Modelling the operation of a Water Treatment Plant based on Artificial Neural Networks

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Abstract: The main purpose of this study is to model the operation of a Drinking Water Treatment Plant (DWTP) using its main operational and water quality parameters in a fast, easy and reliable way. This study is based on a large number of data from recent years (2019-2021). The DWTP has a maximum capacity of 110,600 m^3/day and is located at Hersonissos, Crete in Greece. The methodology that was followed comprised of the development of Artificial Neural Networks (ANN) in the MATLAB programming environment. Since the 1990s the ANN modelling approach has gained popularity for prediction and forecasting due to its ability to capture complex nonlinear relationships. Two models were developed with satisfactory results with regards to Mean-Square Error (MSE) and Regression Coefficient (R) values. The models were able to predict the main operational parameters such as the dosages of coagulants, flocculants and disinfection (O_3, $Cl_{2(g)}$) chemicals rendering them a useful tool for the DWTP operator. For future work a greater number of tests are planned to check different ANN input parameters and architectures with different numbers of hidden neurons.

Keywords: water, treatment, artificial, neural, network

1. Introduction

A reliable forecasting model for each DWTP based on operational parameters is useful for controlling the plant's operation. Water characteristics such as temperature, turbidity and pH are important water quality parameters and there is a significant relationship between these parameters and the amounts of coagulants and flocculants used in water treatment processes in a Water Treatment Plant (WTP) (Maleki A. et al., 2018).

Artificial Intelligence and Machine Learning tools show high performance in fitting complex relationships and prediction in DWTP. These methods are capable of processing data with nonlinear relationships that are difficult to fit with a single mathematical model (Li L. et al., 2021). ANNs are computational techniques that mimic some operational features of the human brain. ANNs are not programmed like conventional computer programs, but they have mechanisms which can learn certain data or patterns. Data in ANNs are connected to each other by weights parallel to synapses. Training of the ANN is done by adjusting these connections through a learning algorithm. ANN modelling usually consists of the following steps: data collection, data analysis and training of the neural network. ANNs can identify intricate nonlinear relationships between input and output data sets. There are various types of artificial neural network available, but the most commonly used are: Multi-layer Perceptrons (MLPs), Radial Basis Function (RBF), General Regression Neural Network (GRNN), Cascade Forward Networks (CFN) and Kohonen's self-organizing maps (SOM) (O'Reilly G et al. 2018).

A neural network derives its computing power through, first, its massively parallel distributed structure and, second, its ability to learn and therefore generalize. Generalization refers to the neural network's production of reasonable outputs for inputs not encountered during training (learning). These two information processing capabilities make it possible for neural networks to find good approximate solutions to complex (large-scale) problems that are intractable (Haykin S. 2009).

Advantages that ANNs bring to water quality modelling include: (i) model building does not require a physics-based algorithm and this makes the modelling approach faster and more flexible; (ii) non-linear relationships can be handled properly and without any effort; and (iii) user experiences and knowledge can be incorporated in construction of a model (Tabari H. & Talaee P.H., 2015).

Aposelemis DWTP treats the surface water of the dam reservoir Aposelemis, which capacity is 25.3 x 10^6 m^3 water. Aposelemis DWTP is a conventional treatment facility consisting of pre- disinfection by ozone (in situ O_3 production), alum coagulation, flocculation, sand filtration and disinfection by chlorine gas ($Cl_{2(g)}$) (Fig. 1). Its daily production capacity is approximately 110,600,000 liters. Although it consistently produces excellent quality drinking water, plant process control could be improved and the prediction of the main operational parameters would be a useful tool. Thus, the project was initiated to investigate ANN process control for the total operation of the Aposelemis WTP.

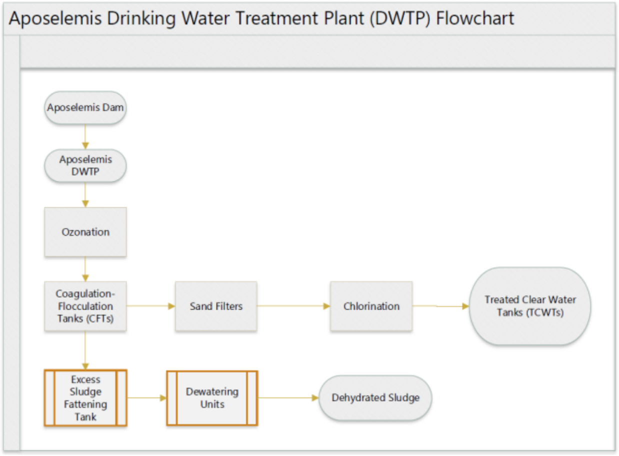

Figure 1. Aposelemis WTP flowchart

The main statistics for the studied parameters of Aposelemis DWTP are given in Table 1.

Table 1. Variables statistical properties

No	Variable	Unit	MIN	MAX	AVERAGE	STDEV
01	ΔH	m	-1.91	4.46	0.00	0.26
02	Q	m^3/d	4,271.00	65,545.00	36,566.41	9,698.51
03	T1	NTU	0.07	27.00	3.56	3.36
04	pH1		6.57	8.38	7.53	0.36
05	T2	NTU	0.01	0.71	0.15	0.07
06	pH2		6.42	7.98	7.31	0.30
07	Cl_2	mg/L	0.02	0.90	0.43	0.12
08	Al	μg/L	8.00	146.00	41.93	22.13
09	Electricity	kWh/d	1,060.40	19,512.80	8,445.80	2,084.76
10	O_3	mg/L	0.00	0.20	0.05	0.02
11	AN PE	mg/L	0.20	0.80	0.39	0.17
12	PACl	mg/L	7.00	80.00	20.22	13.07
13	$Cl_{2(g)}$	kg/h	0.70	3.00	1.99	0.43

ΔH: Daily difference in water height in reservoir, Q: Raw water supply, T1: Raw water turbidity, pH1: Raw water pH, T2: Treated clear water turbidity, pH2: Treated clear water pH, Cl_2: Treated clear water residual chlorine, Al: Treated clear water concentration of Aluminium, Electricity: Daily consumption of WTP electricity, O_3: Residual O_3 after ozonation process, AN PE: Anionic polyelectrolyte, PACl: Poly aluminium chloride, $Cl_{2(g)}$: Chlorine gas supply

The coagulation involves many complex physical and chemical mechanisms, which are difficult to model using traditional methods. The objective of this study is to select the drinking water treatment processes, collect real operational data, build and test the ANN predicting model, including the coagulation, flocculation, sedimentation, filtration, and disinfection process. The neural approach requires very short computational times and it may depict some nonlinear relationships between system inputs and outputs (Wu G.-D., Lo S.-L., 2010).

2. Methodology and equipment

2.1. Data collection and analysis

The ANN model was developed for assisting treatment plant operators to determine real time coagulant dosage for drinking water treatment, with the water purification capacity of 110,600.00 m^3/day. The DWTP operates at 1/3 of its maximum capacity. The coagulant of drinking water treatment used in this study is poly aluminium chloride (PACl).

In order to obtain the input and target data required to develop and validate ANN model, water samples were analyzed at Aposelemis Water Quality Control Laboratory and operational data per five minutes for two years long (708 values for each of 13 parameters, total: 9 204.00 values) were collected from Aposelemis' WTP Supervisory Control and Data Acquisition (SCADA).

The evolution of the different main describers (raw water turbidity and pH) of the raw water quality with time is shown in Fig. 2.

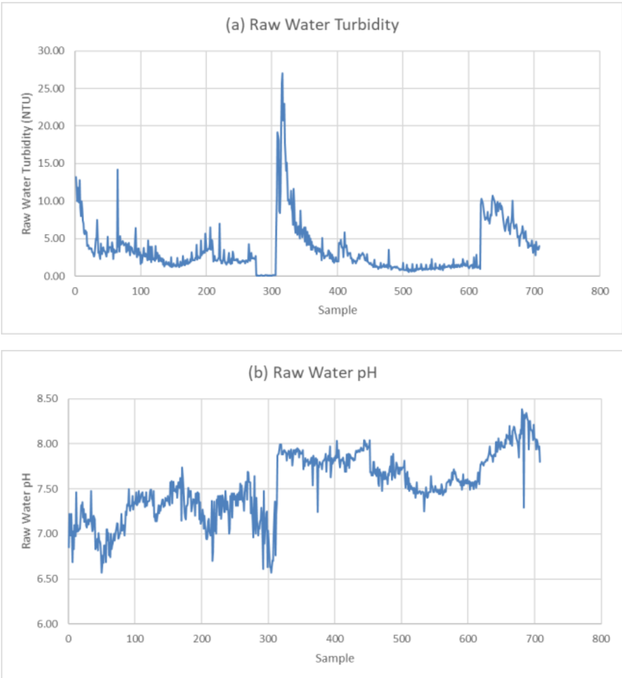

Figure 2. Raw water characteristics: (a) raw water turbidity and (b) raw water pH

In order to use the data to the ANN model, data normalization was necessary. Specifically, the input data of the ANN were scaled linearly between 0.0–1.0 by using the equation:

$$Normalized\ Data = \frac{L - Min}{Max - Min}$$

Where L is the raw value, Max is the maximum of raw value, and Min is the minimum of raw value.

The model inputs consist of operational parameters and raw and treated water quality variables and whereas the model targets are the optimal residual ozone, alum, anionic polyelectrolyte and gas chlorine dosage needed to achieve the desired treated water quality.

2.2. ANN approach

The ANN model was developed by using the Neural Fitting Tool (nftool) of MATLAB R2019a with random division of the 708 values per variable. The selected percentage division of training, validation and testing data was: 70%, 15% and 15% respectively. The 708 individual values per variable were used to design the ANN model for the prediction of the main operational parameters. 496 individual values per variable were used in training subsets, and 106 in validation and testing subsets, respectively. The training samples were presented to the network during training and the network are adjusted according to their error. Validation samples are used to measure network generalization and to stop training when generalization converges under certain criteria. Testing samples have no effects on training and so provide an independent measure of network performance during and after training.

The chosen training algorithm was the Levenberg-Marquardt Algorithm. This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The selected number of Hidden Neurons, which determines the complexity of a problem the network can solve, was 100.

3. Results

The ANN model constructed with 9 Inputs (variables No 01-09 in Table 1) and 4 Targets (variables No 10-13 in Table 1) is reflected in Figure 3 and its results in Figure 4.

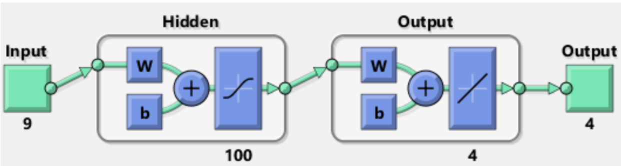

Figure 3. ANN constructed model

Results

	Samples	MSE	R
Training:	496	8.06196e-3	9.31389e-1
Validation:	106	1.18096e-2	8.88789e-1
Testing:	106	1.99117e-2	8.38714e-1

Figure 4. Results of ANN constructed model

Mean Squared Error (MSE) denotes the average squared difference between output and target values. The lower the MSE the better the performance. Zero means no error. Correlation (R) Coefficient measures the correlation between output and target values. An R value of 1 means a close relationship, 0 a random relationship.

The constructed ANN model performed well in predicting the studied main operational parameters. MSE is relatively low for all stages (Fig. 5): training, validation, testing ($8.06x10^{-3}$, $1.18x10^{-2}$ and $1.99x10^{-2}$, respectively). Regression values (Fig.6) approached 1 (R_{all}=0.91059) with the potential to improve. Error distribution is around zero and is close to normal, which indicated that there are no systematic errors in the model. Noteworthy is also the fact that the errors of validation and testing follow the same distribution as the training ones, which indicates that the model does not suffer from overtraining.

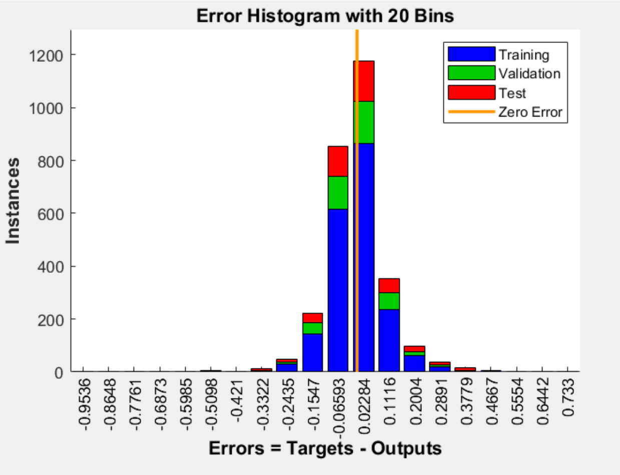

Figure 5. Error Histogram

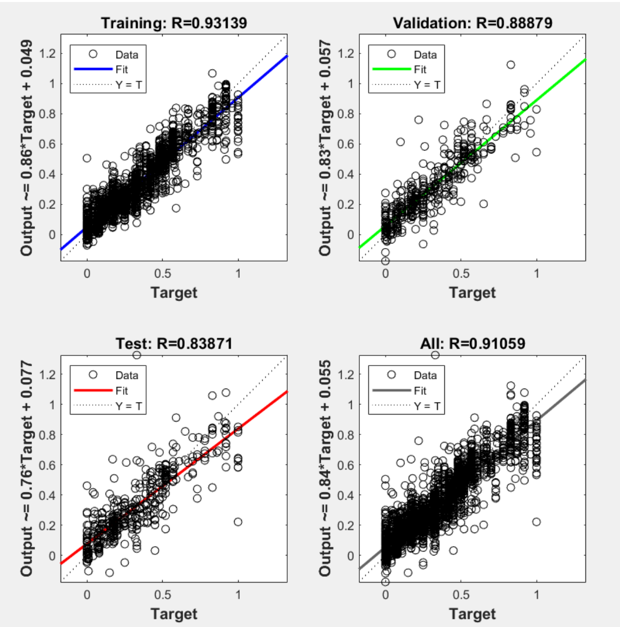

Figure 6. Correlation results

Curious to find what the absolute minimum set of necessary parameters is for an adequate simulation of the process, an attempt was made to simplify the ANN model by using a smaller number of Input parameters (5 Inputs: No 02, 03, 05, 07,08 in Table 1). This approach, as expected, yielded inferior results (shown in the Figures 7, 8 and 9), but also necessitated less input data was slightly faster.

Results

	Samples	MSE	R
Training:	496	1.96650e-2	8.23774e-1
Validation:	106	3.09977e-2	7.68884e-1
Testing:	106	2.97592e-2	7.31232e-1

Figure 7. Results of ANN constructed simplified model

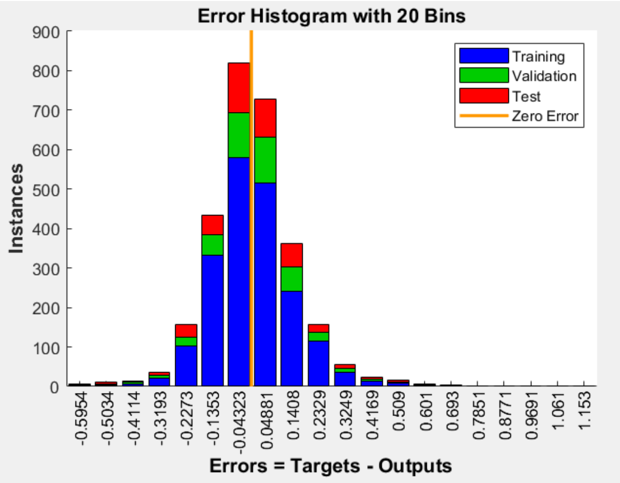

Figure 8. Error Histogram simplified model

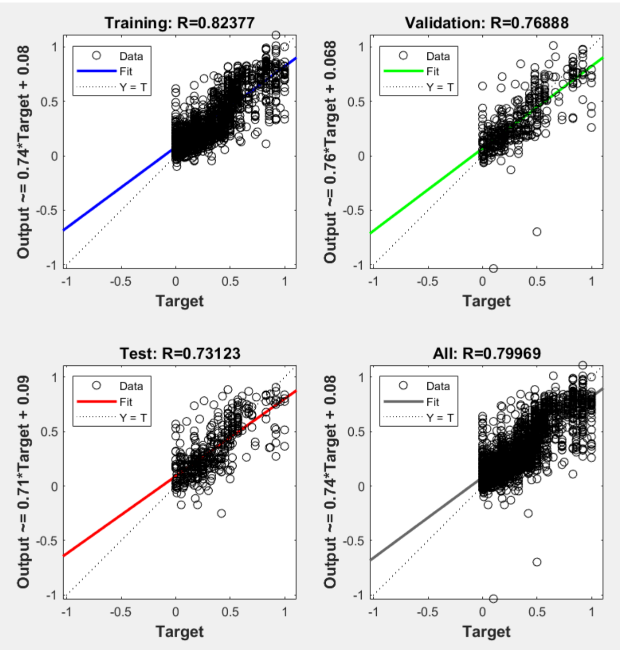

Figure 9. Regression Diagram simplified model

The MSE is relatively low for all stages of the original developed ANN model: training, validation, testing as well as for the ANN simplified model. Nevertheless, the MSE and the Correlation coefficients (R) are lower in the originally designed ANN model compared to the simplified one. Error distribution is around zero and no outliers occurred, both in the originally designed ANN model and in the simplified model. The MSE of the testing stage is the most important because it considers independent values that have not been taken into account during the training or validation stages. In the case of simplified model, the testing error increased by 49% compared to the original one, so a decision is necessary on the desired accuracy of the model, before a choice can be made between the two approaches. In the simplified approach, an outlier simulated value appeared in the validation set, which also indicates that the model did not perform as well as the original and could have started overtraining.

4. Conclusions

In a WTP, when the input data are normalized, the prediction of the main operational parameters can be attained by an ANN model in a very fast, easy and relatively reliable way.

ANN models can be very helpful for the WTP operators to predict the main operational parameters, i.e. coagulants and flocculants dosages, as well as disinfection chemicals dosages (ozone, chlorine). The greater the number of input variables in the studied ANNs model, the better the results were with regarding MSE and R. In any case, the error distribution is around zero and close to normal without extreme values for the studied ANN models. The constructed ANNs model performed well in predicting the studied main operational parameters.

Future work will be focused on greater number of tests for different input parameters and with a different number of hidden neurons.

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