DEVELOPMENT OF NEURAL NETWORK BASED ESTIMATOR TO DETERMINE COAGULANT DOSAGE AND TREATED WATER QUALITIES IN A WATER TREATMENT PLANT

by

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LIST OF ABBREVIATIONS

Alum	Aluminum sulphate
AI	Artificial Intelligence
ANN	Artificial Neural Network
BP	Backpropagation algorithm
DOC	Dissolved Organic Compounds
FBNN	Feedback Neural Network
FFNN	Feedforward Neural Network
GUI	Graphical User Interface
HDPE	High Density Polyethylene
HU	Hazen Units (colour measurement)
JANS	Jabatan Air Negeri Sabah (Sabah Water Supply Department)
LDWS	Lahad Datu Water Supply
LM	Levenberg–Marquardt algorithm
LR	Learning Rate
MAE	Mean Absolute Error
MC	Momentum Constant
MLP	Multiple Linear Perceptron
MIMO	Multiple-input multiple-output
MISO	Multiple-input single-output
MSE	Mean Square Error
NOM	Natural Organic Matter
NTU	Nephlometric Turbidity Unit

PAC	Powdered Activated Carbon
PCA	Principal Component Analysis
PE	Processing elements
r-value	Correlation coefficient
R^2	Coefficient of determination
RW	Raw water
SCADA	Supervisory Control and Data Acquisition
SCD	Streaming Current Detector
SSE	Sum Square Error
TDS	Total dissolved solids
TSS	Total suspended solids
TOC	Total Organic Compounds
TW	Treated water
UVA-254 nm	Ultraviolet Absorbance (254 nanometer)
WHO	World Health Organization
WTP	Water Treatment Plant

PEMBANGUNAN PENGANGGAR BERASASKAN RANGKAIAN NEURAL UNTUK MENENTUKAN DOS PENGENTAL DAN KUALITI AIR TERAWAT DI LOJI RAWATAN AIR

ABSTRAK

Penentuan dos pengental yang optima di dalam proses pengentalan bagi sesebuah loji rawatan air adalah amat mustahak untuk menghasilkan kualiti air terawat yang memuaskan dan untuk mengekalkan operasi loji yang ekonomi seperti mengurangkan tenaga kerja dan mengawal bahan kimia yang mahal. Kegagalan menentukan dos yang optima ini akan mengurangkan kecekapan proses pengendapan dan penapisan di dalam loji rawatan air berkenaan. Secara tradisional, ujian balang digunakan untuk menentukan dos pengental yang optima. Walau bagaimanapun, kaedah ini adalah mahal, memerlukan masa yang panjang dan tidak dapat memberikan tindak balas yang segera terhadap perubahan kualiti air mentah pada masa yang sebenar. Pemodelan seperti rangkaian neural buatan boleh digunakan untuk mengatasi keterbatasan ini. Dalam kajian ini, model rangkaian neural berbalik dibangunkan untuk menganggarkan dos pengental yang diperlukan di Loji Rawatan Air Segama, Lahad Datu, Sabah, Malaysia. Di samping itu, proses model juga dibina untuk menganggarkan kualiti air terawat yang berkaitan dengan dos pengental seperti parameter-parameter kekeruhan, warna, pH dan baki aluminum. Model-model rangkaian neural dengan struktur yang berbeza-beza, termasuk satu dan dua lapisan tersembunyi telah dibangunkan. Untuk proses neural berbalik, rangkaian struktur optima yang diperolehi adalah [11-27-9-1]. Model ini memberikan anggaran baik terhadap julat data yang digunakan dalam latihan, dengan nilai r 0.95, MSE, 0.0019 dan MAE, 0.0024 mg/l, apabila digunakan ke atas data ujian. Untuk proses model, dua jenis model yang berbeza telah dibangunkan iaitu model-model berbilang-masukan satu-keluaran (MISO) dan

berbilang-masukan berbilang keluaran (MIMO). Kedua-dua jenis model tersebut telah dibangunkan untuk menentukan parameter-parameter air terawat seperti pH, kekeruhan, warna dan baki aluminum. Rangkaian struktur yang optima bagi model MISO dapat menentukan semua parameter kualiti air terawat, dengan tepat; nilai r di antara 0.88 dan 0.97, dan nilai MSE di antara 0.0003 hingga 0.0028. Tambahan pula, nilai-nilai MAE yang diperolehi adalah rendah iaitu 0.035 untuk pH, 0.035 NTU untuk kekeruhan, 0.016 HU untuk warna dan 0.017 mg/l untuk baki aluminum. Sebaliknya, konfigurasi optima model MIMO yang diperolehi adalah kurang tepat berbanding model MISO dalam keupayaannya membuat anggaran, dengan nilai-nilai r dan MSE masing-masing di antara 0.27 hingga 0.84 dan 0.0024 hingga 0.0179. Ringkasnya, model-model MISO dapat mengatasi model-model MIMO dalam menganggarkan kualiti air terawat. Secara keseluruhannya, keputusan-keputusan pemodelan rangkaian neural membuktikan bahawa kaedah yang dicadangkan ini khususnya proses model berbalik berupaya menganggarkan dos pengental dengan amat baik. Dengan itu, ia berpotensi besar menggantikan kaedah konvensional iaitu ujian balang memandangkan ciri-cirinya yang dapat memberi keputusan dengan cepat, kos operasi yang murah dan kemampuannya untuk diaplikasikan dalam proses masa yang sebenar.

DEVELOPMENT OF NEURAL NETWORK BASED ESTIMATOR TO DETERMINE COAGULANT DOSAGE AND TREATED WATER QUALITIES IN A WATER TREATMENT PLANT

ABSTRACT

The determination of an optimum coagulant dosage in a coagulation process for a water treatment plant is very important in order to produce satisfactory treated water qualities and to maintain economic plant operation such as reducing manpower and controlling the high cost of chemicals. Failure to do this will reduce the efficiency in the sedimentation and filtration processes in the treatment plant. Traditionally, jar tests are used to determine the optimum coagulant dosage. However, this method is expensive, time-consuming, and does not enable responses to changes in raw water quality in real-time. Modeling, utilising artificial neural networks, can be used to overcome these limitations. In this work, an inverse neural network model is developed to predict the required coagulant dosage in the Segama Water Treatment Plant in Lahad Datu, Sabah, Malaysia. In addition, process models were also developed for the prediction of treated water qualities which are associated with coagulant dosage i.e. the parameters of turbidity, colour, pH and aluminum residue. Neural network models with different network architectures, including single and two hidden layers were developed. For the process inverse model, the optimum network architecture obtained was [11-27-9-1]. This model performed very well over the range of data used for training, with r-value of 0.95, mean square error (MSE) of 0.0019 and mean absolute error (MAE) of 0.024 mg/l when applied on the testing data set. For the process models, two different kinds of models were developed namely the multiple-input single-output (MISO) and the multiple-input multiple-output (MIMO) models. Both types of models were developed to determine the treated water parameters such as pH, turbidity, colour and aluminum

residue. The optimum network architecture of the MISO model managed to accurately determine all the treated water quality parameters with r-values between 0.88 and 0.97 and MSE value which ranged from 0.0003 to 0.0028. Moreover, the corresponding values of MAE were relatively low and were recorded as 0.035 for pH, 0.035 NTU for turbidity, 0.016 HU for colour and 0.017 mg/l for aluminum residue. On the other hand, the optimum MIMO models configuration obtained were found to be less accurate in prediction capabilities compared to the MISO models with r-values and MSE values which ranged from 0.27 to 0.84 and 0.0024 to 0.0179 respectively. In conclusion, the MISO models outperformed the MIMO models in predicting treated water qualities. Overall, the neural network modeling results prove that the proposed technique, particularly the process inverse model can predict the coagulant dosage very well. Therefore, it has a great potential of replacing the conventional method; jar test due to its quick responsive tools, economical operating cost and its capability to be applied in real-time process.

CHAPTER 1

INTRODUCTION

1.1 Project Background

The water industry is working very hard to produce high quality drinking water at a lower cost in order to meet the mandatory drinking water quality standard. Drinking water comes from two major sources: surface water such as lakes, rivers, and reservoirs; and groundwater, which is pumped from wells. Raw water from the source are pumped to the treatment plant and transformed into safe drinking water through treatment processes which involve physical, chemical and biological changes. Since surface water is exposed to the environment and can be easily contaminated, it normally has to go through several treatment processes such as coagulation, flocculation, sedimentation, filtration, pH adjustment, and disinfection processes before the drinking water quality standard can be achieved.

The coagulation process is done by adding coagulant to the water. In this process, the coagulant electrochemically attracts solids and colloidal particles to form a bulky precipitate. The solid precipitate is allowed to settle to the bottom of the sedimentation tank and then removed by discharging it as sludge. The next stage is filtration where the particles passing through the previous stages are removed. The filters are backwashed periodically in order to remove any collected matter. This energy intensive cleaning is required more regularly if the coagulation in the clarification stage is not performing well. In the next stage, the filtered water will go to the disinfection or chlorination process in order to eliminate the available micro-pollutants and finally lime will be added to adjust the pH value. The water is then stored in a contact tank in order to increase the retention time of the chemical reaction, particularly in the disinfection process. Finally the treated water is stored in a reservoir and is ready to be distributed through the water supply network.

Among all the processes involved in the water treatment plant (WTP), the coagulation process is considered as the most important and crucial stage as it allows the removal of dirt and colloidal particles. Coagulant dosing is not only the major control parameters in the coagulation process but it also represents the major operation cost in a water treatment plant. Good coagulation control is very important in order to produce satisfactory treated water qualities and to maintain the economic value of the plant operation. On the other hand, poor control of the same will cause wastage of chemicals, low water qualities and failure in the sedimentation and filtration processes (Valentin *et al.*, 1999). In addition, excessive coagulant dosage particularly aluminum sulphate ($Al_2(SO_4)_3.18H_2O$) has been linked to several medical disorders such as osteomalacia, dialysis enceohalopathy syndrome, Alzheimer's disease and renal failure (Mirsepassi, 2004).

In practice, the required concentration of coagulant dosage to destabilize any colloidal particles in the WTP is typically evaluated by jar testing (Lamrini *et al.*, 2005), a process of off-line dosing tests. Jar testing involves taking raw water samples and applying different quantities of coagulant to each sample. Each sample is then assessed for water quality and the dosage that produces the best result for water quality will be used as the dosing rate. The WTP operators should adjust the required coagulant dosage in conjunction with changes of incoming raw water qualities which often occurs any time.

Other method of controlling the coagulant dosage is using the Streaming Current Detector (SCD) which measures the residual charge on colloidal colour and turbidity particles in the water. As these colloidal particles have a negative charge and the coagulant ions have a positive charge, the amount of coagulant added dictates the magnitude and sign of the electrical charge (Evans *et al.,* 1998). The system controls this net charge at a set point which has been shown by jar testing to provide close to optimum coagulation under a certain range of raw water conditions. However, the disadvantages associated with the SCD method are its high operational cost and its lack of adaptation to various types of raw water qualities (Valentine *et al.,* 1999).

1.2 Problem Statement

To date, almost all the WTPs in Malaysia still use conventional method such as jar test in order to determine the required coagulant dosage. This method is expensive, time-consuming and does not enable responses to changes in raw water quality in real time. Since the raw water parameters like turbidity, pH, and colour change over time, plant operators have to repeat the jar test to determine the required coagulant dosage at any time. Conducting too often jar test consume a lot of chemicals for testing, contribute to higher electricity bills and also require an experienced manpower to obtain good results in determining the required coagulant dosage.

One way to understand the relationships between raw water parameters and the optimum coagulant dosage required is through deriving mathematical models and equations. However, determining an exact mathematical model is very difficult because the relationships are very complex and highly non-linear. Therefore, a different type or method of modeling is necessary rather than conventional mathematical modeling. The artificial neural network (ANN) modeling is a method which is applicable to problems in which the cause-effect relationships are complex, non-linear and no mathematical formula exists, such as the case with determining the optimum coagulant dosage. If enough data that represent all aspects of the problem domain is available, a model can successfully be developed (Tupas, 2000).

Once the model is successfully developed, it can serve as a potential tool to determine the optimal coagulant dosage replacing the existing methods. The optimized model can be implemented online by integrating the existing control system available in many treatment plants such as the Supervisory Control and Data Acquisition (SCADA) system. Moreover, applying this method will not only provide better coagulant control but will initiate advance action if changes of the incoming raw water qualities into the treatment plant occur. In addition to the quickness and convenience of using the ANN model for real-time application, the model could also be useful in operator training by simulating possible scenarios in which the operator would learn the results of various treatment options. All of these various uses show the tremendous benefits of developing and utilizing an ANN model in WTP operations, particularly in determining optimum coagulant dosage instead of relying only to conventional method of jar testing.

In this research, the ANN models are used to model the required alum dosing of a privatized WTP which belong to the State Water Supply Department of Sabah Government. The developed models will enable the plant operators to obtain the required alum dosages and to predict the treated water parameters easily within a short period of time. In addition, the models of some treated water quality parameters such as turbidity, colour, pH and aluminum residue are also developed so that the plant operators can gain better understanding of the relationship between raw water qualities, applied alum dosage, and treated water qualities.

1.3 Research Objectives

The primary goal of this research is to develop the ANN models for coagulant dosage and treated water qualities determination for the Segama WTP. Besides obtaining the primary objective, this research also aims to achieve the following objectives:

1. To study the characteristics and pattern of the raw water parameters in the Segama WTP.
2. To find the appropriate input-output selection used in the ANN models development.
3. To find the best neural network architecture for the process inverse model in the prediction of coagulant dosage and the process models in the prediction of treated water quality parameters.
4. To evaluate the performance of the process inverse neural network model after the elimination of some less significant input parameters via stepwise regression analysis.
5. To evaluate the performance of multiple inputs multiple outputs (MIMO) networks as compared to multiple inputs single output (MISO) networks.

1.4 Overview of the Thesis

The thesis is organized into five chapters which covers the literature review, methodology, results and discussion as well as conclusions and recommendations.

Chapter One gives an outline of the whole thesis which includes the background of the water treatment industry and its challenges in producing safe drinking water. The problem statement portrays the problem faced and the needs of the current research. The research objectives specify the aims of the study to obtain the optimum neural network architectures for the process inverse and process models.

Chapter Two provides the general description of a WTP as well as the case study area of the Segama WTP. Some important water quality parameters together with the coagulation process and its current control methods in WTP are also included. A detailed discussion of the ANN includes the characteristics of the ANN, the design of the ANN models and ANN's application are covered in this section. A review of previous studies as well as the nature of the current work using the ANN in the drinking water industries is also included.

Chapter Three describes the methodology applied in the neural network models development. Data preparation and analysis is outlined in this chapter. Lastly, this chapter also provides details of the neural network model development which includes the significant input-output determination and characteristics of the ANN applied for modeling coagulant dosage and treated water qualities in the Segama WTP.

Chapter Four presents the results and discussion of the research. The results of the data analysis are presented with the inclusion of some raw water patterns and characteristics, data preparation and input-output selection for the appropriate models. The results of the process inverse model and the process models are also discussed in detailed in this chapter.

Finally, Chapter Five summarizes the results obtained in the present study along with the conclusions and recommendations for future study based on the overall results obtained.

CHAPTER 2

LITERATURE REVIEW

2.1 General Description of a Water Treatment Plant (WTP)

Water treatment is a well known process that has been used for many years. However, contrary to most industrial processes in which the quality of the input raw material is under control, the quality of a given raw water source may fluctuate due to natural perturbations. Therefore, raw water is treated differently in different WTPs depending on the quality of the water which enters the plant. Regular water treatment processes require coagulation, flocculation, sedimentation, filtration, and disinfection processes in order to reach safe drinking water quality standards. Other processes such as softening, and fluoridation, may be required depending on the quality of the water source.

In the coagulation and flocculation processes, the coagulant and other chemicals are added to the water in order to form heavier and sticky particles, called “floc”, which attracts dirt and other particles suspended in the water. Then, during the sedimentation process, the heavy particles (floc) settle to the bottom of the sedimentation tanks and the clear water moves to the filtration tanks.

In the filtration process, the clarified water passes through filters, some made of layers of sand, gravel, and charcoal, which help to remove even smaller particles. Finally, in the disinfection process, a small amount of chlorine is added to kill any bacteria or microorganisms that might still exist in the water. The treated water is then placed in a holding tank in order to increase the retention time of the disinfection process and then pumped into an elevated reservoir prior to its distribution. Figure 2.1 shows the processes involved in a conventional water treatment plant.

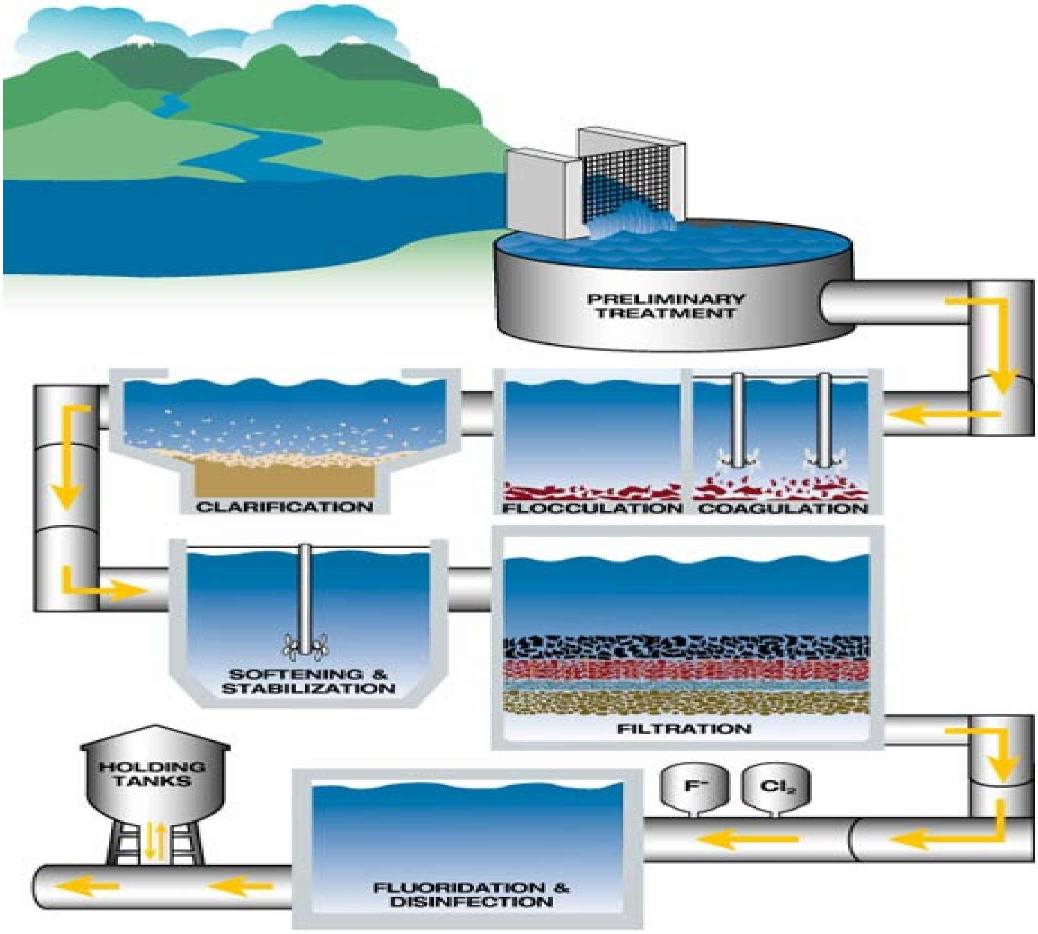


Figure 2.1: Unit processes in water treatment plant
(*Adopted from HACH Company, 2007*)

2.2 Overview of the Segama WTP.

The Lahad Datu Water Supply (LDWS) Sdn. Bhd. is a privately owned company incorporated in Malaysia. It was awarded the concession to treat and supply clean water to Jabatan Air Negeri Sabah (JANS) in East Coast Sabah since 1996. The concession involves providing a clean and reliable water supply to the population and the industries in the Lahad Datu District, Kunak, and Semporna.

The Segama WTP is one of the treatment plants which operates under the LDWS Sdn. Bhd. It was commissioned and fully operational at the end of 1999. Its daily production capacity is approximately 27 million liters and operates on a 24 hour basis in order to serve a population of about 130,000 in the Lahad Datu District. The raw water for the treatment plant is extracted from the Segama River, Lahad Datu, located approximately one km from the treatment plant area and it is pumped through a 750 mm diameter pipeline to the treatment plant.

Before entering the treatment plant, pre-lime is added to the raw water for pH adjustment so that an optimum pH of 5.0 to 7.0 can be reached for alum to coagulate efficiently. In the treatment plant, the raw water is treated via aeration through a cascade aerator in order to oxidize unwanted gasses and metals such as manganese in order to remove the odour. The aerated water then flows into a mixing chamber where alum is added to promote coagulation and flocculation. At the same time, a rapid mixer in the mixing chamber ensures the proper mixing of alum. The aeration and alum addition points are shown in Plate 2.1.

Plate 2.1: Aeration process and chemical addition
(With permission from the Segama WTP)

The raw water then flows into four units of flocculation tanks through a manually operated inlet penstock. The flocculation tanks are divided into three stages which reduce the velocity of the water flow from 0.27 m/s to 0.075 m/s in order to enable bigger size of flocs formation. This is illustrated in Plate 2.2. The flocculation tanks, consist of High Density Polyethylene (HDPE) baffles placed perpendicular to the direction of the flow in a gradually increasing distance.

Plate 2.2: Three stages of baffles type flocculation tank
(With permission from the Segama WTP)

The raw water from the flocculation tanks, which is by now full of big size flocs, enters the bottom compartment of the four units of the lovo type sedimentation tanks and rise up into the upper compartment to overflow into the settled water channel over ‘finger’ weirs as shown in Plate 2.3. Most of the flocculated particles will settle into the lower compartment. The settlement of the bigger flocs size in the lower compartment of the sedimentation tank will then be discharged by opening the plug scour valve at intervals. The retention time of the sedimentation tank is about 2 hours and 30 minutes.

Plate 2.3: ‘Finger’ weirs colleting clarified water in sedimentation tank
(With permission from the Segama WTP)

The clarified water from the sedimentation tank is added with lime for pH correction and flows evenly into six units of rapid gravity filters where filtration process takes place. The filtration tank is illustrated in Plate 2.4. The filtration media used in the rapid gravity filtration system are layers of fine and coarse sand which is filled to a maximum height of 1 meter.

Plate 2.4: Rapid gravity filtration tank
(With permission from the Segama WTP)

In the next step, the filtered water flows through a 600 mm diameter pipeline into the clear water tank, which is divided into two compartments; a holding tank and a treated water tank. The treated water is disinfected by using chlorine; this takes place in the holding tank before it is pumped into a balancing reservoir and ready to be distributed. With the advancement of the technology, the Segama WTP control center is occupied with a SCADA system in order to control, acquire data, monitor and display the status of various equipments and process parameters in the water treatment processes.

2.3 Water Quality

Water quality is used to describe water of a good quality. In general, it depends on what the water is going to be used for. The most polluted water can fulfill all criteria for a hydropower system but will completely fail if it is used for drinking purposes.

Water quality varies from place to place and from time to time even in a particular river system. It is dependent on many factors, both natural and mostly from the influence of human activities. The water quality is basically the result of pure water plus other parameters such as minerals that exist in the water (Jesper, 2004). Rain water is pure but when it reaches the earth, its quality is affected by the soils, rocks, and vegetation over and through which it passes. These parameters may come from many sources: daily human activities or from environment processes such as the effects of different weathers on soils and rocks, biological processes, or from the atmosphere.

The Sabah Water Supply Department (JANS) has to ensure that the treated water qualities reach the water consumers in accordance to the standard of World Health Organization's (WHO). The treated water quality standard for JANS is shown in Table 2.1.

Table 2.1: Treated water quality standard for JANS
(With permission from the JANS)

TREATED WATER PARAMETER	JANS STANDARD
pH	6.5-8.5
Turbidity	<5 NTU
Colour	<15 Hazen
Chlorine Residue	0.2-2.0 mg/L
Aluminum Residue	<0.1 mg/L
Fluoride	<0.7 mg/L
Total Dissolved Solids, TDS	<500 mg/L

Water has many characteristics which can be explained in details. However, due to the limitation of the available data obtained from the Segama WTP, only a few important water parameters is discussed briefly as it is used in the neural network model development in the later discussions.

2.3.1 pH of Water

pH indicates the level of acidity of the water but is actually a measurement of the potential activity of hydrogen ions (H^+) in the water sample (Jesper, 2004). The pH range of most natural waters is about 6.0 to 7.8 but for drinking purposes, WHO has set a standard pH level of between 6.5 and 8.5 (Murphy, 2007).

One factor affecting the pH value of water is the concentration of carbon dioxide (CO_2) in the water. According to Murphy (2007), sources of CO_2 are from the atmosphere, soils runoff, release from bacteria in the water, and respiration by aquatic organisms which dissolve in water to form a weak acid. Natural and unpolluted rain water can be as acidic as pH 5 to 6 because it absorbs CO_2 as it falls through the air.

Since plants consume CO_2 during the day and release it during the night, pH levels in water can change from daytime to night (Jesper, 2004).

In addition, air pollution from car exhaust and power plant emissions increases the concentrations of nitrogen oxides (NO_2, NO_3) and sulfur dioxide (SO_2) in the air. These pollutants travel from one place to another, and react in the atmosphere to form nitric acid (HNO_3) and sulfuric acid (H_2SO_4) (Murphy, 2007). These acids can have an effect on the pH of streams by combining with moisture in the air and falling to the earth as acid rain.

2.3.1 Turbidity

Turbidity is the optical property of a water sample which causes light to be scattered and absorbed rather than transmitted in a straight line through the sample; it is a measure of the cloudiness of the water. The ability of light to pass through water depends on how much suspended material is present in the water (Jesper, 2004). The turbidity may be caused by large amounts of clay, silt, sawdust, wood ash, microorganisms, and plant fibers. Such particles can cause tastes, carry bacteria and plant nutrients, and can cause the chlorine in the disinfection process to be less effective by adsorption and inactivation of the chlorine, or by protection of the bacteria (Judith *et al.,* 2001). The flow rate of a water body is a primary factor influencing turbidity level. High flow rate of water can carry more particles and larger-sized sediment which causes higher turbidity level (Murphy, 2007).

In general, turbidity will increase significantly during and after a rainfall, which causes sediment to be carried into the stream (Behar, 1997). Heavy rains can pick up sand, silt, clay, and organic particles from the land and carry it to surface water. Soil erosion from buildings and road constructions, logging, and mining activities also can contribute to the increasing level of turbidity.

The effluents and wastes from residential areas also add suspended solids and organic materials into a stream. The wastewater may contain food residue, human wastes, and other solid materials that have been thrown out into the drains. Furthermore, when plants and animals which are present in a water body die and decay, suspended organic particles are released and this can contribute to turbidity (Jesper, 2004).

2.3.1 Colour

The colour of the stream water is an indication of its source and it can provide important information about the water quality. According to Jesper (2004), the overall colour of the water may indicate the soil and bedrock types (e.g. red- red sandstone), unnaturally high concentrations of compounds such as iron (red), too much algae (green), or the presence of dyes and other chemicals in the water. Darker coloured waters absorb more of the sun's heat and will raise water temperature. The colour may also result from the contamination of the water source by industrial effluents and may be the first indication of hazardous water source pollution.

The visible colour of water is the result of the amount and character of the dissolved and fine particulate matter present. Naturally occurring minerals such as iron hydroxides, and organic compounds such as humic acids, give water what is called ‘true’ colour (APHA, 1995). ‘Apparent’ colour, measured in Hazen Units (HU), includes not only colour due to dissolved substances but also that caused by suspended material. Natural waters can range from less than 5 HU in very clear waters to more than 300 HU in muddy water (Judith *et al.,* 2001).

The colour of water is an aesthetic parameter and treatment is given to remove or reduce it in order to produce water that will have an acceptable appearance to customers. An aesthetic objective of < 15 HU has been set by WHO for colour in drinking water (Judith *et al.*, 2001). It is very necessary to treat this parameter as colour values above 15 HU can be detected in a glass of water by most water consumers. The removal of excess colour in coagulation process, prior to chlorination process will reduce the production of trihalomethanes (disinfection by-products) which will lead to cancer problem (Milot *et al.*, 2002)

2.3.1 Alkalinity

Alkalinity is not a pollutant; it is a total measure of the substances in the water that have "acid-neutralizing" ability which does not refer to the pH but to the ability of water to resist changes in the pH. Water with low alkalinity is liable to changes in pH while water with high alkalinity is able to resist major shifts in pH (Murphy, 2007).

Alkalinity is important for fish and aquatic life because it protects and buffers against pH changes and makes water less vulnerable to acid rain. The main sources of natural alkalinity are limestone which can contain carbonate, bicarbonate, and hydroxide compounds (Jesper, 2004).

2.3.1 Total Solids

Total solids refer to suspended or dissolved matters in water or wastewater and are related to both specific conductance and turbidity. It includes both the total suspended solids (TSS), and the total dissolved solids (TDS). According to Murphy, (2007), TSS includes a wide variety of materials such as silt, decaying plant and animal matter, industrial wastes, and sewage while TDS may include carbonate, bicarbonate, chloride, sulfate, phosphate, nitrate, calcium, magnesium, sodium, organic ions, and other ions. High concentrations of both TSS and TDS may also reduce water clarity, contribute to a decrease in photosynthesis, combine with toxic compounds and heavy metals, and lead to an increase in water temperature.

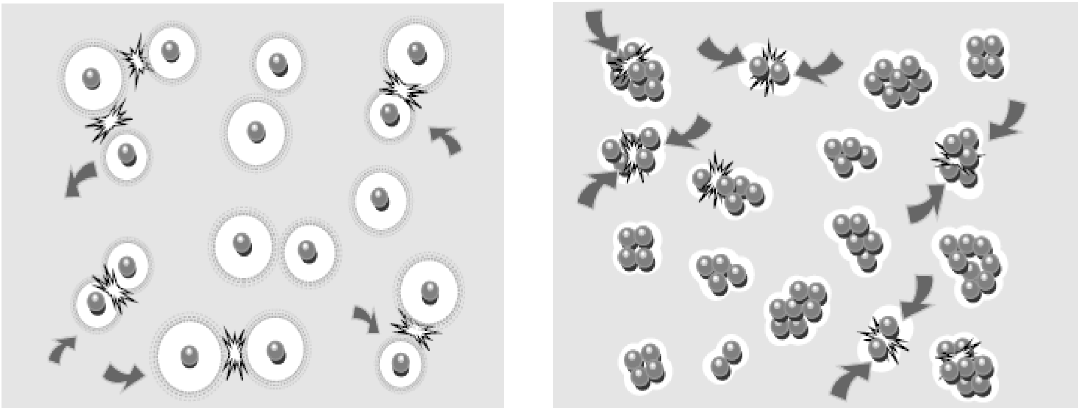
2.3.1 Aluminum Residue

Aluminum exists naturally in some waters but it is also comes from coagulant like aluminum sulphate (alum) which is used by water treatment plants to remove colloidal particles, colour and bacteria. The use of alum in the purification of water may introduce hazards in some individuals, particularly when it is present in high concentration. Water with higher levels of aluminum residue may induce encephalopathy (degenerative brain disease) and dementia in patients with kidney disease undergoing dialysis (Milichap, 1995).

WTPs usually control the treated water to a slightly alkaline condition, i.e. pH between 7.0 and 8.0. As a result of alkaline conditions, aluminum precipitates as fine solid particles which are then filtered out through sand filters in filtration process. However after some times, sand filters become less efficient for particles as small as 4 to 5 microns and therefore fine particles will escape through it and become aluminum residue.

2.4 Coagulation Process

Almost all water source particularly surface water contains both dissolved and suspended particles. The suspended particles may vary in term of its source, composition charge, particle size, shape and density. The correct design of a coagulation process and the selection of appropriate coagulants are based upon the understanding of interactions between these factors. The key of effective coagulation and flocculation is an understanding of how individual colloids interact with each other. Turbidity particles range from about 0.01 to 100 microns in size. Larger colloidal sizes are relatively easy to settle or to be filtered while the smaller the sizes, from 0.01 to 5 microns will make the settling times slower and they may easily escape filtration (Ravina, 1993).



(a) (b)

Figure 2.2: Interaction between (a) charged and (b) uncharged particles
(Adopted from Ravina, 1993)

Figure 2.2 shows the behavior of colloids in water is strongly influenced by their electrokinetic charge. Since the suspended particles are having the same negative charge, they will repel when they come close each other (Figure 2.2-a) and remain in suspension rather than clump together and settle out of the water. As a result, charged colloids tend to remain discrete, dispersed, and in suspension. On the other hand, if the charge is significantly reduced or eliminated, then the colloids will gather together (Figure 2.2-b). Initially the colloids will form small groups, then larger groups and finally into visible floc particles which settle rapidly and filtered easily.

The coagulation process is done by adding coagulant (a highly ionic salt of positively charged) to the water and allow for mixing to occur in vessels like in flocculation chamber as shown in Plate 2.2. Most often, aluminum sulphate or alum ($Al_2(SO_4)_3.18H_2O$) will be used in WTPs. Optimum pH conditions for alum coagulation are generally in the range of about 5.0 to 7.0, while the pH range of most natural waters is from about 6.0 to 7.8. Therefore, some of the alum dose is actually being used solely to lower the pH to its optimum value. When aluminum sulphate is added to water, hydrous oxides of aluminum are formed. The simplest form of these hydrous oxides is aluminum hydroxide; $Al(OH)_3$ which is an insoluble precipitate. However, several more complex, positively charged soluble ions are also formed which include $Al_6(OH)_{15}^{+3}$, $Al_7(OH)_{17}^{+4}$ and $Al_8(OH)_{20}^{+4}$ (Ravina, 1993).

These insoluble precipitates will electrochemically attracts the negative charged of solids and colloidal particles, thus removing undesirable turbidity, colour and organic matter in the form of solid precipitates called flocs. The solid precipitate is removed by allowing it to settle to the bottom of the sedimentation tank and then periodically it will be discharged as sludge. In general, poor raw water qualities which contain higher concentrations of contaminants in the water, require larger amount of coagulant dosage.

Good coagulation control is essential for maintaining satisfactory treated water qualities and economic plant operation. As a result of improper coagulant dosage, too much of it may ensure treatment targets are achieved but this will lead to high cost in relation to excess coagulant dosage and extra sludge waste produced. Too little of coagulant dosage will cause poor performance of treated water and problems in the subsequent processes such as filtration and disinfection.

2.5 Existing Coagulation Control

2.5.1 Jar Test

Conventional method of controlling coagulant dosage relies very much on manual method called jar test. Plate 2.6 shows the apparatus of conducting a jar test, owned by Segama WTP. A lab assistant which is normally supervised by a plant chemist will carry out the jar test, in order to aid plant operator in determining the required coagulant dosage into the plant. The testing involves taking a raw water samples and splitting it into 5 to 6 separate samples. Similar kind and concentrations of chemicals in the actual plant prior to the flocculation process will be applied into the samples.

Plate 2.5: Jar testing apparatus
(With permission from the Segama WTP)

In the Segama WTP, different quantities of coagulant are injected into each of the sample and then stirred, typically by rapid stirring followed by a more gentle stirring in order to simulate conditions in the treatment plant. After stirring, the sample is left for a short time before visually deciding which coagulant dosage has produced the best floc. Based on this finding, a recommended coagulant dosage is prescribed and the agreed value is introduced into the process. Only under extremely differing conditions and with the plant chemist’s advice would this dosage be altered before a new set of jar tests are carried out.

Jar tests are expensive and time-consuming; it can take up to 30 to 45 minutes to get the results of the required alum dosage. Consequently, jar test are generally carried out periodically which means that the tests are reactive rather than proactive as alum dosages are changed in response to the occurrence of water quality problems (Baxter *et al.,* 2001). Furthermore, as a result of the long duration to conduct jar test, they cannot be used to respond to rapid changes in raw water qualities (Joo *et al.,* 2000), and thus are not suitable for real-time control (Yu *et al.,* 2000). In practice, jar test are normally carried out during the plant operator's shift and when the clarified water quality begins to degrade. Therefore, this method only provides a snapshot of influent water qualities and is unable to represent the dynamics in the full-scale WTP system.

2.5.2 Streaming Current Detector

Another method of controlling the coagulant dosage is by using the Streaming Current Detector (SCD) which measures the residual charge on colloidal colour and turbidity particles in the water. Lamrini *et al.* (2005) explained the SCD measures of the electrical current generated between two electrodes by charged ions in a water sample. The ions are hydraulically sheared from free colloidal particles by a motor-driven plunger. Sheared ions carried two electrodes and the result is an alternating streaming current which is proportional to the net charge density of the water. The net charge density depends on the excess positive or negative ions present in the water after coagulation. Experiments have shown that there exists a correlation between SCD output and measured zeta potentials.

The disadvantages of the SCD method are its high operational cost and its lack of adaptation to various types of raw water qualities (Valentine *et al.*, 1999). In addition, this method is not an exact quantitative model which explains the functions and its limited efficiency for raw water quality of having a pH of more than 8 (Lamrini *et al.*, 2005). Even though the SCD is generally adopted as a continuous monitoring method to determine the required coagulant dosage, Dentel (1995) pointed out that the output of the SCD sometimes exhibits a contradictory result for the coagulation activation.

2.6 Artificial Neural Network (ANN)

2.6.1 Overview of ANN Modeling

The ANN modeling technique is a kind of artificial intelligence (AI) application that simulates the human brain's problem solving processes and this is illustrated in Figure 2.3. Just as humans apply knowledge gained from past experience to new problems or situations, a neural network takes previously solved examples, looks for patterns in these examples, learns these patterns and develops the ability to correctly classify new patterns. In addition, the neural network has the ability to resemble human characteristics in problem-solving that is difficult to simulate using the logical, analytical techniques of expert system and standard software technologies (Hussain, 1999; Daosud *et al.*, 2005).

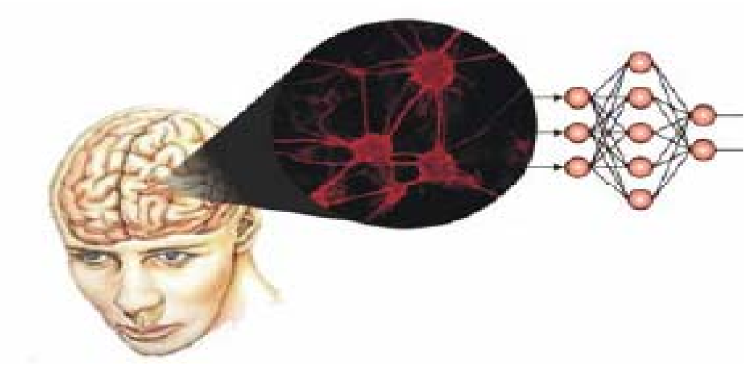


Figure 2.3: From human brain to artificial neural network
(Adopted from Strugholtz, 2006)

ANNs are capable of self-organization and learning; concepts and patterns can be extracted directly from historical data without any complex mathematical formulas or algorithms. Generally, ANNs can be applied to various kinds of problems such as pattern classification, clustering and categorization, function approximation, prediction and forecasting, optimization, associative memory, and process control (Jain *et al.*, 1996).

The ANN technique has several advantages over conventional modeling approaches that makes it especially applicable to the current study. As mentioned before, the ANN approach does not require complex mathematical algorithms, only knowledge of the factors governing the process is needed. In the water treatment industry, many uncertainties exist because of the complex physical and chemical reactions involved among the water parameters. Conventional modeling techniques require mathematical algorithms to describe these uncertainties whereas a neural network simply learns the process based on historical data (Stanley *et al.,* 1998). Therefore, no fundamental equations governing the system need to be derived in the WTP as this would be impossible due to poor process understanding. Furthermore, in most of the WTPs, there is a lot of recorded data which can be applied in the model development.

Any changes in the process or unit operation of the WTP, which would make a conventional model invalid, can be incorporated into the ANN models following a brief period of retraining. More importantly, the ANN models are able to handle the nonlinearity characteristics of the input parameters. In water treatment processes, many of the raw water quality parameters may vary even on an hourly basis in which statistical models that assume a linear structure are not able to cope. All the features of the ANNs allow them to be incorporated into the real-time process control of the WTP operations.

Another benefit of the ANN technique is it is a quick and responsive tool because once the historical data has been computed, the ANN models can be developed and applied in real-time water treatment processes. Advances in computing power have also minimized the time required to develop models, as well as the time required to re-train models to incorporate new data and to reflect process modifications (Baxter *et al.*, 2001). In the drinking water treatment, process modifications occur frequently and the ability to quickly modify with the process changes is another benefit of using the ANN.

The characteristic that really makes ANNs different from other conventional statistical methods is its ability to self-organize or learn. This feature allows ANNs to produce correct or nearly correct responses when presented with partially incorrect or incomplete stimulus, and to generalize rules from the training cases and apply these to new cases (Garret *et al.,* 1992). The network is able to produce the best output according to training examples when new input vectors are presented to the network, and it is fault-tolerant where the system is still able to perform well even when there are errors within the network (Tupas, 2000). This means that mostly correct answers are produced even though data presented to the network is incomplete. Finally, since the ANN models are developed using full scale and real operational data, the scale up