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ANN-BASED SHORT-TERM WASTEWATER FLOW PREDICTION FOR BETTER WWTP CONTROL

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Abstract. This paper presents an approach to predict the amount of the wastewater which enters wastewater treatment plant, using artificial neural network. The method presented can be used to give short-term predictions of wastewater inflow-rate. The described neural network model uses a very tiny set of data commonly collected by WWTP control systems.

Keywords: neural network, wastewater load, flow prediction, WWTP control.

1. Introduction

Wastewater flow-rate is one of the most important wastewater treatment process parameters. It is always a basis for technological calculations, which are needed to control the plant. In particular, the computer systems take wastewater inflow to calculate recirculation flow-rates. Therefore, the ability to predict the hydraulic load to a treatment facility is very beneficial for optimisation of the treatment process [1, 2, 3].

This paper presents an approach to predict wastewater inflow-rate. The prediction is achieved using artificial neural network (ANN) technique.

Artificial Neural Networks (ANN) is a type of artificial intelligence technique that attempts to describe a non-linear relationship between the input and output of a complex system using historic process data. An artificial neural network is an information processing structure that consists of units called neurons. The neurons most often are organized in layers. Input signals are fed into the input layer, and they follow through hidden layers to the output layer. The number of neurons in the first (input) layer must be equal to the number of input signals. Similarly, the number of neurons in the output layer is equal to the number of output signals. Each neuron can be connected with many units in the next layer. Fig. 1 illustrates a simple ANN of perceptron type with three input units, three units in a hidden layer and one output neuron.

Multilayer perceptrons (MLPs) are feedforward neural networks commonly trained with the backpropagation algorithm [4]. They are supervised networks so they require a desired response to be trained. With one or two hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems [5]. Most neural network applications involve MLPs [6].

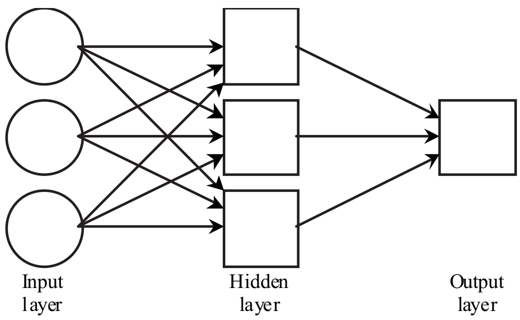

Fig. 1. A simple neural network diagram

2. Experimental

In the work described below, a few assumptions were made:

- the data used to calculate inflow-rates should be commonly accessible in every wastewater treatment plant;

- ANN type: the three layer perceptron with non-linear, sigmoid activation function.

The data were collected at one of wastewater treatment plants in Southern Poland and consist of two subsets: the first one for February and the second one for May 2001. The values were measured every 6 minutes, number of rows in tabulated data was about 14 000. To fulfil assumptions mentioned above, at first only inflow-rate and time (hours) were considered from about 240 parameters measured.

All the calculations were performed using Python script “annt”. It is a small application designed in the Environmental Biotechnology Department that can be run on every PC-class computer, both on the Windows and Unix-like platforms.

3. Results and Discussion

The aim of the calculations was to determine the future wastewater inflow-rate. Since there were too big differences between the closest measured values (data obtained were found to be a bit chaotic), it was decided to determine hourly averages instead of single flow-rates.

The prediction time horizon of two hours was chosen.

3.1. Data Set Preparation

The first task was to determine the best data set to learn the neural network. It is obvious that the actual wastewater inflow-rate depends on many factors. The decision was taken to use only two measured values: time and inflow-rate (current and past values), as described above. To obtain meaningful data sets the raw values were prepared as time-series-like rows, which are shown in Table 1.

The data set consists of 13 635 rows.

The last column in data set is a “future flow”. Since backpropagation is supervised by ANN learning method, the investigated data set must contain predicted values.

3.2. Model Analysis

Approximately 50 % of the plant records (data set rows) were used as a training data set, while 25 % were used as a validating data set and another 25 % as an additional testing set. Validating and additional testing data sets were used for evaluating the ANN performance.

The best number of neurons in the hidden layer was determined by experimentation. The three best networks with different internal structure were chosen for further analysis.

ANN training results show good generalisation capabilities for all of the networks: training and validating errors are comparable.

At the next step mean values of prediction results among all three different ANNs were calculated. Calculation results are shown in Figs. 2 and 3.

Table 1

Description of the data set

Column No.	Column	Description
1	Time	Time – hour of the day
2	Flow	Current wastewater inflow-rate
3	Flow (average) 1	Past wastewater inflow-rate – mean value for 10 past measures (up to one hour in the past)
4	Flow (average 2)	Past wastewater inflow-rate – mean value for 10 past measures from 11 to 20 (from one to two hours in the past)
5	Flow (average 3)	As described above, from two to three hours in the past
6–26	Flow (average 4-24)	As described above, averages for consecutive hours
27	Future flow	This value is to be predicted. Average value of 10 future inflow-rates, starting sixty minutes ahead and ending after sixty consecutive minutes

Table 2

Three best ANNs. The number of units in the input layer was always 26 (26 input values); output unit number was 1 (one output value)

Network No.	Number of units in hidden layer	Training data set error	Validating data set error	Testing (additional) data set error
1	44	326	351	346
2	25	385	399	392
3	11	298	323	317

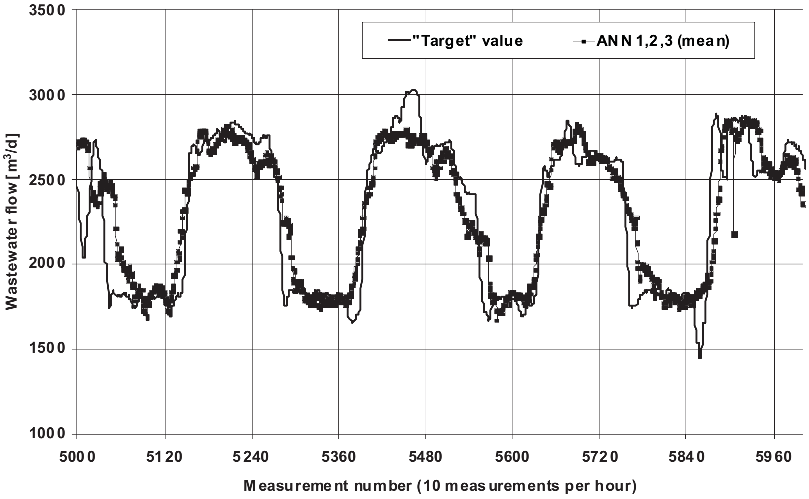

Fig. 2. Calculation results example. "Target" value *vs*. average value of three predictions. Wastewater inflow-rates collected in February 2001

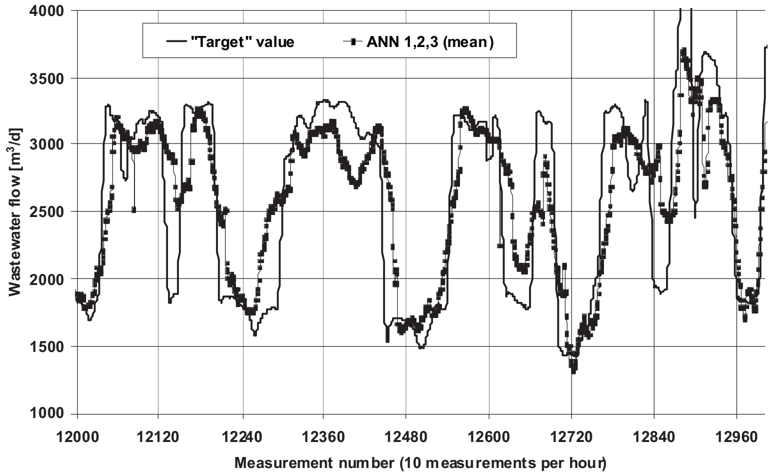

Fig. 3. Calculation results example. "Target" value *vs*. average value of three predictions. Wastewater inflow-rates collected in May 2001

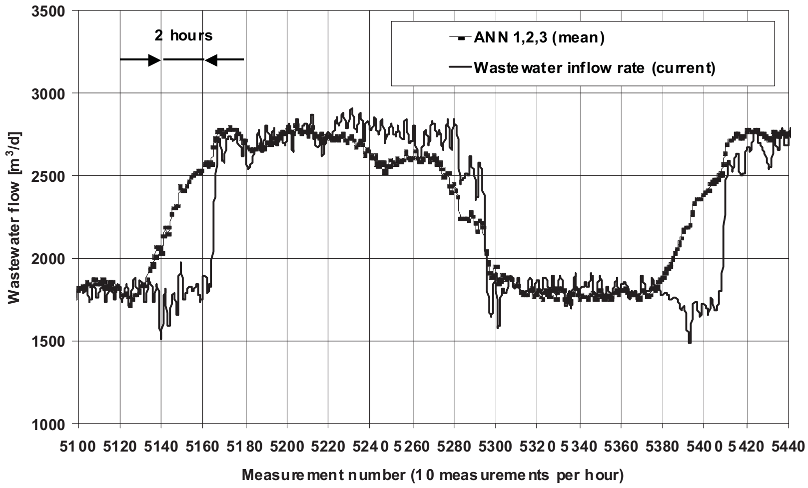

Fig. 4. Current wastewater inflow-rate and computed average value of 10 **future** inflow-rates, starting sixty minutes ahead and ending after sixty consecutive minutes. Wastewater inflow-rates collected in May 2001

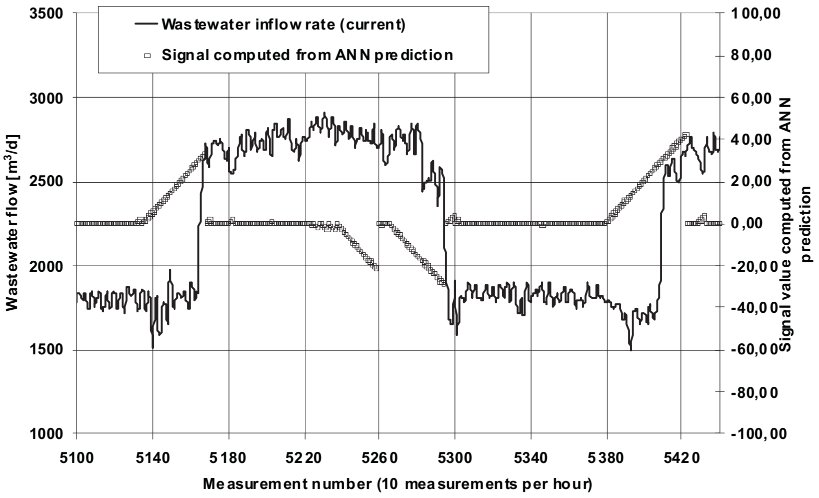

Fig. 5. Wastewater inflow-rate and "signal" value computed from the ANN prediction. Wastewater inflow-rates collected in May 2001

The aim of this work was to predict future wastewater inflow-rate for better wastewater treatment plant control. As described above, prediction time horizon of two hours was chosen. Fig. 4 shows the actual wastewater inflow-rate and computed future inflow values.

In order to utilize the ANN prediction it may be also useful to recalculate computed values. An example simple algorithm is described below.

For $|P_i - Q_i| > T$: $S_i = \mathrm{sgn}(P_i - Q_i) + S_{i-1}$

For $|P_i - Q_i| \le T$: $S_i = 0$

where: i is measurement number; P is the ANN prediction (m^3/h); Q is a current wastewater inflow-rate (m^3/h); S is computed "Signal" and T is a threshold value (m^3/h).

Fig. 5 shows the wastewater inflow-rate and computed "signal" values for threshold value = 100 m^3/h.

4. Conclusions

A model that can predict the amount of wastewater flow would be beneficial for WWTP operation. The method presented in this paper can be used to give predictions of wastewater inflow-rate. The described neural network model uses data commonly collected in WWTP control systems. Since actual wastewater inflow value depends on many factors, introducing more of them should increase prediction accuracy.

While it seems to be achievable to use computed values directly, it is possible to recalculate them into an abstract signal. The signal can be consecutively sent to WWTP control system and interpreted as a virtual sensor signal.

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КОРОТКОТЕРМІНОВИЙ ПРОГНОЗ НА ОСНОВІ ШТУЧНОЇ НЕЙРОННОЇ МЕРЕЖІ ДЛЯ WWTP КОНТРОЛЮ ЗА СТІЧНИМИ ВОДАМИ

Анотація. *В роботі розглянуто підхід до прогнозування кількості стічних вод, що надходять на перероблення з використанням штучної нейронної мережі. Запропонований метод може знайти використання для короткотермінового прогнозу швидкості притоку. Показано, що вказана нейронна мережа потребує невеликої кількості даних, зазвичай зібраних WWTP контрольною системою.*

Ключові слова*: нейронна мережа, завантаження стічних вод, WWTP контроль.*