

DEVELOPMENT OF WWM SYSTEM USING  
MLNN-GA FOR PH PREDICTION OF WATER  
QUALITY IN CATCHMENT AREA

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## SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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DEVELOPMENT OF WWM SYSTEM USING MLNN-GA FOR PH PREDICTION  
OF WATER QUALITY IN CATCHMENT AREA

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## ABSTRAK

Kualiti air adalah sangat penting untuk dijaga kerana air adalah sumber utama dalam kehidupan seharian kita. Di dalam ekosistem akuatik, kualiti air yang baik membolehkan hidupan akuatik menjalani kehidupan seharian yang baik dan dapat meningkatkan pertumbuhan mereka seterusnya memberi banyak manfaat kepada persekitaran. Walaubagaimanapun, kaedah untuk mengumpul data kualiti air masih lagi dengan cara yang manual. Sampel data akan diambil dan dianalisis di makmal. Ini menyebabkan keputusan sampel air yang diperolehi akan mengambil masa yang lama dan tidak boleh didapati secara berterusan. Justeru itu, satu sistem diperlukan untuk memantau kualiti air dan dapat memperoleh keputusan dengan lebih cepat dan berterusan. Dalam kajian ini, Wireless Passive Water Quality Catchment Monitoring (WWM) System atau WWM Sistem diperkenalkan untuk mengumpul kualiti air. Lima parameter yang terdapat dalam system ini ialah keasidan air, suhu air, tahap keamatan cahaya dalam air, kelajuan ombak dan lokasi data yang diambil. Tasik UMP dipilih untuk dijadikan tapak eksperimen. Walaupun begitu, kawasan tasik ini amat luas dan memerlukan banyak WWM Sistem untuk mengambil data. Kaedah ini sangat mahal dalam perbelanjaan untuk membangunkan system ini. Oleh itu, kaedah untuk meramal kualiti diperkenalkan untuk mengurangkan bilangan WWM Sistem yang akan digunakan. Dalam kajian ini, Artificial Neural Network (ANN) adalah salah satu cara yang biasa digunakan untuk meramal kualiti air. Struktur dan fungsi ANN adalah berdasarkan rangkaian saraf biologi. Proses ANN mengandungi tiga lapisan iaitu lapisan masuk, lapisan tersembunyi dan lapisan keluar dan pemberat dalam rangkaian biasanya diubahsuai oleh teknik back-propagation (BP). Teknik ini mempunyai beberapa kelebihan iaitu pantas, mudah dan senang untuk diprogramkan. Walaubagaimanapun, ada beberapa kelemahan dikenalpasti dalam teknik BP ini. Antaranya ialah selalu terperangkap dalam lokal minima, sensitif kepada data bising dan prestasi BP dalam sesuatu masalah bergantung kepada data masuk. Dalam kajian ini, Multi-Layer Neural Network optimasi oleh Genetic Algorithm (MLNN-GA) diperkenalkan untuk meramal kualiti air. Model ini akan meramal nilai pH yang diperolehi dari WWM Sistem berdasarkan nilai pH sekeliling dalam perimeter 100m<sup>2</sup>. MLNN-GA mempunyai tiga lapisan tersembunyi dan Genetic Algorithm (GA) akan mengoptimasi pemberat dalam rangkaian saraf ketika proses latihan. GA mempunyai beberapa kelebihan iaitu kurang terperangkap dalam lokal minima dan boleh beroperasi dalam proses yang kompleks seperti rangkaian saraf yang dipanjangkan. Dalam proses latihan MLNN-GA, bilangan neuron dalam lapisan akan tersembunyi akan diuji untuk memperoleh kejituan yang tinggi. Parameter pH dipilih untuk meramal kualiti air kerana pH adalah satu parameter yang penting dapat mempengaruhi keadaan air. MLNN-GA adalah cara baharu dicadangkan dalam kajian ini untuk meramal kualiti air dari segi nilai pH. Keputusan ramalan akan dibandingkan dengan teknik BP dan purata nilai pH dalam perimeter 100m<sup>2</sup>. Keputusan ramalan diperolehi dari model MLNN-GA dengan kejituan 99.64% mempunyai potensi yang cerah untuk digunakan pada masa hadapan dan WWM Sistem juga berpeluang untuk digunakan untuk memantau kualiti air

## ABSTRACT

Water quality is crucial to maintain as water is a necessity in our daily life. In aquatic ecosystem, good water quality allows aquatic life to have good health and improving their productivity leads to significant benefits to the environment. However, the method of collecting data is still in manual way. Data samples need to be collected and evaluated in the laboratory. It leads the results of water quality took a long time to retrieve and cannot be obtained continuously. Hence, a system is required to monitor the water quality that capable to obtain the results fast and continuously. In this research studies, Wireless Passive Water Quality Catchment Monitoring System or WMM System is introduced to collect the water quality parameters. Five parameters are measured in the system, which are potential hydrogen (pH), temperature, light intensity of water, coordinate of collecting data, and wave velocity. Primary lake at University Malaysia Pahang is selected as the experimental area for the WMM System. However, coverage area of the lake is large and require many WMM Systems to be developed. This method is expensive in terms of budget expenditure. Thus, prediction of water quality is applied to solve this problem with a number of WMM Systems used for collecting data will be reduced. Artificial Neural Network or ANN is one of the methods that commonly used to predict the quality of water. The structure and function of ANN is based on biological neural network. ANN process consists of three layer which are input layer, hidden layer, and output layer and weight of the network usually adjusted by using back-propagation (BP) technique. This technique has several advantages which are fast, simple, and easy to program. However, there are some weaknesses identified in BP such as being often trapped in local minima, sensitive to noisy data, and the performance of BP on certain problems is dependent on the input data. In this research study, Multi-Layer Neural Network optimized by Genetic Algorithm (MLNN-GA) is introduced to predict the water quality. This model will predict the pH value obtained by WMM System based on the value of pH surrounding within 100m<sup>2</sup> area. MLNN-GA contain three hidden layers and Genetic Algorithm (GA) will optimize the weight of neural network during the training process. GA has several advantages, which are less often trapped in local minima and can operate in a complex process such as extended neural network. In training process of MLNN-GA, number of neurons in a hidden layer will be tested to obtain the best accuracy. The parameter of pH is chosen for predicting water quality as pH is one important parameter that can influence the condition of water. MLNN-GA is a new method proposed in this research study for predicting the water quality in terms of pH value. The results of prediction will be compared with BP technique and the average value of pH within the 100m<sup>2</sup> area. The results of prediction obtained by MLNN-GA model with 99.64% accuracy has a significant potential to be used in the future and WMM System has a great potential to be used in monitoring water quality.

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## LIST OF SYMBOLS

$P$	Position in a location data
$L$	Location data
$A$	Analogue input
$D$	Digital input
$SCL$	Clock line
$SDA$	Data line
$T_x$	Transmit
$R_x$	Receive
$V_{cc}$	Voltage at the common collector
$GND$	Ground
$net\ x$	Input value at neuron of 1 <sup>st</sup> hidden layer
$net\ y$	Input value at neuron of 2 <sup>nd</sup> hidden layer
$net\ z$	Input value at neuron of 3 <sup>rd</sup> hidden layer
$net\ k$	Input value at neuron of Output layer
$O_i$	Output value at neuron of Input layer
$O_x$	Output value at neuron of 1 <sup>st</sup> hidden layer
$O_y$	Output value at neuron of 2 <sup>nd</sup> hidden layer
$O_z$	Output value at neuron of 3 <sup>rd</sup> hidden layer
$O_k$	Output value at neuron of Output layer
$W_x$	Weight in between input layer and 1 <sup>st</sup> hidden layer
$W_y$	Weight in between 1 <sup>st</sup> hidden layer and 2 <sup>nd</sup> hidden layer
$W_z$	Weight in between 2 <sup>nd</sup> hidden layer and 3 <sup>rd</sup> hidden layer
$W_k$	Weight in between 3 <sup>rd</sup> hidden layer and Output layer
$E$	Error
$t_k$	Target data
$i$	Input layer
$x$	1 <sup>st</sup> hidden layer
$y$	2 <sup>nd</sup> hidden layer
$z$	3 <sup>rd</sup> hidden layer
$k$	Output layer
$\delta_k$	Delta rule between output layer and 3 <sup>rd</sup> hidden layer
$\delta_z$	Delta rule between 3 <sup>rd</sup> hidden layer and 2 <sup>nd</sup> hidden layer
$\delta_y$	Delta rule between 2 <sup>nd</sup> hidden layer and 1 <sup>st</sup> hidden layer

$\delta_x$	Delta rule between 1 <sup>st</sup> hidden layer and input layer
$\Delta W_x$	Weight adjustment in between input layer and 1 <sup>st</sup> hidden layer
$\Delta W_y$	Weight adjustment in between 1 <sup>st</sup> hidden layer and 2 <sup>nd</sup> hidden layer
$\Delta W_z$	Weight adjustment in between 2 <sup>nd</sup> hidden layer and 3 <sup>rd</sup> hidden layer
$\Delta W_k$	Weight adjustment in between 3 <sup>rd</sup> hidden layer and Output layer
<i>new</i> $W_x$	New weight in between input layer and 1 <sup>st</sup> hidden layer
<i>new</i> $W_y$	New weight in between 1 <sup>st</sup> hidden layer and 2 <sup>nd</sup> hidden layer
<i>new</i> $W_z$	New weight in between 2 <sup>nd</sup> hidden layer and 3 <sup>rd</sup> hidden layer
<i>new</i> $W_k$	New weight in between 3 <sup>rd</sup> hidden layer and Output layer



## LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
MLNN	Multi-Layer Neural Network
GA	Genetic Algorithm
BP	Back Propagation
WWM	Wireless Passive Water Quality Catchment Monitoring
GPS	Global Positioning System
IMU	Inertial Measurement Unit
pH	Potential of Hydrogen
LOS	Line of Sight
MISO	Multiple Input Single Output
MIMO	Multiple Input Multiple Output
MSE	Mean Square Error
RMSE	Root Mean Square Error
SEM	Standard Error of the Mean

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