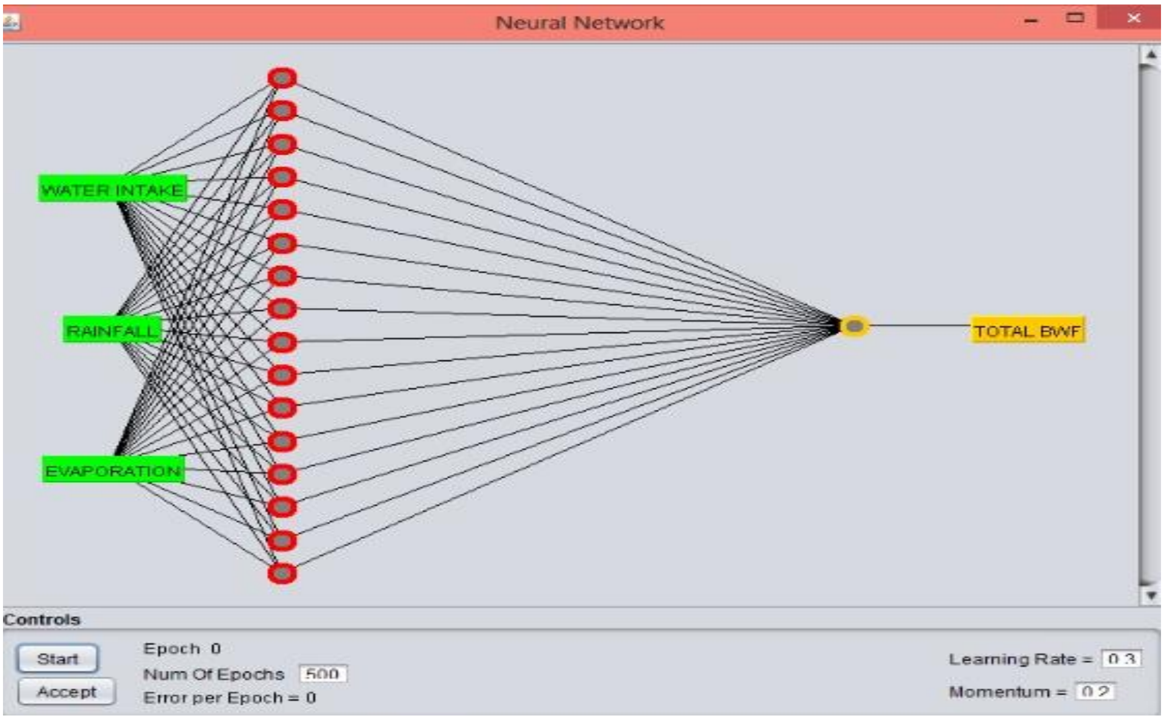


Figure 4.13 Number of hidden layers for ANN in WEKA software

Figure 4.13 illustrates the number of hidden layer by using Artificial Neural Networks algorithm after performing training data sets. Number of neurons was defined by number of hidden layer in Artificial Neural Networks. In order to produce the output, the number of neuron was produce and trained. It will be trained the blue water footprint data sets and produced the predicted value. For the study, 20 hidden neurons were trained as the neuron was adjustable. The lowest RMSE produced during the training will be selected in order to produce the predicted trend.

Table 4.0.14 Analysis of RMSE and hidden neurons at Sungai Lembing WTP

Hidden Neuron	RMSE	Hidden Neuron	RMSE
1	0.0031	**11**	0.0011
2	0.0021	**12**	0.0011
3	0.0016	**13**	0.0012
4	0.0014	**14**	0.0013
5	0.0015	**15**	0.0015
6	0.0013	**16**	0.0014
7	0.0013	**17**	0.0012
8	0.0011	**18**	0.0013
9	0.0011	**19**	0.0010
10	0.0010	**20**	0.0011

By referring to table above, the lowest RMSE was 0.0010 which produced by the hidden neuron 10 was chosen to predict the total blue water footprint at Sungai Lembing because of the lowest RMSE value compared to other neurons. 0.0010 was chosen because it gives the optimum value. The value of RMSE is different depends on the number of hidden neurons that used to train the data sets. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. Thus, the lowest RMSE value for Artificial Neural Network at Sungai Lembing was 0.010.

Table 0.15 Analysis of actual and predicted value of blue water footprint at Sungai Lembing by using ANN

Month	Actual (m^3)	Predicted (m^3)
January 2015	140888.858	140925.467
February 2015	132327.315	132302.007
March 2015	132178.709	132235.682
April 2015	131978.333	132021.546
May 2015	130739.127	130738.008
June 2015	145073.993	144807.677
July 2015	137137.042	138973.639
August 2015	137196.648	137151.774
September 2015	123124.318	123137.995
October 2015	140836.700	140820.175
November 2015	135109.236	135057.224
December 2015	134817.432	134782.631
January 2016	139891.000	139864.527
February 2016	137633.000	137559.618
March 2016	145984.000	145854.639
April 2016	142776.000	142612.259
May 2016	142691.000	142568.844
June 2016	141371.000	141294.715
July 2016	145452.000	145366.282
August 2016	145439.000	145293.907
September 2016	140871.000	140797.514
October 2016	145744.000	145702.257
November 2016	131428.000	131445.168
December 2016	137582.000	137585.389
January 2017	137301.000	137309.258
February 2017	127752.000	127772.613
March 2017	138501.000	138518.397
April 2017	132139.000	132130.017
May 2017	140274.000	140282.020
June 2017	134941.000	134889.739
July 2017	136332.000	136267.282
August 2017	126200.000	126208.851
September 2017	132640.000	132663.244
October 2017	129291.000	129294.728
November 2017	123013.000	122915.847
December 2017	128422.000	128392.603
TOTAL	4905075.711	4905543.544

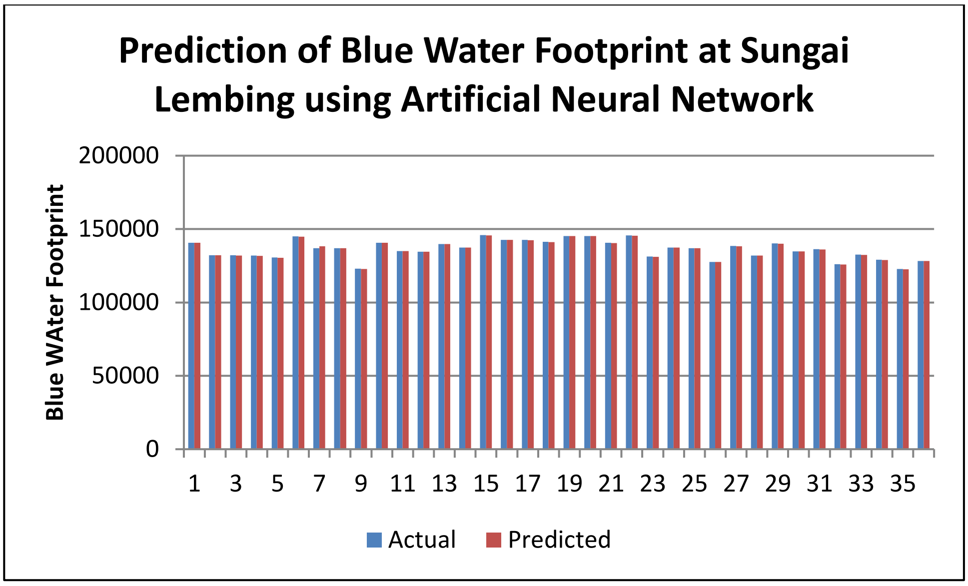


Figure 4.14 Prediction of blue water footprint t at Sungai Lembing WTP using ANN

Figure 4.14 illustrates the actual and predicted value of blue water footprint at Sungai Lembing WTP after undergoes training using ANN. The total actual amount of blue water footprint was 4905075.711m^3 and the predicted amount was 4905543.544m^3. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. In addition, predicted value of blue water footprint at Sungai Lembing in 2018 was 1622954m^3/ year compared to actual value with is 1621408m^3/year. The value was increase to 0.095%. In 2019, the predicted value obtained was 1695945m^3/year. There was decreasing in the value of blue water footprint by 0.054% compared to actual value. Meanwhile, 2020 also shows decreasing amount of blue water footprint in Sungai Lembing by 0.010% from the actual value which is 1586806m^3/year. Overall, Sungai Lembing shows an increasing in amount of blue water footprint in predicted year by 0.010%.

4.3.1.2 Bayesian Networks Algorithm

Table 4.0.16 RMSE value at Sungai Lembing using BN

Algorithm	RMSE
Bayesian Networks	0.0348

By referring above, Bayesian Networks produced 0.0348 of RMSE value which is higher than Artificial Neural Network. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. This results to the fixed one hidden neuron for Bayesian Networks. Thus, Sungai Lembing water treatment plant was chosen Artificial Neural Network as best algorithm due to the lower value compared to Bayesian Networks.

Table 4.0.17 Analysis of actual and predicted value of blue water footprint at Sungai Lembing by using BN

Month	Actual (m^3)	Predicted (m^3)
January 2015	140771.000	141473.756
February 2015	132244.000	125017.573
March 2015	132090.000	147138.868
April 2015	131880.000	139733.296
May 2015	130610.000	148296.068
June 2015	144987.000	136641.927
July 2015	137022.000	132538.915
August 2015	137063.000	145095.745
September 2015	123030.000	146048.283
October 2015	140722.000	142236.853
November 2015	134982.000	139493.223
December 2015	134666.000	149458.475
January 2016	139797.000	143248.791
February 2016	137474.000	130051.863
March 2016	145912.000	141605.526
April 2016	142697.000	133719.414
May 2016	142529.000	142073.936
June 2016	136425.000	129966.842
July 2016	145328.000	139502.488
August 2016	145319.000	140111.677
September 2016	140691.000	135113.070
October 2016	145572.000	139119.925
November 2016	131254.000	143276.418
December 2016	137431.000	144319.665
January 2017	137058.000	144394.866
February 2017	127596.000	127445.080
March 2017	138383.000	143385.121
April 2017	132031.000	140615.598

May 2017	135479.000	137938.323
June 2017	134837.000	139165.809
July 2017	136232.000	145106.979
August 2017	126076.000	157938.369
September 2017	132501.000	139773.509
October 2017	129128.000	154550.843
November 2017	122821.000	145176.161
December 2017	128219.000	151638.957
TOTAL	4890857.000	5082412.214

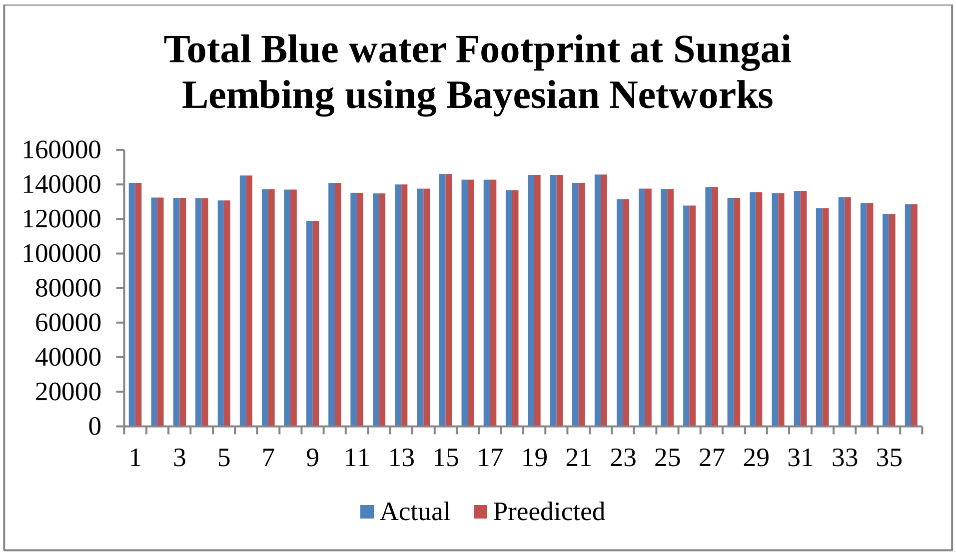


Figure 4.15 Prediction of blue water footprint t at Sungai Lembing WTP using BN

Figure 4.15 illustrates the actual and predicted value of blue water footprint at Sungai Lembing WTP after undergoes training using BN. The total actual amount of blue water footprint was 4890857.00m³ and the predicted amount was 5082412.214m³. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. In addition, predicted value of blue water footprint at Sungai Lembing in 2018 was 1693173m³/ year compared to actual value with is 1620067m³/year. The value was increase to 4.32%. In 2019, the predicted value obtained was 1662110m³/year. There was decreasing in the value of blue water footprint by 1.70% compared to actual value. Meanwhile, 2020 shows increasing amount of blue water footprint in Sungai Lembing by 8.50% from the actual value which is 1580361m^3/year. Overall, Sungai Lembing shows an increasing in amount of blue water footprint in predicted year by 3.77%.

4.3.2 Bukit Sagu Water Treatment Plant

4.3.2.1 Artificial Neural Network Algorithm

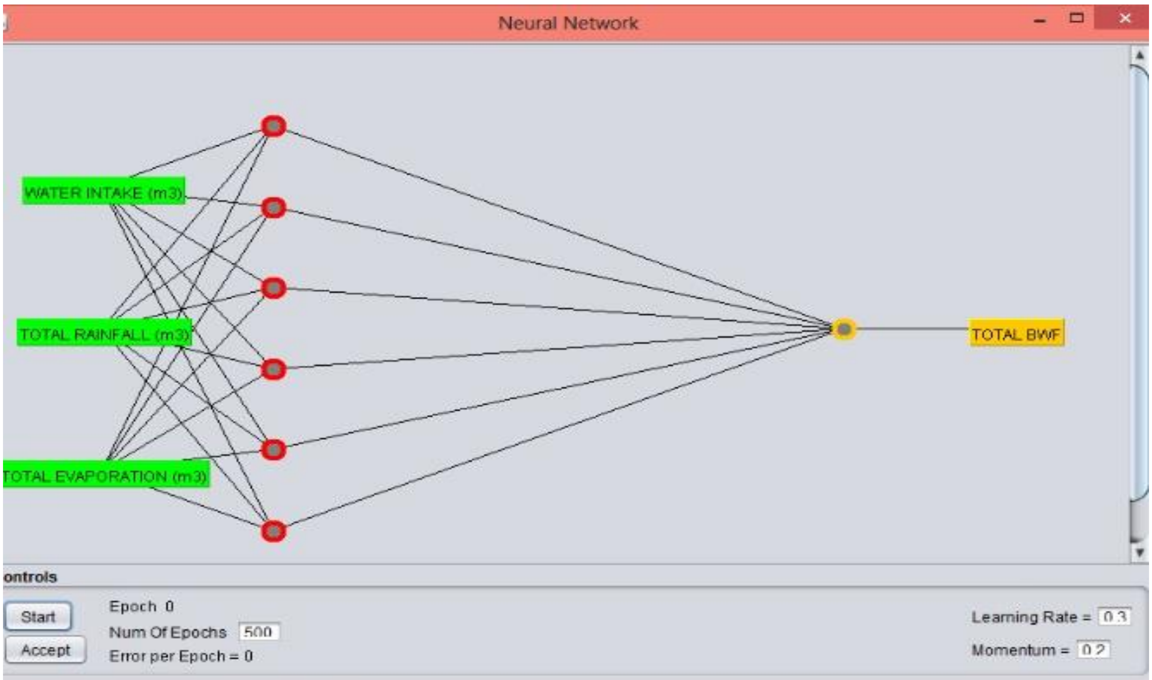


Figure 4.16 Number of hidden layers for ANN at Bukit Sagu WTP in WEKA software

Figure 4.16 illustrates the number of hidden layer by using Artificial Neural Networks algorithm after performing training data sets. Number of neurons was defined by number of hidden layer in Artificial Neural Networks. In order to produce the output, the number of neuron was produce and trained. It will be trained the blue water footprint data sets and produced the predicted value. For the study, 20 hidden neurons were trained as the neuron was adjustable. The lowest RMSE produced during the training will be selected in order to produce the predicted trend.

Table 4.0.18 Analysis of RMSE and hidden neurons at Bukit Sagu WTP

Hidden Neuron	RMSE	Hidden Neuron	RMSE
1	0.0270	**11**	0.0236
2	0.0249	**12**	0.0238
3	0.0243	**13**	0.0237
4	0.0243	**14**	0.0238
5	0.0244	**15**	0.0238
6	0.0234	**16**	0.0235
7	0.0235	**17**	0.039
8	0.0235	**18**	0.0240
9	0.0235	**19**	0.0242
10	0.0235	**20**	0.0249

By referring to table above, the lowest RMSE was 0.0234 which produced by the hidden neuron 6 was chosen to predict the total blue water footprint at Bukit Sagu because of the lowest RMSE value compared to other neurons. The value of RMSE is different depends on the number of hidden neurons that used to train the data sets. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. Thus, the lowest RMSE value for Artificial Neural Network at Bukit Sagu was 0.0234.

Month	Actual (m^3)	Predicted (m^3)
January 2015	158710.938	158566.183
February 2015	130108.525	129770.608
March 2015	108676.184	108612.158
April 2015	56581.670	56554.895
May 2015	142975.584	142883.746
June 2015	144303.375	143414.323
July 2015	161439.582	177453.919
August 2015	158057.266	157657.225
September 2015	107866.500	107710.420
October 2015	185711.547	185305.657
November 2015	190772.589	190125.778
December 2015	164653.528	164305.359

January 2016	183596.979	183138.853
February 2016	175447.827	174772.734
March 2016	181006.632	180298.596
April 2016	198420.768	197699.580
May 2016	175937.643	175349.981
June 2016	155064.117	154603.560
July 2016	169713.335	169174.242
August 2016	158044.707	157385.843
September 2016	161511.190	160963.867
October 2016	186415.984	185926.157
November 2016	171297.675	171050.199
December 2016	178752.736	178491.246
January 2017	172791.250	172564.954
February 2017	160706.416	160547.016
March 2017	171121.920	170922.932
April 2017	157520.953	157224.840
May 2017	188810.354	188519.831
June 2017	167876.059	167381.604
July 2017	173028.817	172672.292
August 2017	175776.748	175517.828
September 2017	189635.864	189411.024
October 2017	186947.902	186811.770
November 2017	185499.936	184986.015
December 2017	189419.328	188997.727
TOTAL	5924202.428	5926772.965

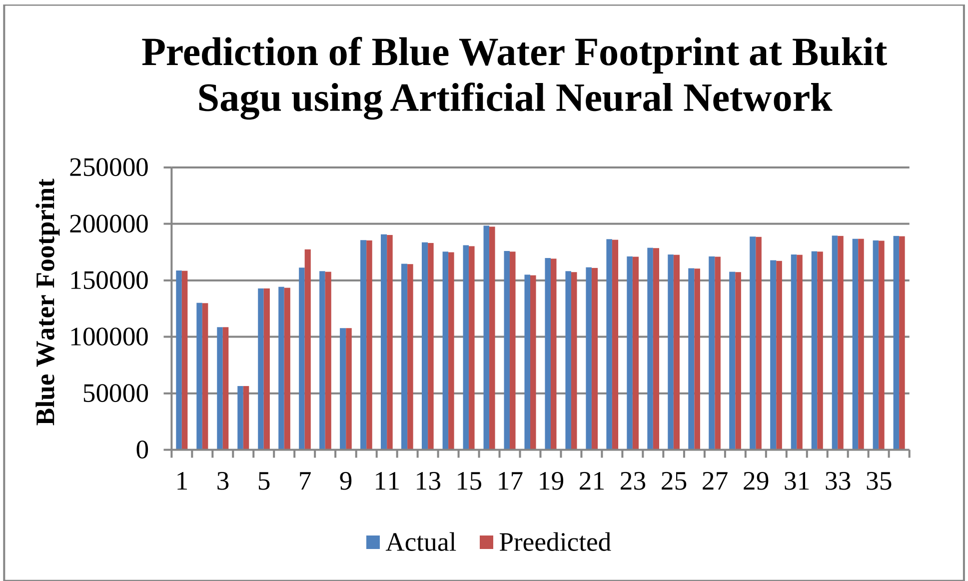


Figure 4.17 Prediction trend of blue water footprint at Bukit Sagu WTP using ANN

Figure 4.17 illustrates the actual and predicted value of blue water footprint as Bukit Sagu WTP after undergoes training using ANN. The total actual amount of blue water footprint was 5924203m³ and the predicted amount was 5926773m³. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. In addition, predicted value of blue water footprint at Bukit Sagu in 2018 was 1722360m³/ year compared to actual value with is 1709857m³/year. The value was increase by 0.726%. In 2019, the predicted value obtained was 20888545m³/year. There was decreasing in the value of blue water footprint by 0.304% compared to actual value. Meanwhile, 2020 also shows decreasing amount of blue water footprint in Bukit Sagu by 0.169% from the actual value which is 2119136m³/year. The predicted amount of blue water footprint was 2115556m³/year. Overall, Bukit Sagu shows an increasing in amount of blue water footprint in predicted year by 0.043%.

4.3.2.2 Bayesian Networks Algorithm

Table 4.0.19 RMSE value at Bukit Sagu using BN

Algorithm	**RMSE**
Bayesian Networks	0.0314

By referring above, Bayesian Networks produced 0.0314 of RMSE value which is higher than Artificial Neural Network. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. This results to the fixed one hidden neuron for Bayesian Networks. Thus, Bukit Sagu water treatment plant was chosen Artificial Neural Network as best algorithm due to the lower value compared to Bayesian Networks.

Table 4.0.20 Analysis of actual and predicted value of blue water footprint at Bukit Sagu by using BN

Month	Actual (m^3)	Predicted (m^3)
January 2015	158710.950	158643.850
February 2015	130108.490	130074.510
March 2015	108676.190	109969.040
April 2015	56581.690	56558.570
May 2015	142975.570	137518.780
June 2015	137648.210	99999.510
July 2015	155724.480	123168.520
August 2015	163772.370	144248.140
September 2015	107866.510	107846.410
October 2015	185711.560	147492.990
November 2015	190772.600	156992.810
December 2015	164653.540	147275.220
January 2016	183596.980	155811.090
February 2016	175447.800	139943.380
March 2016	181006.660	123637.930
April 2016	198420.820	83458.800
May 2016	175937.630	128349.490
June 2016	155064.100	111830.800
July 2016	169713.320	139291.720
August 2016	158044.700	145420.940
September 2016	161511.150	144688.030
October 2016	186415.980	165210.670
November 2016	171297.680	157691.050
December 2016	178752.730	154180.520
January 2017	179094.820	150115.810
February 2017	154402.830	130665.370
March 2017	171121.930	142198.030
April 2017	157520.930	99768.880
May 2017	188810.350	141326.750
June 2017	167876.050	135976.290
July 2017	173028.850	143220.680
August 2017	175776.750	133028.880
September 2017	189635.900	149302.280
October 2017	186947.910	165555.340
November 2017	185499.930	162207.420
December 2017	189419.350	166066.840
TOTAL	5917547.310	4888735.340

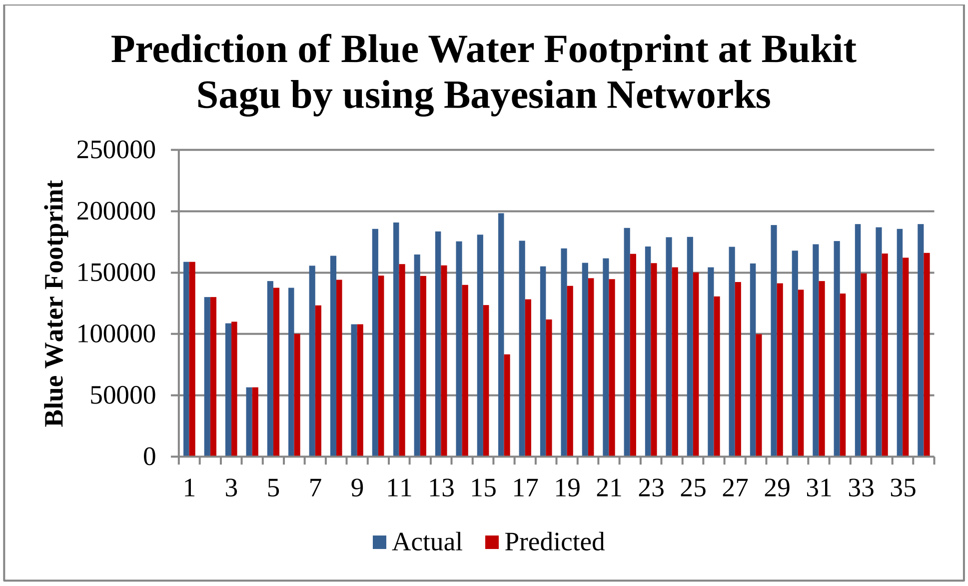


Figure 4.18 Prediction of blue water footprint at Bukit Sagu WTP using BN

Figure 4.18 illustrates the actual and predicted value of blue water footprint as Bukit Sagu WTP after undergoes training using BN. The total actual amount of blue water footprint was 5917547.310m³ and the predicted amount was 4888735.340m³. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. In addition, predicted value of blue water footprint at Bukit Sagu in 2018 was 1519788.35m³/ year compared to actual value with is 1703203.16m³/year. The value was decrease by 12.07%. In 2019, the predicted value obtained was 1649514.42m³/year. There was decreasing in the value of blue water footprint by 27.02% compared to actual value. Meanwhile, 2020 also shows decreasing amount of blue water footprint in Bukit Sagu by 23.25% from the actual value which is 2119135.60m³/year. The predicted amount of blue water footprint was 1719432.57m³/year. Overall, Bukit Sagu shows an increasing in amount of blue water footprint in predicted year by 21.04%.

4.3.3 Bukit Ubi Water Treatment Plant

4.3.3.1 Artificial Neural Network Algorithm

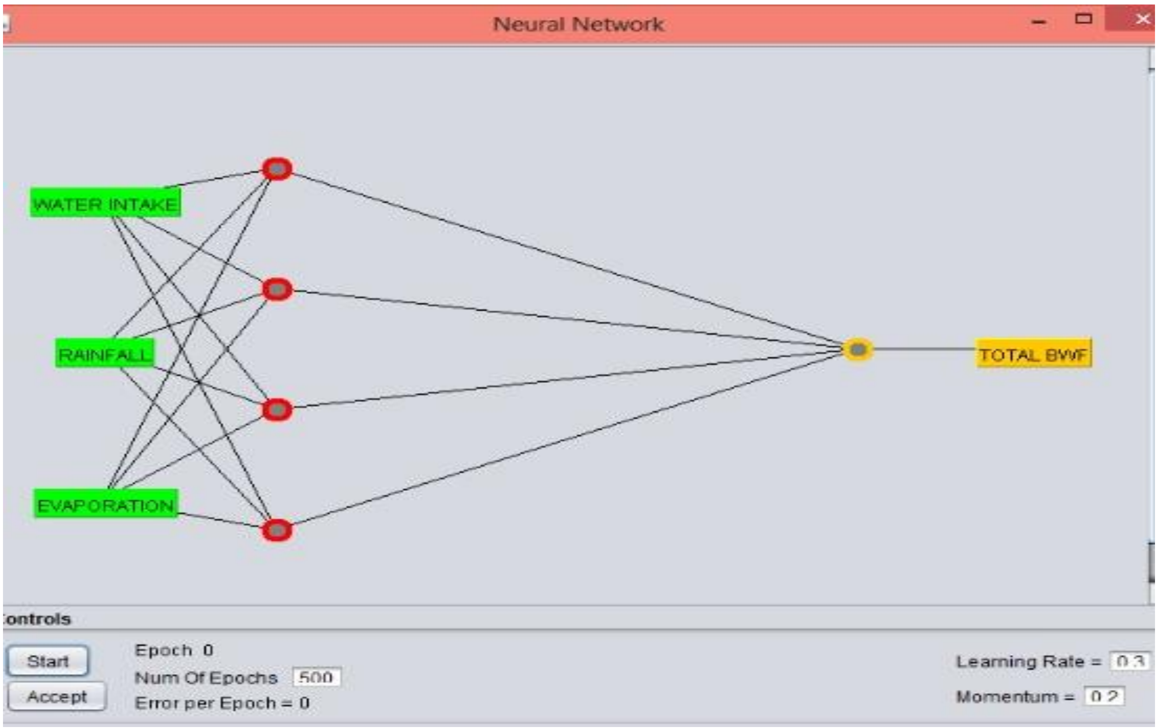


Figure 4.19 Number of hidden layers for ANN in WEKA software

Figure 4.19 illustrates the number of hidden layer by using Artificial Neural Networks algorithm after performing training data sets. Number of neurons was defined by number of hidden layer in Artificial Neural Networks. In order to produce the output, the number of neuron was produce and trained. It will be trained the blue water footprint data sets and produced the predicted value. For the study, 20 hidden neurons were trained as the neuron was adjustable. The lowest RMSE produced during the training will be selected in order to produce the predicted trend.

Table 4.0.21 Analysis of RMSE and hidden neurons at Bukit Ubi WTP

Hidden Neuron	**RMSE**	**Hidden Neuron**	**RMSE**
1	0.0146	**11**	0.0129
2	0.0130	**12**	0.0128
3	0.0130	**13**	0.0128
4	0.0128	**14**	0.0130
5	0.0290	**15**	0.0129
6	0.0130	**16**	0.0128
7	0.0129	**17**	0.0129
8	0.0128	**18**	0.0129
9	0.0128	**19**	0.0128
10	0.0129	**20**	0.0128

By referring to table above, the lowest RMSE was 0.0128 which produced by the hidden neuron 4 was chosen to predict the total blue water footprint at Bukit Ubi because of the lowest RMSE value compared to other neurons. The value of RMSE is different depends on the number of hidden neurons that used to train the data sets. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. Thus, the lowest RMSE value for Artificial Neural Network at Bukit Ubi was 0.0128.

Table 4.0.22 Analysis of actual and predicted value of blue water footprint at Bukit Ubi by using ANN

Month	**Actual (m^3)**	**Predicted (m^3)**
January 2015	821489.466	821081.522
February 2015	810644.125	807978.354
March 2015	890304.631	888076.501
April 2015	865325.472	863003.340
May 2015	892757.094	890341.426
June 2015	820212.305	818957.233
July 2015	838694.981	837596.922
August 2015	823150.693	821864.249

September 2015	639146.532	639303.768
October 2015	772048.475	771232.471
November 2015	743068.634	741656.532
December 2015	744991.554	743548.335
January 2016	750751.527	749779.078
February 2016	686273.256	684798.377
March 2016	841250.449	840372.113
April 2016	698968.480	699533.500
May 2016	697471.298	697189.143
June 2016	661904.237	662155.249
July 2016	725327.477	724982.645
August 2016	714809.584	714213.094
September 2016	639339.188	639590.586
October 2016	655126.605	654875.688
November 2016	701103.193	699659.898
December 2016	754768.868	752666.666
January 2017	708549.858	722671.373
February 2017	574225.063	574570.151
March 2017	676986.710	677112.493
April 2017	689191.948	689286.370
May 2017	709659.418	709471.510
June 2017	745417.731	744193.920
July 2017	755741.092	755082.314
August 2017	731516.093	731767.915
September 2017	728701.080	722110.391
October 2017	687325.145	687129.380
November 2017	556790.358	558328.613
December 2017	647486.593	646921.960
TOTAL	26400519.214	26383103.078

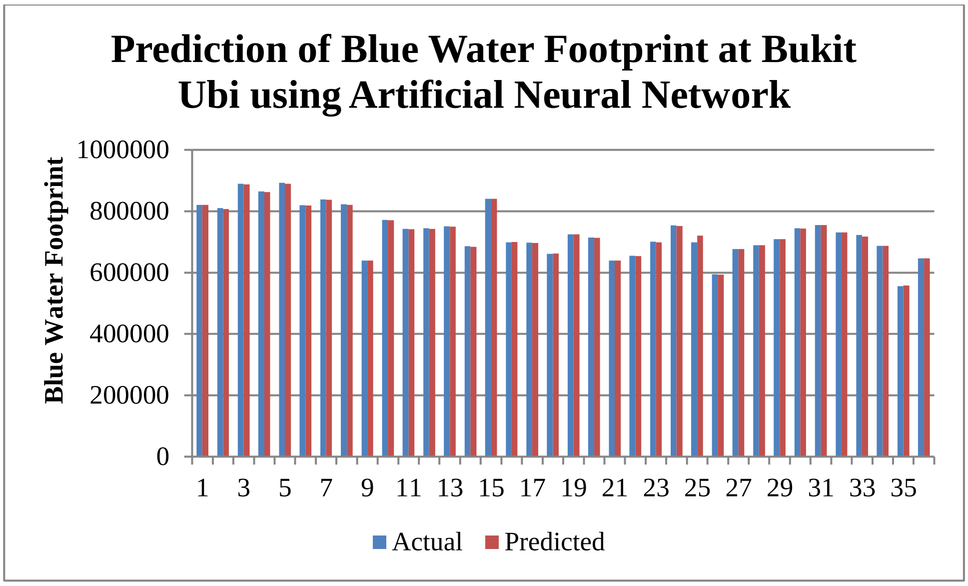


Figure 4.20 Prediction trend of blue water footprint at Bukit Ubi WTP using ANN

Figure 4.20 illustrates the actual and predicted value of blue water footprint as Bukit Ubi WTP after undergoes training using ANN. The total actual amount of blue water footprint was 26400519m^3 and the predicted amount was 26383103m^3. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. Meanwhile for predicted value of blue water footprint at Bukit Ubi in 2018 was 9644641m^3/ year compared to actual value with is 9661834m^3/year. The value was decrease by 0.178%. In 2019, the predicted value obtained was 8519816m^3/year. There was decreasing in the value of blue water footprint by 0.085% compared to actual value. Meanwhile, 2020 shows an increasing amount of blue water footprint in Bukit Ubi by 0.1086% from the actual value which is 8211591m^3/year. The predicted amount of blue water footprint was 8218646m^3/year. Overall, Bukit Ubi shows decreasing in amount of blue water footprint in predicted year by 0.066%.

4.3.3.2 Bayesian Networks Algorithm

Table 4.0.23 RMSE value at Bukit Ubi using BN

Algorithm	RMSE
Bayesian Networks	0.0310

By referring above, Bayesian Networks produced 0.0310 of RMSE value which is higher than Artificial Neural Network. Artificial Neural Networks algorithm can be trained multiple times due to the adjustable neuron. Meanwhile, Bayesian Network cannot be adjustable. This results to the fixed one hidden neuron for Bayesian Networks. Thus, Bukit Ubi water treatment plant was chosen Artificial Neural Network as best algorithm due to the lower value compared to Bayesian Networks.

Table 4.0.24 Analysis of actual and predicted value of blue water footprint at Bukit Ubi by using BN

Month	Actual (m^3)	Predicted (m^3)
January 2015	794460.000	765087.513
February 2015	836746.000	753305.407
March 2015	890007.000	820886.502
April 2015	864985.000	794358.412
May 2015	892342.000	820778.746
June 2015	819896.961	799912.198
July 2015	838374.000	820860.939
August 2015	822331.000	805808.904
September 2015	638764.085	792607.917
October 2015	771577.000	806140.134
November 2015	742431.014	779544.981
December 2015	744267.669	773436.798
January 2016	750266.208	820680.581
February 2016	685828.640	767734.065
March 2016	840969.391	820899.854
April 2016	698715.014	794432.554
May 2016	697130.090	820821.706

June 2016	661396.927	794127.789
July 2016	725025.831	820869.397
August 2016	714131.449	820423.575
September 2016	638764.085	794045.652
October 2016	654469.378	820422.557
November 2016	700366.829	793873.861
December 2016	753919.997	820273.879
January 2017	719508.738	836620.871
February 2017	573744.122	741167.766
March 2017	676610.359	820771.686
April 2017	688857.000	794335.049
May 2017	709200.821	820684.480
June 2017	744940.114	794191.370
July 2017	755195.000	820610.120
August 2017	731104.500	820744.696
September 2017	722299.000	785930.190
October 2017	686800.500	794078.359
November 2017	556141.000	793841.586
December 2017	646759.000	600000.000
TOTAL	26388326.00	28644310.00

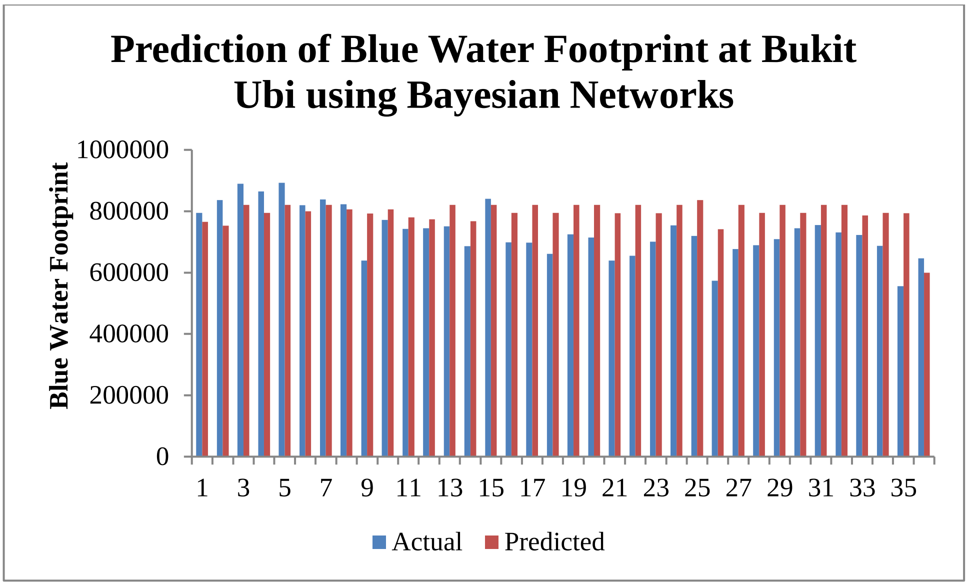


Figure 4.21 Prediction of blue water footprintt at Bukit Ubi WTP using BN

Figure 4.21 illustrates the actual and predicted value of blue water footprint as Bukit Ubi WTP after undergoes training using BN. The total actual amount of blue water footprint was 26388326.00m³ and the predicted amount was 28644310.00m³. The differences between the actual and predicted value is slightly the same due to the least error that been made during the training. In addition, predicted value of blue water footprint at Bukit Ubi in 2018 was 9532728m³/ year compared to actual value with is 9656182m³/year. The value was decrease by 1.30%. In 2019, the predicted value obtained was 9688605m³/year. There was increasing in the value of blue water footprint by 12.05% compared to actual value. Meanwhile, 2020 shows an increasing amount of blue water footprint in Bukit Ubi by 12.86% from the actual value which is 8211160m³/year. The predicted amount of blue water footprint was 9422976m³/year. Overall, Bukit Ubi shows increasing in amount of blue water footprint in predicted year by 7.88%.

CHAPTER 5

CONCLUSION AND RECOMMANDATION

5.1 Conclusion

At the end result of this study, total blue water footprint of Sungai Lembing, Bukit Sagu and Bukit Ubi water treatment plants in Kuantan river basin throughout year 2015 to 2017 has been calculated. The amount of blue water footprint was obtained 1,621,408m^3/year in 2015, 1,696,862 m^3/year in 2016 and 1,586,806m^3/year in year 2017 for Sungai Lembing water treatment plant. Meanwhile for Bukit Sagu water treatment plant was 1,709,857m^3/year in 2015, 2,095,210m^3/year in 2016 and 2,119,136m^3/year in year 2017. Bukit Ubi recorded the highest value of blue water footprint throughout year 2015 to 2017 with 9,661,834 m^3/year, 8,527,094m^3/year and 8,211,591m^3/year respectively.

This might due to the area of the water treatment which is larger than others. The area of Bukit Ubi was 1381.05m^2. Meanwhile area for Sungai Lembing and Bukit Sagu was 331.61m^2 and 276.02m^2 respectively. Moreover, total blue water footprint obtained in Sungai Lembing, Bukit Sagu and Bukit ubi water treatment plant in three years were 4,905,076m^3, 5,924,203m^3 and 26,400,519m^3 respectively. The result indicates that the water resources in three water treatment plants were sustainable to supply for consumer.

In addition, the best algorithm was able to determine by selecting the lowest root mean square error (RMSE) between Artificial Neural Network and Bayesian Networks. Both algorithms will undergo series of training before produced RMSE value. The

RMSE value for Sungai Lembing was 0.001 for Artificial Neural Network and 0.0348 for Bayesian Networks. Besides, Bukit Sagu produced RMSE value for Artificial Neural Network and Bayesian Networks was 0.0242 and 0.0314 respectively. Meanwhile, RMSE value for Bukit Ubi was 0.0128 for Artificial Neural Network and 0.031 for Bayesian Networks. Result shows that the lowest RMSE produced by Artificial Neural Network was lowest compared to Bayesian Networks for all water treatments plant. Hence, Artificial Neural Network was selected for all water treatment plants to be used in prediction of blue water footprint. Besides, predicted trend of blue water footprint in all water treatment plants was able to estimate at the end of study. The predicted trend was estimated to increase in upcoming years due to population increased and high demand of water.

5.2 Recommendation for Future Research

As the recommendation for the future, water treatment plants must take action by proper planning and design while improve the water management at water treatment plants. This is to reduce the overall blue water footprint consumption wasted. Besides, by controlling the water intake will helps in decreasing the blue water footprint. Water intake should limited to water demand only as it contributed the most to the total blue water footprint compared to rainfall intensity and evaporation. A better management of water resources system is essential to sustain all the water demands and present a continuous better quality of water in the future. In addition, uses of closed tank design for all water treatment plant as it will lower the evaporation value. Industrial management must start to use treated waste water in several parts of their process in order to reduce the amount of blue water footprint.

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APPENDIX A
SAMPLE APPENDIX 1

Table 6.1 Example table of blue water footprint analysis used in study

WATER INTAKE (m^3)	AREA					EVAPORATION						TOTAL BWF (m^3)
	AERATION	FLOCCULATION	SEDIMENTATION	FILTERATION	TOTAL AREA (m^2)	PER DAY (m)	TOTAL (m^3)	P FACTOR	TEMP	EVA PORATION	TOTAL EVA PORATION (m^3)	