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Application of Intelligent System for Water Treatment Plant Operation

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ABSTRACT

The water industry is facing increased pressure to produce higher quality treated water at a lower cost. The efficiency of a treatment process closely is related to the operation of the plant. To improve the operating performance, an Artificial Neural Network (ANN) paradigm has been applied to a water treatment plant. An ANN which is able to learn the non-linear performance relationships of historical data of a plant has been proved to be capable of providing operational guidance for plant operators. A back-propagation network is used to determine the alum and polymer dosages. The results showed that the ANN model was most promising. The correlation coefficients (r) between the actual and predicted values for the alum and polymer dosages were both 0.97 and the average absolute percentage errors were 4.09% and 8.76% for the alum and polymer dosages, respectively. The application of the ANN model was illustrated using data from Wyong Shire Council's Mardi Water Treatment Plant on the Central Coast of NSW.

Keywords: *Intelligent system, Artificial neural network, Water treatment plant operation, Coagulation dosage*

INTRODUCTION

Water treatment involves physical, chemical and biological changes that transform raw water into potable water. The treatment process used depends on the quality and nature of the raw water. Water treatment processes can be simple, as in sedimentation, or may involve complex physicochemical changes, such as coagulation. The water treatment system at the Mardi plant consists of rapid mixing of chemicals with the raw water, followed by slow mixing in which the growth of particles is promoted. Finally, the solids and liquid are separated using granular filtration processes. Figure 1 shows the Mardi water treatment system. The non-ionic polymer and alum used here are coagulants whose purpose is basically to promote the coagulation and flocculation of particles. The coagulant dosage required for particular water depends on the influent characteristics such as turbidity, colour, pH and alkalinity as well as other fluid and suspension characteristics.

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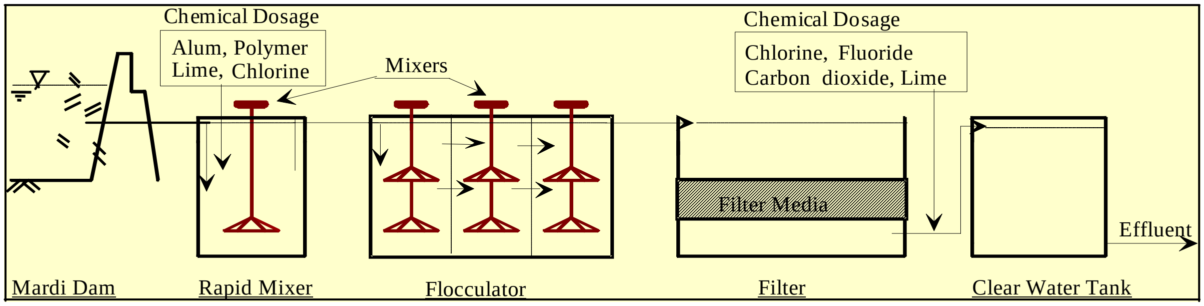


Fig. 1: Flow Diagram for Mardi Water Treatment Plant

The water industry is seeking ways to produce high quality water at a reduced cost. The operation of water treatment plants is significantly different from most manufacturing industrial operations because raw water sources are often subject to natural perturbations. Consequently, the water quality characteristics are variable at different periods. An algorithm to precisely predict chemical dosages for optimum treatment using measured influent parameters does not exist at many water treatment plants. Without a precise knowledge of the characteristics of the material to be removed, most chemical dosage requirements for primary water treatment are determined from experimental laboratory techniques (jar tests), which are conducted at regular time intervals.

To ensure good effluent quality, an operator must adjust the alum and polymer doses in concert with the influent changes which occur over time. Adjustments are usually made once in every 24 hours. Excessive coagulant overdosing leads to increased treatment costs and public health concerns. High levels of residual aluminium have been linked to several medical disorders including osteomalacia, dialysis encephalopathy syndrome, Alzheimer's disease and renal failure (Ossenbruggen, 1985). Underdosing leads to a failure to meet water quality targets and the less efficient operation of the water treatment plant.

An artificial neural network approach for setting chemical dosage levels, based on the water treatment parameters, is being investigated. A predictive model is developed by determining the correlation between water treatment parameters and the chemical dosage levels from a plant with a history of effective water treatment. Two previous studies by Anthony (1992) and Baba (1996) show the effectiveness potential of such an approach.

This paper describes the ANN analysis of daily treatment records covering a five year period at the Mardi Water Treatment Plant which was used to model the daily dosages of polymer and alum.

MATERIALS AND METHODS

1. Artificial Neural Network ANNs are a means of computation based on a contemporary understanding of the biological nervous system. They are able to model the non-linear relationships between parameters and are constructed from several layers of processing elements (PEs) or neurones, as depicted in Fig. 2. These PEs are interconnected and the strength of their interconnections are denoted by parameters called weights. These weights are adjusted, depending on the task, to improve performance, that is, the accuracy of prediction made by the ANN. The first layer, called the input layer, consists of PEs which simply takes on the input values of a pattern. The last layer is termed the output layer and produces the pattern outputs. The layer or layers between them are called hidden layers. The hidden layers also consist of PEs and carry out several calculations. Firstly, they multiply all inputs by a weight, add a con-

stant value (or bias θ_j) and then sum the result (I_j). That is: $I_j = \sum W_{ji} Xi + \theta_j$
Where W_{ji} are the connection weights between PEs, X_i are the inputs and. In the second calculation phase carried out by the PE, the output Yi is calculated using a non-linear transfer function (eg sigmoid or hyperbolic tangent).

$$Y_j = f\,(Ij)$$

The output of a PE can be connected to the input of other PEs (NeuralWare, 1994; Freeman, 1997). This process is shown in Fig 3.

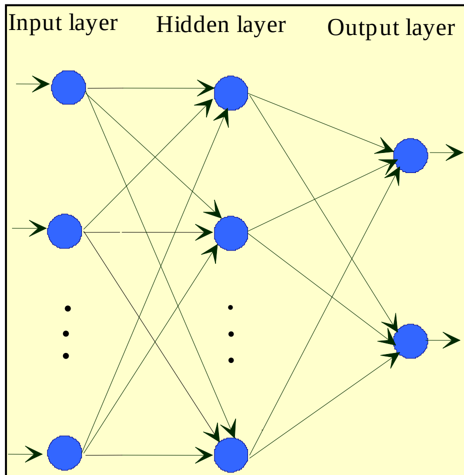


Fig. 2: Typical artificial neural network

The most common type of ANN is the Back-Propagation Network (BPN). The governing equations for a BPN were developed by Rumelhart and McClelland (1998). The BPN is able to model the non-linear relationship between parameters by relating the desired output parameter values to the known input parameter values. A BPN is a multi-layer, feed forward network consisting of fully connected PEs, and was used in this study.

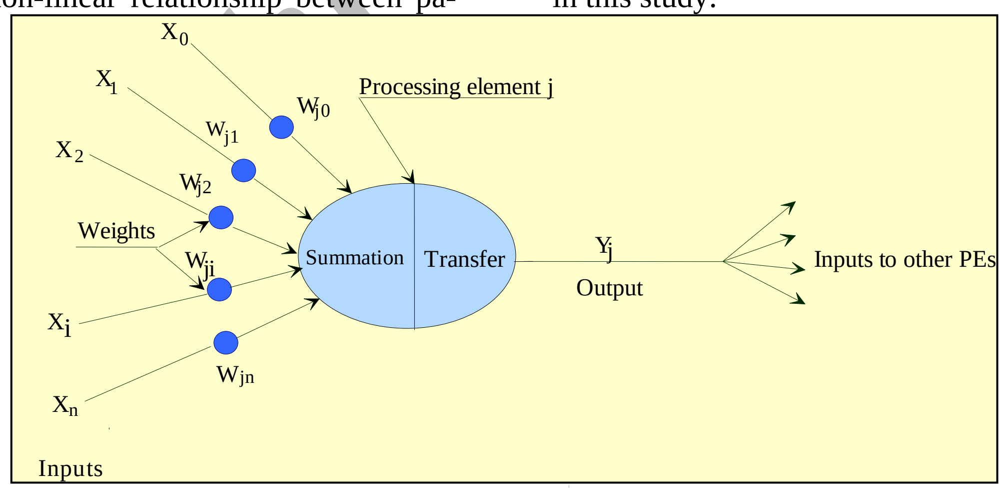


Fig. 3: A single PE in a network

ANN model development All ANN models were developed using the commercially available software package Neural Works Professional II/PLUS (1994). The ANN models which were constructed to determine the significant input parameters consisted of three or four layers of feed forward network. The following 47 input variables were used where the subscript‘t’ refers to the current day.

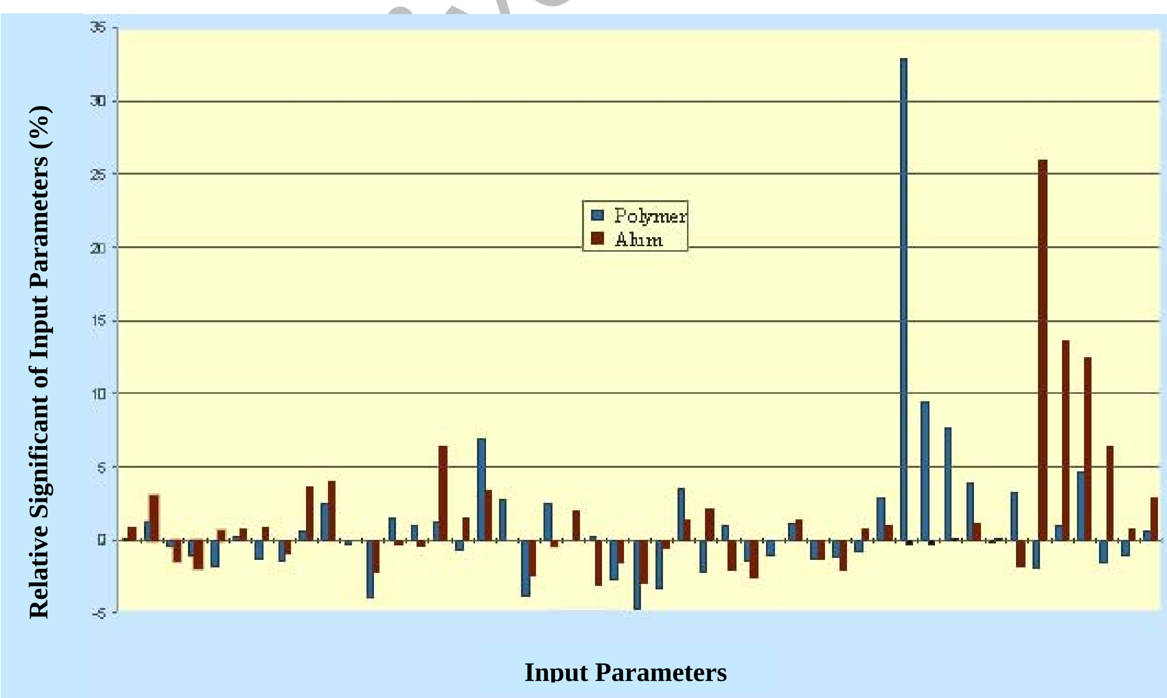
$pH_{(t)}, pH_{(t-1)}, \ldots, pH_{(t-6)}$

Turbidity $_{(t)}$, Turbidity $_{(t-1)}$, . . . , Turbidity $_{(t-6)}$
Apparent Colour $_{(t)}$, Apparent Colour $_{(t-1)}$, . . . , Apparent Colour$_{(t-6)}$
True Colour $_{(t)}$, True Colour $_{(t-1)}$, . . . , True Colour$_{(t-6)}$
Temperature $_{(t)}$, Temperature $_{(t-1)}$, . . . , Temperature$_{(t-6)}$
Polymer Dosage $_{(t-1)}$, Polymer Dosage $_{(t-2)}$, . . . , Polymer Dosage$_{(t-6)}$
Alum Dosage $_{(t-1)}$, Alum Dosage $_{(t-2)}$, . . . , Alum Dosage$_{(t-6)}$

The output variables were Alum Dosage $_{(t)}$ and Polymer Dosage $_{(t)}$.

The ANN employs a supervised learning algorithm referred to as the cumulative delta rule. Two thirds and one sixth of the 1820 days of (available) data were chosen for training and testing. For example, the first and second, fourth and fifth, seventh and eighth days and so on were used for training and the sixth, twelfth, eighteenth days and so on were used for testing. Several ANN models with one and two hidden layers were tested in order to determine the best ANN which consisted of ten PEs contained in one hidden layer. The training rate, momentum and epoch size were 0.8, 0.2 and 16, respectively. In order to obtain the best training iteration, training was stopped at intervals of thousand iterations and the testing set was presented to the ANN. The root mean square (RMS) error was then calculated. The minimum RMS error was obtained at a learning iteration of thirty four thousand during the training period.

A sensitivity analysis was carried out in order to decrease the number of inputs. All parameters with a relative significance of more than 5%, were selected as significant inputs. The significant inputs are parameters which can be effective for the prediction of the alum and polymer dosages. As can been seen in Fig. 4, nine inputs were of significance. These inputs were apparent colour with lags of 0 and 2 d, polymer dosage with lags of 1, 2 and 3 d and alum dosage with lags of 1, 2, 3 and 4 d. The prefixes ‘RW’ & ‘TW’ used in the annotation of the variables along the horizontal axis, denote ‘Raw water’ & ‘Treated water’, respectively.



RESULTS

The nine inputs with relative significance values greater than 5% were selected as inputs for the prediction of the polymer and alum dosages. The training and testing sets with nine inputs were presented to several combinations of one and two hidden layered BPN models to determine the best configured ANN model.

The ANNs were trained using 70000 iterations. This process took 15 min to complete on the PC. The numbers of PEs in the first and second hidden layers were 25 and 5, respectively. The training rate for the first and second hidden layers, output layer, momentum and epoch size was 0.8, 0.7, 0.15, 0.4 and 16, respectively. In order to obtain the best training iteration, training was stopped at intervals of every 1000 iterations and the testing set was then presented to the ANN. The minimum RMS error was obtained at the training of iteration of 67000 during the training period. Figs. 5 and 6 show the actual and predicted values of alum and polymer dosage.

The statistical parameters listed in Table 1 indicate the artificial neural network produces reliable forecasts of alum and polymer dosages based on historical input data.

Table 1: Best results obtained from ANNs

Statistical Parameters	Correlation Coefficient (r)	Average Absolute Error	Average Absolute %Error	RMS Error
Non-ionic Polymer	0.97	0.0048	8.76	0.0067
Alum	0.97	1.08	4.09	1.53

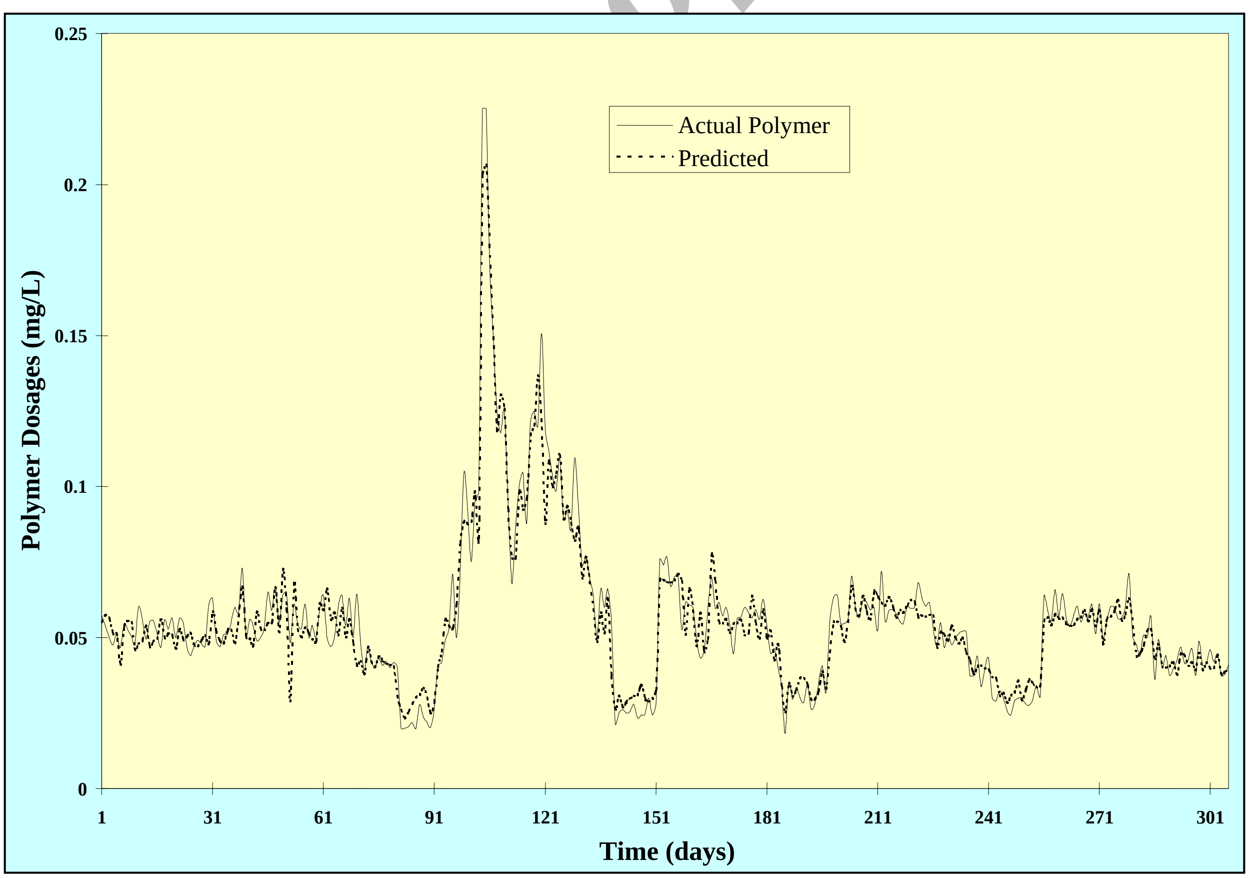


Fig. 3: Comparison of actual and predicted alum dosages

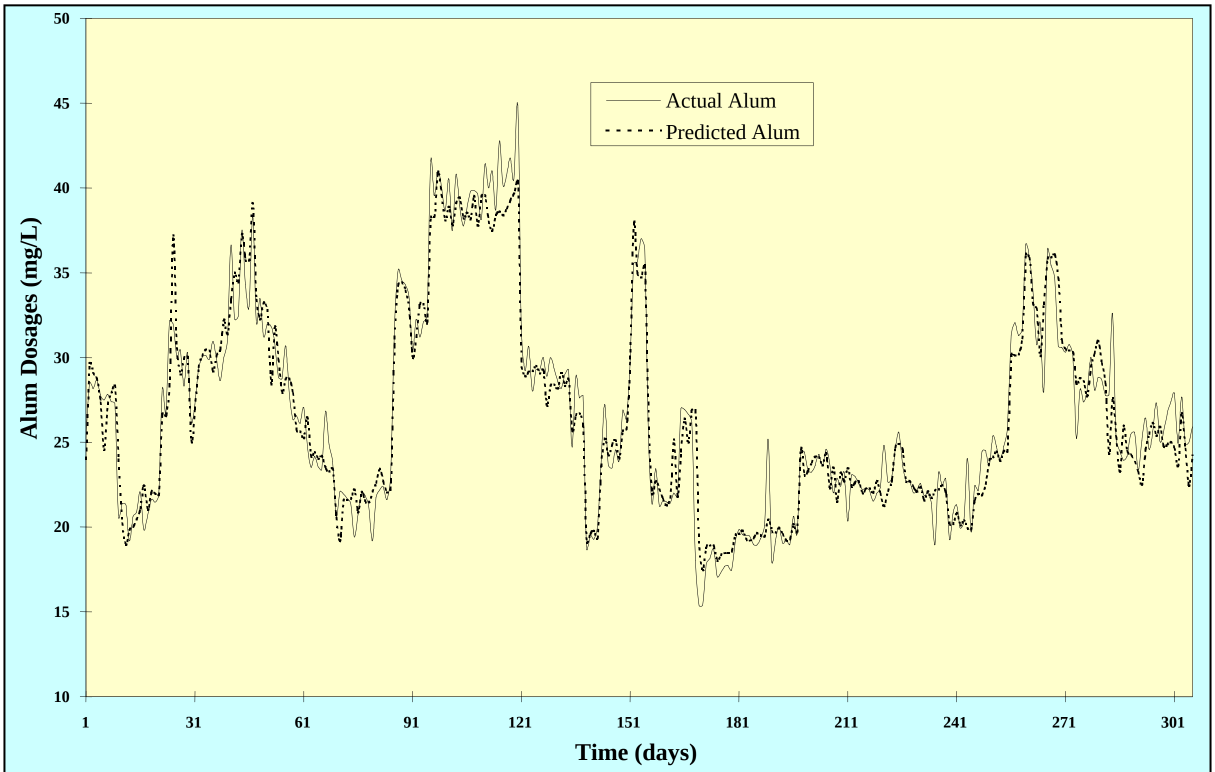


Fig. 4: *Comparison of Actual and predicted polymer dosage*

DISCUSSION

The operation of water treatment plants can be made more effective by using a predictive model. The application of the ANN model is demonstrated for the case of the Mardi Water Treatment Plant using 5 years of influent water quality records. As shown in the study, the ANN based on a BPN algorithm does predict the alum and polymer dosages reasonably well. This conclusion is in agreement with the ANN experiment of Daniell (1991). The correlation coefficients 'r' between the actual & predicted values for the alum and polymer dosages was both 0.97. The corresponding average absolute percentage error was 4.09% and 8.76%. The relatively high correlation coefficients indicate that the ANN has been successful in encapsulating the knowledge and experience of the staff operating water treatment plant. The performance of the network is dependent on the quality and completeness of data provided for ANN training. As such, continuous updating of training data would certainly improve the performance of the ANN. Improved methods for calculating treatment dosages will result in fewer plant upsets and more consistent water quality. More importantly, use of ANN, could result in a reduction in the operating costs.

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REFERENCES

Anthony G C, Glenn W E (1992). Information Processing Coupled with Expert System for Water Treatment Plants. *ISA*, 1 (31): 61-72.

Baba K, Enbutu I, Yoda M (1996). Explicit Representation of Knowledge Acquired from Plant Historical Data Using Neural Network. Proceedings of the International Joint Conference on Neural Networks, San Diego, pp. III-155-60.

Daniell T M (1991). Neural Networks-Applications in Hydrology and Water Resources Engineering. *International Hydrology and Water Resources Symposium*, Perth, 2-4 October, pp. 797-802.

Freeman J A, Akapura D M (1997). Neural Networks, Algorithms, Applications, and Programming Techniques. Addison-Wesley Publishing Company.

NeuralWare Inc. (1994). Neural Computing - A Technology Handbook for Professional II/PLUS and NeuralWorks Explorer.

Ossenbruggen J P (1985). Time Series Models for Treatment of Surface Waters. *Journal of Environmental Engineering*, ASCE, 1 (111): 27-44.

Rumelhart D E, McClelland J (1998). Parallel *Distributed Processing: Explorations in the Microstructure of Cognition*. Cambridge, MIT Press.