1. Чабан В, Ковівчак Я, Гущак Р. Симуляція електромагнетного поля рухомих зубчастих структур. – Preceedings of The 1-st International modelling school, Krym'96, Rzeszow, 1996, pp. 121-123.
2. Чабан В.Й., Гущак Р.І. Комп'ютація електромагнетного поля зубчастих структур // Вісник Держ. ун-ту "Львівська політехніка". – 1997. – С. 134 – 136.
3. V. Tchaban, Y. Kovivchak, O. Tchaban, A. Tymoshyk. 2D-Field Mathematical Model of Turbogenerator. - Proceeding of MS'2002. International Conference on Modelling and Simulation in Technical and Social Sciences, Girona, Catalonia, Spain, 25-27 June 2002, pp. 663-668.

T. Kwater, Z. Kedzior
University of Rzeszow, Ul. Rejtana 16c, 35-959 Rzeszow, Poland

ARTIFICIAL NEURAL NETWORK IN STATE ESTIMATION FOR CONTROLLING OF POLLUTION IN WATER

Introduction

Control of water pollution caused by excessive discharge of industrial and municipal influence into river streams is very important issue in recent years [6]. In recent years, the pollution levels in many rivers have become severe enough that oxygen levels have fallen below minimum needed for survival of fish and other aquatic live. Simple action as supplying oxygen directly into a river using pipe line diffusers and mechanical aerators can prevent ecological disaster [4]. In present time, when computer science reach higher level of development, artificial neural networks become natural instruments to assist in proper society function [2, 5]. Other authors consider river as a cascade of short sections of the river with lumped parameters [4]. Such interpretation is wrong because don't take the river length into consideration and required large number of such sections. For long river time of water flow is essential and taking it into consideration lead to delay time in model. Thus such mathematical model is more difficult and uncomfortably in use. Different approach proposed in that article allows to consider ordinary differential equations instead of partial differential equations [3]. It decreases the difficulty level of considerations and allows to keep nature of processes proceed in river.

Mathematical model of polluted river

The river can be described by first order hyperbolic equations of transportation type in biochemical pollution modelling using only Biochemical Oxygen Demand (BOD) and Dissolved Oxygen (DO) indicators [3]. After linearisation and normalisation of space variable, model of the i-th section takes form:

$$\frac{\partial x_i(t,z)}{\partial t} + \Lambda_i(z)\frac{\partial x_i(t,z)}{\partial z} = A_i(z)x_i(t,z) + B_i(t,z)w_{di}(t,z), \quad (1)$$

where: $x_i(t, z)$ = col[BOD, deficit of DO] - state, $w_{di}(t,z)$ - distributed noise, $\Lambda_i(z) = \begin{bmatrix} \lambda_i(z) & 0 \\ 0 & \lambda_i(z) \end{bmatrix}$ – matrix of water speed; $A_i(z) = \begin{bmatrix} -k_1(z) & 0 \\ -k_2(z) & -k_3(z) \end{bmatrix}$ – matrix of state; $B_i(t,z) = \begin{bmatrix} b_i(t,z) & 0 \\ 0 & b_i(t,z) \end{bmatrix}$ – matrix of distributed noises, with boundary conditions

$$x_i(t,0) = M_i x_{i-1}(t,1) + w_{bi}(t) + R_{bi}u_{bi}(t); \qquad x_i(t_o, z) = x_{0i}(z),$$

where: w_{bi}, u_{bi} - respectively signals of boundary noise and control;

$$M_i = \begin{bmatrix} m_i & 0 \\ 0 & m_i \end{bmatrix} \text{ – boundary matrix of state; } R_{bi} = \begin{bmatrix} 0 \\ r_{bi} \end{bmatrix} \text{ – matrix of controls.}$$

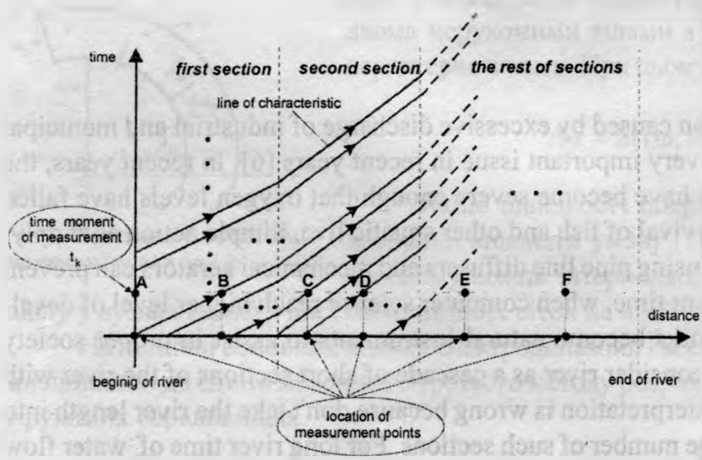

Fig. 1. The characteristics covering whole space of river

Object described by first order partial differential equations can be substituted by set of ordinary differential equations with discrete measurements in the time domain. It is possible with different object interpretation then up to now. The main idea of such approach is consideration of the process along lines connected to moving speed of coordinates of state vector in sub objects. It responds especially to object such river. Equations (1) in space $z \in [0, 1]$ and $t \in [t_0, t_k]$, $t_k < \infty$ along that line, called characteristics, become ordinary differential equations. Continuous in time measurement equation becomes discrete:

$$y_i(t_k) = C_i x_i(t_k) + v_{pi}(t_k), \quad (2)$$

where: v_{pi} - noise of measurement, C_i = [0 1] – matrix of measurements

It is the results of measurement of state, which is moving along chosen characteristic, by stationary detectors in sub object. Such interpretation brings description of object to consideration of large number of characteristics, which cover whole considered space of river (Fig. 1). In the moment tk we received measurements described by equation (2) in points $A, B, C, \ldots$. That points are located along whole river.

State of polluted river described by differential equation of transportation type, while considering function along characteristics, can be described by infinity number of ordinary differential equation. Thus measurements for each characteristic have to been coordinated. In such case measurements become discrete in time. Whereas equations of state are ordinary differential equations, which are continuous. State and measurement equations for one characteristic are given below

$$\frac{d}{dt}x_i(t) = A_i x_i(t) + w_{di}(t), \tag{3}$$

with starting conditions

$$x_i(t_0) = x_0,$$

and measurements described by equation (2).

State estimation for controlling and monitoring

As it was mention earlier we have infinity number of such characteristics, hence the necessity of continuous realisation of estimation process. The estimation process can be divided into two phases: filtration and predic-tion. In filtration phase on the basis of values of estimates from the previous moment t_{k+1} and considering current measurements in moment tk values of state estimates in measurements points for present measurement moment tk are counted. If time spaces between following measurements, it est. t_k and t_{k+1}, are relatively small then the filtra-tion process for long time can be treated as quasi-continuous. In that case quality of estimation near to ideal is expected. With regard to specific of river, big length and relatively small dynamic (time is measured in days), realization in practice of continuous estimation process using approach along characteristics is difficult. Such realization required large quantity of measurement stations located along the river and connected by telephone net. Decreasing quantity of measurement station to the level that guarantee satisfactory quality of estimation seems to be the compromise solution. In order to get information about river state between measurements moments the forecast process based on knowledge of dynamic of processes proceed in river, called prediction, is applied. In prediction phase state estimate up to the next measurement moment, it est. for $t \in (t_0, t_{k+1})$, are calculated. Estimates obtained from filtration are taken as starting values for prediction.

Neural Networks

It is necessary to know characteristics of signals (expressed in above formulas as covariance), which influence on object. In practise it is difficult to estimate. For practical realization above idea of connecting filtration and prediction artificial neural network can be used. We can expect that well worked out artificial neural network allows avoid difficulties of classical filtration approach. The design of two separate artificial neural networks realizing both phases of estimation gave satisfactory results.The two separate artificial neural networks that realize filtration and prediction in system with feedback were proposed for estimation of river state.

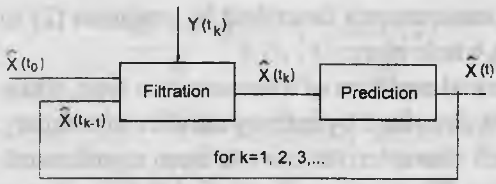

Fig. 2. The estimation system of river state

In order to choose optimal neural network structure, i.e. determine number of hidden layers, quantity of neurons in each layer, transfer functions, learning methods, series of experiments were carried out. The investigations were performed for net with one hidden layer, which contain five neurons with signum transfer function. Increasing number of neurons in hidden layer don't causes considerable improvement of generated estimates. Artificial neural network learning process was performed based on data obtained for mathematical model simulations. The length of learning vector had considerably influence on network work quality. To short learning vector caused that answers generated by neural network were burden with big error. The worsening of ability to generalization take effect as well, what is especially important feature. Whereas excessively lengthening of learning vector did not lead to improvement of estimation quality.

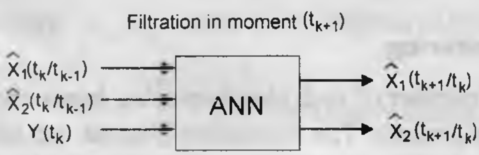

Fig. 3. Artificial neural network realizing filtration phase

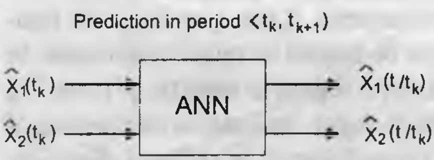

Fig. 4. Artificial neural network realizing prediction phase

Character changes of river state in learning vector had also considerably influence on network work quality. Network learned for small changes generated bigger errors when estimated river with big changes of state. Hence learning data should be possible close to values, which can appear in the real object. We can decide for what range of BOD and DO values neural network should has highest efficiency. In examinations influence of different numbers neurons in hidden layer were considered. From results come out that five neurons in hidden layer is enough.

Finally for realization of filtration phase artificial neural network structure consist of three layers: input with three neurones, hidden with five neurones with signum transfer function and output layer with two neurones were chosen. The learning process was carried out using back propagation method with SSE = 0.001. The learning data vector were obtained from simulation of mathematical model with noise range 0.5 – 10.0 % and starting values for BOD in range 5 – 20 [mg/l], for DO – 10 - -1 [mg/l].

After series of experiments, like for filtration, the following three layers artificial neural network to realize prediction were chosen: input layer with two neurones, four neurones withy signum transfer function in hidden layer and two in output. The learning process was carried out using back propagation method with SSE= 0.00001. The learning data vector were obtained from simulation of mathematical model with noise range 0.5 – 10.0 % and starting values for BOD in range 5 – 20 [mg/l], for DO – 10 - -1 [mg/l].

Coordination algorithm

Each characteristic describes state of specified water portion, which moves freely along the river. This portion of water passes way from beginning to the end of observed river in definite time. In our case it is 30 days. In order to determine state of river pollution coordination of infinity number of characteristics is necessary. In practise it is finite number of such characteristics. The below algorithm was applied to realize coordination task.

The state of polluted river estimation system can start with zero information, i.e. don't need to known the state of river in start of estimation time. System starts working when measurements from specified measurements station located along the river are supplied. On the basis of these measurements in first phase, i.e. filtration phase, state estimations in measurement time for given measurement points are calculated. Calculated values are presumed as a starting data for second phase, i.e. prediction phase, in which state estimates to next measurement moment are counted (1, 2 days). In that phase we obtain estimates of state with time overtake between measurements. In moment of next measurement procedure of estimate counting backs to the first filtration phase, where correction to estimates obtained from prediction are introduced. Then computations of prediction phase are carried out. Procedure repeats itself when next set of measurements appears.

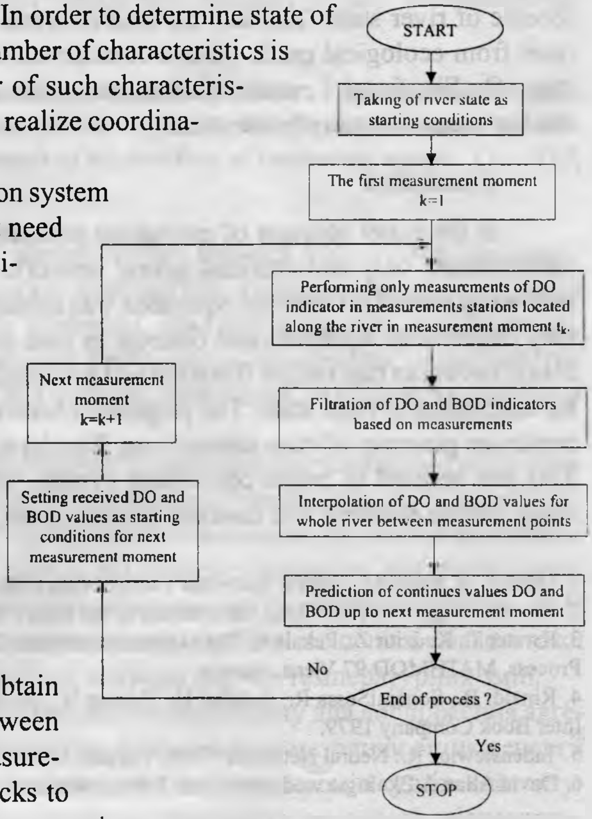

Fig. 5. The coordination algorithm

This algorithm allows to determine actual estimation of river pollution state on basis only DO indicator measurement. Measurements are realized every second day. Number of located measurement stations decided about discrete time between measurement moments (frequency of measurements). One of the feature of such estimation system is ability to

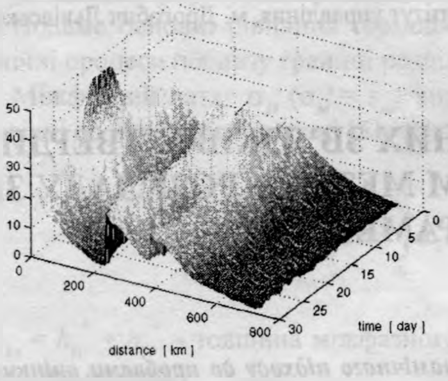

Fig. 6. Distribution of BOD in river

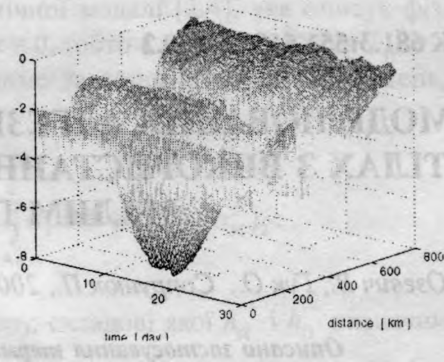

Fig. 7. Distribution of DO in river

foresee of river state. This can be used to create controlling system, which could protect river from ecological crash. Above considerations concern case when river speed is constant. On Fig. 6 and 7 results of algorithm work are presented. The marked line represents the one characteristic of river state.

Conclusion

In the paper solution of estimation problem for pollution river based on deficit DO measurement only and artificial neural networks was proposed. Mathematical model described by partial differential equations was substitute by model with large number of ordinary differential equations and discrete in time measurements. The two separate artificial neural networks that realize filtration and prediction in system with feedback were proposed for estimation of river state. The proposed characteristics coordination algorithm allows to continues generate of state estimations. Results of numerical experiments are satisfactory. This can be used to create controlling system, which could protect river from ecological crash. Future research will concern that problems.

1. Demuth H, Beale M.: Neural Networks Toolbox User's Guide The Math Works Inc.
2. Hertz J, Krogh A, Palme G.R.: Introduction to the theory of neural computation, Massachusetts, 1991.
3. Kwater T., Kedzior Z., Pekala R. The Matematical Model Of Long River And Neural Network In Estymation Process. MATHMOD 97 Viena, Austria.
4. Rinaldi B., SonciniSessa R., Stehfest H., Tamura H.: Modeling and control of river quality Mc Graw-Hill Inter Book Company 1979.
5. Tadeusiewicz R.: Neural Networks PWN: Warsaw, 1993.
6. David Allan J. Ekologia wod plynacych PWN, Warszawa, 1998

В. Юзевич, О. Гук*, П. Сопрунюк
Фізико-механічний інститут ім. Г. В. Карпенка НАНУ,
* Інститут управління, м. Дрогобич Львівської обл.

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МОДЕЛЮВАННЯ АДГЕЗІЙНИХ ЗВ'ЯЗКІВ У ТВЕРДИХ ТІЛАХ З ВИКОРИСТАННЯМ МЕТОДУ РОЗКЛАДУ ЗА МАЛИМ ПАРАМЕТРОМ

Описано застосування термодинамічного підходу до проблеми оцінки кількісних характеристик адгезійних зв'язків у твердих тілах системи адгезив – суб-