Wastewater Effluent Flow Control Using Multilayer Neural Networks

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Abstract

This paper presents the development of neural networks for prediction of pump control actions responsible for distribution and flow control of wastewater in a lift station plant. The input to the neural network is historical wastewater effluent and reservoir level data from City of Houston's Clinton lift station. The network output predicts the future state of 14 pump control actions of a wastewater lift station operation. Seven multilayer neural networks are tested with varying number of layers and neurons to obtain the best performing architectures. The average correct prediction rate of the seven trained networks over 14 pump status is over 96% in most cases.

Introduction

The ever-increasing demands for tighter environmental quality control of wastewater treatment plant operations have encouraged engineers to use new technology for improving plant operational control [1]. Artificial neural networks (ANN) have been applied successfully in the identification and control of dynamic systems. The proposed model is based on a feedforward neural network using backpropagation training algorithm. Thus, ANNs are used to predict distribution/flow-control for the 14 pump future control action under different seasonal rain and surface water flow activities, by applying historical pump data collected over a two-year period as input to the multilayer neural network. Using historical data a neural network can learn and map the relations between variables and generate an output of relatively high accuracy [2]. For this study, the neural network is designed to receive the necessary effluent reservoir's wastewater level information for the previous periods as input to the network, in order to initiate prediction of the 14 pump control actions. The networks were tested on data sets acquired from the City of Houston Clinton lift station plant authorities.

Historical Perspective on Wastewater Management

The traditional wastewater management concept (urban wastewater collection system plus treatment of the wastewater in a central treatment plant) has been successfully applied over many decades in densely populated areas of industrialized countries. Technologies to treat wastewater are now well established and are capable of producing almost any degree of purification [2, 3]. The main issue surrounding the selection of a given process lies in deciding which is the most appropriate and applicable technology. In water treatment, as in many other domains, process monitoring and control relies heavily on accurate and reliable sensor input information. Such information may, however, sometimes be inferred from available measurements of water-flow into the plant and pump actions by using neural network models.

Wastewater Literature Review

There are numerous applications of neural network in the wastewater management sector, including the following:

Water treatment process control—Zhang and Stanley used ANN for determining the optimal chemical dosage in wastewater treatment processes on the basis of the water quality parameters of incoming water [4]. A feedforward control scheme with optional feedback loop was used to check whether the predicted turbidity of effluent water matched the standard, while enabling and disabling the feedback flow of information. The performance of the control scheme is highly dependent upon the accuracy of the neural network models. However, it was concluded that the model's performance improved with less noisy data and implementation of on-line measurement [4].

Water treatment plant parameter prediction—Hanisch and Pires investigated predicting water treatment plant parameters by using backpropagation network to improve the process control and management at each processing level, such as plant input, input to the primary settler, input to the secondary settler, and as plant output [5]. The network models take past and present values of nine parameters, including total water capacity, pH, and conductivity, as input variables. The ANN predicted their future values in total of 29 output variables.

Reservoir inflow prediction—Raman and Sunilkumar investigated the problem of modeling monthly inflow to reservoir by ANN and statistical techniques [6]. The study is based on the measured, monthly inflow data of two reservoirs for a period of 14 years in Kerala, India. The input data for feedforward neural network model is organized into 12 monthly input data sets. The neural network model is built with four input nodes and two output nodes. The ANN approach preserved the mean of the generated series better than the statistical technique.

Wastewater Management and Lift Station Controls

In wastewater systems, the "lift station" is a key part in the process of delivering wastewater to the treatment plant [2, 9]. Unlike most process pipelines, wastewater is a gravity-flow system; however, a number of public pump stations are still necessary to keep the wastewater flowing to the treatment plant. For example, the City of Houston's Clinton wastewater lift station utilizes 14 different size pumps to process an average of 200 million gallons per day (MGD) of wastewater [2]. Sewage flows from its source towards a treatment plant through concrete (or plastic) pipes until reaching a lift station or, ultimately, a wastewater treatment plant. The number of lift stations (often also referred to as pump stations) through which the sewage must flow is dependent on the distance to a treatment plant and the terrain over which the sewage must flow. There are a few different types of lift station constructions, but most new lift stations are composed of two parts: a wet well and a dry well, as shown in Figure 1.

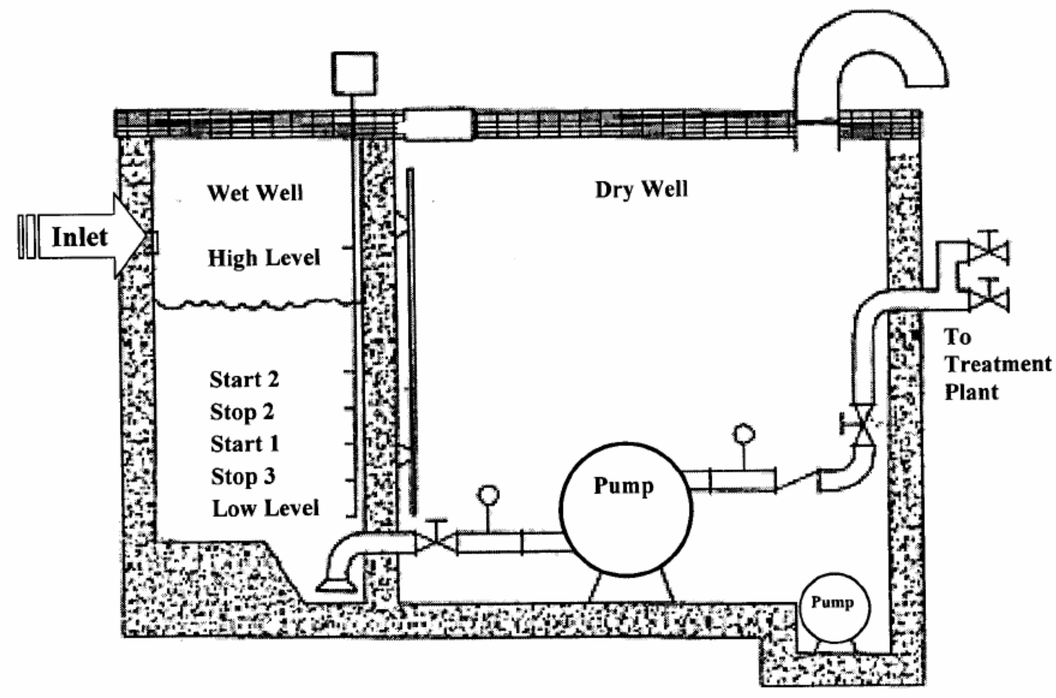

Figure 1: Sample lift station schematic for the City of Houston Clinton wastewater plant

The "wet well" is a concrete-walled receiving chamber, which receives the gravity-fed sewage. Wet wells are typically up to ten feet in diameter and up to twenty-five feet in depth. Adjacent to the wet well is a "dry" well which houses the pumps and valves necessary to "lift" up the sewage so it may continue its gravity-flow journey to a treatment plant [2]. In the wet well the primary controlling input is the wastewater level. The Clinton plant controls the incoming wastewater flow through 14 pumps with different capacities. The pumps are typically controlled by the operators, whose decision is based on his/her experience with the water level in the receiving tank and the corresponding pump(s) necessary to keep the water level at preset thresholds according to the weather and rain activities [2]. The typical operators activate/deactivate a series of pumps based on his experience with that particular weather condition, time of year, and protocols established by the plant's operational procedures. The overall objective of this project is to provide the operators with information on which pumps need to be on or off based on the water level in the receiving tank.

Introduction to Artificial Neural Networks

Artificial neural networks are parallel distributed processing units that mimic behavior of biological neurons. It performs a human-like reasoning, learns the attitude and stores the relationship of the processes on the basis of an existing data set. Therefore, generally speaking, the neural networks do not need much of a detailed description or formulation of the underlying process. Depending on the structure of the network, usually a series of connecting neuron weights are adjusted in order to fit a series of inputs to another series of known outputs. When the weight of a particular neuron is updated it is said that the neuron is learning. The training is the process that neural network learns. Once the training is performed the verification is very fast. Since the connecting weights are not related to some physical identities, the approach is considered as a black-box model. The adaptability, reliability and robustness of an ANN depend upon the source, range, quantity and quality of the data [3].

Proposed Model for Predicting Pump Control Action

The major contributions comprise the following: 1) the development of a multilayer neural network architecture based on history of 14 pump control actions that control wastewater effluent and 2) a preprocessing stage is included with reference to bypassing the variables with diminishing effects without reducing the prediction performance significantly [7]. For this study, neural networks are trained in off-line mode. The value of water level in the wastewater effluent tank is converted into appropriate input to the neural network, resulting in the network's output or pump control action, which in turn is compared with the desired target value. A neural network is built with the inputs that comprises water level and the corresponding pump control actions for preceding 1-hour, 2-hour, and 24-hour periods [7]. Water level and pump controls for the following hour are obtained as output of the neural network models. For both normal and extreme weather situations, the error back propagation for the network with sigmoidal activation function is found to be suitable.

Network Architecture and Training

The network architecture employed for this research consists of three layers with feedforward connections between each layer as shown in Figure 2. The network shown in Figure 2 has 17 inputs that correspond to 17 neurons in the first layer, a maximum of 36 neurons in the second layer, and 14 neurons in the output layer. A constant input 1 is fed to the biases for each neuron. The history of pump status and the corresponding wet well water levels that are applied to the network are depicted by the activity of the input neurons. For this particular network, 17 neurons are employed in the input layer. These neurons represent 14 pump control actions, plus their corresponding wet well water levels for previous 1-hr, 2-hrs and 24-hrs. For this network, 14 neurons were used to represent the Clinton lift station's 14 pumps [7]. The middle layers are called hidden layer because there is no direct connection between the input layer and the output layer. In general, the number of neurons in the hidden layer is determined by trial and error.

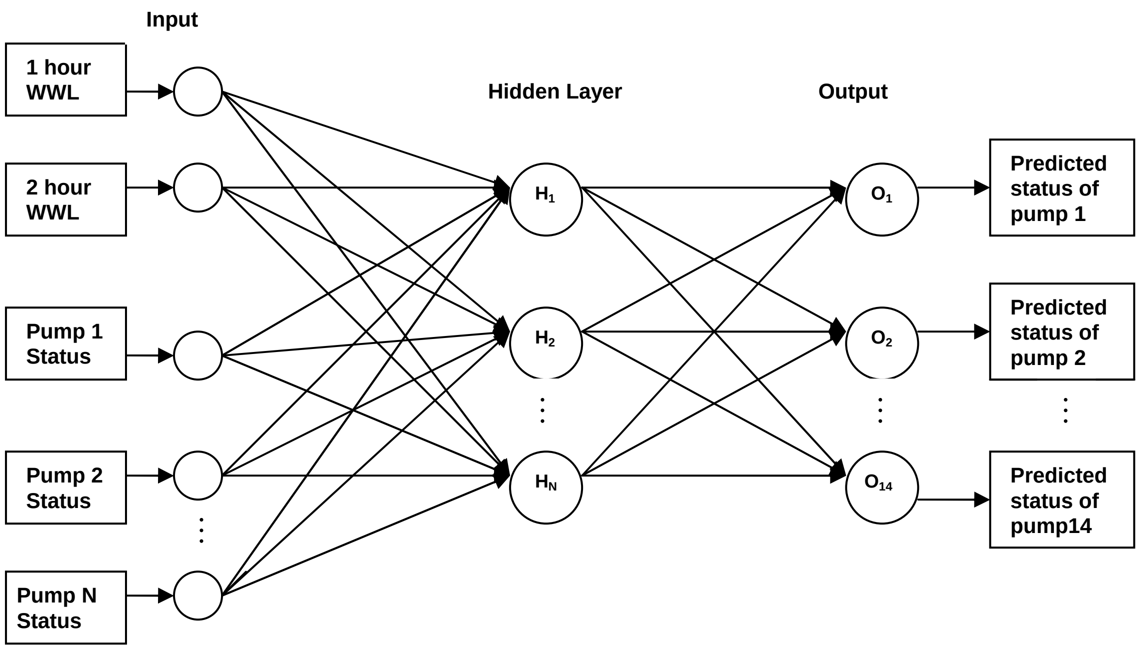

Figure 2: Proposed three layer neural network architecture

Table 1 shows sample training data set for pumps 1-14 as well as the WWL water levels for the Clinton lift station. In Table 1, P1 through P14 represent the pump statuses for the WWL levels indicated. Values under the P columns, 0 and 1, represent the pumps' "off" and "on" statuses, respectively.

Table 1: Sample input pattern for the neural network

1-Hour WWL	2-Hour WWL	24-Hour WWL	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
0.699461	0.725044	0.798001	0	0	0	0	0	1	0	0	1	0	0	0	0	0

Table 2 shows sample output pattern for the network, representing the pump control actions (1 represents pump "on", 0 represents pump "off") for pumps 1 through 14. Many different hidden layer combinations are tested, including single hidden layers with different numbers of neurons, as well as different combinations of multiple hidden layers with varying number of neurons [7].

Table 2: Sample output pattern for the neural network

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
0	0	0	0	0	1	0	0	1	0	0	0	0	0

Neural Network's Training and Test Sets

Two types of training sets are used for training and testing the network. There are a total of 18 months of data available, out of which 12 months of data is used for training and the remaining 6 months for testing the network. For this experiment, a total of 65 training and testing data sets are created, of which 36 sets dedicated to training and the remaining 29 sets for testing the network. Each data set comprises 400 to 4186 sample data from the Clinton lift station [7]. In general, the higher number of training patterns will make the network generalize better. Test sets are patterns set aside from the training sets to test for network over-training and to check the integrity of the network. If a network cannot respond intelligently to data sets outside the training set, then the model will be of little value.

Table 3 shows a sample of the network's predicted output (pump control actions) for a 10-minute interval. In Table 3, each row represents 10 minute sequential time intervals. This is because the original data set from the Clinton wastewater lift station were recorded every 10 minutes. However, in order to establish a consistent conversion method from the network predicted output to a usable form, a number of tests were performed. For output presentation of the status of each pump, it is decided that the range of 0.0000 to <0.5000 will represent the pumps' OFF status; and 0.5000 to 1.000 should represent the pumps' ON status [7]. Throughout this discussion, sample data sets represent that of a single lift station.

Table 3: Sample of predicted output generated by the neural network

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
0.0232	0.7644	0.0526	0.1200	0.2000	0.5187	0.8513	0.2327	0.5861	0.0340	0.6950	0.7450	0.5404	0.0485
0.0232	0.7644	0.0526	0.1200	0.2000	0.5187	0.8513	0.2327	0.5861	0.0340	0.6950	0.7450	0.5404	0.0485
0.0232	0.7644	0.0526	0.1200	0.2000	0.5187	0.8513	0.2327	0.5861	0.0340	0.6950	0.7450	0.5404	0.0485
0.0232	0.7644	0.0526	0.1200	0.2000	0.5187	0.8513	0.2327	0.5861	0.0340	0.6950	0.7450	0.5404	0.0485
0.0232	0.7644	0.0526	0.1200	0.2000	0.5187	0.8513	0.2327	0.5861	0.0340	0.6950	0.7450	0.5404	0.0485
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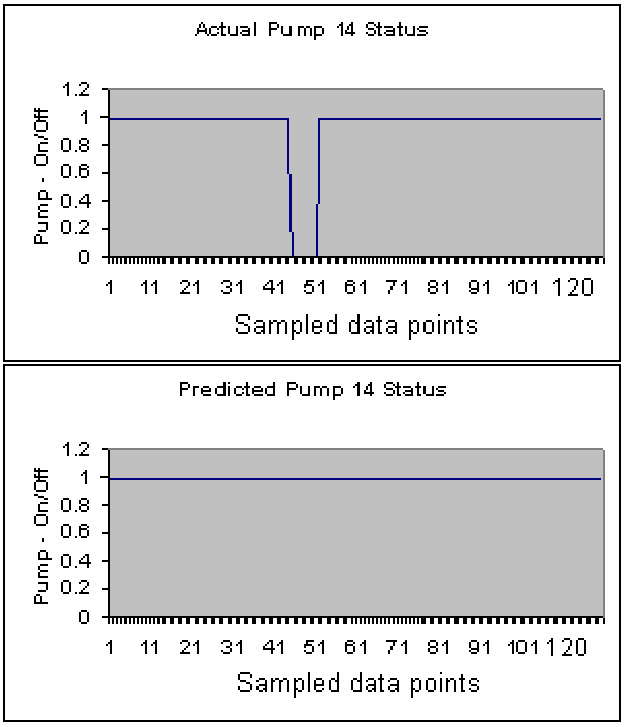
This research utilizes MATLAB's command line network configuration and setup, which allows for more flexibility. When the new network is loaded, it is initialized by automatically setting all initial weights to small random values between -1 and 1.

Network's Results and Analysis for Wastewater Control

For this research experiment, a number of different networks are tested, which produce varying degrees of results. We will present a sample of these networks while specifying the network's architecture, their parameters, and results obtained. An error graph is also provided that compares the network's predicted pump control actions to the network's target values. Figure 3 shows a sample of the results for pump 14 with the network architecture and parameters indicated. In the graphs, actual pump status represents the desired target. Testing results indicated that the network produces 120 correct predictions out of 120 sampled data points, corresponding to 95% correct prediction rate. It is also observed that the LOGSIG transfer function used for the output layer produces better network results [7]. For brevity only the results of pump 14 is depicted for this discussion.



Correct Predictions: 95%
Learning Rate: 0.005
Epochs: 1000
Sampled Data Points: 120
Input Data: WWL 1-hour, 2-hour, 24-hour, Pump1-14 Status
Input Neurons: 17
Hidden Layers: 1
Neurons per Hidden Layer: 24
Output Neurons: 14
Hidden Layer Activation Function: LOGSIG
Output Activation Function: LOGSIG

Figure 3: Network parameters and corresponding results for pump 14

The three-layer network architecture that is tested for this research proves effective and successful. The network parameters are set with the number of iterations at 2,000, the learning rate at 0.005, and the momentum fixed by the neural network software. All input data are normalized, and the output range is between 0 to 1, with the weights and biases iteratively adjusted to minimize the network performance function, mean square error (mse). The MSE error is used to examine how well the network model predicts cases outside and over the training set [10]. Figures 4 shows the MSE error for the network described above during the network simulation experiment. The network is optimized for accuracy on cases available outside the training set. Since the test data error in Figure 4 is declining, it means constructive learning is occurring.

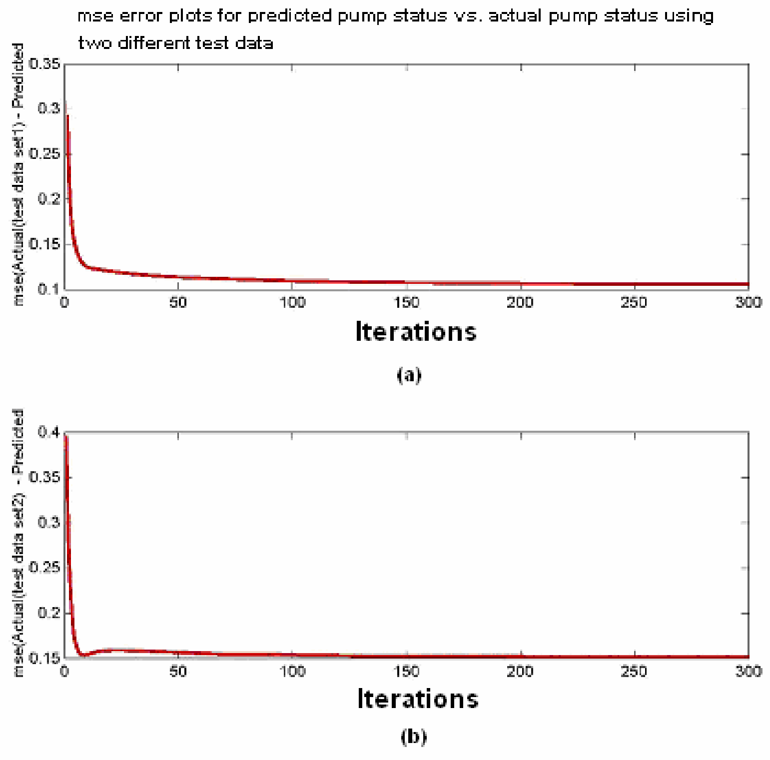


Figure 4: MSE error vs. epochs for two different training data sets

For the training sets shown in Table 4, the network has an overall correct prediction rate of 98.20% for test data sets. Training examples representing extreme weather conditions and activities (heavy load periods such as June 2001) are correctly predicted with 96.90% accuracy. While maintaining the same training parameters in the algorithm, the network is re-trained with the 12 months of training data sets again, to improve network's prediction performance. However, it is observed that the number of iterations required to train the network is reduced.

Table 4: Results of seven neural network architectures

			Hidden Layers				
NN No.	Data Points	Learning Rate	# of Layers	Neurons per Layer	# of Epochs	MSE Error	% Correct Predictions
1	2000	0.001	3	36	2000	0.195	98.98
2	2000	0.001	2	24	3000	0.012	100
3	2000	0.005	2	24	1000	0.024	97.1
4	1035	0.005	1	24	1500	0.13	98.49
5	1000	0.001	1	18	1200	0.177	98.32
6	1000	0.01	1	18	1000	0.191	97.35
7	1500	0.01	1	14	1500	0.158	96.9

For the testing data sets, 97.45% of pump control actions (pump 1 to pump 14) were predicted correctly. The same test data sets are again tested with the newly trained network, where a 96.90% correct prediction rate is achieved (what is the difference between these two results. Both of them say testing). These results are presented in Table 4. In Table 5, the network's performance for each pump for 120 sample points is illustrated. The prediction error for 120 samples shown in Table 5 is typically less than 5.00% and in most cases below 3.00%. However, additional hidden layers do not prove as beneficial and in most cases increases the training period.

Table 5: Sample network output performance

Pump	Total Test Samples	# of Correct Predictions	# of Incorrect Predictions	% Correct Prediction	Prediction Error
1	120	115	5	95.83%	4.17%
2	120	120	0	100.00%	0.00%
3	120	109	11	90.83%	9.17%
4	120	120	0	100.00%	0.00%
5	120	118	2	98.33%	1.67%
6	120	112	8	93.33%	6.67%
7	120	120	0	100.00%	0.00%
8	120	120	0	100.00%	0.00%
9	120	120	0	100.00%	0.00%
10	120	117	3	97.50%	2.50%
11	120	114	6	95.00%	5.00%
12	120	114	6	95.00%	5.00%
13	120	107	15	89.17%	12.50%
14	120	119	1	99.17%	0.83%
Averages	**120**	**116.07**	**4.07**	**96.73%**	**3.39%**

Discussions

In general, neural networks are suitable for problems where the underlying process is not known in detail and the solution can be learned from the input-output data set [11]. In this research experiment, the accuracy of pump control actions replicated by neural network is satisfactory and reproducible. Further investigation of this approach is suggested in terms of improving the performance by selecting additional and suitable input variables, including Total Suspended Solid (TSS), total wastewater flow into the plant, etc. In this research experiment, several data sets are used to train and to test the multilayer neural network. Additional data such as time of day, day of month, and month of the year were also included. However, these types of data (time and date) were not instrumental to the behavior and accuracy of the ANN experimentations. The differences in architecture ranges from networks with different numbers of hidden layers (1, 2, and 3 layers) and neurons to networks with different learning rates (0.001, 0.005, 0.01) and networks with different activation functions and input neurons.

However, it is observed that the prediction rate is lower if input data represents sever weather conditions where pump control algorithm is subjective and takes into account the operator’s experience that is not included in the data sets provided by the City of Houston. This is independent of the input data set (training data or the testing data). The results of the test data indicated that the network performs quite well when pump control actions are not generated in a very small interval of time. For instance, during the heavy period of wastewater and run-offs, some of the pumps are subject to higher operation on demand as well as frequent on/off operations.

Conclusion

This paper presented a multilayer neural network capable of predicting pump control actions for a wastewater lift station operation. The average correct prediction rate of the trained networks is over 96% in most cases, as shown in Table 5. The neural network produces acceptable results—over 96%—even with a new set of test data. Therefore, the proposed neural network is a satisfactory model to perform pump control action prediction for a wastewater treatment plant [7].

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