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Graphical User Interface Application in Matlab Environment for Water and Air Quality Process Monitoring

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The principle aim of water and air quality modelling is to describe and to predict the observed effects of a change in the river and air water system. They can be used to forecast the characteristics of water and air quality conditions in aquatics and air systems in order to ensure the water and air quality objectives will be maintained under a wide variety conditions as well as the condition of air. Therefore, friendly user interfaces is introduced in which it is likely to have the largest impact on whether or not a particular decision support system is actually used by decision makers. Indeed, Graphical User Interface (GUI) has progressively been used in water and air quality management information systems for over a past decade purposely for validation and verification of expert system in reservoir management and also in air pollution index. Numerous researchers have also remarked that appropriate and intelligent use of GUI can help increase the effectiveness of management information systems. The framework of the underlying database is also general (and standardise) enough to allow users to add new input data without major hassle. The system also offers a Graphical Interface Editing Sub-module, which allows a system administrator to change the water quality data of other rivers as well as the air quality data. This study is about exploring more towards the advanced monitoring system of the river water and air quality by neural network approach, which later will be presented in GUI for online testing/prediction which result in ease of monitoring, diagnostic and control.

1. Introduction

The water quality management, which consists of monitoring data, could make some addition to the application of model's prediction. In this study, water quality prediction model could be applied when the modelling is feasible in the situation where the monitoring model is not available or impractical. In advance, the idea of integrating the monitoring and modelling models could provide better information for nearly the same cost. The introduction of prediction model also could help in assessing and predicting future water quality situation if there is a need for different management strategies (Loucks and van Beek, 2005). Application of this water quality prediction model gives a benefit in determining the river water quality status, where it needs the measurement of various water quality variables, to ensure that the water is safe to use for any purpose. The water quality index (WQI) shows the status of the water quality assessment and has been developed with suitability to the rivers, lakes and reservoirs. This WQI approach has applied the concept based on the comparison between the water quality variables and their respective regulatory standards (Khan et al., 2003). It combines several of the water quality variables that have affected to the overall water quality. The simplest WQI has considered variables like dissolved oxygen, total suspended solid, pH and some nutrients (Davis and McCuen, 2005). The monitoring data availability and accuracy have also contributed to the development of these models. The developed model should have also been opted to have the most meaningful and understandable response to the communities; either to inform about the pollutant sources or water quality conditions. Some of the researchers have developed water quality prediction models with a different approach and application. Some of the models were based on regression analysis (Abaurrea et al., 2011), time series (Ömer Faruk, 2010), fuzzy reasoning (Mahapatra et al.,

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2011) and neural network method (Eynard et al., 2011). Their study areas also involved sewage treatment, drinking water management and various other fields.

In the other hand, the air quality monitoring and forecasting tools are necessary to take precautionary measures, such as reducing the effect of a predicted pollution peaks on the surrounding population and ecosystem. Air quality is monitored continuously and manually to detect any changes in the ambient air quality status that may cause harm to human health and the environment. The Malaysian DOE monitors the ambient air quality via a network of 51 monitoring stations. These monitoring stations are strategically located in residential, traffic and industrial areas to detect any significant changes in the air quality which could be harmful to human health and the environment. The efficient methods for the assessment of air quality are needed in order to establish mechanisms for managing pollutant concentration and preventing illness in health-sensitive people. With increasingly severe air pollution, it is important to predict air quality exactly in order to provide actions and controlling strategies so that the adverse effects can be minimised. In response to this concern, several studies on air quality prediction using artificial neural network have been done (Zhang et al., 2012). Unlike other modelling technique, artificial neural network (ANN) makes no prior assumptions concerning the data distribution. ANN is capable of modelling highly nonlinear relationships and can be trained to accurately generalise when presented with a new data set (Kurt et al., 2008). Even though there were successful in many applications of ANN and having considerably less restrictions on the environmental input data, large training data sets are usually required to improve the accuracy and minimise uncertainty in the output data, which up to now has been a significant disadvantage of these models. In addition to that, it is needed a user friendly interfaces that can disseminate the information about the WQI and API in an efficient manner in alerting the health-sensitive people in the surrounding area.

Therefore in this study, GUI that user friendly interface embedded in Matlab^{TM} environment is introduced in which it is likely to have the significant impact on a decision support system that actually used by decision makers (MATLAB, 2012). Indeed, GUI has progressively been used in water and air quality management information systems for over a past decade purposely for validation and verification of expert system in reservoir management and also in air pollution index. Numerous researchers have also remarked that appropriate and intelligent use of GUI can help increase the effectiveness of management information systems

2. Methodology

In this study, two feedforward artificial neural network (FANN) model predictions for WQI and API were developed to be embedded in the GUI for process monitoring. For WQI prediction, two output variables were selected which are predicted BOD and COD as an outputs from NET1 and NET2 respectively after the FANN model development was carried out using the input sets as shown in Table 1. As for NET3 which is a WQI predictor, the network input was based on the output of NET1 and NET2 as shown in Figure 1. The FANN structure for NET3 was based on the Figure 1 and the FANN network training parameters were shown in Table 2. Meanwhile the data distribution for FANN development was shown in Table 3. Similar to WQI prediction, there were also two output variables selected in the air pollution index (API) prediction model. PM_{10} and O_3 predicted outputs were assigned as NET4 and NET5 respectively after the FANN model development was carried out using the input sets in Table 1. For NET6 which is an API predictor, the network input was based on the output of NET4 and NET5 and it applied the MISO structure as shown in Figure 1. In that figure, outputs from NET4 and NET5 were used as an input for NET6.

Table 1: Input sets for WQI and API model prediction

	FANN WQI Prediction NET1 and NET2	NET3	FANN API Prediction NET4 and NET5	NET6
Output	BOD (Net 1) COD (Net 2)	WQI	PM10 (Net 4) O3 (Net 5)	API
Input	Suspended solid NO_3 Kalium NH_3-NL Total solid Zink Turbidity	Biological oxygen demand, BOD Chemical oxygen demand, COD	Wind speed, m/s Ambient Temperature, °C Humidity, %	Particulate matters, PM10 Ozone, O3

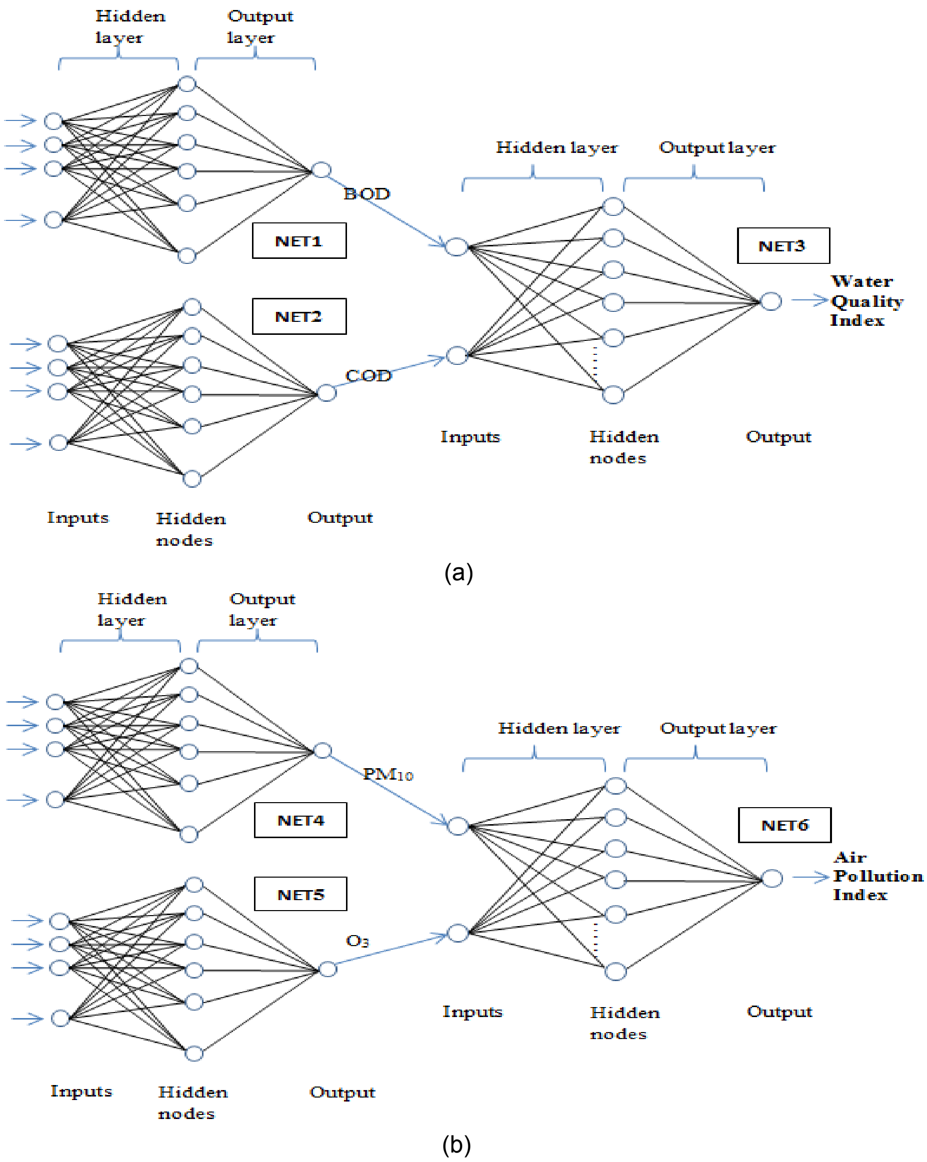

Figure 1: FANN modelling structure for (a) WQI prediction and (b) API prediction

Table 2: FANN network training parameters for WQI (Net 3) and API (Net 6) model prediction

Fix parameters	
Learning rate	0.05
Epochs	1000
Target error goal	10^{-5}
Minimum performance gradient	10^{-5}
Varied parameters	
Number of hidden neuron	1 to 20
Transfer function (hidden layer)	Log-sigmoid (logsig)
Transfer function (output layer)	Linear (purelin)
Training algorithm	Levenberg Marquardt backpropagation (trainlm)

The FANN-based prediction system for WQI and API was developed as an end-user product for GUI. The need of simple and compact system was highly focused during the development of the prediction system. The prediction system was built based on Matlab^{TM} platform and presented as Graphical User Interface (GUI). The implementation of neural network in the system makes the developed GUI had to be user-friendly in terms of loading of data and retraining the networks. The flow chart in Figure 2(a) shows the outlines or the procedure for organising and utilising the GUI data by the callback function in the Matlab^{TM}. In addition, from Figure 2(b), the GUI page layout has six pages for this study. The developments of the pages follow the basic procedures of GUI development as shown in Figure 3(a). However, each of these pages is different from another, based on their purpose and function.

3. Result and discussions

NET3 for WQI was developed based on the prediction output of NET1 and NET2. The output of these networks; BOD and COD estimation values will be used as inputs for NET3 network to predict the values of water quality index (WQI). Apart from the utilisation of other network's output as an input, the development steps for FANN model of this NET3 were much the same as NET1 and others. FANN network with single hidden layer and one output was applied with the Levenberg-Marquardt training algorithm (trainlm) with sigmoid logsig transfer function in the hidden layer and linear purelin transfer function in the output layer. The determination of the number of neurons in the hidden layer was carried out using cross validation technique and it shows that 6 neurons in the hidden layer give good performance in training and testing data while for API is consist of 8 hidden nodes in the hidden layer respectively. Thus, NET3 and NET6 with 6 and 8 hidden neurons were selected as a final architecture or structure of the FANN. Table 3 shows the summary of the NET3 and NET6 WQI and API predictor performance respectively.

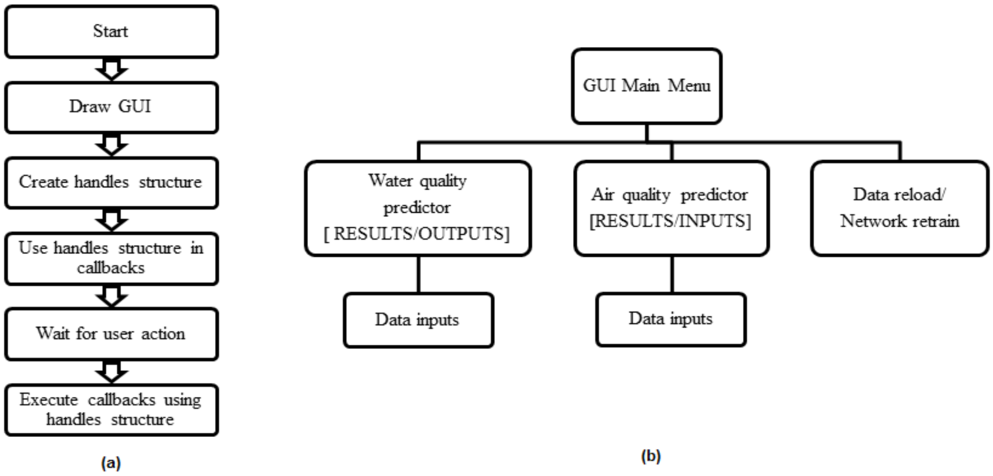

Figure 2: (a) Flowchart of data flow procedure, (b) Page layout for GUI

Table 3: Coefficient determination and mean sum squared error for unseen validation data for WQI and API prediction

	WQI 2-6-1			API 2-8-1		
Data set	No of data	mean squared error (MSE)	Coefficient of determination (r^2)	No of data	mean square error (MSE)	Coefficient of determination (r^2)
Training	800	0.1530	0.9200	1100	0.1936	0.9070
Testing	100	0.1326	0.9300	138	0.1770	0.9297
Unseen/Validation	100	0.1373	0.9000	138	0.1850	0.9031

As shown in Figure 3(a), the GUI main page was displayed once the model of estimation system was executed. This environmental qualities predictor main page shows two main options to the user, the prediction of water quality and prediction of air quality. Each of this option led the user to a specific page for their specific tasks, as shown in Figure 4(a) and 5(b). In Figure 4(b), the GUI layout of water quality predictor main page was displayed. Two main buttons were included in this page, RELOAD and ENTER INPUT buttons with their specific functions and objectives. The other button, HOME was included in the page to bring the user back to the main page of the environmental quality prediction model. Once the ENTER INPUT button was selected, the user was presented with a new page as shown in Figure 4(b). In Figure 4(a), seven inputs for the water quality estimation needed to be filled. These input values are suspended solids (SS), ammonia (NH3-NL), turbidity (TUR), total solid (TS), nitrate (NO3), zinc (Zn) and Kalium (K). The complete input with the DONE button brought the user back to the water quality main page, together with the prediction of COD, BOD and water quality index. The water quality index class also was displayed in the main page. As shown also in Figure 4(b), the RELOAD button connected the user to the neural network reload page, as in Figure 3(b). RELOAD button was built to help the user with a different set of environmental data to use in this estimation system. The user has the option to retrain the estimation model based on their historical data-based using this estimation system. With new input and specific data like COD, BOD and WQI database, user can load this data into the system and retrain the networks. The training progress for the respecting networks can be evaluated by the performance value shown in MSE column.

In Figure 5(a) and 5(b), the end-user layout shows the air quality prediction main page. The GUI layout is nearly the same as the water quality prediction main page, with the same function and objective for the RELOAD, HOME and ENTER INPUT buttons. The HOME button directed the user to the GUI main page as in Figure 5(a) while ENTER INPUT button brought the user to the input page of air quality estimation network. The input page, as shown in Figure 5(b) requires user to enter three input values, wind speed, ambient temperature and humidity. The requirement input values have to be in the range stated in the respective column, so that the input is in the boundary of the network training. Once the DONE button is pressed, the user gets the air quality estimation value on the main page, as in Figure 5(a) together with the results.

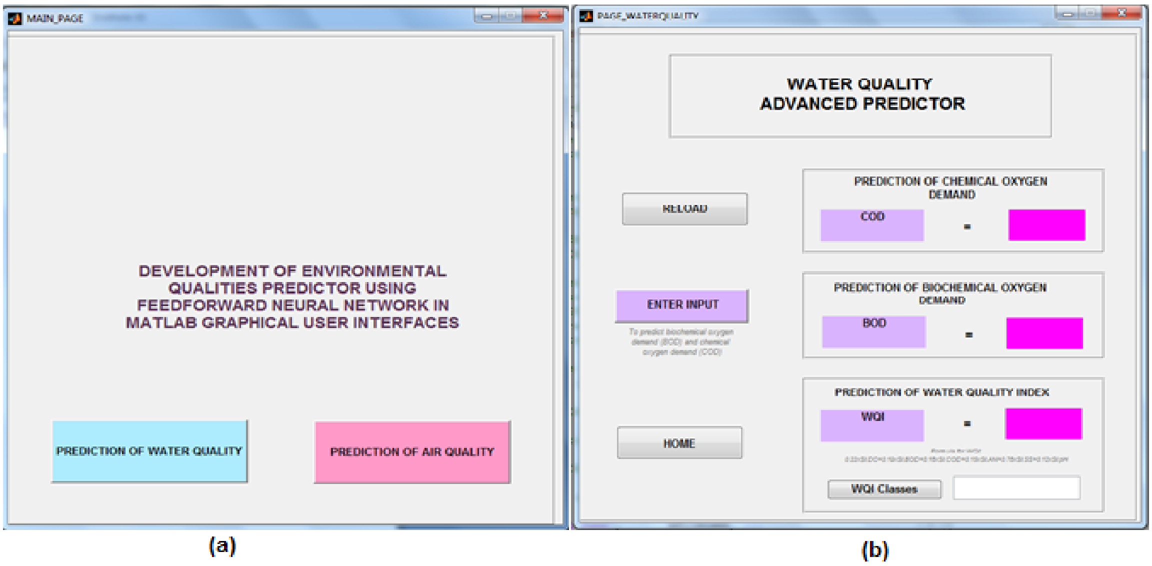

Figure 3: Environmental qualities predictor model: (a) GUI main page (b) Water quality main page

Figure 4: Water quality estimator: (a) Input page, (b) Quality main page with the estimation results

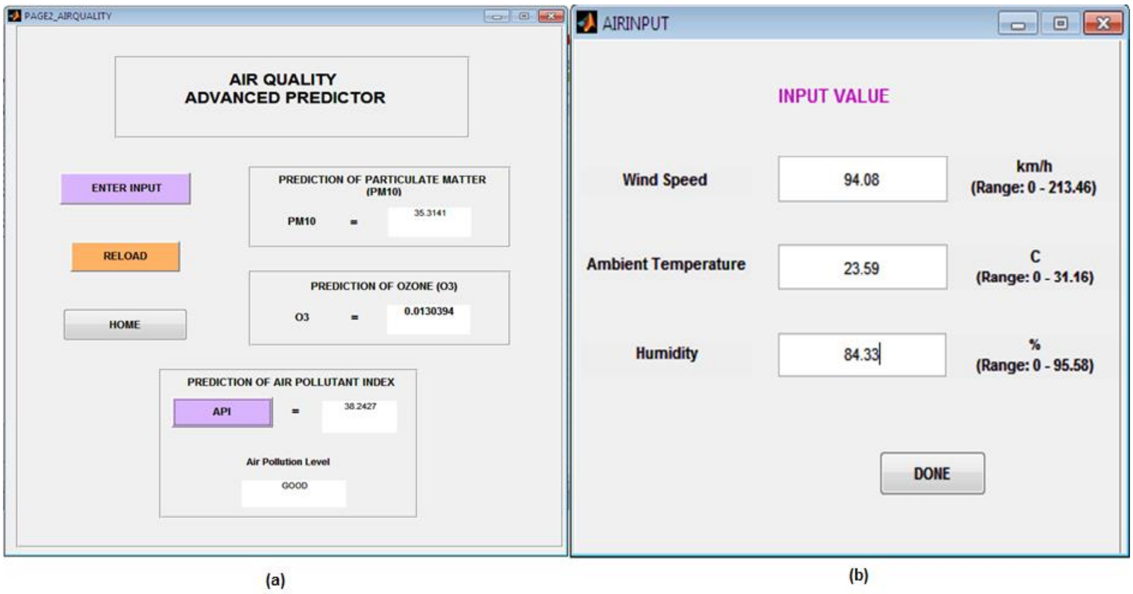

Figure 5: (a) Air quality: Main page with results, (b) Estimator: Input page

4. Conclusions

As a conclusion, the developed GUI for the environmental quality prediction system has been executed quite well. The developed prediction system based on FANN model with the input from the prediction output of NET1 and NET2 for WQI and NET4 and NET5 for API has performed very well. A developed GUI had been positively affected by the simplicity of the FANN model prediction that has been embedded in the system. A simple interface in GUI has been successfully developed with only seven measurable variables needed to predict the water quality and three variables for air quality prediction. This is an advantage for end-users, especially the ones without much knowledge in environmental quality index calculation to predict one.

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